 Biomed. Eng.-Biomed. Tech. 2015; 60(3): 199–205

Surjo R. Soekadar*, Matthias Witkowski, Nicola Vitiello and Niels Birbaumer

An EEG/EOG-based hybrid brain-neural computer interaction (BNCI) system to control an exoskeleton for the paralyzed hand

Abstract: The loss of hand function can result in severe physical and psychosocial impairment. Thus, compensation of a lost hand function using assistive robotics that can be operated in daily life is very desirable. However, versatile, intuitive, and reliable control of assistive robotics is still an unsolved challenge. Here, we introduce a novel brain/neural-computer interaction (BNCI) system that integrates electroencephalography (EEG) and electrooculography (EOG) to improve control of assistive robotics in daily life environments. To evaluate the applicability and performance of this hybrid approach, five healthy volunteers (HV) (four men, average age 26.5±3.8 years) and a 34-year-old patient with complete finger paralysis due to a brachial plexus injury (BPI) used EEG (condition 1) and EEG/EOG (condition 2) to control grasping motions of a hand exoskeleton. All participants were able to control the BNCI system (BNCI control performance HV: 70.24±16.71%, BPI: 65.93±24.27%), but inclusion of EOG significantly improved performance across all participants (HV: 80.65±11.28, BPI: 76.03±18.32%). This suggests that hybrid BNCI systems can achieve substantially better control over assistive devices, e.g., a hand exoskeleton, than systems using brain signals alone and thus may increase applicability of brain-controlled assistive devices in daily life environments.

***Corresponding author: Surjo R. Soekadar,** MD, Applied Neurotechnology Lab, Department of Psychiatry and Psychotherapy, University Hospital of Tübingen, Calwerstr. 14, 72076 Tübingen, Germany, Phone: +49-7071-29 82624, Fax: +49-7071-29 82625, E-mail: surjo.soekadar@uni-tuebingen.de
Matthias Witkowski: Applied Neurotechnology Lab, Department of Psychiatry and Psychotherapy, University Hospital of Tübingen, Calwerstr. 14, 72076 Tübingen, Germany; and Institute of Medical Psychology and Behavioral Neurobiology, University of Tübingen, Silcherstr. 5, 72076 Tübingen, Germany
Nicola Vitiello: The BioRobotics Institute, Scuola Superiore Sant'Anna, Viale Rinaldo Piaggio 34, 56025 Pontedera (Pisa), Italy; and Fondazione Don Carlo Gnocchi, Center of Florence, via di Scandicci 256, 50143 Firenze, Italy
Niels Birbaumer: Institute of Medical Psychology and Behavioral Neurobiology, University of Tübingen, Silcherstr. 5, 72076 Tübingen, Germany; and Ospedale San Camillo – IRCCS, Istituto di Ricovero e Cura a Carattere Scientifico, Venezia-Lido, Italy

Keywords: assistive brain-machine interface (BMI); biosignal fusion; brachial plexus injury (BPI); electrooculography (EOG); sensori-motor rhythms (SMR).

DOI 10.1515/bmt-2014-0126
Received March 1, 2014; accepted November 17, 2014; online first December 9, 2014

Introduction

While there is major progress in the development of assistive devices built for instance to compensate for a lost or paralyzed limb, for example, lightweight and versatile prostheses or exoskeletons [3, 33] (Figure 1A), intuitive and reliable control of such bio-robotic devices is an enormous challenge. Most available bio-robotic devices use electromyography (EMG), as muscle activity-related EMG activity is well assessable, and EMG control can be quickly learned [16]. While many examples demonstrate the versatility of such EMG control, e.g., to control arm prostheses, exoskeletons [11, 25], or robotic legs [10] and wheelchairs [6], EMG control depends on the availability of sufficient muscle activity often compromised or absent in certain patient populations, e.g., in amputees, stroke survivors, or individuals suffering from severe spinal cord or brachial plexus injuries (BPI). Also, tremor and muscle fatigue can substantially reduce applicability and reliability of EMG control [14, 26]. The development of brain-machine interfaces (BMI) that translate electric or metabolic brain activity into control signals of machines or robots promised to overcome these limitations and dependence of muscle activity [7, 17–19, 23, 24, 29] but is associated with other challenges far from being mastered yet [31]. While implantation of invasive BMI systems led to impressive results, e.g., enabling a quadriplegic patient to drink a cup of coffee [5], the risk of the necessary surgical procedures and instability of decoding performance are still to be evaluated in larger clinical trials. Also, many patients refuse surgical procedures, and the cost-benefit ratio often depends on the patients' individual situation

