INVITED PAPER

Towards Noninvasive Hybrid Brain–Computer Interfaces: Framework, Practice, Clinical Application, and Beyond

This paper reviews the use of the hybrid BCI approach for several end user applications in the scenarios replace, restore, improve, and enhance.

By Gernot Müller-Putz, *Member IEEE*, Robert Leeb, *Member IEEE*, Michael Tangermann, Johannes Höhne, Andrea Kübler, Febo Cincotti, Donatella Mattia, *Member IEEE*, Rüdiger Rupp, *Member IEEE*, Klaus-Robert Müller, *Member IEEE*, and José del R. Millán, *Senior Member IEEE*

ABSTRACT | In their early days, brain–computer interfaces (BCIs) were only considered as control channel for end users with severe motor impairments such as people in the locked-in state. But, thanks to the multidisciplinary progress achieved over the last decade, the range of BCI applications has been substantially enlarged. Indeed, today BCI technology cannot only translate brain signals directly into control signals, but also can combine such kind of artificial output with a natural muscle-based output. Thus, the integration of multiple biological signals for real-time interaction holds the promise to enhance a much larger population than originally thought end users with preserved residual functions who could benefit from new generations of assistive technologies. A BCI system that combines a BCI with other physiological or technical signals is known as hybrid BCI (hBCI). In this work, we review the work of a large scale integrated project funded by the European commission which was dedicated to develop practical hybrid BCIs and introduce them in various fields of applications. This article presents an hBCI framework, which was used in studies with nonimpaired as well as end users with motor impairments.

KEYWORDS | Assistive technology; communication; electroencephalogram; hybrid brain–computer interface (hBCI); neuroprosthesis

Manuscript received October 22, 2014; revised January 13, 2015 and February 9, 2015; accepted March 2, 2015. Date of publication May 18, 2015; date of current version May 29, 2015. This work was supported by the European FP7 project TOBI (Tools for Brain-Computer Interaction, 224631). The work of K.-R. Müller and J. Höhne was supported in part by the Bernstein Focus Neurotechnology (BMBF-Fkz 01GQ0850), and the Berlin Big Data Center (FKZ01IS14013A), the BMBF project 'Adaptive BCI' (FKZ 01GQ1115). The work of K.-R. Müller was also in part supported by the National Research Foundation grant 2012-005741) funded by the Korean government. The work of M. Tangermann was supported by BrainLinks-BrainTools, Cluster of Excellence funded by the German Research Foundation (DFG, grant number EXC 1086).

G. Müller-Putz is with the Institute for Knowledge Discovery, Laboratory of Brain-Computer Interfaces, Graz University of Technology, 8010 Graz, Austria (e-mail: gernot.mueller@tugraz.at).
R. Leeb is with the Center for Neuroprosthetics, École Polytechnique Fédérale de Lausanne, CH-1015 Lausanne, Switzerland.
M. Tangermann is with the University of Freiburg, Freiburg, Germany (e-mail: michael.tangermann@blbt.uni-freiburg.de).
J. Höhne is with the Department of Neurotechnology, Berlin Institute of Technology, Berlin, Germany.
A. Kübler is with the University of Würzburg, Würzburg, Germany (e-mail: andrea.kuebler@uni-wuerzburg.de).
F. Cincotti is with the Department of Computer, Control and Management Engineering, Sapienza University of Rome, Rome, Italy.
D. Mattia is with Neuroelectrical Imaging and BCI Lab, IRCCS Fondazione Santa Lucia, Rome, Italy (e-mail: d.mattia@hsantalucia.it).
R. Rupp is with the University of Heidelberg, Heidelberg, Germany (e-mail: ruediger.rupp@med.uni-heidelberg.de).
K.-R. Müller is with the Department of Machine Learning, Berlin Institute of Technology, Berlin, Germany, and also with the Department of Brain and Cognitive Engineering, Korea University, Seoul, Korea (e-mail: klaus-robert.mueller@tu-berlin.de).
J. d. R. Millán is with the Defitech Chair in Brain-Machine Interface, Center for Neuroprosthetics, École Polytechnique Fédérale de Lausanne, CH-1015 Lausanne, Switzerland (e-mail: jose.millan@epfl.ch).

Digital Object Identifier: 10.1109/JPROC.2015.2411333

I. INTRODUCTION

The research field of noninvasive brain–computer interaction [1], [3], [5]–[7] has matured now for more than 20 years. Since the early studies in the beginning of the 1990s, many new research groups have been established and a multitude of brain–computer interface (BCI) systems has been implemented and tested, mainly in healthy young subjects. This variety mainly reflects the brain signal used for control, the signal processing tools employed and eventually the application areas.

A classic approach has been the establishment of a BCI system for communication purposes (e.g., [8]) in patients with severe motor impairment affecting speech and other means of communication. Later on, BCI systems have been extended for control purposes, either for neuroprosthetic devices to restore hand function in spinal cord injured persons [9], [10] and for motorized wheelchair to replace mobility in case of lost limb control [11], [12]. The development of new computer graphics interfaces and their integration with the BCI technology has also allowed to investigate the subjects behavior in virtual worlds [13]–[15]. Finally, as the field matures, BCI systems have explored the enhancement of natural brain functions beyond communication such as for entertainment and other nonmedical applications [12], [16]–[21]. In this regard, the gaming industries have been recently attracted by the field of brain–computer interaction and a marketing endeavor has begun.

The advent of the machine learning approach in the BCI field has led to a remarkable improvement in system performance. As a direct impact of such advancement, the previously long lasting subject training protocols have been significantly shortened [4], [25]–[30], [32]–[37]. Finally, the last 20 years have also witnessed the technological development of both small and light weight multichannel amplifiers that can now be easily connected to small laptop or portable computers [38] as well as the emergence of a new generation of sensors such as dry electrodes [39]–[41]. These recording hardware advancements represent some essential steps to allow researchers to be mobile with their systems.

The vast majority of BCI studies involve healthy users, but the recent technological and neuroinformatics achievements have boosted the number of clinical studies conducted with real end-users and patients [42], [43], [76]. This overall progress and studies are creating a unique opportunity to harness the BCI technology for effective usage in real-life contexts to support people in their daily activities [44] as well as professional caregivers of end-users [46], [47], [66].

In their early days, BCIs were considered as the only control channel whose targeted end-users were severely impaired individuals such as those in a locked-in state [48]. But, thanks to the multidisciplinary progresses achieved over the last decade, these originals goals are being substantially enlarged. Indeed, today BCI technology cannot only translate brain signals directly into new outputs, but also can combine such kind of artificial output with a natural muscle-based output. Thus, the integration of multiple biological signals for real-time interaction holds the promise to enhance a much larger population than originally thought from end-users with preserved residual functions who could benefit from new generations of assistive technologies to healthy people who could improve their neuromuscular performance beyond their normal abilities.

A system that merges a normal BCI together with other physiological signals has been termed "hybrid BCI" (hBCI) [2], [49]. Müller-Putz *et al.* [50] provides the following definition, which is used in this article:

> A hybrid BCI combines existing input devices with a BCI. The BCI should be available if the user wishes to extend the types of inputs available to an assistive technology system, but the user can also choose not to use the BCI at all. Here it is of importance that the BCI itself is active, which means online EEG analysis is performed all the time. On the one hand, the hBCI might decide which input channel(s) offer the most reliable signal(s) and switch between input channels to improve information transfer rate, usability, or other factors. On the other hand, the hBCI could be used to fuse various input channels.

This work, intends to contribute to standardization of BCIs, namely to establish a general framework for hybrid BCIs, which includes interface and architecture definitions (see [50], [51]). It is meant to be the basis for easily enabling researchers to include functional modules from others into their own system, independently of the respective design choices, such as operating systems and development languages. The new hybrid BCI concept also offers the possibility to include not only biosignals from one modality (for example, EEG) but also from other input devices like standard mice and keyboards, and most importantly assistive devices and intelligent devices.

The hybrid BCI concept includes also two new important features, namely, information fusion and shared control logic. While fusion is necessary to form the hybrid control signal out of several possible inputs, the shared control logic uses this control signal as well as information from the application environment to improve the application control depending on the context.

Our motivation is a wider and easier integration of BCI components (i.e., software modules) and collaboration of different labs involved in BCI research, as well as better simpler hardware accessibility. In addition, a standardized BCI system could potentially facilitate the comparison of different systems and therefore also the results produced with these systems making a first step toward standardized BCI metrics. Applying the principle of standardized interfaces used for interconnection is one step to bring current BCI technology closer to the end-user market. Furthermore, new applications, based on hybrid BCI technology, can be created for end-users improving their abilities to manage their daily lives. This article provides a state-of-art review of the hybrid BCI work done in the EU funded collaborative project TOBI (Tools for brain-computer interaction (http://www.tobi-project.org).

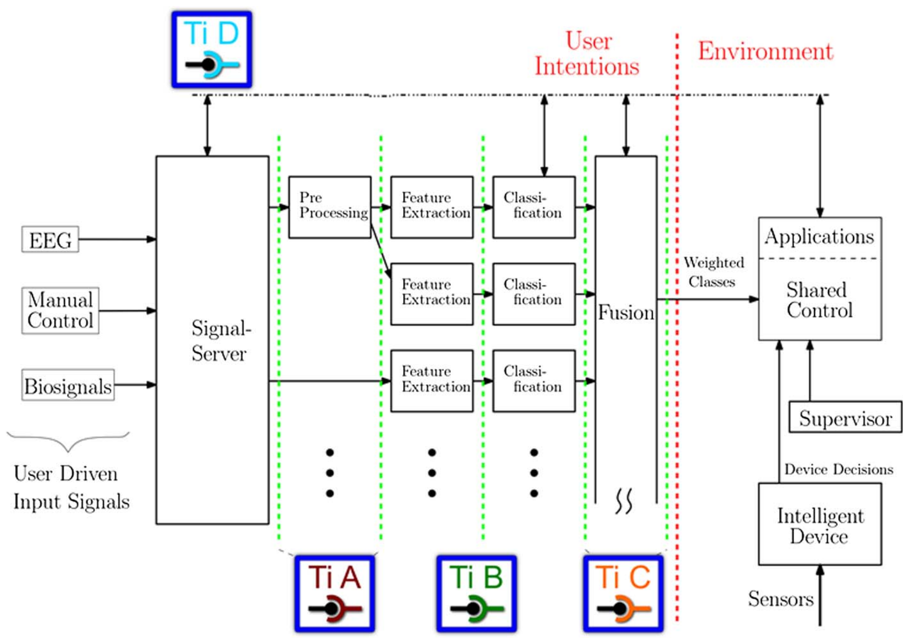

Fig. 1. *Schematic overview of the general structure of the common implementation platform for the hybrid BCI system (modified from [50]).*

II. HYBRID BRAIN–COMPUTER INTERFACING: A COMMON IMPLEMENTATION FRAMEWORK

The design (see Fig. 1) of the common implementation platform is based on the model already suggested by Mason and Birch [52]. The model consists of modules like data acquisition, different signal processing modules, multimodal fusion, and shared control with the application interface. All these modules are interconnected with different interfaces. The signal flow can be explained in the following way: signals (either from EEG, other biosignals like electromyogram (EMG), or from assistive devices) are acquired via different hardware and hardware interfaces (USB port, data acquisition cards, etc.) and provided for further use. This is realized with a special software called SignalServer [51], which implements TiA, the first interface explained later. From here, data can be processed (e.g., in a common BCI signal processing chain, mental state monitoring, error potential recognition, EMG artifact detection, switch signal quality check, etc.) and different control signals are fed to the multimodal fusion module. The task of this module is to decide which control signal (or classification result) is best suited to controlling the application. This means that, having 1) a BCI based on SMR (sensorimotor rhythm) for left-/right-hand motor imagery (MI) classification, 2) an artifact detection algorithm, and 3) a external control signal from an assistive device, the fusion decides which control signal is used for control of the application. Actual implementations are based on static rules, however, dynamic rules can be implemented when suited. The final control signal then goes to the shared control block. This module also receives information from the environment and helps to control the application in the most appropriate way.

