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Improving Continuous Motor Imagery-Controlled Applications with Hybrid Brain-Computer Interface Design Principles

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Abstract

Although brain-computer interfaces (BCIs) become more and more sophisticated these days, low reliability and performance are still issues that have not yet been completely solved. Recently, researchers tended to apply hybrid BCI technology to increase the performance of BCIs. In hybrid BCIs (hBCIs), BCI channels are combined with other channels which can be additional BCI channels or signals from different sources. In an hBCI, the BCI does no longer have to function as a stand-alone application but can be supported by other signals.

The aim of this thesis was to develop and evaluate applications that are based on hBCI technology. A first goal was to develop a monitoring system that can be used to determine the quality of input signals. If signals are combined in an hBCI system, it is useful to know how well a given signal is suited to control an application. Quality ratings of two input signals, one of which BCI, were successfully used to switch between input signals. These quality ratings were based on individual characteristics of the input signals, such as instabilities or lack of activity, and were used to assess the likelihood of each input signal to be suitable as a control signal.

Special interest was focused on the detection of error potentials (ErrPs) during BCI applications. Detecting errors in a BCI can be one way to increase its performance. This procedure can also be considered as a type of hBCI. ErrPs have already been successfully detected in BCIs with discrete feedback. One important aim of this thesis was to use error detection in continuous BCI applications. These continuous applications are especially important for functional assistive devices, for example neuroprostheses or wheelchairs.

The main strategy for successful detection of errors in continuous feedback was to provide additional discrete feedback of correct or erroneous actions. Moreover, a combination of multiple events instead of single trials proved to result in significantly higher detection rates of erroneous events compared to single trial analysis. This novel method, termed "multiple events method", offers new possibilities for error detection in applications for which this was not feasible up to now.

Another important point was the individualized design of BCIs for end-users. The thesis provides two examples that were designed specifically around the end-users' abilities. In one example BCI was used as an optional signal, whereas in another one BCI was the main control signal but was supported by other signals. hBCI principles were applied in both examples.

Kurzfassung

Gehirn-Computer-Schnittstellen (Brain-Computer Interfaces, BCIs) haben sich in den letzten Jahren ständig weiterentwickelt. Dennoch sind eine nicht hundertprozentige Verlässlichkeit und suboptimale Performance noch immer Probleme, die bisher nicht vollständig gelöst werden konnten. In letzter Zeit haben sich besonders hybride BCIs (hBCIs) immer mehr etabliert, deren Ziel es ist, die Funktionalität von BCIs zu verbessern. In einem hBCI werden BCI-Kanäle mit anderen Kanälen kombiniert. Diese Kanäle können andere BCI-Kanäle sein, aber auch Signale, die von anderen Quellen stammen. Das Besondere an hBCIs ist, dass das BCI nun nicht mehr als alleinstehendes System operieren muss, sondern durch die anderen Kanäle unterstützt werden kann.

Das Ziel dieser Dissertation ist es, funktionelle hBCI-Applikationen zu entwickeln und zu evaluieren. In einem ersten Schritt ging es darum, einen Weg zu finden, wie man die Qualität von beteiligten Kanälen in einem hBCI bewerten kann. Werden zum Beispiel mehrere Kanäle abwechselnd für die Steuerung einer Applikation verwendet, ist es sehr nützlich, wenn man jederzeit weiß, wie gut das aktuelle Steuersignal gerade geeignet ist, um die Applikation zu steuern. Es konnte erfolgreich ein hBCI-System vorgestellt werden, das in der Lage war, zwischen zwei Steuersignalen hin- und herzuschalten, je nach aktuellen Qualitätsbewertungen.

Besonderes Interesse galt der Verwendung von Fehlerpotentialen (Error Potentials, ErrPs) in BCI-Applikationen. Auch die Inkludierung dieser Potentiale kann als hBCI bezeichnet werden, da eine zusätzliche Informationsquelle eingebunden wird, die die Performance der Applikation erhöhen kann. Genauer gesagt kann man durch die Erkennung von Fehlern selbige entweder ausbessern oder rückgängig machen. ErrPs wurden bereits erfolgreich in BCI-Applikationen mit diskretem Feedback detektiert. Allerdings geht der Trend immer mehr in Richtung kontinuierlicher Applikationen. Beispiele für solche Applikationen sind Rollstühle oder Neuroprothesen, die sehr wichtige Hilfsmittel für Personen, die für die Verwendung von BCIs in Frage kommen, darstellen können. Daher widmet sich ein großer Teil dieser Dissertation der Detektion von ErrPs in eben solchen kontinuierlichen BCI-Applikationen.

Die Hauptstrategie, um Fehler in kontinuierlichen Applikationen detektieren zu können, war die Verwendung von zusätzlichem diskreten Feedback. Außerdem wurde eine neue Methode entwickelt, bei der nicht mehr nur einzelne Ereignisse klassifiziert wurden, sondern eine Serie von Ereignissen. Damit konnte die Klassifikationsgenauigkeit von fehlerhaften Vorgängen signifikant erhöht werden. Diese neue Methode, die sogenannte "Multiple Events Method", bietet neue Möglichkeiten, in Zukunft Fehler auch in kontinuierlichen BCI-Applikationen zu detektieren, bei denen dies bisher nicht praktikabel war.

Ein weiterer wichtiger Punkt dieser Dissertation behandelt das individualisierte Design von BCIs für Endanwender. Es hat sich gezeigt, dass BCIs speziell an die Bedürfnisse und Fähigkeiten von diesen Anwendern angepasst werden müssen. Es werden zwei verschiedene Strategien behandelt, die BCI sowohl als Hauptsteuerungssignal als auch als Untertützungssignal verwenden. Beide Applikationen basieren auf der Verwendung von hBCI-Technologie.

Contents

Acronyms

Acc accuracy
ACC anterior cingulate cortex
ALS amyotrophic lateral sclerosis
ANN artificial neural network
AR autoregressive
BCI brain-computer interface
BOLD blood-oxygen-level dependent
CAR common average reference
CNS central nervous system
CSP common spatial patterns
ECoG electrocorticogram
ECS error correction system
EEG electroencephalogram
EMG electromyogram
EOG electrooculogram
EP evoked potential
EPSP excitatory postsynaptic potential
ERD event-related desynchronization
ERN, Ne error-related negativity
ERP event-related potential
ErrP error potential
ERS event-related synchronization
FES functional electrical stimulation
fMRI functional magnetic resonance imaging
fNIRS functional near infrared spectroscopy
FN false negative
FP false positive
hBCI hybrid brain-computer interface
JS joystick
LDA linear discriminant analysis
MEG magnetoencephalogram
ME multiple events
MI motor imagery
MRCP movement-related cortical potential
NIRS near infrared spectroscopy
Pe error positivity
PLV phase-locking value
SCI spinal cord injury
SE single event

sLDA shrinkage linear discriminant analysis
SMR sensorimotor rhythm
SNR signal-to-noise ratio
SSAEP steady-state auditory evoked potential
SSEP steady-state evoked potential
SSSEP steady-state somatosensory evoked potential
SSVEP steady-state visual evoked potential
SVM support vector machine
TN true negative
TOBI tools for brain-computer interaction
TP true positive

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1. Introduction

This thesis summarizes work dedicated to improving continuous motor imagery (MI)-controlled brain-computer interfaces (BCIs) with hybrid BCI technology. A main focus lies on automated error detection during functional BCIs. The first chapter gives an overview of BCI in general, the hybrid BCI approach, the integration of error detection into BCIs, and the neuroprosthesis as an application for spinal cord injured end-users. Chapter 2 introduces publications written during the course of the thesis. Chapter 3 discusses how much progress the different publications achieved in advancing towards the initial goal.

1.1. Brain-Computer Interface (BCI)

For people with severe disabilities caused by the effects of diseases, such as strokes, or traumatic events, it can be very difficult or even impossible to interact with their environment due to constrained motor functions. Which motor functions are restricted in particular can vary considerably and depends on the area affected by stroke, the height of a lesion caused by a spinal cord injury (SCI), or the progression of a disease such as amyotrophic lateral sclerosis (ALS). As long as there are some residual motor functions left, these can be supported by a variety of assistive devices [29, 119]. However, the more motor functions are lost, the smaller the range of suitable assistive technology becomes.

In the worst case without any motor functions available, only assistive devices remain that do not require any muscular activity at all. These devices have to rely on detecting mental activity and are therefore called brain-computer interfaces (BCIs). A BCI offers potential end-users with severe disabilities additional means of non-muscular communication or control channels [47, 73, 74, 90, 101, 155]. Lately, the field of application for BCIs also includes healthy users as a target group. Here, BCIs can be used to improve or enhance neuromuscular performances, for example by increasing attention in difficult tasks. Another category involves the use of BCIs in games or in other recreational applications [14]. BCIs have first been mentioned in literature in the seventies [149]. Since then, the number of research labs working with BCIs has been growing constantly. BCIs generally translate physiological processes inside the brain that are caused by intentional or reactive mental activity into control commands. Mental activity can, for example, affect the firing of neurons and the variations in blood flow. These physiologic changes can be detected with appropriate sensors.

A BCI is a closed loop system. Cognitive processes, intentional or attention-based reactions, of the user are acquired, processed, and translated into control commands.

These commands are then used to operate a wide range of different applications. These applications deliver feedback which, in turn, can influence further behavior of the user. By closing the loop this way, the user can adapt to the BCI system, whereas machine learning algorithms allow the system to adapt to the user. The concept of a BCI is visualized in Figure 1.1.

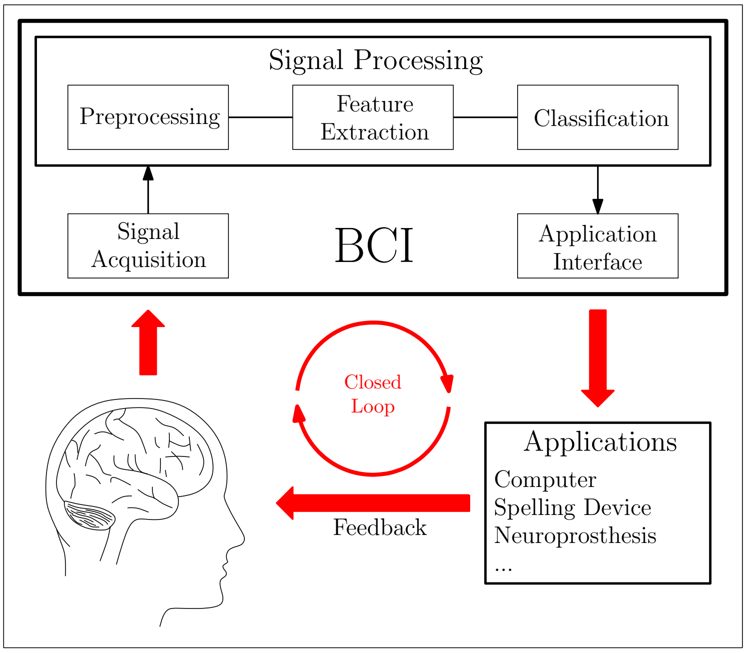

Figure 1.1.: Basic scheme of a BCI. Brain signals from the user are acquired and processed to determine the user's intention. Via an application interface commands are delivered to the application which provides feedback to the user, thereby closing the loop.

BCIs can be designed in many different forms, depending on the combination of characteristics that altogether amount to the BCI system of choice. These characteristics include: (1) the type of the brain signal; (2) the way the selected signal is recorded; (3) the experimental strategy; (4) the mode of operation which can be synchronous or asynchronous; (5) the type of feedback; and (6) the way the signals are processed, Figure 1.2. These characteristics are explained in more detail in the following sections.

1.1.1. Type of Brain Signal and Recording

The decision on which type of brain signal to acquire is usually predetermined by the available equipment. Brain activity affects processes in the brain on many different levels: neurons fire differently in particular situations and blood flow and oxygen saturation changes in active areas. Most common for BCIs is the use of electrical signals since these facilitate a direct measurement of neuronal activity and have a high time resolution. Electrical signals are generated by excitatory postsynaptic potentials (EPSPs) that trigger action potentials of neurons. The electrical activity can be measured with electrodes. Summed potentials on the scalp

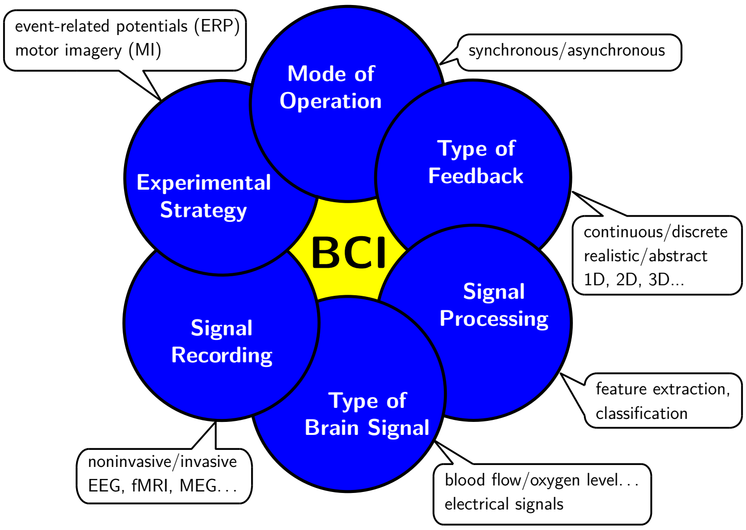

Figure 1.2.: Characteristics of a BCI.

of the subjects are measured with an electroencephalogram (EEG) and directly on the cortex with an electrocorticogram (ECoG), e.g. [78, 125]. Electrical signals of single neurons or clusters of neurons can be measured deep inside the brain with multi- or single-unit electrodes [55, 84]. Here, the sensors can measure single action potentials instead of summed potentials.

EEG is a noninvasive technique, whereas ECoG and electrodes inside the cortex require invasive procedures. In noninvasive BCIs electrodes can be placed on the head without any physical harm to the patient. Invasive BCIs require penetration of the skull and, for multi- or single-unit electrodes, also of the cortex itself. The benefit of these invasive techniques is, however, a higher signal-to-noise ratio (SNR). Electrodes can be placed in close proximity to the source of the signal which is otherwise heavily deteriorated by passing through tissue. However, in spite of this disadvantage, noninvasive techniques offer the only possibility for potential end-users to benefit from BCIs without the need to undergo surgical procedures. EEG-based BCIs can be used at home without professional assistance, e.g. [57, 138], and EEG recording equipment is affordable for private citizens. In the near future, home-use might no longer be limited to noninvasive BCIs: an ongoing clinical trial aims to test an ECoG-based BCI system that can be used by locked-in patients at home (`http://clinicaltrials.gov/show/NCT02224469`).

Electrical activity inherently leads to fluctuations of magnetic fields as well. These can be measured by the magnetoencephalogram (MEG), e.g. [86]. Another way to measure neuronal activity is based on indirect measures. Active areas require more oxygen and the resulting hemodynamic response can be measured with methods such as functional near infrared spectroscopy (fNIRS) [7, 60] or functional magnetic resonance imaging (fMRI) [140, 154]. The drawback of these methods is a low temporal resolution and, in case of NIRS, the limited penetration depth of infrared light as light is already heavily attenuated by passing through the skull before reaching the cortex regions of interest.

This thesis focuses exclusively on BCIs based on electrical activity recorded with EEG.

1.1.2. Experimental Strategy

Pfurtscheller et al. [108] declared that a BCI has to meet the following four criteria: 1) activity must be recorded directly from the brain; 2) at least one brain signal that can be modulated intentionally must be used as an input to the BCI; 3) the signal processing must be real time; 4) some type of feedback is mandatory. The brain signals of a BCI user that can be modulated intentionally can stem from different brain resources and require different approaches. This section provides a few examples.

For one, a BCI can be based on oscillations in the brain, for example on oscillations in the sensorimotor cortex. The band power of these oscillations varies when a person is performing movement but also when the movement is only imagined (motor imagery, MI [110, 114]). Areas of the sensorimotor cortex are associated with specific body parts. Hence, it is known where to measure oscillations related to, e.g. hand, feet, or tongue movements. More specifically, band power in the μ-frequency band (8–12 Hz) and partially in the β-band (13–30 Hz) decreases during execution and imagination of movements in relation to the band power in a reference interval before the onset of the execution/imagination. This process is termed event-related desynchronization (ERD) [111, 113]. This decrease of power is followed by an increase of band power mainly in the β-band after termination of the movement or imagination. This effect is called event-related synchronization (ERS) or post-movement β-synchronization (β-rebound) [116]. Band power in the μ-band was also shown to increase after movement in the same area and during movement in surrounding areas, e.g. in the area representing hand movement during tongue or foot MI [109]. ERD and ERS patterns were also successfully measured in MEG data [65]. Oscillations can not only be manipulated by imagination of movement but also by other more or less complicated tasks. Tasks that were shown to be appropriate for manipulating oscillations are, for example, word association, mental subtraction, mental rotation, auditory imagery, or spatial navigation [43].

Another feasible strategy is to design a BCI based on event-related potentials (ERPs) [82]. An ERP is the brain's response to a specific sensory, cognitive, or motor event. An example is the movement-related cortical potential (MRCP) [100] which is triggered by the intention of movement. Evoked potentials (EPs) are a subset of ERPs. As opposed to ERPs, which can be caused by internal and external events, EPs depend on external stimuli. An EP is time- and phase-locked to the external trigger stimulus. A well-known application that uses EPs is the P300 speller [35]. P300 refers to the distinct positive component of the EP which can be found in the EEG 300 ms after the appearance of rare target events, which subjects had focused their attention on. These rare targets are hidden among a sequence of more common non-target events. The underlying design is called the oddball paradigm [143]. The P300 can be observed after visual [161], acoustic [56, 95], or somatosensoric [105] stimuli. P300 BCIs can achieve high classification rates due to the relatively stable appearance of the P300 component and the advantage that time- and phase-locked signals can be averaged for decreasing the SNR [36, 48, 155]. Many research groups aim to increase the functionality of P300 BCIs by trying to find the best way to present stimuli. Small variations of the appearance of stimuli can have strong effects on performance. For example, the use of faces instead of simply highlighting objects of interest in a P300 speller was shown to increase the performance significantly [61]. However, the drawback of P300 BCIs is the need for external stimuli and the need for multiple repetitions to determine the correct intention of the user. Even if a P300 BCI worked on a single trial basis, each stimulus would have to be presented at least once to identify the oddball stimulus.

EPs can be utilized in a different manner as well: in steady-state evoked potentials (SSEPs) analysis. SSEPs can be recorded when a stream of stimuli with a particular frequency is being focused on by the BCI user. In case of a multitude of different streams of stimuli, the stream the user has concentrated their attention on can be detected as the frequency of this particular stream is more pronounced in the EEG than the frequencies of the other streams. The functionality of SSEPs has been tested successfully with different sensory organs: visual with the steady-state visual evoked potential (SSVEP) [24, 87]; auditory with the steady-state auditory evoked potential (SSAEP) [54]; and somatosensory with the steady-state somatosensory evoked potential (SSSEP) [97]. A drawback of SSEPs in general is, similar to P300, the need for external stimuli. These stimuli generate a constant stream of visual effects, acoustic noise, or vibration that can be irritating over time and can distract the users from the very application they want to control.

More recently, an alternative definition of BCIs is finding recognition. Wolpaw & Wolpaw [157] define a BCI as follows:

> "A BCI is a system that measures central nervous system (CNS) activity and converts it into artificial output that replaces, restores, enhances, supplements, or improves natural CNS output and thereby changes the ongoing interactions between the CNS and its external or internal environment."

The main difference to Pfurtscheller's definition is the removal of the need for intentional control. Thereby, a new kind of BCI is legitimized: the passive BCI [160]. Examples of contributions to a passive BCI are: task engagement, alertness, mood, workload, and error recognition [45].

This thesis focuses exclusively on intentional control with MI as the main BCI control strategy. MI has the advantage that it is not depending on external cues or stimuli. The users can decide themselves when to perform BCI commands. This means that, at least theoretically, the BCI can remain active at all times without interfering with normal life. On top of that, for controlling neuroprostheses, MI is less abstract than P300 or SSEP strategies, as it is based on mental tasks similar to those needed to actually use the functions that are substituted by the prosthesis.

1.1.3. Mode of Operation and Type of Feedback

The next critical step when designing a BCI is to choose the mode of operation and an appropriate feedback system. There are many different ways to meet the requirement of a closed loop system. Basically, a BCI can be operated synchronously or asynchronously. A synchronous, or computer-driven, BCI enables user control only in a predefined manner. The users have to wait for certain states of the BCI when they are permitted or requested to perform a certain task. Therefore, brain activity of interest is contained in predefined periods of time. A between classes classification is facilitated because background activity before or after these time periods can be disregarded [10, 102, 114, 122, 156]. Disadvantages are the inherently limited information rate, as users need to wait for external cues, and an unnaturally restricted freedom for the users to autonomously execute commands whenever they would prefer to.

Asynchronous, or user-driven, BCIs can be activated and used on demand. One difficulty here lies in the detection of the so-called idle state, i.e. correctly detecting when the user does not wish to use the BCI [11, 89, 118, 131, 133]. This can either be achieved by a stable design that makes the BCI insusceptible to false positive activations [94], or by including on/off switches which the users can actuate whenever they want to switch from BCI to idle state or vice versa [117, 132].

To accommodate the mode of operation, the feedback has to be customized to fulfill the needs of the according BCI. Feedback systems can be very basic, with just occasional discrete confirmations, or complex graphically elaborate continuous systems. Feedback can be abstract or realistic, such as moving a cursor or moving one's own hand. It can also be the execution of functional operations, such as opening or closing of a hand, writing a letter in a P300 speller, controlling a neuroprosthesis or a BCI-driven wheelchair, or even playing games. The interest in how important feedback really is for learning how to use a BCI has been gaining more and more weight recently, e.g. [2, 46]. It has been shown that feedback, which is close to the very type of action it substitutes, can have beneficial effects on brain activity (e.g. the comparison of a video feedback of a moving hand versus actual movement of one's own hand by functional electrical stimulation (FES) [53]). An appealing, rewarding feedback can also be of advantage when it comes to motivation. For example, the P300 amplitude in an ERP-based BCI was shown to be related to the users' motivation, which can have a positive or negative impact on the performance [64].

1.1.4. Signal Processing

The final important characteristic of the BCI is the processing of recorded data from raw data to the interface commands needed to operate BCI-controlled applications. The signal processing part is composed of preprocessing, feature extraction, and classification, as can be seen in Figure 1.1.

Preprocessing is the first step after raw data were acquired from the biosignal amplifier, although some preprocessing can already be handled within the amplifiers.

Preprocessing is used to increase the SNR and to remove unwanted frequency components and spatial effects. To narrow the frequency band to the range of interest, high pass and low pass filters are applied. High pass filters remove drifts and slow fluctuations caused by sweat or breathing. Low pass filters remove frequency components caused by high frequency noise, e.g. muscular activity. Usually, a country-specific notch filter is applied additionally to filter out 50 or 60 Hz noise caused by the local power supply. Additionally, spatial filters are applied that can attenuate or amplify local patterns [85]. Spatial filters can encompass electrode pairs (bipolar filter), clusters (Laplacian filter), or all electrodes (common average reference (CAR) or common spatial patterns (CSP) [15, 121]).

The next step is to find features in the EEG that best characterize the selected task. This process is called feature selection: features that are relevant for controlling applications remain, while other features are discarded. Selected features can be band powers of specific frequency bands [12, 99, 115], autoregressive (AR) parameters [17, 136], synchrony of signals, for example represented with the phase-locking value (PLV) [18, 72], or parameters in the time domain [150].

After relevant features have been selected, data sets containing these features can be assigned individual class labels by applying so-called classification algorithms. These classification algorithms perform linear or non-linear transformations from features to class labels. The most basic linear procedure is to set a threshold and assign one class label when the feature of interest is below the threshold and another class label if the threshold is exceeded. A common linear procedure is the linear discriminant analysis (LDA) [42] and, more recently, its regularized version, the shrinkage LDA (sLDA) [8]. Here, two distributions of data are separated by a linear hyperplane on the basis of maximizing the variance between the two distributions while minimizing the variance within each distribution. More complex non-linear algorithms such as artificial neural networks (ANN) [51] including restricted Boltzmann machines [130], non-linear support vector machines (SVM) [79, 139], or random forests [1, 144] have also been successfully used in BCI applications. These classification techniques represent only a small sample of suitable choices for BCIs; a more comprehensive review can be found in [83]. The result of the chosen classification procedure is not limited to discrete class labels that identify the data as one of two or more classes. It can also be expressed as a continuous state, e.g. a likelihood between 0–100 % of the current activity to belong to one class. Classification can be permitted only at predefined points in time or constantly, depending on the feedback application of choice.

The whole process of finding relations between brain activity and intention or state of the user is called machine learning [92]. However, these relations may not be constant over time. By operant conditioning users can become better in modulating the necessary brain activity as they potentially adapt to the BCI via observing feedback. Alternatively, or in conjunction with operant conditioning, an adaptive BCI can update its classification rules online [34, 151].

1.2. Automatic Error Detection in BCIs

The characteristics introduced in Sections 1.1.1–1.1.4 define the core of a BCI. However, BCIs can still be expanded by integrating additional mechanisms that can increase the functionality, reliability, or performance of the system. One example is the use of automated error detection (a comprehensive review can be found in [23] or in [148]). Automatic detection as well as optional correction of errors can be realized by identifying specific reactions of the brain to committed or observed errors. These reactions to errors are the so-called error-related potentials or error potentials (ErrPs).

1.2.1. Error Potentials (ErrPs)

ErrPs in brain activity have first been mentioned in literature in the early 1990s [32, 44]. The first measurement of these potentials was conducted in experiments where subjects had to enter inputs under time pressure. Occasional wrong inputs due to the time pressure proved to elicit specific electrical responses that were derived on the scalp over the anterior cingulate cortex (ACC) [103, 146]. This first type of ErrP is called response ErrP [9]. Over time, different experiments dealing with error detection in BCIs have revealed three more types of ErrPs: the feedback ErrP [91], the observation ErrP [134], and the interaction ErrP [19, 39, 40, 41].

Circumstances in which these different types of ErrPs can be triggered affect the possible integration into functional BCIs. Response ErrPs are only triggered after forced choices, which means that the user is dependent on cues from an interface or from an operator. Feedback ErrPs are recorded after subjects were informed about having committed an error, which is not an option for a BCI as we assume that the program is not aware of errors by itself. The observation ErrP can be recorded when subjects observe behavior that they knew was not correct, which was already shown to be useful in BCI applications [59]. The fourth type, the interaction ErrP, is caused by observing the execution of user-generated commands by a control interface in a way that was not intended by the users. In this case, the users have to believe that the mistake is not theirs but caused by the interface which can very well be a BCI.

Several circumstances affect the manifestation of ErrPs. Falkenstein et al. have summarized main factors that contribute to the triggering of strong, and therefore measurable, ErrPs [33]. The authors highlight two temporal components visible in the ErrP waveform which can be recorded over the ACC. The first one is the error related negativity (ERN, or Ne). The maximum peak of this negative component can be found at the frontocentral area of the ACC and is assumed to be triggered by unconscious comparison processes in the brain. This component is also measured after correct events but is stronger in amplitude after observing errors. The amplitude is inversely proportional to the frequency of errors; it decreases if subjects are pressed for time; it increases if errors are unambiguously recognizable as errors; the amplitude also seems to decrease with age. Hajcak et al. found the

ERN to be significantly larger in high-value trials, i.e., in trials where subjects are more motivated not to make errors [49].

The second component is called the error positivity (Pe). The source for this component is located more posterior than the source of the ERN. Falkenstein et al. claim that the cause for this component is the subjective/emotional evaluation of errors [33]. Pe amplitude is also more distinct in case of a lower frequency of errors and decreases with age [31, 103].

The ErrP in the time domain is usually characterized as the difference of error-minus-correct reaction. However, although most of the studies dealing with errors so far have focused mainly on analyzing the ErrP in the time domain, errors can also cause changes in the frequency domain. For example, Cavanagh et al. found an increase in power around 4 Hz and a phase synchronization between the ACC and the frontal cortex [20, 21].

1.2.2. Integrating ErrP Detection into Functional BCIs

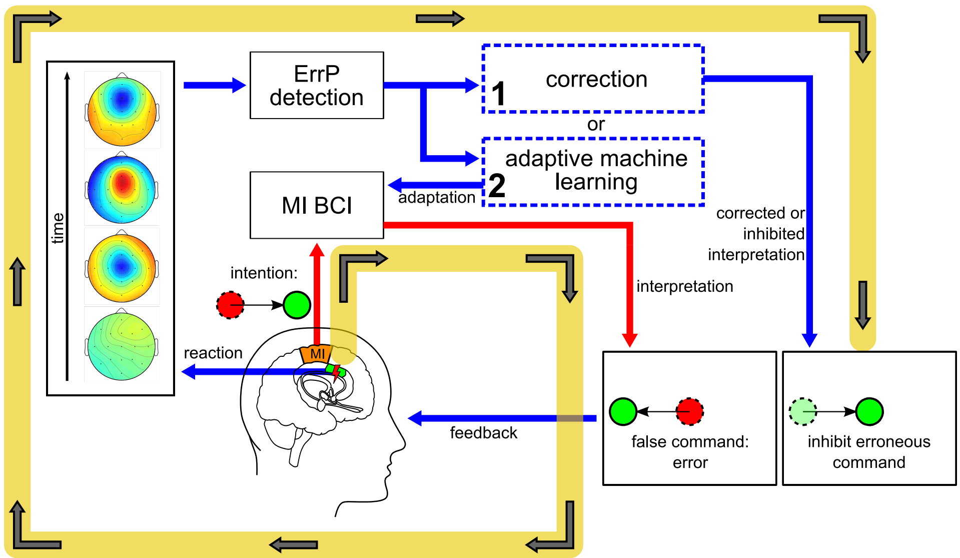

Figure 1.3.: Expanded scheme of a BCI with included error detection. The initial execution of any type of BCI (in this example an MI BCI) is observed by the user via feedback. In case of a wrong interpretation, an ErrP is recorded. The information that the last action was an error can be handled in two different ways: 1) The initial command is inhibit or corrected. Thereby, the negative effect of a wrong command is mitigated and the reliability and performance of the overall BCI increased. 2) The classification procedure of the BCI is adapted via machine learning. Thereby, the next command is less likely to cause an error if the user performs the same mental command. In the long run, this can also increase the reliability and performance of the BCI. The yellow path indicates the process from intention to final execution of an action when the ErrP detection is used to inhibit false commands.

An automatic detection of errors can be useful in all kinds of human-machine interaction [22, 106, 153, 159, 160]. However, a BCI, which is prone to errors and low performance, can certainly benefit the most from this error detection. One of the first endeavors to use, or at least detect, ErrPs in an online BCI was attempted by Schalk et al. [129]. In this study, ErrPs were detected after false, discrete cursor movements. The cursor was controlled via a BCI based on sensorimotor rhythms (SMR). Thereby generated errors were, from the subject's point of view, caused by a mistaken interpretation of commands, which basically describes the occurrence of an interaction ErrP.

The two possible areas of application for online error detection in BCIs are: 1) the automatic correction or inhibition of errors and 2) an adaptive machine learning approach where detected errors update the machine's interpretation of brain signals. The basic scheme of a BCI, augmented with error detection of both kinds, can be seen in Figure 1.3, using the example of a computer-driven MI BCI. In case of the correction or inhibition approach, the process works as follows: the user controls a cursor discretely by modulating brain activity by imagining motor tasks. At predefined times the classifier assigns a class label to the performed mental task which is shown to the user in form of discrete feedback. In this example, the cursor moves either one step to the right or to the left. The presentation of the feedback triggers a reaction which is either positive, when the classification corresponds to the intentions of the user, or negative in case of an error. The time period following the discrete reaction is analyzed by classifying predefined features and the result can either be "ErrP" or "no ErrP". In case the classification detects an ErrP, the previously executed cursor movement is revoked, the cursor returns to its initial position. If preferred, the cursor can also immediately move into the opposite direction. If the error detection is not used to inhibit or correct commands online, the information of positive ErrP detections can be applied in an adaptive BCI. Here, the detection of errors can lead to adaptations of the MI classifier which can affect future interpretations of control commands.

An example for the first area of application is shown in the work of Ferrez et al. [39], who pursued the approach of Schalk et al. [129]. Here, the detection of interaction ErrPs was successfully applied in an online MI BCI, which resulted in an increased bit rate. Ferrez showed that, in a two-class BCI, the most beneficial use of the interaction ErrP is to inhibit the command if an error was detected, instead of selecting the opposite command. This way, negative effects of false positive detections of errors are reduced to a minimum and the potential increase in bit rate is maximized.

Other investigators chose to combine P300-based BCIs with ErrP detection [26, 137, 141, 145]. The inevitable discrete nature of a P300 speller feedback serves as a fitting basis for the implementation of error detection. The selection of a letter results in a discrete feedback after which the brain's response is analyzed for a possible ErrP. In case of a detected error, the letter selection can be revoked or the second-most likely letter can be selected. The proof of a beneficial effect was, for example, shown by Spüler et al. [141], who reported that six ALS patients could increase their bit rate during an online copy spelling task by 0.52 bit/trial when the error correction system (ECS) was activated.

The second area of application is to exploit detected errors for machine learning purposes. Artusi et al. [6] conducted simulations with data from a BCI based on

MRCPs and found a convergence towards the optimal solution when errors were used for adapting classifiers for future BCI trials. Llera et al. [81] demonstrated a significant improvement when comparing static and adaptive classification methods verified by simulations with interaction ErrPs in an MEG-based BCI, which apparently also works in simulations with EEG data [80].

Although the interaction ErrP seems to work in online BCIs, the setting in which the error detection so far has proven to be useful is well-orchestrated to optimize the detection of interaction ErrPs. Examples are the fixation of the error rate for training of ErrP classifiers to around 20 % or the restriction to use discrete feedback only. An important question arises as to whether interaction ErrPs can also be of use if the BCI application is not tailored especially to detect errors, but rather to be functional for the user. This does not concern all types of BCIs, as P300 BCIs, for instance, are already a good match for error detection in their original form. Still, advancement in BCI research relies more and more on continuous and asynchronous control of software and other applications, including assistive devices like neuroprostheses or wheelchairs. In these cases continuous and asynchronous control can offer huge benefits in terms of functionality and autonomy.

The time- and phase-locked nature of ErrPs facilitates detection when the system knows exactly when to look for an error. With continuous, asynchronous feedback the exact point in time of the occurred error is not that trivial to determine. To overcome the need for time- and phase-locked signals, the only way is to rely on signals detected in the frequency domain (as already mentioned in Section 1.2.1). Milekovic et al. [88] analyzed ECoG patterns recorded during a continuous game, although not controlled via BCI, but manually. The investigators detected more than 50 % of two types of errors: outcome errors caused by collisions and execution errors caused by artificially manipulated manual control. These errors were detected within a 6 s long window around the events, indicating that the precise starting time does not have to be known by the system. The same study was reproduced by Spüler et al. [142] with the intent of recording errors with EEG instead of ECoG. Both types of errors (outcome and execution) were detectable. However, locking the classification to the beginning of the event was still more effective than an asynchronous analysis. Interestingly, there was no statistically significant difference in classification accuracies depending on whether temporal and/or spectral features were used in the time- and phase-locked approach.

To conclude and to the author's best knowledge, as of yet, there is no successful implementation of an EEG-based BCI that includes the online detection of errors which are generated within a continuous, asynchronous feedback application.

1.3. Hybrid Brain-Computer Interface (hBCI)

Automatic error detection is just one of many strategies to increase the usefulness and reliability of BCI applications. Error detection is basically just one example of how to make use of additional information in BCIs. The umbrella term for such techniques is the so-called hybrid BCI (hBCI) [90, 93, 108]. The main principle of an hBCI is the combination of a standard BCI with other control or monitoring channels. The idea behind it is that a stand-alone BCI is often not sufficiently adaptable to individual and contextual needs, and control signals derived by mental activity often lack functionality caused by misclassification and generally low bit rates. By including more sources of control and/or information by means of an hBCI, the functionality of a BCI can be greatly increased.

Additional channels can either be used to improve the functionality of the BCI application by supporting BCI control or by influencing BCI choices based on sensory information of the environment. The additional channels can, however, also be used to substitute the BCI channel, in case of lack of concentration or mental fatigue. The other way round is possible as well: BCI can be used to take over once other control channels become unreliable, for instance due to muscular fatigue or spasms.

There are various types of combinations that amount to an hBCI. An hBCI can consist of: (1) different types of BCIs [3, 5], possibly also from different sources, for example EEG and NIRS [37]; (2) a combination of BCI and control channels derived from other biosignals, e.g. electromyogram (EMG) [77] or electrocardiogram (ECG) [132]; (3) BCI and any other control channel powered by remaining muscular activity; (4) a BCI supported by additional information obtained by sensors or derived from contextual situations which can be used to manipulate decisions of the BCI [147]. Error detection is difficult to categorize as it is based on analyzing brain activity but does not constitute a BCI per se. It can also be seen as an additional information source, depending on the current context. According to Pfurtscheller et al., the BCI part in an hBCI has to follow the same rules as any other kind of BCI [108]:

> "(i) the device must rely on signals recorded directly from the brain; (ii) there must be at least one record-able brain signal that the user can intentionally modulate to affect goal-directed behavior; (iii) real time processing; and (iv) the user must obtain feedback."

Apart from that, the definitions for hBCIs are flexible. For instance, different channels can be active simultaneously [16] or sequentially [117].

In the large-scale EU project "Tools for Brain-Computer Interaction (TOBI)" (`www.tobi-project.org`) the project partners expanded the definition of the hBCI to include BCI as an ever-present but optional control channel [93]. If the user does not want to use the BCI, or if the hBCI system detects that the BCI channel is unreliable, it can be deactivated for the present time until the need for BCI arises again eventually.

To make use of this expanded definition, two important components that can be integrated into hBCI systems were defined by the same consortium: the shared control [76] and the fusion logic [77]. These components can be essential for operating a functional hBCI.

Fusion is used to assess different inputs and choose how much weight these inputs can have on decision making. In [77], the weights are continuously adapted depending on the quality of the input. In this case, an MI BCI was combined with an EMG-based control channel. Weights were distributed from ratios of 0:100 % to 100:0 %, including ratios in between. If these weights are limited to binary weights, i.e. either '1' or '0', the fusion can serve as a switch which activates the most appropriate control signal at any given time.

The shared control logic can be applied to facilitate target-oriented BCIs. It depends on contextual information of the immediate environment and aims to simplify complex tasks to easily executable commands. Shared control can also increase safety and reliability of BCIs by prohibiting unsafe commands or inhibiting unnecessary actions. The example described in [147] applies the shared control principle on a mobile robot which can execute complex mobility tasks with a low number of control inputs required from the user.

Further advancement in hBCI research seems promising, given the limitations of stand-alone BCIs. By adding supportive channels, sensors for monitoring, and alternative control channels, the use of a BCI can gain more functionality and reliability. End-users that previously refrained from using BCIs due to an unsatisfying cost-benefit ratio may be convinced to reconsider as long as the BCI part is embedded in an appealing framework.

When designing hBCIs, or BCIs in general, for end-users, it is also important to consider which type of application to control. One important type of application enables end-users to regain control over lost functions of their own body. The following section gives an overview of how this can be achieved by stimulating motor points with electrical currents.

1.4. Functional Electrical Stimulation (FES)

Spinal cord injured individuals have lost the ability to move parts of their body by their own will. The amount of negatively affected functions depend on the level of injury [63]. Function loss of the upper limbs begins with lesions at the superior vertebrae of the thoracic spine (hand muscles) and increases with advanced height of the lesion along the cervical spine from C7–C1. Patients with an injury at level C4 and superior have lost most of their upper limb functions and shoulder movement. The severity of impairment depends on the completeness of the injury as well.

