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Adaptive brain-computer interfaces for users with severe motor impairment

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Abstract

Individuals with severe motor impairment can use event-related desynchronization (ERD) based brain-computer interfaces (BCI) as assistive technology. Operating such ERD-based BCIs is a skillful action. Previous training strategies often required a high number of training sessions, high density electroencephalography (EEG) or BCI expert interaction. The central aim of this thesis is to develop an adaptive BCI training paradigm, that calibrates automatically and adapts to the changing electroencephalographic signal patterns of healthy and disabled users. First, an adaptive BCI training paradigm was developed, based on a distributed software architecture. The system was tested with 12 healthy volunteers. Two more studies explored auto-selecting a user-specific combination of motor-related and non-motor-related mental tasks, first offline in a group of 13 users with spinal cord injury (SCI) or stroke and then online in a group of 14 individuals with cerebral palsy. The adaptive training paradigm in the last study auto-selected a user-specific combination of motor-related mental tasks, supported a non-control state and was tested with 22 users with severe motor impairment (SCI or stroke). Additional projects slightly broadened the scope of this thesis, by exploring the applicability of the generated classifiers for real-world control and by investigating the BCI-related neurophysiological differences between users with cerebral palsy and healthy controls. The adaptive training paradigms presented in this thesis successfully auto-calibrated after minutes and recurrently adapted to the users' brain activity. Every calibration step was preceded by online outlier rejection to assure stability of the trained classifiers. The adaptive BCI training paradigms used only five or less EEG electrodes for actual feedback control and required no BCI expert knowledge from operators or care-givers other than mounting the electrode cap and starting the system. Future research will extend the presented, modular framework with more complex classification methods. Another possible research direction to investigate, is whether these adaptive BCI training paradigms can be effective for rehabilitation after neural injuries like spinal cord injury, stroke or other neurological disorders.

Keywords: Adaptive Brain-Computer Interface (BCI), Electroencephalogram (EEG), Spinal Cord Injury (SCI), Stroke, Cerebral Palsy (CP)

Zusammenfassung

Menschen mit motorischer Einschränkung können Gehirn-Computer Schnittstellen (Brain-Computer Interfaces; BCIs), welche auf ereigniskorrelierter Desynchronisation (ERD) basieren, als Hilfstechnologie verwenden. Bisherige Kalibrierungs- und Trainingsstrategien erforderten häufig viele Trainingssitzungen, übermäßig viele Elektroenzephalographie (EEG) Ableitungen oder auch das Mitwirken eines BCI Experten. Das Ziel dieser Arbeit ist es adaptive Trainingsparadigmen zu entwickeln, die sich automatisch kalibrieren und sich an die sich ändernden EEG Signalmuster von gesunden Menschen und Menschen mit schwerer Einschränkung anpassen. Zunächst wurde ein adaptives BCI Trainingsparadigma entwickelt, welches auf einer verteilten Software Architektur basierte. Das System wurde mit 12 gesunden Menschen getestet. Zwei weitere Studien untersuchten das automatische Selektieren einer benutzerspezifischen Kombination von motor-bezogenen und nicht motor-bezogenen mentalen Aufgaben. Diese Untersuchung erfolgte sowohl an EEG-Daten von 13 Menschen mit Rückenmarksverletzung oder Schlaganfall als auch in einem Echtzeit-BCI System in einer Gruppe von 14 Menschen mit Zerebralparese. Zuletzt wurde das System um einen Zustand erweitert in dem keine Kommandos gesendet werden ("Non-Control Zustand"). Dieses System wurde mit 22 Menschen mit Rückenmarksverletzung oder Schlaganfall getestet. In zwei ergänzenden Projekten wurde einerseits die Eignung der Klassifikatoren aus den Trainingsparadigmen zum Steuern realer Geräte untersucht und andererseits die BCI-relevanten neurophysiologischen Unterschiede zwischen gesunden Menschen und Menschen mit Zerebralparese erforscht. Die adaptiven Trainingsparadigmen in dieser Arbeit kalibrierten automatisch nach wenigen Minuten und adaptierten sich an die Gehirnaktivität des Benutzers. Vor jeder Rekalibrierung, entfernte das System statistische Ausreißer aus den EEG Daten. Die adaptiven BCI Trainingsparadigmen verwendeten nur fünf oder weniger Elektroden zur Berechnung des Steuersignals und erforderten keinerlei BCI-Expertenwissen vom Operator. Zukünftige Forschungsarbeit wird das präsentierte, modulare System um komplexere Klassifikationsmethoden erweitern. Eine weitere mögliche Forschungsrichtung wäre zu untersuchen, ob sich adaptive BCI Trainingsparadigmen zur Rehabilitation nach Rückenmarksverletzung, Schlaganfall oder anderer neurologischer Funktionsstörung eignen.

Schlüsselwörter: Adaptive Gehirn-Computer Schnittstelle, Elektroenzephalogramm (EEG), Rückenmarksverletzung, Schlaganfall, Zerebralparese

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Abbreviations

AdBCI	Adaptive Brain-Computer Interface
AIC	Akaike's Information Criterion
ALS	Amyotrophic Lateral Sclerosis
ANOVA	Analysis of Variance
AAR	Adaptive Autoregressive
AR	Autoregressive
ASIA	American Spinal Injury Association
AT	Assistive Technology
BIC	Bayesian Information Criterion
BCI	Brain-Computer Interface
BP	Band Power
CAR	Common Average Reference
CCA	Canonical Correlation Analysis
CLIS	Complete Locked-In State
CNS	Central Nervous System
CP	Cerebral Palsy
CSP	Common Spatial Patterns
ECoG	Electrocorticogram
EEG	Electroencephalogram
EMG	Electromyogram
EOG	Electrooculogram
EP	Evoked Potential
ERD	Event-Related Desynchronization
ERDS	Event-Related Desynchronization and Synchronization
ERP	Event-Related Potential
ERS	Event-Related Synchronization
FIR	Finite Impulse Response
fMRI	Functional Magnetic Resonance Imaging
GMFCS	Gross Motor Function Classification System

GPS	Global Phase Synchronization
HMM	Hidden Markov Model
HR	Hit Rate
III	Instantaneous Instability Index
IIR	Infinite Impulse Response
ITR	Information Transfer Rate
LDA	Linear Discriminant Analysis
LFP	Local Field Potential
LIS	Locked-In State
LLD	Lower Limb Disorder
LMS	Least Mean Squares
LooCV	Leave-One-Out Cross-Validation
M1	Primary Motor Cortex
MC	Motor Cortex
MEG	Magnetoencephalography
MI	Motor Imagery
MMII	Lower Limb Disorder
MMSS	Upper Limb Disorder
MRI	Magnetic Resonance Imaging
MS	Multiple Sclerosis
MT	Motor-Related Mental Task
NC	Non-Control
nM	Non-Motor-Related Mental Task
PLV	Phase Locking Value
QDA	Quadratic Discriminant Analysis
SCI	Spinal Cord Injury
SCP	Slow Cortical Potential
SD	Standard Deviation
SEP	Somatosensory Evoked Potential
SMA	Supplementary Motor Area
SMR	Sensorimotor Rhythm
SVM	Support Vector Machines
SSVEP	Steady-State Visually Evoked Potential
TPC	Trials per Class
VEP	Visually Evoked Potential
TBI	Traumatic Brain Injury
TCP/IP	Transmission Control Protocol / Internet Protocol
TDP	Time Domain Parameters
UI	User Interface
ULD	Upper Limb Disorder

Contents

Chapter 1

Introduction

1.1 What is a brain-computer interface (BCI)?

Brain-computer interfaces (BCIs) translate patterns of invasively ([51, 94, 104]) or non-invasively ([173, 230]) measured central nervous system (CNS) activity into control signals in real-time ("on-line") [234]. This way BCIs can establish a direct channel of communication and control between a user's brain and the environment. This channel of communication and control can "replace, restore, enhance, supplement or improve" the natural neuromuscular CNS output ([234]). A more recent definition also explicitly mentions BCIs' application as a research tool ([29]). Figure 1.1 shows the resulting closed loop setup. Non-invasive BCIs are the focus of this thesis.

When natural neuromuscular CNS output like speaking or writing is lost due to neural injury or disease, BCIs can be used to **replace** certain lost functionality by using them to interface spellers or other assistive technology ([19, 93, 151]). In some cases, BCIs can help to **restore** normal function, for example with BCI-controlled functional electrical stimulation to restore grasp function ([134, 141]). BCIs can **enhance** natural CNS output by passively detecting mental states such as fatigue, confusion or drowsiness, and by adapting the user interface or the application accordingly. Such systems are referred to as passive BCIs ([166, 238, 240]). BCIs may also be used for rehabilitation after neural injuries, like spinal cord injury (SCI; [40, 48, 52, 190]), stroke ([46, 68, 199]) or cerebral palsy (CP; [207]). Hence BCIs can **improve** the capability of the CNS to produce natural neuromuscular output. As a **research tool** BCIs can help to

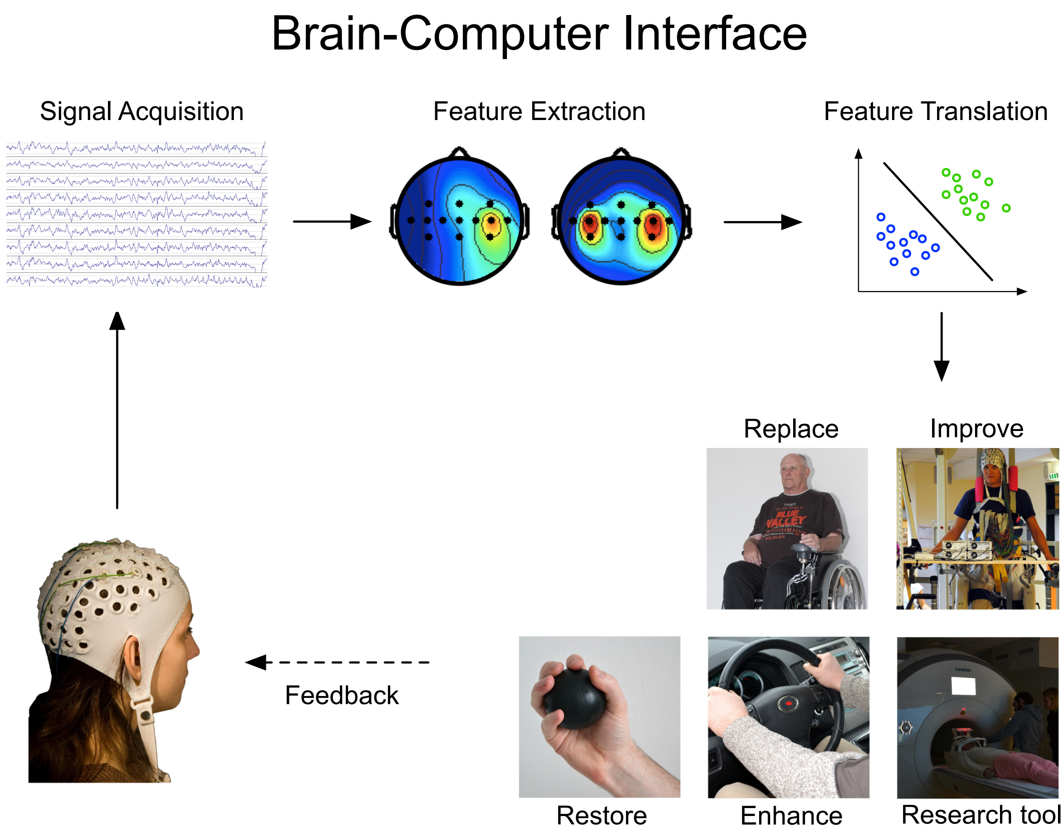

Figure 1.1 – Closed feedback loop of a brain-computer interface and typical applications. The user's brain activity is measured, processed and translated into a control signal. This control signal can be used for a variety of applications as presented by the images at the bottom right. The effect of the control signal on the application is provided as feedback to the user so that the behavior can be adapted accordingly. Photographs from [29].

answer neuroscientific research questions in clinical and non-clinical studies ([208]). For healthy users, especially entertainment ([103, 106, 192, 193]) has been proposed as another non-medical use case of BCIs ([23]). BCIs may also **supplement** natural CNS output by providing an additional way of interacting with the environment. An additional, artificial arm would be an example ([47]). This scenario however lies further in the future.

History of electroencephalography-based BCIs

The capability to measure and record brain activity via electroencephalography (EEG), was first documented by Hans Berger in 1929 ([13]). Translating patterns of brain activity into control signals in real-time, however, required computers with sufficient processing power and was first documented by Jacques Vidal in the 1970s ([217, 218]). In this first BCI, a user could control a computer by focusing visuospatial attention to visual stimuli. In 1991, Wolpaw and colleagues were the first to demonstrate online control of a cursor on a computer screen ([232]). That BCI relied on voluntary modulation of oscillatory, neuroelectric brain activity. This latter type of BCI is conceptually similar to the BCI approaches presented in this thesis.

1.2 Brain signals and types of BCIs

1.2.1 Acquisition of neurophysiological signals

Correlates of neurophysiological activity can be measured by a variety of methods. The BCIs in this thesis are driven by neuroelectrical activity as recorded non-invasively via EEG from the human scalp. EEG is a sum-potential of mainly excitatory post-synaptic potentials from large populations (thousands to millions) of neurons. The contribution of a population of neurons to the EEG increases, if the neurons fire synchronously. Voltage potentials created by neuronal activity propagate through the brain by means of volume conduction. The voltage decreases with the square of distance. Signal contributions from within the brain are therefore more strongly attenuated than those closer to the EEG sensor. The pyramidal cells in the cortical layers II/III and V are assumed to contribute most strongly to the sum-potential measured in scalp EEG ([87, 148]). EEG is particularly well suited for BCIs as it is relatively inexpensive, practical, portable and allows for high time resolution ([156]).

The most common other methods to record neuroelectrical activity are invasive, which means that they require surgical intervention ([145]). To record the electrocorticogram (ECoG) for example, grids of electrodes are placed on the arachnoid mater, which lies above the pia mater and the cerebral cortex ([66, 82, 110]). The ECoG measures the sum of local field potentials (LFPs; [87]). Even more invasive, is the extracellular recording of multi or single unit activity, where microelectrodes are inserted into the cortex to measure spiking activity ([59, 77, 94]).

Invasive recording methods typically have a higher signal-to-noise ratio than EEG. However, the required surgical intervention entails medical risks such as infection. Brain activity can also be measured in terms of the neuromagnetic changes caused by neuronal activity. The most common method to measure neuronal activity in this way is magnetoencephalography (MEG). MEG is regularly used both in the context of BCIs ([32, 127]) but also for basic neuroscientific research. The measured signal is comparable to EEG, the recording method however is more complex. MEG recording devices are large, stationary, expensive and prone to electromagnetic interference from noise sources. Finally, brain activity can also be measured in terms of the metabolic changes that are related to neuronal activity. The most important methods in this category are functional magnetic resonance imaging (fMRI, [201, 229]) and functional near infrared spectroscopy (fNIRS, [11, 202]). Both methods have lower time resolution than EEG, typically at the order of seconds. Measuring neuronal activity using fMRI offers a higher spatial resolution when compared to EEG, but requires a large, stationary and expensive recording device. EEG was used for all BCIs in this thesis and will be assumed for all BCIs from here on.

1.2.2 Types of BCIs according to the used neuroelectrical phenomena

Voluntarily performing specific mental tasks induces spatiospectrally specific power decreases (event-related desynchronization, ERD [167, 168, 169]) or increases (event-related synchronization, ERS [134, 152, 153, 174, 179]) in the ongoing human EEG ([65, 82, 150, 172, 175]). These phenomena do not require external stimulation and can be voluntarily induced by mental tasks like performing motor imagery ([84, 154]), mental arithmetic, word association, mental navigation or mental rotation ([41, 61]). Figure 1.2 shows examples of ERD/ERS patterns induced by imagining movement. BCIs that rely on this type of phenomenon are said to be ERD-based. The adaptive BCIs in this thesis are ERD-based.

Other phenomena, such as evoked potentials (EP), are strictly phase- and time-locked to external stimuli ([35, 36, 188]). EPs merely reflect the brain's physiological response to external stimulation. Event-related potentials (ERP) on the other side are transient deflections in the EEG that are associated with higher order processes like attention or perception. Different stimulus types can evoke EPs or ERPs. Depending on the stimulus type there are visually evoked potentials (VEP; [16, 209, 227]), auditory evoked potentials (AEP; [73, 88]), somatosensory evoked potentials (SEP; [78]), olfactory evoked potentials (OEP; [10, 146]) and gustatory evoked potentials (GEP; [160]). The most important example of an ERP in the field of BCIs is the P300, which is a transient positive deflection in the EEG that can be measured under specific circumstances in the human EEG 250 to 500 ms after the occurrence of an external stimulus ([34, 186, 210]). Specifically, the P300 occurs time- and phase-locked to the onset of a target stimulus in an oddball paradigm ([58, 205]). An oddball paradigm is a random sequence of target and non-target stimuli, where the target stimuli occur less frequently than the non-target stimuli. P300 BCIs have been most commonly implemented based on auditory ([90, 96, 185, 198]), visual ([49, 58, 69, 85, 100]) and somatosensory ([27, 214]) stimuli. When stimuli are presented at a steady frequency so that every new stimulus occurs before the deflection in the EEG that was elicited by the last stimulus has faded, a steady-state response can occur in the EEG. Depending on the type of stimulus this response is called a steady-state visually evoked potential (SSVEP; [9, 128, 138, 147, 216]), steady-state auditory evoked potential (SSAEP; [111, 112, 181, 206]) or steady-state somatosensory evoked potential (SSSEP; [133, 137, 140, 184, 188]). BCIs that rely on such phenomena are said to be EP- or ERP-based.

Slow cortical potentials (SCP) are slow potential shifts, that can be voluntarily induced by the user ([17, 19, 114]). From all commonly used mental strategies to control a BCI, this one typically requires the most user training. BCIs that rely on this phenomenon are typically said to be SCP-based.

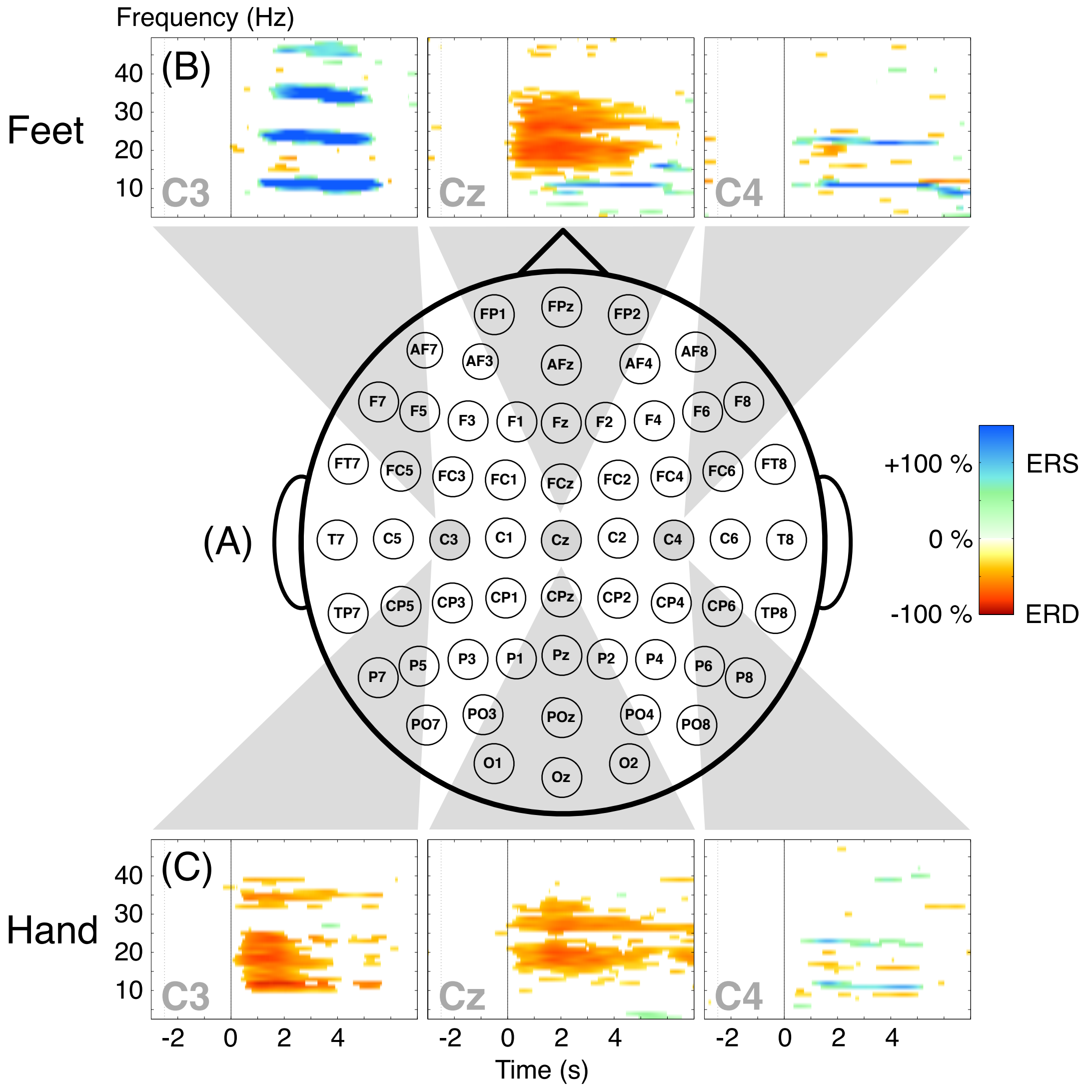

Figure 1.2 – Spatiospectrally specific power modulation in the electroencephalogram. The small circles on the stylized head in Panel (A) indicate standard electrode locations ([81, 161]). The Panels (B) and (C) show decreases (event-related desynchronization; ERD) and increases (event-related synchronization; ERS) in power, relative to a baseline period, as recorded at the locations C3, Cz and C4 ([172]). The x-axis in each map is the time in seconds within the trial. The visual cue, that indicated the task was displayed at second 0. The subjects were relaxing with eyes open, prior to the cue and executing the task after the cue. The period from second -2.5 to 0 was used as a baseline to compute the relative power changes. The y-axis shows the frequency bands. The maps in Panel (B) are averaged across all trials of one condition, where the human subject imagined moving both feet. For the condition in Panel (C) the task was to imagine moving the right hand.

1.2.3 Types of BCIs from the perspective of user interaction

From the user's perspective, BCIs can be classified into the three categories "active", "reactive" or "passive" ([240]): Active BCIs rely exclusively on voluntarily induced, spontaneous brain-activity. This includes mostly ERD- and SCP-based BCIs. They do not require any external stimulation and are generally independent of neuromuscular activity. These BCIs are also referred to as endogenous BCIs ([230]). The ERD-based BCIs presented in this thesis are active BCIs. Reactive BCIs on the other hand, require the user to focus their attention on external stimuli and are hence mostly EP- or ERP-based. As previously mentioned, the used stimuli can be visual, auditory, somatosensory, olfactory or gustatory. Reactive BCIs are typically ([31, 212]), but not always ([2, 3]), dependent on neuromuscular activity. These BCIs are also referred to as exogenous BCIs ([230]). Passive BCIs as the third category do not require any active interaction by the user. They can rely on any of the above mentioned phenomena such as ERD, EP, ERP or SCP. Passive BCIs work implicitly in the background and can improve human-machine interaction ([83, 239, 240, 241]).

Another important categorization for BCIs is the temporal control paradigm, where Mason and colleagues ([117, 118]) differentiate between four paradigms: First *synchronized*, where the BCI can be used periodically, while there is no non-control state available. Support of a non-control state means, that the system can recognize periods of time where the user willingly chooses not to interact with the device ([117]). Examples for *synchronized* paradigms, are many traditional P300 BCIs ([27, 58, 96]), as well as ERD-based BCI training paradigms ([57, 70, 86]). The second paradigm is called *system paced*, which means the BCI is periodically available, and a non-control state is supported. Examples of such systems include more recently developed P300 BCI paradigms that have been extended to support a non-control state ([165, 182, 242]). In the third paradigm, referred to as *constantly engaged*, the BCI is continuously available, but a non-control state is not supported. Examples include ERD-based BCIs where the user is required to perform a certain mental activity to avoid triggering activations ([141, 142]). Finally, in the paradigm called *self-paced* the system is continuously available and does support a non-control state. A number of ERD-based BCIs are examples for this mode of operation ([106, 109, 193]).

1.3 Signal translation

1.3.1 Signal preprocessing

Spatial filtering in the context of EEG-based BCIs, improves the signal-to-noise ratio of the measured brain activity ([24, 121]) and therefore typically allows for higher control accuracies ([176]). Every EEG electrode records sum potentials of neuronal activity from an area of few cm^2 of cortical surface underneath the electrode ([156]). The areas from which neuroelectrical signals are recorded, therefore overlap for adjacent electrodes. Hence, parts of the recorded signal are common in these electrodes. Spatial filtering reduces these common signal parts, which effectively allows to derive a signal from a spatially more focal area of cortex. The most common spatial filters are the bipolar derivation and the Laplacian derivation ([76, 176]), which are also used for the BCIs in this thesis. For a bipolar derivation between two neighboring electrodes the signal from one electrode is subtracted from that of the other electrode. For a Laplacian derivation, the average of electrodes that surround a central electrode in a grid with equidistant edges is computed and subtracted from the one central electrode. Other, more elaborate spatial filtering methods like common average reference (CAR; [121]) or common spatial patterns (CSP; [24, 97, 136, 187]) can be even more effective but require more electrodes. Temporal filtering allows to attenuate energy in certain frequency ranges of a signal that do not contain relevant information ([162]). Given that the choice of frequency ranges is adequate, filtering can improve the signal-to-noise ratio. The most common types of digital filters are finite impulse reponse (FIR) and infinite response filters (IIR) ([162]). All BCIs presented in this thesis use IIR filters. In Figure 1.3, Panel (A) shows EEG as acquired from one channel and Panel (B) shows the EEG signal after spatial and spectral filtering.

1.3.2 Feature extraction

Feature extraction is the process of isolating those specific characteristics of the EEG signal, by which the signal can be classified into control commands using pattern recognition and machine learning techniques. The most important type of feature for the BCIs in this thesis is logarithmic average band power. It is computed by first band filtering the EEG in a specific frequency range, computing power by squaring the signal and applying a moving average (typically over one second) to smoothen the control signal. To make the distribution of band power more Gaussian, which is an assumption of certain classifiers, the averaged band power can be transformed by the logarithm. Previously, logarithmic average band power was used successfully in a variety of BCI implementations ([21, 105, 177, 193]). The Panels (A) to (E) in Figure 1.3 show the steps to compute logarithmic average band power. Other relevant features for BCIs include autoregressive (AR) or adaptive autoregressive (AAR) parameters ([126, 197, 225]), time domain parameters (TDP; [157, 220]) or signal synchrony for example by using phase-locking value (PLV; [30, 99, 102]) or single-trial connectivity estimation ([14]) .

1.3.3 Classification

Classification algorithms assign class-labels to examples of data according to previously defined classification rules ([20]). These classification rules can implement either linear or non-linear transformations from the features, that represent the data, to specific class-labels. For the BCIs in this thesis, linear discriminant analysis (LDA; [20, 60, 195]) was used for classification. Panel (F) in Figure 1.3 shows how LDA can separate data examples into two classes. This classification method assumes data to be Gaussian distributed and places a linear hyperplane between the distributions of two data sets, so that the variance between the two distributions is maximized and the variance within each distribution is minimized. This objective function is called the Fisher criterion ([60]). Logistic regression ([20, 101]) is another example for a linear classifier. More complex, non-linear classification methods such as artificial neural networks ([5, 20, 75]) or support vector machines ([20, 39, 204]) have been evaluated for their efficacy in the context of EEG-based BCIs, but did not substantially outperform linear classification methods ([135]). Please see [113] for a comprehensive review of classification algorithms used for BCIs.

