Motor rehabilitation for hemiparetic stroke patients using a brain-computer interface method

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***Abstract*—Brain-computer interfaces (BCIs) have been employed in rehabilitation training for post-stroke patients. In this study, we present the results of the intervention based on BCI triggered functional electrical stimulation (FES) and avatar mirroring. Seven chronic stroke patients participated in 25 sessions of training over 13 weeks. Seven assessments were conducted to observe any behavioral changes before and after the intervention. The primary outcome measure, i.e. the Fugl-Meyer Assessment of the Upper Extremity (FMA-UE), increased significantly by 6.4 points (p=0.048), which is above the minimal clinically important difference (MCID). The Modified Ashworth Scale (MAS), one of the secondary outcome measures, reduced significantly in both the wrist and the finger (p=0.046 and p=0.047 respectively). This study demonstrated motor function improvement and spasticity reduction in chronic stroke patients (n=7) after BCI triggered FES and avatar mirroring. One limitation of this study is that the small sample size may not adequately represent the diverse stroke population. Further work should include a randomized controlled trial to investigate the effectiveness of BCI triggered FES compared to conventional therapies.**

Keywords—brain-computer interfaces, motor imagery, stroke rehabilitation, functional electrical stimulation, avatar

I. Introduction

Stroke is one of the main causes of mortality and long-term disability worldwide. Stroke survivors often suffer from movement restrictions of their affected limb, leading to reduced use and compensation. Therapies such as constraint induced movement therapy restrict the use of the healthy limb, encouraging patients to use the paretic limbs more often. This method has seen some therapeutic success [1], [2], however this success has been limited to patients with residual movement in their paretic side. For patients with severe paresis, several passive movement therapy approaches are available. One such technique is continuous passive motion therapy, which has shown modest functional improvements in patients. Critically, these passive approaches do not monitor the patients' active engagement in the therapy, which has been shown to be crucial to motor learning and rehabilitation. Current stroke recovery techniques, while somewhat effective, leave much to be desired.

Motor imagery based brain-computer interfaces (BCI) have recently been employed in rehabilitation training for stroke patients to fill the gap between patient expectations and therapy outcomes [3]–[5]. These BCIs record, analyze, and utilize electroencephalographic (EEG activity) in real-time. Patients imagine or perform specific movements such as wrist dorsiflexion of their own limbs, and the corresponding brain activity is acquired by EEG electrodes and sent to an amplifier. If the correct movement is interpreted by the BCIs classification algorithm, sensory feedback is provided via external devices. This sensory feedback stimulates the CNS to induce neuroplasticity for motor rehabilitation [6], [7].

This techniques effectiveness has been shown in multiple studies implementing exoskeletal devices, robots, and functional electrical stimulation (FES), which induces movement of the affected limbs independent of direct patient motor control [2-5]. In addition, virtual reality enhances the cortical reorganization and reduces the interhemispheric imbalance in motor rehabilitation providing real-time visual feedback [11], [12]. During repetitive BCI training sessions, even patients with severe impairments can complete the sensorimotor loop in his/her brain linking coherent sensory feedback with motor intention.

A ready-to-use BCI system, called recoveriX® (g.tec medical engineering GmbH, Austria) was recently introduced to bring the current BCI technology to the stroke affected community. recoveriX provides visual feedback with animated upper extremities in virtual reality (avatar) and proprioceptive feedback producing movement via FES. A depiction of the recoveriX setup can be seen in Figure 1. In

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this study we evaluate the behavioral outcomes of BCI training in chronic stroke patients.

II. Patients and Methods

A. Patients

All participants fulfilled the following inclusion criteria: (1) ability to understand written and spoken instructions; (2) hemiparesis; (3) time since stroke of at least four days; (4) stable neurological status other than stroke; (5) ability to participate in the study for three months; (6) no pregnancy; (7) no implanted medical devices such as pacemakers; (8) no implanted metallic fragments in the upper extremities; (9) no cerebellar lesion; (10) no severe hemi-neglect; (11) no epilepsy; (12) no fractures or lesions in the upper extremities; (13) no severe lung diseases or liver disease; (14) no severe pusher syndrome; (15) ability to maintain a seated position for one hour; (16) no sensory disorder feeling pain or unsuitably reacting to sensory stimuli; (17) no peripheral nervous diseases affecting the upper limbs (brachial plexus pals and cervical radicular syndromes).

