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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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