

# Combining Real-Time Brain-Computer Interfacing and Robot Control for Stroke Rehabilitation

M. Gomez-Rodriguez<sup>1,2</sup>, J. Peters<sup>1</sup>, J. Hill<sup>1,3</sup>, B. Schölkopf<sup>1</sup>,  
A. Gharabaghi<sup>4</sup>, and M. Grosse-Wentrup<sup>1</sup>

<sup>1</sup> Max Planck Institute for Biological Cybernetics, <sup>2</sup> Stanford University, <sup>3</sup> Wadsworth Center,  
<sup>4</sup> Werner Reichardt Centre for Integrative Neuroscience, Eberhard Karls University Tübingen

**Abstract.** Brain-Computer Interfaces based on electrocorticography (ECoG) or electroencephalography (EEG), in combination with robot-assisted active physical therapy, may support traditional rehabilitation procedures for patients with severe motor impairment due to cerebrovascular brain damage caused by stroke. In this short report, we briefly review the state-of-the art in this exciting new field, give an overview of the work carried out at the Max Planck Institute for Biological Cybernetics and the University of Tübingen, and discuss challenges that need to be addressed in order to move from basic research to clinical studies.

Current rehabilitation methods for patients with severe motor impairment due to cerebrovascular brain damage are limited in providing significant long-term functional recovery. In stroke patients, functional recovery beyond one year post-stroke is rare (Johnston et al. [2004]), and functional independence often displays a long-term decline (Dhamoon et al. [2009]). As such, novel strategies in stroke rehabilitation are required.

Robot-assisted physical therapy (Riener et al. [2005]) and motor imagery (Dijkerman et al. [2004], Page et al. [2007]) have been shown to be beneficial in stroke rehabilitation. As such, it appears sensible to develop an integrated rehabilitation strategy, in which patients exert control over robot-assisted physical therapy by means of the decoding of movement intentions using a Brain-Computer Interface (BCI) based on motor imagery. Synchronizing motor intention with robot-assisted therapy may increase cortical plasticity by means of Hebbian-type learning rules (Wang et al. [2010], Murphy and Corbett [2009], Kalra [2010]), potentially resulting in improved functional recovery.

While stroke patients have been shown to be capable of operating a BCI based on motor imagery (Buch et al. [2008], Keng et al. [2009]), to date there is no empirical evidence for a positive impact of BCI-technology on functional recovery. One reason for this may be the insufficient synchronization of movement intent and robotic-based haptic feedback, which in both aforementioned studies was provided at the end of a trial, i.e., not synchronized with the actual movement intent. Indeed, there are several requirements that probably need to be fulfilled by a BCI in order to be suitable for stroke-rehabilitation. Besides the synchronization of movement intent with haptic feedback, these are likely to include a high accuracy in detecting movement intent while maintaining a low rate of false-positive decisions, as well as a high spatial specificity in order to guide cortical plasticity to relevant brain regions. In the past, research has almost exclusively focused on utilizing BCIs for communication purposes. As such,

challenges in the design of BCI systems, that arise in the context of rehabilitation, have not yet been sufficiently addressed. Subsequently, we give an overview of our work at the Max Planck Institute for Biological Cybernetics and the University of Tübingen that aims to address some of these issues.

In our work, we utilize EEG as well as epidural ECoG recordings for detecting movement intentions. While EEG serves as the testbed for healthy- as well as stroke subjects, actual rehabilitation studies are intended to be performed with epidural ECoG. Importantly, we have chosen epidural- rather than subdural implantation of ECoG grids in order to minimize invasiveness and thus reduce the risk of complications. Haptic feedback is provided by means of a Barret WAM 7-degree-of-freedom arm, which is customized to be attached to a subject's impaired arm. While decoding of multiple degrees of freedom from ECoG recordings has been shown to be feasible (Pistohl et al. [2008]), we only aim to decode (one-dimensional) movement intentions of pre-defined trajectories. This is motivated by the consideration that a high classification accuracy and small feedback-delay are probably more crucial for successful induction of cortical plasticity than the complexity of the decoded movement. Accordingly, we ask subjects to either perform a flexion or extension of the elbow joint of the impaired arm. We employ machine-learning methods to decode the recorded signals, and provide haptic feedback by means of the Barret arm whenever an intent to move is detected. Recorded brain signals are analyzed in real-time, and haptic feedback is updated every 300 ms. A time window of 300 ms was chosen, as this provides a good trade-off between a high-classification accuracy and a small feedback-delay. When working with healthy subjects, we replace the movement intent by motor imagery, as this is likely to recruit the same motor planning processes as an actual intended movement (Jeannerod and Decety [1995]).

To date, we have investigated two major issues in the design of BCI-controlled robotics for rehabilitation. First, we have studied the decoding accuracy in classifying movement intent vs. rest in one subject with a hemorrhagic stroke in the left thalamus, using an epidural ECoG grid placed over sensorimotor areas (Gomez Rodriguez et al. [2010a]). We could present evidence that epidural grids are suitable for decoding movement intentions with a high accuracy of roughly 90 %, which is an important step in establishing epidural grids in brain-state decoding. Furthermore, we could provide evidence that, contrary to healthy subjects,  $\mu$ -rhythms (between 8–14 Hz) of the electromagnetic field of the brain did not provide information on our subject's intention. Instead, oscillations in the  $\beta$ - (roughly 20–35 Hz) and  $\gamma$ -band (above 40 Hz) were highly informative, suggesting a cortical reorganization. This was also mirrored in the spatial representation of informative brain regions, indicating a cortical reorganization away from arm-areas in primary motor cortex. While case reports from single subjects are not suitable for generalized conclusions, these results suggest that brain signals in stroke patients may be markedly different from healthy subjects, which should be considered in the design of BCIs for stroke rehabilitation.