A. Interfaces

The interfaces are the most important parts of the common implementation platform facilitating a standardized communication between different blocks independently from the chosen platform and software language. Currently, many BCI laboratories have their own techniques for performing data processing, so common methods to exchange data between different components have to be established. However, a specification which only describes the format of the data to be exchanged between components is not adequate in this case. To achieve true modularity, three methods to transmit and exchange data have been identified: 1) exchange of data within the same programming language, without any compatibility to other components; 2) exchange within the same computer but between different programming languages can be achieved by shared memory; and 3) exchange between different computers to allow distributed processing. Data can be sent over the network using TCP or UDP, or even support local data exchange.

1) TOBI Interface A—TiA: TiA represents an interface mainly developed to transmit raw biosignals (e.g., EEG) and data from simple user driven devices like buttons and joysticks. It is a client-server based system with one server and the possibility to attach multiple clients. The client-server communication is divided into 1) a control connection and 2) a raw data transmission stream. The control connection is only used to transmit meta information from the server to the client and to exchange control commands, both using XML messages. The raw data connection is unidirectional from the server to the client and is used to transmit acquired data in a binary form as a continuous data stream. Up to now, the whole client-server communication is done using network sockets [51].

Although foreseen in the concept, interface TiB was not realized, because feature extraction and classification is often very closely linked, usually in the same thread.

2) TOBI Interface C—TiC: The Interface C was initially designed to connect the classifier-like modules of the hBCI to multimodal fusion or other higher level modules. The classifier outputs are pairs of values and labels. The possible value types used are:

- a vector of distances (e.g., MI);
- a vector of probabilities (e.g., MI);
- a scalar (e.g., regression for MI);
- binary selections (e.g., P300).

Therefore, this interface handles only high-level data that is routed through different modules at reduced speed (typically below 50 Hz). For the reasons above, this interface uses a more general, platform independent and high-level communication based on XML messages over a TCP/IP network than the interface TiA. In this context transmitting XML messages does not cause any significant overhead, while at the same time it ensures that high-level communication follows a human readable format. The main advantage of the TiC implementation has to be found in the portability and scalability of its codebase.

3) TOBI Interface D—TiD: Markers and events are handled with this so called TiD. TiD is a network based protocol which delivers messages in XML via a bus-like system via TCP connections. Such an interface has to be provided to ensure the current flexibility of today's BCI system. Every TiD message is equipped with a timestamp to allow a proper association between an event and the processed data.

4) Fusion: Generally, the fusion module receives classification information (probabilities, class labels, regression values, etc.) from a set of processing modules. Several BCI classifiers or even several different BCIs (e.g., motor imagery, P300, error potential, ...) together with the estimation of other bio-signals (like EMG, etc.) and even assistive devices (like switches) can be merged. Consequently, the output of the fusion is—like the input—based on the interface TiC and is used as input to the shared control or to control the BCI feedback (if no shared control is used). Several examples of fusion will be described in the following sections. Currently, a static approach is used, but the weights could also dynamically update based on the reliability of these input channels, or the confidence/certainty the system has on its outputs. Generally, these weights can be estimated from supervision signals such as cognitive mental states (e.g., fatigue, error potentials) and physiological parameters (e.g., muscular fatigue). Another way to derive the weights is to analyze the performance of the individual channels in achieving the task (e.g., stability over time, influence of noise, etc.).

5) Context Awareness: The main question is how the subject might control a complex application by means of an uncertain channel such as a BCI. An answer to this fundamental issue is the well-known shared control approach [53], [54]. The cooperation between a human and an intelligent device allows the subject to focus his attention on his final target and ignore low-level details related to the execution of an action. For instance, in the case of a BCI-based telepresence robot the introduction of the shared control helps the user to reach the target in less time with a lower number of commands. In this case the role of shared control is to take care of the low-level details related to the navigation task (e.g., obstacle detection and avoidance) [55]. The role of the shared control module is to contextualize the user's intents in the current environment in order to support him in the control of an external application. To do that, the first task of the shared control is to manage all the high-level information coming from the user and the application (environment related messages). For the user-shared control connection, the message's format is defined by the TiC. For the application-shared control interface, the format is strictly application dependent. Generally, these messages are named events. Secondly, the shared control has to compute the events received in order to send the final command to the application. Static rules inside the module (application dependent) are in charge of this task. It is important to note that the same concept of shared control may be used for different kinds of applications (e.g., communication, neuroprosthetic control).

III. HYBRID BCI SYSTEMS IN USE: APPLICATIONS TESTED WITH HEALTHY SUBJECTS

A. Hybrid BCI Based on Fusion of Brain and Muscular Activities

End-user have varying remaining functionalities as possible control signals and practical hybrid BCIs should allow them to use all of them, whenever these control channels are available. For example, these people have sometimes residual activity of their muscles, most likely in the morning when they are not exhausted, but maybe loose this functionality during the day. Hence, in this presented hybrid BCI framework activities from the brain (measured via the EEG) and from the muscles (measured via the

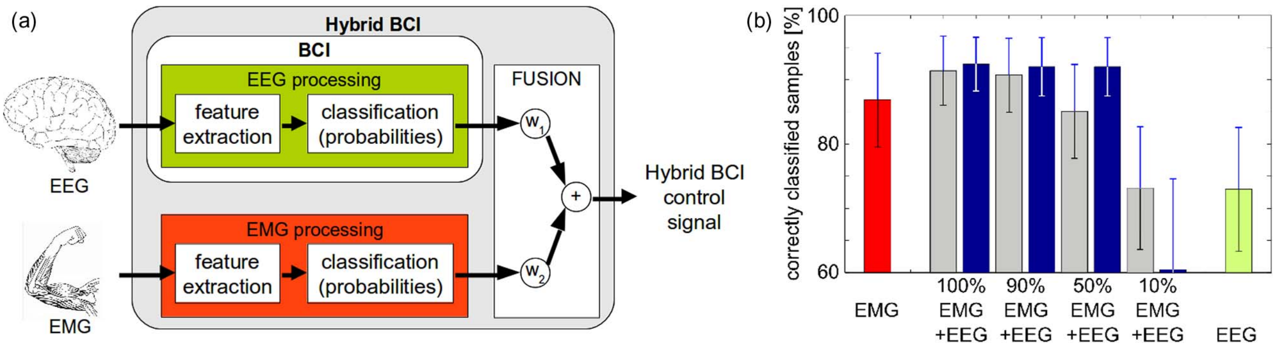

Fig. 2. ***(a) Fusion principle of muscular and brain activities. Both channels are processed separately and the classifier probabilities are fused together. (b) Performance result over the six conditions (mean $\pm$ SD of correctly classified samples over the task period). The outer bars represent the single modalities (EMG: leftmost/red; EEG: rightmost/yellow). The middle bars correspond to the fused modalities with different levels remaining EMG amplitude (100%–10%). For each of these conditions we provide two performances according to the fusion modality: simple fusion (left/light grey) and Bayesian fusion (right/black). Modified from [65].***

electromyogram, EMG) are combined [65]. Both channels are fused to produce a more robust and stable control signal compared to the single modalities [see Fig. 2(a)].

1) Participants and Methods: Twelve healthy subjects participated in standard synchronous BCI recordings, whereby repetitive left and right hand motor execution (depending on a visual cue) was carried out over a period of 5 s (resulting in 60 trials per class). The recorded brain and muscular activities were separately processed, classified and finally fused.

The brain activity was acquired via 16 EEG channels over the motor cortex. From the Laplacian filtered EEG the power spectral density was calculated and the selected features were classified with a Gaussian classifier. The evidence about the executed task was temporary accumulated (exponential smoothing), provided the confidence was above a rejection threshold [66].

The muscular activities were recorded over the flexor and extensor of the left and right forearm. The prehensile EMG activities were rectified and averaged (0.3 s) to get the envelopes. The resulting features were subject-specific thresholded, normalized and classified based on maximum distance.

Finally the two classifier probabilities were fused together in order to generate one control signal. Two classifier fusion techniques were explored: In the first approach the fusion weights were equally balanced between the two classifiers, while in the second one we adopted a naïve Bayesian fusion approach [67].

2) Results: The performances of either one modality alone (EEG or EMG) or the fusion of both were compared based on the correctly classified samples over the task period (0–5 s after the cue). Furthermore, to simulate fatigue of exhausted muscles, the amplitudes of the EMG channel were degraded over the run time (attenuation from 10% up to 100%) [68], so that the EEG activity became more and more important in the fusion. Importantly, however, the same classifier weights for EEG and EMG and the same fusion rules were kept over all conditions. This simulates the realistic situation of a patient who becomes more and more fatigued over the day.

Fig. 2(b) shows that the subjects could achieve a good control of their hybrid BCI independently of their level of muscular fatigue. Furthermore, although EMG alone yields good performance, it is outperformed by the hybrid fusion of EEG and EMG, since we focused on the correctly classified samples over the task period. Remarkably, thanks to the fusion, increasing muscular fatigue led to a moderate and graceful degradation of performance. Such a system allows a very reliable control and a smooth handover, even though the subjects is getting more and more exhausted or fatigued during the day. In more detail, the Bayesian fusion outperformed the simple fusion method, except in the case of 90% attenuation [65]. The reason is that the assumption of stable input patterns while setting up the Bayesian confusion matrices were violated and the performance dropped.

3) Discussion: In summary, the experiment demonstrated the benefits of a hybrid BCI. 1) Multimodal fusion techniques allow the combination of brain control with other residual motor control signals and thereby achieve better and more reliable performances. 2) Increasing muscular fatigue led only to a moderate and graceful degradation of performance compared to the non-fatigued case. 3) The Bayesian fusion approach led to a very constant behavior over a wide range of muscular fatigue, compared to the steadily decreasing performance in case of the simple fusion.

In future work, a dynamical adaptation of the fusion and weighting the contribution of the single modalities should be done.

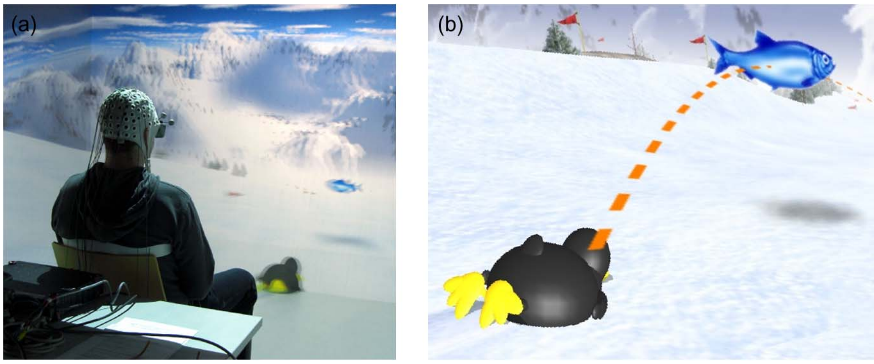

Fig. 3. *(a) The subject observes the scene from a point following the penguin. (b) Intended flight path of penguin. It is necessary to trigger the jump well in advance, otherwise the penguin will not catch the fish (modified from [74]).*

Finally, patients with progressive loss of muscular activity (as in muscular dystrophy, amyotrophic lateral sclerosis and spinal muscular atrophies) could benefit from such a hybrid BCI with dynamic fusion. For example, during early hybrid BCI training the user could still exploit her/his residual motor functions, while with increasing long-term use of the assistive device the transition between the hybrid control and pure BCI control (when muscular activity is too weak to operate them) would be smooth.

B. Multi-Modal Game Control

Transferring BCI technologies outside the laboratory environments and towards real applications, requires that the BCI users are not restricted to focus only on the BCI task, but should be able to perform other secondary tasks partly in parallel. Such multitasking is needed when real world applications are controlled with a BCI.

