Human-computer confluence for rehabilitation purposes after stroke

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Abstract. In this publication, we present a Motor Imagery (MI) based Brain-Computer Interface (BCI) for neurologic rehabilitation. The BCI is able to control two different feedback devices. The first one is a rehabilitation robot, moving the fingers of the affected hand according to the detected MI. The second one presents feedback via virtual reality (VR) to the subject. The latter one visualizes two hands that the user sees in a first perspective view, which open and close according to the detected MI. Four healthy users participated in tests with the rehabilitation robot, and eleven post stroke patients and eleven healthy users participated to tests with the VR system. We present all subjects' control accuracy, including a comparison between healthy users and people who suffered stroke. Five of the stroke patients also agreed to participate in further sessions, and we explored possible improvements in accuracy due to training effects.

1 Introduction

Brain-computer interface (BCI) technology has been used widely for communication and device control in a closed loop system [1]. The choice of the BCI approach depends on which device the user wants to control. The P300 and steady state visual evoked potentials (SSVEP) approaches are based on evoked potentials. Hence, they need an external stimulation device, and are not useful for people suffering from visual impairments if visual stimulation is used. The approach based on changes in sensorimotor rhythms (SMR) is the third popular one. These BCIs rely on power changes in the mu- (8Hz-12Hz) and beta bands (18Hz-26Hz) over regions active during motor imagery (MI). These rhythms are associated with the cortical areas most directly connected to the brain's normal neuromuscular outputs [1]. The MI based BCI was already successfully used for helping people suffering motor impairments. Pfurtscheller et al. demonstrated the MI-BCI based control of functional electrical stimulation for restoring hand grasp in a patient with tetraplegia [2], Millan et al. controlled an intelligent wheelchair via executing three different mental tasks [3], and other systems have been described (e.g. [4], [5]). Recently, the idea of utilizing the MI for neurolog-

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ical rehabilitation became popular. The idea is to use the BCI not to replace lost motor function, but to improve motor functions in patients.

Prior research showed that mentally rehearsing movements (that is, performing MI) could be used as an effective therapy in stroke rehabilitation [6] even if no feedback about the performance is given to the user. MI may be a method to overcome learned nonuse in chronic stroke patients, and could also be practiced by patients with poor motor performance, which otherwise excludes four out of five patients from active movement therapies [7]. A review, comparing the effects of conventional therapy plus MI to those of only conventional therapy proved the positive effects of MI interventions [8]. Zimmermann-Schlatter et al. identified four studies performed in Asia and North America. Two of them found significant effects on the Fugl-Meyer Assessment (FMA) score and in the Action Research Arm Test. One study only found significant effects in the task related outcomes.

The additional advantages of not only performing MI, but also tracking MI with a BCI and presenting online feedback to the user, seem clear: (i) the feedback helps and motivates the patient to perform accurate MI, (ii) the therapist gets feedback about the performance of MI and can track changes over time, and (iii) real-time feedback may increase Hebbian plasticity, which is likely to increase cortical activity [9]. To test this approach, Ang et al. compared rehabilitation success across 54 hemiparetic stroke patients who received either standard robotic rehabilitation or rehabilitation with a MI-BCI and robotic feedback [10]. They showed that significant gains in FMA scores were observed in both groups at post-rehabilitation and 2-month post-rehabilitation, but no significant differences were observed between groups. Furthermore, they proved that hemiparetic stroke patients can operate EEG-based MI-BCI, and that EEG-based MI-BCI with robotic feedback neurorehabilitation is effective in restoring upper extremity motor function after stroke.

This manuscript presents a MI based Brain-Computer Interface (BCI) that can control different feedback devices. The BCI was connected either to an upper limb rehabilitation robot (Amadeo, Tyromotion GmbH, Austria) or a Virtual Reality (VR) system (gVRsys, g.tec medical engineering GmbH, Austria). Both the VR system and the rehabilitation robot provide online feedback to the user about the detected MI. A total of eleven post-stroke patients and a control group of eleven healthy people took part in the VR based experiment. First results from 4 healthy users performing the experiment with sensory feedback with the rehabilitation robot are presented.