1.4 Adaptive BCI training paradigms

Adaptive BCIs typically provide online feedback as early as possible or from the start, and adapt the classifier model online during operation ([98, 123, 221, 224, 225, 231]). In this closed feedback loop, both the user and the BCI are adaptive controllers. While the BCI continues to

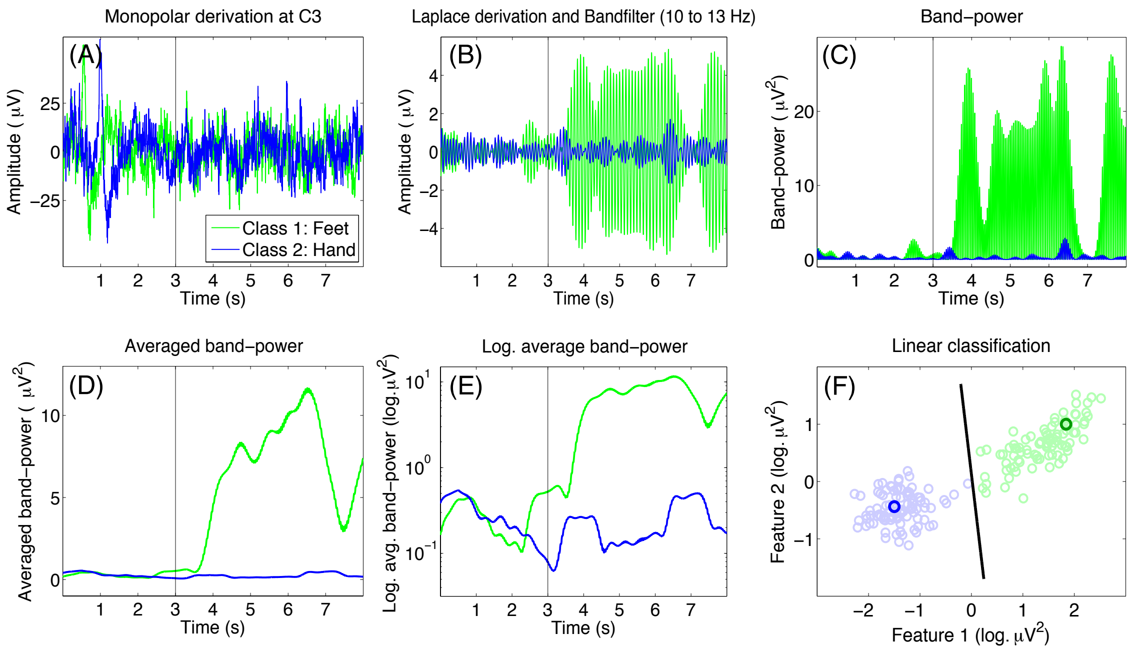

Figure 1.3 – Classification based on logarithmic band-power features, that are extracted from the electroencephalogram (EEG). Panel (A) shows two signals for two movement imagery conditions, recorded as the potential between the electrode at location C3 and the reference electrode (monopolar derivation; band filter between 0.5 and 100 Hz; notch filter at 50 Hz). Panel (B), shows the same signals after Laplace derivation and band-filtering between 10 and 13 Hz. This reveals the amplitude modulation of the sensorimotor rhythm in response to motor activity. To attain a more reliable and stable feature, the signals are squared (see Panel (C)) and averaged over 1 second (see Panel (D)). By applying the logarithm (see Panel (E)), the distribution of the signals becomes more Gaussian, which is an assumption of some linear classifiers like linear discriminant analysis. Finally, the scatter plot in Panel (F) shows the log. average band-power for every trial for two features, band filtered at 10 to 13 and 16 to 24 Hz, respectively. The resulting feature value for a specific trial is the average between second 4 and 8 in the trial.

adapt to the patterns of the user's brain activity, the user on the other side keeps adapting his or her behavior to maximize BCI performance.

Adaptive BCIs can be mainly differentiated according to the type of adaptation that is used: In the context of this thesis, the first type is referred to as "continuous adaptation". With this method, the classifier-model is typically adapted after every trial (e.g. [221, 224,

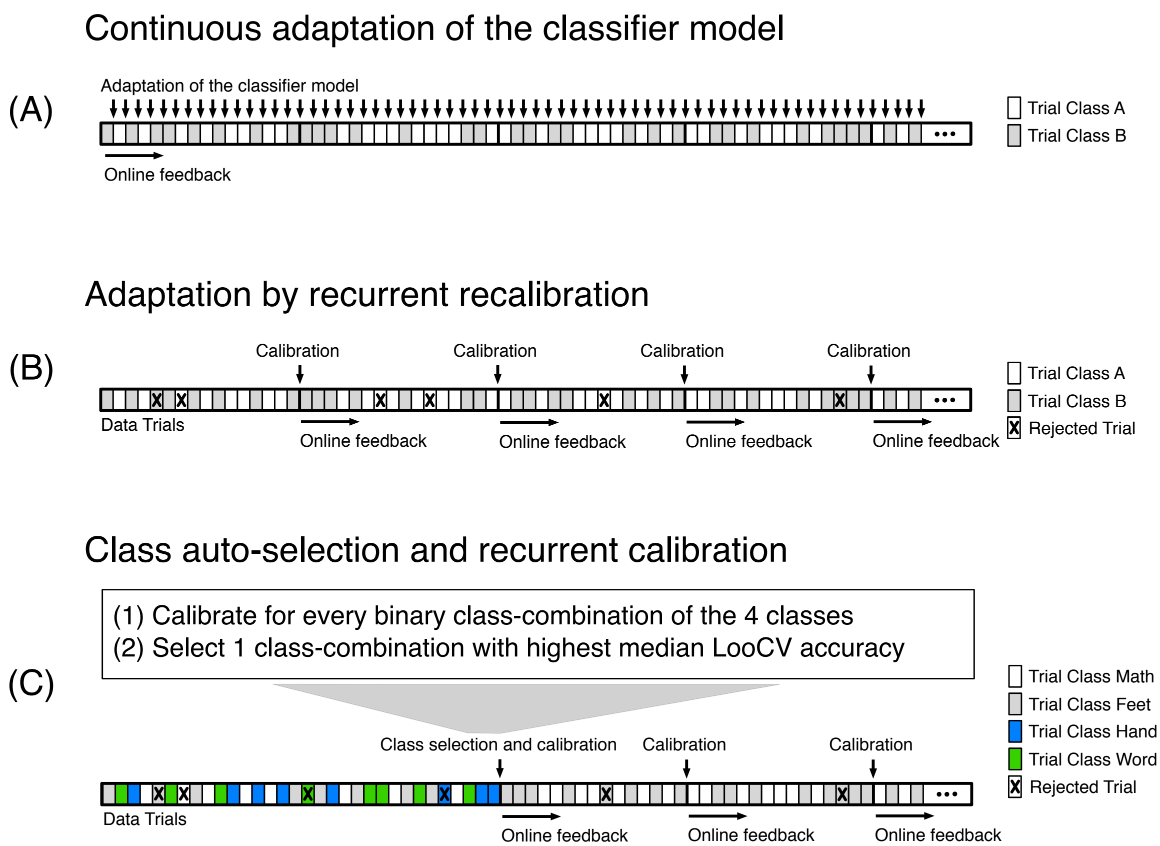

Figure 1.4 – Modes of operation in adaptive brain-computer interfaces. Panel (A) depicts the continuous adaptation mode, where the classifier is modified after every trial ([221, 222, 223, 224, 225, 226]). Panel (B) shows the recurrent adaptation mode, where the classifier is updated whenever a sufficient amount of new data is available. Panel (C) shows the auto-selection and recurrent recalibration mode where the class combination with the highest separability is selected according to a heuristic.

225, 226], see Figure 1.4, Panel (A)). This type of adaptation does not require any memory of previously collected trials. The second type, represents a more general notion of adaptation and is implemented as “recurrent recalibration” (e.g. [200], see Figure 1.4, Panel (B)). This recurrent recalibration includes retraining of the classifier model on a fixed or newly selected set of features. Recalibration generally takes more time than classifier adaptation and therefore typically needs to be run asynchronously in the background. It requires a higher amount of computational resources, but allows for more complex data processing including outlier rejection. To make recalibration possible, all trial information needs to be kept in memory. Systems that rely on continuous adaptation have to start out based on a predefined classifier model. This predefined classifier model can for example be trained based on data that was previously collected from a large group of other users ([221, 225]). In this type of adaptive BCI, feedback can be provided from the start. Adaptive BCIs that rely on recalibration can be configured to start with a predefined classifier so that they can provide feedback from the start, or start without a predefined classifier so that they can start to provide feedback after the first automatic calibration. This first automatic calibration can also include automatic class selection (see Figure 1.4, Panel (C)). With recurrent recalibration, typically a fixed number of new trials per class are collected prior to every recalibration. BCIs that rely on recalibration can be configured to recalibrate based on all collected data ("cumulative mode") or based only on a certain number of the most recently collected observations ("window mode"; see [200]). The work in this thesis relies on adaptive BCIs that use recurrent recalibration in a cumulative operation mode.

1.5 Medical conditions that cause severe motor impairment

For motor impairment, the term paraplegia is used to denote partial or complete loss of function below the waist. If the loss of function affects all four extremities, then the term tetraplegia is used. In analogy, the terms para- and tetraparesis describe a severe weakness in the muscles from the waist down or in all four extremities, respectively. When severe motor impairment limits an individual's ability to perform certain tasks, then this condition is referred to as a disability ([235]).

1.5.1 Spinal cord injury (SCI)

Spinal cord injury (SCI) is typically a result of trauma or disease, and can cause impairment of motor, sensory or even autonomic function ([33, 119]). The specifics of the functional impairment can vary, depending on the location of the injury and the degree to which the spinal cord is severed. In the order from the neck to the legs, the spinal cord is subdivided into the cervical, thoracial, lumbar and sacral section. The cervical section is mainly responsible for the function of hands, arms and neck but also for the muscles that are needed for respiration. The thoracial section is associated with the function of the muscles in the torso. The lumbar and sacral section are generally associated with the function from the waist down to the feet. Typically, SCI affects mainly the function associated with parts of the spinal cord that are below the level of injury. In practice, this entails, that a SCI on a level closer to the head will lead to more severe functional impairment. The classification of SCI is carried out according to the International Standards for Neurological and Functional Classification of Spinal Cord Injury (ISNCSCI; [116]). Especially relevant is the categorization of impairment in the American Spinal Injury Association (ASIA) levels A, B, C, D or E ([116]). ASIA E refers to normal sensory and motor function. ASIA D to A, describe the extent to which motor and sensory function are preserved below the point where both, motor and sensory function are normal on both sides of the body: For ASIA D and C a specific level of motor function is preserved, while in ASIA B only sensory but no motor function is retained. Finally, ASIA A refers to complete spinal cord severance, where neither sensory nor motor function are preserved.

1.5.2 Stroke

Stroke is a medical condition where the blood flow to certain brain areas is interrupted as a result of arterial ischemia or hemorrhage ([50, 144]). During an ischemic stroke, a blood clot or a different form of embolus blocks the blood flow through an artery. This way, blood from the heart can no longer pass to supply the brain cells in the affected area with oxygen and energy. This can cause brain cell death (lesion). A hemorrhagic stroke on the other side, is a condition where a blood vessel in the brain ruptures, so that blood leaks into the brain. The resulting compression of the brain tissue can cause cell death. The specifics of any impairment resulting from stroke, depend strongly on the location of the lesion. Lesions at cortical motor areas for example, may cause motor impairment of the associated extremities. Neural insult to the ventral pons in the brain stem, as a specific example, can lead to a condition where the patient becomes tetraplegic, while retaining consciousness. The condition may leave the patient with only very limited or no means of communication with the outside world. This medical condition is referred to as locked-in syndrome ([203]).

1.5.3 Cerebral palsy (CP)

Cerebral palsy (CP) refers to a range of neurological conditions, where brain injury or abnormal development before, during or after birth ([159]), causes physical and possibly also cognitive impairment ([44, 132]). The condition is non-progressive and, as of the current state of knowledge, there is no cure. However, the specifics of the impairment may change over life as a result of rehabilitation or growing up. The type and characteristics of the associated motor impairment vary across individuals, depending on which brain areas are affected by the condition. In the past, the prevalence of tetraplegia in individuals with CP has been found to range between 20 and 43 % ([159]).

1.5.4 Other medical conditions

Other medical conditions that can lead to severe motor impairment include traumatic brain injury (TBI), multiple sclerosis (MS), Guillain-Barré syndrome and amyotrophic lateral sclerosis (ALS). TBI is an injury to the brain, caused by external physical force. The injury may either penetrate the skull or leave it in tact. TBI can cause a range of impairments, including severe impairment of motor function. The type and degree of motor impairment depends on which areas have been affected by the injury ([115, 213]). In severe cases this can result in medical conditions like locked-in syndrome or disorders of consciousness like minimally conscious state, persistent unresponsive state or even coma ([163, 164]). MS is a chronic, inflammatory disorder of the central nervous system. The disorder causes progressive neurodegeneration by damaging the myelination of axons, which can lead to severe motor impairment ([37, 228]). Guillain-Barré syndrome causes acute weakening and numbing that progresses from the toes and fingers toward the torso within days. At its peak, the disorder causes a high level of motor impairment, possibly including respiratory failure. The cause of the disease is an inflammation of the peripheral nerves that can follow certain infections. Two thirds of the patients recover completely within weeks or months, while the rest may retain some impairment ([80, 237]). Charcot ALS is a progressive, neurodegenerative and fatal disease of the motor system and is the most common form among the motor neuron diseases (MND). ALS causes spasticity and rapidly progressing muscular atrophy, which leads to severe motor impairment, respiratory failure and finally death ([28, 95]).

1.6 Organization of the chapters

Chapter 1, Introduction gives an overview of the most relevant neurophysiological signals, the most important types of brain-computer interfaces and signal processing techniques.

Chapter 2, Motivation and related work reviews the state of the art and limitations of relevant previous work in the field of adaptive brain-computer interfaces.

Chapter 3, Aim of this work points out overall and specific objectives of this thesis.

Chapter 4, Methodology and results summarizes aim, methods, main results and significance of the core papers for this thesis.

Chapter 5, Discussion explains how the findings reported in the core papers contribute to accomplish the aim of the thesis. This section further relates the outcome of the studies to other work in literature and discusses possible limitations of this work.

Chapter 6, Conclusion and future prospects summarizes the main achievements of this thesis and points out possible future research directions.

Chapter 2

Motivation and related work

2.1 Conventional BCI training approaches

Operating an ERD-based BCI is a skillful action and requires a varying amount of training for different users ([4]). Most state-of-the-art ERD-based BCI training paradigms start by collecting cue-guided mental activity, where no feedback is provided to the user. After collecting a substantial amount of data (typically 20 to 30 minutes) a classification algorithm is trained. So, depending on which classifier and processing algorithms are used, the complete training procedure after electrode mounting can typically require between 25 and 45 minutes. The trained classifier is then used to provide online feedback to the user during training sessions. This way, the user can improve his or her performance based on the feedback. The data from these online training sessions are then typically reanalyzed to set up a new classifier for consecutive training sessions. In this iterative approach man and machine mutually adapt to each other. This strategy has proven effective in healthy users ([71, 101, 187, 193]) and users with severe motor impairment ([93, 141, 151, 170, 231]) but is time consuming and strenuous.

One approach to allow for high control accuracy with a low number of training sessions is by using a high number of electrodes (more than 16[1]) and more complex data analytic approaches like CSP ([24, 97, 187]). Such approaches have been shown to be effective both for healthy

[1]The threshold of 16 electrodes was defined for this thesis since most relevant literature used either 6 to 16 or more than 32 electrodes. This threshold therefore is well suited to distinguish these systems in the context of this particular research topic.

users ([6, 21, 67]) and for users with severe motor impairment ([8, 38, 171]). Some disadvantages of approaches that require a high number of electrodes are, that they require more equipment, are more expensive, require longer setup time, are more inconvenient for the user and are overall less practical for sustained use. Many of these disadvantages are especially problematic for end users with severe motor impairment.

2.2 Offline adaptive BCI training approaches

Adaptive BCI training paradigms constitute an alternative to conventional training paradigms. Generally, these systems provide feedback to the user either from the start, or from as early as possible. Then they continuously or recurrently adapt to the user's brain activity over the course of the training, while the user in turn adapts his or her behavior to obtain best possible feedback. The following paragraphs review the relevant literature about offline analyses in the field of adaptive BCIs by descending relevance.

Shenoy et al. (2006) ([200]) used EEG data, previously collected from five healthy study participants, to visualize and quantify the non-stationarities that are introduced by the transition from the offline to the online phase in a BCI experiment. To alleviate the negative impact of these non-stationarities, the authors introduced and evaluated three adaptation schemes. The first two schemes *Rebias* and *Retrain* did not change the CSP-based feature selection ([21, 187]) based on the online data. Instead *Rebias* just adapted the bias term of the underlying LDA classifier, while *Retrain* in addition recomputed the classifier weights. The third approach, *ReCSP* also recomputed the CSP-based feature selection. The three schemes were evaluated using three different modes that determined which data to use during adaptation: *Initial* used only a fixed amount of data from the beginning of the session, while *Window* used a fixed amount of data from the immediate past. *Cumulative*, finally used all data that was collected so far during the adaptation process. The approaches *Retrain* and *Rebias* were found to be most effective, in both modes *Cumulative* and *Window* (see Figure 2.1). Interestingly, even simple adaptation like *Rebias* in the mode *Initial* was already able to counteract some of the non-stationarity.

Vidaurre et al. (2004) ([223]) initially trained a universal QDA classifier model, based on EEG data collected from seven study participants. In preliminary offline analysis, the authors showed that the adaptive QDA classifier effectively adapted to single sessions of EEG data from

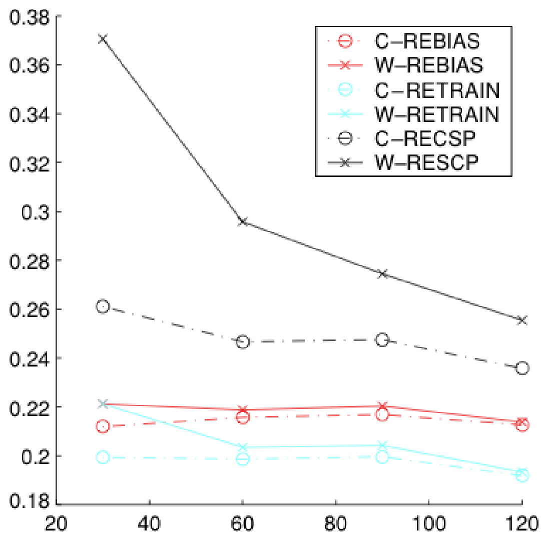

Figure 2.1 – Different adaptation schemes for EEG-based brain-computer interfaces. Offline classification analysis was performed on EEG data of five healthy participants who performed two motor-related mental tasks. Common spatial patterns (CSP) was used for feature extraction and linear discriminant analysis was used for classification. The abscissa shows the number of trials and the ordinate shows the classification error. In the figure legend, the prefix "C" stands for "cumulative", which indicates that all data that was collected up to a certain point, was used for recalibrations. The prefix "W" on the other side, indicates that only data from a specific window prior to a certain point was used for recalibration. "REBIAS" indicates that only the bias term of the classifier was recomputed, wheres "RETRAIN" refers to a complete recalibration of the classifier. "RECSP" included recomputing the CSP weights as well as retraining the classifier. Figure from [200].

three different healthy individuals.

Sykacek and Roberts (2003) ([211]) introduced an adaptive nonlinear classification approach based on variational Kalman filtering. The authors evaluated their method on different data sets, including EEG data collected from eight healthy study participants. The task of the participants in this experiment had been to perform a relax task, a motor-related as well as a non-motor-related mental task. On the EEG data, the authors were able to show a statistically significant improvement in classification accuracy of their method compared to an otherwise similar non-adaptive approach in most task combinations.

Kawanabe et al. (2006) ([89]) showed on EEG data, previously collected from three study participants, that an adaptive classifier based on a Gaussian mixture model (GMM) and a dynamical Bayesian model was able to effectively compensate for the non-stationarities in the transition between offline and online phase in a BCI experiment for some of the tested participants.

Blumberg et al. (2007) ([25]) present two linear classification approaches. Both adapt in an unsupervised manner relying on expectation maximization (EM), but the second approach can incorporate an error signal that indicates whether a data sample was classified correctly or not. The authors demonstrated the effectiveness of both methods on simulated data and on the EEG data from one human subject.

Hasan et al. (2009) ([72]) presented an adaptive classifier that performs unsupervised adaptation of a Gaussian mixture model using expectation maximization. Based on EEG data previously collected from five study participants, the authors showed that their adaptive approach improves overall accuracy in comparison to a static approach by 1-2 %.

Yoon et al. (2009) ([236]) demonstrated that extensions to a dynamic Bayesian model for adaptive classification can improve accuracy in the presence of missing or erroneous labels. The authors evaluated the proposed methods using simulated data and EEG which was previously collected from three healthy study participants.

Hsu (2011) ([79]) showed on EEG data from six healthy study participants that enhanced active segment selection and multiresolution fractal feature vectors in an LDA-based adaptive classification setup can improve accuracy rates.

2.3 Online adaptive BCI training approaches

The following paragraphs review the relevant literature about online adaptive BCIs in order of descending relevance.

Vidaurre et al. (2005) ([224]) presented two variants of an online adaptive BCI that used different feature extraction methods. One implementation used adaptive autoregressive parameters, while the other one relied on logarithmic band power features. Both adaptive BCI systems adapted the classifier on a trial level. Either implementation was tested with six healthy and BCI-novice study participants in three sessions. Logarithmic band power performed slightly better in the first and second session but both methods were equally effective in the third session.

The system did not support automatic online artifact rejection or detection. The authors present high average accuracies from 71.4 % in the first session to 79.1 % in the third session, but do not report how many participants were excluded from analysis due to artifact congestion. In later publications ([225, 226]) involving the same setup and partly data from the same participants, the authors report that many data sets needed to be excluded due to artifact congestion and lack of class separability.

Vidaurre et al. (2006) ([225]) reported results for three additional healthy novice study participants for the previously presented AAR parameter-based adaptive BCI system from Vidaurre et al. (2005; [224]) and noted that data from three additional participants was excluded due to the presence of artifacts. In addition the authors showed in offline analyses on EEG data from three healthy study participants, how their continuous adaptation approach after every trial yielded higher overall accuracy than discontinuous adaptation after three or four runs (120 to 160 trials) of data.

McFarland et al. (2005, 2008) ([124, 120]) used the standard Adaptive BCI training paradigm of the Wadsworth center ([215, 233]), to train four healthy and two disabled users so that they were able to effectively control a cursor across a computer screen and select specific targets, thus emulating mouse cursor control of a computer.

Wolpaw and McFarland (2004) ([231]) presented an ERD-based BCI that continuously adapted linear weights based on a least mean squares (LMS; [122, 123]) algorithm so that the error in a two-dimensional cursor control task was minimized. The authors showed, that after a considerable amount of training (between 40 and 296 sessions) two individuals with SCI and two healthy users were able to control the BCI with an efficacy that was comparable to that in invasive setups with non-human primates.

Vidaurre et al. (2007) ([226]) evaluated and compared four different adaptive BCI approaches, the first two using an adaptive QDA classifier either on AAR parameters or logarithmic band power features. Approach two and three both concatenated AAR parameters and logarithmic band power features but approach 3 used adaptive QDA while approach 4 used Kalman LDA for classification. Approach 1, 2 and 3 were tested in online experiments, each with six healthy study participants. In addition, each approach was simulated with the rest of the data from the other participants. Six additional data sets were collected, but excluded from analyses due to artifact congestion or lack of class separability in the data. The authors found feature concatenation (approach 3 and 4) to yield slightly higher accuracies. In additional analyses the authors also confirmed their earlier finding ([225]) that continuous classifier updates after every trial yielded slightly higher accuracy than discontinuous updates after more than three runs (120 trials).

Vidaurre et al. (2011a) ([222]) devised a sophisticated adaptive BCI training approach that used a high number of electrodes and operated in three phases: Initially the authors selected two of three classes for each user according to previous screening or the preference of the user. The first phase then provided feedback from the beginning on for three runs (300 trials) based on three laplacian derivations around the electrode positions C3, Cz and C4. For classification a universal model was used, which was trained from 48 previously collected data sets. The LDA classifier model was adapted after every trial. Based on the data from the first three runs, the authors then computed CSP filters. These CSP filters remained fixed for the following second phase. During phase two, six laplacian derivations were automatically reselected after every trial and concatenated to the CSP filters. Finally, also the LDA classifier was retrained after every trial. For the third and final phase in the runs seven and eight, spatial filters were retrained based on the runs four to six and remained static from then on. In this last phase, the LDA classifier was continuously adapted in an unsupervised manner after every trial. The authors evaluated their system on eleven study participants (ten with BCI experience). For five of the experienced participants, ERD-based BCIs had previously worked very well, for two of them moderately well and for three of them very poorly. The authors found their system to be highly effective for participants who had previously been successful. Surprisingly, the authors also saw improvements for those users for whom ERD-based BCIs had previously not worked effectively.

Vidaurre et al. (2011b) ([221]) applied their sophisticated adaptive BCI training approach they previously introduced in Vidaurre et al. (2011a; [222]) to a group composed of four BCI-novice participants and ten other participants for whom ERD-based BCI systems were previously found not to work accurately enough. The authors found their system to work better than 70 % accuracy for all four novice participants. More interestingly the system also worked better than 70 % accuracy for five of the ten users for whom ERD-based BCIs were previously found not to work accurately enough (see Figure 2.2).

Millán (2004a) ([129]) presents first evidence, that online-learning by regularly adapting the BCI classifier, can systematically improve classification performance over an offline training

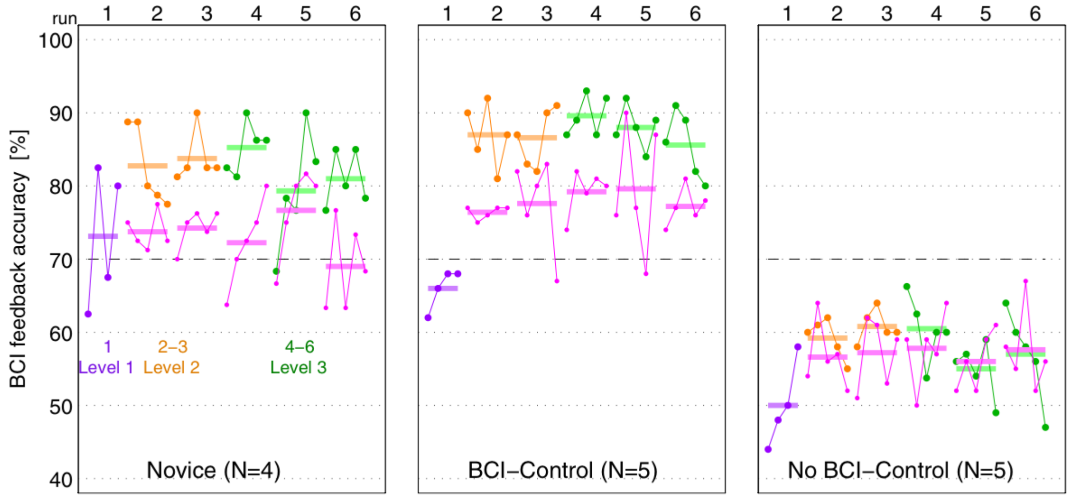

Figure 2.2 – An adaptive training protocol for users, for whom previous brain-computer interface (BCI) approaches were unsuccessful ([221]). The left panel shows the accuracy results for four novice participants, the center panel shows the accuracy results for five users who were previously unsuccessful to attain BCI control but were successful with this approach and the right panel shows the results for users who have previously been unsuccessful and for whom the present adaptive BCI also does not work effectively. Level 1 uses only three Laplacian derivations and continuous classifier adaptation. Level 2 uses common spatial pattern (CSP) filters, Laplacian derivations and continuous classifier adaptation. Level 3 uses fixed spatial filters and unsupervised classifier adaptation. The bars are the accuracy averages over the users for a run and the dots are the averages over the users for a portion of trials within a run. The light pink colored graphs indicate resulting performance if the setup from Level 1 were used for the rest of the session. Figure from [221].

approach. On a related topic, Millán and colleagues also showed that the adaptive classifiers can be used to control real-world applications such as mobile robots or virtual keyboards ([130, 131]).

