recoveriX: A New BCI-based Technology for Persons with Stroke*

D. Irimia, N. Sabathiel, R. Ortner, M. Poboroniuc, W. Coon, B. Z. Allison, and C. Guger

Abstract— **Brain-computer interface (BCI) systems have been used primarily to provide communication for persons with severe movement disabilities. This paper presents a new system that extends BCI technology to a new patient group: persons diagnosed with stroke. This system, called recoveriX, is designed to detect changes in motor imagery in real-time to help monitor compliance and provide closed-loop feedback during therapy. We describe recoveriX and present initial results from one patient.**

I. INTRODUCTION

Brain-computer interface (BCI) systems are tools that can provide communication without movement. Unlike conventional means of communication, such as speech or gesture, and interfaces like mice or keyboards, BCIs rely on direct measures of brain activity [1]. Until recently, most BCIs focused primarily on providing communication for persons with severe motor disabilities, such as amyotrophic lateral sclerosis (ALS, also called Lou Gehrig's disease). However, recent commentary articles have drawn attention to new applications for BCI technology, including helping persons diagnosed with stroke or other motor disabilities [2,3].

For over 20 years, one BCI approach that has received significant attention across numerous publications is the motor imagery BCI [1, 4, 5]. In this approach, users imagine specific movements, usually of the left or right hand, to produce specific patterns of electroencephalographic (EEG) activity that a BCI can detect. These patterns can then be translated into communication or control commands to spell, move a cursor, control an orthosis, or perform other tasks. Even patients who have been unable to perform physical movements for many years may be able to produce the EEG activity necessary for effective BCI control [6].

Many studies have also shown that invasive BCIs can provide more detailed information about the brain's representation of motor imagery [7]. Although invasive BCIs are very promising for applications that use motor imagery, they are not further discussed here, as this article focuses on EEG-based approaches.

EEG-based motor imagery BCIs can discern whether a user is imagining left vs. right hand movement. Thus, they may be helpful for rehabilitation of motor disabilities, when patients are typically required to imagine moving either hand or other movements. During conventional rehabilitation therapy, there is no objective way to determine whether users are performing the expected movement imagery. Patients may be fatigued, bored, depressed, or simply unable to clearly understand task demands. In any of these cases, feedback provided by the rehabilitation technologies and by physiotherapists might convey rewarding feedback, even though this feedback is not necessarily merited by the patient's mental activity. This violates an essential principle of neurofeedback: rewarding feedback should only be provided when patients are performing tasks that should be rewarded [8]. Patients who receive rewarding feedback when they are not imagining the expected movement may learn to continue performing incorrect motor imagery, or other noncompliant task, thus undermining the effort to help them regain movement.

Recent work has sought to overcome this problem by using motor imagery BCI technology to provide an objective index of patients' motor imagery during therapy [9-11]. In this approach, patients perform tasks similar to those used in conventional therapy, such as imagining elbow flexion, wrist dorsiflexion, or more complex movements such as opening the hand or grasping. Patients also wear an EEG cap that provides information about motor imagery, such as which task is being imagined and the intensity of the imagery. This information can be used in real-time to influence feedback, such as:

1) FES stimulation could provide tactile/kinesthetic feedback by activating relevant muscles, such as causing left wrist dorsiflexion only while the patient imagines this movement..
2) Other feedback controlled by the system, such as rewarding sounds or text, and/or real-time movements of an avatar who mimics the detected movement, could provide auditory and visual feedback.
3) The therapist (or other system operator) can say "Good job" if the patient is imagining movement correctly. Otherwise, the therapist can instruct the patient to try different imagery.

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D. Irimia, R. Ortner, N. Sabathiel, and C. Guger are with g.tec Medical Engineering GmbH, Schiedlberg, Austria.

B. Z. Allison, and C. Guger are with g.tec Guger Technologies OG, Graz, Austria. (Corresponding author: R. Ortner, Phone: 0043 7251 22240; e-mail: ortner@gtec.at).

W. Coon is with g.tec Neurotechnology USA, Albany, New York, USA.

M. Poboroniuc is with the Gheorghe Asachi Technical University of Iasi, Iasi, Romania.

Figure 1. One training session with recoveriX. The patient has FES pads on the forearms, which are connected to an FES control system in the left side of the picture. The amplifier is shown on the right. The monitor shows an arrow extending to the right, reflecting that the patient is imagining right hand movement. Concordantly, the FES system is stimulating the right forearm, causing right wrist dorsiflexion.

In addition to this real-time feedback, the capability of objectively detecting motor imagery can make it much easier for a therapist or doctor to review each patient’s progress and respond accordingly. If the patient is not performing motor imagery correctly, medical experts could ask what’s wrong, consider changes to the treatment regimen, review task instructions, provide counseling for depression or other possible causes, or explore other solutions. This paper presents a new system called recoveriX that is designed to detect movement imagery through EEG-based BCI technology, and use this imagery to directly control an FES system and avatar-based feedback. We also present initial results from one stroke patient.

