Human Computer Confluence in BCI for Stroke Rehabilitation

Rupert Ortner[1], Danut-Constantin Irimia[1,2], Christoph Guger[1,3], and Günter Edlinger[1,3](✉)

[1] Guger Technologies OG, Herbersteinstrasse 60, 8020 Graz, Austria
{ortner, irimia, guger, edlinger}@gtec.at
[2] Faculty of Electrical Engineering "Gheorghe Asachi", Technical University Iasi, Iasi, Romania
[3] g.tec medical engineering GmbH, Sierningstrasse 14, 4521 Schiedlberg, Austria

Abstract. This publication presents a novel device for BCI based stroke rehabilitation, using two feedback modalities: visually, via an avatar showing the desired movements in the user's first perspective; and via electrical stimulation of the relevant muscles. Three different kinds of movements can be trained: wrist dorsiflexion, elbow flexion and knee extension. The patient has to imagine the selected motor movements. Feedback is presented online by the device if the BCI detects the correct imagination. Results of two patients are presented showing improvements in motor control for both of them.

1 Introduction

Stroke is the second leading cause of death in the world. According to the WHO, around 6.7 million people suffered a stroke in the year 2012 [1]. In 2010, the absolute number of stroke survivors was 33 million worldwide [2]. Brain-Computer Interface (BCI) based motor rehabilitation has the potential to improve the rehabilitation outcomes of stroke survivors compared to standard treatment [3, 4]. In this approach, well known rehabilitation strategies are complemented by real-time feedback about the patients' cortical activations.

Evidence suggests that motor imagery (MI) provides additional benefits over conventional therapy [5–7]. In chronic stroke training, patients may be able to overcome "learned nonuse", resulting in cortical hand expansion and functional gains [8]. The disadvantage of standard motor imagery is that neither the patient, nor the therapist, receives any feedback about the performed task and the patient's compliance. This lack can also reduce the motivation to perform or continue the training.

Robotic rehabilitation has become popular with recent technological progress. Several robots and orthoses have been developed and tested. A systematic review found that robot-aided therapy appears to improve motor control more than conventional therapy [9]. Meanwhile, several rehabilitation robots for upper and lower limbs are commercially available and are used widely in rehabilitation clinics. The approach

D.D. Schmorrow and C.M. Fidopiastis (Eds.): AC 2015, LNAI 9183, pp. 304–312, 2015.
DOI: 10.1007/978-3-319-20816-9_29

is to assist the patient with movements he or she cannot perform without help. It is known that by performing these movements highly repetitive, functional recovery is applied [10]. Robotic rehabilitation with BCI was proven to result in significantly larger motor gains than standard arm treatment [4, 11].

Functional electrical stimulation (FES) for post stroke patients showed a statistically significant recovery of muscle strength after stroke [12]. FES has been used to restore hand grasp and release in people with tetraplegia, and standing and stepping in people with paraplegia [13]. With FES, one can define distinct movement patterns that are performed by the patient even if he is not able to perform these movements without external help. A big advantage of FES, compared to robots, is its flexibility to stimulate any desired muscle, and hence the possibility to implement a number of different movement patterns for upper and lower limbs within one device.

In BCI based motor rehabilitation, the patient is supported by feedback if the BCI detects correct imagination of motor movements in the cortex and then performs or supports the patients in performing a predefined motor task. With this approach, the sensory feedback loop is closed during rehabilitation, and thus Hebbian brain plasticity is enforced due to coincident activation of motor and sensory neurons [14].

In 2013, we introduced a prototype providing robotic and visual feedback [15]. In the present manuscript, we present a system integrating FES for feedback and wireless EEG acquisition for reduced movement artifacts and enhanced user comfort.

2 System Architecture

An overview of the system is shown in Fig. 1 on the left side. The laptop controls the paradigms, performs the signal processing and displays the results to the therapist. The patient views a second screen where the visual feedback is presented. Electrodes for functional stimulation are placed on the muscles to perform the selected movement

