Brain Computer Interfaces as Stroke Rehabilitation Tools:

Optimization of current strategies

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***Abstract*— Brain-computer interfaces (BCIs) allow human communication without using the brain's normal output pathways. A BCI is a tool that converts signals recorded from the user's brain into control signals for different applications. Most BCI systems are based on one of the following methods: P300; steady-state visually evoked potentials (SSVEP); and event-related desynchronization (ERD). Electroencephalogram (EEG) activity is typically recorded non-invasively using active or passive electrodes mounted on the human scalp. In recent years, a variety of different BCI applications for communication and control were developed. A promising new idea is to utilize BCI systems as tools for brain rehabilitation. The BCI can detect the user's movement intention and provide online feedback for rehabilitation sessions. In many cases, stroke patients can re-train their brains to restore effective movement. Previous work has continued to show that higher density electrode systems can reveal subtleties of brain dynamics that are not obvious with only few electrodes. This paper tries to optimize current BCI strategies for stroke rehabilitation by comparing conventional bar feedback (bFD) to immersive 3-D virtual reality feedback (VRFB). Different electrode montages were also compared.**

Keywords- Brain Computer Interface; virtual reality; electroencephalogram; high density electrodes montage; Stroke rehabilitation; 3D Feedback.

I. 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, automatic tools can identify which mental tasks a user performed at specific times. Most modern BCI applications rely on 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 [1, 2];

Attention to oscillating visual stimuli, which produces steady-state visual evoked potentials (SSVEPs) dominant over occipital sites [3];

Attention to transient stimuli, which produces the P300 event-related potential dominant over parietal and occipital sites [4, 5].

In the last few years, several publications suggested that using motor imagery based Brain-Computer Interface systems (MI-based BCI) can induce neural plasticity and thus serve as important tools to enhance motor rehabilitation for stroke patients [6, 7, 8, 9]. Ang et al. [6] reported higher 2-month post-rehabilitation gain on Fugl-Meyer (FM) assessment scale for patients using a BCI-driven robotic rehabilitation tool compared to a control group (6.0 versus 4.0), but without significant results. However, among subjects with positive gain, the initial difference of 2.8 between the two groups was increased to a significant 6.5 after adjustment for age and gender. Recently, Shindo et al. [7] tested the effectiveness of neurorehabilitation training when using a BCI for controlling online feedback from a hand orthosis. The motor-driven orthosis was hypothesized to help the patient extend his paralyzed fingers from 90 to 50 degrees. That article also concluded that the therapy improved rehabilitation. Grosse-Wentrup et al. summarize the state of the art in this research field [10].

Neurofeedback is a process that uses real-time displays of EEG or functional magnetic resonance imagining (fMRI) to illustrate brain activity, usually with the goal to control central nervous system activity. In MI-based BCIs, neurofeedback is critical to optimize the user's performance. As the user practices the skill, sensory and proprioceptive (awareness of body position) input initiates feedback regulation through the relevant motor circuits. Over time, the skill becomes more and more automatic. The learning mechanism in this case is similar to learning to ride a bicycle [2]. Hence, the 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 [9], Ramos-Murguialday et al. investigated an online proprioceptive BCI system linking hand movements and brain oscillations, eliciting implicit learning effects and producing an increase in sensory-motor rhythms (SMR) related neural network excitation during motor imagery, passive and active movement. Their results demonstrated that the use of contingent positive proprioceptive feedback BCI enhanced SMR desynchronization during motor tasks.

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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 hands of an avatar in a 3-D Virtual Reality Feedback environment (VRFB; see section II). Either the left or the right hand of the avatar moves according to the MI. For comparison, a popular strategy (bFB, e.g., in [1]) 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 detected motor imagination. Nine subjects were recorded with 63 EEG channels. Two subjects performed the same tasks using 63 and 27 channels (see Fig. 1 and 2). For these two persons, we evaluated the resulting accuracy difference.

Recently, Neuper and colleagues compared different BCI feedback strategies [11]. 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.

In the second section of this paper, subsections *A* and *B* describe the mathematical approach of the CSP method used for classification and the data analysis process. Subsections *C* and *D* present the workflow during one MI-based BCI session and the evaluated feedback strategies.

