MULTI-MODAL FEEDBACK FOR BCI BASED STROKE REHABILITATION: A CASE STUDY

A. Lechner1*, R. Ortner1*, D.-C. Irimia1* and C. Guger1*

* g.tec medical engineering GmbH, Schiedlberg, Austria
email: lechner@gtec.at

Abstract: 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. Both, functional electrical stimulation (FES) systems and brain-computer interface (BCI) based rehabilitation are earning year by year more involvement within the rehabilitation field. This paper presents the coupling of a motor imagery based BCI system with two feedback modalities. A multichannel neurostimulator is controlling both hands, performing an extension of the fingers. Secondly, a first-person Virtual Reality Avatar performs the same motor movements. The effectiveness of the proposed method has been tested on a 65 year old stroke patient, performing fourteen rehabilitation sessions within six weeks.
Keywords: BCI, Stroke Rehabilitation, FES

Introduction

In the last few years, several publications suggested that using motor imagery based Brain-Computer Interface (BCI) systems (MI-based BCI) can induce neural plasticity and thus serve as important tools to enhance motor rehabilitation for stroke patients (e.g. Ang, 2011; Shindo, 2012). Ang et al. reported higher 2-month post-rehabilitation gain on the Fugl-Meyer (FM) assessment scale for patients using a BCI-driven robotic rehabilitation tool compared to a control group, 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. (Shindo, 2012) 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 (Grosse-Wentrup, 2011).

Neurofeedback is a process that uses real-time displays of EEG or functional magnetic resonance imaginng (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. Hence, the feedback must reflect the user's task in an appropriate way. When using the BCI for motor rehabilitation, the feedback should be similar to the motor activity.

Most BCI driven rehabilitation approaches use robots or computer controlled orthoses for feedback (Ang, 2011). Alternatives could be visual feedback (Ortner, 2012) or functional electrical stimulation (FES) (Irimia, 2013). The new approach within this publication is to demonstrate a more immersive feedback strategy: the combination of visual feedback and FES, thus stimulate more afferent pathways and give the patient a better illusion of hand control.

Materials and methods

The user, a 65 year old right handed man, suffered a stroke in the left parietal and frontal lobe, around CZ and C3. The treatment started three years after the stroke. The detection of MI was done by the method of common spatial patterns (CSP). The method of CSP creates a set of spatial filter that are optimized for each user separately and hence increase classification accuracy in comparison to fixed filter setups. For more information about the methods of CSP, one may be referred to Guger et al. (Guger, 2000) or Blanketz et al. (Blankertz, 2008). The signal processing and paradigm control was done with an adaptation of RehaBCI (g.tec medical engineering GmbH, Austria), a Simulink based platform that classifies MI and controls external feedback devices via network. Table 1 shows the adapted Simulink block. The amplifier reads in the EEG of the 64 channels (shown in Figure 1 A) with 256 Hz sampling frequency. The spatial patterns are applied before the signal is bandpass filtered between 8Hz and 30Hz. For the four spatially filtered features the variance is calculated and log10 normalized. The LDA classifier is applied on that normalized data. The paradigm block controls the trial timing and sends the feedback information to the FES control and Avatar control. Figure 3 shows additionally a schematic diagram of the experimental setup. The effected hand is the right one, but stimulation was performed on both hands. In total fourteen sessions distributed over six weeks were performed (see **Erro! Fonte de referência não encontrada.**). The sessions were contucted on different days of the week. For the first session, a set of generic spatial patterns and a generic classifier was used to detect MI. For the following sessions, the data of the previous day was used for setting up a specific set of CSPs and classifier. One session consisted of three to five runs, depending on the daily constitution of the patient. One run lasted

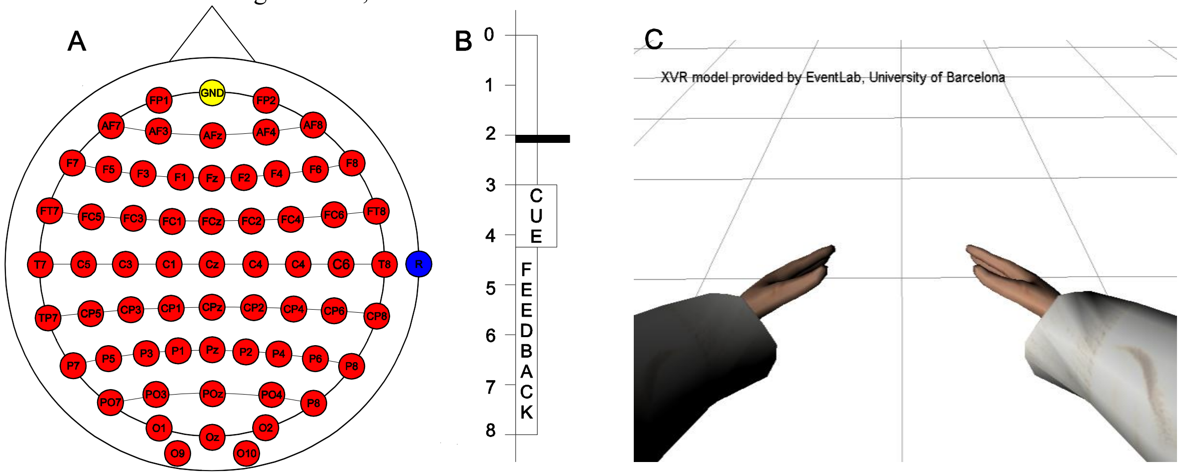

Figure 1: A) Electrode setup: 64 channels of EEG were measured; the ground was placed on the forehead, the reference on the right earlobe. B) trial timing: one trial lasted eight seconds the feedback started at 4.25 seconds until eight seconds. A random interval (0.5s-1.5s) between trials was inserted between trials. C) Avatar feedback.

