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Foreword

The International Brain-Computer Interface (BCI) Meeting Series occupies a unique place among conferences for BCI research by bringing together researchers and stakeholders from diverse disciplines. Neurologists, computer scientists, rehabilitation engineers, physicians, sensor engineers, psychologists, speech-language pathologists, ethicists, and actual BCI users are all active participants in the BCI Meeting Series. Further, the inclusive, retreat-like atmosphere of the BCI Meeting Series provides extensive opportunities for interaction and development of collaborations. The impact of the BCI Meetings Series is demonstrated by the high percentage of citations received by papers from attendees. Of the 499 articles published in 2011 and listed in Web of Science with a topic of “brain-computer interface” or “brain-machine interface,” 28 (5.6%) were part of the special issue resulting from the last meeting. However, citations of the articles in the special issue represent 15.7% of the 776 citations of the BCI papers published in 2011.

The Fifth International BCI Meeting represents the graduation of the BCI Meeting Series to joint organization by a Steering Committee of prominent BCI researchers from around the world. The diversity of BCI research represented in this planning process has resulted in a vibrant, exciting Meeting with increased involvement from the many sectors that make up BCI research.

The papers in these Proceedings show the increasing focus on the future of BCI research and the importance of translational issues to make BCIs practical for people who need them. These papers describe:

- Technical and protocol innovations to enable successful BCI use by people with the most severe motor impairments.
- The importance, flexibility, and advantages of different types of input signals for BCI research.
- Innovative new applications for BCI use by people with and without impairments.
- The interpretation of signals associated with movement, grip, and recognition of errors.
- Appropriate evaluation of BCI performance to understand and improve BCI usefulness.
- Therapeutic effects of BCIs to not only accommodate for impaired function, but facilitate healing.

Together, this BCI Meeting and its Proceedings represent the breadth of BCI research and help us to define the future of BCIs as successful, beneficial tools.

On behalf of the BCI Meeting Steering Committee, I thank you for your interest in the BCI Meeting and hope to see you at this and future installments in the BCI Meeting Series.

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An Improved Auditory Streaming BCI with Voice Stimuli

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Abstract. We have previously shown that it is possible to build EEG brain-computer systems based on voluntary shifts of covert attention between simultaneous streams of auditory stimuli. The system exploits not only the later event-related potential components (P3) which are strongest in response to rare "oddball" stimuli, but also the early (N1 or Nd) components that are attention-modulated on every stimulus occurrence. So far, however, such systems have been based on abrupt artificial stimuli (short discrete beeps or pulses). This creates two problems. First, many subjects find the stimuli annoying, intrusive or otherwise unpleasant. Second, the abstract nature of the stimuli makes the system unintuitive to many users. We would like to build a system in which the stimuli are natural and also semantically indicative of the purpose of the corresponding interface selection. This greatly simplifies the instructions for the users: when they want to say "yes" using the BCI, they must listen to a voice repeating the word "yes", and when they want to say "no", they listen to a voice repeating the word "no". Encouraged by recent findings that natural stimuli can improve auditory BCI performance, we set out to assess, in a within-subject design, whether these new voice stimuli or the beep stimuli of previous studies allow better performance in an 8-channel EEG-based BCI. Despite increased between-subject variability in the ERPs, we find no significant penalty (in fact, a non-significant advantage) for the voice stimuli (mean ± std online performance 76% ± 11) in comparison with the beep stimuli (73% ± 11). We also show, for the first time, that the system can be used on a subsequent day without retraining the classifier. However, without applying transfer learning methods to the problem, this entails a large, significant drop in classification performance (7–10 percentage points on average).

Keywords: EEG, auditory ERPs, attention, auditory streaming BCI, N100, P300, dichotic listening, natural stimuli

1. Introduction

Our previous work [Hill and Schölkopf, 2012; Hill et al., 2012] has shown that binary EEG BCIs can be driven purely by attention to auditory stimuli, which we believe will be an advantage for severely paralyzed users for whom spatial vision is often poor. Höhne et al. [2012] found that natural stimuli (albeit still standardized, semantically empty syllables) can drive an auditory BCI better than artificial stimuli. Encouraged by this, we wished to know whether it was possible, without loss of performance, to adapt our auditory streaming BCI system to use spoken words instead of harsh, meaningless beeps. The beeps' lack of inherent meaning has previously made it difficult to explain the use of the BCI to beginning users, so we wanted to move to stimuli that naturally reflect the options being chosen (spoken words "yes" and "no"). To assess the impact of this change, we ran a laboratory experiment to compare a Beeps condition with a Words condition in a within-subject design. In the same experiment, we also wished to assess, for the first time, the impact of session-to-session transfer on auditory BCI performance.

2. Material and Methods

14 healthy subjects took part in the experiment (7 male, 7 female, ages 22–67, or 39 ± 17.8). Each subject attended for 2 sessions on separate days. With a reference electrode at the right mastoid (TP10) and a ground electrode at the left mastoid (TP9) we recorded EEG from 8 channels of the extended international 10-20 system (F3, F4, T7, C3, Cz, C4, T8, and Pz) using a g.USBamp (g.tec, Graz, Austria) sampling and digitizing at 256 Hz. Signal acquisition, processing and stimulus presentation were implemented using BCI2000 and BCPy2000.

Each session began with a 5-minute pre-recorded audio introduction explaining the experiment. It then consisted of 12 runs: 3 of one condition, 3 of the other condition, 3 more of the first condition, and 3 more of the second. Half the subjects performed the Beeps condition first and the Words condition second; the other half performed the conditions in the opposite order. Each run consisted of 20 trials. Each trial lasted around 15 s in total (including a few seconds' rest) and consisted of an attempt to listen to only the stimuli in the left earphone (to select "no") or only the stimuli in the right earphone (to say "yes"). In the Words condition, the left stream consisted of a synthesized male voice saying *"no"* seven times at a rate of 2 per second. Randomly on each trial, 1, 2 or 3 out of the last 5 *"no"* stimuli were instead target stimuli in which the voice said *"nope"*. The right stream began 250 ms later than the left stream but also consisted of 7 stimuli at a repetition frequency of 2 per second (so the streams were in constant anti-phase). It was a synthesized female voice saying *"yes"* with 1, 2 or 3 target stimuli (*"yep"*). A third synthesized voice gave a spoken instruction at the beginning of each trial: either "*Listen to 'yes' and count the number of 'yep',"* or "*Listen to 'no' and count the number of 'nope'."* At the end of each trial the voice gave feedback: "*The correct answer was {one|two|three}."* No overt response was required from the subject. In the Beeps condition, the standard stimuli were 150-ms beeps at 512 Hz (left) or 768 Hz (right), and the target beeps were amplitude-modulated versions of the standards: the stimuli were thus identical to those of Experiment II of [Hill et al., 2012]. The synthesized vocal cue on each trial was *"Listen to <LATERALIZED BEEP> to say {yes|no}"*.

The signal-processing methods were identical to those of [Hill et al., 2012]. Separate subject-specific classifiers were maintained for Beeps and for Words. In the first session, the classifier was re-trained after every new run of 20 trials. In the second session, the final classifier weights from the first session were used and kept fixed. After each trial and before the voice feedback, the subject heard a bell ring if the trial had been classified correctly online.

3. Results

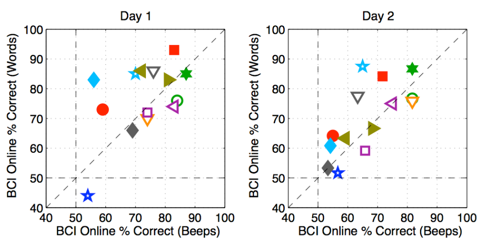

Figure 1. *The left panel shows the results from each subject's first session, and the right shows the results from each subject's second session, when transferred classifier weights were used. Each different symbol shape/color represents 100 online trials from a different subject. The online BCI system's % correct in the Words condition is plotted against its % correct in the Beeps condition. One subject (dark blue star) had to be repeatedly woken up, and performed near chance on both days.*

Fig. 1 shows the results of the within-subject comparison of Words vs Beeps. Words narrowly beat Beeps on day 1 (76.9% ± 11.1 vs. 73.0% ± 10.6) and also on day 2 (70.18% ± 11.9 vs. 66.6% ± 10.4). Neither of these gains was significant at the 5% level in a Wilcoxon signed rank test.

Whether a subject performs better in Words or Beeps depends on the individual. We note, however, that when subjects prefer Words, the preference is often large (for example, on day 1, it is 13.1 percentage points ± 7.5 across 7 subjects) whereas a preference for Beeps tends to be smaller (5.4 pp ± 3.5 across the other 7 subjects).

With 100 trials and Bonferroni correction for 56 simultaneous comparisons, under the null hypothesis that results are binomially distributed with generating probability 0.5, performance must be > 66% to be significantly above chance at the $\alpha = 0.05$ level. On their first day, two subjects (one awake, one asleep) failed to exceed this level with Words; with Beeps, 3 subjects failed. The transfer of weights from day 1 to day 2 caused a 6.7 percentage-point drop in Words' performance on average (Wilcoxon signed rank: $p = 0.005$) and a 6.4 point drop in Beeps' performance ($p = 0.048$). Now 6 subjects fail to reach the threshold with Words, and 8 fail with Beeps.

4. Discussion and Summary

Our results show that an online binary auditory-streaming BCI can be built with as few as 8 EEG channels, and use single trials in which the critical EEG segment is less than 4.5 s long, and still achieve 77% correct on average (93% for the best subject). We also find that there is no significant disadvantage, but rather some non-significant tendency towards improved performance, in switching to more-intuitive natural stimuli (voices saying "yes" and "no" instead of abstract, unpleasant beeps). Finally, we show that there is a large and significant loss of performance when classifier weights are transferred from session to session.

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Limitations of NIRS-Based BCI for Realistic Applications in Human-Computer Interaction

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Abstract. Recent work in human-computer interaction (HCI) has endorsed NIRS-based BCI as suitable for use as a realtime input modality in *realistic* interaction settings. However, several discrepancies between the state-of-the-art NIRS signal processing and the purported applications in HCI suggest otherwise. To investigate such discrepancies and their effects on signal reliability, we conducted a large-scale evaluation of three factors – (1) unrestricted subject movement, (2) variable task duration, and (3) realtime signal processing – factors central to realistic settings. Our findings show high signal unreliability with NIRS-based BCI subject to these three factors, suggesting NIRS-based systems are premature for realistic applications in HCI.

Keywords: Human-Computer Interaction, NIRS

1. Introduction

Within the HCI community, NIRS-based BCI has gained much attention due to recent demonstrations of its use as a passive interaction modality to improve user performance [Solovey et al., 2012]. This work argues NIRS-based systems are better suited for realistic settings (in comparison to other neuroimaging techniques), reporting NIRS as being cheaper, more portable, and more robust to noise. However, state-of-the-art neuroimaging delineates these features still problematic for the use of NIRS-based systems (as well as other techniques) in realistic settings. Such issues (in addition to numerous physical limitations such as portability, ambient lighting, and probe placement) include a multitude of signal processing challenges, importantly: (1) motion artifact detection and removal, (2) separation of task-related and unrelated activation beyond standard 20–60 s task durations, and (3) realtime/single-trial classification. In this paper, we present an investigation of these three key challenges and their implications for realistic NIRS-based applications in HCI. Although our results show high unreliability of the NIRS-based systems and signal processing used currently in HCI, we hope the construction of a such a large, publicly available data set will facilitate steps towards more realistic and more reliable applications.

2. Material and Methods

We conducted a 3-part, 40-subject investigation to address how (1) unrestricted motion, (2) variable task duration, and (3) realtime/single-trial constraints affect signal reliability. These factors were selected for their importance in realistic HCI applications. Current NIRS-based BCI require participants to minimize movement (e.g. using a chin rest); however, standard HCI investigations do not obstruct participant movement. Furthermore, standard HCI tasks can range from 30 s to 30 min in duration, whereas standard BCI tasks range from 20 s to 60 s and it remains to be demonstrated that NIRS-based BCI can be employed in longer tasks. Finally, as passive NIRS-based BCIs are intended to operate in realtime to improve user performance, single-trial processing must be reliable. Based on the primary region of interest to HCI, we sampled only the anterior prefrontal cortex (aPFC).

2.1. Equipment and Analysis

A 2-probe, ISS OxiplexTS[1] tissue oximeter was used to record changes in hemoglobin at 3cm depth in the subject's aPFC at a temporal resolution of 6.25 Hz. We applied three serial centered moving averages to reduce the effects of systemic artifacts (cardiac pulsation, respiration, and Mayer waves) followed by a folding average over trial repetitions, based on [Fekete et al., 2011; Sassaroli et al., 2009; Solovey et al., 2012]. To restricted motion (RM), the subject was seated in the Caravan Zero Gravity chair[2] and was instructed not to move. In the unrestricted setup (UM), the subject was seated in a generic office chair and told he/she may sit comfortably.

[1]http://www.iss.com/biomedical/instruments/oxiplexTS.html
[2]http://www.amazon.com/gp/product/B0032UY0BK/ref

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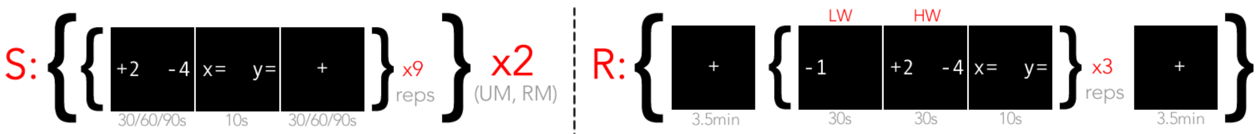

Figure 1: Experimental design. Standard block design (S, left) and realtime/single-trial trial design (R, right).

2.2. Participants and Procedure

40 subjects (18 male), ages 18–45, were recruited via a university website. This study was approved by the Tufts IRB and all participants provided informed, written consent. Based on [Sassaroli et al., 2009], we induced aPFC activation using a simple arithmetic task (see Fig. 1). A standard trial consisted of a task period (30, 60 or 90 s) in which new arithmetic operations (addition or subtraction) were shown every 5 s, followed by an answer period (10 s), and then a rest period (of duration equal to the task period). In each trial, the subject was tasked to remember the starting values and the running sums of two variables.

Following an initial 5-minute baseline measurement, two experimental conditions (standard block design (S), and realistic continuous-task design (R), were administered in a randomized order (see Fig. 1). The standard condition was performed twice, once with restricted motion (RM) and once with unrestricted motion (UM), to test the effects of the latter on signal reliability. To investigate the effects of variable task duration, the participant completed three standard trials of each 30, 60, and 90 s task durations for a total of 9 trials (see Fig. 1, left). To evaluate continuous/realtime processing constraints (R), we adapted the trial described above to create a two-workload variant (see Fig. 1, right). Here, the task period consisted of a low-workload task (LW, *maintaining only one variable*), followed by a high-workload task (HW, *two variables*), followed by an answer period but *no interim rest period* (to emulate the two-workload, realtime task used in [Solovey et al., 2012]). This realtime trial was repeated three times in serial, between two rest periods (pre- and post-task).

3. Results and Discussion

Average task performance was 35.7 % (SD 24.5 %) correct answers, with an average response rate of 98.6 % (SD 4.7 %), indicating the arithmetic task used was difficult but that subjects were attentive. To confirm a task-evoked hemodynamic response, we averaged the first 30 s of all standard RM trials and compared it to baseline activity, finding significant differences (for 38/40 subjects. Thus we concluded the task elicited a significant hemodynamic response in the aPFC, as designed.

Regarding the two experimental conditions (S and R), we found the following: (1) Unrestricted motion significantly affects signal reliability: UM x RM was significantly different for 38/40 subjects for each time variation (30, 60, and 90 s). (2) Signal reliability degrades over time: in the standard 30 s restricted setup (RM, 30 s), the task signal was significantly different from rest. However, this was not the case for the longer trial durations (60 and 90 s; $p > 0.36$). (3) Realtime constraints severely reduces signal reliability. Single-trial analysis of the realtime (R) condition showed significant differences between repetitions of the same workload trials (e.g. LW_1 x LW_2 x LW_3) for 36/40 subjects. Furthermore, at no point during the 3.5 minute post-task rest period did the signal become non-significantly different from pre-task rest for 37/40 subjects. This implies detecting the switch from an active task to no task is not feasible (at least not within a 3.5 minute period), which more importantly, suggests low signal resolution.

The implications of our findings with regards to current NIRS-based BCI applications in HCI targeting the aPFC are the following: (1) motion should be restricted until further advancements in signal processing; (2) task durations should be restricted to the standard 20–60 s range or otherwise explicitly demonstrated for a given task that it is reliably classified for a longer duration; and (3) passive NIRS-based BCI is premature for any aPFC-based tasks. While such issues have been raised and discussed for fMRI and EEG techniques, until now they have not been sufficiently discussed in regards to NIRS. However, we hope that by making such a dataset publicly available, we can further investigate and address the challenges limiting its applications in HCI.

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An Online SSVEP-Based Brain-Computer Interface for Freely Moving Humans

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Abstract. Most of current brain-computer interfaces (BCI) require users remain stationary during recordings because of the perceived difficulty of separating brain EEG data from non-brain artifacts. This study tests the feasibility of bridging an online steady-state visual-evoked potential (SSVEP)-based BCI to a low-cost consumer electroencephalogram (EEG) headset for freely-moving humans. This practice considerably facilitates real-life BCI applications using a mobile and non-tethered EEG system for humans actively behaving in and interacting with their environments.

Keywords: EEG, Low-cost Headset , SSVEP, BCI, Moving Humans

1. Introduction

Steady-state visual-evoked potential (SSVEP)-based brain-computer interface (BCI) has become a promising and direct channel allowing users to communicate with the environment due to its ease of use, minimal user training , large number of commands and high information transfer rate (ITR) [Wang et al., 2006; Müller-Putz et al., 2008; Bin et al., 2009]. SSVEP has also been used in clinical research and evaluation. For example, [Golla and Winter, 1959] first reported distinct electroencephalogram (EEG) in response to photic stimulation between migraine patients and normal. SSVEP might thus be used to predict migraine attacks. However, this BCI application requires continuous monitoring and evaluation of SSVEP of migraineurs in their natural head/body positions and movements. A natural next step is to translate laboratory-derived neuroscience concepts to performance in more real-world environments. Only few studies [Debener et al., 2012; Lin et al., 2013] have explored the feasibility of conducting BCI-related EEG tasks in natural movements, e.g. walking or running. This study extended our recent work [Lin et al., 2013] to construct an online SSVEP-based BCI based on a low-cost mobile EEG headset for freely moving humans.

2. Material and Methods

This study employed a 14-channel wireless EEG headset (Emotiv Systems Inc.) that sampled and filtered EEG signals at 128 Hz and within a band of 0.2-45 Hz, respectively. The electrodes are positioned at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. Three participants walked on a treadmill at speeds of 0, 2 and 4 mile (s) per hour (MPH) and intentionally gazed at one of the repetitive black/white flicker stimuli (of 9, 10, 11, and 12 Hz). An experiment comprised 3 sessions at different walking speeds. Each session repeated the following procedure 10 times: Verbal instructions guided participants to shift their attention on the visual target flickering at from 9 to 12 Hz sequentially. The participants needed to shift their gaze to the target stimulus within 1.5 second. Then, the 14-channel EEG data of 2 seconds were first submitted to canonical correlation analysis (CCA). This study adopted the procedure of self-regulating data [Wang et al., 2006] to sequentially append the acquired EEG signals for improving signal-to-noise ratio (SNR) and SSVEP detectability. That is, CCA used a 2-second moving window advancing at 0.25-second steps continuously. An SSVEP frequency was determined only if the same dominant frequency was detected by CCA in four consecutive windows. A trial was correctly performed if the SSVEP frequency matched the frequency of the target flicker. If an SSVEP frequency could not be detected within 8 seconds, the trial was terminated and labeled as an incorrect trial. This procedure took at least 17 seconds to correctly classify four visual flickers with an average response time of 4.25 seconds.

3. Results

Table 1 shows test results of the online SSVEP BCI in terms of accuracy (%), averaged detection time (sec), total experiment time (sec), and ITR (bits/min) at different walking speeds. On average, the system required less time (172.17 seconds) to complete the entire session and provided better performance (mean accuracy: 90%, mean averaged detection time: 4.31 sec, and mean ITR: 19.14 bits/min) under the standing condition, compared to that of the walking conditions. The performance significantly decreased as the walking speed increased from 2 MPH to 4 MPH (Accuracy: 75.83% vs. 47.50%, ITR: 11.25 bits/min vs. 2.59 bits/min).

Table 1. *Online SSVEP detection results under different walking speeds. Speeds: the speed of treadmill, Accuracy (%): the percentage of correctly detected SSVEP trials, Avg detection time (s): averaged time for detected SSVEP trials, Total time (s):the total time needed to complete a 10-repretition session, ITR (bits/min): information transfer rate.*

Subjects	*Speeds*	*Accuracy (%)*	*Avg. detection time (s)*	*Total time (s)*	*ITR (bits/min)*
S_L	Standing	90.00	4.37	174.75	18.85
	2 MPH	72.50	4.46	178.25	9.63
	4 MPH	40.00	4.34	173.50	1.08
S_S	Standing	90.00	4.26	170.25	19.35
	2 MPH	72.50	4.41	176.25	9.74
	4 MPH	60.00	4.53	181.00	5.24
S_W	Standing	90.00	4.29	171.50	19.21
	2 MPH	82.50	4.40	176.00	14.37
	4 MPH	42.50	4.38	175.25	1.44

4. Discussion

In general, the SSVEP detectability progressively decreased while participants switched from standing to walking, especially a significant drop in accuracy was found at 4 MPH (power walking). Since there were no trials terminated by the decision criterion of 8 seconds, the corresponding decision time did not increase as expected. In line with prolonged averaged time for detecting SSVEPs and completing a session, CCA tended to require longer duration of the EEG signals (and higher SNR) to correctly detect SSVEP frequencies as walking speed increased. The reason can be in part attributed to the fact that the SNR of the acquired SSVEP dramatically degraded and/or participants reported a loss of focus on the flickering target occasionally during fast walking. The decreased accuracy and increased time for SSVEP detection thus resulted in a lower online BCI performance (lower ITR) as walking speed increased.

Despite the poor detectability for fast walking, this study demonstrated the feasibility of bridging SSVEP-based BCI to a low-cost consumer EEG headset on unconstrained humans. The ITR at the standing and slow walking (2 MPH) can satisfy the performance requirement in practical BCI applications. Future work will focus on testing a larger number of users, quantifying the SNR fluctuations at different walking speeds, and optimizing the ITR for real-life applications.

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Transfer Learning for Accelerated P300 Speller Classifier Training

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Abstract. The P300 Speller provides a means of communication by recognizing evoked potentials on the scalp with a software classifier. However, collecting data for classifier training requires an extensive amount of time and effort and delays the user's ability to use the system. We propose accelerating the training process with transfer learning, which leverages previously-collected data and classifiers to reduce training time and improve classification. We perform clustering on the set of classifiers corresponding to 94 P300 Speller training sessions and evaluate the performance of the resulting set of classifiers on the associated datasets.

Keywords: P300 Speller, Transfer Learning, C lassification

1. Introduction

The P300 Speller is a brain-computer interface that allows users to type on a virtual keyboard using brain signals, requiring no neuromuscular control. Users focus on the target character that they intend to spell from a grid of characters on a computer monitor; characters then flash in a controlled random pattern, and the flashing of the target is assumed to elicit a P300 evoked potential that can be observed via electroencephalogram (EEG). A computer then uses a classifier to distinguish target responses from non-target responses, and thereby determine the target character. Each classifier is trained on a selection of training data that must be collected for each subject before he or she can use the system for free spelling. Although collecting more training data can improve the accuracy of the classifier (and therefore the spelling rate), it also prevents the user from using the system to communicate for a period of time and requires a significant amount of effort from the user. Hence, decreasing the amount of training time makes the system more practical for general use.

Because neural responses vary from subject to subject, classifier training is typically performed as an isolated task, using only the current subject's training data. However, since the basis for operation for the P300 Speller is a particular evoked potential, it is reasonable to hypothesize that out of a collection of subjects, some will exhibit similar target responses. Therefore, we propose to accelerate classifier training using transfer learning, which uses knowledge obtained in a previous task to inform the completion of a new task: in this case, we use previously collected training data or classifiers to inform the training of new classifiers for new data. To allow for variation in target response while still providing generalization, we perform clustering on the linear classifiers corresponding to each available training dataset, then determine whether the resulting clusters describe their cluster members' data well enough to be used as classifiers themselves. Classification and clustering are performed using a mixture of logistic discriminants, and applied to a corpus of 94 individual P300 Speller training sessions. This will demonstrate whether transfer learning is a promising method for further development.

2. Material and Methods

2.1. Data

The data collection is comprised of 94 individual P300 Speller training sessions. Each session was collected using the row/column paradigm described in [Farwell and Donchin, 1988] with a 9x8 grid from abled subjects in a laboratory environment. Sessions contain between 30 and 40 spelled characters, collected between the years 2009 and 2012. EEG data were collected at 256 Hz; each flash triggers an 800ms response window that is decimated to 20Hz; then, of the 32 available channels, the 8-channel set determined in [Krusienski et al., 2008] is used for classification: $\{F_z, C_z, P_z, O_z, P_3, P_4, PO_7, PO_8\}$.

2.3. Methods

The data from each training session are used to train a linear classifier via logistic regression, as this classification method does not enforce weight sparsity, which could hamper the classifiers' ability to cluster. Clustering of classifier weights is then performed using the *k*-means algorithm, for several values of *k* ranging from

1 to 30, such that each subject's classifier is assigned a cluster. Each value of *k* is randomly initialized 10 times; each cluster mean is applied as a linear classifier to the datasets assigned to its cluster, and the initialization that produces the highest mean area-under-curve (AUC) is selected for further analysis. Each cluster mean is then applied to all datasets belonging to other clusters, and AUC is calculated for comparison. In addition, an AUC is calculated via cross-validation for each session using only its own data as a baseline.

3. Results

Figure 1 demonstrates that with a sufficient number of clusters, the linear classifiers described by the *k*-means cluster means are effective classifiers for the datasets that would be assigned to them, and are nearly as effective as subject-specific classifiers: using the non-subject-specific cluster means results in an average loss of AUC of less than 0.05 when *k*-means is allowed to determine at least 10 clusters. Cluster membership is increasingly important as the number of clusters increases: cluster-mean classifiers applied to non-member datasets perform markedly worse than subject-specific classifiers.

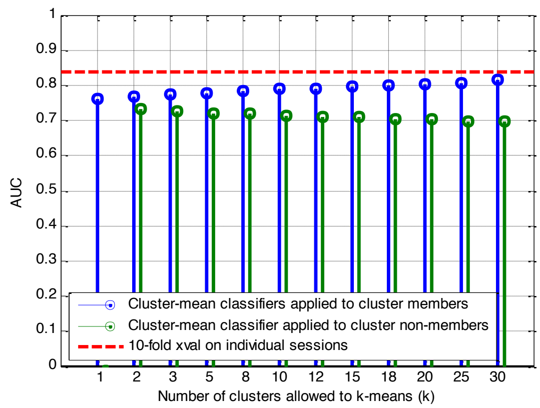

Figure 1. *Mean AUC obtained by applying each cluster mean as a linear classifier to datasets in its cluster (blue) and in all other clusters (green). Compare to mean 10-fold cross-validated logistic regression performed per-session (red).*

4. Discussion

The results in Fig. 1 suggest that separate subjects and sessions share enough similarities to be used for transfer learning, and that further research into using previously-collected training data is merited. Most directly, training time could be reduced for a new participant by collecting only enough training data to accurately select a cluster, then using the cluster-mean classifier. However, more sophisticated methods could use the subject's training data to tune the cluster-mean classifier, potentially improving training speed and accuracy, or incorporate information from all clusters to varying degrees during training. Further, a hierarchical Bayesian model could combine cluster and classifier training on the previously-collected corpus to provide more informative cluster information than *k*-means, while providing a natural method for training classifiers for new subjects.

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"Eyes-Closed" SSVEP-Based BCI for Binary Communication of Individuals With Impaired Oculomotor Function

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Abstract. In this study, we propose a new paradigm for steady-state visual evoked potential (SSVEP)-based brain-computer interface (BCI), which can be potentially suitable for disabled individuals with impaired oculomotor function. The proposed electroencephalography (EEG)-based BCI system allows users to express their binary intentions without a need to open their eyes. A pair of glasses with two light emitting diodes (LEDs) flickering at different frequencies was used to present visual stimuli to 12 participants with their eyes closed. Through offline experiments performed with 11 healthy participants, we confirmed that human SSVEP could be modulated by visual selective attention to a specific light stimulus penetrating through the eyelids. After customizing the parameters of the proposed SSVEP-based BCI paradigm based on the offline analysis results, binary intentions of five healthy participants and one ALS patient were classified in real time. The average ITR of five healthy participants reached 10.83 bits/min, and the ITR of the ALS patient was 2.78 bits/min, demonstrating the feasibility of our BCI.

Keywords: Steady-State Visual Evoked Potential (SSVEP), Brain-Computer Interface (BCI), Eyes-Closed BCI, EEG, ALS Patient

1. Introduction

One of the most widely studied EEG-based BCI paradigm is the SSVEP, which is a periodic neural response elicited by a certain visual stimulus flickering or reversing at a specific frequency. The conventional SSVEP-based BCI systems can provide a high information transfer rate (ITR) and do not require extensive training procedures, but commonly require the basic assumption that the users have normal oculomotor function and are thus able to maintain an open gaze at a given visual stimulus consistently. In practice, however, it has been reported that some patients suffering from serious neuromuscular disorders have difficulty controlling their eyes [Balaratnam et al., 2010]. In particular, many ALS patients have oculomotor impairments causing abnormal visual perception [Okuda et al., 1992]. The main goal of the present study was to develop a new SSVEP-based BCI system that can be potentially used for classifying binary intentions of individuals who have impaired oculomotor function and thus cannot easily use the conventional SSVEP-based BCI systems.

2. Material and Methods

2.1. Design of A Visual Stimulation System

In order to present flickering visual stimuli to eyes-closed participants, we implemented a new visual stimulation system using a pair of glasses, LEDs, and an LED controller as shown in Fig. 1(a). As shown in Fig. 1(b), each LED channel attached at the lateral side of each eye flickered at different frequency. A frequency band of 7-17 Hz was empirically selected as the stimulation frequency band. The frequency band was then divided uniformly into increments of 1 Hz, leading to 11 candidate stimulation frequencies. Since the stimulation frequencies modulating the strongest SSVEP responses differ from one individual to another, different combinations of two stimulation frequencies were determined for each participant.

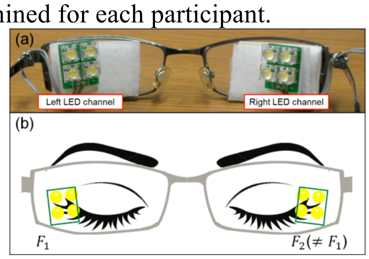

Figure 1. *(a) The newly developed visual stimulation system. (b) A schematic representation of the visual stimulation system.*

2.2. Experimental Procedures

Eleven healthy participants (P1-P11) were recruited for our preliminary offline experiments. They were required to gaze on either the left or right LED for 10 s with their eyes closed, this procedure was repeated 100 times to obtain 50 epochs of SSVEP responses for each of the 'left' and 'right' trials. To acquire EEG data, eight electrodes (POz, PO1, PO2, PO3, PO4, Oz, O1, and O2) were attached to the participants' scalps. We used a simple classification algorithm that searches for the frequency with the largest SSVEP amplitudes.

Five healthy participants (P7-P11) took part in online experiments. According to online experimental paradigm, the participants should begin concentrating on the designated visual stimulus for a certain period. We tested four time periods (2, 3, 4, and 5 s) to investigate changes in the performance of our BCI paradigm. An experimental session consisting of 10 trials (five for left stimulus and five for right stimulus) was repeated three times for each of four different time periods. In addition, an ALS patient (male) who can hardly move his eyeballs and eyelids was recruited, and answered ten yes/no questions using our system. He was asked to attend on the left LED to answer 'yes' and the right LED to answer 'no'. In the online experiments, we used the same classification strategy as in the offline study.

3. Results

In the offline experiments, the average classification accuracy was 74.8% when the analysis window size was 1 s, and it exceeded 90% when the analysis window size was longer than 4 s, demonstrating that the SSVEP responses obtained from individuals with their eyes closed can be classified with high accuracy.

Table 1 shows the results of online experiments with respect to different time periods. The time listed in the second row in the table is that allotted for gazing at each designated stimulus. As shown in the table, the average classification accuracy increased as the time period increased (2 s: 81.3%, 3 s: 90.0%, 4 s: 95.3%, and 5 s: 96.0%). It is worthwhile to note that the average classification accuracy was 81.3% even when the time period was only 2 s, demonstrating that our paradigm could be used for a BCI system requiring quick responses. The highest average ITR was obtained when the given time period was 4 s, suggesting that the trade-off between classification accuracy and ITR should be carefully considered. In the case of the ALS patient, the classification accuracy and ITR were 80% and 2.78 bits/min (the time period: 6 s), demonstrating the practical feasibility of our BCI paradigm.

Table 1. *Results of online experiments with respect to different time periods.*

Participants	Electrodes	Classification accuracy (%)			
		2 s	3 s	4 s	5 s
P7	PO2, O2	80.0	100.0	93.3	100.0
P8	Oz, O2	80.0	80.0	93.3	90.0
P9	POz, PO2	96.7	96.7	100.0	100.0
P10	Oz, O1	73.3	83.3	96.7	93.3
P11	POz, PO2	76.7	90.0	93.3	96.7
Average		81.3	90.0	95.3	96.0
ITR (bits/min)		9.21	10.62	10.83	9.09

4. Discussion

In this paper, we developed a new SSVEP-based BCI system that can be potentially used for classifying binary intentions of individuals who have impaired oculomotor function. Our experimental results demonstrated that the proposed SSVEP-based BCI paradigm for 'eyes-closed' individuals could be used for a practical BCI system.

Acknowledgements

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Transferring BCI Skills to Successful Application Controls

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Abstract. The goal of our research is to enable various end-users to control applications by using a brain-computer interface (BCI). Since applications – like telepresence robots, wheelchairs or text entry systems – are quite demanding a good level of BCI control is needed. However, little is known on how much training is needed to achieve such a level. A second open issue is, if this can be done at rehabilitation clinics or user-centers, without BCI experts present? In this work we wanted to train BCI-naïve end-users within 10 days to successfully control such applications and present results of 23 severely motor-disabled participants.

Keywords: BCI, EEG, motor imagery, application control, end-user, single trial performance, technology transfer

1. Introduction

Brain-Computer Interfaces (BCIs) are no longer only used by healthy subjects under standardized laboratory conditions, but are also introduced to end-users controlling applications in their homes. A challenge in the application of BCIs is the need of training. However, in end users a sufficient level of BCI-performance should be achieved quickly. In this work we want to share the experiences we gained, by starting with BCI-naïve participants, teaching them first to achieve BCI control, evaluating the performance through online BCI experiments and finally controlling applications (like a telepresence robot, a wheelchair and a text entry system). The aim was to do this in 10 days, together with therapists at a rehabilitation clinics or user-centers, and without any BCI experts present.

2. Material and Methods

All participants had to start by left hand, right hand and foot motor imagery during calibration recordings. Afterwards the 2 most discriminable tasks were used for controlling the online feedback or the application.

2.1. Brain-Computer Interface and signal processing

The brain activity was acquired via 16 EEG channels over the motor cortex. From the Laplacian filtered EEG, the power spectral density was calculated. Canonical variate analysis was used to select subject-specific features, which were classified with a Gaussian classifier [Galán et al., 2008]. Decisions with low confidence on the probability distribution were filtered out and evidence was accumulated over time. The BCI training was performed at the clinics without BCI experts present. Only the classifier setup was done remotely by the BCI expert.

2.3. Test of different application prototypes

The first application was a text entry system called BrainTree [Perdikis et al., 2012]. Using a series of left and right BCI commands the participants could select letters out of an alphabetically sorted tree. The visualization implements a so-called Hu-Tucker binary tree (based on a language model) which ensures an optimal but not equal number of commands to reach each character. The second application was a telepresence platform based on the Robotino robot [Carlson et al., 2012]. The subject remotely controlled the robot, steering it to the left or to the right within an office environment. In addition, the subject can intentionally not deliver any mental command to activate the default behavior of the robot, which consists on moving forward and avoiding obstacles with the help of a shared control system using its on-board sensors. The subjects saw a video-transmission from an on-board camera of the robot in parallel with the BCI output. The third application was a powered wheelchair equipped with sonars and webcams, which movements can be controlled similar to the telepresence robot, except that the subject is co-located with it. The subject had to drive the wheelchair to reach several targets. All applications were quite demanding for the subjects, since besides the increased workload and the split attention between the BCI and the application [Leeb et al., 2013], it was also necessary to perform the requested BCI action with certain temporal precision.

3. Results

Up to now, 23 end-users aged 42 ± 14 years (4 female) have participated once every 1–2 weeks for up to 3 hours/day. Ten subjects (S1-S10; re-ordered in descending BCI performance) achieved a very good level of control and could test the applications. Since the whole experiment was limited to 10 sessions (days), not all subjects could test all applications, or train enough to increase their BCI performance. In one subject we had technical problems; two subjects had to be excluded because of inherent muscular artifacts due to their impairments; and one subject decided to stop participating. The subjects are affected by different levels of myopathy (5), spinal cord injury (13), spino-cerebellar ataxia (1), amputation (1), cerebral palsy (1), or locked-in (2). Fig. 1a shows the performance of the online BCI runs before application start using the Youden index (YI), whereby YI = 1 means perfect control and 0 equals chance level. The performances of the applications (see Fig. 1b) are reported for the text entry as the percentage of correctly written characters compared to the total number of written characters [Perdikis et al., 2012], and for the telepresence platform and for the wheelchair as the ratio between the time needed to reach the targets with manual control vs. BCI control [Carlson et al., 2012], all resulting in 1 for perfect and 0 for no control.

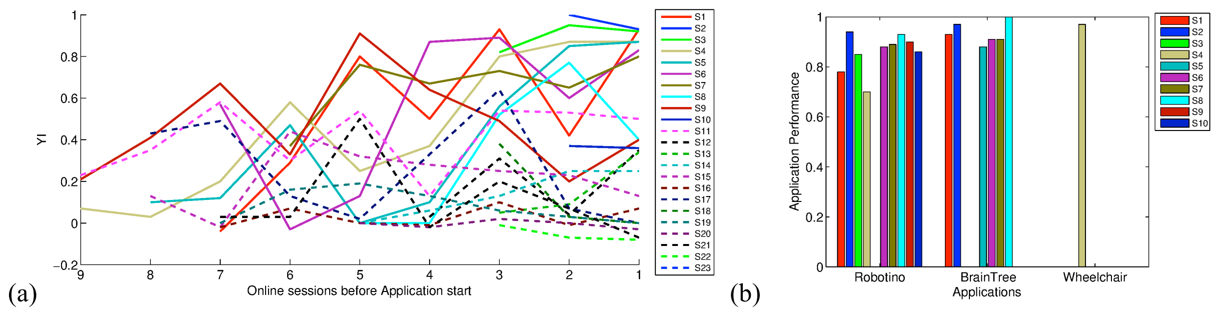

Figure 1. *(a) Performance values (YI) of all online runs averaged per session for all subjects. (b) Application performances of the three applications (Robotino, Braintree, Wheelchair) for the remaining subset.*

4. Discussion

All subjects who achieved good BCI performance could also control the applications successfully (see Fig. 1). Especially whenever end-users reached a YI > 0.6, they mastered the applications equally well as healthy subjects. This is very important, because having a good BCI control does not guarantee good control over the application, due to the necessary split attention between the application and the BCI. Furthermore, BCI training does not require users to achieve 100% performance every trial, but most applications demand almost perfect performance all the time [Leeb et al., 2013]. Unfortunately only half of the participants could test the applications. Due to the strict time limitations of our experimental protocol, we had to stop the training process of those end-user who did not reach a YI > 0.4 over two consecutive sessions within 10 sessions (days). However, for some subjects a longer training would have been preferable. The performance drop of subject S4 in case of Robotino resulted from one single run, in which she intentionally delivered wrong commands believing that the target was somewhere else. Finally, control of the applications could be improved by the use of a hybrid BCI, where key commands (e.g. correction of text-entry errors, pausing the movement of the robot…) are delivered through other channels such as residual muscular activity, which can be controlled reliable but not very often (because of quick fatigue) [Perdikis et al., 2012].

Acknowledgements

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Just a Switch: Timing Characteristics of ECoG-Based Assistive Technology Control

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Abstract. In the development of an implantable ECoG-based BCI system, we have investigated the possibilities of generating quick shifts between high and low levels of brain activity ("brain clicks") using voluntarily modulated brain activity. We conclude that it is possible to produce ECoG-based 'clicks' using both motor execution and covert serial subtraction. These 'clicks' can serve as an input for commercially available assistive technology devices, potentially making communication, as well as environmental control, available for locked in patients.

Keywords: BCI, ECoG, assistive technology, subdural, switch, working memory, sensorimotor

1. Introduction

For most paralyzed patients, there is a variety of commercially available assistive technology available, ranging from devices that turn book pages and robotic arms to dynamic systems that facilitate communication and environmental control, and which can be controlled in a number of ways. For patients with the highest level of paralysis (locked-in syndrome), however, these devices are, so far, less usable because most of them need some form of goal-directed muscle activity to be operated. Brain computer interfaces (BCIs) promise control over devices using brain activity only, thereby potentially improving greatly the communicative abilities, quality of life and independence of this population. The possibilities offered to locked-in patients by a BCI can be maximized if one would make use of the existing commercially available systems, which are the result of years of development and optimization by dedicated people, guided by the wishes of end users. One of the most basic approaches to control an assistive technology device such as a dynamic system is a button press or mouse click. Generating these clicks by brain activity only requires that the user is able to quickly switch on and off the activity in a certain brain area. In the development of an implantable ECoG-based BCI system, we have investigated the possibilities of generating these "brain clicks" using voluntarily modulated brain activity.

2. Material and Methods

Subjects were epilepsy patients who were implanted with subdural ECoG electrodes for diagnostic purposes. Each patient performed a localizer task (movement/rest or covert serial subtraction/rest) with both fMRI and ECoG to select electrodes on motor areas or the dorsolateral prefrontal cortex to be used for the tests. An electrode showing a large response in the 65-95 Hz frequency range during this task was selected for further use. Subsequently, patients performed a second localizer task with shorter intervals of activity and rest. Patients were instructed to respond as quickly as possible to the different conditions. The signal of the preselected electrode was used to estimate an upper and lower threshold for brain activity.

In the Click Target Task, a blue target square was present on the screen (20 trials), for a maximum of 8 s. Patients were instructed to generate the relevant brain activity as quickly as possible once they saw the target. As soon as the patient elicited a switch event, the target changed color and disappeared. The intertrial interval was variable, 3-9 s. A switch was defined as the brain activity crossing the upper threshold as determined by the second localizer task. This task was performed by three patients (Pat1, Pat2, Pat3).

In the Assistive Device Control Task crossing the threshold was translated into a short closing of a relay, simulating a button press. Patients were presented with a commercially available communication device running scanning software, which showed a keyboard on a screen. Lines of characters were highlighted consecutively. When a line was highlighted, it could be selected by activating the switch. Then the individual characters of the row are highlighted for selection. By this method each character of the alphabet can be selected by two activations of the switch. Patients were asked to spell the word 'UMC Utrecht'. Two patients performed this task (Patients 1 and 4 (Pat1, Pat4)). Both patients had a (slightly different) 6x8 matrix of characters, which included the complete alphabet, a space, a backspace, a clear all button, and a number of blank items.

3. Results

Three patients performed the Click Target Task. Pat1 used executed movement of the right hand, and Pat2 and 3 used covert serial subtraction. All patients performed well during the Click Target Task, with 90% or more of the targets 'clicked away' within the maximum trial time of 8 s. For the patient using executed hand movement (Pat1), the average time needed to generate the switch event was 1.3 s (range 0.8-4.6 s), with 2 false alarms (i.e. switch events generated during the intertrial interval). Pat2 and 3 each performed the Click Target Task 3 times using serial subtraction. The average time they needed to generate the switch events was variable, but was between 2 and 3 s for each session (range of all trials of both patients 0.2-7.7 s).

Two patients (Pat1, Pat4) performed the Assistive Device Control Task using executed movement of the right hand (Pat1) or the tongue (Pat4). The scanning software was set such that the interval between two highlighted selections was 2.1 s. Both patients needed ~4 min to spell the words 'UMC Utrecht', with a mean time per character of 20.6 ± 7.8 s, and 22.8 ± 7.8 s, respectively. Pat1 had three misses, which required the system to perform another cycle of scanning before a second attempt to select the character could be made. Pat2 had two misses and two false alarms, which did not result in an incorrectly selected character.

4. Discussion

The data from this study reveal that subjects are able to voluntarily produce quick alternations between high and low levels of brain activity using both motor execution and covert serial subtraction, without a lot of practice. Moreover, these voluntarily generated 'brain clicks' can be used as a control signal for a commercially available assistive technology device running scanning software.

Not surprisingly, the speed with which switch selections were made in the Click Target Task was faster for motor execution than for covert serial subtraction. Even with serial subtraction, however, switch events were made in 3 s or less, which would allow 20 selections per min. In an actual scanning environment, it was possible to spell words with a speed of about 3 characters per min using 'brain clicks' based on motor execution. This value is comparable to several custom spellers: an EEG switch based Hex-O-Spell [Williamson et al., 2009] (2.5-7 characters per min) and ECoG studies with a P300 speller [Krusienski and Shih, 2010] (2.3-4.4 characters per min). [Brunner et al., 2011] report 17 characters per min with one patient. Importantly, the spelling speed in our setup may be increased by optimizing parameters, and practice.

We conclude that it is possible to voluntarily generate ECoG-based 'clicks', which can serve as an input for commercially available assistive technology devices, potentially making communication, as well as environmental control, available for locked in patients.

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Effects of Workload on P300 BCI Signals and Accuracy

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Abstract. Mental workload during a P300 spelling task was experimentally manipulated. As a result of auditory distraction, we found a significantly reduced P300 amplitude in the high workload condition compared to the medium workload condition. Despite high demands of the secondary tasks, 19 subjects were able to spell 100 characters with an average accuracy of 80% (14.8 bits/min) in the medium and 65.5% (10.8 bits/min) in the high workload condition. The study is an important step toward the integration of a mental workload detector into an asynchronous P300 BCI. A system is desirable that pauses if high workload is detected or reduces workload through the adaptation of stimulation parameters. The study further demonstrates the robustness of the P300 speller during a long session with distraction that is encouraging for BCI use in a home environment.

Keywords: P300 Speller, EEG, Workload, Auditory Distraction, Asynchronous BCI, Mental State

1. Introduction

As a first step toward the development of an asynchronous (self-paced) mode of control for the P300 BCI, the current study aimed to identify neurophysiological markers of high workload. A P300 BCI that adapts to the mental state of the user (e.g. pauses if high workload is detected) is highly desirable when designing systems for assistive technology. We experimentally manipulated the workload during a P300 spelling task and were interested in the effect on the P300 amplitude. We hypothesized reduced P300 amplitude with higher workload. We further investigated the effects of intensive use on spelling accuracies during a 2.5 hours BCI session.

2. Methods

2.1. Participants

Nineteen healthy subjects participated in the study (11 female, 8 male, mean age 25 years, SD = 5.08, range: 18-40). Participants were compensated with 8€/hour. None of the subjects had previously participated in a P300 BCI study.

2.2 Data acquisition

The electroencephalogram (EEG) was recorded with 31 active Ag/AgCl electrodes, and sampled at 256 Hz with two g.USBamp amplifiers (g.tec). Channels were referenced to the right earlobe and grounded to position AFz. The BCI2000 software framework was used for stimulus presentation and data acquisition.

2.3. Procedure

Participants completed ten online P300 spelling runs based on the paradigm first described by [Farwell and Donchin, 1988]. In each run, participants had to select 25 predefined characters from a 6x6 matrix. In addition to the primary spelling task, subjects performed a secondary task. In 5 runs, the task induced medium workload and in the other 5 high workload. Runs of medium and high workload alternated in pseudo-random order.

Rows and columns of the 6x6 Matrix were intensified for 62.5 ms and both flashed five times in random order for one character selection. The inter-stimulus interval (ISI) was set to 125 ms. Online classification was performed using stepwise linear discriminant analysis (SWLDA).

The secondary task was a dichotic listening task. For the first five minutes of all runs (20 characters to be copied), two concurrent stories were presented over headphones. One story was presented over the left and another over the right headphone speaker. Participants were either instructed to ignore the stories (medium workload condition) or pay attention to the content of both stories (high workload condition). After the first run of every

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condition, the NASA-TLX questionnaire was administered as a measure of subjective workload. After every run, participants answered 6 questions about the content of the stories.

3. Results

The average accuracy, bitrate, peak amplitude at Pz, the scores of the NASA-TLX questionnaire and the average number of correct answers to the control questions for both workload conditions are displayed in Table 1.

Table 1. *Results of both workload conditions.*

	Medium Workload	*High Workload*
Accuracy (%)	80	65.5*
Bits/minute	14.8	10.8*
Amplitude at Pz (µV)	3.53	2.98*
NASA-TLX	49.52	61.31*
Correct answers	3	4.3*

**all differences between the conditions are significant at the 0.001 level*

Amplitude at Pz was significantly reduced ($p < 0.001$) during the high compared to the medium workload condition. For seventeen subjects, a reduction in P300 amplitude (peak between 200-600 ms post stimulus onset) was found. Subjects answered more questions correct for the high workload conditions, reported a higher workload and their spelling accuracy was lower (all significant at $p < 0.001$). Fig. 1 depicts the grand average at Pz for all participants in the medium and high workload conditions.

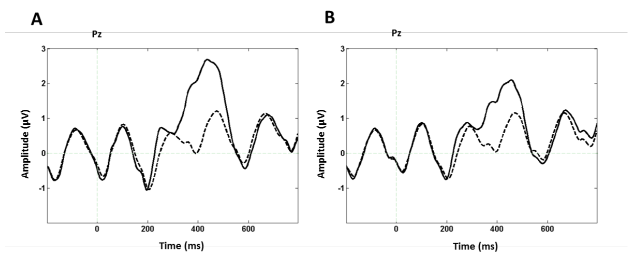

Figure 1. *ERP grand average at Pz for targets (solid line) and non-targets (dashed line) for all participants and all runs with medium workload (A) and high workload (B).*

4. Discussion

As expected, workload affected performance and the P300 amplitude during spelling. Thus, significantly reduced P300 amplitude could serve as an indicator of high workload. Together with data from the frequency domain of the EEG, this information could be used to activate the "stand-by mode" of a BCI. The P300 amplitude at Pz was reduced during the high workload conditions for most, but not for all users. This is in line with findings that show inter- and intra-individual differences regarding the P300 as a measure of workload [Kok, 2001]. Further, the study demonstrates that satisfactory accuracies can be achieved with the P300 speller, even if users are pursuing the task for a long time and are additionally distracted by spoken words.

Acknowledgements

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Objective Indication of Fatigue in SSVEP-Based BCI Through EEG Spectral Analysis

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Abstract. A critical problem in steady-state visual evoked potential (SSVEP)-based brain-computer interfaces (BCIs) is the fatigue that the users may suffer when staring at flashing stimuli. This paper studies an objective evaluation of the fatigue in SSVEP-based BCIs by EEG spectral analysis. The results show that the brain is slowing its activity as a result of the reduced cognitive capacity during fatigue, and the SSVEP amplitude as well as the signal-to-noise ratio (SNR) are influenced by fatigue level.

Keywords: BCI, SSVEP, EEG, Fatigue, Visual Stimulus

1. Introduction

Steady-state visual evoked potential (SSVEP) has been widely used as a non-invasive input for brain-computer interfaces (BCIs). The fatigue of the users when staring at flashing stimuli is one of critical problems in SSVEP-based BCIs. The repetitive visual stimuli usually make the users uncomfortable, tired and consequently reduce the performance, which is a limitation during the application of SSVEP-based BCIs. In order to apply SSVEP-based BCIs to a large number of users, a user-friendly stimulus to reduce fatigue should be considered, while firstly the evaluation of the fatigue and its influence on SSVEP properties should be investigated.

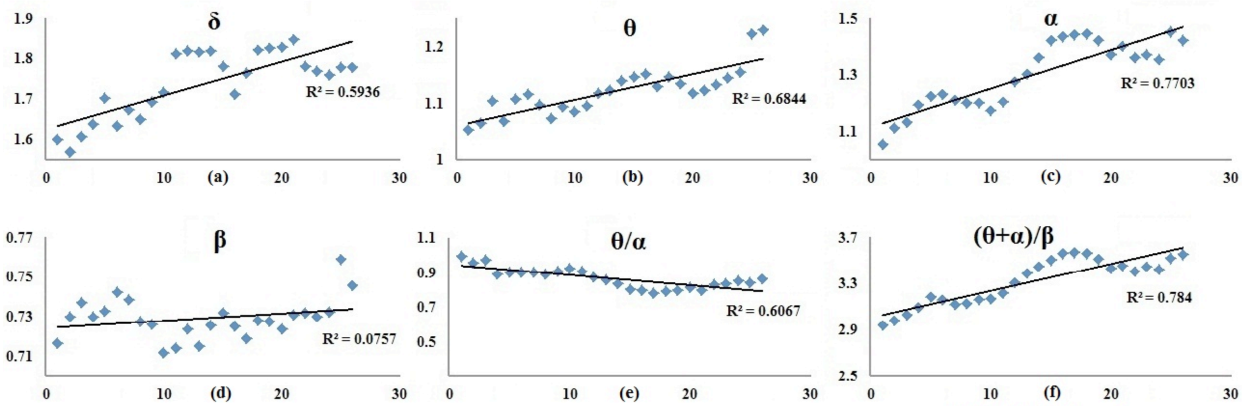
Some SSVEP literature mentioned to use questionnaires or subjects' feeling to describe the fatigue or comfort, which is unfortunately quite subjective and inaccurate [Allison et al., 2010; Bieger and Molina, 2010]. In the case of fatigue, the arousal level and cognitive capacity will be decreased, which are associated with reduced cortical arousal. More specifically, the increases in theta and alpha activity are related to generalized performance decrements on cognitive tasks and increased mental efforts to maintain vigilance level, respectively [Craig et al., 2012; Klimesch, 1999]. Therefore, it is certain that fatigue is associated with significant theta and alpha activity change. This paper proposes EEG spectral indices as objective fatigue measures to help the selection of optimal visual stimulus parameters for SSVEP-based BCIs.

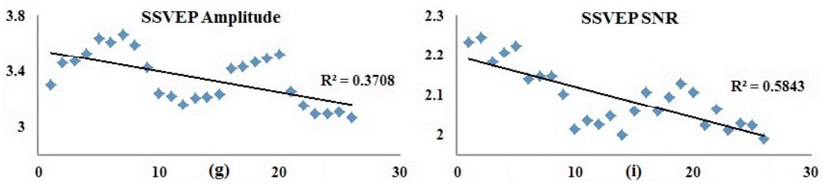
2. Material and Methods

An LCD monitor was used as the visual stimulator (ViewSonic 22", refresh rate 120 Hz, 1680×1050 pixel resolution) and the stimulus was programmed under Microsoft Visual Studio 2010 using Microsoft DirectX SDK (June 2010). EEG was collected from Oz channel by an amplifier (g.USBamp, Guger Technologies, Graz, Austria) during 30 flashing periods (3 s for each). 11 subjects (aged from 22 to 28 years old, 6 males and 5 females) participated in the experiments and were asked to complete a validate self-reported fatigue questionnaire before and after the task work, which was called the Chalder Fatigue Scale (CFS) [Chalder et al., 1993]. The CFS had high reliability and validity, and it was used in this study as a standard reference for fatigue levels. Several EEG spectral indices (δ, θ, α, β), ratio indices (θ/α, $(\theta+\alpha)/\beta$), SSVEP indices were calculated during flashing periods, and paired sample t test was employed to compare the differences for EEG and SSVEP indices at alert and fatigue states.

3. Results

The CFS score was significantly increased ($p < 0.001$) with pre-mean CFS score = 14.91, standard deviation (SD) = 1.22; post-mean CFS score = 25.73, $SD = 4.98$; which indicated the fatigue level is significantly increased after SSVEP-based BCI experiments. For the EEG measurement of fatigue, Fig. 1 showed the average amplitude of EEG and the SSVEP indices as well as the statistical test results. Significant increases were found in θ ($p = 0.039$), α ($p = 0.005$) and the ratio index $(\theta+\alpha)/\beta$ ($p = 0.003$). No significant change was observed in δ ($p = 0.061$), β ($p = 0.244$) and the ratio index θ/α ($p = 0.154$). SSVEP indices, including both SSVEP amplitude ($p = 0.007$) and the signal-to-noise ratio (SNR) ($p = 0.006$) were significantly decreased.





(j) Statistical test results

Index	Alert Mean	Fatigue Mean	Change (*p* value)
δ	1.60	1.78	↑ (0.061)
θ	1.05	1.23	↑ (0.039)
α	1.06	1.42	↑ (0.005)
β	0.72	0.75	↑ (0.244)
θ/α	1.06	0.92	↓ (0.154)
(θ+α)/β	2.99	3.59	↑ (0.003)
SSVEP Amplitude	3.38	2.83	↓ (0.007)
SSVEP SNR	2.23	1.99	↓ (0.006)

Figure 1. *(a)-(i). Average amplitude of EEG and SSVEP indices vs flashing periods; vertical axis: amplitude (μV); horizental axis: flahsing period. (j). Statistical test results; Alert Mean: average amplitude at the begin of experiment; Fatigue Mean: average amplitude at the end of experiment; ↑: increase; ↓: decrease.*

4. Discussion

This study adopted EEG measurements for an objective evaluation of fatigue and the influence of fatigue on SSVEP in SSVEP-based BCIs. The experimental results are consistent with previous research on fatigue monitoring by EEG that the increased θ and α power are associated with the decreased vigilance level and cognitive capacity due to the increased fatigue level [Craig et al., 2012; Klimesch, 1999]. The ratio index (θ+α)/β provides an accurate and quantitative measure of fatigue in SSVEP-based BCI. In addition, it is observed that the SSVEP amplitude and SNR are influenced by fatigue levels. Future study may include an investigation on the fatigue due to other design factors (e.g., visual stimulus frequency, duty cycle, color, etc.) and accordingly a better design of the visual stimuli and the whole BCI system to alleviate the users' fatigue with minimal influence on SSVEP properties.

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Auditory BCIs for Visually Impaired Users: Should Developers Worry About the Quality of Text-to-Speech Readers?

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Abstract. Auditory-based brain-computer interfaces (BCI) have been gaining significant grounds recently, particularly for visually impaired users. The majority of existing auditory BCIs are based on P300 auditory event related potentials. Previous studies have shown, however, that P300s may be affected by the quality of the presented speech stimuli. Since visually impaired users commonly rely on text-to-speech (TTS) readers to e.g., navigate websites and read documents, this study investigated if the quality of the TTS system had an effect on observed P300 amplitudes. An experiment with 14 healthy subjects showed that indeed TTS synthesizer quality plays a significant effect on P300 amplitude. Hence, it is recommended that auditory BCI developers pay careful attention to the quality of the TTS system commonly utilized by the user, as low-quality systems may negatively affect BCI performance.

Keywords: EEG, text-to-speech, P300, auditory BCI, quality

1. Introduction

Auditory BCIs have emerged as an attractive means of communication for blind and vision impaired individuals, such as those with amyotrophic lateral sclerosis (ALS). Auditory BCIs commonly involve the use of an oddball paradigm to elicit a P300 event related potential. More specifically, the user is required to pay attention to a specific "hidden" sound amongst a collection of sounds. The simplest way of eliciting a P300 signal is by presenting subjects with tones of two different pitch frequencies (e.g., high and low), thus resulting in a binary BCI. Recent studies have also shown that spoken words [Guo et al., 2010] or environmental sounds [Klobassa et al., 2009] can be used to develop a multi-class BCI.

The ultimate goal in BCI is to allow users to interact with a computer and/or the environment around them. Within the human-computer interaction domain, there has also been an on-going effort to develop suitable screen reading interfaces for visually impaired individuals. For example, JAWS (Job Access With Speech) is a computer screen reader program for Microsoft Windows that utilizes text-to-speech (TTS) synthesis to read the material on the screen back to the user; VoiceOver provides similar capabilities for Mac OS products. As such, by combining an auditory BCI with a TTS-based screen reader, several applications could be enabled for visually impaired individuals, such as website navigation and document reading, to name a few.

However the quality of existing TTS systems are still poor and clearly distinguishable from naturally-produced speech. Moreover, our previous studies have shown that low-quality speech stimuli can negatively (and unconsciously) affect P300 potentials, both in terms of amplitude and latency. In this study, we investigated the effects of TTS quality on P300 potentials, with the ultimate goal of understanding if TTS reader quality can have a negative effect on P300-based auditory BCIs. An experiment with 14 healthy subjects showed that there is a significant (inverse) main effect of TTS quality on P300 amplitude (i.e., lower quality, higher amplitude). As such, care must be exercised when developing auditory BCIs for the visually impaired with the ultimate goal of controlling a TTS-based screen reader.

2. Material and Methods

Fourteen subjects with normal hearing were recruited to participate in the study (eight female; mean age = 21.57 years; SD = 3.55). Ethical approval was obtained from the affiliated institutes and participants freely consented to participate. Three different TTS systems were chosen from the well-known international TTS challenge [King and Karaiskos, 2009] to represent three different quality ranges, namely high (mean opinion quality score, MOS, of 3.7 out of 5), medium (MOS = 2.8) and low (MOS = 2.1). Four sentences were used to generate 12 synthesized speech samples of approximately 10-second duration each; this was performed for each of the three TTS systems.

Synthesized speech stimuli was presented to the participants in a quasi-randomized fashion, with the only constraint that a given sentence s_i synthesized by the low-quality system had to be presented to the participants prior to

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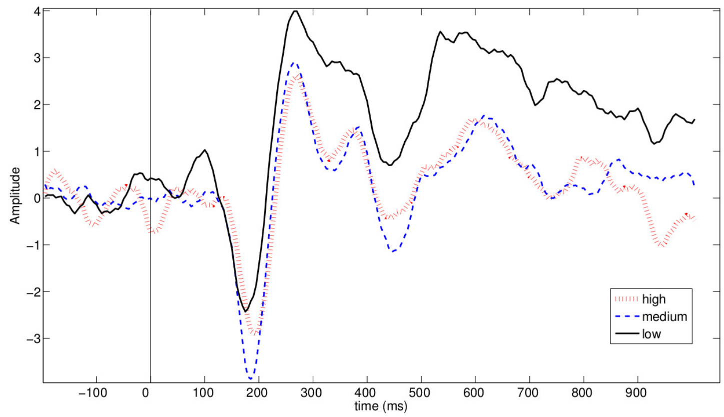

Figure 1: *P300 potentials elicited by low-, medium-, and high-quality TTS stimuli.*

presentation of the same sentence s_i synthesized by the high-quality TTS system, thus to avoid any memory biases. Moreover, an inter-stimulus-interval of 20 seconds was also used to decrease any remaining memory biases of the spoken content. Stimuli were presented binaurally at the individual's preferred listening level through in-ear headphones. And subjects were asked to judge the quality of TTS stimuli by pressing button with options "pleasant" and "unpleasant" as soon as possible at the start of the sentence. A 128-channel BioSemi ActiveII EEG system was used but only the following subset was recorded: 64 EEG-electrodes, 4 EOG-electrodes, and two mastoid-electrodes (right and left). Data was recorded at 512 Hz but down-sampled to 200 Hz and band-pass filtered between 1 and 40 Hz for offline analysis. To quantify the deviance-related effects of P300, we measured the peak amplitude in a fixed time window relative to the pre-stimulus baseline at electrode CPz. The time window for P300 quantification was set from 200 to 600 ms after stimulus onset.

3. Experimental Results and Discussion

P300 signal measured from electrode CPz is depicted in Fig. 1. Here it can be observed that P300 amplitude increases with a decrease in TTS quality. A repeated measures ANOVA was used to verify the difference between P300 peak amplitudes across three different TTS quality conditions, which showed a significant (inverse) main effect for TTS quality on P300 peak amplitude ($F(2,22) = 4.42$, $p < .05$). It is believed that the increase observed in the P300 amplitude with a decrease in TTS quality is due to increased cognitive functioning needed to fully comprehend the low-quality sentences being played back. Further studies are still needed to investigate if these negative effects persist even once the user has become habituated to the poor quality synthesized stimuli. In summary, it is recommended that auditory BCI developers aimed at developing computer interaction applications should pay careful attention to the possible effects of TTS screen reader quality on BCI performance.

Acknowledgments

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BCI Research at Inria Bordeaux: Making BCI Designs Usable Outside the Lab

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Abstract. This paper presents an overview of the recent BCI research conducted by scientists from Inria Bordeaux. It aims at designing practical BCI systems and applications that could be used outside laboratories. More precisely we describe 1) our work on signal processing and machine learning to make BCI more efficient, robust to noise and with minimal calibration times, as well as 2) practical applications in the research fields of spatial cognition and gaming.

Keywords: motor imagery, signal processing, machine learning, calibration, feedback, features, virtual reality, gaming

1. Introduction

Although Brain-Computer Interfaces (BCI) have demonstrated their tremendous potential in numerous applications [van Erp et al., 2012], they are still mostly prototypes, not used outside laboratories. This is mainly due to the following limitations: *1) Performances:* the poor classification accuracies of BCI make them inconvenient to use or simply useless compared to available alternatives; *2) Stability and robustness:* the sensibility of ElectroEncephaloGraphic (EEG) signals to noise and their inherent non-stationarity make the already poor initial performances difficult to maintain over time; *3) Calibration time:* the need to tune current BCI to each user's EEG signals makes their calibration times too long. At Inria Bordeaux, in team Potioc (team.inria.fr/potioc), we notably aim at addressing these limitations, to design practical BCI systems, usable and useful outside laboratories. This is part of our general research objective to make human-computer interfaces, in particular 3D ones, usable and useful for everyone. We describe here our recent work on signal processing to reach this objective and present two practical BCI applications we designed.

2. Signal processing contributions

Performances: To improve BCI performances, we explored and designed new features to represent EEG signals. We notably explored multifractal cumulants and predictive complexity features [Brodu et al., 2012], as well as waveform length features together with an optimal spatial filter that we designed for such features [Lotte, 2012a]. All such features proved useful to classify EEG signals, and, more importantly, increased BCI classification performances (by 2 to 4 % on average) when combined with the gold standard features, namely, band power features.

Stability and robustness: To make BCI more robust to noise and non-stationarities (which incidentally also improves their performances), we proposed to integrate a-priori knowledge into machine learning algorithms. Such knowledge represents any information we have about what should be a good filter or classifier for instance. This can be neurophysiological a-priori, data (EEG signals) or meta-data (e.g., good channels) from other subjects, etc. This knowledge is used to guide machine learning algorithms towards good solutions even with noise and non-stationarities. We successfully demonstrated this approach to learn robust and stable spatial filters [Lotte and Guan, 2011].

Calibration time: To reduce BCI calibration times, we have to design BCI from very few training EEG signals. We have explored three approaches to do so. First, we used statistical estimators dedicated to small sample size problems, such as automatic covariance matrix shrinking [Lotte and Guan, 2010]. Secondly, we used EEG signals from other subjects (who performed the same mental tasks) to regularize machine learning algorithms, which proved even more efficient [Lotte and Guan, 2010]. Finally, we proposed to generate artificial EEG signals from the few EEG trials initially available, in order to augment the training set size in a relevant way [Lotte, 2011]. All these approaches enabled us to calibrate BCI systems with 2 to 3 times less data than standard designs, while maintaining similar classification performances, hence effectively reducing the calibration time by 2 or 3.

3. BCI applications

So far, most of our application-related work has been around Virtual Reality (VR) [Lotte et al., 2013]. Here we focus on two practical applications: using BCI as a tool 1) to study spatial cognition and 2) for multiplayer gaming.

3.1. BCI as a tool to study spatial cognition

We proposed a new application of BCI: using it as a tool to study spatial cognition and transfer from VR Environments (VE) to Real Environments (RE). In particular, since BCI can be used to navigate a VE without any motor activity (see Figure 1, left), BCI can be used to assess how much motor activity and vestibular information is really needed to transfer spatial knowledge from a VE to a RE. To do so, we compared a motor imagery-based BCI and a treadmill to make users learn a path in a VE and retrieve it in the real world. Contrary to previous beliefs, our results suggested that motor activity and vestibular information are not necessary to learn a path in VR. Performing an action - even only a cognitive one (e.g., imagining hand movements) - seems enough to enable spatial transfer [Larrue et al., 2012].

3.2. Multiplayer BCI Gaming

We developed and studied a multiplayer BCI-based video game (see Fig. 1, right) [Bonnet et al., 2013]. In this game, players had to collaborate or to compete (depending on the game mode) to bring a ball towards a given goal, using motor imagery of the corresponding hand. Such an application proved interesting at two levels. First, players enjoyed the game, and enjoyed it even more than its single player version. Second, the BCI performances of several players was improved during multiplayer games as compared to single player ones.

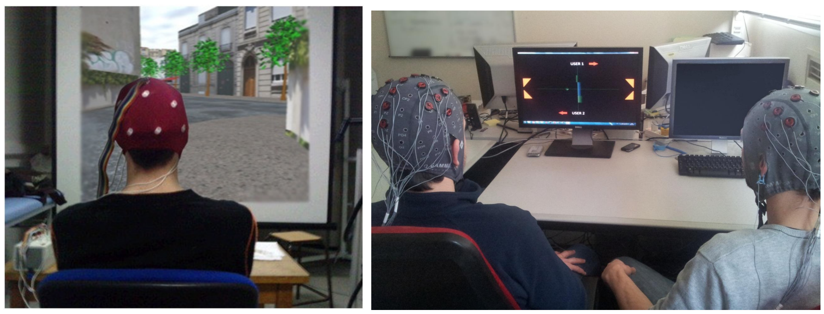

Figure 1: *Left: A user navigating a virtual model of the city of Bordeaux with a BCI, in order to learn a specific path [Larrue et al., 2012]. Right: Two users playing a competitve BCI-based video game [Bonnet et al., 2013].*

4. Discussion and Perspectives

In summary, our research work on signal processing has led to improved BCI performances, robustness and calibration times. From an application point of view, we have showed that BCI could be a tool to study spatial cognition, and stressed once more the advantages of combining BCI and gaming, both for BCI and gaming.

However, much work still needs to be done, with BCI performances still far too low and calibration still necessary. Moreover, besides signal processing, studying educational research made us realize that current BCI feedback training approaches are probably suboptimal and a major cause for BCI limited performances [Lotte, 2012b]. We are therefore working on the design of more efficient user feedback training paradigms. Finally, we are starting a couple of projects on passive and affective BCI, a very promising application area that deserves more attention [van Erp et al., 2012].

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Assessment of the P300 Evoked Potential Latency Stability During C(o)vert Attention BCI

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Abstract. Recently several researchers proposed different P300-based Brain Computer Interfaces which can be controlled even with impaired eye movements (covert attention). However, in all the comparative studies, authors detected lower accuracy for the covert attention modality with respect to the overt one. This study aims to investigate if this decrement correlates with lower stability of the P300 potential evoked during the task. We evaluated the latency jitter of the P300 potential peak evoked by two BCI spellers exploiting overt and covert attention. We found that the P300 latency jitter is significantly higher and accuracy is significantly lower for the covert-attention BCI speller. Considering these results we can conclude that the reduced performance of BCIs based on covert attention could be only partially explained by the absence of discriminant short-latency Visual Evoked Potentials (VEP).

Keywords: Brain Computer-Interface, P300, Latency jitter, C(O)vert attention, Wavelet analysis, NASA-TLX

1. Introduction

The Farwell and Donchin's P300 Speller interface is one of the most widely used BCI paradigm for text writing. Recently, some authors showed that the P300 Speller recognition accuracy significantly decreases when the eyes movements are impaired [Brunner et al., 2010]. User interfaces specifically designed to be operated in absence of eyes movements have been recently reported [Treder et al., 2010; Liu et al., 2010; Aloise et al., 2012]. In all the comparative studies, authors have shown a decrease in system performance using interfaces in covert attention condition with respect to the overt attention one, and they related the overt task based spelling success mainly on the Visual Evoked Potential (VEPs) measured at occipital and parieto-occipital sites [Treder et al., 2010; Aloise et al., 2012]. Also, [Thompson et al., 2013] demonstrated that accuracy achieved with P300 Speller, was strongly correlated with the P300 latency jitter. This study aims to investigate whether the decrease in system performance is fully explained by the absence of VEPs, or if it correlates with a lower stability of the P300 evoked potential elicited in covert attention condition with respect to overt attention one.

2. Material and Methods

Nine healthy female subjects were involved in this study (mean age 27 ± 5). Scalp EEG signals were recorded (g.USBamp, gTec, Austria, 256 Hz) from 8 positions (Fz, Cz, Pz, Oz, P3, P4, PO7 and PO8, referenced to the right earlobe and grounded to the left mastoid). The stimulation interfaces consisted in: i) the P300 Speller, a 6 by 6 matrix containing 36 alphanumeric characters; ii) the GeoSpell interface, in which characters are organized in 12 hexagonal groups of 6 characters each [Aloise et al., 2012]. Each subject performed 4 recording sessions in different days. A session consisted of 6 runs of 6 trials. Each trial (consisting of 8 stimulation sequences) corresponded to the selection of a single character displayed on the interface. Each stimulus was intensified for 125 ms, with an Inter Stimulus Interval (ISI) of 125 ms. At the end of each half-session (3 runs using P300 Speller or GeoSpell), subjects were required to perform the NASA-TLX (Task Load Index [Hart et al., 1988]) workload assessment, in order to evaluate the workload perceived by the subject using the two interfaces. For each participant, BCI performances were assessed offline, according to the number of stimulation sequences averaged during each trial. We used a Stepwise Linear Discriminant Analysis (SWLDA) to select the most relevant features that allowed to discriminate Target stimuli from Non-Target ones. In particular we performed a 3 fold cross-validation exploring all the possible combinations of training (2 runs) and testing (1 run) data set for each session and interface. The maximum Written Symbol Rate (WSR, symbols/minute [Liu et al., 2010]) was calculated for each iteration as a function of the number of stimuli repetitions in the trial. Furthermore, we excluded the contribution of the VEPs in the performance evaluation in order to take into account only the P300 ERP. Only for the P300 Speller interface, we evaluated performances taking into account both VEPs and no-VEPs contribution. In this way, the EEG signal was reorganized in overlapping 600 ms long epochs starting 200 ms (0 ms for the P300 Speller with the VEPs contribution) after the onset of each stimulus. Also, we evaluated the latency of the P300 evoked potential for each trial, in order to estimate the latency jitter for each interface. In this regard, we applied a method based on the Continuos Wavelet

Transform (CWT) and the estimation of the empirical Cumulative Distribution Function (CDF), in order to enhance the signal (P300) to noise (spontaneous EEG) ratio [Hu et al., 2010]. At this point, we first estimated the inverse CWT for each trial, and we detected the latency of the P300 potential as the highest peak of the signal into the epoch. Therefore, we assessed the distribution of the P300 latency for each subject, for a total of 72 trials (4 sessions, 3 runs, 6 trials) for each interface. We evaluated the jitter of the latency subtracting the 3rd and the 1st quartile of the distribution.

3. Results

Results showed a significant decrease in the jitter of the P300 latencies during the P300 Speller task ($p < .05$), with respect to the GeoSpell interface. Furthermore, performance achieved with P300 Speller in terms of WSR, were significantly higher ($p < .05$) with respect to the GeoSpell interface. Finally, NASA-TLX results showed a lower (but not significant) workload perceived by the subjects using P300 Speller with GeoSpell.

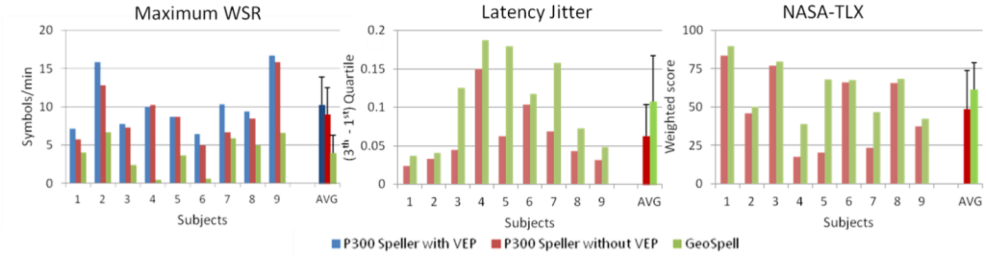

Figure 1. *Maximum value of WSR, P300 latency jitter over exemplary channel (Cz) and weighted NASA-TLX score (mean and standard deviation) over all subjects for each interface.*

4. Discussion

The aim of this study was to investigate whether the decrease in system performance using GeoSpell interface in covert attention condition could be related to a low stability of the P300 potential evoked during the task. We evaluated the P300 latency jitter and performances of nine healthy subjects during the two tasks, excluding the VEPs contribution during the feature extraction stage. The results showed an increase in the P300 latency jitter, consistent with performance evaluation. Preliminary findings indicated that even in the absence of VEPs, the P300 Speller interface used in overt attention modality reaches greater accuracy with respect to the GeoSpell one used in covert attention. Furthermore, both the accuracy and the latency jitter significantly change comparing overt and covert tasks. This result could indicate that the low stability of the P300 evoked potential during the covert task would be one of the causes of the significant decrement of the system performances. Further investigations will address the neurophysiological causes of the high jitter detected during the covert task. A possible hypothesis is that the covert attention modality induces a higher variability of the time needed for the perception and categorization processes of the stimuli. Also, a method to estimate the P300 latency for single epochs could be used to decrease the P300 latency jitter online, improving the system performances.

Acknowledgements

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Towards a Low Cost Mu-Rhythm Based BCI

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Abstract. The purpose of this paper is to evaluate whether mu rhythm based BCIs can be implemented using the low cost Emotiv Epoc EEG device. Synchronisation in the high alpha and low beta band caused by continuous imagery and real toes movement was recorded on 6 healthy subjects. We apply LDA and SVM classifiers in order to classify a trial as movement or non-movement by computing the power of the band of interest on C3, C4, FC3, FC4 standard positions. 10-cross validation results indicate that sensorimotor ERS takes some seconds to develop both in the case of imagery and real movement. The performance is better when classification occurs 5–7 seconds after the movement starts. A simple musical application where the user can move the pitch of a tone up and down in a musical scale is built based on real or imagery toes movement.

Keywords: Event-Related Synchronisation, Emotiv Epoc, Mu Rhythm, Brain Computer Musical Interface, Motor Imagery

1. Introduction

Brain Computer Interfaces can provide a communication pathway for people with severe motor paralysis such as total-locked in Syndrome patients. Using a medical EEG system might be the optimum solution for building a reliable BCI. These systems though require a big preparation time and their high cost might make them inaccessible to the majority of the end-users. On the contrary Emotiv Epoc is a low cost commercial user friendly EEG device and recent research indicates that it is capable of capturing real EEG activity and can be used for building low cost BCIs (e. g., a P300 speller [Duvinage et al., 2012]). In this paper we evaluate the potential of Emotiv Epoc to capture Event Related Synchronisation caused by continuous real and imagery toes movement.

2. Methods

2.1. Empirical Observation

Continuous feet movement has been reported to cause ERS in the high alpha and low beta band, around the FC3 and FC4 standard positions of the EEG [Pfurtscheller et al., 2006; Wang et al., 2010; Jeon et al., 2011]. In order to capture this area of the cortex we had to move the Epoc backwards, placing the four frontal electrodes in the C3, C4, FC3, FC4 positions. Using OpenVibe software, in an on-line scenario, the signal was filtered in the 10–17 Hz band using a fourth order Butterworth band pass filter. The overall power of all four electrodes was computed using a 2 s window with hop size of 100 ms. The power was then plotted on a diagram. Toes movement was observed to cause a gradual increase of the computed power as opposed to the resting state, as a result of ERS in the sensorimotor cortex. This can also be observed when comparing the real movement with non-movement spectrograms of the subjects (Fig. 1).

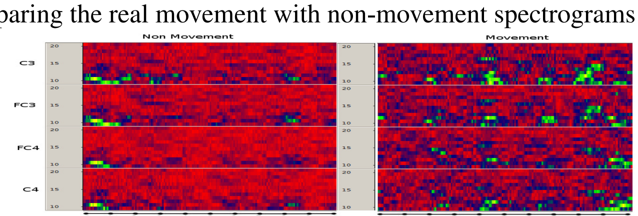

Figure 1: *Non-movement and real movement 10-seconds frequency spectra (7–20 Hz) of one subject.*

2.2. Controlled Experiment

Six male right-handed healthy subjects, of average age 34 years, took part in one real and one imagery movement experiment. All subjects initially observed how real and imagery movement affected the mu power diagram described above. Each session consisted of the following steps: Twelve trials (6 movement and 6 non-movement) of 10 seconds each were randomised. When an arrow pointing upwards appeared on the screen continuous real (in the case of the real movement session) or imagery (in the case of imagery movement session) toes movement should be performed lasting for 10 seconds , while if the arrow pointed downwards they should stay relaxed for 10 seconds. The subjects were instructed to avoid any unnecessary muscular activity.

The data recorder for each subject were used to train an LDA and a third degree polynomial SVM classifier. The signal was filtered in the 10–17 Hz band using a fourth order Butterworth band pass filter. A moving 2 seconds window of hop size 100 ms was applied on each channel and the power of each window was used as a feature for the classifier. The classifiers were trained using different time intervals within the 10 seconds period of each trial. When using time intervals close to the end of each 10 seconds trial the performance of 10-fold cross validation was optimised, while time interval close to the beginning of each trial resulted in worse performance.

As a case study a simple musical application was designed, where the last 3 seconds of a 10 seconds movement or non-movement trial were used to control the control of a melody. Initially the threshold of an LDA classifier is computed by asking the user to perform three ten seconds long movement and non movement trials. Then every ten seconds the user performs a movement or non movement trial depending on whether we wishes to move the melody up or down. When movement is detected (value higher than the threshold) the melody moves up while in the opposite case it moves down.

3. Results and Discussion

In Table 1 the average 10-cross validation performance and variance for 6 subjects, for different time intervals is displayed. Looking at the table we can make the following observations: (i) The polynomial SVM classifier always outperforms the LDA classifier. (ii) Mu rhythm synchronization needs some time to develop both in the case of real and imagery movement. When the last 3 out of 10 seconds are used for the classification, the average SVM 10-fold cross validation performance is 91.65 % in the case of real movement and 85.57 % in the case of imagery movement. The overall performance falls when earlier intervals are used. ERS needs some time to develop. (iii) Real toes movement resulted in stronger ERS than imagery movement. Although in the case of 7–10 s window with SVM polynomial classifier the 85.57 % average performance indicates that an imagery movement based interface is feasible.

Table 1: *10-fold cross validation performance average and variance for 6 subjects for different time intervals after start of a trial.*

	Real Movement				Imagery Movement			
	Performance [*100%]		Variance [*100]		Performance [*100%]		Variance [*100]	
Time Interval [s]	LDA	SVM	LDA	SVM	LDA	SVM	LDA	SVM
7–10	87.79	91.65	0.43	0.36	79.65	85.57	0.81	0.29
5–10	77.95	82.25	0.51	0.84	70.41	75.62	0.41	0.34
2–5	71.17	75.30	1.55	1.31	69.15	74.97	0.82	0.64
0–10	69.31	71.51	1.04	0.80	65.88	69.55	0.12	0.17

As a case study a simple musical application was designed, where the last 3 seconds of a 10 seconds movement or non-movement trial were used to control the contour of a melody. Initially the threshold of an LDA classifier is computed by asking the user to perform three 10s real movement and non-movement trials. Then every 10s the user performs a movement or non-movement trial depending on his intention. When movement is detected (value higher than the threshold) the melody moves up while in the opposite case, it moves down. Preliminary results on one subject indicate that the contour of the melody is controlled with enough accuracy.

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A Comparison of EEG Systems for Use in P300 Spellers by Users With Motor Impairments in Real-World Environments

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Abstract. Three EEG systems that vary considerably in price, portability and features are compared for use with P300 spellers. Data is recorded from seven subjects with severe motor impairments in their home environments and classified using a variant of LDA. These experiments suggest that a portable EEG system with a relatively moderate price may perform as well as an expensive system when used in P300 spellers. Furthermore, systems that are smaller and more comfortable are more practical and deliver a better user experience.

Keywords: Brain-Computer Interface, EEG System Comparison, P300 Speller, Motor Impairment, Home

1. Introduction

The P300 speller is rapidly gaining acceptance as a potential form of assistive technology and several research teams have begun testing this technology in real world environments with users that have severe motor impairments [Nijboer et al., 2008; Sellers et al., 2010]. However, there is little research comparing electroencephalography (EEG) systems and exploring the properties that future systems should have in order to construct practical P300 spellers.

In the present study, we seek to compare EEG systems for use with P300 spellers under real-world conditions. To this end, we have collected data from seven users with severe motor impairments in their home environments using three different EEG systems. This data was analyzed in an offline fashion using relatively well-established techniques for P300 classification. The results of our experiments illustrate that the use of a high-end EEG system does not necessarily yield an improvement in classification accuracy for the P300 speller. Instead, we suggest that portable mid-range EEG systems may provide a better user experience while still delivering acceptable performance.

2. Methods

The three EEG systems that we examine vary considerably with respect to price, portability and a number of features that may affect signal quality and comfort. Specifically, we compare the NeuroPulse Mindset-24R, the g.tec g.MOBI-Lab+/g.GAMMAsys and the Biosemi ActiveTwo. The Mindset is relatively inexpensive and not very portable. The Mindset supports up to 24 passive electrodes with a sampling rate of 512 Hz. The g.MOBILab+ is highly portable with mid-range price and supports 8 active electrodes with a sampling rate of 256 Hz. The ActiveTwo is relatively expensive and moderately portable. The ActiveTwo supports a number of high-end features, such as high-density electrode arrays, 16 kHz sampling rates and a driven-right-leg circuit.

EEG was recorded from seven subjects in their home environments. Two subjects had quadriplegia as the result of high-level spinal cord injuries, including one subject that used a ventilator most of the time. One subject was largely locked-in as the result of a traumatic brain injury and had very limited communication using eye blink responses. The remaining three subjects had severe limitations in movement as a result of advanced multiple sclerosis.

Each subject was seated in front of a computer screen and asked to count the number of occurrences of a given letter within a sequence of flashing characters containing 20 target and 60 non-target characters. This process was repeated three times with the target letters *b*, *d* and *p*, which were selected to represent a difficult scenario. The entire session was repeated on three separate days using a different EEG system during each session. Upon completion of the final session, each user completed a questionnaire regarding their experience.

Since the focus of our work is on comparing EEG systems, we have elected to use a relatively well established algorithm for EEG classification; namely, Linear Discriminant Analysis (LDA) with shrinkage toward the average eigenvalue of the covariance matrix [Blankertz et al., 2011]. The shrinkage parameter and final classification results were obtained using a nested random-subsampling validation procedure. Class labels are assigned after encountering

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six EEG segments by estimating the joint probability of the segments belonging to each class. In order to achieve reasonable estimates of covariance, a subset of 8 channels was selected and decimated to a sampling rate of 32 Hz.

3. Results

In Table 1 we present the final classification accuracies obtained from our experiments. The highest mean classification accuracy was achieved with the g.MOBILab+ at 82.50 % correct. The ActiveTwo followed with a mean classification accuracy of 75.71 %. The lowest mean classification accuracy was obtained with the Mindset at 66.67 %. It is important to note, however, that we are unable to show statistically significant differences in mean classification performance between any of the systems with an ANOVA F-test ($p = 0.39$) or paired t-tests.

Table 1: *Six-Trial Classification Accuracies.*

Subject	ActiveTwo	g.MOBILab+	Mindset
01	**90.00%**	*NA*	37.50%
02	90.00%	**97.50%**	*NA*
03	75.00%	97.50%	**100.00%**
04	55.00%	*NA*	**60.00%**
05	**70.00%**	42.50%	62.50%
06	67.50%	**87.50%**	72.50%
07	82.50%	**87.50%**	67.50%
Mean	75.71%	**82.50%**	66.67%

In order to further investigate the ability of each EEG system to capture the P300 and related waveforms, we also examine averages of time-locked EEG segments. In Fig. 1 we see the difference in the grand averages between the target and non-target segments for each of the three systems at the site P4. We notice that the largest difference in responses is achieved for the g.MOBILab+, ActiveTwo and Mindset respectively, supporting our classification results. The variations in the peak timing across systems may be related to the different methods for synchronizing the stimulus.

4. Discussion

Although it may seem surprising that the ActiveTwo does not achieve the highest classification accuracy, this result may be explained in part by the fact that the P300 speller is a very specific application and that our implementation does not utilize a large number of electrode sites or high sampling rates. In fact, we would argue that the ActiveTwo system may be advantageous in general research settings and, potentially, other types of Brain-Computer Interfaces. Nevertheless, it appears that the g.MOBILab+ may be more appropriate for use in practical P300 spellers.

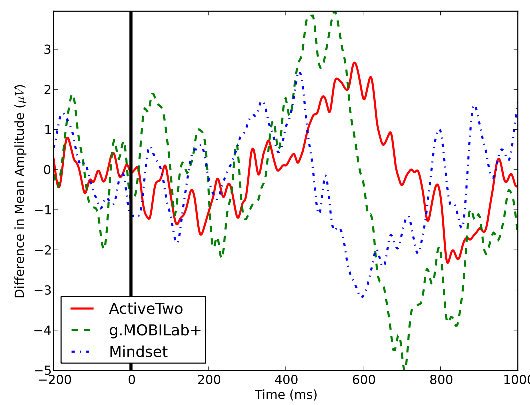

Figure 1: *Difference between the grand averages of the target and non-target responses for each system.*

Perhaps equally as important as classification results is the insight gained by interviewing and working with subjects with motor impairments in their homes. These potential users of P300 spellers overwhelmingly mention the comfort and application time of the EEG cap as concerns. This alone may preclude the use of low impedance systems such as the Mindset because of the lengthy and somewhat uncomfortable cap application process. These users also require systems that are highly mobile and that can continue to function through daily activities and movement. This suggests that an ideal EEG system for use in P300 spellers should be portable, lightweight and have active electrodes that are comfortable but not easily dislodged.

Acknowledgments

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Stability of Local Field Potentials Over 11 Months of Brain-Machine Interface Use

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Abstract. Local field potentials (LFPs) are derived from many thousands of neurons. As such, they may enable long-lasting and stable control signals for brain-machine interfaces (BMIs). Here we assess the stability of LFPs in primary motor cortex of 2 monkeys during 2-D cursor control using an LFP-based BMI. Using a biomimetic BMI decoder without retraining or adaptation, monkeys exhibited high performance that remained stable for over 11 months. Offline, we examined the stability of the LFP features by computing decoders of the brain-controlled cursor velocity from individual features in each session and using them to decode the velocity in the last session. Many of the LFP features showed high correlation with the cursor velocity which grew increasingly stable for over 11 months. This suggests that the monkeys learned a stable mapping between motor cortical field potentials and outputs, and that LFPs will provide a highly stable signal source for BMIs.

Keywords: Brain Machine Interface, Local Field Potentials, Neural Prosthetics

1. Introduction

Brain machine interfaces (BMIs) offer the potential to help people paralyzed from spinal cord injury or stroke regain function. BMIs using action potentials (spikes) from individual neurons as inputs have evolved to the point of early human studies in people with tetraplegia. However, it is unclear whether current recording technologies have the ability to record spikes from many neurons for the decades that a successful device will require. Local field potentials (LFPs) are almost as informative about movement as spikes [Mehring et al., 2003; Bansal et al., 2011; Flint et al., 2012b] and may have better longevity [Flint et al., 2012a].

Greater stability of signals would allow less frequent BMI decoder recalibration. In this study we evaluate the long-term stability of both BMI performance and LFP signals during control of a computer cursor using a static, biomimetic decoder of LFPs over 11 months. Biomimetic decoders are trained on cortical signals during actual behavior. We find evidence that both performance and the behavior of LFPs themselves remain stable during BMI use over a period of at least 11 months. It has been shown that single-unit spikes remain stable during natural movement and spike-based BMI use over a period of 1-2 days and 19 days, respectively [Chestek et al., 2007; Ganguly and Carmena, 2009].

2. Methods

All procedures were approved by the Northwestern University Institutional Animal Care and Use Committee. We recorded LFPs using 96-channel electrode arrays in primary motor cortices of two rhesus monkeys. We trained a Wiener cascade decoder of reach velocity from LFPs recorded during a 2-D random target pursuit reaching task with the contralateral arm. We used the smoothed time-domain signal (local motor potential, or LMP [Mehring, 2004]) plus the power within each of five frequency bands (0-4 Hz, 7-20 Hz, 70-115 Hz, 130-200 Hz, and 200-300 Hz) as features from each electrode, and selected the 150 features with highest absolute correlation coefficient as inputs to the decoder [Flint et al., 2012a]. Monkeys used the BMI to move the cursor in the random target pursuit task. Monkeys trained on the task at least 3 days per week for over 11 months. BMI control with other BMI decoders was also performed on some days but not analyzed here. Performance was assessed by success rate and average time to target.

To evaluate LFP stability, we built Wiener decoders using each of the 150 features included in the BMI, similar to [Chestek et al., 2007]. These sets of single feature decoders (SFDs) were built after each experimental session of LFP-based BMI control. The SFDs were used to predict velocity using data from the very first LFP control session.

Performance of the SFDs (measured as the correlation coefficient, R, between predicted and actual BMI control velocity) was used to assess the stability of each feature during BMI control over time.

3. Results

Performance during BMI control was high: time to target was 0.2 sec/cm (mean over 2 monkeys), comparable to levels for spike-based brain control in the literature. This performance remained stable or improved for a period of over 300 days for both LFP and MSP brain control. Single feature decoder performance was highly stable in many LFP features during this period, and became even more stable over time. This was particularly true of LMP features, many of which had R values with the output exceeding 0.5, but also true of a few hi-gamma band features as well.

4. Discussion

LFPs can be used to control a biomimetic BMI with high performance that was stable over at least 11 months, far longer than has been shown previously. Moreover, many of the LFP features behaved stably during BMI control over 11 months. The LMP, notably, showed the highest correlation with the brain-controlled cursor and the most stability over time. This could perhaps be related to the high number of underlying neural generators contributing to the LMP being more robust to change. Thus, users appear to form a cortical map during LFP-based BMI use that is stable for nearly a year. This is similar to the stable map seen in [Ganguly and Carmena, 2009] with highly-selected single-unit spikes; however, the stability lasted much longer here. This stable map was formed despite the fact that the monkeys also used several other BMI decoders during the study period. Thus, monkeys were able to switch among biomimetic BMIs with ease and still retain a stable cortical representation of the BMI task. This bodes well for long-term BMI use with LFPs without need for frequent recalibration or adaptation.

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Are BCIs Coming of Age as AAC Systems?

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Abstract. This paper discusses the issues central to transitioning brain-computer interfaces (BCIs) to fully functional augmenative and alternative communication (AAC) systems, and the importance of reporting quantitative performance data based on language sampling to show the effectiveness of communication competence.

Keywords: Augmentative and alternative communication (AAC), performance measurement, language activity monitor (LAM), language sample

1. Introduction

In the areas of augmentative and alternative communication (AAC) measurement of performance is essential in research and clinical practice. For brain computer interfaces (BCIs) to come of age as AAC systems measuring the effectiveness of BCIs to support communication would be an expectation. Consequently, as translational research efforts more BCIs out of the laboratory to be recommended by speech-language pathologists (SLPs) as an AAC system then quantitative data are critical to make informed decisions about effectiveness and value. BCI research and development as well as clinical AAC practice benefits from the use of clearly defined or standardized measures to compare performance between and within AAC speakers and systems.

2. Performance Measurement

Various tools and resources are available to support systematic observations of an AAC speaker's communication competence with an intervention. Automated performance monitoring provides quantitative data based on units of measurement to evaluate an AAC speaker's communication competence [Hill and Romich, 2001]. The built-in data logging feature or Language Activity Monitor (LAM) on several AAC systems, integrated and/or analysis software, and external tools offer effective and efficient methods for monitoring gains in performance. The AAC team is responsible for identifying the most reliable and valid measures to collect spoken and written language samples for analysis.

The collection and analysis of language samples is the most authentic procedure for identifying communication competence. The parameters used to measure communication competence are similar across the lifespan and are well documented. Typical data related to the subsystems of language (semantics, morphology, syntax) include standard and defined measure of vocabulary, syntactic diversity, and the length and complexity of utterances. Performance measures that should be routine for AAC system use include frequency of spelling, word prediction or other methods representing language, accuracy, average and peak communication rates (wpm), selection rates (bps), rate index to name a few. A variety of language sampling contexts may be recommended to collect the most representative example of an individual's language functioning and use of a BCI system. Obviously, the most representative sampling would be obtained from communication occurring during activities of daily living. Without using automated data logging, capturing these data would not be possible.

3. Research on Brain-Computer Interfaces (BCIs)

BCIs are showing to be of significant practical value to patients in advanced stages of ALS and lock-in syndrome for whom conventional AAC systems, all of which require some measure of consistent voluntary muscle control, are not satisfactory options. In these individuals, brain signals (e.g. P300 potentials) might be good alternatives to channel for access to assistive technologies. When the Language Activity Monitoring (LAM) function is installed in a P300 BCI system time stamped logfiles can be collected to measure communication performance [Hill, 2004]. Word-based and utterance-based performance measures can be used to evaluate the effectiveness of the BCI system as an AAC intervention with this population over time [Ruff et al., 2011].

BCI studies at the University of Pittsburgh and the University of Michigan as well as the Veteran Administration (VA) HealthCare System are collecting and analyzing performance and outcomes data on BCI use.

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The BCI/AAC model used in these efforts allows the evaluation of performance across three levels: 1) BCI control interface, 2) BCI user interface, including linguistic elements, and 3) communication contexts. Manipulation of the control allows for gaining information on the calibration selection processes of the P300 BCI system. Manipulation of the user interfaces is providing opportunities to compare performance using different methods to represent language. Currently, BCI user interfaces provide access to spelling and word prediction with limited availability of graphic symbols. However, research is planned to implement multi-meaning icons on a BCI system. Providing for multiple AAC language representation methods (LRMs) allows for comparison of the frequency of use of the various LRMs and the communication rates achieved using specific LRMs.

A comparison of research protocols shows that various sampling contexts are being used to report communication performance that includes: 1) copy spelling; 2) picture description tasks; 3) interview tasks; 4) daily conversation; 5) email. In addition, trends in the use of various application programs are being monitored for usage patterns. Having multiple sampling contexts is allowing for the performance comparisons of summary measures identified above.

4. Summary

BCIs are in transition from laboratory-tested control interfaces to an emerging access option for AAC. Since the goal of AAC is to optimize communication for people who cannot speak, systematically studying how BCI features and communication contexts provides opportunities for investigating the variables that affect communication performance and user satisfaction. The BCI studies that use performance data to guide practice will foster BCI systems becoming more mature and functional AAC systems.

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Assessing Information Processing in Patients With Long-Term and Severe Disorders of Consciousness

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Abstract. To study the prevalence of the N100, P200, and P300 event related potentials (ERP) in patients with chronic and severe disorders of consciousness, ERPs were recorded in nine healthy participants and 19 long-term vegetative state and minimally conscious state patients during an auditory oddball paradigm in a passive – listen only – and an active – count the odds – condition at two time points. Significant ERPs were detected in all patients. N100 was significantly more frequent than the P300. In contrast to healthy controls, no evidence was found for differential activity between the passive and the active condition in any patient.

Keywords: EEG, t-cwt, wavelet, P300, disorders of consciousness, vegetative state, minimal conscious state, ERP

1. Introduction

The event-related potential (ERP) P300 has been linked to the processing of attention-demanding stimuli, and is thought to indicate the intactness of a wide cortical network ranging from prefrontal to temporal-parietal areas [Polich, 2007].

The vegetative state (VS) is a severe disorder of consciousness (DOC), presumably characterized by a complete loss of conscious experience despite preserved wakefulness. It is sometimes followed by a minimally conscious state (MCS), in which weak and inconsistent signs of awareness can be detected. In a previous study, up to 32% of DOC patients showed a P300 in an auditory oddball paradigm [Kotchoubey et al., 2005].

We hypothesized that healthy subjects would show an increased P300 in the active condition, and we were interested in whether DOC patients would show a similar increase. Such an increase could be an indicator of preserved command following and thus, consciousness and cognition.

2. Material and Methods

Participants 19 patients with disorders of consciousness (sex: 11 male, 8 female; age: $M = 50$, $SD = 14.19$; diagnoses: 5 MCS, 14 VS; years since onset: $M = 6.18$, $SD = 3.17$; aetiology: 10 hypoxia, 3 trauma-related, 3 intra-cerebral haemorrhage, 3 other; hemispheric localization of lesions: 4 left, 2 right, 3 both, 10 none), whose legal representatives gave informed consent, and nine healthy subjects participated in the study. Patients' diagnoses were ascertained using the Coma Recovery Scale (CRS-R) immediately before EEG measurement.

Procedure Subjects listened to an auditory oddball paradigm (60 odd and 420 frequent tones) in a passive ("listen only"), and an active ("count the odd tones") condition. In 17 patients, the experiment was repeated after a minimum interval of 1 week (T2) to compensate for the possibility of fluctuating arousal levels.

EEG recording and analysis EEG and EOG was recorded (512 Hz) from 31 standard 10-20 system electrode

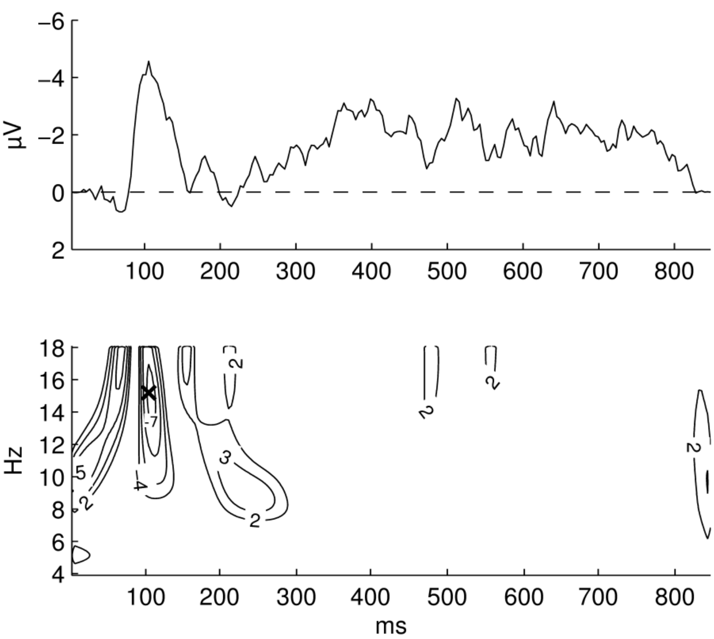

Figure 1. *Top: Average EEG waveform (Fz) of one VS patient showing preserved N100. Bottom: Contour plot of the studentized wavelet coefficients corresponding to the waveform in the top panel in the time-frequency plane. To avoid clutter, contour lines are restricted to the top and bottom ten percent of studentized wavelet coefficients. Bold cross (X) indicates N100.*

locations. Offline, the EEG was bandpass (0.01-70 Hz, 12 dB) and notch filtered, epoched into 850 ms long intervals, and aligned to the 100 ms pre-stimulus baseline. Ocular artefacts were corrected using a regression procedure and trials with absolute voltages in excess of 100 µV excluded. Only datasets with at least 20 trials in each condition ($n = 26$) were considered for the remaining analyses and re-referenced to linked mastoids.

A variant [Real et al., 2013] of the Studentized Continuous Wavelet Transform (t-CWT) [Bostanov, 2003] was used for ERP detection. The method consists of firstly, calculating the continuous wavelet transform for each trial and channel using a Mexican Hat wavelet [Bostanov et al., 2006]. Secondly, student t-values are calculated from the resulting wavelet coefficients, either across all experimental conditions – if one is interested in detecting activity different from baseline – or between experimental conditions – if the focus is on differences between experimental conditions. Thirdly, local extremes are detected using a 2D peak detection procedure. Fourthly, significance of extremes is ascertained via t-max randomization tests [Blair et al., 1993] with an error level of $\alpha = 0.05$. Fig. 1 shows an example of an average waveform (Fz, 409 trials) from a VS patient and the corresponding time-frequency map of studentized wavelet coefficients. In this representation, the N100 is visible as a high-frequency negative peak.

3. Results

Healthy participants: All healthy subjects showed significant activation in the N100, P200 and P300 ranges in all conditions, with the exception of one subject in which no P200 could be detected in the active condition. Seven of nine healthy subjects showed a significantly larger P300 in the active than in the passive condition.

Patient participants: Reliable ERPs were detected in all 17 patients entering the analysis. A P300 was found in two VS, in one MCS and in one patient who was diagnosed with MCS at T1 but VS at T2. No significant difference between the P300 in the active and passive conditions was found in any patient.

The N100 was found more often than the later P300 in both experimental conditions (binomial tests, all $p < 0.05$) at T1 but not at T2. No difference was found for the P200.

Table 1. *Frequency of ERPs by experimental condition and time points in patients. Number before the slash indicates number of subjects where ERP was found, the number after the slash indicates total number of subjects available for the respective analysis.*

	T1		*T2*	
ERP	*Passive*	*active*	*passive*	*active*
N100	12/13	10/10	5/5	9/10
P200	6/13	6/10	4/5	3/10
P300	2/13	1/10	1/5	3/10

4. Discussion

Our results replicate previous findings of a comparatively higher prevalence of the N100 in comparison to the P300, and an overall rare occurrence of a P300 (4/17 = 24%) in DOC patients [Kotchoubey et al., 2005]. In contrast to healthy subjects, in DOC patients the P300 of the active condition was not enhanced compared to the passive condition, possibly due to lack of language understanding, insufficient attention span, lack of motivation or cognitive abilities, or indeed disrupted conscious awareness.

Acknowledgements

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Visual and Stereo Audio Sensorimotor Rhythm Feedback in the Minimally Conscious State

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Abstract. Previously we assessed awareness in a participant, diagnosed minimally conscious (MC), using an EEG-based sensorimotor rhythm (SMR) brain-computer interface (BCI). Here we describe a follow up study conducted over 2 intensive training phases, involving visual feedback and stereo auditory feedback (pink noise and music samples). The participant performed significantly above chance on most runs. Although both feedback modalities produce similar performance, auditory feedback is most suitable for this participant due the uncertainty of the participant's ability to follow visual cues and feedback. Stereo musical feedback is demonstrated for the first time.

Keywords: Minimal Conscious State (MCS), EEG, Motor Imagery, Auditory Feedback, Brain-computer Interface

1. Introduction

Those in the minimally conscious state (MCS) or vegetative state (VS) are often incapable of providing any overt motor responses however there is evidence that a subset of patients with these disorders of consciousness (DoC) can alter their brain activity in response to instructions. Cruse et al 2011 detected significant sensorimotor rhythm (SMR) activations in 19% participants in MC and V states, demonstrating that a subset were capable of sustained attention, response selection, working memory and language comprehension. We showed that real time SMR feedback during assessment of a patient diagnosed MC (Coma Recovery Scale-Revised score (4/23)) could impact on the awareness detection protocol, even though the patient had not communicated for 12 years [Coyle et al 2012]. Here we describe follow-up experiments to determine if the participant can learn to control a SMR-BCI.

SMR-BCIs enable the user to learn how to intentionally modulate their EEG through sensorimotor learning. Visual feedback in this closed loop system excludes those with visual problems. Those in MC/V states often have no/very limited gaze control/visual acuity. It is possible to substitute visual feedback for its auditory equivalent [McCreadie et al., 2013]. We provide the first results comparing visual and auditory SMR feedback in the MC state.

2. Material and Methods

One male participant (aged 28) who contracted juvenile posterior Fossa Astrocytoma in 2001 and, following significant surgery, was diagnosed MC requiring full assistance for all activities of daily living. Informed assent was given by the participant's family/medical teams. Ethical approval was granted by the National Rehabilitation Hospital Ethics Committees. The study was conducted in the participant's home. Phase 1 (visual cues/feedback/verbal prompts) took place approximately 6 months after initial assessment [Coyle et al., 2012]. Phase 2 (stereo auditory feedback) occurred 6 months later. Seven sessions involving 2-4 runs (60 trials/run), circa 1.5 hrs durations, 1-2 per day (morning/evening) were conducted in each phase. In phase 1, 3 bipolar EEG channels were recorded as in [Coyle et al 2012]. In phase 2, 16 channels over sensorimotor areas were recorded using a g.BSamp (www.gtec.at), digitized using a cDAQ 9171 (www.ni.com), oversampled at 2 kHz and average downsampled to 125 Hz. Only results from 3 Laplacian channels around C3, Cz and C4 are reported.

Stereo auditory feedback was given in two forms: as a broadband ($1/f$ or pink) noise, and for the first time music. The broadband noise, commonly used in auditory localization experiments contains cues both above and below 1.5 kHz, essential in the effective localization of an auditory event. A 'musical palette' was comprised of 10 different popular musical genres (e.g., blues, classical etc.). Each style contained three excerpts from tracks from each of three artists. Auditory feedback was presented through a set of ER4P earphones (Etymotic Research, Inc.). The earphones presented the target as a spoken command ("left" or "right") from the corresponding ear. Feedback was modulated by continually varying the azimuthal position of the sounds between $\pm 90°$ using left and right hand movement imagination. Visual feedback was given in the form of the standard ball-basket paradigm and an asteroids avoidance

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game in which the objective is to move a falling ball to one of two baskets on the left or right of the screen or move a spaceship to dodge asteroids which fall towards the spaceship either on the left or right of the screen, respectively [Coyle et al., 2011]. For both feedback paradigms the participant was given verbal instruction on how to control the feedback, during visual feedback periodically the participant was verbally prompted with the correct motor imagery (MI) to perform and to ensure awareness of target during periods of eye shutting/suspected visual acuity degradation. Trial timing was standard with cue at 3 s, feedback between 4-7 s for all feedback types.

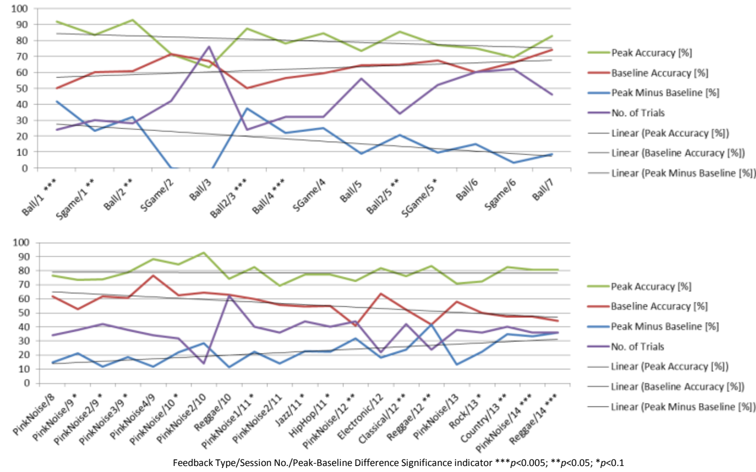

Figure 1. *Visual (top) and auditory (bottom) results. Peak , baseline (500 ms before cue) baseline-peak mCA from LOO-CV and no. of trials in each run after artefact rejection.Visual (top) and auditory bottom results showing peak mean classification accuracy from leave one out cross validation, baseline accuracy (500ms before cue), the difference between baseline and peak, and the number of trials*

The first run in each session used the classifier from the previous day for feedback or was a calibration run (no feedback). The classifier was updated on the data from the first run. Subsequent runs involved either type of visual feedback or pink noise followed by musical feedback (feedback runs reported only). As different runs involved different feedback types and, in the MC condition, awareness is unknown and can vary significantly, analysis is performed run-by-run. Due to the head strap occasionally distorting the electrode cap and/or the participant wheezing and/or teeth grinding it was necessary to reject a substantial number of trials (no. of trials per run are reported). A leave-one-out cross-validation (LOO-CV) was performed on each run using the BCI outlined in [Coyle et al., 2011]. Mean classification accuracy (mCA) is reported along with baseline accuracy (500 ms before cue).

3. Results and Discussion

Fig. 1 shows that there were consistent SMR activations during both phases with the majority of runs showing a statistically significant difference (*t*-test) between baseline and peak mCA. Although both feedback modalities show similar performance (80% visual, 79% auditory across all runs) the difference between peak and baseline is increasing for auditory (15-35%) whilst decreasing for visual (40%-9%). Because of the likely vision impairment it was unclear if the participant was aware when the trial was ending using visual feedback, particularly for the spaceship game where the spaceship is onscreen and can be manipulated continuously during the run. This in addition to the lack of perceivable visual feedback may be a cause of reduced baseline vs. peak differences during phase 1 whereas an improvement is clear in phase 2. The participant seems more alert during audio feedback, the trial cues/ends were clearer and the musical palette seemed to help alertness (based on visual observation and feedback from family members). Interestingly both the musical and broadband noise feedback results averaged over the last 340 trials of each phase produced the same results (80%) suggesting that even though pink noise is easier to localize than music containing multiple instruments/vocals. Pink noise is much less appealing to listen to than music. In summary, the feasibility of using musical stereo audio feedback in SMR-BCIs has been demonstrated.

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Clinical Screening Protocol for RSVP Keyboard BCI Use

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Abstract. We report on development of a clinical screening instrument designed to determine whether people with locked-in syndrome have the requisite minimal skills to use the RSVP Keyboard™ BCI for spelling. A multidisciplinary clinical team identified skills needed and then modified existing subtests or tasks from clinical batteries to screen for hearing, visual perception, sustained visual attention, auditory comprehension, spelling, reading comprehension and literacy, and memory. The screening instrument was administered to 12 individuals with LIS. Testing took no more than an hour. All had reliable yes/no responses and could use eye pointing. Nine were accurate 100% on all tasks; three missed single items on tasks. The tool is appropriate for screening people with different diagnoses leading to LIS to determine if they have skills needed for possible BCI introduction.

Keywords: RSVP, spelling interface, locked-in syndrome, clinical protocol, screening tool

1. Introduction

In order for an individual with locked-in syndrome (LIS) to rely on a brain computer interface (BCI) for spelling, he/she must have adequate cognitive, sensory, seating and positioning, and language skills to perform requisite tasks. We identifed requisite skills for the RSVP Keyboard™, and developed screening tasks to determine if individuals with LIS possess basic functionality for its use. RSVP Keyboard™ is a BCI that relies on rapid serial visual presentation of symbols (letters, backspace, space) with P300 detection. This non-invasive system selects letters by joint evidence from a language model and EEG signals. Using a 200 to 400 ms stimulus time, one large letter is presented at a time on a monitor, thus reducing the visual-perceptual demands of a complicated display.

Assessing cognitive and communication abilities of individuals with LIS presents a number of challenges. Many assessment tools require verbal and/or written responses, which people with LIS are, by definition, unable to provide. Neuropsychological tests have been adapted for patients with classical or incomplete LIS, using yes/no questions that can be answered with eye or facial movements [Lakerveld et al., 2008; Schnakers et al., 2008; Rousseaux et al., 2009]. The range of cognitive and communication skill levels in this group is expansive, from individuals with ALS who may present with solely motor neuron impairments to adults with traumatic brain injuries which affect executive function, learning and memory. Due to this variability among people with LIS, a screening protocol is needed to determine whether patients can understand instructions, learn and complete the tasks required to effectively be introduced to the challenges of the BCI systems. We report on the RSVP BCI screening protocol, designed to determine whether an individual with LIS has the requisite sensory, cognitive, language skills to learn to use the non-invasive RSVP Keyboard™ for communication. The protocol includes structured interview questions, subtests from existing assessment tools that have been adapted for minimal motor responses, and new tasks developed to evaluate skills that are not adequately addressed elsewhere.

2. Material and Methods

Twelve participants with LIS were screened. We cast a wide net in our definition of LIS, including those individuals who are unsuccessful at using use oral speech or writing for language expression because of severe speech and physical impairment, and recruited 10 with incomplete LIS and two with classical LIS: 6 with amyotrophic lateral sclerosis (ALS), 1 with CVA, 1 with severe spastic-athetoid cerebral palsy, 1 with spastic quadriplegia secondary to arterial venous malformation, 1 with Duchenne muscular dystrophy, 1 with spinocerebellar ataxia, and 1 with progressive supranuclear palsy. Three participants were women, 9 were men.

A multidisciplinary clinical team identified the following skills as requisite for use with the RSVP Keyboard™: Visual perception, sustained visual attention, hearing, auditory comprehension, expressive language, memory and attention; reading comprehension and literacy, spelling. Probes about pain interference, medications, motor function, seating and positioning were deemed necessary for learning and use of the BCI. Items came from the following test batteries: PROMIS-P; Coma Recovery Scale- Revised; Western Aphasia Battery; Functional Linguistic Communication Inventory; Boston Naming Test. Tasks were adapted for motor-free responses using a clear, Plexiglas eye gaze board [Goosens' and Crain, 1987] or binary choices with eye blinking, eye movement or consistent, reliable movement of the head, foot or hand. The eye transfer board or ETRAN is a transparent plastic board that contains 4-8 stimulus items placed in the corners. It is held up between the examiner and the patient. The patient looks at a test stimulus and the examiner can see eye pointing to the items (i.e., find the picture of the pencil; spell CAT). It is used for spelling, reading, and language comprehension screening tasks.

3. Results

Participants completed the screening protocol in a single session lasting one hour or less, and they reported that administration time was appropriate for their abilities and endurance. All participants with LIS could reliably indicate yes/no responses, using dysarthric speech, eye movements, blinking, or movements of the head, feet, or hands and eye pointing to the ETRAN board. All participants demonstrated hearing within functional limits for conversation. All could see well enough to read and to identify pictures and objects. Two participants reported experiencing diplopia. Six participants reported problems with pain, though none reported that pain interfered with memory, concentration, or the ability to process new information. Two participants stated that their pain 'sometimes or rarely' made them feel discouraged; one stated that pain was 'rarely' so severe that he could think of nothing else. Two participants (or their caregivers) reported mild difficulties with memory and/or attention. Nine participants scored 100% on all RSVP BCI screening tasks. The remaining three participants missed items on a single task. Eleven participants completed the screening protocol in a seated position, and one was assessed while lying in bed. The materials used in the protocol proved to be easily adjustable for a variety of positions. Two participants (both with spasticity due to either CP or AVM) demonstrated frequent, uncontrolled movements of facial and respiratory muscles, which could potentially interfere with accurate EEG signal acquisition when using the RSVP Keyboard™.

4. Discussion

The RSVP BCI screening protocol is designed to assess the requisite skills for use of the RSVP Keyboard™ by people with LIS. Field testing demonstrates that the instrument can be administered in the home environment to people with LIS resulting from a variety of diagnoses. Administration typically lasts one hour, and varies depending on the response time, yes/no communication method, and fatigability of individual participants; all agreed that the screening time was reasonable for the target population. With questions for sensory (vision, hearing), cognition (attention, memory), communication (expressive and receptive language, reading, literacy, spelling), motor (seating, positioning) skills and pain/medication considerations, the screening instrument appears to address important behaviors that affect BCI learning and use.

The RSVP BCI screening protocol requires only yes/no and eye gaze responses, allowing for use with people with classical or incomplete LIS. Results paint an initial picture of the patient's basic level of function in requisite skill areas. Because subtests were chosen or designed to resemble or duplicate actual RSVP tasks, results are considered good estimations of a patient's potential to learn to use the RSVP Keyboard™ for communication. The general benefit of this screening tool is that we now have a relatively short, comprehensive cognition and communication screen that can be used by the LIS population and addresses the specific skills that are important for BCI learning and use. It is time for the BCI clinical community to design a standard protocol of requisite skills that should be administered so that we have a common means to describe behaviors necessary for BCI learning and use.

Acknowledgements

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Comparison of Checkerboard P300 Speller vs. Row-Column Speller in Normal Elderly and Aphasic Stroke Population

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Abstract. This study evaluates the ability of aphasic stroke patients to use two different P300 visual spellers to communicate. Nine normal elderly subjects and eight aphasic stroke patients used the checkerboard (CBP) and row-column (RCP) paradigms on a 6x6 alphanumeric matrix. We used a stepwise linear discriminant analysis for online classification of training data. Stroke subjects achieved a spelling accuracy of 60-65%. Normals achieved a higher accuracy than stroke subjects with the CBP (89% vs. 65%). CBP was also preferred over the RCP by normals, had a higher accuracy rate and was judged to be easier to perform. Our results indicate that in the elderly population, CBP is a superior paradigm compared to RCP. Our study also demonstrates that aphasic stroke patients can use a P300 visual speller to communicate.

Keywords: Electroencephalogram (EEG), P300 Speller, aphasia, stroke, checkerboard paradigm

1. Introduction

One major goal of current P300 visual speller research is to develop paradigms that significantly improve communication in patients suffering from severe neurologic disorders impairing speech and motor function. Most of the past clinical research subjects were patients with ALS or locked-in syndrome. A group of patients that has not been well-studied is aphasic stroke patients. Stroke is the leading cause of neurologic disease in the United States and those causing aphasias or language dysfunction are some of the most disabling. Restoring effective communication for stroke patients, especially for patients with expressive aphasia, is a potential application for BCI. Another area not well studied is how age may affect performance in BCI tasks, as most studies recruited young adult volunteers. Many of the anticipated clinical applications for BCI would apply to a much older population. Therefore, we studied the performance of aphasic stroke patients compared to an age-matched control group in controlling a P300 visual speller.

2. Material and Methods

2.1. Subjects and Data Acquisition

Nine normal elderly subjects and eight aphasic stroke patients were tested for the ability to control the P300 Speller using both the row-column paradigm (RCP) and checkerboard paradigm (CBP). All stroke subjects had Broca's aphasia and a NIH stroke scale language subscore of 2 or greater, indicative of severe aphasia. All subjects signed a Mayo Clinic IRB-approved consent form. EEG was recorded using a standard 32-channel electrode cap, amplified, band pass filtered 0.5-500 Hz and digitized at 1200 Hz using g.USB amplifiers (Guger Technologies). Stimulus presentation and data recording were controlled by BCI2000. Subjects viewed a 6x6 matrix on a computer screen and P300 Speller accuracy was based on a linear classifer and testing protocol previously described (Krusienski et al., 2008; Townsend et al., 2010; Krusienski and Shih, 2011). At the completion of testing, all subjects completed a testing preference questionnaire and visual analogue scale of paradigm difficulty (1-easiest, 10-most difficult).

Table 1. *Subject Information.*

Subject Number	Age	Gender	Starting Paradigm	Flash Number		Accuracy (%)		Paradigm	Visual Analogue Score	
~	~	~	~	RCP	CBP	RCP	CBP	Preference	RCP	CBP
C01	70	M	RCP	14	10	57	91	CBP	9.0	3.0
C02	58	F	RCP	12	10	93	93	CBP	7.0	4.0

C03	69	M	CBP	8	8	86	100	CBP	8.0	3.5
C04	72	F	RCP	14	10	95	91	No Preference	5.5	5.5
C05	67	F	CBP	12	10	86	86	No Preference	7.0	5.25
C06	78	M	CBP	14	14	75	98	CBP	5.5	2.5
C07	74	F	RCP	12	16	43	98	CBP	6.5	2.5
C08	72	M	CBP	14	10	64	86	CBP	3.0	2.25
C09	64	M	RCP	18	10	73	55	CBP	8.5	3.0
Average:	***69***	***~***	***~***	***13***	***11***	***75***	***89***	***~***	***6.7***	***3.5***

Subject	**Age**	**Gender**	**Starting**	**Flash Number**		**Accuracy (%)**		**Paradigm**	**Visual Analogue Score**	
Number	**~**	**~**	**Paradigm**	**RCP**	**CBP**	**RCP**	**CBP**	**Preference**	**RCP**	**CBP**
S01	80	M	CBP	12	20	36	73	CBP	5.5	6.75
S02	68	M	RCP	14	24	18	55	CBP	8.5	2.0
S03	66	M	RCP	24	12	68	66	CBP	5.0	7.0
S04	60	M	CBP	28	24	75	66	RCP	7.0	5.25
S05	54	M	RCP	12	12	61	68	No Preference	4.0	4.0
S06	54	M	CBP	12	12	77	36	No Preference	8.0	5.0
S07	60	M	RCP	24	8	86	98	No Preference	6.0	6.0
S08	75	F	CBP	Inc.	20	Inc.	55	Inc.	Inc.	Inc.
Average	***65***	***~***	***~***	***18***	***17***	***60***	***65***	***~***	***6.3***	***5.1***

2.2. Data Analysis

The data were analyzed using two-tailed paired t-tests to assess performance differences in flash number, accuracy and visual scale of difficulty between RCP and CBP for normal subjects. Because S08 did not complete the RCP portion of testing, two-tailed unpaired t-tests were used to analyze the data within the stroke group, and to assess for differences between the control and stroke group.

3. Results

Normal elderly using CBP were able to achieve a significantly higher average spelling accuracy (89%) than subjects using the RCP (75%) ($p < 0.01$), and found CBP easier than RCP ($p < 0.005$). Classification flash number was not different. Within the stroke group, there were no differences in test performance when using the RCP and CBP. In comparing normal elderly to stroke subjects, normals had higher accuracy using CBP ($p < 0.01$), but were not significantly different when tested with RCP. Normals needed less flashes with CBP to make a classifier ($p < 0.05$).

4. Discussion

The results indicate that CBP was superior to RCP as a P300 visual speller paradigm, when evaluated in terms of spelling accuracy, subject preference, and ease of use. This study also demonstrates that aphasic stroke patients can use a scalp-based P300 visual speller to communicate. While stroke subjects did not achieve the character selection accuracy attained by normals, their ability to use a BCI visual speller points to another potential clinical application in this fast moving research field.

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Selective Enhancement of Motor Imagery Features Using Transcranial Direct Current Stimulation

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Abstract. Transcranial Direct Current Stimulation (tDCS) has been shown to selectively modulate cortical responses in memory, motor and perceptual tasks. Here we show that this type of stimulation results in targeted enhancement of brain patterns elicited during motor-imagery. Offline analysis suggest this may yield higher classification performance. Experiments with healthy subjects (N = 10) and patients with spinal cord injury (N = 9) supports the idea of using tDCS as a facilitator for using brain-computer interfacing (BCI) in the frame of motor rehabilitation.

Keywords: Transcranial Direct Current Stimulation (tDCS), Motor neurorehabilitation, Motor Imagery, Spinal cord injury (SCI)

1. Introduction

Transcranial direct current stimulation (tDCS) selectively modifies neuronal excitability and reportedly enhances cortical responses to sensory stimulation and to improve performance in memory and perceptual tasks [Utz et al., 2010]. Interestingly, stimulation of motor areas results in modulation of the motor evoked potentials as well as changes in event-related desynchronization during Motor Imagery (MI) tasks [Matsumoto et al., 2010]. In turn, MI-based brain-computer interfacing (BCI) has been proposed as a supporting tool for rehabilitation [Millán et al., 2010]. Here we tested the effects of tDCS in both able-bodied subjects and patients with spinal cord injury (SCI). We found targeted enhancement of MI-related features in SCI patients resulting in improved decoding BCI performance.

2. Material and Methods

Nine SCI subjects (2 women; age 33.7 ± 8.5; lesions site ranged from C4 to C7) took part in the experiment, as well as ten control subjects (5 women; age 33 ± 7.4). None of them had any prior experience with BCI. Each subject participated in two recording days of BCI training (left vs. right MI) separated by at least one week. On each day, two sessions of about 25 min are performed. Immediately before the first session, tDCS stimulation was applied during 15 min over the left motor area (electrode position C3). The type of stimulation – either anodal or sham – was different on each recording day. The stimulation current was set to 1 mA and the ramp time was 7 s. A pause was introduced between the two BCI sessions so that the second session started one hour after the stimulation.

EEG was recorded at 512 Hz with 16 active surface electrodes (Fz, FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2 and CP4 of the 10/20 system. Reference: right mastoid. Ground: AFz). The signal was filtered in the [0.1 100] Hz range plus 50 Hz notch filter, and spatially filtered with a Laplacian derivation. For each channel we estimate its power spectral density (PSD) in the band 4-48 Hz with 2 Hz resolution over the last second. The PSDs were extracted every 62.5 ms using the Welch method with 5 overlapped (25%) Hanning windows of 500 ms. The discriminant power (DP) of these features (16 channels x 23 frequencies) was computed using canonical variate analysis [Galán et al., 2007]. This reflects the ability of each feature for discriminating between left and right hand MI. The most discriminant features are selected for classification using a Gaussian classifier.

3. Results

Higher performance (area under the ROC curve, AUC) was obtained for control than SCI subjects, as shown in Fig. 1a (Wilcoxon, $p < 0.01$ two tailed). Although a large variability across subjects is observed, a more consistent population performance is observed in the SCI group after tDCS stimulation. Nearly significant differences were found when comparing the performance in the tDCS and sham conditions for the SCI group ($p = 0.065$).

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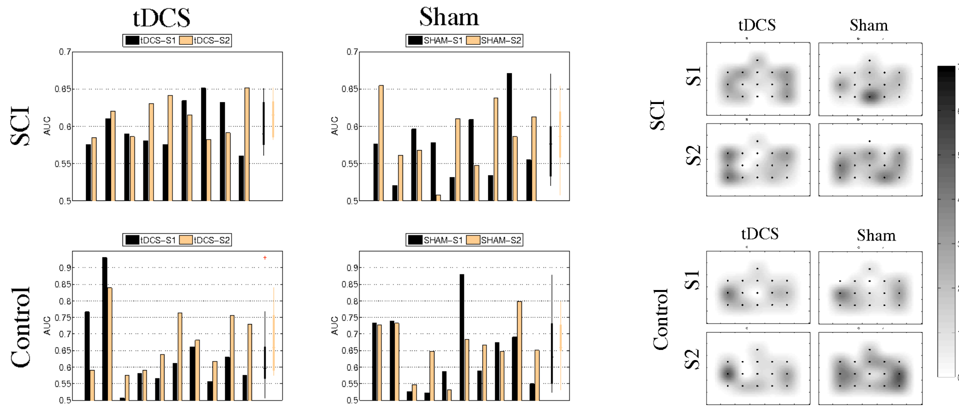

(a) (b)

Figure 1. *(a) Decoding performance (AUC) for all conditions and groups. Each bar corresponds to one subject; rightmost boxplot shows the average performance (b) Topographical localization of discriminant features in the band 6-12 Hz (Top view, Nose up). Gray tones denotes the number of subjects that show discriminant features at each electrode. S1: First BCI session (right after tDCS). S2: Second BCI session (>1hr after stimulation).*

As shown in Fig. 1b both groups (SCI and control subjects) consistently exhibit discriminant activity under the stimulated site (i.e. left motor cortex). Notably, after anodal tDCS SCI subjects show bilateral discriminant activity already at the first BCI session, and features under the stimulated hemisphere remained discriminant during the second session. In contrast, after sham stimulation activity in motor areas was less discriminant at the first session. Similarly, in control subjects, tDCS resulted in strongly localized discriminant information on the stimulated site over the two sessions, while the sham condition presented more bilateral patterns.

4. Discussion

Our results supports the hypothesis that intracranial stimulation enhances cortical activation during motor imagery and lead to discriminant and stable features that can be exploited for BMI. In particular, SCI patients exhibited discriminant activity over the targeted areas immediately after the stimulation, a fact that may facilitate the use of BCI as a supporting technique for motor neurorehabilitation.

Moreover, the present study was performed offline; therefore it still has to be assessed how tDCS influences online control. A related study, where bilateral tDCS was applied to stroke patients during robot-assisted rehabilitation therapy [Ang et al., 2012], reported no significant effects on online performance. The bilateral stimulation they used enhances the ipsilesional hemisphere while inhibiting activation of the unaffected areas. Further work is therefore needed to characterize the type of stimulation (e.g. unilateral vs. bilateral) and the population for which this stimulation effectively influence in the features used by BCI systems.

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BCI-Controlled Videogame for Cerebral Palsy Children

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Abstract. We describe a brain-computer interface (BCI) controlled videogame by integrating a custom made wearable 8-channel wireless EEG system, which samples and wirelessly transmits the EEG and EOG signals to a laptop. The laptop runs a shooting videogame using the features derived from the EEG and EOG. Sixteen cerebral palsy (CP) children were trained to play this game for one month (one hour per week). Their sustained attentional level after training was able to be maintained long enough for exploding the bomb in the videogame for more than 80% of the 30 cues in a 5-min game form the the originally 50% or less before training. These CP children then participated in the Second Mid-Taiwan Assistive Device Videogame Contest in Taichung on Dec. 29, 2012.

*Keywords:*Wireless EEG; Brain-computer interface (BCI); Cerebral palsy; EEG; EOG; Computer game

1. Introduction

Cerebral palsy (CP) children are mostly limited by the activity in their extremities and lack of capability in communication, they are thus in need of assistive devices for conveying their thoughts, training for their skill of communication, and even providing them with entertainments for enriching their life. However, such assistive device can be very specific in terms of how and what purpose the CP patients may use the device. For example, they might not be able to control a device using their hands or feet. As a result, the assistive device may need to utilize the still functioning muscles, such as eyes, cheeks, etc.

Recently, brain-computer interface (BCI) creates the possibilities to utilize the EEG features related to the brain processes of, for example, the P300 activity, motor execution, motor imagery, attentional level, and steady-state responses, etc. [Avanzini et al., 2012; Krusienski et al., 2007; Lim et al., 2012; Pfurtscheller and Neuper, 1997], and use them to control an assistive device, such as moving a cursor. Such a form factor should well fit the requirement of a CP patient due to their lack of muscle activity in their extremities. Here we devised a BCI-based videogame for the CP children to play using their EEG/EOG and, ultimately, to train their sustained attentional level.

2. Material and Methods

2.1. Subjects

A group of 16 CP children were trained to play this videogame and they then participated in an Assistive Device Videogame Contest hosted the Biomedical Engineering Research Center of China Medical University (CMU) in the Love Home of Taichung City, Taiwan on Dec. 29, 2012 (Fig. 1a). The parents and the teachers of these CP children gave the signed informed consent and the agreement for participation for them. The institutional review board of CMU Hospital approved the training process was conducted at Hermei Experimental School, Changhua, Taiwan.

2.2. 8-channel Wireless EEG System

A custom made 8-channel wireless EEG system provided high quality EEG and EOG sampled at 2 kHz per channel with 24-bit resolution. The device weighed 82 g (80 x 50 x 30 mm^3, including battery) and ran on a rechargeable battery for more than 20 hours. The acquired signals were transferred to a PC through a Bluetooth 2.0 channel. Given the ultra lightweight and easy to apply characteristics, the wireless EEG system was very suitable for on-line real-time EEG application, such as BCI. On the other hand, the electrodes used for this training were simply the self-adhesive ECG electrodes used regularly in the clinical environment to ease the application such that the training could be performed at the Experimental School site, where laboratory preparation was not available.

2.3. EEG and EOG Features for Controlling the Videogame

Two-channel EEG from the left and right forehead and one-channel EOG at right canthus were used to control the two actions of the videogame: one for shooting the alien spaceship and the other exploding the bomb. First, the eye blinks were detected from the EOG channel and used to fire the machine gun for 4 . Then, the player needed to blink again to resume the shooting (Fig. 1b). Alternatively, for every 10 s (varied from 8-12 s), a green bear's paw (the bomb) would appear and cease all actions on the screen for 4 s. During this time period, player was required to maintain his/her attentional level such that the green bear's paw would turn yellow and red and, finally, explode to clean all the alien spaceships to gain bonus (Fig. 1c). The EEG features used to derive the sustained attentional level were based on the real-time theta to alpha power ratio extracted from the two EEG channels on the participant's forehead. The performance of the players was evaluated with the percentage (thus, how many times out of the 30) of cases that they could successfully maintain their attentional level to explode the bomb in a 5-min game.

2.4. Training Cerebral Palsy Children to Use the BCI-controlled Assistive Device

Each of the participating CP children was trained once a week for 4 weeks. Each training session lasted for around an hour depending on the condition of the CP child. During the training session, the two channels of EEG and the one channel EOG were recorded for further analysis. The percentage of accurately exploding the bomb using their attention level was also recorded for comparison.

(a) (b) (c)

Figure 1. *(a) The Assistive Device Videogame Contest. (b,c) Operation of the shooting videogame.*

3. Results

After training, all the CP children significantly improved the performance in maintaining their attentional level. More than 80% of the case, the participants could maintain their attentional level for up to 4 s and explod the bomb in the game. Such success rate was initially 50% or less before training. The videogame was then made to end in 5 minutes so as to be used in the Mid-Taiwan Assistive Device Videogame Contest.

4. Discussion

BCI-based assistive device is one of the most effective forms for the CP children due to their limited muscle control for their extremities. Although the CP children participated in the training and the videogame contest were only trained for a month, the effectiveness of the training was reflected in their high accuracy in controlling the videogame as well as the performance in their class, especially in multi-task performing, according to their teachers.

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BCI for Stroke Rehabilitation: a Randomized Controlled Trial of Efficacy

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Abstract. A novel sensorimotor BCI prototype was developed to boost motor recovery of the upper limb in stroke patients. After preliminary testing, the prototype was installed in a rehabilitation ward and validated as an add-on to standard therapy in a randomized controlled trial, involving 26 unilateral subacute stroke patients. Clinical benefits and resting state brain network reorganization closer to normal were observed in the target BCI group.

Keywords: Stroke, Plasticity, Brain Network Analysis

1. Introduction

BCI technology has been proposed to support post-stroke motor rehabilitation either by guiding post-lesional plastic reorganization and/or by allowing neuroprosthesis control eventually leading to better functional recovery [Daly and Wolpaw, 2008; Dimyan and Cohen, 2011]. The neurofeedback mechanism behind Motor Imagery (MI)-based BCI paradigms has been shown to affect brain plasticity under specific conditions [Pichiorri et al., 2011]. In this scenario, a novel MI-based BCI prototype was developed in collaboration with rehabilitation experts to boost motor recovery of the upper limb in stroke patients.

2. Material and Methods

2.1. Prototype and study design

The prototype is shown in Fig. 1a. In the proposed MI-based BCI session two actors take part: the patient and the therapist. The first is trained to gain control of his/her visual hand representation by imaging hand movements (either closing or opening) and he/she receives as a feedback the congruent movements of the visual hand (successful trial). The therapist is fed back with the real-time movement of a cursor on a screen that is actually controlled by the patient EEG relevant feature. An equivalent session of MI practice without BCI serves as a control condition (CTRL). Twenty-six first ever, unilateral stroke patients in the subacute phase were included in the study that was designed following the literature recommendations for new rehabilitative interventions [Dobkin, 2009]. After baseline assessment patients were randomly assigned either to the BCI or to the CTRL groups. Assessments were repeated at the end of the one-month MI training (BCI or CTRL) that was administered as an add-on intervention during admission to a rehabilitation hospital.

2.2. Clinical and Neurophysiological assessments

As for the clinical evaluation, the Fugl-Meyer Assessment (FMA, upper limb) was chosen as primary outcome measure; European Stroke Scale (ESS) and Medical Research Council Scale for muscle strength (MRC, upper limb) were secondary outcome measures. An extensive neurophysiological assessment by means of high density-EEG and Transcranial Magnetic Stimulation (TMS) was conducted. A set of relevant EEG features was extracted from the baseline assessment to allow detection and monitoring of MI practice via BCI (for the BCI group). The same neurophysiological protocol was then repeated at the end of both training interventions (post-) to evaluate the related changes in brain reactivity and plasticity (brain network organization). Such analysis was performed at rest (resting state) expressing potentially stable plastic changes induced by the training itself; resting state data from patients was compared to a group of healthy subjects, by means of two one-way ANOVAs (before and after training). For the BCI group, Power Spectral Density (PSD) maps were obtained from the BCI training sessions.

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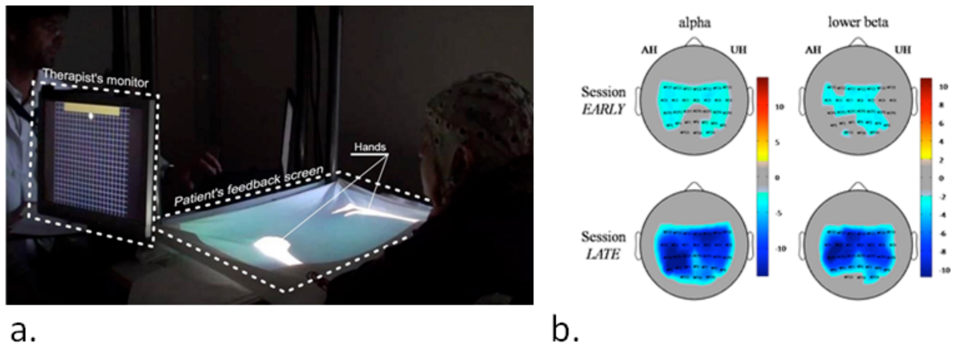

Figure 1. *(a) BCI prototype for upper limb recovery after stroke. (b) Statistical scalp maps (t -test MI vs baseline) for a representative patient. In the early training session, the pattern elicited in alpha and lower beta band was bilateral and t values were just above threshold. In the late session, higher involvement of the affected hemisphere occurred (absolute t values are greater than 10) in both bands. Colors code for t-values. Hot (yellow-red) and cold (blue) color scales stand for significant synchronization and desynchronization, respectively.*

3. Results

No significant differences between groups were observed for epidemiological data, primary and secondary outcome measures at baseline. Both groups significantly improved in all outcome measures from baseline to post-assessment. The FMA estimated Minimal Clinically Important Difference of 7 points was reached by 10 patients in the BCI group and 3 patients in the CTRL group, being this difference statistically significant ($p = 0.02$). A significantly higher effectiveness was obtained in the BCI group as measured with ESS and MRC scales ($p = 0.01$). TMS showed that both groups were able to perform MI capable of increasing motor cortical excitability (increase in Motor Evoked Potential amplitude during MI; BCI group $p = 0.007$; CTRL group $p = 0.03$). Resting state brain network analysis in Beta showed that inter-hemispheric connectivity (expressed as number of connections) was significantly lower in the overall sample of stroke patients (BCI and CTRL; pre-training) with respect to healthy subjects ($p = 0.02$). No significant difference between the BCI and CTRL groups was found. After training, the BCI group displayed an increased in the number of inter-hemispheric connections such that the pre-training significant difference observed with respect to the healthy group disappeared. On the contrary, differences persisted between CTRL and healthy ($p = 0.01$). PSD map analysis revealed a significant pre- post- training power difference ($p < 0.05$) occurring in the lower beta band oscillation recorded only over the lesioned hemisphere sensorimotor strip. An exemplary case of such EEG reactivity is illustrated in Fig. 1b.