A multimodal approach of using an asynchronous BCI in parallel with a manual joystick control signal, while playing a game in virtual reality (VR) was recently demonstrated [74]. A subject sitting in the virtual environment controls the main character of a virtual reality game: a penguin that slides down a snowy mountain slope. While the subject can trigger a *jump* action via the BCI, additional steering with a game controller as a *secondary task* was tested [see Fig. 3(a)]. The experiment profits from the game as an attractive task where the subject is motivated to get a higher score with a better BCI performance. A BCI based on the so-called brain-switch (a short-lasting event-related synchronization (ERS) recorded during imagination of brisk dorsi-flexions of the feet [75]) was applied, which allows discrete asynchronous actions. Fourteen subjects participated, of which 50% achieved the required performance to test the penguin game in four different conditions.

The experiment was performed in two navigation modalities: first the participant played the game while pressing a push-button to trigger the jumps. In the second modality they used the brisk foot motor imagery detected by the BCI to trigger the jump. Furthermore, two levels of difficulty were created and the fish were placed appropriately. In the first level, all fish are placed in a straight line and can be collected without steering the penguin. In the second level, steering with the joystick is necessary in parallel to the jump to be able to collect all the fish [see Fig. 3(b)].

The task performance in the penguin game can be calculated as the ratio of successfully collected fish to the possible maximum. The performance in the manual push-button conditions [mean of 97.22% (straight) and 93.52% (steering)] are much better than in the BCI conditions [mean of 44.68% straight) and 47.69% (steering)], statistically significant within each navigation condition [74]. The result that manual control is better than BCI control is obvious and was expected from the beginning. More interesting are the results within the same navigation condition (push-button or BCI), showing that the usage of the joystick did not interfere with the jump control.

Furthermore, that work wanted to demonstrate that a transfer of the BCI skills to the hybrid application is possible, while showing that the secondary task does not influence the BCI performance. Comparing the BCI performance during the training phase and the game showed not difference, resulting in that a transfer of skills is possible, in spite of the changes in visual complexity and task demand.

Summing up, learned BCI control can be transferred from simple standard training paradigms towards more complex control tasks. More importantly, the results showed that the use of a secondary motor task, in this case the joystick control, did not deteriorate the BCI performance during the game. This implies that the visual complexity and the more demanding task had no impact on the user's success rate. These findings conclude that the chosen approach is a suitable multimodal or hybrid BCI implementation, in which the user can even do other tasks in parallel.

C. Control of Robotic Devices via Shared Control and Context Awareness

In a traditional BCI fashion, controlling complex devices such as brain-controlled wheelchair or mobile

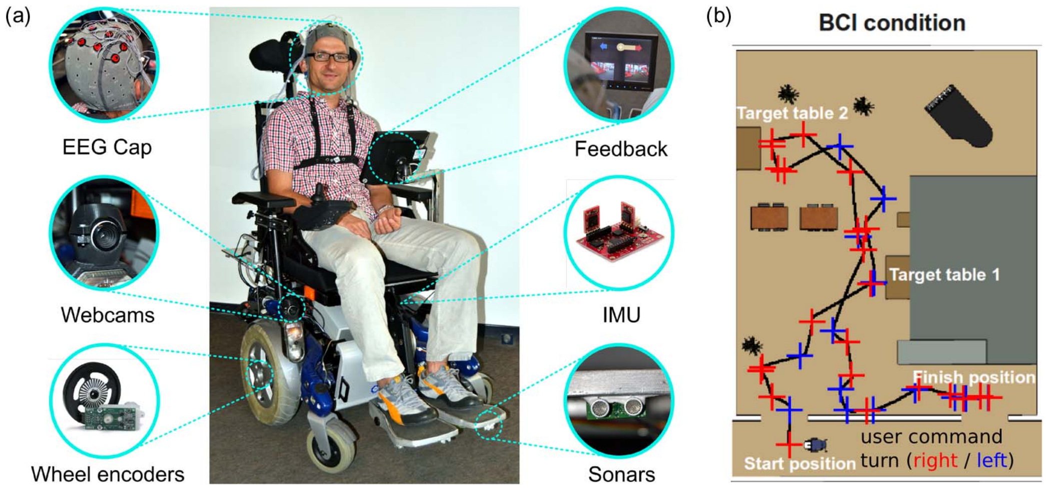

Fig. 4. *(a) Picture of a healthy subject sitting in the BCI controlled wheelchair. The main components on our brain-controlled robotic wheelchair are indicated with close-ups on the sides. The obstacles identified via the web-cams are highlighted in red on the feedback screen and will be avoided by the context awareness system. (b) Trajectories of a subject during BCI control reconstructed from the odometry. The start, end and target positions as well as the BCI triggered turnings are indicated (modified from [81]).*

telepresence platform in natural office environments would be a complex and frustrating task, especially since the timing and speed of interaction is limited by the BCI. Furthermore, the user has to share his attention between the BCI and the device, and also remember the place where he is and where he wants to go. In contrary, combining the above mentioned principles of BCI with context awareness and hybrid approaches allow subjects to control such complex devices easily.

Both types of BCI, either based on evoked or induced activity, have been used to control such devices. In a synchronous evoked P300 based BCI for wheelchair control the system flashes the possible predefined target destinations several times in a random order [79]. The stimulus that elicits the largest P300 is chosen as the target and then, the intelligent wheelchair reaches the selected target autonomously. Once there, it stops and the subject can select another destination.

More natural and suitable in unknown environments is the use of an asynchronous spontaneous BCIs [80]. Thereby, a BCI based on motor imagery is used to extract commands to turn the wheelchair to the left and right. In addition, the participant can intentionally decide not to deliver any mental commands to maintain the default behavior of the wheelchair, which consists of moving forward and avoiding obstacles with the help of a shared control system using its on-board sensors. For controlling, the user asynchronously sent high-level commands for turning to the left or right (with the help of a motor-imagery based BCI) to achieve the desired goals, while short-term low-level interaction for obstacle avoidance was done by the context awareness. In the applied context awareness paradigm, the wheelchair proactively slows down and turns to avoid obstacles as it approaches them.

In an experiment four healthy subjects (aged 23–28) participated successfully in driving the wheelchair [81]. The task was to enter an open-plan environment, through a narrow doorway, dock to two different desks, while navigating around natural obstacles and finally reach the corridor through a second doorway.

It could be demonstrated that both naive and experienced BCI wheelchair users are able to complete the navigation task successfully. Furthermore, in terms of path efficiency, no significant difference between the manual benchmark condition and the BCI condition could be found, although the participants needed longer to finish the task with the BCI.

It is important to highlight that, in this study not only a complex task had to be performed, but also the potential stressfulness of the situation, since the user was co-located with the robotic device that he or she was controlling and was subject to many external factors. This means the user had to put trust in the context awareness system and expected that negative consequences (e.g., a crash) could result in the system failing.

D. Hybrid BCI via the Simultaneous Usage of Motor Imagery and Error Potential

Unfortunately, motor imagery based BCIs are prone to errors in the recognition of subject's intent. In contrast to the other physiological interaction modalities, a unique feature of the "brain channel" is that it conveys not only the information from which we can derive mental control commands to operate, but also information about cognitive signals like the awareness of erroneous responses [69]. Therefore, an elegant approach to improve the accuracy consists in fusing both sources of brain signals. In particular, the latter can be exploited to design BCIs that consist

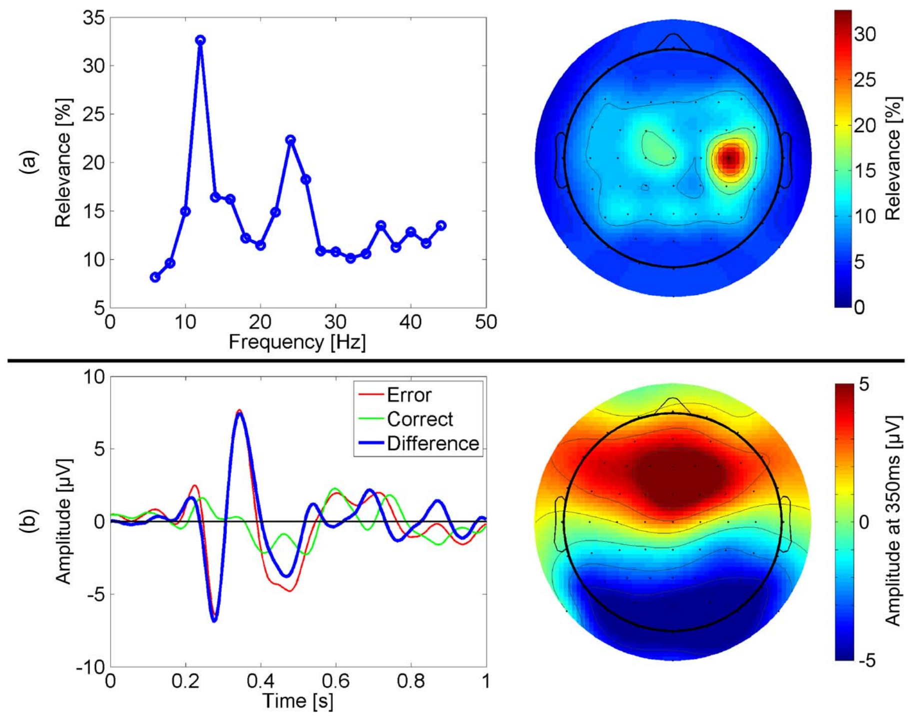

Fig. 5. *(a) Features relevance for motor imagery classification (one subject): discriminant Power of frequencies (top left) and of electrodes (top right). (b) Error Potential detection (one subject): Grand averages (bottom left) of error trials, correct trials and the difference between them (channel Cz). Scalp potential topography (bottom right) at the peak occurring 350 ms after the feedback presentation (modified from [72]).*

of a verification procedure directly based on the presence of error-related potentials (ErrP) in the EEG recorded right after the occurrence of an erroneous recognition by the BCI of the user's mental command [70].

Such a simultaneously detection of erroneous responses of the interface and classification of motor imagery at the level of single trials in a real-time BCI system was presented in [71], [73]. Two subjects had the task to bring a squared cursor to targets located 3 steps away. Left and right movements of the cursor were achieved via MI, analyzed over the last second. After the response of the BCI (i.e., a step bringing the cursor closer to or farther away from the target), a 400 ms window was used to detect the presence of an ErrP. If an ErrP was detected the last erroneous step was cancelled. Fig. 5 shows the used features of both BCIs, the discriminant power of the frequencies and channels in case of the MI-BCI and the time course and topographic average in case of the ErrP-BCI. The analysis showed that the BCI error rate without the integration of ErrP detection was around 32% for both subjects. However, when integrating ErrP detection, the averaged online error rate dropped to 7%, which would yield an increase of the bit rate above 200%. For more details, see [71].

These results confirm that it's possible to simultaneously control a brain-controlled device (via motor imagery) as well as to extract the error-related potentials of this interaction and combined the outcome of both. The combined (hybrid) BCI approach improves the quality of the brain-computer interaction, although neither of these two input channels is perfect. Furthermore, it would also be possible to think about retraining the motor imagery classifier based on the labels extracted from the ErrP detection to allow and online adaptation.

IV. HYBRID BCI SYSTEMS IN USE WITH MOTOR DISABLED END USERS

A. Neuroprostheses in Spinal Cord Injured End Users

For individuals with tetraplegia, restoring limited or missing grasping function is the highest priority [56], [57]. In patients with high spinal cord injury (SCI), restricted upper extremity function can be improved with the use of grasp neuroprostheses based on functional electrical stimulation (FES). With current neuroprostheses, relevant improvements can be achieved in end users with preserved shoulder and elbow, but missing hand function [58]–[60]. In case of a very high lesion with restricted hand and elbow movements, hybrid systems combining FES with orthoses hold promise for restoring completely lost upper extremity function. However, novel user interfaces integrating biosignals from several sources are needed to make full use of the many degrees of freedom of hybrid neuroprostheses. Motor imagery (MI)-based brain-computer interfaces

(BCIs) are an emerging technology that may serve as a valuable adjunct to traditional control interfaces [9].