Kus et al. (2012) ([101]) demonstrated an ERD-based BCI setup that required 16 electrodes and supported three classes. The system allowed for automated feature selection and classifier training after four calibration runs where no feedback was provided. During subsequent synchronous training runs, the classifier was re-calibrated whenever a sufficient amount of trials was available. After four sessions of training, five healthy study participants were able to operate three classes in an asynchronous ERD-based BCI with an average accuracy of 75 %.

Vidaurre2011c ([219]) first showed effective methods to adapt a classifier, which was trained on offline data, to generalize better to feedback data in offline analyses. This was done on data sets from 80 healthy and seven disabled individuals. The second step was performed on newly collected data from eleven healthy individuals. Here the authors first collected calibration data offline and then trained a classifier. The classifier was then used online though, and was adapted after every trial.

2.4 Limitations of previous work

Both, conventional and adaptive BCI approaches have been shown to allow for effective BCI training and for successful, subsequent BCI control of real-world applications for both, healthy and disabled users based on the trained classifiers (conventional: [141, 170] and adaptive: [120, 124, 131, 215, 233]). Despite the successes, of both of these approaches over the years, a number of more recent offline analyses ([25, 72, 79, 89, 200, 219, 223, 236]) and online studies ([224, 225, 226]) indicated, that specifically the part of BCI training may offer potential for improvement by using more elaborate adaptive approaches. While, specifically, the results of the tests of Vidaurre and colleagues ([224, 225, 226]) were very promising, there was still some potential for improvement. For example, the authors consistently report the necessity to exclude 25 % of the users due to artifactual activity or lack of separability in the EEG data. Since the accuracy results for a portion of the study participants have not been reported, it is very difficult to estimate the efficacy of the system for new users, especially for end users. An evaluation where all data is reported would be necessary to generate a more reliable estimate of the efficacy of adaptive ERD-based BCI systems. The fact that the system was not effective for users who produced artifactual activity during operation offers another major opportunity for improvement. The reason why artifacts are so problematic for adaptive BCI designs, is because classifier updates happen after every trial, regardless of whether the trial was artifact contaminated or not. In the absence of outlier rejection, especially high energy EEG artifacts like muscle activity, can strongly deteriorate classification performance of the adapted classifier. In the previously presented designs, the classifier update procedure stalls the online BCI operation. The update procedure is therefore required to be very short and can not include time-consuming outlier rejection mechanisms. To make adaptive BCIs more useful in a practical setup, they need to be robust against occasional short timed interferences like when the user swallows or moves his or her head.

This is even more important for users with severe motor impairment. Performing continuous adaptation typically means, that there is not enough time to perform outlier rejection or more complex types of optimization. At the same time improved adaptive BCI training approaches should also be evaluated with representative samples of end users with severe motor impairment.

Adaptive BCI implementations that used higher numbers of EEG electrodes (40 to 64) were even able to achieve effective BCI control for 50 % of a sample of users for whom ERD-based BCIs had previously been found to be not effective ([221, 222]). There are however, a couple of limitations to these otherwise very promising approaches. The requirement of a large number of EEG electrodes increases setup time, user discomfort and cost of the equipment. BCI systems that require high EEG coverage are therefore slightly less practical, especially for users with severe motor impairment. The sophisticated and elaborate training protocol used in this setup required running through three phases and was semi-automatic. This means, that the procedure still required BCI expert interaction for some procedures in the protocol. To make adaptive ERD-based BCI systems more practical for real-world use, a possible way for improvement would be complete automation of features selection, classifier setup and adaptation. In this ideal case, the person to setup the BCI, which in a real-world setting could be a medical professional or a caregiver, would require no BCI expert knowledge other than mounting the electrode cap and starting the system. Like in earlier designs, also this implementation adapts classifiers after every trial. The authors do not mention whether their system performed outlier rejection. Therefore the question remains, whether excluding artifact congested trials during retraining of the classifiers may improve performance.

2.5 User requirements

Guided by the findings of previous work and by principles of user-centered design ([1, 91, 243]) we identified the following user requirements to make ERD-based BCI training paradigms more practical and effective:

Practicality and user comfort with ERD-based BCI training paradigms are mostly a function of the number of electrodes required to run the system. A lower number of electrodes has a number of advantages: First, electrode setup time increases in direct proportion to the number of sensors. Based on experience we know that using a low number of electrodes causes less discomfort. The impact of setup time and comfort is particularly high for use cases where sustained, daily use would be envisioned, as for example for users with severe motor impairment. Mounting between two and sixteen electrodes typically requires less than 15 minutes. This can be considered practical for mid to long-term use as was demonstrated previously in training studies ([151, 170, 225]). For the purposes of this thesis 16 is therefore defined as the threshold between a low and a high number of electrodes.

Automatic calibration and online adaptation are highly important for the usability, practicality and acceptance of ERD-based BCI training paradigms in a real-world setting. A fully automated calibration procedure would reduce the requirements imposed on the BCI operator to simply mounting the electrodes and starting the system. The system would seamlessly adapt to the patterns of the user's brain activity in the background. Such functionality is important for both, healthy users and individuals with severe motor impairment. In both cases, a BCI expert for calibration would cause additional cost and inconvenience and would render the use of BCIs for particular real-world use-cases impractical. For example: The use of BCIs in clinical settings is less expensive if the caregiver or nurse does not need BCI expert knowledge to operate the training paradigm. With an auto-calibrating system, the only required training is to mount electrodes.

Robustness against artifacts and other interferences is important for usability, especially for users with severe motor impairment for whom it is more difficult to avoid artifacts (both biological and technical from cable sways) as they might suffer from uncontrollable spasms. Robustness and reliability of the system also have an impact on the efficacy and the performance of the BCI system. To use the advantages of online adaptation, online outlier rejection is required. If all trials, including those congested with artifacts are used, the classifier model is skewed and incorrect feedback is provided to the user. Previous work reported how up to 25 % of users needed to be excluded from analysis due to artifacts ([225]).

Performance and efficiency is the speed of information transfer using the BCI. Two factors determine the rate of information transfer: First, the accuracy of the BCI to actually detect the users' intentions during single decisions and second, the number of such decisions per unit of time. A higher rate of information transfer allows the user to communicate faster and in turn can be expected to improve the users' acceptance of the system. While communication speed should be as high as possible, BCIs which are effective but have low communication speed, can still be highly valuable to users who have no other options to communicate.

Effectiveness of a BCI system is determined by whether it can be controlled by user intention. In the past, users for whom BCIs did not work effectively have been referred to as "BCI illiterate" ([22]), "BCI apraxic" or "BCI dyspraxic" (Prof. Jonathan Wolpaw to auditorium at 4th International BCI Meeting 2010, Asilomar, CA, USA). The exact threshold for effective BCI control is typically defined either above the statistical level of chance ([15, 139]) or at a higher fixed percentage as for example 70 % ([92]). The aim is for BCI systems to be effective for as many users as possible.

Chapter 3

Aim of this work

The central aim of this thesis is to develop an improved, adaptive BCI training paradigm and to test it with healthy and disabled volunteers. To complement and support the in-depth research toward the central aim, this thesis also explores the BCI-related neurophysiology of CP and the applicability of the adaptive BCI training paradigm to setup BCI-based interaction with real-world devices.

In contrast to previous work, the adaptive BCI training systems in this thesis will calibrate and even select user-specific task combinations fully automatically. Calibration will require no BCI expert interaction. The systems will generally require less electrodes but are expected to yield comparable or higher accuracies as a result of automatic feature selection and motivating online training. Online outlier rejection mechanisms will assure effective BCI operation even for users with artifact contaminated EEG.

As another important difference, the focus in this thesis will be on testing BCIs with novice participants and all results will be reported to assure generalizability of the findings. Most importantly, the systems in this thesis will be extensively tested with actual end-users with severe motor impairment as a result of a variety of medical conditions.

First tests and analyses will help to assess the specific requirements and needs of users with CP with regard to adaptive ERD-based BCIs. Finally, a seamless technical integration of the adaptive BCI training paradigm with assistive technology prototypes will allow the direct control of smart home devices and internet services via ERD-based BCIs.

3.1 An improved adaptive BCI training paradigm

The main aim, requires to iteratively develop and test an adaptive BCI training paradigm for healthy and severely disabled users. The following specifications are aimed, to be covered:

Requiring less than 16 gel-based electrodes is especially relevant for users with severe motor impairment, as with sustained, daily use, the impact of this criterion on practicality and therefore feasibility becomes particularly high.

Automatic calibration and online adaptation that runs seamlessly in the background allows for outlier rejection or optimization procedures to run online. No BCI expert knowledge should be required from the BCI operator other than mounting the electrodes and starting the BCI system.

Outlier rejection can be considered one of the most important features of an online adaptive ERD-based BCI training paradigm as the inclusion of artifact congested trials during classifier setup can have a strong negative impact on the classification accuracy and therefore on the online training of the user.

Improved effectiveness and performance over previous approaches is important as it directly influences practicality of the system. Suitable approaches to evaluate include the auto-selection of motor-related and non-motor-related mental tasks.

Modularity and extensibility of the framework is especially relevant with respect to future work, where with this adaptive BCI design far more complex and computationally extensive optimizations can be computed in every adaptation step.

An optimized user interface is important, when developing a BCI training paradigm for users with severe motor impairment as they frequently have special requirements as a result of their medical condition (e.g. visual impairment, etc.).

Evaluation of a non-control state preludes future work, which will focus on improving the effectiveness of non-control state detection during BCI control for disabled users.

The aim is to develop and test the adaptive BCI training paradigms in representative samples of healthy and motor disabled volunteers. None of the results should be excluded to give a realistic perspective of the effectiveness of the training paradigms. As for the clinical inclusion criteria, individuals with severe motor impairment, possibly in all four extremities will be considered.

3.2 Neurophysiology and applications

Here, one aim is to integrate the adaptive BCI training paradigm into a context-aware prototype framework. This prototype application allows to control a configurable and extendable number of smart-home devices and internet services via an ERD-based BCI and a special low-bandwidth user interface. This will also confirm earlier findings, that adaptive BCI training paradigms can be used to setup classifiers that can be used for the control of real-world devices.

The other aim here is to investigate the neural processing, that underlies motor tasks in individuals with CP, by comparing known neural correlates between individuals with CP and healthy controls. This will help to further explain the outcome of the tests of the adaptive BCI training paradigms with users with CP and inform future developments.

3.3 Concrete workplan

Based on extensive preliminary analyses and pilot studies, an adaptive BCI training paradigm will be developed as a distributed software framework. The system will be tested over multiple sessions with healthy volunteers ($N_H \geq$ *12; 2-3 sessions*).

Both conventional ([141, 170, 193]) and adaptive ([120, 124, 131, 215, 233])[1] BCI training approaches can be used to setup classifiers for BCI control of real-world applications. A study with healthy volunteers ($N_H \geq 3$) will be performed to confirm, that this holds also for our specific implementation of an adaptive BCI training paradigm, where users first train with the adaptive BCI training paradigm and then use a specialized input interface, to control real-world devices.

As the next step in the core research track, a set of cue-guided EEG data is collected over two sessions from individuals with SCI or stroke, while they perform different motor and non-motor-related mental tasks ($N_{SCI/Stroke} \geq$ *10; 2 sessions*). The data will be analyzed to evaluate the effectiveness of auto-selecting combinations of different mental tasks.

[1] Adaptive classifier training is also a standard option in the widely adopted BCI framework BCI2000 ([191]).

The next step in the main research track of the thesis is to optimize the system from the first project, based on the knowledge obtained from the studies with disabled users, to produce an adaptive BCI training paradigm, that is optimized for users with severe motor impairment. The online tests will be performed by collaborators with end users with cerebral palsy ($N_{CP} \geq 10$).

Next, the data collected from the healthy individuals in the first project will be compared to the data collected from the individuals with CP to identify differences in well-known neural correlates of motor tasks.

As the final step towards the goals of this thesis, the adaptive BCI training paradigm will be improved based on the knowledge gathered in the online experiments with healthy individuals and individuals with CP to produce an adaptive BCI training paradigm that supports a non-control state. This paradigm will then be tested with individuals with severe motor impairment as a result of SCI or stroke ($N_{SCI/Other} \geq 20$). To facilitate future work toward the optimization of non-control state detection during ERD-based BCI interaction, additional data will be collected during the tests in this study. For these additional recordings, users with severe motor impairment will interact with a training paradigm that emulates a specialized low-bandwidth user interface. The classifier from the adaptive BCI training paradigm will be used to provide feedback ($N_{SCI/Other} \geq 20$).

Chapter 4

Methodology and results

4.1 An improved adaptive BCI training paradigm

4.1.1 An adaptive BCI training based on a distributed system

Autocalibration and recurrent
adaptation: Towards a plug and play online ERD-BCI

J. Faller, C. Vidaurre, T. Solis-Escalante, C. Neuper and R. Scherer

IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2012, 20(3), 313-319.
Doi: 10.1109/tnsre.2012.2189584.

Previous work found adaptive BCI training paradigms to lead to effective control during training and subsequent interaction with applications ([120, 124, 130]). The training paradigms, however, required a significant amount of training. Other approaches were faster ([225, 226]), but were still ineffective for users, where the EEG was congested with artifactual activity as there was no outlier rejection prior to classifier adaptation. Other adaptive ERD-based BCI training paradigms allowed for very high performance ([221, 222]), but used a complex training protocol and high density EEG, which is impractical, especially for users with severe motor impairment.

The aim of this work was to implement an adaptive ERD-based BCI training paradigm that is effective for most users, after a limited amount of training. In addition, the system should require only a low number of EEG electrodes (less than 16), calibrate automatically after less than five minutes of data collection and recurrently adapt the classifier during online operation, while requiring no BCI expert knowledge from the caregiver or operator other than mounting the EEG electrodes and starting the system.

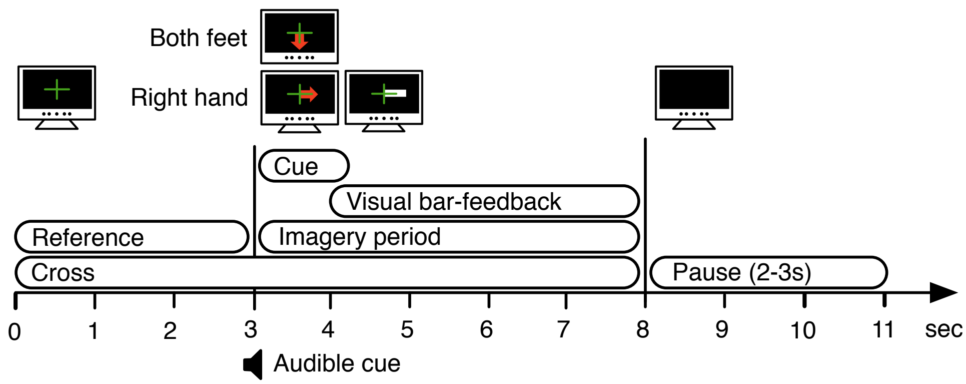

Figure 4.1 – The synchronous adaptive brain-computer interface training paradigm. The task for the user was to perform sustained movement imagery of the right hand or of both feet starting from the cue (second 3) to the end of the cross period (second 8). A trial started with 3 s of reference period, followed by a brisk audible cue and a visual cue (arrow right for right hand, arrow down for both feet) from second 3 to 4.25. The activity period, where the users received feedback, lasted from second 4 to 8. There was a random pause of 2 to 3 s between the trials.

Major contributions: The developed approach was based on a distributed software framework. The system automatically calibrated after less than five minutes and recurrently recalibrated the classifier online during feedback training (see Figure 4.1 for the paradigm). Every calibration was preceded by outlier rejection. The system required only 13 EEG electrodes and optimized features and configuration automatically, so that no BCI expert knowledge was required from the operator. In an evaluation study, all 12 healthy and BCI-novice participants performed better than a conservatively estimated chance level of 58.8 % accuracy (p=0.01; [15, 139]) after two to three sessions of training (see Figure 4.2 for an overview). The final overall median accuracy of 80.2 % over all participants compares favorably to other systems in literature. As a consequence of using online outlier rejection in this system, none of the users had to be excluded from analyses. For actual online operation the system always relied on only five automatically selected EEG electrodes. The analysis showed this selection to be stable over multiple sessions, which means that for repeated and sustained use of this system, using only five electrodes may be feasible.

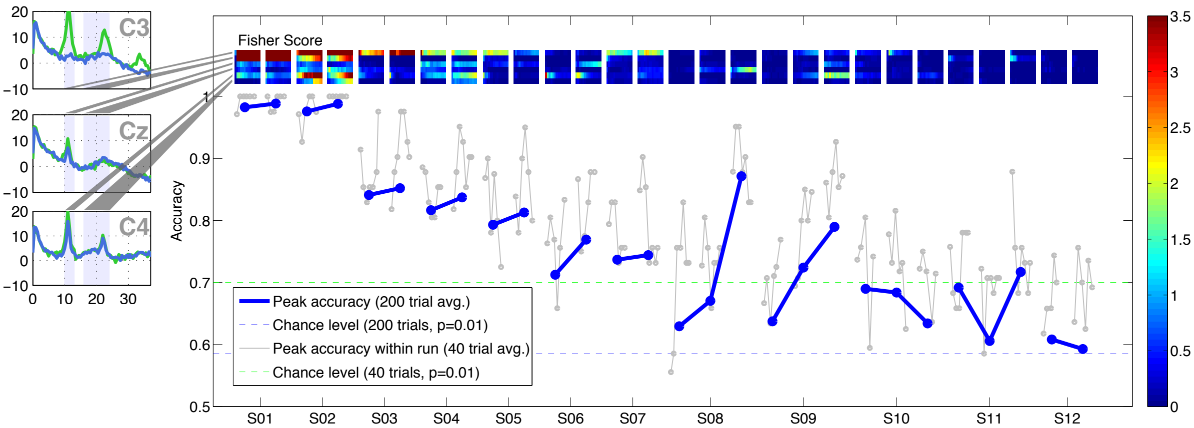

Figure 4.2 – Accuracy overview for the adaptive brain-computer interface for healthy users, along with in-session accuracies and scores according to the Fisher criterion. The blue dots show the peak accuracies for every session and each user. The grey dots show peak accuracies within the sessions. The dotted lines indicate the chance levels for 40 and 200 trials at a significance level of $p = 0.01$. The color plots over every session show the progression of feature separability over the course of one session expressed by the Fisher criterion. The rows depict the six features from top to bottom: (1) α_{C3}, (2) β_{C3}, (3) α_{Cz}, (4) β_{Cz}, (5) α_{C4} and (6) β_{C4} ($\alpha = 10\,\text{to}\,13$ and $\beta = 16\,\text{to}\,24\,Hz$). Blue indicates low, and dark red indicates high feature separability.

4.1.2 Mental tasks in adaptive BCI training for SCI, stroke and CP

Non-motor tasks improve adaptive brain-computer interface performance in users with severe motor impairment

J. Faller, R. Scherer, E. V. C. Friedrich, U. Costa, E. Opisso, J. Medina and G. R. Müller-Putz

Frontiers in Neuroscience, 2014, 8(320).

Doi: 10.3389/fnins.2014.00320.

Selecting user-specific combinations of mental tasks has been shown to improve control accuracy of ERD-based BCIs for healthy users ([21, 64, 158]). More recent findings specifically showed that control strategies which combine a motor-related and a non-motor-related mental task might be particularly effective for ERD-based BCI control ([61, 63, 192]). To the best of the author's knowledge, there has been no research published that investigates the use of non-motor-related mental tasks to operate an adaptive BCI training paradigm in a representative sample of users with severe motor impairment.

This paper investigated, whether auto-selecting a user-specific class-combination during initial auto-calibration in an adaptive BCI training paradigm can improve control accuracy over a standard combination of motor-related mental tasks for users with severe motor impairment as a result of SCI or stroke.

Major contributions: The adaptive ERD-based BCI in this offline analysis required only six EEG electrodes, only two of which were used for simulated BCI control and performed automatic outlier rejection prior to every recalibration step. Our analyses on data from 21 sessions recorded from 13 users with severe motor impairment as a result of SCI or stroke, showed that automatically selecting a combination of motor-related and non-motor-related mental tasks significantly improved simulated online accuracy in comparison to using a standard combination of motor-related mental tasks. At an overall simulated online accuracy of 75.7 %, the system allowed for a conservatively estimated better than chance level of accuracy for eight of nine users in the second session (see Figure 4.3 for an overview).

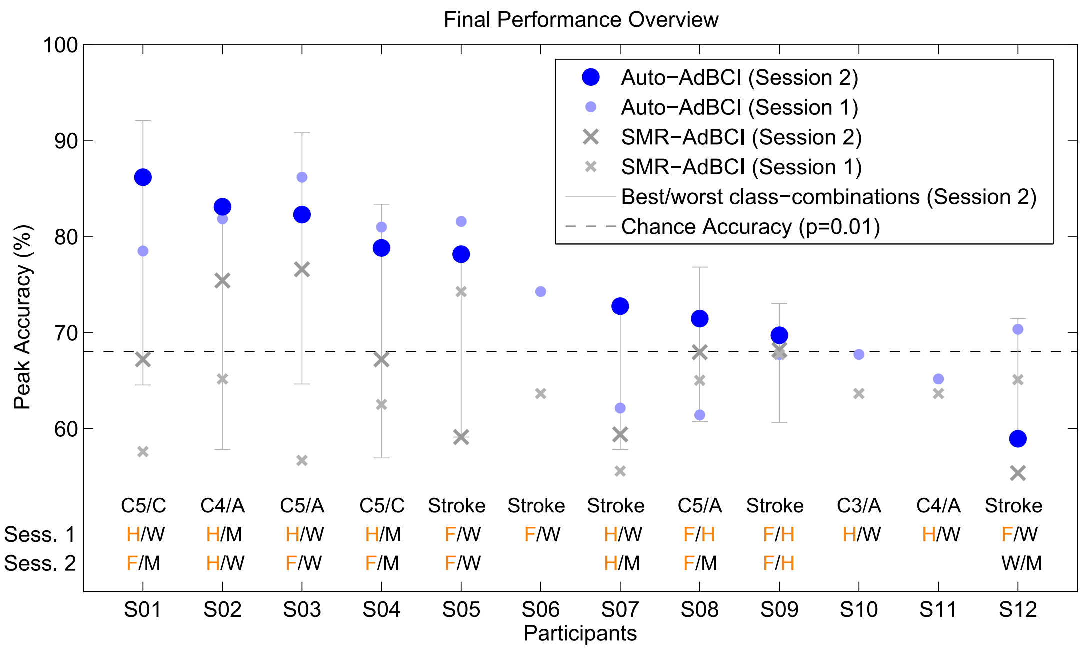

Figure 4.3 – Performance overview for the *Auto-AdBCI* and the *SMR-AdBCI* configuration. The light and dark blue dots show the simulated peak accuracies for the *Auto-AdBCI* on the seen data from Session 1 and the unseen data from Session 2. The light grey whiskers indicate the span between best and worst possible class-combinations for the unseen data of Session 2. The small and large grey crosses show the simulated peak accuracies of the *SMR-AdBCI* on the seen data of Session 1 and the unseen data of Session 2 respectively. The first of the three lines at the bottom indicates pathology. The second and third show the class-combinations auto-selected by *Auto-AdBCI* in Session 1 and Session 2. The single letters are abbreviations for the classes *Feet* (F), *Hand* (H), *Word* (W) and *Math* (M). Letters in orange indicate motor-related mental tasks, while letters in black indicate non-motor-related mental tasks.

On the control of brain-computer interfaces by users with cerebral palsy
I. Daly, M. Billinger, J. Laparra-Hernández, F. Aloise, M. Lloria García, J. Faller, R. Scherer and G. R. Müller-Putz
Clinical Neurophysiology, 2013, 124, 1787-1797.
Doi: 10.1016/j.clinph.2013.02.118.

Only few studies investigated the performance of ERD-based BCIs for users with CP. Most of them used conventional training paradigms and required a high number of training sessions ([123, 151]). Consequently, there is also only very limited knowledge as to how effective adaptive BCI training approaches work for this potential end user group.

The most relevant aim of this study, in the context of this thesis, was to investigate the efficacy of adaptive ERD-based BCI training paradigms using a representative sample of users with severe motor impairment as a result of CP. Only the results of the adaptive ERD-based BCI training paradigm are relevant for this thesis. This includes among other things, specifically the percentage of users for whom the BCI worked effectively.

Major contributions: The adaptive ERD-based BCI training paradigm automatically selected a combination of motor or non-motor-related mental tasks during initial auto-calibration and recurrently calibrated online during feedback training. To the best knowledge of the authors of the article, this is the first published work to show auto-selection of a best task-combination in an auto-calibrating and adaptive BCI training paradigm in an online setting. The system performed automatic outlier rejection prior to every calibration step and required only six electrodes of which only two were used to provide online feedback. For four of the users, not enough data was collected for the system to auto-calibrate. The system worked better than chance for six of the ten other users.

Author contributions: This study was conducted in collaboration with Daly and colleagues. The main contribution of the author of this thesis, was the adaptive ERD-based BCI training paradigm. This work also included, preliminary offline analyses, design, implementation, testing and pilot studies.

4.1.3 A non-control state in adaptive BCI training for SCI and stroke

A co-adaptive brain-computer interface
for end users with severe motor impairment

J. Faller, R. Scherer, U. Costa, E. Opisso, J. Medina and G. R. Müller-Putz

Public Library of Science (PLOS) One, 2014, 9(7), e101168.

Doi: 10.1371/journal.pone.0101168.

Some studies already used adaptive ERD-based BCI training paradigms for users with severe motor impairment ([120, 231]). These systems, however, required a significant number of training sessions and did not support automatic online outlier rejection. Automatic outlier rejection is particularly important for users with motor impairment, who may suffer from spasms or fasciculations. Leeb and colleagues ([107]) explored the efficacy of a conventional training protocol in a large cohort of 24 users with motor impairment. In their discussion the authors highlight the importance of "online adaptation" and the availability of a "non-control state".

The aim of this work was to further optimize the training paradigm presented in Section 4.1.1 and Section 4.1.2 toward the needs of users with severe motor impairment. In addition to previous requirements, the system needed to be more robust to artifactual EEG components and needed to support a non-control state ([107]).

Major contributions: The improved adaptive ERD-based BCI training paradigm automatically selected the most suitable mental tasks during auto-calibration and recurrently adapted to the user during online training (see Figure 4.4). Every recalibration of the classifier was preceded by automatic, multi-stage outlier rejection. In addition, the system supported a non-control state and required only six EEG electrodes of which only two were used to generate the online feedback. In a study with 22 users (20 BCI-novice) with SCI or stroke, the system allowed for an overall interaction accuracy of 68.6 %. The system worked significantly better than a conservative level of chance accuracy ([15, 139]) for 18 of 22 users after only 24 minutes of training (see Figure 4.5). To facilitate future analyses toward improving non-control state detection in ERD-based BCIs for disabled users, additional data was recorded from 20 of the users while they were interacting with a paradigm that emulated a specialized user interface.