4. Discussion

To our knowledge, this is the first study supporting BCI efficacy in stroke rehabilitation as compared to a control condition. The proposed BCI-based intervention yielded to clinically relevant improvements as compared to the MI intervention alone. Moreover, we observed changes in resting state brain network properties (increased number of inter-hemispheric connections) possibly leading to a more normal configuration of the network.

Acknowledgements

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Different Uses of Non-invasive BCI for Controlling Neuroprostheses: Case Studies with End-Users

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Abstract. This work introduces two strategies of how to use a non-invasive brain-computer interface (BCI) for controlling upper extremity neuroprostheses customized for end-users with varying degrees of impairment. One strategy employs a hybrid-BCI for end-users who have remaining muscular functions at shoulder level; the other one uses a control purely based on BCI. We demonstrate the two different BCI-controlled neuroprostheses with case studies, recorded in two spinal cord injured end-users.

Keywords: Electroencephalogram (EEG), Brain-Computer Interface (BCI), Functional Electrical Stimulation (FES)

1. Introduction

Spinal cord injured (SCI) people can benefit from assistive devices including brain-computer interface (BCI) [Wolpaw et al., 2002]. Depending on the level of impairment, BCI can be combined with other signals based on residual movements or muscular activity measured by electromyography (EMG). However, with a more severe impairment, these signals may no longer be available or cause early fatigue. In this case, a BCI system without any other control signals can offer an alternative. Neuroprosthesis users primarily want to control their hand to grasp objects but with reduced elbow function the restoration of elbow flexion/extension is a prerequisite for adequate use of the grasping function. In this work we show two case studies. Both apply BCI to control a neuroprosthesis based on Functional Electrical Stimulation (FES). The first one is designed for end-users who still have elbow and shoulder functions. Shoulder movements are used to control the grasp strength and a motor imagery (MI)-based BCI to switch between two grasp patterns. The second type uses only a MI-BCI as a control method: depending on the length of delivered MI commands—time-coded MI [Müller-Putz et al., 2010]—either discrete commands like opening/closing the hand or continuous commands like moving the arm upward/downward can be elicited.

2. Material and Methods

Two tetraplegic male end-users, both diagnosed with complete SCI at C4/C5, tested the systems. End-user ES, 31 years old, used both systems. End-user TS, 37 years old, only tested the system for switching between grasp patterns. Both had long-term BCI experience and underwent BCI training to set up individual classifiers based on linear discriminant analysis (LDA) for distinguishing between imaginations of feet movements versus rest.

2.1. BCI to switch between grasp patterns

A 2-axis position sensor was placed on the shoulder to use shoulder movements for modulation of the pulse width of FES in a proportional control scheme and thereby modulate the grasping of the hand. The FES electrodes were placed on different positions on the forearm which allowed the user the execution of palmar and lateral grasps, depending on which electrodes were used to stimulate the underlying motor points [Rupp et al., 2011]. BCI was used in a time-coded manner: short or long commands were generated by imagination of feet movements, as trained beforehand. The paradigm consisted of three states: palmar grasp, lateral grasp, and pause. Short commands (1.5-3 s) allowed the user to toggle between the grasp patterns or exit pause mode. Pause mode could be entered via long commands (>3 s). Additionally, the shoulder position was constantly monitored and used to prevent unwanted switches during ongoing shoulder movements. The two end-users were asked to perform two tasks. Each task started in pause mode. Task A required them to exit the pause mode by switching to the first grasp pattern. Using this pattern they should try to move as many objects—fitting to the current grasp pattern—as possible within 120 s. After this time period, they should switch to the second grasp pattern, move objects for 120 s, switch once again back to the first pattern, move objects, and finally return to the pause state. Task B was different: after exiting pause mode, they had 180 s to alternately move one object and switch to the other grasp pattern.

2.2. BCI for continuous and discrete control of a neuroprosthesis

The end-user was asked to perform 10 sequences in order to simulate eating food with a hybrid orthosis [Rohm et al., 2011] (open hand→close hand→move arm up→open hand→return to starting position), each within 180 s. The used BCI was again a time-coded MI, however, now the long commands served as continuous commands: as soon as a long command was detected, the elbow started to flex or extend for as long as the long command remained active. The elbow movement was generated by FES electrodes on the upper arm and by equipping the end-user with an orthosis that facilitated stabilization of the elbow joint and provided a control loop to automatically reach desired angles by changing the pulse width of the electrical stimulation. When the target angle was reached, the elbow joint of the orthosis was mechanically locked to avoid fatigue due to continuous stimulation. Short MI commands were only used as discrete commands: these discrete commands were either used to open/close the hand in maximum and minimum angle positions or used to move the arm to the nearest end position.

3. Results

3.1. BCI to switch between grasp patterns

Both end-users tested this system, end-user ES twice. This end-user needed on average 16.9±12.2 s to switch between grasp patterns, 51.3±59.1 s to switch to pause mode; he transferred 215 objects within 24 min during tasks A and 31 objects during the 12 min of tasks B; 53 switches were rejected in total. End-user TS needed 26.2±27.9 s for grasp toggles and 9.0±1.4 s to enter pause mode. He transferred 138 objects during the 12 min of tasks A and 16 objects during the 6 min of tasks B and had 25 switches rejected.

3.2. BCI for continuous and discrete control of a neuroprosthesis

End-user ES achieved a rate of 73.7% true positive commands, depending on the current position of the arm and hand. Eight of ten sequences could be finished within the time limit. During additional non-control states he triggered 2 false commands/min in contrast to 6.9 commands/min during the active sequence periods.

4. Discussion

Both systems were tested successfully in the two tetraplegic end-users. The high variance of switching times is caused by the necessary switches to revoke false commands. Control for both grasp patterns was improved strongly, for the fine-tuned movements were not possible without the neuroprosthesis. In this first system, BCI is only used as an additional control signal; the main control signal is based on shoulder movements. Negative effects of unwanted BCI switches can be strongly reduced due to the rejection of switches during ongoing shoulder movements. The second system uses the BCI signal as the main component. Additional sensory signals are merely used to allow the system to control the angle of the arm. The BCI task itself is more demanding since performing mental tasks over different time periods can be very difficult. Yet, end-user ES is a very good BCI performer and for him it was possible to successfully control the system and complete most of the required sequences. In conclusion, an exclusive BCI control is feasible in severely disabled people but the performance, e.g. the time needed to move objects, is lower than in the hybrid BCI where BCI is combined with other signals controlled by the user.

Acknowledgements

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Selection Strategies for the RSVP Keyboard™ BCI: Different Strokes for Different Folks

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Abstract. Eight people with locked-in syndrome (LIS) and 18 healthy controls completed calibration sessions on the RSVP Keyboard™ P300 brain-computer interface (BCI) using the mental imagery-based selection strategy of their choice. We report here on BCI users' preferred strategies. Most people chose to rely on speech imagery, with motor imagery second, and sensory, visual or combined imagery used by one person each.

Keywords: Brain-computer interface, augmentative and alternative communication, P300, mental imagery, symbol selection

1. Introduction

The RSVP Keyboard™ is a P300-based spelling interface in which symbols are presented in a rapid serial visual presentation (RSVP) paradigm [Orhan et al., 2012]. The system detects the P300 response elicited when the user sees the desired symbol appear in a series of symbols, and users are encouraged to choose a mental image as a selection strategy, a conscious attempt to alter their brain activity. Here we present the strategies tried and preferred by people with locked-in syndrome (PLIS) and healthy controls when using the RSVP Keyboard™.

2. Material and Methods

Participants included eight PLIS (one classical, seven incomplete) with a variety of underlying diagnoses, and 18 healthy controls. Our definition of incomplete LIS encompasses people who are unsuccessful at using oral speech or writing for language expression due to severe speech and physical impairments. Experimental sessions took place at the homes of PLIS, and in a quiet university lab room for healthy controls. Electroencephalography (EEG) signals were recorded using a 16-channel g.USBamp and g.BUTTERFLY electrodes (g.tec, Graz, Austria).

Before attempting any typing task with the RSVP Keyboard™, users must calibrate the system. During each calibration session, participants are presented with either 50 or 75 sequences of symbols. Each sequence begins with a target symbol, followed by a fixation cross and then a series of 10 symbols. Participants are instructed to watch for the target symbol to reappear in the series of 10 symbols, and to "do something to change your brain activity" when it appears; this is the participant's selection strategy. Participants are provided with examples of selection strategies from various categories including motor, speech, visual, sensory, and auditory imagery. Each person is encouraged to choose a strategy that feels natural, or that is easy to consistently apply while using the RSVP Keyboard™. Before each calibration session, participants are given the option to continue using the same strategy, or to try something different. They are instructed not to switch strategies mid-session. Researchers record the specific strategies tried by each participant, as well as the final strategy used during the RSVP task. Final preferred strategies are determined either by asking the participant or by observing which strategy he or she chooses most often.

For each calibration, classifier accuracy is estimated from the area under the curve (AUC) of true positive versus false positive rate for the calibration target versus non-target classification, under a 10-fold cross-validation.

3. Results

Participants' selection strategies are categorized into five types of imagery: speech, visual, sensory, motor, or a combination of two types. Participants chose a preferred strategy based on ease of use, AUC score, or both. Three PLIS and seven control participants tried two or more types of strategies. The remaining participants were satisfied with their initial choice and did not try other options. Two PLIS and one control did not show a clear preference for any category. This may be the result of limited experience with the RSVP Keyboard™ (the two PLIS had only two calibration sessions each) or not being satisfied with any of the options tried (as with the control participant).

Table 1 indicates how many participants tried each category of selection strategy, and how many participants showed a preference for each category. Examples of actual participant strategies are provided. Speech imagery was the most popular type of selection strategy for both participant groups. Motor imagery was the second most popular

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category among controls, but not one PLIS used a purely motor imagery-based selection strategy. Two did try strategies combining motor and speech imagery, though neither one preferred the combination strategy. The motor components of both combination strategies (moving a finger and clicking a mouse) were small movements that these two participants (both with incomplete LIS secondary to advanced ALS) were physically able to do.

Median tests on AUC scores for all calibrations completed by PLIS, X^2 (3, $N = 43$) = 4.21, $p = .240$, and control participants, X^2 (3, $N = 44$) = 1.87, $p = .601$, indicated that selection strategy did not have a significant effect on classification accuracy for either participant group.

Table 1. *Selection strategies tried and preferred by PLIS and control participants.*

Imagery Category	*PLIS (N = 8)*		*Controls (N = 18)*		
	Tried	*Preferred*	*Tried*	*Preferred*	*Examples*
Speech	8	6	17	11	Imagine saying or screaming symbol name Imagine saying “Bam!” or “Yeah!” or similar exclamation
Visual	1	0	2	1	Imagine a line or slash through target symbol Visualize a pleasant image
Sensory	1	0	0	0	Imagine being pinched on the arm
Motor	0	0	6	4	Imagine punching or grabbing target symbol Imagine swinging a golf club
Combination	2	0	1	1	Imagine saying “There!” and moving right index finger Imagine saying symbol name and clicking a mouse

4. Discussion

Selection strategy might be a variable that affects success in BCI use or strength of P300 signal detection. As such, it is valuable to determine what strategies are used by PLIS and healthy controls. Although speech imagery was the most popular selection strategy among both PLIS and control participants, it was not preferred by all participants. Some BCI users may benefit from strategies based on other types of mental imagery. These results are similar to those of [Friedrich, et al., 2012], who compared the event-related (de)synchronization (ERD/S) responses produced by a variety of mental tasks for potential BCI control, as well as participants’ opinions of those tasks. In that study, there was high variability among participants both in classification simulation results for each task pair and in self-ratings of the imagery quality, ease of use, and enjoyment of each task. In a similar comparison of mental tasks for BCI control, [Curran et al., 2003] found that visual and auditory imagery were more reliable than motor imagery, and study participants reported that the non-motor tasks were easier to perform and required less concentration. Both of these studies included only participants without disabilities.

Interestingly, PLIS avoided using motor imagery-based strategies, and those who tried them (in combination with other imagery) imagined movements they could make in reality. People with congenital motor impairments may lack experience with the movements they are asked to imagine, and those with LIS due to acquired conditions may begin to find motor imagery difficult or unnatural. Motor and sensory impairments may also be associated with changes in the brain itself. Therefore, strategies which can work well for users without disabilities, such as motor imagery, might not be ideal for some PLIS. The data presented here are not sufficient to determine whether certain selection strategies are better than others, or even whether using a selection strategy is preferable to no strategy at all. Future research in this area may be beneficial for determining optimal ways to improve BCI performance, particularly for users with LIS, since selection strategies may improve attention or be associated with EEG changes.

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Enhancing Brain-Computer Interface Performance in an ALS Population: Checkerboard and Color Paradigms

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Abstract. A brain-computer interface (BCI) speller provides non-muscular communication via detection of EEG features. In a non-disabled population, a Checkerboard (CB) stimulus presentation has been shown to improve BCI performance over the standard Row/Column (RC) paradigm. Another improvement is a gray-to-color (CL) paradigm that presents perceptually-salient targets defined by nine unique colors. The current study examines the RC, CB, and CL paradigms in an amyotrophic lateral sclerosis (ALS) population (N = 7). Pilot data suggest improved performance of CB and CL over RC. The results suggest matrices including CB and CL provide more efficient communication and higher user satisfaction in an ALS population.

Keywords: Assistive Devices, Brain-Computer Interface, EEG, P300 Event-Related Potential, Rehabilitation

1. Introduction

Noninvasive brain-computer interface (BCI) provides non-muscular communication via detection of EEG features. In a non-disabled population, and in pilot data from participants with amyotrophic lateral sclerosis (ALS), the checkerboard (CB) presentation paradigm provided better performance than the standard row/column (RC) presentation paradigm [Townsend et al., 2010]. In non-disabled participants, a color condition (CL) that changes groups of gray matrix items to one of nine unique colors improved performance as compared to the standard condition in which gray matrix items change to white [Ryan et al., 2011]. This study examines if these improvements generalize to an ALS population.

2. Material and Methods

The current study uses a 6 x 6 matrix to compare three conditions in an ALS population: 1) CL, 2) CB, and 3) RC (see Fig. 1A). Each participant completed all three conditions in a pseudo-randomized order. The RC condition flashes entire rows and columns of items in random order. The CB condition flashes groups of items in a quasi-random order. The CB has two constraints in selecting the flash groups. The first prevents any adjacent item from flashing simultaneously in the same row or column. The second constraint requires an item to be absent from four or five (depending on the virtual matrix cells that are presented) subsequent flash groups before it flashes again. The CL condition used the same presentation method of the CB and consisted of items represented in gray (stimulus off) that flashed a unique color (stimulus on) to the eight items surrounding it in the matrix. Stimulus presentation, and online processing was conducted with BCI2000 [Schalk et al., 2004]. Electroencephalogram (EEG) was recorded from sixteen electrodes; eight of the electrodes were used for classification (Fz, Cz, P3, Pz, P4, Po7, PO8, & Oz; [Krusienski et al., 2008]). Thirty item selections were used to serve as training data for a stepwise linear discriminate analysis (SWLDA), the resulting SWLDA coefficients were then used for online response classification. Thirty additional selections were presented in the online condition. After each selection the subject was presented with the result of the BCI's character selection to inform the subject whether or not the BCI accurately classified their EEG responses. The number of stimulus presentations was held constant at seven sequences per item selection (one sequence is complete when every item of the matrix has flashed two times) for calibration and online testing. Participants were given a survey to assess their opinion of which condition they preferred.

3. Results

Statistical analyses were not performed due to the small sample size. Nonetheless, some trends are evident in the data. Accuracy in the CL condition was higher than the CB and RC conditions (90%, 80%, & 79% respectively). Information transfer rate (ITR) was higher in RC condition than in the CL and CB conditions (9.63, 7.73, & 6.58

respectively). The CB (and CL) constraints require 33% more flashes of smaller groups than the RC. Resulting in more time required per sequence in the CB, which accounts for the difference in ITR.
Of the seven participants, four preferred the CL and three preferred CB condition. As show in Fig. 1B, the CL and CB conditions require fewer flashes to achieve higher accuracy than the RC condition.

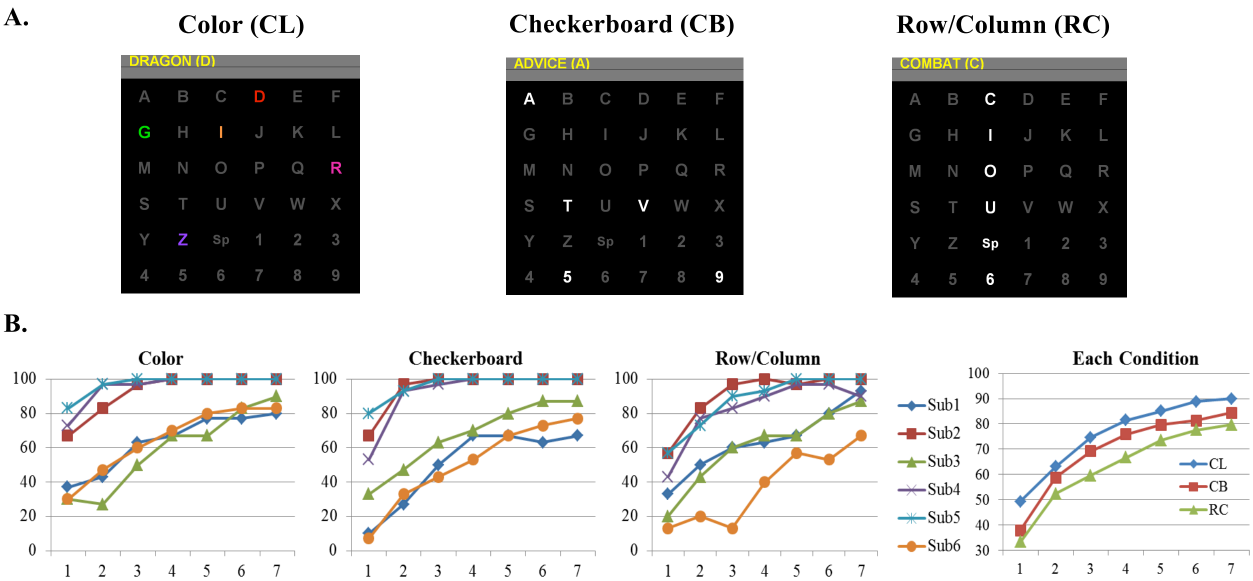

***Figure 1. A)** The three conditions examined: Color (CL), Checkerboard (CB) and Row/Column (RC). **B)** Percent correct by sequence for each participant and for each condition averaged across participants. The performance curve revealed higher initial accuracy in the CL condition for all participants. Participants 2, 4, & 5 reached 100% by the 3rd sequence in CL and CB. This accuracy was not achieved until the 5th sequence in R/C.*

4. Discussion

Pilot data suggest enhanced performance of CL over RC in a ALS population. In addition, CL and CB were preferred over the standard RC paradigm by all participants, despite higher ITR.The current study presented a fixed number of stimulus presentations for each participant and condition. Reducing the number of stimulus presentations should result in higher ITR for the CL and CB condition than RC. The results suggest matrices including CB and CL provide more efficient communication and higher user satisfaction in an ALS population.

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Rapid Prototyping for hBCI Users With Cerebral Palsy

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Abstract. A rapid prototyping system is described that allows efficient development of hybrid Brain-computer interfaces (hBCIs) for users with Cerebral palsy (CP). The system is based upon an expansion of the TOBI framework and is demonstrated to allow rapid construction of a Steady state visual evoked potential (SSVEP) based hBCI system.

Keywords: Cerebral palsy, EEG, rapid prototyping system, hBCI, multi-modal signal acquisition

1. Introduction

Cerebral palsy (CP) is an umbrella term for a range of differing motor and other disabilities caused by damage to the fetal or infant brain. Individuals with CP can experience a range of difficulties relating to motor control, coordination, posture and other difficulties such as speech impairments or cognitive difficulties [Iosa et al., 2012].

Hybrid Brain-computer interfaces (hBCIs) base control on a combination of neural and other physiological signals and have been proposed as assistive devices for individuals with CP [Daly et al., 2012]. An optimal assistive device should simultaneously address various aspects of daily life and offer many user-specified applications (i.e. health monitoring, communication etc.). Usabilitiy should also be optimised via a user-centered interface requiring both monitoring of and adaptation to user states. In addition, because individuals with CP will not only have specific application needs but also a unique set of hBCI-utilisable capabilities, the device should be flexible and readily customisable. Therefore, a system is required which is capable of simultaneously recording, processing, and storing multiple signal types in an environment which allows quick prototyping and testing of customised hBCIs.

Therefore, a rapid prototyping environment is developed based upon open standards for data transmission defined in the TOBI framework [Müller-Putz et al., 2011]. Key aspects are multi-modal signal acquisition, standardised data transmission protocols, support for rapid development and integration of new modules, and data storage mechanisms.

The system may be constructed in a modular fashion and distributed over multiple devices. In the envisioned setup the system is distributed over a central server (laptop) and tablet computers to minimise the complexity of the user-facing components. Support is provided for simultaneous acquisition and processing of physiological signals including EEG, EMG, EDR, ECG, breathing, accelerometers for monitoring limb movement, and blood oxygenation levels. This allows hBCIs to be constructed for control, emotion, and health monitoring.

2. Material and Methods

The system is described and its efficacy demonstrated by constructing an SSVEP hBCI and health monitoring system.

2.1. Rapid prototyping system

The rapid prototyping system is comprised of five sections; signal acquisition, pre-processing, processing, visualisation, and control. Communication is via TOBI interface A (TiA), D (TiD), and C (TiC) [Breitwieser et al., 2012].

The system consists of a computer and one or more tablets. The first handles signal acquisition, pre-processing, and processing. The latter realises visualisation and control. The tablet mainly serves the end-users with applications specifically tailored according to their needs. Additionally, the tablets may be used to provide residual voluntary control by end-users or, if present, caregivers, (e.g. keyboard, microphone). Fig. 1 illustrates the system.

The first module (based on the SignalServer [Breitwieser et al., 2012]) handles signal acquisition and synchronisation. This is extended to handle specific devices applicable to users with CP to provide continuous monitoring of health status and generate alarms upon abnormal values. Additionally, EDR and ECG are recorded for emotional state detection. The acquisition system is chest-worn with ECG sensors, sensors for breathing frequency, a triaxial accelerometer to quantify physical activity and detect falls, and temperature and blood oxygenation sensors. Data is then transmitted to the pre-processing and processing blocks. The final blocks handle visualisation and control.

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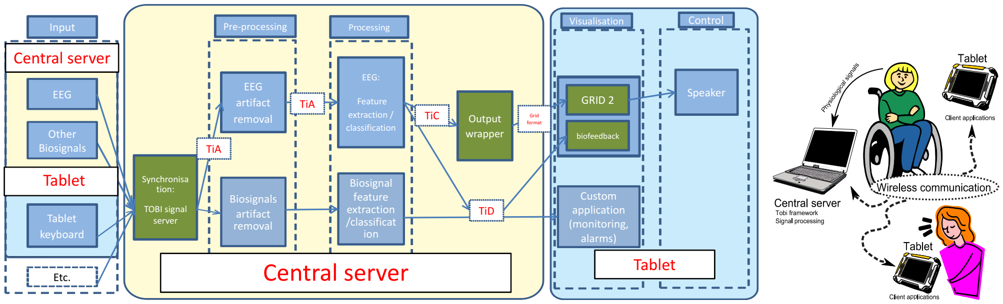

(a) System modules and data flow (b) System overview

Figure 1: Figure 1a, data flow through the system. Data originates in the devices and moves through the blocks. Figure 1b, the system structure, signal acquisition, and processing are in the central server and feedback and visualisation are in the tablets.

2.2. Demonstration

To demonstrate the efficacy of the rapid prototyping environment it is used to build an SSVEP hBCI, with integrated health monitoring, for CP users. Three modules are created. The first attempts to clean the EEG of artifacts [Daly et al., 2013], the second to classify via Canonical correlation analysis (CCA), and the third presents the BCI application and feeds back the classification results. The system is tested with 3 healthy users (all male ages 29–30, two right handed).

Regarding the health monitoring, separate acquisition devices are used to acquire non-EEG biosignals from the user (Heart Rate Variability (HRV), Respiration Rate (RR), temperature values). Artifactual segments are removed and signals are processed in order to highlight variations with respect to baseline values. Processed data and events are sent to the remote user interface (caregiver's tablet) for monitoring purposes and to raise alarms.

3. Results

The rapid prototyping system is successfully used to construct an SSVEP hBCI integrating a health monitoring system. The demonstration system evokes clear SSVEP responses. The hBCI is also observed to operate efficiently and allow acquisition, cleaning, classification, and storage of physiological signals. Additionally, the rapid prototyping system has also been used to develop motor imagery and SSVEP BCIs for users with CP (see [Daly et al., 2012]).

4. Discussion

The rapid prototyping environment is demonstrated to allow efficient construction of hBCIs. Modules may be constructed for all steps of the hBCI pipeline. The use of open standards means the system is compatible with a range of hardware acquisition devices and may be efficiently integrated with any other modules adhering to the same standards.

On-going inter-institutional research will seek to use this rapid prototyping environment to develop hBCI devices to provide help with the assistive living, health monitoring, and emotional state detection needs of individuals with CP.

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The N100 of Averaged ERPs Predicts LDA Classifier Success on an Individual Basis

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Abstract. We examine the success of a common LDA classification algorithm for P300 Speller BCI systems on an individual basis. Experiments performed on 16 subjects (7 with severe motor impairment, 9 with no motor impairment) indicate that the P300 Speller should, on average, work in both client and neurotypical populations. Here, we find that the N100 of an averaged ERP, a measure associated with selective attention, has a significant relationship with LDA classifier results, and may account for a large portion of variability we see in individual success in operating P300 Spellers.

Keywords: Brain-Computer Interfaces, P300 Speller, N100, Linear Discriminant Analysis, Individual Differences

1. Introduction

Brain-computer interfaces (BCI) show great promise for individuals with motor impairments in regaining the ability to communicate. One form of BCI widely studied in hopes of achieving this goal is the P300 Speller. The P300 speller operates by flashing a series of letters to the user. When the target letter is flashed, we expect to see a P300 response, a large positive voltage deflection in the user's brain activity approximately 300 ms after a stimulus presentation as recorded by electroencephalography (EEG). In order for this system to work, however, a computer must be able to classify each letter as a target or a non-target presentation based only on the user's brain activity during each response segment. Classification of EEG segments is commonly achieved using linear discriminant analysis (LDA). Past literature shows a great deal of variability in the success of LDA classification from person-to-person with clients often performing lower than unimpaired. To date, the cause for this variability is unknown.

Here we investigate potential predictors of LDA success on an individual basis by exploring another component of EEG responses, the N100, a negative voltage deflection approximately 100 ms after a stimulus presentation obtained from an averaged ERP. The N100 has been implicated in selective attention, and is known to be affected by individual factors such as fatigue [Hillyard et al., 1973]. This is important in P300 Spellers as the user must selectively focus on a single letter and with extended use, the user may become fatigued. Fatigue may affect his or her ability to attend, thus implicating the usefulness of the LDA algorithm. Many individuals in need of BCI technology cannot communicate verbally and may not be able to voice their fatigue levels or ability to maintain their attention to stimulus presentation. Because of the N100's relationship to selective attention, we hypothesize that the N100 will have some predictive power in determining the success of LDA classification in individuals. We also posit that the N100 may be an effective measurement of fatigue, thus eliminating the difficulty of communication lapses between users and caregivers or researchers.

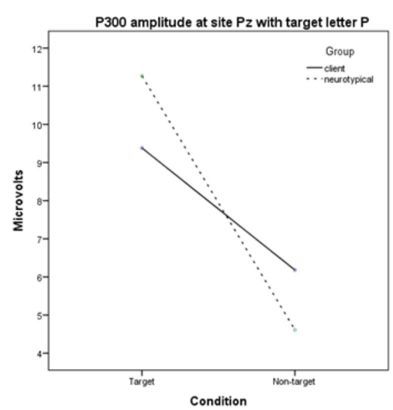

Figure 1. *A comparison of mean P300 amplitudes for clients and neurotypicals in target and non-target letter conditions.*

2. Material and Methods

First, using traditional ERP methodology and repeated measures ANOVA we show that both client and neurotypical participants having no motor impairments produce P300 amplitudes that are, on average, significantly different for a target letter compared to non-target letters ($F = 13.9$, $p = .002$) with no significant differences between the groups ($F = .009$, $p = .93$; see Fig. 1 and Table 1). Thus, we conclude that the P300 Speller should be successful on average for both groups.

Next, we show that LDA is an effective classification tool (see Table 1). Following the suggestions of [Blankertz et al., 2011], we regularize LDA using shrinkage toward the average eigenvalue of the covariance matrix. The shrinkage parameter is selected using 10 repetitions of random sub-sampling validation with a 60%-20%-20% split between the training, validation, and test partitions respectively. Class labels are assigned after encountering six EEG segments by estimating the joint probability of the segments belonging to each class, i.e., by summing the evaluation of the LDA discriminant functions.

Finally, using linear regression we examine if the relationship of N100 and P300 amplitudes from averaged ERPs of both target and non-target stimuli can be predictive of the success of LDA classification in individuals. Our analyses indicate that a model with only the N100 target and P300 target amplitudes significantly predicts LDA success, R^2=.48, $F_{(2, 13)} = 5.97$, $p = .015$. Examination of beta weights reveal that that only the N100 amplitude is the significant predictor, $\beta = -.71$, $t = -3.44$, $p = .004$ and P300 is not a significant contributor ($\beta = .25$, $t = 1.21$, $p = .25$). A separate analysis revealed that if the model is expaned to include N100 and P300 amplitudes for non-target letters, neither of these variables contributes to prediction of LDA success; F $\text{Change}_{(2,11)} = .089$, $p = .92$.

Table 1. *Individual LDA classification results and N100 and P300 amplitudes.*

Client Results				Neurotypical Results			
Subject	**LDA Classification**	**N100 Amplitude**	**P300 Amplitude**	**Subject**	**LDA Classification**	**N100 Amplitude**	**P300 Amplitude**
B001	100	-1.72	4.45	B011	87.50	-4.24	12.13
B002	65.00	-3.75	10.11	B012	80.00	-2.9	12.54
B003	67.50	-4.95	25.44	B013	82.50	-4.46	9.72
B004	47.50	-3.41	5.09	B014	82.50	-7.83	15.03
B005	45.00	-2.95	2.79	B015	95.00	-4.49	13.91
B006	85.00	-1.98	10.21	B016	62.50	-1.52	9.18
B007	95.00	-4.34	7.57	B017	95.00	-4.52	6.52
				B018	55.00	-2.11	14.00
				B019	52.50	-1.81	8.41

3. Discussion

Our data indicate that while the P300 speller should, on average, work successfully, the N100 does have a significant relationship with LDA classification abilities. Individual factors such as fatigue and decline in selective attention may be interfering with users' ability to successfully operate P300 spellers. However, LDA techniques force the limitation of data and may exclude this important N100 information. Future classification algorithms may benefit from including more contextual information in the analysis of neural responses rather than just the P300. In an online BCI, the N100 could be used to provide cues to remind users to attend, thus improving their success rates. Researchers and caregivers may also use the N100 as a means to preselect individuals who will and will not be successful in using the P300 speller; according to our data, an individual with a larger N100 response to visual stimuli should be more successful in operating a P300 speller than an individual with a smaller N100 response.

Acknowledgements

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EEG Correlates of Performance During Long-Term Use of a P300 BCI by Individuals With Amyotrophic Lateral Sclerosis

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Abstract. People with amyotrophic lateral sclerosis (ALS) are using BCI 24/7, a P300-based brain-computer interface (BCI) system, independently, in their homes, for work and play. At the same time speed and reliability remain important issues for these independent users. This study seeks to correlate the EEG in six frequency bands (0-30 Hz), collected from eight electrode locations, as features in a linear model to predict if a P300-based BCI session will be successful. Data were collected from six home users during a copy-spelling calibration task. These data were divided into sessions with accuracy greater than or less than 70%. The prediction accuracy for session performance using information from the frequency bands was 82.72%. Better understanding of which EEG features are correlated with success could lead to better performance and greater system reliability.

Keywords: Brain-Computer Interface, Event-Related Potential, P300 Speller, Amyotrophic Lateral Sclerosis

1. Introduction

Studies demonstrating long-term use of a P300-based brain-computer interface (BCI) by individuals with amyotrophic lateral sclerosis (ALS) reveal considerable variation in day-to-day performance [Sellers et al., 2007; Nijboer et al., 2008] not observed in able-bodied subjects [Krusienski et al., 2008]. This may be explained by changes in attention in ALS patients that have been related to frontal lobe pathology [Bathgate et al., 2001]. In a study of 20 ALS patients, nine had some degree of cognitive impairment and five of these met the criteria for behavioral variant frontotemporal dementia (bvFTD) [Lillo et al., 2012]. Symptoms of FTD include changes in sleep patterns, verbal disfluency, decreased attention, working memory, and responses to sensory stimuli. These factors are likely to affect P300 Speller performance. Mak and colleagues examined the relationship of a wide variety of EEG features and found that root-mean-square amplitude, the negative peak amplitude of event-related potentials at five electrode locations, and the power in the theta frequency band for eight electrode locations were correlated with performance [Mak et al., 2012]. The present study undertakes to use an alternate and more direct approach to examine the relationship between EEG spectral features and performance in independent BCI use by six individuals with ALS.

2. Methodology

The data are comprised of EEG recorded from six individuals with ALS (4M, 2F; average age 53.4) who used a P300-based BCI independently in their homes for communication and control over months and years [Sellers et al., 2010; Winden et al., 2012]. All six subjects wore an elastic cap (Electro-Cap International) with eight electrodes (Fz, Cz, Pz, Oz, P3, P4, Po7, Po8) [Krusienski et al., 2007]. All locations were referenced to the right mastoid with the left mastoid serving as a ground. The EEG was amplified (g.tec Medical g.USBamp); digitized at 256 Hz; and band-pass filtered at 0.5-30 Hz. All aspects of the experiments were controlled by BCI2000. Subjects performed a brief copy-spelling task for offline calibration several times a week during regular home use of the BCI. This copy-spelling task consisted of spelling 20-40 prescribed characters using either the row-column (RCP) [Donchin et al., 2000] or the checkerboard (CBP) presentation [Townsend et al., 2010]. For consistency, the first 20 characters from each session were included in the analysis. Stimulus flash rate and flash sequence number were optimized for individual subjects and sessions, and they are not considered in the present analysis. All subjects had significant performance variations over sessions as indicated in Table 1.

The offline accuracy on a copy-spelling task (i.e., performance) for each session was determined using stepwise linear discriminant analysis (SWLDA) and five-fold cross validation. Sessions having an accuracy above 70% were labeled successful and sessions below 70% were labeled as unsuccessful [Kübler et al., 2001]. The data for each session was segmented by character and the average power for each segment was computed in six frequency bands:

delta (0-4 Hz), theta (5-8 Hz), alpha1 (9-11 Hz), alpha2 (12-14 Hz), beta1 (15-25 Hz) and beta2 (26-30 Hz) [Mak et al., 2012]. A support vector machine (SVM) classifier with linear kernel function was used to classify the spectral features to predict the session labels. Five-fold cross validation was performed where the features corresponding to 50 randomly-selected characters were used for training and the remaining characters for testing.

3. Results

Table 1 shows the session parameters and performance predictions for each subject. The accuracy is the result of the five-fold cross validation for predicting successful (> 70%) or unsuccessful sessions (< 70%) using the spectral features. The sensitivity and specificity are included to indicate that the classification results are not biased due to an imbalance of successful and unsuccessful sessions.

Table 1. *Session information and prediction results.*

Subject	A	B	C	D	E	F	Average
Presentation	CBP	CBP	CBP	RCP	RCP	RCP	
No. Sessions Evaluated	32	6	14	11	38	31	
No. Session. > 70%	8	4	10	4	17	21	
Range of Session Accuracies (%)	4-87	38-90	37-98	2-90	8-95	33-96	
Duration of BCI Use (months)	13	1.5	19	4	7	6	
Session success vs unsuccess prediction							
Accuracy (%)	72.04	97.19	91.39	98.87	69.85	67.02	**82.72**
Sensitivity (%)	73.61	97.43	86.14	99.18	74.17	61.77	**82.05**
Specificity (%)	67.51	97.21	93.68	98.45	64.55	69.92	**81.88**

4. Discussion

These results indicate that simple spectral features can be used to reliably predict P300 Speller performance for a given session. An analysis of the individual features indicated that the theta and alpha1 frequencies have the highest correlation with session performance for most subjects. However, locations of the highly-correlated features did not generalize across subjects. Better understanding of the mechanism of successful BCI use may lead to improved classification, and thus, better more reliable performance. Further this approach might provide BCI users about their BCI readiness on a given day. Such information may save time and effort, and help the user avoid frustration.

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Towards a Novel Control Paradigm Based on Decoding Imagined Movements From EEG

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Abstract. One way to control a limb neuroprosthesis is a brain-computer interface (BCI). A BCI records brain-signals and converts them into control signals. Here, we propose the basis for a novel control paradigm using the imagined movement of one arm in two orthogonal movement planes. We used low frequency EEG signals (around 0.5 Hz) for classification and obtained an average classification accuracy of 69%.

Keywords: EEG, motor imagery, movement planes, movement decoding

1. Introduction

Beside other things, paralyzed persons suffer from lost motor functions, and neuroprostheses are one possibility to restore motor functions. Such neuroprostheses need a control signal, which can be provided by a brain-computer interface (BCI). A BCI records brain activity and transforms it into control signals. Sensory motor rhythm based BCIs (SMR-BCIs) detect the motor imagination (MI) of different body parts, but are incapable of decoding different movement trajectories of the same body part. Recently, it was shown that it is possible to decode trajectories of executed movements from EEG using low frequencies (< 1 Hz) [Bradberry et al., 2010; Ofner and Müller-Putz, 2012]. However, that was not shown conclusively for MI [Poli and Salvaris, 2011]. We found in preliminary experiments that the decoder performance when decoding MI is unacceptable low (the correlation coefficient is around 0.3) and is easily affected by eye movements. However, such a decoding of MI would have two advantages over SMR-BCIs. First, a direct link between MI and neuroprosthesis movement would allow a natural and intuitive control of the neuroprosthesis. Secondly, it would not be necessary to learn the expression of new brain patterns as in the case of SMR-BCIs. This can lead to a reduced training time. Compared to motor execution, movements cannot be measured directly and subjects have to perform known movement patterns, which are synchronized to the system. However, a synchronization as e.g. imagining to follow with the arm a ball moving on a screen is improper, because this causes eye movements. Thus, we implemented a paradigm where subjects imagined rhythmic movements in 2 planes according to the beat of a metronome.

2. Methods

We instructed 9 healthy right-handed subjects, seated in an armchair, to imagine waving the extended right arm in front of the upper body either in the transverse or in the sagittal plane. A beep tone indicated the start of a trial. Simultaneously, a cue in form of an arrow pointing right or up was shown for 0.5 s and indicated the direction/plane of the movement. After 1.5-2.5 s, a metronome started to tick for 20 s with a frequency of 1 Hz, and was used to synchronize movement imaginations to the system. Subjects were asked to fixate the gaze on the cross on the screen to suppress eye movements. We recorded 8 MI runs, each with 5 trials per class, i.e. 80 trials per subject. We recorded the EEG using 68 electrodes covering frontal, sensorimotor and parietal areas and the EOG with 3 electrodes. We removed the influence of eye activity using a linear regression method. First, we applied a band-pass filter with cutoff frequencies at 0.3 Hz and 0.8 Hz. To decode positions, we used two linear models – one for each coordinate – with data from all EEG channels and three time lags in 60 ms intervals. We found the parameters of the linear models with multiple linear regressions. Here, we assumed that subjects imagined movements corresponding to a sine oscillation with a frequency of 0.5 Hz. To classify at trial, we decoded movement positions between second 2 and 19 relative to the start of the metronome (additionally, we also varied the window length), correlated the decoded movements separately for each coordinate with a sine oscillation of 0.5 Hz and assigned the trial to the coordinate (i.e. plane) with the higher correlation. Results were obtained using a 10x10 cross-validation.

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3. Results

Mean values and standard deviations of classification accuracies are shown in Table 1. The grand average is 70% with a standard deviation of 10%. Classification accuracies are significant above 59% with α = 0.05. The mean classification accuracy over subjects with significant EEG based classification accuracies and with non-significant EOG based classification accuracies is 69% (s1, s2, s4, s5, s6). An EOG based classification yield significant accuracies for subjects s7 (62%), s8 (71%) and s9 (77 %), and between 41% and 57% for all others. In addition to the fixed window length of 17 s used for correlation, we also analyzed how the classification accuracy changes in dependence on the length of the window (see Fig. 1). The start offset of this window was fixed to 2 s relative to the start of the MI. The classification accuracy of subjects s1, s3, s5, s7, and s9 peaked at short window lengths. After an eventual peak, all classification accuracies increased with increasing window length except for subject s3.

Table 1. *Mean values and standard deviations of classification accuracies for all 9 subjects, significant classification accuracies are written bold.*

subject	*s1*	*s2*	*s3*	*s4*	*s5*	*s6*	*s7*	*s8*	*s9*	*grand average*
mean value [%]	**71**	**67**	55	**82**	**65**	**59**	**70**	**82**	**78**	70
std. dev. [%]	17	15	16	13	15	17	15	13	14	10

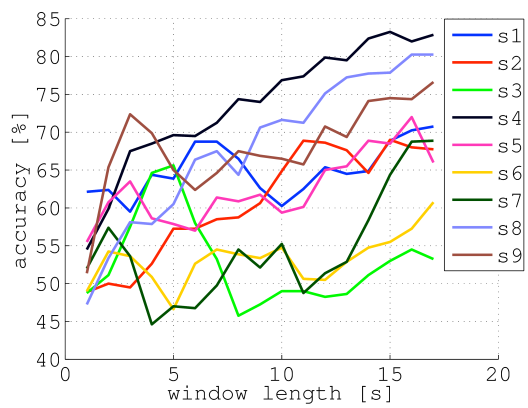

Figure 1. *This plot shows the accuracy in dependence of the correlation window length.*

4. Discussion

We classified in 8 out of 9 subjects the movement planes with significant accuracies. Three subjects show also significant classification results when using solely EOG signals. Although we removed eye activity from the EEG, it still cannot be guaranteed that there is no residual eye activity left in the EEG, which was mistakenly classified. Thus, at least 5 subjects showed significant classification results due to EEG activity when classifying arm MI in two planes. The classification accuracy increased with the window length. This is probably due to the decreasing signal-to-noise ratio of the correlation coefficient. The peak at short window lengths observed in 5 subjects could be an indicator for the presence of two overlayed processes. We proposed a method to *classify* MI of one arm in two planes. This can be the basis for a new mental control strategy for a BCI if the window length can be shortened. Furthermore, as we used the same decoding principles as in [Ofner and Müller-Putz, 2012], we have shown indirectly that *decoding* of MI is possible. However, the performance of such a decoder would be limited.

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Decoding Individual Finger Movements Using Noninvasive EEG

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Abstract. Brain-computer interface (BCI) enables people suffering from severe motor disabilities to control external devices by decoding different patterns of brain activities. One principal challenge, that largely confines the complexity of noninvasive BCI applications, is the limited number of features available to generate control signals. Recent BCI study based on electrocorticography (ECoG) investigated individual finger movements using spectral principal component analysis (PCA). The extracted features demonstrated a great potential in decoding movements of fine body parts, i.e., individual finger movements, which could increase the number of control features for BCI. However, the feasibility of such features in noninvasive BCI has not been tested yet. To advance the development of noninvasive BCI, the aim of the present study is to investigate such spectral features in electroencephalography (EEG). The extracted features were validated by classifying pairwise individual finger movements, resulting in an average decoding accuracy (77.17%) significantly higher than the guess level (50%) in all subjects ($p < 0.05$).

Keywords: BCI, EEG, Individual finger movement, PCA, Noninvasive.

1. Introduction

While EEG has been widely adopted in noninvasive BCI studies [McFarland et al., 2009; Wilson et al., 2009], the limited number of available control features impedes the development of noninvasive BCIs for complex applications [Xiao et al., 2012]. The present study evaluated features about individual finger movements of one hand, which were previously studied using ECoG [Miller et al., 2009], in noninvasive EEG, aiming to advance the development of noninvasive BCI.

2. Material and Methods

2.1. Experimental protocol

During the experiments, subjects performed either rest or repetitive movements of individual fingers from one hand according to visually presented cues. Each trial lasted for six seconds. The first two seconds allowed subjects to rest. The following two seconds provided data for resting conditions with few artifacts by instructing subjects staring at a fixation cross. In the last two seconds, one of five words (thumb, index, middle, ring and little) was randomly presented on the screen, cueing subjects to perform repetitive movements of the corresponding fingers. EEG data were recorded from 128-channel sensor net (Electrical Geodesic Inc., OR, USA) at sampling frequency of 250 Hz. At the same time, bipolar EMG sensors were attached to each finger to detect movement peaks, which were used to extract 1-second segments of EEG data that corresponded to movements in each trial. Data from five subjects were processed and evaluated in the present study.

2.2. Feature extraction and classification

The movement segments as well as resting segments of all trials were referenced to a common average reference (CAR). The EEG temporal potentials were then transferred into spectral powers. Following that, the spectral PCA was performed on data from each pair of fingers. Firstly, the covariance matrix of spectral powers was constructed to reveal inter-frequency correlations and inner-frequency variances produced by trials from different conditions. Secondly, eigenvalues and eigenvectors of the covariance matrix were calculated and arranged according to magnitude of corresponding eigenvalues in a descending order. These eigenvectors were the principal components (PCs) reflecting spectral features related to finger movements. Finally, EEG spectral powers of each trial were projected onto different PCs to acquire projection coefficients, which were features fed to classifiers for decoding.

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The support vector machine (SVM) classifier was implemented to classify movements from each pair of fingers using a five-fold cross validation. Eighty percent of trials were used to train parameters for the classifiers, and the rest for testing. Decoding accuracies were achieved by comparing predicted labels from the classifiers to the true labels. The whole process was repeated 20 times with trials randomly permuted to yield mean decoding accuracies.

3. Results

Features from spectral PCA decomposition are consistent across different subjects and permutations (Fig. 1). The first PCs (blue curves) present a broadband pattern, which is flat and with positive magnitudes at all frequencies. This pattern is consistent with the broadband phenomenon reported in the ECoG study [Miller et al., 2009]. The second PCs (red curves) mainly peak at some low frequency bands, including alpha and beta bands, revealing power changes in these frequency bands during individual finger movements. When implementing projection coefficients of different PCs in the classifiers, different optimal decoding accuracies are achieved for different pair of fingers, with index vs. little the highest at 86.11% and thumb vs. index the lowest at 70.98%. The average decoding accuracy across all pairs of fingers is 77.17%, which is significantly higher than the guess level at 50% ($p < 0.05$).

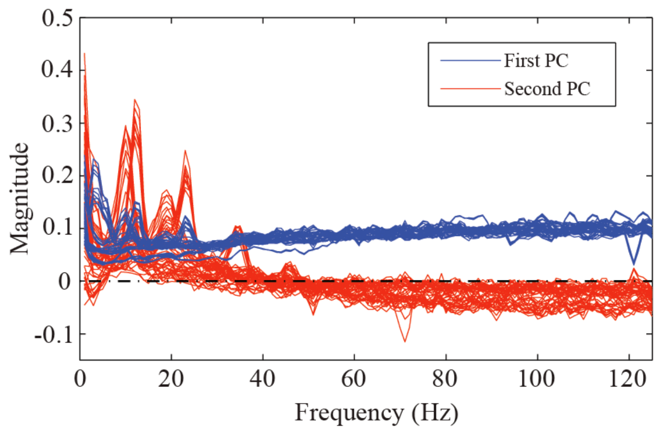

Figure 1. *First and second spectral PCs from 20 permutations and all subjects.*

4. Discussion

With the use of spectral PCA decomposition, the resulting spectral PCs were in line with those in ECoG, suggesting that the spectral features indicative of individual finger movements from one hand exist in EEG as in ECoG. The achieved decoding accuracy further confirmed the validity of such information in EEG. The findings demonstrated that EEG contains useful information to decode individual fingers, which can increase the number of control features for noninvasive BCIs. The present study is promising to advance the development of BCI towards noninvasiveness by transferring features from ECoG to EEG.

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Decoding Complex Hand Movements Using High Density ECoG and High Field fMRI

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Abstract. Implantable brain computer interfaces promise to provide communication for severely paralyzed people. Current solutions focus either on high-dimensional control of a robot arm, or on a single-channel switch or click. We here investigate feasibility of decoding multiple classes from the same patch of cortex, to enable some form of speech. For this it is necessary to identify multiple neuronal states that can be decoded reliably. We postulate that inner sign-language can offer a solution. To test this, we evaluted decodability of representation of complex hand movements in the primary sensorimotor cortex using high field fMRI and high density ECoG. Using simple template matching classification, four hand gestures were classified with up to 100% accuracy with both techniques. Our studies indicate that complex hand gestures exhibit reliable and discriminable spatial representations on sensorimotor cortex which makes them a promising candidate for speech-oriented BCIs.

Keywords: ECoG, fMRI, hand movements, decoding

1. Introduction

Completely implantable and minimally invasive brain computer interfaces (BCI) promise to provide severely paralyzed patients with the ability to communicate independently of their caregivers. In the ideal case these BCIs would allow for reliable, fast, and effortless communication. Therefore, it is necessary to identify brain signals which are easily detected and recognized by a classifier and which can be intuitively generated by the user for use as a control signal. Hand gestures as they are used in finger spelling in sign languages appear to be a promising candidate. The entire alphabet can be represented in form of single hand gestures. The detailed topographic representation [Penfield et al., 1937] and the plasticity of the primary motor cortex (M1) make it likely that each gesture exhibits a reliable and specific representation that can be identified. In this study we therefore map out the neuronal representations of complex hand movements on the motor cortex using ECoG and fMRI. ECoG provides high fidelity signals, with very good temporal resolution. The disadvantage is a sparse sampling of the cortex. fMRI on the other hand provides a complete sampling of the entire cortex and allows studying larger populations of participants, albeit at a low temporal resolution. Those two methods complement each other and can provide detailed insight in the representation of the underlying processes.

2. Material and Methods

The execution of four hand gestures, taken from the American Sign Language alphabet (corresponding to the letters ‘F’,’L’, ‘W’ and ‘Y’), was studied with high density ECoG in epilepsy patients and high field fMRI (7T) in healthy volunteers. To control for the correct execution of the task the actual hand movements were recorded using a 5DT data glove, allowing measuring the movements of the individual fingers.

2.1. High field fMRI

Twelve healthy volunteers (4 male, age 25.78 ± 5.8 years) participated in the fMRI study. They performed two event related sessions; the first one was used as training set the second as test set. The training session consisted of 256 trials (32 trials for each of the 4 movements) and 128 rest trials with a variable inter trial interval (2.6 s-18.2 s). Timing of stimuli was based on interleaved m-sequences to optimize statistical efficiency [Buracas et al., 2002]. The slow event related design included 40 trials (10 for each movement) with a fixed inter stimulus interval of 13 s, this assured that the effects of the previous trial were washed out. Each stimulus was presented for 750 ms. During the inter-trial interval a fixation cross was shown. The fMRI measurements were implemented using a 7 T Philips Achieva MRI system with a 32-channel head-coil. The functional data was recorded using an EPI sequence. The field of view covered the left pre- and postcentral gyrus. During the training and the test session 535 volumes and

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481 volumes, were made, respectively. A high-resolution image was acquired for anatomical reference using a T1 weighted 3D TFE sequence. The data was slice time corrected, realigned, and detrended. The feature selection was based on the training set; voxels that showed task related activity for one of the conditions were selected. As features the sum of the estimated fMRI response, as estimated by a standard FIR analysis, of each voxel and each trial at the 4th 5th and 6th scan after stimulus onset was used. For the test session the raw fMRI signal was used.

2.2. High density ECoG

From 5 patients, undergoing neurosurgery for epilepsy, multi-channel subdural ECoG data was recorded. High-density grids were implanted (32-64 contact points, 1.3 mm exposed surface, inter-electrode distance 3 mm center to center) beside the standard macro grid electrodes and were left in place for one week. In all patients part of M1 as well as S1 were covered around the superior aspect of the primary motor cortex, where hand function could be expected. Each gesture was presented 10 times, providing 40 trials in total. The data was band passed filtered to remove the 50 Hz line noise. Channels containing artifacts were removed. All channels were re-referenced to the common average reference for all included electrodes on the grid. The data was epoched into segments of 2 s before and 3 s after movement onset (based on the data glove readings). The power in the frequency range 65-95 Hz was computed for all epochs using a wavelet transform (Gabor wavelet, 7 cycles). The average power per channel between 1 s before movement onset and 2 s after movement onset were used as features.

2.3. Classification

For classification of the movements, a 'nearest-neighbor' classification procedure was applied [Pereira et al., 2009] for ECoG and fMRI. Individual trials were classified by computing the Pearson correlation between the trial and four templates. The templates consisted of the average response for all remaining trials within the four conditions; for the fMRI the average response was based on the training session for ECoG it was based on a leave-one-out procedure. The trial was classified as the gesture type it had the highest correlation with in a winner-takes-all manner.

3. Results

For the fMRI the average classification accuracy for the gestures was 72% (sem 4.25, chance level 25%) with a range over participants from 49% to 100%. The most informative areas for the classification were located in a confined region in the hand knob area on the primary motor cortex and the adjacent sensory cortex on the postcentral gyrus. The variations in classification accuracy between participants could be explained by variations in the fMRI signals of individual trials, which in turn could be explained by variations in the consistency of executing the gestures. For the ECoG the average classification accuracy was 65% (sem 8.8, chance level 25%) with a range over participants from 47% to 97%. The variations in classification accuracy between participants could be explained by the position of the grid (different part of the hand region were covered in different participants).

4. Discussion

Our studies indicate that complex hand gestures exhibit reliable and discriminable spatial representations on sensorimotor cortex. These representations can be used to classify gestures with high accuracy, using only a confined unilateral area of the brain. Differences in classification accuracy between participants were related to differences in task performance (fMRI) and grid location (ECoG). A simple 'nearest neighbor' classification procedure made it possible to classify both ECoG and fMRI data with high accuracy. For both methods the most informative regions were in the hand region of sensorimotor cortex. Our results suggest that high field fMRI can be used prior to implantation to identify the target area for high-density ECoG electrode grids. We conclude that complex hand gestures are a promising control signal for future multi-mode BCIs. Future work has to show how many gestures can be differentiated and whether imagined movements can be decoded in a similar fashion.

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Controlling an Avatar by Thought Using Real-Time fMRI

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Abstract. We have developed a BCI system based on real-time fMRI. Our approach is based on manually locating the regions of interest responsible for left-hand imagery, right-hand imagery, and feet imagery in the brain, and comparing the mean activity in these areas with their baseline values as a simple classification scheme. Six subjects were able to perform a cue-based task and a free choice task of controlling an avatar using finger and toe motion, and three of these subjects also performed the tasks using only motor imagery.

Keywords: Real-time fMRI, avatar, cue based, free choice, motor imagery

1. Introduction

We have developed a system for decoding mental patterns from fMRI data online, and use these decoded patterns to control an interactive virtual environment. Non-invasive BCIs are often based on recording brain activity using electrodes attached to the scalp, usually by electroencephalography (EEG). However, EEG signals are noisy and it is very difficult to localize the source of the activity that is detected, so the reliability and the information throughput of EEG-based BCI are limited. Motor imagery has also been used with EEG-based BCI for controlling virtual reality including controlling an avatar [Friedman et al., 2010], but the control is usually limited to two or three classes at most, and requires a lot of training. Therefore, we see potential for BCI research in fMRI-based BCI. The current cost and size of fMRI do not make it a viable option for application outside the research lab. Nevertheless, it can be used to explore new mental strategies, localize the corresponding brain areas, and be used to train subjects. Furtherhmore, fMRI-based neurofeedback has been suggested as a promising approach to rehabilitation [DeCharms, 2008]. Our approach goes beyond neurofeedback in using multiple regions of interest (ROIs) as BCI targets and providing virtual reality and even robotic feedback [Cohen et al., 2012].

2. Material and Methods

2.1. The System

Imaging was performed on a 3T Trio Magnetom Siemens scanner, and all images were acquired using a 12 channel head matrix coil. Three-dimensional T1-weighted anatomical scans were acquired with high resolution 1-mm slice thickness (3D MP-RAGE sequence, repetition time (TR) 2300 ms, TE 2.98 ms, 1 mm^3 voxels). For blood-oxygenation-level-dependent (BOLD) scanning, T2*-weighted images using echo planar imaging sequence (EPI) were acquired using the following parameters: TR 2000 ms, TE 30 ms, Flip angle 80, 35 oblique slices without gap, 20 towards coronal plane from Anterior Commissure-posterior Commissure (ACPC), $3 \times 3 \times 4$ mm voxel size, covering the whole cerebrum.

The data coming from the fMRI scanner is saved as Dicom files[1], and processed by Turbo BrainVoyager software (TBV, Brain Innovation, Netherlands)[2], which is a real-time processing, analysis, and visualization application that accepts input from an fMRI scanner. We have developed a system that integrates TBV and the Unity game engine[3] (Unity Technologies, California). Our system now includes a complete tool for running a wide range of real-time fMRI studies with different algorithms, experimental protocols, and virtual environments.

2.2. The ROI-based paradigm

The experiment is divided into three parts. In the first part the subject is given pseudo random motor-imagery instructions and the experimenter manually marks the regions of interest (ROIs) inside the most saturated regions for the three classes. In the second part the subject rests and the brain activity is recorded to serve as a baseline. In the third stage, we instruct the subject to imagine moving his limbs and collect the average values from each ROI every two

[1] http://medical.nema.org/
[2] http://www.brainvoyager.com/
[3] http://unity3d.com/

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seconds. A classification is made using the Z-score formula and is calculated for each measured value by using the mean and standard deviation from the baseline period:

$$z = \frac{x - \mu}{\sigma}. \tag{1}$$

where x is the average raw value in an ROI in the current TR, μ is the mean raw value of the ROI in the baseline period, and σ is the standard deviation value of the ROI in the baseline period. The selected class is the one corresponding to the ROI with the maximal z-score value. The system then transmits the classification result to the Unity engine for rendering. Each ROI is mapped to a different action performed by the subject: turning left, right, or walking forward corresponds to left-hand, right-hand, or legs imagery, respectively.

2.3. Subjects and Experimental Conditions

Six subjects have performed a cue-based task that were intended to evaluate the BCIs accuracy, and a continuous free choice task: the subjects were represented by an avatar and were instructed to make the avatar reach a balloon. These subjects were allowed to use their fingers and toes while lying down in the scanner. Three of the subjects also performed the same tasks using only motor imagery. In the free choice tasks all subjects attempted at least one epoch (including 6 trials) with several temporal frequencies: a classification result was obtained every 2, 4, 6 or 8 seconds. The subjects filled in a questionnaire of 14 Likert-scale questions after each experimental session, and each subject went through a semi-structured interview at least once. The data is being further analyzed and will be reported in the full paper.

3. Results

In the cue-based task subjects reached 85–100 % accuracy. All subjects were able to control the avatar in all free choice conditions. We compared the number of steps that the subjects needed in order to reach the balloon with the minimum number of steps possible. All subjects were able to reach the balloon with the minimum number of steps at least once in all conditions (2, 4, 6 and 8 seconds, using both imagery and motion). The highest average accuracy is obtained when commands are sent every 6 seconds (using both imagery and motion).

4. Discussion

The results of this study indicate that subjects can learn to perform a free choice BCI task (controlling an avatar) using motor imagery, with very little training. The ROI-based method we have presented here is simple and computationally efficient. We are now extending it using machine learning techniques in order to identify more specific multi-voxel brain patterns that may lead to identifying more complex mental states and more classes.

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Pairwise Classification of Phoneme Imagery Using CSP

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Abstract. We recorded EEG signals in three healthy subjects while imagining both the vocalization and places of articulation of four vowels (/a/, /i/, /u/, and /y/) and four consonants (/m/, /f/, /n/, and /ŋ/) in Mandarin Chinese, and a no action state as control. We examined the time-frequency features of phonemes as precise motor imagery and found the significant effects in spectral power lying in 2-12 Hz. Common spatial patterns were applied to EEG signals for spatial filtering, and the performance of pairwise classifications indicates potentiality for a speech neural prosthesis using phoneme imagery with more than 75% phoneme vs. control accuracy averaged across subjects.
Keywords: EEG, Phoneme Imagery, Communivative BCI, Common Spatial Patterns, Phonetic Features

1. Introduction

Brain-computer interfaces (BCIs) have been developed to restore communication and functionality to individuals with severe neuromuscular disorders. In this article, we propose a control scheme towards a true speech neural prosthesis using phoneme speech imagery. Electroencephalography (EEG) was recorded in three healthy subjects while imagining both the vocalization and places of articulation of four vowels (/a/, /i/, /u/, and /y/) and four consonants (/m/, /f/, /n/, and /ŋ/) in Mandarin Chinese as well as a no imagination state as control.

2. Material and Methods

2.1. Recording

EEG data were recorded from 32 Ag/AgCl electrodes (sampled at 500 Hz, bandpass filtering .01-100 Hz, notch filtering 50 Hz) positioned in a NeuroScan headcap on the scalp, according to the international 10/20 system.

2.2. Participants

Three undergraduates, recruited from Tsinghua University, participated in this study (two males, mean age 19.3 years, SD 2). All had normal or corrected to normal vision and none of them had history of neurological disease.

2.3. Stimuli

Nine kinds of stimuli were presented at the center of the screen in font SimSun-ExtB and size 30. Four of the stimuli are vowels; each represents a category of rhymes in the phonological system of Mandarin Chinese. Another four of the stimuli are consonants with distinguishable places of articulation. The phonetic features of the stimuli, together with a non-phonetic symbol # for control, with regard to the articulators are depicted in the Table 1.

2.4. Procedure

Coached beforehand and rehearsed with real movements to ensure correct articulation, subjects were instructed to imagine the movement of articulators as well as the vocalization of the phoneme as soon as they saw the visual target appeared on the screen. Each trial began with a fixation cross against a gray background for a randomized time interval between 1 to 2 s followed by a randomly chosen visual stimulus for 2 s, during which participants were instructed to perform the task of phoneme imagery and maintain the static imagination until the visual cue disappeared. After that, a blank gray screen was displayed for 3 s to serve as a rest interval. 50 trials were performed for each visual stimulus.

Table 1. *Phonetic features of the stimuli concerning articulators.*

Articulator	Status	/a/	/i/	/u/	/y/	/m/	/f/	/n/	/ŋ/	#
lips	unrounded	1	1	0	0	1	1	0	0	0
	rounded	0	0	1	1	0	0	0	0	0
teeth		0	0	0	0	0	1	0	0	0
tongue	high	0	1	1	1	0	0	1	1	0
	low	1	0	0	0	0	0	0	0	0
	front	0	1	0	1	0	0	1	0	0
	back	0	0	1	0	0	0	0	1	0
jaw		1	0	0	0	0	0	0	1	0
alveolar ridge		0	0	0	0	0	0	1	0	0
hard palate		0	0	0	0	0	0	0	1	0
larynx		1	1	1	1	1	0	1	1	0

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2.5. Data Processing

All data processing was performed offline using MATLAB (version 7.14.0, MathWorks, Inc., Natick, MA) and EEGLAB [Delorme and Makeig, 2004]. The recorded EEG signal was re-referenced to the mean of the left and right mastoids and bandpass filtered between 1 and 45 Hz for preprocessing. We performed time-frequency analysis of phonemes vs. control and further filtered the data with the significant frequency band of 2-12 Hz. For all epochs, we selected a time window from 0 to 800 ms and randomly selected 40 of the 50 epochs 20 times per task to compose training data, upon which we applied the CSP method for spatial filtering. EEG training and testing data were decomposed using the spatial filters and then fed into an SVM model with a linear kernel for classification.

3. Results

In Fig. 1, we demonstrate the results of time-frequency analysis, common spatial patterns, and binary classification where we restrict the analysis to the pairwise problem condition vs. condition.

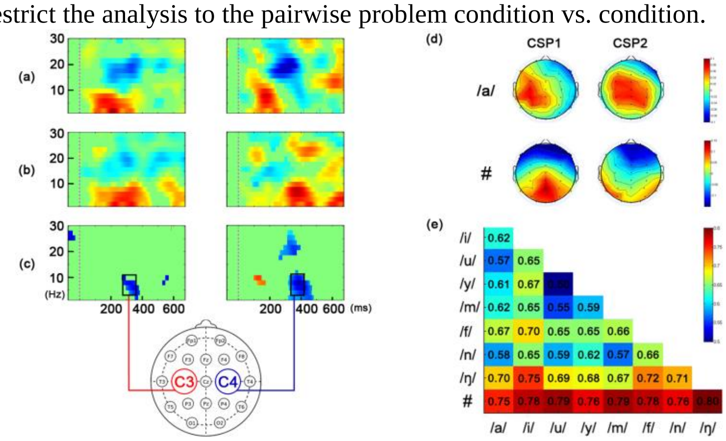

Figure 1. ***(a)*** *ERSP to imagery of /a/,* ***(b)*** *ERSP to control condition, and* ***(c)*** *difference ERSP (/a/ minus control) on electrodes C3 & C4 for subject 3, in which significant phoneme imagery effect in spectral power was assessed with a bootstrap method and coloured in EEGLab ($p < 0.025$).* ***(d)*** *The two most important common spatial patterns of /a/ vs. control classification for subject 3.* ***(e)*** *Pairwise classification accuracies averaged across three subjects.*

4. Discussion

The significance of making BCI speech production more natural and fluent has been elaborated in [Brumberg and Guenther, 2010], and [DaSalla et al., 2009] has performed direct vowel prediction using EEG signals based on speech motor imagery with articulators corresponding to regions of the cerebral cortex [Guenther et al., 2006]. In our research, we have not only expanded imaginary speech movements to other phonemes, but also examined the frequency band of speech processing for EEG signals as in [Wang et al., 2012] and verified that speech articulation can be detected both in the scalp and cortex [Bouchard et al., 2013].

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Development of an Intracortical Eye Movement-Based Brain-Computer Interface

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Abstract. We present an eye-movement-based brain-computer interface (BCI) developed in a non-human primate that decodes intended saccadic eye movements from intracortical signals. We propose that this BCI system could be used to restore simple communication to patients with locked-in syndrome.

Keywords: locked-in syndrome, eye movements, intracortical, monkey

1. Introduction

Brainstem stroke, traumatic brain injury, or neurodegenerative disorders like amyotrophic lateral sclerosis can result in locked-in syndrome, characterized by near-total paralysis despite relatively intact cognitive function. These patients could benefit immensely from a simple, easy-to-use brain-computer interface (BCI) to restore some communication with the outside world. We employ a non-human primate model to test the feasibility of using intracortical eye movement signals to control a BCI, with the aim of eventual application to human locked-in patients. Intracortical recordings can provide much more information-rich signals than the EEG signals used in most previous BCIs developed for this patient population. The saccadic eye movement system has several potential advantages over the arm movement signals typical used for BCI applications: there is a direct mapping between the effector space and a 2D cursor system, unlike the complex degrees of freedom in arm movements; it is specialized for rapid targeted movements that would be ideal for navigating augmentative and alternative communication software; it has minimal reliance on proprioceptive feedback; and there is a tight link between the eye movement system and top-down attentional control, suggesting these signals may be particularly amenable to volitional control. Our results show that eye movements can successively drive a BCI, opening the door to future clinical applications.

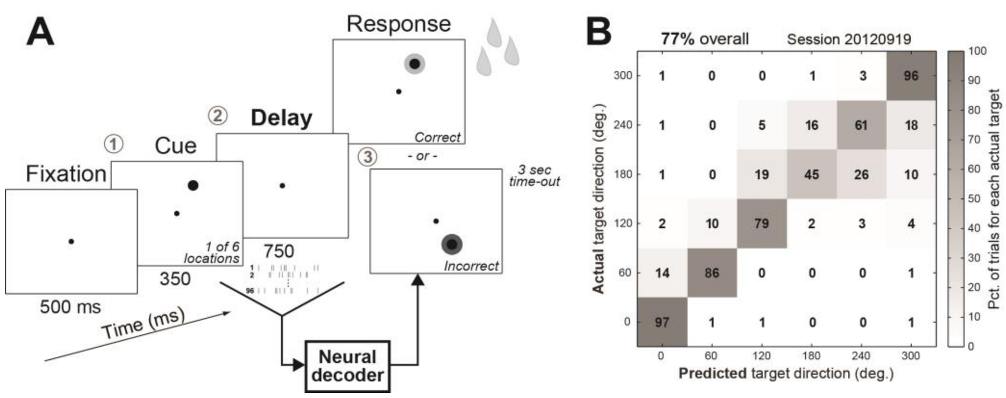

Figure 1. *(A) Brain-controlled delayed saccade task. A spatial cue (1) instructs the saccade location for this trial. Neural activity during the memory delay period (2) is used to decode the intended location, and produce a "virtual saccade" (3) at the end of the trial. (B) Confusion matrix showing decoder performance from an example session. Each matrix cell (heat map and overlaid numbers) represents the percentage of trials for a given instructed saccade location (y-axis) that each location is predicted by the decoder (x-axis).*

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2. Material and Methods

We implanted three 32-channel Utah arrays (Blackrock Microsystems) into the left frontal eye field (FEF), supplementary eye field (SEF), and dorsolateral prefrontal cortex (PFC) of a macaque monkey. Spiking and local field potential (LFP) signals were simultaneously recorded from all 96 electrodes while the monkey performed a delayed saccade task (Fig. 1A). On each task trial, one of six spatial locations was briefly cued. The monkey was trained to hold this location in working memory over a 750 ms delay period, and then execute a saccadic eye movement to the remembered location. On some experimental sessions, a brain-controlled version of the task was performed—the intended saccade was decoded from neural activity during the delay period, and a cursor was then moved to the decoder-predicted location, replacing the overt motor response with a "virtual saccade". Positive or negative reinforcement—liquid reward or an increased waiting time for the next trial, respectively—was then delivered conditional on whether the decoded location correctly matched the instructed one (but independent of any possible overt eye movements). These brain-controlled trials were always preceded by a separate block of standard delayed saccade trials (involving overt saccades) that were used to train parameters for a linear discriminant classifier. The classifier was trained on the mean power within a high-frequency LFP band (80–500 Hz) across the entire delay period, for each channel. This signal provided the highest decoding accuracy in extensive offline analyses (see related abstract from our group).

3. Results

We were able to decode intended eye movements with high accuracy (Fig. 1B). Across 11 BCI sessions, saccade locations were correctly predicted on 72% (± 3% SD) of trials on average, significantly higher than chance accuracy (16.7%) for all sessions ($p \approx 0$; binomial test). Accuracy was much higher (88 ± 2%) when considering only saccade locations contralateral to the implanted arrays (ipsilateral locations only: 56 ± 6%; cf. variation across matrix diagonal in Fig. 1B), reflecting a contralateral representational bias in the implanted cortical areas. These results suggest an improved BCI system could be achieved with bilateral implants or laterally biased sampling of target locations. Though all array channels were used for online decoding, we compared the individual contribution of each of the three implanted areas in offline analyses. SEF signals provided significantly better decoding performance (74 ± 2%) than FEF (25 ± 3%; $p = 3\times10^{-21}$, t-test) or PFC (23 ± 2%; $p = 4\times10^{-23}$), suggesting it is a particularly rich source of signals for an eye movement BCI, though this result may reflect the fact that delay period activity, rather than activity during the actual movement was used for decoding. The monkey quickly learned that overt responses were unnecessary in the brain-controlled task, and often went through multiple successful trials without making any eye movements, indicating saccade intention signals are sufficient to control a BCI. Finally, decoder performance has largely been preserved at almost one year post implant, suggesting our BCI system can have the longevity required for long-term clinical applications.

4. Discussion

We have demonstrated that intracortical eye movement signals can be used to control a simple BCI with a high level of performance. Because of the eye movement system's simple kinematics and control, and its close ties to top-down attention, we expect a BCI using these signals to be relatively easy to learn to volitionally control. This is particularly important for patients with locked-in syndrome, a population with variable residual cortical function that has seen little success with previous BCI systems. We plan to integrate this BCI with our recently developed "app"-based Unlock Project BCI framework [Brumberg et al., 2012] aimed at providing communication and other functionality to locked-in patients.

Acknowledgements

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Mouth Motor Movement Based BCI

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Abstract. While several EEG and Electrocorticography (ECoG) based augmentative and alternative communication (AAC) devices have been developed, they have thus far been restricted making creative use of binary on-off brain signals using non speech related cognitive tasks. In this study we investigate whether we can decode elements of actual speech from sensorimotor cortex. To assess decodability we collected data from subjects performing phoneme pronunciation using both high-field fMRI in healthy volunteers, and high-density ECoG in epilepsy patients. Our results demonstrate that four classes of spoken phonemes produce unique activity patterns in sensorimotor cortex that can be used to discriminate complex mouth motor movements well above chance. These results provide strong evidence that a small high-density ECoG grid, anatomically specific to sensorimotor cortex can provide a robust platform for a BCI AAC device.

Keywords: ECoG, fMRI, Mouth Motor Movements, AAC

1. Introduction

Electrocorticography (ECoG) has been shown to be an important platform for Brain-Computer Interfaces (BCIs) for application in providing an improved communication channel for profoundly paralyzed individuals. While several EEG and ECoG based augmentative and alternative communication (AAC) devices have been developed [Allison et al., 2007] they have been restricted making creative use of binary on-off brain signals using non speech related cognitive tasks. In this study we explore the use of a high-density (3 mm spacing inter-electrode spacing) ECoG grid implant over the mouth motor cortex as the platform for multi-dimensional BCI control.

A BCI device based on complex mouth motor movements would provide an intuitive and robust platform for a communication AAC. Overt and covert motor movements have been shown to produce robust BCI control signals in the gamma range (65-95 Hz) in ECoG signal [Miller et al., 2007]. In addition resent results demonstrate that attempted movements in a paralyzed subject could be used for BCI [Wang et al., 2013]. However, much of the previous work has focused on hand movements. Given the primary role of mouth movements in human communication we believe that a mouth motor based BCI can provide a robust and cognitively intuitive AAC. We are inspired by work of Guenther and Kennedy [Guenther et al., 2009], who were able to show that a Neurotrophic Electrode placed in motor cortex can be used to produce two distinct BCI control channels from attempted pronunciation of two distinct phonemes.

The main goal of this work was to show that multiple complex mouth movements produced through phoneme pronunciation can be discriminated from sensory motor cortical activity. We collected data from subjects performing overt phoneme pronunciation using High-filed Functional Magnetic Resonance Imaging (7 T fMRI) in addition to high-density ECoG. fMRI has the advantage that there is consistency in complete coverage of sensory motor cortex, while high-density ECoG has the advantage of better signal fidelity and temporal resolution. By combining both modalities, the optimal location and size of the implant for the target AAC can be explored.

2. Material and Methods

2.1. High-field fMRI

Data Acquisition: Five healthy volunteers participated in the fMRI study. They performed two event related sessions consisting of 10 trial of each of four (/j/, /l/, /ɔ/, and /eː/) visually cued and overtly pronounced phonemes. Each stimulus was presented for 750 ms with a fixed inter stimulus interval of 13 seconds that assured that the effects of the previous trial was washed out. The fMRI measurements were implemented using a 7 Tesla Philips Achieva MRI system with a 32-channel head-coil. The functional data was recorded using an EPI sequence. The field of view covered the left pre- and postcentral gyrus. A high-resolution image was acquired for anatomical reference using a T1 weighted 3D TFE sequence.

Data processing: First, the data was slice time corrected, realigned, and detrended, Next feature voxels were selected that that showed little variability within the condition and large differences between conditions using an

ANOVA analysis. Finally, the fMRI response for each trial was formed by concatenating the summed FIR analysis response from the 4th 5th and 6th scan after stimulus for each feature voxel.

2.2. High-density ECoG

Data Acquisition: ECoG signal was collected from three intractable epilepsy patients who had research grids implanted on their cortical surface under the dura alongside clinical scale ECoG electrodes. We refer to these grids has high density ECoG grids due to their small size, relative dense 3 mm inter-electrode spacing, and small 1.3 mm exposed surface as compared to clinical ECoG implants. The placement of the grids was targeted at the estimated mouth motor area, but coverage varied across subjects. The subjects were visually cued to pronounce the phonemes /p/, /k/, /u/, and /aː/ or rest and fixate on an '*' on the screen. A microphone recording of their voice was synchronously recorded with the ECoG signal to evaluated task performance. Subjects 1, 2, and 3 performed a total of 246, 85, and 190 correctly performed spoken phonemes or rest conditions over several runs respectively.

Data processing: First, the high-density ECoG signal was re-referenced to a clinical scale electrode that was located on top of the grid and the spectral response was computed using a Gabor Wavelet Dictionary in 1 Hz increments. Next the spectral power for frequencies 65 to 95 Hz was summed to obtain the gamma response for each grid electrode. Finally the ECoG response for each trial was formed by concatenating the gamma response for each electrode from the time period of 0.5 s before and 1 s after voice onset time (determined from the microphone signal).

2.3. Classification

For classification of the phonemes, a nearest-neighbor (template matching) classification procedure was applied for fMRI and ECoG. Individual trials were classified using a leave-one-out procedure. First a template was computed for each class by computing the mean response from all but one trial. Next, the Pearson correlation between the 'left out' trial and the templates was used to classify the trial as the phoneme it had the highest correlation with in a winner-takes-all manner. This was done for each trial in the set of all trials.

3. Results

Using high-field fMRI, we achieved classification scores ranging from 50 to 60% (25% chance) accuracy. The fMRI template maps showed activity across sensorimotor cortex that was consistently focused on mouth motor cortex. Confusion matrices demonstrated that there was no consistent trend towards one phoneme being better represented on the motor cortex than another.

Using high-density ECoG classification rates of 81, 72, and 61% (20% chance) where achieved. While the classification scores were generally better for the ECoG subjects, there was more variability in performance across subjects despite the fact that the detection of speech (ie: the rest condition vs. any spoken phoneme) was above 90% for all subjects. Also unlike the fMRI results, there was a pattern of phoneme preference visible in the confusion matrices. Both subjects 1 and 2 more often confused the voiced (/u/ and /aː/) with each other than with the unvoiced (/p/ and /k/) phonemes. Subject 2, however, showed the strongest ECoG responses for the /p/ and /u/ phonemes and more often confused /k/ and /aː/ with the rest condition.

4. Discussion

In this work we demonstrated that high-filed fMRI can accurately identify good target locations for high-density ECoG implants that were able to discriminate 4 phoneme classes from rest with 81% proficiency when accurately located over the mouth motor area. These results point towards high-density ECoG grids that can be implanted without a full craniotomy when target locations are accurately predicted, as a promising platform for a fully implantable cognitively intuitive AAC.

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Using ECoG Gamma Activity to Model the Mel-Frequency Cepstral Coefficients of Speech

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Abstract: In this study, electrocorticographic (ECoG) data collected from eight subjects was analyzed to obtain the spatiotemporal dynamics of the correlations between the high gamma band (70-170 Hz) and the mel frequency cepstral coefficients (MFCC), an important set of speech features used for vowel and word recognition in Automatic Speech Recognition systems. Significant correlations were found between the high gamma band and the mel frequency cepstral coefficients, which resulted in activations in the expected language-related brain areas. Subject-specific spatial linear regression models were then determined to predict the mel frequency cepstral coefficients from the high gamma band power.

Keywords: ECoG, Gamma, Mel Frequency Cepstral Coefficients, Speech

1. Introduction

High gamma activity from ECoG signals has been found to be highly correlated with speech and motor movements in humans. There have been numerous studies investigating cortical activity using ECoG during various speech tasks to identify and characterize the areas of the cortex most involved in speech production and perception [Crone et al., 2001; Towe et al., 2008; Edwards et al., 2010; Pei et al., 2011; Leuthardt et al., 2012], and even decoding of speech from brain activity [Pasley et al., 2012; Blakely et al., 2008; Kellis et al., 2010; Pei et al., 2011]. In automatic speech recognition systems, well-defined features can be extracted from speech signals to aid in the classification of phonemes, vowels, consonants, and words. A popular set of features used for automatic speech recognition (ASR) are the mel frequency cepstral coefficients (MFCCs) [Vergin et al., 1999], which are a parameterization of the spectral content of speech based on perceptual characteristics of human hearing. By parameterizing the speech spectrum using MFCCs, we accomplish two goals: 1) the speech content dimensionality is effectively reduced to the critical acoustic components and 2) the lower dimensionality aids statistical modeling (by alleviating data size demands) and future applications for ECoG-based speech prostheses. The aim of this analysis is to determine the extent to which high gamma band activity from ECoG is correlated with the MFCCs extracted during concurrent speech. We additionally developed spatial linear regression models for predicting MFCCs from the ECoG gamma band as a step toward neural speech decoding.

2. Material and Methods

ECoG activity was recorded during an overt speech task from eight epileptic patients. The number of electrodes per patient ranged from 58-120. For the task, each subject was presented with scrolling text on a computer monitor which they spoke aloud. The ECoG and speech signals were simultaneously recorded at a sampling rate of 9600 Hz using g.USBamps and BCI2000 software. The data was analyzed as follows: (i) Gamma power envelope: The ECoG signals were highpass filtered with a cutoff frequency of 0.01 Hz and re-referenced using a common average reference (CAR) montage. The resulting signals were lowpass filtered and decimated to 400 Hz. A zero-phase FIR filter was applied to the signals to extract the gamma band activity (70–170 Hz; excluding a window of 116–124 Hz to avoid power line interference). The gamma band power envelope was computed using the Hilbert transform. (ii) MFCCs: The speech signal was divided into overlapping frames of length 256 samples, each of which was then windowed by multiplying it with the Hamming window. The powers of the obtained spectrum were mapped onto the mel scale, a transformation that accounts for non-linear pitch perception. The logarithm of the power was then computed from the spectrum and the discrete cosine transform taken from 12 mel frequency bands. The amplitudes of the resulting spectrum are taken as the twelve MFCCs. (iii) Correlations: The spatiotemporal correlations between the gamma band powers (decimated to 20 Hz to match the MFCCs) and the MFCCs were then obtained at temporal lags between -300 ms and 300 ms. The silence periods were removed from the MFCCs and the corresponding lagged gamma signals prior to computing the correlations. Spatial linear regression models were computed to predict the twelve MFCCs from the gamma band power envelopes at zero lag. The *p*-values for the correlations were computed using a randomization test.

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3. Results

With modeling, 66.67% of the correlations were statistically significant after Bonferroni correction. No clear modeling trends were apparent across MFCCs or subjects. Fig. 1 shows the –log (*p*) values of the spatial correlations between the high gamma band (70–170 Hz) power envelope and one of the representative MFCCs (MFCC 3), at lags from -300 ms to 300 ms, and the comparison of the actual MFCC 3 and the predicted MFCC 3 using spatial linear regression for one of the subjects (Subject H).

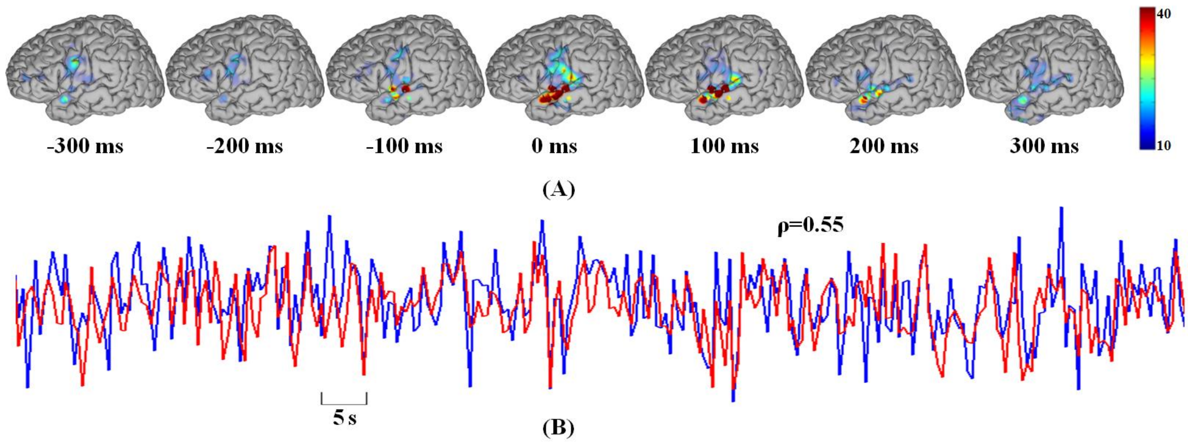

Figure 1. *(A)The spatiotemporal topography of statistically significant gamma-power correlations to MFCC 3 across the entire overt speech production task are shown in 100 ms increments. Color values represent the –log(p) of the correlation. The lower limit is based on statistical significance assessed after a p = 0.05 Bonferonni correction. (B) Blue: Representative time course of MFCC 3 for Subject H. Red: The prediction of MFCC 3 obtained from the linear spatial gamma power model. The Pearson correlation between the two signals over the entire run (178 s) is ρ = 0.55.*

4. Discussion

The results indicate that gamma band power over language-related cortical areas is significantly correlated with MFCCs, perceptual representations of speech. Simple linear spatial models can be used to further enhance the correlations between the gamma activity and the MFCCs. By representing MFCCs using the ECoG signal, a more robust speech representation is utilized as compared to a simple speech power envelope feature or filter bank features that are not perceptually based. MFCCs predicted using our spatial linear regression model can further be used for real-time resynthesis of speech signals. This work develops a natural extension of automatic speech recognition techniques to neurological data, and provides a step toward a neural speech prosthesis.

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Decoding Articulatory Properties of Overt Speech from Electrocorticography

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Abstract. Brain-computer interface (BCI) applications for communication could greatly increase information transfer rates by directly decoding phonemes from cortical signals. We decoded individual phonemes and phonemic classes from electrocorticograms (ECoG) recorded while two subjects read words aloud from the Modified Rhyme Test. Information elicited from electrodes located over facial motor areas demonstrated distinct dynamic changes in high-γ and μ frequency power for different places of articulation, enabling us to correctly identify phoneme class in up to 64% of examples. We correctly classified 35% of all individual consonants by decoding the type and place of articulation. These results demonstrate successful decoding of phonemes from ECoG.

Keywords: Electrocorticography, Speech Production, Phonemes, Communication, Locked-in Syndrome

1. Introduction

A central goal of brain-computer interface (BCI) research is to enable communication for people with locked-in syndrome from such disorders as stroke or amyotrophic lateral sclerosis. BCIs have proven to enable such communication, predominantly via spelling paradigms. However, such BCIs have failed to achieve communication rates comparable to natural speech [Brumberg et al., 2010]. In contrast, recent advances in speech recognition technology have demonstrated that phonetic decoding can perform fast enough for natural speech production. Application of such a phonemic approach to decoding speech production from cortical signals could similarly improve communication rates for potential BCI users. In order to effectively decode intended speech, we first investigate what factors lead to successful decoding of overt speech using electrocorticography (ECoG).

Recent studies have shown promise in decoding speech from cortical signals but hold significant challenges to real BCI-to-speech application. [Brumberg et al., 2010] used action potentials from 31 spike clusters in facial motor cortex of a locked-in subject to classify correctly 21% of 38 American English phonemes, but only classified 24 phonemes above chance levels. ECoG may have greater longevity than spikes; one study used microwire ECoG from facial motor cortex to decode a set of 10 whole words with 48% accuracy in one subject [Kellis et al., 2010]. Studies employing standard-sized ECoG electrodes, with broader coverage area, have analyzed limited sets of phonemes, the best results of which had 91% classification of 2 isolated phonemes [Leuthardt et al., 2011; Blakely et al., 2008], and 41% decoding of phonemes from 4 vowels or 9 surrounding consonant pairs of 36 words [Pei et al., 2011]. Despite their successes, these studies were limited in comparison with the broad phonemic decoding that may be necessary for natural BCI-to-speech communication.

This is, to our knowledge, the first study to analyze all of the phonemes comprising American English as naturally spoken in words using ECoG, enabling several novel capabilities. This methodology enables us to isolate key neural aspects for successful decoding of speech sounds.

2. Material and Methods

This study was approved by the Institutional Review Board at Northwestern University, and subjects gave informed consent prior to experimental testing. Two subjects (female, age 30; male, age 50) who required extraoperative ECoG monitoring for treatment of their drug-resistant epilepsy participated in this study. Electrode placement was determined by medical necessity and included frontal and temporal areas in both subjects.

Subjects read aloud words presented on a monitor every 4 s using BCI2000. Words included the Modified Rhyme Test, a list of 300 monosyllabic words of consonant-vowel-consonant structure. Twenty additional words were included to create a comprehensive collection of General American phonemes in the set. Speech was recorded with a condenser microphone and digitized at 44.1 kHz. We recorded 42 and 48 channels of ECoG (1 cm spacing) at 500 Hz and 1 kHz and bandpass filtered from 0.5 to 250 or 300 Hz for subjects 1 and 2, respectively.

We first determined phoneme onset from spectral audio data. We computed power using short-time Fourier transforms on common-average-referenced ECoG signal for each channel (Hanning window, length 50 ms, 2 Hz bands), normalized by the average spectrum from a 1-s baseline. We extracted features by averaging band-power both over a 50 ms window and over δ (0-4 Hz), μ (8-13 Hz), β (15-30 Hz), and high-γ (70-200 Hz) frequency bands. We decoded the phonemic class (e.g. "bilabial" or "plosive" according to International Phonetic Association distinction) of consonants using linear discriminant analysis (LDA) on the features, selecting features with the lowest p-values (one-way ANOVA), with 10-fold cross-validation [Flint et al., 2012]. We performed simultaneous LDA classifications of place and manner of articulation as well as vocalization properties. We then multiplied posterior probabilities of each classifier to decode individual consonants (Bayesian decoding).

3. Results

Successful decoding of phonemic class (place of articulation) correlated strongly with electrode location. We classified 61% of consonant phonemes in the correct phonemic class (chance = 27%, $p < 10^{-43}$, *t*-test) in subject S2, who had 8 electrodes identified in both tongue and throat motor areas by electrical stimulation mapping. In contrast, subject S1 had only 4 electrodes covering tongue motor cortex; we classified 36% of her phonemes correctly ($p < 10^{-14}$), primarily those involving tongue. Interestingly, phonemes that were misclassified were most often confused for neighboring places of articulation. We correctly classified individual consonants in 35% of cases for S2. This rate was far above chance decoding (chance = 7%, $p < 10^{-131}$ for consonants).

The most discriminative features were high-γ band power increases and mu and beta band power decreases in laryngeal, tongue, and lip motor electrodes. We found a correspondence between p-value and articulatory location. Informative feature times varied by phonemic class: causal features (-250-0 ms) were most significant for bilabial phonemes, while acausal features (0-200 ms) dominated for post-alveolar and dental consonants. This suggests that movement *from* consonant articulation position mattered more for decoding than the movement *to* articulation position for the latter two classes. Features corresponding to lip articulation preceded features for vocalization.

4. Discussion

We attribute decoding success to articulation-based analysis aligned precisely to phoneme articulation onset. Our incorporation of the entire spectrum of articulation enables decoding of consonants using established articulatory principles of phonetics. Importantly, in S2, we found distinct high-γ band power patterns for lip, tongue, and laryngeal activity – a motor somatotopy. Since features for some articulatory classes (e.g. labiodental, palatal) overlapped multiple electrodes, we hypothesize that higher density ECoG grids may better isolate features from neighboring classes. Coverage of laryngeal, tongue, jaw, and lip motor areas best enables phoneme decoding. If phonemic decoding can be further improved, this technology has the potential to result in faster communicative BCI.

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EEG-Based Communication With Patients in Minimally Conscious State

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Abstract. We investigated an EEG-based approach for communication with minimally conscious state (MCS) patients. In a mental imagery paradigm, the patients were instructed to perform imagined sports, navigation and feet movements. Classification accuracies above chance level were reached by three of the four patients performing mental imagery tasks, indicating the feasibility of this paradigm for communication with MCS patients.

Keywords: EEG, BCI, mental imagery

1. Introduction

Brain-computer interfaces (BCIs) based on electroencephalography (EEG) can provide severely motor-disabled people with a new output channel for communication [Birbaumer et al., 1999]. To provide a simple and robust means of communication, the BCI should reliably detect one specific brain pattern such as task specific event-related (de)synchronization (ERD(S)) patterns. A group of patients who are unable to perform any motor movement to use an assistive device are people in a minimally conscious state (MCS). Some of these patients have been proven to be consciously aware [Monti et al., 2010]. Those patients might benefit from such a single-switch BCI. The aim of this work is to investigate whether complex mental imagery and attempted feet movement can be reliably detected in patients with disorders of consciousness, with the general goal to establish an EEG-based communication device.

2. Material and Methods

Four male patients in minimally conscious state (Coma recovery scale was between 9 and 18) aged between 21 and 65 years participated in this study at Albert Schweitzer Clinic in Graz. Informed consent was obtained from the patients' legal representatives. This study was approved by the Ethics Committee of the Medical University of Graz.

Monopolar EEG was recorded from 32 positions with active Ag/AgCl electrodes and a sampling rate of 512 Hz. The patients were either sitting in a wheelchair or lying in bed with their upper part of the body slightly elevated. Each patient participated in three to four mental imagery sessions.

The patients were instructed to perform different mental imagery tasks which should induce distinctive ERD(S) patterns [Goldfine et al., 2011]. In the sports task (S), they should imagine performing one sport of their choice. In the navigation task (N), they should imagine navigating through their house and looking around in each room. In the feet task (F), they should repeatedly attempt to perform dorsiflexion of both feet.

One trial lasted about 12 s, whereas the cue indicating the beginning of the task was presented from second 2 to 3. The task had to be performed between second 3 and 12. All instructions were given verbally. A total number of 45 trials, separated in three blocks by short breaks, was recorded for each task.

A linear discriminant analysis (LDA) classifier based on logarithmic band power features calculated for multiple frequency bands (ϑ: 4-7 Hz; α: 7-13 Hz; β_L: 13-19 Hz; β_M: 19-25 Hz; β_U: 25-30 Hz) was used. A nested blockwise cross-validation (10x10 inner fold; leave-one-out-block outer fold) was applied to estimate the accuracy of each task versus reference (0.5 s before cue) from beginning to the end of a trial.

3. Results

In Table 1, all significant results of the mental imagery paradigm together with the mean Coma Recovery Scale-Revised (CRS-r) scores of the patients across all sessions are summarized. In the mental imagery paradigm, classification accuracies above chance (α = 1%) were reached by three patients in the F or S task. Only the Laplacian channel derivation yielding the highest accuracy is reported. In Fig. 1, the ERDS map of one patient can be seen.

Table 1. *Summary of all significant results of the mental imagery paradigm.*

Patient ID	*Mean CRS-r*	*Mental Imagery*				
		Session	*Task*	*Accuracy*	*Channel*	*Band*
PA_{01}	*18*	*1*	*F*	*70 %*	*Cz*	α
		1	*S*	*68 %*	*C2*	α
		2	*S*	*76 %*	*C2*	α
PA_{02}	*14*	*1*	*F*	*69 %*	*FC1*	ϑ
		1	*S*	*75 %*	*Fz*	ϑ
		3	*F*	*71 %*	*FC1*	ϑ
PA_{04}	*9*	*1*	*S*	*69 %*	*Fz*	α
		2	*S*	*68 %*	*CPz*	β_m

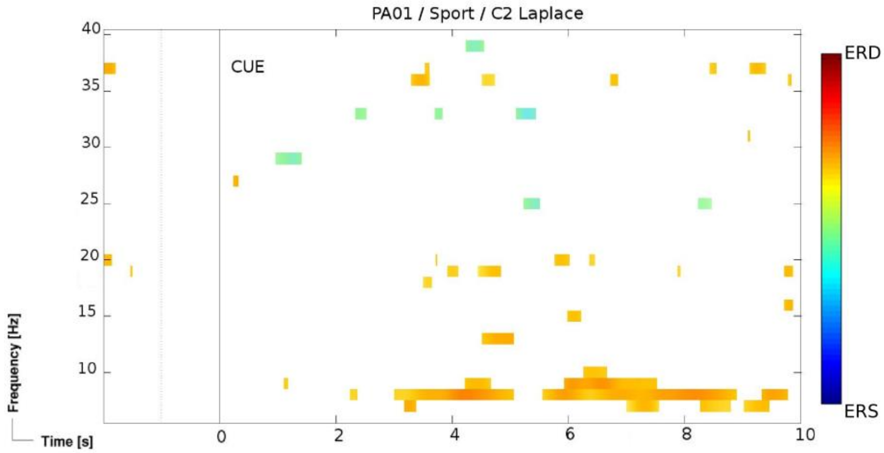

Figure 1. *ERDS map of participant PA01 for the sport task of the second session.*

4. Discussion

Using mental imagery seems to be a promising approach for some of the patients in minimally conscious state to communicate their intent using EEG. Classification accuracies above chance were reached in the foot (F) or sport (S) task but not in the navigation (N) task. This is in line with previous findings indicating that, among other tasks, motor imagery results most frequently in better classification performance than spatial navigation [Friedrich et al., 2012]. As a next step it is planned to perform online experiments and to apply an auditory scanning method as recently described in a study with healthy subjects [Müller-Putz et al., 2013].

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Detecting Brain Responsivity in Disorders of Consciousness: a Brain-Computer Interface-Based Methodology

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Abstract. A method to evaluate the performances of different Brain-Computer Interface (BCI) protocols is proposed. This methodology, besides representing a first step toward the standardization of the evaluation of BCI protocols, provides details on the statistical significance of classification accuracy thus addressing the investigation of the discriminability of different brain responses elicited by means of specific protocols. Results deriving from the application of the method on data from patients diagnosed with disorders of consciouseness (DOC) indicate the value of this BCI-based methodology in supporting the objectifiable detection of brain residual responses indicative of awareness in such severe conditions. Thanks to the integration into a multi-purpose platform for the analysis of physiological signals and to the easiness of use, this methodology paves the way for a systematic detection of *mental states* in non-responsive/non-communicative patients, who represent the challenge of BCI applications.

Keywords: BCI, DOC, Performance Evaluation, ECM, chi-square test

1. Introduction

Recently the Brain-Computer Interface (BCI) technology has been proposed as a possible communication mean for patients clinically diagnosed with disorder of consciousness (DOC), such as vegetative states (VS) or minimally conscious states (MCS) [Lulè et al., 2013]. In this case, BCI technology might capture the brain responses correlated with residual awareness and funnel them outside as overt sign of voluntary communication. This specific application of BCIs demands not only a high level of accuracy in detecting the brain responses but, even more, that brain responses are reliably discriminated from the chance level (i.e. low probability errors).

Here we present a standard methodology, developed within the NPXLab suite (www.brainterface.com) which relies on confusion matrices and on a statistical test to evaluate classification performance and its significance. It is independent from the protocol implemented to elicit the brain responses, a property that boosts the standardization of the evaluation process and it can be applied to the single-subject level. This latter is essential feature when due to the variability of the patients' brain signals, a grand-average analysis might fail in highlight the significant individual responses. The availability of a semi-automated evaluation of brain responsiveness and its integration in a user-friendly and features-reach software application facilitates the translation of the BCI-based technology into clinical practice to support diagnosis of non-behaviorally responsive patients.

2. Material and Methods

3.1. The Extended Confusion Matrix (ECM) and the chi-square test: statistical evaluation of classification

Classification performance can be stored into an ECM, a table where the number of times the brain responses to be classified (classification classes) were correctly classified, misclassified or not recognized [Bianchi et al., 2007], are saved. From an ECM, different performance metrics can be calculated (accuracy, bit rate, mutual information, etc). Also, a statistical test (chi-square test) can be associated to each class to evaluate if the classification results significantly differ from the chance level. This strictly depends on the number of trials (the number of times each brain response is classified) which determines the confidence interval of the chance level. In this way it is possible to validate results by adding information on the accuracy significance. The p-value associated to the accuracy assesses how much significant the classifications are.

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3.2. EEG recording and data analysis

To show the method, data from 4 DOC patients were used. They were administered a classical acoustic oddball P300-based paradigm, during which they were asked to mentally count the deviant tones (targets, T=60) against the standard *(non-targets*, NT=420). The ISI was set to 850ms. EEG potentials were recorded from 32 active electrodes, with a sampling rate of 512 Hz. For classification purposes, data were sub-sampled to 256Hz, ocular and muscular artifacts were identified and 60 NT were randomly selected. A subset of electrodes (F3, Fz, F4, C3, Cz, C4, P3, Pz, P4) was chosen. A post-stimulus period of interest (50 ms to 650 ms) was selected and a leave-one-out validation was applied on the artifacts-free single trials belonging to each class to test the classifier (SWLDA).

3. Results

Results of the classification validation are reported in Table 1. In S1 diagnosed as VS, at significance threshold of 5%, classifications were random for all the trials belonging to both T and NT class ($p > 0.05$). In the second VS case S2, the average accuracy for all the trials was 72.32% and both T and NT class were significantly classified (p_T=0.027, p_{NT}=0). For the two patients diagnosed as MCS, total accuracies were slightly better, 64.46% and 72.73% for S3 and S4, respectively. Both T and NT classes were significantly discriminated from chance ($p < 0.05$).

Table 1*. Classification validation results. The following values are listed: subject, clinical diagnosis, total number of trials, total accuracy, target (T) accuracy and p value, non target (NT) accuracy and p value.* ***Bold values= p<0.05****.*

Subj	*Diagn.*	*Trials*	*Total Acc[%]*	*T Acc[%]*	*p*	*NT Acc[%]*	*p*
S1	VS	109	55.05	49.06	0.891	60.71	0.109
S2	VS	112	72.32	65.38	**0.027**	78.33	**0**
S3	MCS	121	64.46	65	**0.02**	63.93	**0.03**
S4	MCS	110	72.73	67.31	**0.013**	77.59	**0**

4. Discussion

The proposed methodology unveiled that in one VS case (S2) single trial brain evoked responses were classified with a highly significant p-values, thus suggesting the preservation of a command following ability otherwise not detectable by the patient behavioral clinical assessment. The classification validation results obtained for the two MCS patients confirmed, at the level of single trial, the clinical assessment indicating the ability for these 2 patients to discriminate between two different types of stimulations.

It is mandatory to stress that the absence of a positive result in our test (as in the S1 case) could be ascribed to many factors independent from the diagnosis of VS thus, preventing any definitive conclusions on the clinical diagnosis reliability. False negative inducing factors may be: vigilance status at the time of the recording (patient was sleeping), cognitive dysfunction masked by the consciousness disorder that affects the auditory task accomplishment, high signal to noise ratio, the classifier was not the best to extract relevant features. One recommended solution is to obtain patient's multiple recordings at different times and/or to test different translation algorithms to identity the best appropriated for the relevant features. On the other hand, a possible occurrence of false positives (statement on the presence/intactness of patient's cognitive processing ability) has to be considered. In this case, one source of errors might be the capture of brain response components not directly related to a voluntary shifting of attention between T and NT class (in our auditory paradigm) that interfere with the algorithm classification output. A careful stimulation protocol design is the first step to prevent such error source.

This BCI-based methodology implemented in a practical tool offers an effective instrument for a standard evaluation of performance accuracy and for the assessment of the reliability of such accuracy.

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A Platform for the Detection of Brain Activity Changes in Patients Diagnosed With Disorders of Consciousness

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Abstract. A set of tools and methods for the analysis of electrophysiological signal acquired in patients diagnosed with Disorders of Consciousness (DOC) are here outlined. They allow to process data from several different devices and relative to different protocols, thus facilitating the sharing of data, protocols and the evaluation of results across different laboratories and in a homogenous way. Evaluation tools are also provided to detect brain activity in DOC patients.

Keywords: Brain-Computer Interface, Consciousness, Methods, Evaluation, Detection

1. Introduction

Since now, Brain-Computer Interface (BCI) technology main aim has been to provide a mean for restoring communication capabilities to patients who have lost their motor capabilities, such as those affected by severe neuromuscular disorders (e.g. Amyotrophic Lateral Sclerosis). Most of the studies described in the literature focuses on the implementation of new methods, algorithms, protocols, devices for maximizing the information flow from the brain to the external environment without using the normal pathways of nerves and muscles and a wide set of technology has been developed. This last, however, can also be applied in other contexts, such as the one described in this paper, in which BCI expertise has been used for detecting brain activity changes in those patients diagnosed with Disorder of Consciousness (DOC), that fall into two states, Vegetative State (VS) and Minimally Conscious State (MCS) that can be really difficult to discriminate [Lulè et al., 2013]. The main difference among them is that MCS patients preserve some cognitive ability which is hard to detect and that is unavailable in VS: several times, as described in [Monti et al., 2010], MCSs were erroneously diagnosed as VSs. For this reason, the idea of applying protocols aimed at detecting some brain activity that requires awareness or understanding (e.g. P300, N400, etc.) arose. However, the evoked response are in these patients somehow destructured, different across subjects and with respect to those usually described in the literature. For this reason, BCI classifiers represent a valuable instrument which, in most cases, are able to adapt to each subject to detect and discriminate among different brain states: in this case it is not important for example to fully describe in time and amplitude two ERPs, but just that they are different. There is, however, a relevant difference with typical BCIs: these last are usually tuned to maximize the amount of information extracted from the brain, whereas in this study the primary goal is to maximize the accuracy and reliability of the detection process. Thus, it is necessary to implement new tools and methods for answering new questions. Another problem is that this new approach lacks of a standardized procedure and methodology and large reference datasets are missing or hard to obtain. To overcome this and other problems, a set of tools belonging to the BF++ framework [Bianchi et al., 2003] has been implemented or adapted to allow different laboratories to share their data, to use the same evaluation methods regardless on the adopted experimental paradigm thus allowing a faster and coherent growth of this research field and to measure how reliable are the classification results.

2. Material and Methods

Despite classical BCIs, the process for classifying different brain states in this new class of experiments is usually performed offline: this allows to better optimize the evaluation process in order to maximize its robustness. The proposed BF++ platform, which can be downloaded from www.brainterface.com, includes several tools (mostly for free) for the processing and analysis of data. The NPXLab tool, for example, is a complete EEG/ERP reviewer and analysis system which allows filtering signals either in the time or in the spatial domain with methods such as Laplacian, Independent Component Analysis (ICA), Common Spatial Patterns (CSP), etc., to compare, even statistically, evoked responses, to perform spectral analysis and brain mapping and much more. It can read several different file formats (EDF, BCI2000, g.Tec, GDF, ASCII, etc.), thus allowing a wide range of labs to adopt it.

The BCIClassifier is a powerful tool which implements 8 different classifiers (SWLDA, FLDA, BLDA, SRLDA, RLDA, KNN, SVM, ANN), operates on raw or filtered signals (including, ICA and CSP components) and automates training/testing/classification/validation procedures. It also provides confusion matrices to evaluate classification performance and metrics to evaluate protocols/systems. More importantly, a statistical procedure has been also implemented to assess if classifications are due to chance or not: a chi-squared test computes the probabilities (p-values) of making errors stating that the results are not due to chance. Thus, the lower the p-value, the more reliable the results. It is important to underline that, because the test is performed on classification results and not on the signals, they are protocol independent: not only ERPs, but also motor imagery, SSVEP, and fMRI based protocols can be evaluated in this way. This guarantees a wide usability of this procedure.

The way this last tool can be used in the study of DOC patients is simple: subjects are asked to perform a series of cognitive tasks, in which they have to categorize two classes of stimuli. If they are able to perform the task then it is possible to correctly classify it, otherwise the results are due to chance: the statistical test will check this exactly this. In this way, it is possible to deduce if residual cognitive abilities are present in a patient and therefore support the clinical assessment of his/her state.

3. Results

For its simplicity, support of a wide range of file formats and protocols and completeness in either the reviewing or the analysis process, the proposed platform has been adopted by the EU DECODER project: it has been successfully used to analyze data from several protocols from 6 different laboratories. In another report in this conference [Quitadamo et al., 2013] promising results show agreement among the complete processing pipeline of the NPXLab Suite with MCS diagnosed patients, whereas brain activity related to a cognitive task was reported in one VS patients, thus suggesting a misdiagnosis.

4. Discussion

Classifiers can represent a powerful tool to help clinicians to make diagnoses. However, their output is subject to mistakes, false positives (FP) and false negatives (FN), and these may have several causes and consequences.

False positives may be due to systematic errors in the experiment, such as stimuli related artifacts, or statistical random noise. Their occurrence can be easily reduced by repeating the experiment, increasing the number of trials/classifications, which increases the signal to noise ratio, and improving the design of the experiment, as in every cognitive task. The consequences of such errors are to diagnose a VS patient as MCS.

False negative may have different causes and then are much harder to be removed. Possible causes are: subject is sleeping, the task/protocol is too difficult to be performed (e.g. he is not able to recognize familiar voices), activity is not detectable, classifier fails, signal is too noisy, statistical test fails, etc. Repeating the test only increases the probability to find the subject in an awaken state and to reduce the probability of statistical test failure. The consequences of such errors are to diagnose a MCS patient as VS.

Thus, these tools should not be used to perform a diagnosis, but to support it. They include a fully functional EEG/ERP system with advanced filtering techniques such as ICA and CSP, procedure for automating and validating classifications (8 different classifiers are provided), methods for evaluating protocols and to measure the reliability of the results. They are easy to use, support a dozen of different file formats and most of them available for free.

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Using a Brain-Computer Interface to Assess Awareness After Brain Injury

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Abstract. This study asks whether brain-computer interface (BCI) technology can provide a clinically viable tool to assess awareness in patients after brain injury. It also seeks to determine whether brain activity, as observed with non-invasive electroencephalography (EEG), can predict possible recovery, and can thereby assist in prognosis and in planning rehabilitation strategies. We present here the study setup and methodology and some initial data. The paradigm consists of acquiring 32 channel scalp EEG while the participant is asked to imagine making specific hand and feet movements. The EEG data is analysed retrospectively to assess the correlations between conditions and the scalp distributions of mu (8-12 Hz) and beta (18-26 Hz) rhythms.

Keywords: Post-brain injury awareness, Motor imagery, Brain Computer Interfacing, spectral content

1. Introduction

The diagnosis of post-brain injury unawareness (PBU) in patients with severe brain injury can be difficult. Approximately 50 percent of patients with apparent vegetative state will demonstrate consistent cognitive responses one month after traumatic, anoxic, or vascular brain injuries [Levin et al., 1991]. PET scan, functional MRI, and EEG data suggest that the clinical diagnosis of PBU is not always accurate [Cruse et al., 2011]. Incorrect classification of a cognitively aware patient as vegetative may result in incorrect treatment and inappropriate long-term care. Even using the best available protocols, there is always a degree of uncertainty in a diagnosis of vegetative state [Cruse et al., 2011; Chatelle et al., 2012]. Although functional PET and MRI studies may identify patients who have been incorrectly classified as vegetative from a brain injury, the expense and logistical difficulties of obtaining these studies make them impractical for routine clinical use, particularly in the acute rehabilitation setting. An EEG-based Brain-Computer Interface (BCI) can non-invasively monitor the brain for responses to somatic, auditory or visual input [Wolpaw and Wolpaw, 2012]. The equipment and protocol are relatively inexpensive, and can be used conveniently in the acute hospital or rehabilitation setting.

This study aims to evaluate awareness in patients who have been clinically diagnosed with PBU using an EEG-based BCI protocol to determine whether a spoken command produces an EEG response temporally related to an auditory stimulus. It seeks to determine whether there are differences in the medical histories of the patients who respond vs. those who do not, and to investigate the prognostic value of the results.

2. Material and Methods

2.1. Subjects

The current participants are 3 patients with traumatic brain injury who were admitted to the Helen Hayes Hospital (HHH, NY, USA) Neurorecovery Program. The inclusion criteria are: ≥ 16 years of age; JFK Coma Recovery Scale (CRS) $\leq$ 10; no serious co-morbidities; no craniotomy defects; no major scalp lacerations; and informed consent from a legally authorized representative. The study has been approved by the HHH Institutional Review Board. The participant is assessed for recovery from PBU by a trained psychiatrist or psychologist. The primary measure is the CRS. Subscales are comprised of hierarchically-arranged items associated with brainstem, sub-cortical, and cortical processes. The CRS was measured within one to two days of the recording. The Glasgow Outcome Scale (GOS) will be measured weekly as a five-point scale. The Functional Independence Measures (FIM) will be used for measuring the severity of disability.

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2.2. Experimental paradigm

EEG from a 32 channel referential montage is collected while the participants perform two motor imagery tasks. In each trial of each task, the participant hears one of two commands: 'move hands' and 'relax'; or 'move feet' and 'relax'. The commands are pre-recorded in a female voice and delivered via headphones. Each command is followed by an interval of 5.5 s when the participant is expected to perform the cued motor imagery. Before the start of each run (each set of trials), the participant is instructed to imagine moving both hands or both feet from the time they hear the motor command until they hear the 'relax' command. A set of 20 'imagery' and 'relax' trials form a run, which lasts for about 5 minutes. Four runs are collected in total, two for each motor task: hand motor imagery and feet motor imagery. Hand and foot imagery runs are interleaved.

2.3. Data acquisition

EEG data is acquired at 256 Hz sampling rate, using two synchronized FDA-approved 16-channel g.USBamp amplifier units (g.tec, Graz, Austria). The data are collected with 32 gel electrodes pre-embedded in an elastic cap, in a customized montage. The BCI2000 software [Schalk et al., 2004] platform is used for presenting the commands as well as for maintaining the synchronization of the stimulus presentation with the EEG records.

2.4. Data Analysis

The analysis is performed in three main steps: Pre-processing, spectral estimation, determining statistically significant differences between motor imagery and rest conditions (and between hand imagery and foot imagery conditions). These steps were performed with MATLAB and in-house software.

The EEG data are pre-processed by artifact removal (visual inspection) and notch filtering followed by a spatial filter. The data are then notch-filtered at 60 Hz to remove line noise. Subsequently, the data are subjected to a common average reference (CAR) spatial filter.

The next step is determination of the power spectra for all EEG channels. A 4.5 s period of continuous data, starting 1 s after the end of the auditory command, is used from each trial. The power spectral amplitudes for all channels are then determined for each data segment with a short-time fast Fourier transform (STFT), using a Hanning window of 500 ms for 6-28 Hz with a frequency resolution of 2 Hz.

The spectral estimates for each bandwidth and for each channel are then pooled for the hand and feet motor imagery classes as well as for their respective 'rest' classes. A non-parametric Wilcoxon-Rank Sum test is used to find significant differences in the frequency content of the various EEG channels between the motor imagery and rest conditions. Furthermore, the classification accuracy for hand imagery vs. rest and feet imagery vs. rest is determined.

3. Results

We found significant differences in power in the mu and/or beta frequency bands between the motor (hand or foot) imagery and the rest conditions for normal control participants as well as for the first three participants with brain injury. For one of these, analysis of power in the beta band yielded classification accuracies of 74.7% and 61.2% for hand vs. rest and feet vs. rest, respectively ($p < 0.001$ and $p = 0.02$).

4. Discussion

With further data collection and analyses, this study may validate a useful new diagnostic method for evaluation of patients in an apparent vegetative state. The method might provide useful prognostic information and aid in the formulation of individual treatment and disposition plans. Improving the identification of patients who are more likely to regain some function could yield more appropriate treatment strategies and more effective deployment of available resources.

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Classifying Volition for Comatose Patients: a BCI Perspective

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Abstract. Traditional clinical methods for diagnosis of disorders of consciousness are highly subjective and dependant on the patient's ability to move or speak. Objective tools mainly neuroimaging based validation of imagery paradigms akin to those used in brain computer interface applications have partially addressed this problem. But there is now widespread consensus that long term benefits to quality of life for this patient group can be better achieved at the bedside. This work is aimed to develop an objective portable tool at the bedside to establish the ability to respond to command without moving or speaking. A volitional paradigm with a classic motor imagery flavour but specifically designed to utilize the stimuli previously used in fMRI paradigm is developed for this purpose. The neural signatures computed using classifier performance indicate similarity to the areas of brain activation as revealed in the neuroimaging studies. The results show a consistent classifiability of the volitional tasks: 'imagine playing tennis' (IPT) and 'imagine spatial navigation' (ISN) with classification accuracies of more than 90%. The paradigms using these volitional tasks can be further used and implemented on selected patients for objectively detecting awareness.

Keywords: EEG, Minimally Conscious state (MCS), Motor Imagery, Vegetative state(VS) , Volition

1. Introduction

Disorders of consciousness, namely coma, vegetative and minimally conscious states are currently diagnosed on the basis of the patient's clinical history and exhibited behaviour. The clinician's central objective is to determine, beyond reasonable doubt, either that a patient demonstrates no evidence of awareness of self or harbours some inconsistent, but reproducible sign of awareness [Bates, 2005]. This task, as demonstrated in several clinical audits [Andrews et al., 1996], is far from straightforward and there exists a high degree of error in diagnosis (up to 43%). In order to address the principal source of error, namely the highly subjective process of deciding whether an exhibited behaviour is a conscious or unconscious process, research groups have recently started to develop objective tests to reveal signs of awareness [Goldfine et al., 2011]. Furthermore, efforts have been made to develop modes for simple communication [Monti et al., 2010].

Brain computer interfaces can provide non-muscular communication and control of prosthetic devices in persons with severe motor disabilities [Birbaumer et al., 2003]. BCI technology can detect user modulation of neural activity to signal wilful intent. Its success has been mainly with fully conscious, but severely disabled patients unable to move. The training phase of the classic BCI setup presents a potential bedside method to detect awareness in persons without the ability to move or speak after a brain injury.

In this manuscript we evaluate and compare the motor imagery and spatial navigation paradigms with a classic BCI motor imagery paradigm in untrained healthy volunteers. Our objectives were twofold: (a) Do the mental imagery paradigms successfully demonstrated with neuroimaging and validated in healthy volunteers produce similar temporally and spatially resolved patterns of activation detectable using scalp EEG? (b) Can sufficiently robust patterns of activation be detected in untrained BCI volunteers?

2. Material and Methods

Twelve healthy volunteers (11 male, right handed) with no previous experience of BCIs participated in the study, which was approved by the HSSREC, University of Warwick, UK. All subjects gave written informed consent. 32 EEG channels sampled at 200 Hz and bandpass filtered between 0.1 and 70 Hz were acquired using a commercial EEG system (Brain Products GmbH).

Subjects underwent a single EEG acquisition session, during which they were asked to perform two/three tasks in no specific order: (a) task 1: imagine repeatedly moving the dominant upper limb back and forth in the context of swinging a tennis racket to hit a ball versus rest, (b) task 2: imagine spatially navigating through the rooms of their home; concentrating on recreating the contents of each room rather than the act of movement from one room to another versus rest, (c) task 3: task 1 versus task 2 versus rest. In the rest period subjects were asked to relax.

At the start of each trial subjects were instructed to perform the set task if a marker appeared at the top of the computer screen (i.e., IPT or ISN) and change when the marker changed position, which was associated with the other task (e.g. rest). BCI2000 was used for stimulus presentation.

The analysis was designed using the functions from the Biosig toolbox. A single channel classification-performance (SCCP) based selection is robust and speedy method in which the contribution of each channel to the classification process is weighted using Cohen's kappa coefficient. In order to explore all the best combinations, 435 bipolar channel combinations were created. Classification using linear discriminant analysis is carried out on the autoregressive (AAR) features from the bipolar channel combinations using a k-fold cross validation procedure. The channels which generate the highest values of kappa coefficient are selected for the final classification stage.

3. Results

In case of IPT versus R, the channels placed on the motor areas and the frontal areas provide significantly higher contribution in the classification process between task IPT and R. Similarly, in the case of ISN versus R, 10 subjects show clearly highlighted temporo-parietal, occipital and frontal areas. These areas are supposedly associated with the spatial navigation and rest tasks.

Apparently, for almost all the topographic maps involving the rest state, higher values of kappa are observed for the frontal channels in majority of the subjects (11) implying the contribution of the frontal lobe to the rest state mental activity. The neural signatures of the three task volitional imagery provide clearly demarcated the areas of high activity for the 'rest' (frontal areas), 'imagine playing tennis' (central motor areas) and the 'spatial navigation' (parietal areas). Average accuracy achieved across the group for IPT versus R is 87.06%, while it is 86.94% in the case of ISN versus R. For three tasks IPT versus R versus ISN, the average accuracy is 75%.

4. Discussion

This work provides an electrophysiological framework for using established neuroimaging tasks for objective segregation of levels of disorders of consciousness. The SCCP method bypasses the complicated and cumbersome clinical interpretation of the EEG frequencies from brain injured patients but provides a solution to demarcate areas of high separability between these tasks. As these tasks are classifiable with high degree of accuracy, there exists a sub-group of non-behavioural, but intermittently conscious patients transiting through the continuum of impaired consciousness. BCI may be the most effective technique to detect such patients and provide a communication interface.

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A General Framework for Implementing a Multi-Subject Brain-Computer Interface

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Abstract. Recently, multi-brain computing has attracted growing attention in the fields of cognitive neuroscience and neural engineering. The potential of using a multi-subject brain computer interface (BCI) to improve individual human performance has been proposed and demonstrated in offline studies. However, little is known about the feasibility and practicality to implement such a system. This study proposes a general centralized system framework for implementing an online multi-subject BCI and demonstrates a collaborative BCI for group decision making using the proposed framework. The online test results suggest that the proposed framework can greatly satisfy the technical requirements of an online multi-subject BCI.

Keywords: Multi-brain computing, brain-computer interface (BCI), online BCI, collaborative BCI, decision making

1. Introduction

Two heads are better than one, known as collective intelligence, the mechanism and neural basis of which has recently attracted growing attention of researchers in psychology and neuroscience [Bahrami et al., 2010; Eckstein et al., 2011]. The collective intelligence has also been introduced to the neural engineering field. For example, the potential of using a brain computer interface (BCI) based on multi-brain computing, named collaborative BCI, to improve human performance has been explored by recent studies [Wang et al., 2011; Eckstein et al., 2011]. However, although the theoretical aspects of a multi-subject BCI have been proposed in these studies, a general system framework for developing and implementing an online system has not been well established. Therefore, it is of great importance to provide a general system framework of an online multi-subject BCI to researchers. To this end, this study proposes a centralized system framework of an online multi-subject BCI and demonstrates a collaborative BCI for improving group decision making.

2. Material and Methods

The system framework consists of four major modules: (1) an EEG recording module (comprising multiple EEG amplifiers and data recording computers), (2) a stimulus and feedback presentation module (including multiple LCD monitors, one in front of each subject), (3) a data-analysis module (implementing group EEG data analysis on a server computer), and (4) a control module (performing stimulus generation, feedback generation and synchronization control). Fig. 1 shows a schematic overview of the proposed system. In the system, the EEG data from a group of subjects are recorded with multiple EEG amplifiers synchronized by trigger signals from the computer server. A Media-Key multimedia teaching system delivers visual cues to multiple LCD monitors simultaneously. EEG data from each of the subjects are sent to the server via TCP/IP for real-time group data analysis. Visual feedbacks are presented on the screens to all subjects.

This study used the proposed framework to implement a collaborative BCI for Go/NoGo decision making. During the experiment, a series of images including face images (Go tasks) and car images (NoGo tasks) were presented to the subjects. Seven groups of people (three subjects in each group) participated in the experiment. A 16-channel EEG amplifier was used for collecting data from each subject. A two-layer support vector machine (SVM) classifier was applied to predict the Go/NoGo decision with the first and second levels for individual and group classification, respectively. The experiment comprised a training session used to train the classifiers and a testing session used to evaluate the performance of the system. Each session comprised 120 trials.

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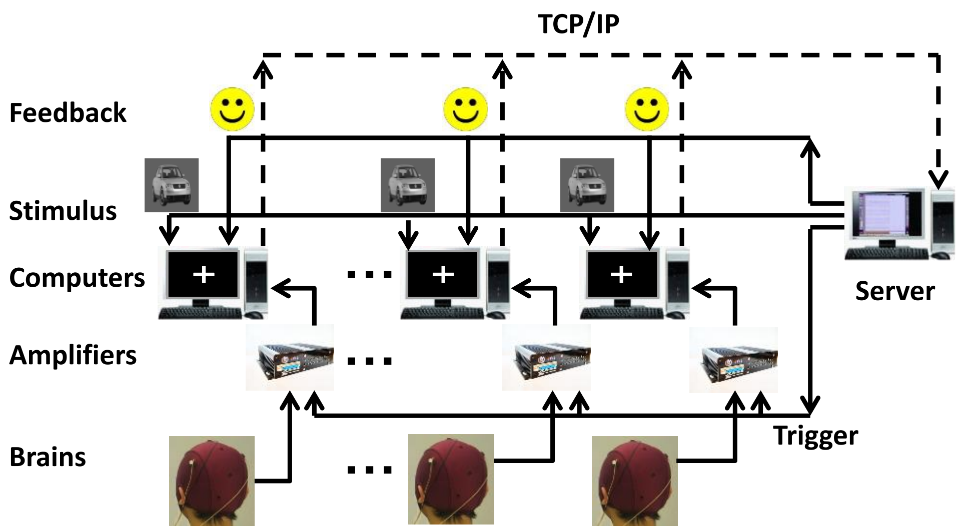

Figure 1. *System framework for an online multi-subject BCI.*

3. Results

Consistent with offline analysis, the online test showed that the collaborative classification significantly improved the performance of the individual classification. Using the EEG data within 300 ms after the stimulus onset, which was about 90 ms earlier than the mean behavioral response time (RT) (393 ± 69 ms), the mean accuracy of the collaborative classification was 82.4 ± 6.1% across all groups. It was 11.6% higher than the average individual accuracy (70.9 ± 6.2%, $p < 10^{-4}$) and 7.6% higher than the best individual accuracy (74.7 ± 4.8%, $p < 10^{-3}$). The results suggest that the proposed framework can greatly satisfy the technical requirements of an online multi-subject BCI.

4. Conclusion

This study demonstrates a general framework for implementing the multi-subject brain-computer interaction. In addition to BCI applications, the proposed framework might have potential for EEG-based group brain imaging of social processes and behavior.

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Cooperating Brains: Dual-BCI as a New Paradigm to Investigate Brain-to-Brain Coupling

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Abstract. Recently, BCI research has started to provide new, elementary insights not only into brain control but also into the basis of neurocognitive processes. Here, we describe a novel BCI paradigm, 'Two-Person-BCI' or 'Dual-BCI', where the joint brain activity of two participants controls a computer. This can serve as a promising new research paradigm for the emerging field of brain-to-brain coupling. The main hypothesis underlying this field is that people's ability to coordinate their brain activity forms the elementary basis for communication, thus creating a so-called 'shared space' [Gallese, 2003]. A key feature of our new Dual-BCI paradigm is that it allows people to coordinate their behavior without using muscular activity. Here, we will show why Dual-BCI is an especially promising paradigm for investigating brain-to-brain coupling, we will describe analysis methods that can be used to detect different types of neural coordination between brains, and provide preliminary results from a first experiment where the paradigm has been applied; see also the companion abstract [Schultze-Kraft et al., submitted].

Keywords: EEG, Hyperscanning, Dual-BCI, Motor-Imagery, Social Interaction

1. Introduction

For a long time neuroscientists have struggled to understand the neural basis of human communication. Traditional approaches that aim to understand the neural basis of human communication have recorded the brain activity of one person at a time (for an overview, see [van Overwalle et al., 2009]). In contrast to the traditional approaches, a fundamental hypothesis of the new field of Two-Person Neuroscience is that the coordination of brain processes between individuals is a central factor for enabling communication. Since the emergence of this new field the number of studies is steadily increasing, and the first results confirm this hypothesis (e.g. [Anders et al., 2011; Kuhlen et al., 2012]).

A critical limitation of the studies conducted so far is that all of them require some form of motor activity for communication/coordination of behavior. Thus, it remains an open question to which degree the obtained results rely on muscular motor activity and/or neural processes underlying those. That is, it would be important to disentangle coordinated neural activity that is simply the result of coordinated behavior from that which is crucial to establish coordination in the first place. To investigate this question, we conceived a new paradigm that allows coordinated behavior, but that does not require any kind of muscular activity: The 'Two-Person' or 'Dual-BCI' setup. In this setup, two participants coordinate their behavior to jointly control a virtual character. Critically, they control the character via BCIs, thus avoiding any kind of muscular activity, because BCIs circumvent the traditional brain-muscle-pathway; instead, they provide steering commands to the computer directly via thoughts. In the remainder of this paper, we will shortly describe the setup of an Dual-EEG-BCI study that we are currently conducting, explain which analyses methods we are going to use, and discuss why we believe the Dual-BCI Setup to be a promising tool to advance our understanding of the neural basis of human communication.

2. Material and Methods

2.1. Dual-BCI Setup & BCI game

In the experiment, ten pairs of participants used motor-imagery to control a game character (a cowboy) in a two-dimensional cooperative maze game, where the cowboy moved around to collect a number of targets (fruits); more details in [Schultze-Kraft et al., submitted]. To be able to test whether neural coordination – if existing – changes with the amount of cooperation that is needed to play the game, we used different experimental conditions that

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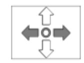
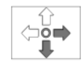
involved different levels of cooperation between both players (Table 1). The conditions are presented in successive blocks, were each block lasts about 10 minutes, depending on how fast participants reach the goal of each level.

Table 1. *Experimental conditions: From top to bottom conditions require an increasing amount of cooperation between both players. The white (gray) circle in row one denotes the game character of player 1 (player 2). The other white-gray circles denote that both players control the same character. White (gray) arrows denote control direction of player 1 (player 2).*

Condition	*Description*	*Illustration*
Individual Control	Each player individually controls a different game character along one dimension (left/right)	
Same Dimension Control	Both players control the same character along the same dimension (left/right)	
Separate Dimension Control	Each player controls the same character along one dimension (left/right vs. up/down)	
Split Dimension Control	Each player controls the same character along one direction of each dimension (e.g. left/up vs. right/down)	

2.3. Data Analysis

A battery of different methods will be used to test the hypothesis that brain activity coordinates while people are communicating, and to identify which features of brain activity are coordinated, if coordination is present. These analyses will include, among others, canonical correlation analyses, between-brain phase locking values, between-brain- and granger-SPoC [Dähne et al., 2012], and frequency band power correlations.

3. Results

At the time of this writing, data recordings are currently in progress. Participants were successful in playing the game in cooperation, showing that they are able to coordinate their behavior as required [Schultze-Kraft et al., submitted]. First results on brain-to-brain coupling will be presented at the conference.

4. Discussion

We introduced ‘Dual-BCI’ as a new tool to investigate brain-to-brain coupling in Two-Person Neuroscience. An especially attractive feature of Dual-BCI is that it allows investigating coordinated behavior without requiring any form of muscular activity. We believe that the Dual-BCI has the potential to open up a new branch within Two-Person Neuroscience and, more general, will help to continue establishing BCI as a method within the neurosciences.

Acknowledgements

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Cooperating Brains: Joint Control of a Dual-BCI

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Abstract. Pairs of participants simultaneously used EEG-based motor-imagery BCIs to jointly play a cooperative computer game. Here, we present this novel 'Dual-BCI' setup, including results on feasibility and user experiences, experiences on the design of Dual-BCI games, especially highlighting possible caveats and potential solutions. In addition, we investigated and compared the simultaneous classifier outputs from both participants and explored the use of both participants' brain signals for simulated online BCI. Importantly, the presented Dual-BCI scenario represents a promising tool for the investigation of brain-to-brain connectivity in human social interaction; see companion abstract [Görgen et al., submitted].

Keywords: EEG, Hyperscanning, Dual-BCI, Motor-Imagery, Social Interaction

1. Introduction

Despite abundant research with non-invasive BCIs, multi-brain BCI studies (BCI applications involving multiple users at the same time) are scarce. The few multi-brain BCI studies that have been conducted involve two participants simultaneously – but individually – controlling a *separate* part of an application (e.g. two-player 'Brain-Pong') [Müller et al., 2006; Göbel et al., 2004]. To the best of our knowledge, the present study is the first one investigating a *cooperative* BCI scenario, in which two participants jointly play a computer game cooperatively controlling a single game character. Here, we present first results on the feasibility and user experience of jointly and continuously controlled BCI applications. We give a detailed description of the Dual-BCI setup, the design of the continuous BCI game, potential caveats and possible improvements. Furthermore, we compare the simultaneous classifier outputs from both players and explore the integration of both participants' brain signals for multi-brain classifiers. In addition to the development of BCI games, one interesting application scenario for the Dual-BCI setup is its ability to serve as a framework for investigating neural brain-to-brain connectivity of inter-personal interaction: Using BCIs to control computers via brain activity alone, people can perform coordinated behavior without any muscular activity, a potential confounding factor of previous studies investigating brain-to-brain connectivity. Refer to our companion abstract [Görgen et al., submitted] for more details.

2. Material and Methods

Ten pairs of participants used motor-imagery to control a game character (a cowboy) in a two-dimensional cooperative maze game, where the cowboy moved around to collect a number of targets (fruits). Fig. 1 illustrates the Dual-BCI setup that we employed. EEG data was filtered using Common Spatial Pattern (CSP). The resulting CSP features were classified using Linear Discriminant Analysis (LDA), the output of which was used as control signal.

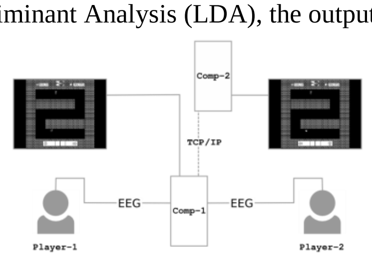

Figure 1. *The Dual-BCI setup: Two players are seated in front of separate monitors. Recording and processing of EEG data is performed by a single computer. All data needed to display the BCI feedback is sent via network to a second computer to display it to the second player.*

2.1. Conditions

Experimental conditions involve different levels of cooperation between both players (Table 1). The conditions are presented block-wise. Additionally, we employed a pure observational condition and a keyboard condition.

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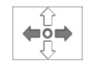
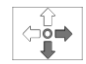
Table 1. *Experimental conditions: From top to bottom conditions require an increasing amount of cooperation between both players. The white (gray) circle in row one denotes the game character of player 1 (player 2). The other white-gray circles denote that both players control the same character. White (gray) arrows denote the control direction of player 1 (player 2). In conditions 1 & 2, the character was controlled in 1D (along the horizontal axis), in conditions 3 & 4 in 2D.*

Condition	*Description*	*Illustration*
Individual Control	Each player individually controls a different game character along one dimension (left/right)	
Same Dimension Control	Both players control the same character along the same dimension (left/right)	
Separate Dimension Control	Each player controls the same character along one dimension (left/right vs. up/down)	
Split Dimension Control	Each player controls the same character along one direction of each dimension (e.g. left/up vs. right/down)	

2.2. Data Analysis

Data analysis is currently in progress. It includes a descriptive statistical analysis of user questionnaires, which were used to collect subjective data on the user experience of the BCI game. Furthermore, we perform correlation analyses between subjective ratings and objective performance. We present detailed histograms of the continuous classifier outputs from both participants during different phases of the experiment and compare these to subjective experience and objective performance. Additionally, we will explore the use of both participants' brain signals for simulated online BCI in order to enhance performance using multi-brain classifiers.

3. Results

3.1. Feasibility

The Dual-BCI system has been tested successfully: Joint control of the cooperative BCI game by two participants using motor-imagery was accomplished.

3.2. Evaluation

Preliminary results show that participants preferred the cooperative 'separate dimension control' condition as compared to 'individual control' and the 'same dimension control' condition in terms of competence, immersion, flow, challenge, empathy and positive affect. This suggests that participants favor playing together and that user experience is enhanced in this cooperative setting. Drawbacks in the 'split dimension control' condition (e.g. level of control difficulty) lead to decreased joy of use in this condition. Descriptive analysis of the participants' continuous classifier outputs suggest bi-modal histograms for participants with good BCI control. Detailed results will be presented at the conference.

4. Discussion

We successfully establish a Dual-BCI setup in which two participants played a cooperative BCI game. To the best of our knowledge, this study provides first results on the feasibility of cooperatively continuous-controlled BCI applications by two persons. Thus, this work constitutes the foundation for further investigation on the benefits of mutli-brain BCIs. One promising application scenario of this approach is its capability of using it as a tool for investigating brain-to-brain coupling between people during human social interaction [Görgen et al., submitted].

Acknowledgements

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Brain-Computer Interface Supported Collaborative Work

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Abstract. BCIs hold the promise for the restoration of communication and control ability to users with severe motor disability, but BCI research has not yet fully addressed the social burdens of their disabilities (i.e., interaction with other people). This study investigated and found differences in performance and brain activity patterns when people perform a task jointly with each other under different collaborative work conditions. We suggest that supporting interaction in BCI-supported collaborative work provide greater benefits for users, including people with severe motor disability.

Keywords: EEG, SSVEP, Turn-by-turn collaborative work, Collaborative BCI, Brainbot

1. Introduction

Despite a considerable amount of ongoing research, current efforts in the area of BCI research and development still have significant gaps [Lebedev and Nicolelis, 2006]. Most existing BCIs are still single-user applications, which do not meet the needs of users who want to work together. Working together and collaboration is common and natural for people in order to complete a job faster or to share expertise for a complex task [Heer et al., 2008]. Collaboration can help to foster the sharing of knowledge, ideas, and skills [Isenberg and Carpendale, 2007]. Due to the rapid advance of BCI technology and aforementioned advantages of collaboration, we envisage that in the near future people, including those with severe motor disability, will be able to perform tasks with other people only through their brain activity. However, there has been a general lack of understanding regarding how BCIs should support collaborative work under various task conditions. As the first step to address these research issues, this study investigated differences in performance when people perform a task jointly with other people only through means of their brain activity under different collaborative work conditions.

2. Material and Methods

2.1. Participants

Two right-handed healthy subjects (mean age: 28.4±1.5; 2 males) volunteered to participate in the study. Subjects had normal or corrected-to-normal vision with no prior experience related to SSVEP-based BCIs. Subjects were not given any financial reward for their participation.

2.2. Data Acquisition and Processing

EEG data was recorded using an EEG cap with 16 electrodes, according to the extended International 10-20 system. Signals were amplified with a g.USBamp amplifier. Fpz and right ear lobe were used as ground and reference, respectively. The EEG signals were digitized at a sampling rate of 512 Hz, with band-pass filtering from 5 Hz to 60 Hz. In order to determine a user's SSVEP responses, we used a harmonic sum decision (HSD) method using signals from two occipital channels (O_1 and O_2) with the target frequencies of 6, 7, 8, 9, and 11 Hz.

2.3. Experimental Design and Procedure

We developed *BrainBot,* a SSVEP-based collaborative BCI for control, constructed using a LEGO Mindstorms NXT kit. Participants were asked to perform a sequence of six activities (G→St3→R→G→St1→R) by controlling *Brainbot,* in which they grasped (G) and released (R) a ball to one of the three target locations (St 1, St2, and St3) beginning at St2 (i.e., Grasping a ball at station 2).

The type of collaborative work (co-work) was manipulated as a within-subject independent variable: (a) individual work where participants perform a task alone, (b) Co-Work 1: turn-based co-work with self-error correction where a pair of users takes turns to perform a task and any error is corrected by the person who made, and

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(c) Co-Work 2: turn-based co-work with error correction by partner where a pair of users takes turns to perform a task and any error is corrected by the partner.

3. Results

To investigate differences in performance and brain activity when a pair of users performs a task jointly with each other under different collaborative work conditions, this study employed several dependent measures, which can be categorized into two types of variables: (a) task performance (task completion time in second, the number of error, and maximum power spectrum in V_{rms}^2) and (b) brain activity pattern in the time-frequency domain.

As shown in Table 1, BCI users showed different performance depending on work conditions, in which collaborative work generally took longer time, made more errors and produced higher signal powers compared to individual work. Fig. 1 also illustrates brain activity patterns can be different under different collaborative work conditions.

Table 1. *Task performance by collaborative work types.*

	Step	G	St3	R	G	St1	R	Total	Average
Task Time	Subject 1	0.50	9.00	12.00	17.30	22.30	34.00	95.10	**15.85**
	Subject 2	0.80	5.30	6.80	44.30	49.30	50.30	156.80	**26.13**
	Co-Work 1	0.50	4.00	12.00	15.25	77.25	86.50	195.50	**32.58**
	Co-Work 2	1.00	19.25	20.50	22.00	23.50	40.75	127.00	**21.17**
No. of Error	Subject 1	0.0	0.0	0.0	0.0	2.0	1.0	3.0	**0.5**
	Subject 2	0.0	0.0	0.0	5.0	1.0	0.0	6.0	**1.0**
	Co-Work 1	0.0	1.0	3.0	1.0	28.0	2.0	35.0	**5.8**
	Co-Work 2	0.0	7.0	0.0	0.0	0.0	8.0	15.0	**2.5**
Max. Power	Subject 1	0.03	0.01	0.02	0.02	0.01	0.02	0.11	**0.02**
	Subject 2	0.07	0.68	0.07	0.05	0.10	0.05	1.02	**0.17**
	Co-Work 1	0.04	0.04	0.02	0.03	0.02	0.04	0.19	**0.03**
	Co-Work 2	0.02	0.03	0.04	0.03	0.03	0.03	0.17	**0.03**

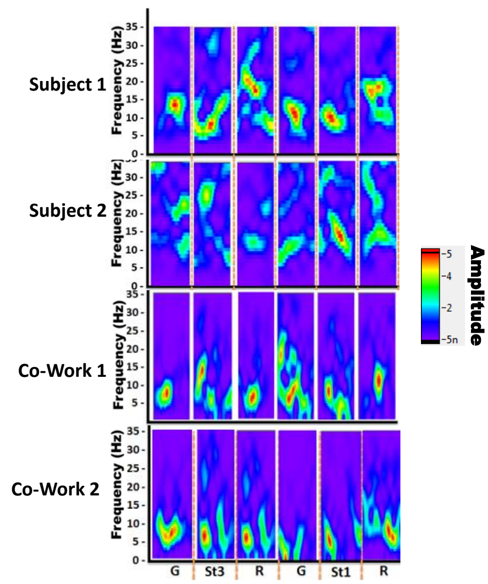

Figure 1. *Short time fourier transform (STFT) analysis by collaborative work types.*

4. Discussion

Through the preliminary analysis of the data collected, we found differences in performance and brain activity pattern between different collaborative work conditions. Working together and collaborating in a group can provide greater benefits for user, including people with severe motor disability. However, little attention has been paid to BCI-supported collaborative work. Thus, this research can be of great significance due to its potential to yield fundamental knowledge of BCI-supported cooperative work, understanding of the support needed for interaction in BCI technology supported group activities, and design considerations for collaborative BCIs.