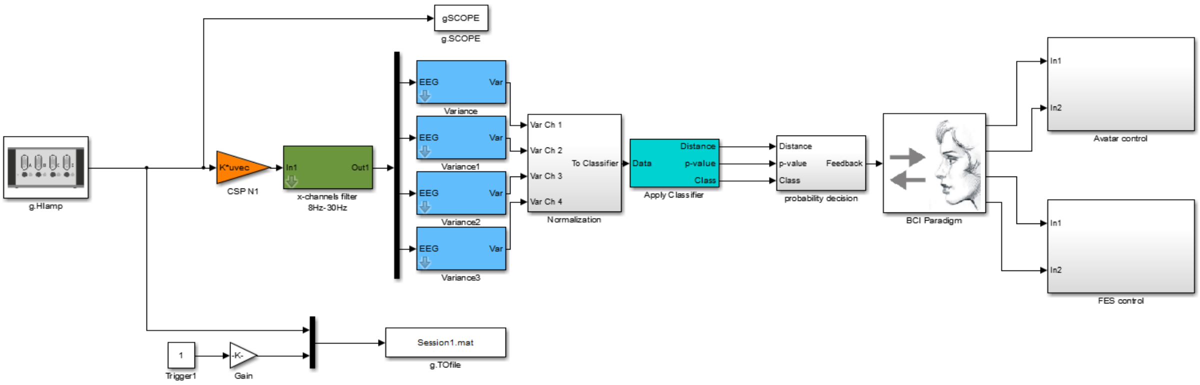

Figure 2: Simulink model for the real-time analysis of the EEG data. The g.HIamp block samples the data with 256 Hz. Data are then bandpass filtered and the spatial patterns applied. The classifier reads finally the normalized variance of the four spatially filtered data streams.

six minutes, wherein 40 randomized trials were executed. The timing of one trial is shown in Figure 1 B. After two seconds a beep appeared, demanding the user's attention. The cue phase started at three seconds, lasting until second 4.25. Within the cue phase, until the end of the trial, the user is asked to imagine motor movement of either the left or the right hand. During the feedback phase, lasting from 4.25 seconds until the end of the trial (eight seconds) the avatar and FES feedback is controlled, performing an extension of the fingers, if classified. Both feedback devices performed the same movement (hand extension and flexion) if MI was detected. For FES a neurostimulator (MOTIONSTIM 8, MEDEL GmbH, Medicine Electronics, Germany) was used. The Avatar feedback was done by showing an avatar in the user's first perspective (see Figure 1 C).

For evaluation of the rehabilitation success, the 9-hole PEG test was performed for both hands, each week during treatment.

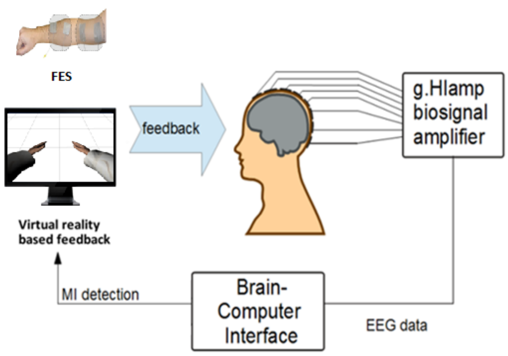

Figure 3: Experimental setup, including g.HIamp, the BCI and the two feedback strategies.

Results

Erro! Fonte de referência não encontrada. shows minimum classification error during the sessions and the results of the 9-hole Peg tests. The error rate decreased from 22.5% to 10% in the last session. It has to be noted that during S12 the error rate reached 35%. In that session the FES feedback did not work, this could explain the bad performance. The 9-hole Peg test was performed for both hands at the end of each week, except in the first week.

Discussion and Conclusion

In this study a multi-modal feedback for stroke rehabilitation was evaluated. All measures, the error rate of classification, as well as the time needed for the 9-hole Peg test decreased over six weeks of training. Unfortunately no evaluation of the 9-hole Peg test was performed before the first session, or after the first week, so only the evolution from the end of the second week until the end of training was assessed. In these tests, the time needed to finish the task decreased for both, the affected (14 seconds) as well as the unaffected hand (13 seconds). An interesting fact is that the affected hand improved between week two and week four by 12 seconds, and then almost stayed constant for the rest of the treatment. The effectiveness of treatment seems therefore be high at the first sessions, and then leverages. The classification error is below 10 % from S 7 until the end of treatment, except in S 12. In this session the FES feedback did not work and only Avatar feedback was provided. It seems that the decrease of classification error correlates with the improvements showed by the 9-hole Peg test, an observation that has to be proven with more patients in the future. The doctor of the patient mentioned also, that FES might have a greater influence than the visual feedback in the rehabilitation process. More measurements can maybe proof that.

			9 hole Peg Test (seconds)	
Session#		**Error rate (%)**	**unaffected hand**	**affected hand**
S1	week 1	22.5		
S2		20		
S3		30		
S4	week 2	37.5	46	52
S5	week 3	17.5		
S6		30		
S7		5	40	45
S8	week4	5		
S9		10	35	40
S10	week 5	2.5		
S11		7.5	32	40
S12	week 6	35		
S13		7.5		
S14		10	33	38

Table 1: Control accuracy of the BCI and results of the 9 hole Peg test during the six weeks of training.

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