Paired Associative Stimulation using Brain-Computer Interfaces for Stroke Rehabilitation: A Pilot study

Cho W., Sabathiel N., Ortner R., Lechner A., Irimia D.C., Allison B. Z., Edlinger G., and Guger C.

***Abstract*— Conventional therapies do not provide paralyzed patients with closed-loop sensorimotor integration for motor rehabilitation. Paired associative stimulation (PAS) uses brain-computer interface (BCI) technology to monitor patients' movement imagery in real-time, and utilizes the information to control functional electrical stimulation (FES) and bar feedback for complete sensorimotor closed loop. To realize this approach, we introduce the recoveriX system, a hardware and software platform for PAS. After 10 sessions of recoveriX training, one stroke patient partially regained control of dorsiflexion in her paretic wrist. A controlled group study is planned with a new version of the recoveriX system, which will use a new FES system and an avatar instead of bar feedback.**

I. INTRODUCTION

In conventional rehabilitation therapy, patients are often asked to try to move the paretic limb, or imagine its movement, while a functional electrical stimulator (FES), physiotherapist, or robotic device helps them perform the desired movement. However, if patients cannot perform the movement without help, there is no objective way to determine whether each patient is actually performing the desired motor imagery task. This dissociation between motor commands and sensory feedback may explain why the therapy does not significantly induce the reorganization of the patients' brain around their lesioned area. To close the feedback loop for paralyzed patients, we used bar feedback and FES based on their motor imagery (MI) [1]–[3]. This paired associative stimulation (PAS) is an important factor for motor recovery [4]–[10]. Neural networks are facilitated when the presynaptic and postsynaptic neurons are both active.

recoveriX is a complete hardware and software platform which can record, analyze, and utilize EEG activity in real-time to "close the sensorimotor loop" for rehabilitation. The patients imagine or perform specific movements such as the wrist dorsiflexion of their paretic limbs. Their corresponding brain activity is acquired by EEG electrodes, then sent to an amplifier. Figure 1 shows the sketch of recoveriX system. The visual and proprioceptive feedback is provided to patients when interpreted as movement intention by classification algorithm. This study presents the measurement procedures and results of one chronic stroke patients after 10 BCI training sessions of recoveriX.

* Cho W., Sabathiel N., Ortner R., Lechner A., Allison B., and Guger C. are with g.tec medical engineering GmbH, Sierningstrasse 14, 4521 Schiedlberg, Austria (phone: 0043 7251 22240 0; fax: 0043 7251 22240 39; e-mail: cho@gtec.at). Irimia D. and Edlinger G. are with Guger Technologies OG, Herbersteinstrasse 60, A-8020 Graz, Austria.

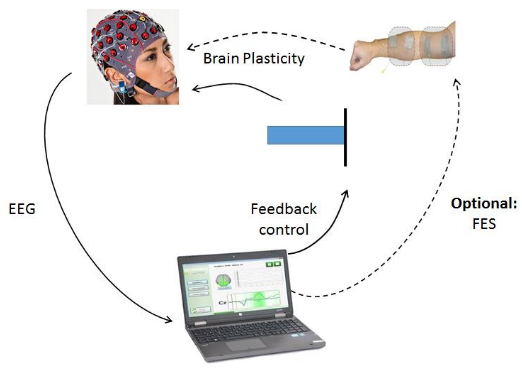

Fig. 1. A schematic illustration of recoveriX

II. METHODS

A. Subjects

One right-handed female patient participated in this study. When the intervention occurred, she was 40 years old (5.5 years after stroke) and had severe paralysis in her left hand with no residual movement. She had received conventional therapy for two years and no significant functional improvement had been observed before her participation to this study. She participated in 10 recoveriX training sessions at the Rehabilitation Hospital of Iasi, Romania.

B. Data acquisition and signal processing

We recorded patients' sensorimotor rhythm using 45 active EEG electrodes (g.LADYbird, g.tec medical engineering GmbH, Austria). The electrodes overlaid the sensorimotor area of cortex. FPz was used as ground electrode, and a reference electrode was placed on the right earlobe. EEG signals were transmitted to an biosignal amplifier (g.HIamp, g.tec medical engineering GmbH, Austria), which then delivered the data to a computer for further processing required in online BCI.

After preprocessing, common spatial patterns (CSP) [11] was applied to transform the data to a new matrix with minimal variance of one class and maximal variance of the other class, which is represented by a transformation matrix, W in equation (1). The transformed matrix reflects the specific activation patterns of the data during motor imagery of left or right hand in this study. The decomposition of a trial X is described by $Z = WX$ ….. equation (1)

The variance of X was projected onto the rows of Z. The variance for one class is largest in the first row of Z and decreases in each subsequent row due to the transformation matrix, W. The optimal number of CSPs is four [11] to classify the left or right trials. Only first and last two rows (p=4) of W were used to process new input data X. Next, the variance (VARp) was calculated. These values were normalized and log transformed according to the formula:

$$f_p = \log_{10}\left(\frac{VAR_p}{\sum_{P=1}^{4} VAR_p}\right) \quad \text{..... equation (2)}$$

where f_p (p=1.4) were the normalized feature vectors and VAR_p was the variance of p-th spatially filtered signal. These four features were classified with a linear discriminant analysis (LDA) classifier.