Acknowledgements

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An Ambulatory BCI-Driven Orthosis for Stroke Rehabilitation

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Abstract. This paper describes a novel brain-computer interface (BCI) with the aim of motor rehabilitation of stroke patients. Movement imagination of dorsiflexion was detected from scalp electroencephalogram (EEG) through movement related cortical potentials (MRCP). Such detection subsequently triggered an motorized ankle foot orthosis (MAFO), which induced passive dorsiflexions. The hypothesis was that the cortical drive to the muscle is enhanced over the use of this system because of the afferent flow resulting from the passive movement that mimicked the sensory feedback of movement execution. In the pilot experiment, extracted MRCP parameters changed consistently after the BCI-intervention. Follow-up experiments are underway to further investigate the feasibility of such a BCI-based stroke rehabilitation system and to quantify the accompanying plastic changes.

Keywords: EEG, MRCP, MAFO, BCI, stroke rehabilitation

1. Introduction

Stroke rehabilitation is now one of the leading healthcare challenges in the world, with a steadily rising prevalence coinciding with a decreasing fatality rate. Mrachacz-Kersting proposed a novel BCI for rehabilitation based on MRCP triggered FES, and their experiments on healthy individuals and stroke patients showed that it altered the cortical output to peripheral muscles [Mrachacz-Kersting et al., 2012; Mrachacz-Kersting et al., 2012a]. However, FES has its side effects, and is not applicable for patients with epilepsy or cardiac pacemakers.

Motorized Ankle Foot Orthosis (MAFO) is a wearable ankle foot exoskeleton, designed specifically for ambulatory rehabilitation of drop-foot [3]. Compared with interventions such as FES, it provides a more natural approach in inducing sensory feedback. Therefore, it may be more effective than FES in inducing neural plasticity. In this study, we present the complete setup for a BCI-MAFO system that is designed as a close-loop rehabilitation tool for drop-foot. We also demonstrate, with preliminary data, that a short intervention with such a system has the potential in inducing cortical plasticity in healthy subjects.

2. Methods

2.1. General System Design

The MAFO used here is a single degree-of-freedom (ankle dorsiflexion and plantarflexion) mechatronic device, which integrates state-of-the-art planar DC motors and planar harmonic transmissions for a compact and light system design [Pons, 2010]. A MATLAB Real-Time Workshop system (Mathworks) was used as the real-time control framework of the MAFO. This allows easy interfacing with other equipment for bio-signal acquisition and processing. MAFO has been subject to extensive electromechanical testing which renders it suitable for clinical research. Various control modes can be implemented in the control architecture of MAFO, in particular it can block the joint for isometric states, and impose isokinetic conditions or arbitrary joint movements.

In the current system, we utilized signal processing techniques of EEG to detect movement intention during imagination [Niazi et al., 2011]. The signal modality used was movement related cortical potential (MRCP), a slow-component in EEG, which is characterized by a slow EEG depression at the corresponding motor cortex area prior to the onset of the imagined movement. It was shown that the latency of such detections with respect to the movement onset was very short (< 50 ms) [Niazi et al., 2011]. Subsequently, the detections were used to trigger the MAFO, which would induce a dorsiflexion upon triggering. Due to the short detection latency, the subjects would actually perceive that they triggered the dorsiflexion by their motor imagination.

2.2. Experiment protocal

Three healthy volunteers (male, age: 29.3 ± 6.6 years) participated in the experiment, which was approved by the local research ethics committee. The subjects sat in a natural position, and wore the MAFO on the left leg. One surface EMG electrode was placed on the mid-belly of the left tibialis anterior muscle. The EMG reference and ground were placed on the bony surfaces of the knee and ankle, respectively. Nine active EEG electrodes (actiCap, Brainproducts) were prepared on Cz, Fz, FC1, FC2, C3, C4, CP1, CP2, and Pz of the international 10-20 system. The EEG reference and ground were left earlobe and AFz, respectively. Both EEG and EMG were acquired by a 16-channel EEG amplifier (gUSBamp, gTec).

A complete experimental session consisted of three parts. For the first part or the pre-intervention the subjects were asked to execute a total of 30 dorsiflexion movements following on-screen instructions by a customized user interface (synchronized mode). The MRCP template was extracted immediately from these pre-intervention EEG recordings [Niazi et al., 2011]. The second part was the BCI-intervention. The subjects performed self-paced imagination of dorsiflexion (asynchronized mode). The motor imagination was detected from EEG in real time using the MRCP template extracted from the pre-intervention data. Upon each detection, the MAFO was triggered to perform a passive dorsiflexion at 40°/s for 15°. The intervention ceased once a total number of 60 dorsiflexions had been triggered in this mode. The last part was post-intervention, which was the same as the pre-intervention, i.e. 30 dorsiflexion executions in the synchronized mode.

3. Results

In this study, offline data from pre-intervention was used to gauge the MRCP detection performance through a 3-fold cross-validation. True positive rate (TPR) of three subjects was 61.3%, 66.7%, and 76.7%, respectively. While the false positive rate (FPR) was 3.1, 2.7, and 0.8 per minute, respectively. This result was in agreement with prior offline studies [Mrachacz-Kersting et al., 2012; Mrachacz-Kersting et al., 2012a; Niazi et al., 2011].

The peak to peak of the MRCP, depression rate prior to the MRCP peak negativity, and rebound rate following the peak negativity changed consistently from the pre-intervention to the post-intervention in all three subjects. The depression rates of the MRCP between post-intervention and pre-intervention increased by 2.4 μV/s, 2.3 μV/s, and 2.5 μV/s, respectively for the three subjects. The change of the peak-to-peak of MRCP was 3.3 μV, 2.5 μV, and -2.8 μV, while the rebound rates were 4.8 μV/s, -0.9 μV/s, and 4.1 μV/s, respectively.

4. Conclusion and Discussion

In this study, we presented a BCI-MAFO ambulatory stroke rehabilitation system. The system extracts motor intentions from scalp EEG, and triggers passive muscle contractions by a wearable orthosis (MAFO). A pilot experiment demonstrated the feasibility of the system concept. Further, we showed that a short intervention of the system has the potential in inducing cortical plasticity, as indicated by the consistent changes in the parameters.

Acknowledgements

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Motor Recovery After Stroke by Means of BCI-Guided Functional Electrical Stimulation

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Abstract. Brain-Computer Interfaces (BCIs) provide a mean to access the damaged motor network of the brain after stroke, and could be used to drive and promote beneficial plasticity. Among the available therapeutic approaches, Functional Electrical Stimulation (FES) is often applied during rehabilitation to directly engage muscles of the affected side of the body, especially when the residual functionality is weak or absent. In this paper, we describe a BCI system for stroke rehabilitation that decodes the attempt to execute a sustained hand extension movement from non-invasive human EEG and activates FES of affected arm muscles, accordingly. The system allows the physical therapist to monitor current brain activity through an EEG-guided visualization. Preliminary results on 4 chronic stroke patients show consistency in the EEG features selected for further training. Three of the patients completed the testing, and they all show recovery of target muscle function. Our results support the idea that BCI can be used to promote beneficial plasticity even during chronic phase, and justify further testing on a larger population.

Keywords: Rehabilitation, Stroke, Brain-Computer Interface, Functional Electrical Stimulation

1. Introduction

Millions of people worldwide are left permanently disabled after a stroke every year [Roget et al., 2012]. Research in the direction of more efficient, faster rehabilitation is then crucial. Brain-Computer Interfaces (BCIs) provide a mean to decode user attempt to execute a movement or its imagery, and could provide a direct feedback on the engagement of motor areas of the brain surrounding the lesion site [Millán et al., 2010]. Among other available practices in rehabilitation, Functional Electrical Stimulation (FES) is often used to directly engage muscles on the affected side of the body during physical therapy. Still, no commercial system provides a mean to directly link the intention to move with muscular response.

In this paper, we report preliminary results of a BCI system for stroke rehabilitation. User's intention to perform a sustained hand extension movement on the affected side of the body is detected through a BCI and used to activate FES of the finger extensor muscle. A physical therapist receives the visual feedback about current BCI performance, motivates the end-user and avoids abnormal user behaviors (Fig. 1).

2. Material and Methods

The EEG was acquired through a gUSBamp with 16 active electrodes mounted in correspondence of the central sulcus and motor cortices. Bipolar EMG derivations of the extensor digitorum (target muscle), biceps, flexor carpi radialis and triceps were also recorded. The data were digitalized at 512 Hz and band-pass filtered in the range [0.1 70] Hz. One FES channel is applied to the extensor digitorum during the on-line sessions.

The experimental protocol consists in three different phases: first, patients undergo an EEG pre-screening session to characterize the initial state of the brain and calibrate the BCI classifier. In the following 2 months, they are trained with on-line BCI feedback and FES for at least 10 sessions. Finally, they perform a post-screening to determine changes in EEG patterns following the treatment.

During both the pre- and post-screening sessions, users are asked to perform (or attempt performing) a full sustained finger extension of approximately 4 s. Each run is composed of 15 trials of motor task and 15 trials of resting, for both the affected and unaffected hand (AH, UH, respectively). Each run is composed of 15 trials where the user is asked to concentrate on the affected hand, trying to execute a full sustained finger extension of approximately 4 s. FES of extensor digitorum is activated every time the BCI is sufficiently confident of motor engagement.

We have been working with 4 chronic stroke patients up to now, all of them suffering a left hemisphere ischaemic infarct. The 4 subjects completed the prototype testing process and were clinically evaluated before and after receiving the treatment (Fugl-Meyer Index for Upper Limb).

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3. Results

In this paper, we present the most discriminant EEG features used by the BCI, extracted from the initial EEG screening session [Galán et al., 2007]. These features are used to train a classifier that judges whether each sample belongs to a motor task or to a resting task (samples with a probability < 0.6 will be rejected). Table 1 reports some information about the 4 end-users, the classifier performance (single sample accuracy) on the pre-screening session data, and the functional Fugl-Meyer (FM) indexes. Fig. 1 shows the experimental setup and the selected EEG features in terms of spatial and frequency location.

Table 1. *Patients information, BCI metrics and clinical indexes.*

Subject ID (Age, Lesion hemisp.1, Gender)	*Time since stroke (months)*	*Number of on-line BCI sessions*	*BCI Classifier Performance / Rejection*	*Fugl-Meyer Upper Limb (pre | post, MAX 66)*
S1 (64, L, M)	10	10	*0.9 / 0.43*	7 | 17
S2 (71, L, M)	14	11	*0.91 / 0.68*	31 | 40
S3 (49, L, M)	10	10	*0.91 / 0.45*	36 | 51
S4 (50, L, F)	19	10	*0.89 / 0.41*	30 | 40

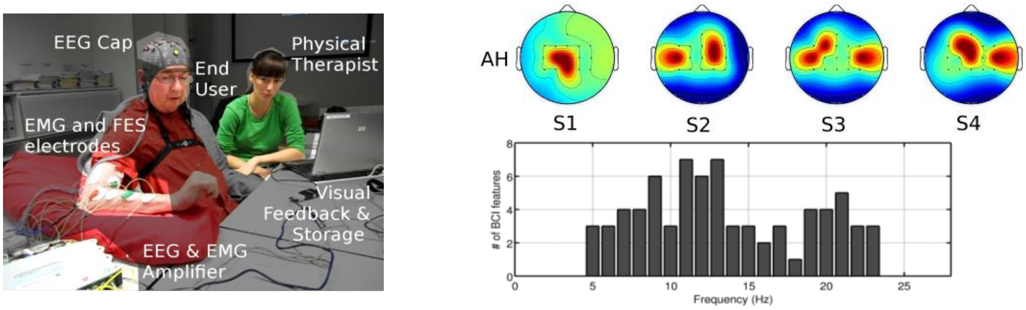

Figure 1. *Experimental Setup (left), spatial (right, top) and frequency (right, bottom) location of the EEG features extracted from the pre-screening session. The number of frequency features is the sum over all 4 patients.*

4. Discussion

The spatial distribution of EEG discriminant features is fairly consistent over our 4 patients: they all have a rather bilateral representation of the motor action, except subject S1 that shows a central representation. Regarding the discriminant frequency components, they consistently localize in the mu and beta bands, except subject S1, who presents very low alpha features. BCI features for the other patients are rather aligned to those of healthy subjects. Interestingly, subject S1 was the most severed individual of our group. Also, we achieve very reliable classification rejecting all samples that are not “safe enough”, as reflected by high single sample accuracy.

We report functional improvements in all our patients, especially in movements involving the extensor digitorum, as reflected by the Fugl-Meyer indexs. Remarkably, also subject S1, for whom the BCI features were rather different from those of the other patients and from healthy subjects, showed functional recovery passing from a totally paretic arm to a very limited but still noticeable voluntary activity of the hand. These results confirm the beneficial effects of direct muscle stimulation according to user intention to perform a motor task. Nevertheless, these initial findings need to be confirmed on a larger population and a control group.

Acknowledgements

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A Scene-Combined Navigation Method Based on Newton's Rings Paradigm for Brain-Actuated Intelligent Wheelchairs

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Abstract. Brain-actuated intelligent wheelchair has become a research hotspot as the elderly and people with disabilities increase year by year. However, these systems suffer from very low information transmission rates (ITR) and low level navigation methods. To overvome these two problems, we firstly adopt the recently proposed Newton's Rings paradigm to improve the ITR and reduce the user's discomfort; then, a new technology called scene-combined navigation method is designed to improve the efficiency of navigation.

Keywords: Intelligent wheelchair, Brain-Computer Interface, Scene-combined, Newton's Rings paradigm, Navigation method

1. Introduction

Many BCI applications have been developed to help people suffering from paraplegia or with other physical impairments to autonomously drive a wheelchair [Luis et al., 2012]. However, several problems lead to their shortages of low efficiency and low robustness.

First and foremost, BCIs provide low information transfer rates and accuracies, and require a concentration effort [Rebsamen et al., 2010], which makes it difficult to control the wheelchair reliably.

Then, usual BCI-wheelchairs based on low-level navigation (e.g., front, back, left, and right) require excessive instructions even in simplistic scenarios [Iturrate et al., 2009].

Aiming at these two problems, we develop a new brain-actuated intelligent wheelchair. On the one hand, a previously proposed paradigm by our team called oscillating Newton's Rings [Jun et al., 2012] is utilized to achieve a relatively high ITR. Then we design an effective and reliable scene-combined navigation method.

2. Material and Methods

2.1. The Newton's Rings paradigm

In a previous study, we utilize a special visual stimulation protocol, called motion reversal, to present a novel steady-state motion visual evoked potential (SSMVEP)-based BCI paradigm that relied on human perception of motions oscillating in two opposite directions. In the present research, the ITR reaches 40.25 ± 8.23 bits/min when we set 9 simulators, which is relatively high as compared to ITRs of P300 BCIs (20-25 bits/min) [Luis et al., 2012].

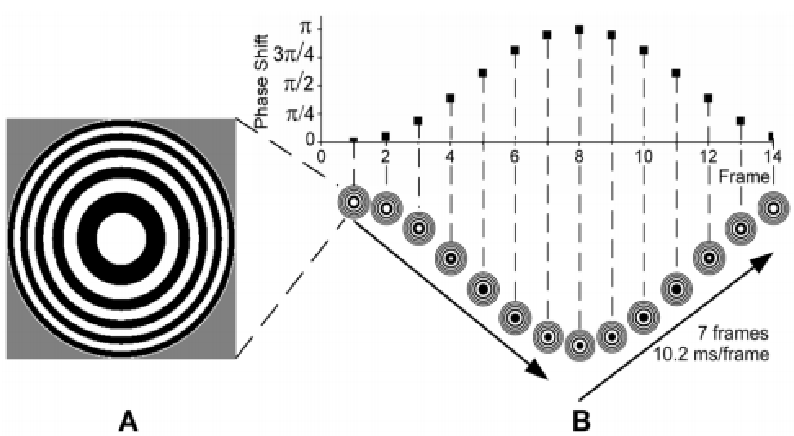

Figure 1. *The Newton's Ring paradigm. (A) A Newton's Ring based stimulator. (B) The motion reversal procedure of the rings. It was illustrated with a 14 Hz motion reversal frequency and each reversal contained 7 frames. The phase of the Newton's ring was modulated by a sinusoid of 7 Hz in [0, π] to produce motion reversals.*

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2.2. Navigation method

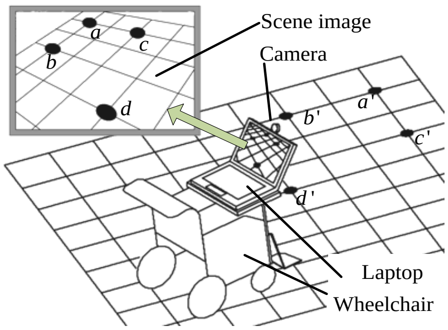

Figure 2. *The scene-combined navigation method. A navigation method which associates the stimulators and the scene is designed to improve the efficiency and robustness of the navigation. A wide-angle camera is mounted on the front of the wheelchair. The stimulators are presented on the scene image captured by the camera. By calibrating the camera, the position of a stimulator (e.g., a, b, c or d in the figure) in the image and the corresponding position on the floor (e.g., a', b', c' or d') are associated. A subject gaze at a stimulator to select his or her desired target position and the computer generates commands to drive the wheelchair there.*

3. Results

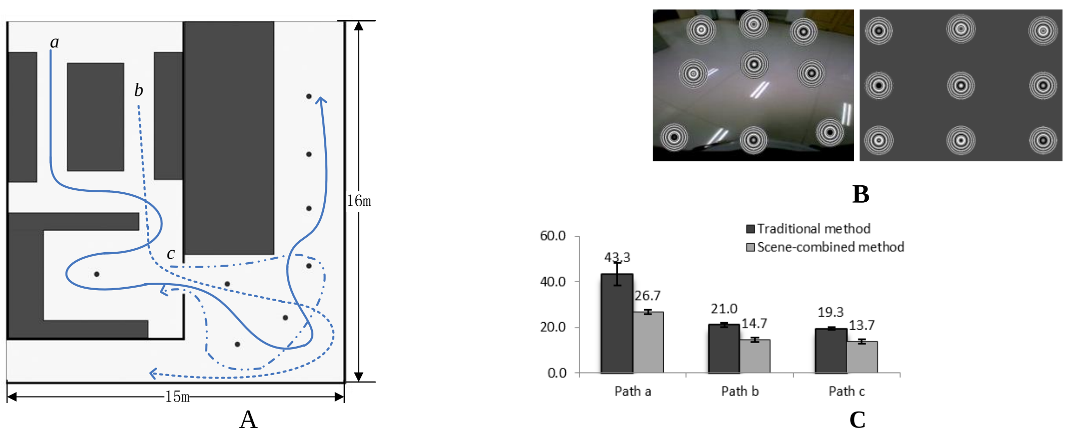

Figure 3. *Experimental validation of the scene-combined navigation method compared to traditional method. (A) Three paths (a, b and c) with different length and complexity are designed to test the new and tradition navigation method. (B) Left: the stimulus pattern of scene-combined method, each stimulator corresponds to a position on the floor; Right: the stimulus pattern of traditional method, each stimulator corresponds to running forward a certain distance or turning a certain angle. (C) The average number of instructions needed for the three paths.*

4. Discussion

Based on the relatively high ITR and accuracy of the Newton's Ring paradigm, we designed an efficient and robust navigation method. The results show that a high-level navigation strategy achieves considerable improvement in efficiency as opposed to a low-level strategy.

Acknowledgements

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Tactually-Evoked Event-Related Potentials for BCI-Based Wheelchair Control in a Virtual Environment

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Abstract. Brain-computer interface (BCI) based wheelchair control may be of value for those not able to operate a wheelchair with a joystick. Technology depending on visual or auditory input may not be feasible as these modalities are dedicated to processing of environmental stimuli (e.g. recognition of obstacles, ambient noise). Herein we thus validated a BCI based on tactually-evoked event-related potentials (ERP) in N = 15 healthy participants. Participants navigated a virtual wheelchair through a building and eleven participants successfully completed the task of reaching 4 checkpoints in the building. We conclude that most participants achieved good wheelchair control and dynamic stopping was of high value for tactile ERP classification.

Keywords: brain-computer interface (BCI), tactile P300, event related potentials (ERP), wheelchair control, dynamic stopping

1. Introduction

People with severe disabilities, e.g. due to neurodegenerative disease, depend on technology that allows for accurate wheelchair control. Brain-computer interfaces (BCI) have been suggested as a control channel for those not able to operate a wheelchair with a joystick (for review, e.g. [Millán et al., 2010]). Herein we explore use of tactually-evoked event-related potential (ERP) based BCIs [Brouwer and van Erp, 2010]. Tactile stimulation has the advantage that it does not use a modality that is also needed for processing of non-BCI related input, e.g. observation of the environment while steering a wheelchair (visual modality) or processing of ambient noise (auditory modality).

2. Material and Methods

Fifteen healthy participants took part in this study (12 female; mean age: M = 21.8 years, SD = 2.9, range 18–27 years). EEG was obtained from 16 passive Ag/AgCl electrodes at positions Fz, FC1, FC2, C3, Cz, C4, CP1, CP2, P7, P3, Pz, P4, P8, O1, Oz, O2 and sampled at 512 Hz (BCI2000 software, g.USBamp amplifier).

2.1. Tactile stimulation and experimental design

Tactile stimulators (C2 tactors; Engineering Acoustic Inc., USA) were positioned at four body locations that represented navigation directions (placed on left upper leg: move left; right upper leg: move right; belly: move forward; lower neck: move backward) and participants focused their attention on the stimulator they intended to select.

The experiment comprised one calibration run, two online copy tasks and finally an online navigation task through the virtual building. (1) Calibration was performed with 30 stimulations per trial and eight trials (each tactor was the target twice). If estimated classification accuracy was below 100%, calibration was repeated once. (2) After calibration, participants performed two copy tasks with adjusted number of stimulations (procedure for selecting the number of stimulations as described in [Kaufmann et al., 2012]). One run was performed with static number of stimulations; one run incorporated a dynamic stopping method with the same maximum number of sequences. This allowed estimating the influence of dynamic stopping on selection accuracy and duration for tactile ERP-BCIs. (3) The BCI was then tested in a virtual environment. Participants were asked to steer a wheelchair through a building and reach 4 checkpoints. The wheelchair was equipped with shared control sensors to avoid object collisions or sliding along walls.

3. Results

Performance estimated offline from calibration data was high (N = 14: 100%, N = 1: 87.5%; calibration repeated once for N = 5 participants). Fig. 1 displays accuracy and duration of target selection for the three online tasks.

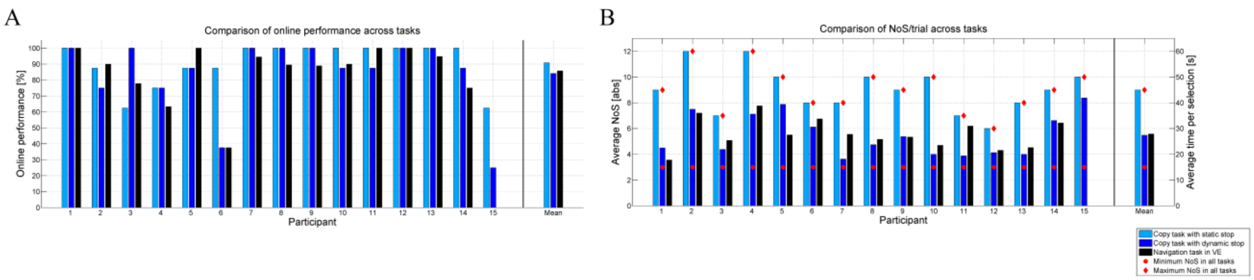

Figure 1. *(A) Performance in online tasks, i.e. two copy tasks and one navigation task (B) Average number of stimulation sequences and time per selection needed in online tasks.*

(1) In the copy spelling task with static number of sequences average accuracy was M = 90.8% (SD = 13.7, range 62-100%) and 9 of 15 participants performed without errors. (2) Performance did not significantly decrease when introducing dynamic stopping (Z = 0.70, p = 48; M = 84.2, SD = 23.4), i.e. most participants maintained the performance level achieved with static number of sequences. However, performance for two participants severely decreased; for one even to chance level. Analysis of selection durations displayed great benefit of the dynamic stopping method in that the number of stimulation cycles was significantly decreased (Z = 3.81, p < 001). (3) Participant 15 did not perform the navigation task as her performance decreased to chance level when using dynamic stopping in the copy task. Thus, N = 14 participants performed the navigation task through the virtual building. Importantly, N = 11 of 14 participants reached the final checkpoint and four of them made no error. Although the navigation task can be regarded as more complex than a simple copy task, performance did not significantly decrease in the virtual environment (N = 14, Z = 0.33, p = 74). Shared control sensors were rarely needed, N = 8 participants did not need it at all. N = 3 participants, however, could not successfully finish the navigation task.

4. Discussion

Tactually-evoked ERPs for wheelchair control are promising in that most of the participants reached the final checkpoint in the navigation task and shared control was only needed by a few of the participants. Overall performance was high and selection times could be significantly decreased with dynamic stopping.

Tactile ERP-BCIs may thus offer a valuable alternative to motor imagery based BCIs considering the findings that about 30% of BCI users do not gain sufficient SMR control (e.g., [Guger et al., 2009]). However, performance varied considerably between participants implying the need for testing larger groups and particularly those in real need to allow for generalization of results. Recent results of a case study with a patient in total locked-in state are promising in that tactile stimulation evoked reliable and pronounced ERPs [Kaufmann et al., 2013].

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Brain Interface to Control a Tele-Operated Robot

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Abstract. An electroencephalography (EEG) based brain computer interface (BCI) system with the ability of choosing among 4 options reliably every 1 second has been developed. The system has been used to control a tele-operated robot or wheelchair. The commands from the BCI system have been used as high and low level commands to control the tele-operated robot/wheelchair. High level BCI commands take advantage of autonomous navigation implemented on the target device for indoor and outdoor environments. The BCI system has been running at Northeastern University while the robot/wheelchair were at Worcester Polytechnic Institute (WPI).

Keywords: SSVEP, BCI, Robot, Wheelchair, Autonomous Navigation, Probabilistic Filtering

1. Introduction

EEG-based brain-computer interfaces (BCIs) can be categorized into three categories, steady state visually evoked potentials (SSVEP) [Sutter, 1992; Nezamfar et al., 2011], event-related potentials (ERP) [Krusienski et al., 2008], and motor imagery signals [Wolpaw, 2012]. Among these categories, SSVEP signals are the fastest and they have higher signal to noise ratio (SNR). Therefore, they are more suitable for control applications. One of the major target groups to use such systems are people who are functionally locked-in, or who have extremely little muscle movements. We developed a closed-loop brain-controlled tele-operated robot system that currently utilizes SSVEP-based command inference and interfaces with a variety of robots including Oryx 2.0, a planetary rover, a standard power wheelchair, and iCreate. The framework allows the operator to provide high and low level control commands to the robotic device, which might be tele-operated or could be providing a lift to the operator. The system can be extended by introducing more comprehensive assistive robots in the control loop and developing an improved inference assessment algorithm.

2. Brain-Computer Interface

The BCI in this work is an EEG-based system that utilizes SSVEP. Signals are generated by showing multiple flickering checkerboards on the screen, representing different command options. Each checkerboard inverts its colors according to a set of pseudo-random bit sequences called M-sequences. When the subject attends to one of the checkerboards to demonstrate the intention to select the corresponding command, a response signal corresponding to the one attended is generated in visual cortex. Consequently, by classifying this response according to the signature responses for each bit sequence, the system can decide on the command intended by the operator [Nezamfar et al., 2011].

2.1. BCI Operation

The EEG signal acquisition is done using a g.USBamp (g.tec). Only one electrode, placed on Oz according to the international 10/20 system, is used to sense and classify the brain activity. During calibration, which takes about 5 minutes, each M-sequence will be presented 50 times. Based on previous analysis [Nezamfar et al., 2011], template signals built using 50 repetitions of M-sequence periods are highly robust and result in high classification accuracy. After examining the calibration performance using 5-fold cross-validation, template signals $\mathbf{t}_i$ in response to each checkerboard's flickering pattern are generated. The distance between the operator's eye and the display was 60 cm and each checkerboard, containing 7×7 checkers, was 7 cm by 7 cm.

2.2. Classification Method

The classifier used is a matched filter classifier. To classify the EEG signal into one of the four choices, classifier extracts EEG signal $\mathbf{y}$ in response to a complete presentation of a sequence using a synchronization signal which marks the beginning of the presentation of the M-sequences along with the EEG signal. Next the correlation $\rho_i = \mathbf{y}^T \mathbf{t}_i$ between each template signal $\mathbf{t}_i$ and the extracted portion of EEG signal $\mathbf{y}$ is taken and the one with the highest correlation will be considered as the decision $D = \arg\max_i \rho_i$. M-sequences used are of length 31 bit, and the frequency of the presentation is 30 Hz, so a complete presentation of a sequence takes about 1.03 seconds. Therefore, the classifier is able to detect decisions roughly every one second. SSVEP responses by nature have about 100 ms delay, in other words the effect of the stimuli shows up in the EEG signals approximately 100 ms after the stimuli onset. The network delay between the BCI system and the robot was 140ms on average. Considering all of the above, the time period between subject making a decision and robot receiving the new command over the network is less than 1.3 s.

2.3. Probabilistic filtering of the human input

In this work, we have proposed and implemented a probabilistic context-aware filter which ensures a desired level of confidence in BCI-generated commands by incorporating the human/BCI probabilistic model with the probabilistic transition model calculated based on the context [Russel, 2010]. The two main components defining a probabilistic filter behavior are sensor model and transition model. The sensor model $P(X_{t+1}|E_{1:t+1})$ describes the probabilistic relationship between the human intended destination (or command) and the actual measured BCI output at time $t+1$ which can be dynamically updated based on the user input log available up to the current moment. Transition model $P(X_{t+1}|X_t)$, describes the probabilistic relationship between the current human intent and next human intent. With these definitions, the belief state can be calculated recursively $P(X_{t+1}|E_{1:t+1}) = \alpha P(E_{t+1}|X_{t+1}) \sum_{x_t} P(X_{t+1}|x_t)P(x_t|E_{1:t})$ where x_t is a particular value of the random variable X_t, and α is a normalizing constant that makes the belief state probabilities sum to 1. Each new BCI command updates the belief state of the user's intention. Now, we can generate a new destination setpoint for the path planner only if probability of one of the values in the belief state exceeds a predefined threshold, and is different from the previously set destination setpoint.

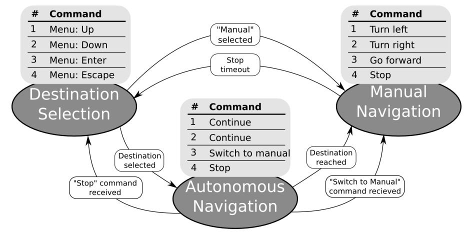

Figure 1: System State Diagram.

3. Results and Discussion

To verify the effect of high level commands with probabilistic context-aware filtering we defined three destinations D_1, D_2 and D_3 as the three high level choices. The subject was asked to move the wheelchair from $D_3 \overset{10m}{\rightarrow} D_2 \overset{6m}{\rightarrow} D_1 \overset{16m}{\rightarrow} D_3$ three times without probabilistic filtering and three times with probabilistic filtering. In total a 192 meter distance was covered in the evaluation. Table 1 shows the time needed to complete each route which verifies that this filtering can reduce the task duration. The target device needs to know the environment, which can be done once and updated each time a task is executed. In this experiment, the wheelchair tachometer, a 2D laser range finder (LIDAR), and an inertial measurement unit (IMU) constitute the perception of the robot. In the BCI system using pseudo-random bit sequences has numerous advantages over using frequencies to induce SSVEP response. Firstly, M-sequences are broadband sequences, therefore it is more robust to background activity in specific frequency bands. Secondly, it allows the usage of more stimulus objects e.g. checkerboards, than the frequency based presentation, because as the frequencies get closer with increasing number of stimuli, the separability of peaks in power spectrum considerably decreases.

Table 1: *Experiment Task Durations.*

Route	Duration W.O. Filter, [sec]				Duration W. Filter, [sec]			
	1	2	3	Avg.	1	2	3	Avg.
$D_3 \to D_2$	60	64	62	62.0	44	51	42	45.7
$D_2 \to D_1$	60	54	40	51.3	35	35	32	34.0
$D_1 \to D_3$	109	145	150	134.7	56	54	75	61.7

Acknowledgments

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Onboard Neural Processor on Vehicular BMI for Rat Toward Long-Term Operation

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Abstract. Brain-machine interfaces with implanted electrodes are promissing to observe and to modify activities in the brain. We have developed an invasive BMI "RatCar" in a form of a small vehicle to let a rat control the vehicle with cerebral motor signals while its body was held inside a pilot cabin. The system consists of an amplifier with band-pass filter, a signal processor computer, and motor-driven sustaining wheels. In this paper, a new vehicle containing all of those units installed inside is proposed. An initial operation test showed that the rat could stably board on the vehicle as the vehicle moved.

Keywords: Extracellular recording, Thin-film electrodes, Motor prosthesis, Motor cortex, Locomotion estimator, Rat

1. Introduction

Brain-machine interface with implanted electrodes are promising to provide methods to directly observe and possibly modify activities in the brain. They may control robotic body according to local neural activities more precisely conpared to non-invasive methods.

We have worked on a vehicular BMI system that we named "RatCar" [Fukayama et al., 2012] in these invasive motor-output BMI category. The device holds a rat inside its body and moves around as a whole, which provides the rat with natural sensory feedback caused by the movement. The ultimate goal is to let a rat to control the device recognizing that the device extended its naural body.

The RatCar is designed to drive wheels according to neural signals in the motor cortices as a rat intends to move its natural limbs. Currently, a rough estimation of the locomotion velocity has been achieved to move the vehicle in a forward direction.

The vehicle now includes an amplifier, a band-pass filter, an analog-to-digital converter unit, and a processor installed inside its body. We believe that this wireless and stand-alone setup enables an experiment for a longer period training a rat to leverage the vehicle as a locomotion method.

2. Methodology

2.1. Vehicle Body

The vehicle has been designed and fabricated as printed in Fig. 1. The vehicle body has a main deck made of aluminum box (*Takachi YM-180; W180xH40xD130*) sustained by 4 metal legs with a ball bearing at the each distal end. These bearings enable the vehicle to run smoothly on the ground. The deck contains an analog circuit for amplification and low-pass filtering of recorded signals inside the electromagnetically shielded body. Meanwhile, an analog-to-digital converter (ADC) unit (*USB-DUX Sigma*) and a handheld computer (*Brule Viliv S5*) are placed on the top.

The *USB-DUX Sigma* also provides output functions (analog and digital) to generate commands to control wheels attached to two rear legs of the vehicle. A motor driver IC (*Toshiba TA-7391P*) drives a DC motor connected to each wheel according to the command.

2.2. Locomotion Estimation

The primary motor cortical regions of a male Wistar rats have been chosen as a neural signal source. A set of neural electrodes (4 recording sites and 1 reference) made of parylene with gold conduction layer (Printed in a lower left part of the Fig. 1) were implanted in ambilateral tissues according to the cortical functional localization in stereotaxic coordinates.

The electrodes conduct extracellular potentials out of the brain and led them to the amplifier and low-pass filter (LPF) circuit which had a gain of 2 dB and high-cut frequency of 800 Hz. The amplified signals were then used as an input to the ADC unit sampling signals in 2 kHz under control of the handheld computer.

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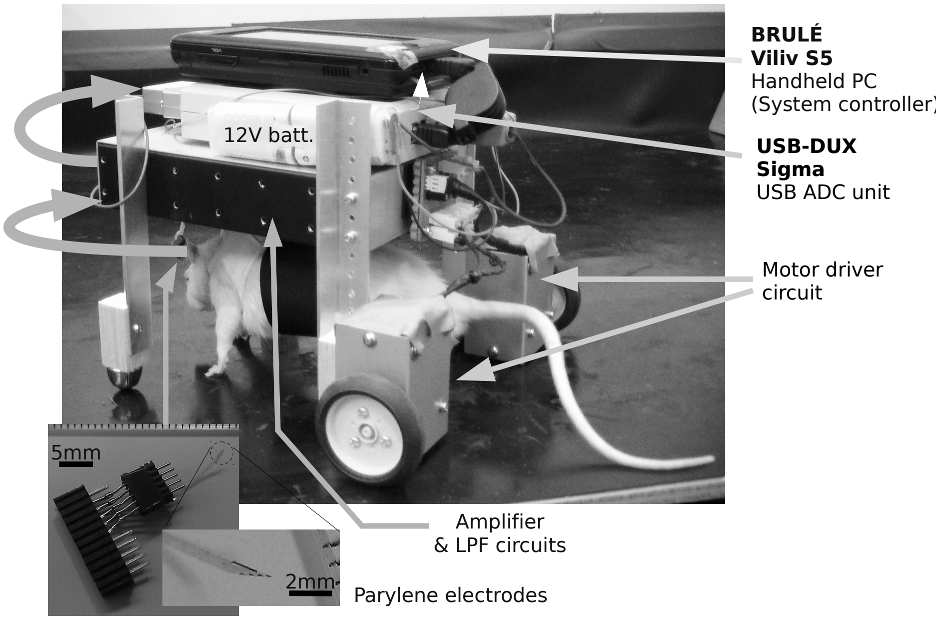

Figure 1: *RatCar vehicle holding a rat inside its "pilot cabin" with an on-board neural recorder, processor, and motor drivers.*

On the computer, self-made software on a Linux platform ran as follows; First, spiking rates of neural firings were extracted from the recorded signals. Then, they were applied to a linear model in a state-space representation where internal states described locomotion velocity and its differential (i.e., acceleration), and outputs vector described firing rates. The observation algorithm of Kalman filters provided an optimal solution for the internal states. Meanwhile, the correlations between those two variables were determined by preceding identification period.

2.3. Vehicle Control

According to the estimated locomotion velocity, the wheel rotation velocity was controlled to move the vehicle. As the vehicle moved forward, the rat was hanged under the vehicle floor with two "hook and loop" fastener. Its limbs were gently touching the ground so that the rat realize that its body was moving, but not able to kick the ground to drive the vehicle itself.

3. Operation Test and Future Directions

As the estimator controlled the vehicle, the limbs of the rat accordingly moved to follow the ground. However, its hindlimbs occasionally showed resistance against the movement. It was not clear whether the movement of the vehicle actually followed the intention of the rat, because the rat cannot complain about the precision of the control. The muscle forces in its limbs to resist against the movement may be used as error signals.

Although we have only tested the vehicle in a short time period up to 1 minute, stability to continue the experiments has been improved compared to former wired configurations that we had often run into nonessential troubles such as tangled cables. This setup enables an experiment to evaluate the estimation by letting a rat reach foods or waters in a longer period of time.

Acknowledgments

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Categorizing Outdoor Places Using EEG Signals

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Abstract. The ability to detect mental states, whether relaxed or stressed, would be useful in categorizing places according to their impact on our brains and many other domains. Newly available, affordable, dry-electrode devices make electroencephalography headsets (EEG) feasible to use outside the lab, for example in open spaces and shopping malls. The purpose of this pervasive experimental manipulation is to analyze brain signals in order to label outdoor places according to how users perceive them with a focus on relaxing and stressful mental states. That is, when the user is experiencing tranquil brain waves or not when visiting a particular place. This work demonstrates the potential of exploiting the temporal structure of EEG signals in making sense of outdoor places. The EEG signals induced by the place stimuli are analyzed and exploited to distinguish what we refer to as a place signature.

Keywords: Mobile Sensing, EEG, Neurology, Pervasive Computing, Social and Behavioral Sciences

1. Introduction

People usually get attached to a place by developing an emotional bond between them and the place. [Cresswell, 2004] has defined the place in geographic research as “space which people have made meaningful”. Perhaps more importantly, places are reproduced through people’s imaginations, memories, emotions and feelings, both positive and negative, and by using different senses [Relph, 1976; Thrift, 2009]. By walking in a place, we can navigate our way and make sense of our surroundings. We look for things that stand out because they are different from their surrounds, or because they have a shape or form or structure that we believe we could recognize again. Sense of smell could lead us to tempting coffee aroma in nearby cafe. Noisy playgrounds and high pollution omitted from traffic could deter us from visiting the same place again [Al-Barrak and Kanjo, 2013].

Many studies have shown that some places can affect our minds and make us feel more relaxed. For example [Stigsdotter, 2004] and [Kohlleppel et al., 2002] have shown that nature and gardens have a positive impact on stress. In addition, cafés, libraries, zoos were proved to reduce stress levels in many people [Korpela et al., 2001]. Therefore, to explore the relationship between people and places, we need to use novel and creative methods. Ubiquitous technologies are able to reveal the respondent’s whole body and senses in generating knowledge and communicating a place.

In this work, we present a novel method for categorizing places based on the current mental state sensed at an outdoor place to guide people to relaxing places. By measuring brainwaves using off-the-shelf EEG headsets, we can detect different mental states. Sensed mental states of subjects can give us valuable information on how people perceive places. In addition, we have correlated the brainwaves with environmental noise levels in order to analyze and process changes in patterns that exist in the surrounding places.

2. Material and Methods

A mobile application for Android devices has been developed to collect EEG, environmental noise and location data. The application connects to NeuroSky EEG headset via wireless connection. Data produced by the headset such as attention, meditation levels, and values for different frequency bands as well as the GPS data and environmental noise levels are saved into log files. The mobile application gives us the ability to move and take the experiments to outdoor places.

Twenty female students participated in the evaluation. We deployed 4 android mobile phones and 4 Mindwave EEG sensor models, daily, for one hour each around our campus. Each user has repeated the test three times which has given us 60 different data sets to analyze. Each user had to walk along the path of 5 distinguished places such as Starbucks, the conservatory, garden, snack shop and student Union. The noise meter and GPS application were installed in the phone and its readings were time stamped along with the various EEG frequency bands, eye blink, attention and meditation levels. A post-experiment interview revealed that the participants were comfortable with the system. All collected data, were subject to inspection and analysis to remove any corrupted data using R project.

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After the process of noise removal, further processing of the data was carried out to chop the samples into small time periods to extract segments that are known to contain the stimuli. For each of the segments, feature were extracted and classes generated accordingly. In order to categorize places to be adapted to users' needs, we must use classifiers. Classification of signal segments into a given number of classes using segments features can be achieved by various statistical and probabilistical methods. Bayesian classifier or Logistic regression are considered for predicting the category.

3. Results

Our initial results look promising showing that modern mobile phones are capable of processing neural signals using an affordable and commercial EEG headset. In this work we have adapted Neurosky mean meditation, but plan to use our own relaxation and stress classification functions.

Mental states of participants at the Campus garden have shown that the majority of the participants perceived the garden as a relaxing place. In addition, when we analyzed the environmental noise levels at the garden, we noticed that the environmental noise was high just before reaching the garden. However, the noise levels were low when the participant reached the garden since our garden is a quite place and therefore the mental states are not affected by the noise in this case. Some places such as cafés can be classified as relaxing places but they hold high levels of environmental noise and therefore need further analysis to detect the correct mental state of the participant.

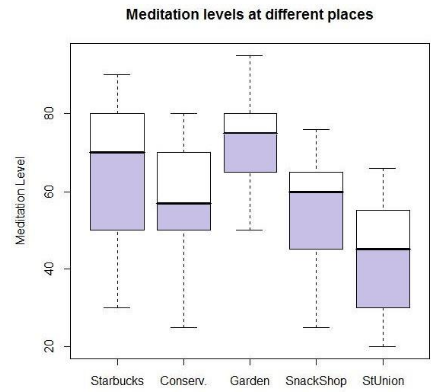

Figure 1. *Meditation levels.*

Fig. 1 shows the places visited by the participants and the different meditation levels perceived by them. Places such as Garden and Starbucks have a high level of meditation which mean that people felt more relaxed in these places, where as student union have the lowest meditation levels among the others

4. Discussion

The mental states sensed at those places are a rich source of information and could be used in understanding the people-place relationship. It is also possible to understand how places affect people since different mental activity can be detected before and at the place. In this work we explored the properties and temporal structure of the EEG signal with the aim to classify outdoor places according to the current mental states with a focus on relaxation/meditation, that is, when the user is experiencing tranquil brain waves or not when visiting a particular place. EEG signals associated with the place stimuli are analyzed and could be used to distinguish the place type.

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BCI Games With Motion Capture and its Possibilities in Rehabilitation

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Abstract. The last decade has seen a growing interest in the use of brain computer interfaces (BCI) in gaming for rehabilitation. There have been cases in which use game dynamics that seek to enrich the flow and entertainment BCI games, however the complexity and randomness of the electrical signals of the brain extracted often hinder the design of video games by limiting the possibilities of interaction and the commands used. In this paper we propose a hBCI that articulates the Kinect sensor as additional sensor input commands of the game, providing motion capture in real time to the interpretation of gestures and movements and the neuroheadset Emotiv EPOC for generating SSVEP by visual stimuli. Preliminary results were obtained from a patient with hemiparesis, the accuracy of the EPOC software for classifying SSVEPs within the game dynamics was 64%, lower than the levels attained in a stage of user training prior to the interaction taht was 86%. Finally, it highlights some features such as portability, fluidity of interaction, the quality of the user experience and the low cost of the mounted system, which becomes an ideal tool for rehabilitation of patients with neuromotor diseases.

Keywords: Kinect, Selective Attention, SSVEP, Emotiv Epoc, Hemiparesis, User Experience

1. Introduction

One of the most promising applications of brain computer interfaces (BCI) is the use in therapies to regain motor control because of diseases such as stroke [Tan et al., 2010]. One of the first researchers to contemplate the option of combining simulations or games in virtual reality (VR) with the BCI was Nijholt et al. [2008], who write that the first games controlled by these interfaces focused on the diagnosis of brain signals in aspects such as the measurement of the attention of the user or the relationship of affective components with the games. Despite impressive advances in BCI systems industry, product diversification and globalization of the study of this area of neuroscience; the state of art in multiple applications shows that the effective interaction with BCI applications and assistive devices control often not maintained for long periods of the time without the help of an expert assistance [Millán et al., 2010]. This statement has led to the BCI community to consider new paradigms of interaction and use BCI systems as an additional input channel for different applications. A hybridization where takes place a combination of multiple signals including at least one BCI channel is called a hybrid BCI (hBCI) [Pfurtscheller et al., 2010]. The combination of signals coming from BCI systems with other biosignals, for example particular biomechanical signals obtained through motion capture (MoCap) systems, can allow a more stable and durable control for an application or a videogame. To achieve the interaction of individuals in immersive games with BCI systems often used a mental strategy known as selective attention, which can be used visual stimuli to generate in the user Steady State Visual Evoked Potentials (SSVEP). In a typical configuration of a videogame BCI each stimulus is associated with a command that controls a specific action within the game. In order to select a command, the user has to focus him/her attention on the respective stimulation by generating the required mental intention [Bernhard et al., 2010]. The combination of motion capture sensor with BCI systems within a videogame could become a novel methodology for therapies to patients with brain problems that directly affecting their motor skills, such a stroke, Parkinson, sclerosis, neuropathies, sequelae of trauma or surgery interventions. In this paper we propose a new paradigm for immersive game where you use a combination of gestures and brain commands to achieve a unique gaming experience.

2. Material and Methods

In CIRAC (Center for interactive computer-assisted rehabilitation) motion evaluations are performed through video games with MoCap using the Kinect sensor. EEG signals are captured using EPOC, the game is made to improve the ability of movement of arms, so the user has to move constantly in order to achieve objects put in the virtual environment. The collection of objects is accounted in the videogame in order to generate positive stimuli and encourage the patient to continue efforts to get scores after each session, at the time of completing certain score, appears on stage an object that obstructs the passage and which must be removed through interaction with BCI system, the user has to fix his/her attention for a few seconds to remove the object successfully lifting mentally (through the generation of SSVEP) and to move forward. The player is trained previously by an animation to record reaction in the EEG when visual stimulus is displayed. The game engine used is Unity3D, which allows a complete integration with the Kinect sensor motion capture data, the EPOC's Cognitive Suite is used to achieve the BCI interaction within the virtual stage. MoCap data for a deep biomechanical analysis using software created by the team are finally collected.

3. Results

The resulting system is intended to serve as interactive tool that facilitates a low-cost implementation of BCI systems with MoCap in video games for rehabilitation of neuromotor diseases, the interaction of movement with the Kinect sensor contributes to physiotherapy dynamics required for the study of the kinematics of the patient; for its part, BCI system adds variables related to the ability to concentrate or different attention deficits presenting patients with brain injuries. We perform a preliminary test conducted with the assembly to a patient with hemiparesis, the classification of the SSVEP using EPOC software showed an accuracy of 64% within the dynamics of the game in only one intervention. This accuracy is lower compared with the training stage where the user reported 86% in a series of test performed to move the object outside the game. The biomechanical analysis shows the curves of movement of each joint of which arcs of movement are extracted based in measurement of Euler angles, in this case the patient has a short arc of motion in the affected shoulder of Fl/Ex 72/12/0, which shows quantitatively demonstrates the inability of the user to move freely right arm, specifically in the elevation. The game flow is kept constant during the operation, because not only EPOC commands are used but also used MoCap techniques and gesture interpretation to provide prolonged entertainment during the therapy. Besides the numerical results that reflect the type of measurements that the platform can do, we formalize an approximate costing of implementing this type of hybrid interaction laboratories in rehabilitation environments and we estimate that the entire platform with the necessary licenses in software and hardware equipment required does not exceed the sum of $ 5000.

4. Discussion

In this project we have embodied design one hBCI and its potential use in videogames for rehabilitation. We design and made a video game using a Kinect sensor as additional peripheral of input, which provides immersive features to the game allowing a better user experience [Nijholt et al., 2009]. Video games that used systems BCI for medical purposes could easily adapt MoCap systems like the Kinect, this in order to improve the disposition of a patient with the therapy, providing more elements which interact in virtual environments. With this paper we want to support the need to complement the use of BCI in games with new input devices that provide more entertainment to the patient and more variables that measure for the rehabilitator.

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Detection of Motor Imagery of Swallow With Model Adaptation: Swallow or Tongue?

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Abstract. Conventional methods to treat dysphagia patients require assistance from speech therapists, which may incur high cost for intensive training. We investigate the use of motor imagery of swallow for dysphagia stroke rehabilitation to answer this question: can a simple yet related motor imagery of tongue protrusion model be used to detect motor imagery of swallow? To achieve successful detection, the non-stationarity of EEG signals across sessions and modalities is addressed with model adaptation by measuring feature consistency between training and evaluation data. Current results on 6 healthy subjects yield average accuracies of 72.12% and 71.81% using swallow model and tongue model based on features of dual-tree complex wavelet transform (DTCWT-FT). This demonstrates the feasibility of using the motor imagery of tongue model to detect motor imagery of swallow for dysphagia stroke rehabilitation purposes.

Keywords: Motor imagery of swallow, motor imagery of tongue protrusion, model adaptation, dual-tree complex wavelet transform

1. Introduction

Brain computer interface have shown potentials in stroke rehabilitation [Daly and Wolpaw, 2008; Gallas et al., 2010], as evidenced by the similar pathways activated by motor imagery and executed movements. Oropharyngeal dysphagia frequently occurs in stroke patients which increases mortality due to pulmonary complications [Gallas et al., 2010]. Conventional methods for treating swallowing disorders are changing food and positions, performing tongue strength training and pharyngeal and effortful swallow maneuvers [Burkhead et al., 2007], and thermal and neuro-muscular stimulation [Kiger et al., 2006]. Both voluntary saliva swallowing and tongue elevation activate the left lateral pericentral and anterior parietal cortex, and anterior cingulated cortex and adjacent supplement motor area [Martin et al., 2003]. These shared activation regions suggest the possibility of using motor imagery of tongue protrusion (MI-Ton) model to detect motor imagery of swallow (MI-SW). In this abstract, we propose a novel method to test the hypothesis that a simple yet related MI-Ton model can be used to detect the complex MI-SW.

2. Materials and Methods

10 healthy subjects with ages of 34.90 ± 8.13 (mean $\pm$ SD) years participated in the experiments by giving a written informed consent. The experiments consisted of three sessions. Each session consists of 80 trials of MI-SW (1st and 2nd sessions) or MI-Ton (3rd session) and 80 trials of idle. Subjects are advised to imagine swallowing a cup of water/juice, or fruit, or food in MI-SW; and imagine protruding his/her tongue as far as possible for MI-Ton. A preparation "+" is shown for 2 s following the acoustic tone. The cue in the form of a virtual character performing swallowing or tongue protrusion, or a filled circle is displayed for 3 s. The subject then performs the action for 12 s after cue disppears and the rest time of 6 s follows at the end of the trial. The EEG and EMG measurements are obtained with 34 channels Neuamps EEG acquisition hardware (30 channels for EEG and 4 for EMG recordings), which are bandpass filtered between 0.5 Hz and 100 Hz. DTCWT-FT features are employed which consist of power, phase, coarse representation and statistical features such as mean, variance, skewness and kurtosis of wavelet coefficients [Yang et al., 2012]. In model adaptation, we assume that a small amount of evaluation data can be used to select the suitable model generated during the n-times and r-folds cross-validation. The features for training data in $(n,r)^{\text{th}}$ model and evaluation data are firstly clustered, the cluster with minimum impurity for training data is selected by

$$\hat{i} = \arg\min_{i} \frac{min(N_{tr}^{0}(i), N_{tr}^{1}(i))}{max(N_{tr}^{0}(i), N_{tr}^{1}(i))} \tag{1}$$

where $N_{tr}^{k}(i)$ denotes the number of features of class "k" in cluster i. The $(\hat{n},\hat{r})th$ model with the maximum number of consistent features (i.e., whose label is consistent with the dominant cluster label) between training ($N_{tr}^{c}(\hat{i},n,r)$) and

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evaluation data ($N^c_{te}(\hat{i},n,r)$) in cluster ($\hat{i}$) is selected by

$$(\hat{n},\hat{r}) = \arg\max_{(n,r)}(N^c_{tr}(\hat{i},n,r) + N^c_{te}(\hat{i},n,r)) \tag{2}$$

3. Results

The session-to-session classification accuracies for 6 selected subjects whose cross-validation accuracy is above 60% are shown in Table 1. The best accuracy is reported by searching 8 non-overlapping time segments, SVM with linear kernel is used as the classifier. It can be seen that average accuracies of 68.75 % and 69.74 % are achieved using

Table 1: Session-to-session classification accuracies (%) for motor imagery of swallow with/without model adaptation

Subject/Session.	No adaptation		With adaptation/no. of trials	
	MI-SW[1]	MI-Ton[2]	MI-SW/30[3]	MI-Ton/40[4]
lj/01	71.25	72.50	76.15	77.50
lj/02	75.63	80.63	74.62	84.17
hj/01	75.63	68.13	75.38	69.17
hj/02	78.13	67.50	83.85	76.67
cr/01	77.50	80.63	83.08	85.00
cr/02	81.25	96.25	84.62	95.83
wy/01	69.38	66.25	74.62	64.17
wy/02	68.75	65.00	70.00	67.50
cc/01	56.25	59.38	56.92	59.17
cc/02	60.00	63.13	63.85	63.33
mt/01	55.63	57.50	62.31	60.00
mt/02	55.63	60.00	60.00	59.17
A_{as}	68.75	69.74	72.12	71.81
t-test	1 vs. 2	3 vs. 4	1 vs. 3	2 vs. 4
P value	0.62 (**xx**)	0.87 (**xx**)	0.0008 (**)	0.044 (**)

A_{as}: Average Accuracy. **xx**: insignificant; **: significant

MI-SW model and MI-Ton model, respectively. The accuracies are further improved with the use of model adaptation, which are: 72.12 % and 71.81 % for MI-SW model and MI-Ton model, respectively. The improvements are significant for subjects ‘lj’, ‘hj’ amd ‘cr’ using MI-Ton model, and subjects ‘hj’, ‘cr’, ‘wy’ and ‘mt’ using MI-SW model.

4. Discussion

Our results on healthy subjects reveal that comparable performance can be achieved by using the motor imagery of tongue model to detect motor imagery of swallow with and without model adaptation. The use of a small amount of evaluation data to select suitable model to classify the test data has significantly improved the classification accuracy, e. g., from 68.75 % to 72.12 %, and from 69.74 % to 71.81 % for swallow model and tongue model, respectively. Statistical paired t-tests at 5 % significance level shows no significant difference in classification accuracies obtained using swallow model and tongue model, both for using model adaptation and not using model adaptation.

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Towards Biometric Person Identification Using fNIRS

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Abstract. We investigate the potential of using fNIRS signals for biometric person identification. Independent sessions for training and testing have been recorded using 8 channels of frontal fNIRS. We extract logarithmic power spectral densities as features to train and test a Naïve Bayes Classifier. We evaluate different frequency bands and report classification results for different trial lengths.

Keywords: fNIRS, near infrared spectroscopy, person identification, biometrics, power spectral densities

1. Introduction

Person identification, i. e. the recognition of an individual within a closed group of people (1 to N matching), using biometric signals, such as iris scans, finger prints, and speech, is widely used for security applications and intelligent user interfaces. Brain activity is known to contain strongly subject-specific signal patterns that are hard to forge and can only be assessed if the user is present and alive. Furthermore, they allow a continuous recognition and can be combined with other techniques in multimodal setups. Up to now, EEG has primarily been used for brain biometric person identification and authentication systems (e.g. [Poulos et al., 1999; Marcel and Millán, 2007]). Functional Near Infrared Spectroscopy (fNIRS) is an promising measurement technique for Brain Computer Interfaces (BCIs) [Coyle et al., 2004]. It is non-invasive, portable, cost-effective, and comes with the benefits of using optical signals, i.e. no electrode gel is required and the signals are not susceptible to electrical artifacts. In this paper we evaluate frontal fNIRS signals for person identification. To the best of our knowledge, fNIRS has not been investigated for biometric applications before.

2. Material and Methods

2.1. Data Corpus

We used an Oxymon Mk III system by Artinis Medical Systems for the data collection. Four optodes (two transmitters and two detectors) were attached to the left and the right side of the subjects' forehead. Using this setup, we measured concentration changes in oxygenated (HbO) and deoxygenated (HbR) hemoglobin at 8 source-detector pairs at a distance of 3.5 cm using a sampling rate of 10 Hz.

fNIRS signals from $N = 5$ healthy volunteers have been used for the evaluation. The recordings contain 10 seconds long trials of different mental tasks (mental calculation, mental rotation, text reading), as well as relax phases of variable length following each trial (15–25 seconds). Only mental calculation trials and the adjoined relax phases have been used for the evaluations presented here (10 trials per session). Within these trials the subjects consecutively subtracted a given number between 7 and 19 starting at a number between 500 and 1000 displayed on the screen. As mental states can change over time (e.g. due to fatigue) and because repositioning of the optodes can strongly influence the characteristics of the recorded signals, we recorded two sessions from each subject at two different days. The data of one day was used for training and the other day was used for evaluation of the system.

2.2. Signal Processing and Classification

External and physiological artifacts influence the raw HbO and HbR signals (see e. g. [Matthews et al., 2008; Cooper et al., 2012]). Therefore, we applied linear detrending to remove signal drifts from each trial. Then, we smoothed out influences of heart beat and high frequency disturbances using a moving average filter (sliding window 1.5 seconds before and after each sample). Logarithmic power spectral densities were calculated using Welch's method and spectral coefficients outside the desired frequency band were discarded. To reduce the dimensionality of the feature space, we combined each five adjacent frequency bins by averaging. The final feature vector consisted of the concatenated values of all channels.

We trained a Naïve Bayes Classifier based on kernel density estimation on the features extracted from the first recording sessions of the five subjects and recognized the subjects' identities from the trials of the other day's sessions.

3. Results

To assess the performance of our fNIRS based person identification system, we evaluated the power spectral density based approach for different trial lengths and frequency bands. Fig. 1 shows the recognition accuracies averaged over the test trials using power spectral density features in the frequency band 0–1 Hz and trial lengths from 1.5 to 25 seconds. Error bars indicate the standard deviations across subjects. Longer windows tended to produce higher recognition rates than shorter ones. Higher frequency bands appeared to produce significantly lower recognition performance using our approach, which can be explained by the slow dynamics of hemodynamic responses. The best average recognition accuracy (above 80 %) could be reached using power spectral density features in the low frequency band 0–1 Hz calculated from a 25 seconds long window.

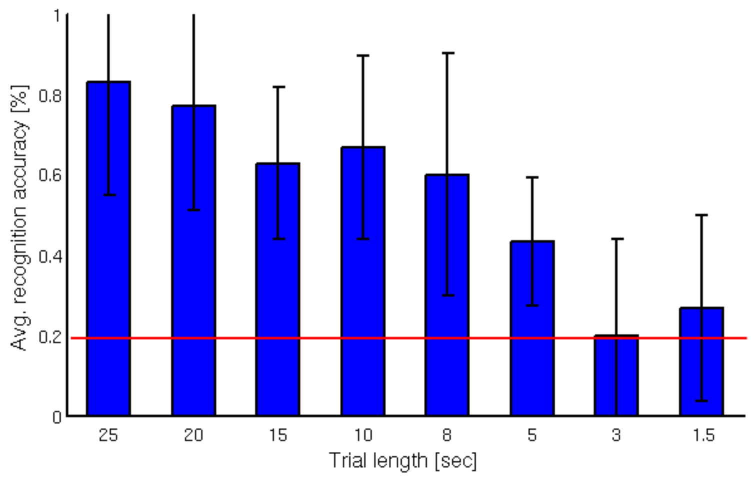

Figure 1: *Recognition accuracies for different trial lengths using power spectral density features in the frequency band 0–1 Hz. Error bars indicate standard deviations across the subjects. The horizontal red line shows the chance level of 20 %.*

4. Discussion

The results of our first study on person identification based on fNIRS data are encouraging. fNIRS signals appeared to contain subject-specific information that enable recognition rates of more than 80 % using logarithmic power spectral density features. We found that predominantly slow frequency components convey relevant information for fNIRS person identification. However, the amount of data that has been used for the evaluations was very limited. To analyze the validity and robustness of fNIRS based person identification, more subjects and multiple sessions per subject over a longer period of time should be assessed in future work. Further analyzes should also investigate the spectral signal properties in more detail, such as slow wave influences by cardiovascular and respiratory activity (e. g. Mayer waves [Julien, 2006; Pfurtscheller et al., 2011]).

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A Neurofeedback Approach to Supporting Characters in Virtual Stories

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Abstract. This paper introduces a fully-implemented Brain-Computer Interface (BCI) technique developed as an input mechanism for Interactive Narratives, based on neurofeedback (NF) of an EEG measure of prefrontal alpha asymmetry. We present the evaluation of a test system using simultaneous EEG input and recording of fMRI, with subjects watching 3D graphical animations while inside an MRI unit. Subjects were able to successfully interact through NF and modify the course of the narrative. The analysis of fMRI results confirmed selective activation of the medial prefrontal cortex.

Keywords: Interactive Narratives, Frontal EEG Asymmetry, Neurofeedback, fMRI

1. BCI and Narrative Empathy

Entertainment has become a popular application domain for Brain-Computer Interfaces, video games in particular [Plass-Oude Bos et al., 2010]. The key to a successful implementation lies in the optimal integration of physiological signals into the gameplay experience. Previous work falls into two broad categories, one involving the detection of signals related to motor control (real and imagined), and the other to a user's internal state (affective dimensions, attention, etc.). In most cases the target gameplay features are self-contained, corresponding to control in games of moderate complexity, or simple moves in more complex online games.

Our objective with this current research was to optimise the mapping between BCI input and gameplay in a more sophisticated media experience. Our target was the specific genre of interactive narrative, in which a generated story (as a real-time 3D animation) varies dynamically with the user's response. We wanted to develop a unified framework that encompass (a) the user's cognitive response to a narrative; (b) an input mechanism that could be integrated with the AI generation mechanisms of the story; and (c) BCI signals that are compatible with both (a) and (b).

Several theories of media psychology (e.g., [Tan, 1996]) have posited that disposition towards story characters is a major determinant of the spectator's experience. One possible mechanism to combine this experience with user interaction thus appears to be one in which the user expresses her direct support for a character when perceiving that the character faces difficulties within a story. This has led us to explore EEG prefrontal asymmetry, as proposed by [Davidson, 1992], originally as a measure of approach/avoidance, to measure disposition towards a character. Although it has been previously mentioned as a candidate technique for BCI, to the best of our knowledge it has not been used to date in a similar context, using NF to modulate an internal state relating an external object.

2. An Interactive Narrative Experiment

We have implemented our BCI techniques within an Interactive Narrative system [Gilroy et al., 2012] that is displayed as a real-time 3D animation (developed using the UDK game engine). This is illustrated in Fig. 1. The presented story is a medical drama featuring a young female doctor as the main character, facing difficult cases as well as conflicts with colleagues. The story is dynamically generated from a set of possible *actions*, using AI Planning techniques to construct a consistent narrative progression, potentially producing in the order of a hundred variants. The default story is biased *against* that character, meaning that without user intervention the story ending will be detrimental to her. As her situation deteriorates, the system offers opportunities for the user to intervene to support her. The first opportunity is determined dynamically, but early enough in the story to be able to "rescue" her, and a second opportunity is generated soon after in case the user's first intervention is not successful.

User interaction with the system consists of prefrontal asymmetry NF, which is activated by the user mentally supporting the feature character. The feedback element is embedded in the visual appearance of the character, who fades to grey when facing difficult situations and is restored to full colour saturation following successful support.

During experimental sessions, the principles behind the interactive narrative were explained to subjects, in particular the fact that at some stages the feature character will face difficulty and that their support will be required to

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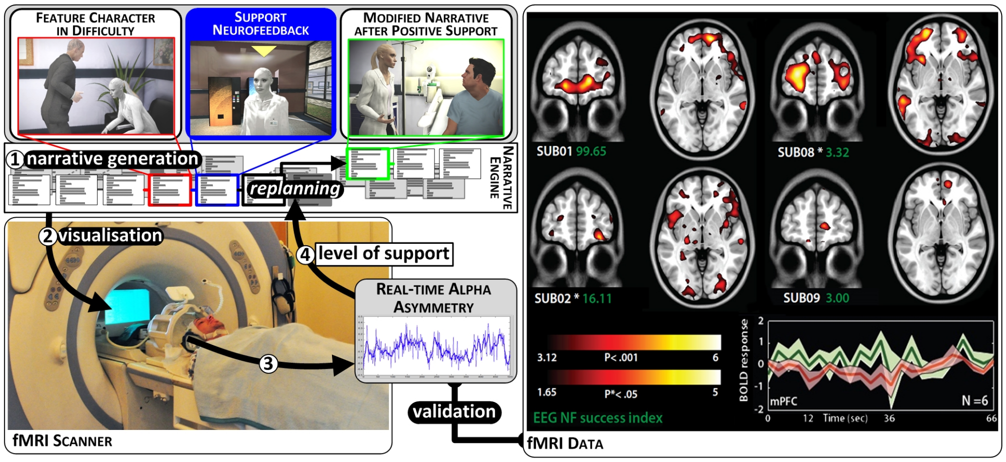

Figure 1: *Setup of NF-based Interactive Narrative experiments. A subject watches an interactive narrative from inside an MRI scanner, equipped with an fMRI-compatible EEG cap. (See main text for details.)*

enable her to overcome the difficulties. Instructions to participants remained generic such as "mentally supporting the character" or "expressing positive thoughts towards her". Subjects also underwent a specific training session that allowed them to practice NF and observe the character's response.

The experimental setup was deployed within an MRI scanner: each subject views the interactive narrative from a mirror-projected LCD screen and is equipped with an fMRI-compatible EEG cap. The subject interacts with the narrative in real-time through NF, at dynamically selected points, depending on the narrative evolution and the feature character's status. A prefrontal alpha asymmetry score is calculated in real-time from the F_3 and F_4 EEG electrodes, which is interpreted as a degree of support expressed towards the character in trouble. This score drives the evolution of the narrative, so that successful support results in a course of action that becomes favourable to the feature character.

3. Results and Discussion

Twelve users were selected for our experiments, undergoing the short training session for NF ($<$ 10 minutes, much shorter than traditionally reported in the literature) using the same virtual environment as used in the narrative, but outside of the MRI scanner. Individual measurements also allowed subject-specific calibration. The experiment was comprised of two consecutive phases: one *active* condition during which the subjects could interact with the narrative through NF, and one *control* condition during which the generated story was replayed with the interaction mechanism disabled. During the experiment, users success in supporting the feature character through NF resulted in a favourable ending for the narrative, which otherwise systematically ends with the demise of the feature character.

Of the initial 12 subjects, only 6 were able to achieve above-threshold changes in EEG alpha asymmetry during the NF phases, thus successfully altering the story. The unsuccessful subjects all completed the experiment: what they saw was simply the default story that they could not modify. We have devised a validation mechanism that compares fMRI data offline between the active and control conditions for the successful subjects, using subtraction techniques. At the anatomical level, the results were in line with our Davidsonian hypothesis, showing asymmetry as expected, with local changes of activity predominantly in the medial prefrontal cortex (Fig. 1, top right). Comparative BOLD measures during NF phases also show higher activation in the medial pre-frontal cortex for successful subjects (Fig. 1, bottom right), and little difference in activation of the premotor cortex (ruling out alternative explanations involving motor cortex activation).

These early results are certainly encouraging as a proof of concept: however, the actual usability of alpha asymmetry as an interface technique will depend on improved training methods which increase the proportion of responsive subjects without imposing lengthy, repeated training sessions.

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Detecting Cognitive States for Enhancing Driving Experience

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Abstract. Intelligent cars exploit environmental information to support drivers by providing extra information and assisting complex maneuvers. They can also take into account the internal state of the driver by means of decoding cognition-related brain activity. Here we show the feasibility of successfully classify EEG correlates of anticipation, movement preparation and error processing while subjects drive in a realistic car simulator.

Keywords: Anticipation, motion related potential, prediction, slow cortical potentials, error related potential, classification, car simulator

1. Introduction

Intelligent cars are expected to support drivers by extra information (e.g. distance to nearest car) and support complex maneuvers. These systems should take context into account and provide suitable and timely assistance, while seamlessly interact with the driver. Recognition of the driver's cognitive states can be useful to better align the car's behavior to the driver's intention, hence enhancing the overall driving experience. Previous studies have focused on detecting the level of driver's drowsiness and attention, as well as emergency braking using electroencephalogram (EEG) in combination with other physiological signals e.g. [Haufe et al., 2011]. Extending these works, we studied brain correlates of cognitive states in order to predict future actions or to evaluate whether the decisions of the intelligent system are coherent with the user intentions. Specifically, we report single-trial recognition of anticipation- and error-related potentials elicited while driving in a car simulator.

2. Material and Methods

Experiments were performed in a realistic car simulator. Steering angles, brake and acceleration pedals position were acquired at 256 Hz. EEG signals were recorded at 2 kHz from 64 channels (extended 10/20) and spatially filtered using common average reference. We simultaneously recorded EOG and one EMG channel on the driver's right leg. Signals were downsampled to 256 Hz and synchronized with the car simulator data. EMG signals were band-pass filtered (20-50 Hz) and smoothed using a moving average (t = 25 samples).

Environmental cues warn the driver about upcoming situations where an action may be required (e.g. accelerate when a traffic light changes to green). Anticipation processes are reportedly reflected by a slow cortical potential (SCP) that develops between the warning and the anticipated stimuli [Walter et al., 1964]. We tested the existence of such signals in a scenario where drivers ($N = 6$) were instructed to accelerate or brake at specific points cued by visual stimuli. EEG signals were filtered the in the 0.1-1 Hz range and segmented into 1 s trials preceding the moments when the driver has to act (i.e. GO trials), and those when no response is required (i.e. NOGO trials). We then use a QDA classifier to discriminate these two types of trials from the activity of the Cz electrode.

We also studied neural activity preceding self-generated actions. We analyze the EEG activity while drivers ($N = 6$) perform self-paced lane changes in a simulated highway. EEG data was filtered as above and segmented into trials corresponding to straight driving and steering actions. A LDA classifier was trained using the signal at the C1, Cz and C2 electrodes in a 500 ms window ending 700 ms before the action [Gheorghe et al., 2013].

Intelligent cars should be able to infer potential driving behavior from the environmental information and previous experience. Nevertheless, these devices are prone to errors that may hinder their performance. Detection of error-related brain activity can be used to improve the performance of such systems as shown in simpler protocols [Chavarriaga and Millán, 2010]. We studied these signals when a driver assistant provides feedback on predicted turning directions. Seven healthy subjects participated in the experiment where visual feedback (i.e. arrows) was provided 1 s before they reach an intersection. Erroneous feedback, pointing to a different direction, was presented 30% of the times. Features were selected using discriminant analysis and fed to a LDA classifier.

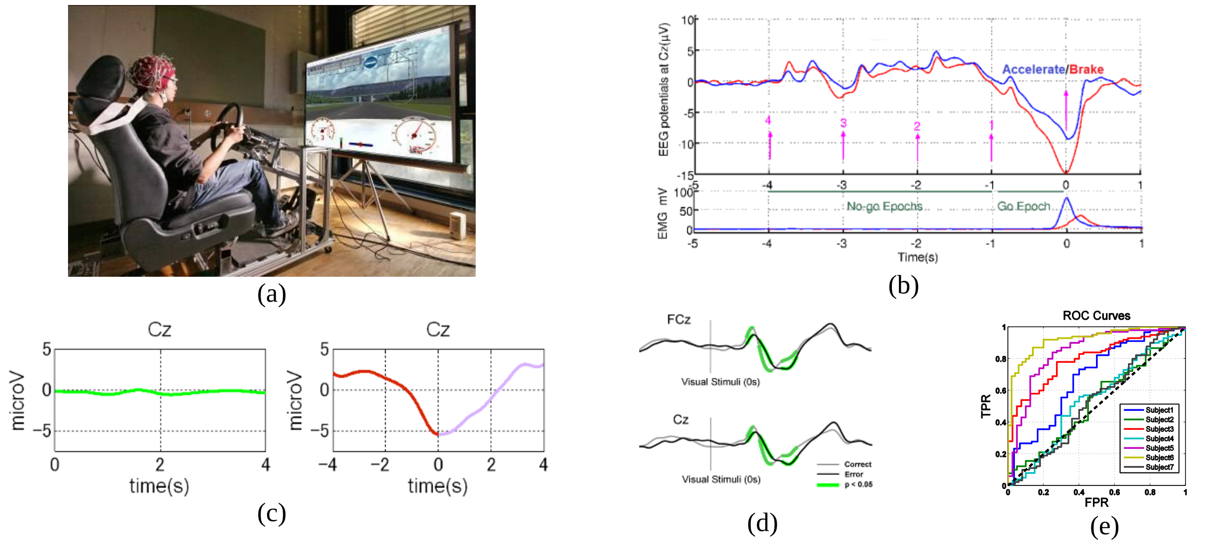

Figure 1. *(a) Experimental setup. (b) Grand average ERP (Cz electrode) for both brake and accelerate conditions. Bottom: EMG. (c) Lane changes. Grand average ERP during straight driving (left) and around lane changes (right). (d) Error-related ERPs after visual stimulus showing predicted directions. (e) Classification of error-related activity.*

3. Results

In the first experiment, we found a centromedial slow negative signal developing well before anticipated actions (accelerate/brake) (Fig. 1b). Average classification performance (AUC) using features up to 200 ms before the action was 0.72 and 0.81 for accelerating and braking actions, respectively [Khaliliardali et al., 2012].

As seen in Fig. 1b, we also found slow negative deflections over central areas–akin to the motion related potentials—starting more than 1 s prior to lane changes. Classification of these actions yields a true positive rate of 68.8 ± 6.6 (5-fold cross-validation), with average detection times of 641 ± 94 ms before the actual steering action. Regarding error potentials, we saw a stereotypic response on frontocentral areas when feedback does not match the user's intention. Statistical differences between error and correct conditions were observed between 200 ms and 600 ms after feedback. In general, error-related activity was recognized above chance level.

4. Discussion

We consistently found neural signatures of anticipation, movement preparation and error processing while subjects drive in a car simulator. Despite the increased noise that can be expected in this realistic scenario, obtained EEG correlates are well in line with those previously reported in simpler experimental paradigms. These signals can be successfully decode cognitive processes while driving intelligent cars.

5. Acknowledgements

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Iterative EEG-Based Natural Image Search Under RSVP

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Abstract. This work extends previous studies on using EEG decoding for automatic image retrieval. We propose an iterative way to integrate the information obtained from the EEG decoding and image processing methods. In the light of real-world BCI applications, we demonstrated that a limited number of EEG channels provide sufficient information about the subject's preference to be exploited in image retrieval by the proposed synergistic scenario. Furthermore, to meet a more realistic scenario we used natural images (i.e., images of objects in their natural environment).

Keywords: EEG, Single-Trial Classification, RSVP, Image Retrieval, BCI

1. Introduction

Humans ability to process visual information outperforms state-of-the art computer methods. For this reason, analysis of EEG responses to visual stimuli has been proposed as a complement to image recognition systems. In particular, using the rapid serial visual presentation (RSVP) protocol. In this scenario, the presented images are labeled based on the EEG activity as target/non-target. Then, the decoded labels are propagated to unseen images based on similarity and data mining methods [Pohlmeyer et al., 2011].

We propose an alternative iterative scenario for coupling the EEG decoding with automatic image labeling. An iteration consists of assigning the EEG-based labels to the presented images (i.e., RSVP sequence) and their propagation to the unseen images. This yields a set of probabilistic labels based on both brain signals and image features. Then, we fuse the labels obtained at each iteration before ranking the whole database and retrieve that target images.

2. Material and Methods

2.1. Experimental Setting

Subjects ($N = 15$) were presented with sequences of natural images at a rate of 4 Hz. They were instructed to count images of a specified object. The experiment consisted of two phases: training and testing. Different sets of images from Corel database were used in the training (1600 images) and testing phases (1382 images). Four search tasks (Elephant, Car, Lion and Butterfly) were given in the training phase, and three search tasks (Eagle, Tiger and Train) in the testing phase. In the training sequences 10 % of images were the targets. The testing phase consisted of four iterations (200 images per iteration). In the initial iteration, a sequence of images was presented (10 % of them targets). The elicited EEG response to each image was decoded to obtain labels for the presented images (target/non-target). This information was used to label the remaining images in the database and obtain the image sequence that was shown in the next sequences.

EEG data were recorded with a 64-channel BioSemi ActiveTwo system, at a sampling frequency of 2048 Hz. The EEG signals were bandpass filtered [1 10 Hz] and downsampled to 32 Hz. The EEG signals were re-referenced by common average reference (CAR) based on 41 electrodes (the peripheral electrodes were excluded).

2.2. EEG-based Image Labeling

The EEG signals from the training phase are used to train a Gaussian classifier (target vs. non-target trials) [Millán et al., 2004], using four prototypes per class. The feature vector is obtained by concatenating samples in the interval from 200 ms to 700 ms after stimulus onset of a subset of 8 channels: Pz, PO3, POz, CPz, Cz, PO4, C3, C4. The feature dimensionality is reduced, keeping only the features with high discriminant power (DP) [Galán et al., 2007].

2.3. Automatic Image Labeling

This step propagates the labels obtained from the EEG decoding to the remaining (unseen) images in the database. We used a semi-supervised approach for automatic image labeling, exploiting a visual similarity graph of the images in database [Yang et al., 2006]. Each node in the graph represents an image, while its state is the probability that the

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image belongs to the target class. Every node is connected to ten neighboring nodes where five of them have been assigned a label based on the EEG. In turn, arcs represent the probability that the connected nodes belong to the same class taking into account their similarity in the image feature space. The images in our database are indexed in two feature spaces: edge histograms and the colored pattern appearance model [Qiu, 2004].

2.4. Iterative Coupling

The EEG-based labels (target/no target) obtained in a given iteration are used for the automatic labeling, i.e., they are used as initial labels in the graph and then propagated to the entire database. Then, a new RSVP sequence for the next iteration is generated from the 200 top ranked images based on their labels. By repeating these steps we are accumulating evidence of the true labels for each image in the database. After the final iteration, the label probabilities for each image are averaged across iterations to obtain the final labeling.

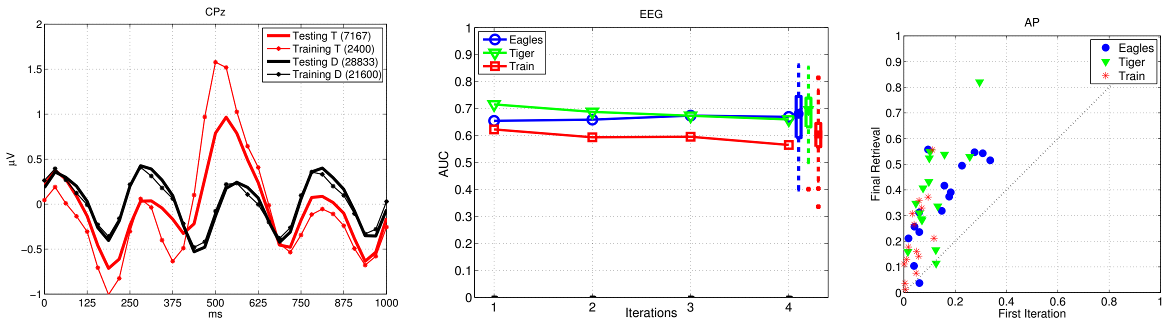

Figure 1: *(a) Grand Average ERP at CPz. T: target; D:non-target; (No of trials). (b) EEG classification performance (AUC averaged across subjects). (c) AP of the top-ranked 200 images across subjects: 4th vs 1st iteration. Colors indicate search tasks.*

2.5. Results and Discussion

ERPs over centroparietal electrodes exhibit a positive peak at about 500 ms after target images are presented (Fig. 1a). The single-trial EEG classification performance, in terms of the area under the ROC curve (AUC) is shown in Fig. 1b. Performance exceeds chance level in all search tasks, although results for task Train were significantly lower (Friedman, $p < 0.05$). This task-dependent differences in EEG performance were consistent with response times (RT) measured in a separate behavioral RSVP protocol using the same images. Accordingly, the longest median RT was found for the class Train, indicating its lower discriminability.

We evaluate the retrieval performance in terms of the average precision (AP) on the top-ranked 200 images (i.e. the mean of the precision scores over these images). A comparison between the retrieval at the first and the last iterations (c.f. Fig. 1c) clearly shows that the iterative coupling results in significant improvement with respect to the labels obtained in the initial iteration. Thus making it less sensitive to EEG labeling errors. These results demonstrate that the limited set of the EEG channels provides sufficient information to make the EEG-based image retrieval operational in the iterative coupling scenario.

Acknowledgments

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Neuroresponsive Media: SSVEP-based Interactive Experiences

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Abstract. We aim at creating a new kind of experience whereby audiovisual content responds to participants' selections and preferences. We have developed a system that allows easily embedding flickering objects in 3D virtual environments. The system is integrated with an SSVEP-based BCI so that it detects when participants attend to the flickering objects. We have evaluted various types of stimuli, including moving stimuli and stimuli with high freqnencies, and implemented an audiovisual scenario of deep space in which various stars are used as BCI targets. We report on the results of our evaluation studies.

Keywords: EEG, SSVEP, BCI, virtual environments, fusion flicker threshold

1. Introduction

The field of human-computer interface is going through a paradigm shift, sometimes referred to as natural user interface (NUI). Brain-computer interfaces (BCIs) have the potential to become the ultimate interface; what could be more natural than controlling devices by thought alone? In practice, however, despite tremendous progress in the field, BCIs are still very difficult to control. In this research we aim at creating new kinds of BCI experiences that would be based on minimal participant effort, while retaining as much accuracy as possible. Specifically, we suggest a framework for audio visual experiences based on the steady-state visually-evoked potential (SSVEP) with BCI targets that are embedded inside the media content. Improvement of user experience is essential not only for healthy users of BCI, but also for patients who may want to use BCIs for various reasons from BCI to control devices.

SSVEP-based BCIs are usually based on low frequencies (5-20 Hz), while using analog stimuli display methods, such as light emitting diodes (LEDs). Our efforts are oriented towards using high frequencies on a screen, digitally and seamlessly embedded in media content. Frequencies higher than 35Hz are considered close or above the Critical Fusion Flicker Threshold (CFFT) – the threshold where a continuous flickering stimulus is perceived constant to the observer, an effect referred to as persistence of vision [Ferry et al., 1892]. BCIs based on high-frequency SSVEP have been successfully previously demonstrated [Wang et al., 2005] By using high frequency objects embedded in the media we aim to construct an interactive experience that can be more enjoyable than current SSVEP-based BCI. Moreover, our approach suggests a generic, flexible, and easy-to-use platform for future research and applications.

2. Material and Methods

2.1. System

We have used 8-channel EEG electrodes located on the subject’s occipital lobe (PO3, PO4, POz, PO7, PO8, O1, Oz, O2, and Fpz and right earlobe, using the 10-20 international system). The BCI hardware and software was developed by g.tec (Austria) and has been customized with their support. In addition, we use Unity (Unity Technologies, USA), a 3D game engine, to display the stimuli inside a virtual environment displayed on a back projected stereoscopic large screen ("power wall"). Since rendering speed is critical for accurate display of flickering stimuli we use a high end graphics card (Nvidia Quatro5000). The BCI system and the unity game engine communicate via a user defined protocol (UDP) over the Internet or over a local network.

In order to present frequencies reliably on a monitor or a projector one has to take into account the flickering refresh rate of the device itself. According to Nyquist’s sampling theorem [Nyquist, 1928], if N is the device refresh rate then it is possible to transmit frequencies as high as $N/2$. Given a frequency $m \leq N/2$, we define the square wave function $f(m)$:

$$f(m) = \begin{cases} 0, & \frac{x}{m} - floor\left(\frac{x}{m}\right) \leq 0.5 \\ 1, & otherwise \end{cases}$$

We sample *f(m)* and *x* in intervals of *1/N*, and *x* is incremented as an integer from *0* to *N*. This method enables us to represent all frequencies bellow or equal to *N/2* even if they do not divide *N*.

2.3. Procedure

A typical session has three parts: first the system computes a classifier, then we validate and improve the classifier with a cue-based classification task, and the third part is a free choice task. In a series of pilot studies we have explored various types of stimuli, varying mostly in shape, frequency, size, and motion, and have eventually settled on an immersive experience that includes a visualization of deep space. In the background there are small stars, intended to create the illusion that the user is moving in space (this experience is typically presented in stereoscopic display). Occasionally larger stars appear, and the user is expected to control these stars by "thought" There are four types of stars, each with different frequency; typically we use 17.1, 24, 30, and 40 Hz, using the 120 Hz projector. When an SSVEP response to a specific star has been detected, the star starts moving towards the user; otherwise it gradually fades out.

Figure 1. *A rich visual experience that includes controlling the behavior of stars with BCI.*

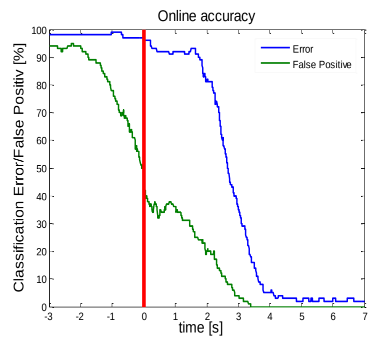

Figure 2. *Error rate and false positive classification, average of five subjects. Highest classification is after 3 seconds of stimuli appearance.*

3. Results

Ten subjects participated in the experiment (ages 24–50, 5 males and 5 females). All participants achieved 80% or higher classification accuracy rates in the cue-based BCI tasks. This is significantly above 25% chance level classification and thus establishes the validity of our display method. The highest rate of accuracy is obtained approximately 3 seconds after the stimulus appears (Fig. 2).

Our main focus is thus on the subjective experience in the free choice tasks. Subjects report that using the interface is very natural, and that the stimuli used for control are not intrusive; this is in sharp contrast to LED based interfaces. In dark lighting conditions even the flicker of 30 Hz stars is barely noticeable. We are now further studying issues of control, sense of agency, and experience in similar media experiences.

Acknowledgements

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EEG-Based Emotion Detection in Music Listening

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Abstract. The study of users' emotions in computer interaction has increased in recent years. In this paper we describe an approach to detect emotion from brain activity, recorded as electroencephalograph (EEG) with the Emotiv Epoc device, during music listening. After extracting features from the EEG signals we characterize the emotional state of a person by mapping their brain activity to a coordinate in the arousal-valence 2D emotion space. We then apply machine learning techniques to classify EEG signals into happy/sad and angry/tender emotional states. The obtained classifiers may be used to automatically tag or recommend music based on the listeners' EEG data

Keywords: EEG, Emotion Detection, Machine Learning, Music

1. Introduction

The study of users' emotions while interacting with multimedia computer systems has increased in recent years. This is due to the growing need for computer applications capable of detecting the emotional state of users and adapt accordingly [Picard and Klein, 2002]. Motivated by every day interaction among humans, the majority of the research in this area has explored facial and voice information as source of emotion cues. However, emotions are not always manifested by means of facial expressions and voice information. Facial and voice information is related only to behavioral expression which can be consciously controlled and modified, and which interpretation is often subjective. A still relatively new field of research in affective brain-computer interaction attempts to detect emotion using electroencephalograms (EEGs) [Chanel et al., 2006; Lin et al., 2010]. There have been several approaches to EEG-based emotion detection, but there is still little consensus about definite conclusions.

In this paper we describe an approach to decoding emotion from EEG data obtained with a (low-cost) Emotiv EPOC headset. Subjects are presented with music fragments previously annotated with particular emotions (i.e. happy, sad, angry, tender) while we record their response EEG activity. We characterize the emotional state of a person by mapping their EEG signals to a coordinate in the arousal-valence 2D emotion space (e.g. happiness is a state with high arousal and positive valence, whereas sadness is a state with low arousal and negative valence). We then apply machine learning techniques to classify EEG signals into happy/sad and angry/tender emotional states. Our approach differs from most previous works in that we do not rely in subject self-reported emotional states during stimuli presentation. Instead, we use a set of emotion-annotated music pieces from films soundtracks.

2. Material and Methods

2.1. Data Collection

EEG data in this study were collected from 4 healthy subjects (2 males and 2 females) with average age of 27.25 during listening to emotion-annotated 12–18 seconds music fragments. Data were collected using the low-cost Emotiv EPOC headset, recently released by the Emotiv Company. This headset consists of 14 data-collecting electrodes and 2 reference electrodes, located and labeled according to the international 10-20 system. Following the international standard, the available locations are: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4. The EEG signals are transmitted wirelessly to a laptop computer. Subjects listened to selected film soundtrack fragments previously tagged according to their emotional content. Based on these annotations, we selected 8 music fragments covering all four quadrants in the arousal-valence emotion plane (2 in each quadrant).

Initially, the subjects are informed about the experiment procedure and instructed to follow the usual guidelines during stimuli presentation (e. g. do not move). Subjects were instructed to close their eyes and not to produce any facial movements during the experiment. Once this was done, the 8 music fragments are randomly presented each one for 12 seconds and a 10 second silent rest is inserted between stimuli. The purpose of the 10 second silent rests is to set a neutral emotional state of mind in between stimuli.

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2.2. Feature Extraction

From the EEG signal of a person, we determine the level of arousal, i.e. how relaxed or excited the person is, by computing the ratio of the beta and alpha brainwaves as recorded by the EEG. We measure the EEG signal in four locations (i.e. electrodes) in the prefrontal cortex: AF3, AF4, F3 and F4.

In order to determine the valence level, i.e. negative or positive state of mind, we compare the activation levels of the two cortical hemispheres. Specifically, we estimate the valence value in a person by computing and comparing the alpha power a and beta power b in channels F3 and F4.

2.3. Learning Task

We approach this problem as a two 2-class machine learning classification problem - we apply a multi-layer perceptron with two hidden layers. In particular, we are interested in inducing two classifiers of the following forms:

$\text{Classifier}_1(\text{EEGdata}([t, t+c])) \rightarrow \{\text{happy}, \text{sad}\}$
$\text{Classifier}_2(\text{EEGdata}([t, t+c])) \rightarrow \{\text{angry}, \text{tender}\}$

where $\text{EEGdata}([t, t+c])$ is the EEG data observed at time interval $[t, t+c]$ and $\{\text{happy}, \text{sad}\}$ and $\{\text{angry}, \text{tender}\}$ are the sets of emotional states to be discriminated. The results reported in this paper are obtained with c=4s and with increments of t of 1 s. For each subject in the EEG data sets we train a separate classifier.

3. Results

The expected accuracy of a default classifier (one which chooses the most common class) for the same tasks we consider in this paper is 50 % (measured in correctly classified instances percentage). The average accuracies we obtain for the happy-versus-sad, and the angry-versus-tender classifiers using a multi-layer perceptron classifier are 86.33 %, and 77.27 %, respectively. We evaluated each induced classifier by performing 10-fold cross validation in which 10 % of the training set is held out in turn as test data while the remaining 90 % is used as training data. When performing the 10-fold cross validation, we leave out the same number of examples per class. In the data sets, the number of examples is the same for each class considered, thus by leaving out the same number of examples per class we maintain a balanced training set.

3.1. Discussion

The difference between the results obtained and the accuracy of a baseline classifier, i. e. a classifier guessing at random, confirms that the EEG data contains sufficient information to distinguish between happy/sad and angry/tender states, and that machine learning methods are capable of learning the EGG patterns that distinguish these states. It is worth noting that also investigated other algorithms (e. g. decision trees and k-NN) and all produced better than random classification accuracies. This supports our statement about the feasibility of training classifiers using the Emotiv Epoc for the tasks reported.

4. Conclusions

We have explored the use of machine learning techniques for the problem of classifying the music-induced emotional state of a person based on EEG data using the Emotiv Epoc headset. In particular, we presented results obtained with a multi-layer perceptron for discriminating between happy-versus-sad and angry-versus-tender states. Our results indicate that EEG data obtained with the Emotiv Epoc device contains sufficient information to train successful classifiers for these emotional states, using machine learning techniques. Furthermore, we proved that it is possible to train successful classifiers without self-assessment information about the emotional states by the subjects.

Acknowledgments

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Using BCI to Play Games With Brain Signals: an Organic Interaction Process Through NeuroBodyGame Wearable Computer

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Abstract. NeuroBodyGame consists of a wearable computer that allows the users to play games with their brain signals through an independent and non-invasive BCI integrated to its technological system that captures the user's brain activity as spontaneous inputs from EEG rhythms on the frontal lobe through two electrodes disposed on F1 and F2 channels according to 10-20 Standard.
Keywords: BCI, NeuroBodyGame (NBG)

1. Introduction

For several years, electroencephalographic activities, and other measures of brain functions, have been considered means to new non-muscular channels of communication for sending messages and commands to the external world. This possibility becomes reality with the development and application of brain-computer interfaces (BCI) responsible for actually enabling this communication process between human-machine or human-machine-human, through the acquisition and encryption of the user's biological information [Zuanon, 2011]. Many studies [Anderson 1998; Altenmüller and Gerloff, 1999; McFarland et al., 2000] have demonstrated correlations between EEG signals and real or imagined movements and between the EEG signals and those from mental tasks.

In this context NeuroBodyGame (NBG) was developed consisting of a wearable computer that allows the users to play games with their brain signals. It is a wearable wireless interface for the brain to interact with the games bundled into the system.

2. Material and Methods

The NeuroBodyGame wearable computer has an independent and non-invasive BCI integrated to its technological system in which the brain output channel is the EEG, and the generation of the EEG signal mainly depends on the user's intention, and not on the peripheral nerves and muscles [Fabiani et al., 1987; Polich, 1999; Donchin, 2000]. This BCI captures the user's brain activity as spontaneous inputs from EEG rhythms on the frontal lobe through two electrodes disposed on F1 and F2 channels according to 10-20 Standard.

In order to achieve all ages two games are being used with the NBG: NeuroBodyGame Dragon which aims at a light user and has a less complex playability and NeuroBodyGame Car which aims at a more experienced user and presents a complex playability. Both games are open source – a fundamental characteristic for providing full remodeling of the programming and integration with the games' controls and the interactor's brain commands.

The usability tests conducted with NBG users throughout the entire process include the analysis of aspects related to comfort, mobility, and adaptability of the user to the brain-computer interface and the integration of brain wave frequencies of the players to the functionalities of the game in question.

Figure 1. *NeuroBodyGame Wearable Computer with brain computer interface integrated.*

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3. Results

The obtained results include the mapping and the association of user's brain activity in real time to game functionalities, which begin to react in accordance with the player's neurophysiologic state. In other words, playability is facilitated or made difficult based on the user's brain wave frequencies as well as how the wearable computer interprets these brain activities and reacts to them, altering their color (front / back) and applying vibrations (back). Specifically the user's brain activity in a frequency period of 9 to 13 Hz enhances the user's playability and the NBG mostly react by showing the color blue. The detection of brain wave frequencies between 14 to 21 Hz, displays the green color and for frequency periods between 22 to 30 Hz the user's playability is made more difficult and the NBG reacts to it by turning to yellow and applying a soft vibration in the area of the back while brain wave frequencies between 31 to 40 Hz make the user's playability even more difficult and the NBG reacts by changing its color to red and by vibrating really intensively.

4. Discussion

The results mentioned above and observed during interaction of a significant number of users – more than 5,000 – during exhibit of the wearable computer at FILE (International Festival of Electronic Art) 2010, lead to the conclusion that the use of brain signals as biological information to configure an organic playability with the games constitutes a fertile field of research, considering the immersion potential the brain-computer interfaces provide when applied to interactive digital systems, such as computer games. Our future studies aim to extend the BCI application on wearable computers to provide increasingly complex levels of interaction between the user's organism and the elements that constitute a game such as characters, scenarios, feedback, besides the playability.

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Distinguishing Between Target and Non-Target Fixations in a Visual Search Task Using Fixation-Related Potentials

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Abstract. The P300 can be used to infer whether an observer is looking at a target or not. Common practice in P300 experiments and applications is that observers are asked to fixate their eyes while stimuli are presented. We investigated the possibility to differentiate between target and non-target fixations in a target search task involving eye movements by using EEG epochs synchronized to fixation onset (fixation-related potentials: FRPs). Participants systematically scanned search displays consisting of six small Landolt Cs in search of Cs with a particular orientation. After each search display, they indicated whether and where target Cs had been presented. As expected, an FRP component consistent with the P300 reliably distinguished between target and non-target fixations. For 8 out of 11 participants, it was possible to classify single FRPs into target and non-target FRPs above chance (62-77% correct). These results are the first step to practical applications such as covertly monitoring observers' interests and supporting search tasks.

Keywords: EEG, eye movement, P300, fixation-related potential, visual search

1. Introduction

The P300 is an event related potential (ERP) occurring approximately 250-500 ms after a target or task-relevant stimulus has been presented. Because the P300 is relatively easy to detect and its amplitude depends on voluntarily controlled attentional processes, it is often used as a control signal in Brain-Computer Interfaces. In P300 BCIs different stimuli are sequentially presented. The stimulus chosen by the observer, i.e., the stimulus that the observer focuses his/her attention on, elicits a P300 that is detected by the computer. Usually, participants using a P300 BCI or taking part in an experiment in which the P300 is investigated are asked not to move their eyes around the time that the P300 occurs. For example, they fixate a fixation cross that is subsequently replaced by a particular visual stimulus, or they fixate a target amongst non-targets and count the number of times it is flashed. However, in natural visual search tasks observers sample their visual environment by self-initiated fixations and saccades instead of fixating a location where the visual stimulus is known to appear. We suspect that the brain's electrophysiological response to perceiving a target amongst non-targets will be similar regardless of whether the eyes are static and targets and non-targets are presented at a fixation location or whether an observer fixates a set of non-targets individually in search for a target. Here we try to infer from EEG whether individuals look at a target object or not in situations with natural eye movements. Rather than locking EEG to stimulus onset, we lock EEG to fixation onset and examine whether we can distinguish target from non-target fixations on a single-fixation basis. If so, this would enable new types of (online) applications like covertly monitoring observers' interests and supporting search tasks as well as more ecologically valid scenarios in EEG studies about visual search, selective attention and detection. Fixation-related potentials (FRPs) have been studied before. However, existing studies look at earlier components than the P300 or differences between target and non-target FRPs may be due to confounding factors. Also, we are not aware of a study that looked at single FRP classification.

2. Material and Methods

Thirteen participants took part in the experiment. In each of four blocks they searched 60 search displays for a target C. A search display consisted of 6 Landolt Cs with four possible orientations: the gap could be at the top, the bottom, left or right. The Cs were arranged in a circle and displayed at the 12, 2, 4, 6, 8 and 10 o'clock positions. It was impossible to detect the orientation of any C other than the one currently fixated. The target C could have any orientation, but remained the same for each individual participant. The non-target Cs had randomly selected other

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orientations. One third of the displays contained 2 targets, one third 1 target and one third no targets so that participants could (almost) never know whether the next C would be a target. Participants were instructed to fixate on each C, starting at the C at the 12 o'clock position and switching to the next in clockwise direction as fast as they wished. When the participants were done, they indicated whether and where they saw the target C.

Eye position was recorded at 50 Hz using a Tobii x50 eye tracker. EEG was recorded at Fz, Cz, Pz, Oz, P3, P4, PO7 and PO8. EOG electrodes were fitted to the outer canthi of both eyes, as well as above and below the left eye. Using the Tobii data we selected fixations on the C's at the 2, 4, 6, 8 and 10 o'clock positions. Subsequently, EOG was used to define fixation onset that was exactly synchronized with EEG. FRPs were defined as EEG samples starting at fixation onset and ending 500 ms after. Only the first fixation on a particular C was included in the analysis. Since in this study we are interested in clean data reflecting the P300, FRPs associated with fixations shorter than 500 ms were discarded. For three participants, this resulted in less than 10 valid target fixations. These participants were therefore excluded from analysis. For classification, data were balanced by selecting random subsets of FRPs such that they contained an equal number of targets and non-targets. The raw time series for eight channels were standardized to have mean zero and unit standard deviation and used as input to a linear support vector machine. For each participant it was estimated whether FRPs could be correctly classified as associated with a target or non-target. These estimates were produced using a ten-fold cross-validation procedure. For each participant and electrode, we also calculated grand average target and non-target FRPs. These served as input for running paired sample t-tests that were used to test for significant differences between target and non-target FRPs (alpha of 0.01). In addition, we checked for significant differences in the 100 ms epoch before fixation onset to verify that FRPs do not differ before fixation onset. To verify that EOG associated with target and non-targets does not systematically differ as intended by our experimental design, we examined EOG 'FRPs' associated with the same set of fixations as used in the FRP analyses in the same way.

3. Results

Grand average target and non-target FRPs are consistent with a higher P300 for a target than for a non-target fixation. The difference is significant at some frames towards the end at the parietal and parieto-occipital electrode sites. Except for one frame at PO8, the 100 ms epoch before fixation onset does not show differences between targets and non-targets confirming that identification of the C happened only after fixation onset. T-tests on the EOG 'FRPs' and the 100 ms before did not indicate significant differences between targets and non-targets, confirming that saccades to targets and non-targets were similar. All 11 participants included in the analysis have average classification accuracies over 56%. For 8 participants, classification performance was significantly higher than chance level ($p < 0.05$) and for one participant, performance is on the verge of significance ($p = 0.05$). The range of classification accuracies for participants with successful classification is between 62 and 77%, with a mean of 70%.

4. Discussion

In the current study we provided evidence for a target-linked P300 in a well-controlled search task involving eye movements, where ERPs were locked to fixation onset rather than to the onset of an externally imposed stimulus. We showed that individual FRPs can be labeled offline as belonging to a target or non-target fixation for most observers with 70% certainty on average. Our findings show that also for later components it is possible to investigate ERPs in contexts with self-paced eye movements and suggest that P300 knowledge that has been gathered within tasks with stationary eyes could be generalized to situations with eye movements. Furthermore, our findings are of relevance in applied fields of research such as passive Brain-Computer Interfaces, augmented cognition and neuroergonomics. While augmented cognition and passive BCI focus on online use of brain signals, offline use of brain signals that reflect the state of the user could also be useful when for instance evaluating different interfaces or studying task performance over time. Remaining questions that we would like to answer mostly relate to the application of FRPs. While the current experiment was designed to investigate FRPs in a controlled manner, for practical applications we need to examine situations that resemble the case that the use of FRPs is envisioned for. One important aspect is the general fixation duration in those situations. In the current setting, we lost a large amount of data because of the < 500 ms exclusion criterion. However, in our restricted search task fixation durations were relatively short. Also, we demonstrated in a later experiment that when targets can be detected in the periphery, i.e. before the target is fixated, the positive target potential occurs close to fixation onset. In this case fixations with shorter durations may also be used to extract FRPs.

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Real-Time Functional Brain Mapping

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Abstract. In this paper, we present the application of brain-computer interface (BCI) technology to the mapping of brain function. Functional mapping seeks to identify those areas in the brain that are involved in producing a particular function, such as receptive speech, and is particularly important for surgical planning prior to resective brain surgery. The presented mapping procedure can be rapidly applied, is comparatively inexpensive, procedurally simple, and also congruent to existing techniques. We expect that this will directly lead to a reduction in patient morbidity and will increase the population of patients that can be effectively treated.

Keywords: ECoG, Brain Mapping, Gamma, Electrical Cortical Stimulation, Epilepsy

1. Introduction

The traditional applications of brain-computer interface (BCI) research have focused mostly on communication and control. The past several years have seen the application of BCI techniques to other important areas, such as attention monitoring, stroke rehabilitation, or functional mapping. Functional mapping seeks to identify those areas in the brain that are involved in producing a particular function, such as receptive or expressive speech, and is particularly important for surgical planning prior to resective brain surgery.

Traditionally, different methods have been used to produce this functional map, most notably electrical cortical stimulation (ECS) mapping, but they all have substantial problems. Patients undergoing resective brain surgery would benefit greatly from a mapping methodology that is safe, can be rapidly applied, is comparatively inexpensive, procedurally simple, and also congruent to existing techniques.

Over the past several years, we have been developing a novel functional mapping procedure. This technique is based on a new detection algorithm, called SIGFRIED [Schalk et al., 2008; Schalk et al., 2008], which is incorporated into our general-purpose BCI software, called BCI2000 [Schalk et al., 2004]. Together with appropriate signal acquisition hardware, this procedure interprets, without configuration by an expert and at the patient's bedside, changes in electrocorticographic (ECoG) signals that are passively recorded from electrode grids that are already implanted in the patient for clinical reasons. Within minutes, this novel method identifies, on a 2D or 3D topographical display that is updated in real time as the patient performs different tasks, those cortical locations whose activity changes in response to the task (see Fig. 1 for results of our mapping in one patient).

2. Material and Methods

The concept of our real-time functional brain mapping procedure is illustrated in the left panel of Fig. 1. Prior to functional mapping, we acquire post-operative CT scans (A_1) and pre-operative structural MRI scans (B_1). From these scans, we reconstruct the grid position (A_2) and cortical surface (B_2), which provides a subject-specific anatomical model (D) for our functional mapping technique (E). At the bedside, we engage the subject in different tasks, such as auditory stimulation (C_1), which modulates brain signals (C_2) in the gamma band (70-110 Hz). BCI2000 software applies the SIGFRIED method to detect these task-related changes, and maps the results in real time onto the subject-specific anatomic model (E).

3. Results

In the right panel of Fig. 1, we present exemplary results from one subject who was implanted over the left hemisphere with 120 electrocorticographic electrodes for the purpose of functional brain mapping and for localizing

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epileptic foci. Location and duration of the implantation were solely determined by clinical criteria. A lateral x-ray (F) and an operative photograph (G) depict the configuration of two grids and three strips. In the example shown in H and J, we presented the subject with voice and tone stimuli that induced cortical power changes in the gamma band. To identify brain regions related to receptive language, the software statistically contrasted the brain signal changes induced by tones with those induced by voice stimuli. The 2-dimensional interface to the investigator (H) presented functional activations in real time using a topographical interface that represents the electrode grid. The interface contained a display of cortical activation at each location for each task condition (i.e., voice, tones or language). Each display contained one circle at each electrode's location. The size of each circle and its tint was proportional to the magnitude of cortical activation. The 3-dimensional interface to the investigator (J) presented the same functional information in real time on the patient-specific anatomical model. The results for cortical stimulation (ECS) mapping of receptive language function (F, red) are congruent with those achieved using our passive SIGFRIED-based method (H/J).

To date, together with our collaborators, we validated the efficacy of our new method for functional mapping in three studies with adult and pediatric patients [Brunner et al., 2009] at the bedside and in intra-operative scenarios [Roland et al., 2010]. We also showcased our method in several relevant conferences and in four dedicated workshops on electrocorticography organized by our group. Finally, we provided our prototype to several clinics in the USA and in Europe, and licensed the technology to a corporate partner. The initial version of the resulting product is about to be rolled out to clinical testing.

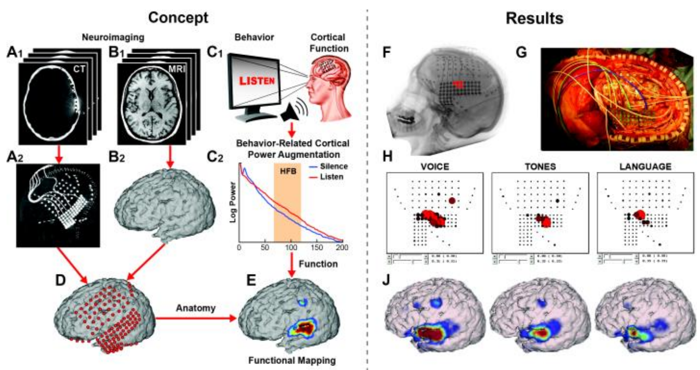

Figure 1. *Functional Brain Mapping of Language Cortex.*

4. Discussion

Our present method gives results that have high concordance to those derived using ECS mapping and has the potential to improve clinical diagnosis. Because our procedure rapidly, accurately, and safely maps functional cortex, its widespread integration in resective brain surgery protocols will directly lead to a reduction in patient morbidity and will increase the population of patients that can be effectively treated.

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Brain-Activity-Driven Real-Time Music Emotive Control

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Abstract. Active music listening has emerged as a study field that aims to enable listeners to interactively control music. Most of these systems aim to control music aspects such as playback, equalization, browsing, and retrieval, but few of them aim to control expressive aspects of music to convey emotions. In this study our aim is to enrich the music listening experience by allowing listeners to control expressive parameters in music performances using their perceived emotional state, as detected from their brain activity. We obtain EEG data using a low cost EEG device and then map this information into a coordinate in the emotional arousal-valence plane. The resulting coordinate is used to apply expressive transformations to music performances in real time by tuning different performance parameters in the *KTH Director Musices* rule system. Initial results show that the emotional state of a person can be used to trigger meaningful expressive music performance transformations.

Keywords: EEG, Emotion Detection, Expressive Music Performance

1. Introduction

In recent years, active music listening has emerged as a study field that aims to enable listeners to interactively control music. While most of the work in this area has focused on control music aspects such as playback, equalization, browsing and retrieval, there has been few attempts to controlling expressive aspects of music performance. On the other hand, electroencephalogram (EEG) systems provide useful information about human brain activity and are becoming increasingly available outside the medical domain. Similarly to the information provided by other physiological sensors, Brain-Computer Interfaces (BCI) information can be used as a source for interpreting a persons emotions and intentions.

In this paper we present an approach to enrich the music listening experience by allowing listeners to control expressive parameters in music performances using their perceived emotional state, as detected by a bran-computer interface. We obtain brain activity data using a low cost EEG device and map this information into a coordinate in the emotional arousal-valence plane. The resulting coordinate is used to apply expressive transformations to music performances in real time by tuning different performance parameters in the *KTH Director Musices* rule system [Friberg et al., 2006].

2. Material and Methods

Our proposed method is depicted in Fig. 1. The process begins with detection of emotion based on the approach by Ramirez and Vamvakousis [Ramirez and Vamvakousis, 2012]. For the data extraction we used the Emotiv EPOCH head set. First we measure the EEG signal from the AF3, AF4, F3, and F4 electrodes. Using band pass filtering i, the signal is split up in order to get the frequencies of interest, which are in the range of 8–12 Hz for alpha waves, and 12–30 Hz for beta waves. Alpha waves are dominant in a relaxed awake mind state, whereas beta waves are indicator of an excited state of mind. The arousal value is computed from the beta/alpha ratio as:

$$arousal = \frac{a_{F3}+a_{F4}}{b_{F3}+b_{F4}} \tag{1}$$

Left frontal inactivation is linked to a negative emotion, whereas right frontal inactivation may be associated to positive emotions. Thus valence is calculated as:

$$valence = \frac{a_{F4}}{b_{F4}} - \frac{a_{F3}}{b_{F3}} \tag{2}$$

As depicted in Fig. 1, each quadrant of the arousal valence plane correspond to one of the studied emotions as follows: high arousal and high valence correspond to happy state, high arousal and low valence correspond to angry state, low arousal and high valence correspond to relax state, and finally low arousal and low valence correspond to sad

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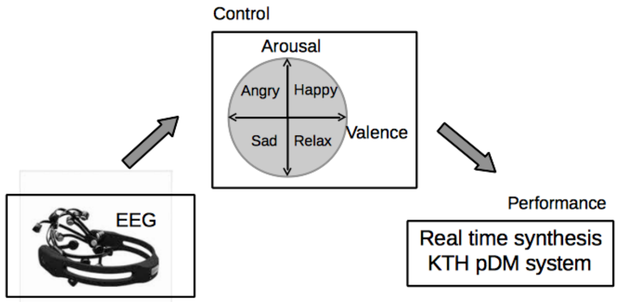

Figure 1: *Theoretical frame work for expressive music control based on EEG arousal - valence detection.*

state. As arousal and valence values are not absolute and vary among subjects, we normalize the values by computing the mean of a 5 second window over the last 20 second window maximum and minimum of the signal. This way we obtain values that range between minus one and one for both arousal and valence values.

For synthesis we have used a real-time based implementation of the KTH group, pDM (Pure Data implementation of Director Musices Profram) [Friberg, 2006]. Thus, the coordinate on the arousal-valence space is mapped as an input for the pDM activity-valence space expressive control. In our implementation, this control is adapted in the pDM program, so the coordinates are rotated to fit the ones of the arousal valence space. Then the transformation of each of the seven the expressive rules takes place by interpolating 11 expressive parameters between four extreme emotional expression values (Bressin and Fridberg, 2000) .

Two types of experiments were performed:a first one listening and the other listening while playing (improvising) with a musical instrument. In both we aim to evaluate if the intended expression of the synthesized song (and the user performance when playing) is reflected in the incoming signal of the listeners brain activity, in a passive listening scenario. The expression of the performance is dynamically changed between to extreme values (happy and sad). A 2-class classification task is performed for both experiments. Features are obtained from the signal by taking four seconds time intervals, and sliding each of this windows every quarter of a second.

3. Results

Two classifiers, Linear Discriminant Analysis and Support Vector Machines, are evaluated to classify the intended emotions, using 10-fold cross-validation. Initial results are obtained using the LDA and SVM implementations of the Open Vibe library. For happy-versus-sad classification we obtained a 76.41 % for passive listening with out playing, and 65.86 % for passive listening when playing an instrument (improvising) along the expressive track using SVM with radial basis kernel function.

4. Discussion

Initial results suggests that the EEG signals contain sufficient information to classify the expressive intention between happy and sad classes. However, the accuracy decrease, as expected, when playing an instrument. This may be due to the fact that the action of playing requires attention, thus, the alpha activity may remain low and beta may remain high.

5. Conclusion

In this paper we have explored an approach to active music listening, implementing a system to control in real time the expressive aspects of a musical piece, by means of the emotional state detected by an EEG device. We have used machine learning techniques (LDA and SVM) to perform a two class classification task between two emotional states (happy and sad). Initial results suggests that EEG data contains sufficient information to distinguish between the two classes.

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Evaluating Hold-Release Functionality in a P300 BCI

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Abstract. We propose a novel P300 BCI functionality in which activation (hold) and deactivation (release) of a P300 BCI speller can be separately controlled. This allows for control of the duration of activations, faster response time for the deactivations and a more analog-like control than using the traditional P300 BCI method.

Keywords: P300, EEG, Perceptual Errors, Activation Characteristics, and Deactivation Characteristics

1. Introduction

To date, P300 spellers have simply produced the selection the user desires, often with the selection used only within the P300 speller application. However, as BCIs move toward clinical use, their role as interfaces to other technology is expanding [Sellers et al., 2010; Thompson and Huggins, 2011]. Assistive technology control interface theory describes interface activation and interface deactivation as distinct properties of any control interface [Cook and Hussey, 2001]. Separating control of activation and deactivation allow precise timing of the duration of the activation. We propose a novel P300 BCI functionality in which activation (hold) and deactivation (release) can be separately controlled. To drive a power wheelchair a traditional P300 BCI, the user would need to choose a predefined direction and distance they want to move. Alternatively, a BCI with hold-release functionality would enable the user to select the direction they want the wheelchair to move and hold that selection until they want to stop. During the holding process, the only information required by the BCI to stop the wheelchair is when the user changes i.e. releases their selection. This allows the BCI to make a release decision from a very few flashes instead of after multiple sequences of flashes. For the BCI user this means a faster response time and a more analog-like control than using the traditional P300 BCI method. We demonstrate that hold-release functionality is possible with a P300 BCI through off-line analysis of data recorded while subjects were performing hold-release tasks. .

2. Material and Methods

To get data to test hold-release functionality we created a 5x6 matrix for a P300 speller with rows and columns flashed for 31.2 milliseconds with 125 milliseconds between flashes and classifier weights created with the least squares option of the BCI2000 P300_GUI. This simulated an eventual application in which a specific release target appears when a selection with hold functionality is initially selected. Two “selectable objects” simulated the hold-release functionality. One object was an ‘X’ in the upper left hand corner of the matrix and the other was ‘O’ in the lower right hand corner.

Two variations on the layout were tested. In layout 1, the rest of the matrix contained numbers to provide the visual clutter typical of a P300 BCI. Layout 2 was designed to remove two common perceptual issues in P300 BCI spellers; adjacency response errors and double flashing errors [Fazel-Rezai and Ahm, 2011]. To remove adjacency response errors we surrounded each selectable option with white space. Therefore no space adjacent to a hold-release object would flash. All other locations were filled with ‘*’ characters for reduced visual clutter of characters while maintaining the same number of rows and columns and thus the same target-to-target characteristics. To remove double flashes we insured that the sequence of flashes never contained flashed groups that created a double flash.

Data was recorded from three able-bodied subjects (1 woman, ages 21, 24 and 57 years) using a 16 EEG electrode cap from Electrode-cap International with electrode location as in (Thompson et al., 2012). Subjects sat in front of a computer screen that contained one of our BCI layouts. We instructed our subjects to select and hold an object until a tone sounded to indicate a switch of target object. Subjects “held” the object by counting how many times it flashed. The target in the upper left corner was designated as the starting target. Subjects performed 10 hold-release runs, 5 using layout 1 and 5 using layout 2. The order in which they used the layouts was pseudo-random. The tone played five times per run creating five transitions between objects. The timing for the tones was pseudo-random and happened 10-60 flashes (7500-12500 ms) apart. All tones where separated by at least 5 flashes, no tones played when a selectable object was flashing and no tones played during the first or last 5 seconds of each run. Subjects were not given feedback regarding whether the object they were holding was selected or not.

3. Results

Accuracy for the hold-release algorithm was 80% or higher for all subjects when calculated with information from one flash of a hold-release object. Using information from two flashes (from any combination of the two selectable objects) increased accuracy to 100%. Mean accuracy from one flash of a hold-release object using layout 1 was 82 +/- 3.0% and mean accuracy using layout 2 was 90 +/- 2.0%. Two-way ANOVA across subjects and layouts showed a strong significance in accuracy depending on the layout used (p=0.0003). The average time for a flash of a selectable object was about 106.25 +/- 81.25 for layout 1 and 103.13 +/- 71.88 for layout 2. Thus classification time took time for an incoming flash plus the 800 ms window after the flash.

4. Discussion

Our results demonstrate that hold-release functionality is possible using P300 BCIs. Using hold-release allows us to extend the use of P300 BCIs to applications that require fast and/or analog-like responses. We tested hold-release functionality using two different layouts. The layout that minimized perceptual errors greatly increased single flash classification accuracy.

Unlike traditional P300 BCI's our paradigm is able to accurately classify a user's decision (between the hold and release selections) after single flashes of a hold-release object instead of after a sequence of flashes. For this reason our paradigm is significantly faster than a traditional BCI. For example a traditional BCI running at four to eleven sequences takes about 8-20 seconds to make a selection while the hold-release decision would take about 1 second. This faster response time comes from a decrease in the amount of information needed to make a classification among fewer targets. Traditional P300 BCIs requires enough information to determine what the new selection is from a large number of targets. Our method only requires knowledge of when a classifier value from a flash is significantly different from what we expect when a user is holding a selection. The largest time requirement for our paradigm is the collection of 800ms of EEG activity after each flash of a hold-release object. The 800ms window of data was chosen to guarantee that the P300 event was captured. Optimization of this time window could further increase the interface responsiveness.

Future work should test hold-release functionality in a real world application such as moving a wheelchair. We have found overall BCI performance to not be significantly affected by wheelchair tilt, but hold-release functionality could be more sensitive to this type of disruption [Thompson et al., 2011].

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The Musical BCI: Control by Selective Listening

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Abstract. The predominant approach in Brain-Computer Interface (BCI) research to reading out bits of the user's intent is to deliver a stream of isolated visual or auditory stimuli and to detect the modulation of event-related potentials (ERPs) by the user's attention. While such BCI systems provide relatively good control, the stimulation is highly artificial and may become unpleasant. In contrast, music allows for a more intuitive way of listening, since the separate information streams integrate into a coherent and hedonistically appealing entity. Here, we explore an alternative approach to BCI control by employing polyphonic pieces of music as stimuli. As control paradigm, the user shifts attention selectively to one of the musical instruments. Since the musical pieces are composed such that each instrument plays tones deviating from a regular repetitive pattern, modulated ERP responses can be used to infer the user's intent in a similar fashion as for existing ERP-based BCIs.

Keywords: ERP, auditory, P300, music

1. Introduction

It is among the supreme skills of a musical performer of a fugue by Bach that its different instruments can be perceived as independently articulated auditory streams [Bregman, 1990] of their own right so that the listener can deliberately focus her attention to the musical beauty of one instrument or the other. We present work on how selective attention in music listening can be used as a new paradigm in BCI, following earlier BCI systems based on visual or auditory attention [Schreuder et al., 2010; Höhne et al., 2011; Hill and Schölkopf, 2012]. We exploit the fact that polyphonic music integrates several instruments into an aesthetic entity and that listeners are able to follow individual instruments while still being immersed in a holistic listening experience. In Western major-minor tonal music, repetition and variation of patterns is an essential part of the structure that plays with the listeners' expectations. Taking advantage of that we implement a 'musical' oddball paradigm by repeating a characteristic pattern for each instrument (standard stimulus) and varying it infrequently (deviant stimulus) without violating the characteristics of the musical idiom. Our hypothesis is that if listeners focus on one instrument a deviant pattern in this instrument triggers an ERP response. The occurence of this response reveals which instrument has been attended to.

2. Material and Methods

In this study ($N = 11$), a minimalistic version of *Just can't get enough* (Depeche Mode) consisting of synthesized bass, keyboard, and drums was used. Each instrumental part is composed of frequent repetitions of a standard one-measure-long pattern, once in a while interrupted by a deviant bar-long pattern. Then these three instrumental parts were overlaid. The stimuli were presented in audio clips of 40 s length, containing between 3–7 deviants per instrument[1]. Ten randomized versions of such clips were generated. In random order, 21 of these clips form a block. On the whole, three of these blocks were presented to the subject. In order to have the attention of the subject focused on the particular instrument, the subject was asked to count the number of deviants per instrument in each clip and report it afterwards using the computer keyboard. Concurrently, we used a 64-channel active-electrode setup with a standard montage to record the brain activity associated with the musical stimuli.

Since the deviants in each instrument had different physical characteristics and, hence, the evoked response differed across instruments, we trained a separate binary classifier for each instrument using regularized linear discriminant analysis. Each classifier was trained to discriminate between attended deviants and unattended deviants of that instrument. We then modelled the classifier outputs as Gaussian probability distributions using maximum likelihood estimates on the training data. In the test phase, we obtained posterior probabilities for each deviant indicating the

[1]Sound example: soundcloud.com/hpurwins/depmod1

probability that the instrument was attended. For each clip, posterior probabilities were averaged within each instrument and the instrument with the highest mean posterior probability was selected as the attended instrument.

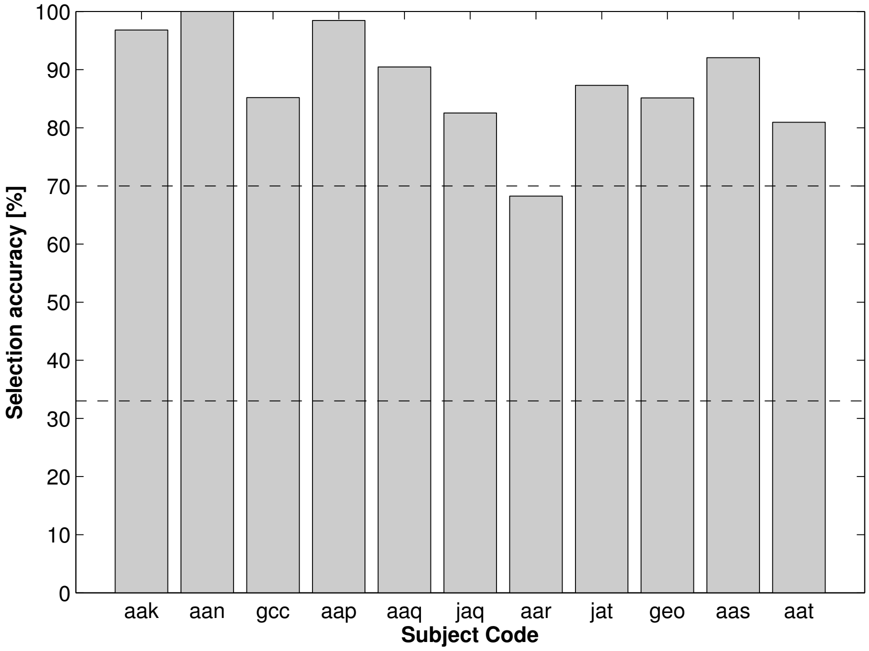

Figure 1: *Instrument classification accuracy for each subject. The lower dashed line indicates chance level, the upper dashed line indicates the 70 % benchmark.*

3. Results

In an offline analysis, we performed a leave-one-clip-out cross-validation, wherein classifiers were trained on all clips but one and then validated on the held out clip. Figure 1 depicts the accuracy of detecting the attended instrument in a clip. Ten out of eleven subjects have a performance above 80 %, the lowest performance is 68 %.

4. Discussion

In this study we addressed the problem of transferring the typical BCI setting to a more enjoyable setting using musical pieces. Our approach is built on the everyday listening ability to follow an individual instrument in polyphonic music. Although the number of possible concurrent streams is limited and our stimulus sequence is not the fastest way to present an oddball paradigm, our results show that it is possible to design a BCI that is linked to an important source of joy for individuals, namely music listening. In future work, we intend to improve the information rate of this paradigm, compare various musical stimuli, and investigate its performance in an online setting. Furthermore, this approach opens an avenue for investigating selective auditory attention to music and how it relates to stream segregation [Bregman, 1990], supported by differentiating the streams with respect to timbre, pitch range, and rhythmical structure. Also this approach could be used to investigate which signatures in a complex musical score involuntarily call the attention of the listener.

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Prediction of Upcoming Emergency Reactions During Simulated Driving Based on ERP

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Abstract. We present an emergency braking assistance system, which is capable of detecting the driver's braking intention in more general emergency situations compared to a previous study [Haufe et al., 2011]. Precisely, the system is applied to three kinds of realistic emergency situation instead of only one. We found a significant positive event-related potential (ERP) deflection for all three kinds of emergency reaction about 300ms post-stimulus in parietal regions. Moreover, the result shows that electroencephalography (EEG)-based prediction of emergency reactions is faster than behavioural responses such as electromyography (EMG) or brake/gas pedal deflections, even though the maximal achievable accuracy of EEG-based prediction is lower compared to other modalities.

Keywords: EEG, ERP, Emergency Braking, Neuro-driving, BCI

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1. Introduction

Prediction of upcoming emergency reactions is important for preventing traffic accidents. If a braking assistance system can predict the driver's intention prior to the behavioral response, this information can be used to apply safety measures in time and thereby to mitigate the impact of traffic accidents or even to avoid accidents. Conventionally, external sensors such as laser or ultrasonic sensors have been used to predict upcoming collisions. Recently, it has been proposed to additionally monitor the driver's mental state based on electroencephalography (EEG) [Haufe et al., 2011], [Papadelis et al., 2007]. In particular, an existing study revealed that an EEG-based assistance system can detect emergency braking 130 ms earlier than a system relying only on behavioural responses. In the present study, the prediction performance of such a system is investigated under more general circumstances in order to overcome the lack of generality caused by the fact that only one specific type of emergency situation was considered in [Haufe et al., 2011]. We find that the event-related potential (ERP) signatures evoked by three different types of emergency stimuli are similar to those described in [Haufe et al., 2011]. Classification analysis moreover indicates that it is possible to detect the various kinds of emergency situations prior to actual braking based on EEG.

2. Material and Methods

2.1. Material

The driving simulator was composed of three 42 " wide screens, a steering wheel, an accelerator and a brake pedal, and a seat. The simulator software was developed using the Unity 3D engine (unity3d.com), which is highly customizable and offers an excellent degree of realism. In the virtual environment, there were three driving lanes, and two virtual vehicles besides the subject's vehicle.

2.2. Methods

2.2.1 Experimental Paradigm

Five healthy subjects (male and right-handed, age 26.2 ± 1.64 years) participated in this study. The subjects' task was to drive a virtual vehicle using the steering wheel and accelerator/brake pedals. They were instructed to follow a lead vehicle within the desired distance mainly on the middle lane. In case of an imminent crash, the participant was instructed to perform immediate braking. The following three types of emergency situation were artificially induced at random intervals.

The brake stimulus The lead vehicle abruptly decelerates.

The cutting-in stimulus A vehicle from the neighboring lane abruptly changes to the subject's lane in the front of subject's vehicle.

The pedestrian stimulus A pedestrian appears quickly in front of the subject's vehicle.

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2.2.2 Data Analysis

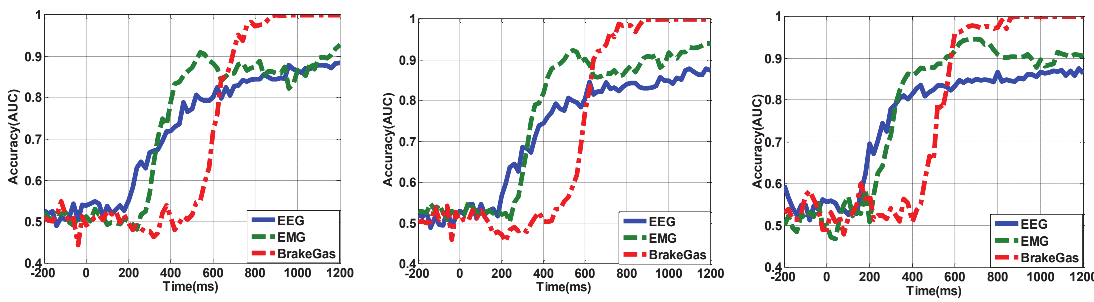
Target segments were defined from -300ms before each stimulus onset to 1200 ms after each stimulus onset. Non-target segments were extracted by moving a window over the entire recording. Baseline correction of EEG data was computed by subtracting the mean amplitude in the first 100 ms of the window. The class-discriminability using optimized combinations of spatio-temporal features was investigated using shrinkage-RLDA (regularized linear discriminant analysis) classification. The first half of target and non-target epochs was used as training set and the second half was used as test set. The class separability of the RLDA output was assessed using the area under the curve (AUC) [Fawcett, 2006] measure. The AUC is given by

$$U = R - \frac{n_1(n_1+1)}{2}, \quad AUC = \frac{U}{n_1 n_2} \tag{1}$$

where n_1, n_2 are the number of test data for each class (target, non-target) respectively, R is the Wilcoxon rank sum statistics of the classifier outputs on test data, and U is the corresponding Mann-Whitney statistics. The known distributions of R and U provide a non-parametric test for the null hypothesis of zero correlation between classifier output and class label.

3. Results

Fig. 1 shows the grand average AUC classification accuracy scores computed from the outputs of linear classifier for each stimulus as a function of classification time relative to the stimulus onset. Furthermore, this figure depicts classification accuracy of different modalities, which are EEG, EMG and brake/gas pedal deflection. Fig. 1(a) depicts AUC scores for the brake stimulus, while Fig. 1(b) and Fig. 1(c) show AUC scores for the cutting-in and pedestrian stimuli respectively. The results show that EEG (neurophysiological response) conveys the same information about emergency situations faster than the EMG (physiological response) and the Brake (technical response).



(a) (b) (c)

Figure 1: *Grand-average AUC scores computed from the outputs of linear classifier for each stimulus. (a) Brake stimulus. (b) Cutting-in stimulus. (c) Pedestrian stimulus.*

4. Discussion

This study demonstrated the possibility of detecting multiple classes of emergency situations in a diversified simulated driving scenario, extending previous research [Haufe et al., 2011]. While these results are preliminary, we intend to acquire more data and improve our analysis methodology in order to obtain more stable results and decrease the number of false alarms.

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Predicting Changes in Neural Tuning During BCI Learning

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Abstract. The tuning of cortical neurons changes as subjects learn to control Brain-Computer Interfaces (BCIs). We hypothesized that these changes may be predicted from patterns of neural activity recorded during natural movements prior to learning. We analysed neural tuning as monkeys learned BCIs with arbitrary mappings between firing rates and cursor position, and compared two learning models to predict tuning changes: uniform vs. constrained. We found that the constrained model explained more of the observed variation, with learning restricted to only a small number of naturalistic dimensions within the neural space.

Keywords: Single-Unit Activity, Motor Cortex, Learning, Plasticity, Optimal Control

1. Introduction

BCIs are redundant motor tasks with more control signals (neurons) than output dimensions (cursor axes), so different strategies at the neural level could drive improvements in performance [Jackson and Fetz, 2012]. Often the strategy that emerges with training appears sub-optimal (e.g. neurons become tuned for directions different from their true action on the cursor) suggesting learning is constrained to a limited subset of dimensions within the neural space. Here we examine whether these constraints reflect activity patterns observed during natural movement.

2. Material and Methods

Spiking activity was recorded from primary motor (M1) and ventral premotor (PMv) cortices of two rhesus macaques (monkey D: $N = 20$ neurons, monkey R: $N = 12$) performing 2D wrist- and 1D brain-controlled cursor tasks over multiple sessions. During brain control, neurons were assigned to *up*, *down* and *off* ensembles according to an arbitrary mapping (*Map1* or *Map2*) represented by a vector in the neural space (**m**). Instantaneous cursor position (y) was determined from neuronal firing rates (v_i, normalized by their range during wrist control) according to:

$$y = \sum_{i=1}^{N} m_i . v_i = \mathbf{m}.\boldsymbol{\upsilon} \qquad \text{where } m_i = \{-1, 0, +1\} \text{ for } down, off \text{ and } up \text{ neurons respectively} \tag{1}$$

Monkeys had to move the cursor to targets appearing at random in *high* and *low* locations on the screen. *Performance* was quantified as the separation between average cursor trajectories following the appearance of high and low targets ($\bar{y}_{high}, \bar{y}_{low}$), which in turn depended on the *tuning* of each neuron (T_i). Therefore, *improvement* across consecutive sessions can be expressed as a vector product:

$$\begin{aligned} & Performance = \int_0^{5s} (\bar{y}_{high} - \bar{y}_{low}) dt \; = \; \sum_{i=1}^{N} m_i . \int_0^{5s} (\bar{v}_{i,high} - \bar{v}_{i,low})\, dt = \sum_{i=1}^{N} m_i . T_i \\ \Rightarrow \; & Improvement = \mathbf{m}.\boldsymbol{\Delta}\mathbf{T} \end{aligned} \tag{2}$$

where the change in tuning across consecutive sessions is also represented by a vector in the neural space (**ΔT**). To maximize improvement, **ΔT** should be aligned with the current map vector **m** (i.e. *up* neurons should become tuned for *high* targets, *down* neurons should become tuned for *low* targets) which we call 'uniform learning'. However, if learning is constrained, tuning changes will be biased to particular dimensions of the neural space. To estimate these dimensions we calculated the *principal components* (PCs) of low-pass filtered (<5 Hz) firing rate profiles observed during natural movements (wrist control performed prior to the first session of brain control). The 'constrained learning' model assumes that the tuning change along each *naturalistic PC* should decrease exponentially with increasing component number:

$$\text{Uniform learning:} \quad \Delta T'_n \propto m'_n \qquad\qquad \text{Constrained learning:} \quad \Delta T'_n \propto m'_n \, . \, e^{-n/N_c} \tag{3}$$

where $\Delta T'_n$ and m'_n are the projections of **ΔT** and **m** respectively along the n^{th} PC. To assess significance, the ability of naturalistic PCs to predict tuning changes of individual neurons was compared against 10000 Monte Carlo simulations of the same constrained model based on random rotations of the neural space.

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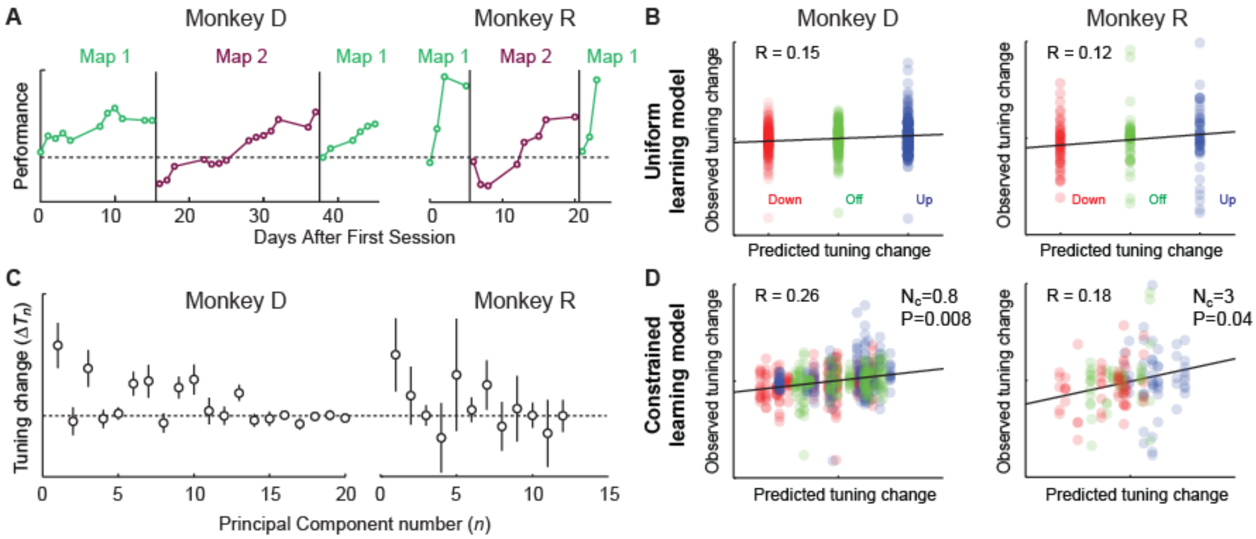

Figure 1. *(A) Training over multiple sessions produces map-specific improvements in abstract BCI performance. (B) Changes in tuning of individual neurons are poorly predicted by their action on the cursor alone. (C) Average tuning changes are biased towards lower principal components of naturalistic activity patterns. (D) Constrained learning model improves prediction of tuning changes for individual neurons.*

3. Results

For both monkeys, BMI performance increased progressively over consecutive training sessions with *Map1* and *Map2* (Fig. 1A). After switching from *Map1*→*Map2* and *Map2*→*Map1*, performance returned to baseline before rising again. Map-specific learning resulted from changes in the tuning of individual neurons, but these were only weakly related to the action of neurons on the cursor (uniform learning model; monkey D: R = 0.15; monkey R: R = 0.12; Fig. 1B). However, when tuning changes were rotated into the naturalistic PC space, map-specific learning was greater along the lower components, with the first PC in both animals accounting for the largest tuning change (Fig. 1C). Therefore we fit a model in which tuning changes along each PC decreased exponentially with increasing component number (Eq. 3), resulting in robust improvements to the prediction of individual tuning changes (constrained learning model; monkey D: R: R = 0.26; monkey R = 0.18; Fig. 1D). Since this new model included an additional free parameter, the decay constant N_c, we compared the predictions based on naturalistic PCs against the same model applied to random rotations of the neural space. The model performed significantly better when constrained to naturalistic PCs versus random rotations (monkey D: P = 0.008; monkey R: P = 0.04).

4. Discussion

Successful BCI performance requires searching for control solutions within a high-dimensional neural space. Constrained learning likely arises from biased exploration along particular dimensions of the space. These dimensions may reflect neural ‘priors’ appropriate for natural behaviors that are co-opted for BCI control. We have shown that principal component analysis of activity patterns recorded during natural movement provides one method to estimate constraints on learning and thereby predict subsequent tuning changes. This or more sophisticated techniques may in future allow decoders to be tailored to constraints on cortical activity such that learning over multiple sessions progresses along dimensions that are optimal for BCI control.

Acknowledgements

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The Effect of Real-Time Positive and Negative Feedback on Motor Imagery Performance

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Abstract. Brain-computer interfaces (BCI) are tools that interpret neural signals and translate them into actionable commands. These systems provide real-time control, and thus real-time performance feedback to the user. Here we investigate the effect of positive and negative feedback, uncorrelated with user motor imagery, on the ability to control an EEG-based BCI. We find that when subjects are presented with real-time positive visual feedback, their EEG signal is more easily classifiable than when they are presented negative feedback. This effect also demonstrates a significant correlation with success gradient; the more perceived success, the more discernible the signal.

