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PRELIMINARY RESULTS OF TESTING A BCI-CONTROLLED FES SYSTEM FOR POST-STROKE REHABILITATION

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ABSTRACT: This work presents the recoveriX system, a hardware and software platform specially designed for stroke rehabilitation, as well as the preliminary results of testing it within clinical environment. Three patients with motor impairments due to stroke participated to the current study. In every session, the patients had to imagine 120 left and 120 right hand movements. The electroencephalogram (EEG) data was analyzed with Common Spatial Patterns (CSP) and linear discriminant analysis (LDA). The feedback was provided in form of an extending bar on the screen. During the trials where the correct imagination was classified, the FES was activated to move the corresponding hand. All patients were able to achieve high accuracies, even above 95% in at least one session, and all exhibited improvements in motor function. These first results showed that the stroke patients can control the motor-imagery BCI system with high accuracy and reflect the efficacy of combining movement imagination, the bar feedback and the real hand movements.

INTRODUCTION

Motor imagery-based brain-computer interface (BCI) have been used to assist people with motor disabilities since many years. The BCI systems extract commands in real-time, commands which can be used to control cursors or external devices like robots or neurostimulators. In the last few years, the control of functional electrical stimulation (FES) devices, termed as neurostimulators, became very interesting for post-stroke rehabilitation. A patient can use the movement imagery to induce real-time movements of specific limb segments.

In the last decade, a new field of application for motor imagery (MI) –based BCI proved to be of great interest. Many publications provide evidence that using MI-based BCIs can induce neural plasticity and thus serve as an important tool to enhance the rehabilitation outcome in stroke patients [1-4]. In here, MI is used to introduce closed-loop feedback within conventional motor rehabilitation therapy. This approach pairs each user's MI with stimulation and feedback, such as activation of a FES stimulator, avatar movement, and/or auditory feedback indicating successful task completion [5].

FES is a rapidly developing technology having the potential to restore the body motor functions. For example, FES has been used to restore hand grasp and release in people with tetraplegia [6] and standing and stepping in people with paraplegia [7]. The feasibility of integrating a non-invasive BCI system with a FES device eliciting foot dorsiflexion by means of surface electrode over the tibial anterior muscle has been investigated in [8]. Five healthy subjects performed 10 trials of idling and repetitive foot dorsiflexion to trigger BCI-FES controlled dorsiflexion of the contralateral foot. The epochs of BCI-FES controlled foot dorsiflexion were highly correlated with those of voluntary foot dorsiflexion (correlation coefficient between 0.59 and 0.77) with latencies ranging from 1.4 s to 3.1s. The classification of the mental states was based on a linear Bayesian classifier. Moreover, all subjects managed to achieve a 100% BCI-FES response (no omissions), and one subject had a single false alarm.

Daly et al. [9] tested a combined BCI and FES system on a patient presenting stroke-related dyscoordination of isolated index finger joint extension of the metacarpal phalangeal joint. The experiment took into account trials in which the user attempted to move a finger and alternate that with relaxation, as well as trials in which the finger movement has been imagined. The BCI2000 software has been used to process the recorded EEG signals. In the first session the patient exhibited highly accurate control of brain signal for attempted movement (97%), imagined movement (83%), and some difficulties with attempted relaxation (65%). During the session number six, control of relaxation improved to more than 80%. In three weeks time, meaning a total of nine sessions, it has been concluded that the patient's volitional isolated index finger extension has been improved.

In [10], Rüdiger Rupp and colleagues made an overview of neuroprosthesis for the upper extremity in individuals with spinal cord injury and its control with noninvasive BCIs.

In this paper we introduce the recoveriX system, a complete new hardware and software platform that can record, analyze and utilize EEG activity in real time to "close the loop" in stroke rehabilitation. Fig. 1 presents a schematic illustration of the conceptual approach used in

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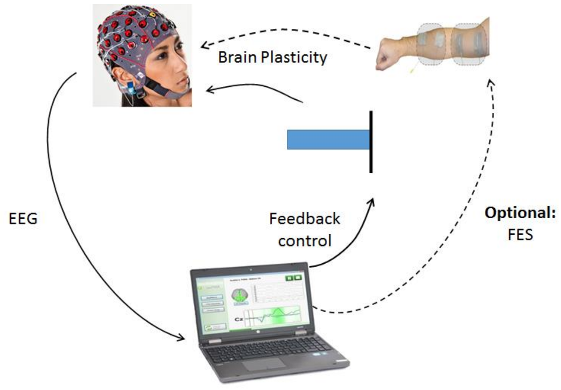