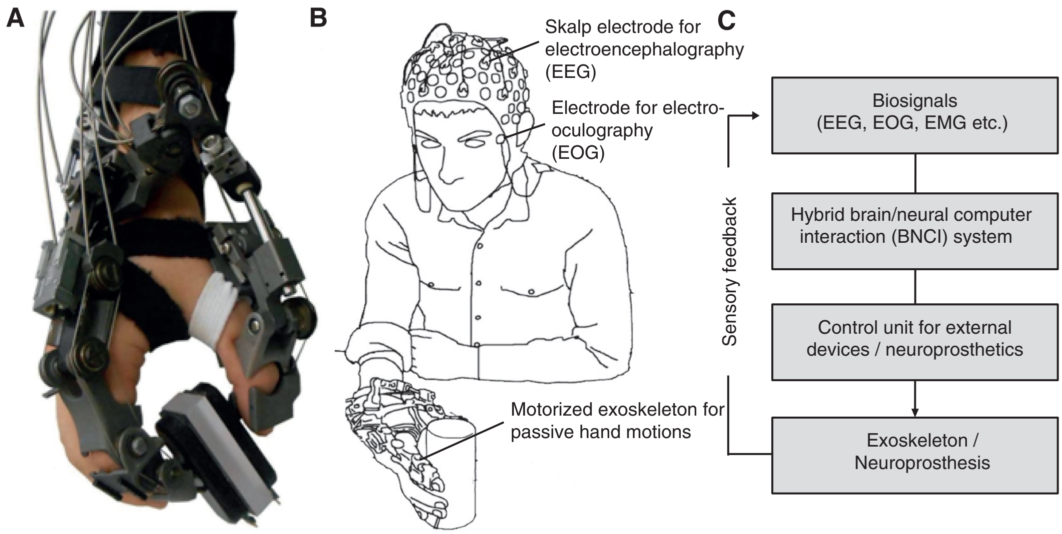

Figure 1 (A) Lightweight and versatile hand exoskeleton allowing for grasping motions developed by The BioRobotics Institute, Scuola Superiore di Studi Universitari e Perfezionamento Sant'Anna, Pisa, Italy [25]. (B) Illustration of a hybrid EEG/EOG brain/neural-computer interaction (BNCI) system setup. (C) Scheme of a BNCI control loop.

[4]. Therefore, noninvasive BMI technology might represent a possible alternative but does not reach high reliability and is susceptible to signal artifacts, particularly when pursued in daily life environments. Furthermore, brain activity, e.g., recorded by electroencephalography (EEG), is highly nonstationary [13] requiring frequent recalibration that interferes with fluent, self-paced (asynchronous) control. Systems that combine or fuse different input signals to control computers or external devices were recently conceptualized as hybrid BMI [20] or hybrid brain/neural-computer interaction (BNCI) systems [8] and are currently broadly investigated [28].

As most neurological disorders or trauma leading to paralysis leave the ability to move the eyes intact, e.g., spinal cord injuries or BPI, fusion of biosignals related to the movement of the eyes and noninvasive recordings of brain activity were recently suggested [27]. Such hybrid BNCI system combining electrooculography (EOG) and EEG (Figure 1B and C) promises to increase applicability and reliability of assistive technology, e.g., to control a hand exoskeleton [2] (Figure 1A). Here we introduce such a system and provide proof-of-principle by evaluating its applicability and performance in healthy volunteers and an individual with complete finger paralysis due to a BPI. Upon a visual signal (cue), participants were instructed to either look at their hand, imaging grasping motions or to relax without any intention to grasp. The intention to grasp (i.e., motor intention) was inferred by detection of motor imagery related modulations of EEG sensorimotor rhythm (SMR, 8–15 Hz) quantified as event-related desynchronization and synchronization (ERD/ERS) [22] and became translated into grasping motions of the exoskeleton. In a second condition, false positive detection of motor intention could be interrupted by full left or right eye movements. While previous BNCI studies focused on EEG/EMG fusion [12], this is the first study that investigated the applicability and performance of an EEG/EOG approach in a patient with complete finger paralysis who controlled grasping motions of a hand exoskeleton.

Materials and methods

Participants

Five healthy BMI-naïve volunteers (HV) (four men, age 26.5±3.8 years) and a 34-year old male patient with complete, flaccid hand paralysis who suffered a left-sided traumatic BPI were recruited at the University Hospital of Tübingen. Healthy participants had to be aged between 18 and 65 years, right-handed, with no known medical conditions, and free of medication. Before the experiment, all participants gave written informed consent approved by the University of Tübingen Ethics Board (401/2012B01). All healthy volunteers were right-handed as assessed by the Edinburgh Handedness Inventory [21], had no physical or neurological symptoms or past history of neurological or psychiatric diseases, and did not take any medication on a regular basis. The 34-year old patient had a traumatic BPI acquired in a motorcycle accident 10 years before admission to the study. The accident resulted in an incomplete root avulsion affecting C5–Th1 on the left side. According to the Medical Research Council scale for muscle strength [15], the patient achieved the following scores in arm and hand function (0=no motion and no palpable muscle contraction, 1=no motion but palpable muscle contraction, 2=movement is possible but not against gravity, 3=active movement against gravity, 4=active movement against gravity and resistance, 5=muscle contracts normally against full resistance): finger extension, 0; finger flexion, 1; elbow extension, 2; elbow flexion, 2; shoulder abduction, 1–2; and shoulder internal rotation, 2. While the patient had no sensibility in the fingers and a hyposensitivity below the elbow, the outer side of the upper arm was hypersensitive for tactile stimulation. Due to cosmetic reasons, the patient preferred to place his hand into the pocket of his jacket and avoided to wear an arm sling in his daily life.