Keywords: EEG, motor imagery, visual feedback, real-time, error potential

1. Introduction

Brain-computer interface (BCI) systems collect and interpret neural signals to provide direct input to a user interface, typically bypassing the peripheral nervous system. Here, we deal with electroencephalography (EEG)-driven BCI systems controlled via motor imagery, specifically right hand versus left hand movement.

We are interested in whether perceived performance has an observable effect on the control signal generated by the subject. Previous studies have demonstrated that negative feedback can generate the feeling of loss of control, associated with global desynchronization [McFarland et al., 1998]. However, another study has demonstrated that presenting subjects with negative feedback following periods of motor imagery (uncorrelated with actual performance) can actually improve the asymmetry of mu-rhythm between hemispheres during motor imagery (a common marker of successful motor imagery performance). However, this did not result in statistically significant differences in single-trial classification [Gonzalez-Franco et al., 2011].

Here we investigate the effect of real-time positive and negative feedback uncorrelated with user motor imagery performance. Real-time feedback is provided throughout the trial (concurrent with task performance), and thus provides the subject constant, updated feedback during the task.

2. Material and Methods

We collected data from seven right-handed subjects (5 female, mean age = 24). All subjects were led to believe they were controlling a real BCI while watching a pre-determined visual stimulus. The presented stimulus consisted of a cursor moving in discrete steps to simulate a typical BCI paradigm. Subjects were instructed to attempt to use right- and left-hand kinesthetic motor imagery to move the cursor either right or left, respectively, with the goal of reaching a target (located at either the left or right extremes of the screen). Each experiment consists of 200 trials split into 10 blocks of 20 trials each. Each block had a set 'success rate' that determined the proportion of trials that ended on the same side as the target. This value changed randomly from block to block.

Data were recorded using a 64-channel BioSemi ActiveTwo system with a sampling frequency of 512 Hz, bilaterally referenced to the mastoids. In addition, EOG activity was recorded at the outer canthus and below the right eye in order to monitor eye movement. Collected data were visually inspected for excess movement artifacts, and trials with excess movement artifacts were removed. Infomax Independent Component Analysis (ICA) was also used to reject data artifacts associated with muscle movements (as determined from scalp maps and spectral patterns).

Motor imagery classification (right vs left) was performed on 600 ms chunks of data, spanning the entire length of time the cursor was in movement. Feature extraction was conducted first by band-pass filtering (with a FIR filter) the data from 7–30 Hz, then using the logarithmic power of data filtered through 3 common spatial patterns (CSP) for each class (total 6) [Müller-Gerking et al., 1999] to provide the feature set for the classifier, linear discriminant analysis (LDA). Classifier performance was validated using complete 10-fold cross validation (with a separate CSPs and a separate classifier generated for each fold), and classification error rate was calculated based on the number of correct versus incorrect classifications for each trial.

3. Results

Instead of carrying out classification on all trials available, for this study individual classifiers were trained for each block of 20 trials. Classification errors within blocks are compared with the pre-determined visually presented success rate of each block, where we found a considerable level of correlation between the two measures as shown in Table 1. Correlation coefficients (calculated using the Pearson product-moment correlation coefficient) for 6 of 7 subjects demonstrate positive correlation between block success and classification rate. This correlation could indicate that apparent subject performance has some effect on actual subject performance, regardless of its dependence.

Table 1: *Correlation between the classification error and failure rate within blocks.*

	S1	S2	S3	S4	S5	S6	S7
Correlation	0.1224	-0.1401	0.3363	0.3170	0.4791	0.4586	0.3178

3.1. Short-term effect of positive and negative feedback

In order to determine the effect of short-term effect of feedback on task performance, we analyzed the collected data using a paradigm where classification of each trial is based on the training from the previous 20 trials (using the same techniques and window size as above). This number of trials was chosen because it is the same as each block size. The classification rate of that trial was then averaged with the following four trials and correlated with the feedback success rate of the previous 20 trials. This analysis demonstrated a more global correlation with the feedback from the previous 20 trials than for block success rate. All subjects indicate a positive correlation between classification and feedback, indicating that feedback success rate is a predictive indicator of classification success.

Table 2: *Correlation between the mean classification error of five trials and failure rate of the previous 20 trials.*

	S1	S2	S3	S4	S5	S6	S7
Correlation	0.2347	0.1561	0.0817	0.3050	0.2022	0.3949	0.5459

3.2. Spectral analysis

We also looked at the difference in alpha and theta power during motor imagery for blocks with more successful (average $= 0.728$) and more unsuccessful (average $= 0.421$) visual feedback and found significant differences ($p < 0.05$) between reactions to cursor movements. Differences appear to be primarily in the frontal and parietal regions, which have been previously implicated in studies on positive and negative emotions [Papousek and Schulter, 2002; Hinrichs and Machleidt, 1992]. Specifically, we see lower right-lateralized alpha power during negative visual feedback for trials in blocks with negative feedback. This is in conjunction with higher parietal power in both alpha and theta frequency bands during periods of negative feedback.

4. Discussion

We have found that perceived subject performance has an effect on actual task performance. This appears to occur regardless of whether that feedback is grounded in actual performance. However, this effect seems to be predicated on feedback presented concurrently with motor imagery. This can provide a good basis for training a subject new to real-time BCIs, as it may be advantageous to present the subject with initial positive feedback in order to induce a positive mental state and generate a better, more detectable control signal.

In addition, given the characteristics of the detectable signal, we find further evidence for a "satisfaction" signal underlying the active motor imagery. This could create more of an interactive bidirectional control loop, possibly improving system performance as well as increasing the number of users who can successfully use a BCI.

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Proposing a Novel Feedback Provision Paradigm for Restorative Brain-Computer Interfaces

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Abstract. Restorative brain-computer interafces (BCIs) have been exploited by a number of BCI labs for the purpose of stroke rehabilitation. The results that are achieved with commonly used technology are rather promising, but inconsistent. In this abstract we propose a novel paradigm for restorative BCI designs, which is based on motor learning theory and the Hebbian learning rule. It is expected to enhance the degree of neuroplasticity in stroke patients.

Keywords: Restorative BCI, Feedback, Hebbian learning rule

1. Introduction

Stroke is a major cause of paralysis. In traditional stroke rehabilitation, repetitive rehearsal of motor actions is exploited with the aim that impaired neural paths become reorganized in the same way that they were established during early development of motor functions. This perspective is based on the activity-dependent plasticity concept [Koganemaru et al., 2010].

Considering the similarity between activity in the sensorimotor area of the human brain during motor imagery and that during motor execution, motor imagery has been suggested as an alternative modality for recovering impaired motor functions after stroke [de Vries et al., 2007]. There is some evidence that application of motor imagery in healthy subjects activates cortical excitability, which increases the amplitude of motor evoked potentials (MEP) in response to transcranial magnetic stimulation [Kasai et al., 1997]. This finding suggests that motor imagery can modulate corticospinal excitability in a similar manner to real motor practice.

However, motor imagery does not involve activation of target muscles and, as a result, does not result in any movement related sensory feedback. However, sensory feedback is critical for optimal motor learning and provides an important component for the modulation and fine-tuning of future planning of motor activities. Thus, in this paper we propose a novel method for providing sensory feedback during motor imagery in restorative BCI. In particular, we describe an approach for providing sensory feedback at a timing that will be optimal for practice-dependent learning based upon Hebbian learning rules. We anticipate that this approach will offer significantly improved therapeutic options for the rehabilitation of stroke patients.

2. Methods

A combination of proprioceptive and visual feedback is thought to be the optimum form of sensory feedback for motor functions [Ramos-Murguialday et al., 2012]. Even though there have been a number of trials providing such feedback for motor imagery based restorative BCI designs, there is no clear rationale provided for the latency used between motor imagery modulation and feedback provision [Ramos-Murguialday et al., 2012; Shindo et al., 2011].

There is evidence that the latency for the efferent route from the primary motor cortex (M1) to the contralateral median nerve is approximately 20 ms [Samii et al., 1998]. In addition, studies show that the required time for sensory feedback to travel from the median nerve to the contralateral M1 is approximately 25 ms [Stefan et al., 2000]. Thus the total time for a motor learning loop is thought to be around 45 ms. Presuming a critical role for the Hebbian learning rule, in practice-dependent motor learning, it is mandatory to provide sensory feedback during motor imagery based BCI training at an interval (i.e. 45 ms) similar to that of actual motor training.

2.1. Proposed design specifications

As the first 250-500 ms of motor imagery does not contain useful features regarding sensorimotor cortex activity [Pfurtscheller et al., 1999], the classification of EEG features is proposed to be carried out using windows of 750 ms length, which slide 20 ms at each classification update cycle. Thus the classifier update rate is defined to be 20 ms (in conformity with efferent latency from the M1 area to the median nerve). In the case of detection of the

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correct imagery by the classifier, stimulatory feedback must be provided. Therefore, a fast and real-time BCI system, with its total transfer time, signal processing and application delay as low as 20 ms is required.

We propose three channels of electroencephalogram (EEG) recordings to be used in this design to make classification update results available in the proposed short time frame.

Concerning the feedback modality, we propose visual and proprioceptive feedback through an orthosis such as the M-28 servomotor to flex 4 fingers of the subject for 1 degree every time that classifier detects the requested motor imagery based on the classification result, while having the subjects to look at their hand (to provide the complimentary visual feedback). A similar paradigm is described in [Ramos-Murguialday et al., 2012].

Regarding the trial duration, we propose to use 2 seconds of rest, followed by 1 second of preparation using showing a "+" sign on the monitor to the subject. Then by showing them an arrow pointing towards their target hand, we instruct them to perform the motor imagery task for 2 seconds.

As for the software platform, we propose BCI2000 to be used as our software platform for its fast and real time processing algorithms. For occurrence of Hebbian based plasticity it is crucial that patients keep imagining 4-finger flexion for a period of 2 seconds, continuously. Regarding the fast proposed update rate (20 ms), sampling frequency is defined to be 500 Hz so as to provide enough sampling data for signal processing.

3. Discussion

We propose a novel design for a restorative BCI system for stroke rehabilitation that its timing is similar to that of motor learning. Subjects are instructed to perform motor imagery and then every 20 ms, they are provided with a proprioceptive/visual feedback. The provided feedback is expected to reach the M1 area after 25 ms and, if the subject keeps modulation of motor imagery, at the time of feedback arrival in the M1 area, it is expected to strengthen the connection between S1 and M1. This may provide the basis for reorganization of neural networks involved in the task leading to improvements in performance. Fig. 1 demonstrates our proposed timing.

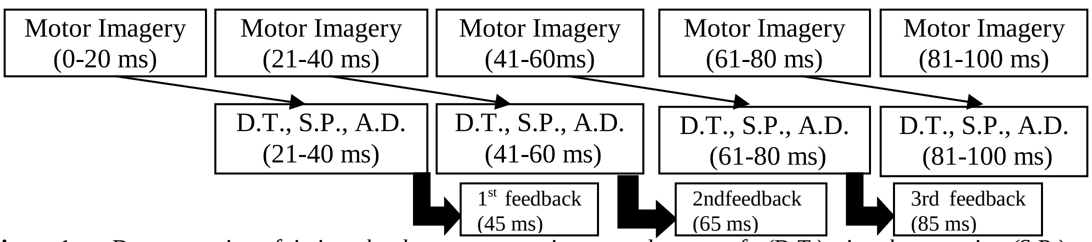

Figure 1. *Demonstration of timing plan between motor imagery, data transfer(D.T.), signal processing (S.P.), and application delay (A.D.) and their consequent feedback arrival time to M1. It is clear that 45 ms after each 20 ms portion of motor imagery, its correspondent feedback reaches M1. Thus assuming continuous modulation of motor imagery by subject, enhancement in plasticity is expected upon Hebbian learning rules.*

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Dynamic Stopping in a Calibration-less P300 Speller

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Abstract. Even though the P300 based speller has proved to be usable by real patients, it is not a user-friendly system. The necesarry calibration session and slow spelling make the system tedious. We present a machine learning approach to P300 spelling that enables us to remove the calibration session. We achieve this by a combination of unsupervised training, transfer learning across subjects and language models. On top of that, we can increase the spelling speed by incorporating a dynamic stopping approach. This yields a P300 speller that works instantly and with high accuracy and spelling speed, even for unseen subjects.

Keywords: Machine Learning, P300, Unsupervised Training, Transfer Learning, Language Model, Probabilistic Model

1. Introduction

The P300 speller was introduced in 1988 [Farwell et al., 1988] to allow locked in patients to communicate. A lot of effort has been put into reducing the calibration time and increasing the accuracy. Our approach goes one step further, we remove the calibration session altogether without accuracy penalty. We have shown that a P300 specific unsupervised algorithm [Kindermans et al., 2012a] can compete with state of the art supervised methods in off-line evaluation. But during on-line usage this method exhibits a warm-up period. The classifier is initialized randomly and therefore it makes mistakes during the initial learning phase. Enriching the classifier with transfer learning and language models suppresses this warm-up period completely [Kindermans et al., 2012b]. Transfer learning allows us to combine subject specific models into a general model, which will be adapted to the new user during on-line spelling. Language models improve the accuracy by exploiting prior knowledge about text.

In this work, we enhance the model with dynamic stopping. When the classifier is confident of its prediction, a dynamic stopping strategy stops the stimuli and outputs the symbol. This results in a drastic increase in spelling speed. We have shown that our approach is very effective in a supervised setting [Verschore et al., 2012]. But the usage of dynamic stopping in an unsupervised BCI speller is unprecedented.

2. Material and Methods

2.1. Unified Probabilistic Model with Dynamic Stopping

The basic model uses the following assumptions [Kindermans et al., 2012a]. Only the intensifications of the desired symbol will result in a P300 response. Furthermore, it assumes that the EEG can be projected into one dimension, where it is Gaussian with a class dependent mean (-1 or 1) and shared variance. This assumption is more general than the one made by LDA. The transfer learning part [Kindermans et al., 2012b] assumes that the vector used to project the EEG into a single dimension is similar across subjects. Therefore we encode that the weight vector for the new subject should be close to those of the other subjects. One should think of this as a special form of regularization. Finally, we add trigram letter models to improve spelling accuracy by using language statistics [Kindermans et al., 2012b]. The whole model is probabilistic and it uses Expectation Maximization style training, where the desired symbols are treated as latent and unknown variables.

This model is reliable from the start, even for unseen subjects. The drawback is that the spelling speed is limited by using a fixed number of epochs per symbol. We can mitigate this by exploiting the probabilistic nature of our classifier in a dynamic stopping strategy. We use the dynamic stopping approach from [Verschore et al., 2012]. When the confidence level of the classifier exceeds 0.99 then we predict the symbol and move onto the next one. We would like to stress that the combination of the unsupervised learning, transfer learning and language models allows us to combine dynamic stopping with the unsupervised speller. This is because spelling has to be reliable from the beginning for dynamic stopping to work.

2.3. Experimental Setup

All our experiments are performed on the Akimpech Dataset (akimpech.izt.uam.mx/p300db/). We used 10 channel EEG data from 22 different subjects with 15 epochs per symbol in the classic 6x6 speller with following parameters: 125 ms stimulus duration, 62.5 ms inter stimulus interval and 4 s pause between symbols.

We re-used the experimental setup from [Kindermans et al., 2012b]. We start by unsupervised training of 21 subject specific models. These are combined into a general model, which is used to initialize the subject specific model for the 22nd subject. Then for each symbol, we feed the classifier the EEG one epoch at a time. After each epoch, we make a prediction. We stop the stimuli and spell the symbol when the confidence level exceeds 0.99 or the maximum number of epochs is reached. We execute 3 EM iterations to adapt the classifier between symbols. This update takes no more than 1.1 s, thus it can be completed during the 4 s pause between symbols. Then we repeat this for the next character.

Table 1. *Results for the model with a fixed number of epochs and dynamic stopping. The model uses subject transfer, trigram letter models and unsupervised learning. DS indicatess dynamic stopping, the numbers indicate the epochs per symbol.*

Error Measure	*TA-5*	*TA-10*	*TA-15*	*TA-DS*
Accuracy [%]	87.0	95.0	97.9	95.3
Symbols Per Minute	2.9	2.0	1.5	4.1

3. Results and Discussion

In Table 1, we have given the results of the setup with transfer learning, a trigram language model for both with and without dynamic stopping. Results are averaged over 22 subjects. We have used the accuracy and the number of symbols per minute [Schreuder et al., 2011] as error measures. It is clear that with an average accuracy of 95.3% across 22 subjects the combination of dynamic stopping and unsupervised learning is very reliable. The average number of epochs is 4.77 and this results in 4.09 SPM. This is a more than 33% increase over the result obtained with 5 epochs. For comparison, a supervised version of this model with a trigram achieves 94.6% accuracy and 3.6 SPM with 5 epochs. On top of that, one should keep in mind that supervised training required 10 minutes of training data. In other words, supervised training wastes as much time in calibration as we need to spell over 40 symbols.

We have discussed the merits of this model in the standard speller, but we feel that it is much more than that. This model can form the basis of extensive research with respect to unsupervised P300 speller. We plan an on-line evaluation of this method. Additionally we will verify the compatibility of this method with other P300 paradigms (e.g. AMUSE [Schreuder et al., 2010]).

Acknowledgements

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Facilitating Effects of Transcranial Direct Current Stimulation on EEG-Based Motor Imagery BCI for Stroke Rehabilitation

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Abstract. This clinical trial investigates the facilitating effects of combining tDCS with EEG-based motor imagery Brain-Computer Interface (MI-BCI) robotic feedback compared to sham-tDCS for upper limb stroke rehabilitation. 32 hemiparetic stroke patients were recruited and screened for their ability to use EEG-based MI-BCI. Subsequently, 17 of these patients who passed screening and gave further consent were randomized to receive 20 minutes of tDCS or sham-tDCS prior to 10 sessions of 1-hour MI-BCI with robotic feedback for 2 weeks. The offline and online accuracies of detecting motor imagery from idle condition for the calibration session and the evaluation part of the 10 rehabiltiation sessions were respectively assessed. The results showed that there were no significant difference in the accuracies of the calibration session from both groups, but the online accuracies of the evaluation part of 10 rehabilitation sessions of the tDCS group were significantly higher than the sham-tDCS group. Hence the results suggest towards tDCS effect in modulating motor imagery in stroke.

Keywords: Motor Imagery, transcrianal direct current stimulation, stroke rehabilitation.

1. Introduction

Transcranial Direct Current Stimulation (tDCS) is a noninvasive, safe, and relatively painless brain stimulation technique for modulating cortical activity, and is also used to facilitate treatments of various neurologic disorders [Schlaug et al., 2008]. A study had shown that reducing excitability in the contra-lesional hemisphere by cathodal tDCS and enhancing excitability in the ipsi-lesional hemisphere by anodal tDCS improved motor performance in stroke [Fregni et al., 2005]. Another study had showed evidence that majority of stroke patients could operate EEG-based MI-BCI [Ang et al., 2011], and preliminary results had shown that EEG-based MI-BCI with robotic feedback rehabilitation is effective in restoring upper extremities motor function in stroke [Ang et al., 2010]. Hence the objective of this clinical trial is to investigate the facilitating effects of combining tDCS with EEG-based motor imagery Brain-Computer Interface (MI-BCI) robotic feedback compared to sham-tDCS for upper limb stroke rehabilitation.

2. Material and Methods

27 channels of EEG data were collected using Nuamps acquisition hardware sampled at 250 Hz from 32 sub acute and chronic patients recruited from a local hospital. Since not all stroke patients could operate EEG-based MI-BCI [Ang et al., 2011], the patients recruited first underwent a MI-BCI screening session. A total of 160 trials of EEG that randomly comprised 80 motor imagery of the stroke-affected upper limb and 80 idle condition were collected. The 160 trials of data were then analyzed offline using the FBCSP algorithm [Ang et al., 2012] without any removal of artifacts such as electrooculogram. 23 out of the 32 recruited patients passed the screening sessions and 17 gave consent for further study. Each subject enrolled for the further study was then randomized into either the tDCS ($n = 8$) or the sham-tDCS ($n = 9$) group. Subjects in both groups first underwent a calibration session whereby the stroke affected-limb of the subject was strapped to the MIT-Manus robot. 160 trials of EEG data that comprised 80 MI of stroke-affected upper limb and 80 idle condition were then collected similar to the screening session. Subsequently, the subjects in both groups underwent 10 rehabilitation sessions for 2 weeks, 5 times a week. Each rehabilitation session comprised of 20 minutes of tDCS or sham-tDCS, followed by 8 minutes of evaluation and 1 hour of therapy using EEG-based MI-BCI that comprised 160 MI of the stroke-affected upper limb with online robotic feedback. For subjects in the tDCS group, direct current was applied using a saline-soaked pair of surface

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sponge electrode from a battery-operated constant current stimulator with at an intensity of 1 mA with the anode placed over the M1 motor cortex of the ipsi-lesional hemisphere and the cathode placed over the contra-lesional M1. For subjects in the sham-tDCS group, the current was only applied for 30 s to give the sensation of the stimulation. During the evaluation part of each rehabilitation session, the online accuracy of detecting motor imagery was first evaluated by collecting 40 trials that comprised 20 MI of the stroke-affected upper limb and 20 idle condition. Online robotic feedback was provided during the evaluation part when MI was instructed and detected.

The accuracies of classifying motor imagery of the stroke-affected limb versus the idle condition of the tDCS group were then compared with the sham-tDCS group by performing session-to-session transfer using the FBCSP algorithm trained on first 80 trials to the subsequent 80 trials of the data collected from the calibration session. Subsequently, the accuracies were also compared by performing session-to-session transfer using the FBCSP algorithm trained on the calibration session to the evaluation part of the 10 rehabilitation sessions.

3. Results

The results on the screening session-to-calibration session transfer show that the average accuracy of classifying the motor imagery of the stroke-affected limb versus the idle condition from the tDCS group (74.22%) is higher than the sham-tDCS group (66.67%), but no significant difference is found ($p = 0.29$).

Fig. 1 shows the averaged online accuracies of detecting motor imagery versus the idle condition across the evaluation part of the 10 rehabilitation sessions. The results showed deviation of online accuracies across subjects and sessions, and the averaged accuracies of the subjects from the tDCS group across most of the 10 rehabilitation sessions are higher than the sham-tDCS group. The average accuracy of classifying the motor imagery of the stroke-affected limb versus the idle condition from the tDCS group (62.22%) is significantly higher than the sham-tDCS group (57.04%, $p = 0.0096$).

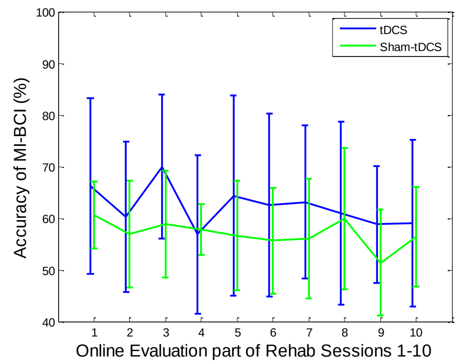

Figure 1. *Plot of the average accuracies of detecting motor imagery (MI) of the stroke-affected hand versus the idle condition for the tDCS and the sham-tDCS group during online evaluation part of the rehabilitation sessions using the FBCSP algorithm trained on data from the calibration session. The accuracies are computed online by performing session-to-session transfer using the FBCSP algorithm trained on data from the calibration session to the evaluation part of each of the 10 rehabilitation sessions. The horizontal axis represents the 10 rehabilitation sessions that the patients underwent.*

4. Discussion and Conclusion

The results showed no significant difference in the accuracies of the calibration session from both groups, but the online accuracies of the evaluation part of the 10 rehabilitation sessions of the tDCS group are significantly higher than the sham-tDCS group. This suggest towards tDCS effect in modulating motor imagery in stroke.

Acknowledgements

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Perceptual Learning via Decoded-EEG Neurofeedback

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Abstract. An experiment was conducted to determine whether decoding auditory evoked potentials during passive listening and providing the classifier output as a neurofeedback signal leads to the enhancement of auditory perceptual discrimination and/or brain responses related to auditory perception. Results indicate an enhancement of both behavioral discrimination and brain responses to frequency stimuli across four days of measurements.

Keywords: EEG, Mismatch Negativity, P3a, Neurofeedback, Perceptual Learning, Brain-Computer Interface

1. Introduction

BCIs are most commonly developed for use as communication devices for patients with motor impairments [van Gerven et al., 2009]. Recently, it has been shown that the same multivariate methods underlying many BCIs can be used to provide novel forms of fMRI-based neurofeedback (NFB) that induce visual perceptual learning in healthy users [Shibata et al., 2011].

An experiment was conducted to determine whether a similar approach is possible using NFB based on decoded auditory evoked potentials (AEPs) measured using EEG. Stimulus sequences containing high-probability ‘standard’ trials and low-probability ‘deviant’ trials were used. In a passive listening setting, deviant trials in these sequences are known to elicit both enhanced P3a responses and the mismatch negativity (MMN). We hypothesized that providing NFB on the differing pattern of AEPs to standards and deviants would lead to a relative enhancement of these components, along with an induced perceptual learning effect that would improve behavioral discrimination.

2. Material and Methods

2.1. Participants

Six participants completed four days of testing. All participants reported normal hearing.

2.2. Stimuli

Harmonic sinusoidal tones were used for the behavioral, offline EEG measurement and NFB portions of the experiment. During both the offline and NFB portions, so-called ‘optimal’ MMN sequences containing 5 types of deviant stimuli were utilized, as described in [Naatanen et al., 2004]. Two of these deviant stimuli served as NFB targets: duration (25 ms vs. 75 ms standard) and frequency (550 Hz vs. 500 Hz standard). Half of the participants’ NFB was based on single-trial AEPs measured for duration deviants and the standard stimuli immediately preceding them, while the other half received NFB on frequency deviants and the standard stimuli preceding them.

2.2. Procedure

At the beginning of the first day, participants completed measurements of their behavioral discrimination thresholds for both frequency and duration using a 2AFC staircase procedure. For the first three days, participants completed offline EEG measurements while watching silent films, followed by a NFB session. On the fourth day, participants completed a NFB session followed by the same behavioral measurements as on the first day.

2.4. Classification analysis and NFB parameters

On the first three days, individual data collected during the initial EEG measurements were used to train two quadratically regularized linear logistic regression classifiers. The fourth day made use of classifiers trained on the previous three days’ worth of individual data. A first classifier was trained on a binary problem consisting all standard trials vs. all deviant trials, and was applied during NFB sessions to the standard trials preceding the target deviants. A second binary classifier was trained on trials for the NFB target (frequency or duration deviant) vs. an equal number of trials in which the same stimulus was measured in an isochronous sequence. During NFB, this classifier was applied to the target deviant trials. The outputs of the two classifiers for the previous five trials were combined into a single value during the NFB sessions to control the amount of blurriness of the films viewed by participants during the NFB sessions.

3. Results

3.1. Behavioral

Behavioral results can be seen in Fig. 1a. Thresholds for frequency discrimination in the post-test were significantly lower than in the pre-test ($p < .01$), with 5 out of 6 participants showing reduced thresholds in the post-test. No effects were observed for duration thresholds, nor were any training group effects observed.

3.2. ERP measurements

ERP plots across the 4 days can be seen in Fig. 1b. For each day and measurement (offline vs. NFB), the mean amplitude of the MMN and P3a components in the individual grand average deviant – standard difference waveforms were computed in a 50 ms window around their peaks using the mean of nine fronto-central electrode locations where AEPs tend to be maximal. These results are plotted in Fig. 1c. For the P3a component, a significant effect of deviant type ($p < .05$) and an interaction of deviant type with measurement day ($p < .001$) were found, with higher P3a amplitudes for 5 out of 6 participants on the final two days (relative to the first day). No significant effects were found for the MMN component.

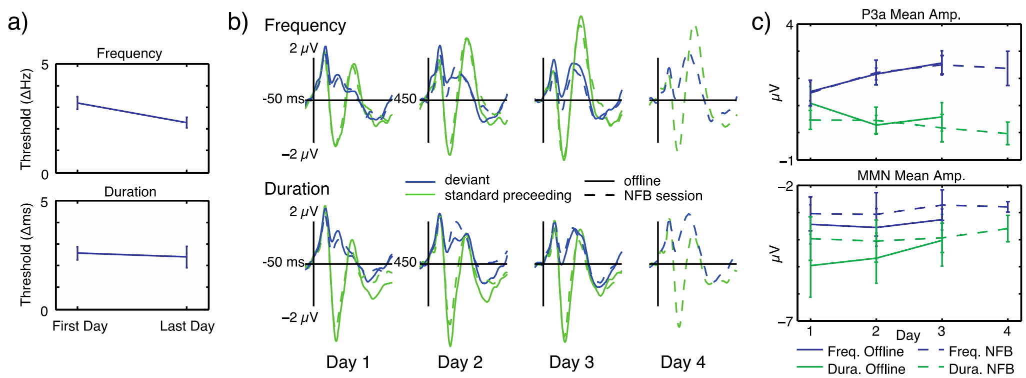

Figure 1. *Behavioral and ERP results. a) Frequency and duration discrimination thresholds on the first and last days for all participants. b) Grand-average ERPs at fronto-central electrode locations across days and deviant types. c) Mean amplitudes of MMN and P3a components across days, session and deviant types.*

4. Discussion

Regardless of which deviant was used to provide NFB to participants, a general enhancement of P3a responses to frequency deviants was observed along with an improvement in frequency discrimination performance. One possible explanation is that effortful control of the NFB mechanism leads to top-down modulation of perceptual processes related to the perception of deviant stimuli, and that this modulation is most apparent in responses to frequency deviants. While additional research is needed to clarify these effects, the present results suggest the potential for novel BCI applications for auditory perceptual learning in healthy users.

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Simultaneous BCI Operation and Electrophysiological Assessment to Identify Brain Signal Features for BCI-Based Rehabilitation

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Abstract. Brain-computer interface (BCIs) for motor rehabilitation might benefit from using brain signals which are tightly coupled to motor system function. We developed an open-source application to perform neurophysiological measurements during BCI use. We used this application to identify brain-signal features that correlated with corticospinal tract excitability independent of their task-related changes. Brain signal features that associate with desirable motor function are good candidates for use in BCI rehabilitation because the plasticity induced by operant conditioning of these features might also support improved motor function. Studies to investigate neurophysiological changes accompanying BCI training of these features are underway.

Keywords: Rehabilitation, plasticity, EEG, TMS, SMR

1. Introduction

One possible mechanism of BCI-based rehabilitation is that rewarding subjects to generate specific brain signals induces structural and functional plasticity in the CNS that facilitates the generation of the rewarded brain signals, and this plasticity also supports improved function [Daly and Sitaram, 2012]. Brain signals that, when rewarded, are likely to induce adaptive plasticity might be identifiable by their association with desirable motor behavior. We developed an open-source application to facilitate electrophysiological assessment during BCI use. In this report we describe the application and its use in identifying brain signals that correlate with corticospinal tract (CST) excitability indexed by the transcranial magnetic stimulation (TMS) induced motor-evoked potentials (MEP).

2. Material and Methods

We developed our experimental software using the BCI2000 platform [Schalk et al., 2004] and its BCPy2000 framework extension [Hill et al., 2007]. Within this environment, we created a flexible application for performing electrophysiological experiments capable of providing feedback about electrophysiological signals, gating task progression based on the properties of these signals, and triggering peripheral or central neural stimulation during the task. Feedback can be driven by electroencephalogram (EEG) activity, electromyogram (EMG) activity, or previously recorded data (i.e., sham). Feedback is provided as the position of a visual stimulus, the frequency of an auditory tone, or the intensity of muscle stimulation. The neural stimulation can be delivered via electrodes over the peripheral nerves or TMS over the brain and the stimulation intensity can be controlled manually or automatically. The stimulus-evoked response (e.g., M-wave or H-reflex for nerve stimulation, MEP for TMS) and its amplitude – or its residual amplitude after subtracting the modeled expected amplitude – can be displayed on the screen or used to control the stimulator intensity.

Seven (3 female) healthy right-handed individuals participated in this study. We recorded 31-channel EEG and left and right extensor dorsii communis (EDC) EMG low-pass filtered at 2 kHz and digitized at 5 kHz (BrainProducts). We did not use high-pass or notch filters so as to mitigate the size of the recorded TMS artifact. Participants were cued to perform right-hand finger extension or imagery upon cue offset. Visual feedback of EMG activation was provided during finger extension trials and participants were instructed to maintain EMG between 5-15% of maximum voluntary isometric contraction. Visual feedback of normalized μ-rhythm (typically 8-12 Hz) power from the C3 surface Laplacian derived signal was provided during 50% of imagery trials and participants were instructed to decrease power as much as possible. Four to six seconds after cue offset, TMS was delivered over the motor cortical representation of the right EDC at 120% resting motor threshold. Each participant performed 150 trials: 50 each of execution (EXEC), imagery with feedback (IMFB), and imagery without feedback (IMAG). Data were analyzed offline with EEGLAB [Delorme and Makeig, 2004].

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3. Results

We identified two independent component clusters relevant to the task: the first cluster's dipoles localized to left medial frontal cortex (L_MF) and the second cluster's dipoles localized to left parietal area (L_Par). Activations from L_MF at cue-offset were greater during EXEC than the other tasks. Both cluster activations exhibited event-related desynchronization (ERD) in both μ- (8-12 Hz) and β- (17-25 Hz) bands. μ- and β-ERD persisted longer during IMFB trials than during IMAG trials.

MEPs were larger during IMFB trials than during IMAG trials. MEP size correlated positively with normalized upper-β power during IMFB trials (using subject-specific frequency-bands, $p < 0.001$). No other consistent correlations between spectral power and MEP size were observed.

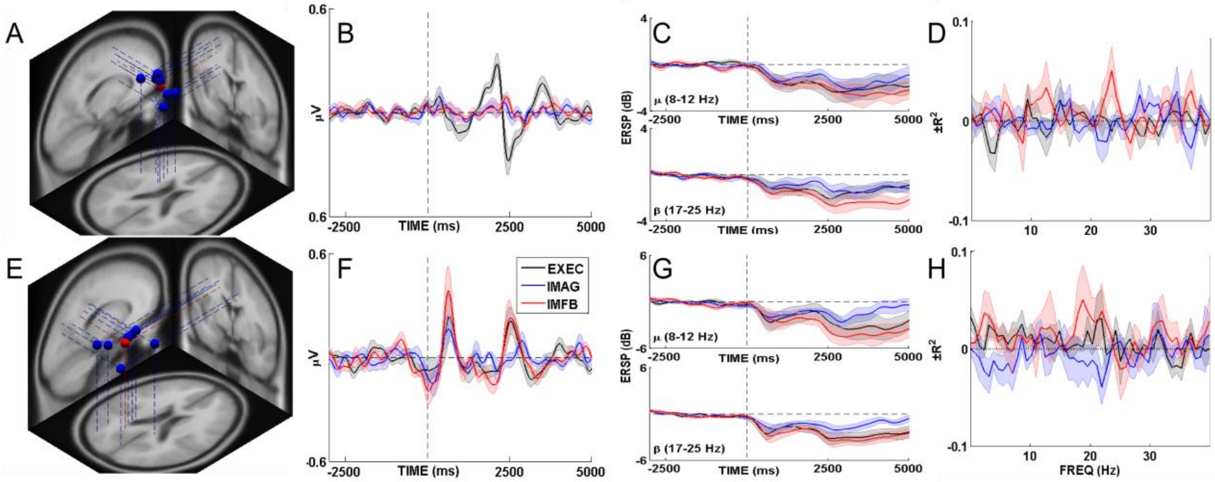

Figure 1. *Dipoles (A,E), event-related potentials (B,F), μ- and β-ERD (C,G), and signed spectral correlations with MEP size (D, H) for clusters L_MF (A-D) and L_Par (E-H).Values were calculated separately for motor execution (black), imagery without feedback (blue), and imagery with feedback (red). Shading indicates ± standard error.*

4. Discussion

We developed and made-available a flexible application for performing various neurophysiological measurements during BCI use. In this preliminary study, we used this software to identify brain signal features that may be suitable for BCI-based rehabilitation. Specifically, signal features that localized to contralateral sensorimotor cortices exhibited typical μ- and β-band ERD, but only those which localized to L_MF activated specifically during motor execution and only L_MF upper-β power correlated significantly with CST excitability.

Both μ- and β-band ERD, at both tested locations, persisted longer during IMFB trials than IMAG trials. Since TMS was delivered at the end of a trial, μ and β power was greater in the interval preceding IMAG MEPs than the interval preceding IMFB MEPs. Additionally, IMAG MEPs were smaller than IMFB MEPs. Thus, MEP size appears to correlate negatively with μ and β power when combining IMAG and IMFB trials, opposite to the MEP correlation with SMA β power observed during IMFB-only trials.

We interpret these conflicting results as follows: topographically diffuse μ- and β-ERD indicates engagement in a motor task and this engagement is also associated with increased CST activation, but within-task CST excitability is indicated by increased synchronization at upper-β in medial frontal cortex. It is as yet unclear whether adaptive plasticity would be better facilitated by BCI training with features that indicate motor task engagement or by BCI training with features that indicate within-task excitability. Studies investigating changes in motor physiology accompanying BCI training using both types of features are underway.

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Investigation of the Utility of Mind-Body Awareness Training in the Early Learning of a 1D Sensorimotor Rhythm Based Brain-Computer Interface

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Abstract. In the present study we present the initial BCI training period of a cohort of 5 subjects with regular exposure to yoga, meditation, or a combination of both practices. The investigation of these mind-body awareness training practices may provide insight into valuable strategies for reducing barriers to BCI fluency that limit the use of these systems by some individuals. The investigated subjects showed rapid training times, and were able to achieve competence in the use of two differentiable control signals, left hand vs right hand and both hands vs rest. Subjects were able to achieve ≥ 80% accuracies in these traditional BCI cursor tasks using standard electrode configurations and with as little as 33 minutes of training time.

Keywords: EEG, Motor Imagery, Yoga, Meditation, Training, Rehabilitation

1. Introduction

Mind-body awareness and the capacity to focus for a prolonged period of time are intuitively important skills that may help to bridge the gap between users who struggle with brain-computer interface control and those to whom it comes naturally. Here we investigate if experience with yoga and/or meditation, examples of formalized mind-body awareness training (MBAT) can accelerate the initial learning of a 1D sensorimotor rhythm (SMR) based BCI. Five practitioners of MBAT were taught to control the movement of a cursor in the left-right and up-down dimensions using SMR and were seen to adopt these systems fluently with very little training when compared to the published literature.

2. Materials and Methods

Five subjects (ages 22–30, 1 male, 4 females) attended three sessions of ten 3-minute experimental trials. Subjects were recruited based on their regular exposure yoga, meditation or a combination of both, having practiced regularly for at least a year. Task competency required four consecutive 3-minute trials with accuracies ≥ 80% or an overall session accuracy ≥ 80%. Subjects imagined each hand to move the cursor left or right, then progressed to an up-down control task, imagining both hands together vs. a volitional rest state. A 64-channel Neuroscan EEG cap using the international 10-20 system was used to acquire the EEG signal. The amplitudes of the 12 Hz components of the C3 and C4 electrodes were used to control the cursor. C3 minus C4 produced the left-right control signal, while C3 plus C4 controlled up-down.

3. Results

The number of 3-minute trials that each subject needed to achieve competency in both tasks is reported in Fig. 1. The subjects required an average of 16.25 3-minute trials to pass the established criteria for competency in both tasks. The theoretical minimum training time to pass the competency criteria in each individual task was 12 minutes (achieved by one of the experimental subjects for right-left and by a separate subject for up-down). The minimum time that a subject required to achieve competence in both tasks was 33 minutes of training.

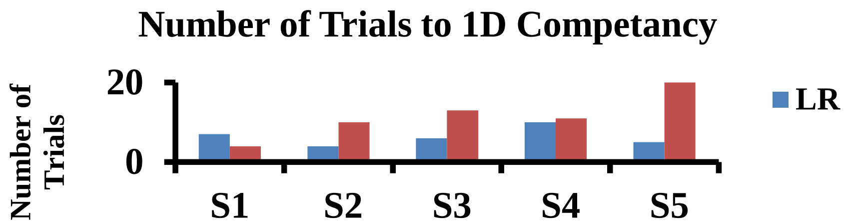

Figure 1. *The number of 3-minute trials for each subject to pass the competency criteria for LR and UD control are reported.*

4. Discussion

Subjects identified the practices of meditation, Yoga-nidra, and Reiki as most helpful to BCI training. These sub-disciplines are aimed at learning to direct focused attention to specific regions of the body. Table 1 provides some of the published literature on SMR BCI training in the general population. In comparison, the dramatic drop in training time, and the ability of all the presented MBAT subjects to achieve high accuracy suggests that MBAT may promote the self-awareness needed to intentionally modulate SMR activity before BCI training has begun. There is an exciting potential to further refine these practices to provide accelerated training times, and enhanced control of SMR modulation for paralyzed patient populations.

Table 1. *1D classification accuracies and training times for contemporary publications in 1D SMR BCI*

Journal, Author, Year	*Number of Subjects*	*1D Accuracies*	*Total Training Time*
Royer, J. Neural Eng., 2011	20 healthy	60-80% (group mean range)	240 minutes
Pichiorri, J. Neural Eng., 2011	10 healthy	75-96% (subject range)	240-320 minutes
Neuper, Clinical Neurophysiology, 2009	20 healthy	77% (group mean)	~75 minutes
McFarland, Clinical Neurophysiology, 2005	5 healthy -2 SCI	48-100% (subject range)	240 minutes

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Training Effects of Multiple Auditory BCI Sessions

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Abstract. Most P300 brain-computer interfaces (BCIs) rely on visual stimulation. This is problematic for patients who have lost gaze control. One alternative P300 BCI design is to use auditory stimuli. We investigated the possibility of improving spelling accuracy by performing multiple sessions per participant. Online accuracy increased from 4 bits/min in the first session to between 5.5 to 5.9 bits/min in the following sessions.

Keywords: EEG, auditory P300, spelling, training effects, spatial cues

1. Introduction

Visual P300 brain-computer interfaces (BCIs) provide a robust and fast communication method using electroencephalography (EEG) signals [Farwell and Donchin, 1988; Kaufmann et al., 2012]. Due to the fact that many severely motor impaired people also experience loss of gaze control, P300 BCIs with non-visual stimuli have to be explored. Among others, auditory stimuli are a promising alternative [Furdea et al., 2009; Schreuder et al., 2010; Käthner et al., 2012]. We investigated possible training effects with a sample of healthy participants when using an auditory P300 BCI for spelling.

2. Material and Methods

2.1. Participants

Eight healthy participants took part in the study. All participants performed five sessions which were between two and five days apart.

2.2. Data acquisition

The EEG was recorded with 16 active Ag/AgCl electrodes. These were located at positions F3, Fz, F4, T7, C3, Cz, C4, T8, Cp3, Cp4, P3, Pz, P4, PO7, PO8, and Oz. The signal was sampled with 256 Hz and filtered between 0.1 and 30 Hz. Stimulus presentation and data recording was performed using the BCI2000 framework [Schalk et al., 2004].

2.3. Auditory speller

A matrix with 25 elements was used (all letters of the latin alphabet except Z). Each column and row was coded with a specific auditory stimulus (five animal sounds (duck, bird, frog, seagull, and pigeon) with an additional spatial component ranging from left, diagonal left, center, diagonal right to right). Each sound had a duration of 187.5 ms followed by an inter-stimulus interval of 250 ms.

The classifier was trained anew for each session using three runs with ten stimulus repetitions in which the participant had to select the symbols from the diagonal of the matrix ("AGSMY"). These runs were also used to set the number of repetitions for the following copy spelling task to the number of sequences needed to reach 70 % accuracy plus two sequences. The calibration was followed by nine copy spelling runs in which a total of 48 selections had to be made. Stepwise linear discriminant analysis (SWLDA) was used for online classification.

3. Results

The eight participants achieved the following average information transfer rates (ITRs) in sessions one to five: 3.95, 5.92, 5.68, 5.52 and 5.58 bits/min (see Figure 1). The average ITR across all sessions and participants was 5.33 bits/min. The highest ITR achieved was 9.76 bits/min and the lowest 1.2 bits/min. The average letter selection accuracy across all participants and sessions was 79 %. Note that the accuracies are not comparable between participants due to a varying number of stimulus repetitions (on average 5.35).

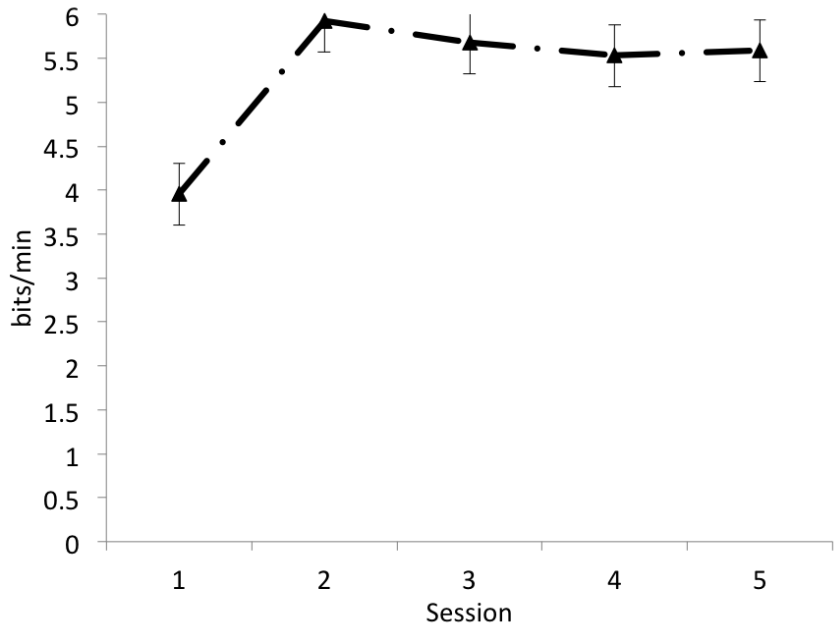

Figure 1: *The figure shows the information transfer rate achieved on average by all participants per session.*

4. Discussion

Online ITRs of on average 5.33 bits/min and letter selection accuracies of 79 % are sufficient to operate an online spelling system. In particular, considering that the number of stimulus repetitions was set individually for each participate to minimize selection accuracy saturation. By performing multiple sessions, thus giving the user an opportunity to adapt to the system, and using natural sounds as stimuli, the ITR increased from 2.76 bits/min in [Käthner et al., 2012] to 5.33 bits/min. We assume that the training effect is due to an increased ability of the participant to focus on the task of attending the target stimuli. It seems that the training effects using an auditory P300 BCI are much larger than during usage of a visual P300 BCI. This should be taken into account when designing and testing new auditory P300 BCI paradigms for and with severely motor impaired people.

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Motivation and SMR-BCI: Fear of Failure Affects BCI Performance

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Abstract. Components of motivation have been shown to affect performance when using a Brain-Computer Interface (BCI) based on sensorimotor rhythms (SMR). However, usually reported results are based on relatively small sample sizes of healthy adults. Therefore, neither conclusions about motivation effects on BCI performance in larger samples nor in clinical samples can be drawn. In this study we correlated the subjective ratings of motivation of *N* = 51 healthy participants and *N* = 11 stroke patients with their SMR BCI performance and found that incompetence fear or fear of failure was significantly related to lower performance.

Keywords: Motivation, Brain-Computer Interface (BCI), SMR

1. Introduction

Psychological variables, such as motivation do have an effect on BCI performance as shown by Nijboer and colleagues (2008) who found the motivation components *incompetence fear* and *mastery confidence* to be related to BCI performance in a relatively small sample of 16 healthy participants when using an auditory SMR BCI. We were interested in (1) whether we could replicate this result in a larger sample and (2) whether it transfers to motor-impaired end-users as suggested by Nijboer and colleagues (2010). To address these questions, we quantitatively assessed components of motivation in healthy subjects and in a sample of stroke patients before BCI training.

2. Material and Methods

We included *N* = 51 healthy participants, all naïve to BCI training prior to this study. Mean age was 24.29 (*SD* = 3.81, range 18 to 36, *N* = 24 participants were female). The clinical sample consisted of *N*=11 stroke patients with mean age of 60.00 (*SD* = 9.47, range 41 to 75, *N* = 4 participants were female, *N* = 5 with left hemispheric and *N* = 6 with right hemispheric lesion).

For motivation measurement prior to the training sessions, the Questionnaire for Current Motivation in BCI was used, which assesses the four components *mastery confidence*, *incompetence fear*, *challenge* and *interest* [Nijboer et al, 2008]. Once before every session, we also measured motivation on a visual analogue scale (VAS) ranging from 0 to 10 (0 = 'extremely unmotivated' to 10 = 'extremely motivated'). For using the SMR BCI, healthy participants were instructed to imagine movement with either the left or the right hand. Modulation of SMR was either fed back online by means of cursor movement or knowledge of result was provided at the end of a trial. In stroke patient motor imagery was contrasted against a rest condition. While for the healthy participants our results are based on one session including 300 trials of 4 seconds duration each, stroke patients finalized between 5 and 12 sessions each including between 80 and 120 trials of 4 seconds duration.

3. Results

Overall, participants' average accuracy was 71.06% (*SD* = 14.44, range: 46.0%-95.0%) in their first session. The R^2 values were on average *M* = .25 (*SD* = .21, range: .01-.70). Spearman's rho revealed a significant positive correlation between accuracy and *interest* (ρ = .53, $p < .001$, see Fig. 1) and a negative correlation between accuracy and *incompetence fear* (ρ = -.43, $p < .01$, see Fig. 1). The QCM-BCI values were measured once prior to testing.

Overall, patients' average accuracy ranged between 77.90% (*SD* = 20.32 in *N* = 11 patients) in session 1 and 52.60% (*SD* = 27.08 in *N* = 3 patients) in session 8. Spearman's rho revealed a significant positive correlation between *mastery confidence* and performance (ρ = .80, $p < .05$) and between *challenge* and performance (ρ = .83, $p < .05$) for the whole patient sample in session 8.

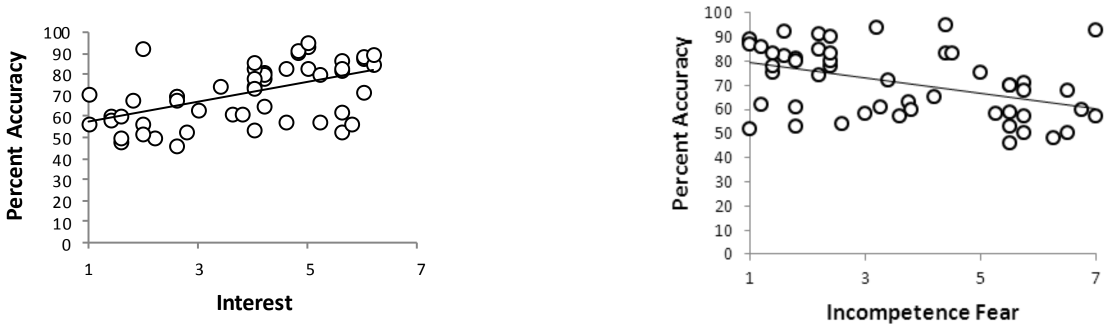

Figure 1. *The correlations between QCM-BCI scales Interest and Incompetence Fear and percent accuracy in healthy subjects.*

When investigating individual patients, we found significant correlations between motivation components and BCI performance in three patients. In patient A we found a negative correlation between *incompetence fear* and performance (ρ = -.61, p < .05, see Fig. 2) and in patient B a significant positive correlation between *interest* and performance (ρ = .62, p < .05). For patient C we found significant positive correlations between the VAS motivation values and performance (ρ = .73, p < .01, see Fig. 2), *mastery confidence* and performance (ρ = .70, p < .05) as well as a negative correlation between *incompetence fear* and performance (ρ = -.68, p < .05). For patient D we found a significant positive correlation between *incompetence fear* and performance (ρ = .68, p < .05, see Fig. 2).

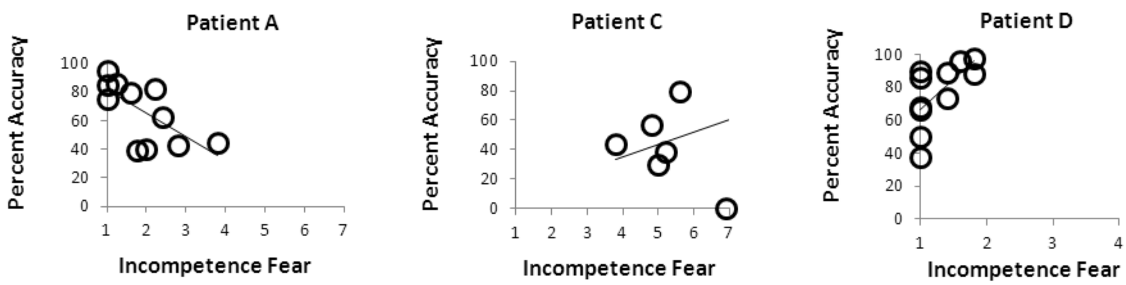

Figure 2. *The correlations between QCM-BCI motivation components and VAS motivation values with percent accuracy for three stroke patients. Every circle indicates one session's accuracy and incompetence fear value.*

4. Discussion

In a sample of healthy participants and a sample of stroke patients, we could successfully replicate the relation between motivation components and BCI performance. Several components of motivation and also the VAS motivation were related to BCI performance. The most consistent result was that *incompetence fear* affected performance in healthy participants and stroke patients alike. To estimate relevance of this effect of motivation on SMR-BCI performance, the clinical sample size will be increased. We recommend monitoring of motivation when applying BCIs in patients, because it could contribute to inter- and intra-individual fluctuations of performance.

Acknowledgements

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EEG-Predictors of Covert Vigilant Attention

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Abstract. A brain computer interface (BCI)-based cognitive state monitoring system able to determine the current, and predict the near-future development of the brain's attentional processes would bear great theoretical and practical implications. The present study investigated the evolution of neurophysiological signals preceding an omission error during a covert sustained attention task. The findings confirm the presence of characteristic EEG signals anteceding inadequate levels of attention by up to 10 s.

Keywords: EEG, BCI, vigilant attention, cognitive state monitoring, covert attention, P300, N200, α-rythm

1. Introduction

Many work environments, especially in safety critical environments require the continuous and consistent attention of a human operator. The monotonous nature of these tasks often leads to momentary inattention which can result in errors and have serious consequences. Brain computer interfaces (BCI) offer a powerful insight into the mental states of users and an additional channel of information, which can be exploited by devices able to dynamically adapt to the user's mood or state [Blankertz et al., 2010]. Several studies have already demonstrated that brain activity carries information presaging the outcome of behavioral responses [Eichele et al., 2010; O'Connell et al., 2009] in attention task using stimuli in the foveal field. The present work aimed at obtaining analogous results in a covert vigilant attention task which more closely mimics a real-world environment where rare critical stimuli may appear on the periphery of the visual field.

2. Material and Methods

Twelve healthy subjects (4 female; 27.4 ± 2.9 years) volunteered for participation in this study. Participants performed a modified "Mackworth Clock test" [Mackworth, 1948], consisting in identifying and reacting to rare double jumps of a pointer that produces regular small jumps every second across dots arranged in a circle. The dots formed a circle with a diameter spanning 10° of the visual field around the center of the fixation cross. Participants were instructed to gaze at the cross in the center of the screen, keep track of the pointer using covert attention and to react as fast as possible to the rare double jumps by pressing a button. The task was designed to impose great strain on cognitive resources [Warm et al., 2008], especially endogenously directed attention, and was chosen to encourage attentional drifting. Participants completed four blocks à 15.5 min each with an average of one double jump every 10 s equating to a total of 360 double jumps over the course of the whole experiment. Neurophysiological data was gathered using surface EEG with 64 electrodes arranged according to the international 10/20 system.

3. Results

The average response time (RT) of the participants included in the analysis was 560 ± 166 ms with an overall accuracy of 65.5 ± 10%. Behavioral data revealed a strong decline in performance and a steady increase in reaction time over the course of each block. The blocks were divided into 5 bins of 3 min and 4.4 s each and two 4×5 repeated measure ANOVA were conducted on the dependent variables performance and RT. A highly significant time-on-task effect on performance, $F_{(4,\ 36)}$=14.483, $p < 0.001$, and RT were found, $F_{(4,\ 36)}$=3.458, p=0.017, confirming the efficacy of the paradigm in inducing a rapid decrease in vigilant attention.

The grand average ERP waveform and the contrast in P3 amplitude between hits and misses, expressed in terms of $sgn\ r^2$ (Fig. 1), show a gradual decline of the amplitude of P3 for trials preceding misses. First signs of the amplitudinal decline of P3 can be observed on the sixth trial preceding a miss. Examination of the N2 suggests an increase in amplitude for trials preceding hits. Moreover, a propensity towards an inadequate attentional cognitive state is also reflected in an increase of α activity over occipital central areas up to 10 trials before target onset. Linear regression analyses of peak amplitude differences between classes revealed a significant positive correlation for the P3 component over channel Cz and a significant negative correlation of α activity over channel POz.

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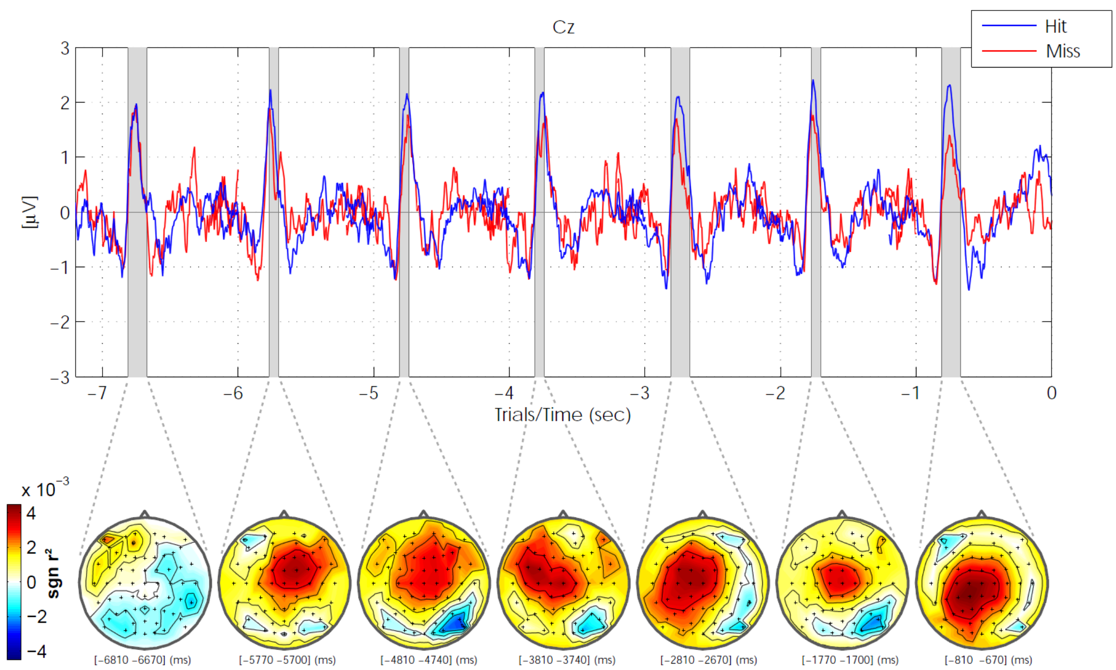

Figure 1. *Grand Average ERP waveform and associated sgn r² scalp topographies for the 6 trials preceding a hit or miss.The sgn r² scalp topographies show the contrast between the peak of the P3 of hit- and miss-preceding trials (marked in grey).*

4. Discussion

The results of this study confirm that neurophysiological signals harbor information pertaining to the subject's current attentional state. ERP features, especially the P3 component, and spectral features of the EEG data seem to possess predictive value up to ten trials before the occurrence of a critical stimulus. In contrast with Eichele et al.'s [Eichele et al., 2010] results, this study did not observe a gradual decline in N2 amplitude preceding errors or misses. This is most likely due to the fact that N2 predominantly reflects visual processing whereas P3 is related to cognitive processing. Therefore an attenuated N2 and a more discriminative P3 is to be expected in a covert attention paradigm. Our results clearly show a decrease in P3 amplitude over central areas and an increase of α activity over central occipital areas for trials preceding misses, corroborating O'Conell et al.'s [O'Connell et al., 2009] findings.

These results are of particular interest with regard to the fact that the P3 and spectral amplitude divergences between trials preceding misses and hits carry anticipatory information in a covert attention paradigm. This strengthens the theoretical feasibility of a BCI-based attention surveillance system in a visually complex environment (e.g. driving, security or medical screenings, cockpit monitoring etc.). Furthermore, the fact that the discussed ERP and spectral features are spatially consistent and confined could be exploited in the form of a reduced subset of electrodes sufficient to predict lapses of attention. Taken together, these findings encourage further investigation towards a BCI-based attention state monitoring system that would possibly prove beneficial to a wide range of work environments and human-machine interfaces. Future studies should investigate whether the propensity towards task disengagement can be detected on a single-trial basis.

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The Effect of Task Based Motivation on BCI Performance: a Preliminary Outlook

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Abstract. Brain-Computer Interface is an alternative method of communication. The present BCI operates via event-related potentials (ERPs) extracted from the electroencephalograph (EEG). Items (i.e., alphanumeric characters and keyboard commands) attended to by the subject should produce a P300 ERP; unattended items should not. Participants are assigned to either a Motivation condition or a Non-motivation condition. We hypothesized that performance on a copy spelling task will be affected by an individual's motivation, or drive, to perform well. Before the BCI task is introduced to the subjects in the motivation condition, they are read a paragraph describing the importance of the task. Subjects in the non-motivation condition are introduced to the BCI task and begin the experiment. Mean accuracy in the motivation group was 93%, significantly higher than accuracy in the non-motivation group, 84% ($t < .001$). These results show that motivation can be an important factor to successful BCI use. Motivation should be considered as a factor that will influence BCI performance in disabled populations because potential BCI users who are less motivated may negate trends in the performance of motivated subjects.

Keywords: EEG, P300, Motivation, Brain-Computer Interface, Event-Related Potential

1. Introduction

A brain-computer Interface (BCI) provides a method of non-muscular communication. The BCI described here uses event-related potentials (ERPs) of the electroencephalogram (EEG) to select items from an array of alphanumeric characters. The paradigm is based on the design first described by Farwell and Donchin, 1988. Subjects observe an array of alphanumeric characters. The items in the array flash in rapid succession, while the subject attends to the specific item they wish to select. Motivation has been shown to affect BCI performance in non-disabled subjects and subjects with amyotrophic lateral sclerosis [Kleih et al., 2010]. Here we present a novel motivation manipulation to further investigate the relationship between BCI performance and level of motivation. We hypothesized that those with higher task-based motivation (i.e., willingness to participate in a task [Appel and Gilabert, 2002]), would perform better on a copy spelling task, and that they would produce higher amplitude ERPs. Given the attentional demands of the BCI, motivation to perform well can have a considerable impact on performance, especially in an ALS population because they often tire quickly and have limited time and access to BCI use.

2. Materials and Methods

Subjects ($n = 14$; 5 male) from the ETSU participant pool were enrolled in the study. BCI2000 was used for data collection and stimulus presentation. The study was approved by the East Tennessee State University Institutional Review Board.

EEG was recorded with a 32-channel tin electrode cap (Electro-Cap International, Inc.). All channels were referenced to the right mastoid and grounded to the left mastoid. Impedance was reduced to below 10.0 kOhm before recording. Two Guger Technologies g.USBamps were used to record EEG data, which were digitized at 256 Hz, and bandpass filtered from 0.5 to 30 Hz. Stepwise linear discriminant analysis was used to classify ERP responses. Only electrodes Fz, Cz, P3, Pz, P4, PO7, PO8, and Oz were used for online BCI operation [Krusienski et al., 2006].

Subjects were randomly placed into the motivation condition or the non-motivation condition. Subjects in the motivation condition ($n = 6$) were read a paragraph stating the importance of the research. For example, they were told that people with ALS and other conditions could have their ability to communicate completely abolished by disease, and because of the importance of this research for these people, they should give 100% of their attention and effort to the task so that the data would be extremely accurate. After being read the paragraph, the subjects were given the opportunity to opt out of the study without penalty if they felt unable to give their full attention to the task. Only one participant chose to leave. Subjects in the non-motivation condition ($n=8$) were not read the paragraph and proceeded with the study. The Stanford Sleepiness Scale [Hoddes et al., 1973] and the On-line Motivation Questionnaire (OMQ) [Boekaerts, 2002] were administered prior to completing calibration and a copy spelling task. Calibration consisted of 18 characters; online testing consisted of 24 characters. Following the BCI task, subjects completed the post task portion of the OMQ and stated their motivating factor for anecdotal purposes.

3. Results

As shown in Table 1, mean accuracy for the motivation group was 93% and mean accuracy for the non-motivation group was 84% ($t < .001$). In addition to performance differences, the r^2 values for the main positive and negative components of the ERP are visually higher for the motivation group (Fig. 1, top left), than for the non-motivation group (Fig. 1, top right). The waveforms at Pz for the motivation group suggest higher amplitude positive peaks and an earlier negative peak than the non-motivation group (Fig. 1, bottom row). Scores on the Stanford Sleepiness Scale were similar in the two conditions. All except for one subject reported being “wide awake” or “functioning at a high level”. Scores on the On-line Motivation Questionnaire range from 17–68. All subjects reported high levels of motivation and the score were statistically similar across conditions (motivation, 57.00, non-motivation 52.71; $t < 1$).

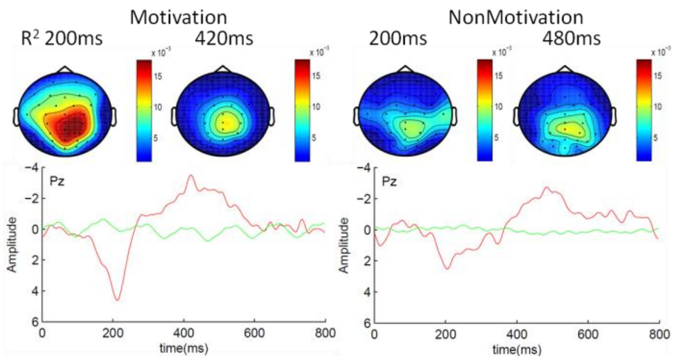

Figure 1. *R2 topographies and Pz waveforms for the motivation group (left) and non-motivation group (right).*

Table 1. *BCI accuracy by subject in the motivation and non-motivation conditions.*

Motivation			Non-Motivation		
Sub	Age	Acc	Sub	Age	Acc
004	19	1.00	002	23	1.00
005	20	0.92	003	19	0.79
009	22	0.63	006	21	0.63
012	21	1.00	008	26	0.96
013	29	1.00	011	23	0.88
015	22	1.00	014	22	1.00
			016	23	0.88
			017	24	0.54
Mean	22.17	0.93		22.63	0.84
StDev	3.54	0.15		2.07	0.17
SE	0.59	0.02		0.34	0.03

4. Discussion

This study examined the effects of a motivation induction on BCI performance. The induction consisted of a paragraph describing the importance of the research, which was read to the motivation group. All procedures were identical for the non-motivation group except they were not read the paragraph. Data show that the motivation group obtained significantly higher accuracy and had larger ERP components than the non-motivation group. Moreover, the two groups did not differ on measures of sleepiness and motivation. Thus, the data suggest that implicit motivation affects task performance. This may be especially important for disabled subjects because they stand to gain the most from BCI use.

Acknowledgements

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EEG Evaluation During Emotional State Elicited by Unpleasant Sounds to be Applied in BCI

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Abstract. EEG-based BCI performance is associated with emotional state like stress or loss of attention of the user. In that sense, this work presents off-line evaluation of the EEG signal in order to inquiry the occurrence of ERD/ERS in the alpha and beta rhythms during the perception of acoustic stimulus. This evaluation was conducted with the purpose of search the correlating EEG signals with user emotional state elicited by unpleasant stimulus. It was found that this kind of stimulus causes a later ERS in temporal scalp regions. Then, aiming BCI applications, the system could have a general class for particular emotional state like stress in which the system switches to a mode that classifies the mental tasks under stress. This approach would improve the BCI reliability, as the number of classes is reduced.

Keywords: BCI, EEG, Unpleasant Sound, Emotional State, ERD/ERS.

1. Introduction

Brain-Computer Interface (BCI) is one of research areas that has been developing relatively fast in the last decades. In this pathway was noticed that the emotional state of the user affects the performance of BCI because induces changes in human biological signals [Picard, 2010]. In the case of scalp electroencephalogram (EEG) signals, for example the loss of attention of the robotic-wheelchair user can cause a decreasing the classification accuracy of EEG-based BCI [Muller et al., 2010]. For this reason, this preliminary work attempts to evaluate EEG signals from BCI user under emotional state elicited by unpleasant sound. This evaluation was conducted with the purpose of search a correlation between EEG signals and user emotional state elicited by unpleasant acoustic stimulus as it is possible that this kind of stimulus increase neural activity in brain cortex. BCI can benefit from adapting their operation to the emotional state of the user. By virtue of its known importance for the paradigm of motor imagination [Pfurtscheller and da Silva, 1999] the goal of the experiments is to verify the occurrence of event-related desynchronization/synchronization (ERD/ERS) in the α (8–12 Hz) and β (14–30 Hz) frequency bands, but during the perception of unpleasant stimulus.

2. Material and Methods

Due to the preliminary aspect of this work one volunteer with no previous history of neurological or psychiatric disorder was stimulated. He has not taken any medication that could have affected the EEG signals and he stated to feel healthy on the day of the experiment. Electrodes placed upon nineteen positions in according to international 10–20 system (see Fig. 1), one-ear reference and one grounding electrode was used. EEG signals were acquired with 200 Hz sampling rate, without artifact rejection and with electrode impedances below 10 KΩ. Common Average Reference spatial filter [McFarland et al., 1997] was applied in order to reduce correlation between channels originated by external noises such as the electric network noise and artifacts of muscular origin.

2.1. Experiment

The experiment consisted of a set of 10 repetitions (epochs), each one lasted 20 s, in which the acoustic stimulus was applied between 5 and 10 s. This stimulus was produced by scraping a sharp knife along the surface of a ridged metal bottle. This sound was ranked with 8.10 ± 1.47 of unpleasantness level [Kumar et al., 2008]. To find out that emotion had been elicited after each repetition, the volunteer filled out SAM self-assessment form [Bradley and Lang, 1994]. In all cases the subject marked most extreme alternatives (arousal close to maximal value and valence close minimal value). These replies would suggest that the volunteer felt himself under negative emotional state like hate or stress during stimulus in accordance with dimensional study of emotional states [Russell and Mehrabian, 1977].

3. Results

ERD/ERS occurs because in the absence of mental activity the individual neurons in a neural mass synchronize with the signal thalamic pacemaker and the mass emits signals in a specific band of frequencies. To inquiry the occurrence of ERD/ERS in the α and β frequency bands for all channels during the perception of acoustic stimulus was followed the classic method [Pfurtscheller and da Silva, 1999]. In the graphs of Fig. 1 the relative power of the EEG signal in α and β bands for all electrodes is shown.

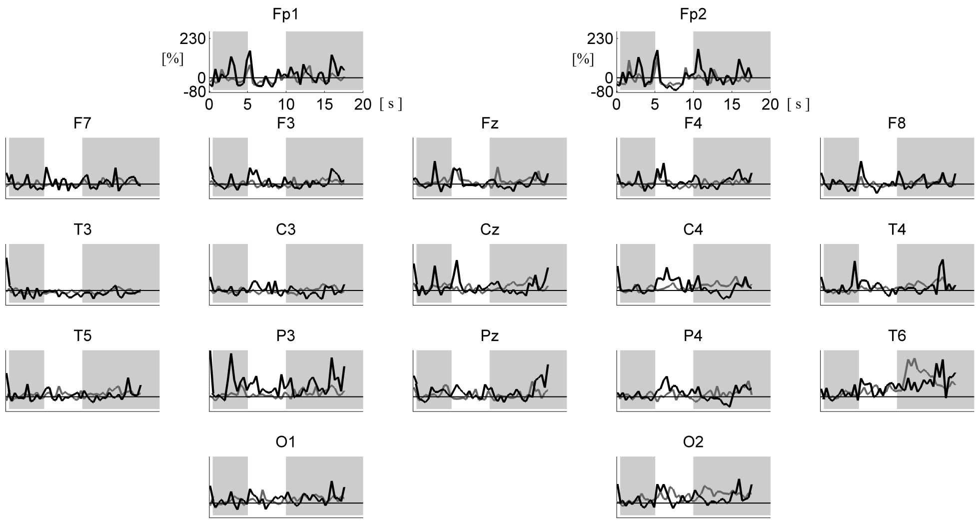

Figure 1: Relative power of α (black) and β (gray) bands. All graphs follow the same scale (-80% to 230% of reference interval). The amplitude and time scales are shown only in $Fp1$ and $Fp2$ channels and omitted in the others. One can notice that a relative decrease in the energy (ERD) during the acoustic stimulus in electrodes $Fp2$ and $F8$. An ERS related to the beginning of the stimulus in electrodes $Fp1$, $Fp2$, $F4$ and $F8$. Also, it worth noting that the energy of β band in electrode $T6$ gradually increases after the stimulus, followed by an slower increase of α band. As the electrode $T6$ is over associative areas of auditory cortex, the high energy plateau measured after the stimulus could be associated to early stages of auditory stress.

4. Discussion

It was observed that unpleasant sound stimulus causes neural activity in frontal and temporal cortex. However by using only ten repetitions we could not observe any significant changes in α and β frequency bands over the frontal electrodes related with neural basis of emotion. The high energy plateau measured over auditory cortex after unpleasant sound could be associated to early stages of auditory stress. Then, a BCI working with n mental tasks would need $2n$ classes to include these tasks under stress emotional state. But, instead of dealing with all mental tasks classes and the new classes under stress, the BCI could have just one more general class for stress in which the system switches to a mode that classifies only the mental tasks under stress. This approach would improve the BCI reliability, as the classification problem is reduced from $2n$ to $n+1$ classes.

Acknowledgments

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The Effects of Motivation on Task Performance Using a Brain-Computer Interface

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Abstract. A brain-computer interface (BCI) is a method of communication that utilizes the scalp recorded electroencephalogram (EEG). A BCI requires no movement, making it a viable communication option for people who are severely disabled. Most BCI research has focused on improving BCI technology through advances in signal processing and paradigmatic manipulations. Research has recently begun to examine the influence of psychosocial factors on BCI performance. Examining psychosocial factors may be particularly important for disabled people who have several co-morbidities. The purpose of the current study is to examine the hypothesis that participants will be more motivated in a free spelling paradigm than in a copy spelling paradigm. Participants completed copy- and free-spelling tasks, order was counterbalanced. Motivation was measured after each task. Preliminary data suggests an increase in motivation after the second task regardless of which task was performed second. No differences were observed in performance accuracy between the two tasks.

Keywords: Brain-Computer Interface, Motivation, ALS, P300, EEG

1. Introduction

Noninvasive brain-computer interface (BCI) uses electroencephalogram (EEG) to provide non-muscular communication. Most BCI research has not considered how psychosocial factors affect task performance and typically considers the participant as a passive observer during BCI use. Recent research has suggested a need for studies that focus on specific qualities of BCI users, such as their levels of motivation and depression [Kleih et al., 2010; Nijboer et al., 2010]. Examination of these factors may increase BCI performance by learning more about individual users, treating them as active participants, and addressing their specific needs. The current study examined the factor of motivation. Participants completed two tasks: copy- and free-spelling. After each task their motivation to perform the task was assessed [Boekaerts, 2002]. It was hypothesized that free spelling would lead to higher motivation ratings and higher accuracy. Learning about how and why a particular person may be motivated or unmotivated can help determine what tasks may lead to higher BCI performance by fully engaging participants in the task.

2. Material and Methods

Participants (n = 16) were recruited from the East Tennessee State University (ETSU) subject pool. All participants provided informed consent and the study was approved by the ETSU Institutional Review Board.

An Electro-Cap International, Inc. cap was used to record the EEG. Stimulus presentation, EEG data collection, and online processing were all controlled using the BCI2000 software [Schalk et al., 2004]. The current study used a stepwise-linear discriminant analysis method (SWLDA) to obtain classification coefficients for each participant.

Participants were fitted with a 32-channel electrode EEG cap and instructed to attend to the screen where an 8 x 9 (72 item) matrix was presented. Participants were then instructed to attend to the target character (the character the participant is currently trying to select) by mentally saying or counting the character when it flashed. Participants were also instructed not to attempt to correct mistakes and continue with the next character if the BCI provided incorrect feedback. Two sets of calibration data for the SWLDA were collected, one for copy spelling and one for free spelling. For each participant, the words used for calibration and copy spelling were randomly selected from a database of 6,000 words. Each word consisted of six characters. Copy- and free-spelling conditions were counterbalanced. Calibration data sets consisted of three words (a total of 18 character selections). The resulting classifiers were used in the copy- and free-spelling conditions.

In the copy-spelling task, three six-letter words in one string with a space in between each word were presented. In the free spelling task, participants constructed a sentence, ranging from 20-24 characters, to spell using the BCI. Before the free spelling task each participant wrote the sentence on a sheet of paper in order to calculate accuracy. They were also instructed to correct BCI mistakes using the BACKSPACE character (denoted “Bs”). If the participant had not completed the sentence before the limit of 24 character selections the task was terminated.

Two surveys were utilized in this study: the Stanford Sleepiness Scale (SSS) was used to measure fatigue [Hoddes et al., 1973]; the On-Line Motivation Questionnaire (OLMQ) was used to measure motivation [Boekaerts, 2002]. Both instruments are self-report measures and were given three times throughout the session. The OLMQ consists of pre- and post- task components. The pre-task OLMQ and the SSS were completed immediately after the first calibration sequence. The post-task OLMQ and SSS were both given after each of the two tasks were completed. At the conclusion of the session, participants were asked a qualitative question describing their motivation for participating in the study. This served as additional data to confirm participants' responses to the surveys.

3. Results

Performance accuracy for the copy-spelling condition was calculated by dividing the number of correct selections by the number of total selections. Performance accuracy for the free-spelling condition was calculated by comparing the actual message to the intended message. Mean accuracy in the copy- and free-spelling conditions did not show a significant difference (89.69% and 86.74%, respectively ($t < 1$)). Motivation after Post test 2 (62.18) was significantly higher than motivation after Post test 1 (56.69; $p < .02$). Fig. 1 shows the relationship between motivation and accuracy for Post Test 1 (the first condition) and Post Test 2 (the second condition).

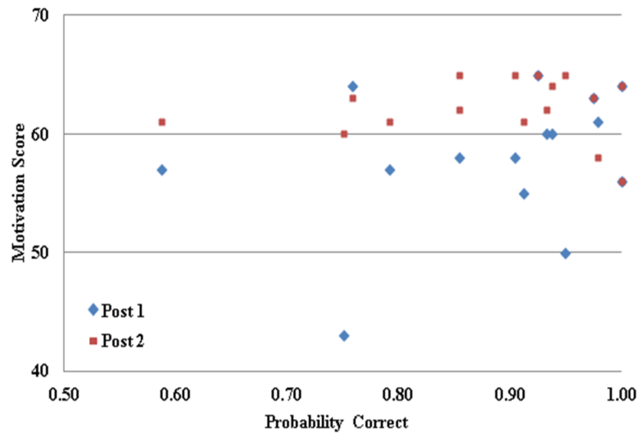

Figure 1. *Average performance accuracy and motivation scores of non-disabled participants for the first (Post 1) and second (Post 2) conditions.*

4. Discussion

This study examined the hypothesis that participants will be more motivated in a free spelling paradigm than in a copy spelling paradigm, and that their accuracy would be higher for free spelling. The current results show that motivation increased after the second task regardless of whether it was copy- or free-spelling. Furthermore, no difference was observed in accuracy between the two tasks. One possible explanation for these findings is that motivation was unaffected because accuracy was similar in both conditions. Another possible explanation is that the personal relevance of BCI use was low for these participants. Nonetheless, factors such as motivation may influence the BCI performance of disabled people. Presumably they have a higher personal investment in the technology.

Acknowledgements

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Towards Neurofeedback for Improving Visual Attention

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Abstract. We investigated the impact of gamma-activity in a task-positive network on performance of subjects in a general measure for attention (D2-test). Subjects modulated their gamma activity previous to each run of the test with a simple neurofeedback mechanism. Results indicate that visual attention can be increased significantly by tuning activity in the investigated network into a specific state.

Keywords: EEG, Passive BCI, Neurofeedback, Visual Attention, Supportive System

1. Introduction

Gamma activity in a fronto-parietal network was found to correlate with performance in motor-imagery based Brain-Computer Interface (BCI) [Grosse-Wentrup et al., 2011]. Specifically it can be used to predict the performance of a subject before each trial [Grosse-Wentrup and Schölkopf, 2012]. Several studies report that gamma activity in task-positive networks is correlated to attention [Corbetta, 2008]. These results lead to the assumptions that the effect found in [Grosse-Wentrup, 2012] could correlate more generally to attention, and that it can be used, due to its BCI-detectability, to train people to increase their attention on the fly. We have investigated these hypotheses in a standardized measure for attention, the D2-test [Brickenkamp, 1978], and with an EEG based BCI approach.

2. Material and Methods

We ran experiments with 20 subjects, not suffering from any neurological or psychiatric disorders. Participants were equipped with a set of 128 active EEG-electrodes (ActiCap, Brain Products, Gilching, Germany) and sat comfortably in a chair. Before the experiment, the experimenter advised the participant and answered related questions. In a first block the D2-test (see Fig. 1) was introduced to the participants. Following, participants were advised to relax for a period of 5 minutes and fixate a cross in the center of the screen. EEG data recorded in this part of the experiment was used to assess the activity of the network investigated in [Grosse-Wentrup, 2012] by beamforming. Then two Blocks of the standard D2-test were performed by the participants. The results of these runs served as a baseline for each participant's performance in the D2-test. Four Blocks of D2 followed, where each run was preceded by a neurofeedback paradigm. The position of the cursor could be controlled by modulating the gamma activity in the investigated task-positive network. The activity was assessed by the previously defined beamformer and translated into the position of the cursor. In two of the blocks subjects were advised to level the cursor up, in the others to move the cursor down. The order of the blocks was randomized between subjects. Also randomized across subjects was the direction of the neurofeedback – for 10 subjects the cursor would move upwards if they *increase* their activity in the gamma network (like described in [Grosse-Wentrup, 2012]) and move downwards if the activity was *decreased*. For the remaining subjects this procedure was inverted.

Figure 1. *Samples of stimuli of the D2-test. Targets are marked grey, all other stimuli are distractors. Each subject was running 7 Blocks of a computerized D2: 1x Training, 2x Baseline, 4x with Neurofeedback, permuted over subjects.*

3. Results

Performance of the participants was measured by errors per run of the D2-test. For each condition ([1] baseline, [2] modulating Gamma up, [3] modulating Gamma down) data from two blocks of D2 were available. The results for each condition were pooled over subjects and tested for statistically significant differences to the other conditions by a permutation test. The results of this analysis are displayed in Fig. 2. For several seconds (see Fig. 2), participants had significantly less errors in condition [2] compared to condition [1] (**) and compared to condition [3] (*). There was no significant difference in errors when comparing conditions [1] and [3].

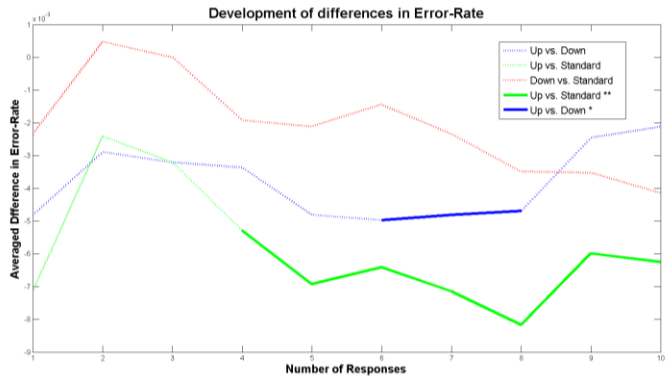

Figure 2. *Differences in error rate between conditions. Solid lines indicate significant differences (*: p<.05 / **: p<.01) within each comparison. X-axis indicates the number of consecutive responses (starting at first response) taken into account.*

4. Discussion

The results of this study show first evidence that attention can be increased by modulating gamma activity in the investigated network. Results indicate two effects. Firstly, we see a clear decrease of error rate between those trials where subjects were asked to increase gamma compared to those with where they were asked to decrease it (green vs. red). Secondly, both neurofeedback conditions show a similar trend (blue) of deceasing error rate over time, which is not the case in the baseline condition (green, red). As the D2 test is a general measure for attention, we expect the positive effect of the neurofeedback training presented here also to apply in various situations and applications. In further studies we will investigate whether the approach presented her could also be used as a Passive BCI [Zander, 2011] informing users about their level of attention during a given Human-Machine Interaction. This could lead to a crucial increase in performance in demanding Human-Machine Systems. This study opens up new fields for applying BCI-technology in a useful way for various populations of users.

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One-Dimensional Imaginary Movement Cursor Control Using Disc and Tripolar Electrodes

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Abstract. We performed a one-dimensional imaginary task for a brain-computer interface (BCI) comparing disc and tripolar concentric ring electrodes (TCREs). Three human subjects acquired substantial control of the cursor with an average success rate of 30 - 66% for disc EEG, and 44 - 100% for TCRE EEG (tEEG).

Keywords: BCI, one-dimentional imaginary task, tripolar concentric electrode, TCRE, TCRE EEG, tEEG

1. Introduction

Brain-computer interface (BCI) is an alternative means of communication with computers that does not depend on the peripheral nerves and muscles, which implements the direct communication and control between the brain and computer devices [Wolpaw et al., 2002]. A BCI may be useful for people who are severely paralyzed to communicate and interact with their environment. Recently, there has been much interest in the area of BCI such as to “move cursor: up, down, right, and left”. The electroencephalogram (EEG) is a non-invasive recording of neural brain electrical activity. Digital processing of EEG signals is an important part of the design of BCI [Wolpaw et al., 2002]. Unfortunately, EEG signals have low signal to noise ratio (SNR), low spatial resolution, and are contaminated by various artifacts from other sources. These characteristics limit measuring the spatial distribution of brain electrical activity and thus necessitate significant preprocessing [Wolpaw et al., 2002]. Recently, enhancements have been applied to EEG making it more accurate by increasing the spatial resolution. One such enhancement is the application of the surface Laplacian to the EEG. The tripolar concentric ring electrodes (TCREs) were shown to estimate the Laplacian significantly better than bipolar concentric ring electrodes and conventional disc electrodes [Besio et al., 2006; Koka and Besio, 2007]. The TCRE EEG (tEEG) provides approximately a four times enhancement in the SNR, three times enhancement in spatial resolution, and twelve times enhancement in mutual information compared to disc electrode signals [Koka and Besio, 2007].

2. Material and Methods

This research is based on recording, analyzing, and comparing disc EEG vs. tEEG based BCIs for real-time one-dimensional cursor control. Three healthy male subjects (1-3, ages 24-40) were the BCI users in this study group. The subject’s task was to move a computer cursor from the center of the screen to a target that appeared in the left or the right of the periphery of the screen. During BCI operation, subjects were seated in a chair, facing a computer screen which was placed about 1.5 meters in front of the subject. The subjects were asked to remain motionless during the recording process. The BCI2000 [Schalk et al., 2004] software application was used to acquire signals recorded from eight surface electrodes (C3, C1, Cz, C2, C4, FC1, FCz, FC2) according to the international 10-20 system, with reference and ground from the right mastoid process. Signals from all the channels were amplified (g.tec GmbH, Schiedlberg, Austria), filtered (0.1-100 Hz) and digitized (sampling frequency was 256 Hz). There were 20 trials in each of 10 runs (one session comprises ten runs). Subjects 1 and 2 had one session and subject 3 had 2 sessions. The mean of the two sessions was used for subject 3. Each trial began with the appearance of the target. The subject’s goal was to move the cursor so that it hits the target.

3. Results

Table 1 shows the accuracy of imaginary cursor movement for each subject using either disc EEG or tEEG. The average accuracies achieved by the three subjects ranged from 30 - 66% for disc EEG, and between 44 - 100% for tEEG. Fig. 1 shows the subjects had significant control from the beginning. A general factorial design of analysis of variance (ANOVA) was used with a single categorical factor being the type of the electrode used (conventional disc EEG vs. TCRE Laplacian tEEG) and the response variable being the BCI trial success rate percent. The effect of the controllable factor that is the human subject was blocked with three levels of blocking factor corresponding to three human subjects who participated in the study. The measurements of response variable (10 replications) were repeated for each type of electrode in three levels of the block factor. There was a significant difference between EEG and tEEG accuracy.

Table 1. *One-dimensional cursor control; accuracy for each subject was calculated for disc and tripolar electrode.*

Runs #	Subject 1 Hit Acc (%)		Subject 2 Hit Acc (%)		Subject 3 Hit Acc (%)	
	EEG	tEEG	EEG	tEEG	EEG	tEEG
1	60	68	43	50	51	62
2	51	64	30	45	55	60
3	54	64	41	58	60	61
4	48	60	35	50	64	57
5	52	58	53	52	61	70
6	54	60	45	47	55	68
7	57	65	47	44	57	85
8	53	63	50	58	60	88
9	60	66	46	78	55	74
10	59	70	51	69	66	100
Mean	54.8	63.8	44.1	55.1	58.4	72.5

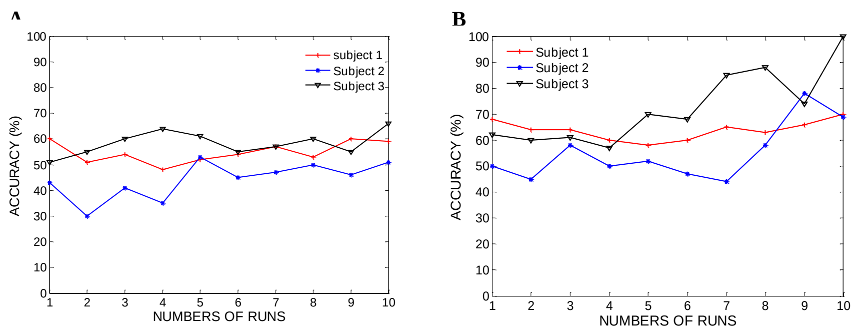

Figure 1. *Hit accuracy of (A) disc electrode, and (B) tripolar concentric ring electrode (TCRE).*

4. Discussion

These results show there is a significant difference in accuracy of the tEEG to disc EEG for new users in real-time one-dimensional center-out cursor control. The tEEG accuracy on average was higher than for the disc EEG. We suspect this advancement is due to the improvement of: four-fold in signal-to-noise ratio, three-fold in spatial selectivity, and twelve-fold in mutual information of tEEG compared to EEG [Koka and Besio, 2007]. In summary, this abstract describes the comparison of one-dimensional BCI control using disc EEG and tEEG by beginner subjects.

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Microneedle Array Integrated on a Flexible Substrate to Fabricate Dry Electrode

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Abstract. Low and stable contact impedance between the electrode-skin interface is crucial for the acquisition of high quality biopotential signals. A layer of gel or glue containing ions is often introduced between the skin and the commerical Ag/AgCl electrode. However, a dry electrode, often made from rigid material, seldom has a gel-like cushion when attached to the skin. This kind of hard contact makes subjects feel uncomfortable due to the higher stress imposed on the electrode to get good contact necessary for low impedance and high quality biopotential signals. A flexible dry electrode can adapt to the surface of the skin by bending more than by pressing. In this study, we developed a flexible dry electrode structure based on a silicon needle array on a PDMS substrate. By coating a layer of conductor on it, a flexible dry electrode was fabricated. The flexible substrate can keep contact with the skin in a natural way. Low impedance can be obtained with low pressure.

Keywords: Flexible dry electrode, biopotential, needle array, PDMS

1. Introduction

Commercial wet electrodes have two shortcomings. First, their preparation time is long. The skin should be cleaned or degreased by soft abrasion to reduce the thickness of the stratum corneum (SC). Electrolytic gel must be applied between the electrode and skin [Matteucci et al., 2007; Yu et al., 2009]. Second, wet electrodes must be operated by professionals and the procedures are complex, so it can hardly be used for home care [Griss et al., 2001]. Dry electrode technology can overcome these disadvantages. There are many types of dry electrodes. One type has a surface composed of microneedle arrays. With this microstructure, the height controlled needles can penetrate the SC barrier of the skin to decrease the interface impedance between electrode and skin [Griss et al., 2001; Griss et al., 2002; Yu et al., 2011]. However, this kind of dry electrode, as shown in Fig. 1A, is fabricated with silicon, metal, or other rigid materials. Although most of these dry electrodes with lower impedance were reported, these dry electrodes are far from an application in the potential market. One reason is the uncomfortable experience [Baek et al., 2008] when one uses the dry electrode. Higher stress must be imposed on the electrode to keep a good contact between the electrode and skin. In this process, the skin, as well as the tissue under the skin, must endure the whole deformation. It will cause discomfort including pain and redness. To overcome these shortcomings, we developed a dry electrode with a micro-needle array on a flexible PDMS substrate. Thus, the electrode can adapt to the curved skin surface and decrease the deformation degree of the skin.

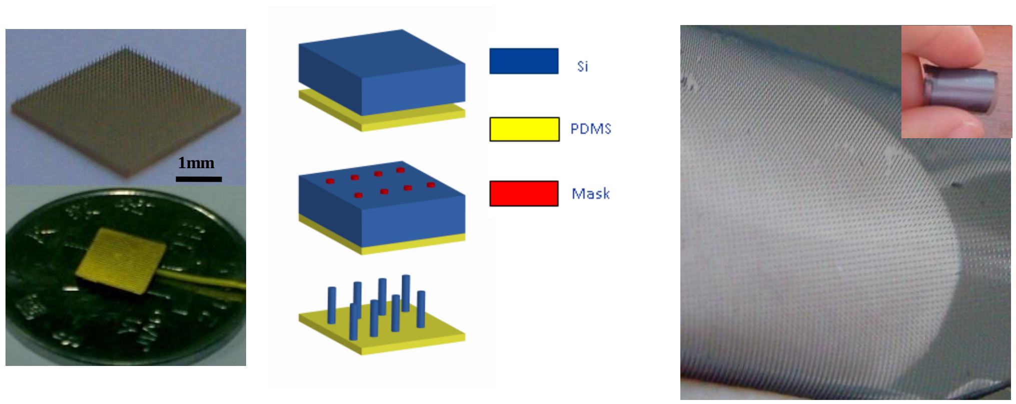
2. Material and Methods

Four-inch double-sided polished n-type silicon wafer with <100> crystallographic orientation, 200 µm thickness and 0.001 cm resistance was used in this study. A layer of PDMS membrane with a thickness of 2 mm was used as flexible substrate.

The production process of the flexible dry electrode comprises three steps. The first step is to bond the silicon wafer to the PDMS membrane. The second step is to produce micro-needle arrays by lithography patterns and deep dry etching processes. The third step is to dice the wafers and sputter the conductor metal layer on both sides of the structure. The metal of the structure side wall establishes front-to-back electrical contact. The fabrication process is shown in Fig. 1B.

3. Results

The completed flexible dry electrode made with a micro-needle array is shown in Fig. 1C. Due to the very strong bond force between the silicon and PDMS substrate (the bond is mainly composed of Si-O), the micro-needle can be fastened on the substrate firmly. The diameter of the micro-needles is 50 µm, the height of the micro-needle is 150 µm, and the space between the needles is 200 µm. The rigid needles combined with flexible substrate can satisfy impedance demands as well as comfort demands for a dry electrode, especially in a long-term wearing situation. Thanks to the substrate made from PDMS membrane, the electrode is flexible and can bend easily around the finger.



A B C

Figure 1. *Rigid dry electrode and improved flexible structure. (A)Rigid dry elctrode made from silicon. (B) Fabrication process. (C) A completed silicon needle array bonding on a PDMS substrate stretching naturally on a finger (inset shows another piece of silicon needle on PDMS structure).*

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Comparisons of the Spatial Resolution between Disc and Tripolar Concentric Ring Electrodes

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Abstract. We compared the half sensitivity volume and the common spatial subspace decomposition of visual evoked potentials as measures of spatial resoulion between conventional disc electrodes and tripolar concentric ring electrodes with a computer simulation. The results suggest that tripolar concentric ring electrodes can achieve much higher spatial resolution than conventional disc electrodes.

Keywords: EEG, CSSD, Spatial Resolution, tripolar concentric ring electrode, TCRE

1. Introduction

Brain Computer Interfaces (BCIs) can provide persons who cannot use their muscles but are cognitively intact with an alternative form of communication and control. Electroencephalography (EEG) measures potentials on the scalp caused by the neural activity of the brain. EEG has high temporal resolution, but suffers from poor spatial resolution due to the blurring effects of the volume conductor [Nunez et al., 1994]. To improve the spatial resolution the surface Laplacian, second spatial derivative, has been applied to EEG.

For conventional electrodes, the global surface Laplacian operation is performed on the spline potential interpolation over the surface. However, a cross validation procedure is required to compute the inverse of an ill-posed matrix in the construction of the spline interpolation equations, which cannot be performed in real-time EEG based applications such as BCI. [Besio et al., 2006] have reported on a local surface Laplacian from tripolar concentric ring electrodes (TCREs), which helps to avoid complex computations in surface Laplacian approximation while achieving improved spatial resolution [Liu et al., 2011]. Two computer simulations were performed for this work to compare the spatial resolution for disc electrodes and TCREs.

2. Methods and Results

Both of the simulations were based on a 4-layer concentric spherical human head model developed by [Cuffin and Cohen, 1979].

The half sensitivity volume (HSV) is defined as the volume where the potential is at least half of the maximum value measured [Malmivuo and Suihko, 1997]. According to the definition, HSV is inversely proportional to the spatial resolution of corresponding electrodes. Fig. 1 shows that the HSV of the TCRE is about 1/10 of the conventional disc electrodes HSV.

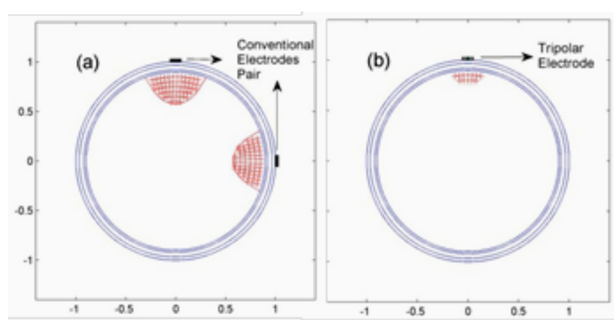

Figure 1. *HSV of disc and TCREs.*

Common spatial subspace decomposition (CSSD) was developed to separate specific brain activities from the background [Wang et al., 1999]. In our simulation an 8 by 8 electrode array, with the electrodes diameter of 1 cm, was placed on the scalp above the visual cortex area with a 1.0 cm center-to-center distance between electrodes. A signal dipole with eccentricity of 0.9 was placed under the electrode array. Two noise dipoles with eccentricity of 0.75 were concurrently activated under the array as background brain activity. Ten samples of visual evoked potentials (VEPs) were generated from the dipoles. In the simulation, we first recorded the background by setting the magnitude of the signal dipole to zero. Then, we recorded the VEP combined with background. Finally, the CSSD was applied to the recorded data to extract the VEP. The TCRE EEG (tEEG), which automatically estimates the Laplacian [Besio et al., 2006], was calculated for comparison.

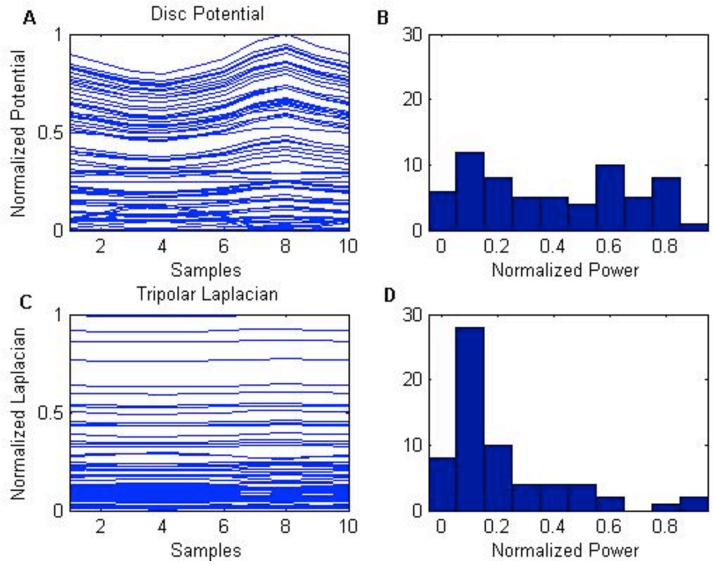

***Figure 2**. The normalized signals of the VEP (A), tEEG VEP (B) and the histograms of their corresponding power.*

Fig. 2A shows the normalized VEP from the 64 conventional disc electrodes. Fig. 2B is a histogram of the normalized power of the VEPs. Fig. 2C and 2D shows the normalized tEEG VEP and histogram of the normalized tEEG VEP power from the array of TCRE at the same locations, respectively. From Fig. 2D we can see that most of the TCREs had low power in the tEEG VEP, 0.5 or less, while Fig. 2B shows the disc VEP was distributed over a wider area of the electrodes array. These results show how tEEG is more specific than EEG.

3. Conclusion

The results of the HSV and the VEP indicate that the TCRE is more focused than the conventional disc electrodes. The cross correlation of the tEEG VEP for the TCREs that had high CSSD were 1.0 or nearly 1.0 meaning that the background interference was attenuated. Due to these properties we should be able to achieve higher spatial resolution with TCREs.

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Non-Invasive Versus Invasive Brain-Computer Interfaces

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Abstract. Surgically-implanted, intracranial Brain-Computer Interfaces (BCIs) are expected in the future to become a radical, game-changing modality for the control of virtual environments by humans whose direct neuromotor response needs to be augmented or replaced altogether. Recent developments in the signal processing of electrocorticographic (ECoG) signals have suggested that surgically-based intrcranial ECoG can form a more efficient BCI than non-surgical scalp EEG. In this preliminary study, we aimed to compare the effectiveness of intracranial versus scalp-based BCIs. We conclude that although surgical BCIs can be effective, specific approaches must be developed to identify and extract the data of interest from ECoG recordings.

Keywords: Brain-computer interfaces (BCIs), P300 speller, Electrocorticography (ECoG)

1. Introduction

Brain-Computer Interfaces (BCI) are powerful tools for enabling communication between people and the surrounding world using direct brain activity recorded non-invasively from the scalp (electroencephalogram, EEG), invasively from the brain surface (electrocorticogram, ECoG), or from deep within the brain itself using depth electrodes [Shih and Krusienski, 2012]. The non-invasive "P300 speller" paradigm is the most frequently used approach that allows subject to spell words or phrases by direct brain-controlled selection from menus presented on a computer screen [Farwell and Donchin, 1988]. People achieve 91% accuracy with a spelling speed of 2-3 characters per minute [Guger et al., 2009]. However, some recent published reports [Shih and Krusienski, 2012] have suggested that invasive ECoG-based BCIs can be faster and more accurate than non-invasive EEG-based BCIs. Yet no studies to date have directly compared non-invasive versus invasive "P300 spellers" in the same individuals. In this study, we performed paired comparisons of the "P300 speller" BCI in both invasive and non-invasive settings in the same subjects. We hypothesized that invasive "P300 speller" will be more efficient than its non-invasive version.

2. Methods

Three patients (3 males; age 25±14.2) diagnosed with intractable epilepsy and undergoing evaluation for resective epilepsy surgery were recruited. They underwent scalp and intracranial testing with P300 speller. Two different types of P300 speller were used: character-based and face-based.

Training: Each participant was initially presented with 3 words (5 characters each). This was done in order to train the linear classifier to distinguish the P300 response. The training included flashing rows and columns – 15 times each. Individual classifier was calculated based on the acquired information. Afterwards a "free spelling" experiment began. All 8 electrodes were used for free speller based on scalp recordings, whereas 8 best electrodes were chosen based on certain characteristics (see Data Evaluation/Analysis section) for free spelling experiment from subdural electrodes. The free spelling began with presenting flashing rows and columns – 15 times each. The number of flashes was gradually decreased while the desired level of difficulty was obtained. The gradual decrease included the following number of flashes: 15, 8, 4, 2 and 1. For each level of difficulty, the 5 character word was used. The EEG data were acquired from 8 electrodes (Fz, Cz, P3, Pz, P4, PO7, POz, PO8) using a g.USBamp (24 Bit biosignal amplification unit, g.tec Medical Engineering GmbH, Austria) at a sampling frequency of 256 Hz. The ground electrode was located on the forehead; the reference was mounted on the right earlobe [Guger et al., 2009].

The ECoG data were acquired using g.USBamp devices (24 bit biosignal amplification unit, g.tec Medical Engineering GmbH, Austria) at a sampling frequency of 1200 Hz. Subdurally placed reference and ground electrodes were used. The number of electrodes varied for each of the individuals. The data was analyzed with g.bsanalyze MATLAB-based program (g.tec Medical Engineering GmbH, Austria) and additional MATLAB scripts. Three main approaches were used to choose best 8 subdural electrodes for free spelling: (1) choosing the signal with the highest amplitude; (2) choosing the signal with the lowest correlation between standard and deviant responses; and (3) significance test based sample-wise computed coefficient of determination, testing the null-hypothesis that target and non-target trials have equal mean amplitude.

3. Results and Discussion

Accuracy in scalp recordings was reaching 100% for 15x15 presentation rate, 70% for 8x8 presentation rate, 60% for 4x4 presentation rate, 80% for 4x4 presentation rate and 0% for 1x1 presentation rate. Interestingly, using faces (of different popular people in this case) instead of simple flashing letters provided with higher accuracy reaching 90% in most of the conditions.

Differently from what was predicted, intracranial recordings did not provide with high "P300 speller" accuracy. It was significantly lower for all presentation rates when compared with the "P300 speller" accuracy achieved with scalp recordings. The difficulty was observed in choosing the right locations for 8 channels needed to calculate the classifier. Electrode locations based on the proposed algorithm #1 were not always concordant with the locations determined by using algorithm #2.

We hypothesized that the failure of intracranial "P300 speller" to provide with high accuracy results was related to the algorithms #1 and #2 used for the selection of major 8 electrodes for calculating the classifier. Therefore, a new approach was developed, which included the following processing steps: 1) The common average reference over all channels was calculated; 2) The triggers on each channels were extracted; 3) Signal was baseline-corrected by using de-trend function; 4) All artifacts were removed from the recording (all trials with amplitudes > 1000 µV are rejected); 5) Sample-wise correlation between non-target and target responses was calculated; 6) Significance test based on the correlation coefficients was used. This new approach lead to the results different from those obtained with previous analysis methods (Fig. 1).

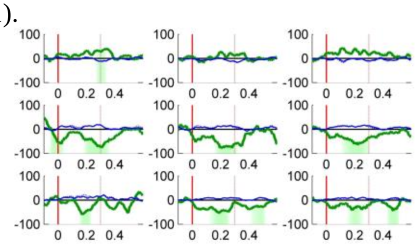

Figure 1. *Example of using approach #3 to process intracranial P300 responses in subject #10. With green is indicated response to targets and in blue – response to non-targets. Y-axis indicates response amplitudes (mkV) and X-axis indicates response latencies (ms). Regions between target and non-target with significant different mean value are highlighted in green.*

4. Conclusions

Intracranial grid placement may provide users with unique opportunity to control real and virtual worlds with high speed and accuracy. However, specific signal processing approaches to achieve this accuracy still need to be developed. Our proposed signal processing algorithm may be of high value to achieve this goal. However, this is the first test of the algorithm the validation of the whole procedure is needed before it may be used in real settings.

Acknowledgements

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Design of Dry Electrodes for EEG Based BCI Systems

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Abstract. In electroencephalography (EEG) based BCI systems, one of the crucial design issues is to acquire high fidelity EEG signals and to provide convenient installation to users. Electrodes are the key components which measure EEG signals from user's scalp. In this paper, we aim to introduce a design of dry electrodes for BCI systems. The proposed electrodes are equipped with six spring loaded probes. They are capable of acquiring EEG signals of good enough quality without usage of conductive gels. To verify the performance of proposed electrodes, we measure contact impedances under various spatial and temporal positions and compared them with those of conventional wet electrodes. Experimental results show that average impedance of proposed dry electrodes is slightly higher than those of the wet electrodes. The impedance difference between proposed dry electrodes and existing wet electrodes is shown to be insignificant without conductive gels. We anticipate to improve the impedance values of proposed dry electrodes by adding an extra electrical circuit.

Keywords: EEG, Dry electrode, Impedance

1. Introduction

Brain-Computer Interface (BCI) systems can acquire user's intentions by analyzing the user's neurophysiological signals. The intentions are then translated into control signals which computer or external machines can understand. In these systems, electrodes are the most important part because this part may affect the signal quality severely. Because amplitude of EEG signals is very small, the signals are easy to be affected by various noise sources such as physiological interference, i.e., electrooculograms (EOG). Moreover, due to usage of conductive gels, electrode installation is also inconvenient and time-consuming. Therefore, development of improved EEG electrodes which provide high fidelity EEG signals and easy installation is one of the most important challenges.

Recently, researchers have studied about dry electrodes for solving these challenges. Dry electrodes are defined as those that do not require the use of conductive gels for installation process. Thus, a user can conveniently attach them to its scalp without any hair arrangement. In this paper, we aim to introduce our dry electrode, show their performance (contact impedance), and compare them with that of conventional wet electrodes.

2. Dry Electrode Design and Impedance Test

2.1. Dry electrode design

Our dry electrodes are equipped with six probes of spring loaded type. These probes contract their length maximum 2 mm when they compressed. This structure provides flexibility and geometric adaptation between the sensor and the irregular scalp surface. Because the probes are easy to touch with the user's scalp through the hairs, any hair preparation is not needed in their installation process. For these reasons, the proposed electrodes provide both a convenience of installation and an appropriate adhesion to measure high fidelity EEG signals simultaneously. Fig. 1 is a picture of the proposed electrode and a diagram showing its structure.

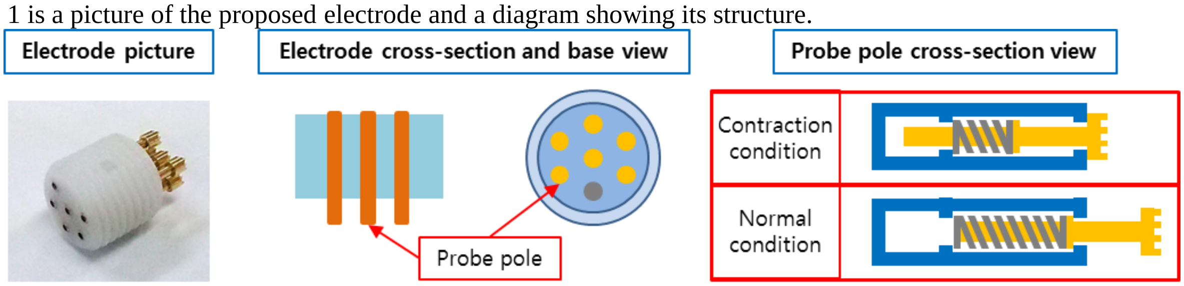

Figure 1. *Dry electrodes picture and structure diagram. Diameter of the proposed electrodes is 8 mm and length of each proves is 3 mm.*

2.2 Impedance test

To verify the performance of the electrode, we measure the contact impedance and compare that with those of conventional wet electrodes. In acquisition of EEG signals, existence of electrical impediments such as hair, outer skin layer, and sweat may lead to a lower contact capability. To make sure of the contact capability, we can evaluate the contact impedance before measurement of EEG signals. The impedance can be obtained by measuring the voltage difference between a reference electrode and a target electrode [Malmivuo and Plonsey, 1995]. A lower impedance means a higher contact capability, and the possibility of high quality EEG signal acquisition.

In order to measure the electrode impedance, we utilize EEG acquisition system named RZ5 neurophysiology workstation, PZ3 low impedance preamplifier and impedance check application (made by Tucker-Davis Technology). Our comparison target is general wet electrodes, named StarDisk(made by Hurev). In the impedance test, we used a single male subject. We measured the electrode impedances at Cz, Fz, and Pz positions based on international 10/20 system. We also recorded the change in impedance from 2 seconds out to 60 seconds. Reference and ground electrodes are installed on the right and the left ear lobe respectively. Note that the wet electrodes use the conductive gels for their adhesion in the installation process.

3. Results

Table 1 summarizes the impedance comparison of both electrodes under various spatial and temporal positions. Owing to the usage of conductive gels, the average impedances of wet electrodes is slightly lower than those of proposed dry electrodes (31. kΩ vs. 19. kΩ). However, according to impedance record of Cz position, the impedance difference between two electrodes is shown to be insignificant without conductive gels.

Table 1. *Comparison of contact impedance between dry electrode and wet electrode. We record the impedance values at the 3 electrode positions(Cz, Fz, Pz) and from 2 seconds until 60 seconds.*

Electrode	*Dry Electrode Impedance*			*Wet Electrode Impedance*		
Section	*Cz*	*Fz*	*Pz*	*Cz*	*Fz*	*Pz*
2s	26 kΩ	46 kΩ	29 kΩ	21.6 kΩ	13.3 kΩ	25.8 kΩ
10s	25 kΩ	39 kΩ	31 kΩ	21.4 kΩ	13.5 kΩ	24.2 kΩ
20s	25 kΩ	36 kΩ	31 kΩ	21.2 kΩ	13.4 kΩ	23.1 kΩ
30s	25 kΩ	36 kΩ	30.8 kΩ	21.2 kΩ	13.2 kΩ	22.5 kΩ
40s	25 kΩ	36 kΩ	30.5 kΩ	20.8 kΩ	13.1 kΩ	22.2 kΩ
50s	25 kΩ	36 kΩ	30.6 kΩ	20.5 kΩ	13.2 kΩ	21.7 kΩ
60s	30 kΩ	37 kΩ	30.2 kΩ	20.4 kΩ	13.2 kΩ	21.1 kΩ

4. Discussion

The impedance values of proposed dry electrodes are slightly higher than those of the wet electrodes. But, the proposed dry electrodes do not required the usage of conductive gels. Therefore, the proposed dry electrodes provide advantages such as convenient installation and feasibility of long-term. We expect that the impedance values of proposed dry electrodes can be improved by adding an extra electrical circuit like impedance converter.

Acknowledgements

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Dry and Wireless EEG-Based Brain-Computer Interfaces for Real-World Applications

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Abstract. This study develops successively high-density, wearable, wireless and portable EEG-based BCI devices that address laboratory-grade data acquisition, long-term comfortable wear, quick user set-up, and high portability. The new BCI devices feature amplifier-embedded active dry EEG sensors, head circumference adapted mechanical designs, miniature supporting electronics, wireless telemetry, and mobile apps for real-time signal processing. Results from initial applications show promise for rapidly enhancing our ability to assess human brain activity in real-world scenarios.

Keywords: Electroencephalogram, dry electrode, Brain computer interface, Congnitive applications

1. Introduction

Electroencephalogram (EEG) is a powerful non-invasive tool widely used in both medical diagnosis and neurobiological research as it provides high temporal resolutionin neuroimaging. Another important advantage of EEG is that it involves sensors light enough to allow near-complete freedom of movement of the head and body, making EEG the clear choice for brain imaging of humans performing normal tasks in real-world environments. This study develops several form factors of dry and wireless EEG-based Brain-Computer Interfaces (BCIs). This study also demonstrates the applications of the proposed Brain-Computer Interface (BCI) systems for real-time cognitive-state monitoring and gaming.

2. Material and Methods

The objective of this study is to design dry, wireless EEG systems that address laboratory-grade data acquisition, long-term comfortable wear, quick user set-up, and high portability. This study first develops amplifier-embedded active dry sensors to acquire augmented EEG data avoiding the need of skin preparation and gel application to ensure good conductivity between the electrodes and skin (Liao et al, 2012; in press). Then, the state-of-the-art sensor technology was combined with a novel head circumference adapted mechanical design to support comfort, fast set-up, and improved stability.

3. Results

Several dry and wireless EEG/BCI devices (MINDO®, Taiwan) have been developed and used to acquire user’s EEG signals continuously (Fig. 1A-D). The active dry sensors amplify measured signals at very early stage to improve signal-to-noise ratios.

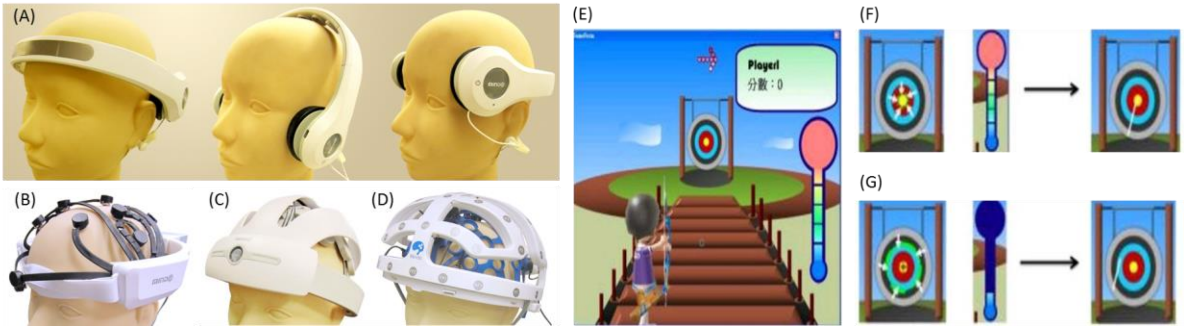

Figure 1. *Dry and wireless EEG devices with successively higher-density (A) 4 channels, (B) 16 channels, (C) 32 channels and (D) 64 channels. (E) A brain-controled application uses the proposed EEG-based BCI systems. The BCI detects the user's attentional level (measured by EEG power) to control the release of the arrow in a Brain Archery game (F) As the attention level increases, the arrow reaches the center of the target and gets a high score. (G) The arrow misses the target center when the player is distracted.*

The novel head circumference adapted mechanical design reduces user set up time and extends the duration of system wearability. Wireless telemtry allows ubiquitous brain monitoring and increases user mobility. The system can easily be used by technicians with limited experience and naïve participants. Figure 1E shows a brain-controlled video game, Brain Archery, in which the player manipulates their attentional level, measured by EEG power, to control the arrow release. A higher attentional level yields a higher score (Fig. 1F). Results of this study showed that most of participants can quickly learn strategies to control their attentional levels and improve their scores, without any training or practicing.

4. Discussion

This study demonstrated truly portable, lightweight, and readily wearable BCIs featuring dry EEG electrodes, a miniaturized DAQ, wireless telemetry and online signal processing. The main goal of the design and development of dry and wireless BCIs is to maximize their wearability, mobility, usability and reliability in real-world environments. We expect that the truly dry, wireless and user-acceptable BCI developed under this study will significantly improve the practicality of real-life applications of BCI for users actively behaving in and interacting with their environments.

Acknowledgements

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Comparison of Invasive Chronic Electrodes for Brain-Computer Interface Applications

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Abstract. Invasive chronic micro-electrodes are capable of recording high quality neural signals at the cellular level and are widely used in animal Brain-Computer Interface studies. However, human implantations remain very limited due to potential risks. Thus, development of electrodes that optimally sample neural signals is an important area of scientific research. In this study we compare two promising electrode technologies: the Neurotrophic Electrode (NE) and the Utah Array (UA). We found that both electrode types recorded task-related LFP signals in a saccade task. The UA recorded many more single- and multi-unit spikes than the NE identified by standard spike sorting techniques, probably due to recording sites being closer to cell bodies. The UA also showed less correlation between signals on nearby channels, resulting in bigger decoding improvements when more channels are considered. These results provide valuable guidelines for further electrode development for BCI applications.

Keywords: Electrophysiology, Invasive BCI, Utah Array, Neurotrophic Electrode, Monkey, Eye Movements, PFC

1. Introduction

Invasive Brain-Computer Interfaces (BCIs) are the only BCI type capable of recording neural signals at the level of individual cells and thus hold much promise for restoration of motor functions in severely paralyzed individuals. To date, there have been only two chronic intra-cortical electrode types approved by the FDA to for implantation in a human brain: the Neurotrophic Electrode (NE) and the Utah Array (UA). These electrode technologies have a number of differences. The NE [Bartels et al., 2008] is hand-made of several micro-wires glued inside a glass cone. The cone is coated with nerve growth factor which stimulates neural growth inside the cone for weeks after implantation. The UA [Maynard, 1997] is a machine-manufactured silicon-based planar microarray, commercially available from Blackrock Microsystems. Its electrode tips are exposed and record from existing cortical tissue. An in-depth comparison of these two electrode technologies can be valuable for guiding further electrode development for BCI applications.

2. Material and Methods

Building on our previous work [Guenther, 2009] we modified the NE design to increase its channel capacity since low channel capacity is one of its primary weaknesses for use in high-throughput BCIs. The resulting cone electrode had 2-3 stereotrodes and higher channel count and was termed the Neurotrophic Array (NA). To test these electrodes we implanted them in a macaque monkey: one cone with 8 wires in pre-frontal cortex (PFC) and another cone with 6 wires in ventral pre-motor cortex (vPMC). We recorded from these electrodes while the monkey performed a delayed center-out saccade task for 6 months after implantation. On each trial the animal was briefly presented with one of 48 possible target locations, followed by a delay period when the monkey needed to hold the target position in working memory. Finally, after a go cue the monkey made a saccade to the remembered location.

A second monkey was implanted with three 32-channel UAs in PFC, supplementary eye fields (SEF), and frontal eye fields (FEF). We recorded neural data from this monkey performing a similar delayed saccade task for one year so far and are continuing the recordings.

3. Results

In the collected NA data, spikes on only two channels and only in two sessions could be reliably separated from noise using standard spike sorting techniques. One of these channels contained a single unit and one potentially included a multi-unit source. In contrast, 50-60% of UA channels recorded clear spiking signals, with about 15-20% recoding isolated single-units. Many channels carried several units simultaneously.

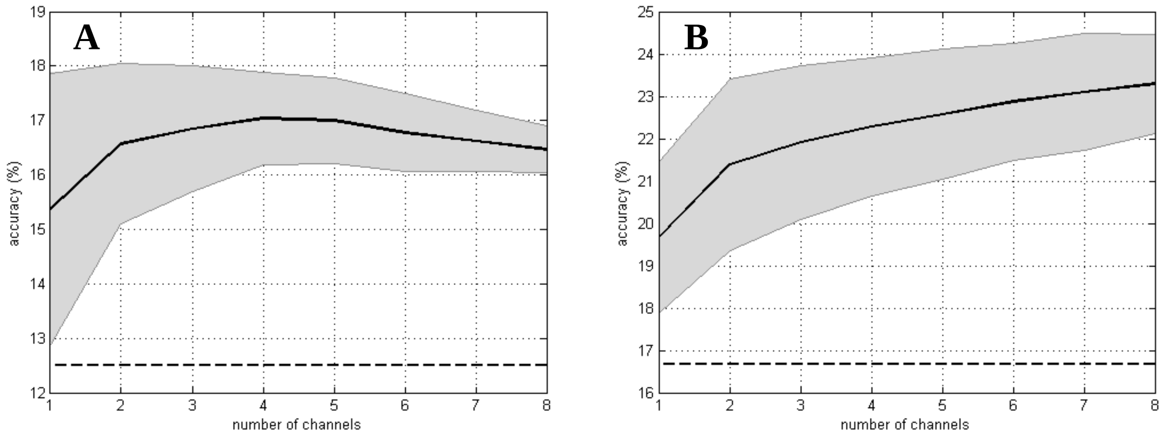

Figure 1. *Accuracy of decoding saccade directions from 15-25Hz LFP band power of PFC electrodes during the delay period across the number of used channels: (A) Neurotrophic Array results for 8 saccade directions; (B) Utah Array results for 6 saccade directions. Dashed lines depict chance performance. Using signals from SEF significantly improves decoding accuracy of the Utah Array (reaching approximately 80% correct), but we restrict analysis in the current abstract to comparing common implantation areas.*

In the current study we focused on comparing signals from PFC where both monkeys (and implant types) had arrays. The UA had 4-5 dB higher power in high gamma frequency range (> 100 Hz) than the NA, while their beta band LFP power was at about the same level. Nearby channels in the NA had significantly higher LFP signal correlation than adjacent channels in the UA.

Both PFC arrays carried significant information (ANOVA, $p < 0.01$) about saccade direction in the LFP beta band (15-25 Hz) during the delay period (8/8 NA channels and 12/32 UA channels). To further investigate information content of recorded PFC beta band we ran a cross-validated linear discriminant decoder on randomly selected subsets of significant channels, with 1 to 8 channels in each set. The resulting decoding accuracies are plotted in Figure 1 as a function of number of channels used for decoding. As we can see from the figure, decoding accuracy peaks around 4 channels for the NA while continuing to monotonically grow for the UA. This result is likely related to higher signal correlation between NA channels, which limits the contribution of additional channels.

4. Discussion

Signals from both the NA and UA contained significant information concerning saccade direction. The NA recorded relatively little clear single- or multi-unit spiking activity. This is likely due in large part to the glass cone design which, although improving mechanical stability, puts recording sites next to cell axons and dendrites instead of somas. This causes a decrease in spike amplitude compared to the UA (which records near somas) and can result in redundant information appearing on different channels that record from the same axon. As a result, in the NA most of the useful information in the signal comes from LFPs. Signals on NA channels are more correlated with each other than those on the UA; such correlations negatively impact the NA's information capacity when considering more than one recording site, as demonstrated by the decoding analysis.

Acknowledgements

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Impedance, Histology, Stability and Longevity of the Neurotrophic Electrode in Rats, Monkeys and Humans

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Abstract. This paper describes the important characteristics of the Neurotrophic Electrode. It has a radical design difference from tine type electrodes and wires because it encourages growth of neural tissue into and through a hollow glass tip where the ingrown neuropil is held securely and thus produces enduring, stable units.

Keywords: Single-Unit Activity, Multi-Unit Activity, longevity, impedance, histology, signal stability, speech prosthesis

1. Introduction

The Neurotrophic Electrode's radical design encourages neural tissue to grow into its hollow glass tip where the tissue is held while in-situ micro-wires record the electrical activity of the ingrown tissue over periods of years. These design aims have been achieved in rats, monkeys and humans with the longest recording period being over 5 years in humans with recordings still continuing until breakdown of the implanted electronics. The electrode has some disadvantages such as destruction of surrounding tissue so that accurate histological reconstruction of the surrounding neurons is not feasible. Also, there is a delay of three to four months until growth is complete and multi-units can be recorded which then have to be separated into single units. However, stability of continuously recorded multi/single units and persistence of local field potentials over years make it more advantageous than any other electrode today for long-term prosthetic use as a BCI. To provide for a wider understanding of its potential, this presentation will provide data on impedances, histology, stability, longevity and numbers of units recorded over years in rats, monkeys and humans over the past quarter century.

2. Material and Methods

Unlike other electrodes, the Neurotrophic Electrode induces neurites to grow into and through its hollow glass tip that contains two to eight, 1 or 2 mil teflon-insulated gold (or occasionally platinum) wires for bipolar recording of the ingrown tissue [Bartels et al., 2008]. It contains proprietary growth factors when implanted into the human cerebral cortex. In rats and monkeys, NGF was commonly used [Kennedy, 1989]. The gold wires are coiled for their full length from the skull. This reduces strain and is very important for longevity. Identification of the site for implantation is achieved using functional MRI with the mute subject making silent (not imagined) vocalizations on an object naming task while in the MRI scanner. Implantation is performed under fully sterile conditions with a Stealth 3D localization system to determine the implant target matched to the fMRI. Following craniotomy and electrode implantation, insulated amplifiers and FM transmitters are plugged into the electrodes, sealed and covered with acrylic cement before scalp closure. Separation of single units from multi-units is achieved using the exclusionary convex hull technique (Neuralynx Inc. Boise, Montana) whereby dissimilar units are excluded from the main group on the basis of outlying height, peak, valley, width and energy. Inter spike interval histogram analyses indicate single units and thus provide criteria for rejection of multi-units. ISIHs, PETH, cross correlations and auto correlations are performed to strengthen the identification of single units across sessions. Multiple functional relationships have been established in rats, monkeys and humans.

3. Results

Impedances were measured at 1 kHz in all electrodes before and after implantation in all rats and monkeys. Impedance initially fell before stabilizing around 100 Hz, sometimes as high as 400 Hz or as low as 20 Hz.

Histological analyses included light and electron microscopy. Normal neuropil (excluding neurons) was found inside the glass cone at 3 weeks to 16 months. Oligodendroglia were found along with myelinated axons, blood vessels, axo-dentritic synapses. No scavenger microglia were found and no gliosis [Kennedy et al., 1992].

Single units stabilized at three to four months when functional studies began. Fig. 1 shows an example of human multi-unit recordings on two channels. Note the similar unit peaks or valleys. Using +/- voltage thresholds, units are separated as shown on the right. Confirmatory evidence was sought as described in methods using ISIHs, PETH, cross correlations and auto correlations.

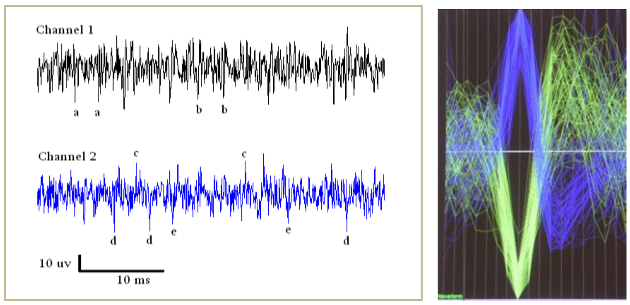

Figure 1. *Left panel: Two channels of human multi-unit data recorded years after the tissue has grown into the electrode tip. Right panel: Two single units separated by using a threshold above and below the data.*

Cluster cut parameter files were used from one recording session to the next. Stable units were found over 16 months in rats and 15 months in monkeys before experiment termination. Human recordings for over five years have been achieved with cluster parameter changes being necessitated only by damage to the electronics when the new electronics had different amplifier gains. Other human recordings included 4.5 and 4 years, and 76 days (all died from underlying diseases) and 89 days (removed deliberately). Functional studies have provided data that will likely produce a speech prosthetic [Guenther et al., 2009].

About 10 to 15 single units can be separated from multi-units recorded from each channel. Thus for the latest monkey implant (Shane @ MIT), 95 units were recorded from 12 mono-polar wires. ISIH indicated single units. PETHs indicated relationship to licking. In humans, 15 to 20 units per channel have been used in speech studies.

4. Discussion

These data detail the impedances, histology, unit numbers, stability and longevity of the Neurotrophic Electrode. The data provide evidence that the principle of growing the brain into the electrode and holding the neuropil within the electrode tip is the key to long-term stability of recorded single units [Kennedy et al., 2011]. Its usefulness as an important component of a speech BCI has been demonstrated [Guenther et al., 2009].

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Multi-Command Tactile and Auditory Brain Computer Interface based on Head Position Stimulation

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Abstract. We study the extent to which vibrotactile stimuli delivered to the head of a subject can serve as a platform for a brain computer interface (BCI) paradigm. Six head positions are used to evoke combined somatosensory and auditory (via the bone conduction effect) brain responses, in order to define a multimodal tactile and auditory brain computer interface (taBCI). Experimental results of subjects performing online taBCI, using stimuli with a moderately fast inter-stimulus interval (ISI), validate the taBCI paradigm, while the feasibility of the concept is illuminated through information transfer rate case studies.

Keywords: EEG, P300, somatosensory evoked potentials, auditory evoked potentials, tactile BCI

1. Introduction

State of the art BCI relies mostly on mental visual and motor imagery paradigms, which require long training and non-impaired vision of the subjects. Recently, alternative solutions have been proposed to utilize spatial auditory [Halder et al., 2010; Schreuder et al., 2010] or tactile (somatosensory) modalities [Müller-Putz et al., 2006; van der Waal et al., 2012] in order to enhance brain-computer interface comfort, or to boost the information transfer rate (ITR) achieved by users. The concept described in this paper, of utilizing brain somatosensory (tactile) modality, opens up the attractive possibility of targeting the tactile sensory domain, which is not as demanding as vision during the operation of robotic interfaces (wheelchair, prosthetic arm, etc.) or visual computer applications. The first successful trial to utilize somatosensory modality to create a BCI [Müller-Putz et al., 2006] targeted a very low stimulus frequency in a range of 20-31 Hz to elucidate the subject’s attentional modulation of steady-state responses. A very recent report [van der Waal et al., 2012] proposed using a Braille stimulator with a 100 ms long static push stimuli delivered to six fingers to evoke somatosensory response related P300. Very encouraging results were obtained with 7.8 bit/min on average and 27 bit/min for the best subject. Here we propose to combine the two above-mentioned modalities in a taBCI paradigm, which relies on a P300 response evoked by the audio and tactile stimuli delivered simultaneously via the vibrotactile exciters attached to positions on the head, thus benefiting from the bone-conduction effect for audio, which could help ALS-TLS (Amyotrophic Lateral Sclerosis / Total Locked-in State) patients with compromised vision and hearing due to weakened blinking and middle ear effusion/negative pressure, respectively. This offers a viable alternative for individuals lacking somatosensory responses from the fingers.

2. Material and Methods

In the experiments reported in this paper, eleven BCI-naïve subjects took part (mean age 21.82 years, with a standard deviation of 0.87). All the experiments were performed at the Life Science Center of TARA, University of Tsukuba, Japan. The psychophysical and online EEG taBCI paradigm experiments were conducted in accordance with the WMA Declaration of Helsinki - Ethical Principles for Medical Research Involving Human Subjects. The subjects of the experiments received a monetary gratification. The 100 ms long stimuli in the form of 350 Hz sinusoidal waves were delivered to areas of the subjects' heads via the tactile exciters HiWave HIAX19C01-8 working in the range of 300-20,000 Hz. The vibrotactile stimulators were arranged as follows. The pairs of exciters were attached on both sides of the forehead, chin, and behind the ears respectively. During the online taBCI experiments the EEG signals were captured with an eight dry electrodes portable wireless EEG amplifier system, g.MOBllab+ & g.SAHARA by g.tec. The electrodes were attached to the following head locations Cz, CPz, P3, P4, C3, C4, CP5, and CP6, as in the 10/10 extended international system (see topographic plot in Fig. 1). The ground and reference electrodes were attached behind the left and right ears respectively. In order to limit electromagnetic interference, the subjects' hands were additionally grounded with armbands connected to the amplifier ground. No electromagnetic interference was observed with the vibrotactile exciters attached to the head. The recorded EEG signals were processed by an in-house enhanced BCI2000 application using a linear discrimination analysis (LDA) classifier with features drawn from 0-600 ms event related potential (ERP) intervals. The sampling rate was set to 256 Hz, high pass filter at 0.1 Hz, and low pass filter at 40 Hz. The ISI was 400 ms and each stimuli length was 100 ms. The subjects were instructed to spell six-digit random sequences of numbers 1-6, which were represented by the exciters in each session. Each target was presented five times in a single spelling trial, and the averages of five ERPs were later used for the classification.

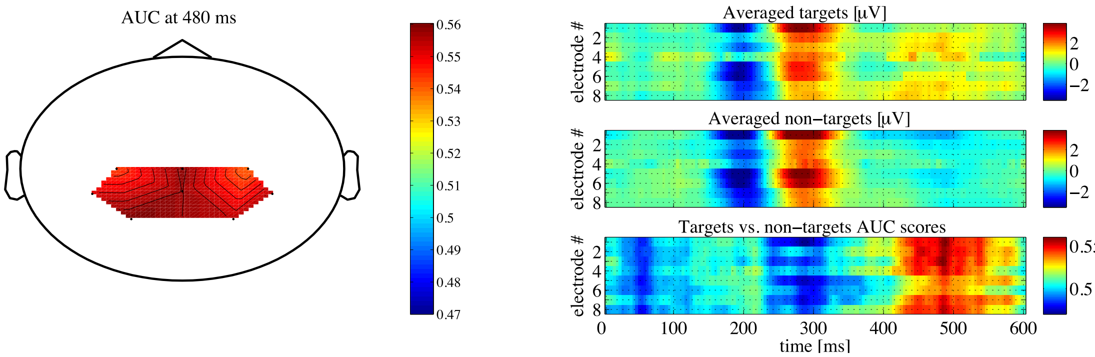

Figure 1. *The averaged ERP responses of the eleven BCI-naïve subjects taking part in the experiment. The left panel presents a topographical plot with the target vs. non-target ERP area under the curve (AUC) for ERP discriminative features extraction [Schreuder et al., 2010] plotted at the maximum value at 480 ms. The right panel presents the averaged ERPs (11 subjects; averaged six-digit sequences spelled in three sessions by each subject) for targets in the top panel; non-targets in the middle; and AUC coefficients at the bottom. The EEG electrode, represented by numbers on the vertical axes is shown in the right panels. The electrode order is as follows Cz, CPz, P3, P4, C3, C4, CP5, CP6.*

3. Results and Discussion

The averaged ERP responses from the eleven BCI-naïve subjects are presented in Fig. 1 for the target and non-target digits separately, together with the area under the curve (AUC) [Schreuder et al., 2010] discrimination coefficient plots marking the most separable latencies. A topographic plot of the AUC coefficient distributions is also presented in Fig. 1, supporting the choice of the eight dry EEG electrodes covering the parietal cortex. The results of online BCI interfacing sessions are summarized in Table 1 in the form of mean accuracies above the theoretical chance level of 16.6%. In our experiments, only one BCI-naïve subject obtained 100%, and likewise one obtained 0% for the six-digit sequence spelling accuracy with the 5-trials averaging procedure. The preliminary, yet encouraging results presented are a step forward in the search for new BCI paradigms for ALS-TLS patients with compromised vision and hearing symptoms.

Table 1. *Summary of the online taBCI interfacing results with the 11 naïve subjects (one subject scored 100% accuracy reaching 12.9 bit/min and one 0% with 0 bit/min).*

ERP averages	Mean accuracy	Accuracy standard deviation	Mean ITR	ITR standard deviation
5	50%	27%	3.22 bit/min	3.6 bit/min

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Feel the BCI Vibe – Vibrotactile BCI Feedback

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Abstract. Controlling a device via a brain-computer interface (BCI) requires the participant to look and to split the attention between the device and the BCI feedback, which is partly contradictory. Therefore, a stimulation system based on 6 coin-motors is developed, which provides a tactile illusion as BCI feedback. Several experiments are conducted to optimize the illusion parameters and to check the influence on the EEG. Furthermore, 6 healthy BCI subjects compared visual with tactile feedback in online MI recordings, and no performance degradation was found.

Keywords: brain-computer interface (BCI), electroencephalogram (EEG), tactile feedback, vibration, motor imagery (MI)

1. Introduction

End-users are starting to control application devices via brain-computer interfaces (BCI), but such a control requires them to look at both (the device and the BCI) and split their attention between both. Imagine controlling a wheelchair with the BCI: on the one hand you have to look where you want to drive your wheelchair, since you want to find the way and avoid obstacles, on the other hand you have to be aware of the BCI feedback, which shows your current brain status and gives information about how close you are to delivering commands with the BCI. Therefore, both visual feedback loops are important for a successful application control, but are competing for the same resource: our visual channel. This split attention is sometimes demanding for the participants [Leeb et al., 2013], especially since most BCI feedbacks are based on a visual feedback. So, is there a chance to reduce the load or to free the visual channel from one of the components? Auditory or somatosensory modalities have already been used in BCI research. Since, we are interested in controlling our applications in a self-paced way without any external cues, evoked activities like auditory BCIs or steady-state-somatosensory potentials are not in our focus. Therefore, we transferred the position of the normal visual BCI feedback bar, into a tactile feedback with stimulators on the neck of the participant. A similar approach was already presented in [Cincotti et al., 2007], but their magnetic actuators interfered slightly with the electroencephalogram (EEG). In this work we first present our new tactile stimulation hardware and optimize the illusion parameters. Furthermore, we analyze the influences of the tactile stimulation on the EEG and compare visual and tactile feedback during online BCI experiments.

2. Material and Methods

2.1. Tactile stimulator

Six coin motors (Precision Microdrives, UK) with a diameter of 10 mm and a typical vibrational amplitude range of 0.5 g to 1.8 g are utilized for delivering tactile BCI feedback. The motors are attached in a horizontal line on lower neck with a center point at the spine and about 2.5 cm of inter-motor-spacing (Fig. 1a). The spatio-temporal vibration pattern (pulse-width modulation) of the stimulator is controlled by the laptop through a single-board microcontroller (Arduino, Italy) to indicate the BCI performance of a subject in a 2-class BCI. A point-based protocol is applied, that converts the current BCI feedback to a spatio-temporal vibration pattern. Thereby an illusory tactile sensation point is placed at one point corresponding to the visual BCI performance. In addition, the amplitude of the vibration increases as the probability approaches to the extreme values.

2.3. Sensation of tactile illusion

The tactile illusion that places the virtual tactile sensation point in between the two real stimulation points [Alles, 1970] is employed to increase the spatial resolution (only 6 motors are attached). This illusion point varies the position depending on the amplitude ratio of the real stimuli. For example, when two motors vibrate with the equal amplitude, tactile illusion is located at the center, whereas when the amplitudes are unbalanced it moves closer towards the larger stimulation amplitude. Hence, if the amplitudes of two motors are properly varied over time, a smooth movement between the two motors appears. To determine the appropriate shape of this amplitude variation between two motors, a preliminary experiment is conducted. Three subjects were asked to rank (1=low–4=high) four stimuli that have different shapes of amplitude variation (linear and three logarithmic) based on the illusory movement characteristics: consistency of perceived strength, position of the illusion, and direction of the movement.

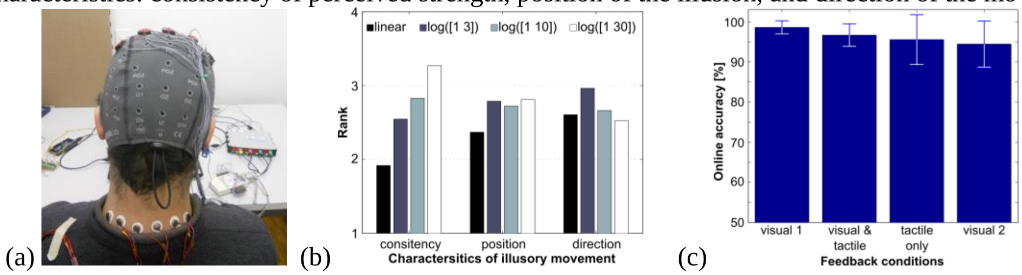

Figure 1. *(a) Subject wearing the EEG cap and placement of the vibrotactile stimulators on the neck. (b) Reported average ranks after normalization of different virtual movements between two motors. (c) Averaged online BCI accuracy during the 4 feedback conditions (only visual, visual and tactile, only tactile and again only visual).*

3. Results

3.1. Characterization for apparent tactile illusion

Fig. 1b shows the results of experiments to determine the shape of the amplitude variation. It shows that consistency increases as the shape becomes more logarithmic over time [Alles, 1970]. However, there is a certain preference to the shape of log([1 3]) in direction when the tactile illusion moves between two motors. For position, subjects preferred logarithmic shape, suggesting that it is better to use log([1 3]) for the point-based protocol.