Figure 1: The schematic view of the recoveriX system.

recoveriX. The user imagines or performs specific movements, such as wrist dorsiflexion. The resulting EEG activity is detected through electrodes positioned in an electrode cap, then sent to an amplifier.
After the signals are amplified and digitalized, they are sent to a computer which manages the data analysis and presentation of feedback. Like in conventional therapy, the recoveriX users are instructed to perform motor imagery and receive feedback (specifically, visual feedback on a monitor and through FES stimulation). Unlike conventional therapy, RecoveriX users also wear an EEG cap that monitors MI that influences the feedback. The key element is the real-time connection between brain activity and feedback. recoveriX provides feedback only when the user correctly imagines the left or right hands movement. Thus, unlike conventional therapy, the feedback is always paired with the brain activity.
This paper presents further details about our system, experimental procedures, results from three patients clinical trials, and future research directions. Many of our future research directions will be addressed within the new RecoveriX project, an SME Instrument active from 2016-2018.

MATERALS AND METHODS

Subjects: Three patients participated in this study, as all of them experienced a sylvian ischemic stroke. Subject 1 is a 61 years old woman, right-handed, who suffered a stroke that left her with difficulties in moving the right hand. One month after the stroke, she participated in 24 recoveriX training sessions. Subject 2 (male, 69 years, right handed) joined our study 4 months after suffering a stroke. At that time, he was not able to perform any kind of movements with the right hand fingers. He performed 22 training sessions with our system. Due to personal problems, patient P2 had to leave the hospital 2 days earlier than planned, therefore missing the last 2 training sessions. The third subject (male, 64 years, right handed) joined our study three months after the stroke and performed 24 training sessions with recoveriX. At the time he started the training, he was able to perform only some limited movements with the left arm.
All three patients were recorded in an open room at the Rehabilitation Hospital of Iasi. The patients were not placed in an anechoic chamber to reduce noise that might affect the EEG, and none of the equipment was placed in a shielded area. During the period the patients attended the recoveriX training session, they performed also conventional rehabilitation therapy consisting of passive movements helped by a physiotherapist.
Data acquisition and experimental paradigm: the EEG data were recorded using a g.HIamp device (g.tec medical engineering GmbH, Austria) with a sampling frequency of 256 Hz and digitally filtered with a 0.5-30Hz 8th order bandpass Butterworth filter. The electrode cap had 45 active electrodes (g.LADYbird, g.tec medical engineering GmbH, Austria) arranged according to the 10-20 International System. Fig. 2 shows the recoveriX system mounted on a patient (left) and the electrode displacement on the scalp (right). The data classification was done using common spatial patterns (CSP) and a linear discriminant analysis (LDA) classifier. The study was approved by the institutional review board of the Rehabilitation Hospital of Iasi, the ethical approval has been granted, and all patients signed an informed consent before the start of the study.
The patients were seated in a comfortable chair in front of a computer monitor that presented cues and feedback (see Fig.2) with FES pads positioned over the forearm of each upper limbs to induce wrist extension and fingers opening. The FES stimulation was provided through an 8-channel neurostimulator (MOTIONSTIM8, Krauth+Timmermann GmbH, Germany). For all patients, the first session was a training session, where each subject got trained regarding the correct motor imagery taks (in all three cases, hand opening), and then conducted two practice runs for getting familiar with the experience of electrical stimulation and visual feedback. During all subsequent sessions, after setting up the system, each patient performed six runs each lasting about 6 minutes. Each run contained 40 8-seconds trials with a randomly chosen inter-trial time interval between 1 to 2 seconds. Each MI trial started with the display of a cross in the center of the monitor. After 2 seconds, a beep informed the user about the upcoming cue. The patients were instructed to start imagining the movement of either left or right hand when an arrow pointing to the left or right side was presented as a cue. After the cue dissapearance, the users began to receive visual and proprioceptive feedback. The visual feedback consisted of a blue bar starting in the center of the monitor and exending to the rignt or left side, according to the classified MI. The patients had to continue imagining the hand opening and closing movements for 4 seconds after the cue, until the visual feedback presentation ended. The neurostimulator induced the fingers and wrist extension of the coresponding hand only if the classified MI was the one dictated by the cue.
Motor assessment: we assessed the motor improvement for patients 1 and 3 using the 9-hole PEG test. In this game, the user has to fill 9 holes of a wooden board with

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Figure 2: The recoveriX system mounted on a patient (left) and the EEG electrode positions over the scalp (right).