Biosignal recordings and experimental setup

For BNCI control, EEG was recorded from seven sites (F3, T3, C3, P3, CZ, GRND, and REF) using a wireless 32-channel EEG system (MOVE®, BrainProducts GmbH, Gilching, Bayern, Germany). EEG was sampled at 200 Hz and bandpass filtered between 0.4 Hz and 70 Hz. A lightweight and robust hand exoskeleton was used allowing for grasping motions of the hand. The exoskeleton was linked to a BNCI system using a custom version of BCI2000, a multipurpose standard BCI platform (www.bci2000.org), integrating different biosignals and translating them into control signals of the exoskeleton (Figure 1C). All participants used the BNCI system under two conditions (condition 1/condition 2). Each condition consisted of three runs with 20 trials in each run (resulting in a total of 60 trials per condition). At the beginning of the study, electric brain activity related to 20 externally paced imagined grasping movements was evaluated to identify the frequency and amplitude of SMR modulation in preparation and execution of motor imagery (calibration run). Then, EEG was recorded for 18 s at rest to calculate the baseline amplitude and variance of SMR in the absence of any motion or initiation of movement. Inability to modulate SMR would result in exclusion from the study.

Time-frequency representations (TFRs) were computed for each participant to ensure that the BNCI is controlled by EEG and not EMG or facial muscles (Figure 2). SMR-ERD was computed for the EEG channel closest to the motor cortex (according to the international 10-20 convention: HV, C3 controlling right hand motions; BPI, C4 controlling left hand motions) using the power method described by Pfurtscheller and Aranibar [22]. Based on the SMR amplitude and variance at rest, a threshold for detection of motor intention during continuous direct brain control was defined. As threshold, a value at two standard deviations of SMR variance at rest was used.

Calibration and testing of the BNCI system

For BNCI control, EEG data were preprocessed using a small Laplacian filter. Computation of SMR-ERD involved the power spectrum estimation (an autoregressive model of order 16 using the Yule-Walker algorithm) of the ongoing EEG signal associated with the specified SMR frequency range within sample blocks of 100 ms. Each trial consisted of 50 sample blocks. Changes of SMR after the first seven sample blocks that related to the intention to move the fingers were translated into passive hand closing motions driven by a motorized exoskeleton. A full closing motion was reached when SMR-ERD was detected across all 43 sample blocks. The onset of each trial during which participants should imagine hand motions (task) or relax (rest) was indicated by a visual signal presented on a computer display. Each trial (task and rest) had a duration of 5 s and was followed by an inter-trial interval (ITI). The length of ITIs was random between 4 and 6 s. Hand motions driven by the exoskeleton could be elicited during the trials throughout all three runs lasting in average 5.5 min. The exoskeleton moved back to a neutral hand position at the end of each trial. Resetting required 1 s independent of the actual position of the exoskeleton. BNCI control was overridden during that time, and