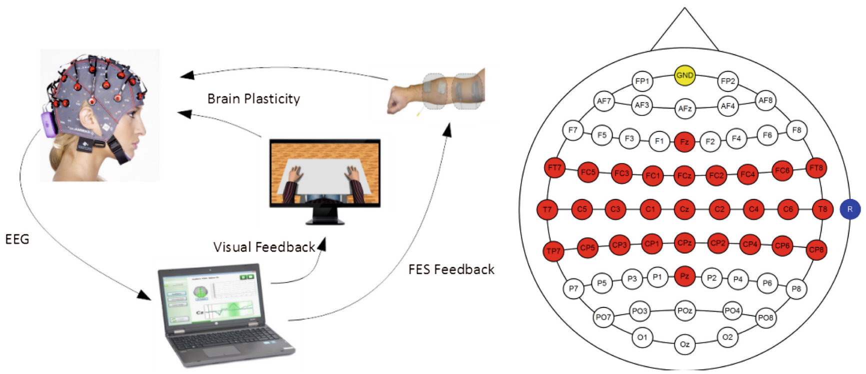

Fig. 1. Left: System overview: The wireless EEG cap records EEG data from 29 positions. The computer classifies the MI and drives the two feedback devices. Right: Electrode setup. The red positions show the 29 EEG electrodes used. The ground is placed on FPz (yellow), with the reference on the right earlobe (blue) (Colour figure online).

pattern. The stimulation of muscles is done by a Motionstim 8 (KRAUTH + TIMMERMANN GmbH, Germany) electrical stimulator, which is controlled by the laptop. EEG is acquired from 29 positions over the sensorimotor cortex. The electrode setup can be seen in Fig. 1, right. The physiotherapist can select one of three different movement paradigms (see below) including moving the wrist, elbow or knee.

2.1 Movement Paradigms

In each movement paradigm, the user's task is to perform one of two possible movements. The visual feedback adapts according to the paradigm, while the electrodes for electrical stimulation have to be placed on the muscles that are doing the selected movements. The three movements can be seen in Fig. 2.

In the wrist dorsiflexion paradigm (i), the two movements are the dorsiflexion of the left and right wrist. In the elbow flexion paradigm (ii), the patient is asked to perform a flexion of the left or right elbow. For the knee extension paradigm (iii), the patient is asked to perform an extension of the left knee or a flexion of the left elbow. The side of the body could be selected to be the extension of the right knee versus the flexion or the right elbow.

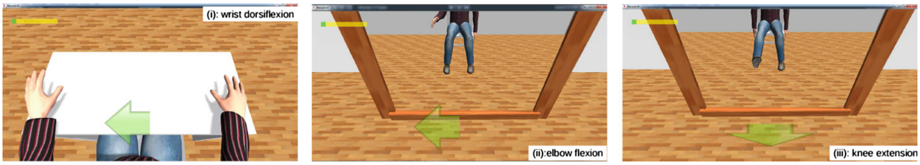

Fig. 2. Movement paradigms: wrist dorsiflexion, elbow flexion and knee extension.

120 randomized trials of movement were performed in each session, with 60 trials for each of the two movements. One trial lasts eight seconds, starting with an attention beep. Three seconds after trial onset, the arrow pointing either to the left side, the right side, or the bottom of the screen is presented, which remains until 4.25 s. This arrow cues the subject to begin MI of the left or right wrist, elbow, or knee, if pointing downwards.

2.2 Movement Classification

Active EEG electrodes (g.LADYbird) are used to acquire EEG data. For discrimination of MI, the method of common spatial patterns (CSP) is used. CSP is a powerful signal processing technique that was shown to extract discriminative information more effectively than other spatial filters like bipolar, Laplacian or common average reference [16, 17].

Before applying the spatial patterns, the EEG data are bandpass filtered between 8 Hz and 30 Hz. Then, the variance is calculated within a time-window of 1.5 s.

These features are normalized, log transformed and classified with a linear discriminant analysis (LDA). Finally, the LDA classification result drives the feedback devices. After each session, a set of spatial patterns and a LDA classifier is generated that can be loaded in the next session. If no subject specific set of spatial patterns and classifier exist, a generic one can be used, which was generated out of a pool of twenty subjects.

2.3 Paradigm Feedback

Feedback is presented visually via the avatar showing the hands and feet in the first perspective (see Fig. 2), and via FES. The two devices operate in parallel to give the patient the illusion that what he sees on the computer screen is what he feels in his hands. Necessary instructions are presented on a computer screen and via voice commands on headphones. Feedback is only activated if the detected MI fits the given instruction, e.g. if the task is to perform a dorsiflexion of the left wrist, then feedback starts only if MI of the left wrist is detected. Otherwise, the feedback devices will not move.