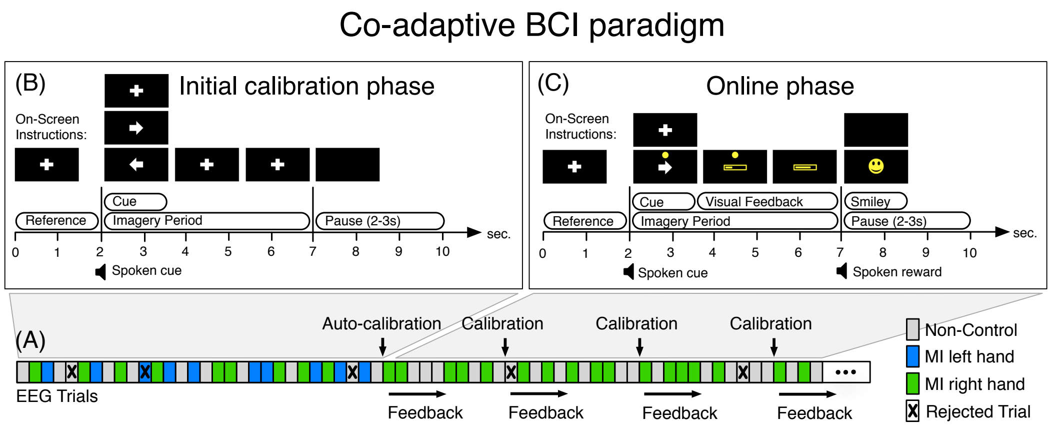

Figure 4.4 – Synchronous adaptive brain-computer interface paradigm for users with motor impairment. Panel (A) shows how the system initially collected trials for three classes *non-control*, *left* and *right* hand movement imagery (MI left/right hand). Panel (B) shows the trial structure for the "Initial calibration phase". After nine "artifact-free" trials per class (TPC) were collected the system auto-calibrated, selected one of the hand MI classes and continued to provide visual, real-time feedback. Panel (C) shows the trial structure for the "Online phase". The system re-calibrated whenever five new artifact-free TPC were available.

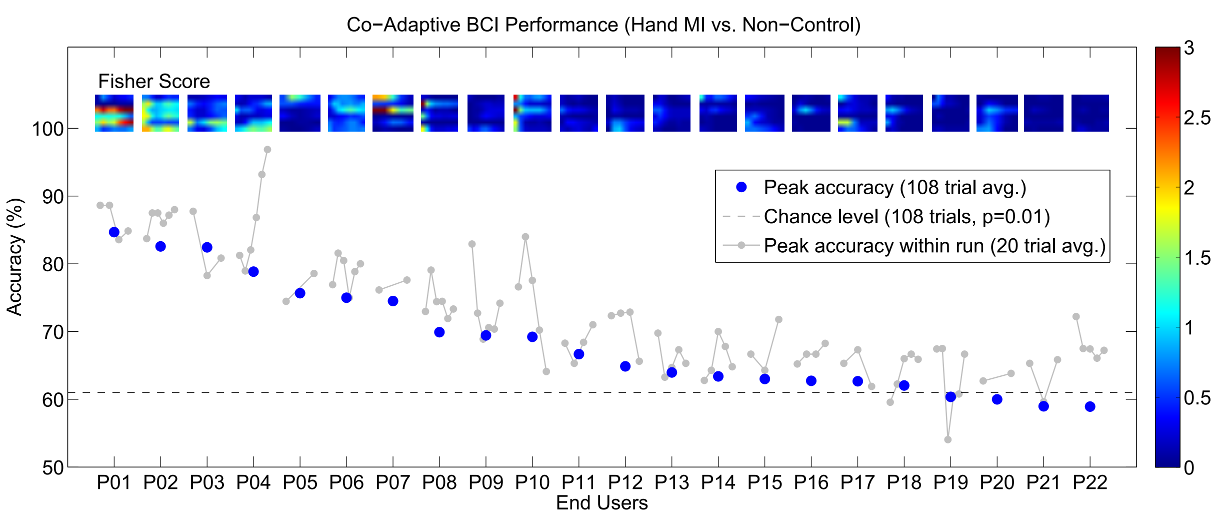

Figure 4.5 – Accuracy overview for all 22 users with severe motor impairment. The blue dots show the overall peak accuracy, while the grey dots depict within session performance. The color coded maps show the Fisher criterion [20] over time (left to right) for the features μ_{C3}, β_{C3}, μ_{Cz}, β_{Cz}, μ_{C4} and β_{C4} (bottom to top).

4.2 Neurophysiology and real-world applications

4.2.1 Control of real-world applications

Prototype of an auto-calibrating, context-aware, hybrid brain-computer interface

J. Faller, S. Torrellas, F. Miralles, C. Holzner, C. Kapeller, C. Guger, J. Bund, G. R. Müller-Putz and R. Scherer

Proceedings of the 34th Annual International Conference of the IEEE Engineering in Medicine and Biology (EMBC), 2012, 1827-1830.
Doi: 10.1109/EMBC.2012.6346306.

It is the common practice to setup BCI classifiers in training paradigms, where the users first learn to control visual feedback using the BCI. The trained classifier can subsequently be used to control real-world applications, including spellers, prostheses or virtual environments. This procedure, has been found effective both for healthy and disabled users in conventional ([170, 193]) and adaptive ([120, 125, 130]) training paradigms.

One aim of this work was to confirm earlier findings, that classifiers from adaptive BCI training paradigms can be used to control real-world applications. Further aims, were to integrate the adaptive BCI training paradigm in a prototype framework, that was context-aware and allowed the user to control a large and expandable number of smart-home devices and internet services.

Major contributions: The adaptive BCI training paradigm allowed for an average control accuracy of 92 % after 11 minutes of training. As expected, the trained classifier was transferable for control of real-world applications. For the control of a special, low-bandwidth user interface, the classifier worked effectively at an average positive predictive value of 72 %. The user interface, consisted of multiple layers, which were automatically generated based on the connected smart-home devices and internet services. The menu changed dynamically, based on the status of the devices. From a caregiver, the system does not require any BCI expert knowledge other than mounting the electrode cap and starting the system. This prototype can be seen as a proof-of-concept for future approaches to include BCI and other assistive technology in an integrated prototype to control smart-home devices and internet services.

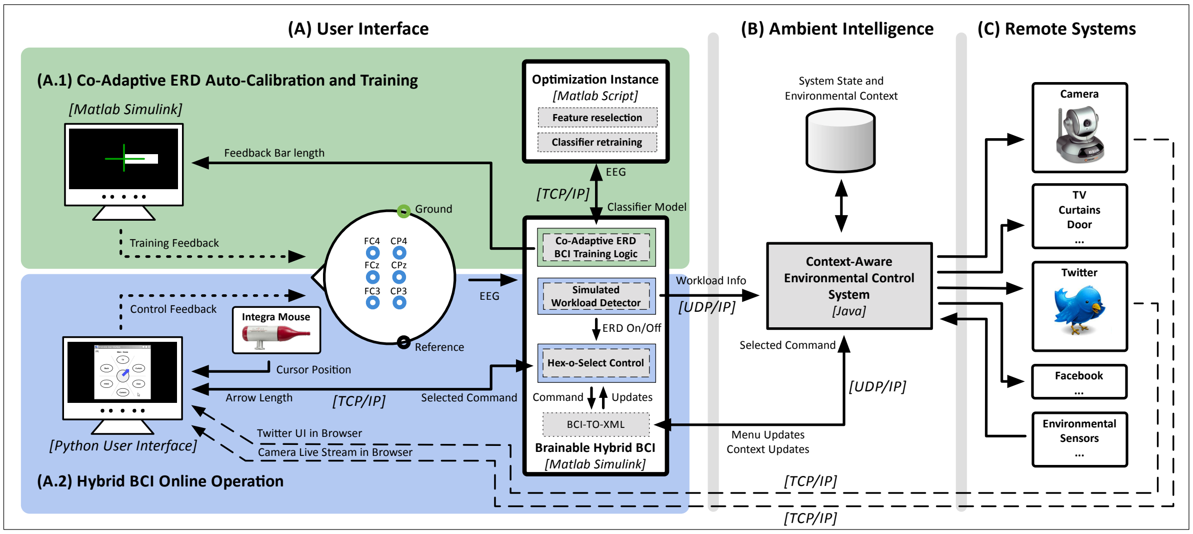

Figure 4.6 – Architecture Overview Diagram of the prototype: The three panels show the system parts (A) User Interface, (B) Ambient Intelligence and (C) Remote Services. The components overlaying the green area (A.1) are used during adaptive BCI training while the components overlaying the blue area (A.2) are used for online control of the connected smart-home devices and services. (Twitter logo, property of Twitter Inc., San Francisco, CA, USA).

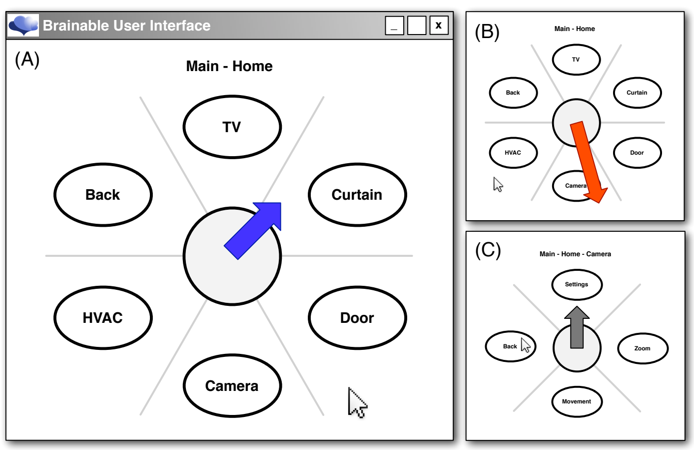

Figure 4.7 – User interface for controlling smart-home devices and internet services. In Panel (A) the arrow length is below selection threshold and the arrow is therefore colored in blue and rotating. In Panel (B) the arrow is extended over the selection threshold and therefore colored in red and not rotating. Panel (C) shows the change to the sub-menu layer "Camera" after a successful selection in Panel (B). The grey color of the arrow indicates refractory period.

4.2.2 Neurophysiology in cerebral palsy and controls

Exploration of the neural correlates
of cerebral palsy for sensorimotor BCI control

I. Daly, J. Faller, R. Scherer, C. M. Sweeney-Reed, S. J. Nasuto, M. Billinger and G. R. Müller-Putz

Frontiers in Neuroengineering, 2014, 7(20), 1-11.
Doi: 10.3389/fneng.2014.00020.

Previous work found BCIs to be potentially suitable assistive technology for users with CP ([151]). Advancing the knowledge about the neural processing of motor activity for individuals with CP could help to improve the effectiveness of BCIs for this potential group of end users. In a previous collaboration with Daly et al., 2013 (Section 4.1.2; [42]), EEG data was recorded from 14 individuals with CP, while they were performing motor and non-motor-related mental tasks, during adaptive BCI training. Another data set, was recorded under similar conditions from 12 healthy individuals during the study presented by Faller et al., 2012 (Section 4.1.1; [57]).

The aim of this work was to explore the neural processing, that underlies motor control in individuals with CP. The approach was to compare well-known neural correlates of motor tasks between the previously collected data sets from individuals with CP and healthy controls. This comparison, specifically included ERD and measures of phase synchrony and phase dynamics.

Major contributions: The analyses showed significantly reduced ERD, phase locking and phase dynamics in the group with CP compared to the healthy individuals. Possible reasons to explain these findings are discussed in detail. Overall these findings suggest a lower level of motor cortical activation in the group with CP. These findings also explain some of the challenges, that were encountered during the earlier tests of the adaptive BCI training paradigm with users with CP. These findings will further inform the future development of BCIs for users with CP.

Author contributions: This analysis was conducted in collaboration with Daly and colleagues. The author of this thesis contributed in substantial parts to conceiving the idea for the analysis, collected one of the data sets, contributed to the data analysis and co-authored the paper.

Chapter 5

Discussion

The work for this thesis developed and tested adaptive ERD-based BCI training paradigms that automatically calibrated and regularly recalibrated seamlessly in the background during online operation. These systems allowed for effective training for both healthy and disabled users. Additionally, it was confirmed, that trained adaptive BCI classifiers can be used to control real-world applications. The work for this thesis further revealed basic neuroscientific findings about the neural processing of motor tasks in users with CP.

5.1 An improved adaptive BCI training paradigm

5.1.1 Effectiveness and performance

The system introduced in Faller et al. (2012; [57]) effectively auto-calibrated and recurrently adapted to the changing patterns of brain activity for the twelve healthy, novice study participants. In only two to three sessions of training, the system was able to reach a control accuracy above the threshold level of 70 % for ten of the twelve users. From the first session on, the control accuracy was statistically significantly better than chance for all twelve users. With a high overall median accuracy of 80.2 % in the last session, the accuracies for all users approximate a uniform distribution which is in accordance with previous findings ([22]).

While a detailed statistical comparison across different paradigms may not be possible, the findings in Faller et al. 2012 ([57]) still strongly indicate a substantial improvement over the performance of previously presented conventional ERD-based BCI approaches, as for example by Guger and colleagues in 2003 ([70]). The system by Guger and colleagues relied on four electrodes, while the present adaptive BCI system provided feedback from five electrodes of a total of 13 that were mounted.

In comparison to a conventional ERD-based BCI by Blankertz and colleagues (2008; [21]), which used 55 EEG electrodes to provide feedback, the present adaptive ERD-based BCI training paradigm achieved comparable performance after only one to three sessions of training when comparing for the class combination right hand versus both feet. This is remarkable considering that the present system required only 13 electrodes, only five of which were used to provide feedback.

A correct comparison to the online adaptive ERD-based BCI training paradigms presented by Vidaurre and colleagues in [224], [225] and [226] is difficult as the authors consistently excluded around 25 % of the recorded data due to artifacts and lack of class separability. The reported accuracies can therefore be seen as overestimating the performance of these systems, as we have to assume that the BCI may have only performed around chance level for the excluded participants.

A comparison to the online adaptive ERD-based BCI training paradigm by Vidaurre and colleagues in [221] and [222] is not sensible as the authors specifically screened study participants by BCI performance. It is safe to assume though, that the performance of these systems, that used 64 electrodes, is higher than that of the systems in this thesis, as Vidaurre and colleagues show how their system works even for users for whom other ERD-based BCIs had not worked previously. The systems presented in this thesis however have advantages in terms of practicality that are pointed out in Section 5.1.2.

5.1.2 Practicality and user acceptance

The operation of the developed adaptive BCI training paradigm required no expert knowledge other than mounting the 13 EEG electrodes and starting the system. From the 13 electrodes only five were actually used for feedback. At the same time the relevant features are typically consistent between sessions. In a practical setting, especially for every day use it should therefore be possible to reduce the number of electrodes to those that were automatically identified to be most relevant by the system. The feedback from the healthy study participants was generally very positive.

5.1.3 Design of the system

The distributed and modular design of the adaptive BCI training paradigm allows to use any other feature extraction and classification method within the same framework. The optimization process runs seamlessly in the background and therefore also allows for computationally extensive analyses. Building on the work of this thesis, future work can now test more sophisticated classification methods by just inserting the necessary computations in the optimization instance. Possible future extensions could include using regularized CSP for feature extraction, more sophisticated outlier rejection methods, online artifact detection or even online data cleaning.

5.1.4 Limitations and possible improvements

For two of twelve participants the adaptive BCI training paradigm did not exceed an accuracy of 70 %. While this rate compares favorably to literature ([70, 225, 226]), it would still be desirable to have the system work for all users. Using more sophisticated classification and feature optimization methods during recalibration could help to achieve that goal. Another possible way of improving the system would be to automatically select a most effective class combination of motor-related and non-motor-related mental tasks ([61]) during initial auto-calibration as presented in Faller et al., 2014a and 2014b ([53, 54]). Supporting a non-control state would be another important potential improvement ([107]).

5.2 Mental tasks in adaptive BCIs for disabled users

5.2.1 Effectiveness and performance for users with SCI or stroke

An improved version of the adaptive BCI training paradigm presented in Section 5.1 ([54]) performed better than 70 % accuracy for seven of nine users with severe motor impairment as a result of SCI or stroke. For eight of the users the system performed significantly better than chance. Interesting to note is that combining motor-related and non-motor-related mental tasks consistently yielded the best results, while using the very common class combination of two motor-related mental tasks was found to be least effective.

One of the major features of this system was the class autoselection heuristic, which predicted effectively, based on only few initial trials, which class combination would be best separable for a particular user. A statistical evaluation showed, that the class autoselection heuristic performed significantly better than a standard system that only used motor-related mental tasks.

To assure that the baseline performance of the motor-related mental tasks was correct, we compared with literature and found the results to be comparable for both SCI ([38, 171, 189]) and stroke ([8, 32, 143]).

5.2.2 Effectiveness and performance for users with cerebral palsy

For users with severe motor impairment as a result of cerebral palsy the adaptive ERD-based BCI training paradigm as presented in Daly et al. (2013; [42]) performed significantly better than chance for six of fourteen users. For four of the users, not enough trials were collected for the system to auto-calibrate. The comparably low performance can be explained by strong artifact congestion of the EEG, which was found especially in users with spasticity.

5.2.3 Limitations and possible improvements

While including motor-related and non-motor-related mental tasks has been shown to improve the accuracy of ERD-based BCIs ([54, 61, 62, 63]), it is not yet clear whether tasks like mental subtraction or word association are as intuitive to end users as conventional motor tasks.

With individuals with cerebral palsy, EEG artifacts caused more problems than for users with other medical conditions like SCI or stroke. For CP, the system was able to achieve significantly better than chance accuracy for six of fourteen of the users, while the simulated adaptive ERD-based BCI ([54]) worked better than chance for eight of nine users with SCI or stroke. The application for users with CP might therefore require additional work with outlier rejection and possibly even online artifact cleaning.

5.3 Non-control in adaptive BCI training for disabled users

5.3.1 Effectiveness and performance

The system presented by Faller and colleagues in 2014 ([53]) was designed to support a non-control state, where users were instructed to relax with eyes open. As Scherer and colleagues ([194]) showed, interaction with a BCI that supports a non-control state, can be more natural and intuitive than controlling a BCI, where the user needs to be constantly engaged ([117]). Constant engagement refers to the fact that the user needs to perform one of the mental tasks all the time. Including a non-control state, precludes the possibility of antagonistic ERD/ERS patterns, which can be expected to reduce the average accuracy. Even with this disadvantage, the system was able to achieve significantly better than chance accuracy for 18 of the 22 users (82 %) with severe motor impairment.

A comparison to an adaptive BCI training paradigm of Vidaurre and colleagues ([225]) showed no significant difference in performance. This result is very promising, as the performance reported by Vidaurre and colleagues is based on a sample of healthy individuals and can be assumed to be overestimated due to exclusion of 25 % of the data. An additional advantage of the presented adaptive ERD-based BCI training paradigm is that it additionally supports a non-control state.

Compared to an extensive study by Leeb and colleagues ([107]) involving users with severe motor impairment and training over multiple sessions, the present system delivered only a slightly lower accuracy. The advantages of the present system were that it supported a non-control state, required only 24 minutes of training and calibrated and adapted automatically without any interaction from a BCI expert.

A system presented by Conradi and colleagues ([38]) showed similar performance (67.7 %) as the present system (69.9 %) in a comparable feedback condition. The presented system complements the existing approach mainly by requiring only two instead of 64 electrodes for control of the feedback bar. Notably, Conradi and colleagues identified their system to be effective for only four of seven (57 %) users, while the presented BCI approach was effective for 14 of 15 (93 %) users with SCI.

In comparison to an extensive study performed by Rohm and colleagues ([189]), the present adaptive ERD-based BCI performed with slightly higher accuracy and requires only six instead of at least 13 electrodes.

In the past, users with severe motor impairment have typically undergone extensive training with conventional ERD-based BCI training paradigms before they were able to perform BCI control in a scenario that involved a non-control state ([107, 141, 178]). In the present study, additional EEG data was collected, while end users were interacting with a specialized training paradigm, which supported a non-control state. Following only 24 minutes of adaptive BCI training, already 55 % of the users were able to achieve better than chance accuracy.

5.3.2 Practicality and user acceptance

The adaptive BCI training paradigms in this thesis allowed for intuitive and effective ERD-based BCI control of a visual feedback bar. For potential end users, these systems can be more convenient and comfortable to use as they require only very few gel-based EEG electrodes. Since the presented BCI systems provide feedback after only minutes of data collection, they can be more motivating and user-friendly than conventional training paradigms, which require lengthy offline data collection at the beginning. From the operator of the BCI, like clinical personnel or a caregiver, the presented BCIs do not require any BCI expert knowledge other than mounting the electrode cap and starting the BCI system. All these characteristics make these systems interesting for setting up classifiers to establish a channel for communication and control for users with severe motor impairment.

5.3.3 Limitations and possible improvements

The training paradigm, that emulated a low-bandwidth user interface, allowed for effective classification for 11 of 20 users. This is a promising result for this preliminary approach. Subsequent offline analyses on this collected data may help to identify better discriminable features or more effective signal processing or machine learning techniques to detect a non-control state. Automatic, individual optimization of parameters such as activation threshold, dwell-time and refractory period after adaptive BCI training can be expected to directly improve classification performance in a BCI setup that allows for a non-control state.

5.4 Neurophysiology in cerebral palsy

The significantly reduced ERD and PLV along with higher baseline band-power suggest an impairment of motor cortical engagement. In healthy controls, high levels of local phase synchrony typically precede the execution of motor tasks. Such a state seems to be reduced or absent in CP. This may be "a result of the inadequate development of the ability to form relevant functional connectivity patterns during early developmental stages" ([44]). Other work that investigated the neurophysiology of CP during BCI operation, used P300 based BCIs ([149, 183]. Nam and colleagues (2012) for example, found lower P300 performance and less localized coherence in users with CP when compared to healthy controls. The differences between the ERD-based and P300 based approaches make a direct comparison insensible. Nevertheless, there seems to be reduced performance in both modalities and the underlying differences seem to be also reflected in changed patterns of connectivity ([44]).

The main implications of these findings for the development of ERD-based BCIs for users with CP are that smaller ERD changes are more difficult to detect. This may pose an additional challenge for implementing ERD-based BCIs for users with CP ([42]). On the other hand, neurofeedback has been previously shown to improve ERD-based classification performance in users with CP ([151]). Therefore, neurofeedback training either during childhood or in adults may be a possible tool to improve motor function of individuals with CP ([44]).

5.5 Control of real-world applications

The adaptive BCI training paradigm was fully integrated in a context-aware software framework, that allowed to control domotic devices and internet services via different BCIs and assistive technology input devices ([56]). The classifier was then successfully used to control a remote camera via a specialized low-bandwidth user interface. The user interface supported multiple layers and was dynamically generated and updated depending on the status of the connected devices. The effective control in this scenario, confirms the findings of previous studies ([120, 130, 170, 193]), that control of a cue-guided training paradigm can be transferred to the control of real-world applications, both using conventional and adaptive paradigms.

As explained in Section 5.1.2, the adaptive BCI setup procedure was very practical and required only 11 minutes. At the same time, the control possibilities via this user interface were extensive: The remote camera, was only one example for a vast number of domotic devices and internet services that were supported by the framework. For example, the user could have also used the ERD-based BCI to turn lights on or off, open or close the curtains or interact in a social network.

Chapter 6

Conclusion and future prospects

6.1 Summary of achievements of this thesis

This thesis presents improved adaptive BCI training paradigms, that were tested with healthy controls and users with SCI, stroke and CP. The training paradigms were based on a distributed system and tended to require less training time, fewer electrodes and no BCI expert knowledge for calibration in comparison to conventional and other adaptive training paradigms. This thesis also confirmed the suitability of the trained classifiers to control real-world applications and explored the basic BCI-related neurophysiology for users with motor impairment. The following paragraphs summarize the main contributions of this thesis.

- An auto-calibrating and adaptive ERD-based BCI training paradigm was developed and tested ([57]). The system performed online outlier rejection and required less than 16 electrodes, only five of which were used to generate the online feedback. Tests with 12 healthy volunteers showed that the system allowed for comparably high accuracies after only two to three sessions of training.

- Adaptive BCI simulations were performed offline on multi-session EEG data collected from 13 individuals with severe motor impairment as a result of SCI or stroke ([54]). The results showed that auto-selecting a user-specific combination of motor-related and non-motor-related mental tasks, improves performance over a condition where a combination of standard motor-related mental tasks is used.

- The adaptive ERD-based BCI training paradigm was extended by initial automatic selection of user-specific combinations of motor-related and non-motor-related mental tasks ([42]). Tests with 14 study participants with severe motor impairment as a result of CP, lead to effective BCI control for six of the users and helped to identify challenges for the application of ERD-based BCIs for users with CP.

- An adaptive ERD-based BCI training paradigm that automatically selects user-specific mental tasks, was tested with 22 individuals with severe motor impairment as a result of SCI or stroke ([53]). The adaptive ERD-based BCI worked significantly better than chance for 18 of the 22 individuals and compared favorably to previous training approaches.

- The neurophysiological differences during the execution of motor tasks in a BCI context between CP and healthy controls were described on basis of an offline analysis ([44]). These findings will inform the future development of ERD-based BCIs for users with CP for the purpose of either restoring communication or for functional rehabilitation.

- The adaptive BCI training paradigm was included and tested in the context-aware prototype systems BrainAble ([55, 56]) and BackHome ([74]). These systems allowed to control a vast and extendable number of domotic devices and internet services via a multi-layered user interface. This work also confirmed again, that classifiers from both conventional and adaptive cue-guided training paradigms can be used to control real-world applications.

Most participants in the studies for this thesis had never used an ERD-based BCI before. Also, none of the users were excluded from reporting and the sample sizes were high compared to previous BCI studies. The results of this work can therefore be assumed to be a good estimate of the performance of these systems in the respective target populations. Figure 6.1 shows an overview of the projects that were carried out and indicates possible future research directions.