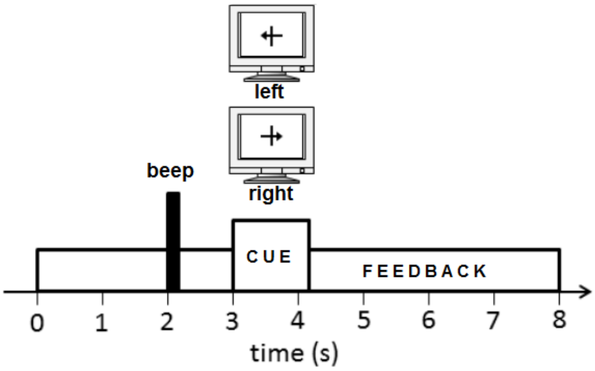

Figure 3. The time course of a single trial.

sticks placed on the table, and then to put the sticks back on the table one by one. The test has to be performed for both hands and the time for accomplishing the task and the number of dropped sticks are counted, representing the score for that evaluation.
The muscle contraction by FES was sufficient enough to cause movement of the affected hand for all patients.
The feedback period lasted four seconds. The time course of a single trial is presented in Fig. 3.
Feature extraction and classification: The CSP method is very well known for discrimination of two motor imagery tasks [11] and was firstly used for extracting abnormal components from clinical EEG [12]. By applying the simultaneous diagonalization of two covariance matrices, one is able to construct new time series that maximize the variance for one task, while minimizing it for the other one.
Considering N channels of EEG for each right and left trial X, the CSP method outputs an N x N projection matrix. This resulting matrix reflects the subject specific activation patterns of the data during motor imagery of left or right hand in this study. The decomposition of a trial can be written as:

$$Z=W \cdot X \qquad (1)$$

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 movement imagination is largest in the first row of Z and decreases with the increasing number of the subsequent rows. The opposite is the case 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 [13] 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, only the first and last two rows (p=4) of W are used to process new input data X. Then the variance (VARp) of the resulting four time series is calculated for a time window T. After normalizing and log-transforming four feature vectors are obtained (2). These four features are used as input for a linear discriminant analysis (Fisher's LDA [14]) classifier which categorizes the MI as left-hand or right-hand movement.

$$f_p = \log\left(\frac{VAR_p}{\sum_{p=1}^{4} VAR_p}\right) \qquad (2)$$

Using the training data recorded during runs 1 to 4, 5 sets of spatial filters and classifiers were calculated from two seconds time windows shifted in time with a 0.5 seconds Hamming window based on the data from the time interval from 4 to 8 seconds in each trial. The classifier with the highest ten-fold cross validated accuracy [15] was chosen to provide the visual and FES feedback while recording runs 5 and 6. These last two runs were used to calculate the online accuracy of the chosen classifier for the current session. The classifier calculated in the previous session was used to provide the feedback while recording the first 4 runs.

RESULTS

Figure 4 presents the BCI control accuracy for all three patients based on the online results. All three patients started with accuracies above 80%. Patient P1 reached an average accuracy of 90.5% over all sessions, while patient P2 reached 85.4% and patient P3 87.1%. Each patient attained accuracy above 96.2% in at least one session. There are sessions were the accuracies were low for all patients. These lower scores are highly correlated with each patient's degree of tiredness, emotional state or other health conditions during that day. Patient 1 reported that she could not sleep during the night before the session 16, when she achieved the lowest accuracy. Patient 2 got a cold and coughed a lot during sessions 15 and 16.
Table 1 presents the score of the 9-hole PEG test for patients P1 and P3, for the paretic and for the healthy hand. For patient P1, the evaluation was performed before starting the first recoveriX training session and the results were considered as baseline for the subsequent evaluations, which were done once at each 3 sessions of training. P3 patient's condition didn't allowed him to perform the 9-hole PEG test before and during the first 6