3 System Validation

Tests were performed on two patients. The paradigm used for both patients was the wrist dorsiflexion paradigm. 21 feedback sessions were done with the first patient (P1, female, 61 years) within a time frame of 12 weeks. The patient suffered from a stroke event of the right hand, which occurred 75 days before the first BCI feedback session was performed. The second patient (P2, female, 40 years) suffered from a chronic stroke, four years before the BCI feedback training started. The stroke resulted in a complete paralysis of her left hand. 10 feedback sessions where performed with this patient. All tests were done at the rehabilitation hospital of Iasi, Romania, and both participants gave written informed consent to participate to the study.

For patient selection, the following inclusion criteria were applied: survivor of a cerebrovascular accident in the territory of the middle cerebral artery, with residual spastic hemiparesis; significant upper limb deficit, defined by the patient as disability in performing daily activities and objectively quantified through submaximal values of the Fugl-Meyer score, ARAT test and Brunstromm scale; stable neurologic status during the last 60 days; and willingness to participate in the study expressed by signing the informed consent.

Exclusion criteria were: significant speaking/understanding and/or cognitive disorders, which do not allow the patient to understand the informed consent and the activities to perform within the study; inability to independently maintain the seat position (without assistance) for about 90 min; presence of pacemakers or other cardiac/cerebral/medullar implants which do not allow the use of FES; presence of a history of epilepsy or seizures uncontrolled by proper treatment.

3.1 Control Accuracy

An evaluation of control accuracy, based on the presented cue and the classified movement, was done after each session. The classifier was applied in steps of 0.5 s of all 120 trials across the session. If the detected MI fitted the given cue, this sample was counted as correct; otherwise, it was counted as incorrect. The average accuracy over all trials was then calculated. Examples can be seen in Figs. 3 and 4. The blue line shows the performance of right wrist dorsiflexion, the green line the performance of the left wrist dorsiflexion, and the black line shows the performance of both hands. The red line marks the time where the cue was presented to the patient. The maximum accuracy level of both sides is marked with a red spot.

3.2 9 Hole Peg Test

For assessment of rehabilitation process, a 9-hole PEG test [18], which measures the time to perform certain tasks, was done before the first session. After every three sessions, the test was repeated. This test could not be performed with Patient P2, because the complete paralysis of her affected hand prevented her from successfully performing the task.

4 Results

Table 1 shows, for every third session, the results of the control accuracy of both patients and the 9-hole PEG test from P1.

The control accuracy stayed relatively constant and even slightly decreased for P1, who performed well from the beginning. Her accuracy in the first and the last sessions can be seen in detail in Fig. 3. In the latter session, she was able to reach the maximum peak faster. P2 showed a clear increase in control accuracy from session one to session ten. The results of the first and the last sessions can be seen in Fig. 4. It shows that she

Table 1. Performance of the two patients. The table lists the control accuracy of P1 and P2 and the results of the 9-hole PEG test from P1.

P1				P2	
Session	Control accuracy (%)	9-hole PEG test		Session	Control accuracy (%)
		Left hand (s)	Right hand (s)		
0	–	31	65	1	63,7
3	95,0	32	54	4	86,2
6	91,2	32	45	7	96,2
9	92,5	31	42	10	96,2
12	95,0	31	42		
15	91,2	29	38		
18	91,2	29	34		
21	88,7	29	30		

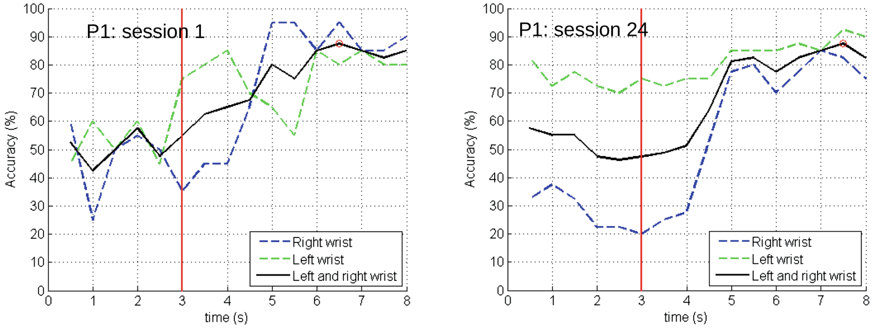

Fig. 3. Control accuracy of patient P1 after the first session (left) and the last session (right). The red line marks the time where the arrow appeared on the screen (Colour figure online).