3.2. Stimulation influence on the EEG

The EEG was recorded from 64 channels (active BioSemi amplifier, fs = 2048 Hz, filter: DC–417 Hz) while different tactile stimulation patterns (all motors / just left side / just right side / wave like / none) were tested 30 times each. Every trial consisted of 5 seconds stimulation and 15 seconds rest. The spectrum was calculated for 1-second epochs (5 per stimulation period and 5 per rest (second 6-11)) and averaged over the repetitions for each condition. No influence of the various stimulation patterns could be found in the EEG spectra while comparing stimulation to rest and over the conditions.

3.3. Online BCI experiments with vibrotactile feedback

Furthermore, to see the influence of the tactile stimulation on the online performance of a BCI (g.USBamp, 16 channels, fs = 512 Hz, filter: 0.5-100 Hz), six healthy trained BCI subjects compared the different feedback modalities: two runs with 15 left and 15 right hand motor imageries were performed for the following conditions: (1) normal visual feedback, (2) visual and tactile feedback, (3) only tactile feedback and (4) again only visual feedback. Fig. 1c shows that no statistical difference in the online performances could be identified, although the variance increased.

4. Discussion

In this work we presented the setup of a tactile stimulator, which can be used to provide smooth tactile BCI feedback on the neck without interfering with the EEG. Subjects are able to perceive this type of tactile feedback well and no online BCI performance degradation could be identified. The next step would be to test our system directly with an application, and to investigate the benefits from the reduced visual workload with more subjects.

Acknowledgements

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Using Generic Models to Improve Tactile ERP-BCI Performance of Low Aptitude Users

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Abstract. Tactile ERP-BCIs may provide unique advantages over visual and auditory BCIs but often suffer from lower user performances. Herein we thus, evaluated the use of generic models for increasing BCI performance of low performing subjects. Such models create a generalized classifier from a pool of calibration sessions. Data of N = 15 healthy participants was used to evaluate different generic models. Preliminary results display the potential of generic models for increasing the performance of those users who do not achieve sufficient accuracy from their own calibration run. Further research will be required to evaluate the effectiveness of different generic models in an online setting with larger sample size.

Keywords: Brain Computer Interface (BCI), event-related potentials (ERP), Generic model, tactile ERP-BCI

1. Introduction

ERP-BCIs offer a high amount of control without the need for long-lasting training sessions. Tactile stimulation allows users to retain visual and auditory senses for non-BCI tasks and can easily be hidden underneath the cloths to reduce visibility of the system. Tactile stimulation was found to be a viable modality for ERP-BCIs [Brouwer and van Erp, 2010]. Although it may yield unique advantages in terms of user-friendliness it was found to achieve lower performance compared to visual or auditory stimulation [Aloise et al., 2007]. It has been shown for the visual modality that some users can use generic model classifiers instead of personalized classifiers to achieve acceptable performances [Jing et al., 2012]. Such models incorporate data from a pool of participants to create a generalized classifier independent from participants' own data. Herein, we evaluated the potential of generic models in tactile ERP-BCIs for increasing accuracy of low performing participants.

2. Material and Methods

N = 15 healthy participants (12 female, mean age 22.5 years, SD = 3.2) participated in the study. Tactile stimulation was applied to participants' left leg, right leg, belly and neck with 4 pairs of vibrate transducers (C2 tactors; Engineering Acoustic Inc., USA; stimulus duration: 220 ms; inter-stimulus interval: 400 ms). EEG signals were recorded from 16 passive Ag/AgCl electrodes and amplified using a g.USBamp amplifier (g.tec Engineering GmbH, Austria). Two data sets per person were included into this offline analysis, i.e. one calibration run and one run for testing of classifier performance. The reported accuracies are based on classification of 48 single sequences.

Offline classification was performed in MATLAB 2010b (The Mathworks Inc., USA) using stepwise linear discriminant analysis. Participants who achieved performances below the required level for communication of 70% [Kübler et al., 2001] were regarded as low performance participants (N = 6). For each participant four different classifiers were generated:

1. *Base model:* Base performances were gained using only participants' own calibration data for classification.
2. *Generic model:* A generic model was computed based on data from the full sample except for the participant on which the model was tested, i.e. the model was different for each participant but comprised data from the remaining N = 14 participants.
3. *Optimized generic model:* Additionally, we created an 'optimized' generic model using only the calibration data of the N = 8 participants who achieved more than 70% performance with their reference classifier. To maintain generic property of the model for those high performance participants, we created classifiers excluding their own calibration data from the optimized model.
4. *Mixed model:* Finally for each participant we created a mixed classifier using the weights from the *generic model* classifier and the participant's personal classifier (*base model*).

3. Results

Different classifiers were used to calculate offline performances for the 6 low performance participants (see Fig. 1a). The three of them who performed worst with their own model (P2, P3 and P15) could achieve higher performances using the optimized generic model classifier. Importantly, optimized generic models boosted

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performance of P3 by 65% and of P15 by 36% of the performance achieved with their own model. However, not all low performers could benefit from generic models. One participant achieved almost the same level of performance and the remainder displayed decreased performances (P8: -4%, P5: -20%; P6: -12% of performance with their own models).

Additionally offline performances were also calculated for the 9 high performance participants. ERPs of some participants well matched the features underlying the generic model, while others displayed great difference. For example participant 1 scored the best performance using the optimized generic model, due to broad similarities between spatio-temporal features (Fig. 1b). On the other hand, participant 9 achieved the lowest performance as his individual pattern did not match the generic model. Our results thus suggest that different models may be needed to account for inter-individual differences.

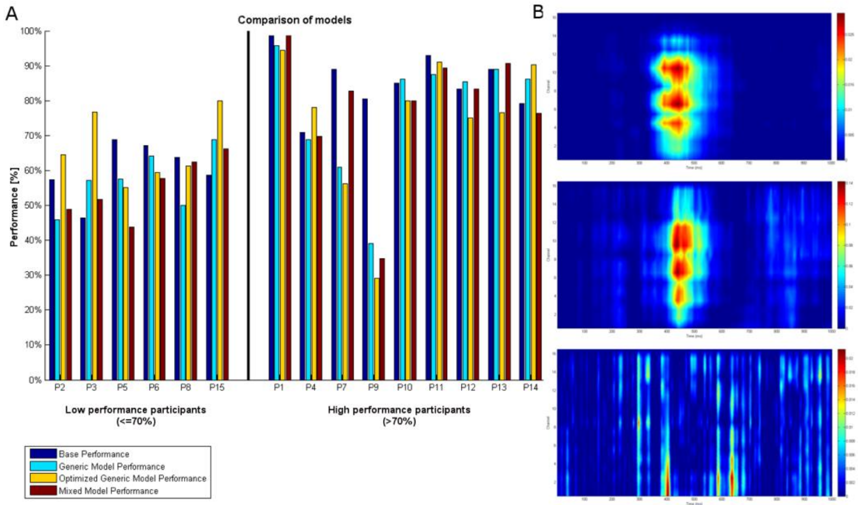

Figure 1. (A) *Average single trial performance, using 4 different classifiers. (B) Determination coefficients for data from generic model (top) vs. data from exemplary participants 1 (middle) and 9 (bottom). Channels are shown on the y-, time on the x-axis and R^2-values are color coded. Please note that color scales are different.*

4. Discussion

Preliminary results show that some low performance users can achieve higher performance using a generic model classifier and particularly display the potential of the optimized model. Some low performance users, however, do not improve using a generic model. Notably for 7 users (4 high performer, 3 low performer) the standard model achieved the highest performance. From data of high performers it can be seen that not all users may display EEG patterns in line with the generic model, e.g. in P9 generic model classifiers did reduce the performance drastically. Despite using features that strongly differed from the generic model, he achieved high performance using his own classifier. Therefore our generic classifier is not generic for all tested participants. Additional participant data is required to evaluate whether there might be different generic models which could account for users not compatible to this generic model. Additional data may also further contribute to a better generalization of the generic model. Furthermore, use of generic models for tactile ERP-BCIs has to proof its validity in an online setting. Finally generic model classifier should be evaluated with the end-user population, to see wether generic models can compensate for lower signal to noise ratios commonly found in end-user data. However, our results are promising in that three participants, who achieved only low performances using their personal classifiers, could benefit strongly from using an optimized generic model classifier.

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A Tactile P300-Based BCI

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Abstract. In this publication a tactile P300-based Brain-Computer Interface (BCI) is presented. It can be used for communication, but is also aimed for testing the consciousness in nonresponsive patients. Three different settings were evaluated: two tactors for testing if a P300 could be detected; three tactors that could be used for simple communication, and a setup with eight tactors that provides more classes and is hence suitable for advanced communication. The BCI was evaluated on 12 healthy users showing a mean accuracy of 100% for classification in the two tactor approach, 80% in the three tactor approach and 69.4% in the eight tactor approach.

Keywords: EEG, P300, vibrotactile Stimulation, minimal conscious state

1. Introduction

Brain-Computer Interfaces (BCIs) for communication are usually controlled via a P300 paradigm. During the last 25 years, several P300 spellers based on visual stimulation have been developed. But for users suffering visual impairments or even in a minimally conscious state, visual stimulation cannot be used any more. For this group of users, a tactile stimulation can be used to elicit the evoked potential. Hence, one can use this way of stimulation for communication and also for assessment of the level of consciousness in patients classified as non-responsive. Kotchoubey et al. tested event related responses to stimuli of different complexity levels in patients with persistent vegetative state (PVS) and minimal conscious state [Kotchoubey et al., 2005]. They found a P300 also in PVS patients although it was associated more frequent to patients with lower level of disability. Therefore, after testing the general appearance of P300, one should present certain command to the patient, like e.g. counting the number of stimuli appearing on the left hand. If the user is able to follow a sequence of commands, the patient could be classified as responsive. For a visual P300 speller, it was shown that healthy users reach an average control accuracy of 91% [Guger et al., 2009] and a group of fifteen people suffering motor impairments reached 70.1% [Ortner et al., 2011] In this paper, the accuracy of a tactile P300 speller is evaluated on twelve healthy users.

2. Material and Methods

Three different scenarios were tested. In the first paradigm, two stimulators were placed on the user's wrists. One tactor delivered a train of standard stimuli (one stimulus was a short vibration of the tactor). The tactor on the other wrist produced the deviant stimulus with a probability of 12.5%. If the user was asked to concentrate on the deviant stimulus, one could evaluate if this person has a P300 reponse. The second paradigm used three tactors. Again, one of the tactors (placed on the user's back) delivered a train of standard stimuli. The deviant stimuli were now delivered on the left and right wrist, one of which conveyed "yes" the other of which conveyed "no". The user had to concentrate on the stimuli given on one of the two wrists to select the answer. This setup could be used for communication if only a simple yes/no response is desired. In the third paradigm, eight tactors were used instead of three. They were placed on the fingers (little finger, ring finger, middle finger, index finger) of the left and right hand. Each tactor flashed with the same probability (12.5%). During one run, the user had to concentrate on each finger in a random order, the commands on which tactor the user should concentrate actually were give via voice.

In each session of the three paradigms, two runs were performed: one to set up a classifier and a second run to test the classifier. Each run of the two-tactor and three-tactor paradigm consisted of 5 sequences, with 15 target events per sequence. The runs of the eight tactor experiment consisted of eight sequences, again with 15 target events per sequence. For each session the accuracy was calculated.

3. Results

Table 1 summarizes the results of the twelve persons. The mean accuracy was at 100% for the two tactors, 80% in the three tactor approach and 69.4% in the eight tactor experiment. Not all persons had enough time to process all of the three approaches, hence some field in the table are empty. When looking at the mean accuracy of the people participating to all three approaches (S1, S3, S5, S6, S7, S8, S9) the mean accuracy was: 100%, 77.1% and 73.2%.

Table 1. *Accuracy (%) of the single sessions.*

User	*two-tactor*	*three-tactor*	*eight-tactor*
1	100	100	50
2	100	100	-
3	100	100	100
4	100	60	-
5	100	40	100
6	100	60	75
7	100	100	62.5
8	100	60	25
9	100	80	100
10	100	100	-
11	-	-	100
12	-	-	12.5
mean	100	80.0	69.4
STD	0	23.1	34.3

4. Discussion

Patients with visual impairments or unknown levels of consciousness need new ways to present the stimuli that will elicit the P300 response, since visual P300 BCIs are not practical for such users. The presented tool could be used for both: for communication and for detection of consciousness in nonresponsive persons. The accuracy in the three tactor experiment was higher than in the eight tactor experiment, but with the higher number of classes the Information transfer rate would be higher in the eight tactor experiment.

Details such as the exact duration of the stimuli or the best location of the stimulator are grounds for further investigation. Also, the methods used in this study, and the potential applications and users, will be expanded. Promising tests on people suffering Locked in Syndrome were already performed and will be published soon [Lugo et al., 2013].

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Brain-Computer Interface Using Chromatic Transient Visual Stimulus Array

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Abstract. Transient chromatic circle was proposed to be a safer and more comfortable stimulation method for brain-computer interface (BCI). This study further developed a chromatic array to elicit chromatic transient visual evoked potentials (CTVEP). This paper introduces a novel encoding/decoding approach using pseudo random sequences in order to increase the number of inputs of the system. The preliminary experiment was carried out using pseudo random gold sequences of length 127, and showed promising results with accuracy of BCI from 96% to 100%. It suggests the potential use of CTVEPs in a practical BCI system.

Keywords: VEP, CTVEP, Pseudo random sequences, BCI

1. Introduction

It is a popular and successful protocol to apply visual evoked potential (VEP) for practical brain-computer interfaces (BCIs), e.g. steady-state visual evoked potentials (SSVEPs) [Parini et al., 2009] or flash onset and offset visual evoked potential (FVEP)-based BCIs [Lee et al., 2008]. However, rapidly flashing stimuli (5-60 Hz) may elicit epileptic seizures, and fast-varying luminance of stimuli may easily fatigue and exhaust users.

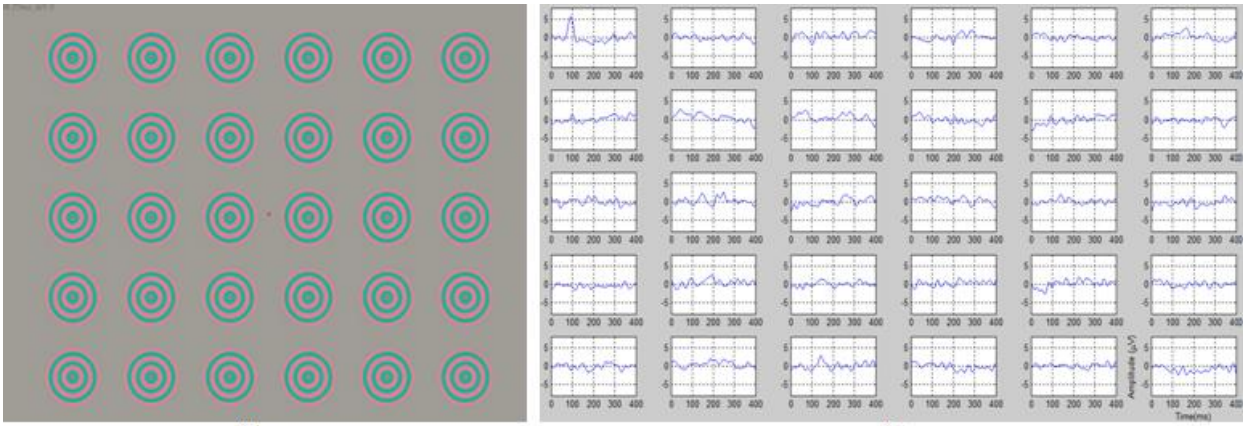
In a previous work [Lai et al., 2011], we proposed a visual stimulation as input for a BCI system, named chromatic transient visual evoked potential (CTVEP) based BCI. This stimulus provides a safer and more comfortable stimulation method than those in the conventional VEP-based BCIs. However, the maximal input number of our previous preliminary CTVEP-based BCI system is only seven. It is necessary to increase the number of commands in practical BCI systems. In the present study, we further develop the CTVEP-based BCI system by exploiting a novel encoding/decoding approach using pseudo random sequences.

2. Material and Methods

A practical panel with thirty visual field circles was presented in a 5 by 6 array on a color monitor. The onset visual stimulation of each visual field location is modulated with a pseudo random Gold sequence of length 127, and the Gold sequences of these locations are pair-wise uncorrelated in order to reduce the inter-location interference in the decoding. All visual field locations are stimulated in parallel with their own individual modulation Gold sequence. Based on color opponent theory, we select a double opponent cell: red-green on and red-green off [Gerth et al., 2003; Tobimatsu et al., 1996]. Fig. 1a shows the locations of 30 visual fields. In onset/offset pattern presentation for the experiments, stimuli were turned on for 33 ms and turned off for 67 ms, resulting in a duty cycle of 33%. Two stimuli states, 'light' and 'dark', were represented as '1' and '0' in the binary sequence, respectively. The time to present one stimulus cycle is 12.7 s.

Three male subjects (22-30 years) with no previous experience of BCIs participated in the study. Visual acuity was normal in all subjects. One subject was asked to repeat the experiment several days later. Electroencephalography (EEG) was recorded binocularly using a SynAmps2 128 Channel Quik-Cap electrode placement system with 2 electrodes (Cz and Oz for active recording, GND for grounding, M1 and M2 for referencing). The subject was asked to focus on one visual field location (randomly selected) in each experiment. Before the experiment, the subject was requested to focus on a specific visual field (with its pre-determined Gold sequence), so that a VEP template could be obtained through a decoding using the known Gold sequence. Since the Gold sequences are uncorrelated with each other, a decoding by correlation can provide an estimate of the response signal for the stimulation in any specific visual field as long as the Gold sequence for this known specific visual field is used as the decoding code, similar to the CDMA wireless communication system.

All zeros from the binary code were converted into '-1' in order to comply with the balanced property of Gold sequences, but also to help in the amplification of the signal-to-noise ratio. The VEP template is used as a matched filter in the command detection step in BCI, after the pseudo random sequence decoding. Before any decoding and matched filtering, the collected EEG signals were first filtered through a 1-30 Hz band-pass filter to reduce some interference out of our interest. Subject can make one selection after one stimulus cycle (12.7 s).



(a) (b)

Fig 1. (a) Thirty visual locations in 5 by 6 array. (b) Results of the decoding process where the first Gold sequence in this case was identified as the stimulating sequence while x-axis is in time (ms) and y-axis in amplitude (μV).

3. Results

As an example shown in Fig. 1b, the decoding by sequence 1 that modulates the stimulation of the focused visual field provides a clear VEP response, while the other sequences decode only background noise, and the difference is made more apparent after matched filtering using the VEP template obtained using the method described in Section 2. All subjects' accuracy is over 96% with mean 98.34% accuracy, leading to a quite reliable and much more efficient BCI system as compared to our previous work [Lai et al., 2011].

4. Discussion

The novel encoding/decoding scheme using pseudo random sequences has been demonstrated with promising results for the CTVEP-based BCI system in order to increase the number of commands, and this BCI solution can get a very high off-line performance. These preliminary results are based on an on-going project, while this paper presented only three subjects. More inputs and higher ITR with high accuracy performance can be achieved based on our solution. We are further improving the encoding/decoding scheme and will build a real-time BCI system with the proposed chromatic transient visual stimulus array.

Acknowledgements

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Design of a Multichannel Cortical Stimulator Prototype for Future Neuroprosthetic Research

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Abstract. Intracranial recording and decoding of neural signals for brain-computer interfaces (BCIs) is rapidly progressing. While much work has been done to explore electrical stimulation of muscles, nerves, and the cochlea for prosthetics, far less has been done to explore the possibility of direct cortical stimulation of the human brain. It has been shown that simple bipolar, biphasic cortical stimulation can induce a wide range of sensory percepts, conceivably allowing for a new means of sensory feedback. These devices could lead to novel, more natural bi-directional BCIs where the user could experience for instance proprioception with a robotic arm. Such devices will undoubtedly require complex spatiotemporal cortical stimulation patterns. Here we present a design of a configurable cortical stimulator prototype based on the Raspberry Pi single-board computer.

Keywords: Cortical stimulation, electrocorticography, functional electrical stimulation

1. Introduction

Past studies have shown that using direct cortical stimulation with bipolar, biphasic pulses to the human visual cortex can create a visual prosthetic to allow individuals to perceive monochromatic shapes in the users' visual field [Schmidt et al., 1996]. Additionally, electrical stimulation of the auditory cortex has produced auditory percepts in humans [Howard et al., 2000; Fukuda et al., 2010]. Functional electrical stimulation (FES) is also considered the gold standard for cortical mapping prior to resection in medically intractable epilepsy and brain tumors. However, in all of these instances the stimulation has typically been performed using very rudimentary and localized bipolar, biphasic stimulation protocols. While traditional stimulation devices may be sufficient for functional mapping and inducing simple sensory percepts, they are not capable of providing the desired fully-configurable spatiotemporal stimulation patterns necessary for complex BCI feedback. In order to fully realize a bi-directional BCI, i. e., including sensory feedback, it is conceivable that more complex spatiotemporal stimulation patterns need to be developed. Here we present the development of a cortical stimulator prototype capable of satisfying these needs.

2. Material and Methods

Stimulating the cortex is a delicate procedure. By stimulating with too large of a current, irreversible damage can be caused to neuronal structures. However, by stimulating with too little current there is no noticeable effect on the subject. For these reasons, this cortical stimulator device is based on existing clinical devices, e.g., the Ojemann stimulator and the Grass S12X, as well as recent patents [Lombardi et al., 2010; Beuter and Modolo, 2010]. The design of this device is broken into three predominant areas, the stimulus design software, the Raspberry Pi (RPi) control unit, and the output circuitry.

2.1. Stimulus Design Software

The stimulus design software is a MATLAB function that accepts a matrix of eight channels of voltage waveforms up to two seconds in length. It is designed to allow unit-calibrated ECoG data to be fed directly back onto the cortex by means of stimulation currents that are directly proportional to the recorded voltages. The software converts these input voltages to currents that will be applied, and performs error checking to maintain the output currents within safe levels of operation. The created current waveforms are then passed via Ethernet to the RPi control unit.

2.2. The Raspberry Pi

The Raspberry Pi is an inexpensive single-board computer running a full Linux kernel, but also contains a multitude of I/O pins similar to most micro-controllers. This unit, shown in the second stage of Fig. 1, accepts a file describing the current waveforms from the primary computer, and upon a button press outputs the eight channels of activity serially to a DAC. All eight channels are updated every 400 µs. The unit also controls the logic of the output circuitry, e. g., enabling the DAC and OTA.

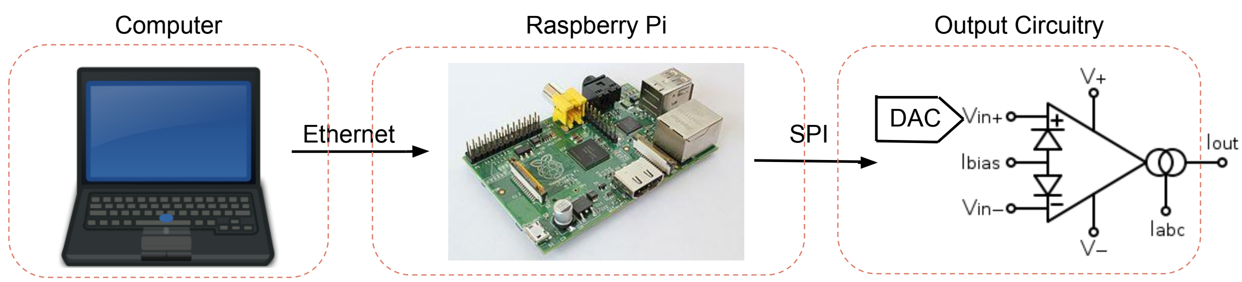

Figure 1: *The three main components to the stimulator prototype include 1) the primary computer running a MATLAB function, 2) the RPi controlling circuitry logic and passing through data, and 3) output circuitry which interfaces with ECoG electrodes.*

2.3. Output Circuitry

The digital waveforms are converted to analog signals using the LTC1660 10-bit DAC. The analog voltage is then converted to a current using traditional transconductance amplifier circuitry, which provides a current output based on a voltage input. The LM13700 operational transconductance amplifier (OTA) with two buffered OTAs in a single package was selected to provide the output currents.

3. Results

To verify the functionality of this prototype, eight simultaneously recorded two-second segments of ECoG data were selected as stimulation waveforms. The waveforms are then output through 1 kΩ loads, which are expected to be comparable to cortical loads. Two of the resulting simultaneous stimulation waveforms captured using a biosignal amplifier are displayed in Fig. 2. The outputs were compared numerically, resulting in the small RMSE of 0.207 ± 0.013. Visually, the output can be shown to nearly perfectly track the desired current on the right of Fig. 2.

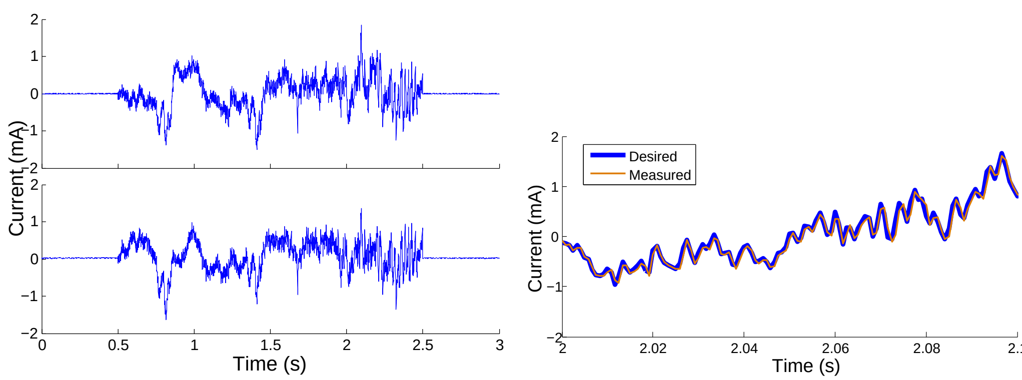

Figure 2: *Two simultaneous outputs from the device are shown on the left. On the right is a comparison showing the desired output tracking the input very well over a 0.1 s interval.*

4. Discussion

This prototype presents a significant and affordable step toward the development of a cortical stimulator unit that is fully programmable and capable of simultaneous multichannel stimulation. One possible limitation of this design is the lack of timing resolution, with a minimal pulse width of 400 µs, compared to 100 µs in predicate devices. However, it should be noted that this device is intended to stimulate in non-traditional waveforms so does not necessitate such short pulses. Additional safety features and testing will need to be pursued prior to any human testing.

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Field Study of an fNIR-Based Brain-Computer Interface for Communication

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Abstract. Functional Near Infrared (fNIR) Brain-Computer Interfaces use light in the infrared spectrum to determine activity levels in the brain by detecting hemodynamic changes. Hitachi Japan developed the Kokoro-Gatari device, a simple fNIR-based communication system for people with locked-in syndrome. Following a successful study in Japan, we performed a year-long U.S.-based study in the home environments of 30 people with ALS, to determine the long-term effectiveness of the Kokoro-Gatari as a communication device. Accuracy ranged from 32% to 100% with an average of just under 70% overall. We also examined average usage (compliance with the study), regional differences, and learning effects.

Keywords: Functional Near Infrared Imaging; Assisstive Communication, ALS

1. Introduction

People with locked-in syndrome cannot speak or move their muscles, and have little or no ability to communicate with their families and caregivers. Restoring communication can be key to improving quality of life for this population, and Brain-Computer Interfaces (BCIs) are a promising solution. However, most BCIs are complex and require extensive training to use, making them difficult for a home scenario. The Kokoro-Gatari (K-G, "Teller of Hearts" in Japanese) device was developed by Hitachi Japan as a simple BCI for home use [Naito et al., 2007]. The K-G is intended to provide augmentative and alternative communication (AAC) for people with Amyotrophic Lateral Sclerosis (ALS), which is a chronic and progressive disease that can cause locked-in syndrome. The K-G device is based on functional Near-Infrared Imaging (fNIR), which utilizes light in the infrared spectrum to detect areas of activation in the human brain generated by mental imagery or tasks. We performed home visits, setting up the K-G system and training 35 people with ALS and their families to operate it. We automatically collected data from the K-G devices over the span of a year in nine states: New Jersey, New York, North Carolina, South Carolina, Georgia, Florida, Alabama, Pennsylvania, and California. Participants were allowed to keep the device after the study if they wished.

2. Material and Methods

The Kokoro Gatari system consists of three components: a headband, an fNIR signal-processing device and a personal computer. Light emitters and a detector are installed in the headband. The light sources are LEDs with the wavelength of 770 nm. The detector is a Si PIN photodiode (PD) located 30 mm away from the LEDs [Sagara et al., 2009]. The emitter of the headband is placed over the left eyebrow of the subject, as close to the temple as possible without contacting the hair (see Fig. 1). This allows language imagery to activate Broca's area (in right-dominant subjects). Suggested imagery included reciting poetry, singing a song, or sub-vocal counting. The device analyzes the blood volume changes in cerebral cortex accompanied by change in brain activity. When ALS patients are asked a question, they answer 'yes' or 'no' by performing a language imagery mental task to activate their brain. The blood volume change is then detected with near infrared light (NIR). When light sources are focused on the patient's head the light penetrates the brain, scatters there and then returns to the surface of the brain. The use of the brain is detected by measuring the intensity of the returned light. When the blood volume, and thus the amount of hemoglobin, is increased during brain usage absorption of the incident light by hemoglobin decreases and the intensity of returned light decreases also.

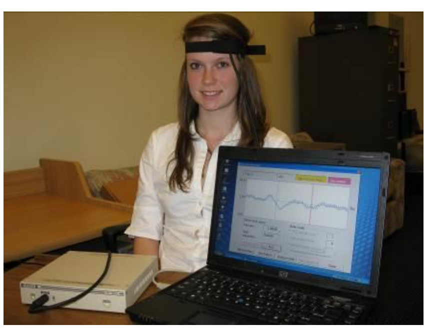

Figure 1. The Kokoro-Gatari

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2.1. Experimental Procedure

Researchers visited 30 subjects' homes throughout the U.S., setting up the K-G device and training the subjects to use it. The study protocol consisted of a calibration session, where the subjects were asked to perform mental language tasks to say "yes" and to think of a nonsense syllable (such as "la") to deactivate their Broca's area to say "no". Subjects were asked to generate a "yes" two times and a "no" two times, which allowed the researchers to set device parameters customized for each subject. After the initial calibration, subjects were prompted by the K-G system to generate a "yes" or a "no" in a randomized sequence for a total of ten answers. The data were automatically sent to the research team in Georgia. Subjects agreed to practice with the K-G at least twice a week for a month; at that time they could continue if they wished.

3. Results

3.1. Effectiveness

Of the 30 subjects, only four (13%) were not able to use the device. The average length of participation was 13.6 weeks, over three months. The average number of sessions per week was 1.92, very close to the promised twice a week. Average accuracy overall was just under 70%, with a range of 32% to 100%. Standard deviation was 9.05. The presence of the investigators (who followed up with most of the subjects) had an effect on the accuracy – with 5% greater accuracy when the investigator was present. Regional culture also had an effect, with western states achieving the best accuracy at 75%, and northern states averaging 61%.

3.2. Learning Curve

As expected, we observed a learning trend in the first few months that leveled off as subjects became proficient at operating the K-G device. Figure 2 shows that early learning fluctuated, and then experienced an increase, which leveled off. The increase after month eight reflects the most successful subjects who used the K-G device longer.

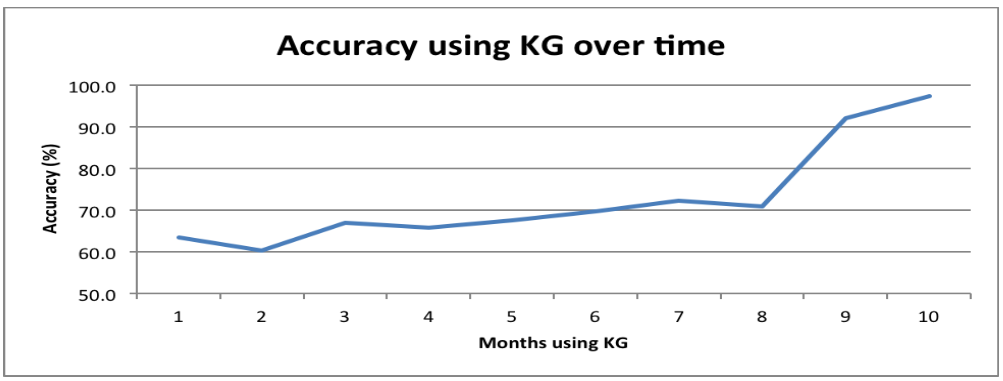

Figure 2. Longitudinal performance averages of all subjects.

4. Discussion

Compliance with this study was impressive from most of the subjects, as evidenced by the nearly twice a week average for practicing with the system. Chronic diseases such as ALS can produce fatigue and illness, so motivation was high for the subjects to be that consistent. The subjects that produced accuracies of less than 50 percent may have had "inverse data"… the calibration of yes and no may have been reversed. A consistent accuracy of 30% may actually be 70%, which could affect the cumulative averages. Overall, 87% of subjects had 60% or higher accuracy.

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Identification of Cortical Target Regions for Intracranial BCI Based on Covert Spatial Attention in 7T fMRI

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Abstract. For a good result in intracranial brain-computer interfaces (BCI), it is necessary to identify the best electrode placements before surgery. We have shown that non-invasive fMRI is suitable for this. We have also shown that covert visuospatial attention (COVISA) can be used for real-time fMRI BCI. In this study we show that these previous results also demonstrate proof of concept of an intracranial (ECoG) based BCI controlled by COVISA by restricting fMRI voxel selection based on limitations of ECoG electrodes.

Keywords: fMRI, ECoG, visuospatial attention

1. Introduction

Aim of our research program is to identify brain regions that provide a reliable control signal for ECoG-based intracranial BCI. We have shown that fMRI can be used to identify ECoG targets [Hermes et al., 2012; Vansteense, 2010]. We recently reported that covert visuospatial attention (without any eye movements; COVISA) can be used for BCI control using real-time fMRI [Andersson et al., 2012], and postulated that this suggests feasibility of COVISA for intracranial BCI. However, all regions in the occipital cortex were used for decoding visual attention, meaning that the results were based on activity that is not accessible with surface electrodes. In the current study, we investigate whether COVISA BCI with fMRI is feasible with only voxels from regions accessible with electrodes. We used fMRI data obtained in a previous study [Andersson et al., 2012], and re-analysed only the data from voxels located at the lateral surface of the cortex (i.e. which is accessible for ECoG), of a single hemisphere (aiming at minimal surgery with a single cranial entry point).

By analysing the fMRI data with the restrictions based on the limitations of ECoG, we could make the results more relevant to the latter modality, thereby making the case for feasibility of intracranial COVISA BCI stronger.

2. Material and Methods

Nine healthy volunteers (age 23–28, right-handed, 5 male) with normal or corrected-to-normal vision and naive to the task participated in the study. The study was approved by the ethics committee of the University Medical Center Utrecht in accordance with the declaration of Helsinki (2008) and all subjects had given their written informed consent.

The subjects were scanned with a 7T Philips Achieva system with a 16-channel SENSE head coil. The functional data were recorded using an EPI sequence (TR/TE = 1620/25 ms, voxel size 2×1.8×1.8 mm). Only the occipital lobe and the most posterior part of the parietal lobe were scanned. Each experiment consisted of 652 volumes from which the first 292 volumes were used as training data and the remaining part served as testing data. A high-resolution image was acquired for the anatomy using a T1 3D TFE sequence.

Subjects were presented with an image containing a central cue surrounded by four target areas located at the top, right, down, and bottom side of the screen respectively. For training the classifier, the first 292 scans were used, during which the central cue alternately indicated which direction (an arrow) to direct attention to, with 9 trials per direction. Subjects kept their gaze fixed to the center at all times. For the rest of the scans (test set), trials continued but now correct decoding of scans was indicated by changing the cue color from an initial red to green (per trial). Real-time decoding resulted in 80% correct, indicating good performance and motivation of subjects.

All brain volumes were blurred and registered to the first one by minimisation of the sum of squared differences using a stochastic gradient descent method [Klein et al., 2007]. After registration, the data were detrended [Tarvainen et al., 2002] and each voxel's signal was normalised to have zero mean and unit standard deviation. A surface mask containing only voxels on the cortical surface (to a depth of approximately 6 mm) was created by subtraction of a solid brain mask and an eroded version thereof and removing the medial surfaces, so that the remaining voxels meet the criteria described in the introduction.

A support vector machine (C-SVM from PyMVPA) consisting of six binary classifiers was used where each separated two of the four classes (directions). Each scan was assigned to the class with the majority vote among these binary classifiers. In order to avoid overfitting, the number of voxels was reduced by selecting the 250 voxels with the highest weight in the trained model for each hemisphere. Clusters consisting of less than 5 voxels were excluded, since only large clusters are suitable for electrode coverage. The classifier was trained on the first 292 volumes (9 trials per direction). In the test data, each trial was classified using only the 5th volume, giving enough time for the haemodynamic response to reach a detectable level.

3. Results

Based on the voxel selection by the classifier, the average performance over 10 trial sessions is 85.0% when using voxels from the left cortical surface and 78.9% with voxels from the right cortical surface, which is respectively 10% and 17% lower than if the whole brain were used (see Table 1). Performance is lower for ipsilateral attention due to contralateral hemifield processing in the visual cortex.

Table 1. *Average performance (in percent correctly classified) over 10 trial sessions.*

Voxels selected from …	*Attention (% correctly classified)*				
	Right	*Left*	*Up*	*Down*	*Average*
Whole brain	94.4	94.4	97.8	94.4	95.3
Left cortical surface	86.7	70.0	93.3	90.0	85.0
Right cortical surface	71.1	84.4	78.9	81.1	78.9

4. Conclusion

By performing the same classification analysis with different criteria on voxel inclusion, we have been able to estimate the implications of the anatomical limitations that have to be considered when planning to implant electrodes. In spite of significant anatomical constraints we could decode the directed attention with a high accuracy. Active voxels (166 on average) were distributed over an average of 8 clusters (2 per attention direction) with a total volume of 1.1 cm^3, which is sufficient for covering with ECoG electrodes. Since the BOLD signal has been shown to map well to changes in the gamma band of ECoG, the current results demonstrate proof of concept of an ECoG based BCI controlled by visuospatial attention. Because of the lack of anatomical consistency in the topography of the visual cortex, spatially restricted fMRI can be used to find the optimum electrode placements.

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Modeling the Electroencephalogram Using Intracranial Signals

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Abstract. This study presents models of electroencephalographic (EEG) event-related potentials (ERPs) using intracranially recorded ERPs from electrocorticography (ECoG) and stereotactic depth electrodes in the hippocampus. The patients had medically-intractable epilepsy and underwent temporary placement of an intracranial electrode arrays to localize seizure foci. Six patients performed one experimental session using the P300 Speller paradigm controlled by scalp-recorded EEG prior to the ECoG grid implantation, and one identical session controlled by ECoG after the grid implantation. All patients were able to achieve excellent spelling accuracy using EEG, and four of the patients achieved roughly equivalent performance in the intracranial sessions. Each EEG-ERP was modeled from the intracranial ERPs. The results indicate that EEG-ERPs can be accurately estimated from the intracranial ERPs for the patients that exhibited stable ERPs over the respective sessions. The resulting models provide a better understanding of the EEG-ERPs and can potentially be used to improve noninvasive BCI methods.

Keywords: Electroencephalogram (EEG), Electrocorticogram (ECoG), Event Related Potential (ERP), P300 Speller

1. Introduction

Event-related potentials (ERPs) have been proven to be reliable signals for controlling EEG and intracranial BCIs [Krusienski et al., 2008; Krusienski and Shih, 2011]. Because the tissue in the human head acts as a volume conductor for the brain's electrical activity, it is conceivable that scalp EEG can be mathematically modeled as a mixture of underlying intracranial signals [Krusienski and Shih, 2010]. It is believed that accurate models will better localize and enhance the desired brain activity of scalp EEG recordings, thus leading to more effective noninvasive BCI processing techniques. Since there are several major issues with simultaneous recording of scalp EEG and intracranial signals in temporarily implanted humans, such as the corruptive effects of the incision and implantation trauma on simultaneously monitored scalp EEG, the proposed approach relates scalp-EEG data recorded pre-intracranial electrode implantation to intracranial data recorded after implantation. Because both EEG and intracranial ERPs are represented using time-domain ensemble averages, their spatial and temporal characteristics are presumed to be well-defined and consistent. Thus, the resulting characteristic responses defined by ensemble averaging were used to create the models relating the scalp EEG and intracranial responses.

2. Material and Methods

2.1. Subjects and Data Acquisition

Six subjects with medically intractable epilepsy were implanted with intracranial grid or strip electrode arrays to localize seizure foci prior to surgical resection and were tested for the ability to control the P300 Speller paradigm using EEG and ECoG signals. Electrode placements and duration of ECoG monitoring were based solely on the requirement of the clinical evaluation without any consideration of this study. Table 1 shows the ECoG electrode locations and P300 Speller accuracy based on a linear classifier for each subject.

Table 1: *Subject Information.*

Subject	# Electrodes	Location	EEG Accuracy (%)	Intracranial Accuracy (%)
A	24	Left Frontal, Lateral Temporal	100	25
B	30	Left Frontal-Parietal	93	100
C	16	Bilateral Hippocampal Depth	100	100
D	30	Left Lateral Temporal, Inferior Frontal	100	44
E	24	Left Lateral Temporal	88	81
F	64	Left Frontal, Parietal, Lateral Temporal	100	88

Prior to electrode implantation, all the subjects performed a BCI session using 32-channel scalp-recorded EEG. The EEG was amplified, bandpass filtered 0.5–500 Hz and digitized at 1200 Hz (to match the typical intracranial rate) using g.USB amplifiers. Stimulus presentation and data recording was controlled by BCI2000. The intracranial sessions were performed between 24 to 48 hours after electrode implantation. All electrodes were referenced to a scalp vertex electrode and recorded using the identical hardware, software and protocols as the EEG data collection. The experimental protocol was based on the protocol used in EEG-based P300 Speller study [Krusienski et al., 2008].

2.2. Data Analysis

Both EEG and ECoG data were lowpass filtered to 20 Hz and decimated to 240 Hz, to smooth the data while retaining sufficient samples for modeling and ERP visualization. Only target stimulus ERPs were used for the construction of the model. For each EEG and ECoG channel, 800 ms of the data following each flash were extracted as the ERP. The average target ERP was computed for each channel. These ERPs were multiplied by a tapered cosine window to deemphasize the beginning and end of the ERPs in the regression models. The first half of the intracranial ERPs and EEG-ERPs were used to train a stepwise linear regression model. The remaining half of the intracranial ERPs were used to generate the predicted ERPs based on the trained model. The actual and predicted waveforms were compared by computing the mean absolute error (MAE), after excluding the highest 5 % of the absolute error values that are believed to be the result of artifacts in the test data. Prior to computing the MAE, the actual ERPs were scaled to unit variance and the corresponding predicted ERPs were scaled by the same factor to remove any amplitude dependencies when comparing MAE across channels.

3. Results

Low MAE models were observed over particular EEG channels for three of the six subjects (Subjects B, C, and F), and these channels were not always necessarily located over the intracranial electrodes. Fig. 1 shows the results for Subject C: (A) shows the relative axial locations of the EEG and hippocampal depth electrodes, with the color corresponding to the task classification accuracy obtained by using that electrode in isolation, (B) shows the MAE with two examples of actual and predicted ERPs.

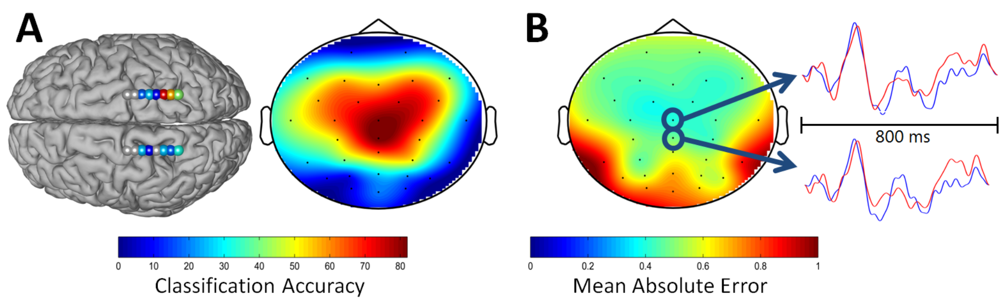

Figure 1: *The results for Subject C. (A) The relative axial locations of the EEG and hippocampal depth electrodes, with the color corresponding to the task classification accuracy obtained by using that electrode in isolation, (B) The mean absolute error topography of the prediction included with two examples of actual (blue) and predicted (red) ERPs.*

4. Discussion

The results indicate that the intracranial models can accurately predict the scalp ERPs when the intracranial electrodes are positioned to capture reliable ERPs. These favorable locations were found to be predominantly over the traditional parietal areas for the P300 as positioned in Subjects B, C, and F. More importantly, as illustrated in Fig. 1, accurate ERP predictions can be determined for the most task-relevant EEG electrodes. Further analysis of the signals and resulting models will provide new insights to the underlying sources of scalp ERPs and can potentially be used to improve noninvasive BCI methods.

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Which Neural Signals are Optimal for Brain-Computer Interface Control?

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Abstract. We compared the encoding and decoding performance of several intracortical neural signals—single units, multi-units, and band-limited local field potential (LFP) power—within an eye movement brain-computer interface (BCI) paradigm. We find that broadband high-frequency LFPs exhibit the best performance, and may be an easily obtainable, high-performance signal for BCI applications.

Keywords: single units, local field potentials, intracortical, decoding, monkey, saccade

1. Introduction

There has been considerable controversy over which neural signals are best for controlling a brain-computer interface (BCI). While single-unit spikes have long been considered the “gold standard” in the field, some recent studies have suggested unsorted multi-unit activity [Stark and Abeles, 2007] or local field potentials (LFPs) [Mehring et al., 2003] provide more accurate decoding, while others maintain the superiority of single units [Bansal et al., 2012]. We compare these signals’ information content and decoding accuracy for saccade direction, using intracortical recordings from a non-human primate performing a delayed saccade task (see related abstract from our group describing an eye-movement BCI system). Both measures suggest the optimal signal is broadband high-frequency LFP power, which likely reflects neuronal spiking near the recording electrode.

2. Material and Methods

We analyzed signals from three 32-channel Utah arrays implanted into the frontal eye field (FEF), supplementary eye field (SEF), and dorsolateral prefrontal cortex (PFC) of a macaque monkey. Spiking and LFP signals were simultaneously recorded from all 96 electrodes while the monkey performed a delayed saccade task. On each task trial, one of six spatial locations was briefly cued. The monkey held this location in working memory over a 750 ms delay period, and then executed a saccadic eye movement to the remembered location. Here we focus our analysis on neural activity during the delay period, which likely reflects motor intentional signals that are most relevant for BCI control. Multi-units were obtained by high-pass filtering the raw data at 250 Hz, and counting all waveforms crossing a channel-specific manual threshold. Single-units were sorted out of the set of suprathreshold waveforms online using multiple time-amplitude windows. LFP signals were obtained by initially filtering the raw continuous data from 0.3–500 Hz, then extracting band-limited power by additional band-pass filtering and computing the magnitude of the Hilbert transform. Standard definitions of LFP bands were used: delta (1–4 Hz), theta (4–8), alpha (8–12), beta (12–30), gamma (30–80), and high-frequency (80–500). Neural information content was quantified by the percent of channels showing significantly different activity across saccade direction in a 1-way ANOVA. A cross-validated linear discriminant was used for decoding analyses; this was found to provide as good or better prediction as other popular decoding methods.

3. Results

Across eight daily sessions, we found significant neural information ($p < 0.01$, ANOVA) about intended saccade direction in an average of $12 \pm 0.6\%$ (across-session mean $\pm$ SEM) of recorded single units, $15 \pm 0.9\%$ of multi-units, and $31 \pm 2.4\%$ of high-frequency LFPs. Significant information was found less frequently in the LFP beta (25%) and gamma (20%) bands, and rarely within other bands. More detailed spectral analyses confirmed these results, showing a peak of saccade information in the beta band (~15–30 Hz), and a strong broadband increase of information at frequencies above ~80 Hz. These results suggest that LFPs, especially in the high-frequency band, may provide particularly information-rich signals for an eye-movement-based BCI.

We then compared the accuracy of these signals for decoding saccade direction (cross-validated percent correct). Again, high-frequency LFPs greatly outperformed (74 ± 1.8%; across-session mean ± SEM) both multi-units (46 ± 1.1%; $p = 8\times10^{-10}$, t-test) and single units (47 ± 0.9%; $p = 1\times10^{-9}$, t-test). Decoding accuracy for all other LFP bands was significantly lower. More detailed analysis of the high-frequency LFP band revealed that decoding performance exhibited a broad optimum at low-cutoff frequencies of ~60–150 Hz and high-cutoff frequencies above ~350 Hz. These results suggest that a broad, high-frequency LFP band provides the best decoding of eye movement signals.

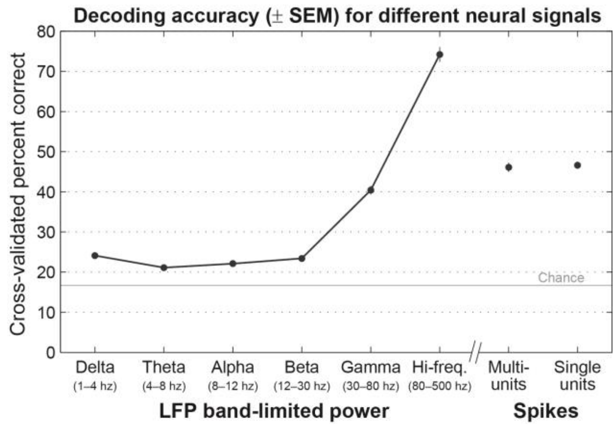

Figure 1. *Decoder performance (percent correct for cross-validated prediction) for several types of neural signals: band-limited LFP power for several frequency bands, unsorted multi-units, and isolated single units. High-frequency LFP power (80–500 Hz) greatly outperforms any other examined signal.*

One remaining question is what underlying neural source these high-frequency LFP signals reflect. We observed moderately strong correlations between high-frequency LFP power and multi-unit spike count within each electrode, and found that a classifier using both types of signals resulted in no performance improvement over high-frequency LFPs alone. These results suggest that high-frequency LFPs may largely reflect local spiking activity (cf. [Ray and Maunsell, 2011]), possibly integrated over a larger volume than traditional spiking signals. This possibility is supported by the fact that the improvement of LFP power over spiking signals is much larger in SEF and FEF—where functional organization for saccade direction might render such integration beneficial—than in PFC, which lacks strong functional organization for saccades.

Finally, preliminary results indicate that higher-order spectral features might also provide useful BCI signals. We found that both the magnitude and phase of delay-period cross-electrode LFP coherence, for all pairs of studied areas, carried information about intended saccade direction. Within individual electrodes, the strength of cross-frequency coupling between high-frequency power and beta/gamma-band LFP phase also reflected the intended saccade. Ongoing efforts aim to incorporate these spectral features into our decoding model.

4. Discussion

We compared several candidate neural signals, and found optimal decoding of intended eye movements from high-frequency LFP power. As alluded to in the Results section, this band most likely reflects integrated spiking signals from the neuronal population near the recording electrode, thus containing more sub-threshold information that is lost in the spike detection process. In contrast to traditional spiking signals, high-frequency LFPs are very easy to obtain, requiring data sampling no higher than ~1 kHz, no computationally expensive spike extraction/sorting algorithms, and no manual intervention. Thus, our results suggest high-frequency LFP power may be an inexpensive, fast, and very information-rich signal for BCI applications.

Acknowledgements

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Transcranial Doppler Ultrasonography-Driven Online Augmentative and Alternative Communication Aid

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Abstract. Transcranial Doppler Ultrasonography (TCD) has been shown to be a promising brain-computer interface (BCI) modality that could accurately differentiate between two mental tasks. However, the success of TCD as an online BCI has yet to be demonstrated. Within this study, TCD is implemented as an online BCI modality for the control of a communication system (scanning keyboard) through the use of two mental tasks: repetitive mental spelling and visual tracking of the TCD signal feedback. Data is classified using Naïve Bayes and a set of time-domain user-dependent features. The preliminary results have shown that the overall training validation accuracy is 79.54 ± 3.42% and the online testing accuracy is 80.32 ± 7.32%. These results are very encouraging and provide the first step towards an online TCD-BCI system.

Keywords: TCD, Online BCI, Mental Task, CBFV Lateralization, AAC

1. Introduction

Individuals who are cognitively aware but have severe motor disorders such as muscular dystrophy, spinal cord injuries or locked-in syndrome often have difficulty interacting with their surroundings. Out of the available technologies that attempt to shorten this communication gap, brain-computer interfaces (BCIs) have been particularly promising, as they allow the users to manipulate output devices through mental activities alone [Tai et al., 2008]. Within the recent developments, transcranial Doppler ultrasonography (TCD) has sparked great interest as a BCI modality because it is affordable and robust against environmental noises [Myrden et al., 2011].

TCD is a non-invasive ultrasound technology that exploits the changes in cerebral blood flow velocity (CBFV). Within the recent years, TCD has been utilized as a functional brain imaging tool to examine the effects of mental tasks on the CBFV, especially the middle cerebral arteries (MCAs) [Lohmann et al., 2006]. Using mental task elicited CBFV changes, previous offline BCI study has achieved over 70% accuracy [Myrden et al., 2011]. In this study, we further explore the possibility of TCD-BCI by designing and implementing an online TCD-BCI system.

2. Material and Methods

2.1. Participants and Instrumentation

Twelve able-bodied participants with normal or corrected-to-normal eyesight are recruited for this study. The participants are all right-handed and have no history of neurological, metabolic, respiratory, cardiovascular, or drug/alcohol-related conditions. The MultiDop X-4 TCD (Compumedics Germany) and the accompanying bilateral headgear with fixed 2 MHz ultrasonic transducer are used to acquire the Doppler spectra of blood flow through the left and right MCAs. The probes are positioned over the transtemporal insonation window as in accordance with the established insonation procedure [Alexandrov et al., 2007].

2.2. Experimental Protocol

Each participant completes three sessions, with three blocks per session. For session one, the first two blocks are for training with the last block for testing. For sessions two and three, the first block is for training while the last two blocks are testing. A one minute baseline level is established prior to each block, which is then used to normalize all ensuing data collected from that same block. A five minute resting period is allowed in-between each block.

For each training block, participants perform a total of 20 mental spelling tasks (activation task) and 20 visual tracking tasks (rest task) that are randomly ordered. A 10 second recovery period is applied after each activation task to allow the participants' CBFV to return to baseline levels. For each mental task, task appropriate cue (Fig. 1) is presented to the participants through the whole task duration.

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Figure 1. *Cues for activation mental task and rest mental task from left to right respectively.*

For each testing block, participants are asked to perform the activation mental task when the target letter is shown on the screen and to perform the rest mental task otherwise. A trained classifier based on the session's training data is used to differentiate participants' intentions and select the appropriate letter.

2.3. Data Processing and Classification

For the first session, 40 activation and 40 rest data segments are collected to train a user-specific classifier. The second and third sessions each has 60 activation and 60 rest data. Each data segment is 15 seconds in duration, from which 44 unilateral and bilateral features are extracted [Myrden et al., 2011].

For the training data, a 10-fold cross-validation is performed on feature vectors selected through a weighted sequential forward search (WSFS) method. In each cross-validation fold, the training data set is randomly split 90-10 for training and validation. The WSFS method was developed as an improvement of the sequential forward selection [Devijer et al., 1982]. Instead of selecting the feature combination with the highest accuracy, the best feature combination for each fold was considered and the feature are regroup according to their contributions across the 10 folds. The feature group with the best performance is the final group used to train the Naïve Bayes classifier.

3. Results and Discussion

The preliminary results from 8 participants are summarized in Table 1 and Table 2, which shows the classification accuracies for offline and online settings respectively. The average accuracy across all participants was 79.54 ± 3.42% for the offline data and 80.32 ± 7.32% for the online data. Both the online and offline accuracies were well above chance levels of 60%, indicating that the repetitive spelling activation mental task and signal tracking rest mental task can be differentiated at above chance level.

Table 1. *Training set validation accuracy*

Participant Number	*SPE (%)*	*SEN (%)*	*ACC (%)*
1	72.50	90.00	81.25
2	83.75	75.00	79.38
3	76.25	70.00	73.13
4	80.00	81.25	80.63
5	75.00	77.50	76.25
6	82.50	86.25	84.38
7	82.50	78.75	80.63
8	73.75	87.50	80.63
Average	78.28	80.78	79.54

Table 2. *Testing set average accuracy*

Participant Number	*SPE (%)*	*SEN (%)*	*ACC (%)*
1	77.46	80.60	78.33
2	82.72	81.08	82.20
3	76.35	70.18	73.17
4	77.64	90.91	81.93
5	79.77	81.82	80.33
6	92.09	76.19	87.50
7	87.36	87.69	87.45
8	86.14	89.04	86.67
Average	79.93	81.11	80.32

The overall online accuracies have improved from the offline accuracies, which could be due to an increase in concentration and additional encouragement from the online feedback.

In this study, the potential benefits of practice were not examined. Despite this, acceptable classification accuracies were obtained. It is possible that participants could achieve an even higher accuracy as they gained further proficiency with the mental tasks. However, it is also possible that further practice could lead to habituation.

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Real-Time Estimation and 3D Visualization of Source Dynamics and Connectivity Using Wearable EEG

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Abstract. This report summarizes our recent efforts to deliver real-time data extraction, preprocessing, artifact rejection, source reconstruction, multivariate dynamical system analysis (including spectral Granger causality) and 3D visualization within the SIFT and BCILAB toolboxes. We report the application of such a pipeline to simulated data and real EEG data obtained from wearable high-density (32-64 channel) dry EEG systems.

Keywords: Wearable EEG, Dry Sensors, Connectivity, Source Localization, Artifact Rejection, Visualization

1. Introduction

Dynamic cortico-cortical interactions are central to neuronal information processing. The ability to monitor these interactions in real-time may prove useful for BCI and other applications, providing information not obtainable from univariate measures, such as bandpower and evoked potentials. Wearable (mobile, unobtrusive) EEG systems likewise play an important role in BCI applications, affording data collection in a wider range of environments. However, reliable real-time modeling of neuronal source dynamics using data collected in mobile settings faces challenges, including mitigating artifacts and maintaining fast computation and good modeling performance with limited amount of data. Here we describe some of the wearable hardware and signal processing we are developing that attempt to address these challenges, contributing to the development of EEG as mobile brain imaging modality.

2. Material and Methods

Our data-processing pipeline is outlined in Fig. 1. The pipeline is implemented in Matlab within our SIFT and BCILAB toolboxes, which are publically available as EEGLAB plugins [Delorme, 2011]. All elements of the pipeline can be controlled "on the fly" via a control panel GUI.

2.1. Wearable EEG Hardware

Cognionics has developed two new high-density (32 and 64 channel) dry wearable EEG systems. Harness and electronics are integrated into a compact and lightweight form-factor. Signals are digitized with 24-bit ADCs at 300 samples/sec and transmitted via Bluetooth. The headsets support a novel, flexible dry electrode consisting of a set of angled 'legs' made from conductive plastic, which flatten on impact. Typical sensor impedances are between 100 kΩ-1 MΩ and high input impedance circuitry on the headset ensure minimal signal degradation.

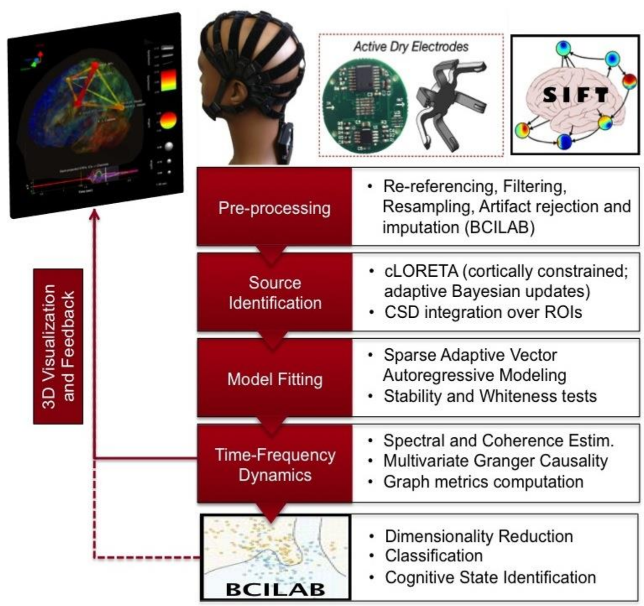

Figure 1. *Real-time data processing pipeline. A Cognionics 64-channel system is depicted above with flexible active dry electrodes.*

2.2. Preprocessing and Artifact Rejection

EEG data is streamed into Matlab, and an efficient online pre-processing pipeline is applied using BCILAB. Preprocessing elements include (though are not limited to) re-referencing, rejection of corrupted data samples or channels with bad channel imputation and/or high, low, or band-pass filtering. Short-time high-amplitude artifacts in the continuous data may be removed online, using a sliding-window Principal Component Analysis, by statistically interpolating any high-variance signal components exceeding a threshold relative to the covariance of a calibration measurement (here one minute of resting data). Each affected time point of EEG is then linearly reconstructed from the retained signal subspace based on the correlation structure of the calibration data.

2.2. Source Reconstruction

Following pre-processing, we estimate current source density (CSD) over a high-resolution cortical mesh. Our default forward model consists of a four-layer (skull, scalp, csf, and cortex) Boundary Element Method (BEM) model derived from the MNI "Colin 27" brain and computed using OpenMEEG [Gramfort, 2010]. For inverse modeling, we have currently implemented anatomically constrained LORETA with a Bayesian MAP update rule for hyperparameter estimation [Trujilo, 2004]. This approach is well suited for real-time adaptive estimation and automatically controls the level of regularization for each measurement vector. Additionally, we segment the source space into 90 regions of interest (ROIs) using Automated Anatomical Labeling [Tzourio-Mazoyer, 2002]. The user can compute spatially averaged, integrated or maximal CSD for any subset of these ROIs.

2.3. Dynamical Systems Analysis

Preprocessed channel or source time-series are forwarded to SIFT and an order-p sparse vector autoregressive (VAR[p]) model is fit to a short chunk of recent data (e.g. 0.5-2 sec). The VAR coefficients are estimated using Alternating Direction Method of Multipliers (ADMM) with a Group Lasso penalty [Boyd, 2011]. Model estimation is warm-started using the solution for the previous data chunk. The regularization parameter is initialized offline, by cross-validation on the calibration data, and adapted online using a simple heuristic based on two-point estimates of the gradients of the primal and dual norms. Model order is selected offline, by minimizing information criteria (e.g. AIC or BIC) on calibration data. Following model fitting and tests of stability and residual whiteness (autocorrelation function or Portmanteau), we obtain the spectral density matrix and any of the frequency-domain functional and effective connectivity measures implemented in SIFT. Graph-reductive metrics such as degree, flow, and asymmetry ratio can be applied to connectivity matrices. Finally, selected measures (power, connectivity, outflow, etc.) are visualized within an interactive 3D anatomical representation. These measures may also be forwarded to BCILAB as features for one of the 13 classification frameworks currently available.

3. Results and Discussion

We have tested our pipeline on simulations and 32- and 64-channel Cognionics data. 64-channel simulated EEG was generated by projecting a VAR system of five coupled oscillators through a realistic forward model. The system dynamics and connectivity graph were accurately reconstructed with a mean AUC of 0.97 ± 0.021. In real data, for a moderate number of ROIs (10-15), we obtain fast cLORETA convergence and good VAR model fit (stable with uncorrelated residuals, $p < 0.05$) exhibiting characteristic EEG $1/f$ spectral shape with prominent eyes-closed occipital alpha gain. On an Intel i7 4-core (2.3 GHz) laptop, preprocessing and source reconstruction typically takes 50-80 ms, model fitting 50-70 ms, and visualization 200-300 ms. We are further validating the pipeline in cognitive tasks, and applying source connectivity information as features for cognitive state classification within BCILAB.

Acknowledgements

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Improving Dynamic Data Collection in P300 Spellers With a Language Model

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Abstract. P300 spellers provide a means of communication that doesn't rely on neuromuscular control. The P300 speller operates by processing the user's EEG data after character subsets are flashed on a screen and these responses are averaged after multiple flashes to improve SNR. Adaptive selection of the number of flashes per character improves spelling speed and accuracy. The goal of this study was to optimize a previously developed dynamic stopping algorithm, a probabilistic method that has the advantage of both assessing the quality of the data currently under consideration and incorporating *a priori* knowledge of the language of the user to increase spelling speed. Participants (n=17) completed spelling tasks using the dynamic stopping algorithm with and without a language model. The addition of a language model significantly improved spelling speed and communication rate.

Keywords: EEG, BCI, P300 Speller, Amyotrophic Lateral Sclerosis (ALS), Dynamic Stopping, Language Model

1. Introduction

P300 spellers provide a means of communication for patients with severe physical limitations who lack the neuromuscular ability to control other forms of assistive devices, such as patients with amyotrophic lateral sclerosis (ALS) [Sellers and Donchin, 2006]. The P300 speller operates by evaluating the user's EEG responses as character subsets are flashed on a screen; when a flashed subset contains the desired character, an event related potential occurs [Farwell and Donchin, 1988]. These responses are averaged after multiple flashes to improve signal-to-noise ratio. Adaptively varying the number of flashes per character improves spelling speed and accuracy. Throckmorton et al. demonstrated improved accuracy and communication speed using a dynamic stopping algorithm which accomplished adaptive selection by maintaining a probability distribution over characters, integrating each classified flash response into the model via a Bayesian update. Data collection was stopped when a character probability reached a threshold and that character was selected as the intended target [Throckmorton et al., 2012]. We hypothesize that incorporating *a priori* knowledge of the user's language will also improve spelling performance. In this study, we optimize the dynamic stopping algorithm to include a language model.

2. Material and Methods

Seventeen non-disabled participants were recruited from Duke University for this study. BCI2000 software was used for stimulus presentation and data collection, with additional functionality added to implement dynamic stopping (DS) and dynamic stopping with language model (DSLM) algorithms. The row/column speller paradigm was used, with letters, numbers and keyboard commands presented in a 9 x 8 grid. EEG responses were measured using a 32-channel electrode cap, with the left and right mastoids used for ground and reference electrodes, respectively. Data from electrodes Fz, Cz, P3, Pz, P4, PO7, PO8 and Oz were used for classification.

EEG data obtained during the training phase was grouped into target and non-target responses and used to train a stepwise linear discriminant (SWLDA) classifier. SWLDA weights were used to calculate classifier responses of the training data and kernel density estimation was used to smooth the histogram of these responses to generate likelihood probability density functions (pdfs). In the testing phase, prior to data collection each possible character is assigned an initial probability of being the target. With each new flash, the classifier response is calculated and used to estimate the character non-target and target likelihoods from the likelihood pdfs. The character probabilities are updated with these likelihood values using Bayesian inference. If a character probability exceeds the threshold, it is selected as the target character. If not, a new flash is presented and the process of updating the character probabilities is repeated. In DS, the initialization probabilities assumed no prior knowledge; hence a uniform distribution was used. In DSLM, the initialization probabilities of alphabet characters were dependent on the previously spelled character, while non-alphabet characters assumed a uniform distribution. A character pair probability matrix was generated from the Carnegie Mellon Online dictionary ("The CMU Pronouncing Dictionary").

3. Results

Fig. 1 shows the theoretical bit rate obtained under DS and DSLM. Theoretical bit rate takes into account accuracy, the number of possible target characters and the time required to complete the task (excluding the 3.5 s pauses between character selections). A significant improvement in theoretical bit rate was observed in DSLM (M=54.42 bits/min, SD=23.78 bits/min), compared to DS (M=46.12 bits/min, SD=20.63 bits/min), $p < 0.0065$ (Wilcoxon signed-rank test). No significant difference in accuracy was observed across participants (DS: M=88.89%, SD=9.32%; DSLM: M=90.36%, SD=8.95%), $p < 0.2426$. Participants completed the task in less time under DSLM (M=6.27 min, SD=2.11 min), compared to DS (M=6.80 min, SD=2.21 min), $p < 0.00025$.

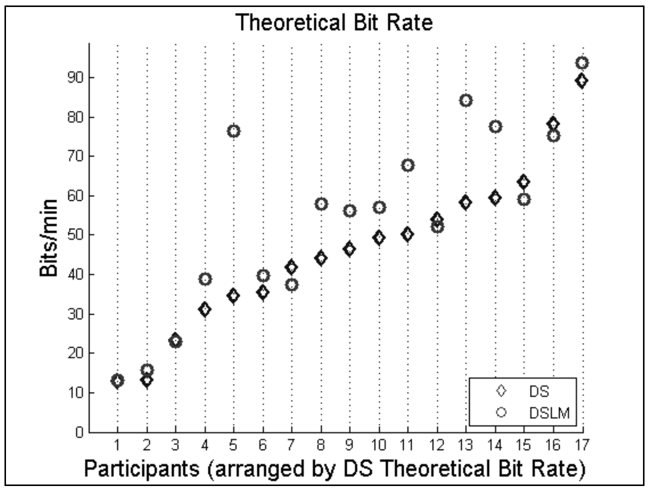

Figure 1. *Comparison of theoretical bit rate between DS and DSLM.*

4. Discussion

Improving spelling speed and communication rate in P300 spellers results in more practical and efficient day-to-day use in patients with severe disabilities, thereby restoring some level of independent communication. The amount of data collection prior to character selection has competing effects on speller speed and accuracy: decreasing it improves speed while increasing it improves spelling accuracy. The DS algorithm has been shown to improve spelling speed and accuracy. Prior knowledge via a language model based on character pairs adds more predictability to the algorithm and can reduce the time required to reach the decision threshold. Although each participant's distribution of flashes for character selection varied widely, character selection occurred on average with fewer flashes under DSLM compared to DS. Some participants observed an increase in accuracy under DSLM; coupled with a reduction in task completion time, this resulted in a significant increase in their theoretical bit rates. These results demonstrate the potential that spelling speed and communication rate in dynamic data collection can be improved with the addition of a language model.

Acknowledgements

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The Use of Phonetic Similarity Cues in Auditory Spellers

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Abstract. This study examines whether the ERPs elicited by a non-target stimulus in an oddball-based auditory speller are modulated by its phonetic similarity to the target. Both N200 and N400 amplitudes were significantly enhanced when a non-target contained the same initial consonant as the target, compared to when it did not. These additional modulations, which have not been exploited in previous studies, were used to train a classifier to provide partial information about target pronunciation, thereby complementing the standard target/non-target classifier. Offline classification results suggest that this approach is useful for enhancing speller performance.

Keywords: Auditory Speller, Phonetic Simiarlity, Speech, Electroencephalography, N2, Oddball Paradigm, Linear Discriminant Analysis

1. Introduction

Although both auditory spellers and visual spellers have generally been based on the oddball paradigm, the performance of auditory spellers using speech stimuli has been lower than that of visual spellers (see e.g., [Furdea et al., 2009]), especially when a “simple” task [Guo et al., 2010] is used. We posit that such a difference in performance arises in part because ERP waveforms are likely influenced by the phonetic similarity between target and non-target stimuli. In particular, the N2 component—one of the primary features for classification—is known to be enhanced in oddball tasks for both standards [Deguchi et al., 2010] and deviants [Nieuwenhuis et al., 2004] when the phonetic overlap among the stimuli is increased. The present study aims to characterize these modulations within the context of auditory spellers, and to assess whether they can be applied to enhance speller performance.

2. Material and Methods

Seventeen healthy native Hong Kong subjects (8 male and 9 female), aged 19–23, took part and were rewarded at about \$7 per hour. Informed consent was obtained from each subject. The data for one subject were rejected since the subject reported that no sounds were heard in one ear during the first two blocks. Each subject completed two phases of training: constant-stimulus (CONST) and variable-stimulus training (VAR), each comprising 3 blocks of 18 runs. In each run, 6 Cantonese syllables were played 10 times each. The syllables were of 200–320 ms duration, and the SOA was 350 ms. Subjects were instructed to mentally repeat the target every time they perceived it.

In the CONST blocks, a single, constant set of 6 syllables was used as stimuli. For the VAR blocks, 18 distinct sets of 6 syllables served as stimuli to ensure that a representative range of phonetic information could be gathered during this training phase. In one of these blocks, syllables in each run were chosen to serve the following three roles: a target (T), a non-target which shared the same initial consonant (SI) as the target, and 4 non-targets which contained different initials (DI), e.g., T: $geoi^2$; SI: $gung^6$; and DI: bun^3, $kwan^4$, $sang^1$, and $ming^4$ (transcription in Jyutping, a standard romanization system for Cantonese). In the other two blocks, the roles of the syllables were adjusted such that the target was either a stimulus that had previously served as either SI (e.g., $gung^6$) or DI (e.g., bun^3). Two testing blocks, comprising runs in which the target shared the initial with 0, 1 or 2 non-target stimuli, were included to assess speller performance for stimuli sets with different degrees of phonetic overlap.

EEG data, acquired at 2048 Hz using a 32-channel BioSemi system, were down-sampled offline to 64 Hz, low-pass filtered at 6 Hz (which was found to provide optimal performance), and the linear trend within each epoch removed. ERP analyses were conducted to identify time-windows for selecting features. A standard target/non-target classifier was obtained for each type of training blocks using shrinkage LDA [Blankertz et al., 2011], with the feature vector associated with each epoch being constructed by concatenating all electrodes. A third classifier was trained using VAR blocks by combining the scores of two binary classifiers, the first discriminating T vs. DI and the second SI vs. T and DI. Since a high score for the second classifier indicated that the stimulus corresponded to a SI non-target, the stimuli with the same initial as the identified SI were more likely to be target—for these stimuli, the score associated with the identified SI was thus added to their scores for the first classifier.

3. Results

Fig. 1(a) shows the grand-averaged ERP waveforms recorded at the vertex (Cz) during the VAR training blocks. Two separate repeated-measures ANOVAs were run with factors: *Stimulus Type* [T, SI, DI] and *Electrode* [Fz, Cz, Pz] to examine the differences in potential within the N200 (188–250 ms) and N400 (375–438 ms) windows. The interaction effects were significant for both N200 [$p < 0.025$; Fig. 1(b)] and N400 [$p < 0.001$; Fig. 1(c)] windows. Post-hoc pairwise *t*-tests with Bonferroni correction were run to assess the differences across conditions. Of special note is that the average amplitude across the three electrodes was significantly larger for SI than DI for both windows, suggesting that these two windows contain cues that can be used to discriminate SI from DI.

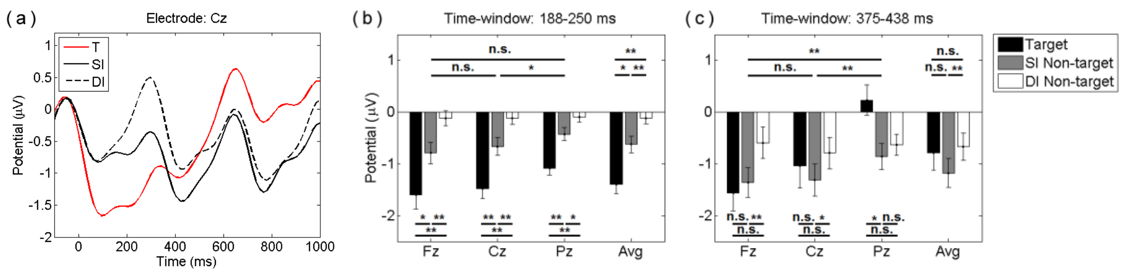

Figure 1. *(a) ERP measured at Cz during the VAR training blocks for the three conditions (T: target; SI: same-initial non-target; DI: different-initial non-targets). (b) Bar chart showing the average amplitudes measured at three electrodes (Fz, Cz, Pz) and the average of these electrodes within the time window 188–250 ms for the three conditions. (c) Bar chart showing the average amplitudes measured within the time window 375–438 ms for the three conditions. ** $p < 0.005$; * $p < 0.05$; n.s.: non-significant.*

Target classification accuracy was assessed using all 10 repetitions using either the CONST or VAR blocks to train the classifier. For runs comprising stimuli that did not overlap in initial, the accuracies obtained using a standard binary classifier were 67.2% (CONST) and 63.5% (VAR), while the corresponding accuracies for runs comprising stimuli that overlapped in initial were 69.8% (CONST) and 67.7% (VAR). The time-window for selecting features in all four cases was 0–1 s. For the latter type of runs, however, by training a classifier that discriminated SI from the other two types of stimuli using features from 0.3–1 s to complement the T vs. DI classifier, an enhanced performance of 73.2% was obtained.

4. Discussion

This study confirms that ERP amplitudes are modulated according to whether a syllable stimulus has the same initial consonant as the target. These modulations can be used to derive phonetic similarity cues for target identification. We have shown that partial information about target pronunciation can be obtained within the time-window 0.3–1 s, resulting in enhanced accuracy of about 5.5% in runs comprising stimuli that overlap phonetically with the target.

Acknowledgements

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On the Need for Both Internal and External Context Awareness for Reliable BCIs

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Abstract. In this paper we argue that for brain-computer interfaces (BCIs) to be used reliably for extended periods of time, they must be able to adapt to the user's evolving needs. This adaptation should not only be a function of the environmental (external) context, but should also consider the internal context, such as cognitive states and brain signal reliability. We demonstrate two successful approaches to modulating the level of assistance: by using online task performance metrics; and by monitoring the reliability of the BCI decoders. We then describe how these approaches could be fused together, resulting in a more user-centred solution.

*Keywords:*BCI, Context-Awareness, Shared Control, Adaptation, Information Theory

1. Introduction

Brain-controlled assistive technology, such as wheelchairs, telepresence robots and neuroprostheses offer promising solutions to the problems suffered by people with severe motor disabilities. However, in order to reliably operate such devices using a BCI in real-world environments, some degree of assistance (shared control) is required to compensate for the relatively low information transfer rate and performance variability of the BCI. The level of this assistance is usually only a function of the external context (i.e. the surrounding environment) [Tonin et al., 2011]. However each person has different needs and abilities, which in turn change over time. We refer to this as the internal context, which encompasses cognitive states and changes in the user's brain patterns. Therefore, we are investigating how we can capture the instantaneous needs of users, such that we can adjust the level of assistance accordingly. We propose to achieve this, by using a combination of online task performance metrics and by simultaneously characterising the reliability of the BCI decoders.

2. Material and Methods

2.1. Online task performance metrics

We propose to use online task performance metrics to modulate the level of assistance provided by a shared control system, such that it is well-matched to the user's current and ever-evolving needs. These consist of metrics commonly used (post-experiment) to evaluate shared control systems. In this experiment, subjects were instructed to navigate around a complex simulated environment, using their left hand to operate a time-restricted 2-button input, which emulated the output decisions of our motor imagery-based BCI. Periodically, subjects were asked to simultaneously perform a demanding secondary (reaction) task with their right hand, which was designed to increase their workload. 18 healthy subjects participated in this part of the experiment [Carlson et al., 2012]. During the experiment we computed online the assistance modulation factor (AMF), based on the number of commands generated by the user, the number of times assistance was required and the effective navigation time.

2.1. Online estimation of brain signal reliability

We also assess the user's current ability to operate a motor-imagery based BCI through the online estimation of the accuracy and command delivery speed. The time to deliver a command (trial length) varies, since we accumulate evidence until we are confident about the classifier output [Tonin et al., 2011]. This variation can occur for many reasons, such as changes in attention, fatigue, stress etc. Shared control could compensate for this by, for example, altering the speed or reaction time of a robotic device according to the predicted BCI trial length. In a separate five subject study, we found that the entropy rate of the EEG signals while subjects control a motor imagery BCI is lower

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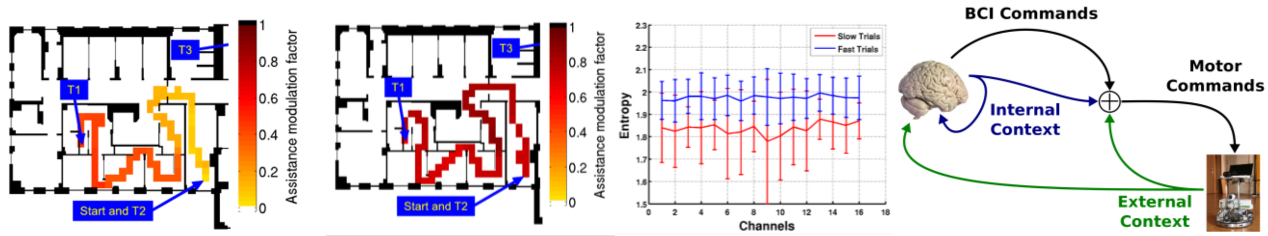

(a) (b) (c) (d)

Figure 1. *Assistance modulation factor when:* ***(a)*** *driving only,* ***(b)*** *driving + secondary task.* ***(c)*** *typical entropies for fast and slow BCI trials across EEG channels.* ***(d)*** *Proposed context-aware adaptive shared control architecture for BCI.*

when subjects take a long time to deliver a command. Based on this, we developed a method to predict whether the current command will be emitted quickly or slowly according to the entropy of the first few samples of each trial.

3. Results

3.1. Online adaptation

Our assistance modulation factor (AMF) was able to reliably track the user's workload, see Fig 1. (a,b). The median level of assistance increases significantly ($p < 0.001$) from 0.687 to 0.985 when the user has to additionally engage in a demanding secondary task. Furthermore, we found a large range of AMF values when the users are only driving (no secondary task); this reflects the variability across subject as some participants yielded a much better level of control than others. Conversely, some participants found the driving task alone to be extremely demanding and to require a high level of assistance even when they were not engaged in a secondary task. We also see an improvement in overall task performance (e.g. completion time) and a high user-acceptance [Carlson et al., 2012]. Altogether, the AMF provided an online measure of the task difficulty–and therefore the amount of assistance required— depending on both the subject and the particularities of the task.

3.2. Online estimation of brain signals

We also found that we can reliably predict the trial length class (i.e. fast or slow) based on the Entropy of the EEG using a LDA classifier, see Fig. 1 (c) [Saeedi et al., 2012]. Performance for all subjects (AUC) exceeds 0.7 based on the data samples acquired before the subject median delivery time. This is especially important in a non-cued, asynchronous protocol; since we don't know when the user began trying to deliver a BCI command, there is no definitive method for measuring how long it took to actually deliver the command.

4. Discussion

In this paper, the two approaches to context-awareness are considered separately, but the results suggest that in the future it would be interesting to combine them. Fig. 1 (d) depicts how we envisage combining both external context, such as environmental features and task performance metrics, with internal context, such as cognitive states and brain signal reliability metrics. Using the results of the online performance metrics experiment, we have shown how we are able to modulate the proactivity of the robotic device, by changing the effective operating distance of the robot's sensors. Simultaneously, we could modulate the physical speed of the device, according to the brain signal reliability, thus matching the speed at which the user can issue commands with the speed of the device, resulting in a more reliable and usable BCI system. We are currently developing some experiments to test the efficacy of such an integrated approach.

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Classification of Auditory Steady-State Responses Incorporating Alpha Waves

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Abstract. We attempted to incorporate alpha waves in an auditory steady-state response (ASSR)-based classification problem. With eight subjects, the proposed system achieved an average classification accuracy of 90 ± 5.65% for a binary classification problem. The average information transfer rate was 6.37 bits/min.

Keywords: EEG, Auditory Steady-State Responses (ASSR), Alpha Waves, Common Spatial Patterns (CSP), Linear Discriminant Analysis

1. Introduction

While many brain-computer interface (BCI) systems are based on EEG arising from visual stimuli, another possible approach is to use auditory stimuli. Since auditory-based BCIs do not involve visual stimuli, they could be used by subjects who are unable to control their eyeball movements. [Kim et al., 2011] built such a BCI system and demonstrated high classification accuracy provided that the signal window sizes are reasonably long (10-20 s), whereas the accuracy with shorter window sizes (~5 s) degraded. In the work described in this paper, we attempted to improve the classification accuracy of a short-time ASSR-based classification problem by incorporating alpha waves, in addition to EEG power spectra of the stimulation frequencies.

Alpha waves are defined as brain waves in the frequency range of 8-13 Hz. There are several theories explaining the causes of alpha oscillations. One of them is memory scanning [Klimesch et al., 2007], and another is paying attention to a certain auditory stimulus [Müller and Weisz, 2012]. [Kelly et al., 2005] report that alpha band features improved classification accuracy in a steady-state visual evoked potential (SSVEP)-based classification problem.

2. Experiments

2.1. Experimental setup

To evaluate our proposed method, we used EEG signals recorded from eight healthy participants (5 male, 3 female; 20-24 years old). The Ethics Committee of Waseda University approved this experiment. EEG data were recorded at a sampling frequency of 500 Hz with five active electrodes (Fz, Cz, C3, C4, and Pz) according to the international 10-20 system. Each subject was seated in a comfortable chair with their eyes closed and provided with stimulus sounds. The sounds were amplitude modulated (AM) ones (left: 2500 Hz carrier modulated by 37 Hz; right: 1000 Hz carrier modulated by 43 Hz).

In each experimental trial, first the subject was played a 2 s indicated sound that he or she was expected to attend to later. Second, the subject listened to both left and right sounds for 5 s and attempted to attend to the indicated sound. Finally, the sounds were stopped, and the subject rested for 2 s to prepare for the next trial. Each subject completed 60 trials with loudspeakers and another 60 trials with headphones. In total, there were 480 data for the loudspeakers and another 480 for the headphones.

2.2. Algorithm

Our algorithm consisted of three steps.

Step 1: For each electrode, four band-pass filtering processes were performed on the raw EEG data with the following pass-bands:

(i) alpha band 1: 8-10 Hz, (ii) alpha band 2: 10-13 Hz, (iii) stimulus signal band 1: 36.9-37.1 Hz, (iv) stimulus signal band 2: 42.9-43.1 Hz

Step 2: The outputs from Step 1 were fed into a common spatial pattern (CSP) filter [Blankertz et al., 2008].

Step 3: Classification was performed by linear discriminant analysis (LDA) [Bishop, 2006].

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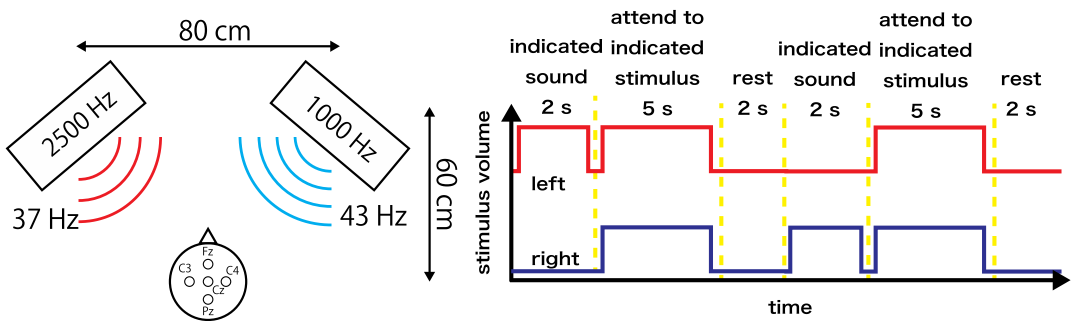

Figure 1. *The experimental set-up. Shown on the left are the positions of the subject and the equipment. The right figure shows the time-series stimulus signals.*

3. Results

Leave-one-out cross validation was performed, and the results are summarized in Table 1. The table also makes a comparison with the results of [Kim et al., 2011].

Table 1. *Classification accuracies.*

Method	*Accuracy for the 8 subjects*								*Average Accuracy [%]*	*Standard Deviation [%]*
	A	*B*	*C*	*D*	*E*	*F*	*G*	*H*		
Proposed method with headphones	85.0	93.3	83.3	100	83.3	91.7	95.0	88.3	90.0	5.65
Proposed method with loudspeakers	95.0	85.0	68.3	93.3	70.0	88.3	86.7	88.3	84.4	9.31
[Kim et al., 2011]									74.0	4.76

The average information transfer rates (ITR) were 6.37 bits/min with the headphones and 4.50 bits/min with the loudspeakers. The proposed method outperformed [Kim et al., 2011] (accuracy: 74.0%; ITR: 2.08 bits/min) at least in this experiment ($p < 0.001$ with headphones, and $p < 0.05$ with loudspeakers).

4. Discussion

We have proposed a new method for ASSR-based classification problems by incorporating alpha wave information. The average accuracy with eight subjects was 90 ± 5.65%, which outperformed previous work reported in the literature. The average information transfer rate was 6.37 bits/min. In future work, it will be interesting to elucidate the reasons why incorporating alpha waves resulted in improved classification accuracy.

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Self-Paced BCI With NIRS Based on Speech Activity

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Abstract. To enable Brain Computer Interfaces (BCIs) to be used intuitively, they should use an input paradigm which is as natural as possible, while the usage of the device is as convenient as possible. In this study, we show that functional near infrared spectroscopy (fNIRS) signals can be used to automatically detect the user's intent to use the system by detecting asynchronous speech activity, which is a very natural form of communication. Thereby, we take a first step towards self-paced BCIs with fNIRS based on speech activity.

Keywords: fNIRS, near infrared spectroscopy, asynchronous, self-paced, speaking modes

1. Introduction

Functional near infrared spectroscopy (fNIRS) is rapidly gaining attention as an imaging modality for Brain Computer Interfaces (BCIs) [Matthews et al., 2008]. First commercial systems are already available [Naito et al., 2007]. The majority of studies on fNIRS based BCIs rely on motor imagery and are operated stimulus locked. This means that the user can only interact with the system in predefined intervals. For an intuitive BCI, the users should be able to decide on their own when they want to operate the BCI. This is leading to a self-paced BCI, detecting idle and voluntary control states. Identifying segments containing activity is a known field of research in speech technologies [Laskowski and Schultz, 2006]. In this study, we show that the fNIRS signals measured during different speaking tasks can be automatically segmented into segments containing speech activity and segments without speech activity.

2. Material and Methods

We recorded 5 male subjects using a Dynot232 system with 32 transmitters and 32 receivers, sampling at 1.81 Hz. On the left hemisphere, four optodes were placed on Broca's area, 10 on Wernicke's area and six on 6 on the lower motor cortex. Additionally, we covered the prefrontal cortex with 12 optodes. Limiting our analysis to channels with an inter-optode distance between 2.5 and 4.5 cm, we considered 252 channels of oxygenated and deoxygenated hemoglobin values. All subjects were recorded over an interval of 37.5 minutes in which they conducted three types of speech activity as prompted by messages displayed on a screen. These were: Normal audible speech; silent speech, which consisted of moving the articulatory muscles as if speaking, but without sound production and speech imagery, for which the subjects had to imagine themselves reading out the displayed sentence. Users were asked to relax when they were not prompted to conduct speech activity. See [Herff et al., 2012b] for more details on the experiment design. The continuous hemoglobin values were then dissected into almost completely overlapping 10 second long windows, allowing for continuous decoding. A simple feature, measuring the difference between the mean of the first 4.5 s and the second 4.5 s in every window, was extracted for oxygenated and deoxygenated hemoglobin of every channel resulting in a total of 504 features. Using the *Mutual Information based Best Individual Feature (MIBIF)* algorithm [Ang et al., 2008], we selected a subset of 50 features which contained the most relevant information.

The data was labeled as containing speech activity (of any of the three modes) or not containing speech activity based on the experiment timings. This approach yielded more reliable results than identifying the modes individually, as more training data for the classes is available. Nevertheless, previous results [Herff et al., 2012b] show that all three modes can be discriminated from inactivity. We trained Support Vector Machines on these selected features to create an automated segmentation method for speech activity based on the fNIRS data.

A 10 fold cross-validation approach was used to evaluate our segmentation method. Both training and test set features were z-normalized with the mean and standard deviation of the training set. No data from the test set was used for feature selection, normalization or training of the classifier.

3. Results

Fig. 1 shows an example segmentation of our method for one of the folds of subject 3. The cross-marked line shows speech activity as labeled using the experiment prompts and the red line shows speech segments predicted by the proposed algorithm. Note that the ground truth might be flawed as well, since we could not control whether our subjects were actually performing the speech tasks when prompted. This typical example clearly shows that our

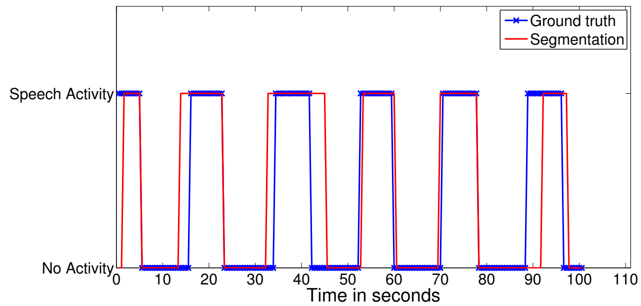

Figure 1: *Segmentation of subject 3's data into speech activity and non-activity. The cross-marked line is ground truth while the red line shows segmentation by our method.*

method extracts most of the segments containing speech activity reliably. The performance is promising on all 5 subjects and is significantly better than chance ($p < 0.05$). Precision and recall are very stable over all subjects and false positive rates are low across all subjects, as well. Frame based accuracies are high with an average of 74 % and are only slightly lower than the 79 % average accuracy achieved in a stimulus locked experiment on the same dataset [Herff et al., 2012b]. Table 1 lists all results for all subjects.

Table 1: *Results for speech activity detection with fNIRS across 5 subjects.*

Subject	Accuracy	True Positive Rate	False Positive Rate	True Negative Rate	Precision	Recall
Subject 1	0.72	0.61	0.20	0.80	0.69	0.61
Subject 2	0.74	0.62	0.17	0.83	0.71	0.62
Subject 3	0.79	0.63	0.11	0.89	0.79	0.63
Subject 4	0.73	0.57	0.16	0.84	0.72	0.57
Subject 5	0.74	0.63	0.17	0.83	0.72	0.63
Average	**0.74**	**0.61**	**0.16**	**0.84**	**0.73**	**0.61**

4. Discussion

We have shown that segments containing speech activity can be continuously decoded from those not containing speech activity based on fNIRS signals alone. Thereby, we make an important step towards self-paced BCI with fNIRS. All methods used in this analysis can be easily transferred to an online scenario. The results in this first study can possibly be extended to make use of the cross-subject capabilities of fNIRS [Herff et al., 2012a].

Acknowledgments

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Predicting the Performance of a MI-Based BCI Based on Pre-Cue EEG Data

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Abstract. One of the main problems in motor imagery based brain-computer interface systems is that some users cannot perform motor imagery (MI) well. Hence, it will be useful to have prior knowledge about the capability of the users in performing MI. This study proposed a novel predictor to evaluate the performance of the users based on the pre-cue EEG data. Group level analysis on $N = 17$ healthy subjects shows that there is a significant correlation $r = 0.49$ between the proposed coefficient and the cross validation accuracies of the subjects in performing MI. The results suggest that having higher frontal theta and lower posterior alpha prior performing MI may enhance the BCI performance. This finding may help in designing a new experiment to improve motor imagery performance.

Keywords: Motor imagery, performance predictor, EEG rhythms

1. Introduction

Motor imagery-based (MI-based) BCI system is widely used for both therapeutic and non-therapeutic applications. It had shown that some users cannot perform motor imagery well and there is a big variation in performance of the users [Blankertz et al., 2010]. One of the possible reasons may be the inability of users in modulating their electroencephalogram (EEG) rhythms. EEG rhythms modulations typically occur during motor imagery. Studies had shown that EEG rhythms have significant role on BCI performance and hence can be used to predict the performance [Blankertz et al., 2010; Grosse-Wentrup et al., 2012; Maeder et al., 2012]. So far none of performance predictors was widely used in different BCI experiments. Predicting the performance of the patients prior to the experiment may be useful; moreover, it may lead to better understanding of the possible reasons of performance variation in different subjects. In this study, we aim to predict the performance of the users based on the pre-cue EEG data. Studies had shown that pre-stimulus alpha activity over occipital and parietal area and theta activity over frontal area contains useful information about attention of the users [Mazaheri et al., 2009]. Hence, we hypothesized that a coefficient based on EEG rhythms from different brain regions be informative in predicting the performance of the users. A novel coefficient $P_\theta/(P_\alpha+P_\beta)$ was proposed of which P_θ, P_α, and P_β are the average EEG band power of theta (4-8 Hz), alpha (8-13 Hz), and beta (13-22 Hz) bands over frontal (F_3, F_z, F_4), central (C_z, Cp_z) and parietal area (P_7, P_3, P_z, P_4, P_8) respectively. To study the effectiveness of the proposed coefficient, we performed a correlation analysis between this coefficient and performance of the 17 healthy subjects. The coefficient was calculated based on the pre-cue EEG data (i.e., 1 second before providing the cue for the subjects).

2. Material and Methods

2.1. Experimental setup

In this work, EEG data from the 17 healthy subjects were collected. Two of the subjects were left-handed, the rest were right-handed. The EEG data from each subject were collected on two separate days, two non-feedback sessions on the first day and three non-feedback sessions on the second day were recorded. During these sessions, the subjects were instructed to perform kinaesthetic motor imagery of their chosen hand or rest right after a visual cues displayed on the computer screen in each trial. Each session comprised of 40 trials of motor imagery and 40 trials of background rest condition and lasted about 16 minutes. Each trial comprised a preparatory segment of 2 s, the presentation of the visual cue for 4 s, and a rest segment of at least 6 s. Each trial lasted approximately 12 s, and a break period of at least 2 minutes was given after each session of EEG recording.

2.2. Pre-processing and Analysis

The recorded EEG data are filtered over θ, α, and β frequency bands. Local average reference filtering was then applied to spatially filter the data by subtracting the average activity of the neighboring electrodes from each single electrode. EEG band power for all the trials were calculated and then averaged in 1 second before the presentation of the visual cue. The EEG powers were finally normalized across all trials. For estimating the performance of the users the Filter Bank Common Spatial Pattern (FBCSP) algorithm [Ang et al., 2012] with support vector machine (SVM) classifier was used. A group level analysis was done to study the correlation between mean of coefficient $P_\theta/(P_\alpha+P_\beta)$ over all trials and accuracies of subjects.

3. Results

Fig. 1 shows the correlation between the proposed coefficient $P_\theta/(P_\alpha+P_\beta)$ and off-line accuracies of the 17 healthy subjects. The Pearson's correlation coefficient of ($r = 0.49$, $p = 0.04$) was obtained. The result of linear regression analysis is shown as a black solid line. As shown, the subjects can be clustered into high performance users (pl, s, ks, lj, kk, hj, ab, zy) and low performance users (hh, hd, wy, kx, ly, at). The three subjects (jh, yz, ad) which are shown in red circles in Fig. 1 are considered as outliers. Higher correlation ($r = 0.68$, $p = 0.006$) was achieved by excluding them from our analysis. The dashed red line is the result of new regression analysis. Performing Mann-Whitney U-test also shows that there is a significant difference ($p = 0.001$) between the coefficient of users with high and low performance. The results suggested that high performance users have higher values of defined EEG rhythm-based coefficient and vice versa.

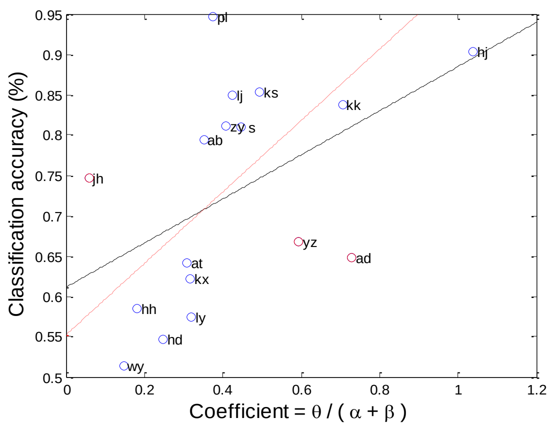

Figure 1. *Correlation of the EEG rhythm-based coefficient $P_\theta/(P_\alpha+P_\beta)$ with BCI classification accuracy. Each circle represents a healthy subject. The black (slope=0.28) and red (slope=0.44) lines are linear regression results considering all the users and all except three users shown in red circles, respectively.*

4. Discussion

Results showed the proposed coefficient $P_\theta/(P_\alpha+P_\beta)$ computed from 1 second of pre-cue EEG data is successful in predicting the performance of the users. The results of correlation analysis suggested that an increase in frontal theta along with a decrease in posterior alpha correlated with an increase in motor imagery performance. In conclusion, monitoring the EEG rhythms over frontal and parietal area before cue may help in improving the user's performance. To have a better understanding about the effectiveness of the defined coefficient, further analysis has to be done on single trial basis.

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Brain Mapping As a Tool To Improve a Physiologically Driven-Feature Selection for Non-Invasive BCI Applications

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Abstract. In the present study, we illustrate how advanced methodologies for the reconstruction of brain sources based on scalp EEG recordings could be of value in improving feature extraction in the field of non-invasive BCI applications. The EEG spectral information extracted offline at cortical and sub-cortical levels and related to three mental imagery tasks performed by 14 subjects during a screening session, allowed the selection of individual spatial/spectral feature sets reliably encoding the physiological substrates of each imagery task. Such features were then used in a online BCI application based on mental imagery proving the feasibility of the present approach.

Keywords: high resolution EEG, source reconstruction, Linear Inverse Problem, sLORETA, statistical mapping, mental imagery tasks

1. Introduction

In the present study we applied a set of advanced EEG brain mapping techniques to increase the spatial resolution of scalp signals in order to improve the feature extraction procedures for non-invasive Brain Computer Interface (BCI) applications. The rationale was to identify the neurophysiological substrates of imagery tasks which are or can be possible candidates to operate BCI systems, with the ultimate aim of addressing a physiologically driven feature selection. As such this approach could not only maximize classification performances but it could also allow the use of the BCI output as a measure of the subject's involvement in the executed task and thereby, to boost the BCI use beyond serving as a new class of assistive technology devices.

2. Materials and Methods

2.1. Experimental Design and Data Acquisition

Fourteen healthy right-handed volunteers (age: 28.5 ± 6.4 years, 6 females) participated to the study. During the EEG (61-channel commercial system; sampling rate of 200 Hz) screening session, subjects were asked to perform three imagery tasks, playing Tennis (T), Spatial Navigation in a familiar environment (N) and bilateral hand grasping (G), or to relax (R). A total of 6 runs (24 trials each run; single trial duration of 15 s; inter-trial interval equal to 2 s) were acquired for each task randomly ordered. The same imagery tasks of the screening were performed during a BCI session where 6 out the 14 involved subjects were asked to control a screen cursor horizontal movement (real-time feedback provided by means of BCI2000 platform). Each BCI session consisted of 4 runs: 2 runs were based on T/N contrast and 2 on G/N contrast, respectively.

2.2. Data Analysis

After pre-processing of the scalp EEG potentials, cortical and sub-cortical patches of relevant activity were reconstructed by means of Weighted Minimum Norm Linear Inverse Estimation [Babiloni et al., 2001] and sLORETA [Pascual-Marqui, 2002]. The obtained waveforms were averaged within each considered EEG frequency band (theta, alpha, beta and gamma). A statistical contrast between task and rest (baseline) conditions was performed (significance level = 5%) and corrected by means of False Discovery Rate to prevent the occurrence of type I errors. Statistical maps were generated for each subject, task and frequency band.

3. Results

Scalp, cortical and subcortical statistical maps relative to the screening session of a representative subject are reported in Figure1 for the three imagery tasks. The cortical and sub-cortical maps revealed 3 distinct patterns of

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EEG significant activity for each imagery tasks, reported in Fig. 1: the left sensorimotor and parietal areas in Beta band for Tennis imagery, the bilateral sensorimotor motor areas in Beta band for Grasping imagery and the left parieto-occipital area corresponding to the para-hippocampal gyrus at sub-cortical level for Navigation task in Alpha Band. Such electrical activations were common to all the investigated subjects.

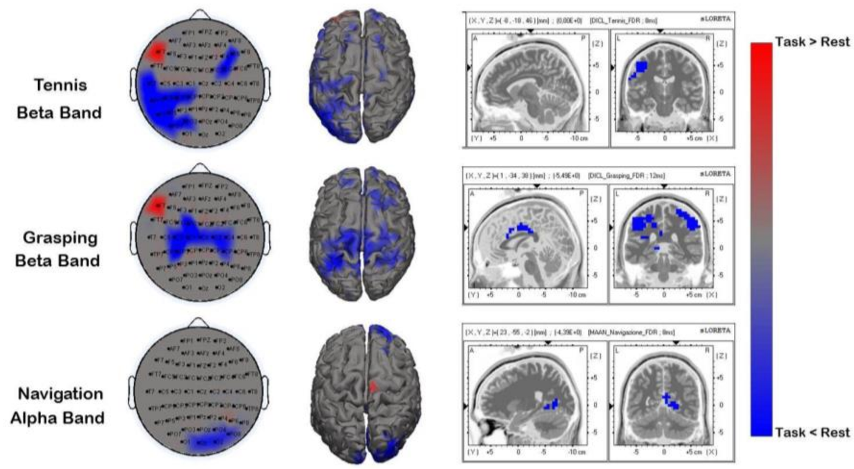

Figure 1. *Statistical maps obtained for a representative subject, for the three mental imagery tasks contrasted with the rest condition. The significant "activations" were represented at scalp (first row), cortical (second row) and sub-cortical (third row) level.*

On the basis of the screening results, the following spatial/frequency control features were selected for the online BCI session: CP3/beta for T, CP3/CP4/beta band for G and PO4/alpha band for N. Similar results were obtained in 3 out of the 14 investigated subjects who showed an online accuracy of 65% (± 1%), 65% (± 10%) and 75% (± 7%) for T/N contrast and of 70% (± 7%), 87.5% (± 10%) and 60% (± 3%) for G/N contrast, respectively.

4. Discussion

These preliminary findings indicate that is feasible to adopt such approach and prompted us to increase the number of observations in order to consolidate the translation of advanced methods for brain source reconstruction into non-invasive BCI applications. Particularly, we target to those applications in which the BCI classification output may function as a real-time objective assessment of the subject's ability to elicit a given activation pattern related to specific cognitive tasks. The relevance resides in detecting mental states in healthy subjects (Wang et al., 2012) or in those clinical conditions characterized by the absence of any behavioral signs of communications like, the disorders of consciousness (Monti et al., 2010).

Acknowledgements

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Classification of Various Mental Task Combinations for NIRS-Based Brain-Computer Interface (BCI)

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Abstract. The goal of this study was to investigate the most sutiable feature type and combinations of mental tasks for the development of practical NIRS-based brain-computer interface (BCI) systems. To this end, we recorded concentration changes of oxygenated [oxy-Hb] and deoxygenated [deoxy-Hb] hemoglobins while eight particiapnts were performing eight different mental tasks. Four different feature sets were extracted from the recorded NIRS signals ([oxy-Hb], [deoxy-Hb], [total-Hb], and a combination of [oxy-Hb] and [deoxy-Hb]), and classification accuracies were estimated for all possible pairs of the eight mental tasks. As a result, the numbers of mental task pairs showing accuracy high enough for practical communication (> 70%) were 5.5 for [oxy-Hb], 4.86 for [deoxy-Hb], 6.75 for [total-Hb], and 6 for [oxy-Hb] + [deoxy-Hb] on avearge, among 28 mental task paris (= ${}_8C_2$). In addition, five mental task combinations commonly showed high classificaton accuracy over 70% in more than half of the participants (none for [oxy-Hb]; two combinations for [deoxy-Hb]; two combinations for [total-Hb]; one combination for [oxy-Hb] + [deoxy-Hb]). In particualr, a combination of right hand motor imagery and mental rotation task only showed high classification accuracy over 70% on average, when using the feature set of [total-Hb]. From the resutls, it was confirmed that the features extracted from [total-Hb] showed best performance in classifying various mental tasks, and the combination of right hand motor imagery and mental rotation task can be a promising candidate task for a practical NIRS-based BCI system.

Keywords: Various Mental Tasks, Single-Trial Classification, Near-Infrared Sepctroscopy (NIRS), Brain-Computer Interface (BCI)

1. Introduction

Brain-computer interface (BCI) has been actively studied using a variety of neuroimaging modalities, such as electroencephalography (EEG), near-infrared spectroscopy (NIRS), functional magnetic resonance imaging (fMRI), electrocorticography (ECoG) and magnetoencephalography (MEG). Among them, EEG has been most widely used and a number of mental tasks have been investigated to realize practical EEG-based BCI systems. Recently, NIRS has attracted BCI researchers' attention [Coyle et al., 2007] because it is portable and non-invasive similarly to EEG. Most importantly, unlike EEG, NIRS is less susceptible to electrophysiological artifacts caused by eye blinks, eyeball movements, muscle activity, and so on. Despite of the above mentioned advantages of NIRS for development of practical BCI systems, investigations on optimal mental task combinations and feature types have been rarely conducted in NIRS-based BCI studies. Therefore, in this study, we investigated which feature type and mental task combination are more appropriate to develop NIRS-based BCI systems.

2. Methods

Eight participants took part in this study, and performed eight different mental tasks: A) left hand motor imagery, B) right hand motor imagery, C) foot motor imagery, D) mental singing, E) mental subtraction, F) mental multiplication, G) mental rotation, and H) mental writing. Each mental task was carried out 20 times for 15 s each.

For the data acquisition, we used a multi-channel NIRS imaging system (FOIRE-3000, Shimadzu Co. Ltd., Kyoto, Japan). Fifty channels broadly placed on the participants' scalps were used to measure the task-related concentration changes of [oxy-Hb] and [deoxy-Hb]. To extract features relevant to each mental task, we used three different window sizes of 5, 10 and 15 s, and consequently making six time windows, i.e., 0–5 s, 0–10 s, 0– 15 s, 5–10 s, 5–15 s, and 10–15 s. The features were extracted by averaging hemodynamic responses in each time window, and four different feature sets were constructed, i.e., [oxy-Hb], [deoxy-Hb], [total-Hb], and a combination of [oxy-Hb] and [deoxy-Hb]. For the feature selection or reduction, the sequential floating forward selection (SFFS) was used, and the selected best feature subsets were classified with linear discriminant analysis (LDA) algorithm. To evaluate the classification accuracy, we used a leave-one-out cross validation (LOOCV) method. The classification accuracy was estimated for all possible combinations of two mental tasks using the four different feature sets.

3. Results

Since the classification accuracy should be at least over 70% for practical communications [Perelmouter et al., 2000], we counted the number of combinations showing classification accuracy over 70%, and calculated their average classification accuracy. Table 1 shows how many combinations of binary mental tasks can be used for practical communication (over 70% classification accuracy). The selected numbers of the mental task combinations were 5.5 for [oxy-Hb], 4.86 [deoxy-Hb], 6.75 for [total-Hb], and 6 for [oxy-Hb] + [deoxy-Hb]. Among the selected mental task combinations, five mental task combinations commonly showed the classification accuracy over 70% in half of eight participants: combination of tasks E and F for [dexoy-Hb], combinations of tasks B/D and G for [total-Hb], and combinations of tasks A and B/E for [oxy-Hb] + [deoxy-Hb]. In particular, the mental task combination of B (right hand motor imagery) and G (mental rotation) commonly showed the average classification accuracy over 70% when the [total-Hb] feature set was used.

Table 1. *The numbers of mental task combinations showing the classification accuracy over 70 %, and their averaged classification accuracies. Num and CA represnt the number of mental task pairs and classification accuracy, respectively.*

Participant	[oxy-Hb]		[deoxy-Hb]		[total-Hb]		[oxy-Hb] + [deoxy-Hb]	
	Num.	CA	Num.	CA	Num.	CA	Num.	CA
P1	12	75.42 %	13	78.12 %	12	77.72 %	12	78.64 %
P2	3	75.00 %	7	75.00 %	3	75.83 %	4	76.88 %
P3	3	75.00 %	5	78.50 %	8	75.00 %	7	78.57 %
P4	10	79.25 %	4	76.25 %	11	80.23 %	7	80.36 %
P5	4	80.00 %	3	81.66 %	8	75.31 %	6	78.33 %
P6	5	76.00 %	5	77.00 %	3	78.33 %	6	77.92 %
P7	5	81.50 %	1	75.00 %	7	75.00 %	5	78.50 %
P8	2	75.00 %	1	75.00 %	2	73.75 %	1	72.50 %
Mean	5.50	77.93 %	4.86	77.07 %	6.75	76.40 %	6.00	77.71 %

4. Discussion

Recently, some BCI studies demonstrated that NIRS can be one of the promising alternatives to EEG. However, there are a number of issues to be investigated in order to develop a practical NIRS-based BCI system. One of the issues might be to find optimal feature extraction methods and mental task combinations. In the present study, we investigated the most suitable feature type and mental task combination among eight different mental tasks, and confirmed that [total-Hb] can be the best feature type for classification of various mental tasks. Also, the mental task pair of right hand motor imagery and mental rotation might be the optimal mental task combination for NIRS-based BCI systems. Besides the concentration values of [oxy-Hb] and [deoxy-Hb], we will continue testing other feature types introduced in previous NIRS-based BCI studies, e.g., slope, laterality and variance of NIRS signals, to provide a useful reference for the selection of optimal feature extraction methods and mental task combinations.

Acknowledgements

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Using Multiple Reward Related Signals in the Adaptation of Neuroprosthetic Decoders

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Abstract. Using neuroprosthetics during daily living presents new challenges that affect design choices in neural decoders. New classes of architectures for neural decoding that are based on reinforcement learning (RL) are being investigated. RL decoders use experience to help shape and adapt the decoder such that the benefits of tasks are maximized for the user. Since RL is based on reward feedback, reward signals are a critical part of the functionality. In this work, we investigate and compare 4 sources of reward related signals that can provide feedback for RL based decoders: the external environment, error-related potentials (ErrP) in EEG and LFPs, and single neuron activity in the Nucleus Accumbens (NAcc).

Keywords: Reward, Adaptive, Decoder, Reinforcement, Learning

1. Introduction

The use of neuroprosthetics in activities of daily living present new challenges that affect the design choices used in neural decoding. These include the dynamics of working in multiple environments, effects of rehabilitation on neuroplasticity, effects of user learning on performance, dependence on a caregiver to help calibrate the system, and the overall stability of neural signals acquired from the neural interface itself. Our laboratory has been investigating a new class of architectures for neural decoding that are based on reinforcement learning (RL) [Mahmoudi and Sanchez, 2011]. RL decoders are inspired by physiological, computational, and behavioral principles involved in the process of using experience to help shape and adapt performance such that the benefits of tasks are maximized for the user. In simple terms, RL decoders work in the following way. When users generate neural activity that leads to successful use of the neuroprosthetic, the functionality of the decoder is reinforced. Conversely, when users generate neural activity and the neuroprosthetic is unsuccessful, the interface is adapted. This framework leads to continuous interaction between user and neuroprosthetic based on success or failure.

Since RL decoding is based on reward feedback, acquisition and access to these signals is a critical part of the functionality. Typically in he development of living organisms, the signals used to reinforce behaviors during learning come from a wide variety of sources. These include the external environment, other individuals, and the organism’s own brain [Holroyd and Coles, 2002]. All could be good candidates for adapting a BCI decoder.

In this work, we investigate 4 sources of reward related signals that can be used to provide feedback for RL based decoders.

2. Material and Methods

Our adaptive neural interface uses actor-critic based RL decoders. As shown in Fig. 1, the actor maps motor related brain activity to intended actions of a prosthetic or assistive device. The actor’s weights are initialized randomly and then adjusted after each trial based on feedback from the critic. The critic provides feedback by decoding the user’s brain activity or environmental cues to determine if the decoded behavior should be reinforced.

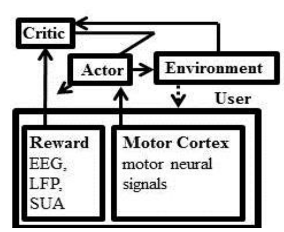

Figure 1. *Reinforcement Learning BCI.*

Multiple sources of reward related feedback can be extracted from the environment and the brain. The differences among them are related to: frequency of expression, robustness of their representation, and modality of acquisition. Our lab has been evaluating several common feedback sources, including environmental cues and several types of neural recordings.

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When reward is from a source other than neural signals from the user's brain, the source is considered part of the external environment. The external environment can include a system with prior knowledge of available actions, another person providing feedback, or the user themselves through feedback such as a button press or eye blink. However, such signals are not always available in the severely paralyzed.

Reward can also come from the electroencephalogram (EEG) in the form of error-related potentials (ErrP). This is typically detected in the 5-10 Hz band from electrode Cz when the user thought an error was committed [Ferrez and Millan, 2008]. By targeting reward centers in the brain such as the Nucleus Accumbens (NAcc), single unit activity (SUA) can also be used to extract reward information. However, a significant challenge is to construct a single reward signal from the distributed representation of the neural population, which may encode many aspects of reward as it is linked to behavior. Local field potentials (LFP) from the NAcc can also produce event related potentials associated with reward.

Our lab is investigating all four signal types as possible sources of reward feedback. To illustrate the use of this class of signals, a support vector machine (SVM) [Muller, Smola et al., 1999] was used to classify human EEG, and LFP and SUA signals from nonhuman primate NAcc. All tested behaviors were a two choice target selection task (33 trials). To preprocess features for classification, the power of the 5-10 Hz band, 1 s window, from Cz EEG was used. Likewise, the power of broadband (1-500 Hz) LFP was used from four electrodes. The vector firing rate of 22 neurons (from 16 electrodes) was used as a feature for the SVM in the case of SUA.

3. Results

Table 1 shows average classification results across two subjects. The classification accuracy of the different sources of reward is comparable: SUA (82%), LFP (75%), and EEG (69%).

Table 1. *Classification Accuracy of Reward Sources.*

	Environment	EEG-ERN	LFP	SUA
Reward	100%	69%	75%	82%
No-Reward	100%	63%	71%	69%

4. Discussion

Overall, the three neural signals provided similar average classification rates. SUA can provide higher spatial resolution, but determining how they relate to global processing such as reward or no-reward can be a challenge. Since LFP is believed to detect the synaptic activity of many neurons and since reward processing is an integrative procedure less preprocessing of LFP was required to extract reward for similar performance. EEG’s major advantage is non-invasiveness. However, EEG has a lower signal to noise than other sources and ErrPs might not be detectable during rapidly paced tasks. LFP appear to have a similar limitation, while SUA may not. The external environment can give feedback that is completely accurate. However, incorporating it into a system may limit its usability in daily life, since additional inputs from the user, such as muscle movements, would be required.

Acknowledgements

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Temporal and Spatial Distribution of Workload-Induced Power Modulations of EEG Rhythms

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Abstract. Changes of workload are correlated with power modulations of certain frequency bands in the human EEG. In order to be able to detect these changes, it is of avail to know the temporal relationship, shape and spatial distribution of EEG band power modulations induced by the workload. Here, we suggest a novel approach that allows to identify the temporal structure of the function that is maximally correlated with power modulations of the theta and alpha frequency bands. We present findings from a case study which demonstrate the validity of the suggested method.

Keywords: EEG, Workload Detection, Alpha, Theta

1. Introduction

A reliable assessment of mental workload of human operators can be used as an adaptive mechanism in brain-computer interfaces (BCIs). Previous studies have shown that the power of oscillatory activity in the human electroencephalogram (EEG) [Buzsáki and Draguhn, 2004] in the theta (4–8 Hz) and alpha (8–12 Hz) frequency bands is modulated by changes in workload during task engagement [Gevins and Smith, 2003; Holm et al., 2009]. In order to improve the decoding of those power modulations, it is crucial to find optimal spatial filters. The Source Power Correlation (SPoC) analysis [Dähne et al., 2012] finds a spatial filter such that power modulations are maximally correlated with a given target function. Here, we present preliminary results of employing an extension of SPoC that, given an initial set of basis functions, simultaneously finds the optimal shape of the target function.

2. Material and Methods

Subjects ($N = 10$) carried out a task on a touch screen, where the aim was to tag and catch objects falling from the top of the screen before they hit the bottom. Every 90 seconds the task difficulty alternated between two conditions: In the low workload condition (L) the interval between objects was constant, subjects reported the task as demanding but not stressful. In the high workload condition (H) the intervals were shorter and varied randomly, resulting in an increased sense of stress and in higher error rates. Each subject performed 4 blocks of 24 minutes each. EEG data were recorded at 1 kHz from 64 electrodes, downsampled to 100 Hz and segmented into epochs of 10 seconds length, ocular artifacts were removed via ICA. Prior to SPoC analysis the dimensionality of the data was reduced via PCA retaining 90 % of the variance. In addition to EEG, heart rate and skin conductivity were recorded during the experiment.

3. Results

As Figs. 1A–C show, the workload paradigm of the experiment clearly modulated the task performance, skin conductance and heart rate of the subjects. Based on the time course of those quantities for the SPoC analysis we chose three initial target functions (Fig. 1D). The scalp maps of the SPoC components (patterns) shown in Fig. 1E-H clearly reflect the known impact of workload on the human EEG as described in the literature [Holm et al., 2009]. On the one hand, variance of the theta frequency band power (Figs. 1E,F) correlated with the optimized target function (right panels) occurs predominantly at mid-frontal electrodes and shows a decrease during low workload condition and an increase during high workload condition. As for the alpha frequency band (Figs. 1G,H), the power variance correlated with the target function is located at mid-central and -parietal electrodes and is negatively correlated with the paradigm, i. e. showing an increase in condition L and a decrease in condition H. The shape of the target functions optimized by SPoC, suggests that the power modulations induced by the experimental paradigm are more of a smooth nature, lacking rough jumps. Finally, we evaluated our results by calculating the correlation between the optimized target

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function and the band power variance estimated by the optimized spatial filter, and compared with the correlation we obtain by analogously employing a Canonical Correlation Analysis (CCA). Results show that SPoC outperforms CCA and that correlations are significant in all four cases.

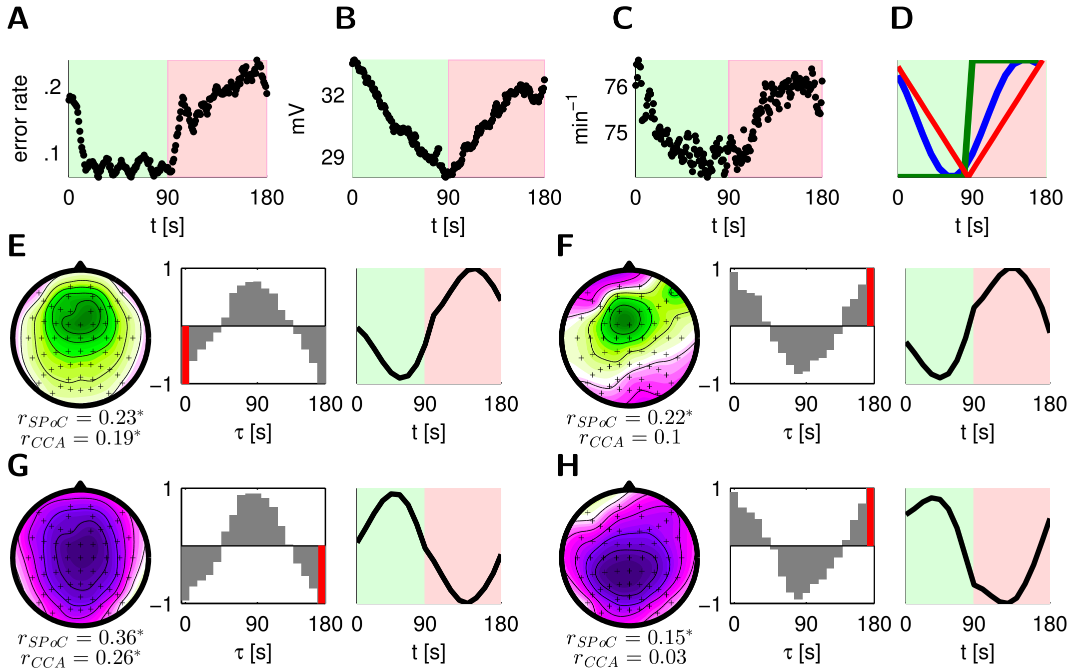

Figure 1: *A–C: Task performance (A), skin conductance (B) and heart rate (C), averaged over all subjects and all L-H-condition-pairs, where L is coded green and H red. D: One period of the set of basis functions used in the analysis. E-H: SPoC results for the theta band and subject 'lh' (E) and subject 'icd' (F) and for the alpha band and subject 'lh' (G) and subject 'bad' (H). Left panel: Scalp map of the SPoC component for which the band power modulation correlates maximally with the target function. Below scalp map: Cross-validated correlations (see text), asterisk indicates* $p < 0.01$. *Middle panel: Temporal filter (optimized by SPoC) which transforms the ongoing power modulations such that the correlation with the target function is optimized. The highest absolute value and its sign (indicated in red) shows the approximate best time shift and sign of the target function, correspondingly. Right panel: One period of the optimal linear combination of the initial target functions after time shifting and sign multiplication.*

4. Discussion

Previous studies have aimed at using EEG in order to develop BCIs that can detect mental workload of humans with the goal of enhancing performance in operator tasks [Kohlmorgen et al., 2007]. In this case study we present an approach in which a spatial filter and a target function are simultaneously optimized via an extension of the SPoC analysis. Our findings confirm the validity of our approach and suggest that further refinements of this approach will provide a valuable improvement for the development of BCIs for workload detection.

Acknowledgments

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On Oscillatory EEG During Palm and Finger Movements

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Abstract. The 63-channel EEG responses of four healthy human subjects to the movements of palm, index finger and little finger of the right hand were investigated as a preliminary study of the EEG-based BCI to detect motor imagery of fingers. The spatial distributions of the sensory motor rhythm (SMR) components on mu, beta and gamma bands were evaluated. It was shown that the mu band ERD during movements and beta band rebound ERS were observed in the hand area on sensorimotor cortex of three subjects, and the high gamma band ERS responses during palm grasping were observed in the contralateral hand area of one subject. It was also shown that clear high gamma band components could be extracted from the responses of one subject to the three tasks by using ICA.

Keywords: EEG, Motor Execution, Sensory Motor Rhythm (SMR), ERD/ERS, High Gamma Band, ICA

1. Introduction

Recently, [Darvas et al., 2010] showed the possibility to detect high gamma (HG) band activity from EEG during motor task execution. It is hypothesized, that information transfer rates of sensorimotor rhythm (SMR) based brain-computer interfaces (BCIs) can be increased by using higher frequencies compared to the slower mu and beta rhythms. In this study, SMR responses in mu, beta and gamma band frequency range to the grasping of palm, tapping of index finger and little finger were investigated with respect to improving BCIs based on motor imagery.

2. Material and Methods

Four right-handed able-bodied male subjects (22-24 years old) participated in the experiments. The study was reviewed and approved by the Ethics Committee on Clinical Investigation, Graduate School of Engineering, Tohoku University. Subjects were seated in sitting inside an armchair in an electromagnetically shielded room and asked to execute one out of three motor tasks (MTs) with their right hand: palmar grasp, index finger tapping and little finger tapping. On each trial, subjects were asked to grasp or tap rapidly three times with a self-paced interval which was longer than 4 seconds. One session consisted of 25 movement trials; MTs were fixated prior each session. Four sessions for each MT were recorded on two different days. The order of the MTs was randomized.

EEG was recorded from 63 Ag/AgCl electrodes placed over the whole head based on the extended international 10-20 system (reference and ground were right and left earlobe, respectively). Additionally, a bipolar EMG was recorded from the extensor digitorum muscle. Signals were bandpass-filtered between 1 and 500 Hz and sampled at 2500 Hz. No notch filter was applied.

The EEG was re-referenced with respect to the common average and time-frequency event-related desynchronization/synchronization (ERD/ERS) [Pfurtscheller and Lopes da Silva, 1999] maps were computed for each MT (frequency step 1 Hz, band width ± 1 Hz, reference period -2 to -1 s prior to movement onset). The onset time of the motor execution was detected from the envelope of the EMG data calculated by the Hilbert transform. Additionally, independent component analysis (FastICA [Hyvärien and Oja, 1997]) was applied to the EEG and identified independent components were analyzed with respect to HG activity.

3. Results

One of the subjects was excluded from further analysis by the excess artifacts. In three subjects, mu band ERD during movements and beta band rebound ERS were observed in the hand area over sensorimotor cortex (Fig. 1(a) left). The responses to finger movements were smaller than those to palm movements, and the spatial distributions of these responses were similar. A HG ERS (maximum at 82 Hz) during palm movements was observed in one of the three subjects (Fig. 1(a) right).

ICA analysis led to significant HG responses in one subject. MT-related unmixing matrices (left) and the ERD/ERS activity in the band (same as in Fig. 1(a) right) of the decomposed data (right) are shown in Fig. 1(b). The

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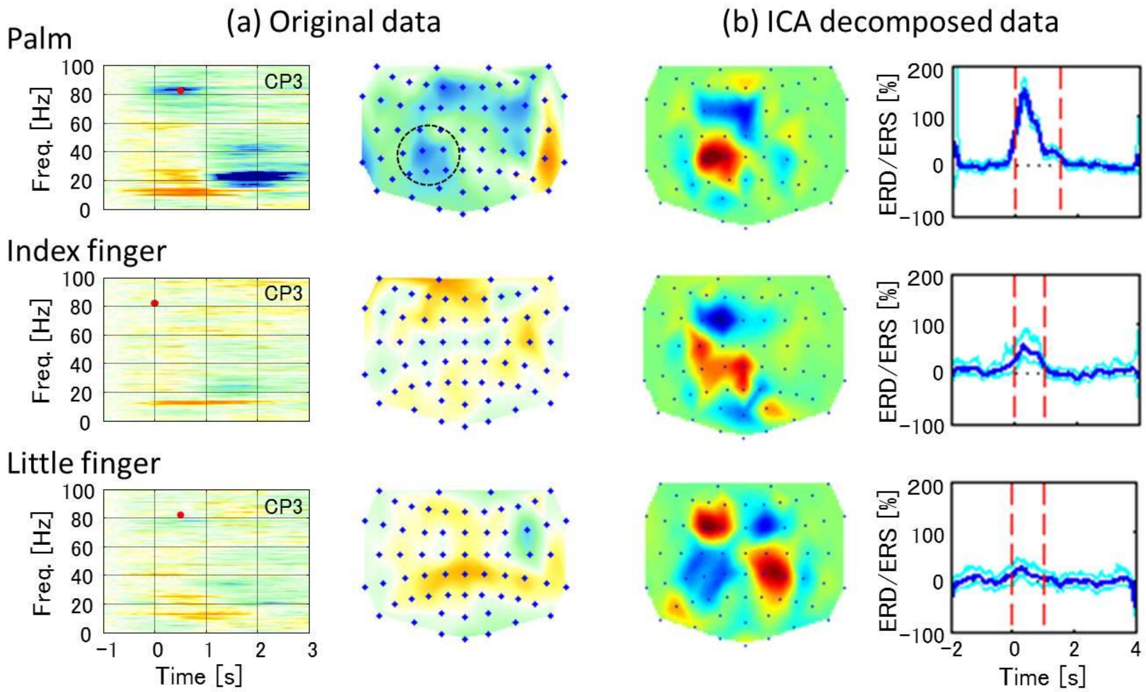

Figure 1. *Responses to the movements of palm, index finger and little finger on one of the subjects. (a) ERD (orange) and ERS (blue) responses of the original EEG. Time-frequency map of ERD/ERS of the measured EEG taken from CP3 (left), and the spatial distribution of the HG response at time and frequency shown on the map by red point, on which the maximum ERS was observed during movement at 80-100 Hz (right: frequency band width is same as the condition for calculating the ERD/ERS maps (±1 Hz)). (b) A selected unmixing matrix obtained by ICA (left), and the ERD/ERS of the corresponding HG independent component at the same frequency and band width shown in the right figures in (a). The Bootstrap confidence intervals (99%) were displayed by cyan lines (right).*

result shows that HG components induced by the movements of palm, index finger and little finger are represented by different independent components. The weight values of the unmixing matrices were localized near to the contralateral (and ipsilateral on little finger) hand area on sensorimotor cortex.

4. Discussion

Mu and beta band ERS/ERD responses were observed in three subjects, whereas the HG response was only found during the palm grasping task in one of the subjects. In this subject, no or poor response in the HG band was observed during or after the rest of the tasks (tapping of index or little fingers). This might be because the magnitudes of the muscle contraction on finger tapping tasks were smaller than that on palm grasping task.

It was found that the ICA could decompose the EEG signal measured from this subject to the significant HG components during all the tasks, as well as the mu and rebound beta band components. The ICA might be useful for designing spatial filters with local spatial distribution for decomposing the target responses to classify motor tasks [Kanoh et al., 2012].

The spatial distributions of the ERD/ERS responses on these frequency bands and the ICA unmixing matrix were similar between three movement tasks. The cortical mapping of the SMR might help to classify precise hand and finger movements or their motor imagery.

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Error Potentials for Brain-Computer Interfaces

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Abstract. The idea to use EEG correlates of errors to correct or reinforce BCI operation has been proposed over a decade ago. Since then a body of evidence has corroborated this approach. In this paper we give an overview of our recent work exploring the possibilities of error-potential applications, involving removing constraints of laboratory paradigms to increase "real-life" validity, and investigating EEG feature-spaces to increase detection robustness.

Keywords: EEG, Error-Related Potentials, Connectivity Analysis, Self-Paced Movements, Driving Simulator

1. Introduction

Non-invasive BCIs recognize user's intentions from EEG features. Mis-classification results in an erroneous command being executed by the BCI. The user's perceptions of such errors have, in turn, their own EEG correlates (error-related potentials, ErrPs). The simple, but ingenious idea to use such ErrPs to correct or reinforce BCI operation has been proposed more than a decade ago [Schalk et al., 2000]. Since then a body of evidence has accumulated, demonstrating the feasibility and usefulness of this approach [e.g. Schmidt et al., 2012]. Nevertheless, integration of these signals into practical BCI requires further characterization in realistic setups. For instance, errors are usually modeled as a binary variable. Here we show how the magnitude of error modulates the resultant ErrPs detectability. We also demonstrate how augmenting ErrP recognition algorithms with more complex EEG features, such as directed connectivity, improves accuracy. In our research we have also investigated ErrPs in several experimental setups, mimicking "real-life" applications, ranging from a driving simulator to robotic platforms. In the last section of this paper we give a brief account of these applications.

2. Error-processing of self-paced movements

Decoding arm kinematics from EEG is receiving empirical support [Bradberry et al., 2010]. However, any on-line BCI application will be prone to errors. The challenge in ErrP recognition here lies in such movements not being discrete sensory events. The onset perception and magnitude of error may vary. We investigated ErrPs induced in subjects operating today's most ubiquitous hand avatar, the computer mouse, in a self-paced reaching task. In some trials we distorted the hand-to-cursor mapping by ± 20°, 40° or 60° (simulating imperfect BCI). Averaged EEG epochs showed the typical readiness potential preceding movement, followed by the ErrP waveform (Fig. 1A). The ErrP's average amplitude follows the degree of the perturbation. We performed off-line classification of non-perturbed vs. perturbed trials in the spectral domain (tests with time domain features gave inferior results). Distribution of discriminant power – found principally in theta band – is shown in Fig. 1B,C with classification accuracy in Fig. 1D.

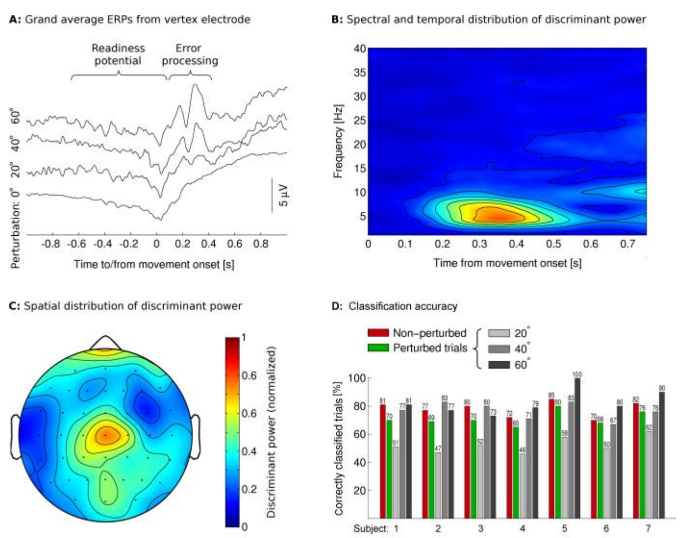

Figure 1. *(A) Group average EEG epochs time locked to movement onset. (B,C) Distribution of discriminant power in the spectral domain between perturbed and non-perturbed trials. (D) Accuracy of classification of perturbed vs. non-perturbed trials.*

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3. ErrP recognition with connectivity features

ErrP detection algorithms typically rely on temporal, less often spectral (see above) features. Here we report the results of an off-line study in which we used directed transfer functions (DTF) as a feature extraction method, reflecting information flow between EEG channels at different frequencies [Zhang et al., 2012]. We applied this to data recorded in a performance monitoring experiment, where subjects viewed on a computer screen a rectangular cursor moving in discrete steps either towards a specified target, or away from it – the latter considered errors. We compared classification accuracy afforded by the connectivity features with time domain features; best results were given by combined features, demonstrating the benefit of including connectivity features in ErrP detection (Fig. 2A-C).

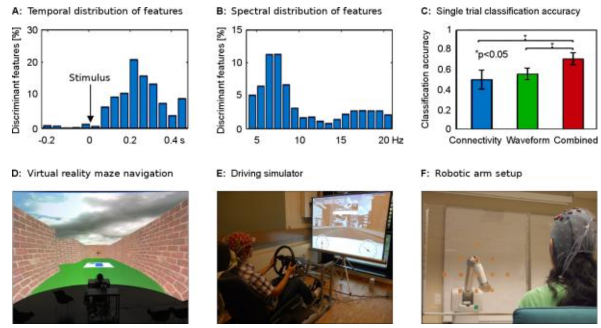

Figure 2. *(A,B) Distribution of discriminant connectivity features in the performance monitoring experiment. (C) Group average classification accuracy of erroneous vs. correct trials. (D) Virtual reality setup used in the maze navigation experiment. (E) Driving simulator. (F) Robotic arm with a subject.*

4. Towards real-life scenarios

We have also tested the laboratory findings on ErrPs in a number of still closely-controlled, but significantly more ecological scenarios. To simulate a BCI-driven telepresence robot (actually deployed in our laboratory) we have devised a virtual reality environment in which the user observes a robot navigating a maze from a first person perspective (Fig. 2D) [Chavarriaga et al., 2012]. At an intersection, the robot suggests a direction via visual or tactile (actuators on user's body) feedback. We found that wrong suggestion elicits an ErrP – regardless of feedback modality – which can be used to guide the robot's path. Another realistic scenario in which we tested usability of ErrPs is a driving task using a car simulator (Fig. 2E). It consists of a BCI system predicting the driver's intended driving direction. As the car approaches the intersection, a cue is displayed instructing the driver which direction to take. This is followed by a probe stimulus (an arrow pointing in one of the possible directions) which - if wrong - also results in a detectable ErrP. Still another scenario employs a robotic arm moving in left, right, up, or down steps (Fig. 2F) [Iturrate et al., 2012]. By setting a goal for the arm to reach and making it known to a human observer, we were able to detect ErrPs evoked by the robot's erroneous movement. Concluding, we believe that reliable usage of ErrP signals could significantly enhance BCI operation, and current research goals should include implementing basic findings into real applications, operating under less and less laboratory constraints.

Acknowledgements

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ERPs in the P300 BCI: Sensitivity to Matrix Size and Task

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Abstract. We investigated, using principal component analysis (PCA) on the 128 channel EEG data from six participants, the structure of the event-related potentials (ERPs) elicited by target flashes in the P300 brain-computer interface (BCI). Besides the P300, target flashes elicited an earlier, frontal positivity: the Novelty P3. The P300 was larger for the 3 participants whose task was to count the target flashes, compared to the 3 participants who merely attended to the target. The Novelty P3 tended to show the opposite pattern. Amplitudes of both components increased with matrix size (and hence with decreasing target flash frequency). These results have important implications for optimizing the performance of the BCI.

Keywords: P300, Brain-Computer Interface, Matrix Size, Task

1. Introduction

Several studies have suggested that in the P300 BCI [Farwell and Donchin, 1988], ERP components besides the P300 distinguish between target- and non-target flashes. In the present study we focus on the P300 [Sutton et al., 1965] and the Novelty P3 [Courchesne et al., 1975], which overlap in time and space (e.g., [Spencer et al., 1999], and in a previous study from our laboratory were implicated as crucial for BCI performance [Kamp et al., 2011]. An investigation of other ERP components is beyond the scope of this abstract, but will be included in future analyses. Thus, we investigated how, in the P300 BCI paradigm, P300 and Novelty P3 respond to parameters known to affect the P300 in standard oddball paradigms: the frequency of the eliciting event and the participant's task. Often, BCI researchers appear to make decisions on these parameters haphazardly; thus, our analysis could help establish better guidelines for P300 BCI use. We manipulated frequency through the size of the matrix: the larger the BCI matrix, the more rare are the target flashes. Furthermore, participants performed one of two tasks: either they counted the target flashes, or they focused on them and noted each flash to themselves.

2. Materials and Methods

Six healthy participants took part in two sessions each. In the first session they used a P300 BCI with 8 channels. The second session, from which we report results here, involved using the P300 speller with a 128 channel EGI system. Participants either focused on the target character and noted every time it flashed (attend condition; n = 3), or they counted the number of times the target flashed (count condition; n = 3). Three experimental blocks, completed in random order, included a 6 x 6 matrix including letters, 9 digits and a space bar, a 4 x 4 matrix including the letters A-P, or a 2 x 2 matrix including the letters A-D. The EEG from 128 channels was corrected for eye blinks, baseline corrected, and re-referenced to linked mastoids. The subject ERPs from target and non-target flashes were then submitted to a spatio-temporal principal component analysis (PCA; [Spencer et al., 1999]).