FES can be used to elicit muscle contractions by stimulating motor points in the vicinity of functional, but inaccessible, muscle fibers. Although more dexterous movements can be induced by invasive application of the stimulation electrodes, FES is mostly used with surface electrodes that can be attached within seconds and do not require surgical procedures. Via electrodes, short current pulses (usually biphasic) are delivered to the motor points of intact motor nerves [126]. Depending on the area between the electrodes, the amplitude of the current, the pulsewidth, and the frequency, basic movements can be accomplished. These movements help to reduce muscle atrophy and can even be of assistance in activities of daily life. For example, by stimulating grasp patterns of the hand, spinal cord injured individuals can interact with objects the way they can not without FES.

As the musculature is still functional but cannot be reached via the interrupted efferent pathways, FES is already established as an important tool in rehabilitation to avoid atrophy of unused muscle fibers and to improve remaining functionalities [50]. Assistive FES devices for lower and upper limb rehabilitation are even commercially available, e.g. `www.bioness.com` [52]. Recently, FES has been finding its way into the field of stroke rehabilitation as well [120].

Given the low number of residual muscle functions, control commands from the brain can be used to trigger FES-induced movements. Hence, FES serves as an ideal application to be controlled with a BCI. A first successful implementation of a BCI controlling FES-induced movements is documented in [112]. Here, a spinal cord injured participant, who could not move his hand at all, was able to cycle through lateral grasp patterns with MI, thereby successfully grabbing and moving a cylindrical object voluntarily.

Coupling of BCI and FES has been reported in many subsequent studies, dealing with different strategies of how to utilize BCI and FES. BCI was coupled with FES in stroke rehabilitation for foot movement [30]. An hBCI was used to control opening and closing of the hand by modulating two different types of brain signals [152]. A hybrid orthosis was designed to support BCI-controlled FES [123]. The versatility of stimulated grasp patterns was increased by placing electrodes following a new design, thereby facilitating palmar and lateral grasp with just one electrode layout [127]. Another work deals with the inclusion of temporal decoding of MI commands to add another layer of command for controlling FES neuroprostheses [98]. A comprehensive review of the current state of the art of FES neuroprostheses can be found in [128].

1.5. Aim of this Thesis

One major disadvantage of MI-based BCIs today is still the fact that many people are not able to control them reliably [13]. This insufficient reliability is already an issue in BCI applications that are mainly performed in laboratory environments. However, its consequences are even worse in BCIs that are aimed to be used at the homes of potential end-users. Many researchers attempt to solve this issue with a wide range of different approaches. Better data acquisition devices, more sophisticated signal processing algorithms, and improved BCI paradigms are just some examples of ongoing research approaches.

Lately, the introduction of hBCIs promises new potential benefits regarding BCI performance, functionality, and reliability. The main point of hBCIs is that BCI channels are no longer to be seen as a stand-alone means of control. BCI channels can be of greater value if they are used in a way that maximizes their potential. This could mean that a BCI receives input from other sources to become more reliable, or that the BCI channel itself is used as a source to support other control signals.

The main goal of this thesis is to increase the reliability and functionality of BCIs in general. This goal is taken on in three different approaches, all of them relying on the principles of hBCI design [93].

The first approach deals with the general functionality of an hBCI which combines two control signals that can both be used to control the same application. For a BCI end-user it can be very beneficial to be able to control an application with different strategies. To provide the user with the best suited control signal at any given time it is crucial to automatically evaluate these signals. In the first study, an hBCI system is designed that can evaluate signals based on individual quality measures. Thereby, the hBCI can switch to the alternative control signal in case the current control signal becomes unreliable over time.

The second approach is aimed to increase the reliability of BCIs by detecting and inhibiting erroneous states. Moreover, this ErrP detection should be possible not only in discrete feedback applications but also during asynchronous BCI applications with continuous feedback. Asynchronous and continuous control is especially important for end-users that want to control a hand/arm neuroprosthesis or a BCI-driven wheelchair. A possible solution for detecting errors in continuous feedback is to provide additional discrete feedback. A problem with ErrP detection is an expected low single trial classification accuracy. A new method is aimed to mitigate this issue by combining a series of events instead of single trials for detecting erroneous states.

The third approach involves the potential end-users of BCIs. These end-users have individual abilities and needs that can hardly be considered in generic BCI applications. In fact, it is important to design BCIs specifically for the individual end-users' needs. The thesis is aimed to find individual hBCI applications to control neuroprostheses which incorporate residual muscular functions and BCI tasks, both in varying levels of complexity. These levels of complexity depend on the users' remaining muscular functions and their performance in operating BCIs. The designed applications have to be tested thoroughly in close collaboration with spinal cord injured end-users.

1.6. Organization of the Thesis

Chapter 1 introduces all the topics that appear in this thesis. A general overview of BCIs is given with the main focus on hybrid BCI technology, error detection in BCIs, and FES as an important application for potential end-users. The aim of the thesis is explained: the evaluation of hybrid BCI components like fusion, shared control, specialized applications including automatic error detection and FES neuroprostheses that are designed for quadriplegic end-users.

Chapter 2 includes short summaries of all the publications relevant for the thesis.

Chapter 3 provides a summary and a conclusion for each publication and their impact on the thesis, as well as an overall discussion about the scientific significance of the thesis. The chapter concludes with an outlook to the future of hBCIs.

All publications that have been introduced in Chapter 2 are attached in the appendix.

2. Materials and Methods

2.1. Primary Publications

2.1.1. Switching Between Manual Control and Brain-Computer Interface Using Long Term and Short Term Quality Measures

[68] A. Kreilinger, V. Kaiser, C. Breitwieser, J. Williamson, C. Neuper, and G. R. Müller-Putz. "Switching between manual control and brain-computer interface using long term and short term quality measures." In: *Frontiers in Neuroscience* 5.147 (2012).

When combining multiple control channels in an hBCI, it is important to choose how these channels can be used together in the most meaningful way. This decision has to be tailored to the individual needs of the user. It might be the case that the user is capable of maintaining control of two channels at the same time, or they could be more inclined to use different channels depending on their mental or physical state. For example, a user who has remaining muscular functions is able to use EMG or manual control to operate an application before fatigue makes this endeavor more and more difficult over time. They then could use a BCI channel which relieves physical burden but demands a heavier mental workload.

A type of binary fusion was introduced in this work which manages this type of scenario. Two input channels, manual control (commercial joystick) and MI BCI, were equally qualified to steer a car in a game and could be used to this end alternately. The decision when to use BCI or manual control was based on individual quality measures which rated the quality of each control channel. These measures were customized for each channel individually and depended on: EMG noise, instability, invariability, and bias for the BCI channel; shaking, low amplitude, invariability, and bias for the joystick channel. As soon as a predefined threshold was exceeded, the system automatically switched from one control channel to the next. The scheme of the switching technique is demonstrated in Figure 2.1.

Ten healthy subjects took part in the study. The study demonstrated that the quality measures were feasible to manage switching between input channels. By doing so, scores in the car game could be increased compared to runs without automatic switching.

The publication offered an example of a framework how the fusion of multiple inputs might work by observing characteristics of signals, e.g. variance, bias, noise, or amplitude.

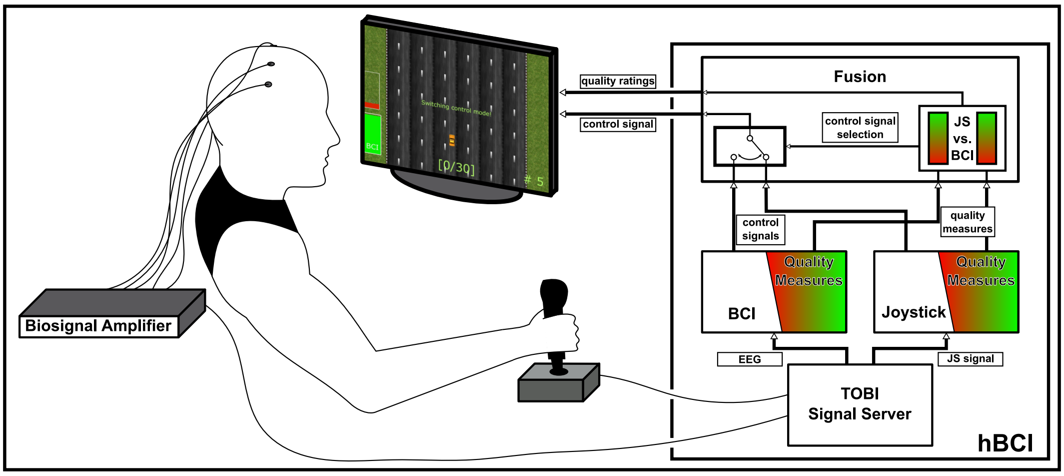

Figure 2.1.: Scheme of switching between two control channels by monitoring individual quality measures. The user can either use BCI or a manual joystick (JS) to control a car game. Whenever the quality rating of the current control channel exceeds a predefined threshold, the fusion switches to the alternative control channel. The user is constantly informed via the feedback about the current control channel and its quality rating.

2.1.2. Error Potential Detection during Continuous Movement of an Artificial Arm Controlled by Brain-Computer Interface

[70] A. Kreilinger, C. Neuper, and G. R. Müller-Putz. "Error potential detection during continuous movement of an artificial arm controlled by brain-computer interface." In: *Medical & Biological Engineering & Computing* 50.3 (2012), pp. 223–230.

The integration of error detection into continuous BCI applications is an important part of this thesis. A neuroprosthesis user can benefit considerably from continuous control, as this will guarantee more natural movements of the assisted limb. When controlling an arm neuroprosthesis, error detection could be useful to indicate when a desired elbow angle is exceeded while moving the arm up or down.

This publication reports on experiments with healthy users who performed MI to control an artificial arm. The movement of the artificial arm was time-coded: the longer MI was detected, the longer the arm would move. Intention and feedback was time-delayed, that is, users tried to imagine MI over a given target time period and then observed the interpretation of the BCI by how long the arm actually moved. Movement was indicated by red and white blinking LEDs in steps of 1 s, foretelling ongoing movement or a soon-to-come stop.

Because subjects knew how long they wanted to control the arm, deviations from a certain expected sequence of LED flashes were assumed to trigger ErrPs. The scheme of the setup is demonstrated in Figure 2.2.

With this discretization of a continuous feedback it was possible to measure different reactions to erroneous LED flashes. Even though detection rates were below expectations, the results of the experiment encouraged further research in the direction of discretization of continuous feedback.

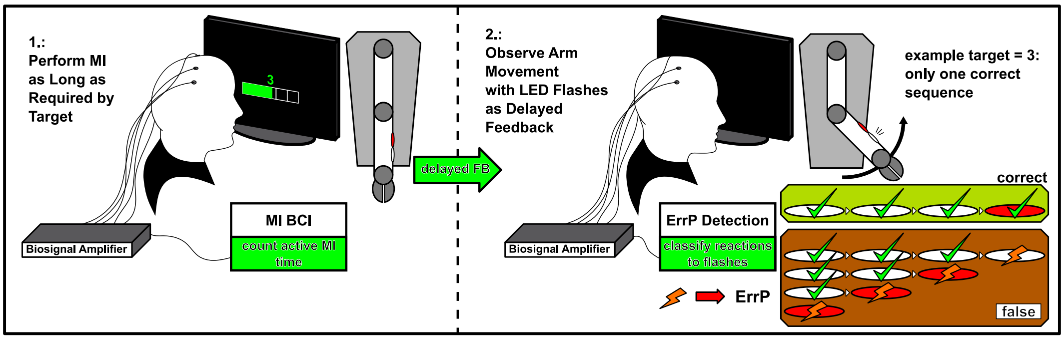

Figure 2.2.: Scheme of the ErrP detection during continuous movement of an artificial arm. In a first part, the subject is required to perform MI as long as the target number indicates, either 1, 2, 3, or 4 s. In the second part, the subject receives delayed continuous and discrete feedback. The artificial arm moves for exactly as long as the BCI detected the ongoing MI. On the moving arm, white and red LEDs show the subject if the arm continues to move for more than 1 s (white) or if it stops within the next second (red). In case of the shown example of a target of 3 s, the subject aims to perform MI for more than 3 s but no longer than 4 s. There is only one correct sequence the LEDs can flash in to indicate a correct performance. If the arm stops too soon, a red flash too early is perceived as an error, whereas if the movement continues for too long, one white flash too many has the same effect.

2.1.3. Neuroprosthesis Control via a Noninvasive Hybrid Brain-Computer Interface

[158] Z. Wu, R. Reddy, G. Pan, N. Zheng, P. F. M. J. Verschure, Q. Zhang, X. Zheng, J. C. Principe, A. Kreilinger, M. Rohm, V. Kaiser, R. Leeb, R. Rupp, and G. R. Müller-Putz. “The convergence of machine and biological intelligence.” In: *Intelligent Systems, IEEE* 28.5 (2013), pp. 28–43.

This work, which is part of a special issue about “The Convergence of Machine and Biological Intelligence”, demonstrates an hBCI design that uses the BCI channel as the main control channel to move a hand and arm neuroprosthesis. The BCI channel is supported by shared control. The shared control logic constantly evaluates information from a hybrid orthosis which includes an angle sensor and a mechanical lock. Commands from the BCI are interpreted differently, according to the current state of the neuroprosthesis. The scheme is shown in Figure 2.3.

This example introduces an hBCI application for BCI users who no longer have the possibility to use control signals other than BCI. In this case, relying on information from an angle sensor and context, the shared control logic can be applied to increase the functionality of this only remaining means of control.

2.1.4. Single versus Multiple Events Error Potential Detection in a BCI-controlled Car Game with Continuous and Discrete Feedback

[66] A. Kreilinger, H. Hiebel, and G. R. Müller-Putz. “Single versus multiple events error potential detection in a BCI-controlled car game with continuous and discrete feedback.” In: *IEEE Transactions on Biomedical Engineering* (2015), in press.

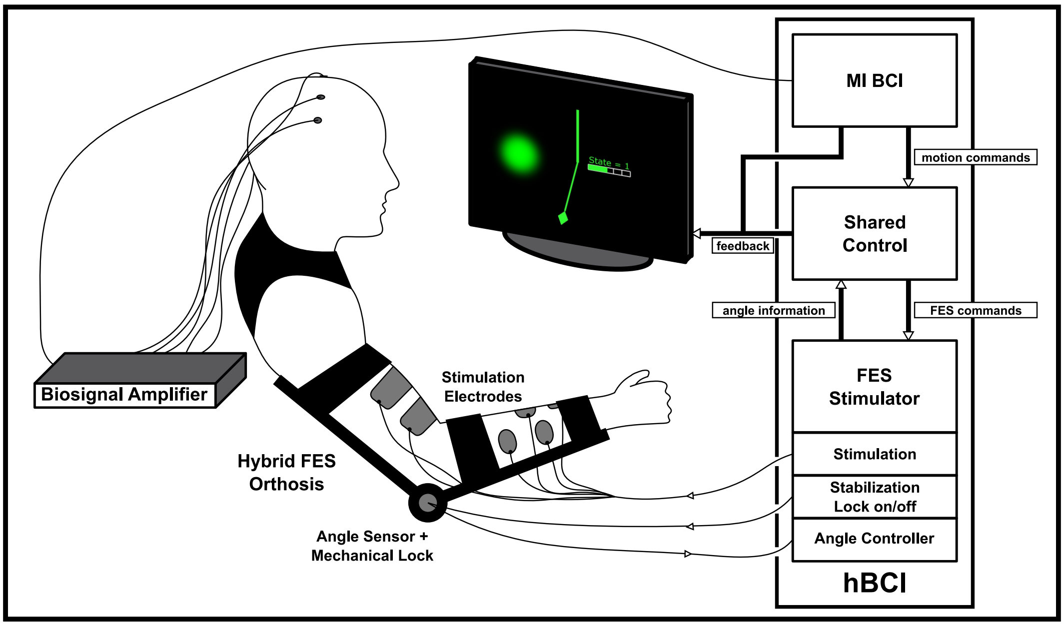

Figure 2.3.: Scheme of the continuous and discrete FES neuroprosthesis controlled by an MI-based hBCI. The user can move the arm continuously up and down by performing long MI commands. Short MI commands are either used to reach the uppermost or lowermost position or to open/close the hand. The interpretation of these commands depends on the current state and is regulated by the shared control logic which evaluates information about the current angle of the hybrid FES orthosis. The orthosis can be locked mechanically to let the users maintain the elbow position without the need for ongoing FES stimulation.

This article concludes the author's attempts to show that detection of erroneous responses is possible and can be used with beneficial effects in an online, continuous, and asynchronous BCI. Insights from previous studies have indicated that ErrP detection in complex, continuous BCI applications based on single trials is not very effective in terms of detection rates. The goal of this study was to mitigate low ErrP detection rates by using a novel technique for detecting errors. This new method is no longer based on single trials alone but combines multiple events for evaluation. Discrete single events are still classified individually, but classifier outputs are averaged over a series of events.

Ten healthy participants performed MI to steer a car to the left or to the right in a vertically scrolling car game. Objects (obstacles or coins) always appeared in clusters of four on opposite sides of the road. Thereby, triggering of multiple events was enforced by the game. This was utilized by analyzing ErrPs not in the conventional single trial way, but grouped together.

With this new approach to average multiple reactions it was possible to find out whenever the collection of such a cluster of objects (MI trial) was more likely to be erroneous than correct. The online application was tested with four subjects: after each MI trial, the whole trial was analyzed and discarded if an erroneous sequence of events was detected. The difference between the new multiple events method and the common single event method based on single trials is visualized in Figure 2.4.

To the author's best knowledge, this was the first implementation of an online error detection within a continuous, asynchronous BCI. The strategy to perform analysis with combined multiple events instead of single trials was also not heard of before.

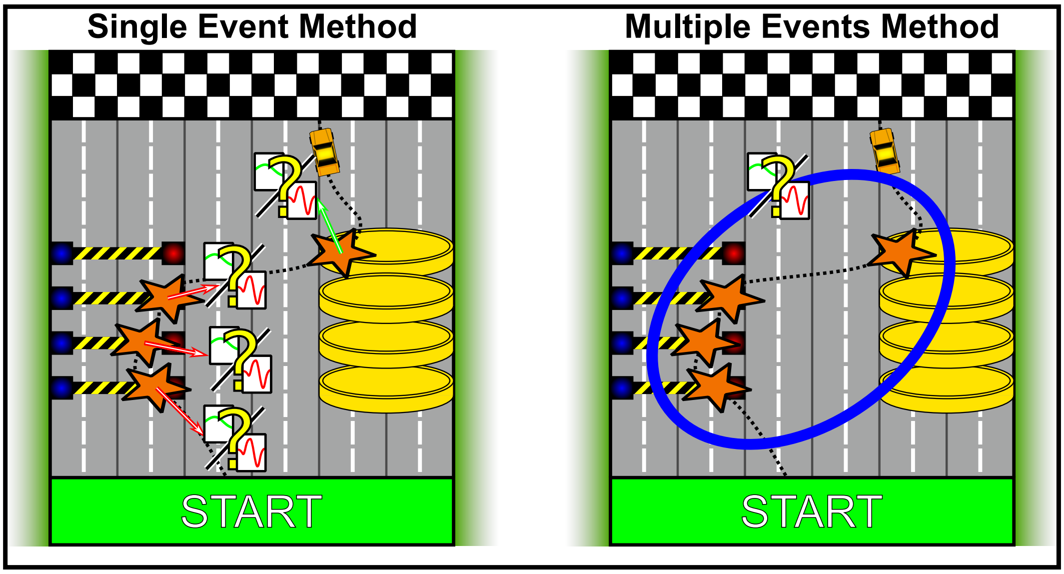

Figure 2.4.: Difference between the single event method and the new multiple events method. In the single event method each collision with an event is classified individually. In this case, the detection rate of erroneous and correct events is equal to the generally low single trial accuracy. In the new multiple events method the classification results of a series of events are averaged. Now, no longer each single event is assessed but the whole series of events. Based on these events, the new method detects whether the activity between the starting and the finishing line was more likely to be correct or erroneous in general.

2.2. Secondary Publications

2.2.1. BCI and FES Training of a Spinal Cord Injured End-User to Control a Neuroprosthesis

[69] A. Kreilinger, V. Kaiser, M. Rohm, R. Rupp, and G. R. Müller-Putz. "BCI and FES training of a spinal cord injured end-user to control a neuroprosthesis." In: *Proceedings of the BMT2013 Conference*. Graz, 2013, pp. 1007–1008.

This publication reflects on the collaboration with one spinal cord injured end-user over the course of more than one year. Two different control strategies for an arm and hand neuroprosthesis were evaluated.

The insights that could be gained from close interaction with an actual end-user revealed the need for individualized BCIs, as there are many requirements for a BCI to work functionally and to actually yield advantages for potential users.

2.2.2. Brain-Computer Interfaces als assistierende Technologie und in der Rehabilitation nach Schlaganfall

[67] A. Kreilinger, H. Hiebel, P. Ofner, M. Rohm, R. Rupp, and G. R. Müller-Putz. "Brain-Computer Interfaces als assistierende Technologie und in der Rehabilitation nach Schlaganfall." In: *Orthopädie-Technik* 6 (2013), pp. 18–25.

This paper is a review article about BCI for neuroprosthesis control and in rehabilitation in general. Several aspects are covered, including the growing importance of BCI in stroke rehabilitation and an outlook on movement decoding.

2.2.3. Hybrid Brain-Computer Interfaces and Hybrid Neuroprostheses for Restoration of Upper Limb Functions in Individuals with High-Level Spinal Cord Injury

[124] M. Rohm, M. Schneiders, C. Müller, A. Kreilinger, V. Kaiser, G. R. Müller-Putz, and R. Rupp. "Hybrid brain-computer interfaces and hybrid neuroprostheses for restoration of upper limb functions in individuals with high-level spinal cord injury." In: *Artificial Intelligence in Medicine* 59.2 (2013), pp. 133–142.

This publication documents another single case study with a spinal cord injured end-user with moderate BCI performance. With a hybrid BCI system that incorporated BCI as a switch the end-user was able to accomplish tasks that otherwise would not have been possible.

3. Discussion and Conclusion

3.1. Overview

The aim of this thesis was to improve the general performance of BCIs by applying principles of hybrid BCI technology. The studies conducted within the framework of this thesis address hBCIs on three different levels: (1) finding a way how different input signals can be evaluated online and processed to be used as a control signal; (2) focusing on error detection which can improve any stand-alone BCI system by increasing its reliability and performance; (3) applying hybrid techniques in BCI-controlled neuroprostheses in close collaboration with spinal cord injured end-users.

3.2. Quality Measures in a Hybrid BCI

The definition of an hBCI includes the need for a combination of BCI with one or more other signals, either BCI signals or signals derived from other body functions or sensors. The definition of how to combine these signals is left open to the designer [96]. If these signals are used in a sequential way or used to control separate actions, the quality of these signals does not really matter. However, if there is only one action to be controlled but more signals are available, the decision on how to combine these signals has to follow some basic rules. Inputs can be fused with different weights between 0 and 100 % or the hBCI system can switch between the available input signals. The former has the advantage that the overall accuracy of the signal can be increased by obtaining information from both signals [77]. The advantage of the latter approach is that whenever one signal is active, the other signal is not needed and the source for this signal, e.g. muscular or brain activity, has time to recuperate.

If there is no additional information at hand that can give immediate feedback on the current quality of one input signal, quality measures can only be obtained by analyzing the signal itself. In the publication "Switching between manual control and brain-computer interface using long term and short term quality measures" [68] this exact problem is addressed. With spinal cord injured end-users in mind, four individual quality measures were defined for both a BCI channel and a manual control channel. Online, fatigue was simulated by deteriorating the manual control signal; the BCI channel was not modified. The monitoring of the signals proved to be useful in deciding when to switch among input channels. Bad BCI performers triggered switches to manual control more often than good performers. Therefore, the suggested hBCI system can serve as a functioning basis when users want the possibility to use different control channels for controlling the same application. A possible scenario could be a neuroprosthesis which can be controlled by either muscular functions or BCI. Here, users may prefer to control the prosthesis with their residual muscle functions at first but might want to be able to use BCI in case of severe muscle fatigue which translates into unreliable commands. During active BCI, the muscles can recuperate until muscle control is needed again when the BCI performance suffers from an ongoing lack of concentration or noisy EEG.

The main purpose of the study based on quality measures was to provide an example of how the allocation of control channels can be managed if no external signals are available. With external signals at hand, the decision rules can be adapted to fit the individual hBCI design. Control channels can also be chosen based on other factors, for example based on context, which can be managed by shared control logic. Information about context can be obtained from sensors, such as cameras, or simply by monitoring the current state of the application. Another way to obtain information about context is to assess how the subjects react to the performance of the application. If the application does not work as intended, reactions to errors can be detected as ErrPs [23]. Basically, ErrPs can also serve as an immediate quality measure and are generally a promising addition to hBCIs.

3.3. Error Detection in Continuous and Asynchronous BCIs

Error detection, as a part of hBCI design, was a main topic of this thesis. Hereby, the aim was not only to show a feasible integration into online BCI applications, but to deviate from the common approach of designing BCI experiments especially for triggering ErrPs. Several different points were addressed to achieve this goal.

A first point was to determine how and how well ErrPs could be triggered and detected during a continuous feedback application. The first published work [70] approached this point by adding discrete feedback to a continuously moving artificial arm. Results were promising, as there were detectable reactions to unintended behavior of the moving artificial arm. However, detection rates were not on par with studies from literature that used discrete feedback alone and a fixed error rate (at least for offline analysis) [40, 71]. Main drawbacks of the study were possibly the detachment of user intention and time-delayed feedback. Additionally, the feedback was complex and for some participants it was difficult to understand which discrete feedback indicated a correct interpretation of the respective mental command. As a result of these two issues, subjects were not as involved and interested in a correct outcome as they could have been. Furthermore, the pacing of the feedback was still synchronous, that is, subjects could not voluntarily move the artificial arm at any desired point in time.

The subsequent publication, "Single versus multiple events error potential detection in a BCI-controlled car game with continuous and discrete feedback" [66], aimed to solve these issues by applying some profound refinements. First, intention and feedback were no longer separated in time. MI commands were constantly monitored, allowing the participants to continuously move the car from one side to the other at all times. Continuous feedback in form of the moving car and discrete feedback in form of collisions with obstacles and/or coins happened during active MI. Second, the experiment was embedded in a game-like environment with easy-to-understand conditions and a scoring mechanism that aimed to increase motivation and involvement. Third, although not absolutely asynchronous due to the appearance of objects at predefined points in time, subjects could control the car even in breaks and they were free to choose when they wanted to start moving the car towards the coin targets: they had 4 s time from the appearance of a coin until the coin reached the level of the car.

The evaluation of offline data revealed a positive effect when combining reactions to multiple events (reactions after colliding with objects on the street). The experiment was structured in two different layers: the MI layer, including MI trials, and the event layer, including single collisions with objects. An MI trial, which lasted from start to finishing line, included multiple events: up to four collisions with coins and/or barriers. By averaging classification outputs of reactions within each MI trial and ordering them according to the side of collision, it was possible to determine the correct intended side of the MI trial. For some subjects this detection yielded even higher accuracies than their original MI performance. The detection of these MI trials based on the new multiple events method was also significantly better than the single trial detection rates for detection of coin collections versus collisions with barriers. The new multiple events method was also tested online and was shown to be feasible. All subjects were able to increase their score during the car game as detected erroneous MI trials were discarded and could be repeated.

Although the obtained results of the two studies dealing with ErrPs look promising, there are still some drawbacks to overcome before online error detection can be a common procedure in BCI applications. One of the main problems is still the low single trial detection rate measured during complex tasks. This can partly be solved with the new multiple events method. However, it is not possible without effort to use this method in any generic BCI as the application needs to be designed to deliver series of discrete events as feedback. Another problem is that classifiers for ErrPs need to be trained before they can be used online. A solution can be not to use ErrPs in the beginning, but to provide error detection only if users have already gained some experience with the BCI application and have generated data for setting up ErrP classifiers in the process. Another possibility would be to use adaptive techniques that train ErrP classifiers while subjects are using the BCI. In any case, up to now, ErrPs do not yet offer convincing arguments which make them indispensable in BCI applications. Further work is still necessary to make automatic error detection in BCIs more attractive.

3.4. Hybrid BCI Applications for Spinal Cord Injured End-Users

The last main part of the thesis deals with individualized BCIs for spinal cord injured end-users by relying on hybrid BCI design principles. The hBCI design was implemented within different setup strategies. Depending on the level of spinal cord injury, BCI was either used as the main control channel or just as an additional, optional input.

When BCI is used as the main control channel, additional signals, for example from sensors, can help to avoid unnecessary and/or potentially dangerous commands. When BCI is only used as an optional signal, the designers have to keep the shortcomings of BCI in mind, e.g. low information transfer rate and imperfect reliability, in order to find a meaningful way to integrate the BCI channel [96].

In the first variant, a time-coded MI BCI was assisted by a shared control logic which monitored the angle of an equipped hand and arm neuroprosthesis [67, 158]. This was facilitated by an angle sensor located in the joint of the hybrid FES orthosis [123]. This orthosis was not only utilized for stabilization purposes, but also to read the angle of the joint which could also be locked mechanically whenever a desired position was reached. The shared control logic ensured that commands from the user were interpreted differently, depending on the current angle of the orthosis and the state of the hand (open or closed). This way, end-users were supported in reaching desired positions: for example, when they almost reached the maximum position of the angle, they only had to perform a short and easier-to-maintain MI command.

In the second variant the main control signal stemmed from a shoulder position sensor. MI BCI was used as a brain switch to select which muscle functions the shoulder movements should control. The brain switch was time-coded: with short MI commands the user could toggle between muscle functions; with long commands the user could enter or exit a pause state. This scheme was applied in two different scenarios. In the first scenario end-users had enough residual elbow functions to perform unassisted reaching tasks but had lost grasp functions completely. Therefore, the brain switch was used to toggle between two different FES-induced grasp patterns (lateral and palmar) and enter/exit pause mode to stop/start stimulation [67, 69]. The intensity of the stimulation depended on the analog level of the shoulder's elevation and was directly mapped to the opening degree of the hand.
The second scenario was aimed to assist end-users without elbow functions but enough shoulder functions to control the shoulder position sensor [124]. The scheme was basically the same as before. However, the brain switch was now used to toggle between FES-induced elbow movement and FES-induced palmar grasp. Additionally, the end-user's arm was supported by the hybrid FES orthosis for stabilization purposes and to avoid fatigue with the lockable joint.
Both scenarios applied shared control principles that monitored activity of the shoulder position sensor and of the brain and only permitted brain switches when the shoulder was currently not moving. A refractory period after successful brain switches was enforced to avoid unnecessary switches.

The collaboration with spinal cord injured end-users affirmed the theory that BCIs need to be individually designed. For users with sufficient elbow functions, the BCI channel is almost unnecessary in terms of actually controlling movements. However, BCI can be useful as an additional switch in case the end-users can no longer control their muscles voluntarily due to fatigue. For end-users who are really dependent on the BCI channel to control the neuroprosthesis, it can be difficult to find a feasible control strategy. Here, it is often necessary to use whatever works best. As a result, end-users often have to imagine moving their feet when they actually want to control their right arm. Possible solutions to these issues might be to provide more sophisticated shared control systems, based on a multitude of sensors that alleviate controlling the hBCI for the end-users. Concerning the mental control strategies, a more natural way would be to directly decode the intentions of the end-user without reverting to the use of unnatural mental tasks. Promising steps towards this direction have already been reported in [67, 104].

3.5. Relation to the State of the Art

This thesis is established on several developments related to hBCI in general and ErrP detection and neuroprosthesis control in particular.

Many researchers have already combined different BCI channels or BCI channels and other channels, and have used these to control hBCI systems either sequentially or at the same time. However, discussions about principle components and the general design of an hBCI have only become a relevant topic recently, mostly within the EU project TOBI. In [93, 96], the basic components of an hBCI are explained in detail, including shared control and fusion logic. In the TOBI project, fusion was defined as a module which distributes weights to input channels, according to the quality of the respective signals. These weights can be derived by analyzing supervision signals or by directly monitoring the performance of the input signal. The study in [68] aimed to provide an example of how the performance of input channels can be evaluated by taking only characteristics of the signals themselves into account. In this work, distributed weights were binary, that is, a signal was either used as the control signal or not used at all. Drawbacks of this approach are that control signals are applied in a redundant manner, which means they cannot be used for controlling other tasks. Furthermore, a continuous weight distribution, as shown in [77], could be beneficial to increase the performance of single control channels. However, a benefit of the binary approach is that every time a signal is not active, its source has time to recuperate.

The quality rating of the BCI channel was based on noise, instability, invariability, and classification bias. Recent studies addressed the characteristics of a good quality EEG signal in more depth [27]. Although it is difficult to determine with certainty that a specific data set of EEG is clean of artifacts, there might be room for improvement by more sophisticated quality measures. The quality rating of channels can also be of use for other applications that do not switch between signals. For example, noise or artifacts can also be detected online and automatically be decreased or removed entirely [28].

Another way to immediately determine the quality in a BCI application is to detect ErrPs. The next two publications “Error potential detection during continuous movement of an artificial arm controlled by brain-computer interface” [70] and

"Single versus multiple events error potential detection in a BCI-controlled car game with continuous and discrete feedback" [66] focused on this approach. Particular interest was directed towards how ErrPs can be detected during continuous feedback applications. Although many researchers have conducted experiments with ErrPs, most are either limited to offline analysis or to specifically tailored applications that are best suited to trigger ErrPs. Online ErrP detection is so far still limited to discrete feedback applications. The main reason behind this is that temporal features of ErrPs are time- and phase-locked. The two publications aimed to overcome this constraint by providing discrete feedback on top of continuous feedback. This combination of two types of feedback was suited to trigger ErrPs, though with very low detection rates.

A similar approach was shown in [142] who repeated the experiment of Milekovic et al. [88] with EEG. In the space game, discrete events were also presented in terms of crashing into objects and in terms of deviation from the intended movement trajectory. Single trial classification accuracies of outcome and execution errors were above random in two different types of analyses. One was based on the usual time- and phase-locked approach; the other one was asynchronous. It was shown that temporal and spectral features were equally well-suited for classification in the time- and phase-locked approach. Spectral features were better in the asynchronous approach. However, asynchronous classification accuracies were generally lower than the accuracies found in the time- and phase-locked approach. Accuracies were also generally lower than in other applications with less complex feedback, concurring with results in this thesis. The reason was stated to be, in part, based on a negative correlation between ERP amplitudes and workload [4].

Another interesting application that uses ErrP detection without any type of active control is shown in [59]. A reaching task where a cursor was moving stepwise towards a goal on a 5×5 matrix was observed by the subjects. Subjects did not have to perform any task other than observing the movement of the cursor. Based on their reactions, a shared control logic computed the most probable trajectory to successfully reach the goal. This approach might also be able to be combined with continuous applications as discrete events, for example direction changes, can easily be presented on top of continuous movement.

The most defining accomplishment of this thesis was found after combining multiple events for ErrP classification in [66]. The low detection rates that were a problem for single trial analysis could be improved significantly when using this novel method.

Concerning FES neuroprostheses it has been shown that restoring grasp functionality is a top priority for spinal cord injured people who have lost this ability [25]. For end-users who can still move their arm due to residual elbow or shoulder functions a neuroprosthesis that focuses only on restoring grasp functionality is sufficient. However, for people with a higher level of injury the elbow function needs to be restored as well in order to let the user reach objects with their hands. All the examples in this thesis take individual abilities and needs of end-users into account and are compliant with the user-centered design concept introduced in [58].

The studies dealing with spinal cord injured end-users are on par and beyond the current state of the art in several points. A new electrode layout, introduced in [127], was used to induce two different grasp patterns with just electrodes on the forearm. Before, these electrodes had to be placed inside the hand which often leads to premature detachment of the electrodes [38]. Furthermore, a neoprene sleeve was applied which had two functions: stabilization of the wrist and saving the locations of the FES electrodes. The first was important, as an instable hand position can affect the effects of stimulation. A similar approach to mitigate this problem was also shown in [75] by using a hand orthosis to synchronize finger movements. The latter was useful to decrease the time needed for preparing the FES system. Furthermore, users reported that reproducing the correct electrode layout for stimulation can be cumbersome [62]. There are not many successful examples for upper arm restoration. Reasons are fatigue, which emerges rapidly if the users' own muscles are stimulated, and the need for external power supply if motor-driven exoskeletons are equipped instead, for example in [135]. However, recently, first successful outcomes with a similar approach as demonstrated in this thesis were reported in [107]. Here, a modular setup includes a passive/active exoskeleton that can be controlled with EMG, buttons, eye-trackers, or BCI. If the exoskeleton is in passive mode, a spring-loaded gravity compensation supports the user's motion. If the user cannot generate enough force, FES can induce shoulder and elbow movements.

Apart from the already mentioned study in [107], which also relies on hBCI principles due to signals from sensors that support control of the neuroprosthesis, and the studies reported in this thesis, hybrid BCI systems for FES control are relatively unexplored. Moreover, continuous control of an FES neuroprosthesis via BCI has not yet been reported in literature, to the best knowledge of the author.

3.6. Limitations

Some compromises had to be made to allow for feasible implementations of the studies. This section specifies associated limitations of each study

Limitations of the study dealing with quality measures in an hBCI [68] were the arbitrarily defined weights that determined the impact of the quality measures. Although the purpose of the study was not to find an exact representation of how different measures contribute to the quality of a signal, a time-intensive analysis might have found better weights or even other quality measures that were not used in the study. Another limitation was the need to artificially deteriorate the joystick signal. The reason for this was that all participants were healthy users who could have used the joystick for a very long time without being affected by fatigue. It would be interesting to see how actual spinal cord injured end-users would perform in this experiment.

A limitation that both ErrP studies [66, 70] had in common concerned the possibility of a low number of trials. Even though the combined number of correct and erroneous trials was generally high, the number of erroneous trials was often comparably low. This was a problem especially for good BCI performers who achieved error rates of less than 20 %. Other limitations concerned the relatively low single trial detection rates of erroneous and correct events. These were lower than results in comparable literature where paradigms were designed in order to detect ErrPs in the best way possible. The studies in this thesis were not designed that way because the main goal was to incorporate error detection in functional continuous BCI applications and not to find BCI applications that can best be used to record ErrPs. However, it turned out that some design choices might lead to better solutions in future experiments. For example, experiments need to be designed to be more straightforward. The tasks in both studies were rather complex and subjects had difficulties in understanding and/or performing well in the experiments.

The new multiple events method [66] provided a solution for how to potentially mitigate low single trial detection rates. Detection rates of correct and erroneous series of events were significantly higher than the single trial detection rates in the common single event method. However, it can be argued that these two results are not entirely comparable as the two methods detect errors on different layers. Furthermore, it was unfortunate that not all participants were able to participate in the online experiment with applied error detection. A cause for this limitation was a more general problem with ErrPs: users who make more errors tend to have lower detection rates, although they would benefit most from online error detection.

Limitations concerning the experiments with spinal cord injured end-users [67, 69, 124, 158] were basically that these were all single case studies. More end-users who could benefit from BCI-controlled assistive devices such as neuroprostheses definitely would have been an enrichment for this thesis.

3.7. Summary and Conclusion

This thesis demonstrates the feasibility of hybrid BCI principles in a variety of examples, including basic implementations of hBCI technology, specific designs focused on error potentials, and hBCI solutions for spinal cord injured end-users.

Underlying principles for a fusion logic were applied online to choose between different control channels based on their individual quality measures. This implementation serves as an important example of how to choose the best control signal when no contextual information is available.

The ErrP was addressed in detail as it is a supervision signal that can give information about the performance of control channels. It could be shown that these ErrPs can be detected during continuous BCI applications. With a new method called "multiple events method" it was possible to increase detection rates of erroneous states significantly, despite relatively low single trial detection rates. This new method combines the classification outputs of a series of events instead of making a decision after each single trial.

