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HOW MANY ELECTRODES ARE NEEDED FOR MULTI-TARGET SSVEP-BCI CONTROL: EXPLORING THE MINIMUM NUMBER OF SIGNAL ELECTRODES FOR CCA AND MEC

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ABSTRACT:
As the SSVEP paradigm (based on steady state visual evoked potentials) requires EEG-measurement, high number of EEG electrodes might be impractical in daily life scenarios because of the time consuming electrode montage. Reducing the number of signal electrodes can shorten preparation time but might compromise signal quality.

This paper explores the number of signal electrodes required to achieve sufficient control over multi-target SSVEP-based BCI systems.

In this respect, two of the most commonly used multi-channel classification methods, the minimum energy combination method (MEC) and the canonical correlation analysis (CCA), are investigated.

Data from six healthy subjects recorded during a copy spelling experiment using eight signal electrodes were analyzed off-line. A spelling interface with 30 flickering targets was used. Results for all possible channel combinations were evaluated, revealing that already three electrode channels are sufficient for reliable BCI control.

INTRODUCTION

Brain-computer interface (BCI) describes a field of technologies providing hope for the severely impaired as brain activity patterns are translated into output commands, allowing control of external devices without using any muscle activity [1]. Among other brain signals that can be utilized for spelling devices are so called Steady-State Visual Evoked Potentials (SSVEPs), which are evoked in the visual and parietal cortexes when gazing at a flickering visual stimulus [2]. Typically, SSVEPs are recorded noninvasively by electroencephalography (EEG). The graphical user interface (GUI) usually presents a set of stimuli flickering with distinct frequencies. If the user focuses on a particular stimulus, the corresponding frequency can be found in the recorded EEG.

Two established SSVEP signal detection methods are the minimum energy combination (MEC) method, an approach based on principal component analysis [3], and the canonical correlation analysis (CCA), a method of extracting similarities between two data sets [4]. One of the major challenges of EEG-based BCIs is posed by the considerable preparation time that is necessary to get ready for the EEG signal acquisition: Usually various signal electrodes are placed at the occipital areas, at the back of the head, which are usually covered with hair. For each of these electrodes electrolytic gel needs to be applied to assure low impedances; usually thresholds below 10 $k\Omega$ are required, depending on the type of electrodes used. A proper preparation can only be done by experienced personal. After use of the BCI-system the hair of the BCI users needs to be washed.

Several studies aiming to circumvent parts of the issues accompanying the EEG preparation procedure have been conducted. Some articles focus on the avoidance of electrolytic electrode gel. Water-based electrodes, for instance, could simplify daily setup and cleanup [5]. Dry-contact electrodes do not require any skin preparation or usage of gel at all [7]. However, the signal-to-noise ratio (SNR) might be considerably lower with these electrodes. Mihajlović et al. compared SSVEP-based BCI performance using dry, water and gel electrode setup[6]. By comparing the raw signal obtained within different EEG channels they found that the severity of noise contribution was higher for dry setup than for water-based setup, and for the water-based than the gel setup. Average classification accuracies across six participants were 63% for dry, 88% for water-based and 96% for gel electrodes.

Other research groups focus on a more practical electrode placement. E.g. Hsu et al. compared the amplitude-frequency characteristics of occipital and frontal SSVEPs; although the latter could be an alternative choice in design of SSVEP-based BCIs, the amplitudes and SNRs of occipital SSVEPs were significantly larger [8]. Similarly, Wang et al. employed EEG signals collected from non-hair-bearing areas such as the neck and ears for their SSVEP-BCI system [9]. While results from their high-density EEG recording (256 electrodes) demonstrated that

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SSVEPs are detectable with behind-the-ear electrode montage, SSVEPs acquired from occipital area were the strongest.

Another approach is to reduce the number of used electrodes in order to shorten the preparation time. Several articles investigated the impact of the number and location of electrode channels. Müller-Putz et al. investigated how the classification accuracy of a 4-class BCI can be improved by localizing individual EEG recording positions [10]. In a study with ten subjects, Friman et al. systematically excluded electrodes from offline analysis and stated that the MEC benefits from more electrodes because of the additional information gained about the nuisance signal [3]. Lin et al. also observed that using more channels for the CCA approach might improve recognition accuracy [4].