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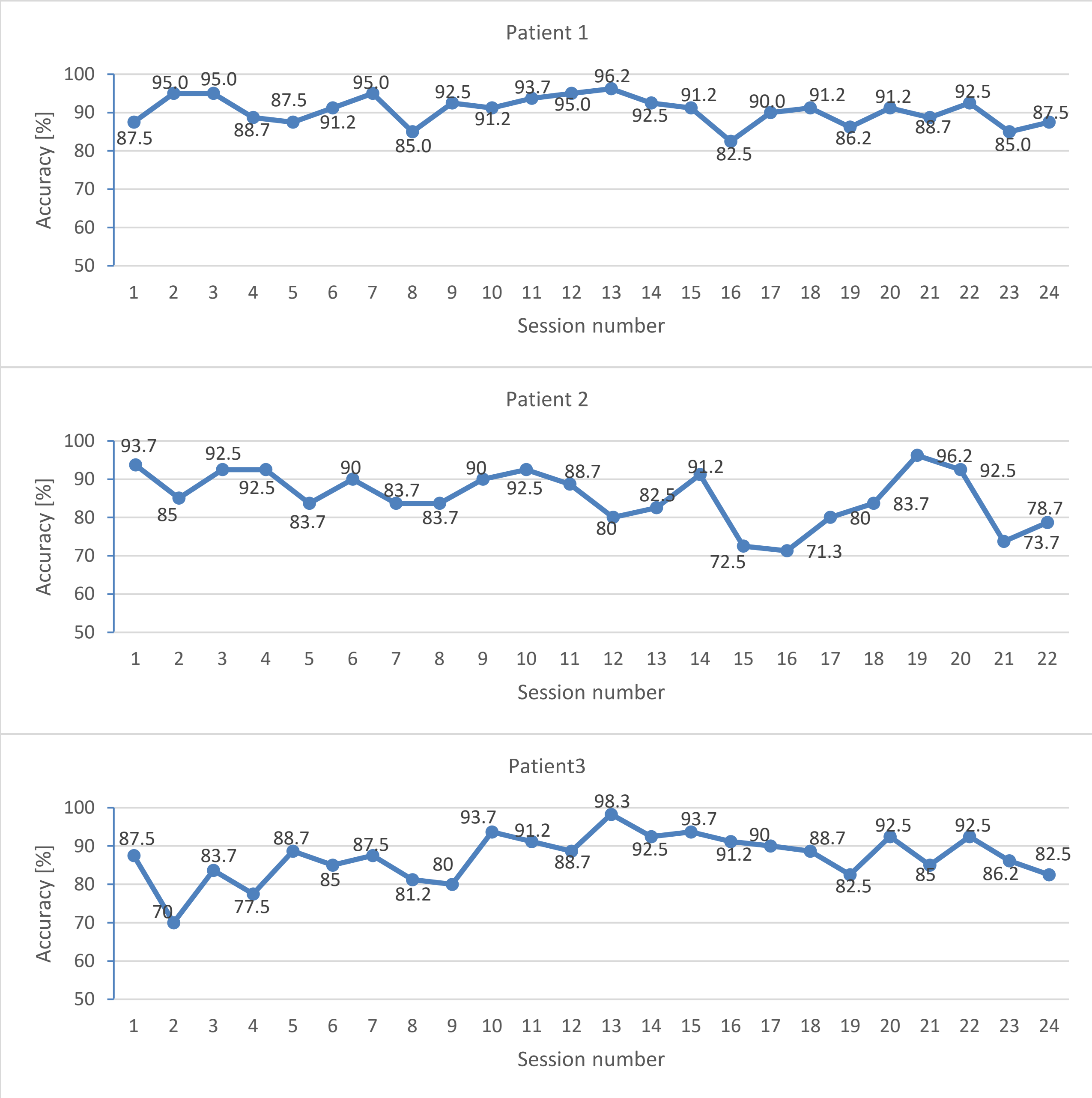

Figure 4. The online accuracy plots of the three patients across the training sessions with the recoveriX system.