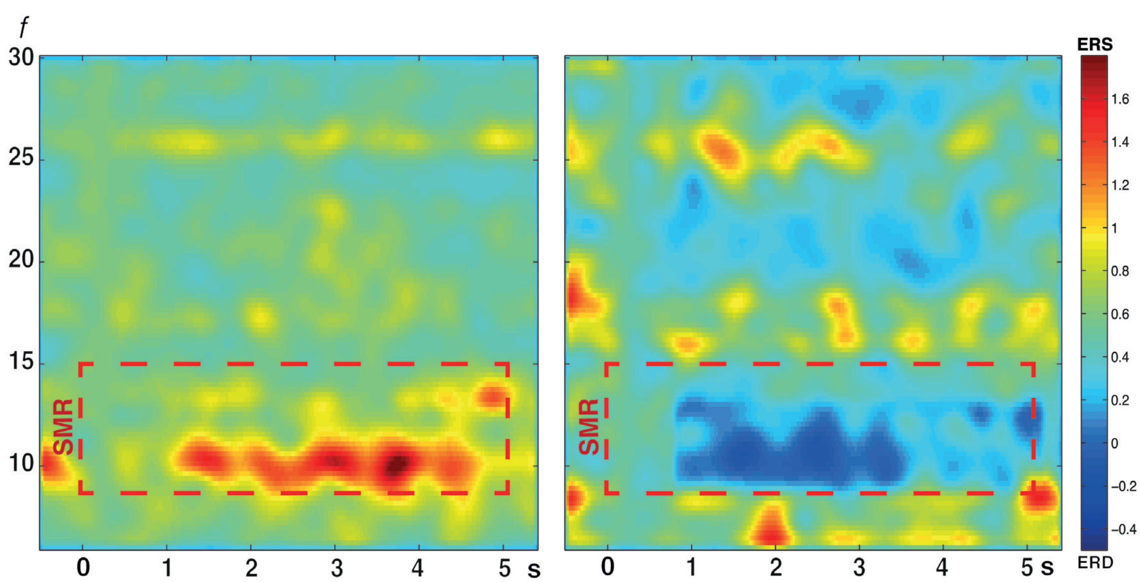

Figure 2 Time-frequency representation (TFR) of rest trials (left panel) and task trials (right panel) in a representative participant. Sensorimotor rhythm (SMR, 8–15 Hz) event-related desynchronization (ERD, dark blue) was detectable shortly after onset of the task (0 s) and translated into grasping motions of a hand exoskeleton. Grasping motions were initiated if the ERD detection threshold was exceeded within a sample block of 100 ms. A full closing motions was reached if ERD were detected in 43 successive sample blocks.

these automatic movements were not included in the calculation of BNCI control performance.

In healthy volunteers, muscle activity was monitored using EMG from finger and arm flexors and extensors (m. brachioradialis, m. flexor carpi ulnaris, m. biceps brachii, and m. triceps brachii) of both arms to exclude overt motions during the task. Trials in which EMG activity during imagery exceeded EMG activity recorded during rest were excluded from further analysis. The number of trials that had to be discarded was automatically added to each run, so that the total number of valid trials across runs and conditions was identical. EOG electrodes were placed according to the standard EOG placements at the right outer canthus and the left outer canthus resulting in positive signals during left eye gaze and negative signals during right eye gaze. At the beginning of the session, a baseline EOG value was calculated while the participant was fixating on a cross. As a next step, an EOG detection threshold for (full) left and right eye movements was assessed. Participants were instructed to move the eyes either to the left or to the right. The instruction to move the eyes was indicated by left and right arrows displayed 15 times each in a random order. After calculating the average maximum EOG values across all trials for both eye movement directions, an EOG detection threshold was set at two standard deviations below this value.

After three runs under condition 1 (BNCI control by EEG only), all participants rested for approximately 10 min before BNCI control under condition 2 (BNCI control with EEG/EOG) was continued. During condition 2, unintended grasping motions of the exoskeleton could be interrupted with EOG signals related to left or right eye movements and resulted in a reset of the hand exoskeleton into neutral position. For the time of the reset (1 s), active BNCI control was blocked and movements excluded from quantification of BNCI control performance.

Offline data analysis

The performance of BNCI control was quantified as the average percentage of time the exoskeleton was moving during each trial for which the instruction was given to move the exoskeleton and trials in which it should not be moved (false positive rate). For all outcome measures, assumption of a normal distribution (Shapiro-Wilk test of normality) was tested. After performing a Levene test for homogeneity of variances, a two-way repeated-measures ANOVA with type III sum of squares and factors “group” (HV/BPI) as between-subject factor and “condition” (condition1/condition2) as within-subject variable was performed. To compare performance of BNCI control between HV and BPI, as well as between the two conditions, *post hoc* t-tests were used.

Results

In four participants and the BPI patient, 11 Hz was identified as the best frequency to detect motor imagery related modulation of SMR-ERD. One participant showed best motor imagery-related SMR modulation at 9 Hz. In the BNCI calibration runs across participants, SMR-ERD reached maximum peaks of 42.1±5.3% relative to the mean signal power during rest as assessed during the calibration runs and had an average value of 26.2±4.3%. The level of significance between the signal power at rest and signal power during task across participants was p=0.0106.

Across all participants, an average 8.4±3.6% of the trials had to be discarded due to EMG activity. For condition 1, evaluation of percent of time the exoskeleton was moving during each trial resulted in 75.45±16.99% in HV and 61.78±22.17% in BPI. During the trials in which no motions should be elicited, the exoskeleton moved for 32.57±21.23% (HV) and 29.93±25.77% (BPI), respectively, of the total time (Figure 3, Table 1). Accordingly, HV achieved an overall BNCI control performance of 70.24±16.71%, while BPI achieved 65.93±24.27% during condition 1 (Table 1).