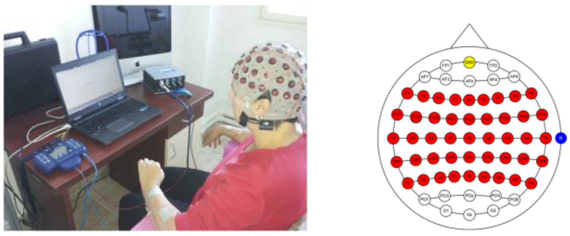

Fig. 2. recoveriX system with patient (left) and the EEG montage (right).

C. Stimuli and Procedure

The patient was seated in a comfortable chair in front of a monitor that presented cues and feedback (see Figure 2) with FES pads placed over the forearm of the affected side. The patient was instructed to imagine the movement of either left or right hand while an arrow was presented on a monitor indicating its movement site and cue. After a delay of 0.5 seconds, the user began to receive visual and proprioceptive feedback. A blue bar moved and updated every 4 ms to the left or right indicating both the direction and magnitude of the motor imagery as visual feedback. The FES would activate with 50 Hz updating rate if the user was imagining hand movement of instructed side. The muscle contraction by FES was sufficient enough to cause movement in the affected hand. The feedback period lasted four seconds, and the inter-trial interval was two seconds.

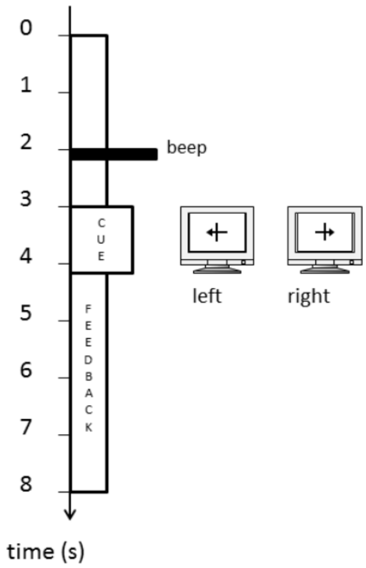

Fig. 3. Time course of a single trial. A fixation cross appears when the trial begins. A short beep cues the user after two seconds. One second later, a visual cue is presented. Online feedback is presented from 4.25 seconds until the end of the trial (8s).

III. RESULTS

Figure 4 presents BCI classification accuracy across 10 sessions. The patient reported that she actively participated in motor imagery tasks as instructed. The accuracy in the first two sessions is slightly over the chance level of 50%, and the accuracy of the remaining eight sessions was substantially higher than that of the first two sessions (see Figure 4). The accuracy dropped to 82.5% in the session number 8 because of the lack of sleep during the previous night.

This result means that the classifier distinguished two different tasks between left MI and right MI in the most training sessions other than the first two sessions. The visual and proprioceptive feedback was not properly provided to the patients with incorrect classification (in the left side of Figure 5), and both feedbacks were presented with correct classification during feedback period (in the right side of Figure 5).

Event related desynchronization plot also showed that the patients was able to perform the MI tasks and here are two examples of the first and last sessions. ERD is observed in both sessions and the statistical comparison between two ERD plots is necessary in the future. However, it is clear that recoveriX training session were based on MI tasks.

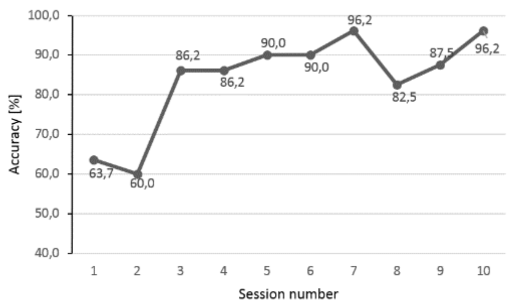

Fig. 4. BCI classification accuracy across 10 RecoveriX training sessions.

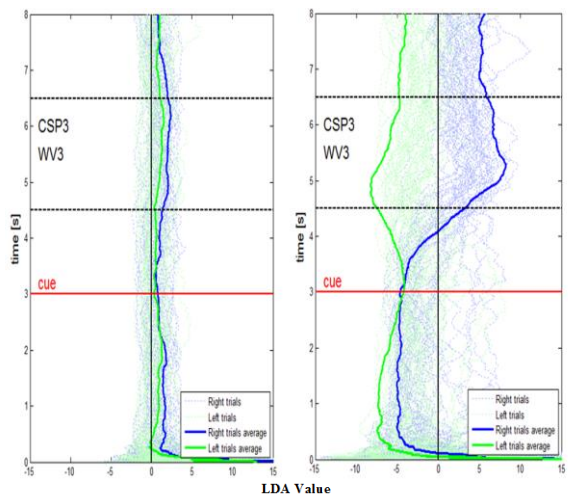

Fig. 5. Linear discriminant analysis (LDA) values of first and last training sessions are presented in the left and right panels, respectively. The dotted blue lines indicate the LDA values of right motor imagery and the solid blue line shows the average of them. The dotted green lines indicate the LDA values of left motor imagery and the solid green line shows the average of them. Left and right trials were expected to have positive and negative LDA values respectively. The classification accuracy were calculated with LDA values in the feedback period (4 ~ 8 sec).

