Rehabilitation through Brain Computer Interfaces
Classification and Feedback Study

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Abstract: A Brain-Computer Interface (BCI) is a tool for reading and interpreting signals recorded directly from the user's brain. Most brain-computer interfaces (BCI) are based on one of three types of electroencephalogram (EEG) signals: P300s, steady-state visually evoked potentials (SSVEPs), and event-related desynchronization (ERD). EEG is typically recorded non-invasively using active or passive electrodes mounted on the human scalp. In recent years, a variety of different BCIs for communication and control applications were developed. A quite new and promising idea is to utilize BCIs as a tool for stroke rehabilitation. The BCI detects the user's movement intention and provides online feedback to train the affected parts of the body to restore effective movement. This publication tries to optimize current BCI-strategies for stroke rehabilitation using immersive 3-D virtual reality feedback (VRFB). Other work has continued to show that higher density electrode systems can reveal subtleties of brain dynamics that are not obvious with fewer electrodes. Hence, we used a larger electrode montage than typical BCI studies.

1 INTRODUCTION

Brain - Computer Interfaces (BCI) allow new communication channels using different mental states. In a typical BCI, a user performs voluntary mental tasks. Each task produces distinct patterns of electrical activity in the electroencephalogram (EEG). Using monitoring systems and on-line signal processing software, automates tools can identify which mental tasks a user performed at specific times. Most modern BCIs rely in one of three types of mental tasks, which are associated with different types of brain activity:

Imagined movement, which produces event-related desynchronization (ERD) dominant over central electrode sites (Guger, 2003 and Neuper, 2009);

Attention to oscillating visual stimuli, which produces steady-state visually evoked potentials (SSVEP) dominant over occipital sites (Friman, 2007);

Attention to transient stimuli, which produces the P300 event-related potential dominant over parietal and occipital sites (Guger, 2009 and Townsend, 2012).

In the last few years, several publications provide evidence that using MI-based BCIs can induce neural plasticity and thus serve as an important tool to enhance motor rehabilitation for stroke patients. Ang et al. (Ang, 2009) reported higher 2-month post-rehabilitation gain for patients using a BCI-driven robotic rehabilitation tool compared to a control group, but without significant results. Recently, Shindo et al. (Shindo, 2011) tested the effectiveness of neurorehabilitation training when using a BCI for controlling online feedback from a hand-orthosis. Also here, the conclusion promises increased rehabilitation results. Grosse-Wentrup et al. deliver a good overview about the state of the art on this research topic (Grosse, 2011).

On MI-based BCI, neurofeedback plays a crucial role to optimize the user's performance (Neuper, 2010). Feedback must reflect the user's task in an appropriate way: for example, when using the BCI for motor rehabilitation, the feedback should be similar to the motor activity.

In this study, two different feedback strategies that can be used for a rehabilitation task are evaluated. During two sessions, the participants were asked to perform MI of either the right or left hand (in random order) as dictated by a visual paradigm. The first feedback strategy shows the

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hands of an avatar in a 3-D Virtual Reality Feedback environment (VRFB, see section II for more details). Either the left or the right hand of the avatar moves according to the MI. For comparison, a popular strategy (bFB, e.g. in Guger, 2003) was used. Here the feedback entails the movement of a bar on the computer screen. This bar always starts in the middle of the screen and extends either to the left or right side of the screen, according to the classified motor imagination. Nine subjects did recordings with 63 EEG channels. Two subjects did the same session with using 63 and 27 channels (See Figs. 1 and 2). For these two persons using 63 and 27 we evaluated the difference in accuracy.

Recently, Neuper and colleagues compared different BCI feedback strategies (Neuper, 2011). There, the realistic feedback consisted of a hand grasping a target, and the bar feedback was similar to the present study. While Neuper used only three bipolar channels for the classification, the present study used a common spatial patterns (CSP) approach that takes advantage of the high number of EEG channels.