II. Methods

A. Common spatial patterns

The method of CSP is often used to discriminate two motor imagery tasks [12] and was first used for extracting abnormal components from the clinical EEG [13]. By applying the simultaneous diagonalization of two covariance matrices, researchers can 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 single trial (denoted by 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 [14] 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:

$$VAR_p = \sum_{t=1}^{T} \left(Z_{p(t)}\right)^2 \tag{2}$$

After normalizing and log-transforming, four feature vectors are obtained.

$$f_p = \log\left(\frac{VAR_p}{\sum_{p=1}^{4} VAR_p}\right) \tag{3}$$

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

B. 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). The single small spots show the electrode positions with 63 or 27 channels. C3, Cz and C4 are marked separately. 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) between 8 Hz and 30 Hz before the four spatial filters were applied. The variance was computed for a moving window of one second. Normalization is done according to Eq. (3). Finally, the LDA classification drives the feedback block of the paradigm.

C. Paradigm and sessions

Before the tests started, the healthy users (all male right handed persons between 25 and 30 years old) 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 first run (run1) was performed without providing 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 trial to trial interval between 0.5s and 1.5s to avoid adaptation. After two seconds, a beep directed the user to the upcoming cue. The cue-phase, during which the subject was told to imagine moving either 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.

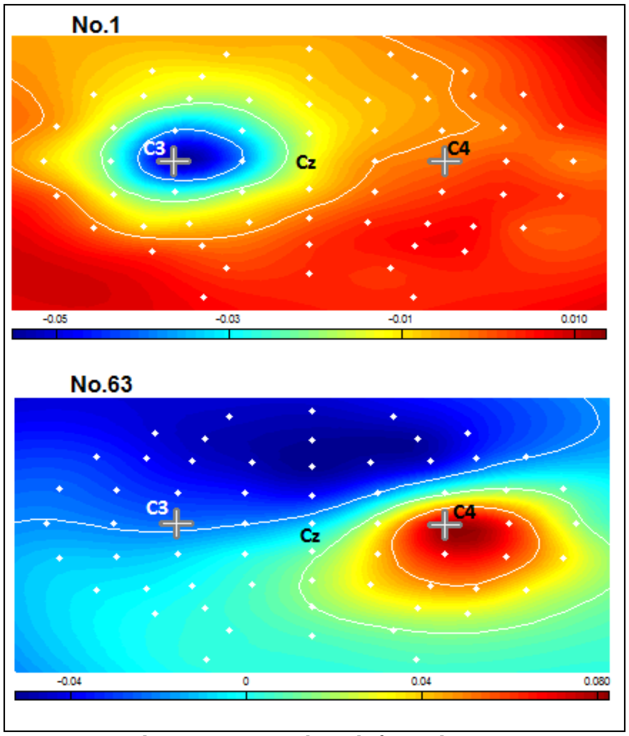

Figure 1. Spatial patterns over 63 channels for S1 during VRFB runs 2, 3, 4 and 5. The upper panel shows the first spatial filter. The lower panel is the last spatial filter.

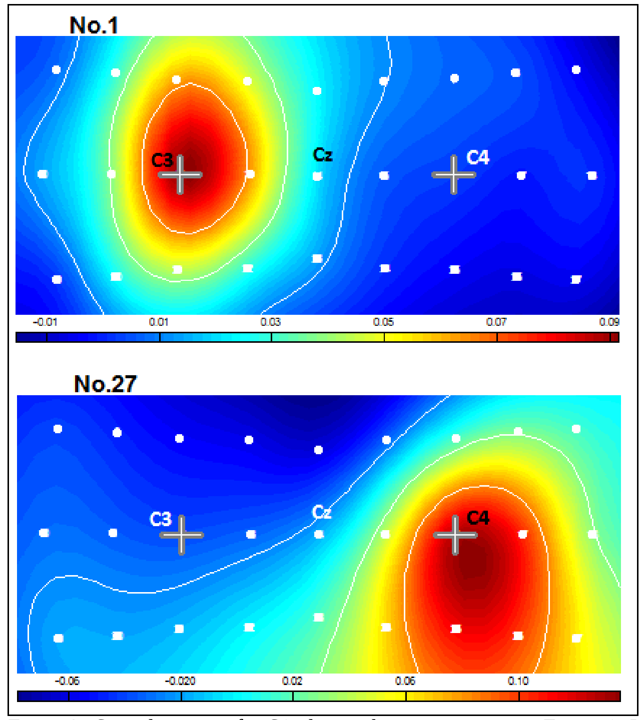

Figure 2. Spatial patterns for S1, during the same runs as in Figure 1. In this figure, only 27 channels were used .