2 Methods

2.1 Detection and classification of MI

For better classification of MI via a Linear Discriminant Analysis (LDA), the EEG channels are spatially filtered with Common Spatial Patterns (CSP). This method yields a set of spatial filters designed to minimize the variance of one class while maximizing variance for the other class. For proper classification, it is sufficient to choose only the four best discriminating filters. These are the two filters leading to the highest variance of class one, and the two filters generating the highest variance of

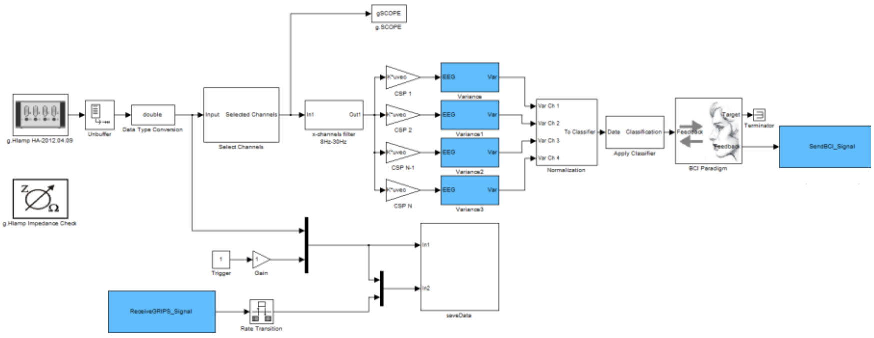

Fig. 1. The used Simulink model. The spatial patterns are applied to 64 bandpass filtered EEG channels. The resulting four channels of variance are normalized before classification. Finally, the BCI Paradigm block sends the feedback to the SendBCI_Signal block that communicates to the VR and the rehabilitation robot. The block called ReceiveGRIPS_Signal receives the position of the single fingers of the rehabilitation robot to save them in synchrony with the EEG data.

class two (while each of the four filters minimizes the variance of the other class). Given N channels of EEG for each left and right trial, the CSP method provides 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 as time-invariant EEG source distributions. Due to the definition of W, the variance for a left hand movement imagination is largest in the first row of Z and decreases as the number of subsequent rows increases. The opposite occurs for a trial with right hand 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 et al. [11] showed that the optimal number of CSPs 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. These values are normalized and log transformed according to the formula:

$$f_p = log_{10}\left(\frac{VAR_p}{\sum_{p=1}^{4} VAR_p}\right) \tag{2}$$

Where f_p (p=1..4) are the normalized feature vectors and VAR_p is the variance of the p-th spatially filtered signal. These four features can be classified with a linear discriminant analysis (LDA) classifier. For a very good overview of the CSP method, please see [12], [13].

2.2 Experimental workflow

The BCI experiment was set up with g.BCIsys, as shown in the Simulink model in Fig. 1. The data were recorded over 64 positions (see Fig. 2A) distributed over the cortex and sampled at 256 Hz. Active EEG electrodes (g.LADYbird) were used to make the preparation procedure faster and easier and to increase data quality. A g.HIamp biosignal amplifier (g.tec medical engineering GmbH, Austria) was used for data recording. The unit has 256 ADCs with 24 bit precision and performs over-sampling to increase the signal to noise ratio. Before applying the spatial filters, the EEG data were converted to double precision and bandpass filtered between 8 and 30 Hz. Then, the variance was calculated within a time-window of 1.5s length. These features were normalized, log transformed and classified with the LDA. The LDA classification result drives the BCI Paradigm feedback block. This block controls the paradigm timing and sends the feedback commands to the external feedback device, either the rehabilitation robot or the VR system. The block ReceiveGRIPS_Signals tracks the actions of the rehabilitation robot and saves this data in synchrony with the EEG data for offline analysis.

2.3 Session timing

One experimental run lasted about six minutes and contained 40 randomized commands of either left-hand or right-hand MI. Fig. 1B shows the trial timing. One trial lasted eight seconds. A random intertrial interval between 0.5 and 1.5 seconds was included between each trial. The cue (command) was presented at 3 seconds. The feedback phase lasted from three seconds until the end of the trial.