During condition 2, the percent of time the exoskeleton was moving during trials reached 76.38±10.67% in HV and 63.48±16.88% in BPI, while the exoskeleton moved during 14.50±10.0% (HV) and 11.43±8.5% (BPI) of the trials in which the exoskeleton should not be moved (Figure 4). The EOG detection threshold was exceeded in 42.21±21.66% (HV) and 35.38±41.37% (BPI) of these trials (Table 2). This corresponded to a BNCI control performance of 80.65±11.28 (HV) and 76.03±18.32% (BPI), respectively. During condition 2, comparison of BNCI control performance between

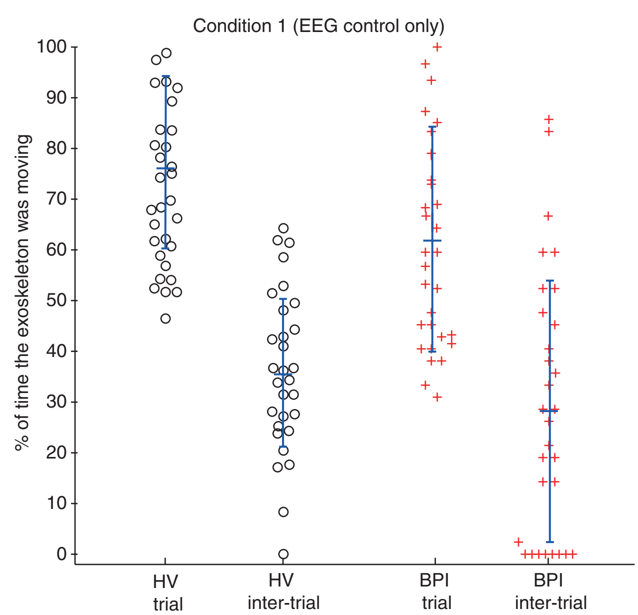

Figure 3 Percent of time the exoskeleton was moving during trials and inter-trial intervals in healthy volunteers (HV, black circles) and in the individual with severe brachial plexus injury (BPI, red crosses) under condition 1 (EEG control only) and condition 2 (hybrid EEG/EOG control).

Table 1 Percent of time the exoskeleton was moving during each trial.

Participant	Movement time during *task* in%	Movement time during *rest* in%	BNCI control performance in%
Condition 1			
Average	75.45+16.99	32.57+21.23	70.24+16.71
1	70.48+26.38	53.24+27.29	55.15+29.10
2	72.89+25.57	28.37+34.54	72.01+31.90
3	85.80+21.11	59.58+30.32	57.26+34.95
4	77.04+20.09	20.49+28.37	78.86+26.31
5	66.26+25.69	11.34+23.27	81.66+26.04
BPI	61.78+22.17	29.93+25.77	65.93+24.27
Condition 2			
Average	76.38+10.67	14.5+10.00	80.65+11.28
1	76.05+24.87	7.68+8.44	87.80+14.26
2	49.38+13.51	12.78+15.78	77.84+21.73
3	82.24+24.65	11.40+9.59	85.89+13.63
4	86.29+21.71	23.94+25.30	76.74+24.72
5	87.00+22.73	20.06+31.16	79.85+29.59
BPI	63.48+16.88	11.43+8.05	76.03+18.32

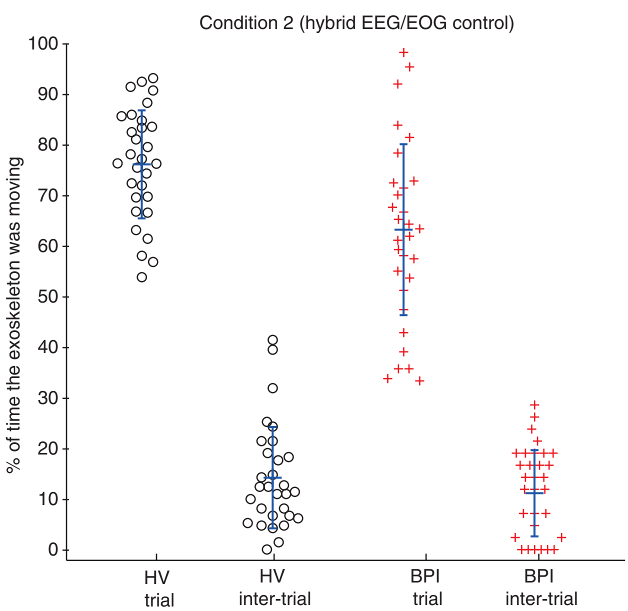

Figure 4 Percent of time the exoskeleton was moving during trials and inter-trial intervals in healthy volunteers (HV, black circles) and in the individual with severe brachial plexus injury (BPI, red crosses) under condition 1 (EEG control only) and condition 2 (hybrid EEG/EOG control).