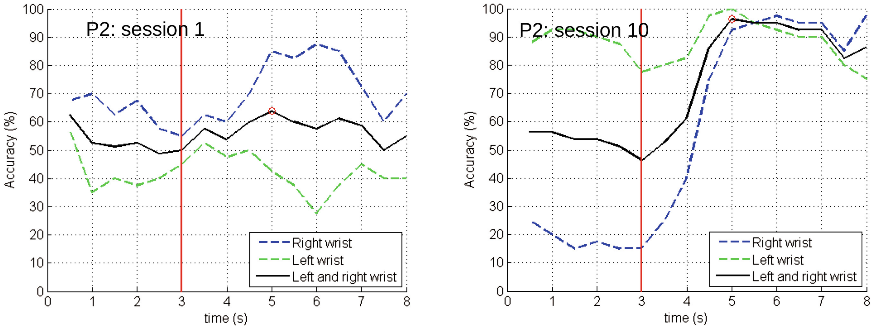

Fig. 4. Control accuracy of patient P2 after the first session (left) and the last session (right). The red line marks the time where the arrow appeared on the screen (Colour figure online).

Fig. 5. Movement of P2 with her affected hand after ten sessions. This movement is done without any external support or functional electrical stimulation.

was not able to control the BCI during the first session, but had good control in the last session.

For P1, the time to complete the 9-hole PEG test with the affected hand decreased from 65 s before the treatment to 30 s after the last session. With the unaffected hand, the time to completion remained nearly constant during the whole treatment.

As mentioned above, the 9-hole PEG test could not be performed for P2, but after the tenth session, the patient regained some control of her affected hand, in the form of a wrist dorsiflexion and a hand grasp. Figure 5 shows the movement she was able to do with her left hand.

5 Discussion

This publication presented a BCI based stroke rehabilitation tool with multimodal feedback. The first evaluation results on two patients are promising, with a clear increase in the performance of the 9-hole PEG test of the affected hand for patient P1.

The random control accuracy of P2 in the first session could be due to the long time of chronic stroke wherein she had no motor control of her affected hand, resulting in learned nonuse [19]. The BCI training seemed to help her overcome this learned nonuse. After ten sessions, she reached good control accuracy, but much more importantly, she started to regain voluntary motor control of her affected hand. P2 left the rehabilitation hospital after the tenth session, so the treatment had to be stopped at this time. It would have been interesting to further explore her performance over a longer time, including additional improvements.

It is clear that the control accuracy cannot reflect the real motor control of the patients. In addition to the present results, it is well known that some persons with normal motor movements are unable to control a MI based BCI [20]. Nevertheless, the accuracy can provide a hint about rehabilitation improvements. P1 was able to reach faster to her maximum control accuracy in the last sessions, and showed an improvement in performing the 9-hole PEG test. P2 showed no motor control and a random control accuracy of the BCI in the beginning, while both changed after some sessions.

This system's use of FES, instead of a rehabilitation robot, allows high flexibility in selection of movement paradigms. Therefore, three different paradigms are implemented; further ones could easily be introduced. Only wrist dorsiflexion has been tested so far. Decisions about which movements should be trained are within the responsibility of the medical doctors and physiotherapists, and depend on each patient's condition. By developing and validating new paradigms with additional movements, we could extend this approach to help a broader variety of patients. For example, a system that can work with knee dorsiflexion could help persons seeking gait rehabilitation.

6 Conclusion

Our overall aim is to combine several feedback modalities for BCI based motor rehabilitation into one device. With this approach, we aim to further foster the stimulation of sensory neurons and thus strengthen the effect of brain plasticity. The chosen modalities, the virtual reality and FES feedback allow us to easily integrate a number of different movement paradigms for upper and lower limbs and hence adjust the rehabilitation to the conditions and needs of the patients.

While the results of the first patients are promising, further patients need to be assessed. We also intend to explore additional movement paradigms and extend this approach to persons with movement disabilities from other causes.

Acknowledgements. This research has been partially supported by the European projects ComaWare (GA no. 650381), DeNeCor (ENIAC JU 2012 GA on. 324257) and CREAM (GA no. 265648).