2.4 Robotic feedback paradigm

Four healthy subjects (mean age 24 ± 5.2 years, 2 left-handed, 2 right-handed) participated in the tests with the rehabilitation robot Amadeo (see Fig. 3B). The Amadeo is a mechatronic finger rehabilitation device that allows each individual finger, including the thumb, to move independently and separately. The positions, as well as the forces of each finger, were measured constantly during the paradigm and saved with the EEG data, allowing detailed offline analysis. One experimental paradigm consisted of 4 runs. With the data of the first 3 training runs, a specific classifier for detecting the MI was generated. No feedback was presented during the training runs. In the following run, this classifier was tested and the online error rate was calculated with the novel run. The robot gave feedback to only one of the two hands. In a real rehabilitation session, this would be the affected side. For the healthy subjects, we

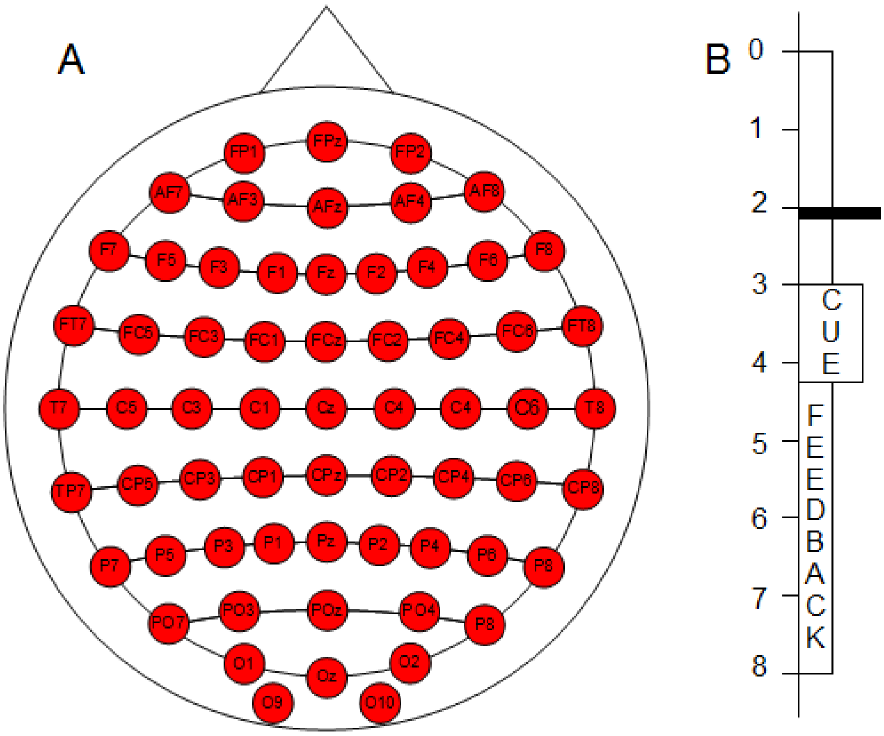

Fig. 2. A: Positions of the 64 active EEG electrodes. The ground electrode was placed on the forehead (near FPz) and the reference on the right earlobe. B: Timing of one feedback trial for either the robotic feedback paradigm or VR feedback paradigm.

selected the dominant hand to receive robotic feedback. The cue was given via a red arrow, pointing either to the left side or the right side of a computer screen. If the cue pointed to the side that was not fixed in the rehabilitation robot, the subject was asked to perform a real (not imagined) full flexion and extension of his/her fingers. If the cue pointed to the other hand, the subject was asked to instead imagine the same movement. When the correct MI was detected, the robot provided feedback by performing a flexion and extension of the five fingers. Within one trial, only one full flexion and extension was done. If no correct MI was detected during the feedback phase of the trial, then the robot performed no movement.

2.5 VR paradigm

Eleven post-stroke patients (mean age 67.5 ± 10.3 years) and eleven healthy subjects (mean age 22.3 ± 4.2 years) participated in the tests with the VR system. The measurements with stroke patients were performed at the Krzeszowice Rehabilitation Center, Poland. The measurements with the healthy users were performed at Guger

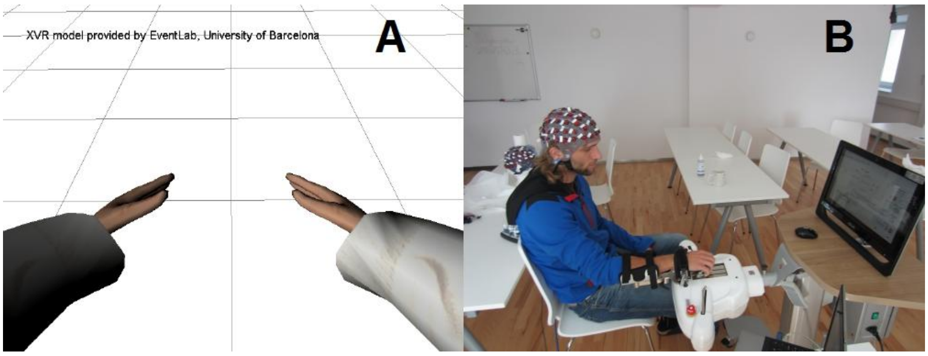

Fig. 3. The two feedback strategies. (A) VR paradigm. (B) Robotic feedback paradigm.