1) Patient and Methods: The individual in a proof-of-concept single case study within the TOBI project [61] is a right-handed 41-year-old man who sustained a traumatic SCI in 2009 and has a complete motor and sensory lesion at the level of C4. He is unable to generate functionally relevant movements of the elbow, hand and fingers on both sides. To restore relevant movements for all day living situations, a so-called hybrid neuroprosthesis consisting of a combination of FES and a personalized orthosis with an actively driven joint is proposed [62]. The system was designed in a modular fashion including an intelligent control approach encompassing two input modalities, namely a single-axis shoulder position sensor and an MI-BCI [see Fig. 6(c)]. With upward/downward movements of the shoulder, the user controls the degree of elbow flexion/extension or of hand opening/closing. The routing of the analog signal from the shoulder position sensor to the control of the elbow or the hand and the access to a pause state is determined by a digital signal provided by the MI-BCI [see Fig. 6(a)]. The user uses short imagination of a hand movement to switch from hand to elbow control or vice versa. A longer imagination leads to a pause state with stimulation turned off or reactivates the system from the pause state [see Fig. 6(b)].

2) Results: After one year of intense training at the end user's home (415 BCI runs on 43 days; 24 trials and around 200 s for each run, the end user's MI-BCI performance ranged from 50% to 93% average: 70.5%). For most of the runs, right hand versus feet MI was employed. The performance of the system was evaluated with different functional assessments. The severely paralyzed end user was able to perform several activities of daily living, among them eating a pretzel stick, signing a document and eating an ice cream cone, which he was not able to perform without the neuroprosthesis.

3) Conclusion: It was shown that with the application of a hybrid FES upper extremity neuroprosthesis consisting of FES and a semiactive orthosis, restoration of not only hand and finger, but also elbow function is possible in a "normal" high tetraplegic SCI individual. He succeeded in performing different functional tasks. Shared control principles have been effectively used to allow for an adequate control of this hybrid FES system, despite the fact that even after extensive training, only moderate BCI performance was achieved. This is, in particular, important in users with a potentially low and/or varying BCI performance.

4) Outlook: The ultimate goal of our work based on the combination of a hybrid BCI-controlled hybrid FES orthosis would be to establish a technical bypass around the lesion of the spinal cord and to provide neuroprosthetis users with an intuitive control that would enable them to accomplish movement in a fluid and transparent manner.

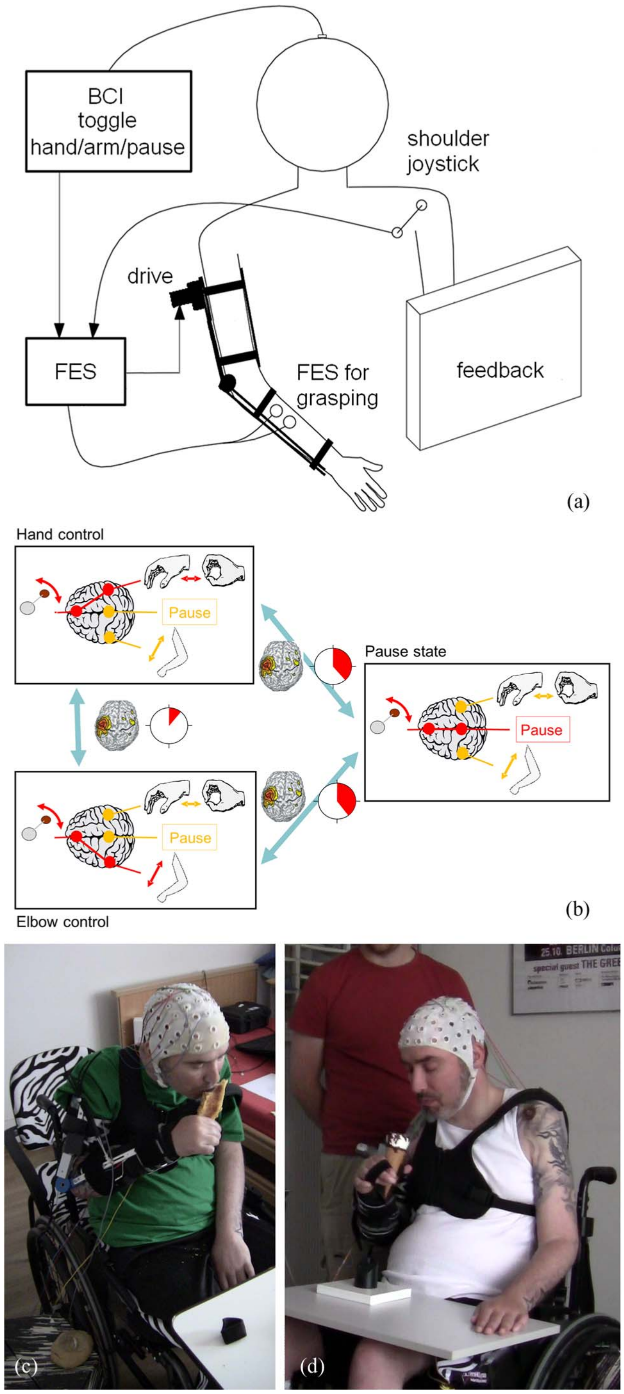

Fig. 6. ***Subfigure (a) Overview of the hBCI control of the upper extremity neuroprosthesis. Subfigure (b) Control scheme of the neuroprosthesis: A short imagination of a movement of the right hand switches between shoulder and elbow control. A long imagination switches to or from a pause state. Subfigure (c) End user with high cervical spinal cord injury and no voluntary finger, hand, and elbow function uses the hBCI-controlled hybrid neuroprosthesis to eat a pretzel stick. Subfigure (d) Same end user eating an ice cream cone.***

The first steps in this direction involving individuals with SCI have already been taken [63], [64].

B. Clinical Evaluation of a Motor Imagery Based Hybrid BCI Speller

1) Introduction: Among all demonstrated BCI applications, text-entry systems hold a special place as improving or restoring communication channels is the top priority of severely disabled people. Nevertheless, the writing speed is still very slow, but could be improved by hybrid approaches. Recently, a novel MI-based hybrid BCI spelling prototype, called BrainTree, was clinically evaluated with end-users [76]. The key ingredients for the successful operation of such a speller are the embedded data-compression, human–computer interaction (HCI) mechanisms as well as the implementation of error-handling through a hybrid BCI approach.

2) Methods: BrainTree is a binary, code-based speller. Character selection relies on the speller's underlying binary tree structure, masked behind a serial, alphabetical visualization. Given a typed prefix, the speller generates a new binary tree, in which characters are leaf nodes. A binary command codeword is thus associated to each character. The user descends the tree with left/right transitions through a two-class MI BCI.

An "undo" functionality complements the primary control modality, allowing a user to return to the previous state (ascend to the parent node) after an erroneous BCI command. This third command implements a hybrid approach (hBCI component) employing a single, bipolar EMG channel and relies on the user's eventual residual muscle abilities. Hu-Tucker entropy coding empowered by a prefix-based language model provides minimum average codeword length (i.e., number of BCI commands needed), thus speeding up spelling, while also respecting the alphabetic ordering (context-awareness-CA-component).

A total of six end-users and ten able-bodied users have participated in BrainTree's evaluation, after undergoing conventional MI training for a maximum of five sessions. The BrainTree evaluation protocol consisted of fixed copy-spelling tasks repeated across three different conditions: 1) hBCI+CA; 2) hBCI (CA disabled); and 3) CA ("undo" command disabled).

3) Results: BrainTree's text-entry usability as error-free task-completion rates was evaluated [76]. The most remarkable finding is the 100% task completion success for both user categories in the hBCI+CA condition. The added value of hBCI and CA in terms of usability are reflected by a 3.1% overall increase in task completion rate thanks to CA and, most importantly, a 18.2% overall increase thanks to hBCI. Concerning efficiency, users were able to type on average at 1.68 characters per minute (cpm) in hBCI+CA, 1.34 cpm in hBCI and 1.76 cpm in CA. These results suggest that hybrid error-handling has a greater impact on usability, while context-awareness on spelling efficiency. Additionally, by means of sensitivity analysis on a validated model for code-based BCI applications, we have shown that an overall command accuracy of 80% seems to be practically necessary for creating a usable, purely BCI-actuated code-based application, thus revising upwards the 70% requirement suggested in [78] and frequently used as a rule of thumb thereafter, a finding in line with [66].

4) Discussion and Conclusions: This study demonstrates the usability potential of code-based MI spellers, with BrainTree being the first to be evaluated by a substantial number of end-users, establishing them as a viable, competitive alternative to other popular BCI spellers.

C. Hybrid P300-EMG BCI for Communication in Severely Disabled End-Users

1) Background and System Overview: Within the life-span of the TOBI project we developed a prototype which allowed the users to control the QualiWorld Assistive Technology software (QW; QualiLife Inc., Switzerland) by means of an P300-based BCI. This prototype offered BCI-controlled communication functionalities such as text-editing, internet browsing, etc. [83]. After initial testing with potential end-users, and considering their feedbacks [43], we endowed the system with an hybrid control, which allowed users to cancel an unintended selection by means of any residual muscular activity detected through their electromyographic (EMG) signal. In severely disabled end-users, such EMG activity can be unreliable or subject to fatigue. Consequently it is often ineffective to operate by itself a conventional assistive device. Though, its sporadic use to cancel an error issued by the P300-based BCI is viable.

The visual stimulation of the P300-BCI was overlaid on top of the QW window. The hybrid system was designed to adapt to several degrees of residual motor activity. In order to reduce the occurrence of false positives, the EMG classification process was enabled only within a certain time window after the presentation of the feedback of the P300 classification. Constraints aimed at discarding muscular activity not intentionally related to the user's need to cancel a wrong P300-BCI selection, were introduced.

Fig. 7 illustrates the system.

2) Proof-of-Concept Study With End-Users: Three end-users (50.3 ± 3.2 years; 1 female, 2 males) with severe motor impairment participated in the evaluation of the hybrid-P300-QW prototype. They all had a severe impairment of the communication capacity, with one communication channel still preserved. Their Barthel Index scores[1] [84] were 0, 35, and 35, respectively. The users' motor

[1]The Barthel Index ranges from 0 (completely dependent) to 100 (completely autonomous).

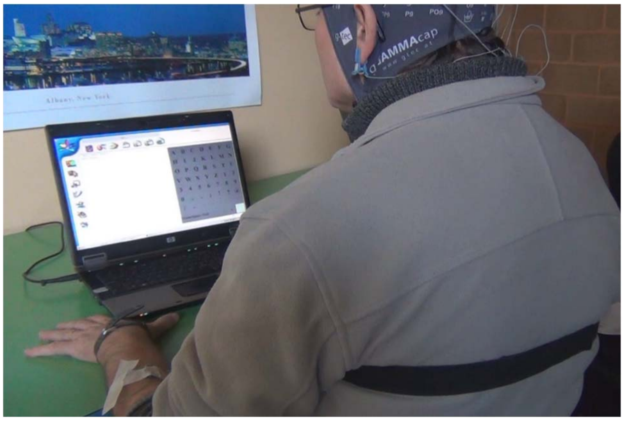

Fig. 7. *An end-user spelling text in the QW assistive software using the hybrid BCI. Intermittent visual stimuli were overlaid on a virtual keyboard to evoke a P300 potential, which was used to select the intended letter. In case of wrong selection, the EMG generated by a slight movement of the hand reverted the last selection.*

disability was the consequence of brainstem stroke, haemorrhagic stroke and amyotrophic lateral sclerosis, respectively.

EEG and EMG signals were recorded by eight electrodes, (Fz, Cz, Pz, Oz, P3, P4, PO7, PO8; right earlobe referenced and grounded to the left mastoid) and 2 active electrodes, respectively. Both signals were amplified using a g.tec (Graz, Austria) USB amplifier.

EMG activity was detected on the most reliable muscle of each user (*flexor carpi radialis*, *extensor carpi radialis longus*, and the *flexor digitorum superficialis*). In fact, the most preserved movements of each user were, respectively: slight extention of the wrist, wrist extention, and incomplete flexion of the fingers.