B. Study Design

Each patient received 25 sessions of BCI feedback training over three months. Two pre-intervention measurements (Pre1 and Pre2) and one post-intervention measurement (Post) were carried out to investigate the rehabilitation effects. Pre1 and Pre2 were scheduled one month and two days before the intervention, respectively, while Post was performed two days after the intervention was completed. The study protocol was approved by the Ethics Committee of the Province of Upper Austria (#D-42-17). All patients gave a signed informed consent before participating in the training.

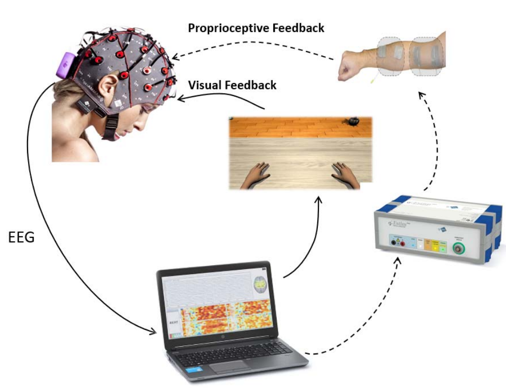

Figure 1. General concept of the BCI system used for this study, recoveriX. A complete BCI system (recoveriX, g.tec medical engineering GmbH, Austria) was used. EEG signals were transmitted to a biosignal amplifier. Two FES devices and avatar were directly controlled via real-time EEG analysis. Each FES device controls one hand side. When the EEG is classified as the correct hand side of motor imagery (MI) during trials, the FES and avatar are activated. FES produces wrist dorsiflexion and the avatar shows the same dorsiflexion in the first-person perspective.

C. BCI Training

One training run consisted of 80 trials and one session contained three runs. The total time of one session was about 60 minutes including preparation and cleaning time. Patients wore EEG caps with 16 active electrodes (g.SCARABEO, g.tec medical engineering GmbH, Austria). The electrode positions were according to the international 10/10 system (extended 10/20 system) at FC5, FC1, FCz, FC2, FC6, C5, C3, C1, Cz, C2, C4, C6, Cp5, Cp1, Cp2, and Cp6. A reference electrode was placed on the right earlobe and a ground electrode at FPz.

Two FES pads were placed on the skin over wrist extensors of the left and right forearms. The FES parameters (g.Estim, g.tec medical engineering GmbH, Austria) were set to a frequency of 50 Hz and a rectangular pulse width of 300 μs. The stimulation amplitude (in mA) was adjusted to find the optimal movement produced by electrical stimulation in both the healthy and affected limbs.

The sequence of motor tasks was specified by the recoveriX software in pseudo random order with randomized inter-trial intervals. Patients were first cued to the start of a trial with an attention beep. Two seconds later, an animated arrow in the avatar window pointed to the expected hand for motor imagery (MI). At the same time, an auditory instruction

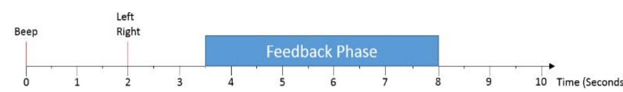

Figure 2. Time sequence of one trial. Two seconds after the attention beep sound, the MI cue of each trial is presented. The feedback phase begins 1.5 seconds later and continues for 4.5 seconds.

saying either "left" or "right" indicated the task of each trial. During the feedback phase, FES and avatar feedback were activated when recoveriX detected MI of the correct hand. If no MI is detected, feedback is deactivated. Feedback was updated five times per second. A depiction of the time sequence of a single trial can be seen in Figure 2.

D. Signal Processing

EEG signals were sent to a biosignal amplifier and were bandpass filtered (Butterworth filter 4th order) between 8 and 30 Hz. Then common spatial patterns (CSP) were applied to transform the data to a new matrix with minimal variance of one class and maximal variance of the other class [13]. Each class reflects the MI of the cued hand versus the MI of the other side. The CSP method calculated a 16 × 16 projection matrix from 16 EEG channels for each left and right trial X. This matrix is a set of special patterns and implies the activated area of cortex during hand MI. The decomposition of a trial is written as $Z = WX$. This transformation projects the variance of X onto the rows of Z and results in 16 new time series. The columns of $A = W^{-1}$ are a set of CSPs and can be considered as time-invariant EEG distributions. The variance for left trials is largest in the first row of *Z* and decreases with the subsequent rows. The opposite occurs in a trial with right trials. The variances were extracted as reliable features of the newly calculated 16 time series for the binary classification (left vs right).