Technologies OG, Austria. Because the patients were not able to participate in longer sessions, the number of runs was reduced to either three, or sometimes two, runs per session. Two runs were conducted if the user was very tired or did not feel good. Hence, training data recorded during such sessions were not sufficient to set up a subject specific classifier. Therefore a generic classifier (generated from a large pool of previously recorded MI sessions of other users) was used. For comparison, the same procedure was tested on the group of eleven healthy users, using the identical generic classifier and always with three runs. Feedback was presented for both hands, visualizing the user's hand in VR as they seen in the user's first perspective (see Fig. 3A). The cue was presented by flexion and extension of the left or right hand. After the cue phase, the user had to imagine the same flexion and extension as seen during the cue phase. A beep indicated the start of the cue phase. A second beep indicated the end of it and the beginning of the feedback phase. The feedback was then presented as flexion and extension of the detected hand side of MI, thus presenting real-time online feedback to the user. If during the feedback phase the detected hand side changed, then the feedback also flipped from one hand to the other.

3 Results

Table 1 shows the mean accuracy of the group of eleven stroke patients and the control group of eleven healthy users. Five of the stroke patients participated in four further sessions. For this extra comparison, the results of this group after the first session and after the fourth session are depicted in the last two columns.

Table 2 shows the results of the healthy users performing the robotic feedback sessions. The mean accuracy across the four users was 86.55%. The accuracy level is averaged over 40 trials.

Table 1. Mean accuracy rates of the two groups participating in the VR paradigm

	Healthy	Stroke		
Session #	1	1	1	4
Participants	11	11	5	5
Mean Acc.	63.77	60.67	59.7	72.48
SD	16.52	13.05	6.08	8.45

Table 2. Accuracy rates of the healthy users participating in the robotic feedback paradigm

Session #	Accuracy (%)
1	92.50
2	95.00
3	68.70
4	90,00
mean Acc.	86.55
SD	13.97

4 Discussion

The aim of this study was to evaluate a novel rehabilitation strategy, which can present feedback either via a rehabilitation robot or a VR system. The error rate during online control was calculated. The robotic feedback was tested only on healthy users with a specific classifier for each session. The groups testing the VR feedback used a generic classifier. This is the reason why the classification result of the latter groups is lower than for the robotic feedback group. The difference in control accuracy between healthy users and stroke patients is only about 3% on average, although the mean age of the stroke patients (67.5 years) is much higher than that of the healthy control group (22.3 years). One very important finding of the study is the improvement of control accuracy of the stroke patients during only 4 training sessions. As could be seen in Table 1, they improved from 59.7% to 72.48%. The motivation of the user and the advances in the rehabilitation process due to the BCI approach depends on the accuracy of the BCI, hence these improvements seem very promising.

One difference between the two feedback approaches was the delay in presenting the feedback. The VR feedback gave feedback in real-time and in synchrony to the MI. If the MI changed during the feedback phase, then also the feedback changed. For the robotic feedback, the user had to first perform the MI, then a full flexion and extension was performed by the robot, regardless of what the user did while the robot moved. In a recent publication, Ramos-Murguialday et al. called this approach discrete proprioceptive feedback, and stated that the feedback contingency is of vital importance to enable neuro-motor-rehabilitation [14]. Gomez-Rodriguez et al. also wrote that synchronization is likely to increase cortical plasticity due to Hebbian-type learning, and could improve the functional recovery [9]. For future studies, we aim to adapt the robotic feedback that way to deliver synchronized online feedback, similar to the VR feedback approach.

The advantage of the robot is that it delivers both visual and proprioceptive feedback, which can stimulate the afferent pathways even more than the VR based feedback and thereby could be more effective. Another future goal will be to investigate the combination of the two rehabilitation strategies.

The BCI communicates to the VR system and the robot via an interface that is based on UDP (g.UDPinterface, g.tec medical engineering GmbH, Austria). With this generic interface, it is easy to create other feedback devices, and we will also evaluate functional electrical stimulation.

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