II. Materials and Methods

Figure 1 shows the recoveriX system. Data were recorded using a g.USBamp (g.tec medical engineering GmbH, Graz, Austria) with a sampling rate of 256 Hz, and digitally filtered with a 0.5-30 Hz bandpass filter. The electrode cap had 64 active electrodes arranged through the International 10-20 system. The recoveriX software managed data classification using common spatial patterns (CSP) and a linear discriminant analysis (LDA) classifier. The FES system was controlled through a g.STIMbox.

The patient described here was a right-handed male who was born in 1951. In Feb 2015, he suffered a stroke that impaired his left side. He was unable to reach his mouth with his left hand, and his left finger movements were slow. He participated in 24 recoveriX training sessions from 5 May to 4 Sep 2015. The study was approved by the institutional review board of the Rehabilitation Hospital of Iasi, and written informed consent was obtained before the start of the study.

The subject was seated about 1 meter in front of a table that included the experimental apparatus, with a monitor about 1 meter in front of the subject that provided visual feedback to him. Each session began with mounting the cap, placing gel in each electrode, and checking signal quality. Next, two FES pads were placed over each forearm, positioned to trigger flexion of the forearm flexor muscles. The experimenter adjusted the pulse duration and current before each session to trigger wrist dorsiflexion without causing discomfort. Figure X shows one training session.

The first session was a training session. The experimenter instructed the subject about the correct motor imagery, and then conducted 2 practice runs so the patient was familiar with the experience of FES stimulation and monitor feedback. After this session, both the experimenter and the subject felt that the subject was ready for further sessions without training. Data recorded from this training session were also used to train the classifier.

In all subsequent sessions, after mounting the cap and FES pads and adjusting the FES parameters as described above, the patient performed four runs that each lasted 8 minutes, with a 30-second break after each run. Each run contained 60 8-second trials, with a 2-second break after each trial. Each trial began with a two second delay, followed by two cues: an arrow pointing to the left or right. Next, the patient imagined moving the left or right hand based on the arrow. For four seconds, the subject viewed a line that extended to the left or right, reflecting the classified motor imagery, and the FES system only activated if this imagery crossed a predefined threshold. The patient performed 24 sessions, not including the training session. Hand function was assessed using a common test called the nine-hole peg test (9-HPT). During the first nine sessions, the patient could not perform this test with the left hand. The patient first completed this test during the tenth session, immediately prior to the first experimental run. Thereafter, the 9-HPT was administered after every third session.

Left arm function was also assessed by asking the patient to raise his left arm as high as possible. This test was performed before training began, and again after all sessions were complete.

Date	Left hand	Right hand
May 5, 2015 – May 15, 2015 (From before session 1 to after session 9)	-	-
Aug 19, 2015 (before session 10)	1’30’’	26’’
Aug 21, 2015 (after session 12)	1’17”	26”
Aug 26, 2015 (after session 15)	1’34”	26”
Aug 29, 2015 (after session 18)	60”	25”
Sep 1, 2015 (after session 21)	1’1”	25”
Sep 4, 2015 (after session 24)	52”	26”

Figure 2. Performance on the 9-PHT. The middle and right columns show the time required to complete the task. The patient could not perform this test before the tenth session. The patient dropped one of the pegs with his left hand during the first 9-HPT session, and otherwise never dropped any pegs.

III. RESULTS

A. Functional improvement

Figure 2 shows the functional improvement measured by the 9-HPT. This figure shows that the patient needed 25-26 seconds to perform the task with the right hand, which is about average. The time required to perform the task with the left hand decreased across sessions, reflecting improved motor function. Figure 3 shows that the patient's efforts to raise his left arm were more successful after training.

Figure 3. The patient's ability to raise the left arm. The left picture was taken before any training, and the right picture was taken after training was complete

BCI performance

Figure 4 shows the BCI classifier performance across the 24 training sessions. Since the classifier was attempting to distinguish two classes (right vs. left), chance accuracy was 50%. An error would mean that the FES would stimulate the wrong hand, and the bar on the computer screen would extend in the wrong direction.

Figure 4. Classifier performance across 24 sessions, including mean and minimum error rates. The x-axis reflects the session number, while the y-axis presents the percent error.

B. Brain activity

Figures 5 and 6 present the four most discriminative patterns of the CSP method, recorded from sessions 2 and 23, respectively. In both figures the upper two patterns show the spatial activity during right hand motor imagery, the lower patterns represent the spatial activity during left hand motor imagery. In session 2 the spatial activity during motor imagery of the affected hand seems indifferent. In the latter session the focus of brain activity moved to C4 during left hand motor imagery which fits patterns one would expect for healthy persons.

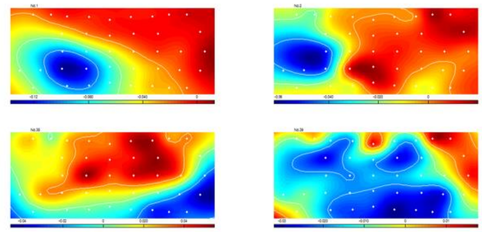

Figure 5. Spatial patterns from session 2. These are topographic maps, with the electrodes shown as white dots. The top two images show activity during imagination of right wrist dorsiflexion, and reflect an activation of regions around C3. The bottom two images show activity during imagination of left wrist dorsiflexion with an indifferent spatial distribution of cortical activity.