Various applications based on hBCI principles were also tested with spinal cord injured end-users. These applications incorporated BCI as the main control channel and BCI as a supportive, optional channel, depending on the individual impairments and needs of the end-users. In total, three different end-users could successfully operate personalized hBCI applications in the laboratory and in daily life situations.

3.8. Outlook

The thesis expanded knowledge of separate principles of hBCI techniques. The next step should be to fuse thereby gained insights. An appropriate application could be the continuous, asynchronous control of a neuroprosthesis with BCI and/or other control signals. This application should include fusion and shared control logic that can monitor the performance of control signals by evaluating the control signals' characteristics by analyzing supervision signals (for example ErrPs) and sensor signals. Fusion can then use this information to weight inputs and fuse or switch between them. Shared control can inhibit or promote specific actions based on contextual information.

Concerning ErrP detection, the next step would be to combine the obtained knowledge from both studies ([70] and [66]) dealing with ErrPs. In the former, the application was already targeting neuroprostheses control but utilized an artificial arm as a substitute. Moreover, intention and feedback were temporally separated, resulting in relatively weak ErrPs. In the latter, these drawbacks were addressed successfully. However, the feedback was embedded in a game. The next logical step has to be combining the advantages of both strategies into a continuous control of a neuroprosthesis.

In the author's opinion this combination seems promising. The only constraint would be that accumulating ErrPs for multiple events analysis takes time. However, since moving a neuroprosthesis is not instantaneous, it can be assumed that there should be enough time for multiple events to occur. In this direction, it will also be interesting how the accumulation of these events can be optimized with respect to a minimum inter-event time and a suitable mode of delivery.

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Appendix A.

Publications

A.1. Switching Between Manual Control and Brain-Computer Interface Using Long Term and Short Term Quality Measures [68]

Distribution of dedicated work:

- Alex Kreilinger: 70 %
- Vera Kaiser: 5 %
- Christian Breitwieser: 5 %
- John Williamson: 5 %
- Christa Neuper: 5 %
- Gernot R. Müller-Putz: 10 %

The experiment was planned in collaboration with all coauthors. Alex Kreilinger designed and programmed the software needed for running the experiment, evaluated all data, and wrote the manuscript. Vera Kaiser helped with subject enrollment and measurements. Christian Breitwieser implemented the signal server tool used for recording EEG and manual control signals. John Williamson provided the basis of the car game feedback which was used in the experiment to be controlled by either BCI or manual control. Christa Neuper and Gernot R. Müller-Putz assisted in all steps of the experiment, from the initial design phase until finishing the manuscript.

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Switching between manual control and brain-computer interface using long term and short term quality measures

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Assistive devices for persons with limited motor control translate or amplify remaining functions to allow otherwise impossible actions. These assistive devices usually rely on just one type of input signal which can be derived from residual muscle functions or any other kind of biosignal. When only one signal is used, the functionality of the assistive device can be reduced as soon as the quality of the provided signal is impaired. The quality can decrease in case of fatigue, lack of concentration, high noise, spasms, tremors, depending on the type of signal. To overcome this dependency on one input signal, a combination of more inputs should be feasible. This work presents a hybrid Brain-Computer Interface (hBCI) approach where two different input signals (joystick and BCI) were monitored and only one of them was chosen as a control signal at a time. Users could move a car in a game-like feedback application to collect coins and avoid obstacles via either joystick or BCI control. Both control types were constantly monitored with four different long term quality measures to evaluate the current state of the signals. As soon as the quality dropped below a certain threshold, a monitoring system would switch to the other control mode and vice versa. Additionally, short term quality measures were applied to check for strong artifacts that could render voluntary control impossible. These measures were used to prohibit actions carried out during times when highly uncertain signals were recorded. The switching possibility allowed more functionality for the users. Moving the car was still possible even after one control mode was not working any more. The proposed system serves as a basis that shows how BCI can be used as an assistive device, especially in combination with other assistive technology.

Keywords: brain-computer interface, BCI, hybrid BCI, assistive technology, electroencephalography, EEG

1. INTRODUCTION

Brain-computer interfaces (BCIs; Wolpaw et al., 2002) provide a means of communication for patients who have lost most of their residual muscle functions and are therefore incapable to interact with their environment. Examples of these kinds of severe impairments are people suffering from symptoms of amyotrophic lateral sclerosis (ALS), people in a locked-in state, and people who have a spinal cord injury close to the brain.

A BCI makes use of brain signals which can be derived from various sources with different methods. In this study we used a non-invasive method to record electrical brain signals, the electroencephalogram (EEG; Mason et al., 2007). EEG-based BCIs can be subdivided into three categories according to the used signal types: first, dynamics of brain oscillations such as event-related (de)synchronization (ERD/ERS; Pfurtscheller and Lopes da Silva, 1999) which establish the basis for motor imagery (MI) BCI (Pfurtscheller and Neuper, 2001; Neuper et al., 2006); second, steady-state evoked potentials (SSEPs; Middendorf et al., 2000; Müller-Putz et al., 2006); and third, evoked potentials (Regan, 1989) with the well-known example, the P300 (Farwell and Donchin, 1988).

The benefit of BCI is the independence from any remaining muscular functions, which means that muscle fatigue is irrelevant. However, one major drawback with BCIs is that the performance for most users is still far from perfect. BCIs are often afflicted with low bit rates, low accuracy, and bioelectrical signals are generally prone to be corrupted with artifacts. Because it is difficult to improve BCI technology itself, applications could be developed that make better use of BCIs, acknowledging the advantages and disadvantages and deal with them in the most appropriate way. For example, a BCI can be used to provide additional communication channels on top of other assistive devices that are used by people who still have some residual motor functions (Rupp and Gerner, 2004).

To increase the attractiveness of BCI technology for patients it is essential to find practical applications that provide maximum control at all times, depending on the current physical and/or mental condition of the patient. Thus, providing the best means of communication at any time would be reasonable. As long as residual motor functions are still working, they offer a more reliable and natural communication channel. However, due to fatigue and/or additional interferences like tremors or spasms, a signal based on motor functions may lose its control capability after a long time of usage. At this moment, a switch to a control mode which is not based on muscular activity might become a lot more attractive and could be used to restore control over the assistive system. This approach can be realized by using a multimodal interface (Blattner and Glinert, 1996; Jaimes and Sebe, 2007) which is able to deal with at least two different control signals. A particular multimodal interface which incorporates BCI is called hybrid BCI (hBCI; Scherer et al., 2007; Allison et al., 2010; Millán et al., 2010; Pfurtscheller et al., 2010). Here, a BCI is combined with any other user-driven signal. This signal can be a biosignal like electromyogram (EMG), electrocardiogram (ECG), electrooculogram (EOG), or EEG not used for BCI, but also sensor signals and other control signals generated from assistive devices like shoulder joysticks, mouses, buttons, and eye trackers (Zander et al., 2011). Moreover, the use of hybrid BCIs may be an interesting tool for healthy users in special working environments where common control mechanisms are unreliable or not enough, e.g., operating an additional EEG-based command in a spacesuit, or also in the field of gaming (Zander and Kothe, 2011).

According to (Pfurtscheller et al., 2010), an hBCI must fulfill following four conditions: "(i) the device must rely on signals recorded directly from the brain; (ii) there must be at least one recordable brain signal that the user can intentionally modulate to effect goal-directed behavior; (iii) real time processing; and (iv) the user must obtain feedback." The hBCI introduced in this paper will follow these definitions except one small deviation: the BCI provided is purely optional, just like any other input into the system; users are not forced to use BCI when there is a better alternative. This approach concurs with the concept developed and described in (Millán et al., 2010). A more detailed description of the hBCI platform can be found in (Müller-Putz et al., 2011).

The combination of multiple inputs can be handled in a few different ways: (i) each input can be linked to a single application; (ii) all the inputs are fused and weighted to generate a single output which controls an application (Leeb et al., 2011); (iii) a monitoring module monitors inputs and decides which is best suited to be used as a control signal.

The goal of this work was to evaluate a practical combination of multimodal inputs with the sole purpose of making an application more usable for patients. This means, on the one hand, that a system should be easy to use and functional all the time by providing different options to communicate with it, but also, on the other hand, that an application can be controlled for a longer time than usual. Interaction with the assistive device should still be possible after the primary control strategy would no longer be possible due to fatigue and/or a growing lack of concentration. Therefore, the hBCI system presented in this paper is relying on the approach (iii): a monitoring module monitors inputs and decides which is best suited to be used as a control signal. A joystick (JS) signal to simulate assistive devices and a control signal derived from an MI-based BCI were constantly monitored and weighted to achieve a solution with long functionality for the user. The weighting was based on four individual quality measures per control mode. These measures were designed to detect signal specific artifacts and malfunctions, e.g., noisy EEG or a joystick signal made unusable due to strong tremors.

The proposed combination of inputs was used in a car game. A constantly moving car could be controlled with either one of the two inputs to collect coins and avoid obstacles. We investigated how well the selection of quality measures could detect a low performance, caused by a poor signal quality. To speed up the simulation an artificial deterioration was used for the joystick signal to simulate signal impairments that can be expected from patients. BCI was not deteriorated, as artifacts were expected to occur all the same.

Additionally, we investigated how the switching capability increased the maximum score when compared to a simulation without switching.

After running the experiments and evaluating the data we could show increased scores and a trend that links good performance during the car game with the quality rating determined by the quality measures.

2. MATERIALS AND METHODS

In the feedback application subjects could move a car on a vertically scrolling street, see **Figure 1**. On the sides of the street coins and obstacles (barriers) appeared randomly. Subjects were asked to collect as many coins as possible with the car while avoiding obstacles. The car was controlled either manually with a joystick, or mentally with BCI. The joystick represented any kind of assistive device, relying on muscular functions. This device could stop working permanently, after a long usage due to fatigue, or temporarily, during periods of tremor and spasm.

BCI on the other hand is prone to noise, distraction, and fatigue as well. Considering the drawbacks of both input modalities, the system offered switching between inputs to increase flexibility and

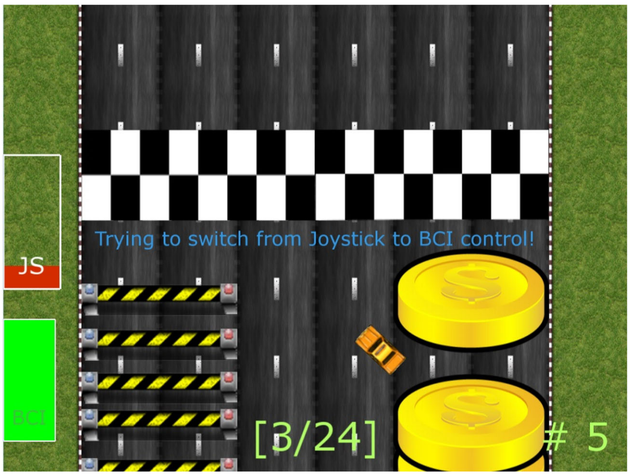

FIGURE 1 | Online car game. The current trial's task is to collect coins on the right side and to avoid the barriers on the left. The active mode is still JS, but a switch to BCI is imminent due to the low quality of the JS input, visualized with a quality bar on the left screen side. The current score in relation to the maximum possible score at the moment is displayed on the bottom of the screen. The right number indicates the number of the active trial. The finish line depicts the end of a trial after which the switching is carried out.

functionality for the users. The switching was carried out whenever the quality rating (QR) of one signal was considerably worse than the other's. An overview of the proposed system is demonstrated in **Figure 2**.

2.1. INPUTS

Both inputs, BCI and joystick, provided control signals from -1 to $+1$ where -1 would move the car to the left side of the street and $+1$ to the right. The joystick was limited mechanically so it could not generate values out of this range. BCI, which used an LDA classifier to discriminate between two MI classes, was saturated at -1 and $+1$. The joystick signal was further processed with artificial artifacts.

2.2. ARTIFICIAL ARTIFACTS FOR THE JOYSTICK INPUT

To simulate the system on healthy subjects instead of patients the joystick signal was deteriorated with artificial noise. This deterioration can be expected from patients with a spinal cord injury at C4/C5 which causes loss of hand control and heavily limited shoulder function. The artificially induced deterioration included tremors (Anouti and Koller, 1995), spasms (Kawamura et al., 1989), and an increasing weakness over time. To speed up the simulation, unrealistically high values were chosen: maximum fatigue was reached within minutes and tremors and spasms occurred frequently as long as fatigue was still low.

2.2.1. Tremors

During periods of a tremor a heavily shaken JS can be expected which renders control completely unreliable. We simulated this effect by adding a normally distributed random signal, band-pass filtered between 2 and 10 Hz, to the recorded JS signal. The tremor signal's amplitude and probability of occurrence was inversely proportional to the current weakness. Every 20 s, with a probability of $p = 100 -$ weakness level in %, either a tremor or a spasm was triggered at random. The amplitude of the tremor signal was affected directly by the current weakness as the whole JS signal was decreased.

2.2.2. Spasms

These involuntary muscle contractions can also have a strong and negative effect. We simulated spasms by applying a heavy bias to either the left or the right. The same rules were applied here as for the tremor activation. The added bias was also reduced with the weakness level.

2.2.3. Weakness

The most important factor was the weakness as it was used to simulate fatigue. The parameters were set to allow a stepwise increase of weakness after each trial. A weakness level of 0% indicated no impairment, whereas 100% were reached as soon as subjects were no longer able to collect coins due to the strong reduction of amplitude. How fast the maximum weakness was reached depended on the stage of the experiment, either at the 10th or the 30th trial. Weakness could recover, with the same rate it was increased before, during times of no active joystick usage.

2.3. QUALITY MEASURES

The currently active control signal was evaluated with four specific long term quality measures. These measures were customized to check specifically for indicators of a bad quality. These indicators could be a high noise level or unreliable behavior like an unstable classifier output. Both signals were measured individually. On top of these long term measures, both input types had one short term measure. Basically, short term measures were an additional effect when the worst indicators, used for long term

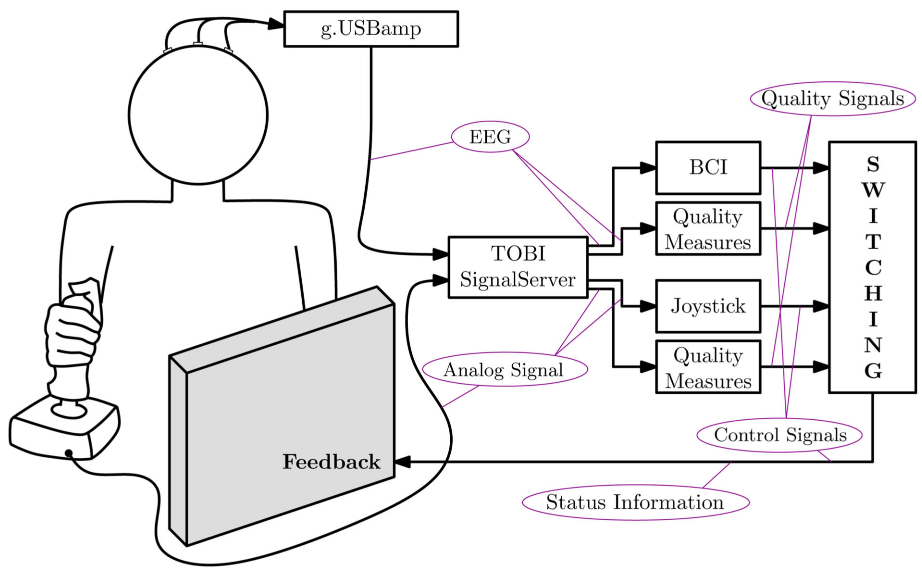

FIGURE 2 | Overview of the online setup. All the data is acquired with the help of the TOBI Signal Server and passed on to Matlab/Simulink. The signals are weighted by specific quality measures and fed to the switching block which chooses the input to use as a control signal. This control signal and information about the current state are passed on to the feedback, the car game.

measures, were detected, e.g., noisy EEG and a heavily shaking joystick. When short term measures were active, control of the car was no longer possible because the car was fixed to the middle lane.

2.3.1. Joystick measures

The quality score depended on following factors: shaking caused by tremors, low range of movement as a result of weakness, invariability (a total lack of movement possibly indicating hardware defects), and bias induced by an imbalanced preference of one side which can be caused by spasms.

2.3.2. BCI measures

These measures monitored the noise of the EEG signal caused by EMG artifacts, instability due to unreliable classification, invariability (indicating hardware or software errors), and also bias for a one-sided classifier output.

The problem about setting the weights for the measures was to find the right values in order to rate negative effects correctly. That is, very strong impairments should cause a fast decrease of quality and minor impairments only a slow decrease. These weights were initially set to arbitrary values. However, we tried to give strong negative effects like strong noise and shaking heavier weights. In contrast, not so acute effects were weighted lower, e.g., effects like fatigue whose influences built up over a longer time. All weights were adjusted empirically while conducting preliminary tests before running the final experiments.

The differently strong impacts on the quality for the final measures were as follows: BCI noise and JS shaking would decrease the quality by 10(%/s), BCI instability by 5(%/s), low JS amplitude by 2(%/s), BCI and JS invariability by 1(%/s), whereas the bias was proportional to the bias itself; a strong bias over a long time would increase the weight steadily. All those measures were able to recover individually whenever they were not currently detected. Additionally, all individual quality measures for one control mode recovered when the other mode was currently active; i.e., BCI measures recovered with 1(%/s) during joystick mode and vice versa. The currently inactive signal was never monitored, i.e., the quality of an inactive signal was only allowed to increase, not decrease. The described measures are also demonstrated in **Table 1**.

$$\mathrm{QR}_{\mathrm{BCI/JS}} = 100 + \sum_{i=1}^{N} \int \mathbf{w_i}\,(x\,(t))\,\mathrm{d}t$$
$$\text{with}\, x\,(t) = \begin{cases} 1 & \text{current mode, noise active} \\ 2 & \text{current mode, noise inactive} \\ 3 & \text{other mode, recovery} \end{cases} \tag{1}$$
$$\text{e.g., } \mathbf{w_{1,\mathrm{BCI}}} = \begin{bmatrix} -10 \\ +3 \\ +1 \end{bmatrix}; \mathbf{w_{2,\mathrm{JS}}} = \begin{bmatrix} -2 \\ +4 \\ +1 \end{bmatrix}$$

Equation 1 shows a simplified formula of how the qualities for both control modes were calculated during the online experiment. In the equation QR depicts the quality rating of one of the two control signals which always ranges between 0 and 100%. $\mathbf{w_i}$ describes the $N = 4$ different weight vectors, one for each quality measure. The indexes of these vectors depend on the current state of detected criteria and on the actual active control mode. The weights either increase or decrease the whole quality of one mode. The equation is simplified inasmuch as it does not include context-sensitive factors that were considered additionally online. These factors are represented in the following list which explains the four long term quality measures per control mode, the relation with short term measures, and how exactly measures were combined in the online model:

Table 1 | BCI and JS quality measures.

BCI			JS		
Measures	**QR↑↓ (%/s)**		**Measures**	**QR↑↓ (%/s)**	
	↓	↑		↓	↑
EMG noise	−10	+3	Shaking	−10	+2
Instability	−5	+1	Low amplitude	−2	+4
Invariability	−1	+4	Invariability	−1	+4
Bias	∝ bias	∝ bias	Bias	∝ bias	∝ bias

Four measures for both control modes, BCI and joystick, are shown. These measures can either decrease the quality (100% + numbers in the second and fifth column) when they are currently detected but also recover over time otherwise (third and sixth column). The bias' measure, as an exception, is depending on the magnitude of the bias itself. The decrease rate of the QR is higher than the recovery rate to allow for a quick response in case of bad input signals. All quality measures of one mode recover with 1(%/s) when the other mode is active at the moment.

- BCI EMG noise: all EEG channels were filtered between 20 and 100 Hz, squared, averaged with a moving rectangle window of 1 s, and logarithmized. A threshold was set before online measurements after subjects were instructed to produce EMG noise and clean EEG. EMG noise was only detected within active trials. When detected, an integrator would start to increase from 0 to 100% with 10% every second. Otherwise the integrator could recover toward the minimum value of 0% with −3(%/s). These and following values are given in **Table 1**, however with inversed signs. EMG noise, when detected, also triggered the short term measure of the BCI signal. This effect was shown in the car game by fixing the car to the middle lane and a swiveling animation of the car.
- BCI instability: this measure was based on the number of zero crossings within active trials. As soon as the middle line of the street was crossed more than three times within one trial, a second integrator increased from 0 to 100% until the trial was over. Anytime else the value could recover.
- BCI invariability: a total lack of LDA variance after 1 s started a very slow increase of a third integrator, also limited between 0 and 100%, which would decrease four times faster in case of any movement. This measure was active at all times.
- BCI bias: as soon as the system switched to BCI, the bias was measured constantly. A one-sided classifier output resulted in a continuously increasing weight. In detail, when the absolute

value of the LDA classifier exceeded 0.2, an integrator was growing either toward +100 or −100%, depending on the sign of the LDA output. This value was multiplied by 1/20. The absolute value was then subtracted with 1 and the final weight passed on to the fourth integrator. This way, the bias weight could lie between 1 and 5(%/s) and recovered with 1(%/s), due to the subtraction.

- BCI combination: the four BCI integrators were either increased or decreased with the specific weights or each decreased with −1(%/s) when JS was currently active. The outputs of all four integrators were added but the total sum was limited to 100%. This total value was finally subtracted from the current BCI QR which started at 100%.
- JS shaking: the absolute value of the derivation of the JS input was smoothed with a moving rectangle window of 1 s length. A predefined threshold was found in foregoing measurements. If the threshold was exceeded, the integrator increased and decreased otherwise. This measure was active all the time. JS shaking was the equivalent to BCI EMG noise in terms of the short term measure, a detection of shaking also rendered control of the car impossible.
- JS low amplitude: the absolute value of the JS input was compared to the threshold value 1/3. Between $\frac{-1}{3} - \frac{1}{3}$ no object collection was possible. Only during active trials, a second JS integrator started to increase or decrease, depending on whether the JS input was below the threshold or not.
- JS invariability: to detect hardware errors, this measure was applied exactly the same way as BCI invariability.
- JS bias: the bias measure was similar to the BCI bias measure. The only difference being the multiplication of 1/10 and a subtraction of 0.5. The resulting weights could therefore range from 0.5 to 10(%/s) with a recovery rate of 0.5(%/s).
- JS combination: JS weights were combined the same way as BCI measures, however, only when the active control mode was JS.

2.4. EXPERIMENT SETUP

The experiment was designed to allow completion within one session, not longer than 3 h. It consisted of three steps: (i) two runs of offline BCI training to set up a classifier for the MI BCI; (ii) two runs with a car game controlled only with a joystick to collect data of runs without the switching system; (iii) six runs with combined BCI and manual control to analyze how well the designed switching approach worked online.

EEG was recorded with a g.USBamp amplifier (g.tec medical engineering GmbH, Austria, Graz). Six Ag/AgCl electrodes were placed anterior and posterior to C3, Cz, and C4 to obtain three bipolar channels. Data was recorded with a sample rate of 512 Hz and filtered between 0.5 and 30 Hz and an activated notch filter at 50 Hz. After the BCI training session, which only needed pure EEG, a joystick was added that provided an analog signal between −1 and +1. This analog signal was later used to control the car; −1 would move the car to the leftmost side of the street; +1 to the right. Both input types were acquired with the TOBI Signal Server (http://www.tobi-project.org/download; Breitwieser et al., 2011), a software that is able to combine multiple inputs and provide data in a standardized and synchronized way for various clients via network protocols.

2.4.1. BCI training

In the beginning, two short BCI training runs were carried out, each with 40 randomized trials of movement imagination, one half both feet and the other half right hand. Subjects performed the standard Graz-BCI training paradigm (Pfurtscheller and Neuper, 2001) to allow selection of features and calculation of a classifier for MI. Trials contaminated with artifacts were removed manually before searching for relevant features. The features consisted of frequency bands recorded over the three bipolar channels. They were selected manually after evaluating ERD/S maps (Graimann et al., 2002). Here, the frequency bands with the most significant differences between hand and feet MI were selected by plotting difference maps of both classes. ERD/S maps showed only significant changes ($\alpha = 0.05$) of frequency band-powers after the cue compared to a reference period between 1.5 and 0.5 s before the cue. The difference maps only showed significant differences between two classes in the time after the cue with the same significance level.

The band-powers of the best found frequency bands were used to generate an LDA classifier. A time window, covering the time between cue appearance and end of trial (5 s), was processed in 100 ms steps. At each step, the features corresponding to one time step were used to calculate a temporary classifier with which the data was analyzed by a 10 × 10 cross-validation. As soon as the whole time window was tested, the best point in time was used to set up the final classifier with the whole data set for online measurements. Additionally, the 10 × 10 cross-validation was nested within a 10 × 5 outer cross-validation that split data into an outer training set and a validation set. Here, classifiers generated at the best points in time, which were found via an inner cross-validation, were applied on unseen data to make sure that these points were really stable and to evaluate potential overfitting.

An online LDA classifier generates two outputs: the class label (−1 or +1) and the distance (an analog value). The distance was used to control the car in the later online runs. Scale and bias of the classifier were adjusted to achieve a distance between −1 and +1 on average, similar to the joystick range, with an average of zero for both classes combined. A possible transgression of −1 or +1 resulted in a saturation during later online experiments. A classification of foot MI would result in a negative distance value and move the car to the left; a classification of hand MI in a positive value and a movement to the right.

Additionally, the offline performance of this chosen classifier was evaluated by testing the classifier's accuracy on all 100 ms steps between 1 s after cue appearance and end of trial.

2.4.2. JS only

The second part of the session simulated a system without BCI to have a comparison of data with only joystick control and data with joystick and BCI combined. Subjects were asked to perform two runs controlling the car game, see **Figure 1**, with just the joystick. The participants were asked to collect coins and to avoid obstacles with a moving car on the screen in front of them. The car was constantly driving with a fixed speed toward the top edge of the screen. One single trial included a sequence of coins and barriers which appeared at the top of the screen, always six coins in a row with six barriers on the opposite side of the street. The interval between coin/barrier and next coin/barrier was 0.5 s. These objects could be reached by the car exactly 4 s after they appeared. The joystick signal was being deteriorated over time in a way that it reached the maximum weakness at 30 trials, out of 40 trials per run; the subjects were not supposed to be able to collect anything during the final trials, because switching to BCI mode was not yet possible.

2.4.3. JS + BCI

The final part of the experiment combined manual with BCI control. Six runs with 40 trials each were carried out. Before starting to record the online runs, subjects were asked to perform a few trials in BCI mode to let the supervisors adjust the bias and the scale of the classifiers, if necessary.

The setup was the same as before with two differences. First, the participants could control the car with the joystick or with the BCI by performing the previously trained MI tasks. Second, the JS weakness reached its maximum already at 10 trials.

An overview of the setup is demonstrated in **Figure 2**. The runs always started with active JS control. The JS signal deteriorated continuously in order to simulate weakness and to force a switch to BCI. A switch was only permitted to happen when the active quality was below 20% and the other one above 50%. Additionally, switches were never triggered within active trials, instead, the system waited for a break to switch to the other mode. The length of this break was automatically increased by 5 s to allow accommodation to the other control mode.

To facilitate switching back after some time, the inactive signal's quality could recover by $1(\%/s)$ per criterion. Subjects were asked to avoid switching as long as possible, i.e., to avert quality reducing factors. The measures that affected the quality were called long term measures.

Additionally, so-called short term measures were used to inhibit control during times of severe noise impairment by forcing the car to the middle of the street and giving a visual alert (swiveling of the car). In BCI mode this could have happened during a detection of noise; in JS mode the inhibition was caused by a detection of strong shaking. The long term quality measures were not influenced by this inhibition: the noise/shaking measure and eventual other measures could still decrease the QR of the current control mode. **Figure 1** shows an excerpt from the ongoing feedback during an online run. Here, the subject was currently collecting coins but the system decided to switch from JS to BCI mode since the JS quality had fallen below the threshold of 20%.

2.5. EVALUATION

After all the runs were conducted, the recorded data was evaluated with following methods.

2.5.1. Score, collection rate, performance measure

We analyzed how well the subjects performed in terms of collected points with "JS only" compared to "JS + BCI" control. This outcome was rated in three different ways:

(i) online scoring was based on adding or subtracting points. Subjects could increase the score +1 by collecting a coin and decrease it with −1 in case of a collision with a barrier. To avoid frustration, the score could never fall below zero. The maximum score in one run was 240 (6×40 coins);

(ii) offline, the rate of positive: negative collection was analyzed. Only the relation between collected coins and barriers was of interest, not the percentage of collected objects out of the maximum possible number. Left out objects on the street were not taken into account (e.g., a missed coin or barrier);

(iii) also offline, a performance measure was introduced, depending on collected coins, barriers, and left out objects. This trial-based performance measure ranged between 0 and 100%. One hundred percent indicated that all possible coins within a single trial were picked up, 50% that either no object at all or the same number of coins and barriers were collected, and 0% were achieved when only barriers were hit. This specific performance measure could be directly compared to the mode-specific QR over time. Later mentioned performance refers to this kind of performance measure. Equation 2 shows how the performance measure per trial (PM_{trial}) was calculated. The $Score_{trial}$ could range between −6 and 6 points, the max ($Score_{trial}$) was 6 points.

$$PM_{trial} = Score_{trial} + \frac{50\%}{\max\left(Score_{trial}\right)} + 50\% \qquad (2)$$

2.5.2. Correlation of time and performance

We evaluated the correlation of BCI performance with time in BCI mode. Because the quality monitoring was purely based on characteristics of the inputs and not on the online performance itself, it was not guaranteed that these two values would show a correlation. However, it would be a good sign of a working switching approach if it was found to be true.

2.6. SUBJECTS

Ten healthy subjects took part in the study, all of them had experience in BCI to permit a short training session of just two runs. Based on results from previous experiments we selected BCI performers with two class accuracies above 60%. They were aged between 21 and 30 years (25.4 ± 3.1 years), half of them were female, and all of them right handed.

3. RESULTS

3.1. BCI TRAINING

The first two runs of BCI training provided good classifiers for all the subjects. **Table 2** shows the mean accuracies in the time period 1–5 s after the cue when applying the classifier that was generated after the best point in time was found by the search with the 10×10 cross-validation. Additionally, the accuracies at the best points in time are shown for each subject. Furthermore, the best points in time found via inner cross-validation were used to create classifiers that were applied on validation data sets within a 10×5 outer cross-validation to check for overfitting. The results, after averaging the achieved accuracies, are also listed in **Table 2**. Therefore, overfitting was shown to not be a large problem. This was done by comparing accuracies achieved by only using the best points in time, without a nested cross-validation, to accuracies that were found with the best points in time, found via inner cross-validation, and tested with a validation set in each loop of the outer cross-validation. The averaged outer cross-validation accuracies were only 2.9% lower than the accuracies achieved without nested cross-validation.

3.2. ONLINE CAR GAME

Figure 3 shows the point collection rates, averaged over all subjects, and all conducted runs. The collected points for both parts are compared: "JS only" on the left and "JS + BCI" on the right. For both types the first increase in points is caused by the JS control which is beginning to stagnate as soon as the artificially appended weakness has reached its maximum at trial number 10 in the combined "JS + BCI" runs, and at 30 trials for "JS only."

The important noticeable difference is that the score starts to increase after the quality of the joystick signal decreased enough to trigger the first switch to BCI in the combined paradigm. In "JS only" mode there was no way to further increase the score. After the time of the first switch, subjects remained in BCI mode for different amounts of time but also had the possibility to go back to JS in case of a bad EEG input. This is also indicated with the increasing SD in the plot. The maximum number of points per run was 240 (40 trials, each with six coins).

Figure 4 illustrates how the monitoring system worked online with the example of the current performance, the signal qualities, the actual control modes, and the occurrence of switches from BCI to JS. Only BCI → JS switches are highlighted to maintain clarity of the figures. To demonstrate the quality evaluation effects two subjects were chosen to represent a good (BCI performance of 77 ± 29%, subject number 1) and a bad (subject number 6 with 57 ± 25%) BCI performer. The subjects were picked according to the values shown in **Table 3**, taking into account the BCI performance and the time in BCI mode. For each of them the left plot shows the course of actions over the whole time (data from all 6 runs), whereas the right one shows one exemplary run to show performance and BCI quality in more detail. The figures consist of five features: (i) the performance, as mentioned in 2.5, visualizing the general performance which is relying on collected coins, barriers, and left out objects; (ii) the QRs of BCI and JS mode, as obtained online by the four specific long term quality measures. The JS quality is only shown in the examples with the single run; (iii) the occurrence of actual system-induced switches from BCI to JS; (iv–v) indication of the current control mode, either BCI or JS.

Table 2 | Offline classification rates after applying the classifier for online use on all time steps between 1 and 5 s after the cue, accuracies at the best points in time, and test results after using validation sets in an outer cross-validation (oCV) routine.

	Accuracy [%]				Accuracy [%]		
S	1–5 s	t_{best}	oCV	S	1–5 s	t_{best}	oCV
1	80.1	92.4	90.0	6	74.9	84.7	85.2
2	62.2	79.6	79.3	7	79.4	86.7	81.6
3	79.1	87.8	81.2	8	82.8	95.7	95.5
4	70.9	87.8	87.5	9	74.4	84.2	83.3
5	73.9	91.3	83.3	10	56.1	71.4	66.4
	Average				73.4 ± 8	86.2 ± 7	83.3 ± 8

For each subject, one to four features were chosen individually. These were band-powers in frequency bands recorded on the three bipolar channels.

The correlation between BCI performance and time in BCI mode is addressed in more detail in **Table 3** and **Figure 5**. The table lists the collection rates and performances in BCI mode and the according times actually spent in this mode. The figure demonstrates the relation between these two values. The plot shows two linear fits, one of them using all subjects and one with subject S8 removed as an outlier. The correlation coefficients were $r = 0.34$ ($p = 0.33$) and $r = 0.6$ ($p = 0.09$), respectively. Apparently, S8's BCI quality was not recognized as a poor one. The measure weighting the bias was not strong enough to decrease it sufficiently to cause a switch but the bias was strong enough to cause a bad performance. Also, the other measures were not triggered very often in order to have an effect on the QR.

The maximum time in BCI mode (100%) was only reachable if there was no switch back to joystick mode at all. That said, 100% means the whole period of all runs minus the first time of joystick mode which was always initiated at the start of a run.

Another important outcome to evaluate was whether the monitoring system actually made sense for the users. Did switches occur more frequently during bad performance? How good was

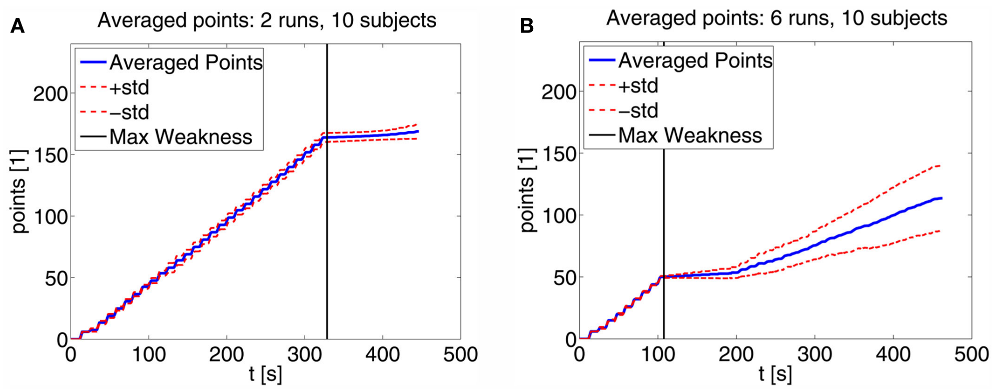

FIGURE 3 | Online scoring during 'JS only' and 'JS + BCI' mode. (A) shows the score during 'JS only' mode. As soon as the maximum weakness was reached after 30 trials, indicated with the black vertical line, collecting coins was only possible with forced overshooting. **(B)** shows the averaged collection of points during 6 averaged runs from 10 subjects over all 40 trials. The first points were always collected with the joystick which was weakened within the first 10 trials up to a point when no more collection was possible. After this stagnation, the monitoring system initiated the first switch to BCI and would continue to monitor both input qualities and decide which control method was best at the moment.

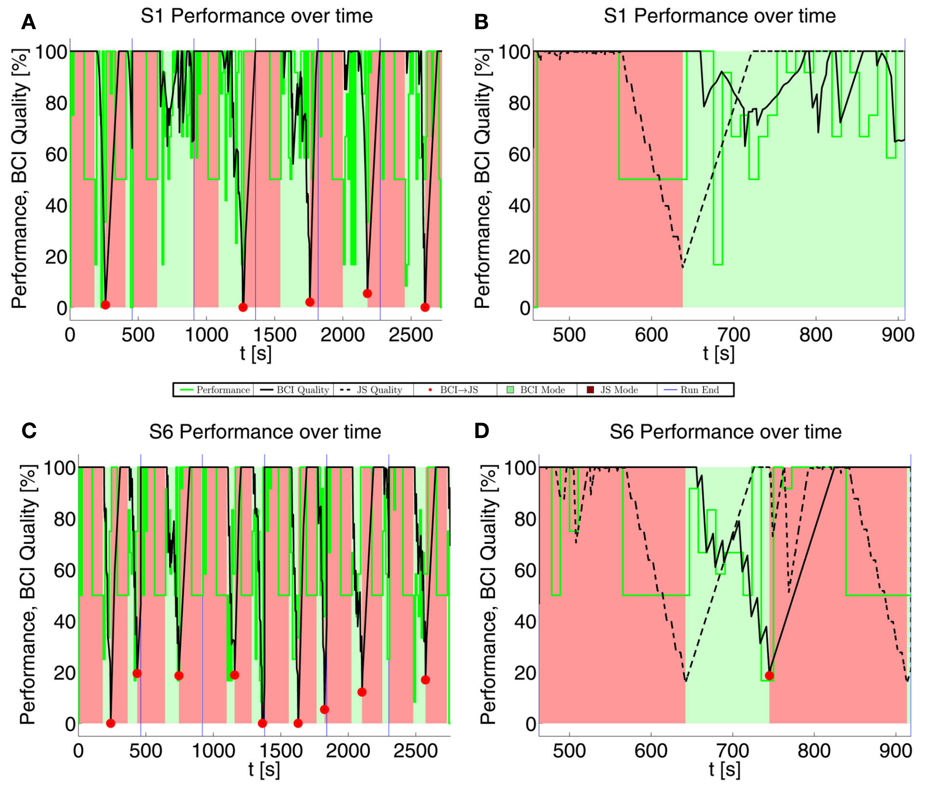

FIGURE 4 | Performance and BCI quality during progress of the whole experiment (A,C) and for one exemplary single run (B,D) for subject S1 who represents a good BCI performer compared to subject S6 as a bad example. The bad performer triggers BCI → JS switches more frequently. Performance depends on currently picked up coins and barriers, whereas the quality decreases and increases due to active quality measures and recovery rates, respectively. The start of a new run is indicated with blue vertical lines. A new run always started in JS mode, no matter in which mode the foregoing run concluded.

Table 3 | Time in BCI mode in relation to BCI performance and object collection rate (pos:neg).

S	pos:neg [%]	BCI perf. [%]	BCI time [%]
1	80:20	77 ± 29	69
2	60:40	59 ± 37	49
3	82:18	78 ± 24	77
4	84:16	81 ± 24	93
5	66:34	65 ± 30	80
6	59:41	57 ± 25	45
7	78:22	74 ± 23	66
8	55:45	54 ± 35	93
9	72:28	69 ± 26	92
10	51:49	50 ± 32	66
Average	69:31 ± 12	66 ± 11	73 ± 17

The performance measures are slightly lower than the collection rates due to the inclusion of missed objects into the calculation. Subjects with a BCI performance above 70% are highlighted in bold black, whereas a performance below 60% is indicated with bold gray.