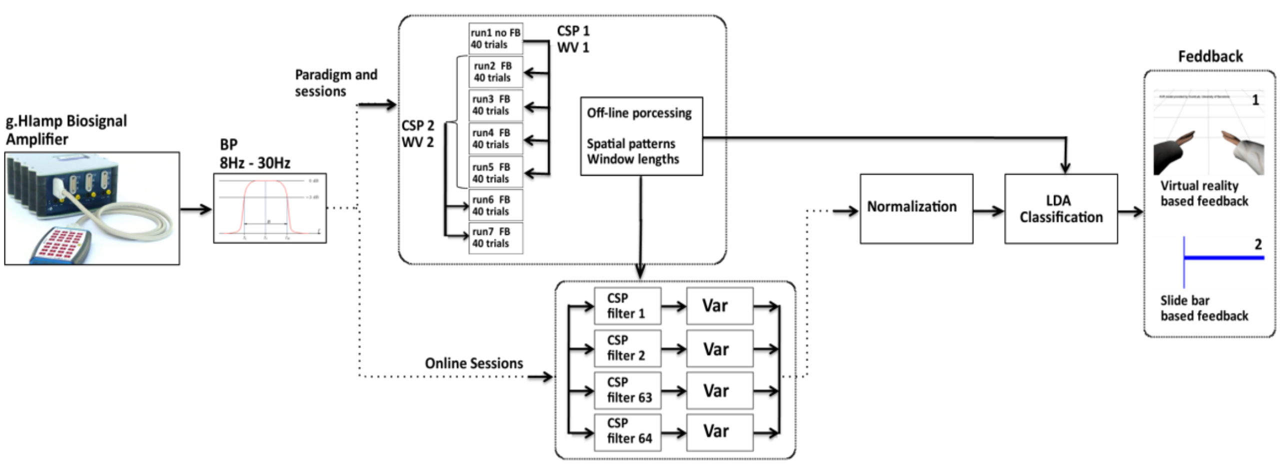

Figure 3. Workflow of the model.

The error rate can be calculated by comparing the presented cue and the classified movement. The error rate, as displayed in Table I, was calculated by applying CSP2 and WV2 onto the merged datasets run 6 and 7. The classifier and the errors were calculated every 500 ms. 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. The "accuracy" term used in this paper refers to the difference between 100% and the calculated error rate.

D. *Feedback strategies*

Feedback strategy number one (bar feedback; bFB, see Fig. 4) is quite common for motor imagery tasks. A bar begins in the middle of the computer screen and extends 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.

The virtual reality feedback (VRFB) strategy instead uses a virtual reality research system (g.VRsys, g.tec medical engineering GmbH, Austria). 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 about 1.5m. The user sees the left and right hands of an avatar from a first-person point of view (see Fig. 5). 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.

III. RESULTS

We first compared results with 27 versus 63 channels across two 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. Table I summarizes the results from these subjects, and a third subject (S3) who was only tested with 27 channels. 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 first number in each cell shows rhe mean error rate, 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 with only 27 channels (see Fig. 2).

These data only reflect estimated error rates 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% to 19.8% (S1, VFRB). The minimum error rate increased in three sessions and stayed constant in one of them (S1, bFB). The only exception where the mean error was higher for 63 channels than for 27 was for subject S1, while using virtual reality feedback. The main reason for this exception was the artifact contaminated EEG signal recorded by one of the electrodes placed on the forehead, where the conductive gel dried while performing the first 5 runs of the session.

Fig. 6 shows an example of the error rate from S1 during the two sessions that used all 63 channels for classification. The black vertical line at second no. 3 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.