According to Mueller-Gerking's work, the optimal number of CSPs was four (to reduce the dimensionality of EEG) [14]. Using an artifact corrected training set, *XT*, only the first and last two rows ($p = 1, 2, 15, and\ 16$) of *W* were used to process new input *X*. Then, the variance (*VARp*) of the times series was calculated for a time window *T*. After normalizing and log-transforming, four feature vectors were obtained via equation 1.

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

A linear discriminant analysis (LDA) classified each trial as either left or right MI. When the input signals were correctly classified according to the assigned task, the feedback devices were triggered. This online classification was updated and controlled the FES and avatar every 25 ms.

Offline classification accuracy was estimated via a 10-fold cross validation. This refers to partitioning a sample of movements into 10 complementary subsets and validating the analysis on one subset (called the validation set or testing pool) and training the CSPs and classifier on the other subsets (called the training pool).

The accuracy was calculated (in steps of half a second) for all trials in the testing pool within a 4.5 second time window beginning 1.5 seconds after the attention beep and ending with the end of the trial. For each step and each trial, the classification result is either 100% or 0%. The accuracy of all trials of the test pool is then averaged for each single step, resulting in accuracy levels ranging between 0% and 100%. After averaging all ten repetitions of the cross validation, the maximum value during the feedback phase was noted as the session accuracy.

E. Assessment

The Fugl-Meyer Assessment (FMA) is a stroke-specific method of evaluating sensorimotor functions, balance, joint mobility, and joint pain for clinical and research purposes. The score indicates the impairment of patients as assessed by therapists or medical staffs with high reliability. We used the FMA of upper extremity (FMA-UE, maximum score=66 points) as a primary behavioral outcome measure because the upper extremities are the task-related body parts during the training. It supports the assessment of the degree of damage and describes the recovery after a stroke.

Six secondary outcome variables were also measured. The 9-Hole Peg Test (9-HPT) measures the time to complete a finger dexterity task [15] and the Box and Block Test (BBT) measures the number of blocks moved from one place to another in one minute [16]. The Barthel Index (BI) is a questionnaire designed to test the patient's ability to care for themselves [17]. The Modified Ashworth Scale (MAS) examines patient spasticity (with a lower score indicating less spasticity in his/her paretic limb). Both the wrist (MAS_{Wrist}) and hand ($MAS_{Fingers}$) were tested for this assessment. The Fahn Tremor Rating Scale (FTRS) scores tremor intensity in the paretic limb. A lower score in the FTRS indicates smaller tremor intensity [18]. Lastly, the Two Point Discrimination Test (TPDT) was conducted as a sensitivity measure, with a lower score indicating greater sensitivity [19].

F. Statistical Analysis

Statistical analyses were carried out using SPSS (ver. 24, SPSS, Chicago, IL, USA). The mean of Pre1 and Pre2 was considered as the baseline value for each outcome measure (Baseline = (Pre1 + Pre2) / 2). Post-assessment represents the outcome measure after completion of the 25 training sessions.

The primary and secondary outcomes were statistically analyzed after a normal distribution was determined with the Shapiro-Wilk test. A two-tailed paired sample t-test or a Wilcoxon signed rank test was used to investigate outcome changes in the Baseline-Post assessment for normally or non-normally distributed data, respectively. The Pearson correlation was used to analyze the relationship between mean classification accuracies and the differences (Post-Baseline) in the FMA-UE. The threshold for significance was set to α=0.05.

III. RESULTS

A total of 7 out of 8 patients successfully met the inclusion criteria and gave written informed consent before participating in the study. One patient was excluded due to paresis in both upper limbs.

The characteristics of the 7 subjects (5 male and 2 female) are shown in Table 1. Five patients were left side affected and two were right side affected. Average time since stroke onset was 9.2 ± 10.7 years and all of them were considered chronic patients.

Table 1. Patient Demographics

Gender	Male	5
	Female	2
Affected side	Left	5
	Right	2
Age		58.6 (21.1)
Time since stroke onset		9.2 (10.7)

Age and time since stroke onset are expressed as mean (standard deviation) in years.

The results of group analyses are shown in Table 2. A significant difference was found in FMA-UE_{total} (p=0.048) in the primary outcome measures. All of the sub-scores of FMA-UE increased after the intervention, but none showed significant differences. In the secondary measures, the MAS_{Wrist} (p=0.046) and $MAS_{Fingers}$ (p=0.047) had significantly decreased. The BI, FTRS, and TPDT did not show any statistical changes. It was not possible for more than four patients to perform the BBT and the 9-HPT due to their severe paresis, and these two measures were not included in this analysis.