2 METHODS

2.1 Common Spatial Patterns

The method of CSP is known for discrimination of two motor imagery tasks (Blankertz, 2008) and was first used for extracting abnormal components from the clinical EEG (Koles, 1991). By applying the simultaneous diagonalization of two covariance matrices, one is able to construct new time series that maximize the variance for one task, while minimizing it for the other one.

Given N channels of EEG for each left and right trial, the CSP method gives an N x N projection matrix. This matrix is a set of subject-dependent spatial patterns, which reflect the specific activation of cortical areas during hand movement imagination. With the projection matrix W, the decomposition of a trial X is described by:

$$Z = WX \tag{1}$$

This transformation projects the variance of X onto the rows of Z and results in N new time series. The columns of W^{-1} are a set of CSPs and can be considered time-invariant EEG source distributions.

Due to the definition of W, the variance for a left movement imagination is largest in the first row of Z and decreases with the increasing number of the subsequent rows. The opposite occurs for a trial with right motor imagery. For classification of the left and right trials, the variances have to be extracted as reliable features of the newly designed N time series. However, it is not necessary to calculate the variances of all N time series. The method provides a dimensionality reduction of the EEG. Mueller-Gerking and colleagues (Mueller, 1999) showed that the optimal number of common spatial patterns is four. Following their results, after building the projection matrix W from an artifact corrected training set X_T, only the first and last two rows (p=4) of W are used to process new input data X. Then the variance (VAR_p) of the resulting four time series is calculated for a time window T. After normalizing and log-transforming, four feature vectors are obtained.

$$f_p = \log\left(\frac{VAR_p}{\sum_{p=1}^{4} VAR_p}\right) \tag{2}$$

With these four features a linear discriminant analysis (LDA) classification is done to categorize the movement either as left-hand or right-hand.

2.2 Data Processing

EEG data were recorded over 63 positions (see Fig. 1) or 27 channels (see Fig. 2) of the motor cortex, using active electrodes (g.LADYbird, g.tec medical engineering GmbH, Austria). A multichannel EEG-amplifier was used (g.HIamp, g.tec medical engineering GmbH) to record the data with a sampling frequency of 256 Hz. The workflow model is shown in Fig 3. The sampled data went into a bandpass filter (Butterworth, 5th order) before the four spatial filters were applied. The variance was computed for a moving window of one second. Normalization is done according to Eq. (2). Finally, the LDA classification drives the feedback block of the paradigm.

2.3 Paradigm and Sessions

Before the tests started, the healthy users (all male between 25 and 30 years old; all right handed) were trained on motor imagery tasks until their performance was stable. After that, the two sessions with different feedback were executed. The workflow can be seen in the middle of Fig. 3. Each session consisted of seven runs; each run included 20 trials for left-hand movement and 20 trials for right-hand movement in a randomized order. The

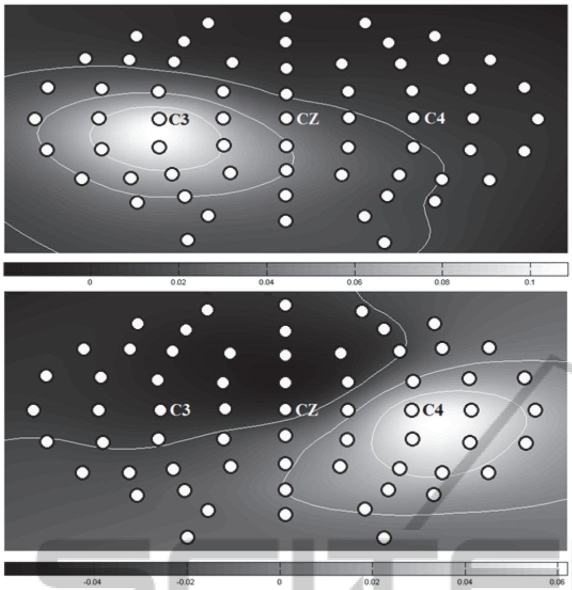

Figure 1: Spatial patterns for S1 during VRFB runs 2, 3, 4 and 5. The upper panel shows the first spatial filter that sets higher weights to electrodes around the region of C3. The lower panel is the last spatial pattern that sets more weight to the region around C4. The single small spots show the 63 used electrode positions. C3, Cz and C4 are marked separately.