For the purpose of evaluation, end-users were required to spell three predefined words (21 letters in total) using the P300-BCI speller and deleting incorrect selections by means of the EMG control.

3) Results: The system was evaluated in terms of three usability domains: effectiveness, efficiency and satisfaction. The three end users controlled the system with a mean accuracy of 86% (96%, 78%, and 83%) and the ITR was on average 8.5 bit/min. End users performed in total 15 correct deletions by means of EMG. Only one end-user missed the deletion with EMG 3 times (out of 11) and in those cases she deleted the wrong selection by means of a P300-based BCI selection. The overall workload, as measured by the NASA-tlx-questionnaire [85], was of 40.5 on average (scores from 0 to 100). All participants rated high levels of satisfaction with the hybrid system; on a visual analogue scale (VAS; ranging from 0 to 10), they indicated 7.9, 8.2, and 7.2 as level of satisfaction, respectively.

4) Conclusions: The proposed hybrid BCI control modality potentially provides end-users with severe motor disability with an option to exploit some residual muscular activity that could not be fully reliable for a proper control of an assistive technology (AT) device. The findings reported in this feasibility study have encouraged the implementation of a clinical trial involving a large cohort of end-users.

D. Severely Paralyzed Patients Control a Gaming Application With Motor Imagery

When setting up a BCI system for paralyzed patients, the technical setup needs to satisfy various requirements. First, the BCI needs to be stable and robust against a variety of experimental factors such as interferences with other medical devices. Second, the attention span of the user might be variable and the BCI system needs to tolerate frequent pause requests, restarts and recalibrations at any time. Third, the BCI system must be flexible enough to exploit rather unusual features of the recorded brain signals. Even for healthy subjects, discriminative neuronal features for the task at hand [e.g., event-related desynchronization (ERD)/ERS effects in the oscillatory domain] do show a significant degree of variance between BCI users. State-of-the-art BCI systems tackle this by calibrating the system individually to each user. Brain features of patients, however, regularly deviate substantially from typical features known from studies with healthy subjects. The deviations may be caused not only by a much weaker expression of standard features, but also by a complete lack of standard features. Instead, the system must be able to deal with completely different and weak features. The three requirements must be satisfied by the system setup, in order to reach the overall goal within a short number of calibration sessions and possibly for each individual patient—an accurate BCI control. The software framework of the BCI system must be prepared to deal with these requirements. This requires substantial flexibility in the data analysis pipeline containing pre-processing with machine learning steps.

Data analysis procedures of synchronous BCI paradigms (such as ERP-based spelling paradigms) are rather established. This enables BCI systems which can be applied "out-of-the-box" [18]. For asynchronous paradigms such as BCIs based on motor imagery/attempted motor execution, there might be multiple relevant features contained in the recorded brain data. This give rises to a variety of analysis procedures. In a recent patient study by [82], a hybrid approach was taken which aims for an "out-of-the-box" BCI system for motor imagery. Its main characteristics were:

1) multiple spectral features (e.g., μ ERD, μ ERS, β ERD, β ERS, brisk β rebound, etc.) features as well as non-spectral features (lateralized readiness potential (LRP), motor-related potentials) were extracted from the EEG data;
2) a hybrid meta-classifier combined all features (cf. also [77])—see Fig. 8(a).

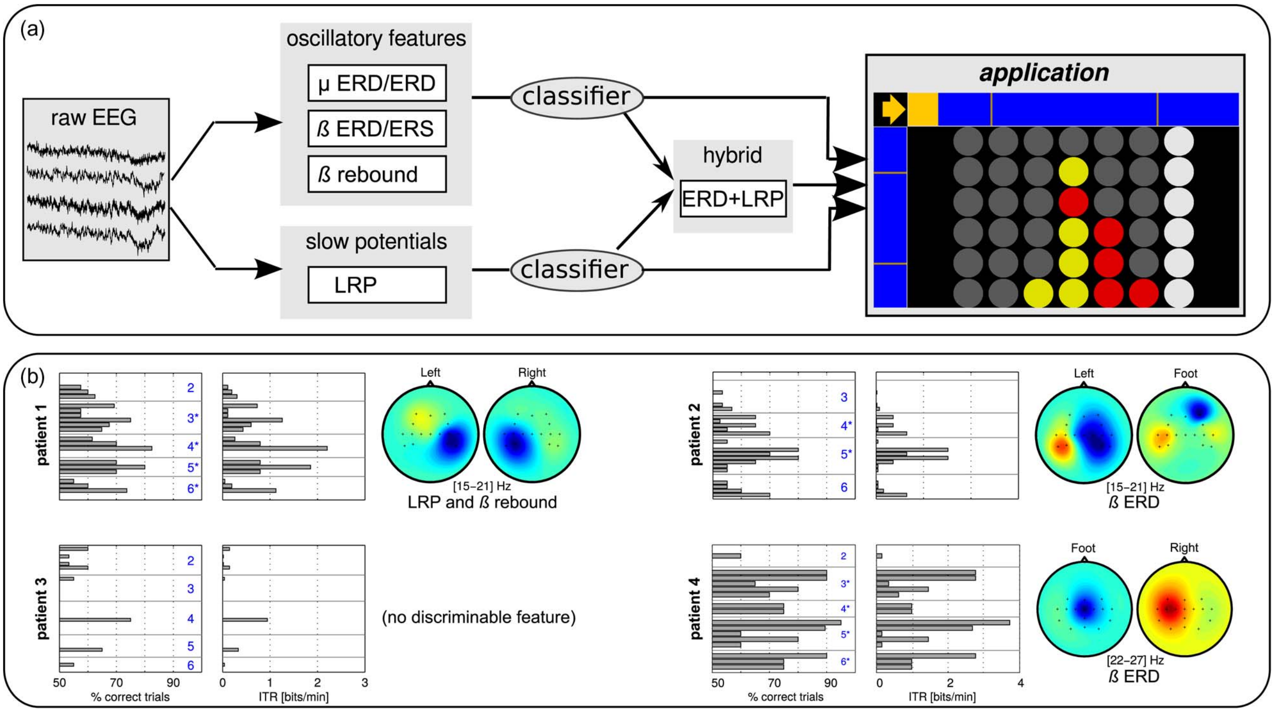

Fig. 8. ***A hybrid approach for a BCI based on motor imagery. Plot A illustrates the internal processing pipeline of the BCI system. A variety of features were simultaneously extracted from the EEG. Plot B shows the results of the study. For each patient, the BCI performance as well as the most discriminable feature is plotted.***

Using this approach, the BCI could be driven by any combination of features in the data.

The strategic game "Connect-4" was implemented as the feedback application of this study. It was chosen as it provides a playful motivation. In addition it is flexible enough to compensate being paused at any time, and the game allowed a wide range of timing adjustments. Importantly, the degree of control provided by a BCI system was sufficient to play the game.

a) Patients: Four severely paralyzed end-users participated in this study. They were characterized by individual and severe brain damages due to stroke or cerebral palsy (for details, please see [82]). Two of these end-users were restricted to the extent, that their AT-based communication was slower than 5 bits/min. Therefore, these end-users can be regarded as the ultimate target group for BCI-support, as the BCI has the potential to directly improve their primary communication abilities. In total, six BCI sessions (with a duration of 1–3 h) were performed with each subject.

b) Results: The flexible BCI framework enabled three out of the four end-users to obtain a significant BCI control after only three to five sessions. The results are shown in Fig. 8(b). While β rebounds could be used for classification for one of the patients, it is remarkable, that none of the users showed exploitable ERD features in the μ band (a standard feature for healthy users). Instead, ERDs in the β band as well as LRP features were found to be discriminable. In order to enable BCI control for the three patients, it was essential to deviate from known ground and instead exploit different features from the EEG. Surprisingly, the most severely paralyzed end-user was performing best, with more than 90% accuracy on a single-trial basis (chance level: 50%). This good performance was obtained during several sessions. For him, it could also be shown that control via BCI was faster and more accurate than what could be reached with his current AT-solution. The latter was based on muscular control of the thumb.

c) Conclusion: The hybrid approach not only improves the integration of BCI technology into other existing AT platforms. This study reveals that the described within-EEG hybrid approach also improves the classification performance and the general usability of the BCI system for motor-related tasks. The proposed flexible data exploitation approach can allow a BCI to be driven by a combination of diverse and multiple features—a necessary prerequisite for a successful application of one BCI system for three out of four severely paralyzed end-users.

E. Hybrid BCI-Driven Tool to Support Hand Motor Rehabilitation After Stroke

1) Background and System Overview: The major focus in post-stroke rehabilitation research has been on motor recovery of hemiplegic limbs, being the most common and disabling consequence of stroke [88]. Present therapies mainly consist of the repeated practice of motor tasks, with the expectation that this task-specific training and practice will induce neural plastic changes and thus improve function [90]. Therapists encourage and reinforce any residual (or recovered) execution of the hand movements, yet ensuring that this does not induce unwanted contractions and spasticity. Evidences from the neuroscience of recovery and restoration are progressively changing the classical approach to stroke rehabilitation [87]. In this respect, BCI technology can encourage motor training and practice by offering an on-line feedback about brain signals associated with mental practice, motor intention/attempt and other neural recruitment strategies, and thus helping to guide neuroplasticity to improve recovery [89]. To this aim, BCI design should incorporate principles of current rehabilitative settings suitable to stimulate patients' engagement during exercise, i.e., assist the practice of a motor task and prevent reinforcement of pathological motor synergies.

To comply with such requirements, a hybrid BCI-driven rehabilitative device was developed within the TOBI project aiming at enhancing motor recovery of the upper limb in stroke patients. The ultimate goal is to let the patients re-learn their motor scheme by having voluntary (covert and/or overt) access to the paralyzed limb.

The device (see Fig. 9) was designed to monitor the activity of the motor cortex and the residual muscular patterns of the paralyzed arm-hand to assist the completion of the requested therapeutic exercise, in order to close the loop between patients' motor intention and sensory perception. As such, the hybrid BCI uses electroencephalography (EEG) and electromyography (EMG) signals generated from the motor attempt to control a FES device which boosts contraction of the target muscles, thus reinforcing a voluntary flexion or extension of paralized hand. In this hybrid approach, the motor intent of a given patient is recognized from the EEG patterns and the muscle contraction is produced via FES only if certain EMG features of the patient's voluntary motor attempt are classified as "correct." In this application, FES driven movements are not meant to substitute the lost motor function to perform daily life activ1ities. Rather, they provide the patient with a natural visual and proprioceptive feedback in order to reinforce cognitive and muscular patterns and thus, leading to a better recovery of these functions.

2) Proof-of-Concept Single Case Study: Here, we described a feasibility study conducted within the lifespan of the TOBI project, involving one stroke patient. The proposed system was tested by a chronic stroke patient in a one-month training with three weekly sessions, in add-on to standard rehabilitation therapy.

Fig. 9. ***A BCI-assisted rehabilitation session. The system monitors both the patient's EEG sensorimotor rhythms from the affected hemisphere and the pattern of residual EMG signals from flexor and extensor muscles of the affected arm. Only when the motor intent of the patient is detected from both signals, and no pathological (opportunistic) patterns are present, the FES assists the motor act by inducing contraction of either the flexor or extensor muscles, thus providing positive reinforcement to the patient. Real time display of EEG and EMG patterns are only available to the therapist, who can guide the patient toward the most effective rehabilitation exercise.***

The patient was a 41-years old male who suffered from a right hemisphere haemorrhagic stroke 18 months before the training started. At the time of the training, he had no cognitive or language impairment, he was able to walk autonomously with a cane and had severe motor deficit in the left arm (National Institute of Health Stroke Scale of 5; upper limb section of the Fugl-Meyer Assessment Scale—FMA of 15/66).