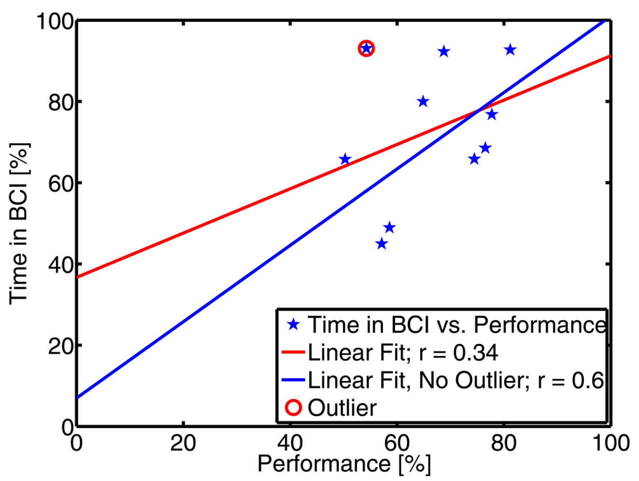

FIGURE 5 | Correlation between time in BCI mode and BCI performance on the basis of all subjects and all the subjects minus one outlier (highlighted star).

the performance directly at the time of switching or some time before? These questions are partly answered with the information in **Table 4**. The good BCI performers are highlighted in bold black, whereas subjects with a performance below 60% are grayed out. Apparently, good performance led to a relatively low number of

Table 4 | Number of BCI → JS switches and performances at respective points in time.

S	Switch #	Preceding trials				
		1 [%]	2 [%]	3 [%]	4 [%]	Mean(1–4) [%]
1	5	47	85	68	73	68
2	6	44	67	81	65	64
3	3	64	86	58	94	76
4	4	77	92	77	90	84
5	4	71	75	63	73	70
6	9	52	57	49	66	56
7	4	65	90	81	67	76
8	3	50	67	42	31	47
9	1	83	100	58	83	81
10	6	42	58	69	42	53
Average		59 ± 14	78 ± 14	65 ± 13	68 ± 19	68 ± 12

The table shows how many switches there were for each subject and how good their performance was at that time. The averaged performances, including one to four foregoing trials, are shown over all subjects.

switches (from BCI to JS), as opposed to higher numbers for bad performers with the exception of subject S8. Additionally, the value of the current BCI performance preceding a BCI → JS switch was low: 59% on average for immediately preceding trials and 68%, averaging the performance of the four preceding trials.

The impact of the short term measures on the online car game can be seen in **Table 5**. The number of possible collections was reduced in case of detected short term measures. The resulting missed objects were considered as left out objects for the evaluation methods. On average, the short term measures were active $0.4 \pm 0.5\%$ of the time in BCI mode and $1.7 \pm 0.5\%$ of the time in JS mode. The maximum possible score for BCI mode was reduced by 4.2 ± 5 points and for JS mode 17.6 ± 8 on average.

4. DISCUSSION AND CONCLUSION

We developed a monitoring system which allowed the combination of two different control signal. The system is based on quality measures that monitor signals and generate quality ratings. The evaluation of the experiment included basically two main points. First, we analyzed how well subjects were able to control the car game in general. Second, the functionality of the switching system was evaluated.

As expected after selecting average and good BCI performer, the scores during the car game, especially when in BCI mode, had a large variance. Also, the BCI accuracy during the online car game was worse due to the fact that subjects had to maintain MI and a good LDA classifier output for a longer time, as opposed to the offline runs where we selected classifier based on the best time of separability. Since we were also interested in how the switching would work for a mediocre BCI signal, this was not disappointing. In fact, the outcomes allowed us to better examine the functionality of the switching system. The system was expected to always use the best control strategy at the moment, in terms of quality rating. We hypothesized that the signal with the best quality would also be the one to achieve the best performance.

After evaluating the relationship between time in BCI mode and BCI performance of the subjects, we found positive correlation coefficients. However, only the calculation with the one outlier S8 removed showed a statistical trend with $r = 0.6$ ($p = 0.09$). However, with the low number of samples (nine subjects), statistical significance was not expected. Analyzing all 10 subjects reduced the correlation coefficient from 0.6 to 0.34 with $p = 0.33$. The outlier can be explained by the relatively low weighting of the classifier bias and that other measures were not affecting the quality rating heavily enough to induce earlier switches. The bias could affect the performance more negatively than it was accounted for in the beginning. Also, subject 8 had difficulties maintaining the classifier output for the time needed to collect all the coins. This outcome points out that measures have to be individually adjusted to each patient and to the used application before it can be used in real life situations. However, we only wanted to show a relatively large number of measures, all combined in one setup. This combination should serve as a basis for further experiments where we can use the findings from this switching system and alter the way measures are used and add or remove individual measures and rules for combination.

The functionality of the system can be best observed in **Figure 4**. The most significant detail is the relation between time in JS and BCI mode. JS mode was active longer for subjects with a low BCI performance, because BCI quality dropped faster and switches from BCI → JS were triggered more frequently. As a result there were not only more BCI → JS switches but also switches back from JS → BCI, because the quality of the JS signal did not have enough time to recover. The reason why switches did not occur exactly at the alleged 20% was that switching was only allowed between trials; therefore, the quality often had time to change for the worse or the better for a few seconds before the switching was actually carried out.

The positive effect of the switching capability is demonstrated in **Figure 3**. Increasing the score was possible, even after JS control was no longer working. The weakness was deteriorating faster for the combination of JS and BCI, 10 trials compared to 30 for "JS only." The period of score stagnation which ranged approximately from 100 to 200 s was purely depending on the choice of weighting for the JS quality measures. Weights of the measures which monitored the small range of motion could be increased to force a faster quality drop in case of weakness and therefore induce an earlier switch to BCI mode.

On top of the individual long term quality measures to determine quality ratings, the short term measures also had a positive effect. These two measures were strictly speaking a byproduct of detected quality measures for BCI EMG noise and JS shaking. When these two measures were detected, the car was forced to the middle of the street, thereby prohibiting possible false but also correct collections, which were in any case not reliable. For BCI there was a higher chance that fewer or no short term measures at all were triggered. On average, the reduction of the maximum possible score and the activated time in BCI mode was lower than in JS mode: 4.2 ± 5 versus 17.6 ± 8 points and 0.4 ± 0.5 versus $1.7 \pm 0.5\%$, respectively. This was based on the fact that subjects had the chance to produce noise-free EEG but could not avoid the artificially induced tremor artifacts in JS mode. For possible

Table 5 | Activation of short term measures and their consequences.

S	BCI time [%]	JS time [%]	BCI max	JS max	−ΔBCI	−ΔJS
1	1.4	2.2	594 → 584	846 → 817	10	29
2	0.0	1.0	420 → 420	1020 → 1013	0	7
3	0.0	1.9	666 → 666	774 → 752	0	22
4	0.0	2.3	810 → 810	630 → 609	0	21
5	0.6	1.9	696 → 690	744 → 726	6	18
6	0.9	1.6	384 → 379	1056 → 1041	5	15
7	0.0	1.7	570 → 570	870 → 850	0	20
8	0.0	0.7	810 → 810	630 → 620	0	10
9	0.7	1.2	798 → 783	642 → 636	15	6
10	0.3	2.0	570 → 564	870 → 842	6	28
Average	0.4 ± 0.5	1.7 ± 0.5			4.2 ± 5	17.6 ± 8

Columns 2 and 3 demonstrate the percentage of time when activated short term measures inhibited the control of the car in both modes. The resulting reduction of possible collections is shown in columns 4–7.

applications with real patients, these short term measures can work as a kind of safety mechanism that can be applied for assistive devices to permit control only with noise-free input signals.

The main concern found in this study was the difficulty to adjust measures, as many parameters have to be adapted to the users' needs in detail. Measures and weights have to be very flexible. Caregivers should be able to add and/or remove measures and to change the weights according to different factors which are very specific. Nevertheless, with some beforehand knowledge, technicians can set up a basic selection of measures and weight ranges to facilitate adjustment for individual usage.

Another problem of the simulation was, in fact, that it was just a simulation. We could only assume how the control would be affected by factors like spasms, tremors, and fatigue. Therefore, the study should also be tested with actual patients who really have to deal with assistive devices that might become unusable over the time of usage as a result of real influences. Here, combining more than one control signal should be really useful for daily activities.

To sum up, the switching approach proved to be promising for future use in experiments with real patients. For these professional users, fatigue and other deteriorating factors concerning assistive devices are highly anticipated and the possibility to additionally use BCI can improve the functionality significantly. The setup also lends itself to be expanded. First, more signals could be combined instead of just two. For example, sensors could be used to give more information about the current state; EMG signals could serve as an additional control mode. A second possible enhancement would be to combine quality measures with a kind of fusion described in (Leeb et al., 2011). Here, we could let the quality ratings determine how much importance each of the used signals gets when they are fused instead of using a discrete switches. Third, the weighting rules can be improved to permit more feasible solutions for users. Finally, the study should also encourage researchers to find measures based on other factors that can also serve online to detect a bad performance, e.g., the loss of controllability (LoC; Jatzev et al., 2008).

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A.2. Error Potential Detection during Continuous Movement of an Artificial Arm Controlled by Brain-Computer Interface [70]

Distribution of dedicated work:

- Alex Kreilinger: 85 %
- Christa Neuper: 5 %
- Gernot R. Müller-Putz: 10 %

Alex Kreilinger designed, programmed, and carried out the experiment, analyzed recorded data, and wrote the publication. Christa Neuper and Gernot R. Müller-Putz gave helpful advice during all stages of setting up the experiment and preparing the manuscript.

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ORIGINAL ARTICLE

Error potential detection during continuous movement of an artificial arm controlled by brain–computer interface

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Abstract Patients who benefit from Brain–Computer Interfaces (BCIs) may have difficulties to generate more than one distinct brain pattern which can be used to control applications. Other BCI issues are low performance, accuracy, and, depending on the type of BCI, a long preparation and/or training time. This study aims to show possible solutions. First, we used time-coded motor imagery (MI) with only one pattern. Second, we reduced the training time by recording only 20 trials of active MI to set up a BCI classifier. Third, we investigated a way to record error potentials (ErrPs) during continuous feedback. Ten subjects controlled an artificial arm by performing MI over target time periods between 1 and 4 s. The subsequent movement of this arm served as continuous feedback. Discrete events, which are required to elicit ErrPs, were added by mounting blinking LEDs on top of the continuously moving arm to indicate the future movements. Time epochs after these events were used to evaluate ErrPs offline. The achieved error rate for the arm movement was on average 26.9%. Obtained ErrPs looked similar to results from the previous studies dealing with error detection and the detection rate was above chance level which is a positive outcome and encourages further investigation.

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Keywords Brain–computer interface · Electroencephalogram · Error potential · Motor imagery

1 Introduction

Severely disabled people, e.g. people affected with amyotrophic lateral sclerosis (ALS) or high spinal cord injuries (SCI) have almost no remaining muscular functions. Brain–computer interfaces (BCIs) allow these people to communicate without requiring any movement [32]. One important application of BCIs is the control of neuroprosthetic devices by bypassing the severed connection between brain and limbs. Here, the BCI converts brain signals into control signals which are transmitted directly to the neuroprostheses.

Information can be obtained by measuring the brain activity directly from its source, accomplished by invasive or non-invasive techniques. Invasive techniques achieve a better signal-to-noise ratio but require surgical operations.

A convenient way to record the brain activity is the non-invasive electroencephalogram (EEG) [15]. Here, the brain activity is measured directly on the skull, however, amplitudes are smaller, the spatial resolution is poor compared to invasive techniques and signals can be influenced by artifacts caused by eye movements or muscle contractions. BCIs can be subdivided into types based on external stimuli and types that measure self-induced patterns. Evoked potentials (EPs) are caused by external stimuli and can be modified by switching attention between different stimulation sources. Well-established representatives are the P300 [5] and steady-state evoked potentials [17, 20]. Both kinds can be caused by acoustic, visual, or tactile sense stimulations. BCIs based on these EPs can work without training [13] and can be prepared quickly,

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depending on the number of electrodes. However, users always have to focus on the according stimuli. On the other hand, BCIs based on self-induced brain patterns require the user's intent to be activated. A noteworthy example is the event-related desynchronization/synchronization (ERD/S) [12, 26] where relative changes in band power within certain frequency bands are measured during tasks that involve the motor cortex.

In spite of being very well established and investigated, these BCIs have in common that they are not perfectly accurate and experience showed that it can be difficult for naive BCI users to generate patterns for more than one class from the start. Through long training, the reliability can improve by learning of both, the patients and the BCI classifiers, e.g. in [14] four ALS patients were able to learn operating a BCI with sensorimotor rhythms over 20 sessions. However, this training can take a lot of time [1, 19, 27, 29]. Another approach is to use a large feature space and complex machine learning algorithms to avoid training [2]. However, this requires a long preparation time as up to 128 electrodes have to be attached. To overcome these hindrances training and preparation time could be reduced by employing simple tasks that are easy to learn and applying only a small number of electrodes [23], and the performance of BCIs may be increased by automatically detecting and correcting errors.

To reduce the long training time, the mental strategy can be kept as simple as possible. The instruction to perform motor imagery (MI) of the right hand is easy to handle and usually produces reliable and classifiable EEG patterns. A time-coded MI [22, 24] approach makes the participants concentrate on this one task, however, for varying amounts of time.

Error correction can be achieved using error potentials (ErrPs) [8, 30]. These potentials are time- and phase-locked and occur after the observation of erroneous events. Until now, four different kinds have been described in the literature: the response ErrP [3], the feedback ErrP [18], the observation ErrP [31], and the interaction ErrP [6]. The interaction ErrP is promising for the correction of errors that occur during the online experiments because it is evoked after the observation of falsely interpreted user commands by an interface. It can be measured in the area over the anterior cingulate cortex (ACC) which is, among other tasks, involved in error processing [16]. ErrPs, however, need fixed points in time to be triggered and referenced. This makes it difficult to find ErrPs when subjects are observing continuous feedbacks. A solution could be to generate discrete events depending on the current state and provide users with a combination of discrete and continuous feedback. Reduced training/preparation time and error detection are investigated with a twofold experiment: time-coded MI is used to move an artificial arm [11] over variable distances. An expected low MI performance resulting from the short training is appreciated for this study to result in enough errors to measure, since the error rate is merely depending on the achieved performance of the subjects. The artificial arm is equipped with LEDs to deliver discrete feedback on top of the continuous one which is the movement of the arm itself. The essential task of this study is to find whether the additional discrete feedback is enough to elicit significant, measurable potentials that might be used in the future experiments for the online error correction.

2 Methods

The experiment consisted of two parts: a first calibration paradigm followed by an application of the generated classifier with active MI and concurrent continuous and discrete feedback. The training part was kept as short as possible because the focus was clearly on the application part, during which the participants were asked to move an artificial arm as precisely as possible.

2.1 Subjects, hardware, and recording

Ten subjects, all healthy and inexperienced in MI, aged between 22 and 32 years, took part in the experiment. There were two females and eight males.

The data were recorded with a g.USBamp (Guger Technologies OEG, Graz, Austria). This biosignal amplifier is capable of recording 16 channels of EEG which were all used for the measurements. The Ag/AgCl-electrode layout, following the international 10–20 system, was designed to cover both of the expected important areas on the scalp. These areas were the region of the motor cortex around channel C3 responsible for the control of the right hand and the area over the ACC at channel FCz. The electrodes were clustered around these channels and recorded monopolarly against a reference electrode at the left mastoid. The ground electrode was mounted on the right mastoid. Before recording, the impedances of the electrodes were checked to be below 5 kΩ. The sample rate was set to 512 Hz with a high-pass filter at 0.5 Hz, a low-pass filter at 100 Hz, and a notch filter at 50 Hz.

2.2 Calibration part

The standard Graz-BCI training paradigm [28] was presented to the participants. However, only one run was carried out to minimise the preparation time. This one run consisted of 20 trials of rest versus 20 trials of right hand MI. The timing of these trials was as follows: at 0 s a cross appeared to signalise the beginning of a trial; the cue appeared at 2 s to either indicate MI or rest, depending on the direction of an arrow; the arrow vanished at 3.25 s, however, the cross still remained present until the end of the trial which was at 7 s; after a random break between 0.5–1.5 s a new trial was started.

Immediately after the first setup run was recorded, the data were manually checked for artifacts which were removed before continuing evaluation by calculating ERD/S maps [10] to find the most promising features. These time–frequency maps plot the averaged relative band power changes compared to a reference period before each trial over time and frequency bands to show differences between active motor tasks and rest periods. The most pronounced features, which were band powers of certain frequency bands at particular channels, were then used to generate a linear classifier based on LDA [9]. During the following online measurements this classifier was used to discriminate between active MI and rest.

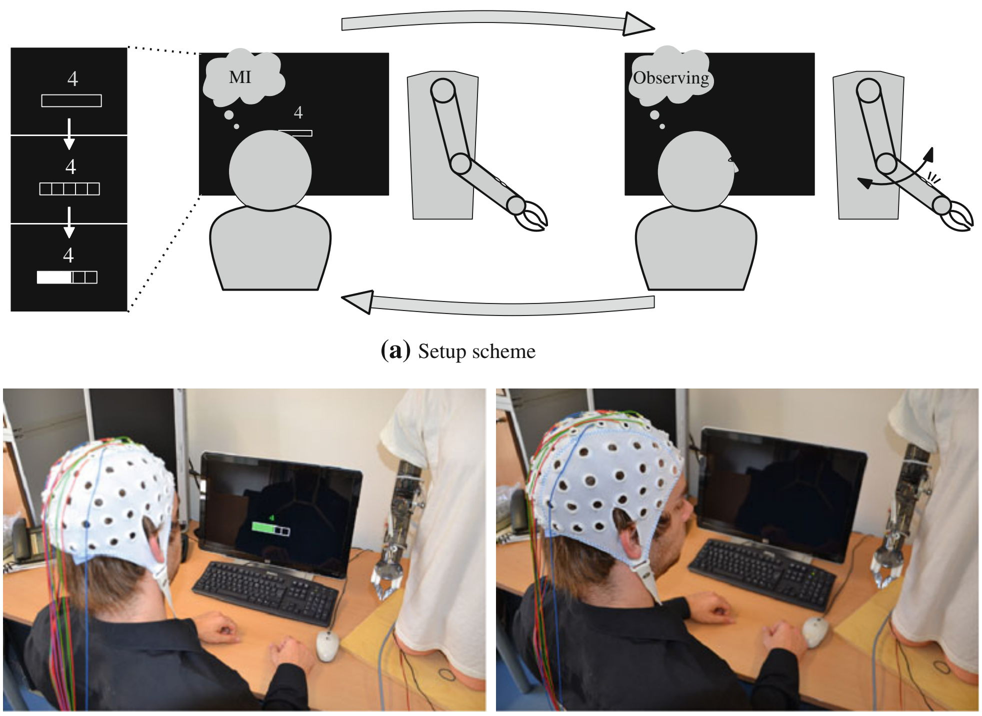
2.3 Application part

The application part consisted of eight runs, 20 trials each. One trial was split into two segments: the MI segment and the observation segment. In the MI segment a target appeared on the screen which told the participants how long they were required to perform MI. The observation segment provided delayed feedback in terms of a moving artificial arm. Here, the subjects were asked to passively observe the movement which should last as long as they were required to perform MI during the preceding segment. This segmentation with a delayed feedback after active MI ensured that the subjects were not distracted from observing the blinking LEDs.

At the beginning of the MI segment a red digit on the screen informed the subjects of the time they should perform MI. This target was either 1, 2, 3, or 4 s. After a break of 1 s, the digit turned green and a bargraph started to fill continuously. A grid indicated the lapse of time in the second-long steps. The bargraph always took 5 s to fill completely. However, subjects should only perform MI for the currently required amount of time, depending on the previously presented target. Thus, the bargraph's sole purpose was to point out how much time already had passed.

As soon as the bargraph was full, another 1-s break was initiated after which the observation segment began. Here, the participants had to slightly shift their vision to the side where an artificial arm was beginning to move exactly as long as the MI was detected during the 5-s period in the preceding MI segment. Figure 1 shows the whole setup and what the subjects were viewing during the different segments.

The aim of the observation segment was to evoke ErrPs whenever the arm would move too long or too short. Since ErrPs can only be triggered after certain discrete events the continuous movement alone was not adequate. Hence, a white and a red LED were mounted on top of the artificial arm to generate discrete events. These LEDs were set to



(a) Setup scheme

(b) Picture of the setup, MI

(c) Picture of the setup, Observing

Fig. 1 Setup of the application part of the experiment. A first active MI segment, where the movement time of the artificial arm was determined by the length of the performed MI time, is followed by an observation segment during which ErrPs were evoked with LEDs blink with a frequency of 1 Hz to indicate the future events. The white LED indicated that the movement would last at least 1 s longer, whereas the red LED preceded a stoppage within the very second. This encoding always resulted in a certain sequence of flashes where only one sequence was correct, according to the current target. The target was the time MI had to be maintained during the preceding MI segment. Subjects were instructed to perform MI at least as long as the number indicated but not longer than the next higher number; i.e. a target of three required MI to be maintained between 3 and 4 s. When the same target of 3 s was correctly detected, this was indicated with a sequence of three white flashes and one red flash. Any discrepancy from this correct sequence should elicit ErrPs. Therefore, it was necessary that the users were aware of which sequence was the correct one before the arm started to move. This was easily accomplished, given the small number of different possible outcomes with only four possible targets.

As soon as the artificial arm stopped, another break of 1 s was started and the next trial could begin by presenting the next target to the subject.

2.4 Analysis

An offline analysis was conducted to find out how well reactions to errors could be distinguished from correct observations. Here, spatial and temporal filters were applied on the data, namely, large Laplacian derivations around FCz and a bandpass between 0.5 and 10 Hz. Afterwards, windows of 1 s following the relevant LED flashes were cut out and arranged into the two classes ‘error’ and ‘correct’. Averaging the EEG for both observations of correct and erroneous blinks produced two waveforms. The difference of these, the error-minus-correct waveform which is the standard definition of the ErrP, was calculated to represent the ErrP and compared with results of the previous studies. Within the 1-s time window a discriminant power (DP) algorithm [7] was used to find out the best features which were points in time in this case. These features were used to generate an LDA classifier which was tested with a 10×10 cross validation.

The performance of the MI task was evaluated by examining how precisely the target times could be reached with the time-coded MI by the individual subjects. Different narrow time windows enclosing the target time ranges were analysed: target time range $\pm$ 0, 0.5, and 1 s. These windows were chosen to show whether subjects could perform the time-coded MI exactly as long as required or at least miss the target only by ± 0.5 or ± 1 s. The most narrow range for a target time of 2 s ($t_{\mathrm{target}} = 2$) would therefore be between 2 and 3 s ($t_{\mathrm{target}} - 0, t_{\mathrm{target}} + 1 + 0$); this was exactly as the task demanded: “perform MI for at least the target time but not longer than the next higher number”. The widest window was between 1 and 4 s ($t_{\mathrm{target}} - 1$, $t_{\mathrm{target}} + 1 + 1$). Afterwards, an offline simulation with the ErrP detection and correction was conducted that took into account the measured ErrP detection rates, which were acquired offline, and a number of selected values. Here, the point was to determine from which detection rate an online application of error correction would be feasible to increase the overall performance. The simulation recognised ErrPs with the accuracy A and misclassified correct LED flashes with $1 - A$. A detected ErrP after a red LED blink would increase the length of the movement; without correction the movement would stop within 1 s after the red blink. An ErrP after a white LED would abort the movement; without correction the movement would continue.

3 Results

3.1 Calibration part

Eight out of ten subjects were able to produce a visible MI pattern, found in the ERD/S maps of the recorded EEG, after only one run. Two subjects were asked to try another run which was improving the pattern for one of them. For the remaining participant with bad results a feature was chosen anyway, however, not a very well-pronounced one. The expected low-online MI performance was accepted because triggering ErrPs should still be possible.

3.2 Application part

Here, two different outcomes are interesting: (1) the performance of the active MI control of the artificial arm, and (2) the activation and detection of ErrPs.

During the measurements, most of the users had the impression that they could control the artificial arm. However, one subject was excluded from all further calculations because he misunderstood the goal of the experiment. Coincidentally, this subject was the one with the worst ERD/S patterns. The average performance describing how well target times were reached, and all the subject-specific rates for differently long time periods are shown in Fig. 2 and Table 1. Figure 3 shows the ERD/S maps for the four different target times for one exemplary subject S9. According to the actual target, the elicited LED blinks could either be correct events or errors, depending on whether the target time was reached, exceeded, or not even reached. Blinks were assigned to be correct as long as there was no deviance from the expected flashing sequence; erroneous blinks resulted from too long or too short movements. By comparing the frequency of occurrence of these blinks an error rate could be obtained. The averaged error rate of all the subjects was 26.9%. The particular error rates are demonstrated in Table 2.

The results of the classification of erroneous versus correct blink reactions after the cross validation can be seen in Table 3. The shown accuracies describe the percentage of correctly classified observations. These classification accuracies were used for the simulation. Figure 4 demonstrates the effect of applied error correction. Only the results for the most narrow time window are shown (time ± 0). The straight line shows the performance without error correction, the other line shows the effect of applied error correction with different error detection rates. The entry at 62.6% stands for the mean value of the calculated accuracies for each subject, the other values were increased stepwise from 50–100% to give an impression of how the performance changes for different error correction accuracies. Each subject's error detection rates were applied individually. Not the averaged value of 61.3% was used but the according values visible in Table 3. The outcome was again averaged for better comparison in Fig. 4. The error-minus-correct waveform—the ErrP—which was measured over FCz with a Laplacian derivation is shown in Fig. 5 for all the subjects, except the one rejected. The thin lines represent each subject's averaged reaction differences, whereas the thick line is the average over all these ErrPs.

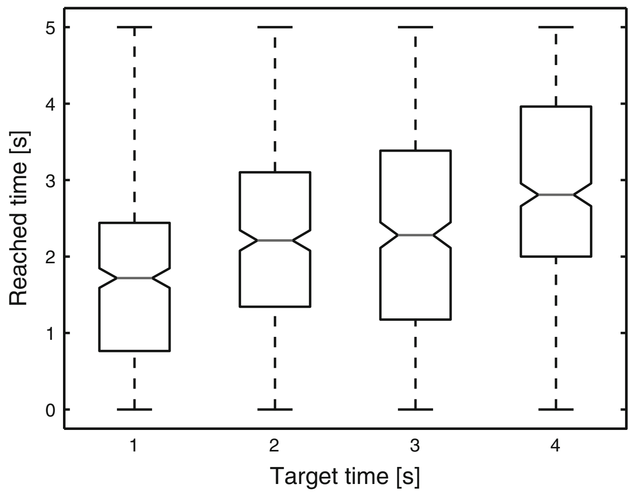


Fig. 2 The results of the MI part, averaged over all the participants. *Each box* presents the median (*central horizontal lines*) and the 25th and 75th percentiles (*edges of the box*) of the detected MI times (reached time) for the four different targets 1, 2, 3, and 4 s

4 Discussion

The concurrent use of continuous and discrete feedback was a first approach to use error detection in applications that are not entirely depending on discrete choices. The experiments were able to demonstrate a possibility of how to provide a simple control strategy that requires only one active class and almost no training time. Most of the subjects could move the artificial arm via the time-coded MI. However, it was difficult for the participants to reach the requested target times precisely. Still, all but two users referred to the control as functioning and had the impression of being in control. The used paradigm consisted of four different targets and a zero class where no target at all was reached. According to [21] the chance level for a 5-class BCI with 160 trials is 25.6%. This value was exceeded by 5 out of 9 participants. Target times 2 and 3 s were difficult to reach for the participants as the required times to perform MI here were very similar and it was harder to estimate how long MI was performed already. Target time 1 s needed only a short activation and for reaching 4 s the subjects simply tried to keep up the imagination over the whole time the bar graph was filling. Also, it was not a problem when subjects continued to maintain MI even when the full 5 s had already passed. In summary, the conclusion emerged that this kind of staged control is not easy to handle for users. However, the main goal was not to achieve a perfect score but to give the subjects the feeling that they really were under control but still to evoke a reasonable amount of erroneous events. Also, the low initial accuracy served as a good example to show how a good error detection rate could improve the results. The low error ratio was ideal for the experiment in two ways: (1) it was still high enough to produce enough erroneous events for later analysis, (2) errors occurred rarely enough to elicit strong ErrPs, as the ErrP is said to be

Table 1 Particular MI results for nine subjects

	MI results (%)									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	Average
$t \pm 0$	23.8	13.8	32.5	28.8	21.9	26.3	14.8	31.9	36.9	25.6 ± 8
$t \pm 0.5$	48.1	31.9	49.4	51.3	43.8	43.8	26.9	56.3	60.0	45.7 ± 11
$t \pm 1$	72.5	53.8	71.9	73.8	68.8	65.0	48.1	76.9	80.6	68.0 ± 11

The results are shown for three different narrow time periods. The values show how well all target times from 1 to 4 s were reached on average

Fig. 3 ERD/S maps of subject S9 who achieved the best results concerning the reaching of time targets. Here, the length of the ERD is clearly increasing with higher target times. The feature used to detect this subject's MI was the band power of the frequency band between 8 and 14 Hz

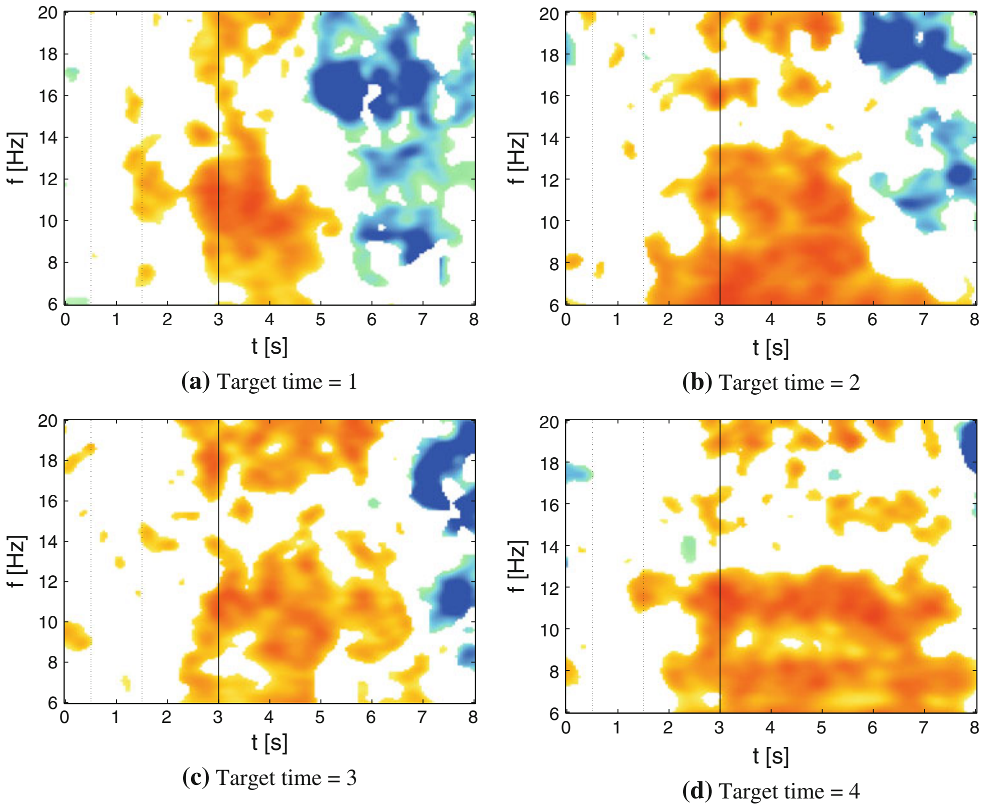


Table 2 Particular error rates for nine subjects

Subjects	Error rate (%)
S1	26.5
S2	35.5
S3	22.4
S4	22.6
S5	29.7
S6	27.2
S7	35.6
S8	20.1
S9	22.2
Average	26.9 ± 6

The numbers describe the percentage of erroneous LED flashes, calculated on the basis of the actual context

Table 3 Particular accuracies for nine subjects

Subjects	Accuracy (%)
S1	57.3
S2	61.2
S3	64.7
S4	63.7
S5	61.4
S6	56.3
S7	62.0
S8	60.4
S9	65.7
Average	61.4 ± 3.1

The values describe the number of correctly classified erroneous and correct blink reactions

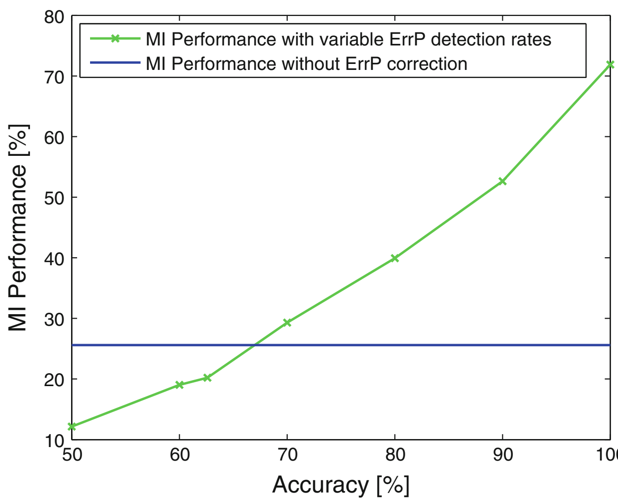


Fig. 4 Different classification accuracies and their effect on the MI performance for the most narrow time period ($t_{\text{target}} - 0, t_{\text{target}} + 1 + 0$) for all subjects. The achieved ErrP accuracy of the recorded data is 61.3% on average. Simulations showed that from an accuracy of 70% the performance starts to increase. The initial MI performance without error correction is visualized by the *horizontal line*

reciprocally proportional to the frequency of errors [4]. The shape of the resulting waveform of the recorded ErrPs looks similar to the interaction ErrP [6] which is caused by falsely interpreted and executed commands by an interface. The noticeable difference is that the waveform seems to be

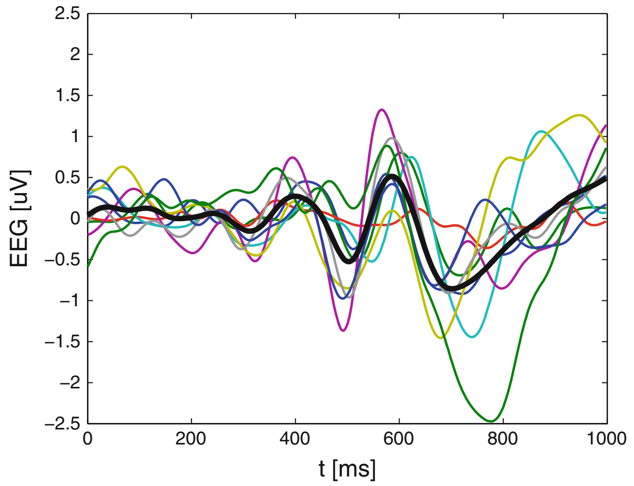


Fig. 5 ErrPs of nine subjects (*thin lines*) and average (*thick line*), recorded over the ACC with a Laplacian derivation around channel FCz. The averaged waveform shows the characteristic interaction ErrP form with a first negative peak followed by a positive peak and by another negative. Time zero depicts the moment when either one of the LEDs flashed. The shown waveforms are the differences between reactions to correct and wrong flashes (erroneous–correct reactions)

delayed for about 200 ms, which could be caused by the more complex processes involved in the generation of the feedback. This possible explanation is also backed in [4]: "... the larger the difference between the representations, i.e. the easier the error is to be detected, the larger and/or earlier the Ne (and sometimes the Pe)". Here, Ne is referring to the error-related negativity, also ERN, Pe represents the positive component after error recognition.

The chance level for detection of correct events and errors is depending on the number of trials which was not the same for each subject. The value was on average 54.2% and could be passed by all of the subjects. Nevertheless, the results were not good enough to be feasible in an online application, which has been found with the offline simulation of online error correction. Reasons for the low detection rates might be the low number of electrodes and the too highly concentrated placement around the allegedly important areas. Future experiments will have to deal with these problems by applying more than 16 electrodes and by using a uniform distribution over the whole scalp to allow common average reference (CAR) as a spatial filter and to include other regions that may have a beneficial effect on the classification. The CAR should prove useful as it suppresses potential noise sources that affect multiple electrodes and on the other hand accentuates signals which can only be recorded on small areas. Further, it would be interesting to include more posterior regions of the brain, as suggested in [25]. Here, later positive components of ErrPs were found to be generated in regions that allow measuring over Cz and even Pz. The downside here is that more electrodes would mean a step back from BCI use in daily life. Therefore, increasing the number of electrodes should only be used for fundamental research about ErrPs.

The simulation of the application part with applied error detection and correction indicated when the usage of ErrP detection would be feasible for online applications. It was shown that from an error versus correct classification accuracy of more than 70% the performance of the MI could improve theoretically, target time windows could be reached with a higher percentage. However, the problem with error correction in this particular case is that especially longer target times are influenced negatively by misclassifications. It is more difficult to pass through a longer row of correct blinks without falsely classifying an error. Therefore, for a reasonable applicability, even higher accuracies should be aimed for. Furthermore, the simulation was based on the actual MI performances achieved by each participant. A better performance level would result in more positive blinks and a reduced need for error correction, again, decreasing the positive effect of applied correction.

This study showed that ErrPs can be recorded during the presentation of a continuous feedback, as long as occasional discrete events are used to trigger the time- and phase-locked ErrPs. Although the obtained accuracies for detection of correct and false events were not enough for online applications, the fact that ErrPs can be evoked and measured during continuous feedback might be useful for the future experiments. Here, it will be necessary to find solutions that integrate discrete events into applications that have a practical use for BCI users. Many studies dealing with ErrPs have adapted paradigms which are optimal for evoking ErrPs but have no further applicability. The other way, which was intended to be demonstrated with this study, would be to use practical applications and to check how ErrPs can be added in the best way.

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A.3. Neuroprosthesis Control via a Noninvasive Hybrid Brain-Computer Interface [158]

This publication is part of a special issue called "The Convergence of Machine and Biological Intelligence" in IEEE Intelligent Systems. Authors listed before Alex Kreilinger were involved in different articles not related to the contribution provided by Alex Kreilinger, Martin Rohm, Vera Kaiser, Robert Leeb, Rüdiger Rupp, and Gernot R. Müller-Putz.

Distribution of dedicated work:

- Alex Kreilinger: 65 %
- Martin Rohm: 5 %
- Vera Kaiser: 5 %
- Robert Leeb: 5 %
- Rüdiger Rupp: 10 %
- Gernot R. Müller-Putz: 10 %

All coauthors contributed in planning the experiment. Alex Kreilinger programmed and carried out the experiments with the one end-user and the healthy subjects. Vera Kaiser assisted in working with all participants. Martin Rohm helped programming the hybrid orthosis needed for parts of the study as well as the neuroprosthesis control in general. Rüdiger Rupp and Gernot R. Müller-Putz supervised planning, running, analyzing, and reporting of the experiment.

two point processes p_i and p_j, define the inner product between their conditional intensity functions as

$$I(p_i, p_j) = \left\langle \lambda_{p_i}(t \mid H_t^i) \lambda_{p_j}(t \mid H_t^j \right\rangle_{L_2(T)} , \\ = E\left[\int_T \lambda_{p_i}(t \mid H_t^i) \lambda_{p_j}(t \mid H_t^j) dt \right] \quad (1)$$

where $\lambda(t|H)$ is the conditional intensity function. This inner product defines a family of cross-intensity (CI) kernels depending on the model imposed on the PP history H_t. We can illustrate the procedure with a simplifying assumption. If the PP belongs to the Poisson family, the conditional becomes the instantaneous intensity function and the inner product simplifies to

$$I(p_i, p_j) = \int_T \lambda_{p_i}(t) \lambda_{p_j}(t) dt, \quad (2)$$

which is the simplest of the CI kernels, the memoryless kernel (mCI). One (among many) nonlinear cross intensity kernel (nCI) can be defined as

$$I_\sigma^*(p_i, p_j) = \int_T \kappa_\sigma(\lambda_{p_i}(t), \lambda_{p_j}(t)) dt, \quad (3)$$

where κ is a symmetric positive definite kernel, which captures nonlinear couplings in the time structure of the intensity functions (such as in renewal processes). Besides providing a bottom-up way of defining the reproducing kernel Hilbert space (RKHS), the advantages of the CI family include the simplicity of estimating the kernel from spike train data, for instance, by using an exponential smoothing function at each spike event location.[7] This kernel becomes a Laplacian and has a free parameter θ that controls the inner product. In a sense, the free parameter is a continuous variable that links spike timing and rate methods—that is, if the kernel is narrow, the transformed events don't overlap a lot in time, and we get our spike time estimates. If we use a broader kernel, there will be overlap between many transformed spikes, and the results are more in tune with the rate methods. More importantly, we obtain a clear mathematical view of the two types of processing, showing that indeed they only differ in the definition of the similarity metric in the RKHS (that is, the inner product). We can estimate nCI in the same way, using one of the conventional symmetric positive definite functions such as the Gaussian function, which will provide nonlinear mixing between the intensity functions.