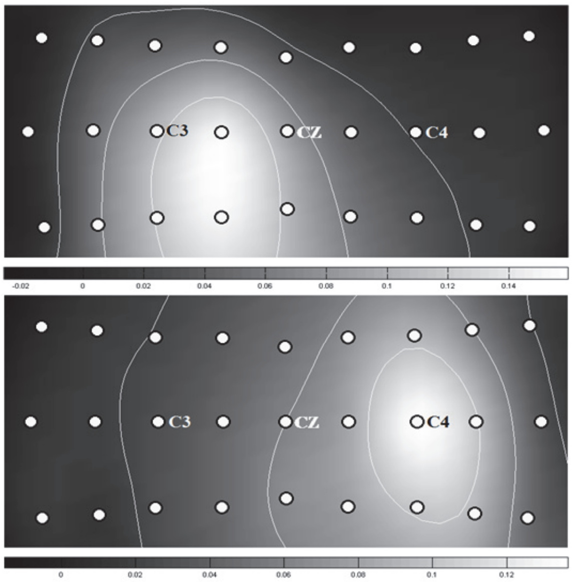

Figure 2: Spatial patterns for S1, during the same run as in Fig. 1. This time only 27 channels were used for computation. The single spots again show the electrode positions.

first run (run1) was performed without giving any feedback. The resulting data were visually inspected, and trials containing artifacts were manually rejected. These data were used to compute a first set of spatial filters (CSP1) and a classifier (WV1).

With this first set of spatial filters and classifier, another four runs (run2, run3, run4, run5) were performed while giving online feedback to the user. The merged data of these four runs (run 2, 3, 4 and 5) were used again to set up a second set of spatial filters (CSP2) and a classifier (WV2) that used a higher number of trials and was more accurate. Finally, to test the online accuracy during the feedback sessions, two more runs (run 6, run 7; merged data: run 6 and 7) were done.

Each trial lasted eight seconds, between each trial there was a random intertrial interval between 0.5s and 1.5s. After two seconds, a beep directed the user to the upcoming cue. The cue-phase, during which the subject was told to perform either an imagination of the left or right hand, started at 3s and stopped at 4.25s. The end of the cue-phase was marked by a second beep. The feedback-phase started at 4.25s and lasted until the end of the trial (8s). The user was asked to perform the MI from the beginning of the cue-phase until the end of the feedback-phase.

Comparing the presented cue and the classified movement, an error rate can be calculated. The error rate, as displayed in Table 1, is calculated by applying CSP2 and WV2 onto the merged datasets run 6 and 7. The classifier and the errors are calculated every half a second. For every such calculation, the classifier was applied to the features and the classification result compared to the cue, resulting in the error rate that was averaged over all trials.

2.4 Feedback Strategies

Feedback strategy number one (bar feedback; bFB) is quite common for motor imagery tasks. A bar begins in the middle of the computer screen and expands either to the left or the right of the screen. If a left-hand movement is detected, the bar grows to the left; for a right-hand movement, it extends to the right side. The length of the bar is proportional to the classified LDA-distance. During the cue phase, in addition to the bFB, a red arrow points to the left or to the right side of the screen, indicating to the user which MI he or she should perform.

Within the virtual reality feedback (VRFB) task, a virtual reality research system (g.VRsys, g.tec medical engineering GmbH, Austria) is used. The user sits in front of a 3D-PowerWall wearing shutter glasses. The size of the PowerWall is 3.2m x 2.45m, and the distance between PowerWall and user is