References

1. World Health Organization: The top 10 causes of death. Available from: http://who.int/mediacentre/factsheets/fs310/en/
2. Feigin, V.L., Forouzanfar, M.H., Krishnamurthi, R., Mensah, G.A., Connor, M., Bennett, D.A., et al.: Global and regional burden of stroke during 1990–2010: findings from the global burden of disease study 2010. The Lancet **383**, 245–255 (2014)
3. Daly, J.J., Wolpaw, J.R.: Brain-computer interfaces in neurological rehabilitation. Lancet Neurol. **7**, 1032–1043 (2008)
4. Ang, K.K., Guan, C., Phua, K. S., Wang, C., Zhou, L., Tang, et al.: Brain-Computer Interface-based robotic end effector system for wrist and hand rehabilitation: results of a three-armed randomized controlled trial for chronic stroke. Front. Neuroengineering, vol. 7 (2014)
5. Zimmermann-Schlatter, A., Schuster, C., Puhan, M.A., Siekierka, E., Steurer, J.: Efficacy of motor imagery in post-stroke rehabilitation: a systematic review. J Neuroeng Rehabil. **5**, 8 (2008)
6. Sharma, N., Simmons, L.H., Jones, S., Day, D.J., Carpenter, A., Pomeroy, V.M., et al.: Motor imagery after subcortical stroke: a functional magnetic resonance imaging study. Stroke **40**, 1315–1324 (2009)
7. Liu, K.P., Lee, T.M., Chan, C.C., Hui-Chan, C.W.: Mental imagery for promoting relearning for people after stroke: a randomized controlled trial. Arch. Phys. Med. Rehabil. **85**(9), 1403–1408 (2004)
8. Liepert, J., Bauder, H., Miltner, W.H.R., Taub, E., Weiller, C.: Treatment induced cortical reorganization after stroke in humans. Stroke **31**, 1210–1216 (2000)
9. Prange, G.B., Jannink, M.J., Groothuis-Oudshoorn, C.G., Hermens, H.J., IJzerman, M.J., et al.: Systematic review of the effect of robot-aided therapy on recovery of the hemiparetic arm after stroke. J. Rehabil. Res. Dev. **43**, 171 (2006)
10. Barreca, S., Wolf, S.L., Fasoli, S., Bohannon, R.: Treatment interventions for the paretic upper limb of stroke survivors: a critical review. Neurorehabilitation Neural Repair **17**, 220–226 (2003)
11. Ramos-Murguialday, A., Broetz, D., Rea, M., Läer, L., Yilmaz, O., Brasil, F.L., et al.: Brain-machine-interface in chronic stroke rehabilitation: a controlled study. Ann Neurol. **74**, 100–108 (2013). doi:10.1002/ana.23879
12. Glanz, M., Klawansky, S., Stason, W., Berkey, C., Chalmers, T.C.: Functional electrostimulation in poststroke rehabilitation: a meta-analysis of the randomized controlled trials. Arch. Phys. Med. Rehabil. **77**, 549–553 (1996)
13. Triolo, R.J., Bogie, K.: Lower extremity applications of functional neuromuscular stimulation after spinal cord injury. Top. Spinal Cord Injury Rehabil. **5**, 44–65 (1999)

14. Grosse-Wentrup, M., Mattia, D., Oweiss, K.: Using brain–computer interfaces to induce neural plasticity and restore function. J. Neural Eng. **8**, 025004 (2011)
15. Ortner, R., Ram, D., Kollreider, A., Pitsch, H., Wojtowicz, J., Edlinger, G.: Human-Computer Confluence for Rehabilitation Purposes after Stroke. In: Shumaker, R. (ed.) VAMR 2013, Part II. LNCS, vol. 8022, pp. 74–82. Springer, Heidelberg (2013)
16. Guger, C., Ramoser, H., Pfurtscheller, G.: Real-time EEG analysis with subject-specific spatial patterns for a Brain-Computer Interface (BCI). IEEE Trans. Rehab. Eng. **8**, 447–456 (2000)
17. Blankertz, B., Tomioka, R., Lemm, S., Kawanabe, M., Müller, K.-R.: Optimizing spatial filters for robust EEG single-trial analysis. IEEE Signal Process. Mag. **25**(1), 41–56 (2008)
18. Beebe, J.A., Lang, C.E.: Relationships and responsiveness of six upper extremity function tests during the first 6 months of recovery after stroke. J. Neurol. Phys. Ther. JNPT **33**, 96 (2009)
19. Taub, E., Uswatte, G., Mark, V., Morris, D.: The learned nonuse phenomenon: implications for rehabilitation. Europa medicophysica **42**, 241–256 (2006)
20. Allison, B., Neuper, C.: In: Tan, D.S., Nijholt, A. (eds.) Brain-Computer Interfaces, pp. 35–54. Springer, London (2010). at http://dx.doi.org/10.1007/978-1-84996-272-8_3