Once the spike trains are transformed into RKHS functions using the mCI (or nCI) kernels, we can operate with them using our toolset of signal-processing algorithms because they now exist on a Hilbert space, a linear space with a well-defined inner product. Possible applications include new statistical tests for stationarity detection, projection of spike trains in principal components, clustering and classification, and adaptive model building for prediction and control.[6] In particular, the recently introduced kernel adaptive filtering (KAF) methodology for time-series analysis[9] can be directly applicable. This is an example of the appeal of spike kernels: KAF algorithms previously developed for continuous amplitude time-series modeling can be applied without any modification to the spike kernels we just defined.

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Neuroprosthesis Control via a Noninvasive Hybrid Brain-Computer Interface

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Brain-computer interfaces (BCIs) could serve as an alternative user interface for controlling assistive technology such as neuroprostheses without relying on residual muscular activity. Over the past decade, noninvasive electroencephalogram (EEG)-based BCIs have matured to a stage where they can be applied to end users in their homes. Portable hardware is commercially available, and personal use is now possible without onsite expert assistance.

However, noninvasive BCIs inherently have a low signal-to-noise ratio (SNR) and poor spatial resolution, resulting in moderate performance and low information transfer rate. These disadvantages can be overcome by a novel approach called hybrid BCI (hBCI). An hBCI integrates the BCI output with other signals originating from biological sources as well as technical sensors. A successful example of such an hBCI is the control of an upper extremity neuroprosthesis. Healthy subjects and one end user with a high-level spinal cord injury (SCI) were able to control elbow and hand movements with BCI commands, supported by input from an angle sensor and a shared control logic. hBCI represents a promising technology for enhancement of BCI-controlled applications.

Background

Brain stem stroke, amyotrophic lateral sclerosis, and SCIs lead to severe motor impairments that reduce the capability of those affected by them to communicate or interact with their environment. For example, SCIs with a lesion above the fifth cervical vertebrae leads to an impairment of upper extremity function in particular. Assistive technology supports these individuals by compensating for restrictions in motor function; neuroprostheses[1] based on functional electrical stimulation (FES), for example, can partially restore lost upper extremity function. Motor points in the vicinity of the desired innervated muscles are stimulated with electrical currents to elicit contractions. This stimulation's strength and pattern can be modulated by any type of analog control signal that can originate from preserved residual functions. However, for users with higher injury levels, the number of functions available for control purposes decreases with an increasing number of functions to be restored. Ultimately, only signals directly generated in and recorded from the brain remain available, introducing the need for BCIs.[2]

BCIs transform signals from the brain, either through hemodynamic or bioelectrical activity, into control signals for applications such as spelling software, neuroprosthesis, and environmental control. By the willful modulation of brain activity, a user can control his or her individualized application. The most common BCIs are based on changes in electrical activity caused by firing neurons. These BCIs differ in the number of collectively measured neurons and recording technique—specifically, single or multi-neuron recordings, electrocorticogram (ECoG), and electroencephalogram (EEG). The first two invasive techniques require electrodes penetrating into the brain's region of interest or placed directly on the exposed cortex, respectively. Electrical brain activity can be measured noninvasively by EEG. Its downside is a lower spatial resolution because electrical sources are farther away from the sensors, causing larger conducting effects. Moreover, signals are heavily attenuated when recorded through the skull. These factors amount to a reduced SNR compared to invasive systems. Still, EEG offers vital advantages: hardware is commercially available, it can be applied in the user's home without the need for onsite assistance, and the equipment can be portable.[3]

Even though EEG-based BCIs can be used for daily applications in a real-life environment, some open issues remain to be solved before achieving market maturity. BCIs still must be configured, sometimes adapted and set up for individual users by experienced professionals. Electrodes must be applied carefully on the head, requiring a kind of cap to fix positions. Wet electrodes still need to be mounted with electrode gel to reduce the SNR. Therefore, the most important goals for researchers are, first, to increase the signal-processing methods' reliability and adaptability and, second, to develop comfortable dry electrode systems that acquire brain signals as reliable as wet electrodes. In addition, BCI software must be designed to allow for easier configuration and adaptation, ideally via remote support.

Assuming these issues will be solved, the problem of large distances between sensors and source persists and cannot be overcome noninvasively. A novel approach is to use BCIs with all their restrictions in terms of reliability and low information transfer rate as one additional component of a user interface. BCIs can be especially valuable if used together with other signals or if guided by context-sensitive decision making based on the environment. hBCI[4] describes a situation where the BCI is not used merely as a stand-alone application but instead is combined with other kinds of signals. These signals can be additional biosignals, signals generated by residual muscular functions via assistive devices, signals from technical sensors, or even signals from other BCIs. Moreover, fusion mechanisms and shared control help define which input signals are used and how. Fusion, for example, can distribute weights to input channels. These weights can be binary to switch channels on/off as well as

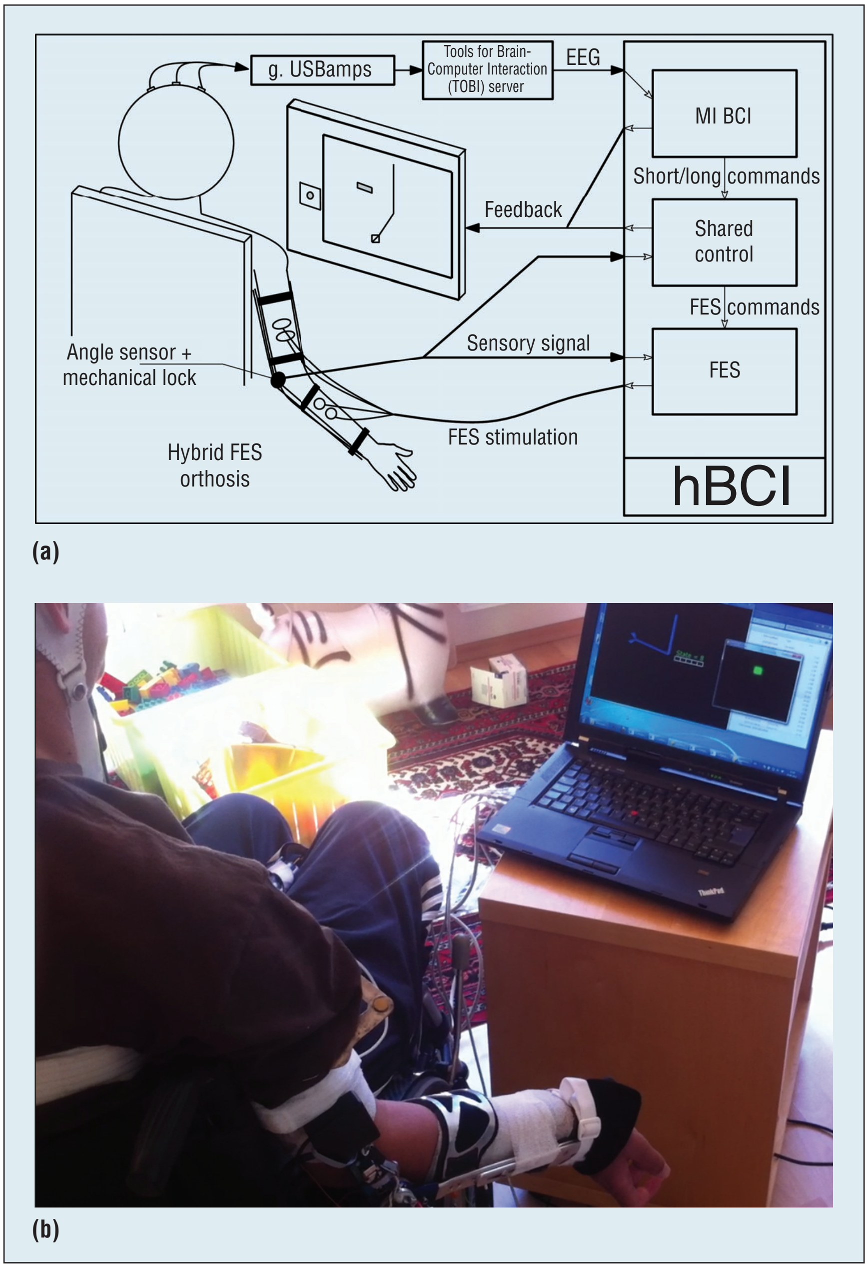

Figure 4. Working with a neuroprosthesis. (a) The scheme shows the setup for a user with a spinal cord injury (SCI). In the hybrid brain-computer interface (hBCI) block, EEG-based motor imagery commands and sensory information are fed to a shared control that interprets commands according to the neuroprosthesis's position. Appropriate commands are sent to visual feedback. (b) The user with SCI performs the experiment. (FES = functional electrical stimulation; MI = motor imagery.)

analog to combine inputs with varying degrees. Shared control analyzes information from the environment and the current state and allows for a context-based control. This facilitates safe and reasonable operation and prohibits dangerous or useless actions.

The involvement of BCI channels depends on the number and quality of other available signals and the type of application. BCI represents an optional input when other reliable signals for control are available. However, with a decreasing number of residual muscular functions, the control may increasingly rely on the BCI. BCIs can also be a backup solution as soon as other channels deteriorate due to fatigue or other performance-decreasing factors. A general rule for setting up any assistive device (including hBCIs) is a user-centered design: the system has to be designed according to the very specific user needs and abilities.

Hybrid BCI for Neuroprosthesis Control

The hBCI concept, with the BCI being the main input modality, is exemplarily demonstrated in the control of an upper limb neuroprosthesis based on FES. The hBCI incorporates an added input through a sensor monitoring the elbow joint angle and a shared control logic to interpret BCI commands in the context of the actual elbow joint angle. Nine healthy subjects and a male user with a complete SCI at the level of C5 took part in the study.

In the first session, participants trained imageries of movements of their right hand or feet. EEG electrodes placed over the motor cortex recorded the generated time-frequency patterns. Later, these patterns were classified online and used to control the neuroprosthesis by performing short or long motor imagery (MI).[5] The neuroprosthesis consisted of FES electrodes to stimulate lower and upper arm muscles and an electrically lockable elbow orthosis that included the angle sensor. Healthy subjects, as opposed to the user with SCI, controlled the arm of a second person to avoid stimulation-induced afferent feedback. This second person was not visible; instead, a video showing the person's right arm from his or her point of view was streamed to the feedback monitor in front of the subject. Figure 4 shows the scheme and a picture of the setup for the SCI user.

Over the course of 10 sequences, participants could trigger discrete commands with short MI (approximately one second) or continuous commands that started when MI was detected for more than 1.5 seconds and lasted as long as MI continued. Long commands continuously moved the arm into the direction furthest away from the current position; a short command opened or closed the hand when the arm was fully flexed or extended, or moved the arm to the nearest end position. When the elbow was supposed to flex or extend, a control loop was initiated within the FES device that adapted the stimulation strength until the desired angle was reached. As soon as the position was reached and the continuous command was ended, the position was locked mechanically.

All participants performed 10 active sequences with a time limit of three minutes each, separated by one-minute break sequences when false-positive (FP) commands were counted. Five subjects in total, including the user with SCI, were able to complete more than half of the sequences. The average true positive rate was 60.1 percent, depending on the commands triggered based on the actual state and target. Altogether, 55.5 percent of all sequences were successfully completed. On average, 8.2 commands/minute were triggered during sequences, as opposed to 4.7 FP/minute during breaks.

Some study participants had difficulties with time-coded MI, resulting in moderate performance: some maintained MI for longer periods of time but found it relatively hard to stop quickly, whereas others were hardly able to perform MI long enough to start the continuous elbow movements. The user with SCI accomplished the second best true positive rate, indicating that people with motor impairments can achieve a performance at least in the range of non-impaired subjects. The degrees of freedom of control and the performance could be increased by introducing additional context-specific classes or external signals, but these extensions must be carefully defined on the basis of the individual physical and mental capabilities and the needs of potential users. BCIs still have to become more accessible, especially for users who could see a real benefit from customized assistive technology in their homes.

The hBCI concept extends the possibilities of BCIs being used not just as a stand-alone system but as an integral component of an individualized assistive technology solution. The application of BCIs could be broadened if combined in a meaningful way with other reliable control signals, but it is difficult to generalize this approach because special needs and abilities can strongly vary between each user. A user-centered design is therefore crucial to find the most viable application of a BCI and to further increase the usefulness of BCIs as a control modality in general. Aside from being used for control of assistive devices, hBCIs can also be of value in the field of rehabilitation for restorative therapeutic applications.

Acknowledgments

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A.4. Single versus Multiple Events Error Potential Detection in a BCI-controlled Car Game with Continuous and Discrete Feedback [66]

The included publication is an early access preprint version which is peer-reviewed and citable but not yet fully edited.

Distribution of dedicated work:

- Alex Kreilinger: 80 %
- Hannah Hiebel: 10 %
- Gernot R. Müller-Putz: 10 %

The design and new approach to detect ErrPs in a continuous BCI feedback application was invented, designed, programmed, and carried out by Alex Kreilinger, as was the analysis and documentation of collected data. Hannah Hiebel helped with subject measurements. Alex Kreilinger wrote the manuscript but Hannah Hiebel and Gernot R. Müller-Putz provided assistance during all stages of the work.

Single versus Multiple Events Error Potential Detection in a BCI-Controlled Car Game with Continuous and Discrete Feedback

Alex Kreilinger, Hannah Hiebel, and Gernot R Müller-Putz *Member, IEEE*

***Abstract*— *Objective:* This work aimed to find and evaluate a new method for detecting errors in continuous brain-computer interface (BCI) applications. Instead of classifying errors on a single trial basis, the new method was based on multiple events analysis to increase the accuracy of error detection. *Methods:* In a BCI-driven car game, based on motor imagery (MI), discrete events were triggered whenever subjects collided with coins and/or barriers. Coins counted as correct events, whereas barriers were errors. The new multiple events method combined and averaged the classification results of single events and determined the correctness of MI trials, which consisted of event sequences instead of single events. The benefit of this method was evaluated in an offline simulation. In an online experiment the new method was used to detect erroneous MI trials. Such MI trials were discarded and could be repeated by the users. *Results:* We found that, even with low single event ErrP detection rates, feasible accuracies can be achieved when combining multiple events to distinguish erroneous from correct MI trials. Online, all subjects reached higher scores with error detection than without, at the cost of longer times needed for completing the game. *Conclusion:* Findings suggest that ErrP detection may become a reliable tool for monitoring continuous states in BCI applications when combining multiple events. *Significance:* The paper demonstrates a novel technique for detecting errors in online continuous BCI applications which yields promising results even with low single trial detection rates.**

***Index Terms*—brain-computer interface (BCI), continuous feedback, electroencephalogram (EEG), error potential (ErrP)**

I. Introduction

RESEARCH on Brain-computer interfaces (BCIs) based on electroencephalography (EEG) is still attracting an ever increasing number of investigators, although the term was first coined in 1973 [1]. A main focus of the work today is to make these BCIs more practical for potential end-users. This objective requires easy-to-use applications which are stable over time and can guarantee reliable and accurate performance. One way to improve the performance of BCIs is to carry out long-term training to increase proficiency. Unfortunately, this is not guaranteed to work for each individual end-user [2], [3], [4], [5], [6]. The long training time can successfully be reduced by using a large feature space and machine learning techniques. However, equipping an increased number of required electrodes can be time-consuming as well [7]. BCIs can also be designed to adapt to the user with so-called adaptive BCIs [8].

Another possibility to increase the performance is to automatically detect errors from recorded brain waves after reactions to particular decisions and thereby permit the BCI system to either correct or inhibit erroneous commands. Distinct errors committed or observed by a person cause detectable potentials, so-called error potentials (ErrPs) [9], [10]. Depending on the way these potentials are generated they are defined as either observation [11], feedback [12], response [13], or interaction ErrPs [14]. Interaction ErrPs can be detected at the region over the anterior cingulate cortex (ACC) [15] and can be measured after a person witnesses a false execution of an intended command. From the user's perspective, an interaction ErrP occurs whenever a command was misinterpreted by the control interface used. In contrast to the other types of ErrPs, which either do not require the involvement of the user or do not emerge in self-paced scenarios, the interaction ErrP seems to be the best choice for increasing performance in BCI applications for end-users.

These interaction ErrPs can be used to increase the performance of BCIs by detecting specific reactions to errors that differ from reactions to correct events. False actions can be inhibited which leads to increased accuracies of BCI-driven systems. Several studies have already mentioned the technical capabilities of error correction for various paradigms [16], [14]. The paradigms used in these experiments have in common that they are designed to work well for ErrP processing. That is, in a discrete feedback, time- and phase-locked ErrPs can be detected by evaluating time periods after discrete events. However, modern BCI applications are no longer limited to discrete applications where only one discrete decision can be made at one given point in time. Instead, continuously controlled applications gain importance as they offer a more natural implementation of BCI for activities of daily living. Relevant examples are a continuously moving wheelchair for mobility [17] or a neuroprosthesis for grasp and elbow functions [18]. Other useful scenarios can be the application of BCIs in games [19] or in virtual reality [20].

An attempt to detect errors offline in a continuous feedback

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application has already been made in [21] by using a space game. However, the game was controlled manually and not using BCI and instead of EEG the authors chose to use electrocorticography (ECoG). Errors could be caused by forced deviations from the intended movement or by collisions with obstacles. These errors could be detected above chance level within a 6 s window around the event. A replication of the study with EEG was conducted by [22]. Here, errors were detected by using temporal and spectral features in time- and phase-locked and asynchronous analyses. The asynchronous analysis achieved results above random but was still inferior to the time- and phase-locked approach. Moreover, analysis was carried out with offline data only.

This study aimed to find and evaluate a feasible method to use ErrP detection in continuous applications online. The time- and phase-locked nature of ErrPs needed for analyzing temporal features was exploited by showing discrete feedback on top of ongoing continuous feedback. This study serves as a follow-up to [23] where this approach was already addressed: A continuous feedback in form of a moving artificial arm was coupled with additional discrete events as triggers and ErrPs were successfully found in offline analysis. However, the accuracy for single trial detection of these ErrPs was not sufficient to be feasible in online applications.

In this work we demonstrate a new method that can be used in continuous BCI applications without relying on single trial error detections. In a continuous, BCI-driven car game based on motor imagery (MI) [24] subjects observed multiple discrete events while moving the car continuously. Although each single event (SE) was classified individually, a decision was only reached after a series of multiple events (ME) were witnessed by the users. This new method is termed the ME method, whereas the old standard method based on single trials, or in this case events, is referred to as the SE method.

In the course of the experiments we also analyzed the impact of different types of feedback: visual feedback alone versus visual and acoustic feedback.

II. Methods

This work describes a series of experiments and analyses. These include sessions for training MI, a car game controlled continuously with MI, analyses to detect ErrPs after observing discrete events, simulations with the new method based on multiple events, and a session where the new method is used to determine false actions in the car game online. The order in which these experiments and analyses were carried out is outlined in Fig. 1.

Subjects, Hardware, and Recording

Five female and five male subjects (24.9±2.3 years) participated in the study. All subjects had previous BCI experience and were reported to be able to control MI-based BCIs. They were selected intentionally to reduce long initial BCI training time in order to not unnecessarily drain their concentration level. Data was recorded with two g.USBamps (Guger Technologies OEG, Graz, Austria). The 32 Ag/AgCl-electrodes were placed on the scalps of the subjects according to a dense 10-20 system. Thereby, all of the important regions for MI (C3, Cz, C4) and ErrP detection (the area over the ACC at channels Fz and Cz) were covered. All channels were monopolar recorded with a reference electrode at the left mastoid and ground on the right mastoid. The sample rate was set to 512 Hz with a high-pass filter at 0.5 Hz, a low-pass filter at 100 Hz, and a notch filter at 50 Hz.

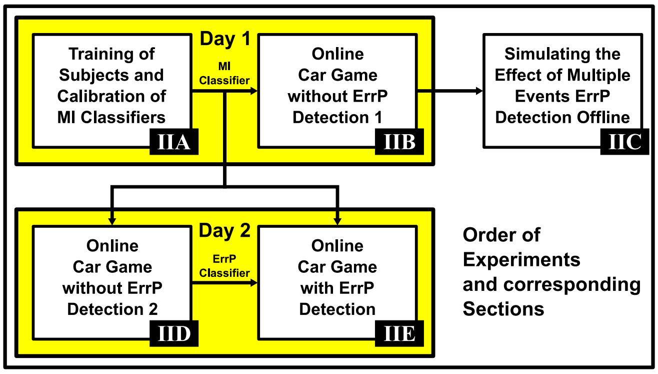


Fig. 1. Order of the experiments and analyses. Experiments with the subjects were divided into two sessions on different days. Subsequent analyses were carried out with data collected during these experiments.

A. *Training of Subjects and Calibration of MI Classifiers*

1) Experiment Setup: The first part of the experiments was conducted to train the subjects in using a BCI and to subsequently calibrate MI classifiers. Two to four training runs with the standard Graz-BCI paradigm [24] were carried out. Subjects were asked to perform MI of the two required classes (right hand vs. both feet), in total 20 trials per class in each run. One trial lasted 7 s: appearance of the cross at 0 s, appearance of the cue at 2 s, disappearance of the cue at 3.25 s, and end of the trial with the disappearance of the cross at 7 s. Subjects were asked to maintain active MI between 3.25–7 s. As a rule, only two runs were carried out. However, subjects who produced a noticeable amount of noisy trials were asked to repeat one or two runs.

2) Analysis: All 32 electrodes were used to perform common average reference (CAR) spatial filtering. The relevant channels for this filtering were at electrode positions C3, Cz, and C4. ERD/S maps [25], [26] were used to visualize distinct patterns. The patterns were based on variations of band power in certain frequency bands related to active MI. Based on the maps, the best frequency bands on channels C3, Cz, or C4 were selected. Per subject, 1–3 frequency bands were selected by this means. These frequency bands were situated mainly in the alpha (8–12 Hz) and beta (13–30 Hz) range on channel C3. The best point in time was found with a 10×10 cross-validation which was repeated in steps of 100 ms within the active MI period (3.25–7 s). This point in time was used to generate the final individual linear discriminant analysis (LDA) classifier for each subject.

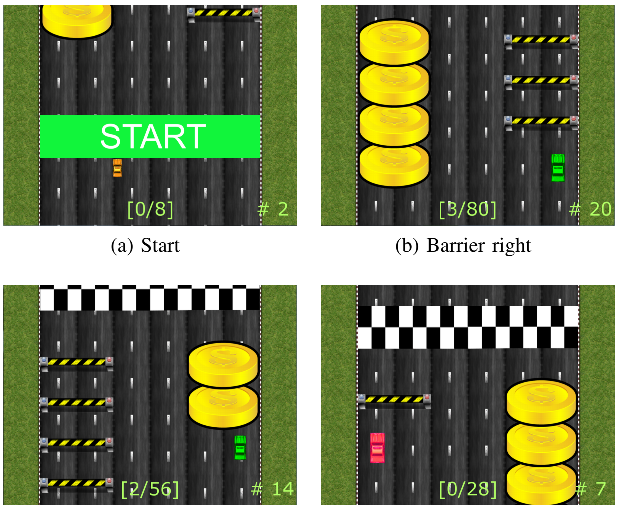
B. *Online Car Game without ErrP Detection 1*

1) Experiment Setup: The generated classifier from training data (Section II-A) was applied to let subjects control the movement of a car in a game. The car was moving at a constant speed on a vertically scrolling street. Subjects could move the car to the left by performing feet MI and to the right by performing right hand MI. Control was active all the time, not just in predefined periods of time. The car continuously moved farther away from the center the more distinctly the current MI task was detected by the classifier which was represented by the amplitude of the classifier output. However, the car's movement was limited by the outermost lanes. Coins appeared randomly on the left or the right side of the street. For each coin appearing, a barrier appeared on the opposite side of the street. Coins were defined as targets and subjects were asked to collect as many as possible while avoiding barriers in the process.

The game consisted of six runs with 20 trials left (coins on the left side) versus 20 trials right (coins on the right side). One of the subjects, S04, had to stop after four runs caused by fatigue and lack of concentration; the others performed in all six runs. During each trial a maximum of four coins could be collected, but also the same number of barriers on the opposite side. The side of the coins and barriers remained constant within a trial. A mixed collection of objects was possible when the MI performance during the trial was unstable, e.g., two coins on one side followed by two barriers on the other side. Coins and their associated barriers appeared at intervals of one second. In total a trial lasted 8 s beginning with the crossing of a starting line at second 0, followed by collectible objects at seconds 3, 4, 5, 6, and ending with the crossing of the finishing line after 8 s. All these events appeared 4 s earlier on the top of the screen. That is, the vertical scrolling speed was set in such a way that the car needed 4 s to reach new objects on the street. Thereby, subjects were able to prepare for oncoming events.

The paradigm allowed a maximum collection of 960 coins within all six runs. Each time a coin was collected, the score increased by $+1$ and decreased by -1 when colliding with a barrier. However, negative scores were not possible. The minimum score was limited to zero in order to not discourage the subjects. Every collision with a coin or a barrier was confirmed by a short feedback event. The impact of the type of feedback was examined by testing two different modalities. Half of the runs were recorded with acoustic (short beeps with differently high frequencies) and visual (temporarily increased size and change of color of the car) feedback combined ('Sound' modality); the other half used only visual feedback without any sound ('NoSound' modality). The sequence of these two different run modalities was randomized for each subject individually in order to avoid possible learning effects. The discrete feedback events were chosen to be neutral for coin and barrier collisions: instead of linking the bright green flashing color and the higher frequency sound to coins, the sounds and flashes were merely dependent on the side of the street where the current collision occurred. Pictures of the car game depicting several random situations can be seen in Fig. 2.

2) Analysis: Reactions to discrete events (collisions with coins and barriers) were analyzed for possible ErrPs. Channels Fz, Cz, and Pz were spatially filtered with CAR and temporally filtered with an 8 Hz low-pass filter. Only data within a one-second window following the discrete events were evaluated. Data were separated into two different classes, the time windows containing either reactions to correct events or to errors. Features were selected with a discriminant power (DP) algorithm [27]. This algorithm analyzed each point in time successively and counted the values (EEG amplitudes) of each class that were outside of the distribution of the respective other class. Up to 30 of the best points in time were used as features. The actual number of features was determined by repeating a 10×10 cross-validation procedure with each number of features. After cross-validating the results, the detection rates for the best number of features of correct and erroneous events for each subject were calculated individually. The results for both classes were averaged to mitigate potential bias effects caused by the typically much lower number of error events. These results are based on detecting single events and the according method to obtain the SE detection rate or accuracy is the SE method. The corresponding measure is termed "SE_Acc_CV" (SE accuracy calculated via cross-validation). Data were analyzed separately for the according feedback modalities 'Sound' and 'NoSound'.



(a) Start (b) Barrier right

(c) Coin right (d) Barrier left

Fig. 2. Different situations during the car game. (a) Start of a trial: new objects appear at the top of the screen and subjects can begin performing the correct MI task to move towards the coin. In this case the MI target is on the left side. (b, c) Collisions with barriers and coins on the right. The color and type of sound is the same for all collisions on the right side, independent from the type of object. (d) Left side collisions have a different visual and acoustic feedback. Crossing the finishing line ends the current MI trial.

To analyze potential differences in SE_Acc_CV caused by the applied feedback modalities, a paired-samples t-test with the independent variable "feedback modality" ("Sound", "NoSound") was conducted (with a significance level of 0.05). Average SE_Acc_CV ([%]) was used as dependent variable. Since the results of the t-test did not show a statistically significant difference between both modalities, the SE_Acc_CV evaluation was repeated for a third pseudo modality named 'Combined' which comprised all data and therefore a larger pool of trials.

The MI performance was obtained by calculating the percentage of collected coins out of all collisions with objects on the street. This part of the study was shown in a preliminary version in [28].

C. Simulating the Effect of Multiple Events ErrP Detection Offline

This section aims to show the potential benefits of a new multiple events (ME) analysis in an offline simulation based on data collected in Section II-B.

1) The Multiple Events ErrP Detection Method: The new approach was to combine consecutive single events for the analysis. The car game was especially designed to force multiple collisions with objects during one single MI trial. The reactions caused by these collisions were classified with LDA classifiers as in the analysis in Section II-B2. The classifier output was positive for a detected error and negative for a correct response. The higher the absolute value the more distinct was the classification. In the new ME approach all classification results of single events within one MI trial were combined for evaluating the whole MI trial. There were four possible outcomes in a single MI trial which had to be evaluated differently:

1) Events only occurred on one side of the road: In this case, all SE classification results were averaged. If the averaged classifier output was positive (erroneous), the original MI target (the side of the road with the coins) was determined to be on the opposite side of where the event collections occurred.
2) Events occurred on both sides of the road with a majority on one side: Classification results from events on the minority side were inverted (multiplied by -1) and then averaged with the other classification results. For example, three events occurred on the left side, all of them errors. One event was on the right side which was correct. With correct classifications the left side events would all lead to positive classifier outputs, whereas that on the right side would be negative. Inverting this classifier output increases the number of averages to four without giving the single event more weight. Since all four classifier outputs now are positive, the averaged result clearly indicates that the MI trial was, in fact, mostly erroneous.
3) Events occurred on both sides an equal amount of times: Classifier outputs on both sides were averaged individually. The side with the lower average was selected as the original MI target. An example for this outcome is also shown in Fig. 3.
4) No events occurred at all: In this rare case it was not possible to determine the target and the MI trial was removed from the simulation.

2) Simulation and Analysis: The capability of this new approach to correctly determine the original MI targets was tested in the offline simulation. As the detection rates of this novel technique were no longer based on single events, the basis of how to report the performance of the approach had to be adapted. Multiple events indicated whether an MI trial as a whole was correct and thereby the original MI target could be determined. The measure to define the accuracy of this determination was the ratio of correctly identified MI trial targets to the whole number of MI trials, from here on referred to as "ME_Acc". This ME_Acc was compared to the detection rates obtained by analyzing single events, "SE_Acc". Additionally, ME_Acc was compared to the original MI performance (in the offline simulation termed "MI_Acc") which was obtained by analyzing the rate of collected coins to collected objects in total. The reasoning behind this comparison was to find out whether the capability of the ME method to determine original targets of MI trials might even be on par with the original MI performance. To mitigate any influence from potential overfitting, data were separated between runs. Each run was used as a test set on which an ErrP LDA classifier, calculated with data from the other runs, was applied. All three measures were calculated in each test set. For ME_Acc all MI trials were evaluated with the new ME method. For SE_Acc all single event classifications were evaluated again. For MI_Acc all coin collections were compared to the total number of events. The results were then averaged over all corresponding runs.

Equations (1)–(3) demonstrate how these three measures were calculated in the offline simulation. In equation (1) true positive (TP) and false negative (FN) values represent correctly and incorrectly classified errors (reactions to collisions with barriers). True negative (TN) and false positive (FP) values represent correct and incorrect classifications of reactions to coin collections. The equation basically describes the balanced accuracy which is the mean of sensitivity and specificity. In equation (2) CorrLeft and CorrRight represent the numbers of correctly classified MI targets, whereas AllLeft and AllRight give the whole number of MI trials. In equation (3) the number of collected Coins is compared to the sum of Coins and Barriers. All measures are averaged over the number of test runs n.

$$\mathrm{SE\_Acc} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left(\frac{\mathrm{TP_i}}{\mathrm{TP_i+FN_i}} + \frac{\mathrm{TN_i}}{\mathrm{TN_i+FP_i}}\right)}{2}\cdot 100 \qquad (1)$$

$$\mathrm{ME\_Acc} = \frac{1}{n}\sum_{i=1}^{n}\frac{\mathrm{CorrLeft_i + CorrRight_i}}{\mathrm{AllLeft_i + AllRight_i}}\cdot 100 \qquad (2)$$

$$\mathrm{MI\_Acc} = \frac{1}{n}\sum_{i=1}^{n}\frac{\mathrm{Coins_i}}{\mathrm{Coins_i + Barriers_i}}\cdot 100 \qquad (3)$$

The simulation was carried out for the two feedback modalities 'Sound' and 'NoSound'. Based on the findings of the t-test described in Section II-B2, which indicated that the modality had no effect on ErrP detection rates, the simulation was also carried out with all data as in the 'Combined' pseudo modality.

To investigate potential differences in classification accuracy depending on method and feedback modality, a 3×2 ANOVA for repeated measures was performed with the within-subjects factors "method" ("SE", "ME", "MI") and "feedback modality" ("Sound", "NoSound"). The averaged accuracy (SE_Acc: detection rate of single events in %; ME_Acc: rate of correctly identified MI trials that included at least one event in %; MI_Acc: proportion of correct events in %) served as dependent variable. A Kolmogorov-Smirnov test was used to check if data followed a normal distribution. Sphericity assumption was assessed by using the Mauchley's sphericity test. In all statistical analyses the probability of a Type I error was maintained at 0.05. For post-tests of significant ANOVA effects, Bonferroni corrections for multiple comparisons were applied.

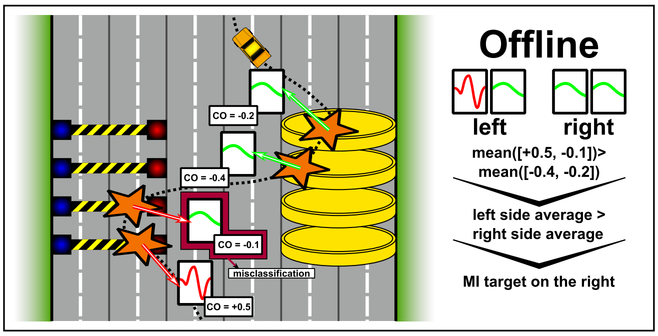


Fig. 3. Possible scenario for the offline simulation. The same number of objects were collected on each side. Each response is classified separately, resulting in different classifier outputs (CO). Detected ErrPs result in positive COs and are visualized as red waveforms. Correct events result in negative COs and are visualized as green waveforms. Both sides' COs are averaged and the side with the higher positive value is identified as erroneous. Although not all individual COs are correct (the second event on the left side is a misclassification), the correct intended direction can be identified after averaging. The MI trial in this example can be classified as 'right side'.

D. Online Car Game without ErrP Detection 2

On a second session, after analyzing data from day 1 and performing the offline simulation, selected participants performed the car game again. This experiment served as precursor for the subsequent online application of ErrP detection.

1) Selection of Subjects: Not all subjects participated; inclusion criteria were based on data from previous sections. The MI performance threshold was set to 70 % because of the minimum correct response rate needed for a feasible BCI application [29]. The level for the error detection rate to be potentially beneficial depends on the initial MI performance and can be calculated with equations (4)–(7) based on Wolpaw's definition in [30], [27]. The original bit rate per trial BR depends only on the MI performance, whereas the new bit rate $\mathrm{BR_n}$ with applied error detection to inhibit detected commands depends on the percentage of transmitted commands p_{ec} and the increased accuracy of the system p_{n}. Remaining variables in the equations are as follows: p describes the original MI performance; c the detection rate of correct commands; e the detection rate of errors; N_c the number of classes. The minimum error detection rate needed to theoretically increase the original bit rate can be calculated individually for each subject. For example, at an MI performance of exactly 70 % the bit rate already increases at an error detection rate of 58.9 %; for an MI performance of 90 % the error detection rate has to be at least 73.9 % to have a beneficial effect. Six of the ten subjects could fulfill the criteria of having an MI performance >70 % and accordingly high error detection rates, based on ME_Acc and MI_Acc values found in the offline simulation with the modality 'Sound'. Unfortunately, two of them were no longer available, leaving four subjects for the final part.

$$p_{\mathrm{ec}} = p \cdot c + (1-p) \cdot (1-e) \tag{4}$$

$$p_{\mathrm{n}} = \frac{p \cdot c}{p_{\mathrm{ec}}} \tag{5}$$

$$\mathrm{BR} = \log_2(N_c) + p \cdot \log_2(p) + (1-p) \cdot \log_2 \frac{(1-p)}{(N_c-1)} \tag{6}$$

$$\mathrm{BR_n} = p_{\mathrm{ec}} \cdot (\log_2(N_c) + p_{\mathrm{n}} \cdot \log_2(p_{\mathrm{n}}) + (1-p_{\mathrm{n}}) \cdot \log_2 \frac{(1-p_{\mathrm{n}})}{(N_c-1)}) \tag{7}$$

2) Experiment Setup: The purpose of this experiment was to generate new ErrP classifiers for the final online task with applied ErrP detection. The setup was similar to the setup explained in Section II-B. The MI classifiers generated in Section II-A2 were reused to avoid time-intensive MI training. The subjects merely performed one short setup run consisting of three left and three right MI trials to adapt the bias of the MI classifier if necessary. The car game was carried out again, but now with only half of the trials, since the used modality was chosen to be 'Sound' exclusively for this and the following experiment. S01 performed only four runs due to a relatively high amount of barrier collections, thereby generating enough data for ErrP classification but later subjects were asked to carry out six runs.

3) Analysis: ErrP classifiers were generated from the newly recorded data, following the method used in Section II-B2. The MI performance of the subjects in the car game was measured in terms of collected coins and barriers.

E. Online Car Game with ErrP Detection

The final experiment was carried out on the same day as the car game without ErrP detection in Section II-D with the same four remaining subjects. The aim was to demonstrate the feasibility of the new ME method in an online experiment alongside the evaluation in the offline simulation.

1) Experiment Setup: In this experiment, the car game was enhanced by embedding the new ME method. The ME method was used to evaluate each single MI trial after the car had crossed the finishing line. There was one important difference compared to how the method was used in the offline simulation. The aim was now no longer the determination of the original MI target but to determine whether the MI trial on the whole was erroneous. In case of an erroneous MI trial, the score of the whole MI trial was discarded and the subject had the chance to repeat the trial. Another difference was that MI trials with an equal number of events on both sides were no longer evaluated. Otherwise, the procedure for the evaluation of one trial followed the explanation in Section II-C1. An example for an MI trial with three errors and one correct event is demonstrated in Fig. 4.

To summarize, an MI trial had a chance to be discarded and repeated if one of the two following situations occurred:

1) All events occurred on one side of the road and the average classifier output for all events was positive.
2) Events occurred on both sides of the road with one majority side with more events. The average classifier output of the events on the majority side and the inverted classifier outputs of the minority side were positive.

The car game with online ErrP detection consisted of six runs with 20 MI trials each, with ten targets on the left and ten targets on the right. As opposed to the previous car game sessions, negative scores were possible in this experiment.