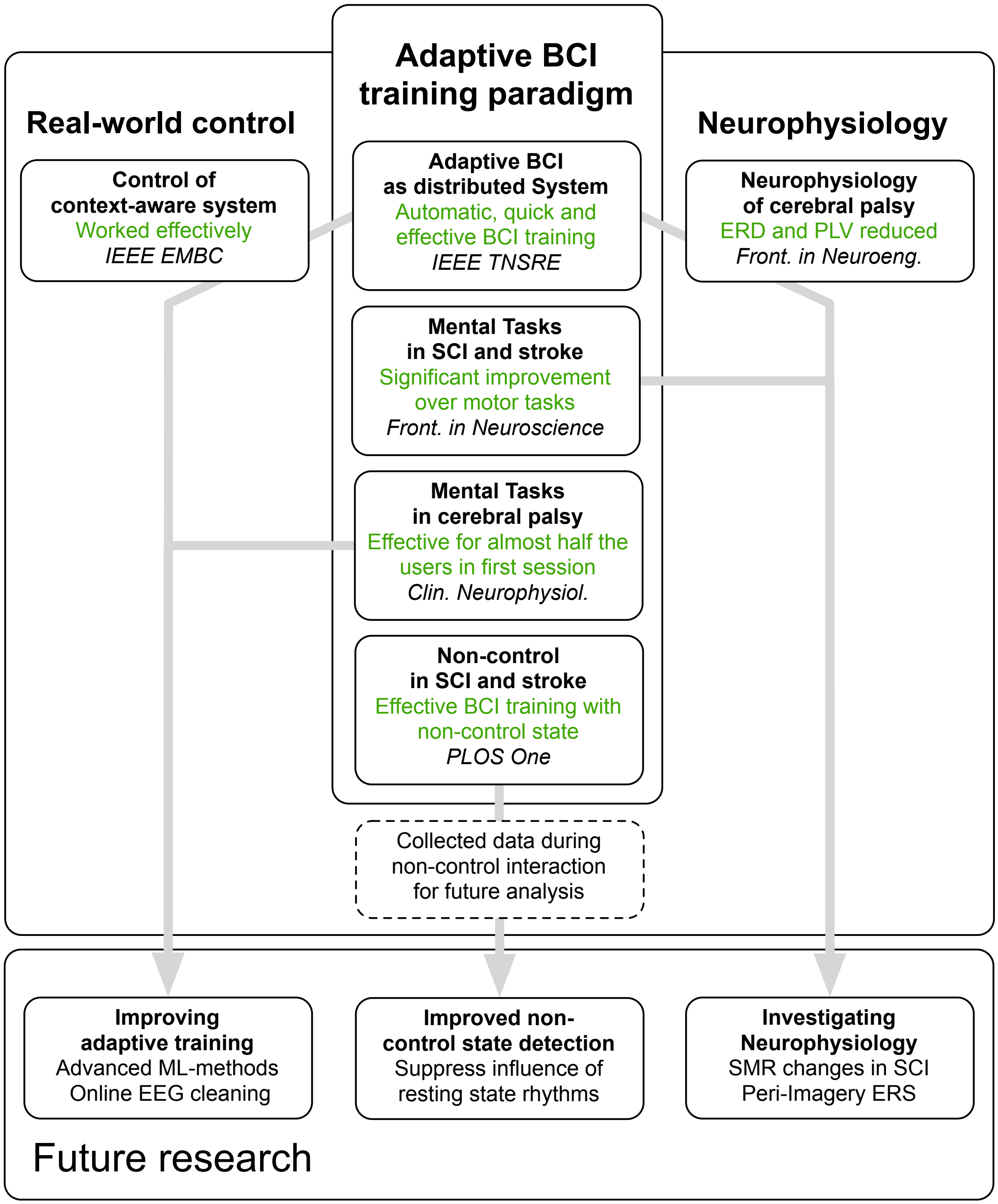

Figure 6.1 – Overview of achievements and possible future work. The areas "Core" and "Additional" show the different projects that were carried out as part of this thesis. The green text summarizes the outcome of the project and the italic text indicates the publication venue. The bottom panel shows possible future research directions. Abbreviations: Event-related desynchronization/synchronization (ERD/ERS), phase locking value (PLV), machine learning (ML), sensorimotor rhythm (SMR) and spinal cord injury (SCI).

6.2 Possible future research directions

Further improving adaptive BCI training paradigms

To improve the efficacy of the presented adaptive ERD-based BCI training paradigm, more elaborate optimization and classifier training procedures could be performed during recalibration. In fact, a novel implementation of an adaptive BCI training paradigm has been already derived from the presented framework. The system was extended to use regularized filter bank CSP ([6]) and a random forest classifier ([26]).

The analyses for this thesis showed particularly strong differences between healthy controls and the user groups SCI and CP. These findings will inform the future development of BCI systems for these groups of end-users. BCIs for users with SCI for example should rely more strongly on task combinations of motor-related and non-motor-related mental tasks. In addition, features from the beta frequency band should be given more attention, as they were found to yield higher separability ([54]). The evaluation with users with CP, suggested that this particular user group could benefit from online artifact cleaning methods. Possible candidate methods have already been proposed, and have been shown to be effective in healthy individuals ([43, 45]).

Further improving non-control state detection

The synchronized adaptive BCI training paradigms presented in this thesis, allowed to control a visual feedback bar. It was further possible to confirm previous findings ([120, 130, 170, 193]), that classifiers trained in conventional and adaptive BCI training paradigms can be used for real-world control. Other studies previously indicated that paradigms, which support a non-control state may be more natural and intuitive for the user ([107, 108, 193, 196]).

As an immediate solution to improve interaction performance with BCIs that support a non-control state, users can train with the training paradigm described by Faller and colleagues in 2014 ([53]). This training paradigm emulates a specialized, low-bandwidth user interface. This way, users can improve their interaction proficiency before using the actual system ([56]) for real-world control.

As a part of this thesis, EEG data was collected from 20 impaired BCI users while they were operating a paradigm to train the interaction with a specialized input interface that supported a non-control state ([53]). This data will be analyzed in the future to improve the BCI performance during the interaction with interfaces that support a non-control state.

Further research into neurophysiology

The neurophysiological analysis on the data from healthy individuals showed peri-imagery ERS to occur online in 50 % of the users ([57]). This feature accounts for very high class separability. Traditional training approaches find this feature in 50 % of the users in the calibration run, but only in 4 % during online operation ([21]). Future analysis could more closely explore whether this phenomenon is specific to adaptive BCI training paradigms or whether the occurrence of this phenomenon could be further facilitated.

It was surprising to find the patterns of separability between motor-related and non-motor-related mental tasks to be different for SCI when compared to healthy controls ([54]). The most likely explanation for this change in neurophysiology is the severance of the spinal cord. A more detailed examination of this phenomenon with high density EEG, artifact cleaning and source reconstruction could help to further learn about the specifics of the brain rhythms that underlie the processing of motor-related and non-motor-related tasks.

Alternative methods to measure brain-activity

All presented adaptive BCI training paradigms in this thesis were tested with gel-based EEG. Recent tests, however, confirmed the effectiveness of water-based electrodes to accurately measure ERD activity ([182]). Using the adaptive BCI training paradigm with a water-based EEG system could shorten setup time and improve practicality, user comfort and user acceptance.

Among invasive methods to measure brain-activity, especially ECoG would be an interesting option to control adaptive BCI training paradigms ([110]). For the adaptive BCI training paradigm, this would require to modify the spatial filter settings and the used frequency bands.

Other potential applications for adaptive BCI training paradigms

As another possible future research direction adaptive ERD-based BCI training paradigms could be evaluated for their efficacy to facilitate rehabilitation after neural injuries such as SCI ([40, 48, 52, 190]), stroke ([7, 12, 155, 180]), CP ([207]) or other neurological disorders ([18]).

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Appendix A

Core publication (1)

Autocalibration and Recurrent Adaptation: Towards a Plug and Play Online ERD-BCI

Josef Faller, Carmen Vidaurre, Teodoro Solis-Escalante, Christa Neuper, and Reinhold Scherer

***Abstract*—System calibration and user training are essential for operating motor imagery based brain–computer interface (BCI) systems. These steps are often unintuitive and tedious for the user, and do not necessarily lead to a satisfactory level of control. We present an Adaptive BCI framework that provides feedback after only minutes of autocalibration in a two-class BCI setup. During operation, the system recurrently reselects only one out of six predefined logarithmic bandpower features (10–13 and 16–24 Hz from Laplacian derivations over C3, Cz, and C4), specifically, the feature that exhibits maximum discriminability. The system then retrains a linear discriminant analysis classifier on all available data and updates the online paradigm with the new model. Every retraining step is preceded by an online outlier rejection. Operating the system requires no engineering knowledge other than connecting the user and starting the system. In a supporting study, ten out of twelve novice users reached a criterion level of above 70% accuracy in one to three sessions (10–80 min online time) of training, with a median accuracy of $80.2 \pm 11.3\%$ in the last session. We consider the presented system a positive first step towards fully autocalibrating motor imagery BCIs.**

***Index Terms*—Adaptive systems, brain–computer interfaces (BCIs), electroencephalography (EEG), event-related desynchronization/synchronization (ERD/S), sensorimotor rhythms (SMR).**

I. Introduction

EVENT-RELATED desynchronization (ERD) [1] based brain–computer interface (BCI) systems constitute alternative communication and control aids for able-bodied and physically impaired users [2]–[4]. Able-bodied and physically impaired users can voluntarily induce amplitude changes of the sensorimotor rhythms (SMR) [5] in the electroencephalogram (EEG) [6] by performing mental tasks, such as motor imagery [7], [8]. Performing different motor imagery tasks for different conditions yields condition-specific patterns of such amplitude changes. The BCI system can then recognize the user input as belonging to either of the conditions, by classifying the detected patterns.

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Despite positive results in a number of subjects [9], [8], motor imagery based BCIs are still not widely used, neither in clinical practice nor for applications with able-bodied users. We identify two main requirements to increase usability and user acceptance in motor imagery based BCI systems: 1) Fast and simple system setup and calibration, and 2) effective online learning and training of either the system [10], the user [11], or both (co-adaptive training) [12]–[17]. An optimal training paradigm should lead to high control accuracy and stability after a very short time for most users.

Conventional BCI training protocols (e.g., [18]) run through the stages 1) data acquisition without feedback, 2) offline analysis of the data and setup of a predictive statistical model, and 3) BCI online operation with feedback based on the generated statistical model. One of the first adaptive online motor imagery based BCIs [13] operated on very low EEG sensor coverage and provided feedback from the first trial, using a standard classifier trained on data from a large pool of subjects. It then continuously adapted the underlying statistical model. In a supporting study, the same authors showed a gradual performance increase in the vast majority of nine able-bodied volunteers over the course of three sessions. However, the system used a fixed number of predefined features and a fixed classifier setup configuration, which may leave room for further improvement. More recent work [15], [16] presented a very sophisticated BCI setup process that proved highly effective in training naive participants and others that formerly could not achieve effective BCI control. This very successful approach used a high number of EEG sensors, automatic parameter selection and required only minimal interaction of a BCI expert.

We propose an autocalibrating online ERD-BCI framework, that offers intuitive co-adaptive learning and training, based on a number of novel features. The system provides (I) positive reinforcement feedback after only (II) minutes of running the paradigm, when subject-specific parameters can first be identified. In regular intervals, our system performs (III) outlier rejection and then seamlessly (IV) reselects one from six standard frequency-bands, that exhibits the highest discriminability between the two classes in the gathered data for the current user. The system then retrains a linear discriminant analysis (LDA) [19] classifier and updates the model in the online system. This system requires (V) only very few pre-assumptions and (VI) zero manual calibration, since most of the parameters are seamlessly selected online to best fit for the current user.

We provide evidence for the efficacy of the concept and its implementation in this system, in an online two-class ERD-BCI study, where ten out of twelve novice users reach a criterion level of 70% [7] accuracy in only one to three training sessions.

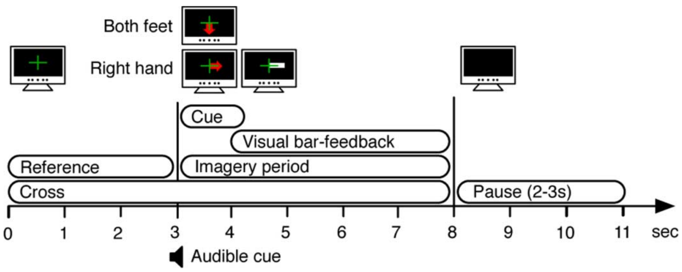

Fig. 1. Trial structure within the synchronous training paradigm. The task for the user was to perform sustained right hand versus both feet movement imagery starting from the cue (second 3) to the end of the cross period (second 8). A trial started with 3 s of reference period, followed by a brisk audible cue and a visual cue (arrow right for right hand, arrow down for both feet) from second 3–4.25. The activity period, where the users received feedback, lasted from second 4–8. There was a random 2–3 s pause between the trials.

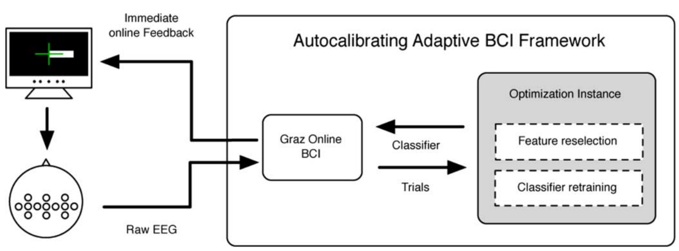

Fig. 2. Architecture overview diagram for the adaptive BCI framework.

II. Materials and Methods

A. Data Acquisition

We acquired the EEG from three Laplacian derivations [20], 3.5 cm (center-to-center) around the electrode positions (according to International 10–20 System of Electrode Placement) C3 (FC3, C5, CP3, and C1), Cz (FCz, C1, CPz, and C2), and C4 (FC4, C2, CP4, and C6). The acquisition hardware was a g.GAMMAsys active electrode system along with a g.USBamp amplifier (g.tec, Guger Technologies OEG, Graz, Austria). The system sampled at 512 Hz, with a bandpass filter between 0.5 and 100 Hz and a notch filter at 50 Hz.

B. Online BCI System

The BCI system was based on a synchronous, two-class Graz BCI training paradigm [21], that used LDA classification on one from six logarithmic bandpower features to provide feedback. In each run, the system randomly presented 20 trials for each of the two conditions (sustained hand or feet movement imagery). Fig. 1 explains the trial structure.

We extended the online BCI system to trialwise send EEG data to a standalone Matlab Optimization Instance and receive classifier-model updates online in return (see Fig. 2). The Matlab Optimization Instance was running on the same machine. All communication was carried out in the trial pauses using a custom socket protocol on top of TCP/IP. In the first run of each session, the system started without giving feedback. The Optimization Instance gathered a small set of trials (10 trials per class) for initial training, and then sent the first set of classifier weights to the online BCI system. The Optimization Instance then sent weight updates at the start of every new run and whenever it had five new trials per class to retrain the classifier during a run.

The online BCI system only provided correct visual feedback, based on the classifier output to the user. The length of the white colored feedback bar in the direction of the cue-arrow, was mapped directly from the current distance from the LDA hyperplane. We chose to only display correct feedback to motivate the participants as much as possible [22]. Also, we wanted to avoid inducing nonstationarities in the EEG, which have been shown to come up as reactions to negative feedback [23].

C. Optimization Instance

The Optimization Instance was running on the same computer, over the course of all runs in one session. It recurrently recomputed LDA weights based on the signal from the three Laplacian channels that it received trialwise, and sent the resulting LDA weights back to the online system.

We conducted a series of simulations on offline data [24] to identify the most suitable classifier training setup and feature bands for this co-adaptive training paradigm. Based on the results, we chose to train the first LDA classifier model after 10 trials per class and then again whenever five new trials per class were available. We always trained on the complete set of available data (cumulative update, cf. [25]).

The training process started by extracting a pool of six logarithmic band power features (α-band, 10–13 and β-band, 16–24 Hz for each of the Laplacian derivations at C3, Cz, and C4; we will from now on refer to these features as α_{C3}, β_{C3}, α_{Cz}, β_{Cz}, α_{C4}, and β_{C4}), averaged over 1 s. The system then iteratively rejected trials that were identified as outliers. Trials were categorized as outliers if the mean over the activity period in at least one of six features was higher or lower than $\pm 3\times$ standard deviation from the grand mean for this condition, in the whole sample-set. Only one outlier was rejected at maximum in each step of the iteration. The recalculated grand mean and standard deviation of the reduced sample-set were used in the next reiteration of the algorithm. The rejection algorithm stopped when no more trials matched the outlier criterion.

The Optimization Instance then selected the one feature that exhibited the highest discriminability between the two classes over the course of the activity period. We used the Fisher-criterion [19] as a measure of discriminability. We decided to classify based on only one best feature, because prior ANOVA on results from the offline simulations had not yielded significant ($p = 0.05$) performance benefits from using a more complex model. Also, less complex statistical models are known to generalize better given a small training set [26].

The system then split the 4 s activity period of the highest discriminable feature into eight adjacent 0.5 s time segments. From every 0.5 s time segment four equi-distant points were sampled as the actual input for LDA training. The system then selected the single time-segment that scored the highest median LDA classification accuracy in the whole activity period (second 4–8) of the accuracy average curve of the test trials after a leave-one-out cross-validation. Finally, the Optimization Instance recomputed a new LDA model using the selected feature and time-segment on the full training set and then sent the resulting weights to the online BCI system.

D. System Test and Validation

Twelve able-bodied, BCI-novice volunteers (seven male, five female, age 24.8 ± 3.0 years) participated in our BCI-study. We decided to conduct at least two sessions for each participant to capture inter-session variance. Based on [7], we use a criterion level of 70% accuracy as the threshold for successful BCI operation. One additional session was recorded for participants who did not reach the criterion level in two sessions, to see whether there would be learning or training effects. We performed a third measurement for S09 since he/she showed strong improvement from session 1 to 2 and was only slightly above the threshold in session 2. The participants performed five runs of 40 trials (i.e., 200 trials) in each session. The pure measurement-time per session was 38 min, however including briefing, montage (10 min) and pauses, 1 session lasted around 90 min. All subjects were right handed and had normal or corrected to normal vision. None of the volunteers suffered from neurological or psychological disorders or had been using medication which could have adversely affected the measurement. The measurements for each participant were carried out on different days within a time frame of five days. The volunteers were compensated with 7.5 Euro/h.

The experimenter thoroughly informed the volunteers beforehand about the nature of the experiment and the specifics of the tasks. All participants gave written, informed consent. The task was to relax and to perform sustained, kinesthetic movement imagery [27] during the complete activity period of the presented trials (see Fig. 1). For condition 1 (arrow right), the task was to imagine a palmar grip with the right hand. The task for condition 2 (arrow down) was to imagine a plantar extension of both feet. For the reference period, we instructed the subjects to relax with eyes open.

The participants were seated in a comfortable chair, 60 cm away from the computer monitor that displayed the paradigm. Their arms were rested on the table before them. The experimenter sat slightly to the left, behind the participant and monitored that the subject adhered to the task. The experimenter informally interviewed the participants in the pauses how they liked the training and whether they preferred the brief offline or online training phase.

E. Evaluation

We report the peak accuracies in the activity period (from second 4–8) in approximately 200 trial curve averages. Notice that the chance level in binary classification for a p-value of 0.01 with 100 trials per class is 58.5% [28].

III. Results

A. Neurophysiological Perspective

In this right versus both feet sustained movement imagery task, many participants exhibited discriminable alpha features at C3 or at C4; particularly with ERD of the idle alpha peak in hand, and strong alpha event-related synchronization (ERS) [1] in foot movement imagery. Some other participants showed synchronization in foot movement imagery in the beta range over Cz. In some subjects like S06 features changed, so that alpha features at Cz instead of C4 became most discriminable.

In fact α_{C3} features were selected in the majority of retraining steps in 60% of the sessions followed by $\alpha_{C4}(16.7\%)$, $\beta_{Cz}(13.3\%)$, $\beta_{C3}(6.7\%)$, $\alpha_{Cz}(3.3\%)$, and last $\beta_{C4}(0.0\%)$. Fig. 5 shows detailed spectra and topological bandpower plots for the first and the last session of each participant.

B. Online Performance

Ten out of twelve subjects reached accuracies above a criterion level of 70% accuracy, with a median accuracy in the last session of $80.2 \pm 11.3\%$. Ten participants showed a performance increase from the first to the second session. This increase is, however, not statistically significant ($p = 0.05$) over the whole group. See Fig. 3 for a grand overview over accuracies along with in-session details about online accuracy and feature discriminability. Table I shows the peak, mean and standard deviation of the accuracies at the end of every session.

Four subjects failed to reach the criterion level within two sessions. Two of these participants reached the level in the third attempt, one did not and one other user (S12) became ill and could not participate in the third session. We still present the first two runs of the subject in order not to bias the results of the study. Fig. 4 shows the accuracy curves for all subjects along with grand mean and standard deviation over 200 trials in the last session along with the respective peak accuracy points.

IV. Discussion

A. Efficacy of the Presented System

The proposed Adaptive BCI framework proved effective to autocalibrate and from then adapt itself to the subject-specific features. The framework successfully addresses the requirements, which we identified in the introduction. 1) Setting up the system was very quick and intuitive, since it was operating on only three Laplacian derivations. The setup did not require any sort of manual calibration. In fact, it did not require any engineering knowledge other than connecting the user to the equipment and starting the two applications. 2) Ten out of twelve novice volunteers reached a criterion level of 70% accuracy in a two-class ERD-BCI setup within only one to three sessions, at a median end accuracy of $80.2 \pm 11.3\%$ in the last session. Within the group of the successful participants, 70% reached the criterion level within the first two runs of the first session (less than 15 min online). The other 30% reached the criterion level in the second or third session. The end accuracies for all subjects appear to be approximating a uniform distribution between chance-level and 99% (see Fig. 3). This is in line with the findings presented in [29].

B. Participants Who Learned BCI Control

The majority of subjects show a slight increase in performance, which is in line with an overall growing separability in the features. Feature discriminability increases particularly strongly in the two participants S08 and S09. These two subjects started from around chance level and eventually reached above 70% accuracy. It is reasonable to assume that they would have been classified as “illiterates” [29] in a conventional screening session. Subject S08 started without measurable discriminability in any feature. From the end of the first session

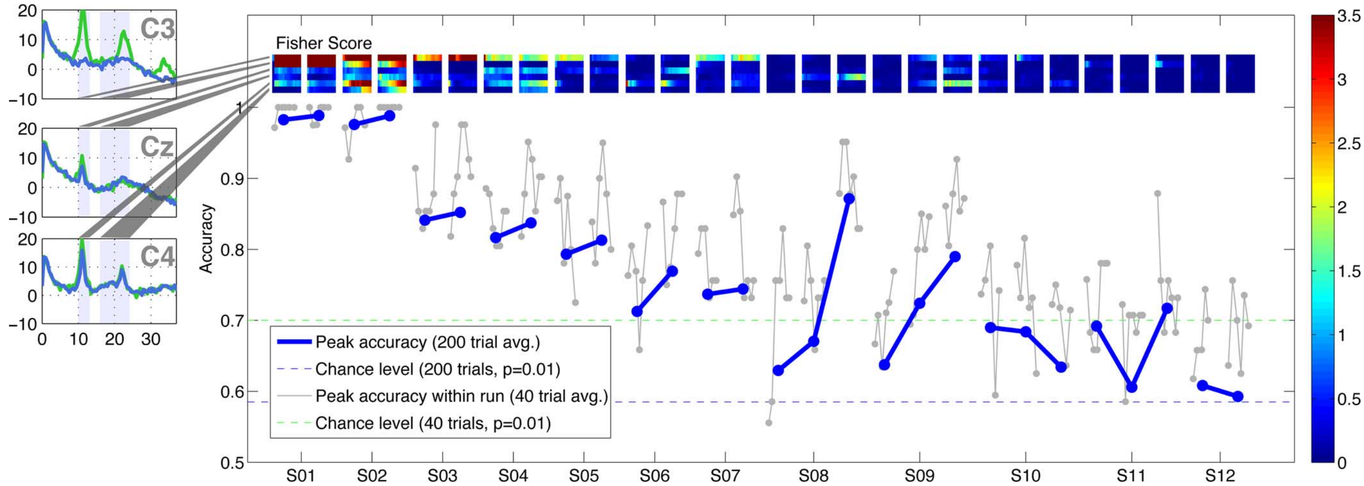

Fig. 3. Overview over the end accuracies for all sessions, along with in-session accuracies and according fisher-scores. The blue dots show the peak accuracies in the activity period in 200 trial averages for each session of each participant. The grey show the 40 trial peak accuracies at periodic, roughly equi-distant points in one session. The dotted lines indicate the chance levels for 40 and 200 trials at a significance level of $\mathrm{p} = 0.01$. The color plots over every session show the progression of the discriminability over the course of one session expressed by the absolute Fisher-score. The rows depict the six features from top to bottom: (1) α_{C3}, (2) β_{C3}, (3) α_{Cz}, (4) β_{Cz}, (5) α_{C4}, and (6) β_{C4} ($\alpha = 10 \text{ to } 13$ and $\beta = 16 \text{ to } 24$ Hz). Blue indicates low, and dark red indicates high discriminability of a fisher-score of 3.5 or higher.

TABLE I
PEAK VALUES FROM THE ACTIVITY PERIOD IN THE 200 TRIAL ACCURACY AVERAGE CURVES AT THE END OF EACH SESSION IN PERCENT

	Session 1	**Session 2**	**Session 3**	**Mean**	**SD**
S01	98.1	98.8	-	98.4	0.4
S02	95.9	98.8	-	97.4	1.4
S03	83.1	85.3	-	84.2	1.1
S04	80.8	83.5	-	82.2	1.4
S05	78.0	80.4	-	79.2	1.2
S06	72.7	77.5	-	75.1	2.4
S07	72.7	74.7	-	73.7	1.0
S08	62.4	66.5	86.5	71.8	10.5
S09	63.6	72.0	80.0	71.9	6.7
S10	67.6	68.6	65.3	67.1	1.4
S11	69.0	59.0	70.6	66.2	5.1
S12	60.9	59.9	-	60.4	0.5
Mean	75.4	77.1	75.6	76.0	0.7
SD	11.8	12.6	8.2	10.9	1.9

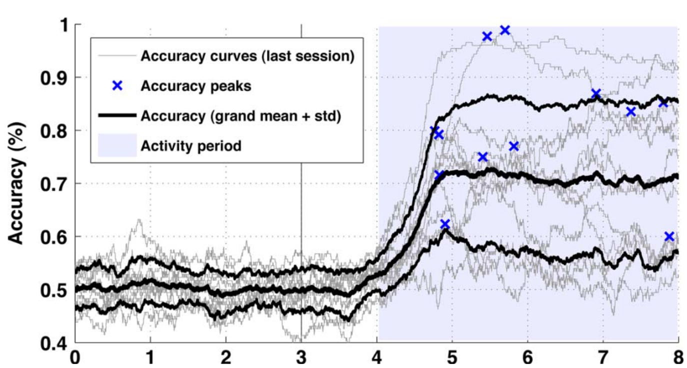

Fig. 4. Overview of the 200 trial average accuracy curves for the last session in all subjects. The blue crosses mark the peaks of maximum accuracy in the activity period of second 4–8.

discriminability in the β_{Cz} feature began to rise gradually, peaking close to the end of the third session. The data of subject S09 showed low levels of separability in the α_{C4} feature in the first session. This was, however, not sufficient to gain above chance control. Starting from half of the second session, separabilities in α_{C3} and α_{C4} gradually increased; then in the third session, α_{C4} presented as a highly dominant feature leading to around 80% accuracy. Figs. 3 and 5 show spectra, accuracies and separabilities for the subjects S08 and S09.

C. Participants Who Had Problems Achieving BCI Control

Two out of twelve participants, S10 and S12, were not able to reach the criterion level. S10 showed low discriminability in the alpha bands over all three sites C3, Cz, and C4. The subject then started the second session with reasonably high discriminability in α_{C3}. Like in the first session the participant reached significantly $(p = 0.01)$ better than random accuracy of 69%. In the third session α_{C4} became the dominant feature, but led to an overall lower accuracy of 65%. This participant exhibited ongoing fasciculations over a number of trials in every session, particularly at the electrode sites C5 and C6. These fasciculations were partly masking features from the Laplacian derivations over C3 and C4. The outlier rejection successfully excluded many affected trials in session 1. In later runs in session 2 and 3, a high number of trials was contaminated with such noise. The artifact rejection then partly failed to exclude a majority of the affected trials starting from trial 136 and 129 in session 2 and 3, respectively. It is reasonable to assume that this noise in the data negatively influenced the efficacy of the system. This emphasizes how important it is for online BCI systems to include robust artifact rejection algorithms, which might help to counteract such undesired phenomena.