Table 2. Differences at Baseline and Post Measurement

	Mean (standard deviation)	
Parameters	Baseline (n=7)	Post (n=7)
FMA-UE_{total}	27.3 (16.6)	33.7 (18.4)*
Shoulder	15.2 (10.5)	19.0 (10.1)
Wrist	2.50 (3.66)	3.86 (4.91)
Hand	5.79 (6.00)	6.71 (5.94)
Coordination	3.79 (0.57)	4.14 (0.69)
BI	89.9 (10.7)	90.0 (16.3)
MAS		
MAS_{Wrist}	2.96 (1.40)	2.29 (1.50) *
$MAS_{Fingers}$	2.71 (1.41)	2.14 (1.35) *
FTRS	7.43 (4.16)	7.43 (4.54)
TPDT	3.92 (0.80)	4.00 (0.63)

FMA-UE: Fugl-Meyer Assessment of the Upper Extremity, BI: Barthel Index, MAS: Modified Ashworth Scale, FTRS: Fahn Tremor Rating Scale, TPDT: Two-Point Discrimination Test, *significant difference within subject factor ($p<0.05$)

The FMA-UE improvement was not related to the mean classification accuracy (p=0.708). Classification accuracies of the first and last sessions averaged across all the subjects were 73.6% and 83.5%. The difference between the first and last sessions was not significant (p=0.208). See Figure 3 for the mean classification accuracies across sessions.

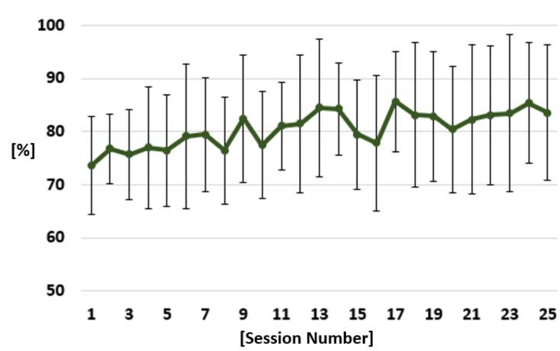

Figure 3. Classification accuracies of each session averaged over all subjects (n=7). Thick green line shows the average accuracy of each session and error bars indicate the standard deviation in [%].
Note: y-axis begins at 50% for visualization.

IV. DISCUSSION

We evaluated sensorimotor recovery after BCI intervention with multiple measures to detect behavioral changes in stroke affected patients. The results showed that the primary measure of this study, FMA-UE, increased by 6.4 points. This was above the minimal clinically important difference (MCID=4.25) [20]. Muscle spasm intensity in the wrist and fingers was also reduced after intervention.

In this current study, FES and avatar mirroring triggered by BCI provided the feedback to link motor imagery to a sensorimotor response and complete the sensorimotor loop. A recent study also showed that MI-BCI controlled FES yielded a 7.87 ± 2.42 (mean ± SD) increase in FMA-UE with 15 stroke patients [21]. In addition, the shoulder, wrist, and hand FMA-UE increased in the study. This study had five fewer sessions compared to the current study, but the training occurred five times per week. Each BCI session was followed by conventional physiotherapy. Also, the time since stroke onset (mean: 8 months) in the study was shorter than the current study (mean: 9.2 years), which could explain their improved FMA scores.

Another study using BCI-cued virtual hand feedback showed a 13.6 ± 8.9 (mean ± SD) point increase in FMA-UE with 14 stroke patients [22]. Training was performed three days per week for four weeks for a total of 12 sessions. This marked difference in training effectiveness may be attributable to the very different characteristics of the subjects – Sub-acute stroke patients were recruited in this study, meaning spontaneous recovery may have boosted motor recovery beyond the contributions of BCI training alone.

Classification accuracy increased by 9.9% on average in the current study, but this increased accuracy was not correlated with motor improvement. Improved classification accuracy implies patients received more sensory feedback, as FES and avatar mirroring were triggered only when the algorithm successfully classified the brain oscillation.

We found improvements in sensorimotor function and reduced muscle spasm intensity after 25 sessions of BCI intervention in stroke affected patients. This present study is limited due to the small sample size (n=7) and further work is necessary to conclude the efficacy or effects of BCI motor rehabilitation training. The patients enrolled in this study cannot represent various characteristics of stroke patients due to their heterogeneous lesion location, level of paresis, and diverse demographics. Therefore, a randomized controlled study is planned to test the hypothesis that this BCI approach with FES and avatar mirroring promotes more functional recovery than other conventional therapies.

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