TABLE I. RESULTS FROM THE SIX SESSIONS

	bFB		VRFB	
	Mean Err. (Min. Err.) (%)		Mean Err. (Min. Err.) (%)	
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)

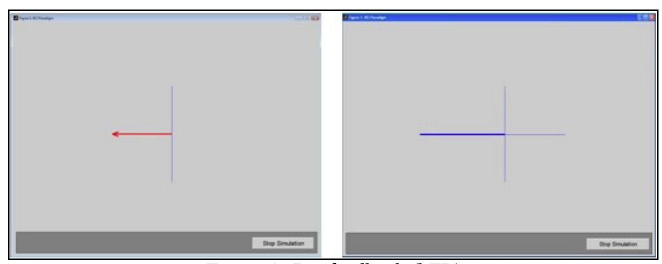

Figure 4. Bar feedback (bFB).

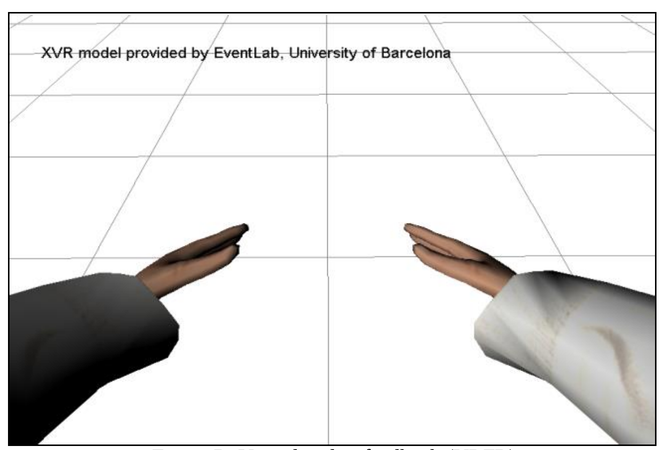

Figure 5. Virtual reality feedback (VRFB).

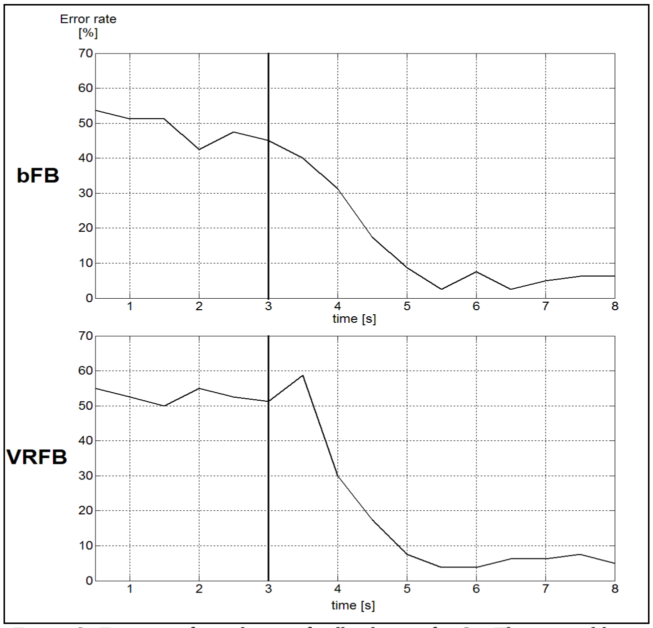

Figure 6. Error rate from the two feedback runs for S1. The vertical bar at 3 seconds indicates the cue onset.

TABLE II. ACCURACY OF 7 SUBJECTS USING THE 63 CHANNEL SYSTEM.

	bFB (63ch)		VRFB (63ch)	
Subject	Mean Err. (%)	Min. Err. (%)	Mean Err. (%)	Min Err. (%)
S4	42.30	33.80	37.30	31.30
S5	5.50	0.00	3.20	0.00
S6	35.50	20.00	37	25.00
S7	45.70	37.50	30.70	25.00
S8	5.20	2.50	14.10	5.00
S9	17.00	11.30	5	1.30
S10	3.90	1.30	4.60	0.00
mean	22.16	15.20	18.84	12.51

Table II summarizes the accuracy results of the seven subjects using all 63 channels. The first number shows the mean error rate and the second number shows the minimum error rate. The averaged and minimal error rates have been calculated using the same methods as Table I. 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 (S4, S5, S7 and S9). Better results are under 5% error in 3 subjects (S5, S6 and S10).

IV. 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 erred, 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 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. 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 channel configurations) are the most important. Furthermore, some positions that are not part of the 27 channel-configuration are important for classification.

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

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