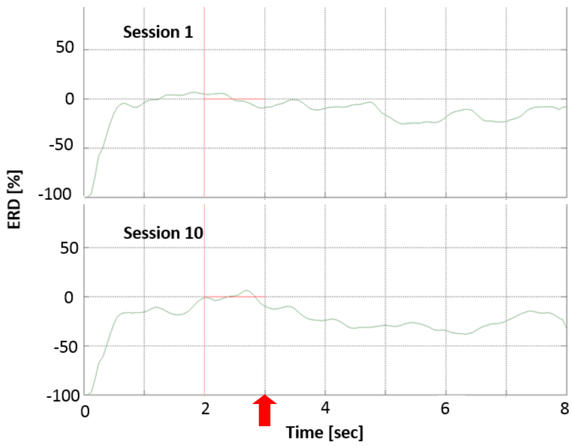

Fig. 6. Event-related desynchronization (ERD) plot of session the first and last (10th) session were produced by g.BSanalyze (g.tec medical engineering GmbH, Austria). This averaged ERD plot was based on 8 ~ 12 Hz frequency bands of the channel C4 which is located on the lesioned hemisphere. The red vertical line indicates a beep sound for attention and 'cue' were presented at three seconds.

After ten training sessions, the patient was able to voluntarily relax and extend the wrist of her paretic side seen in Figure 6. This motor control was not achieved before this recoveriX intervention.

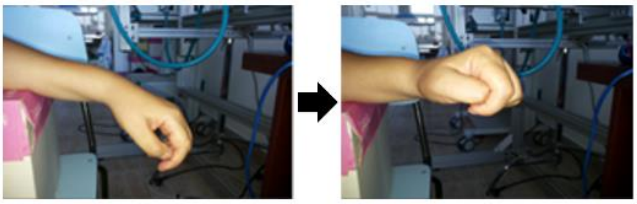

Fig. 6. Voluntary wrist dorsiflexion after 10 recoveriX training sessions. The patient relaxed (left photo) and was instructed to perform a dorsiflexion of her left wrist (right photo).

IV. DISCUSSION

A. Discussion of Results

We showed that the patient could follow the left or right hand motor imagery instructions. Thus, BCI accuracy improved to more than 80% after the second training session. The higher BCI accuracy and LDA values of later sessions implies that the patients learned to use the BCI. This chronic stroke victim did not have any residual movement of her paretic hand even after several conventional physiotherapy sessions, but she regained her partial control of the affected hand after recoveriX training. It was not possible to practice the Nine-Hole Peg Test (9-HPT) and measure the electromyogram (EMG) due to complete paralysis of her left hand before the session started, and alternative behavioral measurements are not available in this pilot study.

B. Future work

This study showed the result of one patient with 10 training sessions alone. The recoveriX system and current training paradigm will be examined with higher number of patient population in comparison with control group for meaningful statistical outcomes.

Figure 7 presents our new g.Estim device (g.tec medical engineering GmbH, Austria), which will replace the current FES device. The new g.Estim is developed mainly for BCI applications, and we are currently developing CE and FDA clearance. In addition, the bar feedback will be replaced with an avatar of patients' upper limbs, and EEG will be wirelessly transmitted to a computer by g.Nautilus (g.tec medical engineering GmbH, Austria), as seen in Figure 8.

Fig. 7. Photo of new FES device, g.Estim

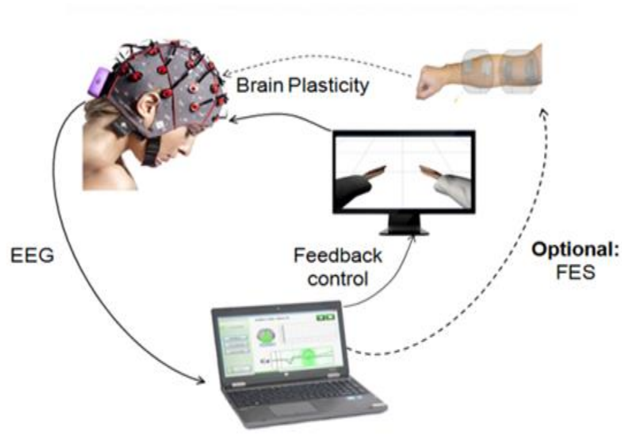

Fig. 8. A schematic illustration of a new recoveriX

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