The accuracy of subject S11 is only marginally better than the criterion level. The data shows highly significant $(p = 0.01)$ ERD during the activity period of both tasks, as compared to the reference interval in various features, including α_{C3}, β_{C3}, β_{Cz}, and β_{C4}. Unfortunately, the activation patterns for both tasks appear to be almost identical, showing slight class specific differences only in β_{C3}. This can have a variety of reasons. We do

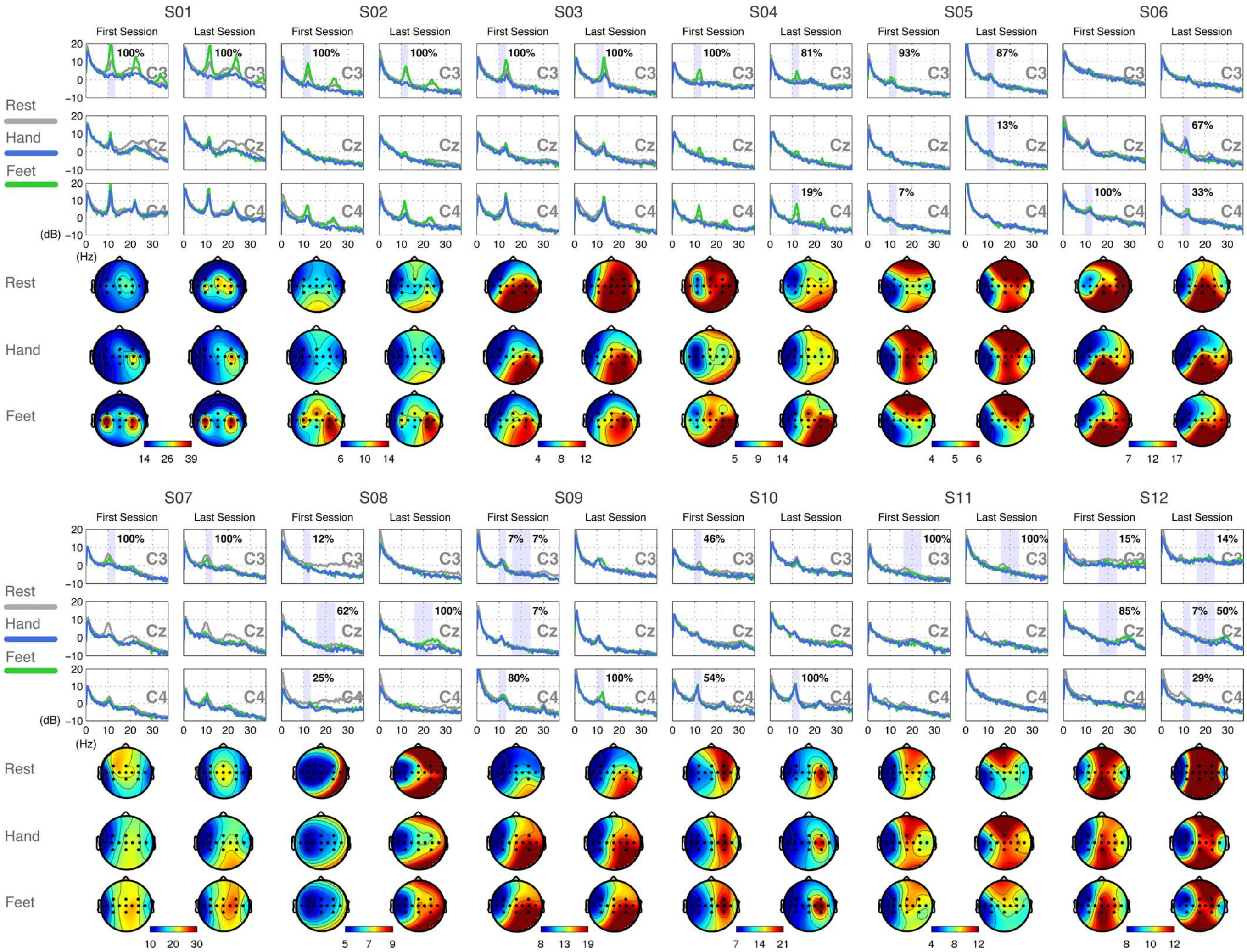

Fig. 5. The plots show spectral and topological details for the first and last session of each participant. The blue line in the spectra shows activity in right hand condition, whereas the green line shows activity in both feet condition. The grey line at the back shows activity in the reference period. The light blue areas along with the percentage numbers at alpha and beta frequency ranges in the spectra indicate how often one particular feature was selected during this session. The spectra are calculated for second 5–7 in the activity period, and second 1–3 in the reference period, and averaged over all online trials. The topological plots show the distribution of bandpower in the frequency ranges of the alpha and beta features. Red indicates high and blue indicates low bandpower.

not assume that the subject could have misunderstood the paradigm, since we thoroughly explained the task and were then regularly rechecking with the participants in the pauses. Maybe it was difficult for the subject to perform the different motor imageries or maybe imagining the movements simply led to the same activation. A solution for this type of problem might be to start with a higher number of imagery types and then to select two best suited strategies during the training process. A similar strategy was used among others in [10]. Another interesting fact was that, although this user did not reach the performance criterion in this three-state-setup (reference and different imageries for condition 1 and 2), he exposes typical features that lead to extremely accurate control in ERD-BCI that use motor imagery and relax with eyes open as the two strategies.

Subject S12 presented with the lowest final accuracies and overall feature discriminabilities in the group. Closer inspection however revealed, that this participant has discriminable features outside the standard alpha and beta bands that we were considering in our system. More specifically, we found a high beta feature at position Cz in the feet movement imagery condition in both sessions. The feature was very similar to that of S08, except in a slightly higher frequency range of 26–31 Hz. The system selected the adjacent standard feature β_{Cz} in 80% of all cases in session 1 and in 50% of all cases in session 2. In the second session, we additionally found a discriminable low alpha feature at position C3 in hand movement imagery condition. The frequency range was 8–10 Hz. Hence, both features were not covered by the standard bands we were using (10–13 Hz and 16–24 Hz). We conclude that the efficacy of the system for users that exhibit such features could be vastly improved by including additional bands, such as 8–10 and 24–30 Hz.

D. Participants With Good Control From the Start

The participants S01, S02, S03, S04, S05, S06, and S07 reach peak accuracies of 74%–99% averaged over 200 trials. Six of these successful users presented with highly discriminable alpha features at C3 which, considering neurophysiology, makes sense for the combination of tasks we use. The α_{C3}

feature was selected by the system in those subjects in the overwhelming majority of the cases (see Fig. 5). From these seven participants, only S06 exhibited features from electrode cites other than C3, namely α_{C4} and α_{Cz}. Sorting the subjects S01, S02, S03, S04, S05, and S07 by either end-accuracy or magnitude of their alpha peak in the condition relax with eyes open, yields almost identical order. The subject with the highest peak shows the highest accuracy and the one with the smallest peak, show the lowest accuracy. This is in line with findings presented in [29].

E. Antagonistic ERD/ERS Effects

The four subjects who achieved the highest accuracies, also exhibited extremely strong peri-imagery ERS (also referred to as antagonistic ERD/ERS patterns, cf. [30]) in the alpha band at site C3 in the feet movement imagery condition (compare the spectra in Fig. 5). This phenomenon accounts for extremely high separabilities, since the magnitude change that it provokes is not bounded by a limit as with ERD. Using bandpower as features, strongly intensifies this effect. The deflection in the α_{C3} features which is caused by peri-imagery ERS is disproportionately large, even after logarithmic transformation. We consider this phenomenon the main factor that led to such high accuracies in these subjects. Previous work found this phenomenon offline in more than 50% of the participants [31]. More recent work confirmed these findings in a large group of participants, but also found that the effect vanishes in the vast majority of users when moving to online operation [29]. We find this phenomenon online in six of twelve subjects, four times left- or bi-lateral and two times right-lateral in the sustained both feet movement imagery condition. In five of these six subjects, this phenomenon contributes to the most discriminable feature.

F. A Note on the User Experience

The participants gave very positive feedback about the training paradigm during interviews in the breaks between the runs. All users preferred the online feedback training over the brief offline phase in the beginning. Here, some statements translated from German: *"I prefer the part with feedback; it makes me put more effort in it." (S09)*, *"I find it more difficult to imagine the movements without feedback." (S02)*, *"I am very unsure what really happens in the beginning." (S03, [referring to non-feedback phase])*, *"It is like a computer game; you want to become better" (S07, [referring to the feedback phase])*. Notice, that the generally positive user experience could be also ascribed to the fact that we only gave positive feedback. We hypothesize based on [22] that this additionally motivated the users and influenced their training success positively.

G. Comparison to Literature

Comparison with online BCI systems in literature is difficult since the applied approaches are often vastly different. We aim to approach the minimal setup time and complexity of systems like [32] on one side, and to achieve the high performance of very sophisticated, high coverage systems like [15] on the other side. We think that our results provide convincing evidence that we meet these expectations, since in comparison, our system performs very well along the important dimensions accuracy, system scale, amount of required expert interaction and how many users achieve successful control.

For the sake of comparison with [32] we recalculate the online accuracy in our study after 75 trials (automatic outlier rejection accounts for the slight variation in trial numbers) in the first session. We ascribe the resulting minimal increase of the mean accuracy for our participants from 75.4 to $78.4 \pm 12.6\%$ mainly to the lower number of trials (cf. [28]). Our study shows higher first session performance than the logarithmic bandpower based system in [32], in the sense that a higher percentage of users reaches the brackets 90–100 (16.7% versus 7.3%), 80–89 (16.7% versus 13.5%), and 70%–79% (33.3% versus 26.2%) in online operation. Our system does, however, require slightly higher coverage than the four sensors used in [32]. In addition, factors other than sensor coverage, paradigm or algorithms, such as the challenging recording environment in [32] could have also contributed to this performance difference.

The system in [10] allows for higher online accuracies in the first session. However, that system uses 64 as compared to 13 sensors and requires expert interaction during calibration. Surprisingly, the end accuracies that our participants achieve in 1–3 sessions of training are only slightly lower than in this very large scale system. Moreover, we achieve the same end accuracies online as [10] calculate in an offline simulation on the calibration data where they use common spatial patterns (CSP), limited to the two imageries that we use (right hand versus both feet) and manually selected single best frequency band.

The system in [15] is a highly sophisticated online SMR BCI system that proved highly effective even in participants that could not achieve SMR control with other systems. Compared to this approach, our system is very simple and low scale, does not require any expert interaction and is effective for a high number of users after a maximum of only three sessions. We consider factors such as practicality, number of sensors, setup time and ease of use, key points in order to make BCI systems useable in practice, especially for applications that involve physically impaired users. The results lead us to conclude that our system offers a very good trade-off between scale and performance, while still allowing for a maximum of usability and practicality.

H. Possible Improvements

First, we currently always use the whole set of data to retrain the statistical model. Other update strategies that use only a recent portion of the data could better facilitate training [25], since more recent feature changes have a higher impact. Second, since we use a statistical model that has a very low complexity, we could consider to start giving feedback after less than 10 trials per class. Another option would be to start the BCI with feedback from a standard classifier model (cf. [18], [13]). The low sensor coverage requirements qualify this system for a combination with dry sensor technology as previously presented in [33]. This would render the presented system even more practical for real-world applications such as clinical or home use. More sophisticated approaches could select optimal, subject specific features using other optimization methods such as distinction sensitive learning vector quantization [24] or genetic algorithms [18].

V. Conclusion

Recent work [15], [16] indicates that co-adaptive methods can strongly increase BCI performance of novice users and also of users who previously could not achieve stable BCI control through conventional training protocols. At least for able-bodied, novice participants, these results appear to be consistent over implementations with both, low and high EEG sensor coverage. The presented system was optimized for rapid setup and fast co-adaptive training, and proved effective in a surprisingly high percentage of 83% of users in this study. This underlines once more, the importance of early feedback in motor imagery BCI training. For the future we will explore ways to improve the efficacy of the system for the minority of users who were not successful with the current implementation. More fine grained feature extraction is one option to address this issue. Our final aim is to improve this type of co-adaptive BCI system to a level of efficacy and intuitivity where they can strongly benefit abled-bodied and physically impaired users.

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Appendix B

Core publication (2)

frontiers in NEUROSCIENCE

ORIGINAL RESEARCH ARTICLE
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Non-motor tasks improve adaptive brain-computer interface performance in users with severe motor impairment

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Individuals with severe motor impairment can use event-related desynchronization (ERD) based BCIs as assistive technology. Auto-calibrating and adaptive ERD-based BCIs that users control with motor imagery tasks ("*SMR-AdBCI*") have proven effective for healthy users. We aim to find an improved configuration of such an adaptive ERD-based BCI for individuals with severe motor impairment as a result of spinal cord injury (SCI) or stroke. We hypothesized that an adaptive ERD-based BCI, that automatically selects a user specific class-combination from motor-related and non motor-related mental tasks during initial auto-calibration (*"Auto-AdBCI"*) could allow for higher control performance than a conventional *SMR-AdBCI*. To answer this question we performed offline analyses on two sessions (21 data sets total) of cue-guided, five-class electroencephalography (EEG) data recorded from individuals with SCI or stroke. On data from the twelve individuals in Session 1, we first identified three bipolar derivations for the *SMR-AdBCI*. In a similar way, we determined three bipolar derivations and four mental tasks for the *Auto-AdBCI*. We then simulated both, the *SMR-AdBCI* and the *Auto-AdBCI* configuration on the unseen data from the nine participants in Session 2 and compared the results. On the unseen data of Session 2 from individuals with SCI or stroke, we found that automatically selecting a user specific class-combination from motor-related and non motor-related mental tasks during initial auto-calibration (*Auto-AdBCI*) significantly ($p < 0.01$) improved classification performance compared to an adaptive ERD-based BCI that only used motor imagery tasks (*SMR-AdBCI*; average accuracy of 75.7 vs. 66.3%).

Keywords: adaptive brain-computer interface (BCI), stroke, spinal cord injury (SCI), event-related desynchronization (ERD), electroencephalography (EEG), assistive technology, mental tasks

1. INTRODUCTION

Electroencephalography (EEG) based brain-computer interfaces (BCIs) can restore communication for severely impaired individuals (Birbaumer et al., 1999; Millán et al., 2010). Here, we focus on BCIs that operate based on the dynamics of oscillatory bioelectrical brain activity. These BCIs exploit the fact that performing motor imagery or other specific mental tasks leads to spatio-spectrally specific power decreases (event-related desynchronization, ERD) or increases (event-related synchronization, ERS) in the EEG (Pfurtscheller and Lopes da Silva, 1999). ERD-based BCIs use signal processing and statistical machine learning techniques to translate patterns of such power changes into control signals.

Operating ERD-based BCIs is a skillful action and requires initial system calibration and user training of varying extent (Allison and Neuper, 2010). Conventional calibration and training paradigms require (a) recording EEG while users perform cue-guided mental activity, (b) offline training of a pattern recognition system, followed by (c) feedback training based on the computed classifier. Typically, the feedback training data is (d) reanalyzed offline to create a more accurate and robust classifier. The common practice of reiterating steps (c) and (d) over multiple training sessions has been shown to lead to effective control even for users with motor impairment (Pfurtscheller et al., 2000; Neuper et al., 2003; Wolpaw and McFarland, 2004; Kübler et al., 2005; Müller-Putz et al., 2005). This approach, however, can be time-consuming and strenuous, especially for users with severe motor impairment.

Using a high number of electrodes with this conventional training approach, has been shown to allow for high control proficiency for healthy users after only one day of training (e.g., Blankertz et al., 2008). Increased setup time, higher user discomfort and higher cost, however, render this approach slightly less practical for clinical and home applications.

In contrast to conventional training approaches, adaptive ERD-based BCI training paradigms provide feedback based on the user's brain activity as early as possible and allow both the user and the system to continuously adapt to each other. In healthy users, adaptive ERD-based BCI training paradigms have been shown to work effectively with both, a low (Vidaurre et al., 2006; Faller et al., 2012b) and a high (Vidaurre et al., 2011) number of EEG electrodes.

Another way to improve the performance of ERD-based BCIs is to optimize the user's control strategy: Selecting a user specific combination of mental tasks for example has been shown to boost control proficiency (Obermaier et al., 2003; Blankertz et al., 2008; Galán et al., 2008). In a similar way, combining motor related control tasks with non-motor related tasks proved as another effective strategy to improve performance Friedrich et al., 2012, 2013; Scherer et al., 2013 in healthy individuals.

We aim to identify a general configuration (three bipolar channels and four mental tasks) for an easy-to-use, auto-calibrating and adaptive ERD-based BCI that auto-selects a user-specific task combination and allows for robust control after a short training time for a large percentage of users with severe motor impairment as a result of spinal cord injury (SCI) or stroke. We used three bipolar derivations for our system because this configuration has proven effective in a large number of studies both for healthy users (e.g., Scherer et al., 2008 or an Adaptive BCI in Vidaurre et al., 2006) and users with motor impairment (e.g., Müller-Putz et al., 2005; Mohapp et al., 2006). Our design gives preference to bipolar (Vidaurre et al., 2006) over Laplacian (Faller et al., 2012b) derivations to require fewer electrodes and hence make the system more practical for clinical and sustained home use by individuals with severe motor impairment. Generally, screening users with more classes increases the chance of effective BCI control. We decided to limit the number of mental tasks to four because of reasons of practicality and usability. With four classes, our system would typically auto-calibrate in less than 6 min.

Inferring from the knowledge with healthy users outlined above, we hypothesized that auto-selecting a user specific class combination of motor-related and non motor-related mental tasks during initial auto-calibration of an adaptive ERD-based BCI ("*Auto-AdBCI*") could increase performance in comparison to an adaptive ERD-based BCI that uses only standard motor imagery tasks ("*SMR-AdBCI*") in individuals with SCI or stroke.

To answer this question, we performed offline analyses on two sessions of 30 channel EEG data from 13 individuals with severe motor impairment as a result of SCI or stroke. On the data from Session 1, we identified the general configuration for the *Auto-AdBCI* by running a minimal adaptive BCI configuration ("*Mini-AdBCI*") for all combinations of every single bipolar derivation and every single class combination and selecting the three channels and four classes that yielded the highest performance. In the same way, we also identified three bipolar derivations for the standard *SMR-AdBCI*. On the data from Session 2, we then simulated both, the *Auto-AdBCI* and the standard *SMR-AdBCI* configuration and compared the performance results.

2. MATERIALS AND METHODS

2.1. EEG SIGNAL ACQUISITION

We recorded EEG from the 30 scalp locations illustrated in **Figure 1** (International 10/20 System of Electrode Placement). The reference and ground electrodes were attached to the left ear-lobe and right mastoid respectively. All signals were recorded using active electrodes and a biosignal amplifier (g.USBamp, Guger Technologies OG, Graz, Austria). The signal was sampled at 256 Hz, with a band-pass filter between 0.5 and 100 Hz and a notch filter at 50 Hz.

2.2. PARTICIPANTS

We recorded two sessions of EEG data from 13 volunteers with severe motor impairment (age 39.1 ± 9.1; 7 female) at the Institut Guttmann Neurorehabilitation Hospital (Barcelona, Spain). Seven of the volunteers were diagnosed with SCI (injury between C3 and C5, ASIA A to C, according to Maynard et al., 1997) and six with different types of stroke. The participants S05 and S09 were in "locked-in state (LIS)" according to the definition in Kübler and Birbaumer (2008). Two participants, S04 and S13 were left-handed, the others right-handed. Four participants could not participate in Session 2. Two of them became ill (respiratory infection; severe pressure sore) and the other two did not have time to come in for the second measurement within the 2 week recording period because of other appointments. We had to exclude the data of participant S13, because it was strongly congested with artifacts. This left data of twelve participants in Session 1 and nine participants in Session 2 for analysis. See **Table 1** for more details. The study, including measurement protocol and consent procedure, were approved by the local ethics board, "Comitè d'Ètica Assistencial de l'Institut

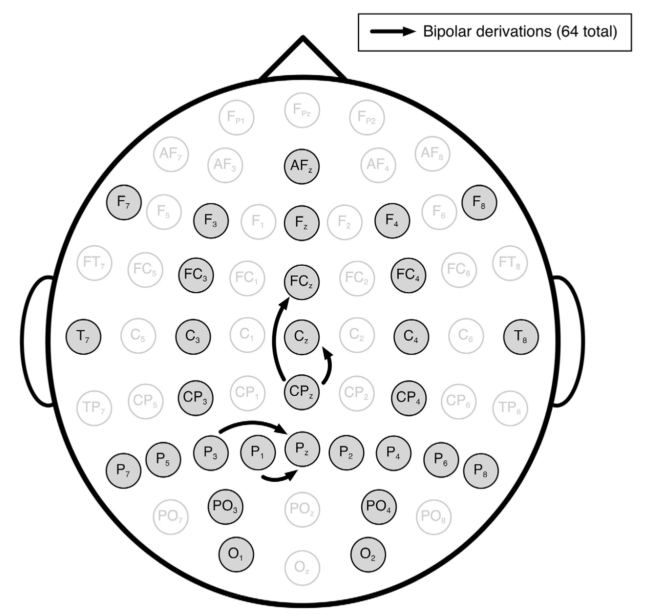

FIGURE 1 | Locations of the 30 EEG electrodes recorded in our study. In total, 64 bipolar derivations were used in our analyses. The bipolars were in sagittal and coronal orientation with one or no electrode positions as gaps in between (four representative examples indicated by the black arrows).

Table 1 | Detailed information about the 13 participants with severe motor impairment.

User	Sex	Age (years)	Months since injury	Pathology	Functional disability
S01	F	43	27	SCI at C5, ASIA C	Tetraplegia
S02	M	38	15	SCI at C4, ASIA A	Tetraplegia
S03	M	36	53	SCI at C5, ASIA A	Tetraplegia
S04	F	33	2	SCI at C5, ASIA C	Tetraplegia
S05	M	42	6	Brainstem stroke	Locked-in state
S06‡	M	45	26	Brainstem stroke	Tetraplegia
S07	F	31	5	Brainstem stroke	Locked-in state
S08‡	F	40	255	SCI at C5, ASIA A	Tetraplegia
S09	F	57	5	Hemorrhagic stroke, left hemisphere	Global aphasia; right hemiparesis
S10	M	37	13	SCI at C3, ASIA A	Tetraplegia
S11‡	M	50	15	SCI at C4, ASIA A	Tetraplegia
S12	F	20	6	Bilateral, intracerebral hemorrhagic stroke	Tetraparesis
S13‡	F	36	58	Basal ganglia and brainstem stroke	Tetraparesis
Mean		39.1	37.4		
SD		9.1	67.8		

The symbol ‡ indicates, which volunteers were not able to participate in the second session. The data of participant S13 was excluded, because it was too strongly congested with artifacts.

Guttmann." Written, informed consent was obtained for every participant. In many cases, written consent had to be provided by the participants' legal representatives as many of the participants were not able to write due to motor impairment. The participants were instructed about the paradigm in person by caregivers with the support of presentation slides and other written briefing material.

2.3. EXPERIMENTAL PARADIGM

We used a modified cue-guided Graz-BCI paradigm (Pfurtscheller and Neuper, 2001, see **Figure 2**). The participants were instructed to perform one of five different specific mental tasks starting from the appearance of the visual cue until the disappearance of the cue and the cross seven seconds later. Two of the mental tasks were motor-related: Sustained imagery of (1) a dorsiflexion of both feet ("*Feet*") and (2) a palmar grasp of the right hand ("*Hand*"). The other three classes were non motor-related tasks: For condition (3), participants were instructed to mentally recall as many words as possible starting with a provided letter ("*Word*"). The letters were drawn from a uniform random distribution over the custom alphabet A, D, E, F, G, H, I, J, C, M, N, O, P, R, S, T, L, and V (adapted for Spanish language). For condition (4), participants were instructed to subtract a given subtrahend (randomly between 3 and 10) from a given minuend (randomly between 15 and 30) and to keep subtracting the subtrahend from the last difference (e.g., $17 - 9 = 8 \Rightarrow 8 - 9 = -1 \Rightarrow -1 - 9 = -10$, etc.) for the duration of the imagery period ("*Math*"). For condition (5), participants were instructed to mentally navigate through a well known building ("*Nav*"). During each run (6 min long), we recorded 25 trials, five for each of the five cue conditions. The sequence of cues was random. In every session we recorded eight runs (i.e., 200 trials per session).

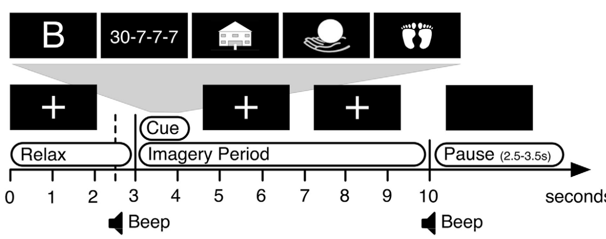

FIGURE 2 | Schematic depiction of the structure of one single trial.

2.4. ANALYSES

To determine three bipolar derivations and four classes for the *Auto-AdBCI* we first simulated the *Mini-AdBCI*—which used only one bipolar derivation and two classes—on all combinations of every single bipolar derivation and every single class combination of all data in Session 1. **Figure 3** shows an overview of the analysis and **Figure 4** depicts how the different adaptive BCI configurations operate.

In the results of the *Mini-AdBCI* simulation, we ranked the bipolar derivations according to the median (second 4–8 in the trial) of the simulated online accuracy over all class combinations. Inspecting the positions in the resulting list sequentially, starting with the best performing derivation, we then added every bipolar derivation to the result set that did not overlap a scalp area covered by a previously added derivation. From the resulting set of bipolar derivations, we finally selected the top three. For these three bipolar derivations, we selected the four of five classes that on average scored the highest median accuracies.

To determine the three bipolar derivations for the *SMR-AdBCI* we simulated the *Mini-AdBCI* on the classes *Hand* and *Feet* of

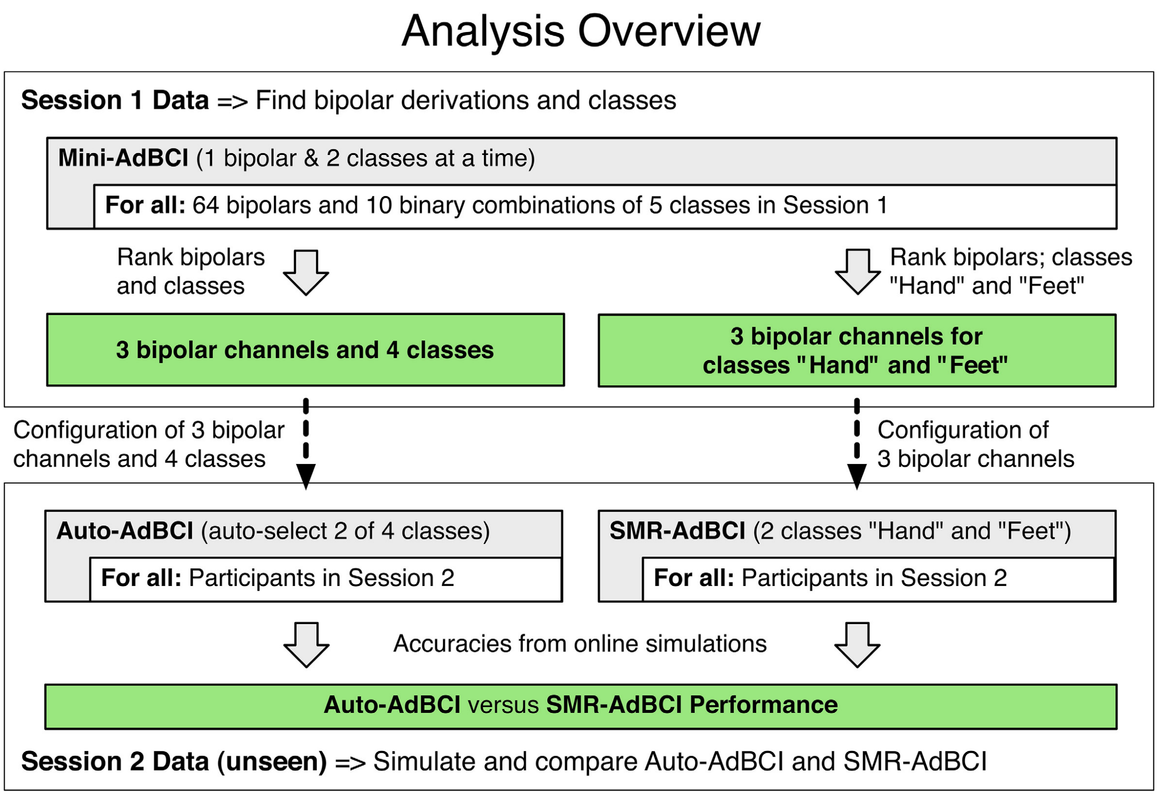

FIGURE 3 | Procedure to determine whether the *Auto-AdBCI* performs better than a standard *SMR-AdBCI*. The boxes with green background show results.

the data from Session 1 and used the same ranking and selection procedure as for the *Auto-AdBCI*.