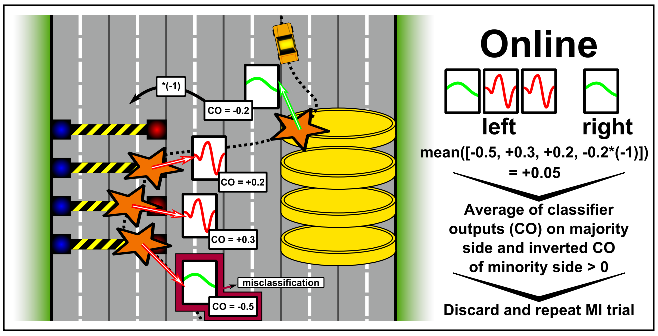


Fig. 4. One possible online scenario. The subject collides with three barriers and then picks up one coin on the opposite side. Each reaction to a collision is classified separately and results in a positive or negative number, with positive numbers indicating the detection of an ErrP. ErrPs are further visualized as red waveforms and reactions to correct events as green waveforms. In this example, the first reaction is misclassified as correct, the rest of the collisions are classified correctly. The left side is the majority side with more collections. The classifier output of the one collision on the right side is multiplied by -1. Because the result after averaging all classifier outputs is a positive number, the whole MI trial has to be discarded and can be repeated.

2) *Analysis:* The functionality of the online ErrP detection with the ME method was evaluated by comparing two different outcomes: the actual outcome after applied ErrP detection versus the outcome that would have been achieved without ErrP detection. This was possible because, without activated ErrP detection, each run would have stopped exactly after the 20^{th} trial. Therefore, the score after 20 trials, including discarded MI trials, was saved at this point for later analysis. Active ErrP detection could prolong a run for as many trials necessary to have 20 trials that were not discarded as erroneous. The expected outcome of the experiment was to trade a longer time needed for completion in order to achieve improved accuracy.

The goal of the ME method in the online experiment was to detect erroneous MI trials. The corresponding performance measure had to be calculated differently than in the offline simulation. This measure, called ME_Acc_Online, was calculated based on equation (8). Here, TP and FN indicate the numbers of detected and missed erroneous MI trials. TN and FP represent the numbers of detected or misclassified correct MI trials. MI trials that were not eligible for being discarded due to an equal number of events on both sides were excluded from this calculation.

$$\text{ME\_Acc\_Online} = \frac{\left(\frac{\text{TP}}{\text{TP+FN}} + \frac{\text{TN}}{\text{TN+FP}}\right)}{2} \cdot 100 \qquad (8)$$

III. Results

A. Training of Subjects and Calibration of MI Classifiers

All the subjects performed short MI training to generate data for setting up LDA classifiers to control the car game in all later experiments. Individual results are listed in Table I. The best accuracies and points in time in relation to the start of the trial at second 0 were determined in a cross-validation procedure. As one single outlier with a high accuracy at one single point in time could whitewash the individual performance, the table also shows the threshold exceeded by at least 10 % of all classification accuracies and the median accuracy within the active MI period (3.25–7 s). These results served as a prediction of how well subjects would be able to control the car game. Their MI performance was closely related to the expected error rate when controlling the game.

TABLE I
MI performance calculated by generated LDA classifiers. Best Accuracy and Best Time demonstrate the peak performances at the best individual points in time during active MI. Upper Ten Percent shows the level of performance which was exceeded for ten percent of points in time tested within the active MI period. The median accuracy serves as an additional measure of performance.

Subject	Best Accuracy [%]	Best Time [s]	Upper Ten Percent [%]	Median Accuracy [%]
S01	74.0	6.1	72.7	68.3
S02	98.5	5.5	95.3	88.2
S03	80.6	5.2	80.0	73.4
S04	81.2	4.5	79.8	76.2
S05	97.5	5.4	96.5	94.4
S06	86.2	3.8	84.1	75.1
S07	96.5	4.6	95.3	87.7
S08	88.0	4.9	87.1	83.2
S09	86.6	3.4	85.1	64.2
S10	78.9	3.6	74.3	58.1

B. Online Car Game without ErrP Detection 1

The results of this part consist of the online MI performance and offline ErrP detection analysis based on the SE method. The first was determined by the scored points during the car game. The second was found by cross-validating ErrP classifications. The online score was increased by $+1$ for each collected coin and reduced by -1 for each collision with a barrier. Subjects could also miss all objects within a trial. In this case the score was not altered and neither a positive nor a negative feedback occurred. Furthermore, the score could never fall below zero points. MI performance influenced the subsequent offline analysis as the number of correct and erroneous trials for ErrP detection was equal to the number of collected coins and barriers. Table II shows the score, number of collected coins versus barriers, the MI performance and the error rate (100 %$-$MI performance) for each participant. The table shows results from all data combined, that is 'Sound' and 'NoSound'. Fig. 5 visualizes these results sorted from highest to lowest score.

The performance-depending rate of errors evoked differently strong ErrPs for the ten subjects. The error-minus-correct waveforms—the ErrPs—for all the participants are demonstrated in Fig. 6. Three channels, Fz, Cz, and Pz, are shown

TABLE II
RESULTS OF THE CAR GAME IN TERMS OF TOTAL SCORE OUT OF 960 MAXIMUM POINTS (640 FOR S04) AND COIN:BARRIER COLLECTION RATE FOR EACH PARTICIPANT. THE MI PERFORMANCE SHOWS THE PERCENTAGE OF COLLECTED COINS AND THE ERROR RATE THE PERCENTAGE OF COLLISIONS WITH BARRIERS.

Subject	Total Score	Coins: Barriers	MI Performance [%]	Error Rate [%]
S01	409	599:192	75.7	24.3
S02	718	782:65	92.3	7.7
S03	588	709:127	84.8	15.2
S04	189	367:185	66.5	33.5
S05	722	797:75	91.4	8.6
S06	202	489:310	61.2	38.8
S07	703	774:72	91.5	8.5
S08	751	823:72	92.0	8.0
S09	100	404:349	53.7	46.3
S10	265	541:302	64.2	35.8

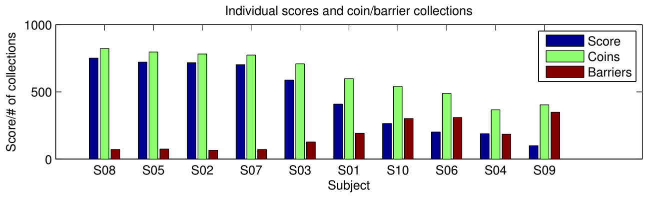


Fig. 5. Barplot showing scores and individual collection rates of coins and barriers in sorted order from highest to lowest score.

for the two modalities 'Sound' and 'NoSound'. The most notable effect is visible over Fz and Cz, the channels directly over the ACC. On average, there is a measurable negativity about 400 ms after the moment of a collision with a barrier. An offline analysis of 'Sound' and 'NoSound' data yielded

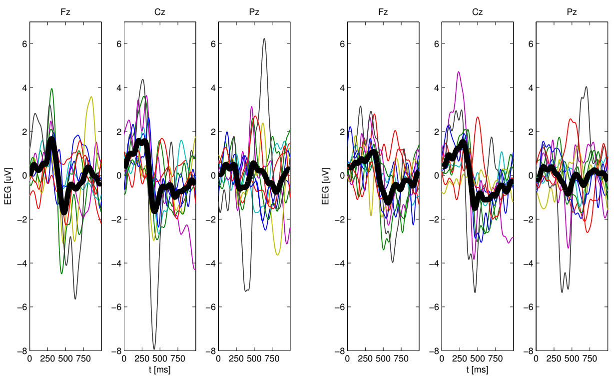


Fig. 6. Recorded ErrPs for all individual subjects and averaged waveforms, shown specifically for 'Sound' and 'NoSound' modalities. Point in time 0 ms is the time of the collision with an object on the street. The measured ErrPs are shown for three different channel locations: Fz, Cz, and Pz.

SE_Acc_CV results for correct and erroneous trials above chance level for all subjects except S09 and S10 in at least one modality. The chance level was on average 54.4 % ('Sound') and 54.3 % ('NoSound'), depending on the number of trials per class [31]. Feature extraction and cross-validation were performed individually for each modality. The comparison of SE_Acc_CVs for feedback with and without sound brought forth following results: the average SE_Acc_CV for detecting correct and erroneous trials was 62.1±9.3 % for the 'Sound' modality and 61.1±8.0 % for 'NoSound'. The results of the *t*-test, which was used to compare SE_Acc_CV between 'Sound' and 'NoSound', showed no significant difference ($t(9)=0.51$, $p=.620$). An additional analysis was thus conducted with all the data combined ('Combined'). Here, SE_Acc_CV was on average 61.2±8.5 %. The new ME method was not yet applied in this analysis.

C. Simulating the Effect of Multiple Events ErrP Detection Offline

The results of the offline simulation show the advantages of the new ME method over the standard SE method. The simulation analyzed both methods by using the same LDA classifiers. In the SE method these classifiers were solely used on single events, whereas in the ME method consecutive single events within whole MI trials were combined as multiple events. The simulation analyzed data from Section II-B. The results are demonstrated in Table III. Data were at first separated according to the two main modalities 'Sound' and 'NoSound'. Later, the whole data set was also analyzed in the 'Combined' modality. This modality, although included in the simulation, was not analyzed statistically as it included data of both other modalities. Values in the columns labeled "SE_Acc" demonstrate individual ErrP detection rates obtained with the standard SE method. "ME_Acc" demonstrates the detection rates for the correct determination of original MI trial targets that were obtained with the new ME method. "MI_Acc" shows the MI performances achieved by the subjects via controlling the car. All these values were averaged over all the runs (three runs for 'Sound' and 'NoSound', and six runs for 'Combined'), which explains the small differences between MI performance in Table II and MI_Acc in Table III. ME_Acc values in Table III indicate how many MI trials can be correctly identified when only looking at reactions to a sequence of discrete events.

The bold numbers in Table III highlight the subjects that can potentially benefit from online ErrP detection, based on the bit rate calculations from Section II-D1. The number of subjects is higher in column "ME_Acc" than in column "SE_Acc" for all modalities. In the case of the modality 'Sound', which was used in later experiments, six out of ten subjects potentially benefit from ErrP detection based on the ME method, while only three would benefit from using the standard SE method.

ANOVA results concerning simulations of 'Sound' and 'NoSound' data revealed a significant main effect "method" ($F(2,18)=21.61$, $p<.001$). Post-tests showed a significantly higher accuracy for "ME" ($M=74.78$, $SD=14.70$) and "MI" ($M=77.26$, $SD=15.03$) than for "SE" ($M=61.98$, $SD=8.19$). Accuracy did not differ significantly between "ME" and "MI". The main effect "feedback modality" did not reach statistical significance ($F(1,9)=0.79$, $p=.396$). The interaction effect "method×feedback modality" was also not significant ($F(2,18)=1.46$, $p=.259$).

D. Online Car Game without ErrP Detection 2

The reason for repeating the car game without ErrP detection was to generate new ErrP classifiers. The results are

TABLE III
COMPARISON OF SINGLE EVENT ERROR/CORRECT ACCURACIES (SE_ACC) VERSUS MI TRIAL DETECTION RATES BASED ON MULTIPLE EVENTS ANALYSIS (ME_ACC) AND ORIGINAL MI PERFORMANCES (MI_ACC). THE VALUES SHOW OFFLINE SIMULATION RESULTS AND ARE AVERAGED OVER ALL RUNS THAT BELONG TO THE CORRESPONDING MODALITIES. BOLD NUMBERS INDICATE SUBJECTS THAT HAVE AN MI_ACC ABOVE 70 % AND WOULD BENEFIT FROM ERRP DETECTION BASED ON THE TWO METHODS SE OR ME, AS SUGGESTED BY INDIVIDUAL BIT RATE CALCULATIONS.

	Sound [%]			NoSound [%]			Combined [%]		
Subject	SE_ Acc	ME_ Acc	MI_ Acc	SE_ Acc	ME_ Acc	MI_ Acc	SE_ Acc	ME_ Acc	MI_ Acc
S01	**66.7**	**81.7**	72.9	59.6	**71.7**	78.3	**62.5**	**76.7**	75.6
S02	**78.9**	**93.3**	92.3	65.7	**88.3**	92.3	71.3	**84.2**	92.3
S03	53.9	**68.3**	82.0	60.2	**79.2**	87.5	54.0	68.3	84.8
S04	60.9	70.0	68.6	55.0	58.8	65.2	57.2	65.6	66.9
S05	67.2	**86.7**	91.2	**75.9**	**91.7**	91.5	71.5	**87.9**	91.4
S06	61.5	69.2	61.1	52.8	52.5	61.1	56.3	59.2	61.1
S07	**76.4**	**93.3**	90.7	70.3	**85.0**	92.3	74.2	**89.6**	91.5
S08	64.7	**89.2**	90.5	61.0	**92.5**	93.4	61.2	**85.4**	91.9
S09	51.0	55.8	53.1	59.7	60.0	53.1	57.8	62.5	53.1
S10	48.9	56.7	66.7	49.3	51.7	61.3	51.3	54.6	64.0
mean	63.0	76.4	76.9	61.0	73.1	77.6	61.7	73.4	77.3
±std	9.9	14.3	14.3	8.0	16.3	15.9	8.0	12.9	15.0

summarized in Table IV, including the number of collected coins and barriers and the directly associated MI performance and error rate. Column "SE_Acc_CV" describes error detection rates that were achieved in a 10×10 cross-validation based on the SE method.

TABLE IV
RESULTS FROM THE REPEATED CAR GAME WITHOUT ONLINE ERRP DETECTION. THE MAXIMUM SCORE IS 480 POINTS (320 FOR S01). THE RATIO OF COINS VERSUS BARRIERS DETERMINES THE MI PERFORMANCE (PERCENTAGE OF COINS) AND THE ERROR RATE (PERCENTAGE OF BARRIERS). SE_ACC_CV DEPICTS THE ERRP CLASSIFICATION ACCURACIES FOUND IN AN OFFLINE ANALYSIS BASED ON THE SE METHOD WITH A 10×10 CROSS-VALIDATION PROCEDURE.

Subject	Coins: Barriers	MI Performance [%]	Error Rate [%]	SE_Acc_ CV [%]
S01	188:107	63.7	36.3	62.1
S02	253:101	71.5	28.5	67.7
S05	428:19	95.7	4.3	71.5
S07	420:56	88.2	11.8	75.0

E. Online Car Game with ErrP Detection

After the new ErrP classifiers were generated based on the SE method, participants were able to control the car game with online ErrP detection based on the new ME method. Their performance during this application is demonstrated in Table V. The results demonstrate the individual increased numbers of scored points when using error detection compared to the score reached after exactly 20 trials including the points from discarded erroneous MI trials. As an inevitable side effect, the number of MI trials needed for completion was also increased.

The performance of the ME method in the online experiment was also measured by the detection rate of erroneous and correct MI trials. The corresponding measure is the ME_Acc_Online, calculated from the TP, FN, FP, and TN numbers that count the true or false detections of correct and erroneous MI trials.

TABLE V
RESULTS OF THE FINAL ONLINE APPLICATION WITH ACTIVATED ONLINE ERRP DETECTION. THE TABLE DEMONSTRATES THE INCREASED NUMBER OF MI TRIALS NEEDED DUE TO DISCARDED TRIALS AFTER ERRP DETECTION AND THE RELATION OF SCORED POINTS WITH AND WITHOUT ERRP DETECTION. THE TRUE POSITIVE (TP), FALSE NEGATIVE (FN), FALSE POSITIVE (FP), AND TRUE NEGATIVE (TN) DETECTION, AS WELL AS THE PERCENTAGE OF CORRECT CLASSIFICATIONS BASED ON THE ME METHOD (ME_ACC_ONLINE) ARE GIVEN FOR ALL TRIALS THAT WERE ELIGIBLE FOR ERRP DETECTION, NOT INCLUDING MI TRIALS WITH AN EQUAL NUMBER OF COLLECTED COINS AND BARRIERS.

Subject:	S01	S02	S05	S07
Trials without ErrP	120	120	120	120
Trials with ErrP	166	145	126	126
ΔTrials [%]	+38.3	+20.8	+5.0	+5.0
Score without ErrP	170	164	374	353
Score with ErrP	182	180	388	367
ΔScore [%]	+7.1	+9.8	+3.7	+4.0
TP	14	15	3	2
FN	15	9	2	0
FP	32	10	3	4
TN	84	85	113	114
ME_Acc_Online [%]	60.3	76.0	78.7	98.3

IV. DISCUSSION

A. Training of Subjects and Calibration of MI Classifiers

This part was performed to calibrate MI classifiers for all the following experiments on day 1 and day 2, see Fig. 1. The results in Table I indicate that all participants were able to successfully perform MI in this computer-driven paradigm. All subjects had MI detection rates higher than 70 % which is said to be needed for feasible BCI control [29]. The MI LDA classifiers, which were generated for each subject, were used in all subsequent experiments.

B. Online Car Game without ErrP Detection 1

In the second experiment on day 1 data for ErrP detection analyses and simulations were collected. MI performance was measured in terms of the percentage of collected coins. Most subjects were able to maintain their level of performance from the previous MI training part. These values can be compared by looking at "Upper Ten Percent" in Table I and "MI Performance" in Table II. Only subjects S04, S06, S09, and S10 performed noticeably worse in the continuous car game. The main difference in difficulty that might be the cause for this decreased performance is the need for maintaining MI for the longer time necessary in order to collect all the coins.

All reactions to positive and negative events (coins and barriers) were analyzed in terms of shape and detectability. The used method was based on the analysis of single events, the SE method. As expected, the most pronounced ErrPs were generated by subjects with a low error rate, except for S03 who did not generate distinct ErrPs even though the error rate was as low as 15.2 %. When considered in total the characteristic waveforms of the ErrP were not as pronounced as hoped for. The measured ErrPs were different to the interaction ErrPs described in [14] (a negative peak followed by a positive and another negative peak). However, there was an error-related negativity (ERN) about 400–500 ms after objects were picked up, as well as a positive peak around 200 ms at channels Fz and Cz, as shown in Fig. 6. Corresponding SE_Acc_CVs were only slightly above 60 %. There are three causes that might explain the indistinct manifestation and low classification rate of recorded ErrPs. First, subjects were able to see where the car was moving and therefore were not exceptionally surprised when colliding with barriers. Second, the time between objects on the street was constant as there was always exactly 1 s between objects. Therefore, the surprise could have been further reduced. These two issues might be mitigated by designing a paradigm in which the discrete feedback events are not as easily predictable. A possible solution could be to deliver a discrete feedback which depends on the amplitude of the classifier output: the time between consecutive discrete feedback events could be decreased when the amplitude of the classifier output increases and vice versa. Third, subjects could have been distracted by maintaining control of the car with MI and by the multitude of visual and acoustic stimuli presented during the game. This theory is backed by a reported negative correlation of workload and amplitude of event-related potentials (ERPs) [32].

We were interested to see if the added acoustic feedback could make discrete events more pronounced. Although, on a descriptive level, 'Sound' modality resulted on average in a slightly higher SE_Acc_CV than 'NoSound', the difference did not reach statistical significance. As visual feedback is the most important part of the car game, this outcome is not surprising. Nevertheless, 'Sound' modality was chosen as the only modality used in experiments performed on day 2.

C. Simulating the Effect of Multiple Events ErrP Detection Offline

The offline simulation expanded the analysis performed in Section II-B2 based on data collected during the car game on day 1. Simulations were carried out for 'Sound' and 'NoSound' separately and with all the data in the 'Combined' modality. The main goal of the simulation was to show the benefits of the new ME method compared to the SE method. In the simulation, each single run was classified with the classifiers calculated from data of the other runs. Classification was carried out with both methods: SE and ME. SE_Acc describes the detection rates of correct and erroneous single events, while ME_Acc describes the percentage of correctly determined original targets of MI trials. ME_Acc can therefore be compared to the detection rates of single events, as they are both determined by ErrP classifiers. ME_Acc can also be compared to the MI performance, MI_Acc, as both determine how well MI targets were able to be identified.

All relevant information is demonstrated in Table III. Here, the most important outcome is the difference between the values in columns "SE_Acc" and "ME_Acc". Although necessarily describing detection rates on two different layers (single events versus whole MI trials determined via multiple events), the comparison strongly suggests that even with low single event detection rates, ErrP detection can still be useful. With the new ME method, a series of single events can be combined to determine whether a sequence of events is correct or erroneous. The columns "MI_Acc" mainly serve as reference points to compare the MI performances to the detection rates of original targets of MI trials with the ME method. ANOVA results showed that these two measures were not different. In some cases, the determinations based on the ME method were even higher than the MI performances. This means that these subjects would have reached a higher score, if, after each MI trial, the just achieved score had been discarded and replaced by the determination found by the ME method. By this means the score would always either increase by $+4$ or decrease by -4 for correct or false determinations, respectively.

D. Online Car Game without ErrP Detection 2

The second instance of the car game without ErrP detection on day 2 with the 'Sound' modality yielded slightly different results compared to the first instance. The "SE_Acc_CV" values in Table IV can be compared to the offline simulation results in Table III, column "Sound/SE_Acc". The SE_Acc_CV decreased for subjects S01, S02, and S07 and increased for S05. Still, these SE detection rates were assumed to be high enough for the following online application with the ME method, given the increase from SE_Acc to ME_Acc which was found in the simulation. The MI performance remained on a very high level for subjects S05 and S07 but decreased noticeably for S01 and S02. S01's MI performance decreased below the initial inclusion criterion of 70 %. However, the subsequent experiment with online ErrP detection was carried out within the same session on day 2, thereby preventing S01 from being excluded.

E. Online Car Game with ErrP Detection

Finally, the new ME method was used to detect ErrPs online in the car game. MI classifiers from the MI training performed on day 1 (Section II-A) were used to control the car. ErrP classifiers were recalculated directly before starting the experiment, based on data collected in the repeated car game without ErrP detection, Section II-D. The reason for choosing to update only the ErrP classifiers was based on the additional time needed to recalibrate MI classifiers. Moreover, for the study design optimized MI control was not of importance and ERD patterns used for MI classification were shown to be relatively stable over time [33].

The results in Table V summarize the effects of the ErrP detection based on the ME method. As expected, a higher accuracy was bought with more time needed to complete the 20 MI trials of each run. An MI trial was only counted if it was not determined to be erroneous. Of course, the MI performance of the individual subject and the performance of the ErrP detection classifier were both accountable for how much time was really needed for completion: if a subject committed more errors, more MI trials had to be discarded and repeated; if the ErrP detection resulted in many false positive detections, many MI trials had to be repeated for no reason.

The scores achieved could be improved for all of the four subjects, the two medium performers gaining the greatest benefits. Yet, even the two high performers could still increase their scores by about 4 %, although there was not much room for improvement. The maximum score was 480 points, which would have required picking up every single coin on the road, and the two high performers already scored about 380 points. A very positive outcome was the low number of FPs which, when they happened, were especially frustrating for the subjects because correct MI trials had to be repeated. For all subjects but S01, the ME_Acc_Online was similarly higher than the SE_Acc_CV as already shown in the offline simulation with SE_Acc and ME_Acc. A possible explanation for why S01's ME_Acc_Online was not as good could be the MI performance which was also lower on day 2 than on day 1.

V. Conclusion

We were able to demonstrate a feasible new ErrP detection method based on multiple events: the multiple events method. This method was specifically designed to work in continuous BCI-controlled applications. Detection rates of ongoing states, in this case MI trials, were compared to the single event detection rates achieved with the standard single event method. For all subjects, the combination of multiple events lead to better results than the detection of single events.

The functionality of the multiple events method was also tested in an online experiment. Here, all of the subjects were able to increase their score in a car game with a trade-off of a longer time needed caused by repeating MI trials.

The experiments showed that the incorporation of error detection is possible in continuous applications even with low single event ErrP detection rates. As long as there is a way to generate discrete events during continuous control, ErrP detection can basically be included in any kind of feedback. Possible examples for the future include a BCI-controlled neuroprosthesis that gives discrete information about the current movement in certain short intervals. If the direction is not intentional for a time, the ErrPs accumulated by the discrete events could be used as a safety mechanism to stop the movement or to alter its direction.

With this new technique of combining multiple events for error detection, otherwise unused applications might regain interest if their performance can be improved to permit reasonable functionality.

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A.5. BCI and FES Training of a Spinal Cord Injured End-User to Control a Neuroprosthesis [69]

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- Martin Rohm: 15 %
- Rüdiger Rupp: 10 %
- Gernot R. Müller-Putz: 10 %

All coauthors contributed equally in planning the demonstrated experiments. Alex Kreilinger programmed and carried out the experiments with the one end-user. Vera Kaiser assisted in working with the end-user. Martin Rohm helped programming the hybrid orthosis needed for parts of the study as well as the neuroprosthesis control in general. Rüdiger Rupp and Gernot R. Müller-Putz offered valuable guidance throughout planning, running, analyzing, and reporting the experiments.

BCI AND FES TRAINING OF A SPINAL CORD INJURED END-USER TO CONTROL A NEUROPROSTHESIS

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Abstract: *This article exemplarily summarizes the steps necessary for application of a brain controlled neuroprosthesis in one spinal cord injured end-user. After screening an extensive training has to be performed until the final use of a neuroprosthesis based on functional electrical stimulation (FES) and controlled by a motor imagery (MI) brain-computer interface (BCI) is possible. The end-user maintained a very high BCI performance over a period of more than one year and successfully managed to control synchronous and asynchronous BCI applications.*

Keywords: *EEG, BCI, FES, neuroprosthesis*

Introduction

A spinal cord injury (SCI) above the neurological level of C5 leads to a loss of motor and sensory functions in the lower and upper extremities. Tetraplegic patients are normally wheelchair bound and no longer able to perform grasping or even elbow or shoulder movements. To compensate this motor impairment, end-users can be provided with neuroprostheses based on functional electrical stimulation (FES). These neuroprostheses induce contractions of innervated muscles by applying short current pulses via surface electrodes placed near dedicated motor points. The FES-generated movement patterns can be modulated by any kind of control signal originating from unaffected parts of the body. This signal can be obtained e.g. from a shoulder position sensor but also from a brain-computer interface (BCI) which translates thoughts—e.g., motor imagery (MI)—into commands by evaluating brain activity directly at its origin [1]. Control signals from different sources can be merged in a hybrid BCI [2]. Here, we introduce two control techniques tested in one end-user with SCI. First, a combination of a shoulder position sensor for analog control of the grasp and a BCI for switching between grasp patterns. Second, a neuroprosthesis for restoration of hand and elbow movements with BCI as the sole control signal.
The aim of this article is to present the steps from the first screening until the final successful control of BCI applications together with evaluation results.

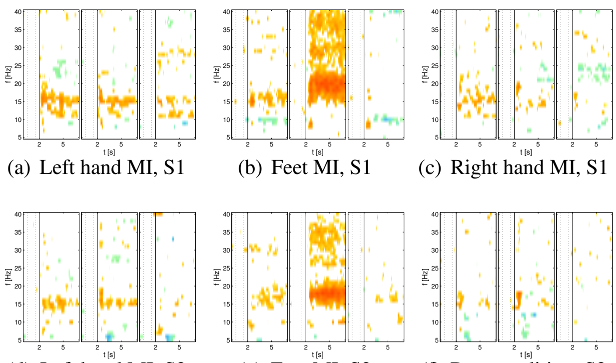
Methods

End-user: the 31 years old male end-user is diagnosed with a motor and sensory complete lesion (ASIA Impairment Scale A) at the level of C5 caused by an accident in 2010. He is not able to move his hand/fingers but has residual muscle control of his shoulder and partly the elbow. His range of motion of hand and finger joint is not restricted. All hand and finger muscles are paralyzed but innervated.
Data recording and processing: initially, in June 2011, EEG was recorded with 15 electrodes placed on the head to have Laplacian and/or bipolar derivations around the motor cortex. Signals were acquired with a g.USBamp (Guger Technologies, Austria) with a sample rate of 512 Hz and filtered between 0.5 and 100 Hz with a notch filter at 50 Hz. Later, different electrode layouts were used as well, mostly consisting of nine electrodes at positions C3, Cz, and C4 and anterior and posterior.
Data were analyzed for significant changes in band power in certain frequency bands, depending on the type of mental strategy. This was realized by plotting event-related desynchronisation/synchronisation (ERD/ERS) maps [3] between 5–40 Hz which show relative changes in band power in different frequency bands during MI for the three relevant channels C3, Cz, and C4. The most promising frequency bands of the best channels for the mental tasks with the best distinguishable patterns were selected manually as features to generate LDA (linear discriminant analysis) classifiers for later online use. In a 10$\times$10 cross-validation process the best point in time for classification was found and used to set up the final classifier.
Data of online sessions were also analyzed with ERD/ERS maps. Additionally, performance was evaluated via classification accuracy, speed, or number of false positives/min.
Training: the end-user started training with a BCI based on motor imagery (MI), i.e., the imagination of movements of hands or feet. Thereby generated brain patterns, in this case ERD, were intended to be found in a first screening session performed with the standard Graz-BCI paradigm [1]. The goal was to find limbs for which imagination of movements produced distinct patterns and then to proceed online with this mental strategy. In addition to BCI training, we also started with FES-assisted muscle training to achieve a fatigue resistance in both arms sufficient to control a grasp neuroprosthesis.
Online BCI sessions: training was continued by applying the LDA classifier online to control a liquid-cursor feedback to reach cue-paced tasks in a two-class BCI. In fact, the end-user performed offline training only once at the beginning and once after one year after the start of training. Online training was performed in eight sessions, classifying left hand versus feet MI. After offline and online

training, two neuroprosthesis applications were controlled by the end-user. In the first one he could choose between a lateral grasp or a palmar grasp pattern with a BCI and open/close his hand continuously with a shoulder position sensor. Individual stimulation profiles and electrode positions were used to realize both grasp patterns [4]. In this experiment he was asked to move objects with the dedicated grasp type in a limited time period and switch between the grasps when necessary.
In the second BCI application he controlled a neuroprosthesis for hand and elbow functions solely with BCI [5]. In both applications he used time-coded MI, the best active class (feet MI) versus a rest condition. Depending on the length of the performed imagination, either different switches were triggered, or commands were executed as long as the command was active. He had to perform ten predefined sequences, consisting of short commands to open/close the hand and long commands to move the arm upwards or downwards continuously.

Results

Fig. 1 shows ERD/ERS maps after the first screening (S1) and after the second offline training session (S2) one year later. The pattern on Cz in the beta frequency range did not change and was used constantly in all online sessions, including the two BCI-driven neuroprosthesis applications.



(a) Left hand MI, S1 (b) Feet MI, S1 (c) Right hand MI, S1

(d) Left hand MI, S2 (e) Feet MI, S2 (f) Rest condition, S2

Figure 1: ERD/ERS maps from the first screening session and an offline training session one year later. For each session three images show relative changes in band power for different frequency bands on the three channels C3, Cz, C4 (from left to right). In S2 Right hand MI was replaced by a Rest condition to set up a classifier for discriminating an active versus a rest class.

On average he achieved 82.7±7.9 % classification accuracy for the eight online BCI training sessions. He could control the first BCI application and moved 215 objects within 24 min and switched between grasp types in 16.9±12.2 s.
In the hand/elbow neuroprosthesis he performed second best among nine healthy subjects [5]: the true positive rate (correct use of short or long commands) was 73.7 % and he could successfully perform 8 out of 10 sequences. During active control he managed to trigger 6.9 commands/min, as opposed to only 2 commands/min during resting periods.

Discussion

This work shows that several prerequisites must be fulfilled for a successful use of non-invasive BCI-controlled neuroprostheses. The end-user needs to be compliant to FES training, has to be able to generate distinct ERD patterns and has to be able to voluntarily activate these patterns in an MI-BCI. Our end-user fulfilled all of them which seems not always to be the case [6]. He was able to control the grasp neuroprosthesis for functional tasks and in everyday life settings. He is not in need of an elbow neuroprosthesis but he successfully showed that such a form of control, solely based on BCI, is feasible in end-users with impaired elbow and shoulder functions. Therefore, controlling a neuroprosthesis with BCI based on MI seems to be a promising way for restoration of the upper extremity function in selected end-users.

Acknowledgement

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A.6. Brain-Computer Interfaces als assistierende Technologie und in der Rehabilitation nach Schlaganfall [67]

Distribution of dedicated work:

- Alex Kreilinger: 35 %
- Hannah Hiebel: 20 %
- Patrick Ofner: 20 %
- Martin Rohm: 5 %
- Rüdiger Rupp: 10 %
- Gernot R. Müller-Putz: 10 %

This publication reviews the state of the art in BCI challenges with a focus on neuroprosthetics and stroke rehabilitation. Alex Kreilinger coordinated inputs from coauthors and wrote most of the manuscript. Main parts written by Alex Kreilinger involve examples for hBCI and neuroprosthesis control. Hannah Hiebel provided a state of the art section about BCIs in stroke rehabilitation. Patrick Ofner wrote about movement decoding and gave an outlook on future activities in BCI research. Other coauthors helped in writing and putting together the manuscript.

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Brain-Computer Interfaces als assistierende Technologie und in der Rehabilitation nach Schlaganfall

Brain-Computer Interfaces as Assistive Technology and in Stroke Rehabilitation

Brain-Computer Interfaces (BCIs) finden mittlerweile den Weg aus der Forschung in Applikationen unter Alltagsbedingungen. Nicht nur bei assistierenden Technologien finden BCIs Verwendung, auch in der funktionellen Schlaganfallrehabilitation. Aktuelle Entwicklungsarbeiten fokussieren individualisierte BCIs für Anwender sowie das Erforschen von Grundlagen über die Neuroplastizität des Gehirns. Dieser Artikel gibt eine Übersicht über aktuelle Entwicklungen anhand von Studien und Einzelfallbeobachtungen.

Brain-computer interfaces (BCIs) have found their way from the lab into real-world applications. They are used not only in assistive technology but also for functional stroke rehabilitation. Current research focuses on customising BCIs for users and basic research into cortical neuroplasticity. This article presents current developments based on recent studies and single-case investigations.

Einleitung

Ein Brain-Computer Interface (BCI) bietet Menschen wie Schlaganfallpatienten oder Hochquerschnittgelähmten Möglichkeiten, mit ihrer Umwelt trotz körperlicher Beeinträchtigung zu kommunizieren [21]. Dies wird durch das Auslesen von Signalen direkt vom Gehirn und deren Umsetzung in Signale zur Steuerung von assistierenden Technologien ermöglicht. In dem Artikel von Kaiser et al. [5] wurden bereits einige wichtige Forschungsarbeiten zum Einsatz von BCIs und deren Verbesserung in der Anwendbarkeit demonstriert. Diese Forschungsarbeiten befassen sich hauptsächlich mit der Steuerung von Neuroprothesen auf der Basis der funktionellen Elektrostimulation (FES) bei querschnittgelähmten Anwendern durch auf BCIs aufbauende Benutzerschnittstellen (hybride BCIs [9, 13, 17]). Ein besonders wichtiger Aspekt der Arbeit von Kaiser et al. [5] besteht im Aufzeigen von Möglichkeiten, wie BCIs in bestehende assistierende Systeme sinnvoll integriert werden können.

Dieser Artikel soll an die Übersicht von Kaiser et al. anknüpfen und aktuelle Weiterentwicklungen im Bereich Neuroprothesensteuerung und Schlaganfallrehabilitation dokumentieren und einen Blick in die zukünftigen Möglichkeiten von BCIs wagen.

Insbesondere im Bereich der Neuroprothesensteuerung wird während der Arbeit mit Anwendern schnell offensichtlich, wie groß der Bedarf für ein individualisiertes Hilfsmittel ist, welches speziell auf die Bedürfnisse und Möglichkeiten für den jeweiligen Benutzer zugeschnitten ist. Je nach Grad der Einschränkung eines Querschnittgelähmten ändern sich die Erwartungen an die assistiven Technologien. Verfügen die Anwender z. B. über keinerlei motorische Restfunktionen in der Hand, ist eine Wiedererlangung der Greiffunktion das wesentlichste Bedürfnis. Mit zunehmend rostralem neurologischen Level der Rückenmarksschädigung liegen auch Einschränkungen der Ellenbogen- und Schulterfunktion vor. Ohne eine ausreichende Schulter- und Ellenbogenkontrolle kann auch eine durch eine Neuroprothese vollständig wiederhergestellte Greiffunktion nicht sinnvoll eingesetzt werden.

Bei den Betroffenen sinkt gegenläufig zu der Zahl der wiederherzustellenden Funktionen die Anzahl der verbliebenen Steuermöglichkeiten. Eine gebräuchliche Möglichkeit zur analogen Kontrolle der Griffstärke der Hand ist die Verwendung eines Positionssensors auf der gegenüberliegenden Schulter. Dies ist natürlich nur für Anwender sinnvoll, die noch eine ausreichend stabile Schulterfunktion zur Verfügung haben. Bei stärkeren Beeinträchtigungen können Schulterbewegungen nicht mehr zur Steuerung herangezogen werden, sei es durch mangelnden Bewegungsumfang oder durch eine zu hohe Anstrengung während der Verwendung. In diesem Fall bietet sich das BCI als alternative oder unterstützende Technologie an [11, 16]. Hierbei kann das BCI als ausschließliche Steuerungsquelle verwendet werden, oder nur einen zusätzlichen Freiheitsgrad zur Steuerung zur Verfügung stellen, um muskuläre Ermüdung zu verlangsamen oder gar nicht erst entstehen zu lassen.

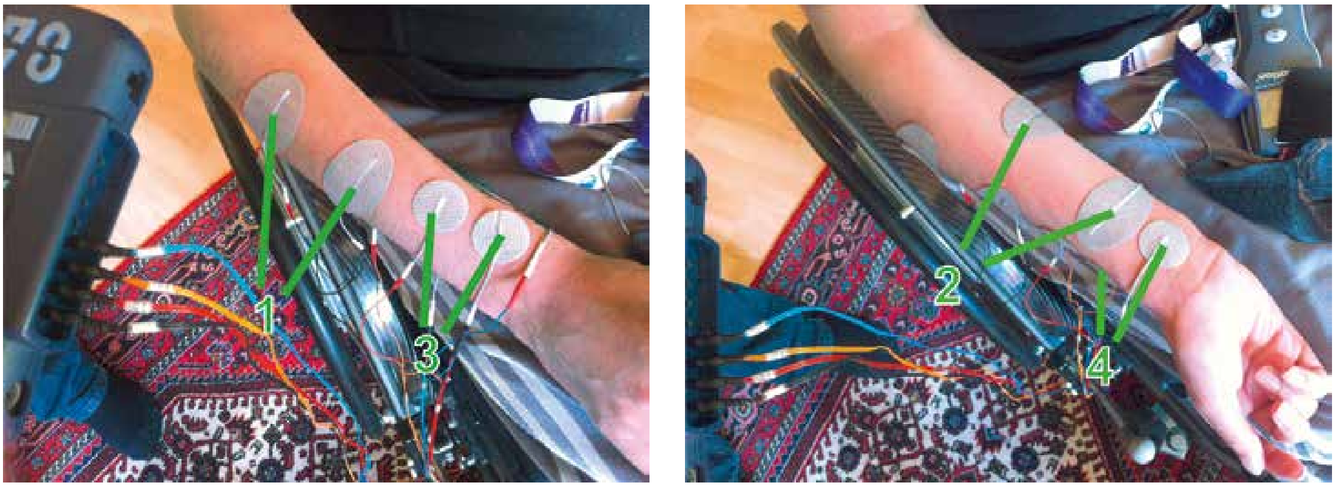

***Abb. 1** Platzierung der Elektroden für Handextension (1) und Handflexion (2) sowie von Elektrodenpaaren (3) und (4), die sich eine gemeinsame Elektrode teilen und die spezifischen Griffmuster des Daumens erzeugen.*

Anwendungsszenarien für BCI-kontrollierte Neuroprothesen

Im Folgenden sollen anhand verschiedener Einzelbeispiele die Möglichkeiten zur Integration eines BCIs in das Steuerungskonzept einer Neuroprothese bei Querschnittgelähmten mit unterschiedlich ausgeprägten Funktionseinschränkungen der oberen Extremität aufgezeigt werden.