The presented paper further investigates the minimum number of signal electrodes for multi-target SSVEP-based BCI applications. In this respect, a spelling performance with a 30-target spelling application was evaluated. All possible channel combinations were evaluated off-line and ranked according to detection accuracy. In addition, the SSVEP response detection obtained with the MEC were compared with results obtained later off-line using CCA.

The paper is organized as follows: the second section describes the experimental setup, and introduces the tested spelling application and used classification methods. The results are presented in the third section, followed by discussion and conclusion.

MATERIALS AND METHODS

Participants: BCI performance of six healthy volunteer subjects (two female, mean age 23.8 years) is evaluated in this paper. All participants were recruited from the Rhine-Waal University campus in Kleve. This research was approved by the ethical commitee of the medical faculty of the University Duisburg-Essen; the experiment was conducted in accordance with the Declaration of Helsinki. Before participation, subjects gave written informed consent. Participant information was not directly linked to experiment data, but stored pseudonymously. The EEG recording was conducted in a typical laboratory room with good light conditions and little background noise. Participation was not linked with a financial reward.

Hardware: Participants were seated on a comfortable chair in front of a computer monitor (BenQ XL2420T, resolution: 1920×1080 pixels, vertical refresh rate: 120 Hz) at a distance of about 60 cm. The used computer system operated on Microsoft Windows 7 Enterprise running on an Intel processor (Intel Core i7, 3.40 GHz).

Ag/AgCl electrodes were used to acquire the signals from the surface of the scalp for the EEG recording.

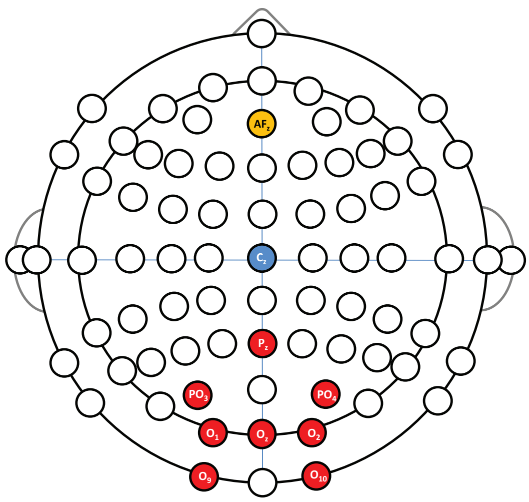

Figure 1: Signal electrodes used in the on-line experiment. Eight signal electrodes were placed at $P_Z, PO_3, PO_4, O_1, O_2, O_Z, O_9$ and O_{10}. Ground was placed over AF_Z, the reference electrode over C_Z.

Electrode placement in accordance with the international 10-20 system was applied. The ground electrode was placed over AF_Z, the reference electrode over C_Z, and the eight signal electrodes were placed at $P_Z, PO_3, PO_4, O_1, O_2, O_Z, O_9$ and O_{10} (see also Fig. 1). In order to assure high signal quality, standard abrasive electrode gel was applied between the electrodes and the scalp to bring impedances below 5 $k\Omega$. A g.USBamp (Guger Technologies, Graz, Austria) EEG amplifier was utilized with a sampling frequency of 128 Hz. An analogue band pass filter (between 2 and 30 Hz) and a notch filter (around 50 Hz) were applied.

Signal Acquisition: The MEC [2, 3] was used for on-line SSVEP signal classification. This method creates a set of channels (a weighted combination of the electrode signals) that minimize the nuisance signals. For EEG detection, we consider N_t samples of EEG data. The sampled EEG signal data from N_y electrodes can be written as $N_t \times N_y$ matrix

$$Y = X_f A + B. \tag{1}$$

The $N_t \times 2N_h$ model matrix X_f associated with the N_h harmonics of a stimulus frequency f is defined by

$$X_f(t, 2k-1) = sin(2\pi k f t) \tag{2}$$
$$X_f(t, 2k) = cos(2\pi k f t) \tag{3}$$

for $k = 1, \ldots, N_h$. The matrix A contains the amplitudes for the expected sinusoids and B contains the information that cannot be attributed to the SSVEP response. The noise and nuisance signal can be estimated by removing the SSVEP components from the signal. In this respect, the signal Y is projected

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on the orthogonal complement of the SSVEP model matrix,

$$\tilde{Y} = Y - X_f(X_f^T X_f)^{(-1)} X_f^T Y. \qquad (4)$$

As $B \approx \tilde{Y}$, an optimal weight combination for the electrode signals can then be found by calculating the eigenvectors of $\tilde{Y}^T\tilde{Y}$ (please refer to [2] for more details). The calculated SSVEP power estimations $\hat{P}_f$ of the frequency f in the spatially filtered signals were then normalized into probabilities,

$$p_f = \frac{\hat{P}_f}{\sum_{j=1}^{N_f} \hat{P}_j}. \qquad (5)$$

For the implemented application, power estimations for $N_f = 30$ frequencies, considering $N_h = 2$ harmonics, were evaluated.