3. Results

As shown in Fig. 1, our PCA identified a parietal P300 and a fronto-central Novelty P3. The scalp distributions ("spatial factor loadings") closely corresponded to those obtained in prior PCA analyses of the P300 and Novelty P3 (e.g., [Spencer et al., 1999],). Both the Novelty P3 and the P300 were more positive-going for target- than non-target flashes, but the Novelty P3 peaked earlier (at about 300 ms, compared to 400 ms after the target flash for the P300). Therefore, we replicate the finding that in the P300 BCI both the P300 and the Novelty P3 distinguish between target and standard flashes and that they are distinct ERP components.

All participants who counted the target flashes showed larger P300 amplitudes than all participants in the group that merely attended to the targets. The Novelty P3 tended to show the opposite pattern. Besides this effect of task type on P300 amplitude, both Novelty P3 and P300 amplitudes were sensitive to matrix size such that larger matrices (and hence decreasing target flash frequency) were consistently associated with greater ERP amplitudes.

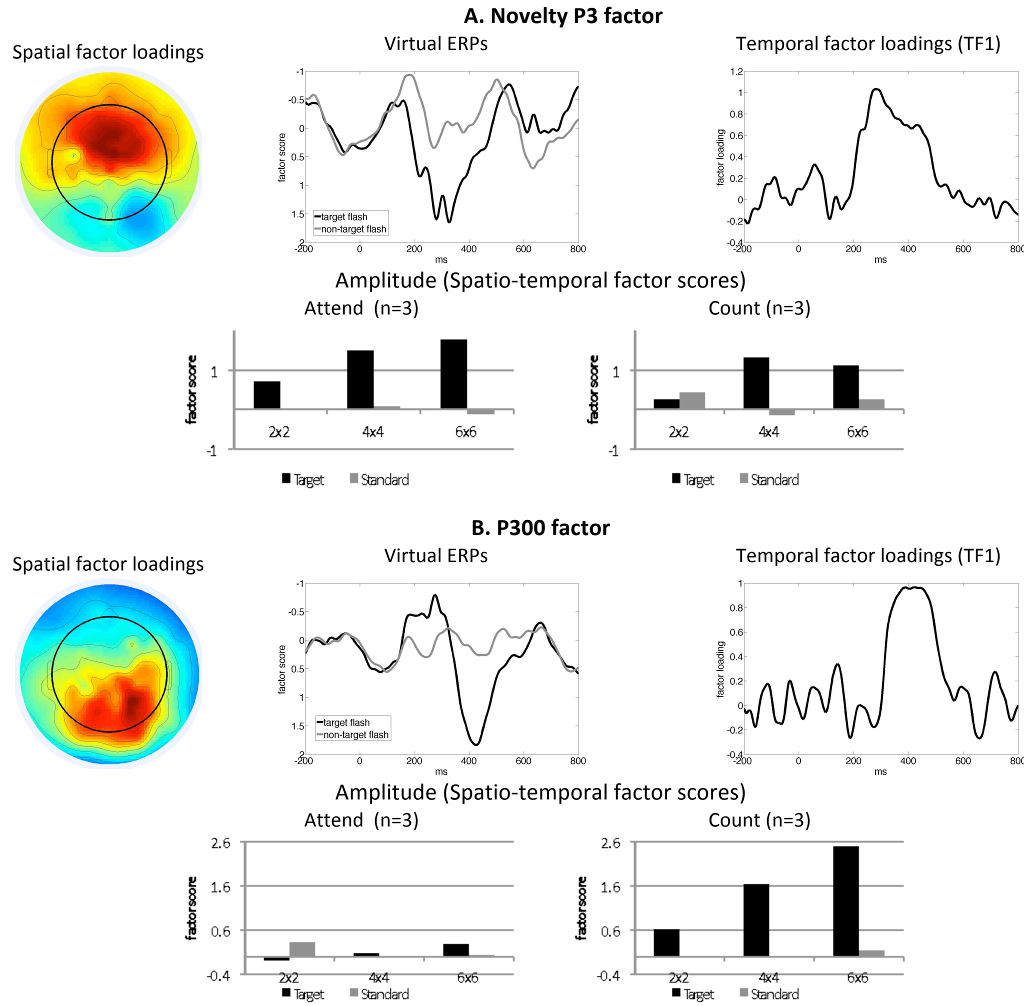

Figure 1. *Novelty P3 and P300 PCA factors. Shown are scalp distributions ("loadings"), "Virtual ERPs", the temporal factors we analyzed, and spatio-temporal factor scores as measures of ERP amplitude (cf. [Spencer et al., 1999]).*

4. Discussion

Our data show that the P300 elicited in the P300 BCI is sensitive to the participant's task, suggesting that the task that is given to an individual using the BCI should be chosen carefully in experiments and home BCI use. Both components also responded to target frequency. Future analyses will establish if the ERP patterns directly translate to differences in classification accuracy, so that the results can be used to improve performance of the P300 BCI.

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Electrocorticographic Gamma Band Power Encodes the Velocity of Upper Extremity Movements

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Abstract: Subjects undergoing subdural electrode placement for epilepsy evaluation performed a series of six elementary upper extremity movements. Depending on grid location, the electrocorticographic (ECoG) signals in the high gamma band were found to encode the velocity of these movements. To the best of our knowledge, this represents the first comprehensive study of elementary upper extremity movements and their relationship to ECoG signals. This information can potentially enable brain-computer interface control of six degrees-of-freedom prostheses.

Keywords: BCI, electrocorticogram, ECoG, kinematics, high gamma band, decoding

1. Introduction

Electrocorticogram (ECoG) has been explored as an alternative signal acquisition platform to intracortical microelectrodes in brain-computer interface (BCI) control of upper extremity prostheses. Unlike their intracortical counterparts [Hochberg, 2012], ECoG electrodes do not penetrate the cortex, and may have a long-term signal stability advantage. However, how well arm, hand, and finger kinematic parameters can be decoded from ECoG remains unclear.

2. Materials and Methods

Subjects were recruited from an epilepsy patient population undergoing subdural electrode grid implantation involving the primary motor cortex. Up to 64 channels of ECoG data were recorded with two Nexus-32 amplifiers (Mind Media, The Netherlands). Signals were acquired at 2048 Hz in a common average reference mode.

Subjects were asked to perform a series of 6 elementary movements, as tolerated and as permitted by time: (1) pincer grasp/release; (2) wrist flexion (F) and extension (E); (3) forearm pronation and supination; (4) elbow flexion and extension; (5) shoulder forward flexion (FF) and extension; (6) shoulder internal rotation (IR) and external rotation (ER). Subjects first performed 4 sets of 25 continuous repetitions of each movement type (1-6), with each set intervened by a 20-30 second rest period. An electronic goniometer (movements 1-2) or gyroscope (movements 3-6) was used to measure the trajectory, (position, $\theta(t)$, and velocity, $\dot{\theta}(t)$), and their signals were acquired by an integrated microcontroller (Arduino, Smart Projects, Turin, Italy).

To determine if ECoG signals encoded the above movements, they were bandpass filtered (80-160 Hz), and their instantaneous power, $P(t)$, was calculated. $P(t)$ was visually inspected, and those movements whose $P(t)$ were deemed highly correlated with either $\theta(t)$ or $\dot{\theta}(t)$ were further analyzed by an automated decoding system. This system performed classification to determine idling and movement epochs from ECoG signals, followed by trajectory decoding during those epochs that were classified as movement.

Half of the ECoG data was used to train the decoding system while the other half was used for testing. Subsequently, the roles of these data segments were reversed and the above procedure was repeated. To classify ECoG into idling and movement states, a linear regression model was first generated between $\dot{\theta}(t)$ and $P(t)$. A pair of thresholds was then applied to the estimate $\hat{\dot{\theta}}(t)$ to determinate the transitions from idling to movement states, and vice versa. The threshold values were found by minimizing the mismatch between the estimated state transitions and the ground truth, as determined by the measured trajectory. Subsequently, from $\dot{\theta}(t)$ and $P(t)$ corresponding to movement epochs, a second linear regression model (trajectory decoder) was generated to estimate $\hat{\dot{\theta}}(t)$.

Offline estimates $\hat{\dot{\theta}}(t)$ were determined by first classifying the test ECoG data into either idling or movement classes. For each ECoG epoch classified as idling, $\hat{\dot{\theta}}(t)$ was set to 0. Conversely, for epochs classified as movement,

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$\hat{\dot{\theta}}(t)$ was estimated by the trajectory decoder. The correlation coefficient between $\dot{\theta}(t)$ and $\hat{\dot{\theta}}(t)$ for each movement type was calculated.

3. Results

Three subjects were recruited for this study. During visual inspection, $P(t)$ was found to be visually correlated with trajectory for several movements. The classification and trajectory decoding results for each of these movements are summarized in Table 1. A representative velocity decoding is shown in Fig. 1.

Table 1. *Summary of results, showing study subjects, subdural electrode placement description, movements represented by visual inspection of signal, and results of classification and trajectory decoding system. Note that results are reported in pairs, corresponding to the two validation sets (see Section 2).*

Subject	Movements Represented (Visual Inspection)	Idle/Movement Accuracy (Ratio Correctly Decoded)	Trajectory Decoding Accuracy (X-Correlation)
S1 (20 yo F, Left 8x8 temporal-frontal grid, 1x6 posterior frontal strip)	Grasp, Wrist	Grasp: 0.85, 0.81 Wrist: 0.89, 0.83	Grasp: 0.68, 0.66 Wrist: 0.46, 0.52
S2 (27 yo F, Right frontal-parietal 6x8 grid)	Grasp, Elbow, Shoulder	Grasp: 0.73, 0.89 Elbow: 0.80, 0.80 Shoulder IR/ER: 0.68, 0.80 Shoulder FF/E: 0.82, 0.87	Grasp: 0.54, 0.62 Elbow: 0.44, 0.53 Shoulder IR/ER: 0.62, 0.53 Shoulder FF/E: 0.53, 0.69
S3 (35 yo F, Right frontal-parietal 2x6 strip)	Grasp	Grasp: 0.89, 0.88	Grasp: 0.62, 0.64

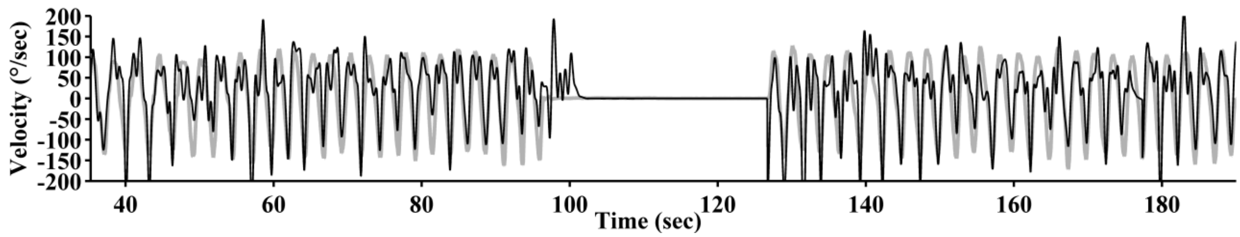

Figure 1. *ECoG-decoded (thin line) and measured (thick line) velocities during shoulder FF/E for Subject S2.*

4. Discussion

The results here indicate that velocities of elementary upper extremity movements are encoded within the power of ECoG signals in the high gamma band. The ability to decode these movements can eventually translate to the full BCI control of a 6-degrees-of-freedom upper extremity prosthesis. Such level of control may be necessary to adapt to the many unique situations presented in everyday life and may be a requisite to restoring independence to those with upper extremity paralysis. There have not been previous comprehensive efforts to elucidate the decoding of these movements from ECoG signals, and the results presented here bolster the potential of using ECoG signals for BCI-controlled upper extremity prostheses.

A combination of classification and regression was used to decode movement trajectories from ECoG signals. The most salient features encoding for movement kinematics were found in the high gamma band (80-160 Hz). These findings are consistent with prior studies [Miller, 2007]. The gamma band likely represents cortical activity of the neuronal generators controlling each of these movement types. Given the anatomical proximity of these generators in the motor cortex, future work will focus on investigating the discriminability of these movements.

Acknowledgements

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Cortically-Derived Error-Signals During BCI Use

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Abstract. Standard training regimens for decoders used in brain-computer interfaces (BCI) typically involve a calibration phase where training data is collected a priori within the context of a known task. Such a paradigm is not applicable in the general case of BCI use where the tasks are not known a priori. A potential solution to this problem is to derive a “reward” or “punishment” signal from the neural data itself. One example of such a signal is an error signal generated whenever the BCI fails to reach a goal the subject seeks to achieve. In this study we trained five human subjects to use a simple, one-dimensional electrocorticographic (ECoG). We demonstrate that invariant to multiple task parameters, there exist robust cortical signals that are correlated with failure to successfully complete the task. Further, we show that these error signals can be used to infer the outcome of new executions of the task. Our results suggest that such signals could potentially be utilized as reinforcement signals in the general case where task structure is unknown.

Keywords: Error potentials, adaptive classification, reinforcement learning, performance

1. Introduction

During the initial phases of use of a brain-computer interface (BCI), the standard procedure is to calibrate a feature selection algorithm and/or decoder based on training data collected during a known task structure. While this is a suitable method for operation of BCIs that will be used within tightly constrained structures (e.g., P300 speller), it may not be appropriate for abstract task environments. One proposed solution to handle the latter case is to derive information from the users themselves to serve as a positive or negative reinforcement signal to the BCI. Previous work using electroencephalography (EEG) has demonstrated that there exist neural responses that can be used to classify trial success, both in use of a BCI [Buttfield, 2006] as well as non-BCI paradigms [Blankertz, 2003], however these responses develop on timescales of up to 550 ms, limiting their potential use in a real-time BCI. As an alternative to EEG, electrocorticography (ECoG) is a signal modality that may allow for extraction of similar error signals on faster time scales. Recent work has shown that outcome-related error signals can be derived from frontal and parietal cortices during an overt motor task [Milekovic, 2012], and that these signals can be classified on a single trial basis [Milekovic, 2013]. It has yet to be shown that there exists a neural correlate of errors in BCI tasks that can be derived from ECoG data and whether such a signal can be detected on a single-trial basis.

2. Material and Methods

Five subjects with intractable epilepsy were implanted with platinum sub-dural ECoG electrodes for the purpose of seizure focus localization at Harborview Medical Center and Children’s Hospital in Seattle, Washington. Data were sampled at either 1000 Hz or 1200 Hz.

All subjects performed variants of the standard right-justified box task. BCI paradigms were driven by spectral power changes in the high-gamma (HG, 70-100 Hz) frequency band of a single electrode, selection of which was done with an initial screening task. Subjects were instructed to conduct/imagine movement or rest to control the cursor. The vertical extent of any given target was determined by the current task difficulty (i.e., the number of different potential targets). A cursor travelled from left to right across the screen at a fixed horizontal velocity, while its vertical velocity was updated every 40 ms based on spectral changes in the control feature.

Trials and electrodes containing obvious artifacts were hand-identified and discarded. Signals were common average re-referenced and spectral power was estimated by band pass filtering and finding the envelope of the resultant signal. All samples from successful trials were compared to those of failed trials and clusters were formed by grouping all significant (two-sample *t*-test, $p < 0.05$) contiguous samples. To correct for multiple comparisons, clusters generated by this method were then tested for significance against distributions generated through 1000 repeated random regroupings of trials ($p < 0.01$). Resultant features of greater than 150 ms were then used as learning features for subsequent classification analyses, which were performed using a linear discriminant analysis classifier and a standard 5-fold validation procedure.

3. Results

Subjects performed a number of variants of the BCI task, using overt and or imagined movements and attempting to select from between two and seven targets (occupying 50% and 14.3% of the total target area, respectively). Performance varied with movement type and target count. The mean number of trials performed by each subject was 358.6 (s.d. 124.2) with a mean overall accuracy of 76% (s.d. 9.5%).

In four of the five subjects we found statistically robust ($p < 0.01$, see methods) neural correlates of error trials (missed target), the majority of which occurred in the time period immediately after trial ended ($t > 3$ s). Generally, there was an increase in HG during the post-trial period in missed trials relative to successful trials, though this was not exclusively the case.

To verify that these error signals could be detected in real-time, we trained an LDA classifier on subsets of the data. For the four subjects in whom we found error signals, the classifier obtained a mean peak classification accuracy of 77% (s.d 8.0%). We performed these classification analyses on subsets of the error signal features to test the sensitivity of the classifier to feature count (see Fig. 1b).

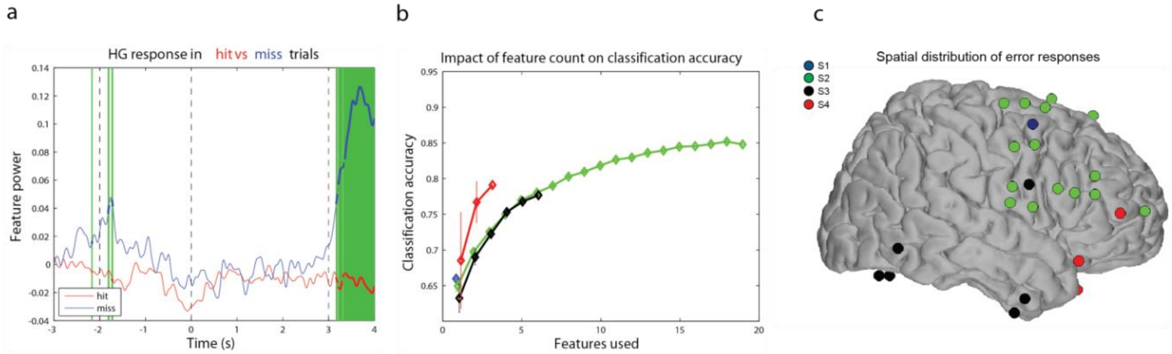

Figure 1. *(a) mean HG response of an example electrode. Online control begins at t = 0 and the trial ends at t = 3. Significant differences between successful (red) and failed (blue) trials are highlighted in green (b) Classification accuracy as a function of feature count. Error bars represent SEM. (c) Spatial distribution of electrodes exhibiting error potentials, different subjects are shown in distinct colors.*

4. Discussion

In this study we demonstrated that, in ECoG, there exist neural correlates of BCI trial outcome that have predictive value in evaluating the success or failure of a specific trial. These error signals typically occur directly after the trial has concluded, though we found some in-trial and even pre-trial indicators of trial outcome, though similar to EEG based studies, maximal classifier performance is obtained when error response latencies of 500 ms or greater are considered. Our findings indicate that it would be feasible to train a classifier to detect these error signals in real-time. This has significant implications for the design of co-adaptive BCIs as such an error signal could serve as a neurally-derived reinforcement signal for adapting a BCI in real-world applications.

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Unsupervised BCI Calibration as Possibility for Communication in CLIS Patients?

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Abstract. In this paper we present first results that a Brain-Computer Interface (BCI) can be calibrated online in a completely unsupervised manner. Thereby it is possible to provide a user with contingent feedback without the need for any goal-directed action. Since the extinction of goal-directed thinking is the assumed cause, why there are no reports of successful BCI communication in patients suffering from complete locked-in syndrome (CLIS), we discuss if unsupervised calibration could be used to enable communication in those patients.

Keywords: Brain-Computer Interface (BCI), complete locked-in syndrome (CLIS), goal-directed thinking, unsupervised learning

1. Introduction

The main motivation for Brain-Computer Interface (BCI) research is to give paralyzed patients a new means for communication. Although BCI communication works for patients who have some remaining muscle-control, using other communication methods that utilize the remaining muscle control are more effective in most cases. Therefore, the use of BCI technology would be especially interesting for people suffering from complete locked-in syndrome (CLIS), who have no remaining muscle control. Despite the extensive research in this area, so far there are no reports of successful BCI communication in CLIS patients.

One reason that BCI did not work for CLIS patients yet, is the assumed extinction of goal-directed thinking [Kübler and Birbaumer, 2008]. Due to the CLIS, the patient lacks voluntarily motor control and thereby feedback. Since cognitive activity does not result in any feedback, the missing feedback might be responsible for the extinction of goal-directed thinking.

Disregarding the recent introduction of classical conditioning for BCI control, there are two approaches, how a person is enabled to control a BCI: (1) In the neurofeedback approach the user is given feedback of certain parameters of his brain activity and the user learns to voluntarily control his brain activity to alter the feedback. (2) In the supervised machine learning approach the computer learns to decode the user's brain activity. Therefore, a supervised calibration phase is needed in which certain instructions are given to the user which actions to perform or which stimuli to attend. To ensure that the machine learning is working properly, the user is required to voluntarily follow these instructions.

Taking under consideration the assumed extinction of goal-directed thinking in CLIS patients, both approaches do not work, because: (1) the patient is not able to voluntarily alter his brain activity and (2) the patient is not able to voluntarily follow any instructions and perform voluntary actions.

In this paper we show first results of a BCI based on code-modulated visual evoked potentials (c-VEPs) that can be calibrated with unsupervised machine learning and we discuss that an unsupervised BCI calibration may provide the user with contingent feedback without the need for the user to voluntarily alter his brain activity or follow any instructions.

2. Material and Methods

Based on our recent developments for improved classification [Spüler et al., 2012] in a c-VEP BCI and a method for unsupervised online adaptation [Spüler et al., 2012a], we developed a method that allows a completely unsupervised calibration of the c-VEP BCI. This method will be presented elsewhere in more detail. Although the c-VEP BCI can be used with 32 stimuli, only 2 stimuli were used during the unsupervised calibration.

To show that an unsupervised calibration is possible, the method was evaluated offline on data from 18 sessions (9 healthy subjects, 2 sessions each) with each session consisting of 640 trials. The first 64 trials were used for unsupervised calibration, while the remaining 576 trials were used for accuracy estimation.

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To show that the unsupervised calibration can also be used online, we performed an online study with 8 healthy subjects. The subjects were instructed to decide freely, which target to attend, but not to switch the target consistently every trial and not to attend one target for more than 5 consecutive trials.

3. Results

The offline analysis resulted in an average accuracy of 90.85% (± 12.58%), with only 2 sessions having an accuracy below 70% and 6 sessions having an accuracy of 100%. In the online study, the 8 subjects achieved an average accuracy of 85.06% (± 9.9%) and only 1 subject had an accuracy below 70%.

4. Discussion

With the offline analysis and the online study we have shown that an unsupervised calibration of a c-VEP BCI is possible and can be used online for BCI control. In this paper we do not concentrate on the methodology used for unsupervised calibration, but rather want to discuss the implications that an unsupervised calibration might have for communication in CLIS patients.

Arguably, the c-VEP BCI system with unsupervised calibration mentioned in this paper won't be useable by CLIS patients, since it depends on visual stimulation. But we have shown that an unsupervised calibration of a BCI is possible and enables BCI control without (1) the user voluntarily altering his brain activity and (2) without the user voluntarily following any instructions which target to attend. Thereby we are able to give the user feedback which stimulus he is (voluntarily or involuntarily) attending to without the need for any goal-directed action. Since the unsupervised calibration method is giving feedback during calibration, it can run continuously and without the need for an operator to start or stop the BCI or change any parameters. Therefore it would be possible to give the user contingent feedback 24 hours a day.

One could argue that this would be also possible with steady state visual stimulation without the need for unsupervised learning. But for this to work, the stimuli are needed and precise knowledge about the nature of the stimuli (i.e., the frequency of the steady state stimulation) and how they influence brain activity.

In theory, unsupervised learning could be used to calibrate BCIs without external stimulation just based on internal brain states, without any goal-directed action of the user. If such a calibration would be possible in a reliable way, CLIS patients could be provided with contingent feedback linked to some arbitrary internal brain state. Since missing contingent feedback is the assumed cause for the extinction of goal-directed thinking [Kübler and Birbaumer, 2008], regaining contingent feedback may reverse extinction. [Birbaumer et al., 2012] point out analogies between REM-sleep and CLIS, since both result in complete paralysis and missing voluntary behavior. But in contrast to REM-sleep, it is still unknown if voluntary behavior can return in CLIS patients.

Since the authors have a strong computer science background, but lack a solid psychological education, this paper aims at encouraging a discussion if unsupervised calibration might open new possibilities regarding communication in CLIS patients and if research in this direction should be pursued.

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Strategy for Reducing Calibration Time With Invariant Common Spatio-Spectral Patterns

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Abstract. Most variability in neural signals is dominated by the variability of background noise. Thus, whenever BCI online feedback is conducted, the performance heavily depends on how readily classifier is generated reflecting the variability of user's brain state. For this, it is common practice to have a calibration phase (generally time-consuming) every online feedback session. In this work, a new concept for reducing calibration time is proposed with invariant CSSP treating noise effect as follows: 1) collect training data after a few early calibration phases according to common practice, and 2) apply iCSSP to online feedback with this pre-collected training data and ongoing acquired background noise. This strategy requires the collection of reasonable training data during early calibration phases, but does not require a calibration phase for every online feedback, and zero-calibration can eventually be achieved in some sense. We tested our idea with a total of 4 subjects. Each subject participated in the same motor imagery experiment on multiple days and we thus acquired data from two or three sessions for each participant. Our proposed concept and the conventional online paradigm are tested with iCSSP. For compasion, conventional CSSP was applied in the same manner. The results show that our proposed concept using iCSSP had comparable performance over all sessions/subjects to conventional one, while CSSP had a notable loss in performance. It is evident that our concept using iCSSP is quite robust to session-to-session variability. Thus, zero calibration can be achieved with iCSSP and pre-existing training data.

Keywords: EEG, Motor Imagery, Invariant Feature Extraction, Session-to-Session Variability, Zero Training

1. Introduction

Brain computer interface (BCI) can be achieved by modulating a user's neuronal signals accordingly. A neuronal signal that implicitly expresses brain activity is too dynamic and rapidly changing to control in a steady manner, and this variability yields low BCI performance, which is a big obstacle for BCI development. In practice, a time-consuming calibration phase is essential for collecting newly changing neural activity and regenerating a classifier with new information for each online feedback session. This calibration phase is generally time-consuming (tens of minutes) and may cause early fatigue for users, decreasing user's performance. Various ideas for reducing the calibration time have been presented using classifier adaptation [Vidaurre et al., 2011] and source imaging [Ahn et al., 2011].

It is believed that most variability in neural signals results from variability in background noise, or signals that are not associated with the control signal. This motivates us to design a strategy in which zero calibration is achievable if a classifier properly dealing with the session-to-session changes in noise exists. That is, when a classifier is simply updated with pre-existing training data (e.g., acquired from early calibration sessions or different subjects) and session-related noise in each session, the calibration phase is no longer needed and short-time noise acquisition immediately prior to the online feedback is sufficient. Our recently proposed invariant common spatio-spectral patterns (iCSSP) method [Cho et al., 2012] is an extractor that incorporates the background noise effect in the conventional CSSP framework, and can diminish the noise effect. In this work, we tested our proposed concept by applying iCSSP with Fisher linear discriminant analysis (FLDA) to a total of 4 subjects, where each subject takes part in multiple sessions.

2. Materials and Methods

Invariant Common Spatio-Spectral Patterns (iCSSP) estimates the spatio-spectral filters that maximize variance for one class and simultaneously minimize variance for non-stationary noise and the variance of another class [Cho et al., 2012]. iCSSP can be formulated as follows: Let $S(\tau)_i$ be τ-delayed S_i denoting the EEG signal [representing the (#channel) by (#sample) matrix', Σ be the spatio-spectral noise covariance or the covariance matrix of $\hat{N} = \left(N^T \quad N(\tau)^T\right)^T$, which is expressed by N (#channel) by (#sample) representing noise signal, and $N(\tau)$ be τ-delayed N. For class i (i = 1 or 2) and $\hat{C}_i$ (representing the covariance matrix of $\hat{S}_i = \left(S_i^T \quad S(\tau)_i^T\right)^T$),

$$\max_{w_1}\left(\frac{w_1^T\hat{C}_1 w_1}{w_1^T\hat{A}_2 w_1}\right),\quad \max_{w_2}\left(\frac{w_2^T\hat{C}_2 w_2}{w_2^T\hat{A}_1 w_2}\right),\quad \text{where}\quad \hat{A}_i=(1-\xi)\hat{C}_i+\xi\Sigma,\ \ \xi\in[0,1]. \tag{1}$$

Since Σ correctly estimates the various noise structures, iCSSP can be robust to noise. In the present study, ξ was confined to values ≥ 0.05. τ was determined by 10-fold cross validation.

Data Sets and Evaluation: Four subjects who provided written informed consent participated in the same motor imagery (right/left hand or foot) experiments on multiple days (two or three days). Two or three sessions were thus collected per subject. See Fig. 1b for details. Sixty-four EEG electrodes (Biosemi ActiveTwo) were attached to the scalp according to the 10-20 international system, and signals were digitized at a 512 Hz sampling rate. A total of 60 offline and 75 online trials per class were collected for each subject. This data was spectrally (8-30 Hz) and temporally (0-4 seconds after cue onset) filtered. Among the multiple sessions per subject, a single session that yielded good performance in online feedback was selected as the training data. Then iCSSP trained with this pre-chosen training data and session-related background noise (subjects looked at the arbitrary feedback without imagination) was applied to other sessions and the online and offline feedback performance was measured. For comparison, conventional CSSP was applied in the same manner.

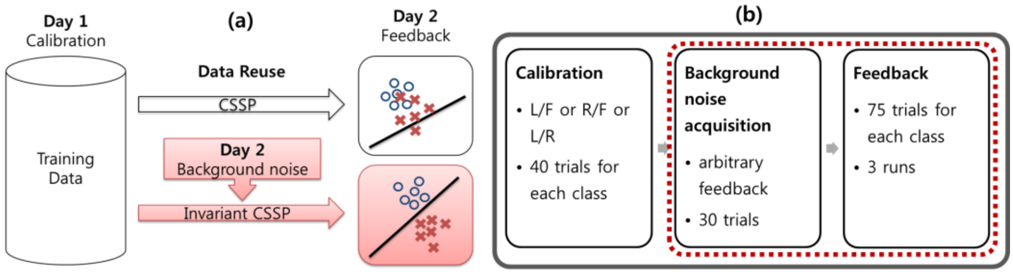

Figure 1. *(a) Illustration of our proposed concept. (b) Experimental paradigm (conventional: solid box; our proposed: dotted box) for online feedback.*

3. Results and Discussion

Table 1a shows the performance of CSSP and iCSSP in the conventional online feedback paradigm, which involved collecting calibration data and noise, generating the classifier with calibration data, and finally applying it to online feedback. Table 1b shows the performance of CSSP and iCSSP using our proposed concept. For our proposed concept, iCSSP is quite robust over sessions as compared with CSSP, and iCSSP is very comparable to the results for conventional iCSSP/CSSP. Session s3/2 in Table 1b shows interesting results, with remarkably higher performance for iCSSP. It is expected that the calibration and feedback phases had very different characteristics due to signal variability, indicating that the classifier trained with the same session calibration data strongly discriminated against the online data. In conclusion, this investigation shows that if reasonably informative training data are available in advance, then zero calibration is achievable with the acquisition of session-related noise data only (Fig. 1b).

Table 1. *Online and offline feedback performances (a) Conventional paradigm using the same session data only. (b) Our proposed method using the best-session calibration data (colored) and the session-related noise.*

Subjects/Sessions		***s3/1***	***s3/2***	***s5/1***	***s5/2***	***s6/1***	***s6/2***	***s6/3***	***s8/1***	***s8/2***	*Mean (standard deviation)*
Classes		LR	LR	RF	RF	RF	RF	RF	LF	LF	
(a) online	CSSP	86	64	83	91	87	78	55	92	97	74.4(±14.8) %
	iCSSP	83	62	83	87	89	78	53	92	97	**73.6(±15.5) %**
(b) offline	CSSP		**61**	**89**			**58**	**51**	**91**		70.0(±18.6) %
	iCSSP		**91**	**85**			**77**	**49**	**92**		**78.8(±17.7) %**

Acknowledgements

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Self-Calibration in an Asynchronous P300-Based BCI

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Abstract. Reliability is an important issue to use Brain Computer Interface in real life contexts. In this work we investigate whether a continuous adaptation of control parameters in P300-based BCI can improve the accuracy of the system over time and we propose an algorithm able to label unsupervised data on-line allowing for automatic recalibration of the system without the need for frequent explicit calibration sessions.

Keywords: EEG, Brain Computer Interface (BCI), P300, self-calibration

1. Introduction

In order to use Brain Computer Interfaces (BCIs) as assistive technologies outside experimental contexts they should ensure reliability and should not require complex configuration and calibration procedures. Since there are evidences about the variability of the P300 potential morphology across different sessions [Thompson et al., 2012], classification methods for partial/complete unsupervised learning in P300 based BCI were proposed in order to hide/avoid the calibration process to the user [Lu et al., 2009; Panicker et al., 2010; Kindermans et al., 2012]. However the proposed methods were tested on brief controlled BCI sessions (1-2 hours), and they are not able to recognize when the user is not attending to the stimulation (No-Control) or to dynamically adapt the speed of selection (Dynamic Stopping). In this work, i) we investigated if a continuous adjustment of the control parameters can boost P300 based BCI accuracy in repeated BCI sessions in a day and ii) we propose and evaluate a self-calibration algorithm that starting from an asynchronous classifier [Aloise et al., 2011a] can correctly label data from on-line sessions, allowing for the continuous adaptation of the classifier parameters.

2. Material and Methods

Ten healthy subjects with previous experience with P300 based BCIs were involved in this study (5 male, mean age 25 ± 3). Scalp electroencephalographic (EEG) signals were recorded (g.USBamp, g.tec, Austria, 256 Hz) from 8 scalp positions (right earlobe referenced and grounded to the left mastoid). The stimulation interface consisted in the 6 by 6 Farwell and Donchin's matrix Speller. Each subject underwent 5 recording sessions in the same day at well-defined times: 10:00 AM, 12:00 AM, 2:00 PM, 4:00 PM and 6:00 PM. A session consisted of 6 runs of 6 trials each. A trial consisted of 8 random repetitions of the 12 stimulation classes. Two additional No-Control runs were acquired for each session in order to collect data affected by artefacts.

The asynchronous classifier relies on the introduction of a set of thresholds in the classifier and defined as explained in [Aloise et al., 2011a] in order to manage the Dynamic Stopping and the No-Control features. The asynchronous classifier performance were assessed by an off-line cross-validation both in Intra-Session condition (the training and testing dataset belong to the same session) and in Inter-Session condition (the training and testing dataset belong to two different sessions). For each session we considered all the combinations of 5 runs for training (3 Control runs and the 2 No-Control runs) and 3 runs for testing. Score values were assessed by using a Stepwise Linear Discriminant Analysis (SWLDA). Finally, we compared the communication efficiency [Bianchi et al., 2007] in the inter- and intra-session condition, assuming a cost of 1 for unwanted abstentions (the users only need to repeat the trial), and a cost of 2 for misclassifications (they need to undo the selection and select again the desired symbol).

In order to collect correctly labeled data for the continuous recalibration of the asynchronous classifier we introduced a second threshold yielding error rate fixed to 0%. When the first threshold is exceeded the value of the score relating to the classified class is compared to the second threshold; if the latter is exceeded the epochs relating to the current trial are labeled according to the classification result and stored for further recalibration. We first defined the classifier and the thresholds parameters using data from the first session, and then every time we stored 5% of new data from the other sessions, we removed the same amount of the oldest data from the training dataset and we updated the classifier weights and the thresholds values. The Self Calibration (SC) communication efficiency was compared to the one obtained when no recalibration (NC) was applied during the day.

3. Results

Intra-Session cross-validation showed higher correct classification rate with respect to Inter-Session (Fig. 1A). Efficiency was significantly higher for the Intra-Session (0.30) condition with respect to Inter-Session condition (0.24) as assessed by a paired t-test ($p < .01$). On average the SC algorithm (Fig. 1B) increased the corrected classification rate from 71.7% to 78.4%. The SC Efficiency (0.30) was significantly higher with respect to NR (0.24) as assessed by a paired t-test ($p < .05$). Despite the different values for correct classifications between the Intra-Session and the SC condition, the Efficiency remains the same, since the SC allows on average to reduce stimuli repetitions with respect to Intra-Session Condition (2.36 and 3.1 respectively). The SC on average stored 41% of new data for recalibration, and only the 2% of stored data was incorrectly labeled.

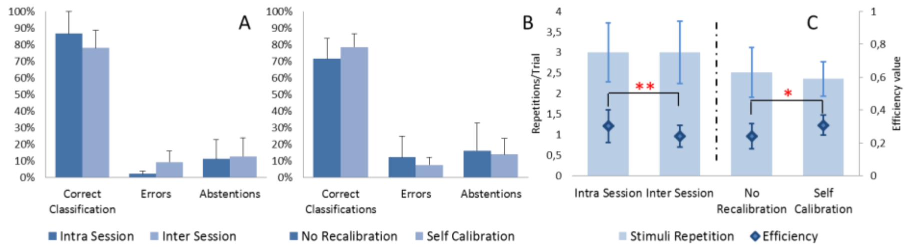

Figure 1. **A**) *Intra and Inter Session conditions mean classification performance for the asynchronous classifier. B) Mean performance of the asynchronous classifier with Self-Calibration and with No Recalibration across different sessions in a day. C) Mean Efficiency values (dots) and number of Stimuli Repetitions (bars) for all the considered conditions (**p< .01, *p<.05).*

4. Discussion

In this work we demonstrated that continuous update of control parameters increases the accuracy of P300 based BCI among several sessions in the same day. We improved the asynchronous classifier introducing an algorithm that can automatically perform a recalibration of the system using unlabeled data from on-line sessions and ensuring the stability of the performances. After an initial supervised calibration session, the whole recalibration procedure will be hidden to the user, which is an important point to increase the usability of BCI systems as assistive technology. Furthermore considering the higher variability exhibited by potential end users with respect to healthy subjects [Aloise et al., 2011b], we expect that the proposed system would be more effective if tested with end users.

Acknowledgements

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Probabilistic Co-Adaptive Brain-Computer Interfacing

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Abstract. Brain-computer interfaces (BCIs) are confronted with two fundamental challenges: (a) the uncertainty associated with decoding noisy brain signals, and (b) the need for co-adaptation between the brain and the interface to account for non-stationarities that emerge over time. We introduce a new approach to brain-computer interfacing that addresses these challenges using the framework of partially observable Markov decision processes (POMDPs). POMDPs provide a principled way to handle uncertainty and achieve co-adaptation: (1) Bayesian inference is used to compute posterior probability distributions ("beliefs") over brain and environmental state, and (2) actions are selected based on belief distributions so as to maximize total expected reward. By employing methods from reinforcement learning, the POMDP's reward function can be updated over time to allow for co-adaptive behavior. We illustrate our approach using a simple non-invasive BCI system which optimizes the speed-accuracy trade-off for subjects based on the amount of uncertainty measured in their brain signals. Our results demonstrate that the POMDP-based BCI can detect changes in user brain state and co-adaptively switch control strategies on-the-fly to maximize reward.

Keywords: Probabilistic BCI, Co-Adaptive Control, SSVEP, EEG, POMDP

1. Introduction

We propose a new approach to BCI design that combines Bayesian inference over brain states with an optimzing control scheme for selecting actions. The resulting framework, which is based on POMDPs [Cassandra et al., 1994], allows the BCI to handle uncertainty in decoding as well as to co-adapt with the user to converge to optimal task strategies. The proposed approach generalizes to a wide variety of applications, including both invasive and non-invasive BCIs for communication and robot control.

2. Methods

The POMDP framework allows us to model a decision process in which an agent acts in the world to affect outcomes, which are rewarded based on a reward function. In this model, the agent views the world indirectly through an observation function. We illustrate the use of this model for deciding when to collect more information from the brain and when to stop and make a decision about the user's intent, similar to [Park et al., 2011]. The relative weights of the users' preference for accuracy versus expediency are expressed through the reward function. We demonstrate the framework using an EEG BCI based on steady state visually evoked potentials (SSVEPs).

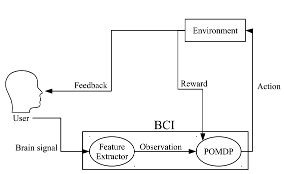

Figure 1: System flowchart

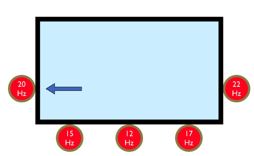

Figure 2: *During data collection phases, the user sees cues indicating which stimulus to fixate on*

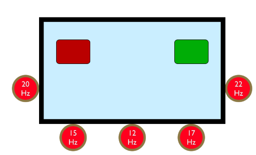

Figure 3: *During the co-adaptive experiment, the user's goal is to select the 'green box' stimuli*

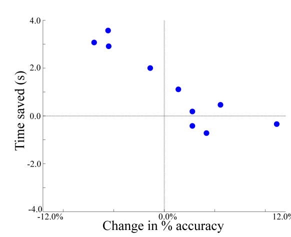

Figure 4: *Plot comparing average POMDP's performance to fixed-window classification for each user*

The reward function implicitly encodes the mapping between the various brain states we are tracking and control. For instance, in a task involving only movement left and right, and an SSVEP-type BCI with 5 channels, the reward function would tell our agent which action to take (moving left or right) given a particular brain state it may be in (the

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choice of SSVEP channel). Through reinforcement learning, we allow this control mapping to be non-stationary. In our experiment, reinforcements are given implicitly since the task has a pre-defined failure mode. We note that this signal could also be derived in a task-independent way using user perception of system failure [Gürel and Mehring, 2012]. This reinforcement process allows the user the freedom to *search the space of possible brain states* for those that work best for them. The result is a BCI which adapts to the user's behavior, who is also adapting to the BCI and the present situation (see Fig. 1).

We train the POMDP's observation model using labeled data. We collect the data through a training paradigm where the subject focuses on each flashing LED in a random order (Fig. 2). The POMDP's policy is then approximated using apre-packaged method (see [Kurniawati et al., 2008]). We present results from two experiments. In the first, the user provides us a data set using the same paradigm as our training data collection. In post-processing, we fix the POMDP's reward function and then run it in simulation to examine its trade-off between speed and accuracy.

In the second experiment, we present the user with a pair of targets. Their goal is to hit the green target. The user is free to pick any mapping between one of the SSVEP frequencies and a target. The BCI automatically modifies the reward function depending on the success of the users control in each trial (see Fig. 3).

3. Results

Overall, we saw the POMDP model gave users either an increase in accuracy, a decrease in decision time, or both, for one fixed parameterization. We should note that in practice the reward function would be tuned to the particular user's needs. We found that varying the reward function (e. g., changing the penalty for waiting an additional time step) allows one to trade off time spent collecting data with the expected accuracy of the decision.

An additional advantage of this model is that the BCI adjusts its behavior according to the expected usefulness of future observations. If the observation function indicates a particularly noisy brain signal, the BCI automatically accepts making decisions with less confidence.

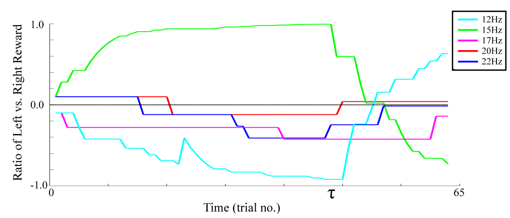

Figure 5: *Co-adaptive convergence of the POMDP BCI for User 1's 5-channel experiment. At first, the user tried various channels but found that 12 Hz and 15 Hz had the most accurate performance. Occasional misclassifications resulted in other channels changing as well. At trial τ, the user switches the mapping of 12Hz and 15Hz.*

In experiment 2, we found the co-adaptive system adjusted to non-stationarities imposed by the user's changing control strategies. Consider Fig. 5 which depicts the effect of changing control mappings for one of the users. Because some channels were difficult to classify for this user, they decided to change their mapping to use the 12 and 15 Hz stimuli. At time τ in Fig. 5, the user swapped their control mapping but the POMDP BCI was able to recognize this change in the user's strategy through reinforcement and it co-adapted with the user over several trials to converge to an appropriate policy.

4. Conclusion

Our results suggest that the POMDP framework is well-suited to handling uncertainty in BCI systems and provides a principled approach to achieving co-adaptation between the brain and the BCI. Our results from an SSVEP BCI demonstrate that this model offers the ability to choose the control scheme the user finds most intuitive in a given situation. It also provides a balance between accuracy and speed in a principled manner.

5. Acknowledgments

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Robotic Arm Control Using a Non-Invasive EEG-Based BCI

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Abstract. EEG based BCI has the potential to become widespread owing to their ease of use and noninvasiveness. Previous studies have demonstrated control of anthropomorphic robotic arms through invasive brain computer interfaces. Using noninvasive scalp EEG, we demonstrate continuous control of a human sized robotic arm in two-dimensions to complete grasping and maneuvering tasks that mimic real world situations.

Keywords: EEG, Motor Imagery, Robotics, BCI

1. Introduction

Brain computer interfaces have been shown to hold great promise to restore lost functions in patients suffering from various diseases and to enhance functions in healthy population [He et al., 2013]. Invasive brain computer interfaces have successfully demonstrated three-dimensional control of a robotic arm using an electrode arrays in humans [Collinger et al., 2012; Hochberg et al., 2012]. Invasive recording limits the usefulness of these approaches to only the most extreme cases. EEG based noninvasive control in two dimensions [Wolpaw and McFarland, 2004] and three dimensions has been recently shown in virtual cursor [McFarland et al., 2010] and virtual helicopter tasks [Royer et al., 2010; Doud et al., 2011]. These have been controlled solely by using motor imagination of the arm, leg, and tongue combined to control each dimension individually simultaneously with the other dimensions. Hybrid systems have been used to control 2 degree of freedom robotic arms [Horki et al., 2011]. Control in a virtual task is a useful proof of concept but does not insure an individual will be able to control an object in physical space in their immediate surroundings. Controlling physical objects and the interaction of these with an individual's environment is vital to allow a disabled individual to be more independent in their environment. We hutilized motor imagery to allow subjects to control two-dimensions of a robotic arm; one dimension of translation and opening/closing of the hand, to pick up and move blocks in a task similar to the box and block task used to evaluate upper limb mobility.

2. Material and Methods

Four healthy subjects participated in these experiments. Subjects performed multiple 2D control tasks with a robotic arm using both translation and hand opening/closing to allow us to evaluate the control enabled by motor imagery EEG-based BCI. To move the arm left and right, motor imagery of the left and right hand grasping, respectively were used. To move the arm up, motor imagery of both arms grasping was used, and relaxation was used to move the arm down. To open and close the hand, imagery of right foot movement was used as a switch to completely open or close the hand. Task 1 consisted of controlling the arm in two-dimensions in the XZ plane to move to a randomly selected target. Tasks 2 and 3 were 2D claw tasks consisting of either vertical or horizontal movement of the arm plus hand opening and closing. Claw tasks required three control steps performed in a specified order to correctly complete the entire task ('3 steps') but partial completion of two of the steps, moving to the target and closing the hand on the cube, were recorded ('2 steps'). Closing the hand prior to moving to the target position did not allow completion of the task. Grasp and translation were controlled simultaneously to allow the subject to parallel naturalistic limb movement when reaching for an object. The EEG signal was processed using a 16^{th} order ARMA model and classified with a linear classifier. The arm was under complete subject control using visual feedback with no intelligent control assistance provided.

3. Results

All subjects were able to correctly complete all of the assigned arm tasks (Fig. 1). Subjects had the best performance with the 2D translation task wherein the subject controlled the X and Z direction simultaneously while guiding the hand to one of four indicated targets; mean performance over all subjects was 42%. The claw task where the subject needed to lower the hand, close the hand, and raise the hand back up had an intermediate performance with an average of 27% correct two step and 18% correct three step trials. The claw task where the subject needed to move the hand either left or right to the target, close the hand, and move the hand back to the center had the lowest performance with an average of 11% correct two step and 3% correct three step trials.

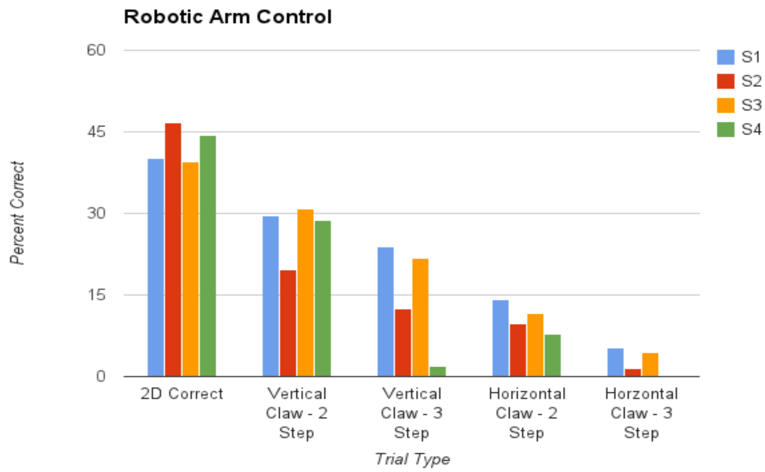

Figure 1. *Robotic Arm Control. The mean accuracy for each subject on the three different 2-D trial types. '2-Steps' indicates the subject correctly moved to the target and grasped the block. 3-Steps indicates the subject correctly moved to the target, grasped the block, and moved the block to the completion area.*

4. Discussion

We demonstrate successful control of a robotic arm in two-dimensions using a noninvasive EEG system to perform three different tasks that would be used in real world situations. Subjects demonstrated sufficient control to maneuver and successfully pick up and move a 2 cm cube across a table as well as lifting it from the table. This work illustrates the difficulty in performing high-dimensional control on devices located adjacent to the user. Future work in developing intelligent assistive control of the arm to generate shared human-computer control could be used to improve subject performance at the cost of increased sensing and computational calculations.

Acknowledgments

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Brain-Computer Interface Controlled Robotic Gait Orthosis

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Abstract. An able-bodied individual utilized walking motor imagery to operate a brain-computer interface (BCI) controlled robotic gait orthosis. This provides preliminary evidence that restoring brain-controlled ambulation is feasible, and it may lead to future BCI-controlled lower extremity prostheses for those with spinal cord injury.

Keywords: BCI, EEG, SCI, Robotic Gait Orthosis, Ambulation, Walking, Gait

1. Introduction

Excessive reliance on wheelchairs in individuals with tetraplegia or paraplegia due to spinal cord injury (SCI) leads to many medical co-morbidities such as cardiovascular disease, metabolic derangements, osteoporosis, and pressure ulcers. Treatment of these conditions contributes to the majority of SCI health care costs. Therefore, in addition to increasing independence and quality of life, restoring able-bodied-like ambulation in this patient population can potentially reduce the incidence of these medical co-morbidities. However, no biomedical solution exists that can accomplish this goal, and hence novel methods are required. A brain-computer interface (BCI) controlled lower extremity prosthesis may constitute one such novel approach.

This concept was first explored in the authors' prior work [Wang et al., 2012; King et al., 2012] in which able-bodied and SCI subjects used an electroencephalogram (EEG) based BCI to successfully control the ambulation of an avatar within a virtual reality environment. This motivated the current study, which integrates a BCI with a lower extremity prosthesis (Lokomat, Hocoma, Switzerland). For safety reasons, the feasibility of this system was first tested in an able-bodied individual.

2. Materials and Methods

A 41 year old, able-bodied male underwent a 64-channel EEG recording (256 Hz sampling rate, 0.1-40 Hz bandpass filter) while engaged in alternating epochs of idling and walking kinesthetic motor imagery (KMI). These data were analyzed using a combination of classwise principal components analysis (CPCA) [Das and Nenadic, 2009] and approximate information discriminant analysis (AIDA) [Das and Nenadic, 2008] for dimensional reduction, followed by Bayesian classification. This generated an EEG prediction model for online BCI operation. A treadmill-suspended robotic gait orthosis (RoGO) system (Lokomat) was then interfaced with the BCI (Fig. 1A). In 5 online tests, the subject utilized walking KMI/idling to ambulate/idle with the BCI-RoGO system as prompted by 1-min alternating walk/idle cues over a 5 min period. The online performance was assessed with cross-correlation analysis, omission, and false alarm rates.

Electromyogram (EMG) was measured to rule out BCI control by voluntary leg movements. To this end, lower extremity EMG were measured under 3 baseline conditions: active walking (subject voluntarily walked while the RoGO servos were turned off); cooperative walking (subject walked synergistically with the RoGO); and passive walking (the subject was fully relaxed while the RoGO made walking movements). Pairs of surface EMG electrodes were placed over the left quadriceps, tibialis anterior (TA), and gastrocnemius muscles (Fig. 1A), and signals were acquired with a bioamplifier (MP150, Biopac, Goleta, CA), bandpass filtered (0.1–1000 Hz), and sampled at 4 kHz. In addition, a gyroscope (Wii Motion Plus, Nintendo, Kyoto, Japan) with a custom wristwatch-like enclosure was strapped to the distal left lower leg (proximal to the ankle), and was used to measure leg movements (Fig. 1A).

3. Results

The offline accuracy of the EEG prediction model was 94.8 ± 0.8% (10-fold cross validation, chance: 50%). The CPCA-AIDA EEG feature extraction maps are shown in Fig. 1B. The subject's salient features during walking KMI were dominated by bilateral arm, likely due to arm swing KMI, and medial frontal areas. The cross-correlation between instructional cues and the BCI-RoGO walking epochs averaged over the 5 online sessions was

0.809 ± 0.056 ($p < 10^{-5}$). Also, there were on average 0.8 false alarms and no omissions per session; results for each session are shown in Table 1. A video of an online session can be found at http://youtu.be/W97Z8fEAQ7g.

The analysis of EMG and gyroscope data indicated that no movement occurred prior to the initiation of the BCI decoded "walking" states (Fig. 1C). When compared to the 3 baseline conditions, the EMG during online BCI-RoGO walking in all 3 muscle groups were statistically different from those of active or cooperative walking conditions ($p < 10^{-13}$), and were not different from passive walking ($p = 0.37$). Since passive walking generates some EMG activity [Mazzoleni et al., 2009], these results confirm that the BCI-RoGO system was wholly BCI controlled.

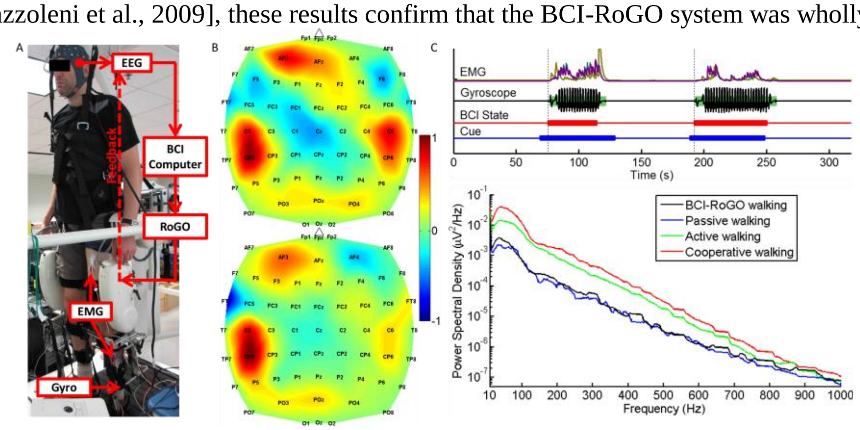

Figure 1. *(A) Subject suspended in the RoGO. A monitor presented instructional cues. (B) The CPCA-AIDA feature extraction maps at the 8-10 Hz bin (one map for each of the 2 classes). (C) Top: A representative online session showing epochs of idling and BCI-RoGO walking (red: decoded BCI states; blue: instructional cues). The thick/thin blocks indicate walking/idling. Corresponding EMG (gold: quadriceps; teal: TA; purple: gastrocnemius) and BCI-RoGO walking as detected by the gyroscope. (C) Bottom: Quadriceps EMG PSD similar to passive condition.*

Table 1. *Cross-correlation between BCI-RoGO walking and cues at specific lags, number of omissions and false alarms.*

Trial	X-Corr. (lag in sec)	Omissions	False Alarms (duration in sec)
1	0.771 (10.25)	0	1 (12.0)
2	0.741 (4.50)	0	2 (5.5, 5.5)
3	0.804 (3.50)	0	1 (5.3)
4	0.861 (4.50)	0	0
5	0.870 (12.00)	0	0

4. Discussion

These results provide preliminary evidence that restoring brain-controlled ambulation is feasible, and justifies further investigation in individuals with SCI. If successful, this may lead to the future development of BCI-controlled lower extremity prostheses for free overground walking. Furthermore, this system can also be applied to incomplete motor SCI, where it could lead to improved neurological outcomes beyond standard physiotherapy.

Acknowledgements

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Eye-to-Eye Contact: Controlling Robot Using P300 BCI

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Abstract. A brain–computer interface (BCI) is a system for direct communication between brain and computer. The BCI developed in this work in principle is based on a protocol described by Farwell and Donchin in 1988 using P300 by spatially distributed target and nontarget visual stimuli. For BCI robot control in this work we used target and nontarget visual stimuli located at the same place but coded by different colors. As a place for stimulus representation we selected eyes of the controlling robot NAO. Each color is used as a target associated with a specific robot action. In a pilot study on 3 subjects we tested this eye-to-eye BCI loop and have got 87%, 84% and 91% effectiveness to control elementary actions of a robot.

Keywords: Brain–computer interface, colors perception, oddball paradigm, P300, brain-robot interface, NAO robot

1. Introduction

In the last decade BCI actuated devices developed in research laboratories throughout the world, searching an options for applications of this technology in medicine, brain-controlled virtual simulation environments, military [Wolpaw et al., 2002], in the game industry [Kaplan et al., 2012], and other human activities. More and more studies are done using BCI to control robots, robotic manipulators such as BCI-actuated robotic hands, robotic wheelchairs, prosthetic devices. Amongst the numerous BCI paradigms, those based on the P300 component in EEG are among the most successful and well studied [Guger et al., 2009]. Usually, in BCI, P300 ERPs are triggered using oddball procedures [Farwell and Donchin, 1988]. The ‘oddball’ paradigm relies on an infrequent but task-relevant stimulus being embedded in a series of frequent irrelevant stimuli. The sustained attention to the target stimuli is one of the main conditions for the effectiveness P300 based BCI. Numerous attempts have been made to try to improve on it, including using colors and shapes as the object features which would capture more attention [Takano et al., 2009; Ikegami et al., 2012]. Nevertheless, the effectiveness of BCI, especially when it’s very important (like in medicine or military use), is still not high enough. Recently, a new approach to drawing the attention in the BCI appeared which is based on the use of natural stimulus to automatically capture the attention. For example, some studies used faces as a target [Kaufmann et al., 2012]. The best option here would be the placement of stimulus elements directly on the controlling device. In this paper we propose a system of BCI robot control, based on P300 waves, where the source of stimulus is placed directly in an eye of a robot. It is well known that eyes are the one of the most attractive elements of face. It is also best decision because the regular stimulus matrix for P300 triggering usually placed on a stand-alone computer screen that significantly restricts the use of the BCI technology. In this pilot study we test the hypothesis whether eyes located target/non-target sequences of visual stimulus would be effective for robot control.

2. Material and Methods

The pilot study involved three subjects. Data acquisition, stimuli presentation, online signal processing, and classification were done with an in-house Python program. EEG was recorded at 500 Hz sampling rate at Cz, Pz, PO7, PO8, O1, O2 against a reference at the right earlobe with ground electrode at Fpz. The main difference of our BCI from the standard P300 BCI is that instead of characters, such as letters or symbols spatially spread in the matrix, we used 3 (red, green, blue), or 5 (red, green, blue, yellow and purple) colors – flashing in same place - in the eyes of a humanoid robot NAO H25, made by Aldebaran Robotics, France. The robot eyes are circle and have a 0,76 inch in diameter and 3 inches between the eyes. All participants featured the same set of 3 or 5 colors. The duration of a single stimulus was 120 ms and the time between the onsets of subsequent stimulus, was 175 ms, as was optimized in our previous work [Ganin et al., 2012a]. Stimulus (3 or 5 colors) flashed randomly in the left or right eyes separately. Participants were instructed to sit at a distance of 35 inches from the robot and silently count the number of lighting of the target stimulus. The target stimulus each time was one of the backlight colors in the right or left eye. Five possible target stimuli were associated with five elementary robot commands: raise right/left hand, turn

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right/left, one step forward. Thus, the target stimulus was presented randomly in one or the other eye with a probability of 1/3 or 1/5. Each target stimulus was repeated 10 times.

3. Results

Each subject had a training session in which the position (left or right eye) and the color of the target stimulus was indicated. The duration of the training was usually 3-5 minutes. After training, the subjects were asked to activate thru BCI a given sequence of actions to the robot, for example, turn to the right, raise the hand, make one step forward, turn to the left, etc. of 12 (for 3 colors) or 20 (for 5 colors) consecutive items. Each subject performed the task 7 times with a 3-4 minutes rest intervals. In total, he made 84 commands for 3 colors and for 5 colors 140 comands. For each subject we counted the number of correct decisions as % of a total number of attempts to control the actions of the robot. It was shown that all 3 well trained and highly motivated subjects were able to perform the robot control with the reliability 87%, 84% and 91% in the case of 3 colors flashing in one position (6 commands for both eyes) and 78%, 82% and 86% for 5 colors (10 commands for both eyes) respectively. We did not compare the effectiveness of different color features and colour sets because of insufficient statistics at the moment.

4. Discussion

The study was considered as a preliminary test of possible beneficial effects from the use of target feature of colored stimulus given to the subjects in one place – in the eyes of a robot in P300 BCI paradigm. Earlier [Treder et al., 2012] it was shown that the presentation of stimulus with different features in the same place on the screen allows to create an efficient path for the P300 BCI. In our paper we show that P300 BCI paradigm can work efficiently even if the stimulus differ only in color. Perhaps the effectiveness of such the design could be explained by the fact that the stimulus was presented in the robot eyes and such an efficiency is associated with the natural capture of the user's attention to the eyes of another person. This eye-to-eye P300 technique could be used to manipulate a different kind of humanoid robot with eyes highlighted in different colors. Our next study would explore the possibility of code modulation of P300 based on target color combinations or 2D-3D sets of color stimuli. Code modulation would significantly increase the number of commands to control the robot's actions in a human-robot communications technology, called "eye-to-eye" paradigm, which would be the base to the building of a “brain-robot interface” (BRI).

Acknowledgements

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Humanoid Robot Control With SSVEP on Embedded System

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Abstract. In this study we implemented a low-cost, single EEG channel brain computer interface (BCI) running on an embedded computer. The BCI uses steady-state visual evoked potentials (SSVEP) to control the motion of the Kondo KHR-3HV humanoid robot. The subject attends to one of the flickering LEDs attached to the arms of the robot in order to move an arm. SSVEPs are identified by a simple spectrum analysis of the EEG signal.

Keywords: EEG, SSVEP, Robot Control, Emotiv, Raspberry Pi, Python, Linux

1. Introduction

Brain computer interfaces (BCI) are devices which create a communication channel between human brain and the outside environment by observing the brain activity with invasive or non-invasive methods. [Wolpaw et al., 2002]. This can assist people with neurodegenerative diseases in moving their wheelchairs, using a robot to grasp a glass of water and even in spelling a word using several cognitive paradigms.

Steady-state visual evoked potentials (SSVEP) are potentials elicited by the brain of a subject who is presented a flickering visual stimulus. They contain the fundamental frequency of the flickering rate and also some of its harmonic components depending on the stimulation frequency [Herrmann, 2001]. SSVEP can be detected using non-invasive electroencephalography (EEG) with frequency spectrum analysis methods.

Recent studies regarding humanoid robot control with SSVEP are based on display units which stream live video of the robot's view using cameras. The stimulation is either done by overlaying flickering patterns on the stream [Gergondet et al., 2011] or by placing LEDs around the display unit showing the stream [Bryan et al., 2011]. This study proposes a single channel, low-cost and wireless BCI based on SSVEP for controlling the arms of a humanoid robot using an EEG headset and an embedded computer. The frequency spectrum of the captured EEG signal is analyzed to discriminate between two possible SSVEP frequencies that may be elicited by the flickering LEDs attached to the arms of the robot, if the subject attended to one of them.

2. Material and Methods

2.1. EEG Setup

We used Emotiv EPOC, a battery-powered headset which can acquire 14 channels of EEG signal and transmit them wirelessly to its USB dongle. The headset internally applies a notch filter (At line frequency 50 or 60 Hz) and a 5^{th} order band-pass filter (0.2-45 Hz) to the signal. Although the internal sampling rate is 2048 Hz, the data is delivered with a rate of 128 samples/second.

For this study, only single channel of EEG is acquired through the occipital region where SSVEP response is prominent [Herrmann, 2001].

2.2. Humanoid Robot

Kondo KHR-3HV is a battery-powered humanoid robot with 17 degree of freedom which can mimic human movements. It has an embedded microcontroller board RCB-4 which can be driven using its serial USB dongle.

2.3. Embedded Hardware

Raspberry Pi Model B, a 35$ low-cost embedded computer with 700MHz ARM11 CPU, 256MB RAM and 2 USB ports, is used as the processing unit of the BCI. The board attached to the back of the robot, can be powered using a battery pack through its USB power input.

2.4. BCI Design

The whole software is written in Python programming language and runs on Debian Linux. We picked Python as it is a free, open-source and platform independent programming language with strong scientific computing capabilities.

The software runs in three concurrent processes: SSVEP stimulator which flickers the LEDs at 7.5 Hz and 10 Hz respectively for the left and right arm using the general-purpose I/O (GPIO) pins of the board; decryption process which decrypts the packets encrypted by the USB dongle; main process which performs an FFT using SciPy (Scientific Python Suite) on the acquired signal and sends a left or right arm command to the robot if an increase in power is detected at 7.5 Hz or 10 Hz. The concurrency is required in order to not miss the tagged samples sent by the headset. Tagging is done by the headset by simply enumerating each packet with a sequence number between 0-127.

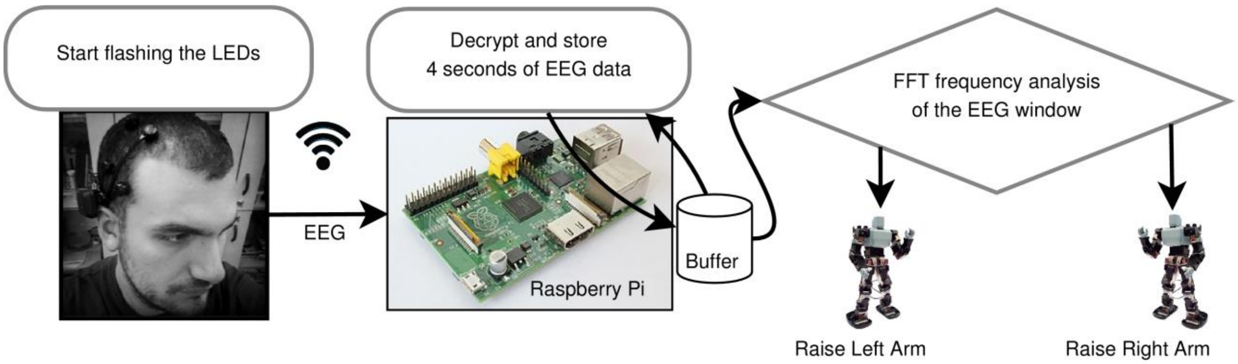

Figure 1. *Flow diagram of the BCI system.*

3. Results

In this study, we demonstrated a very low-cost BCI system for controlling the arms of a humanoid robot using a cheap embedded computer which runs Linux. The system has been successfully used by a single healthy subject to control the arms of the robot.

Usage of an embedded system is also the key to support ultimate portability: The computer can be attached to the back of the robot without causing any problem of balance. The developed BCI software is practically guaranteed to run on any operating system and architecture as Python is an interpreted language, e.g. there is no need to build the software against a specific architecture.

4. Discussion

Although the processing capabilities of Raspberry Pi are quite limited, there may be still room for performance improvements during EEG analysis. Linear classification performance of SSVEP on this platform should be investigated in order to possibly realize a faster BCI. Finally, more control over the movement of the robot can be achieved using additional LEDs.

Acknowledgements

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Intelligent Adaptive User Interfaces for BCI Based Robotic Control

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Abstract. The inherent lower bandwidth of a two-class BCI is still a major challenge in making BCI practical for day-to-day use. In this paper we present an intelligent adaptive user interface (iAUI) to facilitate enhanced robot control via BCI. The iAUI is a user-centric graphical user interface (GUI) that facilitates multiple controls needed in controlling a powered wheelchair or a robotic device using just a two-class motor imagery (MI) brain-computer interface (BCI). The iAUI offers a continuously updated prioritized list of all the control options (in the form of forward, left, right, backward and start/stop) for selection via a BCI by utilizing the information obtained from the sonar sensors mounted on the robotic device. Results on multiple participants in player-stage simulation as well as the physical robotic arena show that the iAUI addresses to a large extent the inherent lower bandwidth of a BCI for effective control of a robotic device.

Keywords: brain-computer interface (BCI), graphical user interface (GUI), motor imagery (MI), wheelchair, EEG

1. Introduction

There are normally only two output commands in a two-class brain-computer interface (BCI) e.g., left hand vs. a right hand/foot imagery (MI), for every trial. This limited communication bandwidth renders control of assistive devices such as a smart wheelchair or a telepresence mobile robot, which require multiple motion commands, a significant challenge. There are several interfaces available in the literature; some utilizing shared control strategies, however these have not been strictly user-centric in terms of offering true independence while controlling a robotic wheelchair. This paper proposes a GUI using a 2-class MI BCI to perform a multi-task robotic control, and is referred to as an intelligent adaptive user interface (iAUI). The iAUI is implemented by sharing the real-time knowledge from the robotic device (in the form of sonar sensor information) and is effective in suitably controlling the device whilst minimizing the effort required by the user.

2. Method

As shown in Fig. 1, the BCI user is expected to perform 2-class MI (i.e., left or right hand) in accordance with the display of commands through the iAUI and control the device in the robotic arena. The iAUI is composed of four main modules namely the communication module (CM), the information refresh module (IRM), the adaptation module (AM) and the monitor module (MM) (i.e., iAUI front-end). The commands that are offered to the BCI user (e.g., Backward, Forward, Left, Right, Halt and Main) are displayed on the MM such that the most likely command is placed at the top-most location ready for selection at the start of a scan cycle. The two options at the top-most location have the highest probability of being chosen by the BCI user. This prioritization of the options solely depends upon the dynamic situation of the robot with reference to the environment i.e., the obstacles surrounding the robotic device as detected from the sonar sensor readings. These most likely options presented through the iAUI are expected to be the easiest and quickest to access and thereby reduce the decision-making time. The simulated and the physical robotic arena have various obstacles (see Fig. 1). The location of the robot in the arena is displayed as a visual scene on the left side while the corresponding GUI associating the user's mental imagination is displayed on the right side. In Fig. 1, A-A' and B-B' displays a graphical view to understand two of the various adaptive forms of the interface using an example. Assume that the robot begins from a starting position in the robotic arena marked (A') and is to be maneuvered towards the 'Target' position shown by an orange colored marker. At position in (A'), the two most probable choices displayed are 'Forward' and 'Right'. The BCI user performs a left hand MI and issues the command 'Forward'. When the robot begins to move in the forward direction, the left and right hand sides of the robot get blocked and only the front and backward sides remain open (shown in (B')). This information is sent to the interface in the form of sonar sensor values. Thus, the interface adapts immediately after the user's 'Forward' command and alters the first two probable choices as 'Backward' and 'Forward' (shown in (B)). Thus, the user has the opportunity to select the 'Forward' and the 'Backward' choices in the first instance, as these are the most suitably available choices.

3. Results and Discussion

The number of commands needed to reach the specified destination (Room 1, Room 2 and Cupboard (see Fig. 1)) in the simulated arena considering 100% BCI accuracy is detailed in Table 1. If a command is to be selected from the two options on the 2nd (or 3rd) rung of the iAUI (see Fig. 1), then the user is expected to perform no imagination i.e., one (or two) no-control (NC). Forty-two commands are required to reach the three targets through the iAUI and forty-six are needed through the non-adaptive interface. However, only 31 NC commands are required through the iAUI, while 45 NCs are required through the non-adaptive interface. This suggests that the adaptive nature of the iAUI is very valuable in minimizing the time loss through NC i.e., the iAUI prioritizes the commands available to the user so that the user is preferably not required to perform NC and go to the next available choice. The probabilities of the control tasks that are more likely to be expected from the BCI user are adapted and their position accordingly reordered to enhance the otherwise low communication bandwidth. The results are comparable with some of the contemporary designs in the literature by calculating the overall cost using nominal time, mission time, mission time ratio, concentration time and concentration time ratio [Rebsamen et al., 2010]. The average cost in maneuvering the device to the three target locations is 1.98 using the iAUI while it is 2.21 with the non-adaptive interface.

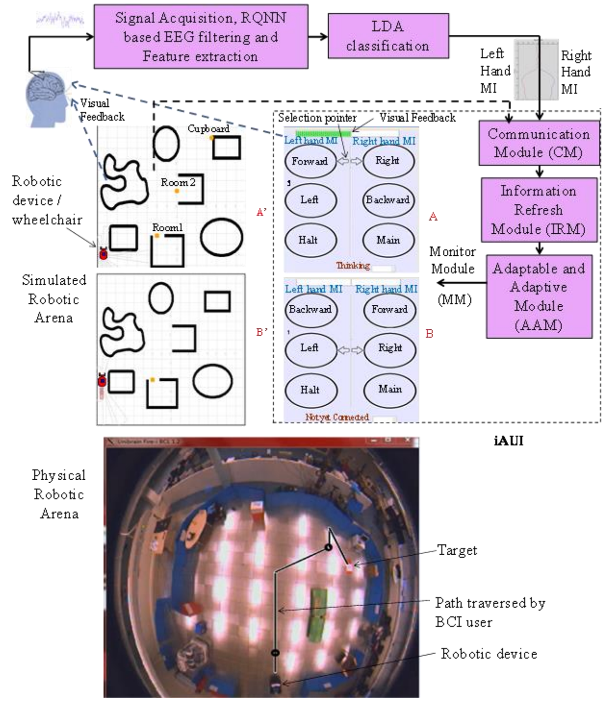

Figure 1. *iAUI architecture within the complete BCI system.*

The iAUI has been evaluated using five subjects in a player-stage simulation and three subjects in a physical robotic arena (see video isrc.ulster.ac.uk/Staff/VGandhi/VideoRobotControlThroughMI). One session consisting of forty trials was used to train the classifier before beginning the session on any day. The average cost with five subjects maneuvering the device to the three destinations in the simulated arena is 4.42, 8.00, 7.86, 12.47 and 10.16. The average cost with three subjects maneuvering the physical mobile robot to the two target destinations is 3.66, 11.17 and 11.62. The path traversed while maneuvering the robotic device to Target 1 by one of the BCI users is shown in Fig. 1. Most of the subjects reached the targets on the 1st or 2nd attempt and were easily acquainted with the adaptive interface as the sessions progressed. The major advantage with the iAUI is the user-centric display of choices being made available for user selection, which is the novelty of the presented interface. A preliminary and a comprehensive study of the iAUI with a comparative analysis are detailed in [Gandhi et al., 2009; Gandhi, 2012].

Table 1. *No. of required commands.*

Destination	iAUI	Non-adaptive
Room 1	13 / (07)	13 / (13)
Room 2	09 / (07)	11 / (12)
Cupboard	20 / (17)	22 / (20)

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Single Trial Classification of Imagined Hand Postures

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Abstract. Motor imagery (MI) based brain computer interface (BCI) systems are mostly used in the design of robotic/prosthetic arm control. MI signals are asynchronous and hence have the potential of being used in systems that require dynamic manipulation. In MI there is a significant amount of user adaptation involved; to address this issue there is a need to design BCI that is intuitive for the user to adapt to. Towards this goal, in this study we present that with significant accuracy, it is possible to decode imagined hand postures sensed using EEG.
Keywords: EEG, Motor Imagery

1. Introduction

Motor imagery (MI) has been utilized in numerous BCI systems for the design of systems that control cursors in multiple dimensions, manipulating virtual objects in 3D, controlling robotic arms for performing simple daily life tasks [Ramoser et al., 2000; Blankertz, 2010; McFarland et al., 2010; Doud et al., 2011]. Studies based on human cortical activity associate μ-band (8-12 Hz), β-band (18-26 Hz) and γ-band (>30 Hz) with motor output [Miller et al., 2007]. The lower bands exhibit supression of amplitude in response to MI, event-related desynchronization (ERD) is spatially localized, higher bands exhibit increases in amplitude known as event-related synchronization (ERS).

With the use of micro-electrode implants, it has been show that non-human primates could control a robot arm [Carmena et al., 2003] for reaching out and grasping objects without moving their own. In this study, we investigate the possibility of single trial classification of EEG signals sensed during the imagery of specific hand-posture types: extension and closed.

2. Material and Methods

2.1. Experiment description

EEG data was collected from two subjects, one male and one female. During the experiment the subject was seated in front of a computer monitor and was asked to relax and avoid body movements and eye-blinks during the trial periods. Each experiment consisted of imagining two hand postures – extension and closed, for each hand, resulting in four trial types (classes). A total of 200 trials were presented with equal number of trials from each class selected in random order. Each trial started with the fixation sign presented at the center of right/left half of the screen, indicating which hand this imagery trial belongs to. An image of the posture type was shown for 5 seconds after fixation; Fig. 1 shows the images used for right hand.

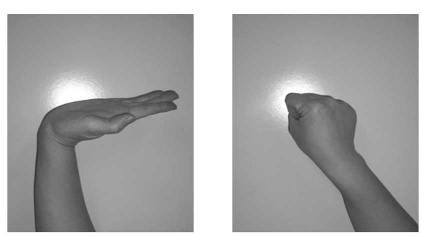

Figure 1. *Hand postures used in the experiment, left image shows extension while right image shows closed.*

2.2. EEG recording

EEG was acquired using two 16 channel g.USBamps (g.tec, Graz, Austria) connected in daisy-chain configuration. A total of 32 channels sampled at a rate of 256 samples/second were used.

2.3. Common Spatial Pattern Filtering and Fisher's Linear Discriminant Analysis

We used the Common Spatial Pattern Filter method to project data from two classes such that the ratio of projected energy of one class to that of the other class was maximized [Ramoser et al., 2000]. Let $\mathbf{X} \in \mathbb{R}^{\boldsymbol{Nc\times T}}$ be the EEG data samples in matrix form corresponding to one trial (where Nc denotes the number of EEG is channels and T is the number of temporal samples in each trial). The CSP transformation is given by

$$\mathbf{Z} = (\mathbf{B}'\mathbf{P})'\mathbf{X} \tag{1}$$

where $\mathbf{P}$ is the matrix that whitens the composite covariance ($\mathbf{C}_c = \mathbf{C}_1 + \mathbf{C}_2$), sum of individual normalized class covariance where $\mathbf{C}_i = \mathbf{XX}'/trace(\mathbf{XX}')$, where $i \in \{1,2\}$ and $\boldsymbol{B}$ is the matrix containing the eigenvectors of whitened $\boldsymbol{C}_i$. Features are extracted from CSP projected data by picking subsets of most discriminative signals as indicated by eigenvalues. Further, to reduce dimensionality of Z rows corresponding to largest m and smallest m eigenvalues were selected given as $\boldsymbol{Z}_p$. Fisher's linear discriminant was used to classify feature vectors derived from

$$f_p = log\left(\frac{var(\mathbf{Z}_p)}{\sum_{i=1}^{2m} var(\mathbf{Z}_i)}\right) \tag{2}$$

3. Results

Area under the curve (AUC) estimated using 10-fold cross-validation for two subjects is presented. Binary classification has been done on extension and closed imagined hand postures data for each hand (right and left). Fig. 2 shows the variation in AUC with increasing number of CSP filters. Blue curve in the plots corresponds to the right hand classification results and green curve shows the classification accuracy for the left hand.

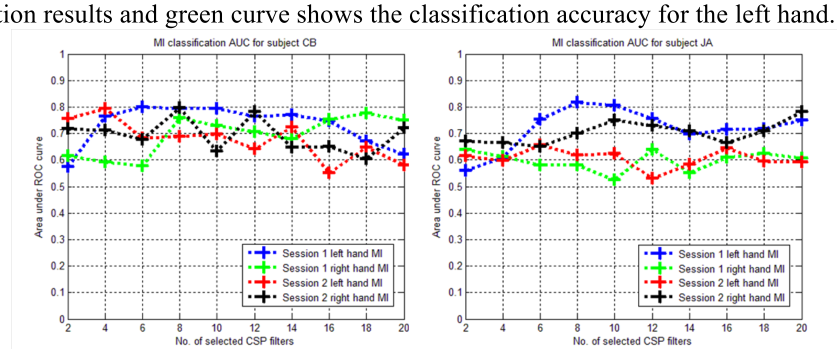

Figure 2. *AUC for binary CSP-based classification between extension and closed hand postures.*

4. Discussion

Using the CSP method we have shown that AUC up to 80% is achievable in the classification of posture imagery for naïve subjects. This accuracy is comparable to right/left hand classification for the same subjects. Therefore it is conceivable that complicated hand posture imagery classification with EEG is feasible with high accuracy with subject training and improved pattern recognition.

Acknowledgements

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SSVEP Based Brain-Computer Interface Combined With Video for Robotic Control

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Abstract. Many BCIs rely on visual stimuli with constant stimulation cycles that elicit steady-state visual evoked potential (SSVEP) activity in the electroencephalogram (EEG). This study compared frequency-coded and code-modulated VEP methods in a new type of BCI that used streaming video to help control a robotic device.

Keywords: EEG, BCI, SSVEP, c-VEP, robot

1. Introduction

Most BCIs rely on one of three kinds of brain signals based on the EEG: event related desynchronization (ERD) associated with motor-imagery, event-related potentials and SSVEP [Wolpaw et al., 2002]. This work is focused on BCIs based on visual evoked potentials (VEP), which can be derived over the visual cortex during appropriate visual stimulation. Frequency coded systems use targets with different stimulation frequencies, where visual stimuli over 6 Hz lead to a phenomenon called steady-state VEP or SSVEP. This behavior can be used to extract features for target identification, for example with power spectral density analysis [Cheng and Gao, 1999]. An alternative type of stimulation is based on code sequences instead of constant periods and was presented in [Bin et al., 2011; Bin et al., 2009; Sutter, 1992]. In contrast to the c-VEP system in [Bin et al., 2011], we want to investigate, if the (i) frequency-coded (SSVEP or f-VEP) or the (ii) code-modulated approach (c-VEP) is more applicable for continuous control with on-screen stimulation to steer a robot in a telepresence application.

2. Material and Methods

The EEG was recorded with 256 Hz sampling frequency using a g.USBamp biosignal amplifier (g.tec medical engineering GmbH, Schiedlberg, Austria) from 8 active EEG electrodes placed on PO7, PO3, POz, PO4, PO8, O1, Oz and O2 position. The user sat in front of the computer screen including video feedback and overlaid BCI controls. The aim was to steer the robot through a given path, by using the video system and the BCI controls only. This video system was implemented by the Technische Universität München (TUM) and contains a software package to visualize the video stream coming from a camera.

The f-VEP BCI acquired data 0.5-60 Hz band-pass filtered and used a minimum energy (ME) method to determine a spatial filter that improves the signal-to-noise ratio (SNR). A Levinson AR model (order 7) estimated the SNR based on 2 s EEG data. The c-VEP BCI followed a template matching strategy that required a 3 minute training run to generate a reference signal or template. This template consisted of 200 averaged pseudo-random sequences visualized in the center of the screen. Data was 0.5-30 Hz band-pass filtered and then used within a canonical correlation analysis (CCA) to find a base that maximizes the correlation between the template and the target EEG. The resultant spatial filter was then used together with the templates for online classification. Both approaches used a linear discriminant analysis (LDA) for target identification, where the classification result was updated every 200 ms. A zero class provided an idle state that occurred when no target was selected by the user. This entails rejecting any classification result for which the residual error probability of the classification result was larger than 3 %, which was an empirical value.

Eleven subjects aged 27.36 ± 5.84 years participated, where each subject first performed a BCI training run to set up a subject specific weight vector. In the next run, the on-line accuracy of the BCI system was tested across 20 trials without moving the robot. One trial consisted of 3 s rest and 7 s of visual stimulation. Next, the subject had to steer the robot along a given track using the four BCI controls, presented as squares on the screen and enabled zero class. The entire track was 170 cm long and contained four 90° turns - two left and two right. Additionally a tracking system recorded the taken path of the robot during movement. Subjects having more than 2 standard deviations error from the average path were excluded, to provide valid results for movement duration comparison.

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3. Results

The online accuracy test run showed that the maximum achievable accuracy without the zero class is 98.18% for the c-VEP BCI and 91.36% for the f-VEP BCI. For trial duration above 4 seconds, the mean accuracy is 94.51% for the c-VEP BCI and 84.18% for the f-VEP BCI, as shown in Fig. 1. If the zero class is enabled, the accuracy reduces about 20-30%, as the false positive selections decrease and the false negatives increase. Without zero class, the random accurcy of 25% was reached around 0 s. From -3 to 0 s the buffer from the previos trial got emptied.

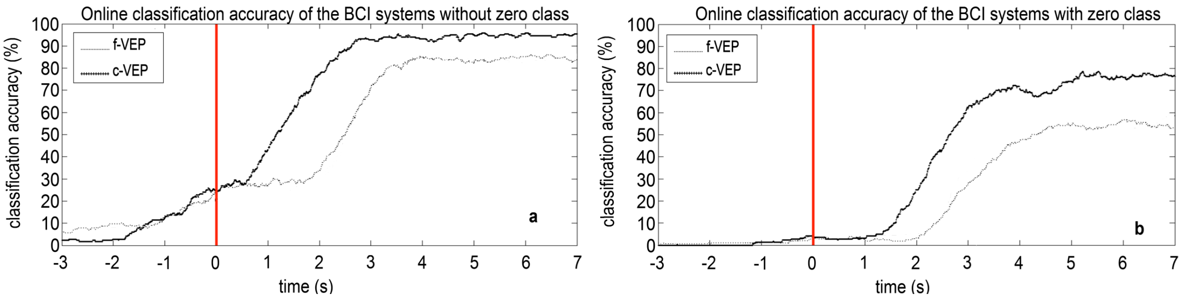

Figure 1. *Online accuracy test run. The vertical bar indicates the start of flickering within one trial. The f-VEP accuracy rises later, as it requires larger moving window filters.*

Table 1 shows the individual task completion time of the subjects to steer the robot through the track. The average duration was 240.45 s for the c-VEP BCI and 477.30 s for the f-VEP BCI.

Table 1. *Time to finish the route for every input method and each indiviual subject.Grey highlighted subjects had to be excluded, as they showed high deviations from the given track (corrected mean and std. are shown in paranthesis).*

Subject	*S1*	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*	*S9*	*S10*	*S11*	***Mean***	***Std.***
f-VEP (s)	170	187	426	252	312	183	-	1158	679	1256	150	**477.3 (573.4)**	**416.8 (466.0)**
c-VEP (s)	149	163	194	272	233	209	507	298	145	298	177	**240.4 (222.5)**	**104.6 (69.4)**

4. Discussion

We successfully validated two ways of a BCI based on VEP and showed that they could be used to continuously control a remote robot with high control accuracies. The c-VEP BCI showed higher performance and seemed to reflect a shorter latency, as the system takes less time to settle classification performance. The zero class allowed stopping the robot and suppressing randomized movement, including the side effect of increased latency. Also, the 2 s EEG buffer sizes affect latency and accuracy of the system. Therefore, the update rate of 200 ms does not guarantee a short reaction time. Aim of further research is to reduce latency of the system, while keeping high accuracy.

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Task Identification Using Fluctuation Analysis

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Abstract. Task identification processes for motor control routines were performed using a fractal index. EEG data from 40 healthy subjects were analyzed. The main finding is the identification of significant changes in such index from electrodes near to the motor cortex, which support the utilization of this index as input for a BCI paradigm.

Keywords: DFA, EEG, Task Identification

1. Introduction

Fractal indexes as derived from EEG or ECoG signals have been used in different neurological studies such as sleep stage identification, anesthesia monitoring, etc. Recently the utilization of such indexes as input for a BCI has also gained interest [Reza and Moradi, 2004]. Yet, changes detected by fractal indexes have not been found consistent or in agreement with physiological phenomena. Fractal indexes can be estimated via different methods such as Higuchi, box counting, DFA (Detrended Fluctuation Analysis), among others [Eke et al., 2002]. In this work DFA was used to identify the realization of tasks that involve motor control [Pfurtscheller and Silva, 1999].

2. Material and Methods

Forty healthy subjects were recruited to perform an attentional task, which consisted in pushing a button when a visual stimulus was detected. Recordings of 20 channels EEG for each subject were performed in two conditions: *passive*, stimulus presentations without subject response; and *active*, stimulus presentation with response

Epochs of 2 seconds synchronized with the stimulus presentation were selected, and for each epoch of each channel, a fractal index (α) was estimated using DFA [Peng et al., 1994]. For each subject two sets of indexes per channel were conformed, α_p and α_a corresponding to *passive* and *active* periods respectively.

2.1. Statistical Test

Mann-Whitney tests for each channel of each subject were performed to probe median changes between the two sets of motor activity indexes described before. Population results were averaged to find the top five channels which presented major differences between both activities. The corresponding α values of these channels were used as inputs for task identification using a Support Vector Machine with Gaussian kernel (SVM) [Burgess, 1998].

2.2. Task Identification

Task Identification was evaluated using a 20-fold cross-validation routine, assessing accuracy and area under ROC curve (AUC) for each subject. Cross-validation process consisted in taking 70 % of the total number of epochs for each subject (randomly) to construct a classifier and to test it over the remaining 30 %. Accuracy and AUC values were estimated and averaged for each subject. The summary of these results are shown in the next section.

3. Results

3.1. Statistical Tests

The scalp distribution on figure 1 (a) shows in terms of population ratio which channels have a significant statistical differences at $p < 0.05$ for $H_o : \alpha_p = \alpha_a$, whereas figure 1 (b) shows the ratio with $p < 0.025$ for $H_o : \alpha_p > \alpha_a$.

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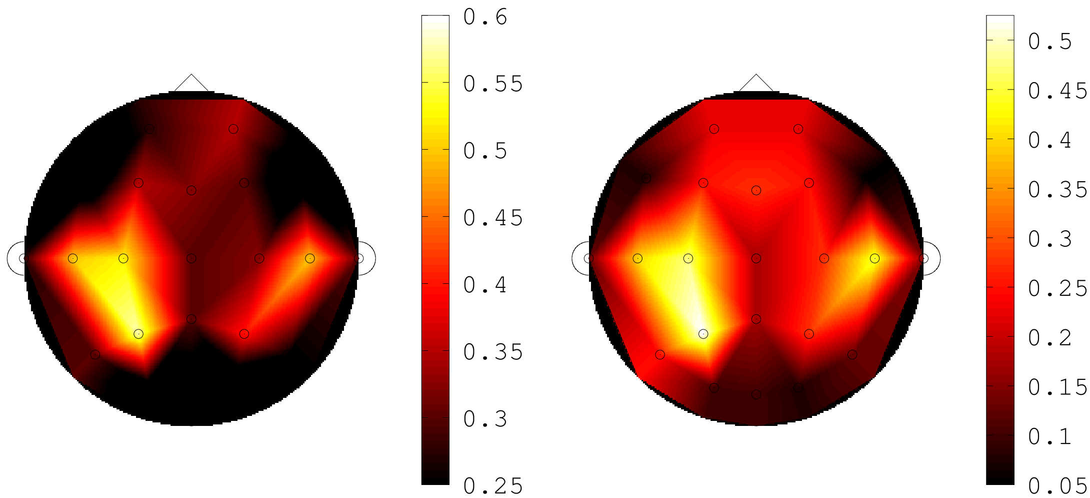

(a) $\alpha_p = \alpha_a$

(b) $\alpha_p \leq \alpha_a$

Figure 1: *Scalp distribution of population ratio at* $p < 0.05$ *for* (a) $H_o : \alpha_p = \alpha_a$ *and* $p < 0.025$ *for* (b) $H_o : \alpha_p \leq \alpha_a$

3.2. Task Identification

Table 1 shows mean values of accuracy and AUC from the top 5 channels selected as suggested by the statistical analysis. Note that these values of AUC are above the chance line (i.e. 0.5).

Table 1: *Mean Values for Task Identification analysis*

index	value
AUC	0.72474 ± 0.19103
Accuracy	0.65441 ± 0.15586

4. Discussion

The main finding of this study is the identification of significant changes in the fractal index α as derived from EEG data collected from those electrodes near to motor cortex (in both hemispheres). In addition, the task identification, accuracy and AUC values suggest that this index could be used as input for a BCI application. The mean time for estimating the α index over a series of 256 sample is 5.1 (1.1) ms using a non-optimized algorithm (Intel Core 2). Given that α values were apparently larger for *passive* periods, these findings seem in accordance with the consideration that neurons become desynchronized during realization of motor control routines [Pfurtscheller and Silva, 1999].

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High Performance Prediction of 3D-Trajectory of Hand From ECoG With Recursive N-way Partial Least Squares for BCI Application

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Abstract. In the present article a tensor-input/tensor-output blockwise Recursive N-way Partial Least Squares algorithm for recursive tensor factorization and multi-linear regression is applied for prediction 3D-trajectory of hand from the ElectroCorticoGram (ECoG) for Brain Computer Interface (BCI) applications. The method combines the Multi-way (tensors) decomposition with a consecutive calculation scheme and allows blockwise treatment of tensor data arrays of huge dimensions as well as the adaptive modeling of time dependent processes with tensor-input and tensor-output variables. Applied to BCI, the algorithm provides an efficient adjustment of the decoding model. This algorithm will be used in CLINATEC® BCI platform which is designed to allow a tetraplegic subject to pilot an exoskeleton thanks to ECoG recording by means of a wireless fully implantable device: WIMAGINE®.

Keywords: Adaptive Control, BCI, Multi-Way Analysis, Partial Least Squares, Recursive Calculation, Tensor Factorization

1. Introduction and Method

Neuronal signal decoding represents a challenging task. For the real-life applications, the need for an easy use Brain Computer Interface (BCI) system is one of the crucial problems. The Recursive N-way Partial Least Squares (Recursive NPLS, RNPLS) algorithm [Eliseyev et al., 2011] was proposed for adaptive, fast and easy BCI system calibration in the case of tensor-input and vector-output data.

In this article, the generalized tensor-input/tensor-output RNPLS algorithm was applied to predict 3D-trajectory of the monkey's right hand from its ECoG recordings. The Recursive NPLS method is derived from the N-way Partial Least Squares [Bro, 1996] and Recursive Partial Least Squares [Qin, 1998] approaches. It unites both the multi-way data representation of the first one with the recursive calculation scheme of the second one. In the recursive method, the information of decomposition of observation tensors ($\underline{\mathbf{X}}$ and $\underline{\mathbf{Y}}$) is captured by their loading tensors, as well as by the coefficient matrix. They are iteratively updated according to the new data. The size of the loading tensors and the matrix of coefficients are defined by the dimensionality of the variables and do not depend on the number of observations. As a result, the algorithm always keeps the size of the processing data.

2. Data

Data used in the experiments was taken from the publicly available database (http://neurotycho.org/data/20100802s1epidural-ecogfood-trackingbkentaroshimoda). It contains the ECoG signals of Japanese macaque recorded simultaneously with continuous 3D trajectories of its hands. The ECoG signals were recorded from the 64 electrodes implanted in the epidural space of the left hemisphere of the monkey. The hand motion was recorded by means of an optical motion capture system. This system registered positions in 3D of the markers attached to shoulders, elbows, and wrists of the monkey. Precise description of the experiment and the dataset can be found in [Shimoda et al., 2012]. For the tests, one recording (about 17 minutes, sampling rate 1000 Hz) was chosen randomly from the database.

To train the algorithm, 5000 time epochs were randomly selected among recorded time moments. As a result the training set includes 0.5% of the entire recording. The test set contains 3000 random epochs of the same file out of training.

To form a feature tensor $\underline{\mathbf{X}}$, each ECoG epoch was mapped to temporal-frequency-spatial space by continuous wavelet transform. The frequency band consisted from 3 sub-bands, namely, [0.6, 7.8] Hz with step $\delta f = 0.2$ Hz,

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[8, 48] Hz with step $\delta f = 2$ Hz, and [50, 300] Hz with step $\delta f = 10$ Hz. Sliding windows $[t - \Delta\tau, t]$, $\Delta\tau = 1$ s with step $\delta\tau = 0.005$ s were considered for all electrodes $c = 1, 2, ..., 64$. The resulting dimension of a point is (84x201x64) $\approx 10^6$, whereas the training tensor $\underline{\mathbf{X}}^{training} \in \Re^{5000\times 84\times 201\times 64}$. The response tensor $\underline{\mathbf{Y}}^{training} \in \Re^{5000\times 3\times 3}$ (5000 epochs with 3 coordinates for 3 markers on the monkey hand). Thus, the dimensional of the training dataset $\left\{\underline{\mathbf{X}}^{training}, \underline{\mathbf{Y}}^{training}\right\}$ justifies the choice of the RNPLS algorithm for the model identification.

Any preprocessing technics (chewing artifacts extraction, common average reference, etc.) was not applied. To identify the decoding model with RNPLS, the training set was split into 5 subsets of 1000 points.

3. Results

To validate the generalization ability, the identified RNPLS model was applied to the test data set $\left\{\underline{\mathbf{X}}^{test}, \underline{\mathbf{Y}}^{test}\right\}$, $\underline{\mathbf{X}}^{test} \in \Re^{3000\times 84\times 201\times 64}$, $\underline{\mathbf{Y}}^{test} \in \Re^{3000\times 3\times 3}$. Predicted motion of the right hand was correlated with its real position. The resulted correlations between the observed and predicted coordinates are: Shoulder: (R_X^2, R_Y^2, R_Z^2)=(0.62, 0.80, 0.85); Elbow: (R_X^2 , R_Y^2 , R_Z^2)=(0.54, 0.84, 0.83); Wrist: (R_X^2 , R_Y^2 , R_Z^2)=(0.63, 0.85, 0.82). On average (R_X^2, R_Y^2, R_Z^2)=(0.60 ± 0.05, 0.83 ± 0.03, 0.83 ± 0.02).

4. Discussion

The RNPLS algorithm performs multimodal data analysis, i.e. it can be applied to the multi-way data and preserves the structure of the data, improves robustness of the results as well as allows identifying relative impact of each dimension.

The algorithm is an efficient approach for BCI system calibration. It allows easy adjustment of the BCI system to the changing in neural signals as well as preserves the structure of the data that simplifies results interpretation. Moreover its prediction accuracy is comparable or outperforms the results previously reported for the given database (wrist coordinates correlations: 0.47 ± 0.12, 0.56 ± 0.10, 0.68 ± 0.06 with Unfold-PLS [Shimoda et al., 2012]; 0.52 ± 0.13, 0.67 ± 0.04, 0.74 ± 0.04 with Higher-Order Partial Least Squares [Zhao et al., 2012]; 0.50 ± 0.13, 0.67 ± 0.04, 0.73 ± 0.04 with NPLS [Zhao et al., 2012]; 0.50 ± 0.12, 0.67 ± 0.04, 0.74 ± 0.03 with Unfold-PLS [Zhao et al., 2012]).

This algorithm will be used in CLINATEC® BCI project which includes the realization of a fully implantable device, WIMAGINE®, to measure and transmit ECoG data wireless to a terminal, and means for a tetraplegic subject to pilot effectors with a large number of degrees of freedom, such as an exoskeleton, after training.

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Decoding Grip Types from Premotor, Parietal, and Motor Cortex

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Abstract. Despite recent advances in developing neural interfaces for controlling prosthetic arms and grippers, the ability to decode and execute different grasping patterns remains a major challenge. Here we present a simple Bayesian decoder for classifying a wide range of different grip types. Simultaneously recorded multi and single unit activity from AIP, F5, and M1 was used to decode grip types performed on 50 different objects with an accuracy of 54% and 67% (2% chance level) during motor planning and execution, respectively. The results demonstrate the possibility of accurately decoding grip types well before movement execution.

Keywords: hand, grasping, decoding, grip type, parietal cortex, premotor cortex, motor cortex

1. Introduction

The complexity of the human hand, which can be controlled in more than 20 degrees of freedom, makes the decoding of hand and finger movements challenging [Hochberg et al., 2012; Collinger et al., 2013]. The use of neuronal activity from higher cortical areas that represent motor programs rather than individual finger movements might help reducing this dimensionality. Here we employed spiking activity from macaque anterior intraparietal cortex (AIP), ventral premotor cortex (F5), and the hand area of primary motor cortex (M1) to decode grip types performed on a wide range of objects.

2. Material and Methods

2.1 Experimental task and hand-tracking

A monkey was trained to grasp 50 different objects in a delayed grasping task. The animal first placed its hand at rest and fixated a red LED before a randomly selected object was presented (cue epoch). The animal then had to withhold movement execution until, after a short delay (planning), the fixation LED dimmed (start of execution). To find the grip types performed on the objects, the monkey was trained to wear a data glove based on electromagnetic sensors [Schaffelhofer and Scherberger, 2012] providing 27 degrees of freedom of the animal's hand and arm. The joint angles collected while holding the objects were used to classify the 15 most different grip types by applying hierarchical clustering based on the Euclidean distances between the joint angle vectors of individual trials.

2.2 Decoding

Simultaneously to the monkey's hand kinematics, we recorded neuronal activity from 6 floating microelectrode arrays (FMA; MicroProbes, Gaithersburg, MD, USA) chronically implanted in AIP, F5, and M1 (192 channels). We used spiking activity from the planning epoch as well as during motor execution to decode both the grip types performed on the objects as well as the 50 objects being grasped, using leave-one-out crossvalidation. The mean firing rates of all single and multiunits were measured and defined as the input parameters to a naive Bayesian decoder that has been shown to perform well for this kind of data [Subasi et al., 2010; Townsend et al., 2011].

3. Results

We predicted the grip types performed on the 50 objects from 10 different recording sessions. During the planning epoch, movement intentions could be decoded with an accuracy of 54% ± 4% (mean ± sd) using spiking activity from F5, AIP, and M1 together (chance level 2%). The highest decoding accuracy was achieved during motor execution (67% ± 5%, mean ± sd). An example recording session is illustrated in Fig. 1. Performing a neuron drop analysis for individual areas revealed that AIP and F5 (*t*-test, $p < 0.01$) achieved the highest decoding accuracy in the cue epoch (AIP: 47% ± 3; F5: 49% ± 4%; mean ± sd). During motor planning, F5 showed the exclusively best performance (46% ± 5%), whereas in M1 decoding was most accurate during motor execution (59 ± 8%).

Furthermore, hand kinematics recorded with the electro-magnetic tracking glove was used classify the 15 most different grips performed on the objects. These 15 grip types could then be decoded with an accuracy of 74% in the planning epoch and 87% in the execution epoch (see Fig. 2).

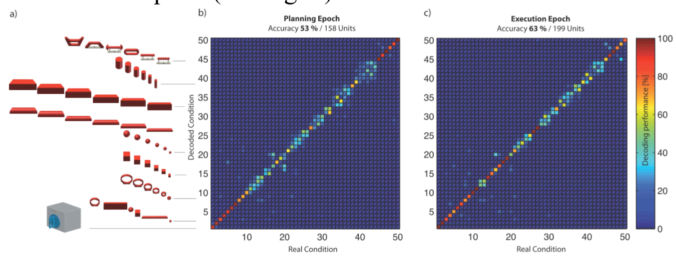

Figure 1. *Object decoding performance. (a) Set of 50 different objects being grasped. (b-c) Confusion matrices showing the grasp decoding accuracy using the combined spiking activity from AIP, F5 and M1 during movement planning and execution.*

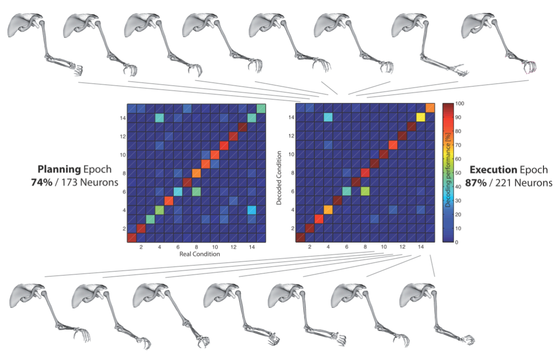

Figure 2. *Grip type-decoding performance. Using simultaneously recorded neurons from AIP, F5 and M1 allowed to accurately predict grip types during motor planning and execution.*

4. Discussion

These results clearly demonstrate the possibility of accurately decoding a wide range of different grip types from higher cortical areas related to hand grasping, like AIP and F5, well before movement execution, in addition to using the movement execution epoch for which primary motor cortex is particularly well suited. Furthermore, maximum likelihood classifiers, using signals from higher cortical areas, can be employed to predict discrete grip types instead of a large set of individual joint angles that would otherwise be necessary to describe the hand shape [Velliste et al., 2008; Vargas-Irvine et al., 2010]. Such a strategy can effectively reduce the dimensionality of the decoding problem in order to predict grip types rather than individual degrees of freedom of the hand.

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Classifying Speed and Force From Movement Intentions Using Entropy and a Support Vector Machine

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Abstract. In this work, we classified movement-related cortical potentials (MRCPs) associated with two levels of task force and speed with a linear and an optimized support vector machine (SVM). Features were extracted using Approximate Entropy (ApEn), Sample Entropy (SaEn) and Permutation Entropy (PeEn) calculated from the initial negative phase of the MRCP. Classification accuracies for the optimized SVM reached 68 ± 7% and 71 ± 10% (force and speed, respectively); with the linear SVM they reached 59 ± 8% and 64 ± 13%.

Keywords: Movement-related cortical potentials, movement intention, neuromodulation, task variability, entropy, support vector machine

1. Introduction

Brain-computer interfaces (BCIs) have been used as means for paralyzed patients to communicate or control an external device using brain signals. The combination of BCIs with sensory stimulation, such as electrical stimulation, could be used for neuromodulation in a rehabilitation setting for stroke patients. For this purpose, a protocol was proposed by Mrachacz-Kersting et al. [2012], where plasticity was induced when pairing the peak of maximum negativity of the MRCP from motor imagination with peripheral electrical stimulation. The protocol was implemented as an asynchronous BCI system by Niazi et al. [2012], where the movement intention (initial negative phase of the MRCP) was detected online with limited latency and triggered an electrical stimulator. To improve this intervention, afferent feedback from the electrical stimulation should match the movement intention and in this way close the motor control loop. In this scenario, it would also be possible to introduce task variability, which is important when relearning a motor skill [Krakauer, 2006]. To replicate various types of movements, it is necessary to decode the information about speed and force from the brain signals. Speed and force is encoded in the MRCPs [Nascimento et al., 2006] and different levels have been classified from single-trial EEG using optimized wavelets as features [Farina et al., 2007]. To improve the classification accuracies, the non-linear dynamic methods ApEn [Pincus, 1991], SaEn [Richman and Moorman, 2000] and PeEn [Bandt and Pompe, 2002] could potentially be applied as features. Entropy has previously been used as features in other BCI applications (e.g. [Wang et al., 2012]). In this work the possibility of using ApEn, SaEn and PeEn to discriminate between two levels of force and speed from the movement intention was explored.

2. Material and Methods

Six healthy subjects (two women and four men: 30 ± 6 years old) performed three types of cued isometric dorsi-flexions of the right ankle, which was fixed to a pedal with a force transducer. The maximum voluntary contraction (MVC) was determined at the start of each session followed by 50 repetitions of each cued movement type. The tasks were I) 0.5 s to reach 20% MVC, II) 0.5 s to reach 60% MVC and III) 3 s to reach 60% MVC. These were performed in three blocks. To assist the subjects in performing the movements with the correct speed and force, they were cued by a custom made program. Force was used as input to the system so the subjects were continuously provided with visual feedback on how well they matched their movements to the desired force profile. Ten channels of continuous monopolar EEG (sampled at 500 Hz) were recorded from FP1, F3, F4, Fz, C3, C4, Cz, P3, P4 and Pz, with the reference electrode on the right earlobe and ground electrode at nasion. The recordings were divided into epochs so data from the movement onset (determined from the force), and 3 s prior, was kept for further analysis. Epochs containing eye activity (125 µV in FP1) were rejected from further analysis (≈ 6 per task). The data was bandpass (0.05-10 Hz) and spatially (Large Laplacian) filtered. For discriminating between force (task I vs. task II) and speed (task II vs. task III) the ApEn, SaEn and PeEn were calculated for each epoch and used as features. The false-nearest neighbors' algorithm was used for determining the optimal embedding dimension (m = 2). The tolerance was 0.2x standard deviation and the time lag was 1. Each combination of features was classified using an SVM with a linear or with a non-linear decision boundary. A Gaussian kernel with an optimized kernel width and regularization parameter was used. The two optimization processes allowed maximization of the classification accuracy when applied to the training set. The optimized parameters were applied to the test set for evaluation of the classification accuracy. Classification accuracies [%] were obtained using 3-fold cross-validation.

3. Results

The results are presented in Table 1. The best performance for the linear SVM was obtained using SaEn as a feature when discriminating between the two levels of force (59 ± 8%) and ApEn for discriminating between the two levels of speed (64 ± 13%). For the optimized SVM the best performance was obtained when combining ApEn with PeEn for discriminating between the two levels of force (68 ± 7%) and ApEn with SaEn when discriminating between the two levels of speed (71 ± 10%). The highest classification accuracies were obtained with the optimized SVM.

Table 1. *Classification accuracies (mean ± standard deviation across all subjects) for each task pair using a linear and an optimized SVM for each set of features (left column). Fast 20 (% MVC) = Task I, Fast 60 = Task II and Slow 60 = Task III.*

Features	*Fast 20 vs. Fast 60 Linear SVM [%]*	*Fast 20 vs. Fast 60 Non-linear SVM [%]*	*Fast 60 vs. Slow 60 Linear SVM [%]*	*Fast 60 vs. Slow 60 Non-linear SVM [%]*
ApEn	59 ± 12	66 ± 8	64 ± 13	69 ± 11
PeEn	54 ± 9	64 ± 7	54 ± 11	65 ± 6
SaEn	59 ± 8	66 ± 9	59 ± 15	69 ± 11
ApEn+PeEn	57 ± 11	68 ± 7	62 ± 13	71 ± 11
ApEn+SaEn	55 ± 10	67 ± 9	61 ± 15	71 ± 10
PeEn+SaEn	56 ± 12	68 ± 8	59 ± 16	70 ± 11
ApEn+PeEn+SaEn	58 ±11	68 ± 8	62 ± 13	71 ± 11

4. Discussion

The classification accuracies that were found when using the different types of entropy indicate that entropy can be used for discriminating between the two levels of force and speed. However, the classification accuracies that were obtained are in general lower compared to preliminary results using four temporal features (76 ± 9% and 82 ± 10% for force and speed, respectively) and what has been found previously using optimized wavelets [Farina et al., 2007]. Therefore, it should be investigated further if the features, extracted from the non-linear dynamics methods could complement the four temporal features and optimized wavelets to improve the classification accuracies further.

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3D Trajectory Reconstruction of Upper Limb Based on EEG

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Abstract. The main goal of this paper is to simultaneously decode movement velocity of both hand and elbow from electroencephalography (EEG) signals. The result can support motor rehabilitation using a robotic arm and assist people with disabilities to control an upper limb neuroprosthesis in natural movement. In recent works, researchers have estimated hand movement velocity from EEG signals. However, such studies are insufficient to apply motor rehabilitation, since they only considered hand movement trajectory. Sometimes patients take wrong elbow movement in motor rehabilitation even though their hand movements are correct. In this study, we explore to decode not only hand but also elbow velocity from EEG signals when subjects move upper limb.
Keywords: BCI, Arm Movement Trajectory, EEG, Upper Limb Rehabilitation, Elbow Movement Trajectory

1. Introduction

Recent research shows the possibility of decoding hand movement trajectory using low frequency (< 1 Hz) components of the EEG signals [Bradberry et al., 2010]. In addition, multiple studies have also shown that these components also convey information about movement onset, directions and velocity [Lew et al., 2012].

When patients are trained with end effector-based robot-assisted rehabilitation system, they often lack supervision to verify that movements are performed in the correct manner. To this end, it is useful to assess the kinematics of the different joints of the arm. In turn, monitoring of the neural correlates of these joints –and eventual discrepancies with the observed behavior- can be useful to better understand and assist motor neurorehabilitation. In this work we apply previously reported methods to decode the kinematics of both hand and elbow. Although this preliminary study was performed with able-bodied subjects, we hypothesize that this approach may be useful for evaluating and supporting motor neurorehabilitation.

2. Material and Methods

2.1. Experiments

Three healthy right-handed male subjects participated in the experiment. Subjects sat comfortably in front of a panel containing four target buttons (up, down, left and right) on the vertical plane, and a home position button on the horizontal plane. They were instructed to perform the center-out task from home button to reach the targets buttons. The experiment was composed of 5 runs of 20 trials each. A resting period of 3 s was interleaved between trials. Subjects began each trial with their right hand on the home button. After 2 s, an auditory cue informed the subject which target to reach. Targets were equally and randomly selected among the four directions. Following another 2 s, a beep sound informed the subject to reach the target button. After some time, other cue requests the subject to move the hand back to the home button. The protocol is detailed in [Lew et al., 2012].

The EEG was acquired using 64 channels arranged in the 10/20 system electrodes at a sampling rate of 4096 Hz (ActiveTwo, BioSemi). Hand and elbow 3D position were recorded using a motion tracking device (accuTrack 500, Atracsys) at a sampling rate of 4111 Hz. Both recording streams were synchronized via hardware triggers.

2.2. Data Processing

The continuous EEG data were down-sampled to 128 Hz and common average referencing (CAR) was used to remove the global background activity based on all the recorded channels. A zero-phase, fourth-order, low-pass Butterworth filter with a cutoff frequency of 1 Hz was then applied to the EEG data. The continuous EEG data was segmented into trials and the average value of the baseline period - defined as the 500 ms time window prior to the auditory cue - of each trial was subtracted from the EEG of that trial.

To decode the movement velocity of the upper limb, we used a linear model method [Bradberry et al., 2010],

$$x[t] - x[t-1] = a_x + \sum_{n=1}^{N} \sum_{k=0}^{L} b_{nkx} S_n[t-k] \tag{1}$$

$$y[t]-y[t-1]=a_y+\sum_{n=1}^{N}\sum_{k=0}^{L} b_{nky}S_n[t-k] \tag{2}$$

$$z[t]-z[t-1]=a_z+\sum_{n=1}^{N}\sum_{k=0}^{L} b_{nkz}S_n[t-k] \tag{3}$$

where $x[t]-x[t-1]$, $y[t]-y[t-1]$, and $z[t]-z[t-1]$ represent the velocities of movement at time t in the x, y and z axis. L(=10) is the number of time lags and $S_n[t-k]$ represents the voltage difference measured at EEG sensor n at time lag k, and the a and b variables are weights obtained through multiple linear regression. N is the number of electrodes used in analysis. For decoding we use 21 electrodes covering the motor areas: FC5, FC3, FC1, FCz, FC2, FC4, FC6, C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4 and CP6, according to the International System 10/20.

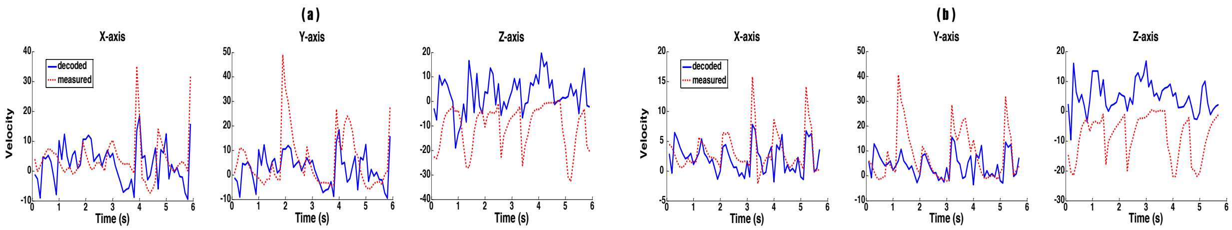

Figure 1. *Decoder example : The comparison between the measured velocity (dotted line) and decoded velocity (solid line) from subject 3 in the time domain. (a) Velocity of hand movement. (b) Velocity of elbow movement.*

3. Results

We reconstructed three-dimensional hand and elbow movements from EEG signals using the linear model as shown in Fig. 1. We quantified the decoding accuracy using the mean of the correlation coefficient *r* between measured and reconstructed hand and elbow velocity across 10 cross-validation folds. Mean correlations value for hand velocities are 0.31, 0.27 and 0.15 for x, y and z coordinates respectively. Corresponding correlation values for elbow velocity are 0.31, 0.3 and 0.16. We obtained similar decoding accuracy for both hand and elbow movement velocity, with lower correlation values for the z coordinate (all $p < 0.02$).

4. Discussion

This paper shows that it is possible to decode both hand and elbow movement trajectory from low frequency EEG signals. In [Bradberry et al., 2010] r-values for x/y/z-axes were 0.19, 0.38 and 0.32, which are similar to decoding accuracy comparing this study result. But decoding accuracy of each axis is different. The worst decoding accuracy is x-axis in [Bradberry et al., 2010] and is z-axis in this study.

In the future, we will study the decoding of kinematic parameters when subjects perform both motor execution and imagination of the upper limb. Also, we will implement the online decoding of the movements and perform experiments with subjects with motor disabilities to compare with the results obtained in able-bodied subjects.

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Muscular Activity Estimation From EEGs Using Principal Component Analysis for Brain Machine Interface

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Abstract. In this paper, aiming to estimate the force/torque information from the brain activity to help and support the human's daily life, we estimate the human's muscular activity from EEGs by PCA (Principal Component Analysis). The concept of the proposed approach using PCA is explained, and then the proposed approach is verified by experiments. The results show that the estimation of EMG from EEG is possible and this implies a great potential to use EEGs for supporting human's activities.

Keywords: EEG, EMG, Muscular Activity Estimation, PCA, BMI

1. Introduction

Recently, a lot of BMIs (Brain-Machine Interfaces) are being developed to control external devices and robots. For example, an "EEG keyboard" is developed to input characters by gazing at the character shown on a display [Yamada, 1996]; electrical powered wheelchairs are controlled moving forward, turning left or right by motor imagery [Millán et al., 2004; Vanacker et al., 2007]. Such BMIs select the desired modes from the several predetermined patterns of the motion intention. On the other hand, in many situations to support human's daily life, the force/torque information in the motion is necessary as well as the motion intention. Recently, a study on muscle activity reconstruction is reported [Yoshimura et al., 2011] by estimating the signal source, in which, the signal source at the brain cortex from EEG is estimated and its spatial resolution is compensated with fMRI.

To further explore the potential applications of BMI, we consider whether it is possible to estimate the muscle activity directly from the EEG in motion. In this paper we propose an approach to achieve this purpose when a subject flexes his arm while holding a load. The experimental results show that the estimation of EMG from EEG is possible and this implies great potential to use EEG for supporting human's activities.

2. Material and Methods

2.1. Relationship between EEG and EMG

There are a lot of literatures on the relationship between EEG and EMG. The coherence in beta wave band between EEG and EMG during isometric motion is reported in [Halliday et al., 1998]. The fact that gradual potential fluctuations occur in EEG immediately before a human motion is revealed in [Kornhuber and Deecke, 1965]. From these, we believe that human motion, or saying, muscular activity, can be estimated from brain activity by exploring the relationship between EEG and EMG.

2.2. Acquisition and processing of EEG and EMG signals

In measurements, the subject (a healthy young man) is sitting in a chair and his 4 CH EEG signals over the sensorimotor area (C_4-A_2, F_4-A_2,C_3-A_1, F_3-A_1) and his 1 CH EMG signal of biceps brachii of his left arm are measured and recorded at the same time. In the measurement process, the subject closes his eyes in order to prevent noise caused by blink. Firstly, the subject holds a 3 kg dumbbell vertically downward. Then, the subject flexes his left arm (elbow joint) at arbitrary time moment to horizontal position in a few second while holding the dumbbell. The same measurement is performed 26 times.

The electrodes embedded in a head cap are positioned according to International 10–20 method. C_z is right at the top of his scalp and used as ground, and the right wrist is used as body earth. The sampling frequency is 1kHz. The EEG signals are amplified 200,000 times by an amplifier (UBIO-II, Unique Medical Co.Ltd., Tokyo, Japan) and a built-in filter with 1–100 Hz bandwidth. While the EMG signals are amplified 10,000 times by another amplifier (DELSYS

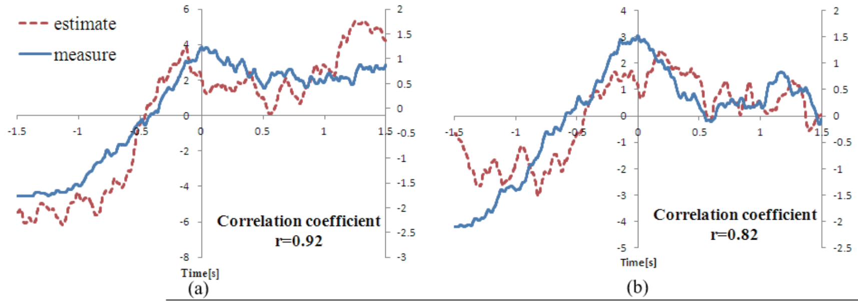

Figure 1: *EMG estimation results from EEGs.*

Inc., Boston, MA, USA), and a built-in filter with 20–450 Hz bandwidth. These signals are acquired through 12-bit A/D converters in a multi-functional interface board, and further processed with our proposed approach in computer. The measured signals are processed with moving average to remove the power supply noise of 50 Hz. Then the EMG is taken its absolute value. All of EEGs and EMG are further passed to a low-pass filter of 1 Hz to get smoothed signals. In this study, the maximum value of EMG is used as onset and the data of all EEGs and EMG signals between 1.5 s before and after the onset are extracted to be used as signal data. Further, these signal data are normalized and used as input data for estimation.

2.3. Proposed approach using PCA

Our proposed approach to estimate EMG from EEG is divided into two steps, Step 1 and Step 2. In Step 1, the eigenvectors l_i and principal components z are calculated with the above measured EEG and EMG signals by principal component analysis (PCA). Then these obtained principal components and eigenvectors are averaged as $\bar{x}$ and $\bar{l}$, and further used in Step 2. In Step 2, EMG is estimated from EEGs by the following equation,

$$\hat{y} = \frac{\bar{z} - (l_1x_1 + l_2x_2 + \cdots + l_Mx_M)}{l_{EMG}} \tag{1}$$

where, x_i $(i = 1,2,\ldots,M)$ (here $M = 4$) are the measured EEGs, $\hat{y}$ is the estimated EMG, $\bar{z}$ is the average of principal component, and $\bar{l}_i$ is the average of eigenvector. In this study, $\bar{z}$ and $\bar{l}_i$ are considered as constants.

3. Results

Here, 10 sets of the measured and preprocessed EEGs and EMG signals are used to calculate the eigenvectors and principal components. Then the remained 16 sets of EEG signals are used for EMG estimation. The estimated EMGs are compared with the actually measured EMGs and the results are evaluated with correlation coefficient. Two results are shown in Fig. 1, in which, the solid curve represents the actually measured EMG and the dashed curve is the estimated EMG. The center vertical axis is the estimated value and the right vertical axis is the measured value. Fig. 1(a) shows the best result, in which the correlation coefficient is 0.92, while Fig. 1(b) shows the median result, in which the correlation coefficient is 0.82. This means that direct EMG estimation from EEGs is possible, and this implies a great potential to use EEG for supporting human's activities.

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Individual Selection of Mental Tasks and Frequency Bands Boosts Performance in a 4-Class Brain-Computer Interface

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Abstract. This study aimed at optimizing a 4-class brain-computer interface (BCI) individually in order to achieve high on-line performances for all users within few sessions. Eight able-bodied individuals participated in 10 sessions over 5 weeks. In the first screening session, users performed seven different mental tasks (i.e. mental rotation, word association, auditory imagery, mental subtraction, spatial navigation, motor imagery of the left hand and motor imagery of both feet) while multi-channel EEG was recorded. Out of these seven mental tasks, the best 4-class combination as well as the most discriminative frequency range was selected for each user independently and used for online control. All users achieved mean online accuracies between 58-93% in single-sessions in the present 4-class BCI. This protocol is highly individual adjustable and thus can increase the percentage of users who gain and maintain BCI control. A high priority for future work is to examine this BCI protocol with severely disabled users.

Keywords: BCI, 4-class BCI, EEG, Mental tasks, Event-related (de)synchronization (ERD/S), Individual adjustments, Disabled users

1. Introduction

One way to control a brain-computer interface (BCI) involves recording the changes in the rhythmic activity of the brain's electrophysiological signals through electroencephalography (EEG). Motor imagery is mostly used as control strategy. Additionally, the use of non-motor tasks can lead to good BCI performance e.g. [Curran et al., 2003; Millán et al., 2004]. However, studies including able-bodied as well as disabled individuals revealed huge individual differences in best task combinations for all mental tasks [Friedrich et al., 2011; Friedrich et al., 2012]. Therefore, the present cue-guided experimental protocol was designed to make an individual selection of control strategies and frequency range possible. These individual optimizations should increase performance within few sessions.

2. Material and Methods

This study included 8 able-bodied participants (3 male, aged between 20-36 years, right-handed) who were initially naïve to the use of a BCI. Each volunteer participated in one screening session (i.e. session 1; 42 trials per task) and then in 9 feedback sessions (i.e. sessions 2-10; 60 trials per task and session) over a period of 4-6 weeks.

Participants performed the following seven mental tasks in the screening while multi-channel EEG was recorded: Mental rotation (ROT), word association (WORD), auditory imagery (AUD), mental subtraction (SUB), spatial navigation (NAV), motor imagery of the left hand (HAND) and motor imagery of both feet (FEET). Out of these seven mental tasks, the 4-class combination and frequency range with the highest offline accuracy was selected for online control. The data was classified by means of common spatial patterns (CSP) and Fisher's linear discriminant analysis (LDA) and optimized individually concerning the number and time of classifier adaptation. Continuous online feedback and discrete feedback was provided to the users.

3. Results

The results showed that the selected task combinations and frequency bands differed between the users (Table 1). However, for every user one motor imagery task (hand or feet or both) and one brain-teaser task (word association or mental subtraction but never both) was selected. The mental rotation task was also included in the majority of task combinations. The results showed that the most promising combination of tasks in a 4-class BCI were (1) one motor imagery task, (2) one brain-teaser task, (3) a mental rotation task, and (4) one more dynamic imagery task (auditory imagery, spatial navigation or another motor imagery task). As can be seen in Table 1, the lower border of the frequency range was in the alpha band between 8-10 Hz in the screening and between 8-11 Hz in the updates for all users. The upper border was not as narrow and varied in the beta range between 13 to 30 Hz between users. The mean online performance showed a linear increase over sessions in 6 users and a stable performance in 2 users. From session 5 on, all users performed better than chance in every session ($p \geq 0.25 \pm 0.055$). All users managed to control all 4-classes above chance and achieved mean accuracies between 58-93% in single-sessions (Table 1). User C achieved accuracies > 80% in all single classes with a mean performance of 93%.

Table 1. *Selected tasks, frequency range and online performance per user. The first columns indicate which task combination was selected for BCI control. For the selected task combination, the frequency range between 8-30 Hz with the highest offline accuracy was used for the calculation of the classifier (Screening). After some feedback sessions, the frequency band optimization and the classifier were recalculated (Update1). For 3 users, the update was made another time (Update2). The peak performance is indicated in the last columns with the highest online accuracy and in which session it was achieved.*

User	Task combinations							Frequency range [Hz]			Online Performance	
	ROT	WORD	AUD	SUB	NAV	HAND	FEET	Screening	Update1	Update2	Accuracy	Session
A	x	x				x	x	8-30	11-26	-	80 %	10
B	x		x	x		x		9-17	8-15	-	58 %	10
C	x	x				x	x	8-19	10-25	-	93 %	7
D		x	x		x	x		9-26	9-14	9-15	73 %	9
E	x		x	x		x		9-15	8-16	-	66 %	10
F	x	x			x		x	8-30	8-13	-	64 %	6
G			x	x	x	x		8-20	11-23	10-25	75 %	9
H	x			x	x	x		10-30	9-20	11-30	85 %	6

4. Discussion

BCI performance was substantially improved by individual optimization of task combinations, frequency range and classifier adaptation in comparison to previous 4-class online studies with different mental tasks [Friedrich et al., in press]. Comparing our results to motor imagery-based BCIs, performance was comparably high e.g. [Wolpaw and McFarland, 2004]. In the present BCI protocol, all users performed above chance. Thus, the probability that everyone could gain and maintain BCI control was increased by the selection of user appropriate control strategies and adjustments. The results confirmed that the best BCI control strategies are highly individual, e.g. [Millán et al., 2004]. However, a pre-selection of reliable and robust control strategies from which the users can select is important, as a screening with many mental tasks is time consuming and exhausting for participants. A high priority for future work is to examine this BCI protocol with severely disabled users. Not only motor impaired users but also individuals with neurodevelopmental disorders, such as autism spectrum disorder, may benefit substantially from a BCI that can be adjusted individually. To that end, we have begun exploring the use of EEG-based BCI as well as other physiological signals (e.g. EMG, ECG) to train children on the autism spectrum to improve their social skills.

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EEG Independent Component Polarity Normalization by Convex Relaxation of a Two-Way Partitioning Problem

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Abstract. Independent Component Analysis (ICA) is a popular method for finding independent brain and artifact sources in EEG data. But there exists an inherent indeterminacy in the polarity of the scalp-map and activation associated with each Independent Component (IC) which can interfere with interpretation and use of the learned ICs from multiple subjects. In particular, these polarities are often required to be assigned in a coherent manner before IC activations can be used in multi-subject inference or in training Brain Computer Interface (BCI) algorithms that use data from more than one subject or recording session. Here we propose an IC polarity normalization method based on the convex relaxation of a two-way partitioning problem and evaulate its performance on a sample RSVP Target detection EEG dataset.

Keywords: EEG, BCI, ICA, Independent Component Analysis, Scalpmap, BCI, Polarity Normalization

1. Introduction

Independent Component Analysis (ICA) is a popular method for finding independent brain and artifact sources in EEG data [Bell and Sejnowski, 1995; Delorme and Makeig, 2003; Jung et al., 2001; Makeig et al., 1996]. Because ICA is a blind source separation problem there are two inherent indeterminacies, one is the order of ICs (irrelevant in EEG analysis) and the other is the scaling of activations and scalpmaps [Comon, 1994]. The latter is because the only observable quantity for each source is the potential recorded at scalp electrodes and it remains the same if both scalp-map and activation are multiplied by a non-zero scaling factor.

Normalization of scalp-maps so they all have an L-2 norm of one (in the appropriate physical units, e.g. microvolts) partially fixes this problem but the ambiguity in scalp-map polarities still remains. To perform multi-subject analyses and online classifier learning, it is desirable to normalize the IC scalp-map polarities before calculating averages over IC activities associated with experiment events (otherwise, incompatible polarities may results in signal cancellation). Polarity normalization could be achieved by making ICs with similar scalp-maps to have similar polarities (which corresponds to the inner product of their scalp-map vectors to being positive, when signals are real). We show how this can be achieved using convex relaxation of a two-way partitioning problem.

2. Material and Methods

We want to find a vector of scalp-map polarities $x \in R^n, x_i \in \{-1, 1\}$ which minimizes the negative sum of normalized scalp-map inner products , $W_{i,j} = \frac{-s_i s_j^T}{\|s_i\|\|s_j\|}$ with S_i as the ith column of scalp projection matrix S. The inner products comprise the components of a matrix W. The scalar quantity $x^T W x$, subject to the constraint that the components of x are either +1 or -1, provides an aggregate measure of the total dissimilarity across scalp-maps which is the quantity that we desire to minimize with respect to the x-component signs. This is because $x^T W x = \sum_{i,j=1..n} x_i x_j W_{i,j}$ gives the sum of scalp-map inner products after changing their polarities according to the signs of the components of the x vector. We can formulate this as the following optimization problem [Boyd and Vandenberghe, 2004]:

$$\text{minimize } f_0 = x^T Wx, \text{ subject to } \quad x_i \in \{-1, 1\} \tag{1}$$

Note that this problem is not convex since the domain of $x_i \in \{-1, 1\}$ is not convex, re-writing this equation in the equivalent form

$$\text{minimize } \mathrm{tr}(WX), \text{ subject to } X \geq 0, \ \mathrm{rank}(X) = 1, \ X_{ii} = 1, \ i = 1, \dots, n \tag{2}$$

with variable $X \in S^n, X = xx^t$ (since $\mathrm{tr}(WX) = \sum_{i,j=1..n} X_{i,j} W_{i,j}$ and $X_{ij} = x_i x_j$). We now drop the $\mathrm{rank}(X) = 1$ constraint to obtain the convex optimization problem. Since this new problem is less constrained, its optimal value will provide a lower bound on the optimal value of the original problem (3). After solving problem (4), we are able to obtain the vector of polarities x from $X = x^t x$ using the real Schur decomposition $X = UTU^T$where U is a unitary matrix ($U^{-1} = U^T$) and T is an upper triangular (in this symmetric case, diagonal) matrix. If X is low rank (recall that we have relaxed the problem by allowing it to have a rank more than one), we can ignore all elements of this matrix, except the highest value on the diagonal, located at $T_{n,n}$.

3. Results

We used 266 scalp-maps from ICA decompositions of 15 sessions associated with 7 subjects during a Rapid Serial Visual Presentation experiment [Bigdely-Shamlo et al., 2008]. Fig. 1 (left) shows a number of these scalp-maps with solid rectangles enclosing sample IC pairs with a similar pattern but reversed polarities. Our goal is to minimize such occurrences by changing the polarity of some of these scalp-maps. Fig. 1 (right) shows scalp maps of the ICs from Fig. 1 (left) with normalized polarities using the covex relaxation method described above. The polarities of all the pairs displayed here are corrected after applying the normalization method.

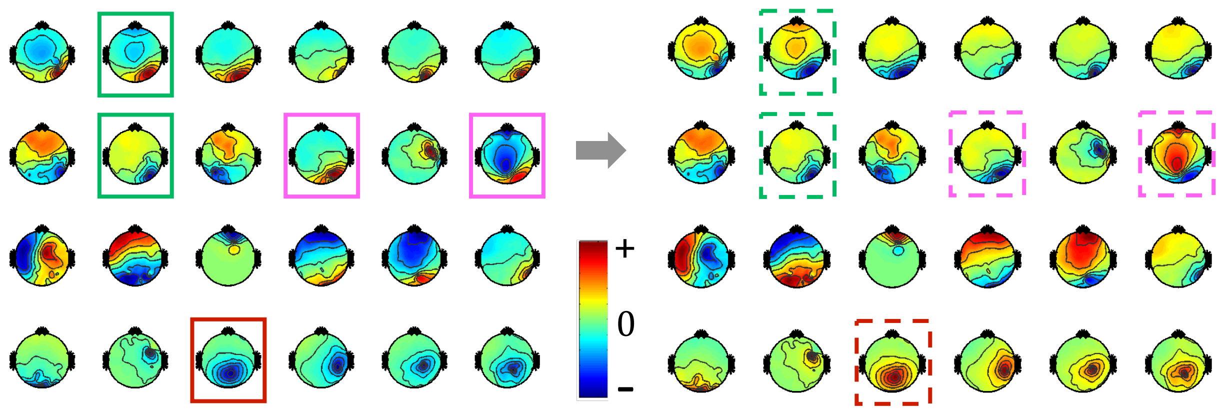

Figure 1. *(left) Sample scalp-maps before polarity normalization. IC pairs for which one IC is a candidates for polarity reversal are surrounded by colored rectangles (right) same scalp-maps after polarity normalization using convex relaxation method. Dashed rectangles indicate IC pairs highlighted on the left as candidate for polarity change. The polarities of all the pairs displayed here are corrected after applying convex polarity normalization.*

4. Discussion

We showed how scalp map polarities may be normalized using a convex relaxation of the two-way partitioning problem. This method could improve applications of ICA-based multi-subject BCI and EEG analysis using temporal features by normalizing the polarity of these features across components from different subjects and sessions.

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Tensor Decomposition on EEG of Music Imagination

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Abstract. A new application of tensor decomposition is presented, here used to find shared variance between the EEG of different cognitive tasks. By analysing four datasets, each focusing on perception and imagination of musical sounds with differing levels of complexity, the overlap between tasks can be assessed for different stimuli. All data sets show fronto-central and more central components as the largest sources of variance, fitting with projections reported for the areas contributing to the N1/P2 complex. They are shown to be decomposable into parts that load primarily on to the perception or imagery task, or both, thereby adding more detail than 2-dimensional decomposition. The relevance to brain-computer interfacing more generally is in feature detection methods for potential cross-task classification, here demonstrated for imagination of music.

Keywords: EEG, tensor decomposition, music imagery, stimulus complexity

1. Introduction

Imagination is of specific interest to the field of Brain-Computer Interfaces (BCIs), where covert mental tasks need to be decoded from the brain signal to be used to drive a device. Recent results indicate that the electrical brain activations of imagining music show considerable overlap with those of perception [Schaefer et al., 2009; Schaefer et al., 2011]. The overlap between tasks is relevant for BCIs as it may allow for cross-task classification, as already demonstrated by [Vlek et al., 2011], by training a classifier on the relatively low-effort task of listening when aiming to classify imagined rhythmic patterns, thereby reducing potential fatigue from just the training phase.

The current work focuses on shared activation between music perception and imagination, and the impact of stimulus complexity on this overlap. This will provide an indication of the useful features for potential cross-task classification, and inform stimulus choices when using imagined music as a task for BCI. To this end, new analyses are presented of four datasets that each contains perception and imagination of musical material, namely rhythmic accents, monophonic melodies, more complex rhythms and ecologically natural music stimuli. We apply tensor decomposition (parallel factor analysis or PARAFAC, see e.g. [Rasmus, 1997]) on the EEG responses to see the extent of shared activation for perception and imagination, and investigate the timing signatures of common networks.

2. Material and Methods

The details of each experiment are shown in Table 1. Considering the differences between the datasets, the preprocessing steps were tailored, and described elsewhere in full detail, see [Vlek et al., 2011; Schaefer et al., 2009; Desain and Honing, 2003; Schaefer et al., 2011] for accents, melodies, rhythms and natural music, respectively. The basic pre-processing procedure was to 1) remove linear trends, 2) remove 'bad' channels, identified as those with more than 3-SD more power than the average channel power, 3) re-reference to the common-average, 4) spectrally filter with a pass-band of 1-25 Hz. After this pre-processing for each dataset, the ERPs were computed by averaging the individual stimulus responses over all subjects and stimulus repetitions. These ERPs were then used as input to the PARAFAC decomposition, using a cross-validation procedure to define the number of components. Further specifics of the method can be found in [Schaefer et al., 2013].

3. Results

The results are not identical, but some commonalities are seen between the datasets. Three of four experiments (accents, melodies and natural music) show perceptual frontal and parietal components (A2, A4, M1, M4, NM1 and NM2), which are also present but shared in the fourth experiment (R1 and R3). Two experiments show a frontal and parietal shared component (A1, A3, R1 and R3), which might be combined in the natural music experiment (NM4). All experiments except the accenting show a purely imagery-based frontal component (M4, R2 and NM3, explaining 11.5, 14.5 and 5.3% of the variance respectively.) With the exceptions of the first component for every experiment, the peak activity of the components is in the beginning of each stimulus.

Table 1. *Summary of the experiments, where 'P stimulus' is the perceived stimulus, 'I stimulus' is what was played during imagery. Other rows show details on the stimuli, the participants, trialnumbers and EEG channels used in data collection.*

Experiment	*1: Accents*	*2: Melodies*	*3: Rhythms*	*4: Natural Music*
P Stimulus	Accented metronome	Melodies	Rhythm patterns	Music
I Stimulus	Metronome	Notes rendered without pitch	Single prompt	Onset prompt
No. of stimuli	3 metric patterns	4 isochronous melodies	5 simple rhythms	2 full music fragments
Stim. length (ms)	1000 to 2000	375	3360 to 5352	3000
Trials, participants	96, 5	36, 11	150, 1 (5 sessions)	160, 10
EEG channels	64	28	21	256

4. Discussion

The PARAFAC components show central and fronto-centrally distributed activation to explain most of the variance, consistent with reports of the projections of the (composite) auditory N1/P2 response. The data suggest that there is an aspect of brain activation related to imagery that is independent of stimulus complexity, but that the aspects of imagery that are shared with perception do vary with characteristics of the stimulus, although this appears to decrease with stimulus complexity, indicating that cross-task classification of music imagination may become less feasible with increased stimulus complexity. Further discussion on the cognitive interpretations of these components, as well as a comparison with Principal Component Analysis (PCA) can be found in Schaefer et al. (2013). Although not yet widely used on EEG data (with notable exceptions in the frequency domain), we here demonstrate the potential and usefulness of PARAFAC decomposition for cross-task feature identification.

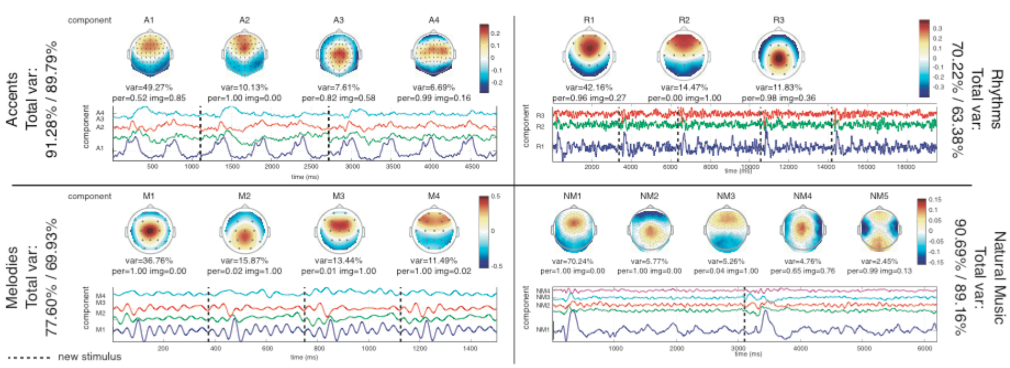

Figure 1. *The distributions of the tensor components are shown for each dataset, the average explained variance per dataset and the proportion of the explained variance for each task. The dotted lines denote different stimuli.*

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Performance Enhancement by Sparse Representation of EEG Signals for Motor Imagery Based BCI systems

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Abstract. We evaluate a sparse representation based classification (SRC) scheme which was proposed in our previous work [Younghak et al., 2012] as a high performance classification method for motor imagery (MI) based BCI systems. For the comparison of classification accuracy, we use two widely used classification methods, linear discriminant analysis (LDA) and support vector machine (SVM). We analyze eight different data sets acquired from our motor imagery based BCI experiment. We use a CSP filtering for feature extraction. From the results, the SRC method shows improved classification accuracy than the other two classification methods.