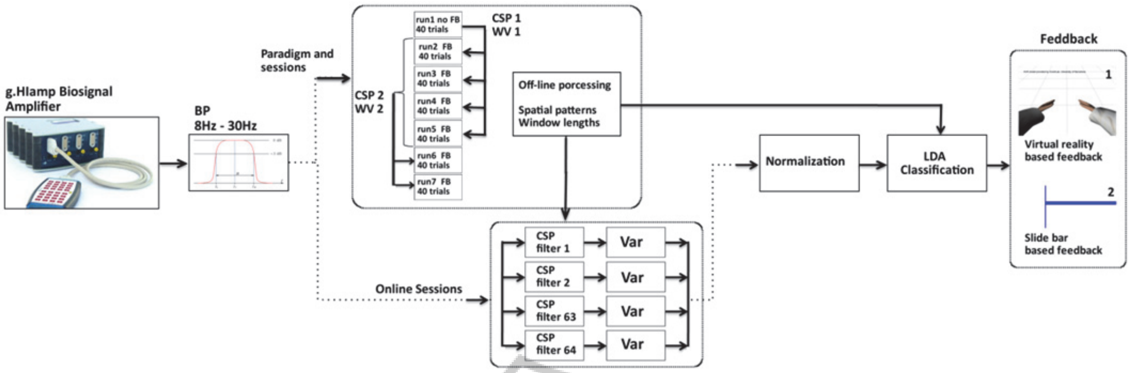

Figure 3: Workflow of the model. The biosignal amplifier records the data that is bandpass-filtered between 8 Hz and 30 Hz. Four CSPs are applied, and the variance within a moving window T of one second is computed. The LDA classifier is then applied to the normalized variances. The output of the classifier drives the feedback block that gives feedback according to the chosen session.

about 1.5m. The user sees the left and right hands of an avatar from a subjective point of view (see Fig. 4). The only movement the avatar performs is the continuous opening and closing of either the left or the right hand. No modulation of the speed of the movement is done. During the cue-phase (from second 3 until second 4.25 of the experiment), the user needs to know which MI has to be performed. In the VRFB task, the opening/closing of one of the hands provides this information. After second 4.25, a second beep appears, and the observed movement of the avatar is the feedback to the performed MI.

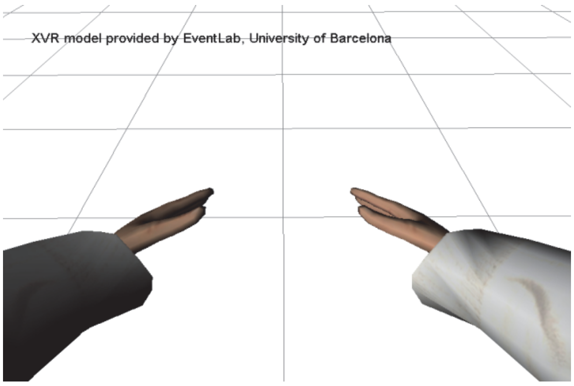

Figure 4: Virtual reality feedback. During the feedback session, the fingers of either the left or the right hand close and open according to the classified movement.

3 RESULTS

Table 1 summarizes the results from the three subjects. For each session, the averaged error rate over all trials and over the single time-steps starting from 3.5s until 8s is shown. These values reflect the accuracy resulting from applying CSP2 and WV2 to the data of runs 6 and 7, and show the online accuracy that the users experienced during these runs. The number in parentheses shows the minimum error for the single time-steps. For S1 and S2 the error rate was recorded twice: once with all 63 channels and again when cutting out 27 channels (positions are shown in Fig. 2). This reflects of course only an estimated error rate that the user would have experienced if only the subset of 27 electrodes would have been used. For S3 only the 27 channels were recorded. In three out of four sessions the error rate increased as the number of electrodes was reduced, but in one session, it increased from 14.8% up to 19.8% (S1, VFRB). The minimum error rate increased in three sessions and stayed constant in one of them (S1, bFB).