To answer our research question, we simulated the previously determined configuration of the *Auto-AdBCI* on the data from Session 2. Likewise, we ran a simulation of the *SMR-AdBCI* configuration, on the same data from Session 2. To avoid over-fitting, we only used the results from the unseen data of Session 2 in our statistical comparison. For the sake of completeness, we also ran both simulations on the seen data of Session 1.

2.5. DETAILS ON ADAPTIVE BCI CALIBRATION

Similar to previous implementations (Faller et al., 2012b) the simulated adaptive ERD-based BCIs here (1) collected seven artifact-free trials per class (TPC), (2) did the initial calibration, (3) proceeded to apply the most recent classifier to new trials and (4) re-calibrated on all collected trials, whenever seven new artifact-free TPC were available (see **Figure 4**). In comparison to Faller et al. (2012b) we reduced the number of initially collected TPC from ten to seven and increased the number of TPC collected between recalibration steps from five to seven. Collecting only seven TPC for initial calibration has proven effective in another previous study (Faller et al., 2012a) and allows our present approach to auto-calibrate in an online setting within 6 min, even though here, we collect data for four instead of two classes. We deem quick auto-calibration very important for usability and practicality, especially in a BCI for end users. From experience with our online Adaptive BCI systems we knew that collecting either five or seven TPC prior to recalibration did not make a difference in efficacy or usability, but here this change was important for practical reasons as it reduced the computational effort for the close to 15000 Adaptive BCI simulations in our analyses.

In this section we explain the classifier "calibration" procedure that is used by all three adaptive BCI configurations and the "class selection and calibration" procedure that is used for initial calibration in the *Auto-AdBCI* (see **Figure 4**).

For regular classifier calibration, the algorithm first extracted logarithmic band-power features (averaging over 1 s) from every bipolar derivation that was used in this particular adaptive BCI configuration (one or three). Features were extracted for the bands 8–10, 10–13, 13–16, 16–24, and 24–30 Hz. These bands have been previously found to show power modulation in response to performing the specific mental tasks we use (Neuper and Pfurtscheller, 2001; Faller et al., 2012b; Friedrich et al., 2012). From these five features, the system always selected the one with the highest separability in the window from second 4–8 in the trial according to the Fisher criterion (c.f. Bishop, 2007; Faller et al., 2012b).

The system then trained a linear discriminant analysis (LDA, Bishop, 2007) classifier using the selected feature. Here, the system split the time-window from second 4–8 into eight adjacent 0.5 s time-windows and performed leave-one-out cross-validation (LooCV) for every one of them. The window that produced the overall highest median accuracy (second 4–8 in the

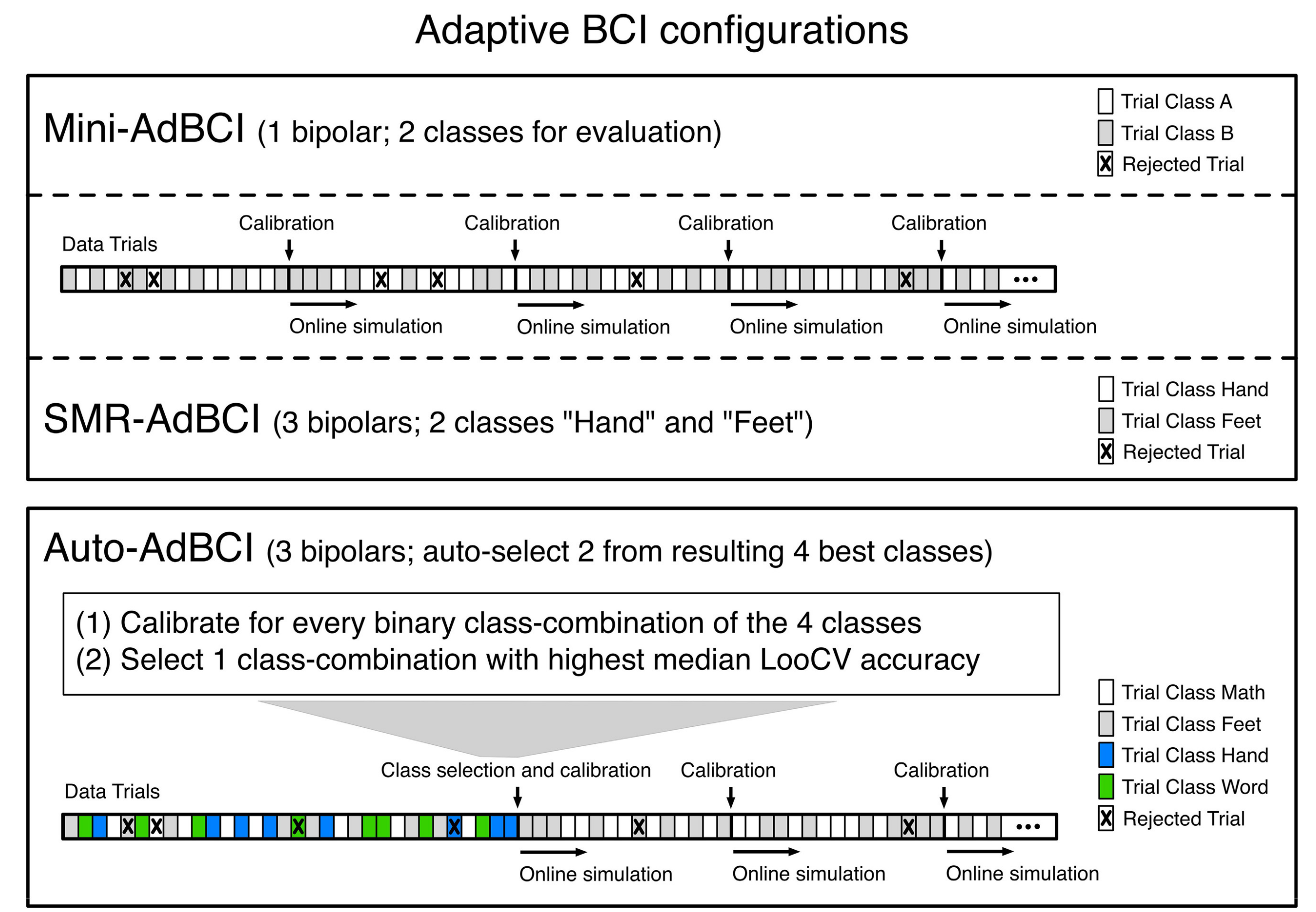

FIGURE 4 | Overview of the three Adaptive BCI configurations used in our analyses. The information on which channels and classes were used for each Adaptive BCI configuration is shown in parentheses next to the names of the configurations. The bar in every panel, represents the trials in one session, which the Adaptive BCIs process one by one. The crosses in some trials of the example bars indicate how some trials are removed by the outlier rejection.

trial) was used to compute the new classifier, which was from then on used in the simulation.

The *Auto-AdBCI* configuration started collecting data for four instead of two classes. During initial auto-calibration the system then selected two of the four classes in the following way: The *Auto-AdBCI* first performed the regular calibration procedure for every one of the six binary combinations of the four classes and then selected the one class combination, that produced the highest LooCV median accuracy during calibration. If multiple class combinations had the same median LooCV test accuracy, the system picked the class combination whose best feature had a higher separability according to the Fisher criterion.

2.6. OUTLIER REJECTION

Our adaptive BCI system used trial-based outlier rejection, which worked in multiple phases: First, the method removed outliers by thresholding amplitude and the statistical measures kurtosis and probability of the EEG (Delorme et al., 2007). For the amplitude, the threshold was $\pm 100\,\mu V$. For kurtosis and probability the threshold was ± 3.5 times the standard deviation from the respective sample mean. Afterwards, the outlier rejection mechanism iteratively removed trials based on the distribution of the logarithmic band-power for all feature bands (Faller et al., 2012b). This outlier rejection was done separately for the relax period (second 0–3) and the relevant part of the imagery period (second 3–8). The epochs from the relax period were pooled over all conditions, while the imagery period epochs were processed condition specific. The outlier rejection removed on average $12.5 \pm 3.1(SD)\%$ of the trials. For seven of twelve participants we found some of the lateral channels T3, T4, P7, and P8 to be congested with artifacts. We manually excluded the affected channels for these users prior to analysis.

2.7. PERFORMANCE EVALUATION AND STATISTICS

For system internal model selection and to identify the most effective bipolar derivations and classes in our analyses, we rely on the median accuracy between second 4 and 8 in the trial of the simulated online accuracy as a performance measure. For these purposes, this measure has proven robust and reliable (Faller et al., 2012b). To measure final simulated online BCI performance, however, high accuracy in a much shorter time window is relevant. Krausz et al. (2003) for example, showed how in a

"Basket Paradigm," the trial length can be optimized for each user to increase BCI performance. For the final results, we therefore report the peak accuracy within the window from second 4–8 in the trial. Assuming a conservatively low number of 30 TPC in the online simulation, the level of better than chance accuracy for a significance level of $p = 0.01$ in a binary decision task is 66.7% (Müller-Putz et al., 2008). To test the difference hypothesis of our research question we conducted a mixed design repeated measures analysis of variance (ANOVA) with one between-subject factor "Pathology" (2 levels, SCI and Stroke), one within-subject factor "BCI-Type" (2 levels, *Auto-AdBCI* and *SMR-AdBCI*) and the dependent variable "Simulated online peak accuracy." We examined the two main effects and their interaction on the results from Session 2. Normal distribution was confirmed by the Kolmogorov-Smirnoff test and Greenhouse-Geisser Epsilon was used for correction. We considered p-values smaller than 0.05 statistically significant.

3. RESULTS

3.1. CHANNELS AND CLASSES FOR THE *SMR-ADBCI* AND THE *AUTO-ADBCI*

In the analyses on the data of Session 1 we identified the bipolar derivations at Cz (FCz-CPz), Pz (P1-P2), and P4 (CP4-PO4) (see **Figure 5**) to produce the highest accuracy. Over these three selected channels we further found the mental tasks *Math*, *Feet*, *Hand*, and *Word* to perform best, leading us to reject class *Nav*. When limiting the classes to *Hand*, and *Feet* for the *SMR-AdBCI* we identified the bipolar derivations C3-CP3, again Cz (FCz-CPz), and CP4-P4 (see **Figure 5**) to produce the highest accuracy.

3.2. PERFORMANCE OF THE *AUTO-ADBCI*

By BCI-Type, we found an overall peak accuracy of $75.7 \pm 8.4\,(SD)$% for the *Auto-AdBCI* system and an overall peak accuracy of $66.3 \pm 7.2\,(SD)$% for the *SMR-AdBCI* system. That means the performance of the *Auto-AdBCI* was 9.4% accuracy higher than that of the *SMR-AdBCI*. This difference was statistically significant [$F_{(1,\,7)} = 15.705$, $p < 0.01$]. The *Auto-AdBCI* system worked significantly better than chance

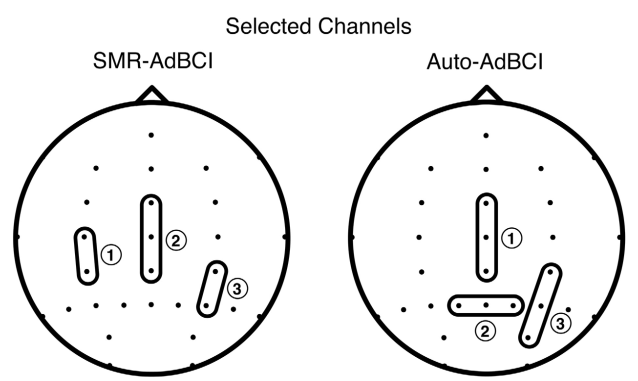

FIGURE 5 | The selected bipolar derivations for the *SMR-AdBCI* and the *Auto-AdBCI* system. The annotated numbers show the ranking of the bipolars, with number one performing the best.

for eight of nine users, while the *SMR-AdBCI* system worked significantly better than chance for six of nine users ($p < 0.01$, Müller-Putz et al., 2008).

By Pathology, we found an overall peak accuracy of $75.6 \pm 7.0\,(SD)$% for users with SCI and $65.2 \pm 8.1\,(SD)$% for users with stroke. That means the average performance of both BCI-Types is 10.4% higher for users with SCI than for those with stroke. This difference was statistically significant [$F_{(1,\,7)} = 10.406$, $p < 0.05$]. There was no statistically significant effect of the interaction of Pathology and BCI-Type on the peak accuracy [$F_{(1,\,7)} = 0.017$, ns].

Figure 6 shows the peak accuracies for the simulations of the *Auto-AdBCI* and *SMR-AdBCI* systems on the seen data of Session 1 and the unseen data of Session 2. **Table 2** shows the simulated online peak accuracies, separately for the two sessions and pathologies.

4. DISCUSSION

Our findings support our hypothesis: In our sample of nine individuals with SCI or stroke in Session 2, auto-selecting a user specific class combination of motor-related and non motor-related mental tasks during initial calibration of an adaptive ERD-based BCI significantly increased performance in comparison to an adaptive ERD-based BCI that used only motor-related mental tasks.

4.1. PERFORMANCE OF THE *AUTO-ADBCI*

The *Auto-AdBCI* successfully auto-calibrated and adapted to the patterns of oscillatory brain activity of the users with severe motor impairment in our study. On the unseen data of Session 2, a high number of eight of nine users performed better than chance. For seven of nine users the system performed higher than 70% accuracy which had previously been found necessary to effectively operate a spelling application (Kübler et al., 2001).

Figure 6 shows how the simulated performance of the *Auto-AdBCI* configuration on the unseen data of Session 2 (dark blue dots) is in most cases very close to that of the best possible class combination (upper end of gray whiskers), which indicates that our comparably simple auto-selection heuristic was overall very effective. The simulated online accuracy of the *Auto-AdBCI* on the unseen data of Session 2 was less than 5% lower than an average with the best-possible class-combinations but more than 15% better than an average with the worst-possible class-combinations (see **Table 2**). In over 80% of all sessions, the *Auto-AdBCI* selected a class-combination where one class was either *Hand* or *Feet* and the other class was either *Word* or *Math*. The less than 20% of all sessions where the *Auto-AdBCI* selected class-combinations where both tasks were either only motor-related or non motor-related are with the five of twelve users for whom the system worked least effectively. From the gray whiskers in **Figure 6** we see, that, at least in Session 2, none of the other class-combinations perform substantially better, which indicates that this is not a problem with the heuristic approach of the *Auto-AdBCI*. With respect to the selected class-combinations, we found no indication that there may be a systematic difference between the pathologies SCI and stroke.

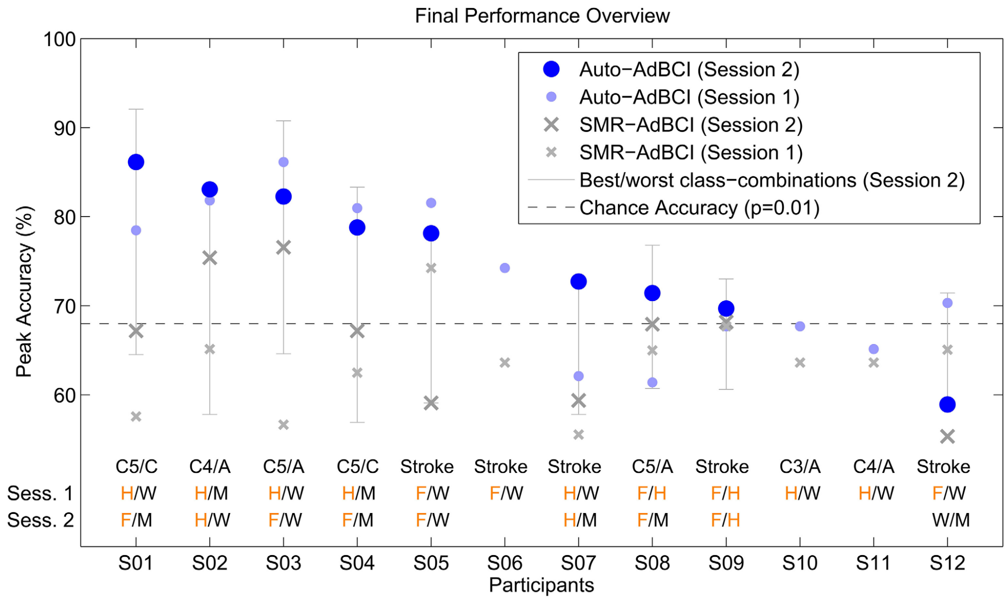

FIGURE 6 | Performance overview for the *Auto-AdBCI* and the *SMR-AdBCI* configuration. The light and dark blue dots show the simulated peak accuracies for the *Auto-AdBCI* on the seen data from Session 1 and the unseen data from Session 2. The light gray whiskers indicate the span between best and worst possible class-combinations for the unseen data of Session 2. The small and large gray crosses show the simulated peak accuracies of the *SMR-AdBCI* on the seen data of Session 1 and the unseen data of Session 2 respectively. The first of the three lines at the bottom indicates pathology. The second and third show the class-combinations auto-selected by *Auto-AdBCI* in Session 1 and Session 2. The single letters are abbreviations for the classes *Feet* (F), *Hand* (H), *Word* (W), and *Math* (M). Letters in orange indicate motor-related mental tasks, while letters in black indicate non motor-related mental tasks.

Table 2 | Simulated online peak accuracies for sessions and pathologies.

		Peak accuracies for different Adaptive BCI configurations			
		Best class-combination	**Auto-AdBCI**	**SMR-AdBCI**	**Worst class-combination**
Session 1[†]	Stroke	73.2	71.2	65.2	57.6
	SCI	80.8	74.5	62.0	60.2
	Mean (*SD*)	77.6 (6.1)	73.1 (8.5)	63.4 (5.1)	59.1 (2.5)
Session 2	Stroke	73.9	69.9	60.5	59.1
	SCI	85.3	80.3	70.8	60.9
	Mean (*SD*)	80.2 (7.7)	75.7 (8.4)	66.3 (7.2)	60.1 (2.8)
Mean (*SD*)		78.4 (6.1)	73.6 (7.7)	64.5 (3.5)	59.5 (2.1)

The Auto-AdBCI, initially auto-selected one of six class combinations according to a heuristic. Based on seven trials per class, the heuristic tried to select a class-combination that would allow for a highest possible peak control accuracy over the session. To compare, we simulated the overall session accuracy not only with the auto-selected class-combination (Auto-AdBCI), but also with all other class-combinations. The column "Best Class-Combination" is the average when considering for every user only the one class-combination that eventually produces the highest overall accuracy. In analogy, the column "Worst Class-Combination" considers for every user only the one class-combination that eventually produces the lowest overall accuracy. [†]Notice, the data of Session 1 is "seen data" as it has been previously used to determine the configurations of the BCIs.

Our analyses again highlighted some important points to keep in mind for bringing BCIs to end-users. For example the issue with artifactual activity in the EEG of users with motor impairment: After we had to remove one or more artifact congested lateral EEG channels in the data of more than half of the participants, the automatic outlier rejection of our system still had to remove on average 12.5% of the trials. The other issue is that users with severe motor impairment often are also more susceptible to illness, have limited mobility and independence and are therefore more likely to miss BCI training sessions.

4.2. COMPARING TO OTHER STUDIES THAT INVOLVED USERS WITH SCI OR STROKE

High inter-subject variability in EEG studies and differences in the used paradigms make a detailed comparison to independent population samples in other BCI studies difficult. In addition, most previous BCI studies involving individuals with SCI or stroke did not consider non motor-related mental tasks but instead focused mostly on motor-related tasks. We therefore decided to check whether the performance of the *SMR-AdBCI* which we used as baseline, is comparable to the results of existing studies. If the performance of the *SMR-AdBCI* is comparable to other systems, then this supports the findings in our study, that the *Auto-AdBCI* does perform better than a purely motor imagery based system. We compare results of other studies to the result of the *SMR-AdBCI* on the unseen data of Session 2. We consider higher performance better, but a high number of sensors less practical for home or clinical use with impaired end users.

For end users with SCI, Pfurtscheller et al. (2000) and Müller-Putz et al. (2005) showed effective ERD-based BCI control based on motor-related tasks in early case studies. Later, Pfurtscheller et al. (2009) found an overall accuracy result, lower than that of our *SMR-AdBCI* (61.7 vs. 70.8%) in offline analyses on seven individuals with SCI using 16 electrodes instead of 6 in our setup. Conradi et al. (2009) found a higher overall accuracy of 75% in four tetraplegic volunteers, but they used 64 instead of 6 electrodes and screened the participants from a larger group, which makes the results incomparable. In a recent study, Rohm et al. (2013) found an accuracy result comparable to our *SMR-AdBCI* (65.7 vs. 70.8%) in ten individuals with SCI over a large number of sessions.

For end users with stroke, Mohapp et al. (2006) found accuracy results in ten hemiparetic individuals, that were comparable with those of the *SMR-AdBCI* (67.1 vs. 60.5%). The minor differences could be explained by the stronger impairment of the participants in our sample. In a study involving eight stroke survivors, Buch et al. (2008) found an overall accuracy of 52.8% (median) in the first session and an overall end-accuracy of 72.5% (median) after 20 sessions of training. We deem the overall accuracy of 59.2% (median) we found with the *SMR-AdBCI* in Session 2 comparable. More recently, Ang et al. (2011) found a higher overall accuracy of 74% in a large sample of 54 stroke survivors, but they used a higher number of electrodes (27 instead of 6).

We find that the *SMR-AdBCI* performs at a similar level as comparable ERD-based BCI systems with users with similar pathology. This supports our main finding, that the *Auto-AdBCI* performs better than a standard adaptive BCI that relies only on motor tasks.

4.3. ANALYSIS OF CLASS SEPARABILITY PATTERNS

Overall, but especially in users with SCI, we found higher class separability as soon as non motor-related mental tasks were involved, which explains the overall significantly higher performance in the *Auto-AdBCI* when compared to the *SMR-AdBCI* (75.7 vs. 66.3% peak accuracy). In addition, we found stronger class separability in the group SCI as compared to the group Stroke, which is also reflected in the results of our statistical performance comparison. It is interesting to note, that the patterns of separability in the group SCI show distinct spatio-spectral differences to those of the healthy controls. The patterns in the group Stroke, are more similar to those of the healthy controls.

Figure 7 shows topographical projections of feature separabilities (Fisher criterion) after outlier rejection for different class combinations, frequency bands and user groups (SCI, Stroke and Healthy). The data set of the healthy individuals is from a similar study (Friedrich et al., 2012). That study included all the mental tasks used here, except the second motor task *Feet*.

In the group SCI, we found interesting differences to the groups Stroke and Healthy: Most importantly, for the combination of motor-related and non-motor related mental tasks we found strong, topographically focal separability around the vertex, most prominent in the feature bands 13–16 Hz and 16–24 Hz. For task combinations of non-motor related mental tasks we found a similar, spatio-spectrally even more focal pattern of separability between 16 and 24 Hz.

These observations are in accordance with reports in literature: Curt et al. (2002), Alkadhi et al. (2005), Conradi et al. (2009) and most recently Gourab and Schmit (2010) found performing motor tasks to cause increased but more diffuse activity in cortical motor areas (including increased central beta ERD) in individuals with SCI when compared to healthy controls. Curt et al. (2002) suggested that this phenomenon might be a result of "sprouting or rewiring" which "may occur close to the SCI segments." This would also explain the differences in the separability patterns when comparing to the groups Healthy and Stroke. In the groups Healthy and Stroke, the spinal cord is in tact and such "sprouting" would therefore not occur. Gourab and Schmit (2010) on the other hand speculated, that the increased ERD activity they found in users with SCI during attempted execution of a foot movement would be due to "increased difficulty in attempting movement with the paralyzed extremity." For the purpose of BCI operation, it is relevant to note, that the patterns of SCI survivors seem to show stronger class separability when involving non motor-related mental tasks than when only motor-related mental tasks are used.

In the group Stroke we found activation patterns that are weaker but otherwise similar to those in the group Healthy. This is in accordance with earlier studies, which found motor-related tasks in individuals with stroke to produce similar patterns of separability as in healthy controls (Mohapp et al., 2006; Ang et al., 2008; Buch et al., 2008; Sharma et al., 2009). Our present study confirms the similarity of the separability patterns between healthy users and individuals with stroke now also for task combinations that involve non motor-related mental tasks.

4.4. LIMITATIONS AND FUTURE PROSPECTS

A limitation of the present study is that the results were obtained through offline analyses. Tests with online implementations will show whether non-motor related mental tasks like "Word" or "Math" are also practical for real world applications. Another limitation of the present system is performance: Our system showed significantly improved accuracy over previous approaches. Still, an average of 70–75% accuracy may not be enough to attain satisfactory control in a real world setting for many end users. Based on previous findings involving online ERD-based adaptive BCIs (Vidaurre et al., 2006, 2011; Faller et al., 2012b) we are hoping to see the additional closed-loop feedback lead to even higher system performance, especially with training over multiple sessions. As a next step it will be important to explore whether the advantages of the presented approach also translate to user

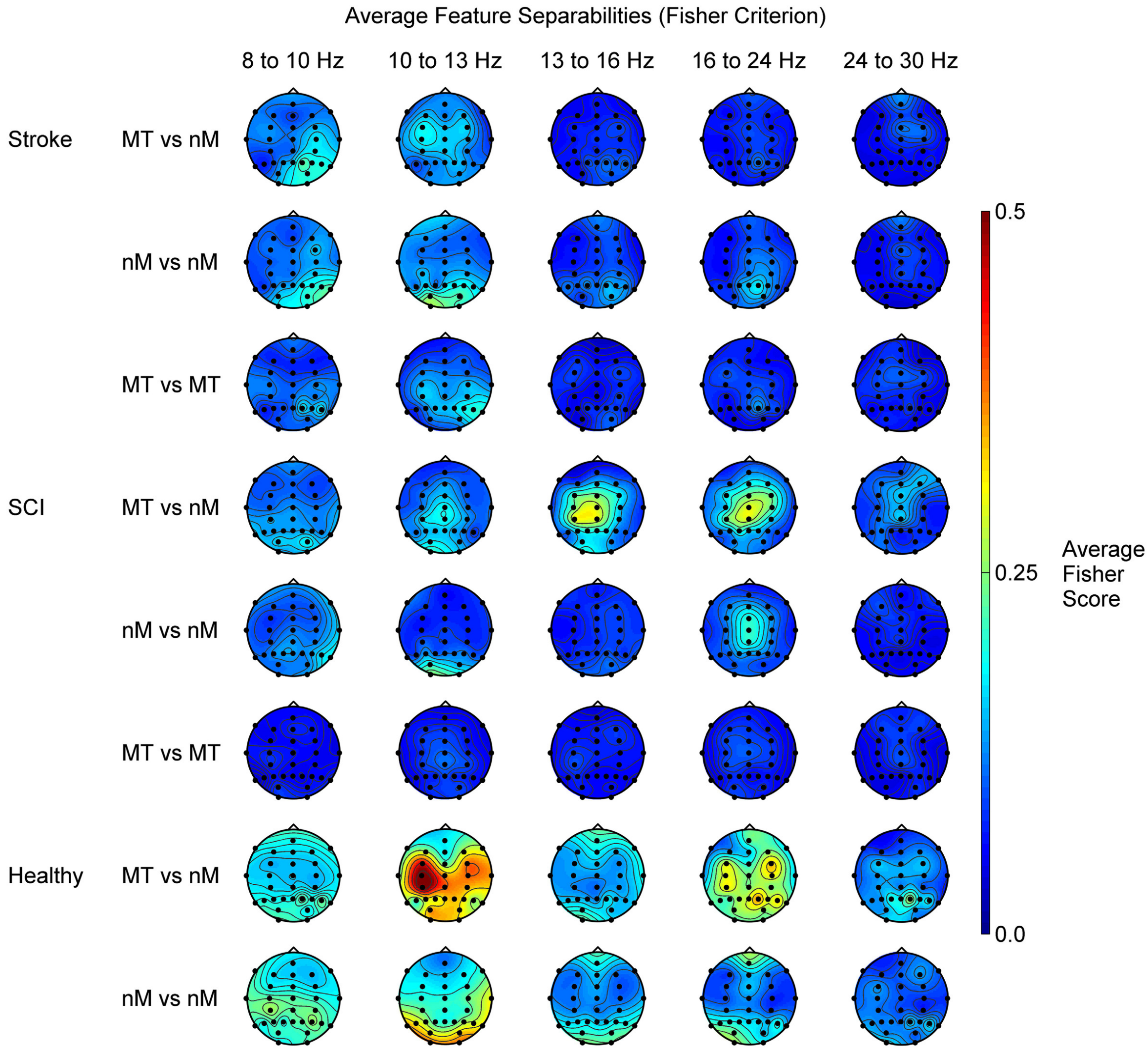

FIGURE 7 | Topographic projections of the average feature separabilities (Fisher criterion) for the dimensions pathology, class combination type and frequency band. The abbreviations "*MT*" and "*nM*" stand for motor-related and non motor-related mental tasks respectively. The row *MT* vs. *nM* for example shows an average over all class combinations where one class is a motor-related and the other one is a non motor-related mental task. The data for group Healthy, did not include the class *Feet*. For the class combinations *MT* vs. *nM* and *nM* vs. *nM*, for the users with motor impairment we therefore excluded the class *Feet*. The data is averaged across 2 sessions for 9 healthy users (Friedrich et al., 2012) and 12 with severe motor impairment.

populations with severe motor impairment as a result of medical conditions other than SCI or stroke, like amyotrophic lateral sclerosis (Kübler and Neumann, 2005) or cerebral palsy (Neuper et al., 2003). In another research direction, it would be interesting to evaluate, whether adaptive ERD-based BCIs could be useful tools for neuro-rehabilitation (Dobkin, 2004; Daly and Wolpaw, 2008) after neural injuries like stroke (Grosse-Wentrup et al., 2011), SCI (Cramer et al., 2007) or other neurological disorders.