During the training, the patient was asked to perform attempted finger extensions of his left hand. EEG patterns relative to the attempted movement (i.e., desynchronization above the affected hemisphere on central and centro-parietal electrodes at sensorimotor relevant frequencies) were used to drive the FES device Fig. 10, left panel). The EMG signals were employed as a gating system in order to prevent FES activation in the case of pathologic co-contractions or increased spasticity (see Fig. 10, right panel). Each training session comprised from four to six runs of 20 trials each and lasted approximately 1 h (EEG cap montage time excluded). The training was carried out in a real rehabilitative environment (i.e., the hospital gym facility).

At the end of the one-month training, we observed a trend toward an increase of the arm section FMA score (18/66). More relevantly, the patient reported to have increased perception of his own affected left hand resulting in an increased confidence in the attempt to use it during daily life activities (despite the severity of the motor

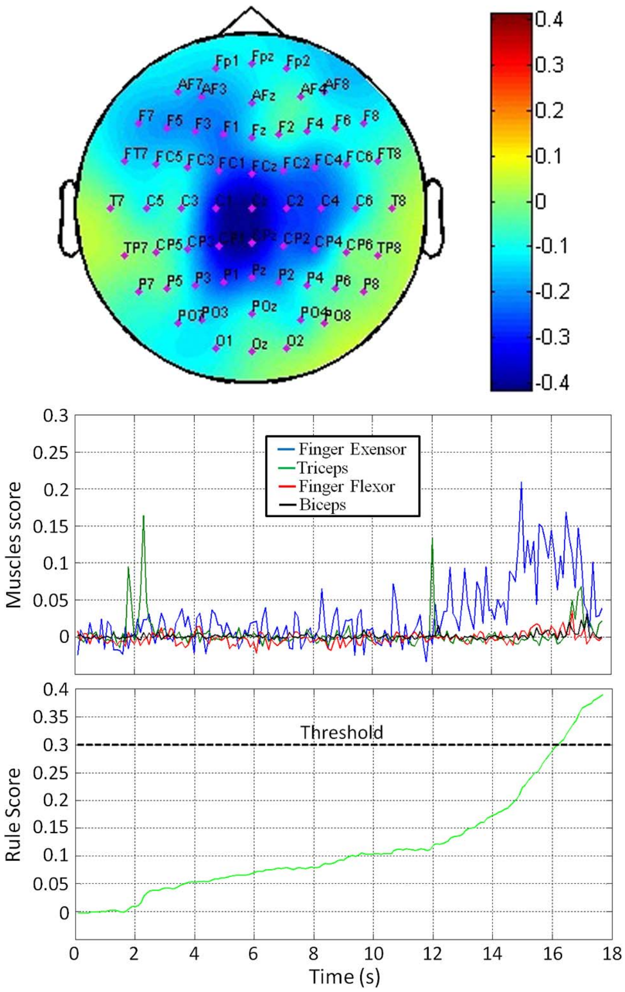

Fig. 10. ***Upper panel: head topography of significant changes (R2) in the EEG spectral power at 21–22 Hz, during left (affected) hand finger extension attempt. The hybrid BCI monitored the amplitude of EEG desynchronization at the central and centroparietal electrodes on the above the right affected hemisphere. Lower panel: Linear envelope of the EMG signals collected from four arm muscles during a hand extension exercise. Contraction of the distal extensor muscle alone was the pattern to be reinforced in this exercise. Prolonged adherence to this pattern was measured in real time through an index (Rule Score).***

deficit). Though preliminary and qualitative, these results are encouraging in terms of acceptability of the approach by patients and of the professional end-users.

3) Conclusions: BCI appears a potential technology to support post-stroke motor training and thus to facilitate neuroplasticity phenomena. Nevertheless, the translation of an approach from basic system neuroscience research into clinical practice has just begun. Future studies should anticipate some issues related to clinical trial design such as optimization of components interventions, definition of appropriate outcome measures and definition of who may benefit.

V. GENERAL DISCUSSION, CONCLUSION AND OUTLOOK

Due to enormous progress over the last years hybrid BCIs nowadays represent practical and robust solutions in the field of AT and neurorehabilitation. The present paper has embedded the major hBCI activities into the broader context of more than two decades of research in noninvasive BCI and has proposed a standardized architecture of typical hBCI systems. The application of this hBCI framework was successfully applied in a number of studies involving both unimpaired users and individuals with severe motor impairments. Clearly the systematic harvesting of physiological signals (cf. [86]) and *a priori* or context information that is fused in the respective hBCI has shown immense progress in practice.

All presented single studies were based on the architecture described in the beginning of this work. More details can be found elsewhere (see [50]) and the framework can be downloaded at http://tools4bci.sourceforge.net/. By using the interfaces described earlier, we were able to combine our custom made signal processing modules, independently from programming language and platform, without reprogramming and thus, the framework built a common basis for all collaborators in this project and lead to successful implementations of new paradigms tested with healthy subjects but also to novel work with end users in need of new technology. It is clear that not all "TOBI interfaces" will be used in every single future study. However, we believe that our common implementation framework is an important contribution to the BCI field as it provides a unifying approach to integrate in a principled way any potential component necessary to design functional hybrid BCIs for long-term operation.

A number of challenges remain. From the theoretical perspective, the ideal fusion of heterogeneous information sources needs to take into account variable information content between the sources, different degrees of nonstationarity (cf. [91]) finally robustness aspects (wrt., outliers, nuisance channels). In practice, all mentioned issues are not easily accessible and need to be estimated from limited data. Thus, methods that can help to adaptively reestimate the statistical properties of hBCI constituents will be a future focus of research. In practice, it is clearly not trivial to find the ideal combination of biosignals or context information that can enhance and enrich a hBCI. At this point we do not have a comprehensive user model and therefore need to rely on experiments to explore how the ideal hBCI should be configured for a novel paradigm and or a new end user. Practically, when working with end users it is furthermore important to integrate personal needs, availabilities and constraints into the design of a hBCI system, since personal preferences for human machine interaction may play a decisive role.

A clear outcome of the current research work is that in the future BCI technology will evolve to an essential component in the field of assistive technology. With the help of the concept of the hybrid BCI, which allows additional control inputs besides the "brain"-channel become reality in the near future. ■

REFERENCES

[1] J. J. Vidal, "Toward direct brain-computer communication," *Annu. Rev. Biophys. Bioeng.*, vol. 2, pp. 157–180, 1973.

[2] S. Amiri, R. Fazel-Rezai, and V. Asadpour, "A review of hybrid brain-computer interface systems," *Adv. Human-Comput. Interact.*, vol. 2013, pp. 1–8, 2013.

[3] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," *Clin. Neurophysiol.*, vol. 113, no. 6, pp. 767–791, 2002.

[4] T. Zeyl and T. Chau, "A case study of linear classifiers adapted using imperfect labels derived from human event-related potentials," *Pattern Recogn. Lett.*, vol. 37, pp. 54–62, 2014.

[5] G. Dornhege, J. d. R. Millán, T. Hinterberger, D. J. Mcfarland, and K.-R. Müller, Eds., Toward Brain-Computing Interfacing. Cambridge, MA, USA: MIT Press, 2007.

[6] J. d. R. Millán *et al.*, "Combining brain-computer interfaces and assistive technologies: State-of-the-art and challenges," *Front Neurosci.*, vol. 4, p. 161, 2010.

[7] B. Allison, S. Dunne, R. Leeb, J. d. R. Millán, and A. Nijholt, *Towards Practical Brain-Computer Interfaces: Bridging the Gap from Research to Real-World Applications*. Berlin, Germany: Springer-Verlag, 2012.

[8] N. Birbaumer *et al.*, "A spelling device for the paralysed," *Nature*, vol. 398, no. 6725, pp. 297–298, 1999.

[9] G. Pfurtscheller, G. R. Müller, J. Pfurtscheller, H. J. Gerner, and R. Rupp, "'Thought'-control of functional electrical stimulation to restore hand grasp in a patient with tetraplegia," *Neurosci. Lett.*, vol. 351, no. 1, pp. 33–36, 2003.

[10] G. Müller-Putz, R. Scherer, G. Pfurtscheller, and R. Rupp, "EEG-based neuroprosthesis control: A step towards clinical practice," *Neurosci. Lett.*, vol. 382, pp. 169–174, 2005.

[11] F. Galán *et al.*, "A brain-actuated wheelchair: Asynchronous and non-invasive brain-computer interfaces for continuous control of robots," *Clin. Neurophysiol.*, vol. 119, no. 9, pp. 2159–2169, 2008.

[12] J. d. R. Millán *et al.*, "Asynchronous non-invasive brain-actuated control of an intelligent wheelchair," in *Proc. 31st Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2009, pp. 3361–3364.

[13] R. Leeb *et al.*, "Brain-computer communication: Motivation, aim and impact of exploring a virtual apartment," *IEEE Trans. Neural Syst. Rehab. Eng.*, vol. 15, pp. 473–482, 2007.

[14] F. Lotte *et al.*, "Exploring large virtual environments by thoughts using a brain-computer interface based on motor imagery and high-level commands," *Presence-Teleop. Virt.*, vol. 19, no. 1, pp. 54–70, 2010.

[15] S. Haufe *et al.*, "EEG potentials predict upcoming emergency brakings during simulated driving," *J. Neural Eng.*, vol. 8, no. 5, p. 056001, 2011.

[16] J. d. R. Millán, "Adaptive brain interfaces," *Commun. ACM*, vol. 46, no. 3, pp. 74–80, 2003.

[17] K.-R. Müller *et al.*, "Machine learning for real-time single-trial EEG-analysis: From brain-computer interfacing to mental state monitoring," *J. Neurosci. Meth.*, vol. 167, no. 1, pp. 82–90, 2008.

[18] B. Blankertz *et al.*, "The Berlin brain-computer interface: Non-medical uses of BCI technology," *Front Neurosci.*, vol. 4, no. 198, 2010.

[19] Z. Khaliliardali, R. Chavarriaga, L. A. Gheorghe, and J. d. R. Millán, "Detection of anticipatory brain potentials during car driving," in *Proc. 34st Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2012, pp. 3829–3832.

[20] S. Scholler *et al.*, "Towards a direct measure of video quality perception using EEG," *IEEE Trans. Image Process.*, vol. 21, no. 5, pp. 2619–2629, 2012.

[21] A. K. Porbadnigk *et al.*, "Single-trial analysis of the neural correlates of speech quality perception," *J. Neural Eng.*, vol. 10, no. 5, p. 056003, 2013.

[22] J. d. R. Millán, P. W. Ferrez, and T. Seidl, "Validation of brain-machine interfaces during parabolic flight," *Int. Rev. Neurobiol.*, vol. 86, pp. 189–197, 2009.

[23] D. de Negueruela, M. Broschart, C. Menon, and J. d. R. Millán, "Brain-computer interfaces for space applications," *Pers. Ubiquitous Comput.*, vol. 15, no. 5, pp. 527–537, 2011.

[24] L. A. Gheorghe, R. Chavarriaga, and J. d. R. Millán, "Steering timing prediction in a driving simulator task," in *Proc. 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2013.

[25] B. Blankertz, G. Curio, and K. R. Muller, "Classifying single trial EEG: Towards brain computer interfacing," *NIPS*, vol. 1, pp. 157–164, 2002.

[26] J. d. R. Millán *et al.*, "A local neural classifier for the recognition of EEG patterns associated to mental tasks," *IEEE Trans. Neural Netw.*, vol. 13, no. 3, pp. 678–686, 2002.

[27] J. d. R. Millán, F. Renkens, J. Mouriño, and W. Gerstner, "Brain-actuated interaction," *Artif. Intell.*, vol. 159, no. 1–2, pp. 241–259, 2004.

[28] B. Blankertz, G. Dornhege, M. Krauledat, K. R. Müller, and G. Curio, "The non-invasive Berlin brain-computer interface: Fast acquisition of effective performance in untrained subjects," *NeuroImage*, vol. 37, no. 2, pp. 539–550, 2007.

[29] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe, and K. R. Müller, "Optimizing Spatial Filters for Robust EEG Single-Trial Analysis," *IEEE Signal Process. Mag.*, vol. 25, no. 1, pp. 41–56, 2008.