In another study, we have investigated the effect of haptic feedback on BCI-decoding accuracy (Gomez Rodriguez et al. [2010b]). Typically, feedback in BCIs is provided in the visual domain, e.g., by a cursor on a screen, which is expected to have little influence on sensorimotor areas. Haptic feedback, on the other hand, triggers sensorimotor

feedback loops that activate brain areas similar to those used for decoding of motor imagery (Müller et al. [2003]). As such, haptic feedback may interfere with the decoding of movement intentions. We have studied this issue using the same paradigm employed in stroke rehabilitation, albeit with six healthy subjects and EEG recordings. We utilized a  $2 \times 2$  design, in which we trained a classification algorithm from EEG data recorded once with and once without haptic feedback, and tested the resulting classifiers again in conditions with and without haptic feedback. We could provide evidence that haptic feedback during training as well as during feedback sessions does not only not interfere with decoding accuracy, but even improves the detection of movement intent.

While both studies are important steps towards an integrated stroke therapy that combines BCI-decoding with robot-assisted physical therapy, a proof-of-principle study, that demonstrates a positive impact of BCI-technology on functional recovery, remains outstanding. We believe that the major problem, that needs to be addressed as an intermediate step, is an investigation of the properties of a BCI-system that are optimal for inducing cortical plasticity. In particular, it is currently unclear which trade-off between classification accuracy and feedback-delay is optimal in terms of inducing neural plasticity. Furthermore, the brain states, that are currently employed for detecting movement intention, are chosen in order to maximize classification accuracy. It is not obvious that these states, that typically consists of spatially distributed bandpower features, should also be the ones that are most suitable for inducing neural plasticity. As cortical plasticity aims to re-activate dormant cortico-cortical connections, connectivity measures between cortical areas may be more promising for inducing neural plasticity.

## Bibliography

- E. Buch et al. Think to move: a neuromagnetic brain-computer interface (BCI) system for chronic stroke. *Stroke*, 39(3):910, 2008.
- M.S. Dhamoon, Y. Park Moon, M.C. Paik, B. Boden-Albala, T. Rundek, R.L. Sacco, and M.S.V. Elkind. Long-term functional recovery after first ischemic stroke. *Stroke*, 40:2805–2811, 2009.
- H.C. Dijkerman, M. Ietswaart, M. Johnston, and R.S. MacWalter. Does motor imagery training improve hand function in chronic stroke patients? A pilot study. *Clinical rehabilitation*, 18(5):538, 2004.
- M. Gomez Rodriguez, M. Grosse-Wentrup, J. Peters, G. Naros, J. Hill, B. Schölkopf, and A. Gharabaghi. Epidural ecog online decoding of arm movement intention in hemiparesis. In *Proceedings of the 20th International Conference on Pattern Recognition Workshop on Brain Decoding*, August 2010a.
- M. Gomez Rodriguez, J. Peters, J. Hill, B. Schölkopf, A. Gharabaghi, and M. Grosse-Wentrup. Closing the sensorimotor loop: Haptic feedback facilitates decoding of arm movement imagery. In *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics Workshop in Shared Control for Brain-Machine Interfaces*, October 2010b.
- M. Jeannerod and J. Decety. Mental motor imagery: a window into the representational stages of action. *Current Opinion in Neurobiology*, 5:727–732, 1995.
- M. Johnston, B. Pollard, V. Morrison, and R. MacWalter. Functional limitations and survival following stroke: Psychological and clinical predictors of 3-year outcome. *International Journal of Behavioral Medicine*, 11(4):187–196, 2004.
- L. Kalra. Stroke Rehabilitation 2009: Old Chestnuts and New Insights. *Stroke*, 41(2): e88, 2010.
- A.K. Keng, G. Cuntai, K.S.G. Chua, A.B. Ti, C. Kuah, W. Chuanchu, P.K. Soon, C.Z. Zheng, and Z. Haihong. A clinical study of motor imagery-based brain-computer interface for upper limb robotic rehabilitation. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC 2009)*, pages 5981–5984, September 2009.
- G.R. Müller, C. Neuper, R. Rupp, C. Keinrath, H.J. Gerner, and G. Pfurtscheller. Event-related beta EEG changes during wrist movements induced by functional electrical stimulation of forearm muscles in man. *Neuroscience Letters*, 340:143–147, 2003.
- T.H. Murphy and D. Corbett. Plasticity during stroke recovery: from synapse to behaviour. *Nature Reviews Neuroscience*, 10(12):861–872, 2009.
- S.J. Page, P. Levine, and A. Leonard. Mental practice in chronic stroke: results of a randomized, placebo-controlled trial. *Stroke*, 38(4):1293, 2007.
- T. Pistohl et al. Prediction of arm movement trajectories from ECoG-recordings in humans. *J. of Neuroscience Methods*, 167(1):105–114, 2008.
- R. Riener, T. Nef, and G. Colombo. Robot-aided neurorehabilitation of the upper extremities. *Medical and Biological Engineering and Computing*, 43(1):2–10, 2005.
- W. Wang, J.L. Collinger, M.A. Perez, E.C. Tyler-Kabara, L.G. Cohen, N. Birbaumer, S.W. Brose, A.B. Schwartz, M.L. Boninger, and D.J. Weber. Neural Interface

Technology for Rehabilitation: Exploiting and Promoting Neuroplasticity. *Physical Medicine and Rehabilitation Clinics of North America*, 21(1):157–178, 2010.