The CCA approach, on the other hand, works on two variable sets (see e. g [4]). Here, one set was chosen to be the electrode signals Y, and the other was the SSVEP model matrix X_f associated with the $N_h = 2$ harmonics of a specific stimulation frequency f. CCA was applied for each of the 30 stimulation frequencies; weighted vectors a and b such that the linear combinations $x_f = X_f^T a$ and $y = Y^T b$ are maximally correlated were found by solving

$$\max_{a,b} \rho_f = \frac{E[x_f^T y]}{\sqrt{E[x_f^T x_f]E[y^T y]}}. \qquad (6)$$

The maximum canonical correlation ρ_f was calculated for each frequency f; the frequency associated with the highest correlation value determined the output command.

The on-line experiment was conducted using the MEC. The classification was performed on the basis of the hardware synchronization of the EEG amplifier (g.USBamp). EEG data were transferred blockwise to the computer. Each block consisted of 13 samples (101.5625 ms with the sampling rate of 128 Hz). Block-wise increasing classification time window were used (refer to [2] for more details). If a particular stimulation frequency had the highest probability, exceeded a certain predefined threshold and the classification time window exceeded 20 blocks (approximately 2 seconds), the corresponding command was classified. After each classification the flickering stopped for approximately 914 ms (9 blocks).

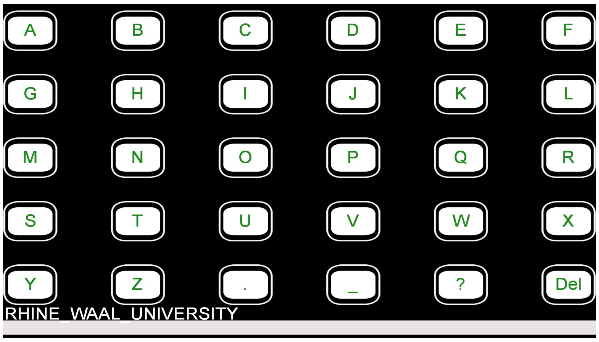

Figure 2: Graphical user interface used in the on-line experiment. The spelling task was to write "RHINE WAAL UNIVERSITY" (name of our University). In total, 30 frequencies between 6.1 Hz and 11.7 Hz flickered simultaneously.

During this gaze shifting period, the targets did not flicker and the user changed his or her focus to another target unhindered (please also refer to [2] for more details).

Software: The spelling interface displayed 30 selectable buttons representing the alphabet plus additional characters (see Fig. 2). Each button flickered with a specific frequency. The button sizes varied between 130×90 and 170×120 pixels in relation to the SSVEP amplitude during the experiment as described in [2]. Each button was outlined by a frame which determined the maximum size a box could reach. Additionally, to increase user friendliness, command classifications were followed by an audio feedback.
To implement the 30 stimulation frequencies a frame-based stimulus approximation was used (see e. g [12, 11]). Frequencies between 6.1 and 11.7 Hz (logarithmic distributed resolution, as suggested in [13]) were implemented. This range was used in previous studies as well, as it avoids overlapping in the 2-nd harmonics frequencies while still allowing a sufficient difference between frequencies [14].

Experimental Setup: After signing the consent form, each participant was prepared for the EEG recording. Then participants went through a short familiarization run, spelling short words such as "KLEVE", "BCI" or "BRAIN". Thereafter, participants were instructed to write the phrase "RHINE WAAL UNIVERSITY". Spelling errors were corrected via the "delete" button. The entire session took on average roughly 30 minutes.