[30] S. Lemm, T. Dickhaus, B. Blankertz, and K.-R. Müller, "Introduction to machine learning for brain imaging," *Neuroimage*, vol. 56, no. 2, pp. 387–399, 2011.

[31] R. Tomioka and K. R. Müller, "A regularized discriminative framework for EEG analysis with application to brain-computer interface," *Neuroimage*, vol. 49, no. 1, pp. 415–432, 2010.

[32] J. d. R. Millán, P. W. Ferrez, F. Galán, E. Lew, and R. Chavarriaga, "Non-invasive brain-machine interaction," *Int. J. Pattern Recogn. Artif. Intell.*, vol. 22, no. 5, pp. 959–972, 2008.

[33] J. d. R. Millán *et al.*, "Adaptive Brain Interfaces for Physically-Disabled People," in *Proc. 20th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*Hong Kong, 1998, pp. 2008–2011.

[34] J. d. R. Millán *et al.*, "Local Neural Classifier for EEG-based Recognition of Mental Tasks," in *Proc. IEEE-INNS-ENNS Int. Joint Conf. Neural Netw.*, Como, Italy, 2000, vol. III, pp. 632–636.

[35] J. d. R. Millán and J. Mouriño, "Asynchronous BCI and Local Neural Classifiers: An Overview of the Adaptive Brain Interface Project," *IEEE Trans. Neural Syst. Rehab. Eng.*, vol. 11, no. 2, pp. 159–161, 2003.

[36] A. Buttfield, P. W. Ferrez, and J. d. R. Millán, "Towards a Robust BCI: Error recognition and online learning," *IEEE Trans. Neural Syst. Rehab. Eng.*, vol. 14, no. 2, pp. 164–168, 2006.

[37] T. Kaufmann, S. M. Schulz, C. Grünzinger, and A. Kübler, "Flashing characters with famous faces improves ERP-based brain-computer interface performance," *J. Neural Eng.*, vol. 8, no. 5, p. 056016, 2011.

[38] S. Debener, F. Minow, R. Emkes, K. Gandras, and M. de Vos, "How about taking a low-cost, small, and wireless EEG for a walk?" *Psychophysiol.*, 2012, 10.1111/j.1469-8986.2012.01471.x.

[39] F. Popescu, S. Fazli, Y. Badower, B. Blankertz, and K. R. Müller, "Single trial classification of motor imagination using 6 dry EEG electrodes," *PLoS One*, vol. 2, no. 7, 2007.

[40] C. Guger, G. Krausz, B. Z. Allison, and G. Edlinger, "Comparison of dry and gel based electrodes for P300 brain-computer interfaces," *Front. Neurosci.*, vol. 6, no. 60, 2012.

[41] C. Grozea, C. D. Voinescu, and S. Fazli, "Bristle-sensors-low-cost flexible passive dry EEG electrodes for neurofeedback and BCI applications," *J. Neural Eng.*, vol. 8, no. 2, p. 025008, 2011.

[42] F. Aloise *et al.*, "Asynchronous P300-based brain-computer interface to control a virtual environment: Initial tests on end users," *Clin. EEG Neurosci.*, vol. 42, no. 4, pp. 219–224, Oct. 2011.

[43] C. Zickler *et al.*, "A brain-computer interface as input channel for a standard assistive technology software," *Clin. EEG Neurosci.*, vol. 42, no. 4, pp. 236–44, 2011.

[44] E. W. Sellers, T. M. Vaughan, and J. R. Wolpaw, "A brain-computer interface for long-term independent home use," *Amyotroph. Lateral Scler.*, vol. 11, no. 5, pp. 449–55, 2010.

[45] R. Leeb *et al.*, "Are we ready? Issues in transferring BCI technology from experts to users," in *Proc. 5th Int. Brain-Computer Interface Conf.*, 2011.

[46] A. Riccio, F. Leotta, S. Tiripicchio, D. Mattia, and F. Cincotti, "Can Severe Acquired Brain Injury Users Control a Communication Application Operated through a P300-Based Brain Computer Interface?" in *Proc. 5th Int. Brain-Computer Interface Conf. 2011*, Graz, Austria, 2011.

[47] D. Mattia, F. Pichiorri, M. Molinari, and R. Rupp, "Brain Computer Interface for Hand Motor Function Restoration and Rehabilitation *Towards Practical Brain-Computer Interfaces*. New York, NY, USA: Springer, 2013, pt. 2, pp. 131–15310.1007978-3-642-29746-5_7. [Online]. Available: http://www.springerlink.com/content/j1847t5654245675/)

[48] A. Kübler, B. Kotchoubey, J. Kaiser, J. R. Wolpaw, and N. Birbaumer, "Brain-computer communication: Unlocking the locked in," *Psychol. Bull.*, vol. 127, no. 3, pp. 358–375, 2001.

[49] G. Pfurtscheller *et al.*, "The hybrid BCI," *Front. Neurosci.*, vol. 4, no. 30, 2010, 10.3389/fnpro.2010.00003.

[50] G. Müller-Putz *et al.*, "Tools for brain-computer interaction: A general concept for a hybrid BCI," *Front. Neuroinf.*, vol. 5, no. 30, pp. 1–10, 2011.

[51] C. Breitwieser, I. Daly, C. Neuper, and G. Müller-Putz, "Proposing a standardized protocol for raw biosignal transmission," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 3, pp. 852–859, 2012.

[52] S. G. Mason and G. E. Birch, "A general framework for brain-computer interface design," *IEEE Trans. Neural Syst. Rehab. Eng.*, vol. 11, no. 1, pp. 70–85, 2003.

[53] O. Flemisch *et al.*, "The H-Metaphor as a guideline for vehicle automation and interaction," in *NASA, NASA/TM-2003-212672*, 2003

[54] D. Vanhooydonck, E. Demeester, M. Nuttin, and H. Van Brussel, "Shared control for intelligent wheelchairs: An implicit estimation of the user intention," in *Proc. 1st Int. Workshop Adv. Service Robot.*, 2003, pp. 176–182.

[55] J. R. Wolpaw, "Brain-computer interfaces as new brain output pathways," *J. Physiol.*, vol. 579, pt. 3, pp. 614–619, 2007.

[56] K. D. Anderson, "Targeting recovery: Priorities of the spinal cord-injured population," *J. Neurotrauma*, vol. 21, pp. 1371–83, 2004.

[57] G. J. Snoek, M. J. Ijzerman, H. J. Hermens, D. Maxwell, and F. Biering-Sorensen, "Survey of the needs of patients with spinal cord injury: Impact and priority for improvement in hand function in tetraplegics," *Spinal Cord*, vol. 42, pp. 526–532, 2004.

[58] M. B. Popovic, D. B. Popovic, T. Sinkjaer, A. Stefanovic, and L. Schwirtlich, "Clinical evaluation of functional electrical therapy in acute hemiplegic subjects," *J. Rehab. Res. Dev.*, vol. 40, pp. 443–453, 2003.

[59] D. Popovic *et al.*, "Clinical evaluation of the bionic glove," *Arch. Phys. Med. Rehab.*, vol. 80, pp. 299–304, 1999.

[60] G. Alon and K. McBride, "Persons with C5 or C6 tetraplegia achieve selected functional gains using a neuroprosthesis," *Arch. Phys. Med. Rehab.*, vol. 84, pp. 119–124, 2003.

[61] M. Rohm *et al.*, "Hybrid brain-computer interfaces and hybrid neuroprostheses for restoration of upper limb functions in individuals with high-level spinal cord injury," *Artif. Intel. Med.*, vol. 59, no. 2, pp. 133–142, 2013, 10.1016/j.artmed.2013.07.004PMID: 24064256.

[62] M. Rohm *et al.*, "Modular FES-hybrid orthosis for individualized setup of BCI controlled motor substitution and recovery," *Int. J. Bioelectromagn.*, vol. 13, pp. 127–128, 2011.

[63] G. R. Müller-Putz, R. Scherer, G. Pfurtscheller, and R. Rupp, "Brain-computer interfaces for control of neuroprostheses: from synchronous to asynchronous mode of operation," *Biomed. Tech.*, vol. 51, pp. 57–63, 2006.

[64] Z. Wu *et al.*, "The convergence of machine and biological intelligence," *IEEE Intell. Syst.*, vol. 28, no. 5, pp. 28–43, 2013, 10.1109/MIS.2013.137.

[65] R. Leeb, H. Sagha, R. Chavarriaga, and J. d. R. Millán, "A hybrid brain-computer interface based on the fusion of electroencephalographic and electromyographic activities," *J. Neural Eng.*, vol. 8, no. 2, p. 025011, 2011.

[66] R. Leeb *et al.*, "Transferring brain-computer interfaces beyond the laboratory: Successful application control for motor-disabled users," *Artif. Intell. Med.*, vol. 59, no. 2, pp. 121–132, 2013.

[67] G. Rogova and V. Nimier, "Reliability in information fusion: Literature survey," in *Proc. 7th Int. Conf. Inf. Fusion*, 2004, pp. 1158–1165.

[68] N. A. Dimitrova and G. V. Dimitrov, "Interpretation of EMG changes with fatigue: Facts, pitfalls, and fallacies," *J. Electromyog. Kinesiol.*, vol. 13, no. 1, pp. 13–36, 2003.

[69] G. Schalk, J. R. Wolpaw, D. J. McFarland, and G. Pfurtscheller, "EEG-based communication: Presence of an error potential," *Clin. Neurophysiol.*, vol. 111, no. 12, pp. 2138–2144, 2000.

[70] P. W. Ferrez and J. d. R. Millán, "Error-related EEG potentials generated during simulated brain-computer interaction," *IEEE Trans. Biomed. Eng.*, vol. 55, pp. 923–929, 2008.

[71] P. W. Ferrez and J. d. R. Millán, "Simultaneous real-time detection of motor imagery and error-related potentials for improved BCI accuracy," in *Proc 4th Int. Brain-Computer Interface Workshop*, Graz, Austria, 2008b, pp. 197–202.

[72] R. Chavarriaga and J. d. R. Millán, "Learning from EEG Error-related Potentials in Noninvasive Brain-Computer Interfaces," *IEEE Trans. Neural Syst. Rehab. Eng.*, vol. 18, no. 4, pp. 381–388, 2010.

[73] B. Blankertz *et al.*, "BCI bit rates and error detection for fast-pace motor commands based on single-trial EEG analysis," *IEEE Trans. Neural Syst. Rehab. Eng.*, vol. 11, no. 2, pp. 127–131, 2003.

[74] R. Leeb, M. Lancelle, V. Kaiser, D. Fellner, and G. Pfurtscheller, "Thinking Penguin: Multi-modal brain-computer interface control of a VR Game," *IEEE Trans. Computat. Intell. AI Games*, vol. 5, no. 2, pp. 117–128, 2013.

[75] G. Pfurtscheller and T. Solis-Escalante, "Could the beta rebound in the EEG be suitable to realize a 'brain switch'?" in *Clin. Neurophysiol.*, vol. 120, pp. 24–29, 2009.

[76] S. Perdikis *et al.*, "Clinical evaluation of BrainTree, a motor imagery hybrid BCI speller," *J. Neural Eng.*, vol. 11, no. 3, p. 036003, 2014.

[77] G. Dornhege, B. Blankertz, G. Curio, and K.-R. Müller, "Boosting Bit Rates in Noninvasive EEG single-trial classifications by feature combination and multi-class paradigms," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 993–1002, 2004.

[78] A. Kübler, N. Neumann, B. Wilhelm, T. Hinterberger, and N. Birbaumer, "Predictability of brain-computer communication," *J. Psychophysiol.*, vol. 18, no. 2–3, pp. 121–129, 2004.

[79] B. Rebsamen *et al.*, "A brain controlled wheelchair to navigate in familiar environments," *IEEE Trans. Neural Syst. Rehab. Eng.*, vol. 18, no. 6, pp. 590–598, 2010.

[80] G. Vanacker *et al.*, "Context-based filtering for assisted brain-actuated wheelchair driving," *Computat. Intell. Neurosci.*, 2007.