Schulterbewegungsbasierte Neuroprothesensteuerung mit Griffumschaltung durch das BCI

Als erstes Beispiel wird die Umschaltung des Griffs einer Handneuroprothese erläutert. Das BCI wird in dieser Art der Steuerung als binärer „Brain-Switch" eingesetzt und der Grad der Handöffnung/-schließung über einen Schulterpositionssensor vorgegeben. Die BCI-basierte Griffumschaltung wurde zusammen mit der Neuroprothese an zwei männlichen querschnittgelähmten Anwendern (ES und TS, 31 und 37 Jahre alt) getestet, beide mit einer kompletten Querschnittlähmung auf Höhe von C5 ohne Finger- und Handfunktion.

Durch Anbringen von vier Elektrodenpaaren am Unterarm der Anwender ist es möglich, zwei verschiedene Greifmuster mittels FES zu generieren: den Palmargriff (auch Zylindergriff) und den Lateralgriff (auch Schlüsselgriff) [19]. Durch die Verwendung einer gemeinsamen Elektrode für zwei Elektrodenpaare konnte die Anzahl der platzierten FES-Elektroden reduziert werden, was aufgrund der limitierten Oberfläche am Unterarm notwendig wurde. Diese Anordnung wird in Abbildung 1 demonstriert.

Im Stimulationsgerät (MotionStim, Medel, Hamburg) gespeicherte Stimulationsparameter sorgten dafür, dass ein analoger Wert den Öffnungsgrad der Hand steuerte. Diesen analogen Wert konnten die Anwender durch Heben und Senken der Schulter selbst beeinflussen. Die Möglichkeit zur Griffumschaltung wurde über ein asynchrones BCI umgesetzt. Hier konnten die Anwender entweder den Griffmodus wechseln oder in einen Pausemodus schalten. Die Anwender wurden durch ein diskretes (aktueller Modus) und kontinuierliches (aktuelle BCI-Aktivität) graphisches Feedback informiert. Als BCI-Kanal wurde ein zeitkodierendes BCI verwendet, das auf der Bewegungsvorstellung (motor imagery, MI) basiert [7, 12]. Mittels kurzer Bewegungsvorstellungen der Füße konnte zwischen Griffmustern hin- und hergeschaltet werden, mit Langen wurde der Pausemodus aktiviert. Um diese Vorstellungen mit ausreichender Genauigkeit detektieren zu können, wurde ein BCI-Training durchgeführt, um einerseits die Anwender mit der Bewegungsvorstellung vertraut zu machen und andererseits genug Daten für die Erstellung von Klassifikatoren zu sammeln. Das Schema der Applikation wird in Abbildung 2 dargestellt. Bilder, die die graphische Oberfläche zeigen und Fotos, die während der Ausführung gemacht wurden, werden in Abbildung 3 und 4 gezeigt.

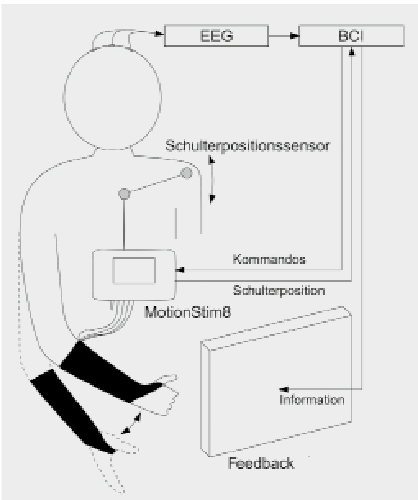

***Abb. 2** Schema des Griffumschaltungsexperiments. Die Stärke des Griffs wird mit dem Schulterpositionssensor analog eingestellt, während die Art des Griffmusters mit einem zeitkodierenden BCI eingestellt werden kann. Der Anwender sieht anhand eines diskreten und kontinuierlichen Feedbacks jederzeit, welcher Modus gerade aktiviert ist und erhält sofort Rückmeldung über eventuell detektierte Gehirnaktivität.*

Die Applikation wurde bei der Durchführung von zwei verschiedenen Aufgaben getestet. In Aufgabe A sollten die Probanden das System starten, indem sie die Pause mit einer Bewegungsvorstellung beendeten, um dann im ersten aktiven Griff Objekte zu bewegen. Nach drei Minuten wurden sie dazu aufgefordert, den Griff zu wechseln und Objekte, die für diesen Griff besser greifbar waren, zu bewegen. Nach drei Minuten sollte noch einmal der Griff gewechselt werden, um ein letztes Mal drei Minuten lang Objekte zu bewegen. Zuletzt sollten die Anwender in den Pausemodus zurückkehren. In Aufgabe B hatten die Probanden drei Minuten Zeit, alternierend den Griff zu wechseln und ein dazu passendes Objekt zu bewegen. Es wurden auch Prinzipien des hybriden BCIs verwendet, indem aktuelle Bewegungen des Schulterjoystick bei even-

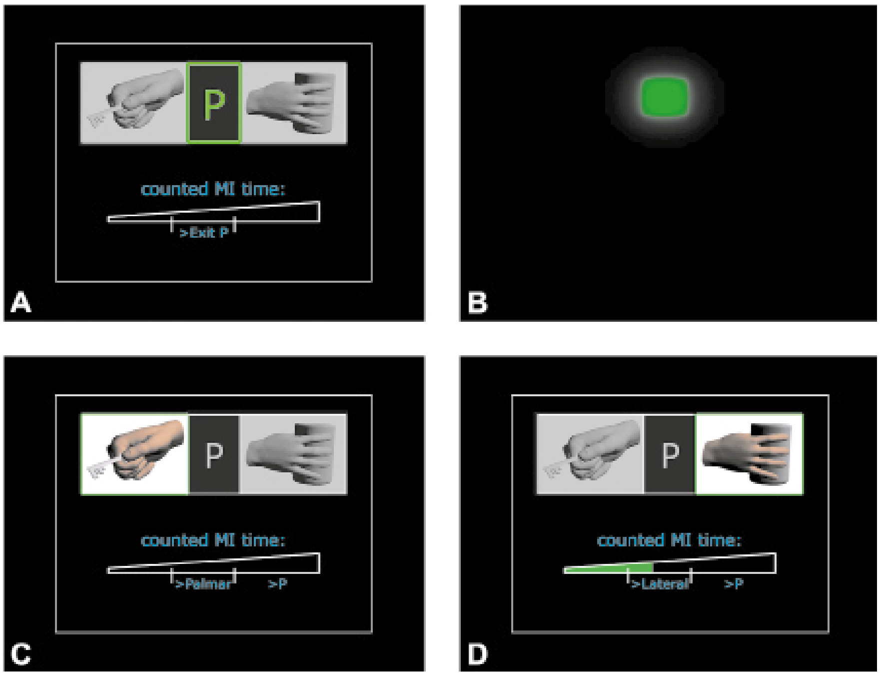

***Abb. 3** Diskretes und kontinuierliches Feedback. (A) zeigt den Anfangszustand des Systems bzw. den später auswählbaren Pausemodus. In (C) und (D) werden die beiden Griffmuster gerade verwendet. Der in (D) sichtbare Balken informiert den Anwender über die Dauer einer detektierten Bewegungsvorstellung (counted MI time). Je nach Länge werden entweder die Griffmuster gewechselt oder in Pause geschaltet. (B) ist ein ständig aktives kontinuierliches Feedback, welches Informationen über die Stärke der detektierten Vorstellung gibt und in einem zweiten Fenster dargestellt wird.*

tuellen BCI-Schaltvorgängen berücksichtigt wurden. Es kann z. B. davon ausgegangen werden, dass bei bewegter Schulter zum Öffnen und Schließen der Hand nicht auf einen anderen Griff umgeschaltet werden soll. Daher wurde eine Fehlererkennungsroutine in den Stimulator implementiert, die alle BCI-Schaltvorgänge während Schulterbewegungen verwarf. Mit dieser Maßnahme konnte die Zahl unbeabsichtigter Griffwechsel in erheblichem Maß reduziert werden. Beide Anwender führten den Versuch zum Nachweis der Wiederholbarkeit zweimal aus.

Anwender ES benötigte im Schnitt 16,9 ± 12,2 s, um zu einem Griff oder zwischen den Griffen hin- und herzuschalten, 51,3 ± 59,1 s, um in den Pausemodus zu schalten. Er schaffte es, 215 Objekte während der 24 Minuten in Aufgabe A zu bewegen und 31 Objekte während der 12 Minuten in Aufgabe B. Es wurden dank der Fehlererkennungsroutine 53 ungewollte Aktivierungen unterdrückt. Anwender TS benötigte 25,5 ± 27,9 s für Griffumschaltungen und 22,3 ± 15,6 s, um in die Pause zu wechseln. 253 Objekte wurden von ihm während Aufgabe A, 28 Objekte während Aufgabe B bewegt. 29 Schaltungen wurden verhindert. Beide Anwender hätten die Gegenstände ohne Neuroprothese nicht mit einer Hand zielgerichtet transferieren können.

BCI-Steuerung einer Hybrid-Neuroprothese für kontinuierliche und diskrete Ellenbogen-/Handbewegungen

In einer zweiten Konfiguration wird das BCI als einzige Steuermodalität verwendet, um eine Arm- und Handneuroprothese sowohl kontinuierlich als auch diskret zu kontrollieren [8]. Diese Konfiguration wurde mit neun gesunden Probanden und dem querschnittgelähmten Anwender ES evaluiert. In Anlehnung an die zuvor beschriebene Konfiguration wurde ebenfalls ein zeitkodierendes BCI verwendet, allerdings wird hier nicht nur zwischen kurzen und langen Kommandos unterschieden. Kurze Kommandos (Bewegungsvorstellung zwischen 0,75 und 1,5 s) werden als diskrete Kommandos behandelt: In Abhängigkeit der Position des Arms und der Hand kann die Hand geöffnet oder geschlossen werden oder das Ellbogengelenk in maximale Flexion oder Extension bewegt werden. Ein langes Kommando wird als solches nach 1,5 Sekunden erkannt und bewegt den Unterarm in Richtung des Endwinkels, welcher am weitesten von der aktuellen Position entfernt ist.

Für diese Art der Steuerung wurden zusätzlich zu den Elektroden am Unterarm noch Elektroden am Oberarm platziert. Zusätzlich wurde eine elektrisch blockierbare Ellenbogenorthese zu Stabilisierungszwecken und zur Messung des Ellenbogenwinkels montiert [18]. Über die Messung des Ellenbogenwinkels und Anpassung der Stimulationspulsweite der Oberarmelektroden wird der gewünschte Sollwinkel eingeregelt. Bei Erreichen des Zielwinkels wird das Gelenk mit einem magnetischen Mechanismus verriegelt, um eine Dauerstimulation und die damit verbundene vorzeitige Muskelermüdung abzuwenden.

Der Versuchsablauf war für die gesunden und den querschnittgelähmten Probanden unterschiedlich: Während gesunde Probanden zur Minimierung von stimulationsbedingten Einflüssen die Aufgabe hatten, die Neuroprothese an einer zweiten Person zu bewegen, führte der querschnittgelähmte Anwender den Versuch einmal ohne Neuroprothese und einmal mit der Neuroprothese am eigenen Arm durch (Abb. 5). Ziel war die zehnmalige Durchführung einer vorgegebenen Bewegungsabfolge. Es sollten je nach aktueller Hand- und Armposition kurze und lange Kommandos richtig abgerufen werden, um ein Objekt in maximaler Extension zu greifen, es in maximaler Flexion loszulassen und abschließend in die Anfangsposition zurückzukehren. Für die Durchführung der gesamten Sequenz standen allen Probanden jeweils drei Minuten Zeit zur Verfügung. Diese war unterbrochen von einer einminütigen Pause, in welcher unbeabsichtigte Kommandos (false positives, FPs) gezählt

Abb. 4 Die beiden Anwender ES und TS während der Ausführung des Experiments. Die obere Reihe zeigt die zeitliche Abfolge einer Objektbewegung mittels Zylindergriff (palmar grasp). In der unteren Reihe wird ein Holzstab mit dem Schlüsselgriff (lateral grasp) bewegt.

wurden. Eine Übersicht von konzeptbezogenen Befehlskonstellationen von langen und kurzen Kommandos in Abhängigkeit von verschiedenen Hand- und Armpositionen sind in Abbildung 6 erläutert.

Im Mittel konnten die gesunden Probanden 60,2 ± 11,4 % richtige Kommandos erzeugen, je nach aktueller Hand- und Armposition. Die Zahl der ausgeführten Kommandos pro Minute während aktiver Sequenzen war mit 8,2 ± 1,3 bedeutend größer als die Zahl der falsch positiven Kommandos pro Minute während der Ruhephasen mit 4,7 ± 2,6. Im Durchschnitt wurden nur 22,6 ± 6,5 min von den 30 Minuten benötigt, um alle 10 Sequenzen zu beenden (positive oder negative). Es konnten 55,5 ± 36,2 % dieser 10 Sequenzen erfolgreich absolviert werden. Hervorzuheben ist, dass der Anwender ES mit einer Rate von richtigen Kommandos (TP) von 73,7 % und mit 80 % erfolgreicher Sequenzen in unter 20 Minuten das System besser als der Durchschnitt der nicht behinderten Probanden bedienen konnte. Damit war er der zweitbeste Teilnehmer bei diesem Experiment.

BCIs zur Unterstützung der Handfunktion nach Schlaganfall

Auch im Bereich der Schlaganfallrehabilitation konnten weitere Fortschritte erzielt werden. Bisherigen Erkenntnissen zufolge geht nach unilateralem Schlaganfall insbesondere eine Aktivierung noch intakter motorischer Areale in der geschädigten Hemisphäre mit funktionalen Verbesserungen einher [2]. Mithilfe des BCIs können diese Aktivierungsmuster detektiert und durch gezielte Rückmeldung (Feedback) positiv verstärkt werden. In dem Beitrag von Kaiser et al. [6] wurde anhand einer Stichprobe von 29 Schlaganfallpatienten gezeigt, dass die Stärke und Lokalisation spezifischer Komponenten des EEG-Signals bei Bewegungsvorstellung und -ausführung mit dem Ausprägungsgrad der motorischen Beeinträchtigung in Zusammenhang stehen. Diese Erkenntnisse stellen eine wesentliche Grundlage für die erfolgreiche Anwendung der BCI-Technologie in der Schlaganfallrehabilitation dar. Bislang ist nämlich noch unzulänglich geklärt, welche messbaren neurophysiologischen Korrelate mit funktionalen Verbesserungen oder Verschlechterungen in Verbindung gebracht werden können und demnach positiv verstärkt oder aber abgeschwächt werden sollen.

Ein zunehmend verfolgter Ansatz im Kontext der Schlaganfallrehabilitation ist die Nutzung einer BCI getriggerten FES. Die Basis für diese Therapieform besteht in der Annahme, dass die direkte Kopplung der Bewegungsintention mit einer tatsächlich auftretenden Bewegung und die damit verbundene sensible, propriozeptive Rückmeldung in besonderem Maße geeignet sein könnte, um entsprechende Aktivierungsmuster zu verstärken und neuroplastische Veränderungen in der geschädigten Hemisphäre zu stimulieren. Bei einer FES-induzierten Bewegung wird nämlich der motorische Kortex in ähnlicher Weise aktiviert wie bei aktiv ausgeführten Bewegungen [10]. Bei der getriggerten FES geht man einerseits davon aus, dass durch den sensorischen Input die Plastizität des ZNS gefördert wird. Andererseits weiß man, dass ein motorisches Training nur bei aktiver Partizipation der Betroffenen erfolgreich sein kann [3]. Hier leistet das BCI einen wichtigen Beitrag, weil es speziell bei Schwerbetroffenen kortikale Aktivitätsmuster erkennen und in eine FES getriggerte motorische Reaktion mit einhergehender sensorischer Rückmeldung im Sinne eines geschlossenen Regelkreises überführen kann. Erste Anwendungen der Kopplung eines BCI mit einer FES stellen eine vielversprechende Ergänzung zu üblichen Trainingsprogrammen dar [4].

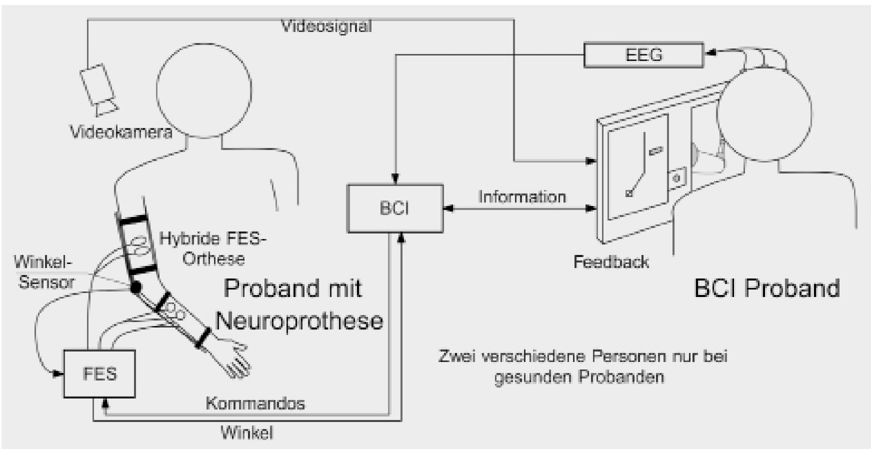

Abb. 5 Schema der kontinuierlichen und diskreten Hand-/Ellenbogensteuerung. Bei den Versuchen mit gesunden Probanden steuerte ein Proband mit dem EEG die FES des Arms eines zweiten Probanden. Bei dem Versuch mit einem Menschen mit Querschnittlähmung steuerte dieser die FES des eigenen Arms. Ein abstraktes Feedback gibt zu jeder Zeit Auskunft über den aktuellen Winkel des Arms und den Zustand der Hand. Ein kontinuierliches Feedback zeigt außerdem detektierte Bewegungsvorstellungen an und ein sich aufladender Balken die Länge der gerade vorgestellten Bewegung.

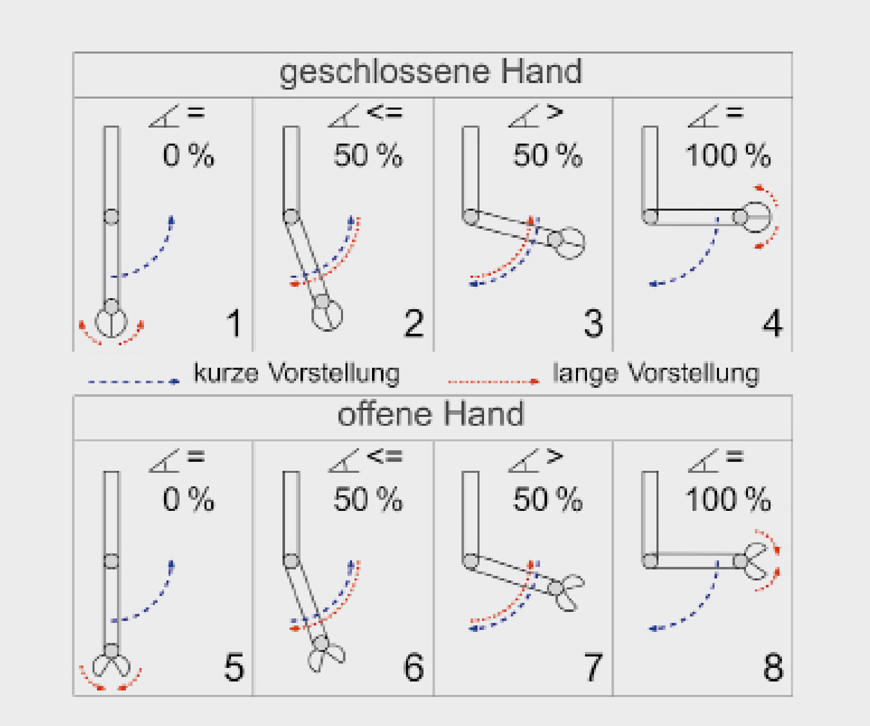

***Abb. 6** Zusammenhang von ausgeführten Kommandos in Abhängigkeit von Arm- und Handposition. Kurze Bewegungsvorstellungen erzeugen eine diskrete Aktion, lange Vorstellungen steuern direkt eine Flexions-/Extensionsbewegung des Ellenbogens.*

Vergleich von FES- und Video-Feedback während einer BCI-Kontrolle

In der Arbeit von Hiebel [4] wurde der Einfluss zweier Arten von Feedback auf sensomotorische Aktivierungsmuster im EEG während einer BCI-gesteuerten Anwendung untersucht. 15 gesunde, rechtshändige Personen sollten sich entweder Bewegungen ihrer rechten Hand vorstellen (motor imagery) oder sich entspannen und keine aktive Aufgabe ausführen (Ruhebedingung). Wurden die mit der Bewegungsvorstellung assoziierten Aktivierungsmuster richtig detektiert, löste dies entweder eine FES-induzierte Bewegung der rechten Hand aus oder initiierte ein Video, welches dieselbe zuvor individuell gefilmte Handbewegung auf einem Computermonitor zeigte. Während des Feedbacks sollten die Personen die entsprechende Bewegung beobachten sowie sich weiterhin mental vorstellen, die Bewegung selbst auszuführen.

Der experimentelle Aufbau wurde derart gewählt, dass in der FES-Bedingung die eigene rechte Hand sichtbar auf einem Tisch vor den Personen neben dem horizontal platzierten Monitor lag. In der Video-Bedingung wurde der Monitor so positioniert, dass sich die im Video gezeigte Hand an derselben Position befand wie die eigene Hand in der FES-Bedingung. Auf diesem Weg sollte der Einfluss des multisensorischen FES-Feedbacks (visuelle Bewegungsbeobachtung und propriozeptive Rückmeldung) gezielt mit dem Einfluss des Video-Feedbacks (visuelle Beobachtung derselben Bewegung) verglichen werden. Die aufgezeichneten EEG-Aktivierungsmuster wurden zwischen beiden Feedback-Bedingungen verglichen, wobei der Schwerpunkt auf der Analyse „korrekter Bewegungssequenzen", in denen das entsprechende Feedback tatsächlich ausgelöst worden war, lag.

Die Ergebnisse zeigen eine deutlich stärkere Aktivierung des sensomotorischen Kortex während des zusätzlichen FES-Feedbacks, welche am stärksten über den sensomotorischen Repräsentationsarealen der Hände ausgeprägt war. Die schon bei vorangehender Bewegungsvorstellung vorhandene Aktivierung nahm während des FES-Feedbacks deutlich zu, hingegen zeigte sich kein Anstieg während der Beobachtung des Video-Feedbacks. Im Gegensatz zur Video-Bedingung waren die Aktivierungsmuster in der FES-Bedingung denen aktiv ausgeführter Bewegungen sehr ähnlich. Zudem wurde im Mittel eine höhere Online-Klassifikationsgenauigkeit in der FES-Bedingung (82,6 %) als in der Video-Bedingung (75,3 %) erzielt.

Dekodierung von Bewegungen mittels BCI

Ein Nachteil der aktuellen BCI-Technologie ist die unzulängliche Natürlichkeit der mentalen Strategien. So werden z. B. Fußbewegungsvorstellungen verwendet, um eine Neuroprothese der Hand zu steuern, falls die messbaren Effekte einer solchen Fußbewegungsvorstellung denen einer Handbewegungsvorstellung überlegen sind. Es wäre zweifellos intuitiver, wenn die Funktion einer Extremität über Bewegungsvorstellungen der gleichen Extremität gesteuert werden könnte. Darüber hinaus ist die Art der vorgestellten Bewegung meistens nicht mit der tatsächlich ausgeführten Aktion identisch, was eine zusätzliche Abstrahierung zur Folge hat. Die nächste Evolutionsstufe in BCI-gesteuerten Neuroprothesen wird es demnach sein, Bewegungsvorstellungen direkt in exakt entsprechende tatsächliche Bewegungen umzusetzen. Diese Möglichkeit einer einfach zu erlernenden, intuitiven Kontrolle würde als positiven Nebeneffekt das Erlernen von mentalen Strategien überflüssig machen und die Trainingszeit erheblich verkürzen. Zur Umsetzung eines solchen Kontrollschemas befassen sich verschiedene Forschergruppen vermehrt mit Gehirnsignalen im niederfrequenten Zeitbereich (< 5 Hz), welche ein hohes Potenzial zur nichtinvasiven Dekodierung von Bewegungsvorstellungen bieten. In einer Studie von Waldert et al. [20] wurden Handbewegungsrichtungen aus der 3 Hz tiefpassgefilterten MEG-Aktivität über bilateralen Motorarealen dekodiert. Erste Schritte in diese Richtung unter Verwendung des EEGs wurden von Bradberry et al. [1] unternommen. Hier wurde gezeigt, dass Frequenzen unter 1 Hz mit der Geschwindigkeit der Hand während tatsächlich ausgeführten Armbewegungen in allen drei Raumrichtungen korrelieren. In der Studie von Ofner und Müller-Putz [14] wurde unter Verwendung von niederfrequenten EEG-Anteilen auch die Hand-Position während einer selbstständig ausgeführten Bewegung (keine externe Zielvorgabe) dekodiert.

Unter Verwendung der Dekodierungsprinzipien der Studien von Bradberry et al. und Ofner/Müller-Putz [1, 14] wurde in einer weiteren Untersuchung von Ofner und Müller-Putz [15] gezeigt, dass Armbewegungsvorstellungen in der Sagittal- und Transversalebene voneinander unterschieden werden können. In dieser Studie stellten sich neun gesunde Testpersonen eine rhythmische Armbewegung in diesen zwei Ebenen vor, während die Bewegungsvorstellung mithilfe eines Metronoms getaktet wurde. Unter Annahme einer sinusförmigen Bewegung wurden die Positionen der Hand in beiden Ebenen dekodiert. Hierzu wurden die EEG-Signale der letzten 180 ms in vier Zeitschritten bandpassgefiltert (0,2 – 0,8 Hz), anschließend wurden die Positionen in beiden Ebenen mit multiplen linearen Regressionen berechnet und mit einer Sinusschwingung korreliert. Die Bewegungen wurden nun der Ebene zugeordnet, die eine höhere Korrelation aufwies. Im Mittel über alle neun Testpersonen wurde eine Klassifikationsgenauigkeit von 70 % erreicht.

Diskussion

Die beiden Experimente mit unterschiedlich starker BCI-Integration konnten erfolgreich durchgeführt werden und zeigen, dass die hochquerschnittgelähmten Endanwender Funktionen der Hand oder des Ellenbogens kontrollieren können, zu denen sie ohne Unterstützung durch die bereitgestellten assistierenden Technologien nicht in der Lage gewesen wären. Die unterschiedliche Verwendung des BCIs in diesen Beispielen verdeutlicht, dass bei der Konfiguration von BCI-basierenden assistierenden Technologien die individuellen Anforderungen der Anwender im Sinne eines „User Centered Design (UCD)“ beachtet werden müssen.

Im ersten Szenario der Griffumschaltung wird das BCI als zusätzlicher Eingabekanal verwendet. Diese moderate Einbindung dient dazu, einer vorzeitigen Muskelermüdung vorzubeugen, da die auf muskulären Restfunktionen basierende Schultersteuerung nur bei Bedarf verwendet wird. Durch die BCI-gesteuerten Modi kann der Anwender die Stimulation ohne jeglichen muskulären Aufwand aktivieren und deaktivieren bzw. das aktuelle Griffmuster verändern.

Das zweite Beispiel zeigt die Verwendung von BCI bei sehr stark motorisch beeinträchtigten Menschen und verzichtet gänzlich auf muskuläre Restfunktionen zur Steuerung. Die Ergebnisse von nicht motorisch beeinträchtigen Probanden zeigen, dass ein auf Bewegungsvorstellungen basiertes BCI schwierig zu bedienen ist. Der Grund dafür ist die Schwierigkeit, die Bewegungsvorstellung über verschieden lange Zeiträume gezielt aufrechtzuerhalten und bei Bedarf wieder zu beenden. Manche Probanden konnten sich vorwiegend kurze Bewegungen besser vorstellen, manche fanden es einfacher, längere Vorstellungen durchzuführen. Die jeweils anderen Bewegungsvorstellungsarten waren dafür schwieriger zu bewerkstelligen.

Der an dem Experiment teilnehmende tetraplegisch Querschnittgelähmte konnte das BCI sowohl mit kurzen als auch mit langen Bewegungsvorstellungen sehr gut bedienen. Er hatte mit montierter Neuroprothese mit 73,7 % die zweitbeste TP-Rate aller Teilnehmer und konnte 8 von 10 Sequenzen innerhalb des gesetzten Zeitlimits erfolgreich absolvieren. Ob diese Einzelfallergebnisse auf ein größeres Patientenkollektiv generalisierbar sind, müssen weitere Untersuchungen mit Hoch-Querschnittgelähmten zeigen. Allerdings zeigen die Ergebnisse, dass Ergebnisse aus Untersuchungen mit Nichtgelähmten weder in positiver noch in negativer Richtung auf Querschnittgelähmte übertragbar sind.

Beide Neuroprothesensteuerungen verwendeten für eine zuverlässigere Benutzung des üblicherweise nicht fehlerfreien BCIs Prinzipien des hybriden BCIs. Bei der Griffumschaltung werden durch Überwachung der Schulterbewegung viele falsch positive BCI-Schaltvorgänge verhindert. Bei der kombinierten Hand- und Ellenbogensteuerung wird die Ellenbogenbewegung gemessen und je nach Höhe werden nur spezielle BCI-Kommandos zugelassen.

Die Ergebnisse unserer Forschung zeigen, dass sensorisches Feedback in Form einer FES-induzierten Bewegung entsprechende sensomotorische Gehirnregionen deutlich stärker aktiviert als Feedback in Form von ausschließlich visueller Beobachtung derselben Bewegung. Die mithilfe des BCIs durch Bewegungsvorstellung initiierten FES-vermittelten Bewegungen waren mit kortikalen Aktivierungsmustern assoziiert, wie sie auch bei aktiv ausgeführten Bewegungen auftreten. Bei visuellem Feedback über ein Video der eigenen Hand traten diese Aktivierungsmuster in deutlich geringerem Ausmaß auf.

Basierend auf diesen Erkenntnissen scheint eine Nutzbarkeit einer BCI-gesteuerten FES-Neuroprothese im Kontext der Schlaganfallrehabilitation aussichtsreich. Die intensive Aktivierung sensomotorischer Regionen durch propriozeptive Afferenzen in Verbindung mit der Triggerung über eine willkürliche Aktivierung des entsprechenden Motorareals könnte zu einer erhöhten kortikalen Reorganisation und damit Wiederherstellung motorischer Funktion führen. Die Klassifikationsergebnisse deuten darauf hin, dass die wiederholte somatosensorische Wahrnehmung der FES-induzierten Bewegung Personen in stärkerem Maße als das pure Beobachten die Vorstellung der entsprechenden Bewegung erleichtert.

Zuverlässige Aussagen über die Effizienz dieses Feedbacktrainings können jedoch erst nach weiteren BCI-Trainingsstudien getroffen werden. Im Rahmen zukünftiger Forschungsarbeiten wird die prinzipielle Frage geklärt werden, inwieweit überhaupt bei Schlaganfallpatienten noch verbliebene Aktivität in der geschädigten Hemisphäre detektiert und zur Steuerung einer FES-Neuroprothese genutzt werden kann. Darauf aufbauend müssen klinische Studien zeigen, welche kortikalen Veränderungen mittels FES-BCI-Training im Vergleich zu konventionellen Rehabilitationsmaßnahmen erzielt werden können und inwieweit diese mit erhöhten motorischen Funktionsverbesserungen einhergehen.

In weiteren Versuchen mit Nichtgelähmten konnten wir zeigen, dass die Vorstellung von rhythmischen Armbewegungen in einer Ebene nachträglich aus dem EEG dekodiert werden kann. Die nächsten Schritte werden sich mit der Entwicklung von Algorithmen beschäftigen, welche die vorgestellte Armposition in Echtzeit dekodieren können. Diese könnte dann mittels inverser Kinematik auf die Neuroprothese übertragen und somit eine intuitive Kontrolle ermöglichen.

Auf dem Weg dorthin sind aber noch viele Fragen offen, z. B. ist zu klären, ob nicht rhythmische, transiente Bewegungsvorstellungen dekodiert werden können, ob die dekodierte Position auch von anderen Parametern beeinflusst wird (Blickpunkt, Position von externen Zielen), welches Koordinatensystem zur Repräsentation der Armposition am besten geeignet ist (Gelenkswinkel, kartesisches Koordinaten-System in zwei oder drei Dimensionen, lineare oder nicht-lineare Achsen) oder inwiefern fehlerbehaftetes Feedback die Dekodierung beeinflusst. Bei einem idealen Dekoder würde die Steuerung der Neuroprothese mit natürlichen Bewegungsvorstellungen erfolgen. Dies hätte den weiteren Vorteil, dass keine neuen mentalen Strategien erlernt werden müssten, was die Trainingszeit für den Umgang mit der Neuroprothesensteuerung erheblich verkürzen könnte.

Anhand der vorgestellten Studien wird im besonderen Maß deutlich, dass nur durch eine interdisziplinäre Zusammenarbeit von Forschungsinstitutionen wie der TU Graz und des Universitätsklinikums Heidelberg relevante Fortschritte auf dem Gebiet der BCI-gesteuerten Neuroprothesen erreicht werden können. Ein wesentlicher Schritt hierzu sind Studien mit motorisch eingeschränkten Endanwendern (Personen im locked-in state, nach Schlaganfall oder Querschnittlähmung), da an Nichtgelähmten gewonnene Erkenntnisse nicht zwangsläufig auf die Zielgruppe übertragbar sind. Die Grundlagenforschung wird in Zukunft für Alltagsaufgaben geeignetere und natürlichere, intuitiver kontrollierbare Systeme hervorbringen, welche den potentiellen Anwenderkreis für BCI-kontrollierte Neuroprothesen erweitern werden.

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A.7. Hybrid Brain-Computer Interfaces and Hybrid Neuroprostheses for Restoration of Upper Limb Functions in Individuals with High-Level Spinal Cord Injury [124]

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Hybrid brain–computer interfaces and hybrid neuroprostheses for restoration of upper limb functions in individuals with high-level spinal cord injury

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ABSTRACT

Background: The bilateral loss of the grasp function associated with a lesion of the cervical spinal cord severely limits the affected individuals' ability to live independently and return to gainful employment after sustaining a spinal cord injury (SCI). Any improvement in lost or limited grasp function is highly desirable. With current neuroprostheses, relevant improvements can be achieved in end users with preserved shoulder and elbow, but missing hand function.
Objective: The aim of this single case study is to show that (1) with the support of hybrid neuroprostheses combining functional electrical stimulation (FES) with orthoses, restoration of hand, finger and elbow function is possible in users with high-level SCI and (2) shared control principles can be effectively used to allow for a brain–computer interface (BCI) control, even if only moderate BCI performance is achieved after extensive training.
Patient and methods: The individual in this study 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 either side. He underwent extensive FES training (30–45 min, 2–3 times per week for 6 months) and motor imagery (MI) BCI training (415 runs in 43 sessions over 12 months). To meet individual needs, the system was designed in a modular fashion including an intelligent control approach encompassing two input modalities, namely an MI-BCI and shoulder movements.
Results: After one year of training, the end user's MI-BCI performance ranged from 50% to 93% (average: 70.5%). The performance of the hybrid system was evaluated with different functional assessments. The user was able to transfer objects of the grasp-and-release-test and he succeeded in eating a pretzel stick, signing a document and eating an ice cream cone, which he was unable to do without the system.
Conclusion: This proof-of-concept study has demonstrated that with the support of hybrid FES systems consisting of FES and a semiactive orthosis, restoring hand, finger and elbow function is possible in a tetraplegic end-user. Remarkably, even after one year of training and 415 MI-BCI runs, the end user's average BCI performance remained at about 70%. This supports the view that in high-level tetraplegic subjects, an initially moderate BCI performance cannot be improved by extensive training. However, this aspect has to be validated in future studies with a larger population.

1. Introduction

The bilateral loss of the grasp function associated with a motor complete or nearly complete lesion of the cervical spinal cord severely limits the affected individuals' ability to live independently and return to gainful employment post injury, which severely compromises their quality of life. Any improvement in lost or limited grasp function is highly desirable not only from the patients' point of view [1,2], but also for economic reasons [3]. Together with the fact that individuals with tetraplegia are often young people who have been injured in sporting and diving accidents, rehabilitation specialists have always focused on finding ways to improve an impaired or lost upper extremity function. Since to date none of the neuroprotective or

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neuroregenerative treatments has led to relevant improvements in humans, specialists' endeavors have primarily resulted in methods for compensating for individual functional deficits. Among those are surgical procedures, in which tendons of strong muscles are rerouted from their original attachment to a new one to restore the action that has been lost [4].

However, surgical functional rehabilitation is only possible if a sufficient number of muscles are still under voluntary control. This is not the case in patients with lesions above C5, who constitute about 20% of the entire European spinal cord injury (SCI) population. In this subgroup of SCI individuals, a handful of technological solutions for restoration of the upper extremity function are available. Among them are motor-driven orthoses, which due to their costs, complexity and size are intended to be used as training devices rather than as personalized support systems [5,6]. Thus, today the only clinically applicable possibility for restoring a permanently lost upper extremity function – at least to a certain extent – is the application of neuroprostheses based on functional electrical stimulation (FES). Over the last 20 years, several FES systems with different levels of complexity have been developed and introduced to end users. These FES systems deliver short current impulses to efferent nerves that cause paralyzed muscles to contract [7]. On this basis, FES artificially compensates for the loss of voluntary muscle control. When using FES for motor substitution, the easiest and least expensive way of improving a very weak or lost function is the application of non-invasive neuroprostheses that use multiple surface electrodes [8–10]. Before meaningful movements are possible, individuals with a chronic SCI need to undergo extensive muscle training. This low-frequency FES training can reverse the profound disuse atrophy of the paralyzed muscles even many years after the SCI. The time required to achieve sufficient fatigue resistance and force depends on the individual status of the muscles and ranges from weeks to months [11].

Most of the current neuroprostheses for the upper extremity can be used for grasp restoration only in SCI individuals with preserved voluntary shoulder function and active elbow flexion. Even with the most sophisticated device, namely the implantable Freehand® grasp neuroprosthesis, only a restoration of finger, thumb and wrist movements was possible [12]. Only a few experimental studies with implantable devices demonstrated the feasibility of supporting the elbow function in very selected subjects with high-level SCI [13]. One of the main challenges in restoring elbow flexion is the rapid muscle fatigue that occurs due to the substantial weight of the forearm and the non-physiological synchronous activation of the paralyzed muscles through external electrical pulses. Additionally, the main elbow flexor (biceps) muscle is often denervated, since its associated motor neurons are destroyed due to the spinal trauma [14].

The fact that in individuals with high-level SCI only a few residual functions are preserved also has an impact on the selection and setup of an appropriate user interface for autonomous control of a grasp neuroprosthesis. User interfaces that rely on either the movement or the underlying muscle activation from a non-paralyzed body part can hardly be applied in this patient group [15,16]. A general problem in the selection of the appropriate user interface is the interference of an assistive device (AD) with the natural body functions. For example, people with tetraplegia often wish to eat without extensive support from caregivers. If a neuroprosthesis is to be used for eating and drinking, control movements involving the mouth cannot be applied. The same holds true if gaze or head movements are intended to be used for neuroprosthesis control [17].

Brain–computer interfaces (BCIs) are technical systems that provide a direct connection between the human brain and a computer [18]. Such systems are able to detect thought-modulated changes in electrophysiological brain activity and transform such changes into control signals. Most of the BCI systems rely on brain signals that are recorded non-invasively through placement of electrodes on the scalp. At present, these electroencephalogram (EEG)-based BCI systems can function in most environments with relatively inexpensive equipment and therefore offer the possibility for practical BCIs to gain relevance in the rehabilitation field. One type of EEG-based BCI exploits the modulation of sensorimotor rhythms (SMRs). These rhythms are oscillations in the EEG occurring in the alpha (8–12 Hz) and beta (18–26 Hz) bands and can be recorded over the sensorimotor areas. Their amplitude typically decreases during actual movement and similarly during mental rehearsal of movements (motor imagery (MI)) [19,20]. Several studies have shown that people can learn to modulate their SMR amplitude by practicing MI of simple movements e.g., hand/foot movements [21]. This process occurs in a closed loop where the system recognizes the SMR amplitude changes evoked by MI and these changes are instantaneously fed back to the users. This neurofeedback procedure based on operant conditioning enables BCI users to control their SMR activity and thus that of an AD.