Keywords: EEG, BCI, Motor Imagery, SRC, CSP, LDA, SVM

1. Introduction

In BCI systems, classification algorithm is needed to transform extracted features of a user's intention into computer commands to control the external device. In the EEG based BCIs, widely used classification methods are linear discriminant analysis (LDA) and support vector machine (SVM) [Lotte et al., 2007]. In our previous study, the sparse representation based classification (SRC) method has been introduced and applied with high classification accuracy to the EEG based BCI application [Younghak et al., 2012]. In the SRC method, dictionary design is very important. To make the uncorrelated dictionary for different classes, the CSP filtering has been used [Younghak et al., 2012]. In this study, we aim to compare the BCI classification accuracy of the SRC method with that of LDA and SVM, which are most widely, used classification methods in the BCI field. We use the same feature extraction setup using the CSP filters for the three classification methods. To evaluate classification accuracy, we collect data sets from eight different subjects. Each subject data set obtained from our own motor imagery (MI) based BCI experiments.

2. Material and Methods

2.1. Experimental data

In this study, we use eight data sets. These data sets acquired from four healthy male and four female subjects (average age = 24.63 and SD = 4.37). These data sets contain EEG signals generated from the left and the right hand motor imagery experiments. There are 5 runs. One run consists of 20 trials for each class. The number of total trials is 100 for each instruction (class). One trial consisted of 4-6 s resting time period (blank screen) and 3 sec instruction time period. The resting time period is randomly selected between 4 and 6 s. Instructions are represented at the center of the monitor screen. These experimental data sets were recorded by active electrodes in a cap. We use Active Two EEG measurement system made by Biosemi, Inc. The sampling rate of these data sets is 512 samples per second and the number of EEG channels is 64. The channel positions are selected from international 10/20 standard.

2.2. Methods

After collecting EEG data sets, we use a band pass filtering with 8-15 Hz frequencies to extract the frequencies which are related to motor imagery signals. For a feature extraction, we use a band power of 8-15 Hz signals after applying a spatial filtering. We use a common spatial pattern (CSP) as a spatial filtering, which is a widely used method for motor imagery based BCI applications [Blankertz et al., 2008]. To compare classification accuracy of the SRC method, we use two most widely used classification methods in the BCI field, namely, linear discriminant analysis (LDA) and support vector machine (SVM). To evaluate the classification accuracy for each subject, we use the leave-one-out (LOO) cross-validation which is useful for increasing the number of independent classification tests with a given limited data trials.

3. Results

We have analyzed eight data sets. Table 1 shows the classification results. We compare the classification accuracies of LDA, SVM and the SRC method. For each subject, we compute average accuracy for different numbers of CSP filters (The CSP filters varied from 1 to 64). From the result, the SRC method shows the best classification accuracy for seven data sets. For subject A, SVM shows the best accuracy. However, the accuracy difference is very small e.g., 0.41%. In addition, the SRC has the best mean classification accuracy and the smallest standard deviation for eight datasets. To confirm our results statistically, we use a paired *t*-test. We performed the *t*-test using paired SVM (or LDA) and SRC classification results for all subjects. The obtained *p*-values of the *t*-test represented in the last row of Table 1. All the *p*-values are less than 0.01. This means that the difference between the SRC method and the SVM (or LDA) is statistically significant.

Table 1. *Classification accuracies of LDA, SVM and SRC for eight data sets*

Subject	*Average accuracy (%)*		
	LDA	*SVM*	*SRC*
A	91.25	**93.47**	93.06
B	76.78	79.17	**84.39**
C	94.09	95.34	**95.81**
D	80.95	82.58	**85.40**
E	82.36	86.72	**89.84**
F	89.73	90.38	**92.92**
G	91.36	93.97	**96.03**
H	80.55	81.17	**85.42**
Mean (Std.)	85.88 (6.43)	87.85 (6.33)	**90.36 (4.79)**
p-value	0.0007	0.0063	

4. Conclusions

In this study, we compare the classification accuracies of the SRC and widely used LDA and SVM methods. Specifically, SVM has been well known for robust classification performance in many BCI researches. To evaluate the classification accuracy, we use our motor imagery based BCI experimental data sets acquired from eight different subjects. We use a CSP filtering to extract feature vectors for the three classification methods. We compare the classification accuracies of SRC, LDA and SVM methods. From the results, the SRC method is shown to provide the best classification accuracy regardless of the number of CSP filters.

Acknowledgements

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Performance Prediction in Motor Imagery BCI

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Abstract. We propose a strategy for predicting user's performance in motor imagery BCI. It is composed of four band powers (theta, alpha, beta, gamma) of resting state; it comes from the recent investigation of neurophysiologcal characteristics that alpha and beta powers are positively correlated, and theta and gamma are negatively correlated with BCI performance in motor imagery. Our proposed predictor yielded the correlation value of r = 0.59 for 61 motor imagery subject datasets, and the correlation reached to r = 0.7 when 7 outliers (determined by Whisker length of 1.5) were excluded. Our predictor is far simpler and comparabale (or slightly better) to Blankertz's.

Keywords: BCI, subject variability, session variability, performance predictor

1. Introduction

Motor imagery has been commonly used as a control paradigm in BCI research and development since ERD (event related desynchronization) is known to be a generally notable feature. However, a significant number of subjects experience some trouble in generating detectable ERD. In [Blankertz et al., 2010], it was reported that α and β bands of resting state are positively correlated with BCI performance, and a predictor was proposed using potential decrease of α power, which can be estimated through an iterative fitting algorithm. Recently, the influence of γ on sensory motor rhythm was revealed in [Grosse-Wentrup et al., 2011]. In addition, four band powers of resting state were investigated by [Ahn et al., 2012], reporting the existence of significant positive (α or β) and negative (γ) correlations with BCI performance. Further, they found that θ had negative correlation with BCI performance as high as α (up to r = 0.5). From their findings, we propose a performance predictor yielding potential performance (PP), as formulated in equation (1). It is composed of four band powers and corresponding coefficients. To see its practicability, and 61 motor imagery subject datasets acquired from two different EEG systems were used.

$$PP = \frac{c_1 \alpha + c_2 \beta}{c_3 \theta + c_4 \gamma}. \tag{1}$$

2. Material and Methods

2.1. Data 1: Offline data (52 subjects)

For each of 52 subjects, 100 motor imagery trials for each class (left/right) were acquired using Biosemi Active 2 (64 channels, sampling rate: 512 Hz). To estimate performance (off-line), each dataset was spectrally (8-30 Hz) and temporally filtered (0.4–2.4 s after cue onset) since this zone is most informative for motor imagery [Ahn et al., 2012], then 10-fold cross-validation using CSP (common spatial pattern) and FLDA (Fisher linear discriminant analysis) was applied. For the analysis of PP, resting state (open eyes) signal was recorded during 1 minute and bandpass filtered (1-100 Hz).

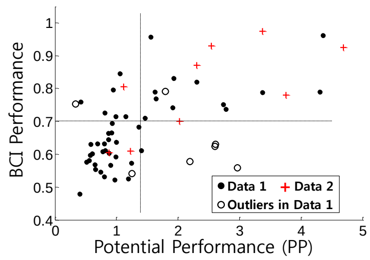
2.2. Data 2: Online data from BCI competition 2008 dataset 2b (9 subjects)

Second group of datasets was acquired from BCI Competition site, in which users conducted motor imagery (left/right hand) with feedback [Leeb et al., 2007]. The data was digitized at 250 Hz and bandpass (0.5-100 Hz) and notch (50 Hz) filters were applied. Only 3 channels (C3, Cz and C4) were available; we could not apply CSP and FLDA to get BCI performance. Actual performance was estimated from the competition winner's result, which was expressed in kappa value ($\kappa = (P_o - P_h)/(1 - P_h)$, P_o: expected performance, P_h: hypothetical probability of chance agreement). Assuming theoretical chance agreement in 2 class problem yields $P_h = 0.5$, the kappa value was converted into an estimate of expected performance P_o. This estimate was used as a BCI performance in this work.

Resting state (open eyes) signal (1 minute) before online session was bandpass filtered (1-100 Hz) for further investigation of PP.

2.3. Resting state and potential performance (PP) calculation

It was reported from [Ahn et al., 2012] that significant correlations with BCI performance occurred on mainly central area in the brain, and θ and α focused notably near C3 and C4 channels. Thus, two channels (C3 and C4) were selected for target channels in this work. From the resting state, the four band powers (θ: 4-8 Hz, α: 8-13 Hz, β: 13-30 Hz, γ: 30-70 Hz) were estimated for each of two channels. Each band power was averaged over these two target channels. For simplicity, all coefficients (C_i) in equation (1) were set to 1. In Fig. 1, PP and BCI performance were plotted for all 61 subjects and the detailed statistics were described.



	Data1	Data2	All
r	0.48	0.69	0.59
r^2	0.23	0.48	0.34
p	3.3372e-004 **	0.0396 *	6.5700e-007 **
After outliers are rejected			
r	0.64		0.70
r^2	0.41		0.50
p	2.1194e-006 **		2.8352e-009 **

* < 0.05, ** < 0.001

Figure 1. *Two dimensional plot of PP and BCI performance (left) and its correlation analysis result (right). Two cases of inclusion and exclusion of 7 outliners were statistically compared.*

3. Results

Data 1 yielded a correlation of r = 0.48 between PP and BCI performance. Data 2 (red + in Fig. 1) yielded higher value of r = 0.69. Combining Data 1 and Data 2, r = 0.59 (61 subjects) was observed. The correlation got increased up to r = 0.70 (54 subjects) when 7 outliers determined by the boxplot of the band power distribution with Whisker length of 1.5 were excluded. Our proposed potential performance predictor using two channels C3 and C4 only showed comparable (or slightly higher) result than that (r = 0.53) of Blankertz. One interesting thing from Fig. 1 is that the relationship between PP and performance may not be linear; its distribution is denser near 1 as PP.

4. Discussion

There may exist other factors affecting BCI performance variability. This means that neurophysiological factor could innate the limitation to estimate user's performance. Thus, the combination of our proposed potential performance (PP) with other existing factors or more channels will facilitate better prediction of BCI performance. In addition, it could be improved further if the coefficients in equation (1) are optimized in a proper manner. Our predictor is greatly advantageous in that it requires simply four kinds of band powers of resting state, which enables us to easily apply for predicting a user's potential performance in motor imagery BCI.

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On Classifying Artifactual Independent Components: Generalization Ability to Different Electrode Setups

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Abstract. BCI system development relies on data from healthy subjects, who unconsciously might utilize artifacts for BCI control. As these systems are typically developed for people with severe motor disabilities, a high sensitivity level of a BCI system for artifacts must be considered problematic. A robustness analysis of a state-of-the-art classification approach for the automatic rejection of artifactual independent components reveals, that this method robustly performs for a wide range of electrode setups, and that simple re-training ensures high rejection accuracy even for drastically reduced electrode numbers.

Keywords: Artifact Removal, EEG, Independent Component Analysis (ICA), Blind Source Separation (BSS), Machine Learning

1. Introduction

The analysis of EEG signals is often impeded by muscular or external artifacts, especially for EEG with small data set sizes. Consequently the reliability of single-trial analysis methods (as in BCI) and data visualizations for introspection may suffer. A common counter-measure is to decompose the original EEG into independent source components (ICs) and reconstruct it after dismissal of hand-selected artifactual ICs [Jung et al., 2000].

Avoiding this time-consuming process, recently proposed algorithms classify ICs into artifactual and non-artifactual components. Demonstrating good performance on similar validation data, the question arises how well these methods generalize to data acquired under novel experimental conditions. First studies suggest that generalization is possible (e.g. [Viola et al., 2009; Winkler et al., 2011]), but a detailed assessment of robustness is lacking. Here, we take a step forward by analyzing the generalization ability of an IC classification algorithm we recently proposed.

2. Material and Methods

2.1. Experimental setup, ICA unmixing and data split

The artifact classifier was set up using expert-labeled independent components gained from several conditions of a reaction time study [Winkler et al., 2011]. EEG data from 121 approx. equidistant sensors was available for eight healthy, right-handed male subjects. In total, 43 runs of 10 minutes duration were available, of which 28 from five subjects were used as training sets, and 15 runs from three subjects as test sets. After high-noise channels were rejected based on a variance criterion, they still had 104 electrodes in common. Prior to the IC computation via TDSEP [Ziehe et al., 2004], a 2 Hz high pass filter was applied, and a dimensionality reduction to 30 PCA components was performed in order to reduce artificial splits of sources. Two experts hand-labeled the 30 ICs per data set into artifactual and non-artifactual components, resulting in 840 training- and 450 test ICs.

2.2. The artifact classifier

The artifact classifier was a linear classifier based on six features that were selected in a feature selection procedure described in [Winkler et al., 2011]. The mean local skewness aims to detect outliers in the time series of an IC. Three features describe a $1/f$ fit of the IC to the spectrum and its log band power in the α band (8–13 Hz). Contrary to these first four features, the two remaining ones directly depend on the electrode setup, as they extract information about the scalp pattern of an IC: (1) Range Within Pattern characterizes the difference between the minimal and maximal activation in a pattern. (2) Current Density Norm is derived from the source localization of an IC, which is based on its pattern. We considered 2142 locations arranged in a 1 cm grid and computed the source distribution with minimal l_2-norm. This norm was used as a feature. The underlying idea is that noisy patterns and patterns originating outside the brain represent more complicated sources, which are characterized by larger l_2-norms.

2.3. Analyzing the classification performance for different electrode setups

Two different classification strategies were compared: One *fixed* IC-classifier was pre-trained on features of the full 104-channel data. Its performance was estimated on test data of setups varying from 16 to 104 channels (all approx. equidistant and covering the whole scalp). Alternatively, a *re-training* of the IC-classifier was performed for each montage, on features computed on training patterns cut to the specific montage. The performance of the re-trained classifiers again was tested on the full and the reduced setups.

3. Results

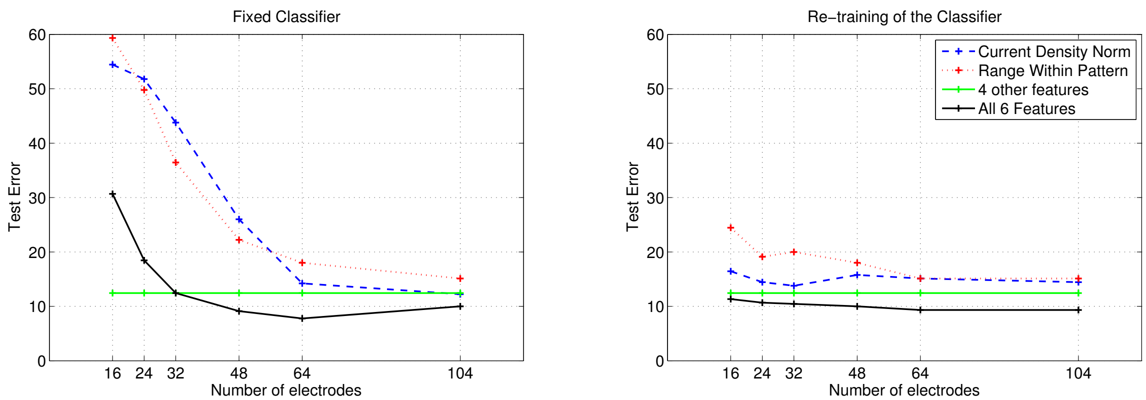

Figure 1: *Classification error estimated on the test sets for different channel setups for a fixed classifier (left plot) and a classifier re-trained for each channel setup (right plot). The chance level performance is at 50 %.*

For the 104 channel setup, a classifier using the full six features achieves a low error rate of 10.0 % only, which outperforms the use of only four pattern-independent features (12.4 %). The *fixed* classifier generalizes robustly over a large range of 104 to 48 electrodes in the test sets. The increased error of up to 30.6 % for the smallest set of 16 electrodes is associated with the bad performance of both single features which are based on the pattern (over 50 %).

For the re-training strategy, the error increase of the single *Range Within Pattern* feature was less pronounced (from 15.1 % to 24.4 %), and the *Current Density Norm* feature even remained relatively stable. Using the re-trained classifier, the overall error for 16 electrodes remained at 11.33 %, which is comparable to inter-expert disagreements. For this reduced setup, the classifier weight of the *Range in Pattern* dropped, while the weight for *Current Density Norm* remained stable.

4. Discussion

We have analyzed the generalization ability of an IC classification algorithm we recently proposed to different electrode setups. For this analysis, two human experts judged the components based on patterns showing 104 electrodes, while we restricted the electrodes that the classifier saw. We showed that classification was relatively robust to a decrease from 104 to 48 electrodes - roughly half the number of electrodes - from training to testing. However, performance dropped after more electrodes were removed. We demonstrated that recomputing the features and retraining the classifier based on the specific electrode montage of the test set alleviates the problem.

Acknowledgments

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Basis Selection for Increased Interclass Separability of EEG Signals

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Abstract. We present an adaptive feature selection method for the classification of EEG signals. The algorithm determines the most discriminative channels and regions of the time-frequency plane. Promising results are obtained when classifying signals associated with real and imaginary hand motion of a healthy subject.

Keywords: BCI, EEG, cosine packet transform, best basis, Kullback-Leibler divergence, classification

1. Introduction

In recent years Brain-Computer Interfaces (BCI) have proven their ability to translate human intentions and cognitive states – reflected by specific brain signals – into control signals for computer applications and neuroprosthetic devices. A review of the different steps that form a standard BCI can be found in [Nicolas-Alonso and Gomez-Gil, 2012]. In the feature selection step, the Modified Discrete Cosine Transform (MDCT, [Princen et al., 1987]) is an efficient and energy-compacting example of the many ways by which a signal can be linearly expanded. The corresponding basis may be visualized as a tiling of the time-frequency plane, delineating the regions in which most energy of the basis functions is concentrated. We propose to select a basis which maximizes the separability of two or more classes of EEG signals. The divergence between different basis coefficients may then be used to determine which spatial and time-frequency features are the most discriminative for the purpose of classification.

2. Material and Methods

Our data consists of 64-channel EEG recordings of a right handed, 26 years old male with no disabilities. The sampling rate is 512 Hz. Each trial started with the user fixating a cross on a screen for 1.5 s during which he was allowed to blink. The subject was then presented with a visual cue for 2 s. The cue was chosen randomly among a resting symbol, an arrow pointing right, and an arrow pointing left. If a directional arrow appeared, the user had to move or, depending on the session, imagine moving the corresponding ipsilateral hand. The subject had to remain motionless during the following 2 s (in case of real movement) or 4 s (in case of imagined movement). During the real movement session, the total number of trials was as follows: 88 for real left hand movement, 88 for real right hand movement, 44 for resting. During the imaginary movement session, the total number of trials was as follows: 250 for imaginary left hand movement, 250 for imaginary right hand movement, 125 for resting. Similarly acquired data of the same subject has been presented in [Fruitet et al., 2011].

As we are interested in the mu- and beta-rhythms that characterize motor activity, we start by bandpassing the EEG recordings in the 8–24 Hz range and focus on the 21 electrodes ranging from FC5 to FC6, from C5 to C6, and from CP5 to CP6. We then apply a Cosine Packet Transform (CPT) to the signals of each channel. The CPT performs a dyadic division of the time axis, computing a MDCT of each time block. The best basis algorithm by [Coifman and Wickerhauser, 1992] is employed on the resulting tree structured family of bases (each corresponding to specific tilings of the time-frequency plane) to find the normal basis which maximizes the symmetric Kullback-Leibler divergence (KL Div., [Kullback and Leibler, 1951]) between two or more classes of signals. We choose to average the computed divergence measures along all channels, so that the selected basis is the same for all channels. The basis coefficients of each signal are then ordered according to their discriminative power (again based upon the KL Div. measure). For classification purposes, a candidate EEG signal is classified as belonging to the class of signals to which the KL Div. between basis coefficients is, on average, the lowest. Our classification results are compared to the ones obtained by training a linear kernel support vector machine (SVM) with the power spectral densities (PSD) of the signals.

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3. Results

Table 1 provides an overview of the classification accuracy for different binary problems as determined by leave-one-out cross-validation. For the classification tasks involving real motion only 25 % of all coefficients were used (sorted according to their discriminative power), for the imaginary tasks 50 % of all coefficients were used. The performance of the two classification methods appears to be comparable. Fig. 1(a) shows how our algorithm may be used to discern the most discriminative channel and time-frequency locations between two classes of signals. Fig. 1(b) shows how, thanks to the sparsity of MDCTs, the classification result rapidly stabilizes when considering more and more coefficients. In this case the recall rates for real left hand motion, real right hand motion, and rest are 75 %, 72 %, and 82 %, respectively.

Table 1: *Recall rates of the two described classification methods applied to four different binary problems.*

Recall rate of	PSD+SVM	CPT+KL Div.
real hand motion (left or right) vs. rest	99 % / 73 %	93 % / 86 %
real left hand motion vs. real right hand motion	75 % / 76 %	80 % / 75 %
imaginary hand motion (left or right) vs. rest	92 % / 50 %	72 % / 75 %
imaginary left hand vs. imaginary right hand motion	70 % / 72 %	70 % / 56 %

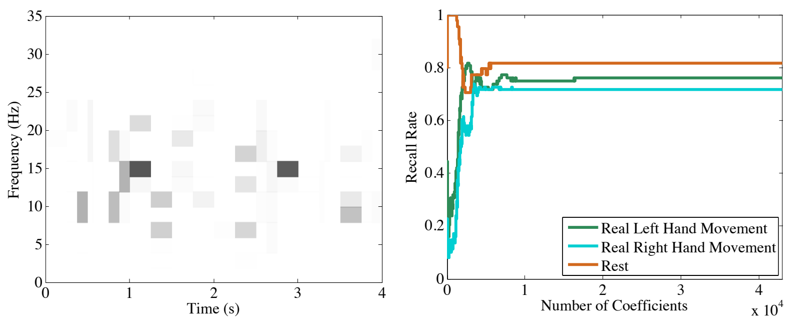

Figure 1: (a) *KL Div values for the FCZ channel when discriminating between real right hand movement and rest. For this classification task the FCZ channel was among the ones with the largest KL Div values. Time 0 corresponds to the onset of the visual cue, and high values in the mu- and beta-range may be observed in the following second.* (b) *Recall rates for a multiclass classification task versus the number of considered basis coefficients.*

4. Discussion

We employed the CPT together with a best basis selection algorithm to increase the interclass separability of EEG signals. Our preliminary results indicate that this approach leads to acceptable classification results. However, compared to other algorithms it allows one to detect and interpret the most discriminative channels and time-frequency locations. Let us briefly mention that classifying the best basis coefficients by means of SVM instead of by the least KL Div. led to only minor improvements in recall rates, which supports the use of the best basis algorithm to discriminate between signals.

Acknowledgments

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Increasing the Spectral Signal-To-Noise Ratio of Common Spatial Patterns

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Abstract. Common Spatial Patterns (CSP) is a popular method for extracting class-discriminative oscillatory neural signals in Brain-Computer Interface (BCI) studies. Here we suggest a mechanism to increase the spectral signal-to-noise ratio of CSP by way of regularizing the CSP objective. The approach is evaluated on a data set containing $N = 80$ subjects and a significant increase of classification performance is observed.

Keywords: EEG, SMR-BCI, CSP, SSD, Regularization, cwSSD

1. Introduction

Brain-Computer Interfaces (BCI) rely on the extraction of a class-discriminative and possibly low-dimensional representation of neural sources from high dimensional and noisy data. In the case of motor imagery (MI) driven BCI, a widely used method for obtaining such a representation is the Common Spatial Patterns Algorithm [Blankertz et al., 2008]. CSP optimizes spatial filters such that the contrast of spectral power (approximated by variance of the band-pass filtered signal) between two MI classes is maximized. Recently and in a non-BCI context, a novel spatial filtering method was suggested which decomposes oscillatory EEG/MEG data such that the extracted components have a maximized signal-to-noise ratio (SNR) in the frequency band of interest. This method is called Spatio-Spectral Decomposition (SSD) [Nikulin et al., 2011] and was shown to outperform independent component analysis (ICA) in the extraction of components with pronounced spectral peaks. In this contribution, we propose a fusion of CSP and SSD in order to obtain higher classification performance in a BCI setting by combining the positive aspects of both algorithms (between-class contrast and optimized SNR in the spectral domain). We refer to this methods as *class-wise Spatio-Spectral Decomposition* (cwSSD).

2. Material and Methods

The objective function of cwSSD encodes the core ideas of CSP and SSD and is given below:

$$f(\mathbf{w}) = \frac{\mathbf{w}^\top \mathbf{C}_i \mathbf{w}}{\mathbf{w}^\top (\alpha \mathbf{C}_{1+2} + (1-\alpha)\mathbf{C}_n)\,\mathbf{w}}, \tag{1}$$

where $\mathbf{C}_i$ denotes the covariance matrix of class $i \in \{1,2\}$, $\mathbf{C}_{1+2}$ denotes the covariance matrix of both classes together and $\mathbf{C}_n$ denotes the covariance matrix of noise. For $\mathbf{C}_i$ and $\mathbf{C}_{1+2}$ the data is band-pass filtered in the frequency band of interest (e.g. 8 to 12 Hz). However, $\mathbf{C}_n$ is obtained by taking the covariance of data that is filtered in bands that are neighboring to the band of interest (e.g. 6 to 8 and 12 to 14). $\mathbf{C}_{1+2}$ and $\mathbf{C}_n$ are normalized using the trace norm. The parameter α allows to interpolate between standard CSP ($\alpha = 1$) and SSD ($\alpha = 0$).

The performance of cwSSD is evaluated by re-analyzing a MI BCI data set consisting of N=80 subjects [Blankertz et al., 2010]. For each subject, calibration (75 trials per class) and online (150 trials per class) BCI data was collected. A subject-specific frequency band and time interval was used for both CSP and cwSSD, and 3 components per class were selected each. Linear discriminant analysis (LDA) was employed as a classifier, acting on log-var features of the spatially filtered data. CSP/cwSSD as well as subsequent LDA were trained on the calibration data and applied to the online data. A subject-specific α was obtained by cross-validation on the calibration data.

3. Results

Fig. 1 (**A**) shows the classification accuracy on the online data in a scatter plot. cwSSD achieves higher accuracy than CSP for 55 % of the subjects while the performance is worse for 29 % of the subjects. The mean accuracy

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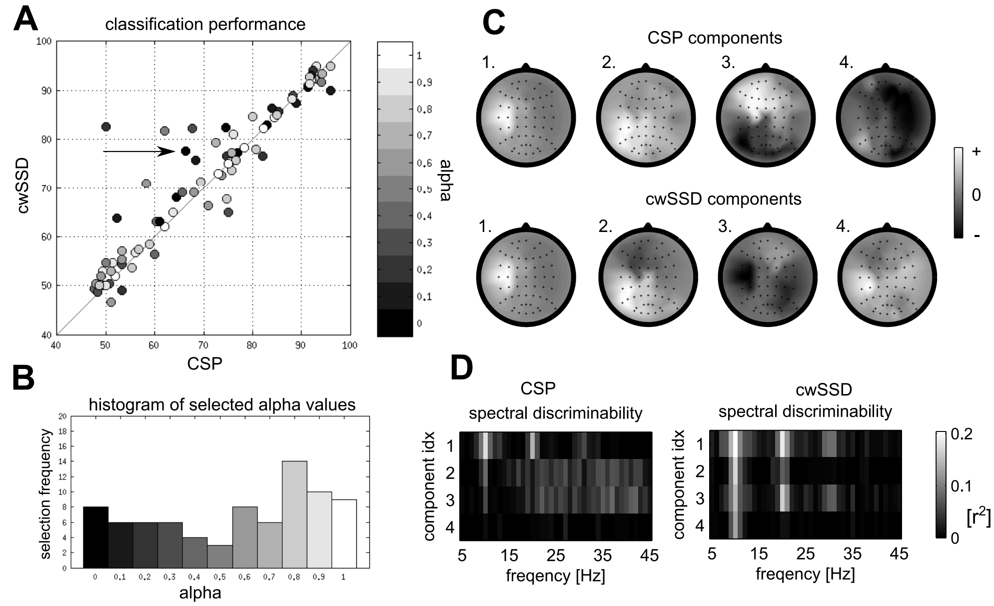

Figure 1: *Results of comparing CSP and cwSSD on data from N=80 subjects. (**A**) Scatter plot that shows the classification performance obtained on the online data for CSP (x-axes) and cwSSD (y-axes). Each point corresponds to a subject and the color of the point indicates the selected α value for cwSSD. (**B**) Histogram of selected α values. (**C**) CSP and cwSSD components of a representative subject (indicated by the arrow in **A**) with improved performance. (**D**) R-square values for 1 Hz frequency bins (5 Hz to 45 Hz), computed for the components displayed in (**C**).*

of cwSSD is 71.72 % ($\pm$15.08) while that of CSP is 70.07 % ($\pm$ 15.6), with the improvement being statistically significant ($p = 0.011$, paired-sample t-test). The histogram of chosen α values is depicted in part (**B**) of the figure. Spatial patterns of the 4 most class-discriminative components of a representative subject are shown in Fig. 1 (**C**). The spectral SNR of the CSP/cwSSD components is assessed by way of computing r-square values for 1 Hz frequency bins of the spatially filtered signal. For the subject depicted in Fig. 1 (**D**), one can observe pronounced peaks at 10 Hz, as well as at the harmonics (20 and 30 Hz).

4. Discussion

The presented method (cwSSD) can be regarded as a special case of the general framework for regularization of CSP, described in [Lotte and Guan, 2010]. Thus, the combination of the objective functions of CSP and SSD represents an effective regularization of the original objective of CSP. The highest gain in performance was achieved for subjects who had less than 80 % accuracy with CSP, rendering our approach a suitable alternative in BCI settings where users have difficulties in controlling the application. Ongoing research effort is focused on further exploitation of the increased spectral SNR, for example by using narrower frequency bands or by taking the increased harmonic spectral peaks into account as well.

Acknowledgments

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Bayesian Priors for Classifier Design in RSVP Keyboard

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Abstract. We design an adaptive classifier using Bayesian priors for RSVP Keyboard™, a brain-interfaced alternative augmentative communication system designed for people with locked-in syndrome. RSVP Keyboard™ employs regularized discriminant analysis classifier optimized by cross-validation using noninvasively acquired evoked response potentials from electroencephalography (EEG) in sequential symbol-by-symbol typing. Using EEG data recorded by RSVP Keyboard™, we perform offline analysis on the effect of online updates of the classifier on the system performance. Results indicate that instead of using a long calibration session, a shorter calibration session with online updates to the classifier would provide similar typing accuracy.
Keywords: EEG, ERP, Bayesian Inference, Classification, Conjugate Priors

1. Introduction

RSVP Keyboard™ is a brain-interfaced alternative and augmentative communication system in development [Orhan et al., 2012]. This typing system is based on rapid serial visual presentation (RSVP) of symbols and utilizes electroencephalography (EEG) signals for classification of event related potentials (ERP). EEG signals from the 500ms interval following stimulus onset are used in a regularized discriminant analysis (RDA) classifier [Friedman, 1989]. In the current closed-loop on-line RSVP Keyboard™ implementation, this classifier is calibrated using k-fold cross-validation with data collected immediately prior to testing and the parameters of this model remain fixed throughout use. However, it is conceivable that these parameters could continue to be updated during test as decisions are made and estimated labels become available. This would be especially useful if nonstationarity (due to environmental factors, as well as fatigue, attention, and vigilance levels of the operator) in test session changes signal statistics significantly enough to cause degradation in performance. To overcome this issue, in this study, we propose to use a classifier that can be adaptively and sequentially updated during a typing session.

2. Methods

From each of 4 healthy participants, we collected EEG data during 3 calibration sessions. Each calibration session consists of 100 sequences, each sequence having 1 target and 9 non-target symbols (2 classes). Data collection is done using 8 EEG channels with 256 Hz sampling frequency, which is then downsampled by a factor of 4 such that each channel contains 32 vector-valued samples. The first calibration session data (100 sequences) is used to train an RDA classifier. For the proposed classifier, we employ different number of sequences in calibration, whereas RDA calibration sequence count is 100. Using half of the data from second and third sessions, the proposed classifier is then updated to simulate system operation providing on-line EEG data (in two simulated test sessions). The performance of the proposed classifier update scheme and the RDA classifier obtained from 100 sequences is tested by using the second halves of session 2 and 3 data sets. Test data is kept separate from data used for batch calibration and on-line adaptation to prevent over-fitting and over-estimating the performance. We report the difference between the proposed and static-RDA classifiers' accuracies averaged over time and subjects as a function of number of sequences used for the initial calibration of the proposed method. The accuracy is defined as the ratio of correctly detected target ERP samples to the total number of sequences in (held-out) test data.

The proposed online update to the classifier is obtained by modeling temporal EEG features for each class with multivariate Gaussian distributions and then by employing the Expectation Maximization (EM) algorithm assuming conjugate priors for the class means and covariance matrices [Bishop, 2006]. Gaussian and Wishart probability density functions are assumed as the regularization priors for mean and covariance, respectively. The posterior expected values for these parameters are computed using the priors and the observed data according to following equations:

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$$\beta_k^n = \beta_k^{(n-1)} + N_k^n \qquad \mathbf{m}_k^n = \frac{1}{\beta_k^n}(\beta_k^{(n-1)}\mathbf{m}_k^{(n-1)} + N_k^n\overline{\mathbf{x}}_k^n)$$
$$(\mathbf{W}_k^n)^{-1} = (\mathbf{W}_k^{(n-1)})^{-1} + N_k^n\mathbf{S}_k^n + \frac{\beta_k^{(n-1)}N_k^n}{\beta_k^{(n-1)} + N_k^n}(\overline{\mathbf{x}}_k^n - \mathbf{m}_k^{(n-1)})(\overline{\mathbf{x}}_k^n - \mathbf{m}_k^{(n-1)})^T \tag{1}$$

In (1), k is the class label, n is the time index, β_k^n is the confidence (scaling) parameter, N_k^n represents the number of observed data points, $\mathbf{m}_k^n$ is the mean value of the prior distribution of class mean, $\overline{\mathbf{x}}_k^n$ is the mean value of the observed data, $\mathbf{W}_k^n$ represents expected value of the inverse covariance prior and $\mathbf{S}_k^n$ is the covariance of observed data. These expected values are used in QDA to calculate the scores (EEG features) for each symbol.

3. Results

Fig. 1 illustrates the average accuracy difference between the proposed and the RDA classifiers as a function of different initial calibration lengths for the proposed method. This preliminary result indicates that with on-line adaptation, the EEG classifier module of RSVP Keyboard™ could be on average as accurate as using data from 100 sequences by only requiring less than 50 sequences a 50% reduction in initial calibration time).

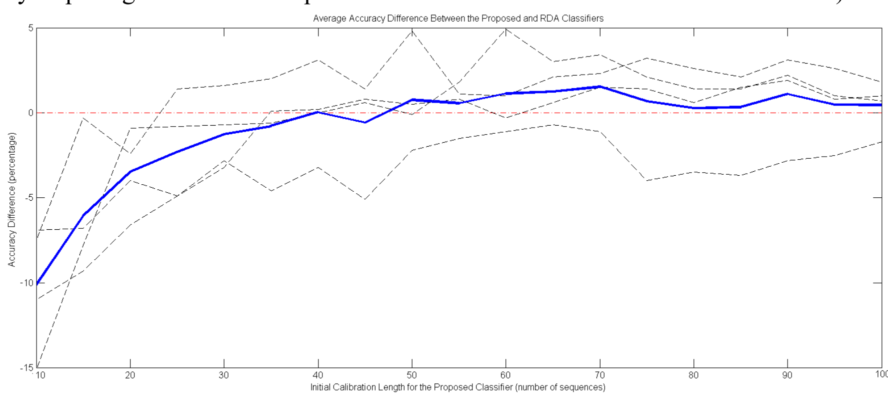

Figure 1. *Accuracy difference between the proposed method and RDA as a function of initial calibration length for the proposed method: (blue) average, (black dashed) individual subjects, (red dash-dot) zero difference line.*

4. Discussion

We demonstrated that a Bayesian conjugate prior based calibration of RDA-based EEG classifier in RSVP Keyboard™, an ERP-based spelling interface, can allow for short calibration sessions if followed by in-use on-line adaptive calibration. Regularization is a useful procedure for systems suffering from the curse of dimensionality, as in this case, and our plans include the incorporation of regularization into the calibration process in future. We will also incorporate adaptive calibration procedures to track possible nonstationarity in EEG signal/feature. This will allow us to have longer periods of use without the need to recalibrate from scratch.

Acknowledgments

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A Stimulus-Free Brain-Computer Interface Using Mental Tasks and Echo State Networks

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Abstract. We propose an EEG classification algorithm for the mental task BCI paradigm that uses Echo State Networks (ESN). In this approach, ESN are used to model the dynamics of EEG during each of several mental tasks. Classification is performed by applying several of these models and assigning the class label associated with the ESN that produces the lowest forecasting error. Experiments performed on 14 subjects using a portable EEG system achieve information transfer rates as high as 15 bits-per-minute with four tasks and 21 bits-per-minute for two tasks.

Keywords: Brain-Computer Interface, Electroencephalography, Recurrent Neural Network, Echo State Network, Mental Task

1. Introduction

The mental task paradigm for operating brain-computer interfaces (BCI) allows a user to issue instructions to the system by performing one of several predetermined mental tasks [Keirn and Aunon, 1990]. For example, a user might silently sing a song to move a cursor to the left or visualize a geometric figure to move it to the right. This approach does not require external stimuli and may yield discriminable signals with high degrees of freedom. When combined with user practice and machine learning, we believe that this approach may yield fluid, second-nature control.

In previous work, we proposed a generative EEG classification algorithm for use with the mental task paradigm that uses Recurrent Artificial Neural Networks [Forney and Anderson, 2011; Forney, 2011]. Here, we extend this work to use a fast and powerful recurrent network architecture known as Echo State Networks (ESN) [Jaeger, 2003]. We then explore the performance of this system on data recorded in a controlled laboratory environment as well as in home environments with users that have severe motor impairments.

2. Modeling and Forecasting EEG Signals

First, we show that ESN are capable of accurately modeling EEG signals. This is done by training an ESN to forecast an EEG signal a single step ahead in time given only the current signal value as input. When applied to an 8-channel EEG signal with a sampling frequency of 256 Hz and a bandwidth of 4–100 Hz, this technique achieves a root-mean squared error as low as 7 % of the signal range.

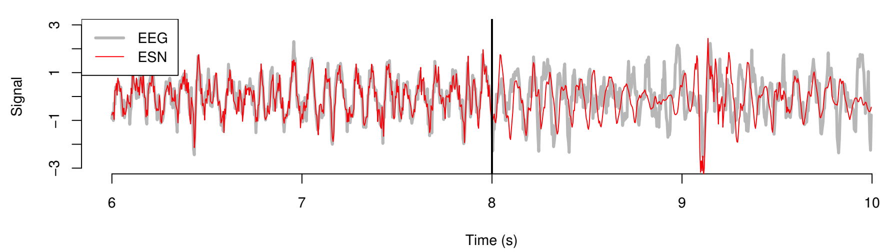

Figure 1: *A trace illustrating an ESN transitioning from forecasting to an iterated model at the 8-second mark.*

To further support our claim that ESN are able to capture the dynamics of EEG, we also explore iterated models. In this approach, a feedback loop is placed from the outputs to the inputs of a trained ESN so that it autonomously produces artificial signals. In Fig. 1, we see the transition from forecasting, before the 8-second mark, to an autonomous signal, after the 8-second mark. These autonomous signals have rich dynamics that are not clearly periodic. A spectral analysis confirms that they contain transient frequencies generally matching those in the underlying EEG.

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3. Classification of Mental Tasks

Next, we use the models described in the previous section to construct a generative classifier. This is done by training a separate ESN to forecast sample EEG recorded during each mental task. We then have an ESN associated with each mental task that can be viewed as an expert at modeling the corresponding EEG. Previously unseen EEG is labeled by applying each ESN and selecting the class label associated with the model that produced the lowest forecasting error.

Table 1: *Subjects without impairments in our lab.*

	2-Tasks		4-Tasks	
Subject	CA (%)	IT (bpm)	CA (%)	IT (bpm)
01	85.00	11.70	62.50	13.54
02	80.00	8.34	42.50	3.15
03	90.00	15.93	55.00	8.82
04	95.00	21.41	65.00	15.34
05	65.00	1.98	45.00	4.06
06	95.00	21.41	62.50	13.54
07	70.00	3.56	40.00	2.34
08	95.00	21.41	62.50	13.54
09	75.00	5.66	53.13	7.79
Mean	83.33	12.38	54.24	9.12

Table 2: *Subjects with impairments in their homes.*

	2-Tasks		4-Tasks	
Subject	CA (%)	IT (bpm)	CA (%)	IT (bpm)
10	40.00	0.00	27.50	0.07
11	70.00	3.56	55.00	8.82
12	50.00	0.00	15.00	0.00
13	87.50	13.69	56.25	9.54
14	60.00	0.87	37.50	1.65
Mean	61.50	3.63	38.25	4.02

Finally, we evaluate our classifier on EEG recorded from 14 subjects using g.tec's portable g.MOBILab+/g.GAMMAsys with eight active electrodes. Nine subjects had no disabilities and recording took place in a laboratory. Five subjects had severe motor impairments and recording took place in their homes. Following cues on a computer screen, each subject performed four mental tasks: *silently count backward from 100 by 3s, imagine left hand clenching, visualize a rotating cube and silently sing a song*. Five repetitions lasting 10 seconds were recorded for each task totaling 200 seconds of EEG per subject. The data was split 60/40 into training and test partitions and all parameters were tuned using cross-validation over the training partition. We first classify all four mental tasks and then only the two tasks with the best validation performance. Class labels are assigned at two-second intervals. We measure classification accuracy (CA) in percent correct as well as information transfer rate (IT) in bits-per-minute (bpm).

In Table 1 and Table 2 we summarize the final test results of these experiments. Many subjects outperform the random CA of 50 % for two tasks or 25 % for four tasks. Performance varies greatly, however, with some subjects achieving IT as high as 21.41 bpm and others achieving an IT of zero. A comparison of mean classification accuracy using t-tests with pooled variance also suggests significantly higher performance among subjects without disabilities in the laboratory than among those with disabilities in their homes ($p_{\text{2-task}} = 0.017, p_{\text{4-task}} = 0.047$).

4. Discussion

We have introduced a BCI that uses ESN to classify EEG in the mental tasks paradigm. Using this approach, we have observed information transfer rates that are competitive with the state-of-the-art. However, the modest classification accuracies obtained suggest that further refinements may be necessary for interactive use.

Acknowledgments

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An Auditory Brain-Computer Interface Based on Three-Stimulus Oddball Paradigm

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Abstract. The auditory brain-computer interface (BCI) based on three-stimulus oddball paradigm was studied to obtain a binary decision in this paper. The signals were decomposed by empirical mode decomposition(EMD) in order to reduce noise and improve signal-to-noise ratio. The principal component analysis(PCA) method was used for extracting the P300 feature. The feature signals were sent to support vector machines (SVM) to be classified. Experimental results showed the classification accuracies for four participants can achieved more than 85%.

Keywords: Brain-computer interface, Auditory, P300, EMD, PCA, SVM

1. Introduction

Brain-computer interface can provide severely disabled people with non-muscular communication. However, many people with disabilities, including people with late-stage amyotrophic lateral sclerosis (ALS) who have impaired eye movements, are unable to maintain gaze and use visual BCI [Sellers et al., 2006; Klobassa et al., 2008]. In addition to the loss of act control ability, the patients may also suffer from decrease in attention span. Therefore, it is important that a paradigm optimized for ALS patients should reduce the workload. The goal of this study was to evaluate a BCI design based on a modified three-stimulus paradigm that would permit the user a binary selection with high accuracies.

2. Experiments and Methods

2.1. Experiments

EEG was recorded with six Ag/AgCl electrodes (FCz, Fz, Cz, CPz, Pz and Oz) in a standard clinical 32-channel electrode cap. The study enrolled four volunteer participants. Each participant was asked to participate in two tasks. In each task we presented three kinds of tones: two targets were pure tones, five standard tones were white noise. The two tasks varied in the frequency of the target tones while standard tones remained constant (white noise). In task 1, target one at 1000 Hz, target two at 4000 Hz. In task 2, target one at 100 Hz, target two at 4000 Hz. All the standard tones were presented to the both ears, but the target tones were mono. Each stimulus lasted 100 ms with a randomized inter stimulus interval (ISI) of 250-400 ms. The intensity of each tone was 75 dB sound pressure level.

Prior to the experiment, participants were given a question, such as 'Is the basketball is round?' and they would response 'yes' or 'no'. Participants had to attend to target one when they want to reply 'yes', otherwise attend to target two. In the experiment, participants attend to the target stimulus that they wanted to choose and ignore the other target and the standard stimuli to make a binary selection. At the same time, they were asked to quietly say the direction (left or right) of the target tone without tongue movement when the target stimuli appeared. The accuracy of correct responses to the yes/no question is 100%. All participants were required to complete four runs of 20 trials.

2.2. Feature extraction and classification

The original data epoch (from 200 ms before the stimulus-onset to 800 ms after the stimulus-onset) for each stimulus was extracted. And then, all epochs were referred to the mean amplitudes of the pre-stimulus baseline. P300 response is usually elicited when a rare stimulus appears in a sequence of common stimulus. Conventionally, averaging the responses to the target stimuli of the oddball paradigm can obtained the P300 response. However, it is required long time and cannot be applied to online BCI systems. EMD was used to decompose the data after preprocessing. A sequence of superposition of components called intrinsic mode functions (IMF) was obtained. We selected the IMF in the frequency range of 0-4 Hz and reconstructed the data which eliminated the high frequency information and retained the P300 characteristic. Finally, the features were focused from reconstructed signals by the method of PCA, which reduced the data dimension. SVM [Guo et al., 2010] was used to discriminate the target and non-target by whether elicited the P300 response. For each participant, the data contained 80 trials in one task, in which the features of 40 trials were used to train a two-class SVM classifier. The remaining trials were used to test.

3. Results

To investigate whether the P300 component can be elicited in single trial by EMD, we showed the grand average of 20 times original signals and the reconstructed EMD components in Fig. 1.

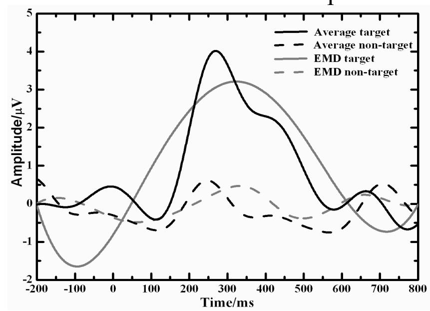

Figure 1. *The grand average of original signals and the reconstructed EMD components.*

Comparing the waveform in Fig.1, the largest difference between the target response and non-target was a positive deflection with latency of 250-550 ms. A clear P300 was also elicited in the reconstructed signals, which suggests that EMD can be used to extract the feature in single trial. The main features of 6 channels were concentrated in one component after using PCA, and the data dimension was reduced. Then the features were classified by SVM.

Table 1. *The classification accuracies of the two tasks.*

Participants	*Task 1 (%)*	*Task 2 (%)*
1	91.67±2.16	92.25±1.35
2	89.16±1.08	90.02±1.22
3	86.43±1.76	86.42±2.05
4	87.51±1.02	87.87±1.52

The classification accuracies for each participants achieved more than 85%, as shown in Table 1. Moreover, the results showed that three participants achieved better performance in task 2. The reason might be that the frequency interval of the target stimuli in task 2 is longer and participants can easily distinguish targets and non-targets.

4. Discussion

In this paper, we showed that an auditory BCI system based on three-stimulus paradigm by extracting the time-frequency features with the method of EMD and PCA is feasible. When design the experiment, the frequency interval of two kinds of target stimuli need to be longer. Then the targets and non-targets can be easily distinguished. Furthermore, the pitch, duration, ISI of the stimuli tones will be necessary to discuss.

Acknowledgements

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Denoising and Time-Window Selection Using Wavelet-Based Semblance for Improving ERP Detection

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Abstract. Wavelet denoising has been successfully applied to Event-Related Potential (ERP) detection, but it usually works using channels information independently. This paper presents an adaptive approach to denoise signals taking into account the channels correlation in the wavelet domain. Moreover, we combine phase and amplitude information to automatically select a time window which increases ERP detection. Results on the P300 speller show that our algorithm has a better accuracy with respect to the VisuShrink wavelet technique and the XDAWN algorithm among 22 healthy subjects, and a better regularity than XDAWN.

Keywords: Event-Related Potential, Denoising, Wavelets, Signals correlation, Single-trial detection, Brain-Computer Interfaces.

1. Introduction

The P300 oddball paradigm such as used in the speller by Farwell and Donchin is the most frequent paradigm used in Brain-Computer Interfaces (BCI) especially for people with severe disabilities. But the signal-to-noise ratio is so low that it is necessary to apply preprocessing techniques to improve the P300 detection. This paper presents a new method to denoise EEG signals, which considers the shared information in the wavelet domain of all channels, based on their phase angles correlation. Also, our algorithm selects an appropriate time window for each subject, extracting the interval of interest to effectively discriminate between classes.

2. Material and Methods

2.1. Wavelet-based Semblance

The Wavelets Transform represents a signal $x(t)$ in terms of scaled and shifted versions of a mother wavelet, $\psi(t)$. The wavelets coefficients are obtained through equation $W_{\psi}^{x}(a,b) = \langle x(t)|\psi_{a,b}(t)\rangle$, where a and b are the scale and translation parameters respectively. Semblance analysis [Cooper, 2009] compare two signals $x(t)$ and $y(t)$, using Continuous Wavelet Transform (CWT) or the Discrete Wavelet Transform (DWT), based on phase correlations between its wavelet decompositions W_{ψ}^{x} and W_{ψ}^{y}. The first step is to compute the cross-wavelet transform, $W_{\psi}^{x,y} = W_{\psi}^{x} W_{\psi}^{y*}$, where $*$ denotes the complex conjugate. The cross-wavelet amplitude is given by $A = |W_{\psi}^{x,y}|$ and its local phase is defined as $\theta = tan^{-1}(\Im(W_{\psi}^{x,y})/\Re(W_{\psi}^{x,y}))$, where $\Re$ and $\Im$ correspond to the real and imaginary parts respectively. The *semblance measure* S to compare two signals using θ, is defined as $S = cos^{n}(\theta)$ where n is an odd integer greater than zero. Its values range from -1 to 1, where $S = 1$ indicates that signals are correlated , $S = 0$ uncorrelated and $S = -1$ inversely correlated. It is possible to combine the phase information S and the amplitude A as follows $D = cos^{n}(\theta)|W_{\psi}^{x} W_{\psi}^{y*}|$.

As an extension of the *semblance*, the Mean Resultant Length (MRL) [Cooper, 2009] compares N different signals (ranging from 0 for uncorrelated signals to 1 for fully correlated signals) and it is compute for each time t and scale a as:

$$MRL(t,a) = \frac{\sqrt{(\sum_{i=1}^{N} \Re(W_{\psi}^{i,t,a}))^2 + (\sum_{i=1}^{N} \Im(W_{\psi}^{i,t,a}))^2}}{\sum_{i=1}^{N} |W_{\psi}^{i,t,a}|} \tag{1}$$

2.2. Signal Denoising

The fundamental hypothesis of wavelet denoising is that wavelets are correlated with the informative signal and not correlated with the noise, which globally means that small coefficients correspond to noise. Let $x_c(t)$ be the signal recorded by the c^{th} channel (or electrode) $c \in \{1,\dots,C\}$ at time t, $t \in \{1,\dots,T\}$. The matrix of recorded EEG signals can be defined as $X \in \Re^{TxC}$. The MRL is computed using the DWT wavelet decomposition of all channels $W_{\psi}^{x_c}$, through Eq. 1. It is possible to establish a correlation threshold τ_d in order to set to zero all coefficients that are below it. After this process we can reconstruct the signal using the filtered wavelet coefficients.

2.3. Time-Window Selection

The P300 responses have a different latency for each person but are studied during a predefined time window after the stimulus onset. We propose to automatically find an efficient time window by detecting where the discriminative information lies to remove features which do not carry useful information. The denoised signal can be denoted by $\widetilde{x}_c(t)$, where c correspond to the channel and t to the instant when the signal started to be recorded. Each $\widetilde{x}_c(t)$ has a label to indicate to which class belongs. Let $\mathscr{M}$ be the set of all signals, $\mathscr{M}$ is composed by signals belonging to the target class $\mathscr{T}$ (containing a P300 wave) and signals $\mathscr{N}$ which are non-targets, $\mathscr{M} = \{\mathscr{T}, \mathscr{N}\}$. The Grand Averages GA for each class are computed as $GA_{\mathscr{T}} = \frac{1}{C|\mathscr{T}|}\sum_{i=1}^{C}\sum_{\widetilde{x}\in\mathscr{T}}\widetilde{x}_i(t)$ and $GA_{\mathscr{N}} = \frac{1}{C|\mathscr{N}|}\sum_{i=1}^{C}\sum_{\widetilde{x}\in\mathscr{N}}\widetilde{x}_i(t)$ where the operator $|.|$ denotes the cardinal number. After obtaining the Grand Averages, we compute the CWT $W_{\psi}^{GA_{\mathscr{T}}}$ and $W_{\psi}^{GA_{\mathscr{N}}}$ to finally compute D. The original time window of 1s can be reduced to the interval $[t_{lo}, t_{up}]$ applying a threshold τ_w, $0 \leq \tau_w \leq 1$ to the normalized average of D.

We called the combination of the signal denoising and the window selection using the wavelet-based semblance the Denoise and Window Selection (DWS) algorithm.

3. Results

Firstly, we compared ours methods, DWS_1 (using the same time window for all channels) and DWS_2 (using different time windows per channel) to the wavelet denoising technique called *VisuShrink* (Stein Unbiased Risk Estimator) [Donoho and Johnstone, 1995] and the XDAWN algorithm [Rivet et al., 2009]. 10 channels (Fz, C3, Cz, C4, P3, Pz, P4, PO7, PO8, Oz) for 22 healthy subjects were recorded at 256 sps using the g.tec gUSBamp EEG amplifier. An eighth order Chebyshev bandpass filter, 0.1–60 Hz and a 60 Hz Notch were used (see akimpech.izt.uam.mx/p300db). Two different sessions of approximately 16 letters each were used to train and test a Support Vector Machine (SVM), which in single-trial corresponds to 5520 realizations for training and 5895 for testing with a time segment of 1s.

Algorithms DWS_1 and DWS_2 perform significatively better, showing that the conjoint channel information is useful for P300 single-trial detection (see Table 1). Finally, we compare DWS_1 and DWS_2 in Table 2. Our algorithms reduce the window selection roughly to [20, 850] ms. DWS_2 used a smaller time window.

Method	mean	std	min	max	paired t-test with DWS1
None	48.23	15.55	18.10	76.19	1%
XDAWN	51.03	15.80	24.44	80.00	1%
Filter [0.1-20] Hz	53.60	14.14	28.25	79.52	1%
VisuShrink	54.80	13.90	33.02	78.57	5%
DWS_1	**55.83**	**13.49**	**34.29**	80.95	-
DWS_2	55.41	13.88	33.97	**81.90**	5%

Table 1: Results using Coiflet at level 3, $\tau_d = 0.999$ and $\tau_w = 0.9$. The average and the standard deviation of the letter percentage accuracy over all subjects and the minimum and maximum accuracy obtained among subjects are reported. The last column reports the significance level of a paired t-test.

		DWS_1	DWS_2
t_{lo} (ms)	min	1	1
	mean	20	23
	max	98	305
t_{up} (ms)	min	488	277
	mean	848	820
	max	1000	1000

Table 2: Results obtained by DWS_1 and DWS_2 on the time-window selection. t_{lo} and t_{up} are respectively the lower and the higher bounds in milliseconds found over all subjects and channels.

4. Discussion

In this paper, we introduce a new method based on the wavelet-based semblance to exploit the correlated information among channels. This technique removes noise and establishes automatically an appropriate time window adapted to each subject. We empirically demonstrate using the P300 speller application that our method is useful to remove undesirable component of the signals, improving the letter accuracy compare to the other methods and showing more stability than XDAWN. Further studies are needed to automatically select the thresholds.

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Efficient Adaptive Stimulus Sequencing for Improved P300 Speller Performance

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Abstract. In the quest for ever higher information transfer rates to aid communication through a Brain Computer Interface, an often overlooked method is the adaptation of stimulus sequences based on early acquired data. Consequent stimulations are constrained based on the already obtained information to increase information transfer. We investigate a novel algorithm targeting the ubiquitous P300 speller, although the theory is applicable in many Brain Computer Interface paradigms. The proposed implementation of adaptive stimulation is based on a model of experimental stimulus responses. Simulations show a reduction of required stimuli by 27.4 % compared to a reference P300 speller in selecting a target out of 6 items. The computational efficiency of the algorithm allows scaling to more items, where it shows increasing performance benefits.

Keywords: adaptive algorithm, stimulus sequencing, visual speller, P300 optimization, BCI

1. Introduction

The development of brain computer interfaces is motivated by the prospect of efficient non-muscular communication for people suffering from severe neurodegenerative diseases [Wolpaw et al., 2002]. The P300 speller [Farwell and Donchin, 1988] in particular relies on the interaction between attention and stimulus presentation. A P300 event related potential is observed in the EEG signals of a subject when an item is highlighted while being attended to by the subject [Polich, 2007]. This correlation between attention and detectable EEG changes allows subjects to make a voluntary choices between several sequentially presented items.

Each item selection requires multiple presentations for adequate accuracy. The adaptive algorithm discussed here uses early obtained information to predict beneficial stimuli later in the sequence. This allows a higher information throughput, enabling faster and more accurate use of the speller interface.

2. Materials and Methods

In the P300 speller, the response of each stimulus is classified as belonging to the target class with a certain probability. A belief state is continuously updated during speller use, estimating the probability of each item being a target item:

$$b_{x,n} \sim \prod_{i=1}^{n} \begin{cases} P(+ \mid r_i), & x \in s_i \\ 1 - P(+ \mid r_i), & x \notin s_i \end{cases}, \tag{1}$$

where $b_{x,n}$ is the belief at iteration n if x is the target item, as function of the target probability $P(+ \mid r_i)$ given response r_i and stimulus s_i at iteration i. The item x with highest belief $b_{x,n}$ is selected as the believed target at iteration n.

The proposed algorithm estimates the probability of reaching a future belief state from the current state, assuming a future stimulus. For each combination of a stimulus and an assumed target, either a target– or non-target response is expected. Probability density functions (PDF's) of response probabilities are modeled after experimental data obtained from [Geuze et al., 2012] (20300 classified responses among 10 subjects). These are approximated by Beta distributions, and assumed symmetric between target– and non-target responses. Considering a PDF of future responses, a belief state update yields a PDF of future belief states.

Assuming a desired outcome is one where the believed target matches the assumed target, the probability of a desired future belief state given a future stimulus is described by:

$$P(t_x, b_x \mid s_y) = P(b_x \mid t_x, s_y) \cdot P(t_x \mid s_y), \tag{2}$$

where t_x indicates x being the assumed target, and b_x our belief that x is the target, given s_y, a stimulus of item y. $P(b_x \mid t_x, s_y)$ is the integral of the future belief state PDF for t_x, s_y over the subspace where the belief in item x is highest. We assume that the prior probability $P(t_x \mid s_y)$ is uniform. The best future action is the stimulus s_y which maximizes the probability of desired outcomes $\sum_x P(t_x, b_x \mid s_y)$ over all items x.

In implementing this algorithm, several practical issues are taken into account. First of all, there is an observed processing delay of around 4 stimulations (800 ms at a rate of 5 Hz) between presentation of an item and the corresponding belief state update. Furthermore, due to a P300 refractory period [Martens et al., 2009; Polich, 2007], target stimuli within a short period after each other do not evoke as strong a P300 response, and are often incorrectly classified. To minimize inaccurate classification, no repeated stimuli are allowed within a window of 600 ms (3 stimulations).

3. Results

Simulation results stimulating individual items out of 6 total (5000 trials) and 36 total (1000 trials) are shown in Fig. 1, using response Beta distributions with $\alpha = 3.599, \beta = 2.022$ for target responses and inverted for non-target ones.

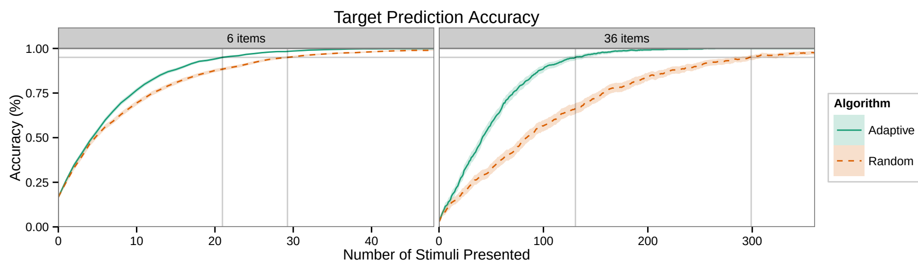

Figure 1: *Accuracy as function of the number of stimuli comparing the adaptive algorithm to the reference random algorithm. Results from a simulation with 6 items and 36 items. 95 % CI indicated as shaded area. Gray lines indicate 95 % accuracy.*

Similar performance is observed for a range of model parameters covering individual subject observations. Additionally, the behavior is not sensitive to inaccuracy in the response model (offset of up to $\pm 2\sigma$ of the inter-subject variation), or to overestimation of the P300 refractory period by up to 400 ms.

4. Discussion

With the current implementation, the required stimuli to attain an accuracy of 95 % are decreased by 27.4 % (95 % CI: 19.9 %–32.4 %) compared to random stimulation with 6 items. Similar improvements are expected using the common 6×6 grid layout [Farwell and Donchin, 1988], where stimuli consist of either rows or columns. When stimulating individual items, relative improvements increase with more items. The algorithm, as implemented in MATLAB and without significant optimization, is able to process 1500 trials per second (6 items) on regular equipment.

An alternative method is proposed by [Park et al., 2011], where partially observable Markov decision processes are used to select the most beneficial future action. Performance is similar to our approach (stimulations at 95 % accuracy compared to random decrease by 22.7 %, 95 % CI: 15.6 %–31.2 %) for the same parameters and constrains (6 items, target response distribution $\alpha = 1.228, \beta = 0.625$). Importantly, our approach does not require pre-computations.

While care has been taken to faithfully reproduce an experimental environment, it is important to experimentally verify the simulation results. [Martens et al., 2009] suggests that P300 refractory effect affects responses even for intervals of over 1 s, therefore it would be beneficial to accurately measure such effects and incorporate them into the response model. This would allow for an accurate handling of the decreased classification accuracy.

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EEG Channel Optimization Based on Differential Evolutionary Algorithm for BCI Application

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Abstract. This paper discusses implementation of Differential Evolutionary algorithm for EEG channel optimization. P300 brain-computer interface speller based on the region-based paradigm was used. The EEG signals were recorded from 8 channels from 23 subjects. The results of channel optimization show that the number of channels can be reduced for different subjects without decreasing the accuracy significantly.

Keywords: EEG Channels, P300, Optimization, Differential Evolutianry Algorithm, Region-based Paradigm

1. Introduction

It is usually desirable to record the EEG signals from more electrodes to have a better classification results and decrease the error. However, increasing the number of channels brings more challenges. First of all, it could generate a large size of data which is not necessary useful in adding more information due to the redundancy in EEG data and correlation between channels. Second, increasing the number of EEG channels also increases the computational time and may create limitations for real-time applications. Low speed of brain computer interface (BCI) systems has been one of the main challenges in most BCIs. Therefore, by minimizing the number of EEG channels, a channel optimization method could create a reasonable balance between having a high accuracy and low computational time. Taking a quick look into the literature reminds that lots of efforts have been trying to solve the optimization problem for the EEG signals [Atyabi et al., 2012]. However, there are a few published papers that have applied Evolutionary Algorithms (EV) for channel optimization.

The application of Discrete Particle Swarm Optimization (Discrete PSO) for selecting electrodes from definite regions of the subject's scalp was shown in [Jin et al., 2008] and average classification accuracy of 77% was reported. Multi-Objective PSO (MOPSO) on the motor imagery EEG data was used in [Hasan et al., 2009] where 57% classification accuracy for 3 different classes was obtained. In their next work [Hasan et al., 2010], Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) on the same dataset was implemented and then compared with the MOPSO method. It was shown that 1% improvement was achieved using MOEA/D. The average number of used electrodes with MOPSO and MOEA/D was 4 and 10 electrodes, respectively. It seems that obtaining 1% improvement in accuracy does not worth to increase the number of efficient electrodes from 4 to 10. This paper addresses applying the Differential Evolutionary (DE) algorithm to reduce the number of EEG channels in detecting P300 signals from the region based paradigm [Fazel-Rezai and Abhari, 2009].

2. Material and Methods

Differential Evolution (DE) is a stochastic, population-based search strategy developed by Storn [Storn and Price, 1995]. The DE algorithm is a population based evolutionary algorithm like genetic algorithms using the similar operators; crossover, mutation and selection. The main difference from other evolutionary algorithms is in the reproduction step where offspring is created from three parents using an arithmetic crossover operator. It means that mutation is applied first to generate a donor vector, which is then used within the crossover operator to produce one offspring. The DE does not make use of a mutation operator that depends on some probability distribution function, however introduces a new arithmetic operator which depends on the differences between randomly selected pairs of individuals. Also the DE is defined for floating-point representation of individuals, called the parameter vectors. Our applied DE algorithm is summarized as follows:

Initialize each individual to contain K randomly selected EEG channels.

For t=1 to t_{max}

a. For each two randomly selected individual (x_k, y_k) combinations
   i. Apply the mutation to create the donor vector
   ii. Apply Crossover operator to have offspring (z_k)

iii. Evaluate the fitness function on all $f(x_k, y_k, z_k)$

b. If $e(r) \leq 0.01$, report the best combination of channels and exit.

Here, $e(r)$ is defined as an error function between resulted accuracy from offline data and the new accuracy applying the DE algorithm, while t_{max} is the maximum trail numbers for each K channel selection.

The region-based paradigm [Fazel-Rezai and Abhari, 2009] was used for spelling two words ('PEBBLE!' and 'MX85+Z&') from 23 subjects (6 females) with the approval of the University of North Dakota (UND) Institutional Review Board (IRB). The DE optimization algorithm was applied on the EEG signals recorded from eight channels at FZ, CZ, PZ, OZ, P3, P4, PO7, and PO8 locations according to the international 10-20 system. EEG signals were sampled with a frequency of 256 Hz and filtering was done using a 0.1 Hz high pass, a 30 Hz low pass. Six flashes with a flash time of 100 ms and a blank time of 150 ms were considered. Linear Discriminant Analysis (LDA) was used as the classifier. Also, the experiment was implemented using the g.GAMMAbox and g.USBamp for recording and g.BSanalysis for classification, all of them from products of Guger Technologies (g.tec).

3. Results

The proposed algorithm was implemented on the above dataset for all 23 subjects where $\mathbf{k} = 3, 4, 5$, i.e., the number of selected channels was 3, 4 and 5. Each step yields to different number of combinations of channels as parents as well as offsprings. Table 1, shows the total trial number of search for the chosen **k** values.

Table 1. *Channels combination numbers.*

Combination parameter	Parents Pair	Total trial numbers (t_{max})
k =3	42	1722
k =4	70	2415
k =5	42	861

The DE algorithm starts with choosing 3 channels combination randomly and then shows the convergence with not almost running over the whole trial numbers. The results show that the combination of channels is highly subject dependent and varies from each subject to another one. However, the number of best channels was almost the same for all subjects for $\mathbf{k} = 3$ and $\mathbf{k} = 5$. The results showed a slight improvement in accuracy for $\mathbf{k} = 4$.

4. Discussion

In some trials, the accuracy was suddenly decreased. In close exploration, we noticed that the original EEG channel which was selected randomly had already weak signal, maybe due to not good electrode contact to skin. So it is recommended to double check the EEG recorded signals not only at the starting of experiment, but also during the experiment. In addition, when the accuracy was not close to the target with three channels, increasing the channel numbers resulted to better accuracy almost over the whole dataset. In comparison to other algorithms, DE converges faster and with more certainty than many other global optimization methods through tremendous tests. Meanwhile, it requires only few control parameters, and it is robust and simple in use. The next step is to implement the DE algorithm in real-time mode spelling. This is the advantage of DE method compared to conventional methods that usually are required to be implemented to offline data because of required computational time.

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Implementation of a New Independent SSVEP-Based BCI

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Abstract. Brain–computer interfaces (BCI) employing steady-state visually evoked potential (SSVEP) modulations have been investigated increasingly in the last years because of their high signal-to-noise ratio and information transfer rate. However, independent SSVEP BCI based on covert attention show a drop in robustness which makes it difficult to use on patients with impaired or nonexistent ocular motor control. In the present paper, offline analysis is aimed at investigating the influence of feature extraction algorithms on the performance of covert SSVEP BCI. We have shown that the use of Thomson multitaper method or Lock-in Analyzer System with our new Checkerboard pattern and only the first harmonic yielded an average accuracy of approximately 79 % across nine subjects (with three subjects at more than 85 %) with 7 s window length. The short 6 or 7 s concentration time, the concise training, the robustness make this method very well suited for detecting command following and testing communication in non-communicating patients.

Keywords: EEG, SSVEP, covert attention, feature extraction.

1. Introduction

Current brain-computer interfaces (BCI) [Wolpaw et al., 2002] relying on steady-state visually evoked potentials (SSVEP), while demonstrating high information transfer rates and considerable robustness, depend on gaze control [Müller-Putz et al., 2005]. This rules out applicability to those whose severe disabilities extend to impaired or nonexistent ocular motor control. Independent SSVEP BCI based on covert attention have been proposed but have shown a drop in robustness. First covert SSVEP BCI were based on block pattern [Kelly et al., 2005]. While this approach works on healthy controls who can control their gaze, it is not suitable for patients without gaze control. They could unintentionally move their gaze on the wrong stimulation or move their gaze away of both patterns preventing detection of their wish. Other stimulation patterns take the advantage of the ability to covertly attend to one of two overlapping stimuli by presenting either mixed vertical and horizontal lines or moving dots. In [Lesenfants et al., 2011], we proposed a new covert "checkerboard" stimulation pattern which enables a better discrimination between two stimuli and compared its performance with lines pattern [Allison et al., 2008]. We showed that the new checkerboard pattern outperformed the lines pattern. We also demonstrated that the addition of second and third harmonics don't lead to significant accuracy increase in covert attention. In the following, we will study the influence of different feature extraction algorithms with this new pattern, 7 s stimulus duration and a single harmonic.

2. Material and Methods

Twelve healthy subjects (5 men; age range 22–43 years old, 28.3 ± 5.7) participated in the study. Subjects were seated 30 cm from self-constructed stimulation panel. The panel is a 7 by 7 cm "checkerboard" made of red and yellow 1 by 1 cm light emitting diode (LED) squares with a white fixation cross in the middle (Fig. 1). During the experiments, yellow and red squares were programmed to flicker at 10 and 14 Hz respectively. EEG signals were recorded at location P_3, P_1, P_2, P_4, PO_7, PO_3, PO_z, PO_4, PO_8, O_1, O_z and O_2, referenced to P_z. Ground electrode was placed behind the right mastoid. Amplifier used was a BrainVision V-Amp amplifier with a band pass filter between 0.01 and 100 Hz and a sampling frequency of 250 Hz. Each subject underwent a total of 6 runs, each lasting around 5 min. Each run contained 10 7 s trials separated by 23 s period (10 s of rest and 13 s of auditory instruction delivered via headphones). Checkerboard pattern was continuously flashing during a whole run. During a run, an equal number of both stimuli was presented in random order. The subject was instructed to fix his/her gaze on the white cross in the middle and to concentrate on one of the stimulus. EEG signals were preprocessed with a Butterworth fourth order low-pass filter with a cutoff frequency of 60 Hz and a Butterworth fourth order highpass filter with a

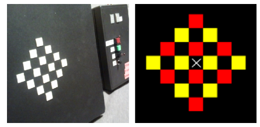

Figure 1: *Electronic visual stimulation unit.*

cutoff frequency of 5 Hz. An IIR Notch filter ($f_c = 50$ Hz, $Q = 35$) was also apply to the data. Frequency features were extracted from each trial with four feature extraction algorithms proposed in the literature: discrete-time Fourier transform (DFT), multitapers spectral analysis (PMTM), canonical correlation analysis (CCA) and lock-in analyzer system (LAS). Classification performance were computed with a linear discriminant analysis (LDA), and assessed with a 10×10 folds cross validation.

3. Results

The impact of the feature extraction algorithms was evaluated on nine out of twelve subjects. Subjects SC10 to 12 were rejected due to chance level classification. We concentrate on the four state of the art algorithms previously described. Averaged across these subjects produced maximum accuracy of 79.3 ± 9.7 % for PMTM, while the use of LAS produced a mean accuracy of 76.8 ± 9.1 %. Discrete-time Fourier transform and Canonical Correlation Analysis gave worst results for both case (59.3 ± 11.6 % for CCA, and 71.8 ± 9.9 % for DFT respectively).

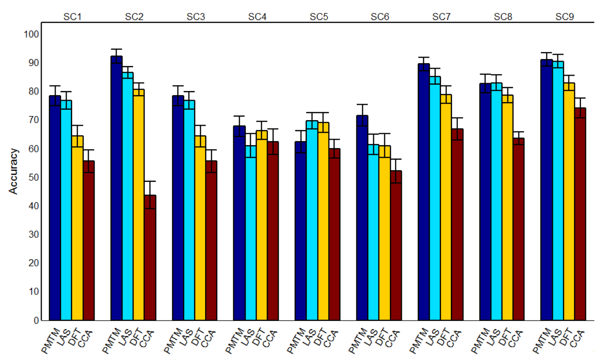

Figure 2: *Classification accuracy and standard deviation (in percent) for each subject obtained with Multitapers Spectral Analysis (PMTM), Lock-in Analyzer System (LAS), Discrete-time Fourier Transform (DFT) and Canonical Correlation Analysis (CCA).*

4. Discussion and conclusion

We have demonstrated the feasibility of achieving significantly relevant accuracy with a novel independent BCI based on the brain mechanism of covert attention, by using SSVEPs elicited by a checkerboard pattern. This may encourage the reconsideration of VEPs as a viable option in BCIs that are truly independent of neuromuscular function [Wolpaw et al., 2002]. Subjects succeeded in reaching an average accuracy of 79.3 % with three subjects out of nine at more than 85%, which exceed accuracies of previous covert SSVEP-based BCI ([Allison et al., 2008; Zhang et al., 2010]) by at least 5 %. The short concentration time (6 s or 7 s), the absence of training, the robustness make this method very well suited for detecting command following and testing communication in non-communicating patients.

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Frequency Recognition of AM-SSVEP Using Modified CCA and PSDA

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Abstract. Steady-state visual evoked potential (SSVEP) response to amplitude modulated stimulus (AM-SSVEP) has been suggested to ease eye fatigue for SSVEP-based BCIs. AM-SSVEP has at least two non-multiple harmonic frequencies, which can be good 'features' to classify AM-SSVEPs. However the frequency recognition method was scarcely investigated for multi-harmonic frequencies. In this study, the modified canonical correlation analysis (CCA) and power spectral density analysis (PSDA) were applied to recognize multi-frequency components of AM-SSVEP. From spectral analysis, seven different harmonic frequency components were identified. Combinations of the harmonic frequencies were employed to estimate the canonical correlation and the sum of SNR from CCA and PSDA, respectively. As a result, the modified CCA outperformed the modified PSDA, and the use of the combination improved recognition accuracy. In particular, the modified CCA with the combination of AM-harmonics using 4 s EEG data seemed to be suitable for a reliable SSVEP-based BCIs.

Keywords: SSVEP, Amplitude modulated stimulus, frequency recognition, multi-harmonic frequency, CCA, PSDA

1. Introduction

Low-frequency steady-state visual evoked potential (SSVEP) has been utilized in brain-computer interface (BCI) because of its high amplitude. But a visual stimulus flickering at low-frequency can cause eye fatigue and even epileptic seizure. Recently a high-frequency stimulus, flickering at higher than 30 Hz, was suggested as a new modality for SSVEP-based BCI with low eye fatigue [Diez et al., 2011]. But high-frequency SSVEP-BCIs made lower performance than low-frequency SSVEP-BCIs [Volosyak et al., 2011]. In our previous study, amplitude-modulated (AM-) stimulus was suggested to encompass advantages of both low- and high-frequency SSVEPs [Chang et al., 2012]. While the AM-stimulus flickers at high carrier frequency, it carries low frequency message in the carrier. Thus, low-frequency SSVEPs under 30 Hz can also be exploited to recognize AM-SSVEP. In this study, we investigated frequency recognition methods for AM-SSVEP that has multi-harmonic frequencies including both low- and high- frequency bands. Modified power spectral density analysis (PSDA) and canonical correlation analysis (CCA) methods were compared in terms of classification performance.

2. Material and Methods

2.1. AM-stimuli

The AM-visual stimulus was fabricated using an LED array flickering as an amplitude-modulated sine wave. The AM-sine wave was generated as the product of a message sine wave $m(t)$ at f_m and a carrier sine wave $c(t)$ at f_c. Using trigonometric functions, AM-sine wave $S(t)$ was expressed as

$$S(\mathrm{t}) = c(t)m(t) = -\frac{1}{2}[\cos(2\pi(f_c + f_m)t) - \cos(2\pi(f_c - f_m)t)]. \quad (1)$$

Eq. 1 shows AM-stimulus consists of $f_c + f_m$ and $f_c - f_m$ (f_{fund}s) components. f_cs were in high-frequency range (higher than 40 Hz) and f_ms were in low-frequency range (average 11 Hz). Four pairs of f_m and f_c were used in the study: (12, 40), (11, 41), (11, 40), and (10, 40); corresponding f_{fund}s were (52, 28), (52, 30), (51, 29), and (50, 30).

2.2. Experimental settings

Ten subjects participated in the experiment, having consented to the participation. The four AM-stimuli were attached at the cardinal points of a monitor that represented a target. When a target was indicated, subjects had to focus on the relevant LED array for ten seconds without eye or chin movement. Last 9.5 s-length electroencephalogram (EEG) signal was further analyzed to exclude movement noise generated while subjects located a target. EEG data was measured using g.USBamp (g.tec, Austria; f_s = 512 Hz) at O1, Oz, O2, PO3, POz, PO4, P1, Pz, P2, P3, P4, P5, P6, PO7, PO8 referenced and grounded at A1 and Fpz, respectively.

2.3. EEG analysis

Harmonic frequencies of AM-SSVEP (f_{AMH}s) were reported as $2f_c$, $2f_m$, $f_c \pm f_m$, $f_c \pm 3f_m$ [Chang et al., 2012]. We performed spectral analysis on the 9.5 s data using g.BSanalyze (g.tec, Austria) to confirm the previous report, where the average power over all trials was estimated in terms of the target. Spectral peak frequencies, where SNR was larger than 3, were compared between targets; the frequency commonly appeared in the spectra of more than two targets was defined as f_{AMH}. Modified CCA and PSDA were implemented using the harmonic frequencies for frequency recognition of AM-SSVEP [Bin et al., 2009]. Modified CCA method used a canonical variable (Y) as *sine* and *cosine* of combination of f_{AMH}s and its second harmonics. A class with the highest maximum correlation between EEG signal and Y was assumed as the target where a subject attended. On the other hand, modified PSDA method estimated the sum of SNR at the combination of f_{AMH}s; a class with the highest sum was assumed as the target. EEG signal was a segment of 15-channel data, whose window length varied from 1 s to 9s. For both CCA and PSDA, every combination of f_{AMH}s included f_{fund}s because it was the fundamental stimulus frequencies. Only the highest accuracy among those of the combinations of f_{AMH}s was further considered. Statistical analysis was performed using two-way ANOVA ($\alpha = 0.05$).

3. Results

3.1. AM harmonic frequencies

The reported six AM harmonic frequencies were entirely found in this study. Besides, compared to our previous study, one more f_{AMH} was identified at $2f_c - 4f_m$. Thus 32 combinations of five AM harmonic frequencies ($= 2^5$) including $f_c \pm f_m$ were employed to generate a canonical variable and to estimate SNRs.

3.2. Performance

The estimated accuracy was $85.7 \pm 17.3\%$ for CCA and $62.0 \pm 19.6\%$ for PSDA, which was significantly different by $23.7 \pm 1.9\%$ ($p < 0.001$). Average accuracy of every combination of f_{AMH}s was significantly higher than that of f_{fund}s ($79.6 \pm 20.9\%$ for the combination and $68.0 \pm 21.5\%$ for f_{fund}s; $p < 0.001$). Window length was another factor that affected accuracy ($p < 0.001$). The best combination of f_{AMH}s was proved to be better than f_{fund}s for both modified CCA and PSDA by $11.6 \pm 2.2\%$. Interestingly, there was an interaction between frequency recognition method and window length ($p < 0.01$).

4. Discussion

We found a new harmonic frequency in the spectra of AM-SSVEPs. The new AM harmonic frequency was lower 40 Hz, whereas the estimated frequency range under the previous experimental condition was higher than 44 Hz. This might hinder the identification of the component in the previous study. AM-stimulus is described as the sum of two frequency components as Eq. (1), so that we utilized the sum of SNR rather than a combination of SNR at f_{AMH}s as a feature. In the results, accuracy increased as window length increased, resulting in average accuracy of 85.5 ± 15.9 % with 9 s EEG data. And the modified CCA with combination of f_{AMH} was the best to recognize AM-SSVEP. Finally, the modified CCA with the combination using 4 s-EEG data was assumed to be suitable for reliable SSVEP-BCI with accuracy of higher than 95% ($97.0 \pm 4.5\%$).

Acknowledgements

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Phase Information Enhanced SSVEP-BCI Using a Canonical Correlation Analysis Neural Network

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Abstract. This paper proposes to utilize the phase information to enhance steady-state visual evoked potential based brain-computer interface (SSVEP-BCI) based on a canonical correlation analysis neural network (CCA-NN). The preliminary offline results show that the proposed scheme can achieve a better classification accuracy than the standard CCA and the modified CCAs since it identifies the target by considering the flexible phase information.

Keywords: BCI, SSVEP, canonical correlation analysis (CCA), neural network (NN), phase information

1. Introduction

Recent years have witnessed a great success of steady-state visual evoked potential based brain-computer interfaces (SSVEP-BCIs) which can provide satisfactory performance with ease configuration and little user training [Bin et al., 2009; Wang et al., 2010; Volosyak, 2011]. Among the existing SSVEP-BCIs most utilize either the frequency information or phase information of SSVEPs for identification. More recently some work has been reported which make use of both frequency and phase information of SSVEPs simultaneously to improve the system performance [Jia et al., 2010; Pan et al., 2011; Shyu et al., 2012]. In particular, a modified canonical correlation analysis (CCA) called phase constrained CCA (p-CCA) is proposed in [Pan et al., 2011] to enhance the classification accuracy. If the phase information in p-CCA can be variable in a specified range rather than fixed at a value, it should be more suitable to practical applications. This study aims to use a CCA neural network (CCA-NN) with flexible phase information to improve the classification accuracy.

2. Phase Information in Canonical Correlation Analysis

Standard CCA (s-CCA) finds out the maximum correlation coefficient between two sets X and Y by finding two optimal projection matrices (W_X and W_Y). In general, SSVEP-BCIs using CCA detect the gazed-target by finding which reference signal (Y_k) has the maximum correlation with the multi-channel SSVEPs (X). Then the stimulus frequency (f_k) of reference signal (Y_k) is decided as the gazed-target. s-CCA only considers frequency information in reference signal (i.e., $Y_k=[\sin(2\pi f_k t),\cos(2\pi f_k t)]^T$), so it is possible to find an unreliable projection direction (W_X) which means that the combined signal (X^TW_X) has different phase from SSVEPs. It is unreasonable since SSVEP is phase-locked to stimulus.

In p-CCA the reference signal with additional phase information (i.e., $Y_k=[\cos(2\pi f_k t+\theta_k)]^T$) can make sure the combined signal with the similar phase as SSVEPs. However, the constant phase information does not conform to reality because SSVEP's phase usually has a large phase deviation around 20^o~40^o [Jia et al., 2011; Lee et al., 2010]. As a result, a CCA-NN is proposed to solve this issue.

2.1. Canonical Correlation Analysis Neural Network

In [Lai and Fyfe, 1999] artificial neural networks are adopted to implement CCA. Neural networks can find the weight vectors (W_X and W_Y) by optimizing a cost function. For example, the cost function shown in Eq. 1

$$J = E(xy) + \lambda_1(1-x^2) + \lambda_2(1-y^2) + \lambda_3(C_1W_Y - \lambda_4^2) + \lambda_5(C_2W_Y - \lambda_6^2)\,, \qquad (1)$$

where $x=X^TW_X$, $y=Y^TW_Y$, $C_1=[1\ 0]$, $C_2=[1\ 0]$, and λ_j (j=1,2,3,4,5,6) are Lagrange multipliers, is proposed to find the maximum correlation coefficient while the variance of weights are constrained to 1 and the phase information can be constrained within ($0,90^o$) ($W_Y(1) \geq 0$ and $W_Y(2) \geq 0$). In fact, W_Y implies the phase information of the combined signal (i.e., $\arctan(W_y(2)/W_y(1))$). In this study, the flexible phase information within (θ_k-45^o, θ_k+45^o) is embedded in CCA-NN by means of constraining W_Y.

2.2. Offline Data Analysis

Six health subjects participated in the experiment where a visual stimulator presenting 6 frequency-tagged flickers (17.14 Hz, 15 Hz, 13.33 Hz, 12 Hz, 10 Hz and 7.5 Hz) was used. All subjects were indicated to gaze at one of 6 flickers in turn. Each dataset was divided into training set (for the phase information calibration) and testing set. s-CCA, p-CCA, and CCA-NN were applied in this offline data analysis respectively.

Table 1. *Offline classification accuracy and phase deviation of the combined signal.*

Subject	*Classification accuracy*			*Phase deviation*		
	s-CCA	*CCA-NN*	*p-CCA*	*s-CCA*	*CCA-NN*	*p-CCA*
S1	94.4%	99.1%	99.1%	77.1^o	34.9^o	0
S2	96.3%	98.2%	98.2%	76.2^o	33.0^o	0
S3	75.9%	79.6%	75.0%	75.6^o	40.4^o	0
S4	79.6%	89.0%	82.4%	76.3^o	34.0^o	0
S5	79.6%	82.4%	71.3%	75.5^o	34.8^o	0
S6	96.3%	95.4%	85.2%	75.3^o	60.4^o	0
Average	87.0%	90.6%	85.2%	76.0^o	39.6^o	0

3. Results and Discussion

In Table 1 it can be found that CCA-NN can achieve the best classification accuracy. The average phase deviation around 40^o indicates that the phase information of the combined signal can be constrained in a small range in CCA-NN. One interesting finding is that the large phase deviation seems to degrade the improvement (S6).

In summary, the phase constraint in s-CCA is too loose but in p-CCA it is too rigid. CCA-NN is the most generalized as it is able to constrain the phase in a selected range. The preliminary results show that CCA-NN can achieve the highest enhancements in terms of classification accuracy. Future work may include investigations on several problems. First, the convergence speed of CCA-NN is too low for an online application. Second, in the above experiment all the flexible phase information is constrained within (θ_k–45^o, θ_k+45^o) but this interval should actually be adapted to the measured SSVEPs.

Acknowledgements

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Comparison of P300 Responses in Auditory, Visual and Audiovisual Spatial Speller BCI Paradigms

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Abstract. The aim of this study is to provide a comprehensive test of three spatial speller settings, for the auditory, visual, and audiovisual paradigms. For rigour, the study is conducted with 16 BCI-naïve subjects in an experimental set-up based on five Japanese hiragana characters. Auditory P300 responses give encouragingly longer target vs. non-target latencies during the training phase, however, real-world online BCI experiments in the multimodal setting do not validate this potential advantage. Our case studies indicate that the auditory spatial unimodal paradigm needs further development in order to be a viable alternative to the established visual domain speller applications, as far as BCI-naïve subjects are concerned.

Keywords: EEG, P300, auditory evoked potentials, multimodal BCI

1. Introduction

Contemporary brain computer interface (BCI) paradigms rely mostly on unimodal approaches [Wolpaw and Wolpaw, 2012]. Recently proposed solutions enhance the existing paradigms by adding spatial stimuli variability [Halder et al., 2010; Schreuder et al., 2010; Muller-Putz et al., 2006; van der Waal et al., 2012] in order to augment the brain-computer interfacing comfort or to boost the information transfer rate (ITR) achieved by the users. We tested this with 16 BCI-naïve subjects, in a simple five Japanese hiragana (a i u e o) spatial speller task to compare the interfacing accuracy variability and the users' subjective comfort. In order to do so, we designed three spatial tasks with visual letters and synthetic vowel representations originating from the congruent spatial directions using a virtual sound panning technique. We compare the results based on unimodal and bimodal spelling experiments and draw conclusions for possible future research directions.

2. Material and Methods

In the experiments reported in this paper, 16 BCI-naïve subjects took part (mean age 21.81 with a standard deviation of 0.75). All the experiments were performed at the Life Science Center of TARA, University of Tsukuba, Japan. The online EEG BCI experiments were conducted in accordance with the WMA Declaration of Helsinki - Ethical Principles for Medical Research Involving Human Subjects. The subjects of the experiments received a monetary gratification. The 200 ms long spatial unimodal (visual or auditory) or bimodal (audiovisual) stimuli were presented from five distinct spatial locations. In the case of visual and audiovisual speller paradigms, large size hiragana characters were flashed one at a time on a big computer display positioned in front of the subject (as in a usual oddball based P300 visual speller). In the case of the auditory modality, we designed a vector based sound amplitude panning application, which positioned a virtual sound image at a spatial location congruent with a visual letter (positioned at -45°, -22.5°, 0°, 22.5°, and 45° in front of the head). Each subject first conducted a short psychophysical test with a button press response to confirm understanding of the experimental set-up in each modality. During the online BCI experiments, the EEG signals were captured with a 16 active electrodes EEG amplifier system, g.USBamp by g.tec. The electrodes were attached to the following head locations Cz, CPz, POz, Pz, P1, P2, C3, C4, O1, O2, T7, T8, P3, P4, F3, and F4, as in the 10/10 extended international system (see topographic plot in Fig. 1). The ground and reference electrodes were attached at FCz and the earlobe respectively. The recorded EEG signals were processed by the in-house enhanced BCI2000 application using a linear discrimination analysis (LDA) classifier with features drawn from 0-600 ms event related potential (ERP) intervals. The sampling frequency was set to 512 Hz, the high pass filter at 0.1 Hz, and the low pass filter at 100 Hz, with a power line interference notch filter set in the 48-52 Hz band. The inter-stimulus interval (ISI) was set to 500 ms and each stimuli length was 200 ms. The subjects were instructed to spell five random sequences of hiragana letters, which were presented visually, audibly or audiovisually in each session respectively. Each target was presented ten times in a single spelling trial and the averages of ten ERPs were later used for the classification in order to make the experiment easier for novices.

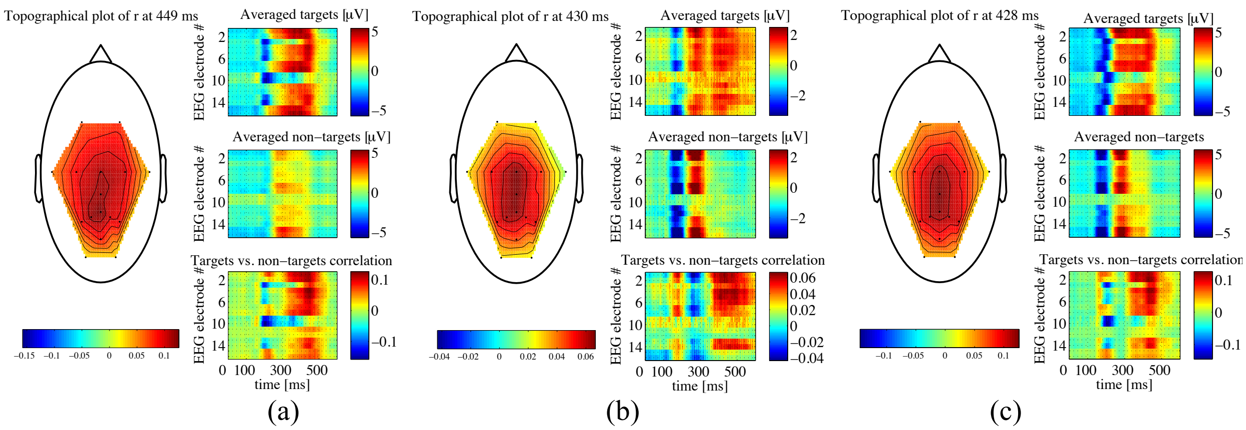

Figure 1. *The averaged ERP responses of the 16 BCI-naïve subjects taking part in the experiment. Each panel (a), (b), and (c) presents topographical maps of target vs. non-target response correlation coefficient distributions at the most discriminative latency. The averaged ERPs are also presented separately, together with correlation coefficient time series on the right side of each panel. Panel (a) presents visual speller results; (b) auditory; and (c) audiovisual. The interesting "longer" P300 averaged response deflection visualized in the top panel (b), and in the correlation time series, was not reflected in better accuracy scores (see Table 1). The EEG electrode on the vertical axes is shown in the right panels. Electrode order is Cz, CPz, POz, Pz, P1, P2, C3, C4, O1, O2, T7, T8, P3, P4, F3, and F4.*

3. Results and Discussion

The averaged ERP responses from the 16 BCI-naïve subjects are presented in Fig. 1 for the three tested modalities. The results shown in panel (b) of the Fig. 1 are encouraging, since a more distinct (longer latencies) P300 response is observed in the auditory unimodal paradigm. Unfortunately, this observation could not later be confirmed in the form of correct spelling accuracies in the online BCI experiments reported in Table 1, where the classical visual unimodal paradigm still resulted in the best scores. The topographic plots presented in Fig. 1 confirm the classical P300 response scalp positions with more localized distributions for auditory unimodal experiments. The preliminary, yet encouraging results presented call for more research on spatial auditory BCI paradigms in order better to utilize the encouraging "longer" P300 response.

Table 1. *Summary of the online BCI interfacing results with the 16 naïve subjects in auditory, visual and audiovisual modalities.*

Modality	*Mean accuracy*	*Standard deviation*
Auditory	52.5%	27.2%
Audiovisual	91.3%	12.6%
Visual	95.0%	11.5%

Acknowledgements

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Listen to the Frog! An Auditory P300 Brain-Computer Interface With Directional Cues and Natural Sounds

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Abstract. A new auditory brain-computer interface (BCI) using natural sounds with directional cues was investigated in a healthy sample. Eleven participants reached within two sessions mean classification accuracies of 70% and 90% and information transfer rates of 4.23 and 5.45 bits/min.

Keywords: EEG, auditory P300, spelling, natural sounds, directional cues

1. Introduction

Severely disabled patients such as in late stage of amyotrophic lateral sclerosis (ALS) might lose eye gaze and thus, the ability to control an eye tracking system for communication. These patients are in the utmost need of brain-computer interfaces (BCIs). The paradigm presented here combined approaches of different auditory BCIs [Furdea et al., 2009; Klobassa et al., 2009; Schreuder et al., 2010; Käthner et al., 2013] by using natural sounds with directional cues as auditory stimuli for a P300 BCI. Natural sounds were selected as they showed best differentiation in a pretest.

2. Material and Methods

2.1. Participants

Eleven healthy participants (mean age 24.27 years, *SD* = 7.14), naïve to auditory BCIs took part in the study.

2.2. Auditory speller with directional cues

In this auditory P300 speller, the letters were arranged in a 5 x 5 matrix. Five different animal sounds coded both rows and columns of the matrix. Directional cues [Käthner et al., 2013] were added to the animal sounds for an easier differentiation. For the selection of a letter, the participant selected in a first step the target row and after a short break the target column of the letter within ten sequences. A visual support matrix was displayed on a screen.

The measurements took place on two consecutive days. After a screening phase (15 letters) in the first session the participants wrote 48 letters in the Copyspelling mode with online feedback in both the first and second session. For the online classification of the second session, the classifier was again trained with the screening runs of the first session.

2.3. Data acquisition and processing

The electroencephalogram (EEG) was obtained from 28 active Ag/AgCl electrodes (Easycap, Germany) at the positions F3, Fz, F4, C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, CP6, P3, P1, Pz, P2, P4, PO7, PO3, POz, PO4, PO8, Oz. The EEG was sampled at 500 Hz and filtered between 0.1 and 30 Hz with an additional notch filter (50 Hz) with a BrainAmp amplifier (Brain Products, Germany). The BCI2000 software in combination with the BrainVision Recorder 2.0 controlled stimulus presentation, recording and online classification.

Stepwise linear discriminant analysis (SWLDA) was used for classification of the data.

3. Results

3.1. Classification accuracy

Mean classification accuracies of the new auditory P300 speller are listed in Table 1. Significantly higher classification accuracies could be found in session two when retraining the classifier with the first three runs of the second session ($Z = -2.67$, $p < .01$) instead of using the screening block of the first session for classification. For the offline classification accuracies the remaining 32 letters had been classified.

Table 1. *Classification accuracies of both sessions.*

	Session 1 (online)	*Session 2 (online)*	*Session 2 (offline)*
% correct letters (*SD*)	76.72 (21.63)	69.64 (13.64)	90.18 (9.27)
% correct selections (*SD*)	86.64 (14.84)	82.73 (9.22)	94.82 (4.85)

3.2. Information transfer rate (ITR)

The online information transfer rate (ITR) in the first session ranged between 0.4 and 6.31 bits/min (M = 4.23 bits/min). After retraining the classifier offline ITR in the second session ranged between 3.84 and 6.65 bits/min (M = 5.45 bits/min).

4. Discussion

The results of the healthy sample show the feasibility of the auditory spelling paradigm with online accuracies of 70% and higher. After retraining the classifier significantly higher accuracies could be reached in the second session. This indicates a training effect which might be based on the higher complexity and workload of the auditory speller. The use of natural sounds in combination with directional cues is promising for auditory spelling. Investigations in patients without and with visual impairments will indicate the applicability in the target groups. In contrast to the first group, patients with visual impairments would not be able to use the visual support matrix. In this group, however, the letter matrix is widely used for communication and only the allocation of the sounds to the rows and columns would need to be learned by the patients.

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Auditory Brain Computer Interface Using Natural Sounds

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Abstract. This study is about user-friendly Brain Computer Interface (BCI) paradigms using Auditory Steady State Response (ASSR). Stimulation methods used in previous ASSR-based BCI studies have a problem that stimulation sounds induce auditory stress to subjects. We replaced high-frequency mono-tone carriers of stimuli with natural sounds. In our experiment, stimuli were composed of two different amplitude modulated natural sounds (water streaming, cicada singing). In stimulation periods, subjects selectively concentrated on one sound. Three subjects participated in the experiment, 50 trials were performed for each subject. Averaged classification accuracy was 90%. Subjects felt more comfortable when using our proposed stimulation than mono-tone carrier stimulation. This result shows that natural sounds are suitable stimulation carriers for long-term ASSR-based BCI applications.

Keywords: EEG, Brain Computer Interface, Auditory Steady State Response, Natural Sound, Auditory Stimuli

1. Introduction

Total locked-in syndrome is a condition in which a patient is aware and awake but cannot move due to complete paralysis of nearly all voluntary muscles in the body, including their eyes [Smith et al., 2005]. Patients with total locked-in syndrome have no way to communicate with the outside world. Recently, there are many studies trying to apply ASSR to BCI [Lopez et al., 2009; Kim et al., 2011]. However, stimuli used in previous ASSR studies were harsh sounds that made subjects uncomfortable when using the system. In this study, we suggest a new stimulation method which can reduce subject's auditory stress.

2. Methods

2.1. Stimuli

Proposed stimuli were composed of water streaming sounds on the left side and cicada singing sounds on the right side. Each side of sound was amplitude modulated with different frequencies. (Left: 38 Hz, Right: 42 Hz)

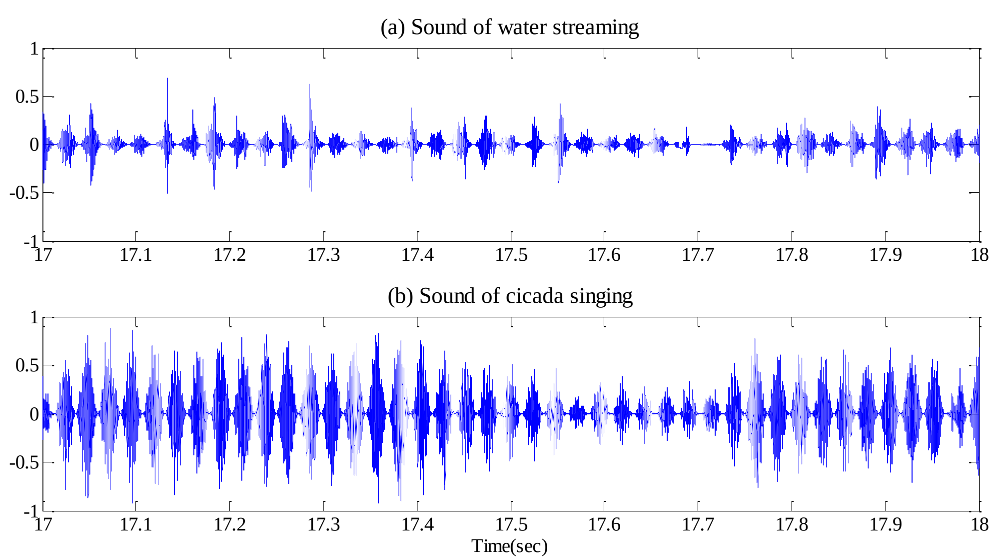

Figure 1. *Amplitude modulated natural sound stimuli. (a) sound of water streaming, (b) sound of cicada singing.*

2.2. Data acquisition

The conventional physiological signal acquisition system (QEEG-8, LAXTHA Inc., Daejeon, Korea) was used for measuring electroencephalogram. EEG signals are measured at electrodes Cz, Oz, T7, T8 (international 10-20 system). Measured analog EEG signals converted to digital signals with 16-bit resolution and 512 Hz sampling rate by National Instruments data acquisition system (NI-USB-6255, National Instruments, Texas, USA). Data storing and analysis were performed using Matlab (Matlab R2012b, The MathWorks Inc., Massachusetts, USA).

2.3. Experimental protocol

Subject sat in comfortable chair wearing earphone (MX400, Sennheiser Ltd, Bucks, UK). One trial was defined as auditory instruction (5 s) and auditory stimulation (20 s). In stimulation period, subject were presented with water streaming sound with 38 Hz modulation frequency on the left ear and cicada singing sound with 42 Hz modulation frequency on the right ear. When stimulation started, subject focused on the sound selectively according to the instruction [Heo et al., 2012].

2.4. Feature extraction and classification

Features were extracted from power spectral density of each electrode. Spectral power of 38 Hz and 42 Hz in each electrode (Cz_38, Cz_42, Oz_38, Oz_42, T7_38, T7_42, T8_38, T8_42) and ratios between the spectral powers of 38 Hz and 42 Hz in each electrode (Cz_38/Cz_42, Oz_38/Oz_42, T7_38/T7_42, T8_38/T8_42) were selected.

For the classification, Linear Discriminant Analysis (LDA) was used. 5-fold cross-validation was performed because of small number of trials. Classification accuracy was calculated with respect to each feature.

3. Results

Table 1 shows best features and their classification accuracy for each subject. Maximum classification accuracy was 92%, minimum accuracy was 88% and average classification accuracy was 90%.

Table 1. *Best features for each subject and classification accuracy*

	Subject #1	*Subject #2*	*Subject #3*
Best Feaures	Cz_38 Hz, Oz_38 Hz	Cz_38 Hz, Oz_38 Hz	Oz_38 Hz
Classification accuracy	0.92	0.88	0.90

4. Discussion

As shown in the results section, natural sounds are available carrier for auditory stimulation in ASSR-based BCI. Users feel more comfortable when using natural sounds than mono-tone sounds used in previous studies. For practical BCI, user comfort is one of the important factors. So, natural sound is more suitable than mono-tone sound for practical long term BCI applications.

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A Novel Approach to Auditory EEG-Based Spelling

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Abstract. We investigated whether listener assisted scanning, an alternative communication method for persons with severe motor and visual impairments but preserved cognitive skills, can be used for spelling with EEG. To that end spoken letters were presented sequentially, and the participants made selections by performing either motor execution/imagery or a cognitive task. The motor task was a brisk dorsiflexion of both feet, and the cognitive task was related to working memory and perception of the human voice. The initial results indicate that task related EEG changes could enable auditory spelling independent of any muscle activity or spatial cues, thus complementing existing auditory scanning protocols and spatial auditory paradigms for spelling applications.

Keywords: EEG, Listener assisted scanning, Motor Imagery, Beta rebound, Working memory

1. Introduction

In listener assisted scanning, messages or letter choices are presented to a person acoustically in a sequential fashion until a selection is made. The goal of this work is to investigate whether listener assisted scanning can be used for spelling with EEG. We hypothesize that, when spoken letters are presented sequentially, the participants can communicate the intended letter by performing either motor execution/imagery or a cognitive task. To test this hypothesis we evaluate brisk feet dorsiflexion execution/imagery [Pfurtscheller and Solis-Escalante, 2009; Müller-Putz et al., 2010] and a cognitive task related to working memory [Ruchkin et al., 1992; Klimesch et al., 2001] and perception of human voice [Xu et al., 2012].

2. Material and Methods

Five healthy people (3 male, 2 female, college aged) participated in this ongoing experiment. Participants gave informed consent prior to the beginning of the experiments and received monetary compensation afterwards.

The EEG was recorded with 29 active electrodes overlying the frontal, central, and parietal scalp areas. The EOG was recorded with three active electrodes, and the EMG from both legs. The EEG amplifiers were set up with a bandpass filter between 0.5 and 100 Hz, and a notch filter at 50 Hz. The EEG/EOG were sampled at 512 Hz, the EMG at 2000 Hz.

Spoken letters of the English alphabet, generated by a text-to-speech program, were presented sequentially (SOA 550 ms including 50 ms pause; 14.3 s for the whole alphabet) through a right headphone for one of several predefined words: "brain","power", "husky" and "magic". For each target letter, the alphabet was presented two to four times. The participants performed one of the following tasks in the copy spelling mode: brisk feet motor execution/imagery triggered by the target letter (ME/MI); discrimination of the target voice's gender and comparison to the following repetition (i.e. whether the target voice's gender has changed or it remained the same, reporting through single/double button press) as a cognitive task; mental repetition of the target letter as a control condition.

We balanced the order of motor and cognitive tasks, and voice of presentation. We randomized the order of words, and pseudorandomized the cognitive task and the control condition. Participants received no feedback. We analyzed the central beta rebound and movement-related cortical potential (MRCP) in the motor tasks, and late positive component (LPC), slow negative wave, as well as frontal theta band oscillations in the cognitive task.

For event-related potential (ERP) analysis we defined a single epoch as 1250 ms following onset of a spoken letter, baseline corrected to preceding 250 ms. The epochs were bandpass filtered between 1 and 12 Hz, downsampled by selecting each 16th sample, and the features were extracted from 9 preselected electrodes (F3, Fz, F4, C3, Cz, C4, P3, Pz, and P4). For each task we classified target epochs versus an equal number of randomly selected non-target epochs. To avoid overfitting we used Bayesian linear discriminant analysis (BLDA) as a classifier, and nested blockwise crossvalidation (leave-one-run-out outer fold, 10 x 5 inner fold, ten repetitions with resampled references). To estimate the influence of eye movement artifacts we applied the same procedure to features extracted from the three EOG electrodes.

To analyze the percentage of power decrease (ERD) or power increase (ERS) relative to a reference interval (0.5 s preceding the stimulus onset), a time-frequency map for frequency bands between 4 and 40 Hz (35 overlapping bands using a band width of 2 Hz) was calculated. Logarithmic band power features, calculated by band-pass filtering, squaring and subsequently averaging over the trials, were used to assess changes in the frequency domain. To determine the statistical significance of the ERD/ERS values a *t*-percentile bootstrap algorithm with a significance level of $\alpha = 0.01$ was applied.

3. Results

The estimated average mean accuracy obtained on outer fold for different tasks is summarized in Table 1. Also summarized in Table 1 are the results of ERD/ERS analysis.

Table 1. *Results of ERP and ERDS analysis. For ERP analysis single trial accuracies (outer fold, mean from ten repetitions) are shown for different tasks. Applying the same ERP analysis procedure to features extracted from the three EOG electrodes only once resulted in significant (p = 0.01) accuracy (marked with an asterisk) . The ERDS analysis for ME and MI task was conducted on a single orthogonal Laplacian derivation centered at Cz electrode position, whereas analysis for COG task was conducted on a single bipolar derivation AFz-Fz.*

Subject	ERP_{ME} [%]	ERP_{MI} [%]	ERP_{COG} [%]	Central β ERS_{ME}	Central β ERS_{MI}	Frontal ϑ ERS
S1	83	59	44	-	-	$+_{p = 0.01}$
S2	75	57	66	$+_{p = 0.01}$	$+_{p = 0.05}$	-
S3	80	54	62	$+_{p = 0.01}$	$+_{p = 0.01}$	$+_{p = 0.01}$
S4	68	45	53	-	-	-
S5	48	61	62	$+_{p = 0.01}$	$+_{p = 0.01}$	$+_{p = 0.01}$
$\mu \pm \sigma$	71 ± 14	55 ± 6	57 ± 9			

4. Discussion

The initial results indicate that task related EEG changes could enable auditory spelling independent of any muscle activity or spatial cues, thus complementing existing auditory scanning protocols [Müller-Putz et al,. 2013] and spatial auditory paradigms for spelling applications[Höhne et al., 2011; Schreuder et al. 2011].

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Motor Imagery BCI Feedback Presented as a 3D VBAP Auditory Asteroids Game

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Abstract. Typically, a brain-computer interface (BCI) relies upon visual feedback which is impractical for those with vision problems, whilst long term use of the system can often become tedious. This study demonstrates the feasibility of using 3D vector base amplitude panning (VBAP) as a technique for presenting auditory feedback in the form of an asteroids avoidance game. Seven healthy participants were presented with both visual then auditory feedback for comparison. Auditory feedback was presented using 1, 2, or 8 loudspeakers. Results show no difference in performance with some subjects scoring markedly better than others.
Keywords: Sensorimotor rhythms (SMR), brain-computer interface (BCI), audio feedback, games, vector base amplitude panning (VBAP)

1. Introduction

Motor imagery (MI) brain-computer interfaces (BCIs) typically present feedback visually which relies upon the vision of the user remaining intact. However, amyotrophic lateral sclerosis sufferers have shown to exhibit ocular instabilities even from the early stage of the disease [Balaratnam et al., 2010]. Similarly, those in minimally conscious or vegetative states may also benefit from feedback methods which do not depend on the visual channels [Coyle et al., 2012]. It may be possible to improve the performance of a BCI by exploiting our inherent ability to localise an auditory event in the free field by adjusting its relative position and hence provide feedback of sensorimotor rhythms (SMR). Our findings show that results are comparable to other feedback modalities hence it is expected that the system will be more appealing to use over longer periods.

2. Material and Methods

Mu and beta rhythm EEG (8-13 Hz) was recorded from 7 healthy participants (6 male, mean ages 26 years ± 6.3, 2 naive) using 3 bipolar channels (C3, Cz, C4, FPz ref.) sampled at 125 Hz. Pre-processing was carried out using a 'neural time-series prediction pre-processing' model which uses self-organising fuzzy neural networks with common spatial patterns to maximize signal separability [Coyle, 2009]. XNA (Microsoft) was used to provide timings and visuals for both groups whilst Max/MSP (Cycling '74) provided auditory feedback. M-Audio AV20 powered speakers produced audio through a low latency audio interface (MOTU Ultralite Mk3). Sessions contained 240 trials (trial = 8 s) (Fig. 1) with audio and visual sessions interleaved. Visual training and feedback followed the classic arrow-ball/basket paradigm (Fig. 1a,b). Run 1 was used to train parameters, run 2 presented feedback whilst run 3 presented an asteroid avoidance game [Coyle et al., 2011]. Each auditory session contained 4 runs (run 1 for training) and mimicked the visual session in timing (Fig. 1). Auditory training presented spoken commands from left or right. One of three types of auditory feedback: single speaker (mono), dual speaker (stereo) or multiple speakers (VBAP) was presented, based on our previous work [McCreadie et al., 2013].

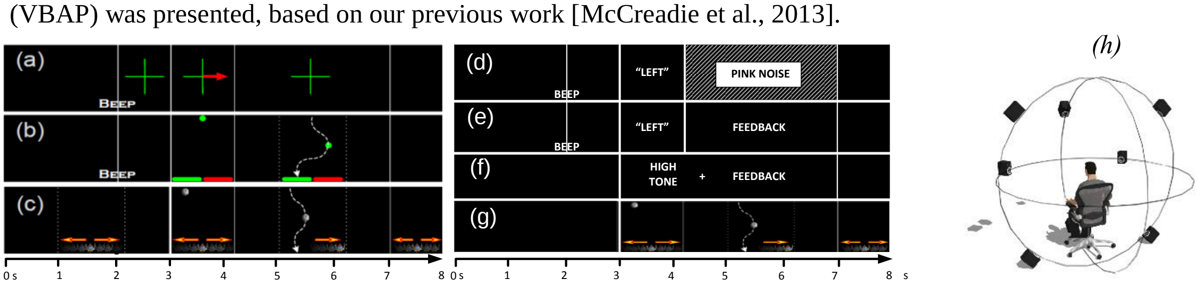

Figure 1. *(a) Visual training with no feedback (b) visual ball and basket (c) visual space ship game (d) audio training (e) stereo audio feedback (f) mono audio feedback (g) audio VBAP space game (h)VBAP speaker layout*.

Mono: The left target was indicated by a sawtooth wave at 196 Hz whilst right was assigned 1661 Hz. Feedback was given by a resonant filtered pink noise (196-1661 Hz) based on the time varying signed distance (TSD) classifier output which was perceived by the listener as an increasing and decreasing pitch to indicate correct MI.

Stereo: Speakers positioned at ±90°θ presented the target as a spoken command ("left"/"right") from the corresponding loudspeaker. Output from the classifier or TSD was indicated by continually varying the azimuthal position of pink noise between ±90°. The addition of the broadband noise ensured that adequate spectral information was contained both above and below 1.5 kHz.

VBAP: Similar to the visual game, an auditory equivalent was delivered using VBAP. Speakers were positioned at: 90°θ 50°ϕ, -90°θ -32°ϕ, -45°θ 0°ϕ, 0°θ 50°ϕ, 0°θ -32°ϕ, 45°θ 0°ϕ, 90°θ 50°ϕ, 90°θ -32°ϕ (Fig. 1 (h)). The listener assumed control of a virtual auditory spacecraft similar to the visual session. The asteroid appeared from above and fell towards the ground over time with a beacon sound reinforcing the target direction, the aim being to avoid a collision and MI causing the spacecraft to move left or right. The sound of the asteroid was represented as a pink noise mixed with a tone which swept in frequency from 1.5 kHz to 150 Hz then summed (to simulate a falling sound) before passing through a tremolo effect set to an inverse sawtooth (freq.7.5 Hz). The target was indicated by a beacon sound (1 kHz sine wave) which occurs at either 90°θ, 0°ϕ or -90°θ, 0°ϕ combined with pink noise pulsed at 4 Hz. Each pulse lasted 30 ms with a fade-in and fade-out time of 5 ms.

3. Results and Discussion

Results are presented as the offline mean classification accuracy (mCA) from a 5-fold CV performed on individual runs, each run consisting of 60 trials (30 left, 30 right). Table 1 shows results from each subject obtained from every type of run. Whereas some subjects clearly perform better than others, all participants perform well overall with only two scores below 70%.

Table 1. *Subject classification accuracy means for each run.*

	Visual				Auditory				
Subject	Run1	Run2	Game	Mean	Mono	Stereo	VBAP	Mean	Mean
A	74.33	73.00	72.40	**73.24**	71.33	72.50	71.00	**71.61**	**72.43**
B	68.83	76.67	74.20	**73.23**	76.60	79.07	78.20	**77.96**	**75.59**
C	74.67	73.80	73.67	**74.05**	72.67	72.00	69.59	**71.42**	**72.73**
D	83.67	81.03	83.00	**82.57**	81.67	82.17	82.10	**81.98**	**82.27**
E	76.27	73.47	73.73	**74.49**	73.20	79.43	80.00	**77.54**	**76.02**
F	78.13	76.47	80.53	**78.38**	76.47	70.34	71.13	**72.65**	**75.51**
G	72.73	75.60	72.75	**73.69**	74.63	73.43	73.25	**73.77**	**73.73**

Mean classification accuracy results were calculated for each group and for every session. A t-test revealed no significant difference in performance between groups with the auditory group showing greater improvement. An ANOVA revealed no significant difference between the CA of any of the runs.

All subjects performed above the criterion of 70% although some outperformed others by the end of the experiment. Whilst no difference in performance between groups was observed, the auditory group showed the greatest improvement over time. Auditory feedback offers the visually impaired an alternative method of BCI control and freeing up the visual pathway may be advantageous for the visually able who need not focus on visual feedback. The development of a spatial auditory VBAP BCI paradigm creates a path to further advancement for more innovative multidimensional games which it is expected will go a long way to alleviating the tedium often experienced in longer training sessions.

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Optimized P300-Based BCI Using a Multi-Faces Pattern

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Abstract. Recent work showed that the face paradigm was superior to the canonical flash approach that has dominated P300 BCIs for over 20 years. However, face repetition effects may occur if the same face was shown repeatedly. Repetition effects would decrease the amplitude of ERPs, and thereby decrease BCI classification accuracy. To decrease these repetition effects, two new stimulus patterns called “masked face pattern” and “multi-faces pattern” were presented in this paper. Two other stimulus patterns (canonical flash pattern and face pattern) were also evaluated as control conditions. The multi-faces pattern yielded the highest accuracy and information transfer rate among four patterns and succeeded in improving the face pattern.

Keywords: BCI, ERP, Face pattern, Masked face pattern, Multi-faces pattern, face repetition effects

1. Introduction

It has been proved that face stimulus is better than flash stimulus [Kaufmann et al., 2011]. However, all face paradigms only use the same face as stimulus, which will lead to face repetition effects [Neumann et al., 2008]. Face repetition effects will decrease the performance of ERP identification. The First goal of this paper is to survey the method to avoid the face repetition effects, which could improve the performance of ERP-based BCI system. [Martens et al., 2006] proved that masked face could decrease the face repetition effects. Based on this result, a new paradigm using masked face was designed for BCI system. Another paradigm using multi-familiar faces was also presented to avoid face repetition effects. The second goal of this paper is to decrease the error motion of key functions.

2. Material and Methods

Two healthy subjects (aged 21 and 27) participated in this pilot study. Eight more subjects are being studied in an adapted online version, and additional details will be submitted as a full journal paper. EEG signals were recorded with a 64 channel g.USBamp and a g.EEGcap with a sensitivity of 100 µV, band pass filtered between 0.1 Hz and 30 Hz, and sampled at 256 Hz. 62 channels were used (see Fig. 1A).

Fig. 1B shows the display presented to all subjects, which was a 3 × 4 matrix with blue boxes. Gray function icons are beside the boxes. Instead of grouping the flashed characters into rows and columns, we developed an alternate flash pattern approach based on binomial coefficients [Jin et al., 2010]. We used the set of k combinations ($k = 2$) from set $n = 12$. Only the gray cells (3 × 4 matrix) flash and are used as function buttons (see Fig. 1C). Hence, there were twelve flash groups, and between one and three boxes changed during each flash (see Fig. 1B and 1C). There were four conditions in the study, which differed only in the way that these boxes changed. In different conditions, some of the boxes would change by changing to green, changing to a face, changing to a masked face, or changing to randomly selected faces (one of 5 different faces) (see figure 1D). Most face images were obtained by photographing the people who the subjects considered familiar. In all conditions, the delay between the onset of each flash pattern was 250 ms.

In systems to control wheelchairs or other mobile robots, “forward” and “backward” are critical functions. Errors could be especially dangerous. Non-targets in the same flash group as the target are more likely to be incorrectly classified as target than other non-targets [Townsend et al., 2010]. In Fig. 1C, “5, 11” and “6, 12” represent icons to move the system continuously forward or backward. To decrease errors in these functions, flash groups 5 and 11 are only related to one icon (forward) and flash groups 6 and 12 are only related to one icon (backward) (see Fig. 1B and 1C). Our new design prevents false positives that result from incorrectly selecting a non-target icon within the same flash group as either of these critical functions.

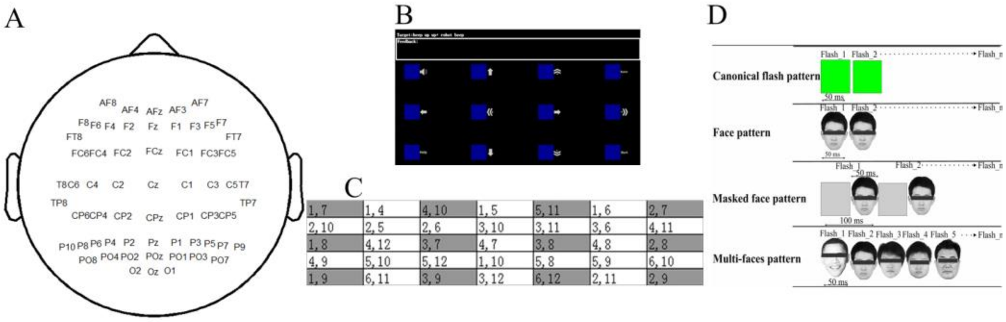

Figure 1. *Screen, configuration of stimuli, stimuli pattern and electrodes Only the gray boxes in panel C were relevant to the 3x4 matrix used in this work; the white boxes are presented only for comparison with our earlier work. In panel D, faces are portrayed with censor boxes (during the experiment, censor boxes were not presented).*

3. Results

Since this is a study in progress, we present preliminary offline results from two subjects. Fig. 2 shows that the multi-faces pattern yields better performance than the other patterns. This result suggests that face repetition effects could be decreased by using multiple faces as described here, and that further improvements are likely.

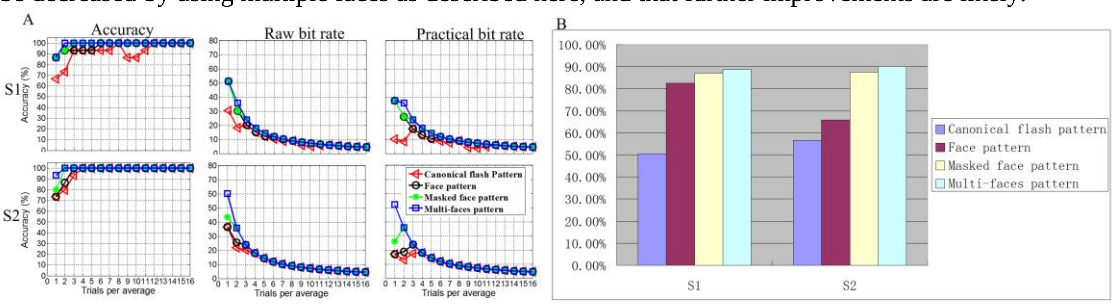

Figure 2. *A: classification accuracy, raw bit rate (RBR) and practical bit rate (PBR) based on offline data; B: classification accuracy using single trials.*

4. Discussion

This paper introduces two improvements. (1) Using the multi-faces pattern could decrease face repetition effects and improve the performance of BCI systems. (2) Our new design reduces the likelihood of erroneously selecting icons that correspond to critical functions, such as wheelchair movement.

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A New Stimulation Method of Virtual Speller for Simultaneous P300 and SSVEP Responses

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Abstract. In this paper, we introduce a new hybrid stimulation method for virtual speller. The virtual speller is desinged to elicit P300 and SSVEP reponses simulanously. It is 6-by-6 matrix and the column is filckering specific frequency and the row is turned off in a random order. The result of experiment with a healthy male subject shows the possiblity of the development of hybrid based BCI system.

Keywords: P300, SSVEP, hybrid paradigm, virtual speller, EEG

1. Introduction

There has been emerging interest in hybrid paradigm for brain-computer interface (BCI) recently. [Pfurtscheller et al., 2010; Allison, 2010; Leeb, 2010] A hybrid car has two engines: internal combustion engine and electric motors. They cover their weakness to each other, so the hybrid car has enhanced energy efficiency and reduced CO_2 output as a result. On the other hand, for BCI system, there are many paradigms such as P300, SSVEP, ERD, motor imagery and etc. They also have their own weakness respectively. For example, it takes longer time for averaging in P300 paradigm and the number of flickering frequency is needed as many as targets in SSVEP paradigm. They also can be combined to each other to cover the weakness and to enhance the performance of BCI system.

In this study, we designed a hybrid virtual speller which is combined P300 and SSVEP paradigm. With proposed speller, for 36 targets selection, only 6 different frequencies is used for SSVEP and only row is used for P300 response, which means no more time needed to column averaging. The proposed virtual speller covers their own weakness, so it could make BCI system enhanced ITR or accuracy as a hybrid car.

2. Material and Methods

2.1. Virtual Speller

Virtual speller is composed with 6 x 6 matrixes. Each target has a LED bar covered with translucent paper which is respective English alphabets or numbers printed on it. (see Fig. 1). Each column of the matrix is flickering specific frequency (25, 45.45, 19.61, 16.16, 29.41 and 35.71 Hz) and each row is turned off in a random order. Random row is turned off for 200ms and inter stimulus interval(ISI) is 400 ms. The size of individual target is 7x4.5 cm and matrix is 54x38.8 cm.

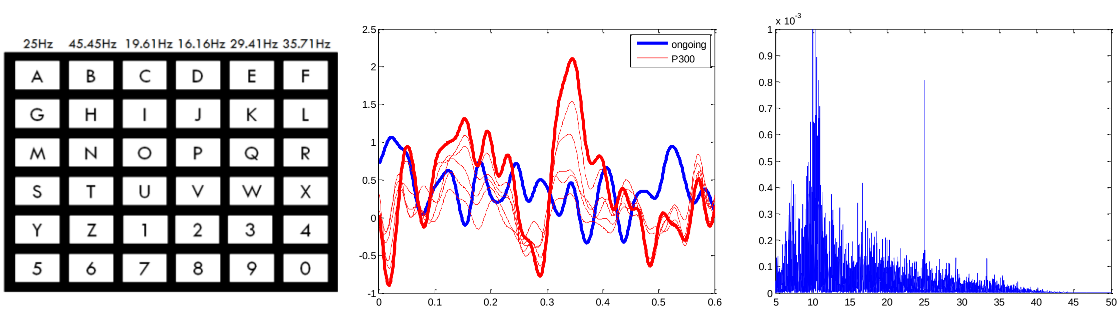

Figure 1. *Virual Speller(in the left), averaged 60 times of P300 response in Pz(bold red) and ongoing EEG (blue) in the middle, SSVEP respones of 25 Hz in the occipital region (in the right). The P300 and SSVEP responses are acquired at the same time with the hybrid speller.*

2.2. Signal Acquisition

EEG signal was acquired at Fz, Cz, Pz, Oz, P3, P4, O1 and O2 with a multi-channel EEG acquisition system (LXE3208, Laxtha Inc., Daejeon, Korea). EEG signal and trigger signal from virtual speller which is controlled by a MCU are digitalized by NI-DAQ system. Data were stored and processed by MATLAB R2012b.

2.3. Experiment

One healthy subject (31 year old, male) is participated in this experiment. He is asked to gaze individual target (A, B, C, D, E) in the matrix for 3 minute respectively and to rest for 30 seconds.

3. Results

P300 response at Pz and SSVEP at O1 are shown in Fig. 1 when the subject was gazing letter ‘A’. Positive peak of 60 times averaged P300 is shown in bold red line in the middle of figure. Also, SSVEP response of 25 Hz is shown in the right of it.

4. Discussion

We introduced a hybrid simulation method for virtual speller for BCI. It is designed to elicit P300 and SSVEP simultaneously. We found out that P300 and SSVEP responses can be acquired in the same time. With proposed speller, the number of frequency for SSVEP responses can be reduced to 6 and averaging time also reduced by half for 36 targets. However, it is necessary more experiment with more subjects to generalize the result and online and evaluation of performance of proposed system with such as ITR or accuracy.

Acknowledgements

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Error Analysis of the Region-Based P300 BCI

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Abstract. Recently, there have been several attempts to improve the P300-based brain computer interface (BCI) paradigm by going beyond the matrix-based or row/column P300 design introduced around 25 years ago. Region-based paradigm was introduced as an efficient paradigm for eliciting P300 in 2008. In this paradigm, characters are presented in seven regions on the screen and regions are flashed randomly in two levels. In this region-based paradigm 49 characters, numbers and signs are presented. The efficiency and acceptability evaluating parameters such as information transfer rate, accuracy and adjacency error showed improvement by implementing region-based paradigm in several other publications. In this paper, an analysis is performed on the accuracy of each region for the data collected from 10 subjects.

Keywords: EEG, BCI, P300, Paradign Design, Region-based P300

1. Introduction

In P300 BCI systems, spelling based on the paradigm introduced by Farwell and Donchin [Farwell and Donchin, 1988] has been one of the most discussed and used paradigms. In this Row/Column (RC) paradigm, a 6 by 6 matrix of characters and symbols was presented for spelling application, in the way that the rows and columns were flashed randomly based on an oddball paradigm. P300 BCI has also been used in other applications such as virtual environment, smart home, and wheelchair control [Su et al., 2011; Edlinger et al., 2011; Rebsamen et al., 2008]. In an error analysis done in [Fazel-Rezai, 2007], it was shown that there is human error in generating false P300 due to adjacency of character in the matrix-based paradigm. Therefore, a region-based (RB) paradigm was introduced [Fazel-Rezai and Abhari, 2008; Fazel-Rezai and Abhari, 2009]. Several other paradigms (e.g., [Townsend et al., 2010]) have also been investigated to improve the performance of the P300 BCI in which the paradigm is not based on row/column flashing. In our other papers, RC and RB paradigms are compared and adjacency problem of RC paradigm is discussed [Fazel-Rezai, 2007; Gavett et al., 2012], however in this paper the objective is to investigate the adjacency problem in RB paradigm.

2. Material and Methods

The idea of RB paradigm [Fazel-Rezai and Abhari, 2008] is to have flashes of several regions instead of rows and columns. In the first level (level 1) of the paradigm 49 characters, numbers and signs are presented in seven regions. In each region, 7 characters are located. Regions are flashed randomly and as one region is selected, the paradigm goes to the second level (level 2). In the level 2, the 7 character of the selected region are placed in the region with the same pattern. The placement of the regions is shown in Fig. 1. Similar to the Farwell and Donchin paradigm, the user is instructed to attend a specific character in one of the 7 groups while each group of 7 characters randomly flashes. After several flashes of each group the desired group is identified. In the second level, individual characters of the selected group are distributed into the 7 regions. Similarly to the first level, different regions are flashed while the subject attends to one region (i.e., character). The desired character is selected by identifying one of the 7 regions. In this paper, we performed an analysis to determine if there is any difference in error of each region and if there is any adjacency similar to what was reported in row/column paradigm [Fazel-Rezai, 2007]. For this purpose the experiment was done for 10 normal subjects (2 females) ranging in age from 19-29. Subjects were explained the procedure, asked to read and sign the consent form obtained from the Institutional Review Board (IRB) from the University of North Dakota (UND). Subjects were seated in front of a computer screen, and were told to relax and avoid any unnecessary movements during testing. Products of Guger Technologies (g.tec) were used, including g.GAMMAbox and g.USBamp for recording and g.BSanalysis for classification. MATLAB and Simulink were used for the paradigms on the computer. Eight channels, FZ, CZ, PZ, OZ, P3, P4, PO7, and PO8, based on 10-20 system

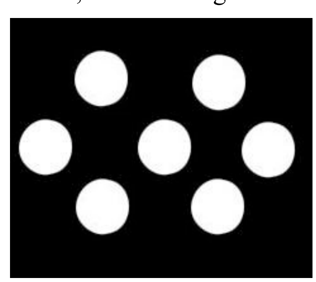

Figure 1. *Regions.*

were utilized for signal recording. An electrode at the FPZ location was considered as a ground channel and one electrode on the right mastoid was considered as a reference. Subjects had calibration and training with spelling two words ‘WATER’ and ‘LUCAS’. The training repeated three times base on linear discriminant analysis (LDA) classifier. After training, the word ‘PEBBLE!’ appeared on top of the screen and subjects’ task was to copy spelling all characters. Each character was flashed six times. After the character was selected, it was shown under the intended character. After finishing the first word, subjects copy spelled ‘MX85+Z&’. The characters of the words were selected in the way that all regions would be selected four times. The time required for spelling each character was 21 seconds. Subjects filled out two questionnaires for evaluation of their fatigue level, mood, and feelings.

3. Results

The errors in a row/column paradigm were reported in a matrix of numbers where at the center of the matrix all correct spelling and to the left/right and top/bottom of the center errors were displayed [Fazel-Rezai, 2007]. This approach was followed later by several authors [Townsend et al., 2010; Fazel-Rezai and Abhari, 2008], which has advantage that the adjacency problem can be clearly identified in the paradigm. In a similar analogy, the correct detection of target and the errors for a region-based paradigm for 10 subjects are displayed in Fig. 2. The center circle with black background shows the target region and surrounding circles show the error in each region based on the distance from the target region. The difference of error for two words had less than 1% difference. The average accuracy of all 10 subjects for both words was 84.06% and 80.96% for levels 1 and 2, respectively.

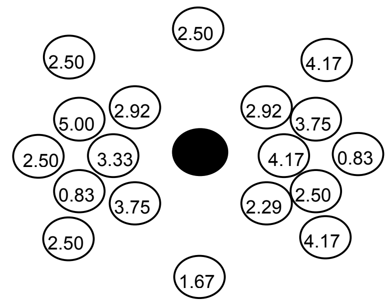

Figure 2. *Region error distribution (%).*

4. Discussion

A similarity with less than 1% difference for two words shows that there is no difference in spelling a word with specific meaning and a collection of characters and symbols. Comparing accuracy obtained for level 1 and level 2 showed no significant difference. The distribution of the errors in Fig. 1 also shows that there is no dominant region with high error. Therefore, compared to the row/column paradigm that its accuracy can be affected by adjacent characters due to false generation of P300, the adjacency did not have any effect of the accuracy in the region based paradigm.

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Effects of Varying Relevant Content in a Fixed BCI Matrix

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Abstract. Wadsworth Center has developed a portable, 8-channel EEG-based BCI system for independent home use by people with ALS and other disorders. This use is enabled by Wadsworth BCI-360, a BCI2000-based software package that ensures reliable operation of the BCI device and provides a range of applications. In BCI-360, the calibration exercise and many of the P300-based applications depend on a 9 x 8 matrix containing 72 cells and 72 items. Other applications may require, and users may prefer, far fewer matrix items. Varying the number of cells in a matrix alters the target-to-target interval (TTI), and changes in TTI have been associated with changes in classification accuracy in a P300 copy-spelling task. Here, we have examined the effects of content (item relevance and number) using a 72-cell, 9 x 8 matrix with fixed TTI on BCI accuracy and P300 amplitude. Initial results from eleven healthy subjects show that content are associated with small changes in the evoked response and classification accuracy. A standard matrix size would simplify design and reduce the training and support needed for independent use of the BCI system.

Keywords: *EEG, ERP, BCI, TTI, Home Use, Augmentative Communication, BCI Applications, Matrix Size*

1. Introduction

Brain-Computer Interfaces (BCIs) allow real-time communication and control through novel neural outputs [Wolpaw and Wolpaw, 2012]. Studies of the P300-based BCI are, by now, quite numerous and many of these studies demonstrate use of the electroencephalographic or EEG-based method by individuals with disabilities [Sellers et al., 2012]. This method requires minimal training and little calibration data, is relatively robust, and provides success for a large portion of the population [Guger et al., 2009]. Studies have demonstrated that longer target-to-target intervals (TTIs), longer inter-stimulus intervals (ISIs), and smaller target-to-non-target (T/NT) ratios can increase the amplitude of the P300 [Gonsalvez and Polich, 2002; Sellers and Donchin, 2006]. McFarland demonstrated that increasing the TTI, on average, increases both the P300 amplitude and the accuracy on a P300 copy-spelling task [McFarland et al., 2010]. The BCI-360, a BCI2000-based software package that ensures reliable independent operation of the P300-based BCI home system, depends on a 72-item, 9 x 8 matrix for the calibration task, WordPad and Email applications. Other applications use matrices with fewer cells. As a consequence, the number of stimuli presented for each trial is reduced; the T/NT ratio is increased; and the TTI is decreased. In this study, we examine only the effects of reduced item number and relevance in a 9 x 8 matrix with a fixed TTI on calibration accuracy and P300 amplitude to determine if a standard matrix can be applied to the home system.

2. Material and Methods

Data are comprised of eight channels of EEG collected from eleven healthy subjects. The EEG was amplified (g.USBamp); digitized at 256 Hz; and band-pass filtered at 0.5-30 Hz. All aspects of the experiments were controlled by BCI2000. The stimuli were presented in groups of cells, assembled in pseudo-random fashion according to the checkerboard paradigm [Townsend et al., 2012], flashed at 8 Hz in a 9 x 8 matrix of 72 cells.

Five displays were configured in the 9 x 8 matrix as follows: A) Standard 72 relevant items; B) 36 relevant items surrounded by 36 dashes for non-relevant items; C) 36 relevant items surrounded by 36 blank cells for non-relevant items; D) 18 relevant items surrounded by 54 dashes for non-relevant items; and E) 18 relevant items surrounded by 54 blank cells. Displays A, B, and D illuminated six items in a group. Displays C and E illuminated one to five items in a group. Ten target characters (1;20!45:Z3) were cued in the same order twice for the five displays over two separate days for a total of 40 items per display. Each target item was flashed ten times in the 120 stimuli presented per character. The TTIs for all displays ranged from 250 to 2750 ms. The initial display for subjects was randomized. Classification coefficients were derived from all five displays using the stepwise linear discriminant function (SWLDA) [Krusienski et al., 2008] using day-one data. System accuracy was defined as classification of day-two data using these coefficients. Coefficients derived from day-one Display A data were also applied to Day Two data from the four other displays.

3. Results

The average accuracies for each condition when coefficients derived from Day One data were applied to the same condition on Day Two were the following: A) 72%; B) 73%; C) 80%; D) 75%; and E) 76%. Accuracies for the reduced content matrices (B through E) were not significantly different from the standard 9 x 8 matrix (Display A). Coefficients generated from Display A (Day One) were applied to the Day Two data from the four remaining conditions. The averages for each display were: B) 73%; C) 76%; D) 76%; E) 73%.

The average peak amplitude of the target trials for the P300 (bin: 230-450 ms) at Pz for each display are as follows: A) 1.97 µV; B) 2.83 µV; C) 2.26 µV; D) 2.36 µV; E) 2.56 µV. The amplitudes for the reduced content matrices (B through E) were not significantly different from the 9 x 8 matrix (Display A). The latency range of the P300 for all the conditions fell between 230 ms and 324 ms (mean 251 ms). The greatest mean amplitude for the P300 was noted at location Cz for the combined Blank Displays, C and E (Fig. 1). The greatest amplitude for the Late Negativity (LN) (bin: 400-800 ms) was for Display A (72-item, 9 x 8) at location Cz.

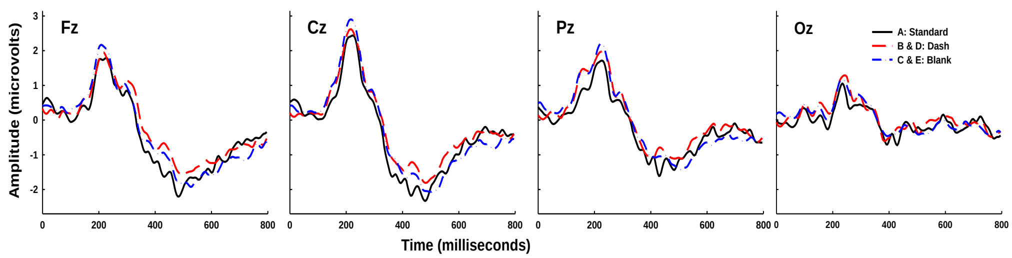

Figure 1. *Averaged waveforms for target trials for all eleven subjects. The solid (black) lines represent responses to the standard Display A (72 items); the dashed (red) line responses to Displays B and D (Dash Displays), and the dot-dash (blue) line to Displays C and E (Blank Displays).*

4. Discussion

In sum, the average amplitude of target P300 increased and classification accuracy improved slightly with reduced content in a 9 x 8 matrix. These changes were not significant. These preliminary results suggest that a standard matrix may be an acceptable alternative to reducing matrix size across P300-based applications in BCI-360. A standardized matrix size, with a consistent TTI, may lead to more stable performance and, thus, reduce training and support for independent users. Further studies of BCI applications use with home-users and with both fixed and variable TTIs will be needed to confirm these results.

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BCI Using Space-Time-Frequency Coding Protocol

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Abstract. Many recent studies introduced some novel protocols for achieving further improvements in brain-computer interface (BCI). We argued that BCI protocol, one of the most significant issues in BCI study, should adopt the strategy of space-time-frequency (STF) coding which would highly enhance its efficiency. In this paper, we presented our work on the parallel BCIs which is the preliminary stage of STF coding applied in BCI. Two P300+SSVEP-B sub-systems with different frequency codes shared the same time code in the proposed BCI. Four subjects participated in this study and performed the offline experiment. The result showed the highest information transfer rate (ITR) of 139 bit/min with an average of 95.65 bit/min. It demonstrated that the parallel BCIs were effective in boosting bit rate, and the STF coding protocol was a promising approach to improve BCI communication.

Keywords: Brain-Computer Interface, BCI Protocol, Space-time-frequency coding, P300, SSVEP-B

1. Introduction

Recently, brain-computer interfaces (BCIs) have got tremendous progress in mental control. The achievements are mainly based on the conventional BCI protocols, i.e., P300, SSVEP and Motor imagery. However, these BCI protocols have almost reached their limits in communication ability by current technology [Ahi et al., 2011; Volosyak, 2011], although efforts are being made from different aspects, such as hardware and algorithms [Nicolas-Alonso and Gomez-Gil, 2012]. Therefore, researchers begin designing novel BCI protocols for further progress. For reactive BCIs, the coding method is the first reason determining the accessible bandwidth of communication. In this paper, we review BCI protocols and argue that the space-time-frequency (STF) coding is a promising protocol to boost ITR of BCI.