RESULTS

For the evaluation of the BCI performance we considered the command accuracy P (the number of correct command classifications divided by the total number of classified commands C_n) as well as the commonly

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Table 1: Results from the analysis of the copy spelling task with different numbers of channels. Average accuracies [%] and ITRs [bpm] over all participants for the best channel configurations are provided for CCA and MEC. Additionally, the amount of combinations surpassing accuracy thresholds of 90% and 70% are listed. The last column displays the mean accuracy over all combinations with the given number of electrodes.

Electrodes		Acc. (ITR) of the best combination		Combinations acc. >90%		Combinations acc. >70%		Mean acc. (ITR) over all combinations	
No.	Best combination	CCA	MEC	CCA	MEC	CCA	MEC	CCA	MEC
1	O_Z	48 (15)	48 (15)	0/8	0/8	0/8	0/8	38 (10)	38 (10)
2	O_Z,O_{10}	67 (25)	66 (24)	0/28	0/28	0/28	0/28	54 (17)	49 (15)
3	P_Z,O_Z,O_{10}	84 (34)	87 (37)	0/56	0/56	20/56	12/56	67 (24)	63 (22)
4	P_Z,PO_4,O_Z,O_9	93 (41)	93 (41)	4/70	5/70	55/70	55/70	77 (30)	76 (29)
5	P_Z,PO_4,O_Z,O_2,O_9	96 (42)	97 (43)	18/56	22/56	55/56	55/56	85 (35)	85 (35)
6	P_Z,PO_4,O_1,O_Z,O_2,O_9	98 (45)	99 (45)	19/28	19/28	28/28	28/28	91 (39)	92 (40)
7	P_Z,PO_3,O_1,O_Z,O_2,O_9,O_{10}	99 (45)	100 (46)	7/8	7/8	8/8	8/8	96 (42)	97 (43)
8	P_Z,PO_3,PO_4,O_1,O_Z,O_2,O_9,O_{10}	98 (45)	100 (46)	1/1	1/1	1/1	1/1	99 (45)	100 (46)

used information transfer rate (ITR) in bits/min (see e. g [1]). The number of bits per trial B is given by

$$B = \log_2 N + P \log_2 P + (1 - P) \log_2 \left[\frac{1 - P}{N - 1}\right],$$

where N represents the overall number of possible outputs ($N = 30$, given by the number of targets). To obtain ITR in bits per minute, B is multiplied by the number of command classifications per minute.

In the on-line experiment the MEC with eight signal electrodes was utilized. All participants completed the copy spelling task without any errors achieving a mean ITR of 45.9 bpm.

For the off-line analysis the recorded electrode signals were re-evaluated and channel combinations were ranked according to detection accuracy using the MEC as well as the CCA. The time windows for the off-line classifications were determined by the on-line performance.

In order to investigate to what extend classification accuracy drops with fewer electrodes, channels were excluded systematically. E. g, to examine detection accuracy using only five channels, the off-line analyses was carried out with all $\binom{8}{5} = 56$ options to choose five out of eight recorded signals. All possible combinations composed of the eight recorded signals were evaluated using the numerical computing environment MATLAB. Electrode combinations were ranked according to the accuracies achieved in the simulated experiment. Results based on the off-line analysis are provided in Table 1, Fig. 3 and Fig. 4.

DISCUSSION

In the following we want to summarize and discuss the most relevant results from the off-line analysis.

As also observed by Müller-Putz et al., optimal recording channels differ between subjects, but some electrodes tended to be important in a larger number of subjects [10]. All participants, achieved peak performance with all eight channels. As expected, the accuracy generally increases if a higher number of channels is used. But some of the combinations using less than four electrodes worked surprisingly well. With the channel combination P_Z,O_Z,O_{10} average accuracies above 85% were achieved.

The results obtained with single electrodes show that for most participants the O_Z electrode yielded highest accuracies, followed by O_1 and O_2 (see Fig. 3). The relevance of the P_Z electrode for multiple channel combinations can also be seen in Tab 1. The best electrode combinations using three electrodes or more all included P_Z. Further, the analysis of combinations using seven electrodes (all but one of the electrode signals) showed that the combination excluding P_Z was by far the weakest. While the average of all combinations using seven electrodes was above 95%, the combination excluding P_Z yielded less than 85% accuracy. Interestingly, one participant, subject 2, reached 100% accuracy with channel P_Z alone.

Though electrodes O_9 and O_{10} yielded lowest accuracies of all single electrodes, all of the highest ranked combinations (with more than one electrode) included either O_9 or O_{10} (see Tab. 1).