the conditions (EEG, EEG/EOG) and groups (HV, BPI) using a repeated-measures ANOVA (rmANOVA) revealed a main effect for "condition" (F(1, 32)=7.4724, p<0.01, ∗∗) but not for "group" (F(1, 32)=0.0592, p=0.809) and no interaction between the factors (F(1, 32)=0.0598, p=0.808). A *post hoc* t-test indicated no difference in BNCI performance between HV and BPI under condition 1, while performance improved significantly in both HV and BPI, between condition 1 and condition 2 (p<0.05, ∗). Also, there was no difference in BNCI performance between HV and BPI under condition 2, indicating that EOG improved BNCI control performance similarly in HV and the paralyzed participant. After the experiment, all participants reported that they experienced the exoskeleton's movement contingent upon their imagination of grasping motions and that control under condition 1 (EEG only) was more difficult and exhausting compared to condition 2 (hybrid EEG/EOG control). They further stated that they felt more in control of the device under condition 2 with the system promptly responding to their eye's movement and that they did not experience any changes in control within sequential runs in either condition.

Table 2 Percent of task trials interrupted by EOG.

Participant	% of task *trials* interrupted by EOG
Average	42.21+21.66
1	63.83+31.35
2	27.88+3.52
3	54.14+24.39
4	76.95+17.14
5	38.52+17.66
BPI	35.38+41.37

Discussion

We have introduced a novel hybrid BNCI system merging EEG and EOG signals to control a hand exoskeleton and tested this system in a group of five healthy volunteers and a patient with complete flaccid finger paralysis after severe traumatic BPI. Following calibration, participants used motor imagery of hand grasping motions to control the hand exoskeleton using EEG only (condition 1). While all participants were able to control the BNCI system in a semi-autonomous control mode in which visual cues were presented to evaluate the degree of control at an average performance of 70.24±16.71% (HV) and 65.93±24.27% (BPI), inclusion of EOG control significantly improved performance to 80.65±11.28 (HV) and 76.03±18.32% (BPI), respectively (Figure 5).

Whereas synchronous, externally cued EEG-based BNCI control with repeated re-calibration of the system is associated with frequent interruptions of control (e.g., every 5 or 10 s), such operation mode can provide significantly higher performances ranging up to 80–90% [32] per trial in average but limits the system's practicality in daily life where continuous

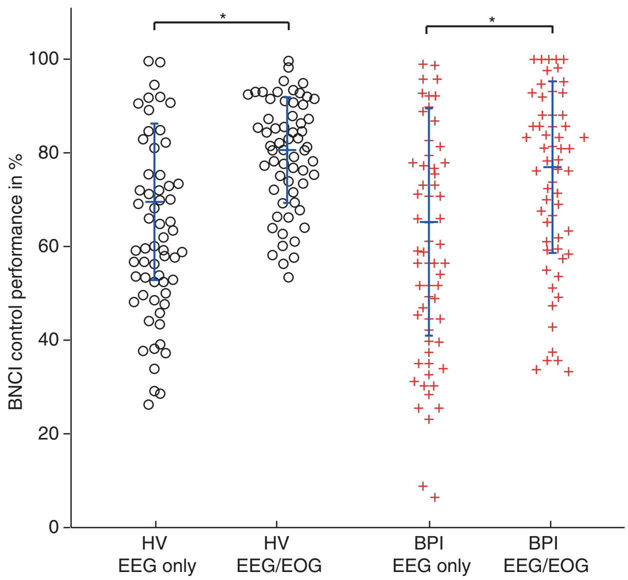

Figure 5 Performance of hybrid BNCI control of healthy volunteers (HV) and the patient with complete finger paralysis due to a severe brachial plexus injury (BPI) in each trial. Trials were averaged across HV participants. Fusion of EEG/EOG signals significantly improved BNCI control performance in HV and BPI.

control during an extended period of time (in the range of a few minutes) is desirable. Therefore, a semi-autonomous paradigm was used in which participants controlled the BNCI system without any re-calibration for approximately 10 min in total, while a visual cue was presented to indicate when to perform a grasping motion. To assess the performance of the system in fully asynchronous mode, a real grasping task without a visual cue needs to be performed. Currently, there is no BMI or BNCI system available reaching 100% classification accuracy or control performance of a robotic device or hand exoskeleton. This does not only limit the applicability of these systems but becomes a serious safety issue when unintended commands or movements are performed. Due to the susceptibility of EMG to fatigue, our findings suggest that inclusion of a biosignal providing high reliability and accessibility such as EOG might improve assistive systems in daily life environments. Future research is necessary to show if such novel approach can indeed improve control of assistive devices in daily life environments. It is for instance unclear whether the EOG error correction mechanism has a negative impact on the ability to manipulate objects that require large eye deflections.

While not tested here, additional inclusion of EMG might further improve the system's degrees of freedom and reliability.