[81] T. Carlson and J. d. R. Millán, "Brain-controlled wheelchairs: A robotic architecture," *IEEE Robot. Autom. Mag.*, vol. 20, no. 1, pp. 65–73, 2013.

[82] J. Höhne *et al.*, "Motor imagery for severely motor-impaired patients: Evidence for brain-computer interfacing as superior control solution," *PLoS One*, vol. 9, no. 8, 2014, 10.1371/journal.pone.0104854.

[83] A. Riccio *et al.*, "Workload measurement in a communication application operated through a P300-based brain-computer interface," *J. Neural Eng.*, vol. 8, no. 2, p. 025028, 2011.

[84] F. I. Mahoney and D. W. Barthel, "Functional evaluation: The barthel index," *Maryland State Med. J.*, vol. 14, pp. 61–65, 1965.

[85] S. G. Hart, "Nasa-task load index (nasa-tlx); 20 years later," in *Proc. Human Factors Ergonom. Soc. Annu. Meeting*, 2006, vol. 50, no. 9, pp. 904–908.

[86] S. Fazli *et al.*, "Enhanced performance by a Hybrid NIRS-EEG Brain Computer Interface," *NeuroImage*, vol. 59, no. 1, pp. 519–529, 2012.

[87] M. A. Dimyan and L. G. Cohen., "Neuroplasticity in the context of motor rehabilitation after stroke," *Nature Rev. Neurol.*, vol. 7, no. 2, pp. 76–85, 2011.

[88] P. Langhorne, F. Coupar, and A. Pollock, "Motor recovery after stroke: A systematic review," *The Lancet. Neurol.*, vol. 8, no. 8, pp. 741–754, 2009.

[89] J. J. Shih, D. J. Krusienski, and J. R. Wolpaw, "Brain-computer interfaces in medicine," *Mayo Clin. Proc.*, vol. 87, no. 3, pp. 268–279, 2012.

[90] S. R. Zeiler and J. W. Krakauer, "The interaction between train-ing and plasticity in the poststroke brain," *Current Opinion Neurol.*, vol. 26, no. 6, pp. 609–616, 2013.

[91] P. Bünau, F. C. Meinecke, F. Kiraly, and K.-R. Müller, "Finding stationary subspaces in multivariate time series," *Phys. Rev. Lett.*, vol. 103, p. 214101, 2009.

ABOUT THE AUTHORS

Gernot Müller-Putz (Member, IEEE) received the M.Sc. and Ph.D. degrees in 2000 from Graz University of Technology (TU Graz), Austria, in 2000 and 2004, respectively, He received the "venia docendi" for medical informatics at the faculty of computer science from TU Graz, in 2008.

He is head of the Institute for Knowledge Discovery and its associated BCI Lab. Since October 2014, he has been full professor for semantic data analysis. He has gained extensive experience in the field of biosignalanalysis, brain–computer interface research, EEG-based neuroprosthesis control, hybrid BCI systems, the human somatosensory system, and assistive technology over the past 15 years. He has also managed several national and international projects and is currently partner in 2 EU FP7 projects (BackHome, ABC) and coordinator of BNCI Horizon 2020. Recently, he received a Horizon 2020 project, MoreGrasp, which started in March 2015 and is coordinated by him. He organized and hosted six international Brain-Computer Interface Conferences over the last 13 years in Graz, Austria, the last one in September 2014 in Graz, Austria. He is also a steering board member for the International BCI Meeting, which takes place in the United States usually every three years (last time in 2013). He is review editor of *Frontiers in Neuroprosthetics*, and since 2014, he has been an Associate Editor of the *Brain-Computer Interface Journal* and of the IEEE Transactions on Biomedical Engineering.

Robert Leeb (Member, IEEE) received the M.Sc. in electrical and biomedical engineering from Graz University of Technology, Austria, and received the Ph.D. degree in computer science, also from Graz University of Technology, Austria.

He is scientist and biomedical engineer at the Center for Neuroprosthetics at École Polytechnique Fédérale de Lausanne, Switzerland, where he works on the transfer of brain–computer interface (BCI) technology towards its clinical partner at the Clinique Romande de Réadaptation (SUVA) in Sion. Furthermore, he is senior postdoctoral researcher at the Chair in Non-Invasive Brain-Machine Interface at École Polytechnique Fédérale de Lausanne in Switzerland, where he works on hybrid brain–computer interfaces and the transfer of BCI technology towards patient applications. His research interests include brain-computer interfaces (BCI) systems, neurorehabilitation devices, biosignal processing, hybrid BCI approaches, multimodal human computer interaction, and virtual reality systems.

Michael Tangermann graduated in 2000 from the University of Tübingen in computer science (diploma, major) and biology (minor). He received the Ph.D. in 2007 on his research on novel machine learning approaches for brain–computer interface (BCI) systems in the lab of Prof. Dr. Wolfgang Rosenstiel (University of Tübingen), performed in close cooperation with the labs of Prof. Dr. Niels Birbaumer (University of Tübingen) and Prof. Dr. Bernhard Schölkopf (Max-Planck Institute for Empirical Inference, Tübingen).

From 2005 to 2013, he was a member of the Berlin BCI (BBCI) research lab (Prof. Dr. Klaus-Robert Müller and Prof. Dr. Benjamin Blankertz), first at Fraunhofer FIRST.IDA then at the Technical University of Berlin, Germany, Department Machine Learning. Since 2013, he has been heading the brain state decoding research lab (http://www.bsdlab.uni-freiburg.de) at the University of Freiburg, Germany. Within the cluster of excellence BrainLinks-BrainTools, he investigates novel machine learning approaches for BCI, especially in the context of clinical BCI applications. He actively supports the scientific community by co-organizing the BBCI data analysis competitions, BCI-related workshops and reviewing activity. He is associate editor for *Frontiers*, has hosted a special issue on the latest BCI competition and engages as an editorial board member of "Brain-Computer Interfaces." His interests are in BCI-supported rehabilitation after stroke, auditory BCI paradigms, patient BCI, covariates of BCI performance, adaptive decoding of brain states, analysis of non-stationary brain signals (EEG-, MEG-, and ECoG data), mental state monitoring for user interface design.

Johannes Höhne received the B.Sc. degree in bioinformatics from the Free University Berlin, Germany, in 2007, and the M.Sc. degree in computational neuroscience from the Bernstein Center for Computational Neuroscience (BCCN), Berlin, Germany, in 2010. He received the Ph.D. degree from the Technical University of Berlin, Germany, in 2014.

He has been working on machine learning techniques for neurotechnology. His current research interests include neuroimaging and auditory brain–computer interfacing.

Andrea Kübler received the Ph.D. degree and is a biologist and psychologist.

She is an Associate Professor at the University of Würzburg, Institute of Psychology, and her major research topics within the field of BCI are psychological aspects, and neuroscientific basis of BCI control and studies with patients in the field. She is working on using neurofeedback for communication, rehabilitation and therapy, i.e., for replacing and improving lost or impaired function.

Febo Cincotti received the M.Sc. degree in biomedical engineering and the Ph.D. degree in biophysics.

He is an assistant professor at the Sapienza University of Rome. His research interest include the design and assessment of methods and applications of neurophysiologic biosignal processing, including real-time brain–computer interfaces (BCIs). He is the coauthor of over 200 papers in the field of biomedical engineering. He is/was principal investigator in several EU projects, in the context of which he proposed new clinical applications of BCIs. He was coordinator of an national research project on the use of BCIs for domotic control, and received grants from the Italian ministries of health and education. In 2013, he received the National Scientific Habilitation as full professor. He is a senior research scientist and co-founder of the Neuroelectrical Imaging and BCI lab at the Santa Lucia Foundation of Rome.

Donatella Mattia (Member, IEEE) received the M.D. degree from the University of Rome "Sapienza", Italy in 1987. In 1991, she became neurologist at the same university and received the Ph.D. degree in "physiopathology of movement disorders" in 1996, from the Department of Neuroscience, "Sapienza" University of Rome.

During her Ph.D. program, she was a research fellow at the Montreal Neurological Institute and Department of Neurology and Neurosurgery, McGill University, Montréal QC, Canada. She is currently the director of the Laboratory of Neuroelectrical Imaging and Brain Computer Interface, at the Fondazione Santa Lucia, IRCCS, Rome, Italy. Her research interests are focused on advanced EEG signal processing to investigate the basis of human motor and cognitive function and application of the EEG-based BCI technology in a clinical setting as rehabilitation tool.

Rüdiger Rupp (Member, IEEE) received the diploma degree in electrical engineering with focus on biomedical engineering and the Ph.D. degree from the Karlsruhe Institute of Technology (KIT), Germany, in 1994 and 2008, respectively.

From 1994 to 1996, he was a research assistant at the Institute for Biomedical Engineering and Biocybernetics (Prof. G. Vossius) at KIT. Since 1996, he has been with the Spinal Cord Injury Center (Prof. N. Weidner) of Heidelberg University Hospital, Germany, where he holds the position as the head of the "Experimental Neurorehabilitation" group. He is author of more than 100 journal articles and book chapters and holds two patents. His research is dedicated to the development of innovative technology to help individuals with spinal cord injury (SCI). His main research interests include upper extremity neuroprostheses, application of functional electrical stimulation for therapeutic purposes, development and clinical validation of novel methods and devices for locomotion therapy, gait analysis and movement feedback in incomplete SCI and realization of software projects for standardized documentation of the rehabilitation outcome.

Dr. Rupp is member of IFESS, VDE, DMGP, DGOOC, ISCoS and ASIA. He received the Innovation Award for Medical Technology from the German Federal Ministry of Research and Education (BMBF) in 2005, the Konrad-Biesalski Award from the German Society for Orthopedics and Orthopedic Surgery (DGOOC) and the Innovation Award from the German Spinal Cord Injury Foundation (DSQ) both in 2008.

Klaus-Robert Müller (Member, IEEE) studied physics in Karlsruhe from 1984 to 1989 and received the Ph.D. degree in computer science at Technische Universität Karlsruhe in 1992.

He has been a professor of computer science at Technische Universität Berlin, Germany, since 2006; at the same time he has been the director of the Bernstein Focus on Neurotechnology Berlin, Germany. After completing a postdoctoral position at GMD FIRST in Berlin, he was a research fellow at the University of Tokyo, Japan, from 1994 to 1995. In 1995, he founded the Intelligent Data Analysis group at GMD-FIRST (later Fraunhofer FIRST) and directed it until 2008. From 1999 to 2006, he was a professor at the University of Potsdam. His research interests are intelligent data analysis, machine learning, signal processing, and brain-computer interfaces.

Dr. Müller was awarded the 1999 Olympus Prize by the German Pattern Recognition Society, DAGM, and, in 2006, he received the SEL Alcatel Communication Award. In 2014 he received the Berliner Forschungspreis des regierenden Bürgermeisters. In 2012, he was elected to be a member of the German National Academy of Sciences-Leopoldina.

José del R. Millán (Senior Member, IEEE) received the Ph.D. degree in computer science from the University Politècnica de Catalunya, Barcelona, Spain, in 1992.

He is with the Defitech Chair in Brain-Machine Interface, Center for Neuroprosthetics, École Polytechnique Fédérale de Lausanne (EPFL) where he explores the use of brain signals for multimodal interaction and, in particular, the development of noninvasive brain-controlled robots and neuroprostheses. In this multidisciplinary research effort, he has brought together his pioneering work on the two fields of brain–machine interfaces and adaptive intelligent robotics. He was a research scientist at the Joint Research Centre of the European Commission in Ispra, Italy, a senior researcher at the Idiap Research Institute in Martigny, Switzerland, and a visiting scholar at the Universities of Stanford and Berkeley of California, as well as at the International Computer Science Institute in Berkeley, CA, USA. His research on brain–machine interfaces was nominated finalist of the European Descartes Prize 2001 and he has been named Research Leader 2004 by the journal Scientific American for his work on brain-controlled robots.

Dr. Millán is the recipient of the IEEE-SMC Nobert Wiener Award 2011 for his seminal and pioneering contributions to noninvasive brain–machine interfaces.