This findings might be interesting for the design of, optically more pleasing and more practical EEG-caps. For example, signal electrodes could be implemented in the side and back straps of typical head mounted displays (HMDs) used for virtual reality (VR) simulations in respect to the aforementioned locations; some articles already tested the SSVEP method successfully in a VR HMD (see e. g [15]).

In general, results achieved with CCA and MEC are relatively equivalent. There seems to be no difference between the methods for different time windows (see Fig. 4). This is consistent with previous findings by Cecotti et al. [16]. The optimal electrode combinations between the methods differed only slightly.

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It is worth noting that the mean accuracy over all combinations with less than three electrodes was slightly higher with the CCA. For combinations with four electrodes or more the mean for the MEC was slightly better (see Tab. 1).

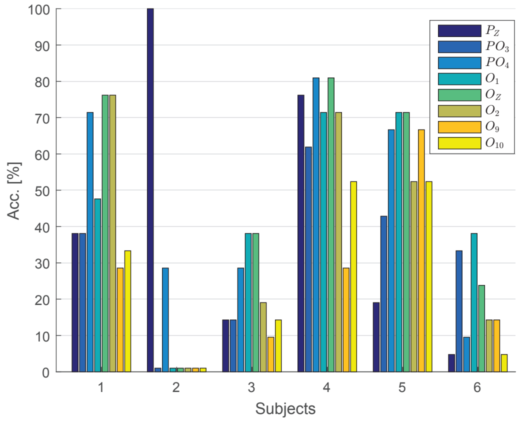

Figure 3: MEC detection accuracies for individual channels. The entire experiment was re-evaluated off-line for each single electrode.

The increased channel number could be more relevant for the MEC, as it might lead to a more precise estimation of the noise and nuisance signals due to the additional information gained.

Fig. 4 also addresses the importance of classification time window length. A dynamic time window with minimal length of roughly 2 seconds was used, a rather typical value throughout BCI literature (see also [16]). It should be noted though, that some studies reported good results with smaller time windows as well [2, 11].

Note that we tested these two methods in a rather standard form and they usually could be improved in several ways. Training sessions to choose electrode scalp path as suggested by Lin et al. could improve the CCA. Instead of sinusoidal reference signals, EEG training data could be incorporated in the CCA templates, reflecting natural SSVEP features (see e. g [17]). While the MEC does not require additional training, a user specific calibration could enhance accuracies as well [18, 19]. Longer test sessions with a broader population including participants of the target group (severly disapled people) are required to further investigate results under conditions that are as realistic as possible.

CONCLUSION

The effect of channel selection of two multi channel SSVEP detection methods (MEC and CCA) was investigated. Though both methods benefit from a larger number of electrodes, presumably because of the additional information gained about the nuisance signal, some electrode configurations using a lower amount of channels yielded good results.

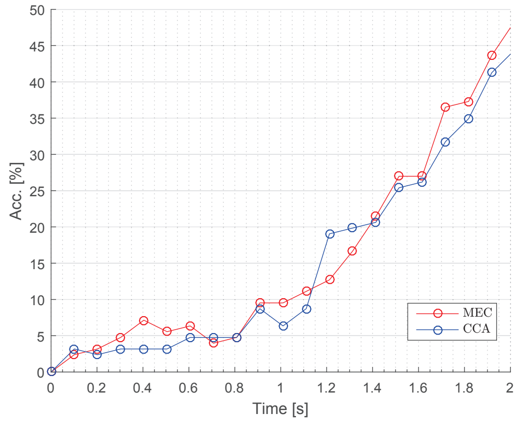

Figure 4: Comparison of MEC and CCA. The grand average accuracy achieved using all eight recorded signals is displayed as a function of the classification blocks for both MEC and CCA. Dynamic classification windows with a minimum length of roughly 2 seconds were used in the on-line experiment. Chance level in target identification was 3.33%.

For both methods the minimum number of channels required to achieve classification accuracies above 70% was three. Especially the channel combination P_Z,O_Z,O_{10} yielded good results for both methods which might be relevant for the design of practical EEG-caps. Optimal channel sets all included the P_Z electrode.

The comparison of mean classification accuracies show no significant difference between the CCA and MEC. Further improvement of the detection could allow a greater reduction of electrode channels and simplify the setup.

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