While we aimed to provide proof-of-principle that a patient with complete chronic finger paralysis can improve control of exoskeleton-driven grasping motions when using a hybrid EEG/EOG BNCI system as compared to EEG control only, it was not the aim of this study to evaluate possible functional benefits related to the use of this system. Most likely, only patients with sufficient shoulder and elbow function, e.g., after high cervical spinal cord injury, will benefit from such device.

To compensate for the susceptibility to fatigue or decreasing EMG signal quality over time, adaptive weighting of fused biosignals might further enhance daily-life applicability. While the ability to modulate SMR was comparable between the severely paralyzed BPI patient and healthy volunteers, individuals with brain lesions, e.g., following stroke or a traumatic brain injury, in which this ability is compromised might not have achieved such good control. It was shown, however, that the majority of chronic stroke patients with severe paralysis could learn to modulate ipsilesional SMR [1]. This suggests that the introduced EEG/EOG BNCI system might be also applicable in these patient populations, e.g., in the context of BMI-related neurorehabilition that strives to increase ipsilesional brain activity by providing closed-loop sensory feedback [30]. Alternatively, in stroke patients in which voluntary modulation of ipsilesional brain activity is insufficient for control, signals from the contralesional, unaffected motor areas might be used [9]. Besides restoring the patients' ability for grasping motions using a hand exoskeleton, it is unclear, though, whether such application would lead to motor recovery.

Conclusion

Hybrid BNCI systems that fuse biosignals from different sources, e.g., EEG and EOG, can lead to better performance in control of a hand exoskeleton than systems that use brain signals alone. Future studies should investigate to what extend such hybrid BNCIs can increase applicability of assistive devices in real life scenarios and identify the main factors influencing user acceptance.

Acknowledgments: The authors would like to thank Dr. Marco Cempini and Mario Cortese (The BioRobotics Institute, Scuola Superiore Sant'Anna) for their valuable support in preparing the figures. This work was supported by the German Federal Ministry of Education and Research (BMBF, grant number 01GQ0831, 16SV5838K to SRS and NB); the European Commission under the project WAY and BNCI 2020 (grant numbers 288551 and 609593, respectively, to SRS and NB); the Deutsche Forschungsgemeinschaft (DFG, grant number SO932-2 to SRS and Reinhart Koselleck Project support to NB); Volkswagenstiftung (VW) and the Baden-Württemberg Stiftung.

References

[1] Buch E, Weber C, Cohen LG, et al. Think to move: a neuromagnetic brain-computer interface (BCI) system for chronic stroke. Stroke 2008; 39: 910–917.

[2] Cempini M, Cortese M, Vitiello N. A powered finger-thumb wearable hand exoskeleton with self-aligning joint axes. IEEE/ASME Trans Mechatron 2014; 99: 1–12.

[3] Cempini M, De Rossi SMM, Lenzi T, et al. Kinematics and design of a portable and wearable exoskeleton for hand rehabilitation. Proc IEEE Int Conf Rehab Robot 2013;2013:6650414.

[4] Collinger JL, Boninger ML, Bruns TM, Curley K, Wang W, Weber DJ. Functional priorities, assistive technology, and brain-computer interfaces after spinal cord injury. J Rehabil Res Dev 2013; 50: 145–160.

[5] Collinger JL, Wodlinger B, Downey JE, et al. High-performance neuroprosthetic control by an individual with tetraplegia. Lancet 2013; 381: 557–564.

[6] Del R Millan J, Galan F, Vanhooydonck D, Lew E, Philips J, Nuttin M. Asynchronous non-invasive brain-activated control of an intelligent wheelchair. Conf Proc IEEE Eng Med Biol Soc 2009; 2009: 3361–3364.

[7] Millán JDR, Rupp R, Müller-Putz GR, et al. Combining brain-computer interfaces and assistive technologies: state-of-the-art and challenges. Front Neurosci 2010; 4: 161.

[8] Future BNCI: a roadmap for future directions in brain/neuronal computer interaction research, Future BNCI Program under the European Union Seventh Framework Programme, FP7/2007-2013, grant 248320; http://www.brainable.org/Documents/Future_BNCI_Roadmap.pdf.

[9] Ganguly K, Secundo L, Ranade G, et al. Cortical representation of ipsilateral arm movements in monkey and man. J Neurosci. 2009; 29: 12948–12956.

[10] Hargrove LJ, Simon AM, Young AJ, et al. Robotic leg control with EMG decoding in an amputee with nerve transfers. N Engl J Med 2013; 369: 1237–1242.

[11] Kiguchi K, Hayashi Y. An EMG based control for an upper-limb power-assist exoskeleton robot. IEEE Trans Syst Man Cyber B 2012; 42: 1064–1071.