These observations suggest that a BCI may be a valuable component in a neuroprosthetic user interface. A major advantage over other user interfaces is that it can be operated independently from residual motor functions. Furthermore, MI-based BCIs have enormous implications for providing natural control of grasping and reaching neuroprostheses in particular in individuals with high-level SCI since they rely on volitional signals recorded from the brain directly involved in upper extremity movements.

The feasibility of MI-based BCI systems for control of neuroprostheses using surface [22] as well as implantable [23] electrodes was shown in tetraplegic SCI users with a loss of hand and finger function. One of the major limitations of studies involving humans in this field is that the results were obtained in selected users with high BCI performances [24]. This raises the question as to what extent the published results can be generalized to a user population of non-selected persons. The results of a recent study involving a small group of individuals with paraplegia and tetraplegia show that motor imagery-induced EEG patterns can be discriminated in the first training session in only half of the participants. However, it is unclear whether extensive training sessions will lead to a sufficient BCI performance in at least some of the individuals with SCI with initially low or moderate performance [25]. Subjects with SCI also show a diffuse and broadly distributed event-related desynchronization (ERD)/synchronization (ERS) pattern during attempted foot movements in contrast to the focal beta ERD/ERS pattern during foot movement attempted by healthy subjects [26]. This shows that tetraplegic BCI users in general may not achieve the high performance of paraplegic or healthy individuals, although they have the greatest need for this type of system.

Therefore, the aim of this work is to show that (1) with the support of hybrid FES systems consisting of an FES system and semiactive orthosis, restoration of not only hand and finger, but also elbow function is possible in users with tetraplegia and (2) shared control principles can be effectively used to allow for adequate BCI control of this hybrid FES system in end users in whom only a moderate BCI performance is achieved even after extensive training.

2. Patients and methods

2.1. Characteristics of the end user

The individual in this single case study is a right-handed 41-year-old man with a traumatic SCI sustained in August 2009. He is affected by a complete motor and sensory lesion (American Spinal Injury Association (ASIA) Impairment Scale A [27]) with a

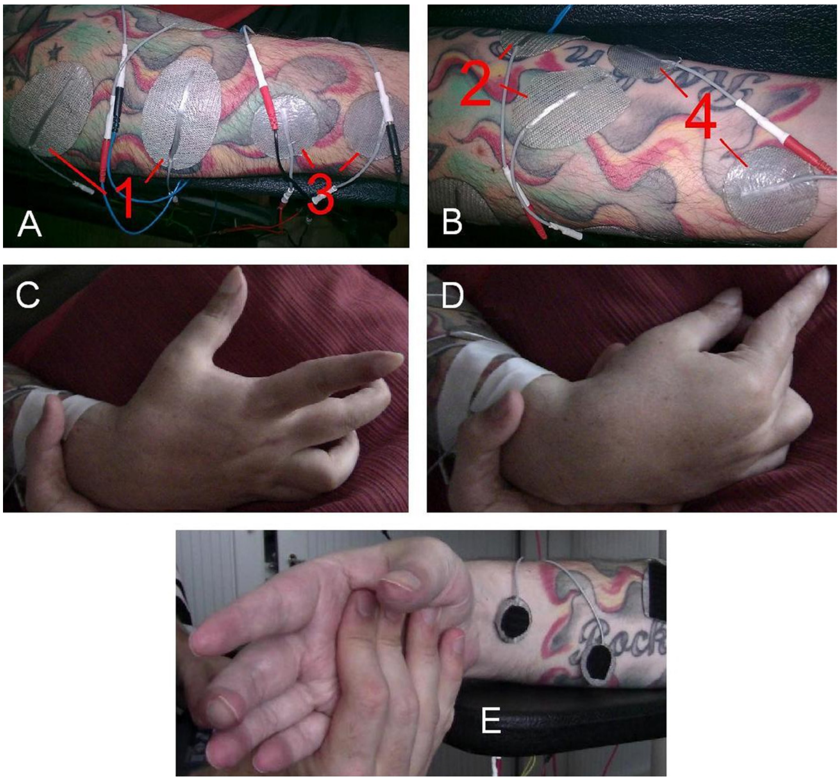

Fig. 1. Electrode positions for the muscle training together with the assigned channel numbers of the Motionstim. Stimulation electrodes for extensor muscles are shown in A and for flexors in B. Picture C shows the finger extension and D the finger flexion. Picture E depicts the electrode setup for thumb abductor stimulation for generation of a palmar grasp pattern.

neurological level of injury of C4. He does not suffer from pain and has a minor overall spasticity. His active and passive joint mobility are at the level of the

- shoulder: active abduction, extension and flexion up to 30°; all grade 3/5; full passive range of motion (ROM).
- elbow: no active flexion (biceps grade 0/5 and brachioradial muscle grade 0/5); no active extension (triceps grade 0/5); full passive ROM.
- forearm: no active supination (grade 0/5) possible; no active pronation (grade 0/5); full passive ROM.
- wrist, thumb and fingers: no active movements possible (grade 0/5); almost full passive ROM in finger joints; full wrist and thumb ROM.

All arm muscles could be electrically stimulated sufficiently except the biceps, which exhibited severe signs of denervation.

Since he was unable to perform any manipulation tasks, the patient was referred to our institution for screening for study participation. He had never participated in any clinical trial previously and was naive to BCI or FES applications.

2.2. FES and BCI training

Before the end user can use a BCI-controlled neuroprosthesis successfully, he first had to undergo FES and BCI training. At the start of the FES training program, the stimulation frequency was set to low frequencies (2–6 Hz = single twitches) in order to carefully activate the passive structures of the muscles such as ligaments and tendons. Since the spasticity did not increase during or after the training, the stimulation frequency was increased until tetanic muscle contractions were elicited (16 Hz). FES training was performed with the Motionstim stimulator (Medel GmbH, Hamburg, Germany) with its original firmware. The Motionstim provides eight independent stimulation channels and generates biphasic, constant current impulses for stimulation of innervated muscles. The advantage of this device is that it can be used as a stand-alone device for training as well as for dedicated applications by simply switching between standard and proprietary firmware. The programming of one's own application is supported by a simple system developer kit, which includes functions for basic graphical user interfaces and for control.

FES training was performed on a regular basis (approx. 3 times/week, 45 min per session) starting in August 2011. Stimulated muscles included the deltoids on both sides and the right triceps. Since the right denervated biceps does not contribute to a functional movement, it was not trained. The aim of training the forearm muscles was to strengthen the muscles required for a two-grasp pattern, namely a lateral pinch for grasping small items and a palmar grasp for manipulating larger objects. For this purpose, the finger extensors (extensor digitorum communis; electrode pair (EP) 1 in Fig. 1A), the finger flexors (flexor digitorum superficialis, flexor digitorum profundus; EP 2 in Fig. 1B) and the thumb extensor (extensor pollicis longus; EP 3 in Fig. 1A) and flexor (flexor pollicis longus; EP 4 in Fig. 1B) of the right hand were stimulated via four separate pairs of surface electrodes.

After two months of regularly performed FES training, the finger muscles showed no signs of fatigue at the end of the 45 min training session. Therefore, a level of fatigue resistance was reached that was sufficient for successful restoration of the hand function by FES. After approx. 20 min of stimulation, the triceps showed signs of fatigue, which were counteracted by a slight increase in stimulation currents. The hand posture in extension direction was nearly physiological (Fig. 1C); the hand posture in flexion direction

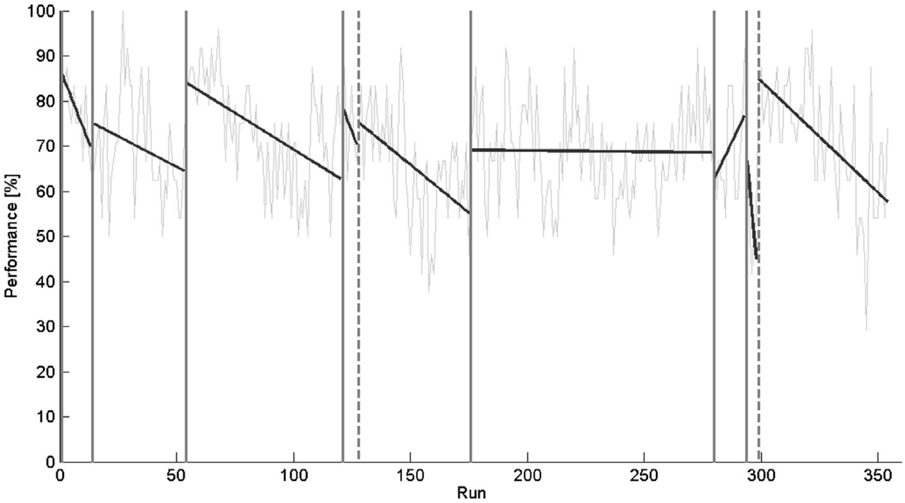

Fig. 2. Light gray: performance of 351 MI-BCI runs (around 200 s each). The abscissa contains the number of runs, the ordinate the performance in %. Each vertical line (dark gray) indicates the calculation of a new classifier; classifiers represented in dotted lines were used twice because their respective predecessor did not lead to a change in classifier setup. The nine diagonal lines indicate regression lines of the performance values of the respective classifier (at the beginning of the line).

was not optimal, but still sufficient for both a lateral and palmar grasp (Fig. 1D). In order to achieve a palmar grasp pattern, the thumb abductor was additionally stimulated (Fig. 1E) starting in May 2012.

For both the training and the testing sessions, an individualized neoprene sleeve (see Section 2.4) for quick fixation of FES electrodes was used. The measured force of the thumb flexion during lateral grasp was 2.5 N during the majority of the trials.

Starting in August 2011, BCI training was also performed. For this training, 13 EEG electrodes on positions C3, Cz and C4 of the 10–20 system (Laplacian montage) were used at the beginning. After the first three offline sessions, the number of electrodes was reduced to nine (Laplacian derivation of C3 and Cz). All channels were referenced to the left mastoid and grounded to the right mastoid. Electrode gel was used to keep the impedances below 10 kΩ. The EEG was amplified with a g.tec USB amplifier (g.tec, Graz, Austria), bandpass (8th order butterworth) filtered between 0.5 and 100 Hz and sampled at 512 Hz.

The subject performed the standard Graz-BCI training paradigm [28] to obtain subject-specific bandpower features, which were selected after manual evaluation of ERD/ERS maps [29]. The most reactive bandpower features were weighted by a linear discriminant analysis (LDA) [30]. The frequency bands and weights were saved as a classifier and were further used for training sessions. New ERD/ERS maps were calculated regularly and a new classifier was built and tested (for details, see Fig. 2).

Performance was calculated by dividing the number of correct trials by all trials of a run. A trial was classified as correct when its average classifier output was above a predefined threshold for one class, e.g., motor imagery of the left hand, and below the same threshold for the other class, e.g., motor imagery of the right hand. The threshold was chosen such that there was no bias toward one or the other class.

415 MI-BCI runs were recorded and 351 of these runs were evaluated. Due to a different electrode setup, the residual 64 runs were not taken into consideration.

To assess the online performance independently of cued trials, where only true or false positives exist, 14 trials of an intentional non-control (INC) test were conducted at irregular intervals between November 2011 and July 2012. In this INC test, the user was requested to not elicit a BCI switch for one minute and subsequently elicit a switch as quickly as possible.

2.3. Elbow and hand orthosis

In order to achieve a stable elbow position without causing fatigue in the upper arm muscles, an elbow orthosis was developed as an adjunct to the Motionstim device for FES [31]. Its main components (Fig. 3) are a self-locking, electrically lockable/delockable elbow joint with a configurable weight support system to support elbow movements. The orthosis is available for the left and the right side and can be extended via a rotational wrist module, a module for ulnar–radial abduction and a thenar wrist-stabilizing orthosis module. Possible control devices include a 2-axis shoulder position sensor and electromyographic recording hardware for measuring residual muscle activity in the presence of electrical stimulation pulses.

The device's modularity allows it to be personalized to accommodate users' different neurological statuses and functional needs. In the case of the end user in our study, whose denervated biceps could not be used for functional restoration, the orthosis was equipped with a strong (7.5 Nm torque) anti-gravity module for supporting the elbow flexion. The extension was generated by stimulation of the triceps. Additionally, a wrist-stabilizing module was used to keep the wrist in neutral position enabling proper finger flexion.

During all experiments, care was taken to ensure that the technical joint axis of the orthosis was correctly aligned to the anatomical elbow joint axis of the user sitting in a wheelchair.

2.4. Neoprene sleeve to facilitate FES training

Easy and reliable mounting of electrodes is a prerequisite for enhancing the usability and, in turn, the acceptance of FES in end users and caregivers. To this end, a neoprene sleeve was manufactured based on the individual size and length of the user's right forearm. After determining the individual position of the stimulation electrodes on the forearm (Fig. 1A and B) self-adhesive Velcro strips are placed on top of the electrodes (Fig. 1E). Then the sleeve is fitted to the forearm starting with the opening of thumb and aligning the ends on the ulnar side (Fig. 3D). If the sleeve is removed from the arm, the Velcro strips hold the electrodes in place on top of the neoprene. With this procedure, all electrode positions are ultimately defined, facilitating reproducible and accurate placement of the FES electrodes and efficiently reducing the setup time for the

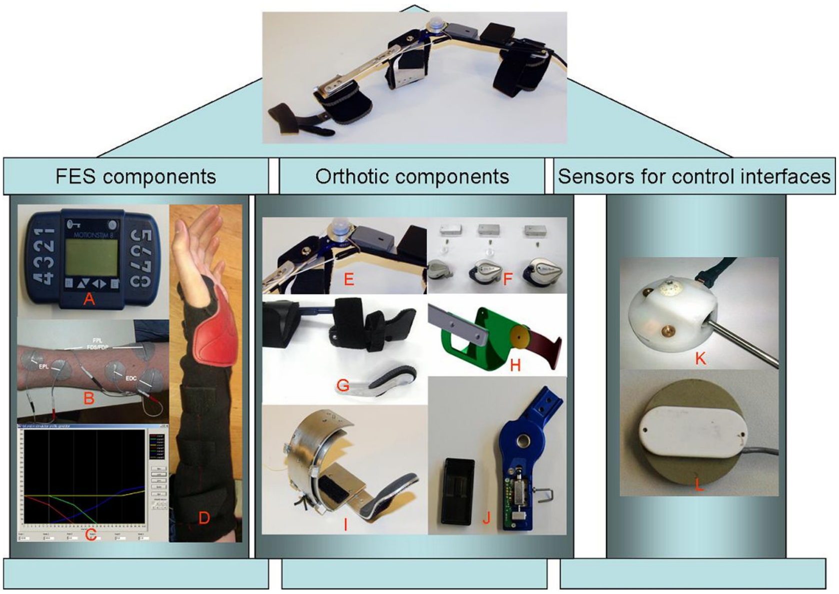

Fig. 3. A fully equipped hybrid FES orthosis (top) together with its main components: A self-locking elbow joint (J) with a configurable weight support system (E and F) and an FES device and its software tools (A and C) together with self-adhesive surface electrodes (B and D). The orthosis can be extended via a rotational wrist module (J), a module for ulnar–radial abduction (H) and a thenar wrist-stabilizing orthosis module (G). Control devices include a 2-axis shoulder position sensor (K) and an electromyographic recording hardware (L).

FES training [32]. The flexion movement is improved by binding the strong middle and ring finger together with the weaker index finger.

2.5. Hybrid BCI control concept

The control concept of the neuroprosthesis is based on the hybrid BCI [33], which in this case consists of the combination of an MI-BCI and an analog shoulder position sensor (Fig. 3K). After donning, the sensor has to be calibrated according to the residual shoulder ROM of the user.

To define meaningful stimulation patterns, e.g., for coordinated opening and closing of the hand, a stimulation profile generator (Fig. 3C) was programmed. The basis of a profile is the assignment of 64 command nodes (horizontal axis) to stimulation pulsewidths (vertical axis) separately for each stimulation channel (for details, see Ref. [32]).

The proprietary software of the Motionstim device maps the analog command value provided by the shoulder position sensor to the corresponding command node and selects the predefined pulsewidths for each stimulation channel. Therefore, through protraction and retraction or elevation and depression (user-dependent) of the shoulder, the user can control the degree of elbow flexion and extension or of hand opening and closing by stimulating the corresponding muscles (biceps and triceps for elbow movements and finger extensors/-flexors for finger movements, respectively).

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 the digital brain switch provided by the time-coded MI-BCI. Prior to using this kind of MI-BCI, users have to perform standard BCI training to set up an individual LDA classifier to distinguish between an active MI versus a rest class. The online BCI system provides the users with real-time feedback that indicates current detection of the active class and the state of the system. This feedback helps the users realize when and how long the detection occurs and allows them to influence the length of the detection. A short detection of MI switches from hand to elbow control or vice versa. A longer detection leads to a pause state with muscle stimulation turned off and elbow joint of the orthosis locked. The pause state can be exited by another short MI detection, which reactivates the previous control mode (Fig. 4B). The wiring of all components can be seen in Fig. 4A and the setup of the complete BCI-controlled upper extremity neuroprosthesis in the end user is depicted in Fig. 4C.

To minimize artifacts originating in FES pulses in the EEG signal, a ring electrode was connected to the upper arm and to the equipotential bonding conductor connection of the EEG amplifier [34].

2.6. User-centered design

For functional evaluation of the FES-generated grasp, a dedicated hand function test (grasp-and-release-test (GRT) [35]) was performed together with three activities of daily living (ADLs). During the GRT, the number of items successfully transferred in two minutes was recorded.

The ADL task of the initial testing sessions was to pick up and eat a pretzel stick (Fig. 5). The intended sequence was for the subject to (1) leave the pause mode and enter the arm state, (2) switch to hand state and grasp the pretzel stick, (3) switch back to arm mode, lift the stick to his mouth and bite it and (4) lower his arm after biting and switch to hand mode in order to release it. For successful completion of this experiment, four BCI switches have to be elicited at certain time points.

This first experiment revealed several weaknesses of the setup. First, the subject was not able to grasp objects securely due to low finger and thumb flexion forces. He initiated several attempts to take another bite of the pretzel stick but failed. Secondly, the stimulated triceps was too weak to fully extend the elbow against the strong anti-gravity support. A rotational, spring-based anti-gravity support system was applied to flex the elbow and, in so doing, compensate for the missing support of the denervated biceps. Third, the ends of the rod of the shoulder position sensor were placed on the acromion and the sternum. Due to the subject's limited trunk stability, he shifted to one side while using the orthosis, which negatively affected the performance of the shoulder control. Fourth,

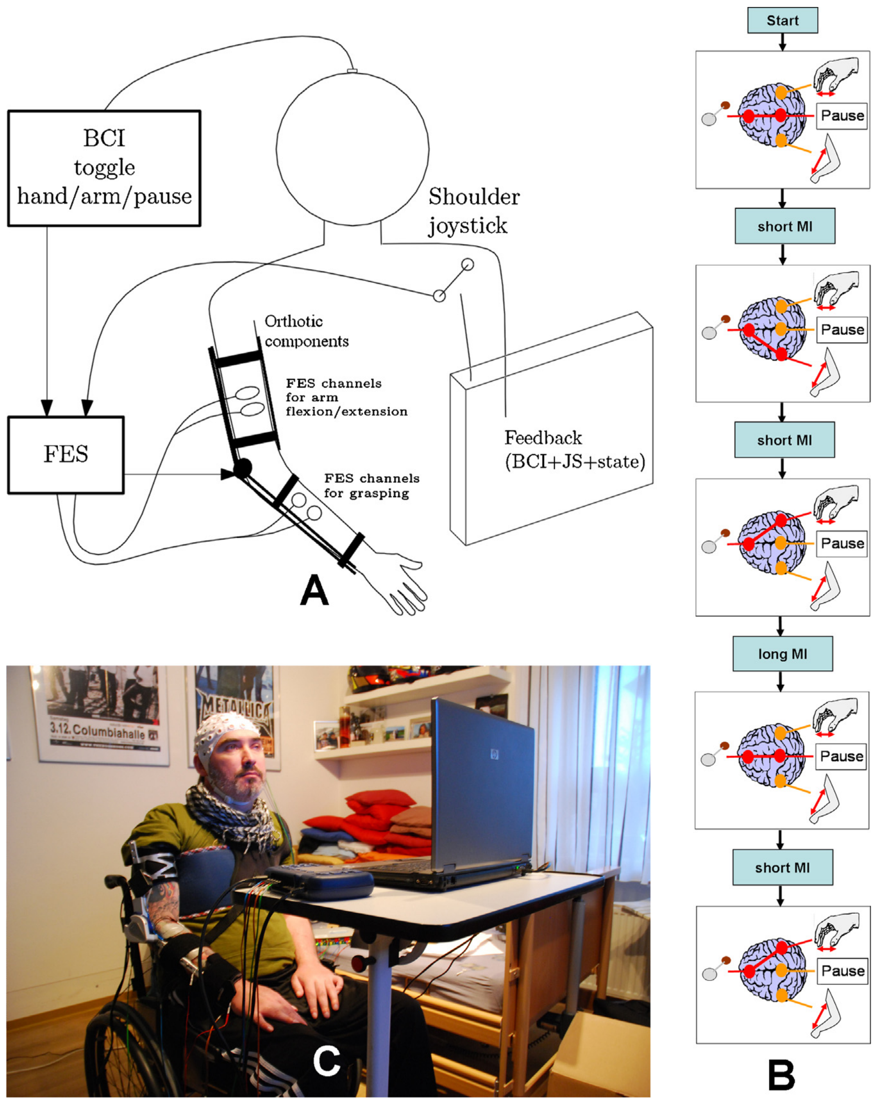

Fig. 4. Schematic overview of the setup (A, top), example flowchart of the hybrid control scheme integrating the shoulder joystick and the MI-BCI (B, right) and the setup of the complete neuroprosthetic system in the end user (C, bottom).

with increasing time during the tests, the orthosis tended to shift proximally due to slipping.

Based on the experiences of the first testing sessions, several improvements were introduced with respect to the user-centered approach. First, the positions of the forearm and triceps electrodes were optimized, resulting in increased finger force and a larger range of elbow motion (0° fully extended, ~140° fully flexed). To reduce the influence of the upper body posture on the output of the shoulder joystick, a flexible belt was used to comfortably secure the subject's trunk to the backrest of the wheelchair. To reduce the sliding of the orthosis, its clamps were coated with an adherent layer made of neoprene.

With this improved second version of the hybrid FES orthosis, a second task was performed, namely a writing task. For this task, the end user grasped a pen with a lateral grasp from a lower surface, lifted it upwards, transferred it over a sheet of paper and signed his name on the paper. Afterwards, he returned the pen to its initial position. After several writing trials it became obvious that the stimulated triceps fatigued too early and was not able to fully extend the elbow. Therefore, the system was extended with a small electrical drive that lifts the end user's forearm until maximum flexion of the elbow. The drive was attached at the proximal end of the orthosis including a magnet and a reed switch to detect the maximum flexion of the elbow joint. The rest of the setup remained the same as for the pretzel task.

To enhance the usability of the system and to reduce the user's overall workload, several shared control principles for making the system more robust were introduced. A BCI switch gating mechanism was implemented, which allows for eliciting a BCI switch only when the shoulder joystick has not been moved in the previous seconds. The rationale for this approach is the observation that a user who moves the shoulder wants to move the hand or elbow but does not want to switch between the control of these two. Furthermore, after a BCI switch has been elicited, further switches are rejected for several seconds. When calibrating the shoulder joystick, a smaller range is used than actually measured. This has the advantage that if the user cannot reach the calibrated value, he is still able to control the system without the need for re-calibration. When using the orthosis equipped with the electrical drive for elbow flexion, no BCI switch can be elicited during motor movement or if the elbow reaches the maximum flexion position, in which the hand is near the mouth.

For overall evaluation of the hybrid BCI-controlled upper extremity neuroprosthesis, a visual analog scale (VAS) was used to assess the users' mood, motivation and general device satisfaction and the National Aeronautics and Space Administration task load

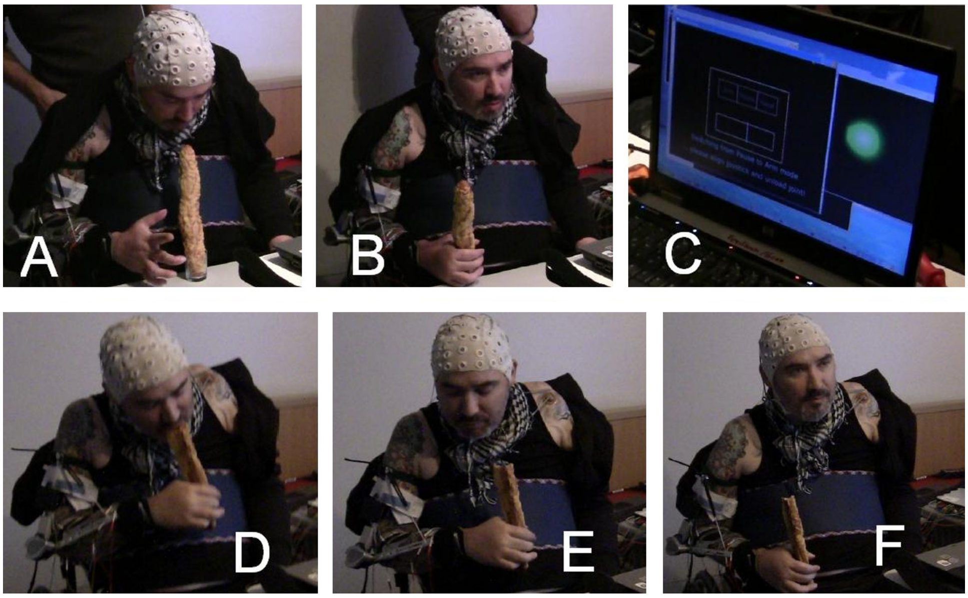

Fig. 5. Sequence of pictures showing the eating of a pretzel stick. The user starts in the hand control mode, lifts his left shoulder to open the right hand to grasp the pretzel stick (A). After successfully grasping the pretzel stick (B), the user emits a short ERD pattern by performing a movement imagery of his right hand to switch from hand control to elbow control (C). The user concentrates on not emitting another BCI command but instead on lifting his shoulder to flex the elbow. Now, the user can take a bite of the pretzel stick (D). Finally, the user lowers his left shoulder to extend the elbow (E) and move to a resting position (F).

index (NASA-TLX) questionnaire was used to measure the subjective workload [36]. VAS questionnaires were assessed after every experiment and workload was measured a total of four times.

3. Results

3.1. Results from MI-BCI online training sessions

For MI-BCI training, starting in August 2011, 415 MI-BCI runs were recorded on 43 days at the end user's home. The end user achieved an average performance of 70% with a standard error of 11.91% (Fig. 2). After three screening sessions, during which 30 offline runs were recorded, it became obvious that foot imagery vs. right hand imagery delivered the strongest pattern and therefore this paradigm was used for training. In the subject, the most reactive frequency band was identified as between 23 Hz and 26 Hz. Small adaptations in the weights and frequency bands were undertaken and, at the beginning, the classifier was retrained at every online session. After seven sessions with no significant training effects, the classifier was kept unaltered. The calculation of the signed r^2 after 30 online training sessions showed the validity of this frequency band. Unfortunately, on 46% of all training days there were no reactive frequency bands at all, whereas on other days strong features were present (Fig. 6). The end user succeeded in 5 out of 14 trials of the INC test.

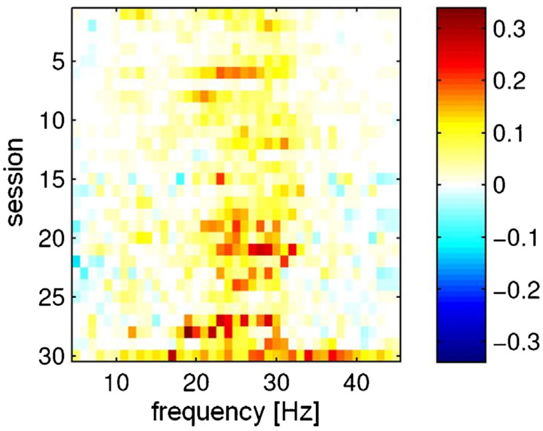

Fig. 6. Signed r^2 for C3 Laplacian channel. Darker colors (red or blue) indicate a higher reactivity and therefore more information content. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

3.2. Evaluation of FES-induced grasp patterns

Without any AD, the participant was unable to perform any GRT task. However, with the hybrid FES orthosis system, the user was able to successfully perform GRT tasks. The GRT tasks were selected on the basis of the higher force of the restored grasp pattern in this end user i.e., the lateral grasp. Within trials of one minute duration, the user succeeded in transferring pegs and blocks over the frame of a box (Table 1) 17 out of 26 times. Single blocks were more difficult for him to handle than double blocks.

For performing the GRT, the user did not need to elicit a brain switch. He locked the orthosis such that his hand was slightly below the edge of the box and he performed small lifting movements with residual elevation movements of the right shoulder.

3.3. Evaluation of activities of daily living

The first experiment involved picking up and eating a pretzel stick (Fig. 5) and was performed a total of 11 times on three training days. During the only successful session, one BCI command was falsely classified as positive and was manually corrected by the experiment supervisors. However, the subject had the possibility of switching from an undesired grasp to a desired one by eliciting another switch (see Section 2.5 for details). After the experiment, an INC task was performed during which the user did not deliver a command for 50 s and was subsequently able to voluntarily deliver a command within 9 s (Table 2). The analysis of the VAS data showed that while the end user was generally highly motivated (7.25/10) and was generally satisfied with the system (6.8/10), he reported high workload when simultaneously using shoulder movements and BCI for control.

The writing task was repeated ten times in total on six different training days (one day without BCI). The individual succeeded with this task four times, despite the fact that he has no wrist function and moves his hand only by using his residual shoulder function. The result was highly dependent on how well the user was able to grasp the pen. The average trial time was 3.19 min. In total, two falsely classified switches occurred that were corrected by the subject himself. The user's mean motivation was 6.8/10, the mean mood was 7/10 and the mean device satisfaction was 7.4/10 (Table 3).

The third task involved eating an ice cream cone. This experiment was repeated four times in total on three different training days (once without BCI) and the subject succeeded every time. He securely grasped the cone from a special holder, lifted it

Table 1
Results of selected GRT tasks.

Item	Trials	Attempts	Completions
Single blocks	1	1	0
Double blocks	1	7	7
Pegs	3	18	10

Table 2
Evaluation of the intentional non-control test. Success means that the subject was able to intentionally not deliver a switch for one minute and elicit a switch afterwards (required time is given in column 3). Column 4 shows the time until a switch occurred during the first minute in which a switch should not be elicited. If something is entered in this column, it means that the trial was not successful.

Trial	Success	Time to elicit an intentional switch after 1 min [s]	Time until a non-intentional switch occurred [s]	Comments
1	Yes	9		
2	No		50	
3	Yes	9		
4	No		25	
5	No		12	
6	No		25	While looking at the experimenter
7	Yes	15		
8	No		28	
9	Yes	10		
10	No		40	
11	No		25	While talking
12	Yes	4		
13	No		5	
14	No		5	

Table 3
The mean values of end user's motivation, mood and device satisfaction together with some remarks during the signature task.

Trial	Motivation	Mood	General device satisfaction	User remarks
1	9	9	6	Some part of the system was always weak today
2	9	9	7	Grasp was nice, it takes long to perform the task
3	6	7	10	Everything was perfect
4	1	1	6	It was nice from my side. Interesting to see that my mood does not affect the overall performance
5	9	9	8	The BCI worked nicely from my side, but there were some difficulties with the software

to his mouth and ate it at a leisurely pace (Fig. 7). The average trial time was 2 min. No falsely classified switches occurred during the trials. The user's mean motivation was 8/10, the mean mood was 9/10 and the mean device satisfaction was 10/10.

The end user reported a high subjective workload during the trials, reflected by an average of NASA TLX of 68/100 after four testing sessions. Mental and physical strain contributed the most to this result. The subjective workload during the ice cream-eating task was remarkably lower (55.6/100) than for the other tasks (72/100).

4. Discussion

In this single case study, a non-invasive hybrid FES orthosis for restoration of hand and elbow function was developed, tailored to the individual needs of a person with high-level cervical SCI and successfully used for and evaluated in different functional tasks, i.e., the GRT and three ADL tasks.

In the course of the trials, the hybrid FES orthosis was iteratively improved to reflect a user-centered approach incorporating the user's feedback [36]. More importantly, an intelligent control concept was employed to make the BCI-controlled neuroprosthesis more reliable. This encompasses a BCI switch gating mechanism depending on the shoulder joystick movements and a refractory period after a switch, a robust calibration procedure and a rejection of BCI switches during motor-driven elbow movements and in maximum elbow flexion position. These shared control principles

Fig. 7. Sequence of pictures showing the subject eating an ice cream cone. The user starts in the hand control mode, lifts his left shoulder to open the right hand to grasp the ice cream cone (A). After successfully grasping the ice cream cone (B), the user emits a BCI command to switch from hand control to elbow control and lifts his shoulder to flex his elbow (C). Now, the user licks the ice cream (D). Finally, the user lowers his left shoulder to extend the elbow (E) puts the cone back in its original place and switches back to hand mode to release the cone (F).

helped to compensate for the moderate level and day-to-day variances of the end user's BCI performance, in particular during the task of eating an ice cream cone. Although each of these measures target different flaws in the complex setup, when taken together, they contribute equally to the enhancement of the usability of the neuroprosthesis.

In Ref. [37], a similar hybrid FES orthosis for the restoration of reaching and grasping movements is presented. It features a lower and upper arm orthosis including an angle sensor, an electrical drive for elbow movements, voice control, a force feedback glove and FES for generation of finger movements. The authors successfully demonstrated its feasibility in five individuals with high-level SCI. However, in contrast to our study they provide no data on the performance of the neuroprosthesis with real ADL tasks and on the evaluation of the FES components alone.

Data on the course and performance of MI-BCI training in individuals with chronic high-level SCI is sparse. In one study, two C4, three C6 and four C7 end users were trained to operate an MI-BCI with the goal of controlling a robotic arm [38]. It is remarkable that the average performance of all subjects was determined as 70.5%, which is the same value that our end user achieved. In this study, the frequency bands between 5 and 35 Hz were analyzed to find distinguishable features, similar to our study. In three of the subjects in Ref. [38], the online performance was up to 20% worse (in a two-class task) than the offline performance. In contrast, our end user performed similarly in offline and online tasks. Additionally, the authors did not explicitly state how many offline runs were used for classifier training, so it is possible that their classifiers were trained too intensively on the same dataset. This may result in overfitting and therefore suggesting a far higher offline performance than actually achieved during online trials. Furthermore, online experiments are more demanding, which may also affect the performance.

Interestingly, some individuals subjectively rated their online performance as good even though in objective terms, it was only slightly above chance level. Similar behavior also sometimes occurred in our end user during the use of the BCI-controlled neuroprosthesis. A possible explanation could be that due to the implemented shared control principles, commands from the BCI control channel are only accepted if they fit into the context of the situation. For example, BCI switches are only accepted if the user does not move his shoulder to open or close his fingers. With this control scheme, false-positive BCI switches are effectively rejected, which may lead to the user's impression of at least not producing wrong commands.

One of the subjects in the aforementioned study fell asleep during the training, which was sometimes the case in our end user as well. After the trials, he often mentioned mental and physical fatigue, which can be attributed to the demanding tasks, the complex system with two input modalities and the time-consuming donning, which took at least one hour.

Even after 415 MI-BCI runs, it is remarkable to see that the end user's average performance did not show any trend toward improvement, but remained at about 70%. The results of the INC test are moderate and underline the varying BCI performance. In our end user, no training effect can be seen besides large day-to-day variances in the BCI performance. A possible explanation for this moderate average performance can be found in Ref. [26], where it is stated that movement-related ß-band modulations are significantly different in subjects with SCI as compared to non-injured individuals. In detail, a correlation was found between decreased ERS amplitude and the severity of the impairment of the limb in which the movement was attempted. This result is in line with our findings.

In another study, authors compared the BCI performance of 15 end users with complete SCI, eight of them paraplegic and seven tetraplegic [25]. It was found that five of the paraplegic individuals had an accuracy above 70% but only one tetraplegic person achieved this performance level. The reason for this is still unclear. It can be speculated that the missing sensory loop restricts the vividness of the imagined movements and therefore the performance. This statement is supported by [39], who showed the positive correlation of cortical activation and vividness of the imagined movement. The cited success rate is in line with our results. However, the authors claim that training is expected to improve the performance, which we cannot support on the basis of our single case study, in which almost one year of training did not improve the BCI performance.

Other BCI paradigms based on detection of P300 or steady state visual evoked potentials (SSVEPs) were not taken into consideration as alternatives for neuroprosthesis control since they rely mainly on a visual cue. However, visual attention on the grasp and the position of the hand in space is extremely important in the group of neuroprosthesis users with high-level SCI, since these individuals have neither a touch sensation nor a proprioceptive afferent feedback. Additionally, neither P300 nor SSVEPs support a natural, movement-based control scheme for the neuroprosthesis and the user has to concomitantly concentrate on visual signals on a screen or flickering lights, which may increase the workload and lead to mental fatigue after a while [40].

Several end-user studies include only carefully selected SCI individuals showing a high BCI performance [22,24,41]. However, BCI systems that claim to be meaningful in the sense of improving ADLs should also target non-selected end users who have only a moderate performance. This means that more sophisticated control concepts are needed to compensate for the potentially lower performance. The results from the writing task clearly show that the end user was highly motivated to take part in the prototype testing, since he hoped to improve his quality of life, namely gaining more independence from the support of caregivers and family members. However, the system is complex and its overall performance depends on the reliability of every single component. The orthosis, shoulder joystick and the electrode sleeve have to be aligned correctly, the user must not be physically tired and have a stable posture and has to reliably achieve at least a moderate BCI performance. Furthermore, the end user stated a high subjective workload during the trials. Interestingly, the subjective workload during the ice-cream-eating task was remarkably lower than for the other tasks. This workload may decrease even more with practice [36].

5. Conclusion

In this proof-of-concept single case study, it was shown that with the application of 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 non-selected tetraplegic SCI user. He succeeded in performing different functional tasks (GRT and three tasks of daily living).

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.

Even after 415 MI-BCI runs, it is remarkable to see that the average performance of the end user in the study did not improve over one year of regular BCI training but remained at about 70%. This supports the view that in high-level tetraplegic subjects, an extensive BCI training period does not necessarily lead to superior results. However, this statement has to be validated in future studies with a larger population.

Although some predictors for BCI inefficiency in healthy subjects are described in literatures [42–45], currently no predictors exist in individuals with SCI as surrogate markers for the final BCI performance after training. During screening of study participants, this issue must be made very clear and, especially in the case of tetraplegic end users, it is entirely possible that only low to moderate performance will be achieved [25]. Even if there is some increase in performance with training, it may not be sufficient for controlling the neuroprosthesis to perform ADL tasks. Furthermore, it has to be continuously emphasized that after the study it is not guaranteed (not even likely) that the end users will be able to continue to use the BCI-controlled neuroprosthesis, because of the lack of its commercial availability and support. In order not to raise false hopes, potential study participants need to be carefully informed about the general flaws of MI-BCI systems, namely their difficult handling and varying performance.

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 neuroprosthetic users with an intuitive control that would enable them to accomplish movement in a fluid and transparent manner. The first steps in this direction involving individuals with SCI have already been taken [46].

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