Currently, most BCI protocols adopt either time or frequency strategy. The time coding strategy discriminates the commands by coding the epoch of stimuli, such as P300, cVEP [Bin et al., 2011] and mVEP [Guo et al., 2008], while the frequency coding strategy uses orthogonal frequencies to code commands, such as SSVEP and SSmVEP [Xie et al., 2012]. In addition, the space coding strategy has been proved to be available in BCI system [Andersson et al., 2012; Treder et al., 2011]. However, so far there is no report on joint coding strategy over space, time and frequency for BCI protocol.

STF coding, as a potent approach for high speed communication, is considered to jointly use of space, time and frequency coding strategies [Liu et al., 2002]. To approach STF coding of BCI, we first develop a novel BCI system called the parallel BCIs which are based on the time-frequency coding protocol. The parallel BCIs consist of two independent P300+SSVEP-B subsystems [Xu et al., 2013]. Frequency codes are different with both subsystems but the same for characters in each, while time codes are the same for subsystems but different with characters in each. Therefore, each character has a specific code different with others.

2. Material and Methods

In this study, two independent P300+SSVEP-B spellers of different flicker frequencies (15 Hz and 17 Hz) are built by LED stimulators and a FPGA control. Each speller has the same screen consisting of 3 by 3 red light LEDs between which the horizontal and vertical distances are 3.2 cm. The two horizontal screens are 8.3 cm apart and controlled by the FPGA which sends different frequency codes but the same pseudorandom sequence of oddball stimuli to them. LEDs in each speller are extinguished individually with the duration of 200 ms and the ISI was 0ms. Characters are pasted on each LED to make difference.

Four right-handed healthy subjects (23-26 years of age; 2 females) participated in this study. All subjects gave written informed consent. In the experiment, all subjects sat in front of the screens with a distance of 70 cm. They were required to focus on a specified character and to silently count the number of times that the target character was interrupted, until a new character was specified for next selection. All characters would be interrupted once in a stimuli round and five rounds composed a stimuli block. 18 blocks were conducted for each subject. EEG was recorded by 32 electrodes whose location follows 10-20 system. Data were down sampled at 200 Hz for SSVEP classification and 40 Hz for ERP.

3. Results and Discussion

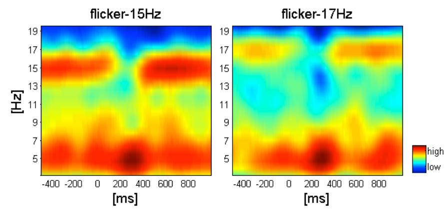

Figure 1. *Typical responses of Oz to different spellers are displayed with time-frequency energy distribution.*

Fig. 1 presents the features of SSVEP-B and ERP by time-frequency analysis. It is obvious that the frequencies of SSVEP and its blocking changes with the flicker frequency while ERPs are relatively steady. The canonical correlation analysis (CCA) was used to discriminate the intent screen by addressing SSVEPs, while stepwise linear discriminant analysis (SWLDA) was adopted to select the attentive character by finding ERPs. To validate the improvement of parallel BCIs, we investigate the accuracy and Wolpaw's ITR in this study. The results show that the average accuracy reaches 87.5% after 1 round and 98.6% after 5 rounds, and the ITR reaches the maximum of 139 bit/min with an average of 95.65 bit/min.

In this study, we investigate the performance of parallel BCIs which code the command set through time and frequency lattice. The results have demonstrated the effectiveness of parallel BCIs in boosting ITR. As there are only two frequency codes used in this work, which may limit the ITR enhancement, more benefits will be obtained by increasing frequency codes.

STF coding is a promising strategy to enhance the BCI communication ability through giving more bandwidth, which has the advantage of single coding strategy used in previous studies. Therefore, designing a proper STF coding strategy is a significant issue in BCI research. And it is also a considerable topic in constructing hybrid BCIs.

Acknowledgements

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BCI-based Operation of Off-the-Shelf Software Applications: Towards a General-Purpose Application Control Framework

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Abstract. Applications for (hybrid) brain-computer interfaces ((h)BCIs) are usually custom-made and adapted to compensate for the low information transfer rates achieved by such devices. Users are consequently not enabled to operate off-the-shelf software applications. Here, we introduce a general-purpose application control framework that allows (i) flexible and easy mapping of (h)BCI outputs to keyboard and mouse inputs and (ii) creating customized graphical user interfaces (GUI) and overlay elements for providing essential visual feedback. We demonstrate the validity of the framework by interfacing the popular puzzle-platform video game Portal2 (Valve Corporation) and a hBCI consisting of 3-class SSVEP and 7-class electromyogram-based (EMG) hand movement detection.

Keywords: EEG, Hybrid BCI, SSVEP, EMG hand detection, off-the-shelf applications, universal control

1. Introduction

Off-the-shelf software applications are typically designed for use with standard physical human-computer interaction (HCI) devices such as keyboard and mouse. Assistive technologies including Brain-Computer Interfaces (BCIs) and hybrid BCIs (hBCI) [Pfurtscheller et al., 2010] usually extract data from user at considerably lower information-transfer rates and provide fewer control signals. Hence, (h)BCI users cannot benefit from the large number of available off-the-shelf applications. To solve this issue, we started developing methods for mapping BCI output signals into keyboard and mouse input (KB&M) for applications, e.g. for the game World of Warcraft (Blizzard, Inc.) [Scherer et al., 2012]. In this paper, we introduce our general-purpose application control (GPAC) framework. The GPAC allows (i) mapping of BCI outputs to KB&M inputs and (ii) creating custom user interfaces (UIs) that can be overlaid to applications and provide essential BCI feedback or stimuli for BCIs that are based on visual evoked potentials (VEPs).

2. Material and Methods

2.1. General-Purpose Application Control (GPAC) Framework

The GPAC converts information (e.g. classification result) received over TCP/IP from the (h)BCI into a set of predefined actions (Fig. 1(a)). These actions can either simulate KB&M inputs or modify customized graphical user interface (GUI) elements. An application running as a window in focus receives the KB&M inputs and triggers mapped in-app actions. KB&M inputs include keyboard key press and release, mouse button press and release, and relative mouse cursor movements. Individual KB&M inputs can be linked by macros, which can be used to trigger more complex in-app actions. The IEE allows customizing the UIs of applications by placing basic interface elements such as textured icons, mono-color or checkerboard icons and progress bars for dwell timers anywhere on the screen. Each of these elements can be decorated with animations or defined as steady-state VEP flicker with predefined frequencies. XML configuration files allow rapid and easy definition of finite-state machines for graphical user interface (UI) layouts (masks) and KB&M macro sets for individual applications.

2.2. The Portal2 game and basic requirements for gameplay

Players have the task of solving a series of puzzles by teleporting the player's character and simple objects by placing a set of portals. Objects include a cube that can be used to trigger switches and redirect laser beams (Fig. 1(b)). Meaningful interaction with the game requires (i) self-paced (h)BCI operation (on-demand access) and

(ii) the ability to select between ten different control commands: seven for navigating the player's character and three for selecting special actions.

2.3. hBCI and mapping of in-app actions

We selected a hBCI consisting of a 7-class EMG-based hand movement detection system and 3-class SSVEP-BCI. Not focusing on flickering stimuli and not performing predefined hand movements should not generate hBCI output and thus allow self-paced control. SSVEP detection was based on canonical correlation analysis, Fisher's linear discriminant analysis and dwell timers (1 s). Hand movement detection involved movement on-set detection, followed by time domain-based feature extraction and support vector machine classification. EEG was recorded from 13 occipital sites; EMG from 16 monopolar electrodes placed on the users forearm.

The hand movements hand closed, hand open, wrist flexion, wrist extension, radial deviation, ulnar deviation and thumb extension were mapped to the in-game commands walk forward, walk backward, turn left, turn right, look up, look down and jump forward, respectively. The 3 SSVEP stimuli were mapped to the commands place orange portal, place blue portal and activate the cube. Fig. 1(b) illustrates the adapted GUI.

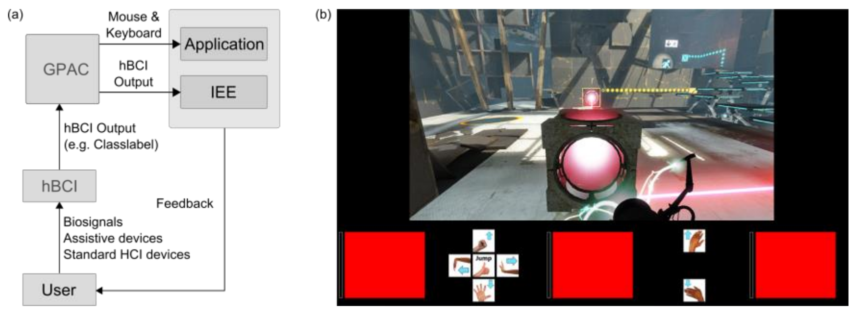

Figure 1. *(a) Scheme of the general-purpose application control framework. (b) Screenshot of the custom GUI. Ten basic interface elements are located in the lower part of the screen. The seven small icons show the mapping of hand movement to in-app navigation commands. After hand movement detection the arrow in the related icon changes from color blue to green. The three large plain-colored icons flicker at different frequencies and are used to elicit SSVEPs. Whenever corresponding SSVEPs are detected, an animated dwell timer bar is shown on the left side of the SSVEP icon and on completion the whole icon is framed by a green border indicating a selection.*

2.3. Experimental paradigm

Two able-bodied individuals (S1 and S2) participated in this study. Firstly, users were familiarized with Portal2 by playing level 2.1 and 2.2 by standard HCI inputs. Secondly, to get a reference performance, users were asked to play the levels by mouse only (all commands mapped on mouse buttons/wheel). Finally, after SSVEP-BCI and EMG hand detection calibration was performed, users were asked to replay the levels by hBCI.

3. Results

The time required to successfully finish levels 2.1 and 2.2, respectively, by hBCI (mouse) was 75 s (32 s) and 280 s (54 s) for S1, and 116 s (33 s) and 210 s (66 s) for S2. To test for false positive detections, 60 s of data was recorded and subjects were asked not to activate hBCI control. S1 triggered no FP selection; S2 triggered 1 FP. Hand movement classification accuracies of over 96% were computed for both users from the EMG calibration data.

A video of the experiment is available at http://www.youtube.com/watch?v=ZUsY3YsyiAw.

4. Discussion

The presented GPAC allows controlling off-the-shelf software applications by non-standard HCI devices. The IEE is a valuable extension that allows customizing interfaces and providing visual feedback for hBCI user.

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A Hybrid Control of a P300-Based BCI: a Solution to Improve System Usability?

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Abstract. A P300 based BCI system was designed to control an assistive technology software (Riccio et al., 2011). Subsequently a hybrid (electromyographic, EMG) control devoted to the correction of spelling errors was introduced in it. The *hybrid* version of such system would provide severely disabled end-users with a way to exploit not otherwise functionally reliable residual muscular activity. Eight healthy subjects and two severely motor impaired end-users participated to the system testing. Preliminary findings are in favour of the superiority in *efficiency* of the *hybrid* control with respect to the *no-hybrid* (only BCI-based) as indicated by the observed improvement of the performance (expressed as time for selction and percent of errors) that was associated with a decrease of the system usage frustration perceived by the users.

Keywords: Brain computer interface, Hybrid, Electromyography, Event related potential, Communication

1. Introduction

A hybrid Brain Computer Interface (BCI) is a BCI combined with at least one other system or device enabling people to send information [Allison et al., 2010]. In a previous study, we reported on a developed system in which a P300-based BCI was combined with a QualiWorld Assistive Technology (QW) software for communication and environmental control [Riccio et al., 2011]. Such BCI-based system was successfully tested with severely disabled potential end-users [Zickler et al., 2011] and according to their feedbacks on system's usability, we endowed the system with a *hybrid* control that subserved the function of deleting uncorrected selections by means of electromyographic (EMG) signal generated by the end-user's residual muscular activity.

2. Material and Methods

Eight healthy volunteers (4 males, 4 females; mean age 30) and two severely disabled end-user (female, 48 year old; male 56 year old) participated to the study. The end-users had severe motor disability due to brainstem ischemic stroke and hemorrhagic stroke.

To fully adhere to a user-centered design, the *hybrid* system is adaptable to several degrees of residual motor activity and the customization of the EMG control channel is obtained during a screening session wherein the end-users' target muscle is identified on the basis of their residual functional voluntary movements. For the same reason the visual stimuli eliciting P300 are adaptable to user's needs in terms of shape, colors, dimension and position. The visual stimulation is overlaid on top of the QW window through a proxy.

A calibration session was performed in order to define the EMG control features, such as the onset and offset of signal amplitude thresholds and the optimal time window for the EMG signal onset and offset to occur in order to operate the delete command. The same session was also devoted to identify the best stimulation modality (least number of sequences needed to achieve the 100% offline accuracy) within four stimuli changing for shapes (dot vs. grid) and colors (red vs. green). In a different session, participants were asked to spell online three predefined words (21 characters) using the system under two conditions: *(i) No-hybrid task*: uncorrected letter selections were deleted by means of the BCI control operating a backspace command integrated in the QW virtual keyboard; *(ii) Hybrid task*: the errors were canceled by exploiting the EMG control signal; in case of failure, the user had to delete the wrong letter as in the previous condition. For between conditions comparative purposes, the number of sequences of stimulation was set at the minimum number of sequences needed by a given user to reach 80% of accuracy in order to artificially introduce spelling errors in a controlled manner. EEG and EMG signals were acquired using 8 EEG (Fz, Cz, Pz, Oz, P3, P4, Po7, Po8) and 2 EMG active electrodes, respectively. All EEG channels were referenced to

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the right earlobe and grounded to the left mastoid, amplified using a g.tec USB amplifier (Graz, Austria) and recorded by the BCI2000 software.

Healthy volunteers data set: the comparison in terms of *efficiency* between the two modalities was performed by means of a non-parametric Wilcoxon test. The system *efficiency* was evaluated in terms of *i)* time for selection (*TIME*; ratio between the total time to successfully complete the task and the minimum number of selections needed to execute it), *ii)* percent of errors (*ERRORS*; ratio between the number of BCI errors and the total number of BCI selections) and *iii)* users *FRUSTRATION* (the NASA-tlx workload factor; "*How insecure, discouraged, irritated, stressed, and annoyed were you?"*). Only qualitative description will be reported for the 2 end-user data set.

3. Results

Significantly lower scores relative to *TIME* and *ERRORS* were obtained in the *hybrid task* with respect to the *no-hybrid task* ($p < 0.05$, Fig. 1a, 1b). Further, the level of *FRUSTRATION* perceived by the healthy users resulted significantly lower for the *hybrid* condition ($p < 0.05$). The end-users achieved *TIME* and *ERRORS* mean values lower in the *hybrid task* (*TIME*=19.13 sec; 39,38 sec. *ERRORS*=19.3%, 3,3%) as compared to the *no hybrid task (TIME*=34.8; 45,31 sec. *ERRORS*=33.9%, 6,6 %). The perceived *FRUSTRATION* was also lower while using the *hybrid* modality function (3.3; 0,6) with respect to the *no-hybrid* (4.6; 1,6).

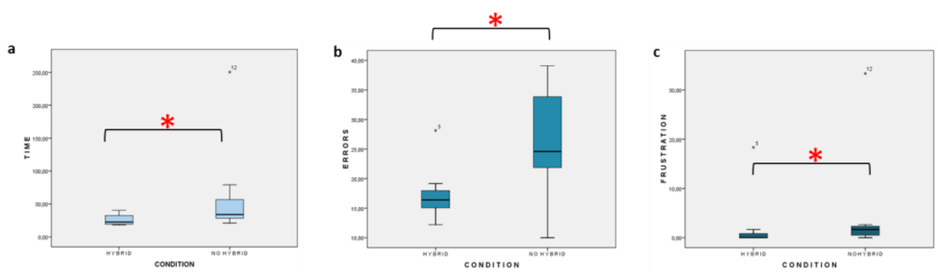

Figure 1. *Plots showing statistic comparison between the "hybrid task"and the "no-hybrid" task in healhy volunteers (n=8). Variables are: (a) time of selection (TIME), (b) percentage of errors (ERRORS) and (c) perceived frustation (FRUSTRATION)*

4. Discussion

The findings obtained from healthy subjects support the initial assumption that the integration of the EMG channel into the system would yield to an improvement of the system *efficiency*, as indicated by the significant decrease of the *time for selection* and of the *percentage of errors* in an on line spelling task performed under the *hybrid* and *no-hybrid* task modality. One can speculate that the observed decrease of the *percentage of errors* under the *hybrid* task might be ascribed to a reduced psychological demand of the BCI-based spelling letters due to the possibility of correcting errors by exploiting the EMG channels. The lower level of perceived *frustration* associated with the *hybrid* task could be a consequence of the performance enhancement. The similarity in the system usage performance showed by the 2 end-users corroborates the added value of the hybrid control concept. A larger sample of end users is currently involved in the study.

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Investigation of Optimal Mental Task Combinations for EEG-Based Brain-Computer Interface (BCI)

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Abstract. A number of EEG-based brain-computer interface (BCI) studies have adopted well-known mental task combinations (e.g., left- vs. right-hand motor imagery) without finding an optimal mental task combination most appropriate for each individual. In this study, we compared classification accuracy for various mental imagery task combinations with the aim to provide a reference useful for determining individual-specific mental tasks. Nine participants performed eight different mental imagery tasks during EEG recordings. We estimated classification accuracies for all possible mental task combinations, when the numbers of mental tasks were two, three, and four. Results showed that certain combinations of motor and non-motor imagery tasks tended to result in higher classification accuracy than combinations of solely motor imagery tasks. On the other hand, brain activity patterns elicited by "mental multiplication," "left hand motor imagery," and "geometric figure rotation" were not well discriminated when these tasks were performed simultaneously. Moreover, performing similar type of mental tasks at the same time did not result in high classification accuracy.
Keywords: BCI, EEG, various mental imagery tasks, optimal combination of mental tasks

1. Introduction

Brain-computer interface (BCI) systems employ various mental imagery tasks, e.g., motor imagery, spatial navigation, auditory imagery, and mental calculation. However, a considerable number of individuals (15-33%) have difficulty generating distinct task-related brain activity patterns for given mental tasks, thereby failing to achieve classification accuracy high enough to be used for practical BCI applications. One of the solutions to circumvent the BCI illiteracy issue would be using individualized mental task combinations instead of using a fixed set of mental tasks. In the present study, we investigated a variety of issues to be considered in selecting individual-specific mental task combinations: i) What are the best and worst mental task combinations? ii) Which mental task is the most distinguishable and which is the least? iii) Do combinations of motor imagery tasks show higher performance than other combinations? iv) Can mental tasks of a similar kind be used together?

2. Material and Methods

2.1. Experimental Procedures

Nine healthy participants took part in this study. Seven participants performed each mental task 20 times, and two participants (P5 and P9) performed each mental task 15 times. A total of thirty electrodes were used for the EEG recording. We conducted a series of experiments with eight different mental tasks (task A: mental character writing, task B: mental multiplication, task C and D: right and left hand motor imagery, task E: mental singing, task F: geometric figure rotation, task G: mental subtraction, and task H: tongue motor imagery). According to the experimental paradigm, the participants carried out the designated mental task for 10 s for each trial.

2.2. EEG Data Anaysis

The extracted raw EEG signals were spatially filtered using a common average reference (CAR) to compensate for common noise components. Spectral band powers and their inter-hemispheric asymmetry rations were calculated to construct feature vectors. The frequency bands were separated into five sub-frequency bands: theta (4-7 Hz), alpha (8-13 Hz), low beta (14-20 Hz), high beta (21-30 Hz), and gamma (31-45 Hz). We estimated classification accuracies for all possible combinations of mental tasks, when the numbers of mental tasks were two, three, and four. The numbers of the possible combinations were 28 (= ${}_8C_2$), 56 (= ${}_8C_3$), and 70 (= ${}_8C_4$) for two, three, and four mental tasks, respectively. We used the leave-one-out cross validation (LOOCV) method to evaluate classification accuracy, considering the relatively small number of task trials. In every cross-validation step, the sequential forward feature selection (SFFS) method was used to select the best feature subset for the training dataset, at which time the number

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of selected features was limited to less than 10 to prevent over-fitting. The remained trial was then classified by a linear discriminant analysis (LDA) classifier trained using the selected best feature subset.

3. Results

Table 1 presents the best and the worst five combinations of mental tasks for each number of mental tasks. The mental task combinations including task A (mental character writing) and task C (right hand motor imagery) showed high classification accuracy regardless of the number of mental tasks. On the contrary, the mental task combinations, including tasks B and F, tasks D and F, and tasks B and D, showed relatively low classification accuracy (task B: mental multiplication, task D: left hand motor imagery, and task F: geometric figure rotation). As a result of counting the number of times that each mental task was included in the best or worst five mental task combinations, tasks A (mental character writing) and C (right hand motor imagery) were most frequently included in the best five mental task combinations. In contrast, tasks B (mental multiplication), D (left hand motor imagery), and F (geometric figure rotation) were most frequently included in the worst mental task combinations.

To investigate how well a set of different motor imagery tasks can be distinguished from each other compared to other mental task combinations, we ranked the mental task combinations consisting of solely motor imagery tasks. In most cases, combinations of motor imagery tasks did not yield high classification accuracy, and their rankings were about average (17th for left hand vs. right hand, 22th for left hand vs. tongue, 13th for right hand vs. tongue).

We also ranked the combination of mental tasks B (mental multiplication) and G (mental subtraction) among all possible combinations of two mental tasks (28 (=8C2)). In most cases, the combination of two arithmetic calculation tasks showed poor classification accuracy compared to the other combinations (ranking: 21st for P1, 7th for P2, 18th for P3, 16th for P4, 8th for P5, 19th for P6, 24th for P7, 24th for P8, and 1st for P9).

Table 1. *The best and worst five mental task combinations when the numbers of mental tasks were two, three, and four, respectively. Motor imagery tasks are shown in underlined italics type (Tasks C, D, and H).*

Ranking	The number of the best mental tasks						The number of the worst mental tasks					
	2		3		4		2		3		4	
	MC	CA (%)	MC	CA (%)	MC	CA (%)	MC	CA (%)	MC	CA (%)	MC	CA (%)
1	(A, *C*)	95.00 (±2.32)	(A, B, G)	92.03 (±7.34)	(A, *C*, E, F)	84.72 (±8.81)	(B, F)	74.44 (±21.17)	(B, *D*, F)	74.26 (±20.19)	(*D*, E, G, *H*)	70.78 (±12.72)
2	(A, G)	93.88 (±3.65)	(A, *C*, F)	89.63 (±8.77)	(A, B, *C*, G)	84.67 (±11.14)	(*D*, F)	79.35 (±16.14)	(*D*, E, F)	76.23 (±20.53)	(B, *D*, E, F)	71.52 (±18.92)
3	(G, H)	92.59 (±7.07)	(A, *C*, *H*)	89.25 (±4.92)	(A, B, G, *H*)	84.67 (±10.12)	(*D*, E)	79.43 (±17.73)	(*D*, E, *H*)	76.85 (±16.82)	(*D*, E, F, *H*)	73.19 (±19.12)
4	(*C*, E)	91.85 (±6.30)	(A, B, *C*)	89.19 (±4.99)	(A, B, *C*, *D*)	84.58 (±7.75)	(B, *D*)	79.72 (±18.53)	(B, *D*, E)	77.96 (±14.51)	(B, *D*, F, G)	73.19 (±18.89)
5	(B, *C*)	91.75 (±8.02)	(A, *C*, E)	88.76 (±7.84)	(A, *C*, *D*, *H*)	84.49 (±11.56)	(B, *H*)	83.98 (±14.82)	(B, *D*, *H*)	79.44 (±20.84)	(B, *D*, E, *H*)	74.95 (±16.62)

4. Conclusion

Many BCI studies have introduced various kinds of mental tasks. However, because some participants cannot produce discriminable brain activity patterns for specific combinations of mental imagery tasks (BCI illiteracy), it is an important research topic to find the optimal mental task combination most appropriate for each individual. In the current study, in order to provide a useful reference for the selection of optimal mental task combinations, we investigated the suitability of a variety of mental task combinations for mental-imagery-task-based BCI.

Acknowledgements

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A Portable Immersive Virtual Reality Platform for Motor-Imagery Guided Rehabilitation of Hemiparetic Stroke

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Abstract. Stroke is a devestating illness that can have a profound impact on productivity, mobility and quality of life. Current practices for stroke rehabilitation rely on complex robotic actuation devices or a trained therapist to actuate a patient's paralyzed limbs during the imagined or attempted actuation of the paretic muscles. Here we propose a low cost, immersive virtual reality (VR) platform for the rehabilitation of upper extremity deficits that are caused by stroke. Four hemiparetic patients suffering from basal ganglia stroke were introduced to the platform and trained to control a brain-computer interface in conjunction with the standard 1-dimensional cursor task. Patients achieved classification accuracies as high as 77.5% using this VR platform, and grouped average performances were comparable to those achieved using the traditional BCI cursor task.

Keywords: EEG, Motor Imagery, Basal Ganglia, Stroke, Virtual Reality, Anaglyph, Rehabilitation

1. Introduction

The rehabilitation of stroke depends on a patient's early mobilization and the use of the deficit extremity. Mental practice using the deficit limb, in conjunction with actuation by a physical therapist plays an important role in reestablishing damaged pathways and recovering function. Mental practice without adequate feedback is difficult and brain-computer interfaces may offer a novel solution [He et al., 2013; Silvoni el al., 2011; Ang et al., 2011]. Here we propose a novel system for providing realistic, 3-dimensional visual feedback to promote accurate mental practice using a sensorimotor rhythm based brain-computer interface.

2. Materials and Methods

Four subjects with histories of basal ganglia stroke and unilateral limb paresis were trained in SMR BCI control using virtual reality (VR) and traditional 1D cursor feedback (BCI2000). Subjects attended up to three training sessions, each consisting of 10 3-minute trials. In the VR task, the subjects placed their arms inside the front of a box, and viewed a 3D anaglyph video of real human arms from the top of the box such that as they looked "through" the top of the box it was as though they could see their own arms. The video's position was controlled by the position of the 1D traditional cursor, running in the background. Moving the cursor to the left and right extended the left and right arms respectively. Auditory cues signaled the target direction in both tasks.

3. Results

Overall, the group weighted average percent accuracy was 64.0% in the cursor task compared to 65.6% in the VR task. Subject 1 scored 80.5% on average in the standard cursor task and 69.2% in the Virtual Reality task. Subject 2 scored 46.5% in the cursor task compared to 58.4% in the VR task. Subject 3 demonstrated nearly identical performance accuracies in both the cursor task and VR task, performing 54.2% and 54.1%, respectively. Subject 4 demonstrated an average accuracy of 87.4% in the cursor task compared to 77.5% in the VR task.

We additionally tested the expectation that our patient population may operate the sensorimotor-based brain-computer interface in a deficit dependent manner, having lost connection and feedback from the affected limb for a prolonged period. Fig. 1 demonstrates that accuracy was not substantially different between targets presented on the patients' deficit and non-deficit sides. This is an interesting finding that implies that a lack of meaningful feedback from the affected limb does not substantially limit the utility of the healthy cortex in basal ganglia stroke patients for BCI applications.

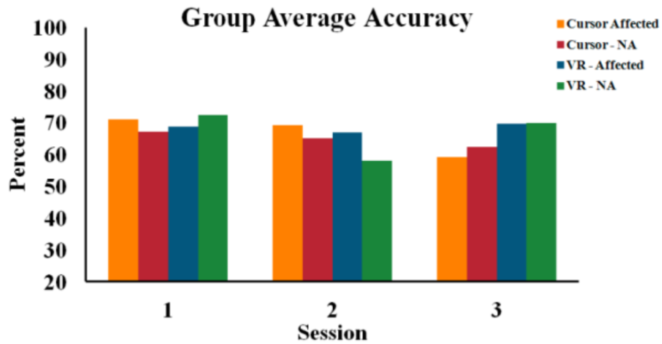

Figure 1. *Grouped percent accuracies by VR vs traditional cursor control task and affected vs nondeficit (NA) side.*

4. Discussion

The system provides a cost effective option for presenting 3D video of arms in alignment with the subject's real arms, together producing a powerful illusion of embodiment. All subjects reported that they could easily imagine the presented arms being their own arms when using this immersive 3D system. For elderly stroke patients, the complex instructions related to BCI and the concept of motor imagery can be difficult to understand. Many quickly abandoned more abstract motor imagery in favor of mentally reaching out to grab the 3D cups. Using this system, patients have the potential for targeted rehabilitation and mental practice with relevant feedback before movement of the deficit limb is possible. The system retains the level of feedback that is necessary for BCI control by hemiparetic stroke patients while providing crucial visual cues.

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Design of Optimal Keyboard Layouts for a Mental Speller

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Abstract. Most mental spelling systems based on brain-computer interface (BCI) technology require subject's eye movements to detect a target character. However, many patients with severe neuromuscular disorders have difficulty quickly moving their eyeballs from a letter to another. In this study, we introduce optimal keyboard layouts that can reduce the visual scanning distance. The average eye-scanning distance was calculated for each keyboard layout generated by genetic algorithm (GA), and then optimal keyboard layouts with shortest eye-scanning distance were found. We tested most frequently used 268 English words, and compared the eye-scanning distances estimated for the proposed optimal keyboard layouts and a conventional layout with an alphabetical arrangement. As a result, our proposed optimal keyboard layouts could significantly reduce the average moving distance by about 1.4 times.

Keywords: Mental Speller, Optimal Keyboard Layout, BCI, Electroencephalography (EEG)

1. Introduction

One of the most widely studied applications of electroencephalography (EEG)-based brain-computer interface (BCI) is the BCI speller, which enables the disabled people to express their thoughts by focusing on target characters. Most of conventional BCI spellers are commonly based on the basic assumption that the users have normal eye movements and thus are able to maintain an open gaze at a target character consistently. However, it is difficult for many neuromuscular patients to quickly control their eyes [Balaratnam et al., 2010; Sharma et al., 2010], requiring some interval between consecutive typings to provide the patients with time to move their eyeballs from one letter to another. Therefore, reducing the time required for visual scanning should enhance the overall performance of the mental speller.

To date, most BCI spellers have used an $n \times n$ matrix keyboard layout generally displaying each character in alphabetical order, without considering the patients' impaired oculomotor function. Thus, a keyboard layout design to reduce eye movements required for spelling target characters is required. In this study, we found optimized keyboard layouts that minimize the eye-scanning distances using genetic algorithm (GA).

2. Material and Methods

To search optimal keyboard layouts, we used GA, which is one of the most popular heuristic optimization algorithms. Three different population sizes were tested, 20, 40, and 60. Each individual in the population corresponded to a 5 by 5 matrix keyboard layout in which twenty-five English alphabets were randomly placed except the alphabet 'Z' (the least used one).

The objective function to be minimized was defined as the mean eye-scanning distance taken when typing widely used 268 English words. When the population size of 20 was used, five pairs of individuals were selected based on the fitness proportionate selection, also known as roulette-wheel selection, and then five offspring (25% of the population size) were then generated by order crossover. Finally, five worst individuals were replaced by the newly generated offspring, and this procedure was repeated 2000 times. To alleviate premature convergence due to trapping in a local optimum, the generated offspring were randomly mutated with a predetermined probability. In the cases of the population sizes of 40 and 60, the numbers of iteration were set to 1000 and 670, respectively, in order to match the total number of individuals (approximately 40,000) tested in the three different population datasets. The individuals having the best fitness values were selected for each population as the optimal keyboard layouts. The mean eye-scanning distances of the optimal keyboard layouts were compared with that of the conventional keyboard layout arranging characters in alphabetical order. For the calculation of distance, we assumed that the both width and height of each cell were 1.

3. Results

Fig. 1 shows the optimized keyboard layouts when the population sizes were set to 20, 40 and 60, respectively. The mean eye-scanning distances taken when the eyes move from one character to another were 1.85, 1.85 and 1.87 for the population sizes of 20, 40 and 60, respectively. In the case of the conventional keyboard layout (alphabetical order), the mean eye-scanning distance was 2.68. It is worth noting that the most frequently used five letters (E, T, A, O, I) were placed around the centers of the optimized keyboards, as shown in Fig. 1.

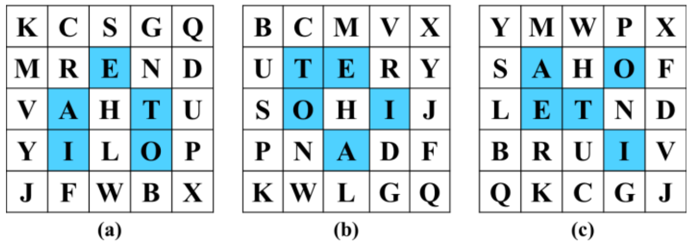

Figure 1. *The optimal keyboard layouts- (a) population size: 20, (b) population size: 40, (c) population size: 60. The turquoise-colored cells denote the most frequently used five letters in English words, i.e.,E, T, A, O, I.*

Fig. 2 shows a representative example demonstrating that the optimal keyboard layouts can reduce the eye-scanning distances, compared to the conventional keyboard layout. A word 'WATER' was used for the example. In particular, we could confirm from visual inspection of Fig. 2 that the optimal keyboard can significantly shorten the eye-scanning distance.

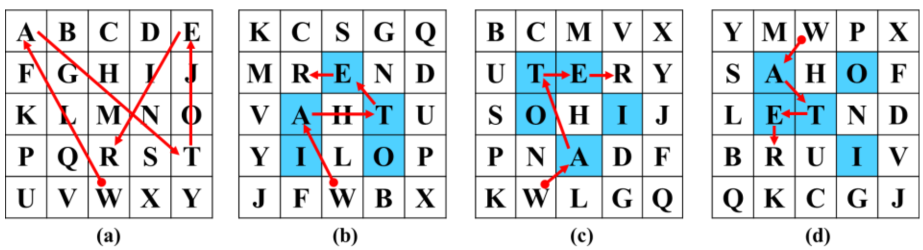

Figure 2. *Examples of eye movements needed to visually scan a word 'WATER'- (a) the conventional keyboard layout (alphatecial order); the optimal keyboard layouts when population sizes were (b) 20, (c) 40, and (d) 60.*

4. Discussion

In the present study, we designed optimal keyboard layouts that can reduce the eye-scanning distance when applied to BCI spellers. Considering that some patients suffering from neuromuscular disorders have difficulty controlling their eyes [Balaratnam et al., 2010; Sharma et al., 2010], we expect that BCI spellers adopting the proposed optimal keyboard layouts can not only reduce tiredness of the patients, but also increase the performance of the BCI spellers.

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Comparison of Adaptive Symbol Presentation Methods for RSVP Keyboard

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Abstract. RSVP Keyboard™ is an EEG based letter-by-letter typing system specifically designed for people with locked-in-syndrome (LIS). It uses rapid serial visual presentation of symbols and classification of event relatedpotentials with the aid of a language model. We designed various adaptive symbol presentation methods for each sequence of visual stimuli and compared the efficacy of these methods using estimated task completion accuracy and speed with rigorous modeling and Monte Carlo simulations, based on EEG data collected for calibration purposes.

Keywords: EEG, ERP, BCI, Language Model, Kernel Density Estimate, Symbol Presentation design

1. Introduction

Brain computer interfaces (BCI) have been designed to assist people with severe motor disabilities or locked-in syndrome with communication and control when motor control is not possible. Practicality of noninvasive portable acquisition systems, like electroencephalography (EEG), further attracted the researchers to BCI systems. Existing noninvasive BCIs for typing use many repetitions of stimuli to increase accuracy at the cost of speed [Pfurtscheller et al., 2000; Krusienski et al., 2008]. However, speed is also crucial aspect of peer-to-peer communication.

To develop a system that achieves high accuracy and speed simultaneously, in our previous work we have demonstrated rapid serial visual presentation (RSVP) in conjunction with language models (RSVP Keyboard™) in order to assist letter selection during the brain-typing process. RSVP relies on temporal rather than spatial separation of stimuli, and EEG responses for the visual stimuli are classified using regularized discriminant analysis applied to stimulus-onset-locked temporal features from all channels. Fusion of language and EEG evidence is achieved using a probabilistic framework, assuming that these are conditionally independent given class labels [Orhan et al., 2012].

Currently, RSVP Keyboard™ presents random permutations of the 26 letters in English alphabet, a space symbol and a backspace symbol (we call this set a sequence). If repetition is needed, all symbols are repeated multiple times (maximum number of repetitions is bounded) to improve classification accuracy until a desired confidence level is reached [Orhan et al., 2012]. However, using all 28 symbols in a sequence might not be necessary for a specific target symbol to be selected successfully. Depending on the context, some symbols might be highly unlikely to be chosen. Therefore, an adaptive symbol presentation method based on the evidence provided by EEG and language model (LM) might decrease the number of symbols in a sequence and the total symbol selection time. In this study, to further increase the typing accuracy and communication speed, we investigate different sequence selection methods, demonstrating their typing performances using Monte Carlo simulations on prerecorded EEG data.

2. Methods

In RSVP Keyboard™, the user is assumed to show positive intent exactly for all occurrences of one symbol per epoch (section in which user attempts to select a target symbol for typing). Each epoch contains a set of sequences, currently containing all 28 symbols. In this study, using Monte Carlo simulations on multiple pre-recorded calibration data with different performance (different area under the receiver operating characteristic (ROC) curve (AUC) values), and changing the number of symbols in a sequence (N_T) and maximum number of sequences in an epoch (N_{MAX}), we propose to compare the typing performance of three different subset selection methods. We select ten different sentences and aim to spell a phrase in each sentence (called the copy phrase task). Task difficulty is determined by requiring each letter of the target phrase to have a likelihood ratio against the highest competing non-target letter within a specified interval: (1) Hard: (0.3, 0.5], (2) Very hard: (0, 0.3].

We employ a 6-gram character-based LM that is trained using a one-million sentence sample of the New York Times portion of the English Gigaword corpus. We apply our simulation model to the copy phrase task and report the estimated performance in terms of average time to complete the whole task (T_{est}), and probability of successful phrase completion (P_{est}). In other words, P_{est} represents the typing accuracy and T_{est} represents the typing duration. We use the target and non-target EEG responses from the calibration data and perform kernel density estimation with cross validation on the features extracted from these raw responses. During simulation, we draw samples from these densities to obtain simulated EEG evidence for target and non-target symbols. The EEG evidence is fused with the LM to compute the posterior probabilities used for decision making. Simulations, utilizing the EEG responses to the RSVP paradigm from participants, are a close representation of the typing performance.

Three subset selection methods we compare here are as follows: Method 1 (M1) uses the full set (28 symbols); Method 2 (M2) displays a k-element subset of the alphabet having the highest posterior probabilities after fusion with EEG evidence at the end of each sequence; Method 3 (M3) displays a k-element subset with the highest probabilities, while giving priority to symbols with fewer number of repetitions, for instance, for $N_T = 7$ after 4 sequences every symbol will be shown exactly one time.

3. Results

Using 100 Monte Carlo simulations and calibration data with AUC = 0.7662 and 0.8330, respectively, we obtain the results summarized for analysis in Fig. 1.

		AUC =0.7662					AUC = 0.8330				
		M 1	M2		M3		M 1	M2		M3	
		N_T=28	N_T=14	N_T=7	N_T=14	N_T=7	N_T=28	N_T=14	N_T=7	N_T=14	N_T=7
T_{est} (min)	N_{MAX} = 2	26.44	15.06	9.68	13.770	8.6324	22.02	12.55	8.79	14.821	9.509
	N_{MAX} = 4	38.44	22.66	15.02	24.867	14.223	21.40	13.31	10.27	19.372	15.140
	N_{MAX} = 8	40.81	24.48	18.03	39.086	27.707	20.91	12.41	9.52	19.277	21.703
	N_{MAX} = 16	39.25	23.32	17.22	41.616	45.334	20.31	12.30	9.13	18.258	21.308
P_{est}	N_{MAX} = 2	0.093	0.117	0.096	0.023	0.018	0.644	0.647	0.464	0.247	0.219
	N_{MAX} = 4	0.512	0.468	0.370	0.117	0.012	0.984	0.973	0.861	0.721	0.261
	N_{MAX} = 8	0.962	0.959	0.879	0.522	0.123	1.000	1.000	0.999	0.991	0.697
	N_{MAX} = 16	0.982	1.000	0.998	0.930	0.559	0.999	1.000	1.000	1.000	0.991

Figure 1. *Performance analysis results for three different symbol selection methods for two different accuracy levels.*

4. Discussion

The current version of RSVP Keyboard^{TM} operates using method 1 with $N_{MAX} = 4$. We first observe that a simple change in our current system by changing the N_{MAX} from 4 to 8 or 16 does not increase the estimated total task duration, but increases the accuracy drastically. Secondly, we demonstrate that the second method has the best typing performance among the three. To see this from Fig. 1, if we compare the (M2, N_{MAX} = 8 or 16) with (M1, N_{MAX} = 4 or 8), we observe that M2 improves both speed and accuracy. A similar comparison between M1 and M3 illustrates that M3 performs similar to M1 and may not be the best symbol presentation option. In our future work, we will develop symbol presentation methods relying on sequential dynamic state space models and provide a more quantitative analysis of adaptive symbol selection methods to increase speed without sacrificing accuracy.

5. Acknowledgements

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Effects of Varying Presentation Rate and Sequence Length on User Performance with the RSVP Keyboard BCI

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Abstract. This study investigated the effects of varying two presentation parameters of the RSVP Keyboard™ brain-computer interface (BCI) on user performance. Character presentation rate was set to either 5 or 2.5 Hz, and the number of characters per sequence was set to either 10 or 28. Participants completed a word copying task under the resulting four conditions, and typing rate and error rate were calculated. Both presentation rate and sequence length were found to significantly affect typing rate, with 5 Hz being faster than 2.5 Hz and 10 characters per sequence being faster than 28. Neither parameter had a significant effect on error rate.

Keywords: BCI, augmentative and alternative communication, P300, typing rate, rapid serial visual presentation

1. Introduction

Brain computer interface (BCI) shows great promise as a communication method for people with locked-in syndrome (LIS) and others with severe disabilities. The RSVP Keyboard™ is a non-invasive, P300-based BCI system designed for use as a typing and communication tool by people with LIS. Its unique features include rapid serial visual presentation (RSVP) of stimuli [Orhan et al., 2012] and an integrated language model which is combined with information from P300 responses to support spelling accuracy [Orhan et al., 2011].

One drawback to the RSVP Keyboard™ and other BCI-based typing and communication systems is their relatively slow rate of text generation. This study was designed to examine whether a faster character presentation rate or reduced character sequence length would increase typing rates for users of the RSVP Keyboard™.

2. Material and Methods

A convenience sample of eight adults without disabilities (two men and six women) was used. Participants reported within normal sensory, cognitive, communication abilities. Three were from minority groups, and three were non-native but fluent speakers of English.

Experimental sessions took place in a quiet room at OHSU. Electroencephalography (EEG) signals were recorded using a 16-channel g.USBamp (g.tec, Graz, Austria) with active electrodes in a cap at approximate 10-20 locations, with a reference electrode at TP10 and ground at FpZ. Stimuli were presented on a laptop screen following the RSVP paradigm and consisted of 28 characters, including the letters of the alphabet plus “<” for backspace and “_” for space. To generate the EEG classifier, participants completed calibration sessions consisting of 50 sequences of 10 characters. Prior to each sequence, participants were shown a target character, which they were instructed to detect when it reappeared in the 10-character sequence. Classifier accuracy was estimated from the area under the curve (AUC) of true positive versus false positive rate for target versus non-target classification.

During the task, phrases were presented one at a time at the top of the laptop screen, with a target word designated in a contrasting color. Phrase sets were chosen from the *New York Times* portion of the English Gigaword corpus. Participants were instructed to copy the target word using the RSVP Keyboard™, and to correct any errors by selecting the “<”. Participants copied two or three target words for each condition; the participant would attempt a third word only if she did not copy the first two correctly. The program moved to the next phrase when one of the following criteria was met: the target word was copied correctly, the participant spent ten minutes attempting to copy a word, five consecutive incorrect characters were chosen, or 32 sequences were presented.

Before beginning the experimental conditions, participants completed a calibration session with characters presented at 2.5 Hz, and then attempted a “warm-up” word copying task. For the warm-up task, characters were presented at 2.5 Hz and 28 characters per sequence (the default settings for the RSVP Keyboard™ in previous work), and target words were chosen to be highly predictable by the language model, and therefore easy to copy.

After the warm-up, participants completed a word copying task under four different conditions. Presentation rate was set to either 2.5 or 5 Hz, and sequence length to either 10 or 28 characters, resulting in the following conditions: 2.5 Hz/10 characters, 2.5 Hz/28 characters, 5 Hz/10 characters, and 5 Hz/28 characters. The 10-character sequences

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included the eight most likely letters as determined by the language model (taking into account posterior probabilities from prior sequences), plus "_" and "<". The 28-character sequences contained the full set of stimuli and were divided into two 14-character blocks. Phrase sets were chosen such that all target words were four letters long and were equally predictable by the language model. Each participant completed the four conditions in a different order, with conditions with the same presentation rate kept together to avoid additional re-calibrations. Participants re-calibrated at the appropriate presentation rate prior to each pair of conditions with the same rate. If a participant did not achieve an AUC of 0.85 or above on her first attempt, she could re-calibrate a second time.

Typing rate was calculated for each condition by dividing the number of characters in the final output by the time, in minutes, required to complete the condition. Error rate was calculated by dividing the number of incorrect selections by the total number of selections for each condition. If an incorrect letter was selected, only the "<" was accepted as correct for the following selection.

3. Results

A repeated measures ANOVA found that both presentation rate ($F(1,7) = 5.851$, $p = .046$) and sequence length ($F(1,7) = 150.669$, $p = .000$) had significant effects on participants' typing rates. Participants were able to produce more characters per minute with a presentation rate of 5 Hz than with 2.5 Hz, and with 10 characters per sequence rather than 28. Neither presentation rate ($F(1,7) = .004$, $p = .954$) nor sequence length ($F(1,7) = .320$, $p = .589$) had any significant effect on error rate. These results are presented in Table 1.

The condition with the highest mean typing rate used settings of 5 Hz for presentation rate and 10 characters per sequence ($M = 3.93$, $SD = 1.410$). This condition was compared to the next fastest condition (2.5 Hz and 10 characters per sequence, $M = 2.63$, $SD = .762$) using a paired samples t test. The difference in typing rate between these two conditions approached significance ($t(7) = -2.312$, $p = 0.054$).

Table 1. *Typing rate and error rate results. Data are presented as mean (SD), range.*

Presentation Rate [Hz]	*2.5*		*5*		*p*
Sequence Length [characters/sequence]	*28*	*10*	*28*	*10*	
Typing Rate [characters/minute]	1.49 (.972), .69-3.75	2.63 (.762), 1.67-3.72	1.92 (1.056), .58-3.93	3.93 (1.410), 1.78-6.76	Rate: .046 Length: .000
Error Rate [%]	20.3 (27.46), 0-68.8	9.0 (13.70), 0-36.4	14.9 (18.23), 0-51.5	15.2 (22.43), 0-66.7	Rate: .954 Length: .589

4. Discussion

The results of this study indicate that a faster presentation rate (5 Hz vs. 2.5 Hz) and shorter sequences (10 characters vs. 28) can increase typing speeds for healthy participants completing a word copying task using the RSVP Keyboard™ BCI, without any increase in error rate. Similarly, [Sellers et al., 2006] found that shorter inter stimulus intervals allowed subjects to produce text at a higher bit rate using the P300 Speller (with row-column stimulus presentation). Adjusting stimulus display parameters such as these may make the RSVP Keyboard™ and other BCI-based typing tools more effective for users with a variety of needs and abilities. Future research will examine the effects of varying presentation rate and sequence length on the performance of participants with LIS.

Acknowledgements

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A Motor Imagery Based Asynchronous BCI Speller

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Abstract. In this paper, we present a motor imagery based asynchronous BCI speller. The speller paradigm is implemented by combining 2D control strategy and a mental switch in a well designed interface, in which the mental switch and 2D control are both based on a three-class motor imagery system. The experimental results (two subjects participated) demonstrates the satisfactory performance of the proposed speller.

Keywords: Motor Imagery, Asynchronous protocol, BCI speller

1. Introduction

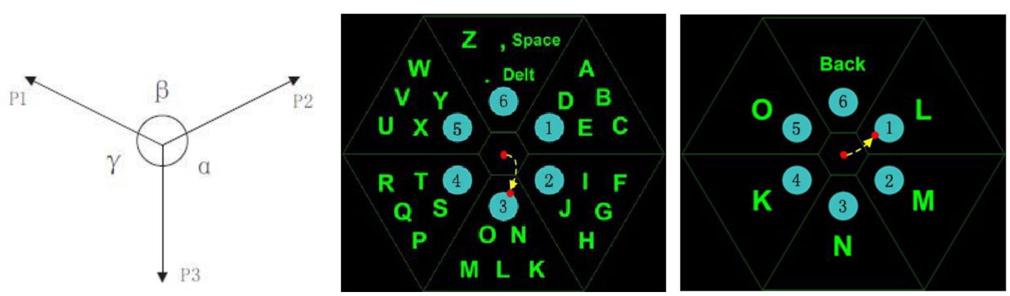
Motor imagery based BCI spellers cannot use full size virtual keyboard on the screen due to their limited commands. Therefore, motor imagery based speller always has a special interface. Depending on the operation protocol, BCI spellers work in synchronous and asynchronous modes, whereas the latter is a natural course of interaction that spells the characters depending on user's intention. In this paper, we developed a motor imagery based asynchronous BCI speller, which combines 2D cursor control strategy and a mental switch in Hex-o-Spell interface [Blankertz et al., 2006].

2. Material and Methods

2.1. 2D control strategy and asynchronous protocol

In a previous study [Xia et al., 2012], we presented a three-class (left hand, right hand and feet) motor imagery based BCI for 2D cursor control. The predicting probabilities (P1, P2, P3), obtained from Support Vector Machine classifier, are projected to three vectors, as shown in Fig. 1(a). P1, P2, and P3 are the probability of the left hand, right hand, and feet imagery respectively. The angle between two vectors is 120 degree and the norm of the vector is equal to the value of the corresponding output probability. To hit the target located in the area between two vectors, the user performs two corresponding motor imagery tasks simultaneously to generate a speed vector, by which the cursor is driven directly to the target.

To work in asynchronous mode, the motor imagery mental switch needs to be opened prior to spell, for which the predicted probability of the motor imagery task should exceed a threshold in a duration $\triangle t$. Considering variation of the user's status, we set three conditions for the mental switch: (1) threshold 0.9 with duration 0.5 s; (2) threshold 0.85 with duration 1.0 s; (3) threshold 0.8 with duration 1.5 s. If the user achieves one of the three conditions, the switch opens.



(a) (b) (c)

Figure 1: *Speller paradigm (a) three-class MI based 2D control, (b) first layer, (c) second layer.*

2.2. Asynchronous spelling paradigm

We designed a novel Hex-o-Spell interface consisting of two-layer structure as shown in Fig. 1(b,c). In the first layer, each block includes five letters (or specific symbols) and a target ball, while in the second layer, there are only one letter and a target ball in each block. At the beginning of experiment, the user opens the mental switch and uses 2d control strategy to move the cursor to hit the ball of the block with target letter in the first layer (Fig. 1b). And then, the paradigm will extend to the second layer (Fig. 1c). Following the movement of the cursor to hit the ball of the target block, the speller outputs a letter and ends the current trial. Then, the system automatically changes to idle state automatically and begins to monitor mental switch.

Table 1: *Average Accuracy, CPM, ITR and Switch type*

Subject	Accuracy (%)	CPM	ITR (bits)	Switch type1 (%)	Switch type2 (%)	Switch type3 (%)
S1	100	11.90	61.54	91	7	1
S2	100	9.74	50.34	97	2	1
Mean	100	10.82	55.94	94	4.5	1.5

3. Experiment

The EEG was measured using a 16 channel g.USBamp system using band-pass filtered between 5 and 30 Hz and sampled at 256 Hz. Electrodes were placed according to the international 10–20 system. Thirteen channels in motor cortex area were selected (FC3 FCz FC4 C5 C3 C1 Cz C2 C4 C6 CP3 CPz CP4), the ground and reference electrodes were fixed on Fz and the right earlobe respectively. Two subjects participated this study, and they both joined previously 2D control experiment [Xia et al., 2012].

In online spelling experiment, each subject spell English word in 3 runs (Run1 WOMEN DESK WATER HAND MEMORY; Run2 ZONE BABY FACE TAXI JUNE; Run3 QUICK VIDEO GOLF HOUR PENCIL). Subject repeated the experiment 3 times. We set the 'no'error protocol in this experiment that means subject should correct spelling mistake.

4. Results

To evaluate the performance of the proposed speller system, we calculated the accuracy, the characters per minute (CPM), information transfer rate (ITR). As shown in Table.1, the average spelling accuracy is 100 % for two subjects. The average CPM and ITR are 10.82 letters/min and 55.94 bits/min respectively. To evaluate the efficiency of switch, we calculated the percentage of switch type using in online experiment. Two subjects used switch type1 over 90 % that means they can switch from idle state to work state in 0.5 s. Both users rarely use switch type 2 and 3.

5. Discussion

In general, the performance of motor imagery based BCI speller is not good as visual stimuli based speller due to its limited commands. In this work, we developed an asynchronous BCI speller only using three-class motor imagery tasks. Comparing with recently published synchronous speller with average CPM 9.39 [Hwang et al., 2012], our results are satisfactory and comparable.

Acknowledgments

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BCILAB: A Toolbox for Rapid Development of Advanced BCI Designs

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Abstract. BCILAB is a new open-source MATLAB-based toolbox aimed at helping advance the state of the art in designing and building Brain-Computer Interfaces (BCIs) and Cognitive Monitoring systems with a focus on electrophysiological signals. These systems translate, in real time, brain and/or other biosignals into control signals useful to computer applications, thereby offering communication and control pathways to their users that extend the brain's natural motor output channels. To address the challenges of accurately and robustly translating a person's brain signals into estimates of cognitive/affective state, and of solving the related inverse problems given the least amount of (relatively costly-to-acquire) data, BCILAB includes an extensible component framework for advanced signal processing, machine learning and related probabilistic inference, optimization and system evaluation, which covers over 100 methods and method variants. To validate the toolbox implementation we present analysis results for several data sets (17 subjects total) pooled from the BCI Competitions III and IV.

Keywords: BCI, EEG, Toolbox, MATLAB, CSP, Motor Imagery

1. Introduction

Here we present BCILAB, a new open-source toolbox for MATLAB (The Mathworks, Natick, MA) that attempts to facilitate both the development of new BCI approaches and implementations as well as comparisons with methods already published in the scientific literature.

The main design aim of BCILAB is to assist practitioners in the experimental neurosciences, the computational and mathematical sciences, and in application design and engineering in efficiently developing and testing new brain-computer interface (BCI) models. Both a graphical user interface (GUI) shown in Fig. 1 and a scripting interface are provided to allow researchers to perform analysis and online experiments. A complementary set of plug-in frameworks allow methods developers to rapidly implement new methods and make them available for later re-use in numerical and real-time experiments, as well as to test new methods against already existing approaches.

2. Material and Methods

To validate the overall toolbox implementation we replicate a part of the analysis performed in [Lotte and Guang, 2011], which itself is a comprehensive re-analysis of publicly available data sets from the BCI Competitions III and IV, together comprising data from 17 subjects. The underlying task is a variant of the well-established motor imagery scenario (cf. [Pfurtscheller and Neuper, 2001]), which is one of the two most frequently used experimental designs in the clinical BCI field and a widely accepted benchmark. An analysis of event-related potential phenomena as relied on, for example, by P300 spellers [Farwell and Donchin, 1988] is omitted here due to space limitations.

3. Results

The mean and median classification accuracy of all algorithms across the data from all subjects is summarized in Table 1. Chance level here is 50%. In agreement with the reference analysis by [Lotte and Guang, 2011], the highest accuracy across all the data is attained by the three regularized variants of the basic Common Spatial Pattern (CSP) algorithm: using Tikhonov regularization (TRCSP), diagonal loading regularization (DLCSPcv) and the recently-proposed DLCSPauto which uses regularized shrinkage estimators for the covariance matrices on which CSP is based. We also present results for the Spectrally Weighted Common Spatial Patterns (Spec-CSP) approach by [Tomioka et al., 2006] as a representative method that learns its spectral filter adaptively.

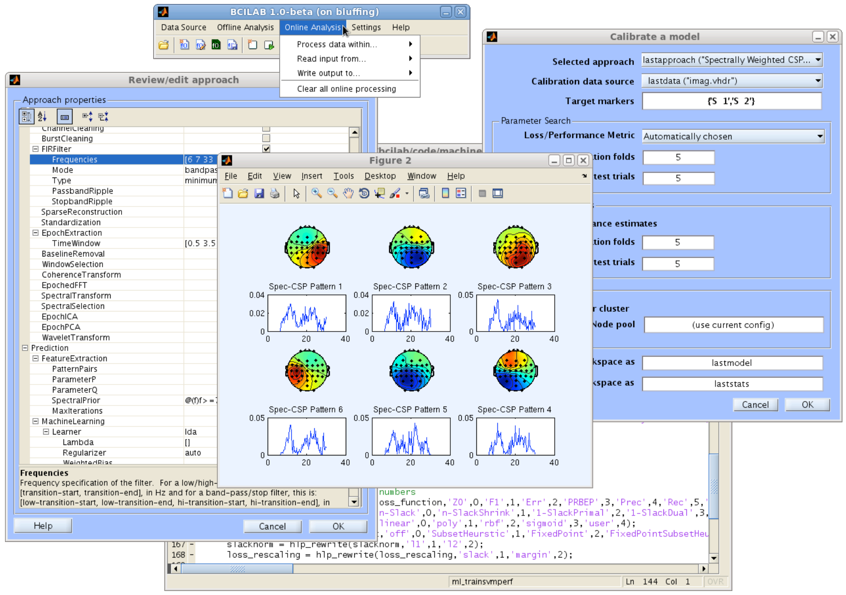

Figure 1. *A sample subset of BCILAB's graphical user interface panels showing the main menu, a model visualization, a model configuration dialog, an evaluation setup dialog, and the script editor.*

Table 1. *Classification accuracy of a representative sample of algorithms for oscillatory processes applied to motor imagery data across 17 subjects from the BCI Competitions III and IV.*

Algorithm	*Median Accuracy (%)*	*Mean/Std. Dev. Accuracy*
CSP	75.8	75.8±15.3
TRCSP	75.8	75.2±15.4
DLCSPcv	76.2	75.9±16.0
DLCSPauto	**78.2**	**75.9±16.3**
Spec-CSP	77.4	75.3±17.1

4. Discussion

The results of the presented method comparisons show that state-of-the-art BCI performance can be achieved by applying BCILAB to a representative BCI task. The methods used in the analysis support online processing and are part of the open-source toolbox and available at ftp://sccn.ucsd.edu/pub/bcilab/.

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Characterizing the SSVEP Spectrum Using a Broadband Noise Stimulus

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Abstract. Steady-State Visual Evoked Potentials (SSVEPs) are oscillating components of the EEG that are detected over the occipital cortex, having frequencies corresponding to visual stimulus frequencies. SSVEPs have been demonstrated as effective signals for rapid and reliable control of a BCI. While SSVEPs tend to be most prominent in the range of 5-40 Hz, the optimal stimulus frequencies are subject-dependent and can reside anywhere within that range. In traditional approaches the user's optimal SSVEP frequencies are determined by an exhaustive evaluation of predefined frequencies. The proposed approach aims to quickly characterize the SSVEP spectrum to identify the optimal SSVEP frequencies using a single broadband noise stimulus.

Keywords: Steady-State Visual Evoked Potentials, Spectral Analysis, EEG

1. Introduction

SSVEPs have proven to be very effective control signals for EEG-based BCIs [Cheng et al., 2002; Kelly et al., 2005; Müller-Putz et al., 2008]. In order to continue pushing the performance limits, various aspects of visual stimulus design and presentation have been examined in the context of BCI [Lee et al., 2011; Jia et al., 2011]. In spite of this sophisticated recent work, there are opportunities to improve traditional fixed-frequency SSVEP approaches. In most SSVEP-BCI designs, the subject is presented with multiple simultaneous stimuli. The optimal frequencies for fixed-frequency stimuli are highly subject-dependent and harmonic frequency relationships must also be considered [Zhu et al., 2010]. Therefore, it can be cumbersome to design an optimal BCI interface using multiple fixed-frequency stimuli.

Several recent studies have examined the use of broadband (i.e., containing equal power at all frequencies within the band) visual stimuli such as white noise [Lalor et al., 2006] and m-sequences [Bin et al., 2011]. In [Lalor et al., 2006] band-limited white noise visual stimuli were used to successfully develop a linear model of EEG visual-evoked potentials. Using the same linearity assumptions and stimulation approach, it is conceivable that stimulation with this noise can approximate the full SSVEP frequency spectrum. The proposed method aims to efficiently characterize the SSVEP spectrum to identify the optimal SSVEP frequencies using a single broadband noise stimulus.

2. Material and Methods

Data were collected from five able-bodied subjects (4M, 1F; average age 25). The subjects wore an electrode cap fixed with sixteen active electrodes (g.tec g.GAMMAsys) focused over the occipital sites (Fz, Pz, Poz, Oz, Po3, Po4, Po7, Po8, O1, O2, Oi1H, Oi2H, Poo1, Poo2, Poo3, Poo4). All locations were referenced to the left mastoid with the right ear serving as a ground. The EEG was amplified (g.tec g.USBamp) and digitized at 256 Hz. All aspects of the experiments were controlled by BCI2000. A custom stimulus presentation application was written using C++, which flashes a square with variable frequency and intensity on a monitor with a 60 Hz refresh rate. The subjects sat 60 cm away from the monitor with the flashing square occupying 7 x 7 degrees of visual angle. Eleven stimulus conditions were examined: ten frequencies where the square alternated between black and white at the sub-harmonics of 60 Hz from 5-30 Hz; and a band-limited white noise (at 30 Hz based on the monitor refresh rate) that changes each frame based on a uniform random distribution of 256 gray-scale intensities between black and white. Each condition was presented sequentially in a counterbalanced fashion for one minute, with a 30-second break between conditions. Two minutes of baseline data were also collected.

Data were analyzed on a per-channel basis. The EEG signals were first band-pass filtered between 2 and 35 Hz. For each channel and stimulus condition, the EEG power spectra for 1-second sliding data windows (using a Hamming window) and 1-sample overlap were computed using a 2048-point FFT. The power spectra for the baseline condition were computed using the identical procedure. The Fisher Ratio (squared difference of the means over the sum of the variances) between the resulting spectra for each stimulus condition and the baseline spectra was then computed for each spectral bin as a measure of discriminability from baseline.

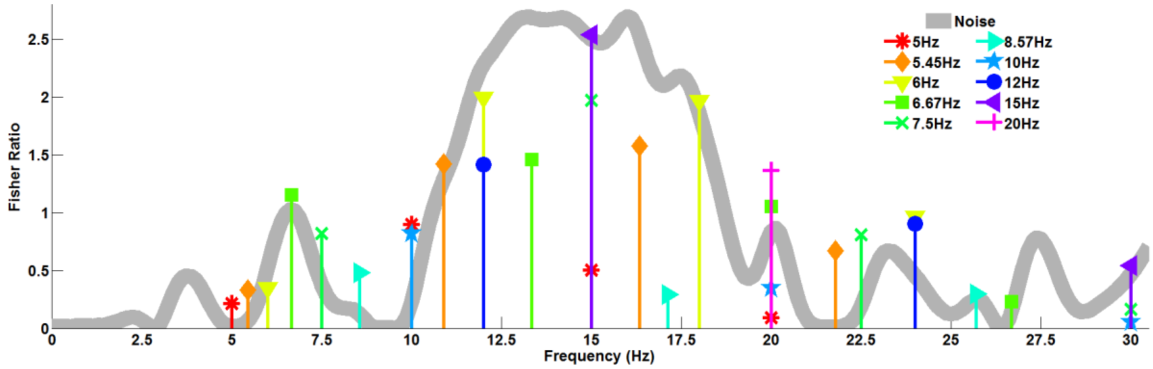

Figure 1. *Results for a representitve subject from channel Oz. The Fisher Ratio of the noise power spectrum and the baseline power spectrum is shown as the solid gray trace. The Fisher Ratios of the SSVEP power spectrum and the baseline power spectrum for each stimulus frequency are shown as the colored stem plots. The fundamental frequency and the subsequent three harmonics are plotted for each stimulus condition.*

3. Results

Fig. 1 shows the results for a representative subject at channel Oz. The Fisher Ratios for each SSVEP stimulus condition at the fundamental frequency and the subsequent three harmonics are plotted as the colored stems. The gray trace shows the scaled Fisher Ratio for the band-limited white noise stimulus across the entire frequency spectrum. Because the objective is to identify the optimal SSVEP frequencies, the Fisher Ratio of the noise is scaled to align with the SSVEP data to better illustrate the relationship between the noise and SSVEP spectra.

4. Discussion

The Fisher Ratio of the noise stimulus spectrum closely aligns to the distribution of the Fisher Ratios for the majority of the SSVEP frequency conditions and their respective harmonics. While this method appears to give a strong indication of the optimal and undesirable SSVEP frequencies, it does not provide a complete and definitive characterization in its current form. This is due to two primary factors: (1) the stimulus frequencies are highly limited by the monitor's refresh rate and (2) the relationship between the programmed stimulus sequence and the EEG is clearly not linear. Future studies will extend these results by presenting continuous stimuli on an LED display that is not limited by a refresh rate, and to better characterize the nonlinear relationship between the stimulus sequences and the EEG.

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SSVEP-Based BCI Stimulation Frequency Selection Training and Detection Approaches

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Abstract. In recent years, there has been increased interest in using steady-state visual evoked potentials (SSVEP) in brain-computer interface (BCI) systems because of its fast and reliable communication. A training procedure capable of individually evaluating the suitable stimulation frequencies to be part of a SSVEP based asynchronous BCI application as well as the spatial distribution of the evoked response has been developed. 5 novel detection methods suitable to be implemented in a real-time BCI application are compared. Both training and detection methods were evaluated for the construction of a 2 degrees of freedom BCI application with promising results. The most successful one has been integrated within the assistive technologies free open source platform AsTeRICS.

Keywords: EEG, SSVEP, Enobio, BCI, AsTeRICS

1. Introduction

Our approach presents 5 detection methods based on different aggregation functions to be used in an asynchronous self-paced SSVEP based BCI application. We describe the main stages of the system, namely for training (selecting the best frequencies and its spatial distribution) and for detecting the VEP.

2. Method

2.1. SSVEP Response

SSVEP is a resonance phenomenon manifested as oscillatory components in the user's EEG matching the frequency of an external stimulation source and its harmonics. Since the spectrum of spontaneous brain activity shows a log-decrease in power with increasing frequency, it might be difficult to discriminate event-related peaks from ongoing brain activity in the high part of the spectrum. Supposing that the energy level at the stimulation frequency is larger than the energy of its adjacent frequency bins, the following feature f has been defined to evaluate the response at the stimulation frequency bin denoted as f_{flicker} (in Hz).

$$f(f_{flicker}) = \frac{2 \cdot PSD(f_{flicker})}{PSD(f_{flicker}-1)+PSD(f_{flicker}+1)} + \frac{2 \cdot PSD(2 \cdot f_{flicker})}{PSD(2 \cdot f_{flicker}-1)+PSD(2 \cdot f_{flicker}+1)} \quad (1)$$

2.1. Training Procedure

SSVEP is a subject dependent phenomenon where the elicited response depends on the stimulation frequency. Hence it is necessary to individually evaluate the best stimulation frequencies to be used. A training method has been developed for this purpose being also in charge of delivering the spatial distribution of the evoked response. The training procedure is performed through a set of training measurements composed of N non-stimulation periods of duration Tn followed by N stimulation periods of duration Ts where the visual stimulus is presented at f_{stim}. Spatial filters are calculated at each stimulation period according to [Friman et al., 2007]. Each calculated spatial filter is applied to the entire training signal. Stimulation and non-stimulation periods are extracted and f (1) calculated at $fstim$ in a sliding window. The area under the ROC curve (AUC) is evaluated, where the features corresponding to the stimulation periods are marked as the positive class and the ones to the non-stimulation periods as the negative class. The spatial filter with the largest AUC is chosen to be used in the detection process. Lastly the Ns stimulation frequencies selected to be used in the BCI application, which present this same number of freedom degrees, will be the ones corresponding to the training measurements delivering the largest AUC.

2.2. Detection Procedure

The goal of the detection process is to determine which stimulation frequency was responsible of eliciting the SSVEP. For each frequency under evaluation the vector W is built by concatenation of the f calculated upon Eq. 1 in a sliding window as in the training. Data fusion of vector W components is carried out based on one of the following

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aggregation techniques: arithmetic mean (M1), Euclidean mean (M2), geometric mean (M3), harmonic mean (M4) and ordered weighted averaging (M5) delivering the aggregation value K. The stimulation frequency selected as the one responsible of eliciting the evoked potential is the one corresponding to the largest K.

2.3. Experimental Procedure

This study compares the 5 former aggregation procedures w.r.t. SSVEP detection performance. Four subjects S1 to S4 participated in six recording sessions. Stimulation frequencies evaluated were 12, 14, 16, 18, 20 and 22 Hz. Each session consisted of one recording per stimulation frequency. In each recording, $Ts=4\,s$ and $Tn=8\,s$, 15 sequences of stimulation/non-stimulation periods were presented. In order to reproduce the set-up of a binary BCI application, visual stimulus was rendered using two stimulation LED sources. The stimulation source on the right of the subject presented the stimulation frequency under evaluation, while the one on the left a random frequency among the others selected for the experiment. The user was told to attend the stimulation source on his right without blinking during the stimulation. EEG was acquired using 3 Enobio® channels placed in O1, Oz and O2.

3. Results

Each recording was split into 3 training intervals formed by 5 stimulation/non-stimulation periods each in order to evaluate the best two stimulation frequencies for each subject. We compute the AUC associated to each parameter in each training interval, and the average of these AUCs. Table 1 presents the averaged AUC calculated for each stimulation frequency. The two stimulation frequencies that delivered the largest average AUC for each user (in bold in the table) were chosen as the ones to be used in the detection performance evaluation for the different aggregation methodologies. For each subject the detection performance evaluation was performed based on 3-cross-fold validation. So we compute the remaining detection parameter, spatial filter coefficients, over 1 training interval and measure the performance of the proposed aggregation techniques on the other 2. Table 2 shows the average of the positive detection percentage per subject and per aggregation operators compared.

Table 1. *Training procedure average AUC.*

	12Hz	14Hz	16Hz	18Hz	20Hz	22Hz
S1	**0.93**	0.81	**0.85**	0.79	0.77	0.82
S2	0.67	0.66	**0.70**	0.67	0.69	**0.77**
S3	0.91	**0.92**	0.90	**0.92**	0.91	0.82
S4	0.56	0.69	**0.86**	0.77	**0.82**	0.78

Table 2. *Positive Detection percentage and mean ITR.*

	M1	M2	M3	M4	M5
S1	96.6	93.3	98.3	98.3	96.6
S2	88.3	85.0	88.3	90.0	90.0
S3	100	100	100	100	100
S4	91.6	91.6	91.6	88.3	91.6
Avg	94.2	92.5	94.6	94.1	94.6
ITR	0.68	0.61	0.70	0.68	0.70

4. Discussion and Future Work

A training procedure capable of delivering the stimulation frequencies that elicits the largest response and its spatial distributions has been successfully implemented. This leads to the implementation of very reliable SSVEP detection working in real-time. The SSVEP detection for the selected stimulation frequencies shows an excellent detection accuracy for every subject as shown in the described tests. Geometric mean and ordered weighted averaging methods deliver the best results but with no significant difference with the other methods.

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Towards Implicit Control Through Steady-State Somatosensory Evoked Potentials

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Abstract. We present a reliable reactive BCI based on steady-state somatosensory evoked potentials (SSSEPs). As the stimulation frequencies are higher than 40 Hz this system ensures no interference with BCIs relying on ERPs or SMR. Hence, the presented system can be combined with other BCIs broadening the bandwidth of communication.

Keywords: Reactive BCIs, steady-state somatosensory evoked potentials (SSSEPs), Hybrid BCIs

1. Objective

The study presented here aims at extending the scope of interaction with Brain-Computer Interfaces (BCIs), by introducing a BCI system which does not interfere with most of the established BCI systems. This is done by using a BCI based on steady-state somatosensory evoked potentials (SSSEP) working with signal frequencies of more than 40 Hz, hence lying above those frequencies generally associated with human cognition [Ward, 2003]. Additionally, the presented BCI is a reactive BCI (rBCI) [Zander and Kothe, 2011], aiming to provide a solution for implicit control over a Human-Machine System [Rötting et al., 2009] and thus to reduce cognitive demands for human-machine interaction. As a consequence, the presented BCI system may possibly be combined with other BCIs, such as a motor imagery BCI, and can thus add degrees of freedom to interaction with future BCI systems.

2. Approach

Reactive BCIs usually make use of two different types of features in the EEG. They are either based on detection of changes in or appearance of event related potentials (ERPs) typically caused by appearance of stimuli relevant to the user or on the detection of steady-state evoked potentials (SSEPs). The latter are potentials which are evoked from perceiving a stimulus that is modulated in a specific frequency, leading to differences in the spectral domain of the EEG of that same frequency. Prior work in the field of rBCIs is mainly based on visual stimulation, such as the P300 Speller [Farwell and Donchin, 1988]. Also, most of the work with SSEPs was based on visual input [Lalor et al., 2005; Müller-Putz and Pfurtscheller, 2008] whereas some work also included tactile [Brouwer and van Erp, 2010] or auditory [Nijboer et al., 2008] stimuli, thus providing a proof of concept that this approach can potentially be transferred between modalities. As the visual and the auditory domain of users in Human-Machine Systems usually are occupied during operation, we investigate rBCIs that rely on tactile stimulation. Our approach transfers the knowledge gained from the rBCIs mentioned above to this modality and investigate the reliability of the resulting implicit control. We modulate specific frequencies in the EEG by steady-state somatosensory evoked potentials (SSSEPs) with auditory speakers as tactile stimulators. The frequency domain of the tactors is kept above 40 Hz and thereby excludes (1) interference with typical BCI-applications that are based on evoked potentials since those usually consist of waves within a lower frequency band (0.5 Hz–5 Hz) and (2) covering of the frequency domain which is generally assumed to be related to cognition [Ward, 2003].

3. Method

Data sets from 8 participants were included in the preliminary analyses. EEG was recorded using 64 impedance-optimized electrodes (BrainProducts, Gilching, Germany). Tactors used for the experiment were developed by Eagle Science (Haarlem, The Netherlands) and are based on auditory speaker modules. Compared to tactors that are driven by unbalanced motors, the stimulation with auditory based tactors is very precise and well adjustable regarding the frequency and amplitude of the vibration. Two tactors were placed on the participants' palms of the left and right hand. The used form of stimulation was derived from Tobimatsu et al. [1999]: Each tactor was vibrating with a carrier-frequency of 128 Hz sine modulated with a sine of 41 Hz on one hand and 59 Hz on the other one. Prime number frequencies were used for modulation to reduce overlapping frequencies. Each trial started with the presentation of a randomly selected letter from the set 'L', 'R' at the center of the screen for 2 s.

Hereafter, the letter was replaced by a fixation cross for 3.8 s. Simultaneously the tactors started vibrating and participants were asked to focus their attention on the vibration on the left hand side if the initial letter had been 'L' or on the vibration on the right hand side if it had been 'R'. After 2.8s of the stimulation period the amplitude was reduced by half for 0.125 s (amplitude twitch, similar to [Müller-Putz et al., 2006]). Participants completed 120 trials, 60 for each tactor. A linear weighting was derived for each class respectively (attention on left or right tactor) by averaging differences between the estimated power of the frequencies of 41 Hz and 59 Hz and normalizing it by the respective averaged bandpower derived from the two seconds of data before the stimulus. For classification, features were extracted by a similar procedure. Again, but here on single trial data after the amplitude twitch, bandpower was estimated for both frequencies, and normalized by the bandpower of the prestimulus data. The resulting vectors were each linearily combined with both weight vectors, resulting in a 4 dimensional feature space. Single-trial offline classification was performed with BCILAB [Delorme et al., 2011], generating a regularized linear discriminant analysis for each participant by crossvalidating the trials along the aforementioned approach.

4. Results

The estimated accuracy was 65.5 % (SD: 3.7 %) on average across subjects.

5. Discussion

For each participant the classification accuracy was reliable, but probably not sufficient for useful control. This hints to a problem caused by instability of the feature vectors and non-stationarity of the signal for which a solution needs to be found. Future research should focus on new types of feature extraction dealing with this problem. Improvement of the linear weighting to a spatial filter could be a solution, which would have to be tested on data from a higher number of participants. A hybrid application combining the approach described here with e. g. a motor imagery BCI should be promising to increase the bandwidth of information transfer in BCI-based applications.

Acknowledgments

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Cloud-Based Analysis of EEG Signals for BCI Applications

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Abstract. In this work we explore the feasibility of using a cloud-based approach to analyzing EEG signals for use in BCI. A cloud-based approach allows us to move analysis away from the user, offering a three-fold benefit. First, it means we can perform more complex analyses as the user transmits data. We are also able to develop algorithms which utilize data from multiple users. This also allows us to leverage demanding analysis algorithms from mobile devices such as smart phones/tablets with limited resources. For this approach to be feasible, we need to ensure that data is processed quickly and reliably, handling any lags that may be incurred due to network communications.

Keywords: EEG, Stream Processing, Motor Imagery, Mental Tasks, Collaborative Classifications, Neural Network

1. Introduction

As EEG collection devices become smaller and more mobile, the need to perform EEG analysis on small-factor devices such as mobile phones or tablets grows. These devices have limited processing power, but are equipped with networking capabilities that allow them to transmit data to a remote resource pool for advanced processing. One approach is to dedicate a single machine to each user wishing to remotely connect for classification, but this leads to wasted resources and does not scale well. We propose interleaving computations as an effective and scalable method of supporting many concurrent users within a pool of limited resources.

2. Approach

In this work we use a feedforward artificial neural network (ANN) with time-delay embedding for the mental task BCI paradigm. We are building on work introduced in [Anderson and Bratman, 2008; Anderson et al., 2011; Ericson et al., 2010], using similar neural networks and a time-delay of 3 timesteps. Our focus is not on accuracy, instead we mark all classifications as passing or failed based on our ability to classify data in a timely manner.

As we are sending data to be classified in a remote resource pool, we have further compressed signals by sending all data generated for the last 250 ms to be classified together. We consider responses which take more than 250 ms as failed. We use this measure across all our experiments. This time period was chosen as it is a good fit for our processing footprint, but is fully adjustable. We can classify signals of this length in 10 s of milliseconds, leaving plenty of time left over for any communications overheads we may incur from our approach.

2.1. Data

We classify EEG signals generated by an able-bodied adult male, gathered by the CSU BCI lab[1]. Four tasks are recorded from the user: imagined right hand movement, imagined left leg movement, counting backwards from 100 by threes, and imagining a computer display tumbling in three dimensions. The dataset is separated into five different recording sessions, where each recording session has 10 five-second recordings for each of the four tasks. We use four of our five datasets for training, reserving the fifth for testing. The EEG data was gathered using a NeuroPulse Mindset 24R amplifier with 19 electrodes arranged using the international 10-20 specifications and a sampling rate of 512 Hz.

2.2. Network Setup

In our experiments we used identical machines to support all processing of EEG signals and to stream pre-recorded EEG signals into the resource pool for classifications. This resource pool consists of machines with four 2.4 GHz cores, 16 GB RAM, and gigabit ethernet connection, with round-robin load balancing. For classification, we are using a group-of-experts approach, where multiple ANNs are trained with slightly different initial weights, allowing each to learn a slightly different solution. Each user has a dedicated group of experts trained on their own data, which users can tune as needed.

[1]www.cs.colostate.edu/eeg

Each machine in the resource pool also has a generic group of experts. This group of experts has access to new training data from *all* users currently utilizing that machine. This allows the system to take advantage of hosting computations for multiple users – it can learn patterns across many users simultaneously, which can lead to increases in performance [Wang and Jung, 2011].

3. Results

We first focused on determining the maximum number of users we could support on a single machine. This sets an upper bound for all further stress tests. As we add more machines and users we put more strain on the communications infrastructure, so we will likely only be able to support fewer users. In our first attempt, we tried to support 30 concurrent users on a single machine. This means that there are effectively 31 unique computations on a machine (one generic, and one dedicated to each user). With 30 users, we only had one message that returned in over 250 ms out of 150,000 messages sent, leading to a failure rate of 0.0006 %. As the one failed message proved to be one of the first messages sent, we believe that this was purely an initialization overhead. We then tried to support 35 concurrent users on a single machine, which had a failure rate of only 0.2 %. When we moved up to 40 concurrent users the failure rate jumped up to 0.5 %, but the magnitude of failure went from a 9.5 second delay to 30 seconds. To minimize the magnitude of failures, we decided to cap further tests to 35 concurrent users.

Using the information found in our initial stress tests, we scaled up to a resource pool of 40 machines. We hope to support just as many distinct computations in this setup as we found in the first set of experiments (35 users/machine). As we expect to overload our communications substrate, we started with 25 users per machine, a total of 1000 computations. With 1000 concurrent users, we saw a failure rate of 0.005 %, with a worst-case response time of just over one second. We next moved on to support 35 users per machine (1400 computations). When supporting 1400 users, we saw a massive jump in the number of failed computations, up to 0.8 %. We also saw a drastic change in the probability density of response times. Looking at these response times (Fig 1), it is clear that attempting to support more users would lead to more failed computations.

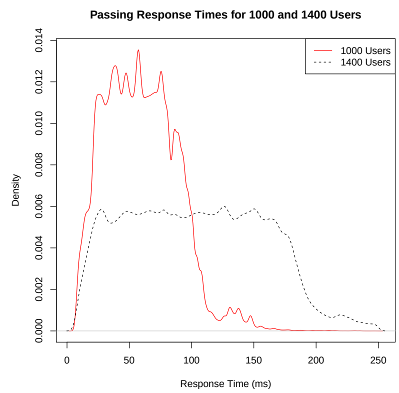

Figure 1: *Density functions of passing response times in milliseconds for 1000 and 1400 users on a cluster of 40 nodes.*

4. Discussion

While we have been working with neural networks for the mental task BCI paradigm, there is nothing to preclude the use of another algorithm, or even a different paradigm within our framework. We can support arbitrary processing in a number of programming languages, such as C, C++, C#, Java, Python, and R [Ericson and Pallickara, 2012]. Different algorithms will have slightly different processing requirements and different paradigms will have different communications overheads, but by modifying the rate at which messages are passed to the network for processing we can account for any of these changes.

While we have explored methods of supporting multiple users concurrently, there are cases where it may not be feasible for users to remain constantly connected to a cluster, such as when there are in places with poor wireless connections, or when the user is on a data-limited connection, such as a 3G or 4G network. In these situations, it makes sense to use an offline model such as we see adopted into some mobile voice recognition applications. The phone is regularly updated with new models which have been developed after sampling across multiple users. These are small-form models, which allow quick classifications on the mobile device itself, so users do not require a constant live connection to outside servers. Users would still, however, be able to access models trained with data from multiple users, potentially leading to much better results.

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Towards a Free and Open Source BCI System Written in Python

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Abstract. The following paper describes the current state of our effort to create a completely free and open source BCI System in Python. A general BCI system consists of three parts: signal acquisition, signal processing, and feedback and stimulus presentation. Accordingly, our software consists of three parts: Mushu for the signal acquisition, Wyrm for the signal processing and Pyff for the feedback and stimulus presentation. All three components combined form a complete BCI system. Through usage of well defined interfaces each component can also be used stand-alone in a different setting (e. g. as part of a different BCI system). The whole system runs on all major operating systems, like Windows, Mac OS and Linux, is written in Python and is free and open source software licensed under the terms of the GNU General Public License.

Keywords: BCI, Python, Signal Acquisition, Signal Processing, BCI Feedback, Software

1. Introduction

In this paper we describe the three software components which will form together a complete, free and open source BCI system written in Python.

Similar projects to create complete BCI systems exist, like BCI2000 [Schalk et al., 2004] or OpenVibe [Renard et al., 2010]. BCI2000 is free only for non-commercial and educational usage and OpenVibe being truly free software is licensed under the terms of the GPL. Both are written in C/C++ which gives better performance, but makes it also much harder to write BCI experiments and applications for non-computer scientists. OpenVibe mitigates this by allowing for an drag- and drop like approach for visual programming of experiments.

We decided to use Python as the programming language of choice because we think it is an excellent general purpose programming language with a large and comprehensive standard library. Together with SciPy, NumPy and matplotlib [Jones et al., 2001], Python is a powerful and free alternative to commercial packages like Matlab. Studies [Prechelt, 2000] have shown that programming in high level languages like Python significantly shortens the amount of time needed to implement a solution and leads to shorter and thus less error-prone code compared to more low level languages like C or C++. This is particularly important for software which is going to be used and modified not only by computer scientists, but students and researchers from different fields.

2. Components of our BCI System

Fig. 1 shows an overview over the general structure of a BCI system. EEG data is measured via EEG caps from the subject's head and the signal is amplified through the EEG amplifiers. A signal acquisition software collects the data from the amplifier and forwards it to the signal processing where usually some machine learning algorithm extracts information from the EEG data and forwards it to the feedback/stimulus presentation.

With Mushu [Venthur and Blankertz, 2012] we are providing the signal acquisition part, with Wyrm the signal processing, and with Pyff [Venthur et al., 2010] the feedback and stimulus presentation. All three components will form a complete BCI system written in Python.

2.1. Mushu

When doing BCI experiments with EEG data one always has to use EEG amplifiers to acquire the brain signals. Those amplifiers usually come with their own software and different vendors have different formats for saving and online streaming of the EEG data. Often the software provided by the amplifier vendors only runs on Microsoft Windows systems, leaving out the Mac OS and Linux users. With Mushu solve those problems altogether: we want a signal acquisition software that runs on all major operating systems, that supports a wide range of EEG hardware, that produces and outputs data in a standardized format independent from the amplifier. We already reverse-engineered the g.USBamp and the EPOC [Venthur and Blankertz, 2012] system and wrote pure Python drivers which allow to

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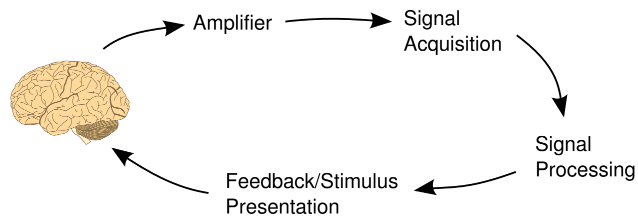

Figure 1: General structure of a closed loop BCI system. EEG data is acquired from the subject, fed through the amplifier and collected by the signal acquisition. The signal acquisition forwards the EEG data to the signal processing where information is extracted from the data and forwarded to the feedback/stimulus presentation.

use those systems on all Operating Systems without the need for external drivers. Other drivers for systems like: BrainAmp, TMSi Mobita, and Enobio will follow.

2.2. Wyrm

Wyrm represents the signal processing part of our system. It is suitable for online experiments and off-line analysis. Wyrm is currently under development, but it already contains crucial parts of a BCI toolbox like Common Spacial Patterns (CSP) [Blankertz et al., 2008] for processing, and Linear Discriminant Analysis (LDA) for classification. Wyrm is not yet ready for the public to use but a prototype doing successful classification already runs in our lab.

2.3. Pyff

Pyff is a framework to develop and run BCI feedback and stimulus applications in Python. It was designed to make the development of feedback and stimulus applications as easy as possible. We particularly developed it with non-computer scientists in mind which often create and implement new BCI paradigms. The framework communicates with the rest of the BCI system via a standardized communication protocol using UDP and XML and is therefore suitable to be used with any BCI system that may be adapted to send its control signal via UDP in the specified format. We also provide adapters for BCI2000 and any TiC (www.bcistandards.org/softwarestandards/tic) compatible BCI.

3. Outlook

At the time of writing this abstract. The here introduced BCI system is still work in progress. While Pyff is mature and published years ago, Mushu and Wyrm are working prototypes and not yet ready for release. The source code is nevertheless publicly available and contributors are invited to test the code and contribute. We continue to develop this system and aim for having it in a usable state in 2014.

Mushu, Wyrm, and Pyff are free- and open source software licensed under the terms of the GNU General Public License (GPL). The repositories are github.com/vethur/(mushu,wyrm,pyff).

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Bringing Big Data to Neural Interfaces

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Abstract. The purpose of this paper is to present a new community-wide research entity to be launched called the Neural Engineering Data Consortium (NEDC). The purpose of the NEDC is to accelerate Brain Computer Interface research by creating, curating, and archiving massive neural datasets for the neural engineering community. The need for massive datasets is justified by the innate variability in neuronal activity. By pooling the resources of the neural engineering community and making such massive datasets available, we will enable investigators to improve BCI performance metrics and increase robustness. A proof of concept data corpus comprising 12,000 clinical EEGs is presently under development.

Keywords: Big Data, Machine Learning, EEG, Data Mining

1. Introduction

The past two decades have seen an explosion in Brain Computer Interface research dedicated to using neural signals for controlling prosthetic interfaces to the external world. However, despite significant progress in recent years, overall progress in the field does not appear to have been commensurate with the scope of investment (over $200M in the last decade from NIH and NSF alone). In particular, efforts to commercialize research findings have been tepid, hampered by a general lack of robustness when translating technologies to uncontrolled environments beyond the research laboratory. It has become evident that the field would benefit from a new paradigm in research and development that focuses on robust algorithm development.

In response to the current state of Neural Engineering research, we are launching the *Neural Engineering Data Consortium* (NEDC). The purpose of this organization is to focus the attention of the research community on a progression of neural engineering research questions and to generate and curate massive data sets to be used in addressing those questions. The existence of massive common data corpora has proven to substantially accelerate research progress by eliminating unsubstantiated research claims. The NEDC will also broaden participation in neural engineering research by making data available to research groups who have significant signal processing expertise but who lack capacity for data generation. This effort is modeled in part after similar successful endeavors, particularly in the human language technology field where a data consortium has led to systematic research and technology advances over a 20-year span.

2. NEDC Structure and Role

2.1 Overview

The NEDC is designed as an independently operated community resource with the goal of providing some measure of value to research labs running the gamut from the largest and most well established groups down to small unfunded labs. The NEDC does not seek to compete for funds with other members of the community, nor does it seek to supplant the existing roles of any members of the community or undermine their autonomy. Rather, we envision the NEDC as a communal utility whose actions will serve the greater good. The NEDC operates independently under the auspices of Temple University.

Working with a group of community stakeholders, the NEDC will be developing a series of research questions that can be addressed with a series of progressively difficult tasks. Various federal funding agencies will then contract the NEDC to design and execute data collection protocols. A critical role of the NEDC is to design data collection protocols that account for all the various biases that can compromise complex data models and that are large enough to accurately account for data variances. In the case of neural data, this may well require corpora that are orders of magnitude larger than what any single PI or group could realistically collect.

Data generated by the NEDC will be released to the consortium members, including both funded and unfunded PIs, as well as members of industry. Investigators will pay a tiered consortium fee to secure access to the data. The value of giving unfunded investigators discounted access to data has been well documented; many of the best contestants in the Berlin Brain-Computer Interface contests were small laboratories without the means to generate their own brain interface data [Blankertz et al., 2006]. Providing labs such as these with access to data is therefore a means of significantly improving the community's overall progress at little or no effective cost.

2.2 Data-Driven Research Challenges

Perhaps the most critical aspect of the NEDC's mandate is to issue research challenges and to independently score and arbitrate the results in much the same way as the Berlin Brain-Computer Interface contest has. Contestants would use a set of training data to create a model, and would then use that model to decode a set of test data. The NEDC would then score the results and periodically announce ranked winners. This is a vital aspect of the NEDC because it makes it possible for research labs to compare performance on the very same data. In this sense, it will be possible to disambiguate the best modeling and neural decoding methods from less promising approaches. This is not possible under the existing research model, in which each lab uses its own data to test its algorithms; even existing shared data sets are not sufficiently rich to adequately evaluate any given neural decoding algorithm.

3. EEG Data Corpus

The NEDC is presently creating its first data corpus as a proof-of-concept to demonstrate the value of big data as well as our own operational capabilities. Using so-called "found data," we are creating what will be the world's largest publicly available database of clinical EEG data. The data comprise over 12,000 clinical EEG records made at Temple University Hospital over a ten-year period. Although information disclosing a patient's identity, such as name and corresponding video will be redacted, other demographic information such as gender, age, ethnicity, relevant medical history, and medications will be retained. In this manner, for example, it will be possible to mine the completed data set for statistically significant changes in EEG activity in response to various medications. In this regard, the NEDC is not only creating a tool of relevance to biomedical community, but is also developing and demonstrating our capability for managing and disseminating data of the magnitude we envision for the future. The EEG dataset is expected to be complete and available by the end of 2013.

4. Discussion

Many of the engineering challenges facing the BCI community such as high variance signals and incremental progress in improving signal processing performance are common to other engineering fields; lessons learned in those areas suggest ways forward for BCI investigators. In the human language technology (HLT) area, these engineering challenges have been effectively managed by the creation of the Linguistics Data Consortium (LDC). The LDC (*www.ldc.upenn.edu*) was founded 20 years ago in response to a realization that progress in speech processing was being impeded by a lack of common data sets and a lack of common research goals. The lack of common research goals fragmented the community and made it difficult to make meaningful inroads into any one research topic. The LDC was launched with support from NSF and DARPA and, although an independent entity, is managed administratively through the University of Pennsylvania.

The LDC performs three principal functions: (1) defining research problems of interest to the community at large (2) designing and executing data collection protocols to create massive data corpora and (3) distributing the data to consortium members and then, in collaboration with NIST, independently verifying signal processing performance claims from the competing laboratories. HLT research demands large data sets that are often beyond the capacity of any one organization to collect. These data sets are critical to the sophisticated machine learning algorithms employed in state of the art systems. As a result of LDC's influence, HLT performance has been steadily improving as datasets have increased in size from minutes of data to tens of thousands of hours of data. Further, these vast data sets have enabled the development of sophisticated unsupervised learning paradigms that have dramatically decreased the cost of developing systems.

The BCI field is ready for this type of innovation. The NEDC hopes to lead the way by creating such synergies within the bioengineering community. NEDC will collaborate closely with LDC so that we can build on their best practices and leverage their considerable expertise in experimental design, data annotation and distribution.

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Long-Term Independent BCI Home-Use by a Locked-In End-User: An Evaluation Study

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Abstract. The ERP-BCI controlled application *Brain Painting* was installed at a locked-in ALS-patient's home. BCI was operated by the family independently of BCI experts. In more than 11 months the end-user painted in 140 BCI sessions (and ongoing). The *Brain Painting* was evaluated by the BCI end-user in terms of *satisfaction*, *frustration* and *enjoyment* using a visual analogue scale (VAS). Overall, satisfaction was moderate to high (M = 6.82 of 10, SD = 3.46). The study demonstrates that independent BCI home-use is possible. Moreover, *Brain Painting* has become an important part in the end-user's life (personal statement).

Keywords: Brain Computer Interface (BCI), independent home-use, ERP, user-centered design, evaluation, locked-in state

1. Introduction

Brain-Computer-Interfaces (BCI) enable persons with severe motor impairments, such as amyotrophic lateral sclerosis, to communicate and control their environment. Despite intensive research, BCIs could hardly be established at the patient's home [Sellers et al., 2010]. Main problems are e.g., too complex and not easy to use software and time-consuming set-up. In this study we installed the BCI-application *Brain Painting*, which was successfully tested and evaluated by healthy as well as motor restricted subjects [Münßinger et al., 2010; Zickler et al., 2013], at the patient's home. *Brain Painting* utilizes an ERP-BCI for painting on a virtual canvas by selecting from various painting options (e.g. brush size, color, etc.).

2. Material and Methods

2.1. Subject

One locked-in patient (72 years old), diagnosed with amyotrophic lateral sclerosis (ALS), who used to be a painter, was considered as potential BCI end-user. As she had no existing application for creative expression, *Brain Painting* immediately awoke her interest. Currently, she is using an eye-tracker for communication.

2.2. BCI-set-up and application

The easy-to-use *Brain Painting* application was installed at the end-user's home. An initial calibration was performed once and the family was trained to set EEG-cap and to operate the BCI system. The patient and the family used the BCI independently at home and BCI experts intervened only few times, e.g., when technical problems occurred or parameters had to be changed. This was realized via remote control. BCI data and evaluation reports (see below) were automatically transmitted and stored on a remote server, enabling the experts to follow BCI use and end-user's experience. EEG was recorded with an 8-channel active electrode cap (g.tec, Austria) from centro-parietal regions. After two months the family was visited for a second time, in which a new calibration was conducted. Nine months after start a new *Brain Painting* with Einstein face-stimulation [Kaufmann et al., 2012] was installed and calibrated.

2.3. Evaluation

After every *Brain Painting* session the end-user evaluated the *Brain Painting* session. On visual analogue scales (VAS), ranging from 0 to 10, the end-user rated her s*atisfaction* with the *Brain Painting* session (*0 = not satisfied at all – 10 = very satisfied)*, her experienced *frustration (0 = not frustrated at all – 10 = very frustrated)*, and the level of *enjoyment (0 = not enjoyed at all – 10 = very enjoyed)*. In the initial test phase, only VAS satisfaction was rated (first 8 sessions). After this proof-of-principle phase evaluation was extended (sessions 9 to 140). To evaluate a positive or negative trend over time, Pearson correlations between each scale and time (session) were calculated.

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3. Results

The end-user painted in about 140 sessions within 11 months without presence of BCI experts. Setup of BCI equipment took about 20 - 40 min, while setup and operation of the application took approximately another 10 - 20 min. Mean total painting time was $M = 67.54$ ($SD = 41.83$, range: 2 - 198) minutes. After integration of face stimuli, the number of sequences used for stimulation could be decreased from 10 to 5, thereby allowing for faster command delivery. Overall, the end-user was moderately to highly *satisfied* ($M = 6.82$, $SD = 3.46$), showing a positive trend over time ($r = 34$, $p < 001$). Ratings for VAS Satisfaction across all 140 sessions are depicted in Fig. 1. *VAS enjoyment* ratings indicated that the end-user enjoyed the painting in most of the sessions, with an average of $M = 7.37$ ($SD = 3.38$, $r = .30$, $p < .001$). On the other hand, *frustration* was low, with an average over all sessions of $M = 3.19$ ($SD = 3.5$, $r = -.30$, $p < .001$). One of the main reasons for her dissatisfaction and frustration were technical problems, especially in the first BCI sessions. Further sources of dissatisfaction were bad or not good control due to possibly not sufficient electrode gel or bad cap placement, tiredness/bad concentration and loss of control due to drying electrode gel or shifting of cap after 2 - 3 hours of painting.

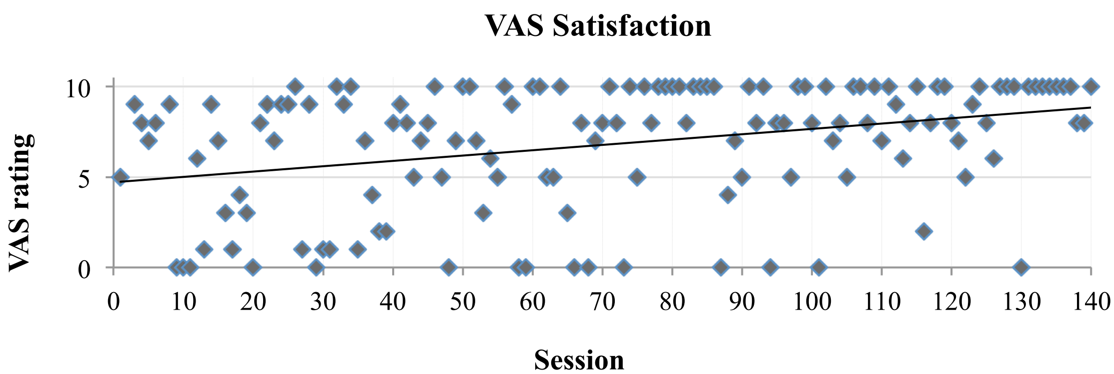

Figure 1. ***VAS Satisfaction****: Satisfaction was rated on a visual analogue scale (0 = not satisfied at all – 10 = very satisfied). Note that ratings in sessions 2 and 7 are missing.*

4. Discussion

Our results demonstrate that expert-independent BCI home-use is possible. However, BCI use is challenged by technical problems and varying BCI control. Nevertheless, a positive trend in *satisfaction* and *enjoyment* is evident. With Einstein stimuli she is able to paint more efficiently. For the end-user *Brain Painting* has become an important part of her life. “I paint three times per week, but if I could, I would like to paint every day” (personal statement of the painter).

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Evaluation of Four Different BCI Prototypes by Severely Motor-Restricted End-Users

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Abstract. Within the TOBI project (tools for brain computer interaction, tobi-project.org) different BCI prototypes have been developed for (1) communication, (2) motor substitution, (3) entertainment and (4) motor recovery. Here, we report on evaluation results of four TOBI prototypes: Qualilife-P300-Communication, Brain Painting, Connect-Four and Hybrid-P300-Communication. BCI prototypes have been tested and evaluated by 11 end-users. Main obstacles for daily BCI use were the EEG cap/electrodes, time-consuming and complicated adjustment, low effectiveness and low speed. Highest satisfaction was expressed for the brain painting application.

Keywords: Brain Computer Interface (BCI), end-users, user-centered design, evaluation

1. Introduction

Following a user-centered approach, in TOBI different BCI prototypes have been developed and consecutively evaluated by end-users. In this paper we report on evaluation results of four BCI prototypes, two communication and two entertainment prototypes. To acknowledge the user-centered approach, we assessed satisfaction with the device.

2. Material and Methods

2.1. Subjects

11 patients (one female) tested the TOBI-BCI prototypes. Four were diagnosed with amyotrophic lateral sclerosis, two with stroke/cerebral bleeding, one with pontine infarct, two with spinal muscular atrophy, two with muscular dystrophy (Duchenne) and one with infantile cerebral palsy. Since patients were severely disabled or in the locked-in state (two), patients were considered as potential end-users of BCI.

2.2. Evaluation of BCI prototypes

The BCI-prototypes were the Qualilife-P300-communication [Zickler et al., 2011], Brain Painting [Zickler et al., under revision], Connect-Four [Holz et al., under revision] and Hybrid-P300-Qualilife [Holz et al, in preparation]. N = 9 patients tested one prototype, N = 1 patient tested two and N = 2 patients tested three prototypes, resulting in N = 4 patients per prototype. Three prototypes used the P300 as input, and Connect-Four SMR amplitude. End-users were asked how satisfied they were with different aspects of the BCI [Extended Quest 2.0, Demers et al., 2000; Zickler et al., 2011]. *Satisfaction* was rated on a scale between 1 (not satisfied at all) and 5 (very satisfied). End-users were asked whether they could imagine using the BCI in their daily life (interview).

3. Results

Table 1 displays results of *satisfaction* ratings with the Extended Quest 2.0 for the four prototypes and results of the interview. Overall, lowest *satisfaction* scores were indicated for *dimensions (e.g. due to "EEG-cap and gel", "cables restrict mobility, e.g. Bluetooth would be useful", M* = 3.38*), adjustment (e.g. "takes too long, too complicated", "can be erroneous"), M* = 3.33*)*, *effectiveness* (e.g. "too low", "it is exhausting to reach the goal", *M* = 3.65), speed (e.g. "too slow", "for communication less sequences needed in the P300-matrix), *M* = 3.5) and *aesthetic design.* (e.g. "cap looks unaesthetic/like in hospital", *M* = 3.46*)*. Overall, end-users were highest satisfied with *safety* and *learnability* (M = 4.79 and 4.73). Best evaluated, regarding satisfaction and daily-life use, was the Brain Painting prototype. End-users could rather imagine using the entertainment BCI prototypes than those for communication. Both locked-in end-users could imagine using the BCI in their daily life (tested Connect-Four).

Table 1. *Results of Extended Quest for the four BCI prototypes. Satisfaction ratings of N = 12 end-users range between 1 = not satisfied at all and 5 = very satisfied. N = 4 end-users tested each BCI prototype (Lowest average ratings displayed in bold). *one (locked-in) end-user who did not gain control over BCI, can nevertheless imagine to use the BCI if it "works better".*

	QL-Communication (N=4)	Hybrid-QL-Communication (N=4)	Brain Painting (N=4)	Connect-Four (N=4)	Average over all
1: Dimensions	3.5	3.5	3.75	2.75	**3.38**
2: Weight	4.08	4	4.75	4.25	4.27
3: Adjustment	3.08	3.25	3.75	3.25	**3.33**
4: Safety	4.67	5	5	4.5	4.79
5: Comfort	3.5	3.5	4.5	3.75	3.81
6: Ease of Use	3.58	4	4.25	3.5	3.83
7: Effectiveness	3.58	3.25	4.25	3.5	**3.65**
8: Prof. Services	4.5	4.5	5	4.75	4.69
Quest total score	**3.81**	**3.88**	**4.41**	**3.78**	**3.97**
9: Reliability	4.08	4.25	4.25	3.5	4.02
10:Speed	3.25	3.5	3.75	3.5	**3.50**
11: Learnability	4.42	4.75	5	4.75	4.73
12: Aesthetic Design	3.08	3	4	3.75	**3.46**
Quest added item score	**3.71**	**3.88**	**4.25**	**3.875**	**3.93**
Can you imagine to use BCI in your daily life?	**Yes: 0 No:4**	**Yes: 1 No:3**	**Yes: 3 No:1**	**Yes:2* No:1**	

4. Discussion

The results indicate, that BCIs, at the current state-of-the-art, are not competitive with other AT-solutions, but would be a solution for locked-in end-users, if it can be a better or even the only solution for them to communicate. Therefore BCI use in daily-life strongly depends on the life-situation of the person, meaning the persons' existing solutions for communication. BCI-users prefer using the entertainment programs (for creative expression and games) in their daily life. These are probably considered as "additive" assistive applications for daily life, since for this purpose, the obstacles do probably matter less (e.g. lower speed).

Acknowledgements

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Correctly Applying Fitts' Law to Brain Control Interfaces

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Abstract. Fitts' Law is a popular performance metric in neural interface movement control studies. However, no studies have investigated whether movement trajectories in neurally-controlled dwell-to-select tasks conform to the Fitts' Law empirical model. We show that Fitts' Law applies to best-case performance in a typical neural cursor control task, only if a correction is made for the dwell-to-select behavior. A trend of movement times consistent with Fitts' Law is seen in experimental data containing many sub-optimal trials using a peak fitting method. We also show that the information transfer rate (ITR) is often incorrectly assessed.

Keywords: Performance Metric, Fitts' Law

1. Introduction

We evaluate the ability of Fitts' Law to describe trajectories observed in manual- and brain-controlled cursor positioning tasks performed by a macaque. To our knowledge, only one study has evaluated brain-controlled cursor positioning performance at multiple difficulty levels [Simeral et al., 2011]. For a survey of recent studies using Fitts' Law, see supplement to [Gilja et al., 2012]. Trials at multiple difficulty levels are necessary for evaluation of the predictive power of the Fitts' Law model, which in turn is a prerequisite for its valid use as a performance metric.

Fitts' Law [Fitts, 1954] predicts movement time T for a range of precision positioning tasks as a function only of movement distance D and target width W:

$$T = a + b \times ID = a + b\log_2\left(\frac{D}{W}+1\right) \tag{1}$$

where a and b are free parameters, and the Index of Difficulty term (ID) captures task difficulty as a function of only the *ratio* between target distance and width. The above Shannon formulation was developed by [MacKenzie, 1992], and uses a slightly different ID definition from the original study. Movement times consistent with Fitts' Law are observed in a wide range of pointing and positioning tasks, yet the model is known to be fragile in that it holds over only a restricted set of IDs, target widths, and distances. Further, the original study observed a departure from model predictions below an ID of 2, but many BCI studies since use an ID of 1.5 or less, depending upon the ID formulation used.

To create a task compatible with Fitts' Law and also feasible under neural control, many studies replace the *click-to-select* behavior with *dwell-to-select*. In a dwell-to-select task, movement trajectories are effectively terminated when the cursor crosses the target boundary (without subsequently exiting the target area). In 1D, this has a consequence of allowing zero movement time when the target boundary is located at the movement start point, i.e. when $D = W/2$. We will investigate whether a correction to the ID definition is required for dwell-to-select tasks in Section 3.

2. Experiment Design

Manual isometric and neural velocity-controlled 1D cursor control tasks were performed by a macaque. A 1s dwell was required for selection of circular targets of varying width and distance. Neural control used 4 single units, selected based on firing rate and strength of tuning to wrist torque, with deviations from baseline firing rates mapped to horizontal cursor velocity.

Candidate Fitts' Law models were fit to the data using a peak fitting method, thus selecting the most common trial time at a given ID. Trial time histograms at each ID were filtered with the highest-bandwidth Gaussian filter at which the tallest peak was also the lowest time peak, using the same filter at all IDs.

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3. Results

We first validate the peak fitting method using manual control data. In figure 2, a standard Fitts' Law regression to trial time histogram peaks shows good quality of fit. However, some trial times are predicted to be negative, consistent with the fact that trials below an ID of 0.585 will begin inside of the target. To fix this, we can calculate *ID* using distance to the target boundary, obtaining a similar quality of fit and non-negative trial times at all non-negative *ID* values.

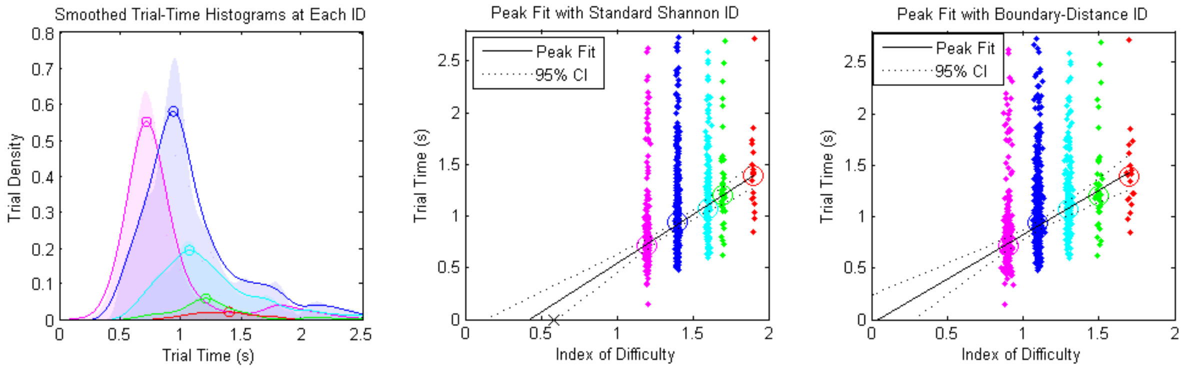

Figure 1: *Fitts' Law evaluation of manual cursor task.* Left, *histograms of trial times at different IDs. Shading reflects optimal smoothing at each ID; solid line denotes histograms smoothed with same filter at all IDs.* Center, *standard Fitts' Law regression to histogram peaks* ($R^2 = 0.98$)*, with individual trials shown with added jitter for context. Black '$\times$' denotes ID at which target boundary is at start location.* Right, *Fitts' Law regression with ID calculated using distance to target boundary* ($R^2 = 0.98$)*.*

Next, we apply the corrected Fitts' Law model to brain control performance on two different days. Under lower brain-control performance, the distribution of trial times is more uniform, perhaps due to increased difficulty of achieving successful dwell relative to executing the gross movement. On days with lower overall performance and poorer motivation, more uniform trial times were observed under manual control as well.

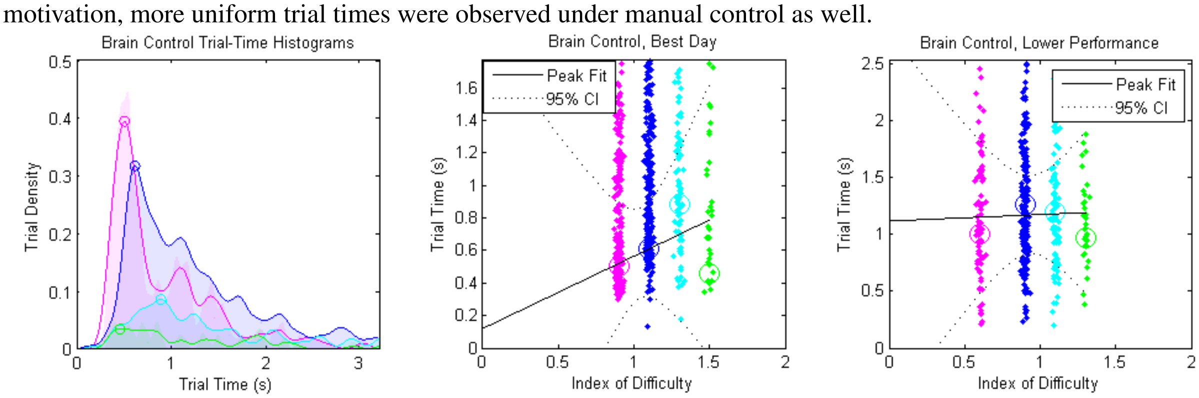

Figure 2: *Fitts' Law evaluation of brain control task.* Left, *histograms of trial times at different IDs.* Center, *Fitts' Law peak fit* ($R^2 = 0.38$) *on same day as above manual performance.* Right, *brain control on day with manual Fitts' Law model fit* $R^2 = 0.90$.

4. Discussion

We have shown that a simple adjustment of Fitts' Law is needed to restore reasonable (non-negative) predictions of movement times in dwell-to-select tasks. Our results suggest that the explanatory power of Fitts' Law should be verified in every experiment when there is any uncertainty about task proficiency and motivation. In particular, one recent study assumed a zero y-intercept of the model [Gilja et al., 2012], while our data and other Fitts' Law studies indicate otherwise. Finally, without strong predictive power of the model, claims about information transmission rates of a given brain control interface cannot be made.

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Preliminary Design and Performance Standards for Brain-Computer Interfaces Desired by Potential Users With Neuromuscular Disease

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Abstract. Development of brain-computer interfaces requires an understanding of the end user's needs and priorities for use of the technology in everyday life. We surveyed potential BCI users with neuromuscular disease to identify preferences for BCI electrode type, BCI performance, and top prioirty applications. Our preliminary data with this group suggests BCIs are beginning to approach the end users' desired levels of performance.
Keywords: Brain-computer interface, neuromuscular disease, performance standards, assistive technology

1. Introduction

Research in Brain-Computer Interfaces (BCIs) has provided an option for empowering individuals who cannot move or have limited functional movement through an alternative means of controlling technology. Using the electrical signals emitted from their brain, individuals can express their needs and direct a variety of assistive devices without physical movement. Further advances in this field require an understanding of the constraints under which potential end user operate as well as the priorities they assign for BCI use. Systematic inclusion of potential end users can enhance the development of an effective and practical BCI [Cornwall and Jewkes, 1995; Hill, 2006].

2. Material and Methods

Our previous work in this area [Huggins et al., 2011] asked 61 people with amyotrophic lateral sclerosis (ALS) to share their perspectives and preferences on the use of BCIs. Survey research is also continuing in people with spinal cord injuries (SCI) [Moinuddin et al., 2012]. Currently, we are extending this work to persons with neuromuscular disease involving significant impairment of arm and leg function. The University of Michigan's Muscular Dystrophy Clinic as well as a search of the University of Michigan patient listings provided the initial pool of 30 participants. A 60–90 minute telephone survey addressing current use of assistive technologies, interest in BCI, and preferences for BCI performance and training was administered to each person either directly or through a caregiver.

3. Results

The preliminary data has been collected from 7 people with NMD (n = 4 women). The data thus far suggest a strong interest by NMD participants in the different options for electrodes and BCI training. While 87% reported a willingness to use dry electrodes, 71% were also willing to use non-invasive EEG gel electrodes. In addition, 57% were willing to have electrodes surgically implanted. All of the respondents agreed that they would invest in 2-5 training sessions to obtain a useful BCI. A daily setup time of 21 to 30 minutes was considered acceptable by 71%.

The survey also asked respondents to choose the minimum BCI performance they would consider acceptable. Eighty-six percent of the group stated that a BCI accuracy of at least 80% would be deemed useful. For accidental exits from a standby mode during device usage, one accidental exit every hour was acceptable to 86% of respondents. In addition, when asked about the rate of text generation, 71% responded that a minimum speed of 15-19 letters per minute would be needed for them to find the device useful.

We asked participants to select the most important BCI design feature. A large majority rated "the speed with which the BCI works" (43%) as their top choice followed by "the functions the BCI would provide" (29%). A similar series of questions were asked regarding their choice for the most important functions a BCI could provide.

Half of the group maintained that an ability to "communicate with someone in case of emergency" was paramount; another 25% felt the use of a BCI to "operate a power wheelchair" was most important.

As seen from these preliminary data, people with NMD report considerable interest in the use of BCI to enhance function. A majority were willing to have surgery to get a BCI and would participate in sufficient training sessions (57%) although this level of agreement was less than that reported by persons with SCI (67%) and ALS (72%). Gel electrodes were also less acceptable to people with NMD (71%) and SCI (53%) than to those with ALS (84%). Both the NMD and ALS (72%) groups seemed to be receptive to average BCI speeds (15-19 letters per minute); for the participants with SCI, however, a minimum of 20-24 letters per minute was favored by the majority (67%). With regard to accidental exits from a stand-by mode, a majority (84%) of respondents with ALS considered an exit every 2 – 4 hours acceptable, and 75% of persons with SCI stated an exit every 3 hours was acceptable, a comparison which seems to reflect more moderate expectations by the NMD group, where 86% found one accidental exit every hour acceptable.

4. Discussion

Overall, the responses for this group suggest current BCIs are beginning to approach the desired levels of performance. Additional features (beyond communication) should be supported and made available to give these individuals the ability to perform their desired operations.

Acknowledgements

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Towards a Broad-Scale Usability Evaluation of Hybrid BCIs

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Abstract. For the study, three graphical user interfaces (GUIs) were designed for their prospective use in controlling a brain-computer interface (BCI)-driven upper-limb neuroprosthesis. The action selection was divided into two stages: selection and confirmation that were controlled using event-related potentials (ERP) or motor imagery (MI). By evaluating usability on a broad-scale including behavioural, subjective and EEG data, the study provides valuable insights into the underlying dynamics that cause the differences in performance across the GUIs.

Keywords: Usability, User-Centered, Ease of Use, Hybrid BCI, Motor Imagery, ERP, Neuroprosthetics

1. Introduction

In contrast with the tremendous increase of usability evaluations in the field of human-computer interaction, the awareness of the importance of a user-centered perspective in the field of BCI assistive devices for patients is only growing moderately. Most BCI systems are exclusively evaluated in terms of classification accuracy and speed [Pasqualotto et al., 2012]. Besides including these common efficiency measures, the evaluation of further usability aspects such as ease of use, learnability and workload could improve user efficiency and satisfaction [Plass-Oude Bos et al., 2011]. Nonetheless usability is typically evaluated by means of questionnaires and behavioural data, it is a "golden opportunity" to extract usability-related features from the brain by recording the same neurophysiological signal the BCI is controlled with [van de Laar et al., 2011]. Within the context of the MUNDUS project [Pedrocchi et al., 2010], three different BCI GUIs were proposed for a prospective use in controlling a neuroprosthesis. The present work strikingly demonstrates the benefit of a broad-scale methodology by evaluating the usability of the interfaces based on results obtained from various data sources.

2. Material and Methods

Twelve healthy subjects (6 female; mean age: 26.2 ± 2.9 years) took part in the study. Brain activity was recorded using 64 electrodes placed according to the international 10-20 system. Three different GUIs were presented to each subject. The order of the GUIs was counterbalanced across the participants. The task for each GUI consisted of a two-stage action selection. First, subjects selected one of six symbols representing possible actions executed by a neuroprosthesis, and then they had to confirm or cancel this selection. For the experiment, a solely ERP-based and two hybrid combinations were tested: (1) selection with ERP, confirmation with ERP (ERP-ERP), (2) selection with ERP, confirmation with MI (ERP-MI) and (3) selection with MI, confirmation with ERP (MI-ERP). The ERP paradigm for the selection and confirmation stage was derived from the Center Speller [Treder et al., 2011]. For more details about the GUI design see [Pascual et al., 2013]. For the assessment of usability aspects, the NASA-TLX (workload) and the *use quality* dimension (ease of use and learnability) of the User Experience Questionnaire (UEQ) were administered after each GUI.

3. Results

Table 1. *Behavioural and questionnaire results of each GUI and corresponding statistics.*

	ERP-ERP	*ERP-MI*	*MI-ERP*	*F-value*	*P-Value*
Selection Accuracy	98.46 %	96.55 %	83.47 %	$F_{(2, 18)} = 6.315$	$p = .025$*
Confirmation Accuracy	96.26 %	93.38 %	92.24 %	$F_{(2, 18)} = 1.061$	$p = .367$
NASA-TLX (scale: 0 to 100)	28.83	35.00	62.50	$F_{(2, 18)} = 19.627$	$p < .001$*
Use Quality (scale: -3 to +3)	1.83	1.33	0.79	$F_{(2, 18)} = 4.913$	$p = .020$*

Behavioural (accuracy) and questionnaire results (Table 1) were analyzed using one-way repeated measures ANOVAs (α-level: 0.05). For offline ERP analysis, the filtered and down-sampled signal was divided into overlapping epochs ranging from -200 to 800 ms relative to the onset of the stimulus. As a measure of discriminability of target vs. nontarget, the *sgn* r^2 was computed for all channels. The grand average is shown in Fig. 1 for the comparisons of the selection and confirmation stage.

4. Discussion

Results clearly indicate that the ERP-ERP GUI surpasses both hybrid approaches in terms of effectiveness. However, the lower accuracies cannot solely be traced back to the MI mode itself. For the confirmation stage, the ERP-MI GUI is even more accurate than the MI-ERP GUI (see Table 1). Although this finding is not of statistical significance, it is unexpected insofar as the exact same paradigm was applied for the ERP-ERP and MI-ERP GUI. Observations of a lower P3 discriminability for the hybrid GUIs (see Fig. 1) provide a neurophysiological explanation since the online classification depends on the discriminability of the P3. Elucidation to the neurocognitive dynamics accounting for the lower P3 discriminability and the ensuing lower performance could be found in our questionnaire data. Workload and use quality scores seem to correlate with the discriminability of the P3: the higher/lower the workload/use quality score, the lower the P3 discriminability. Studies [Cox-Fuenzalida et al., 2006] showing how sudden changes in workload drastically impair performance confirm our observations made for the switch from the mentally high loading MI selection paradigm to the lower loading ERP-based confirmation. Other studies [Reuderink et al., 2009] point towards frustration as having a detrimental impact on BCI performance (as reflected in the low use quality score for the MI-ERP GUI). Nevertheless, the utility of *sgn* r^2 as e.g. a workload or frustration index remains open and needs further investigation. In any case, the broad-scale methodology of the present study proved to provide valuable insights into the underlying dynamics causing the performance differences between the GUIs.

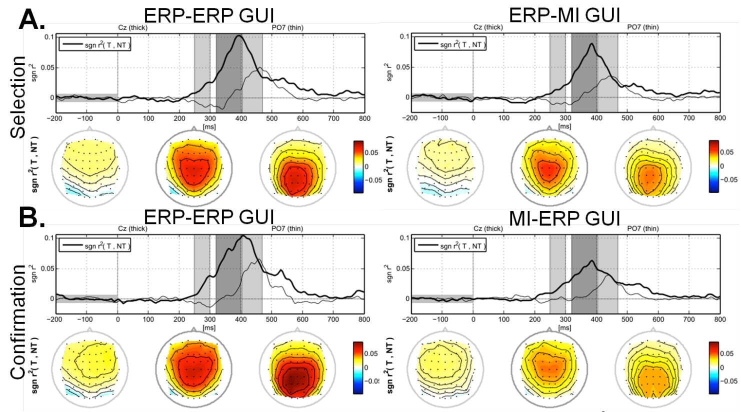

Figure 1. *Graphics A. and B. plot the time evolution of sgn* r^2 *between targets and nontargets for electrodes Cz and PO7 in the first row and the scalp plots for the grey shaded time intervals in the second. A. compares the selection stage between the ERP-ERP and ERP-MI GUI while B. compares the confirmation stage between the ERP-ERP and MI-ERP GUI.*

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The Brindisys Project: Brain Computer Interfaces as Assistive Technology for People with ALS

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Abstract. The Brindisys project aims at designing and developing a general assistive technology to support communication and autonomy in people with Amyotrophic Lateral Sclerosis (ALS) from the onset of the disease to the locked-in phase. The prototype consists of a specific interface allowing for communication and environmental control that can be managed both with conventional/assistive input devices and with a P300-based Brain Computer Interface (BCI). This work describes the system functionalities and reports a preliminary assessment with end users.

Keywords: ALS, P300 Potential, Brain Computer Interface (BCI), Assistive technology

1. Introduction

Persons with Amyotrophic Lateral Sclerosis (ALS) experience a progressive loss of muscle strength that eventually prevents any movement. In this course, independence and communication ability are increasingly impaired. In each phase of the disease, this condition can be temporarily compensated by adopting an assistive device, tailored to the current functional deficit. When muscular contraction is eventually impossible, BCIs could be a solution by detecting the voluntary modulation of brainwaves, and convert them into messages and commands to interact with the environment [Cincotti et al., 2008; Millán et al., 2010].

The Brindisys project (Brain-computer interface devices to support individual autonomy in locked-in individuals) aims at developing a new assistive system designed to preserve communication and interaction with the external world in people with ALS during all the stages of the disease. In fact, the proposed device is designed to be operated with several input devices, coping with user's motor abilities.

2. Material and Methods

2.1. The Brindisys System

The Brindisys system consists of two main components: a tablet PC that allows several applications for communication and environmental control, and an application that can overlay BCI stimuli on the user interface. The novelty of the proposed prototype is in making seamlessly accessible its functionalities both with conventional/assistive input devices relying on the current user's residual motor abilities (touch screen, mouse, keyboard, joystick, buttons, and head tracker) and with a P300-based BCI. It was indeed designed in order to follow the user from the onset of the disease to the complete loss of motor abilities. This way, the user can start using the system and familiarize with it before the BCI becomes the only way to communicate with the external world.

All calibration and configuration procedures of the BCI have been simplified, so that the system can be operated by people with limited technical competence. Moreover, new classification algorithms have been developed in order to increase system reliability and usability [Aloise et al., 2011].

2.2. The role of end users and system functionalities

The Brindisys project focused on users through the planning, design and development of the system (user-centered design). To identify users' requirements, 7 end users, 13 caregivers and 20 stakeholders were interviewed

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about both communication and environment control needs of people with ALS, all of them recruited from the ALS Center (Sapienza, University of Rome). Two focus groups about the potentialities of a BCI were carried out. This first phase allowed defining the system functionalities. As far as the communication is concerned, the system provides three main applications: (i) an alarm bell to draw the attention of the caregiver; (ii) a text writing function for both face to face and remote (e-mail, SMS) communication; and (iii) fixed sentences or keywords for quick communication. For the environmental control, simple functions have been required by users such as TV control, movement of armchair/bed, lights control and doors opening [Caruso et al., 2013]. These functions have been implemented using the KNX standard to control devices available in an apartment designed for people with limited mobility, where preliminary assessment took place. Users were successfully involved in the prototype assessment.

2.3. Evaluation

Usability of the Brindisys system was evaluated in terms of effectiveness (reliability), efficiency (workload, NASA-tlx), and satisfaction (Visual Analogue Scale VAS for overall satisfaction and System Usability Scale SUS for perceived satisfaction and usability). Three end users with ALS (2 male, 1 female; age 56, 59, 75 years; ALSfrs 9, 37, 38) were involved in the evaluation protocol, which included two sessions: during the first one, the subjects operated the prototype using the input device coping with their motor abilities (buttons and automatic scanning, touchscreen and keyboard and mouse respectively), while during the second session they operated the prototype by means of BCI. The required tasks were the same for both sessions, and each session consisted of (i) a communication task: spelling of predefined sentences and (ii) an environmental control task: performing of some actions on the environment mimicking real-life situations. During the experimentation, users' feedbacks and suggestions were collected in order to improve system features for the final release of the prototype.

3. Results

The three end users successfully completed the experimental protocol. All subjects were able to complete the proposed tasks controlling the Brindisys prototype with the P300-based BCI and reaching on average a 95% classification accuracy (ranging from 89% to 100%). The end users showed high satisfaction (VAS, 0-10) with both the BCI-device (ranging between 8.3 and 10, average 9.4) and conventional/assistive input devices (ranging between 9 and 10, average 9.6). The usability perceived by the end users and measured by means of the SUS (0-100) was on average 73.75 for the BCI and 59.1 for the conventional/assistive input devices. Furthermore the BCI exhibited a comparable efficiency in terms of required workload (29.2) compared to muscular input devices (31.5).

4. Discussion

This work provides an overview of the first prototype of the Brindisys system and reports the preliminary results about assessment with end users. The achieved classification accuracies far exceeded 70%, thereby fulfilling the criterion for satisfactory communication. Furthermore these preliminary results showed a high level of user satisfaction and system usability comparable to the ones exhibited with conventional/assistive input devices. Despite not conclusive, the results indicate the potential effectiveness and usability of the proposed system.

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Autonomy and Social Inclusion for the Severely Disabled: The BrainAble Prototype

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Abstract. Severely disabled individuals often suffer from high caregiver dependence and are at risk of social exclusion. The prototype developed in the EU Project BrainAble (www.brainable.org) offers access to common smart-home devices and popular Internet services, using electroencephalography (EEG) and non-EEG inputs. Here we describe our user-centered design approach and the software architecture of the system.

Keywords: Assistive Technology, Social Inclusion, Smart Home control, Ambient Intelligence, Non-invasive Brain-Computer Interfaces

1. Introduction

Individuals with severe functional disability often suffer from high caregiver dependence to perform basic tasks and are at risk of social exclusion. This is a result of their limited mobility and sometimes even limited ability to communicate. Existing assistive technology (AT) solutions are often not integrated in easy-to-use frameworks, lack compatibility with desired devices or popular internet services or require an AT expert to assemble and configure a heterogeneous setup of different components specifically for one user.

In a user-centered design approach, we created a fully integrated, context-aware [Navarro et al., 2011; Zander and Kothe, 2011; Scherer et al., 2012] framework that offers disabled users access to a large number of common devices and popular online services via a number of different input modalities, including electroencephalography (EEG) based brain-computer interfaces (BCIs). The system can also monitor the user's physiological signals and the environmental context. All signals are processed by an Ambient Intelligence system at the core of the system that assists the user wherever possible based on context and behavioral patterns.

2. Material and Methods

The system architecture consists of (1) the User Interface (UI), (2) the Ambient Intelligence, and (3) the Remote Systems. The UI supports two input menus, either of which can be used to access all functionality of the prototype: First, the Matrix Menu (Fig. 1, (A.1)) is similar to a P300 matrix interface. Second, the Hex-o-Select Menu (Fig. 1, (A.2)) is based on Hex-o-Spell [Blankertz et al., 2006]. Some of the supported input modalities seen in Fig. 1, (A.3) are specific to one menu type, others work with both. The specific combination of menu type and input modality can be selected easily and flexibly according to the ability, needs and preference of the disabled user.

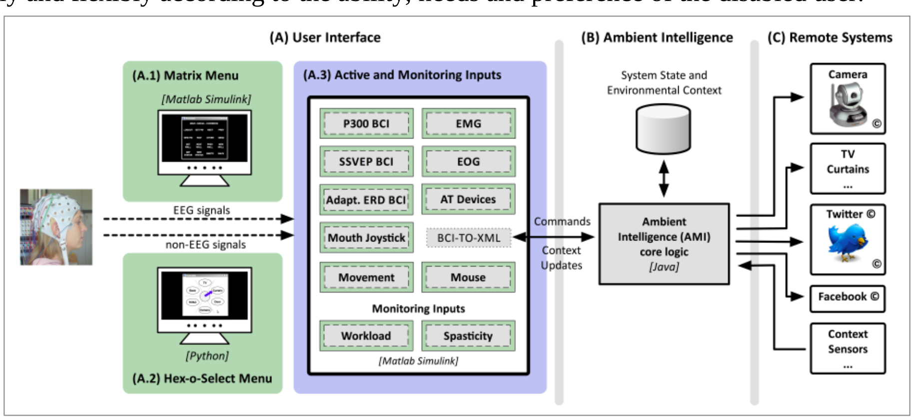

Figure 1. *Architecture Overview Diagram. Example of integrated web-camera top-right, D-Link © DCS-5220.*

As active EEG based input modalities the BrainAble prototype offers P300 [Ortner et al., 2011], steady-state visually evoked potentials (SSVEP, [Ortner et al., 2010]), and online co-adaptive event-related desynchronization (ERD, [Faller et al., 2012a]) based BCIs. As non-EEG based input modalities, movement tracking, electromyogram (EMG), electrooculogram (EOG), mouth joystick, and other AT devices are supported. The system can monitor cognitive workload based on EEG [Faller et al., 2013] and detect spasticity based on EMG. Some BCI inputs can be combined with other BCI or non-BCI inputs into Hybrid BCIs [Faller et al., 2012b; Allison et al., 2010].

The BCI-TO-XML module [Putz et al., 2011] facilitates bi-directional communication of user commands and context-updates between Ambient Intelligence (AMI) core logic and UI. The AMI communicates with smart home devices (e.g. TV, light, automatic doors, etc.) and Internet services (Facebook©, Twitter©) via the Universal Control Hub (UCH; ISO 24752; OpenURC Alliance, www.openurc.org). In addition the AMI collects information about user behavior and context to actively assist the user during his interaction [Navarro et al., 2011].

3. Results

In multiple iterations, we successfully tested modules and the whole BrainAble prototype with 100+ severely disabled users. We made improvements based on control performance measures as well as formal and informal feedback from users and caregivers. Some results are already published [Faller et al., 2012a; Ortner et al., 2011].

4. Discussion

The BrainAble prototype allows disabled users to control a large and expandable number of common smart-home devices and popular Internet services using a variety of EEG and non-EEG input modalities. A caregiver can easily try a number of input modalities for disabled individuals and leave them with a customized, most effective configuration. Some users will be able to use a standard AT Joystick, while others might require using P300 or even ERD based inputs. This work will continue within the FP7 EU Project BackHome (www.backhome-fp7.eu).

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Measuring (Limitations on) Control Precision in BCI

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Abstract. To be useful for real-world neuroprosthetic applications, continuous BCI control will need to be much more accurate than the performance typically reported in contemporary studies. It is tacitly assumed that prolonged practice with a neuroprosthetic will allow a user to reach such levels of control, but it is not yet known whether current methods of BCI signal induction, measurement and signal processing will in fact allow this. Typical methods for demonstrating control do not scale easily to allow comparison of beginner-level and expert-level performance on the same axis, to allow this question to be addressed. Aiming to fill this gap, we developed a novel method for precise measurement of continuous control in BCI, based on a computer game in which the player moved a cursor left and right to catch descending targets. The game difficulty level (reflected in both the width of the cursor and the speed with which the targets moved) was adjusted using a weighted up-down psychophysical staircase procedure, configured to converge on a hit rate of 65%. This kept the level of challenge constant over a wide range of player ability levels. We validated the method by using it to evaluate the differences in performance, and possible learning effects, between four different types of control signal in an EEG experiment with 4 healthy subjects. We showed that the method was able to distinguish reliably between the four controller conditions: chance performance, motor-imagery BCI performance a little above chance, accurate direct control using digital input devices (Nintendo Wiimotes), and "pseudo-BCI" in which the input was mediated by the Wiimotes but processed using the same signal-processing pipeline as the EEG. In particular, the contrast between direct and pseudo-BCI controllers allowed us to expose and quantify the performance limitations imposed by the EEG signal-processing pipeline.

Keywords: EEG, Motor Imagery, Control, Performance Assessment, Computer Games

1. Introduction

Typically, BCI control is demonstrated by having the subject guide a cursor to hit targets that can appear in one of a number of discrete locations. By contemporary standards, if a subject were to use a BCI to hit a target in one of 16 locations with, say, 97% or 98% accuracy, this would be considered very impressive. However, this still falls far short of the level of control that the real world demands from humans every minute of every day. Imagine, now, using a neuroprosthetic device to drive a wheelchair along the edge of a busy road, or chop onions with a sharp knife: a control system that "only" misses 1 time in 40 or 50 would still clearly be inadequate. We generally hope and assume that *practice* with a long-term-fitted neuroprosthetic will fill this gap. But to establish whether this is true, let alone to quantify users' progress meaningfully, we will first need appropriate techniques for measuring control performance. Measuring the frequency of vanishingly rare errors is an inappropriate technique due to its low statistical power. Rather, we need a measurement system that presents a single adaptive scale on which beginners (barely above chance performance) and experts (close to real-world performance) can both be represented. This system must adapt rapidly, reliably and repeatably to these different levels of control, adjusting the difficulty of the task so that the user never approaches a performance ceiling, but also never feels frustrated by the appearance of no control at all (assuming their level of control is indeed above chance). Ideally, the system should also be presented in an engaging, motivating form, to encourage subjects to perform well over many repeated measurements. Here we present and validate such a system, which is based on one-dimensional computer-game control.

2. Materials and Methods

Four healthy subjects took part in the experiment, each subject attending for 10 sessions on separate days. **T**he game involved moving a cursor (in the form of a cart) left and right on the screen to catch falling targets. There were three active controller conditions, and one random baseline condition, as detailed below. In each 90-minute session, the subject played 3 games in each of the 3 active conditions, for a total of 9 games. The controller conditions were:

- *BCI Controller*: cart velocity was controlled by imagined hand movement (left hand to go left, right-hand to go right). The 16-channel EEG signal was translated via (1) surface-Laplacian spatial filtering; (2) buffering and detrending in 500 ms moving windows; (3) spectral amplitude estimation in 3 Hz bands via AR model of order

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20; (4) differential linear weighting of amplitude features, chosen using BCI2000's OfflineAnalysis tool based on 20 left-hand and 20 right-hand cued motor imagery trials at the start of each session; (5) normalization to mean 0 and variance 1, calibrated using 20 further trials in which the moving cursor was visible.

- *Direct Controller*: the player held a Nintendo Wiimote controller in each hand: shaking the left Wiimote caused the cart to move left, and shaking the right Wiimote caused it to go right.
- *Pseudo-BCI Controller*: the player held the Wiimotes and shook them as in the Direct condition. However, translation into cart velocity was different: the accelerometer power in each Wiimote inversely modulated the amplitude of an artificial white noise signal, which was then passed through exactly the same signal-processing pipeline as the BCI signal, starting with stage (2) and ending with a separately-calibrated normalization stage (5).
- *Random Baseline*: the same as the BCI condition, except that the control signal was derived from a replay of the subject's EEG from each game, with a 3-minute time-shift. The shift abolished all meaningful control of the cart.

Each game concluded with an adjustment phase in which a game-difficulty variable d was adjusted according to the procedure of [Kaernbach, 1991]. $\exp(d)$ was proportional to the speed of the falling targets, and inversely proportional to the width of the cursor; d increased by an amount S_{up} every time the player hit a target, and decreased by an amount S_{down} every time the player missed. We set $S_{up} = 1.0$ and computed S_{down} according to Kaernbach's formula $S_{up}/S_{down}=p/(1 - p)$, where p is the target hit rate on which the procedure converges (we used $p = 0.65$). The staircase procedure continued until the change in d reversed direction 8 times. The final d value was computed as the median of the last 6 reversals: this value was used as the starting difficulty level in the next game.

3. Results and Discussion

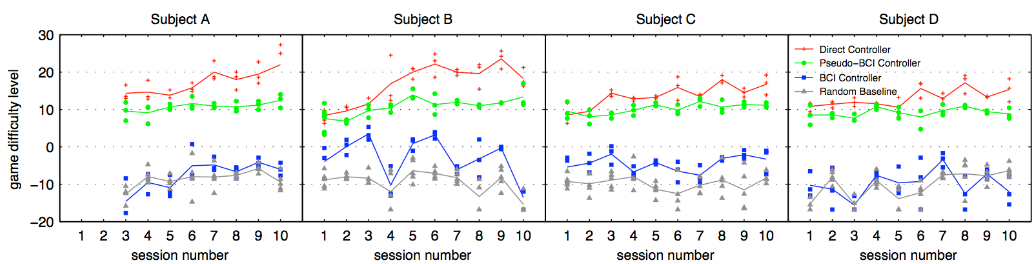

Figure 1: *Performance levels are plotted as a function of number of sessions, for each subject (panels left to right), in each of the four controller conditions (different symbol shapes/colors). Each point marks the result of the adjustment phase at the end of a game. Solid lines show the session means. Subject A's first two sessions were discarded due to changes in the game framework.*

Spearman correlation analysis showed that Direct-Controller performance improved significantly over time for all 4 subjects ($p < 0.0005$ in all cases). This shows that our method is sensitive enough to track improvements in control even when the starting level is very much better than beginner-level BCI control as measured on the same scale. Furthermore, Fig. 1 reveals that the individual measurements overlap very little between the four controller conditions (although clearly only subjects B and C achieved BCI control above chance). This shows that the method is sensitive and precise enough to distinguish at least these four levels of control on a session-by-session basis. Finally, the difference between Direct and Pseudo-BCI performance was significant overall for every subject, and on a single-session basis in 24 out of 37 individual two-tailed two-sample t-tests. This shows that the EEG signal-processing pipeline alone imposes a performance ceiling below the maximum that can be achieved in this game. Pseudo-BCI control also appears to improve more slowly than subjects' Direct Controller performance, suggesting that the pipeline may be a limiting factor on subjects' rate of learning as well as on their absolute level of control.

We conclude that a simple computer game of this kind, in combination with the weighted up-down adaptive procedure, is a promising approach for tracking BCI performance at both high and low levels of control. It seems suitable for probing the extent to which specific aspects of current BCI systems, such as the temporal integration performed in the signal-processing pipeline, impose limits on the performance levels that users are able to reach.

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