Table 1: Results from the six sessions. The first number in each cell shows the mean error rate beginning from 3.5 seconds until 8 seconds. The number in parenthesis shows the minimum error rate within this time.

	bFB		VRFB	
Subject	27ch	63ch	27ch	63ch
S1	12.8 (2.5)	12.75 (2.5)	14.8 (5)	19.8 (4.5)
S2	20.8 (11.25)	19.9 (5.0)	25 (12.5)	19.2 (5.9)
S3	25.0 (8.0)		21.8 (10.0)	
mean	19.5 (7.25)	16.3 (3.75)	20.5 (10.1)	19.5 (5.2)

Fig. 5 shows an example of the error rate from S1 during the two sessions that used all 63 channels for classification. The black line at three seconds indicates the onset of the cue. The error rate before the cue is about 50 percent and then drops below ten percent for both sessions. It stays below ten percent from second 5.5 until the end of the trial, showing the good control the subject had.

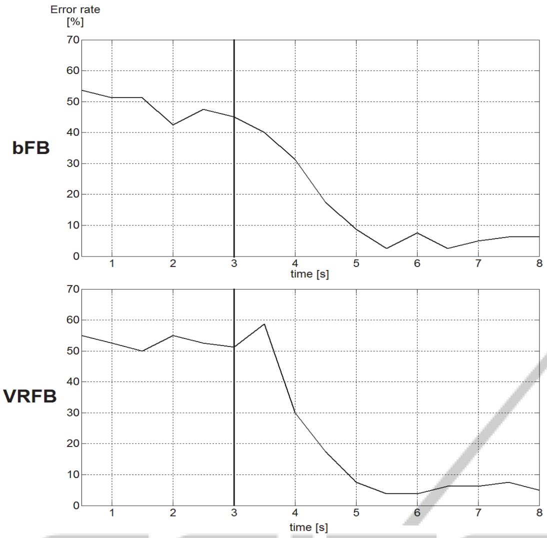

Figure 5: Error rate from the two feedback runs for S1. The vertical bar indicates the cue onset.

Table 2 summarizes the accuracy results of the seven subjects using all 63 channels. The average and min error rate has been calculated in the same way as the Table 1. The results show a significant performance variance between subjects. In three out of seven subjects, the error rate increased with the VRFB, but overall, the bFB yielded worse results compared to the virtual reality (S1, S2, S4 and S6). Better results are under 5% error in 3 subjects (S2, S6 and S7).

Table 2: Accuracy of 7 subjects using the 63 channel system. The first number shows the mean error rate, and the second number shows the minimum error rate. The accuracy has been calculated using data trials beginning from 3.5 seconds until 8 seconds.

	bFB		VRFB	
Subject	Mean Err.	Min. Err.	Mean Err.	Min Err.
S1	42.30%	33.80%	37.30%	31.30%
S2	5.50%	0%	3.20%	0%
S3	35.50%	20%	37%	25%
S4	45.70%	37.50%	30.70%	25%
S5	5.20%	2.50%	14.10%	5%
S6	17%	11.30%	5%	1.30%
S7	3.90%	1.30%	4.60%	0%
mean	22.16%	15.20%	18.84%	12.51%

4 CONCLUSIONS

This study compared two different feedback strategies for performing MI for stroke rehabilitation. The VRFB provided realistic feedback that was similar to the imagined movements. Hence, we expected this strategy would lead to better classification. This hypothesis was not consistent with the results. In fact, performance was slightly worse with the VRFB in comparison to the bFB sessions. After the sessions, subjects said that it was quite disturbing when the classifier did a misclassification and hence the “wrong” hand moved during the VRFB session. We propose that this mismatch between expected and actual feedback was primarily responsible for both this cognitive dissonance and worse performance. In future studies, we will test to give only feedback when the correct hand is classified.

The BCI performs better using 63 EEG-channels instead of 27. This result should encourage the use of larger montages when practical. Furthermore, the comparison of the spatial patterns shows that electrodes that are mounted over the motor cortex and near C3 and C4 (which are present in the 63 and 27 channels configurations) are the most important. Also, positions that are not part of the 27 channel-configuration play an important role for classification.

The results we obtained with 64 electrodes encourage us to test 128 EEG-channel montages in future work. Also, the current study shows results achieved by healthy users only. A future goal will be to utilize the lessons learned here for rehabilitation of patients suffering stroke.

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