[12] Leeb R, Sagha H, Chavarriaga R, Millán J del R. A hybrid brain-computer interface based on the fusion of electroencephalographic and electromyographic activities. J Neural Eng 2011; 8: 025011.

[13] Liyanage SR, Guan C, Zhang H, Ang KK, Xu J, Lee TH. Dynamically weighted ensemble classification for non-stationary EEG processing. J Neural Eng 2013; 10: 036007.

[14] Matsumoto Y, Seki M, Ando T, et al. Analysis of EMG signals of patients with essential tremor focusing on the change of tremor frequency. Conf Proc IEEE Eng Med Biol Soc 2012; 2012: 2244–2250.

[15] Medical Research Council. Aids to the investigation of peripheral nerve injuries. 2nd ed. London: Her Majesty's Stationery Office, 1943.

[16] Micera S, Carpaneto J, Raspopovic S. Control of hand prostheses using peripheral information. IEEE Rev Biomed Eng 2010; 3: 48–68.

[17] Müller-Putz GR, Daly I, Kaiser V. Motor imagery-induced EEG patterns in individuals with spinal cord injury and their impact on brain-computer interface accuracy. J Neural Eng 2014; 11: 035011.

[18] Müller-Putz GR, Scherer R, Pfurtscheller G, Rupp R. Brain-computer interfaces for control of neuroprostheses: from synchronous to asynchronous mode of operation/Brain-computer interfaces zur steuerung von neuroprothesen: von der synchronen zur asynchronen funktionsweise. Biomed Tech 2006; 51: 57–63.

[19] Müller-Putz GR, Scherer R, Pfurtscheller G, Rupp R. EEG-based neuroprosthesis control: a step towards clinical practice. Neurosci Lett 2005; 382: 169–174.

[20] Müller-Putz GR, Schreuder M, Tangermann M, Leeb R, Millán Del RJ. The hybrid brain-computer interface: a bridge to assistive technology? Biomed Tech (Berl) 2013; 58. doi: 10.1515/bmt-2013-4435.

[21] Oldfield C. The assessment and analysis of handedness: the Edinburgh inventory. Neuropsychologia 1971; 9: 97–113.

[22] Pfurtscheller G, Aranibar A. Evaluation of event-related desynchronization (ERD) preceding and following self-paced movement. Electroencephalogr Clin Neurophysiol 1979; 46: 138–146.

[23] Pfurtscheller G, Guger C, Müller G, Krausz G, Neuper C. Brain oscillations control hand orthosis in a tetraplegic. Neurosci Lett 2000; 292: 211–214.

[24] Pfurtscheller G, Müller GR, Pfurtscheller J, Gerner HJ, Rüdiger R. 'Thought'-control of functional electrical stimulation to restore hand grasp in a patient with tetraplegia. Neurosci Lett 2003; 351: 33–36.

[25] Pons JL, Rocon E, Ceres R, et al. The MANUS-HAND dextrous robotics upper limb prosthesis: mechanical and manipulation aspects. Auton Robot 2004; 16: 143–163.

[26] Potvin JR. Effects of muscle kinematics on surface EMG amplitude and frequency during fatiguing dynamic contractions. J Appl Physiol 1997; 82: 144–151.

[27] Ribeiro P, Brasil F, Witkowski M, et al. Controlling assistive machines in paralysis using brain waves and other biosignals. Adv Hum Comput Interact 2013;2013:369425.

[28] Rohm M, Schneiders M, Müller C, et al. Hybrid brain-computer interfaces and hybrid neuroprostheses for restoration of upper limb functions in individuals with high-level spinal cord injury. Artif Intell Med 2013; 59: 133–142.

[29] Rupp R, Rohm M, Schneiders M, et al. Think2grasp – BCI-controlled neuroprosthesis for the upper extremity. Biomed Tech (Berl). 2013 (in press). doi: 10.1515/bmt-2013-4440.

[30] Soekadar SR, Birbaumer N, Slutzky M, Cohen LG. Brain-machine interfaces in neurorehabilitation of stroke. Neurobiol Dis 2015 (in press).

[31] Soekadar SR, Cohen LG, Birbaumer N. Clinical brain-machine interfaces. In: Tracy J, Hampstead B, Sathian K, editors. Plasticity of cognition in neurologic disorders. New York: Oxford University Press 2015, Part 3, Chapter 15, pp. 347-361. ISBN: 978-0-19-996524-3.

[32] Soekadar SR, Witkowski M, Mellinger J, Ramos A, Birbaumer N, Cohen LG. ERD-based online brain-machine interfaces (BMI) in the context of neurorehabilitation: optimizing BMI learning and performance. IEEE TNSRE 2011;19: 542–549.

[33] Vitiello N, Lenzi T, Roccella S, et al. NEUROExos: A powered elbow exoskeleton of physical rehabilitation. IEEE Trans Robot 2013; 29: 220–235.