Figure 5. The snapshots with the moves that patient P2 was able to do after 22 sessions of training with recoveriX.

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Table 1: The results of the 9-hole PEG test for patients P1 and P3

Sessions	Time [s] / dropped PEGs			
	Paretic hand		Healthy hand	
	P1	P3	P1	P3
0	65 / -	-	31 / -	-
3	54 / -	-	32 / -	-
6	45 / -	-	32 / -	-
9	42 / -	90 / 1	31 / -	26 / -
12	42 / -	77 / -	31 / -	26 / -
15	38 / -	94 / -	29 / -	26 / -
18	34 / -	60 / -	29 / -	25 / -
21	30 / -	61 / -	29 / -	25 / -
24	30 / -	52 / -	29 / -	26 / -
Time improvement [sec]	35	38	2	0

training sessions. After 9 sessions of training, the motor functions of his left hand improved, and he was able perform the test for the first time. In his case, the results of the evaluation after the 9th session were considered as baselines for the next evaluations.

The last line of Tab.1 presents the time improvements of each hand for patients 1 and 3. Both patients improved the time exercise of the paretic hands with 35 seconds, respectively 38 seconds, and the time exercise for the healthy hands remained relatively constant. After the last training session, P1 managed to perform the test with the paretic hand in 30 seconds, almost the same time as with the healthy hand.

Patient 2 could not perform the 9-hole PEG test during the study. He started to move the thumb after the 12th session, and during the last sessions of training he started to perform small range voluntary movements also with the other fingers. Fig. 5 presents two snapshots taken while patient 2 performed voluntary movements with his right hand after the last session of training.

DISCUSSION

Results discussion: Before starting this study, we supposed that patients will have difficulties in achieving high accuracies. These first results showed the opposite. This may occur because these patients are highly motivated to participate in a study to improve their motor functions. All patients reported that they were eager to come back for further recoveriX sessions especially after they seen the first functional improvements. The high accuracy, coupled with rewarding feedback, also motivated the patients to perform the motor imagery effectively. In addition to motivating patients, the blue bar feedback is important to maintain patients' attention. A feedback is also provided by the FES system that actively moves the hand as long as the person imagines the movement. This activates tactile and proprioceptive systems that feed back to the sensorimotor system. The BCI system is able to manage this feedback, and the CSP and LDA algorithms can adapt to changes in each user's brain activity. Even though motor improvements were reported after the last training session for all three patients, in this early stage of the study we do not exclude the possibility that the motor improvements were due spontaneous remission or due to concomitant physiotherapy. This crucial point will be better discussed after testing the system on a higher group of patients and the results compared with the ones of a control group, as planned. Anyway, even though a control group is missing the feedback from the clinicians has been a positive one and according to their experience dealing with patients in the same condition, the recoveriX system has certain potential to induce voluntary hand movement in stroke patients.

Future research directions: This paper validates the recoveriX approach from a technical perspective by demonstrating that, at least with the three patients using the prototype system presented here, our system can function in real-world settings. Up to now we found that the participants to our study had sometimes difficulties with the bar feedback when the classification was incorrect, because it was hard to associate the corresponding movement with the feedback. Therefore, one of our future development directions involve improved immersive software to present feedback and maximize the patients' engagement by replacing the graphically simple feedback with more advanced environments such as different views of an avatar whose movements attempt to mimic the movements that the user imagines [16]. At the beginning of each trial, the left or right hand moves for 1 second, which triggers the patient to start the corresponding movement imagery. When the BCI system correctly classifies the activity, then the avatar hand movement is prolonged and the FES is triggered. When the classification is wrong, then the avatar and the FES are temporarily inactive. Apart of the avatar feedback, we are also exploring improved hardware. In this work the experiments were performed using 45 channels wired electrode cap with gel electrodes. Recently, we developed a wireless version of the system using only 16 gel electrodes overlying over the motor areas. The new amplifier is lightweight (only 70 grams), placed on the back side of the electrode cap

Figure 6. The experimental setup with avatar feedback and FES.

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and transmits wireless, in real time, the recorded data to the laptop/PC.
The FES device will be replaced by our new g.Estim neurostimulator developed mainly for BCI applications. Fig. 6 illustrates the future setup of the system, using the avatar, wireless EEG cap and the new neurostimulator.

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