IV. DISCUSSION

The results presented here are from a single subject, and should be regarded accordingly. We previously presented promising results from data recorded in 2014 from two stroke patients [12]. Briefly, one patient who suffered a stroke in 2014 participated in 21 training sessions later in 2014 and in Jan 2015. With the unaffected left hand, his time to complete the 9-HPT varied between 29 and 32 seconds. With the impaired right hand, his time to complete the 9-HPT was 65 seconds before training, and 30 seconds after training. The second patient suffered a stroke in 2010 that left her with severe difficulty with left wrist dorsiflexion. Unlike the two patients mentioned above, she did participate in conventional physiotherapy (in 2010), with no improvement. After ten sessions of recoveriX training in 2014, she was able to dorsiflex her left wrist to create an angle of about 20 degrees above her left forearm. Her improvement is especially interesting because she was unsuccessful with conventional therapy, and because she showed improvement in the chronic stage after stroke, when improvement is less likely. Nonetheless, we reiterate that these are initial results. To clearly demonstrate that training with recoveriX yields results superior to conventional physiotherapy, further testing will require a controlled comparison between conventional physiotherapy and recoveriX-based therapy with more subjects. We have begun such a comparison, and results should be available in several months. However, the present results do show that recoveriX-based therapy can be

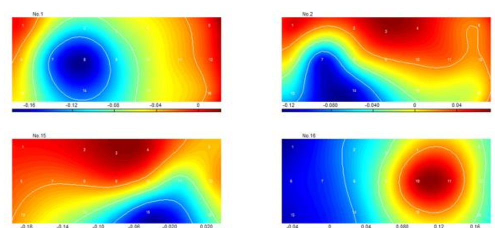

Figure 6. Brain maps from session 23. The four images are arranged in the same fashion as the preceding figure. The pattern at the bottom right shows the activity of motoric regions around C4 during imagination of right hand movements.

effective, and are sufficient to encourage further research.

Three aspects of our results with the patient detailed here merit further discussion. First, the functional improvement shown in Figure 2 was not monotonic. The patient's performance declined during the 9-HPT after session 15, then improved substantially in the 9-HPT after session 18, then increased by one second in the 9-HPT after session 21. This may simply be due to noise, but could also reflect meaningful local changes that merit further study.

Second, the classifier performance shown in Figure 4 not only exhibits no monotonic decrease, but actually becomes worse from the first to the last session. This applies to both the minimum and mean error rates. This is not especially unusual with motor imagery BCIs. Subjects often show considerable variability during training, and a minority of subjects seems unable to learn to control brain activity to reduce error and attain effective control [8, 13]. What makes this result interesting is that it is not correlated with functional improvement. Thus, patients who conduct therapy based on motor imagery BCIs could regain motor function even if they neither improve nor attain excellent BCI performance, as reflected by classifier accuracy. Indeed, classifier performance depends on numerous factors that are not necessarily reflective of the changes induced by training.

Third, the brain activity shown in Figures 5 and 6 does suggest improvement. Prior to training, imagination of right wrist dorsiflexion shows a classic pattern of focal activation in site C3, whereas left wrist dorsiflexion shows no corresponding pattern in site C4, where it would be expected. After training, right wrist dorsiflexion produces a similar pattern over C3. However, left wrist dorsiflexion produces activity over C4 that is much more consistent with activity seen in healthy persons.

Three other topics merit future research. The first is the possibility of extending this approach to help stroke patients with trouble moving other areas. For example, FES pads might be placed such that they trigger elbow extension, knee extension, or ankle dorsiflexion. This could allow rehabilitation of other upper-limb deficits and help persons with lower-limb movement difficulty. Speech deficits are also common after stroke. Helping with speech restoration is probably further in the future, since most patients need to improve more muscle groups and FES pads on the throat or face can be problematic.

Second, improved methods to engage and motivate patients could improve the overall rehabilitation process, leading to better functional outcomes while creating a more enjoyable experience for patients. Different patients who have used our approach report that they are highly motivated to compete against themselves due to the virtual feedback. The experience of near-immediate feedback that rewards correct motor imagery is not available in conventional physiotherapy. Future work might further develop the avatar and background and create game-like tasks or environments.

A third topic for future research is the prospect of helping persons with motor disabilities that do not result from stroke. For example, traumatic brain injury also produces deficits in the CNS, while potentially leaving the PNS and relevant muscles intact. This approach might potentially be further extended to reduce the symptoms caused by Parkinson's Disease, or even PNS-based disabilities cause by spinal cord injury, cerebral palsy, or other conditions.

Overall, the work presented here suggests that recoveriX-based training can yield functional improvement in persons with difficulty controlling their upper limbs resulting from stroke. However, additional research is needed to solidly demonstrate its superiority over conventional therapy and explore other avenues. Future work could provide information leading to improvements in classifier parameters, experimental protocols, and methods to interact with users.

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