5. CONCLUSION

In our sample of nine individuals with SCI or stroke, auto-selecting a user specific class combination of motor-related and non motor-related mental tasks during initial calibration of an adaptive ERD-based BCI significantly increased performance in comparison to an adaptive ERD-based BCI that used only motor-related mental tasks. This could have very strong implications on the use of ERD-based BCIs, especially for clinical applications: As of now, most BCI protocols still exclusively rely on motor-related mental tasks. Our findings show that including non motor-related mental tasks can significantly improve performance for potential end users with SCI or stroke.

AUTHOR CONTRIBUTIONS

Josef Faller, Reinhold Scherer, and Elisabeth V. C. Friedrich contributed equally in conceiving the experiment. Reinhold Scherer implemented the data acquisition system. Josef Faller performed all data analyses. Josef Faller, Elisabeth V. C. Friedrich, Ursula Costa, Eloy Opisso, and Josep Medina collected the data. Josef Faller, Reinhold Scherer, Eloy Opisso, Josep Medina, and Gernot R. Müller-Putz wrote the manuscript.

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Appendix C

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On the control of brain-computer interfaces by users with cerebral palsy

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HIGHLIGHTS

- We evaluate the control of Brain-computer interfaces by 14 users with cerebral palsy.
- Eight users were able to control at least one of the BCIs with significant accuracy.
- Analysis of the results reveals that BCIs may be controlled by some users with CP.

ABSTRACT

Objective: Brain-computer interfaces (BCIs) have been proposed as a potential assistive device for individuals with cerebral palsy (CP) to assist with their communication needs. However, it is unclear how well-suited BCIs are to individuals with CP. Therefore, this study aims to investigate to what extent these users are able to gain control of BCIs.
Methods: This study is conducted with 14 individuals with CP attempting to control two standard online BCIs (1) based upon sensorimotor rhythm modulations, and (2) based upon steady state visual evoked potentials.
Results: Of the 14 users, 8 are able to use one or other of the BCIs, online, with a statistically significant level of accuracy, without prior training. Classification results are driven by neurophysiological activity and not seen to correlate with occurrences of artifacts. However, many of these users' accuracies, while statistically significant, would require either more training or more advanced methods before practical BCI control would be possible.
Conclusions: The results indicate that BCIs may be controlled by individuals with CP but that many issues need to be overcome before practical application use may be achieved.
Significance: This is the first study to assess the ability of a large group of different individuals with CP to gain control of an online BCI system. The results indicate that six users could control a sensorimotor rhythm BCI and three a steady state visual evoked potential BCI at statistically significant levels of accuracy (SMR accuracies; mean ± STD, 0.821 ± 0.116, SSVEP accuracies; 0.422 ± 0.069).

1. Introduction

Cerebral palsy (CP) is a non-progressive condition caused by damage to the brain during the early developmental stages, i.e. from the early stages of pregnancy through to 3 years old, and resulting in motor, and other, impairments (Holm, 1982; Odding et al., 2006). CP is caused by a one-time event and classified as "non-progressive" meaning the condition does not get worse with time (Badawi et al., 2008). However, specific symptoms may change over time as the individual's body grows and develops (Panteliadis and Strassburg, 2004).

CP can result in a range of symptoms and may be considered to be an umbrella term for any disabilities of movement, coordination, balance, posture, muscle tone regulation etc. resulting from damage during the brain's early development (Fong, 2005; Badawi et al., 2008). Individuals with CP may have a range of difficulties related to motor control including executing intended movements, automatic movements, and controlling postures (Krigger, 2006). Additionally, the brain damage may also in some cases result in

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problems with speech, comprehension, or mental retardation (Miller, 2004). In some cases CP may render the individual completely paralysed, in others frequent muscle spasms may occur (Krigger, 2006).

Individuals with CP may encounter a range of difficulties in everyday life. Communication may be very difficult as speech may be severely impaired or impossible (Miller, 2004). Additionally, individuals with CP may have severe restrictions on their independence and may have to rely on care-givers for many of their activities of daily living (Panteliadis and Strassburg, 2004).

A potential tool proposed to help with the communication and independent living needs of individuals with CP is a brain-computer interface (BCI) (Neuper et al., 2003; Mir, 2009).

BCIs are devices which allow control of a computer, or other device, via either the controlled modulation of neurological activity or the evocation of electro-potential changes. As such they can allow their users to control external devices for communication (Wolpaw et al., 2002), locomotion (Leeb et al., 2007), neuroprosthesis control (Müller-Putz et al., 2006; Neuper et al., 2006), environmental control (Aloise et al., 2011), entertainment (Nijholt et al., 2009), or rehabilitation (Prasad et al., 2009; Ang et al., 2010; Kaiser et al., 2012).

BCI control often uses the electroencephalogram (EEG) to measure brain activity and is most commonly based upon one of three paradigms; P300 event-related potentials (ERPs), steady state visual evoked potentials (SSVEPs), or sensorimotor rhythm (SMR) changes. P300 ERPs are changes in amplitude in on-going EEG in response to a particular stimulus or event and may be used to identify which option from a set of choices a BCI user is attending to Farwell and Donchin (1988).

SMR BCIs base control upon the modulation of on-going oscillatory activity in response to a range of mental tasks (Pfurtscheller and Neuper, 2001). For example, these can include motor imagery in which the user imagines movement in some part of their body (Pfurtscheller and Neuper, 2001), mental arithmetic in which the user attempts some mentally engaging arithmetic task, and word association in which the user attempts to recall words that begin with a specified letter (Del R Millan et al., 2002; Obermaier et al., 2001; Faller et al., 2012; Friedrich et al., 2012).

SSVEPs are a response to attention by the user to a regularly oscillating visual stimuli (Calhoun et al., 1995; Calhoun and McMillan, 1997; Jones et al., 1998; Ming and Shangkai, 1999; Middendorf et al., 2000). When attending to such a stimuli oscillatory activity at the corresponding frequency in the EEG recorded from the users occipital cortex increases in magnitude. Thus, by inspecting the power spectra of the EEG recorded over this region it is possible to discern which of a range of target stimuli the user is attending to Middendorf et al. (2000).

There is only a small amount of previous work attempting to investigate the potential use of BCIs by individuals with CP. One previous study, Neuper et al. (2003), investigated the long term use of a BCI by a single individual with CP and found that BCI control was possible for this individual. A motor imagery based BCI was provided and, over a period of several months, the individual was trained to use it, achieving an average level of accuracy of above 70 %. However, there are no studies exploring the potential use of BCIs by populations of individuals with CP between whom particular motor function impairments, neurological damage, and other, individual specific conditions such as degrees of spasticity may vary greatly. Additionally, the nature of the brain damage in individuals with CP and related symptoms makes it unclear whether such individuals will be able to (1) generate the necessary modulations in their neurological activity to control a BCI, and (2) produce EEG with a small enough amount of artifacts for use in BCI.

Therefore, to begin to answer these questions a feasibility study is conducted. Fourteen adults with CP are engaged in experimentation with two different online BCI systems in order to investigate if they are able to achieve online control and to assess the quality of their EEG. Two commonly used BCIs are chosen, the sensorimotor rhythm (SMR) based BCI and the steady state visual evoked potential (SSVEP) based BCI. Note, P300 BCIs were not investigated at this stage as prior pilot studies with a small group of 6 individuals with CP showed more users were able to produce a significant SSVEP response than P300. Additionally, users indicated a preference for either SSVEP or SMR BCIs over P300 based BCIs.

The two BCIs used in this study represent very different control paradigms involving different cognitive processes and different cortical regions. SMR-based BCIs involve attempting mental tasks, with cortical activation primarily located in the motor cortex regions. In contrast, SSVEP BCIs involve attending to oscillatory stimuli with neurophysiological responses located primarily in the occipital cortex. Therefore, these two BCIs allow individuals with CP to attempt two diverse control paradigms.

We set out to investigate whether individuals with CP are able to gain control over either an SSVEP or a SMR-based BCI.

2. Methods

2.1. Subjects

Fourteen individuals with CP voluntarily participated in this study (seven male, age range 20 to 58 with a median age of 36, SD = 10.97). Institutional review board (IRB) ethical approval was obtained for all measurements. Details of the participants are summarised in Table 1.

2.2. Recording

EEG was recorded from 16 electrode channels via the g.tec GAMMAsys system with g.LADYbird active electrodes (g.tec, Austria). Channels were arranged primarily over the motor and parietal cortical areas according to the international 10/20 system.

We used channels AFz, FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4, PO3, POz, PO4, O1, Oz, and O2. The reference electrode was placed on either the right or left ear according to the particular condition of each subject and the ground electrode was placed either behind the left ear at either TP7, TP9, or at FPz (again according to particular subject conditions).

Accelerometer sensors were used to record the subjects head movements in the x, y, and z dimensions by placing a PLUX accelerometer at position Fz (xyzPLUX triaxial accelerometer). Additionally, for some subjects, a PLUX blood pressure sensor was placed on one finger of either the left or right hand (bvpPLUX). The hand and finger used varied from subject to subject according to comfort and the particular condition of each individual with CP.

Synchronisation of signal timing between the EEG and the accelerometer was achieved via the TOBI signal server (Müller-Putz et al., 2011; Breitweiser et al., 2011). EEG data was sampled at a frequency of 512 Hz and saved to file during both training and feedback runs while the accelerometer and blood pressure were both sampled at a rate of 128 Hz. Only the EEG signals were used in this study with the other physiological signals retained for future analyses.

2.3. BCI systems

Two online BCI systems were implemented to test the ability of individuals with CP to control either an SSVEP or an SMR based BCI. Users were shown demonstrations of each BCI prior to beginning the measurements. This was to familiarise them with the tasks and make sure they understood what was required.

Table 1
Subject details. GMFCS denotes the Gross motor function classification system score, Orthopaedic disorders are denoted by codes which indicate lower limb disorders (MMII) or upper limb disorders (MMSS). The subjects dominant hand is either left (L), right (R), bilateral (B), or unknown (–).

User	Gender	Age	GMFCS	Orthopaedic disorders	CP type	Sensory disturbances	Dominant hand
01	M	53	V	MMII, MMSS	Dystonic	–	L
02	M	36	V	MMII, MMSS	Dystonic-spastic	–	L
03	F	52	IV	MMII	Spastic diplegia	Myopia	R
04	M	22	IV	MMSS, MMII	Acquired cerebral damage	–	R
05	M	32	V	MMII	Acquired cerebral damage	Blindness, left eye. Deafness, left ear.	B
06	F	20	-	MMII, MMSS	Dystonic	–	–
07	M	34	IV	MMSS, MMII	Athetosic	–	L
08	F	58	IV	MMII	Spastic diplegia	Myopia	R
09	F	32	IV	MMII	Spastic	–	L
10	F	36	V	MMII, MMSS	Spastic	–	L
11	M	38	V	MMII, MMSS	Dystonic-spastic	–	L
12	F	36	V	MMII, MMSS	Dystonic	Myopia	L
13	M	37	IV	MMII, MMSS	Spastic	–	–
14	F	31	IV	MMII, MMSS	Spastic	–	–

Individuals with CP who participated in our pilot study reported that they felt more comfortable and secure when given some measure of control over the experimental setting. Thus, users were free to choose which system they would like to try. After each run they were again asked if they would like to (1) continue with the current system, (2) try the other system, or (3) stop. Users reported that giving them these choices helped them stay motivated and allowed them to feel more secure and comfortable in the novel setting of the EEG measurement environment.

When given free choice of which paradigm to choose, it was hypothesised that users may exhibit strong preferences for one paradigm. This preference may bias the results. For example, if the SSVEP paradigm was chosen first by all users then lower results at the SMR BCI may be explained, in part, by subject fatigue from first attempting the SSVEP BCI.

To determine if there was such a bias in choice, either in terms of a preference for one or the other of the BCI paradigm types or in the order paradigms were selected, two tests were applied. First, the number of times each paradigm type was chosen was assessed against the null hypothesis of equal probability of each paradigm being chosen. Second, the fraction of times each paradigm was chosen within each of the first three runs (subsequent runs were not completed by enough users for valid statistical testing) was assessed against the same null hypothesis. Rejection of the null hypothesis in the first test would indicate a significant preference for one or other of the paradigms by the subjects. Rejection of the null hypothesis in one or more of the runs in the second task would indicate that there is some preference for the order of the runs exhibited by the subjects.

2.3.1. SSVEP

The SSVEP paradigm consisted of four square targets in the form of four red boxes arranged on a computer screen in a quadrangle. Stimuli were rapidly changed between red and black colours at frequencies of (clockwise from top left) 6.66 Hz, 8.57 Hz, 12 Hz, and 15 Hz. These frequencies were chosen based upon pilot experiments with three healthy subjects. Users were periodically cued to attend to one of the targets via an arrow placed in the centre of the screen and remaining in place for 6 s. Additionally, a fifth null condition was cued by a cross appearing for 6 s in the centre of the screen. Feedback about successful accomplishment of the task was provided immediately by highlighting a selection frame around the target. Inter-trial intervals were uniformly distributed between 3–5 s.

Each condition was randomly chosen from a uniform distribution for each trial. Trials were grouped into runs and one SSVEP run consisted of 20 trials with equal numbers of trials for each class.

Classification was performed via the canonical correlation analysis (CCA) method described in Seber (1984) and applied in Horki et al. (2010). Correlations were found between two sets of data (1) the EEG recorded on multiple channels arranged over the occipital cortex and (2) the SSVEP stimulation frequencies. The largest correlation coefficient was used to identify the stimuli the user was attending to. Thresholding was used to test for the null condition that the user was not attending to a stimuli. Thresholds were initially set to 0.2 for each of the four SSVEP stimulation frequencies based upon a prior pilot study with 3 healthy subjects.

CCA was applied in a sliding window to segments of the EEG of length 2 s with a step size of 0.0625 s. Feedback was presented to the user if the output of the CCA method exceeded the threshold for 0.5 s consecutively.

In addition to the classification accuracy it is interesting to ask in what percentage of trials the users manage to achieve correct feedback. Thus, the "hit rate" (HR) was measured as the percentage of trials for which a user managed to produce a sufficiently large SSVEP response to achieve correct feedback.

2.3.2. Sensorimotor rhythms

The sensorimotor rhythm paradigm – based upon work in Faller et al. (2012) – consisted of an initial calibration phase followed by an online feedback phase.

During the calibration phase the user was asked to perform four different mental tasks in response to a cue. The tasks were:

1. Kinaesthetically imagined movement of either hand
2. Kinaesthetically imagined movement of the feet
3. Mental arithmetic
4. Mental word-letter association

No feedback was provided during this initial phase. Instead the system used the data recorded to select the two of the four tasks which were best suited for individual control.

The timing of individual trials was as follows.

Second 0: a fixation cross appeared in the centre of the screen and remained there for the duration of the trial.

Second 1.5: a cue appeared on screen indicating which task to perform. This cue remained until second 3.5.

Remaining time: the time from the appearance of the cue to the end of the trial at second 8 was designated as the imagery period and the user was instructed to perform the cued task during this time and halt when the cross disappeared.

One of the four different conditions was randomly chosen from a uniform distribution for presentation to the user during each trial.

After sufficient trials were recorded in the calibration phase for accurate estimation of the class boundaries the BCI automatically proceeded to the feedback phase. The two most discriminative classes were selected for use and randomly presented to the user, following the same timing as used in the calibration phase, during each trial.

During the imagery period in the feedback phase a bar was displayed on screen indicating the LDA classifier distance estimated from attempting to classify features from the users SMR strength. Increased LDA classifier distance causes the bar to fill from left to right. Additional feedback in the form of a smiley face was presented to the user in the case of the classifier prediction matching the true class label for more than 50 % of the duration of the imagery period in the trial.

An individual run in both the training and feedback phases contained 32 trials. The number of trials per class was balanced per run, thus, in the training run there were 8 trials per class and in the feedback run there were 16 trials per class.

The exception to this arose when sufficient trials for classification were gathered from the calibration phase in the middle of a run. In this case the run changed from the calibration to the feedback phase immediately and the run may therefore be said to have contained both calibration and feedback trials.

During the feedback phase the distribution of the EEG components related to the tasks continued to be estimated to attempt to further improve the accuracy with which the system responded to the user.

During both the calibration phase and feedback phase artifacts in the EEG were automatically identified and labelled. This allowed comparisons to be made between the classifier outputs and any patterns or repetitions found in the generation of artifacts. Artifacts were automatically identified via the thresholding of a number of key metrics from the EEG as described in Faller et al. (2012).

There were four stages to the classifier setup outlier rejection, feature selection, segment selection, and classifier training. Outlier rejection was based upon thresholding kurtosis, probability, and statistical properties of the features. Logarithmic band power features were then extracted from the EEG in the bands 9–14, 13–17, 16–24, and 23–29 Hz. During the calibration phase the feature that showed the highest between-class discriminability (as measured by Fischer's score) and the time period (within the activity period) that scored the highest median accuracy after leave-one-out cross-validation, was used for training the LDA classifier applied during the online feedback phase.

The LDA classifier was applied in a sliding window approach during online classification. A window of width 1 s was used with a step size of 1 sample. This is further detailed in Faller et al. (2012).

2.4. Performance

Online classification performance is reported for both the SSVEP and SMR BCI systems. The statistical significance of the performance was calculated at each time point against the null hypothesis of equal probability of each class being selected by the classifier. The subsequent significance level ($p < 0.05$) is illustrated against the plots of performance accuracy over time.

Additionally, it may be argued that there was a multiple comparisons issue related to the calculation of the significance on a sample by sample basis. However, this was a non-trivial problem as there was a large amount of dependency between subsequent EEG sample points. Thus, a Bonferroni multiple comparisons correction was not appropriate. To this end the mean area under the accuracy curves for each BCI system was also calculated. The area was calculated during the imagery period for the SMR BCI and during the SSVEP stimulation period for the SSVEP BCI. The significance of this area under the accuracy curve was then estimated via a bootstrapping approach.

Multiple bootstrap replications of the performance curves were generated via first shuffling the class labels prior to calculating classification accuracy. Mean areas under the accuracy curves were then calculated from each bootstrap replication and used the estimate the distribution of mean areas under accuracy curves under the null hypothesis of random classification. From this the significance of the observed accuracy curve was estimated.

2.5. Relationships between subject details and performance

It is interesting to ask if there is a relationship between any of the subject details, such as age, CP type etc., and their performance with each of the BCIs. For example, if some sub-group of subjects (e.g. some age group) perform better at one type of BCI then this could inform and guide the design of future BCI systems for subgroups of individuals with CP. To this end stepwise multi-linear regression was performed with subject details as predictor variables and the resulting accuracies at controlling each of the BCIs online as the criterion variables. Two separate regression analyses were performed (1) for the criterion variable SSVEP performance accuracies and (2) for the criterion variable SMR performance accuracies. The predictor variables used were subject gender, age, Gross motor function classification system (GMFCS) score, orthopaedic disorders, CP type, sensory disturbances, and dominant hand.

3. Results

3.1. Run order

Table 2 lists the orders of runs selected by each user.

It is worth noting that all users tried both tasks with no observable preferences. This is confirmed by the tests for bias in paradigm selection performed. Over all runs and subjects null hypothesis (that there is equal probability of each paradigm being chosen) is not rejected ($p = 0.104$). Table 2 lists the p values of probabilities of rejecting the null hypothesis that each paradigm is equally likely to be chosen during each run. Note, for run three the null hypothesis is rejected ($p = 0.035$). However, is may be argued that it is necessary to apply multiple comparisons correction to correct for the three runs. When Bonferroni correction is applied the null hypothesis is no longer rejected as $p = 0.035$ is greater than the adjusted significance level of $p = 0.0167$.

Users commented on the first day of measurements that false positive selections of SSVEP stimuli were distracting. Therefore, from the second day of measurements onwards (users 4 to 14) the thresholds, used by the CCA method to identify the SSVEP stimulation frequency the users were attending to, were adjusted from 0.2 to 0.3 for each stimulation frequency. This had the effect of reducing the number of false postive identifications as desired. However, it also reduced the number of true positive identifications, making it harder for the users to produce any feedback.

3.2. SSVEP

During attempted online control of a BCI via SSVEP, 5 users were able to achieve control at a statistically significant level ($p < 0.05$). Fig. 1 illustrates online classification accuracies achieved by the best performing user for each stimuli who was able to control the SSVEP BCI at statistically significant accuracies ($p < 0.05$). Table 3 then lists the peak and mean online accuracies over all stimuli achieved by each user when attempting to control the 5-class SSVEP BCI online along with the HR, the percentage of trials for which users were able to achieve correct feedback.

However, it's important to note that a multiple comparisons correction may be necessary to adjust for the multiple subjects in the study. Bonferroni correction may be used to do this. The alpha significance level is adjusted by $1/N$ were N indicates the number of comparisons and in this case equals 13. After applying

Table 2
Order and number of BCI runs chosen by each user. SSVEP denotes the choice to try the SSVEP BCI for a particular run. SMR denotes the choice to try the SMR BCI for a particular run. The subscripted SMR choices (SMR_t and SMR_f) denote runs for which the user had to go through 4 class trials to train the classifier (SMR_t) and trials for which feedback was provided (SMR_f). Feedback was provided as soon as enough trials had been gathered by the classifier for adequate classification results to be obtained. Therefore, for runs during which feedback was provided from a point part way through the run the number of training/feedback trials in the run are indicated in parenthesis and the subscripts are dispensed with. The final row indicates the probabilities of bias in the selection of BCI paradigms by users during each run assessed against the null hypothesis of equal probability of each paradigm being selected.

User	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8
01	SSVEP	SSVEP	SMR_t	SMR (18/14)	SMR_f			
02	SMR_t	SSVEP	SMR (9/23)					
03	SMR_t	SSVEP	SMR_t	SSVEP	SMR (23/9)	SSVEP		
04	SSVEP	SSVEP	SMR_t					
05	SSVEP	SSVEP	SMR_t	SMR (10/22)	SSVEP			
06	SMR_t	SSVEP	SSVEP					
07	SMR_t	SSVEP	SMR_t					
08	SSVEP	SMR_t	SMR (8/24)	SSVEP	SMR_f	SSVEP		
09	SMR_t	SSVEP	SMR (13/19)					
10	SSVEP	SMR_t						
11	SSVEP	SMR_t	SMR (2/30)					
12	SMR_t	SSVEP	SSVEP	SSVEP	SMR_t	SSVEP	SMR_t	SMR_f
13	SSVEP	SSVEP	SMR_t	SMR (9/23)				
14	SSVEP	SMR_t	SSVEP	SMR (11/21)				
p	0.183	0.061	0.035	–	–	–	–	–

Bonferroni correction we observe that three users exhibit significant ($p < 0.05$) peak and mean classification accuracies.

Accuracies may be listed on a per stimulation frequency (class) basis using a one-vs-rest classification scheme. The balanced accuracy and Cohen's kappa are reported to adjust for the bias in the number of trials. Mean and standard deviations of balanced accuracy values for each stimulation frequency and the null condition (when the user does not look at any stimuli) are listed in Table 4. A 2x2 Anova with the factor stimulation frequency revealed no significant effect of frequency on performance $F_{(4,69)} = 0.57$, $p = 0.683$.

Note, users 1 – 3 had CCA thresholds set to 0.2 while the remaining users had thresholds set to 0.3. Significant classification accuracy is achieved by some users with each threshold value.

3.3. Sensorimotor rhythms

During attempted online BCI control clear sensorimotor rhythms are visible in 12 users with artifacts contaminating the spectra in the remainder. Examples of good, artifact free, spectra generated by a user are illustrated in Fig. 2. ERD/S spectra are illustrated on common average referenced (CAR) channels FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, and CP4 for each of the 4 mental tasks employed.

The online classifier identifies enough trials to be trained with 10 users and online classification is statistically significant ($p < 0.05$) in 8 of those users. Of those users, two exhibit significant correlations between the classifier output and the automatically identified artifacts present in the signal. Thus, of the 14 users who attempted online BCI control via SMR modulation 6 were successful.

Online classification accuracies achieved by the 6 users able to control the SMR based BCI at statistically significant accuracies, without significant correlations found with the automatically identified artifacts, are illustrated in Fig. 3. The peak online classification accuracy for each user during the SMR based BCI control in the period 2–6 s relative to the cue, the corresponding *p*-values, and the correlation R-values and *p*-values between the classifier output and the automatically identified artifacts are listed in Table 5. Additionally, the hit rate (HR), the percentage of trials for which each user is able to achieve a smiley feedback, is listed.

3.4. Signal quality

During the online measurements considerable EMG and movement related artifacts were observed in 3 users with transient EMG observed in another 8 users. The remaining 3 users exhibited relatively clean EEG with only occasional blinks and EOG. In two users classification results were significantly correlated with artifacts (one of whom produced statistically significant online peak control accuracies). In the remainder (12 users) this was not the case. The following further general observations may be made on the EEG recorded from individuals with CP.

Considerable EMG and other artifacts are present on occipital channels in the majority of individuals. These arise from neck muscles and/or head supports exerting pressure on the occipital electrodes. While efforts were made to prevent head supports exerting pressure on occipital electrodes this was not always feasible for the complete duration of the measurement session. Periods of short-lived transient EMG may also be observed over the whole head in many users. However, these are often short lasting (<10 s). Electrode pop artifacts also occur frequently due to involuntary head movements causing pulling at leads in some users.

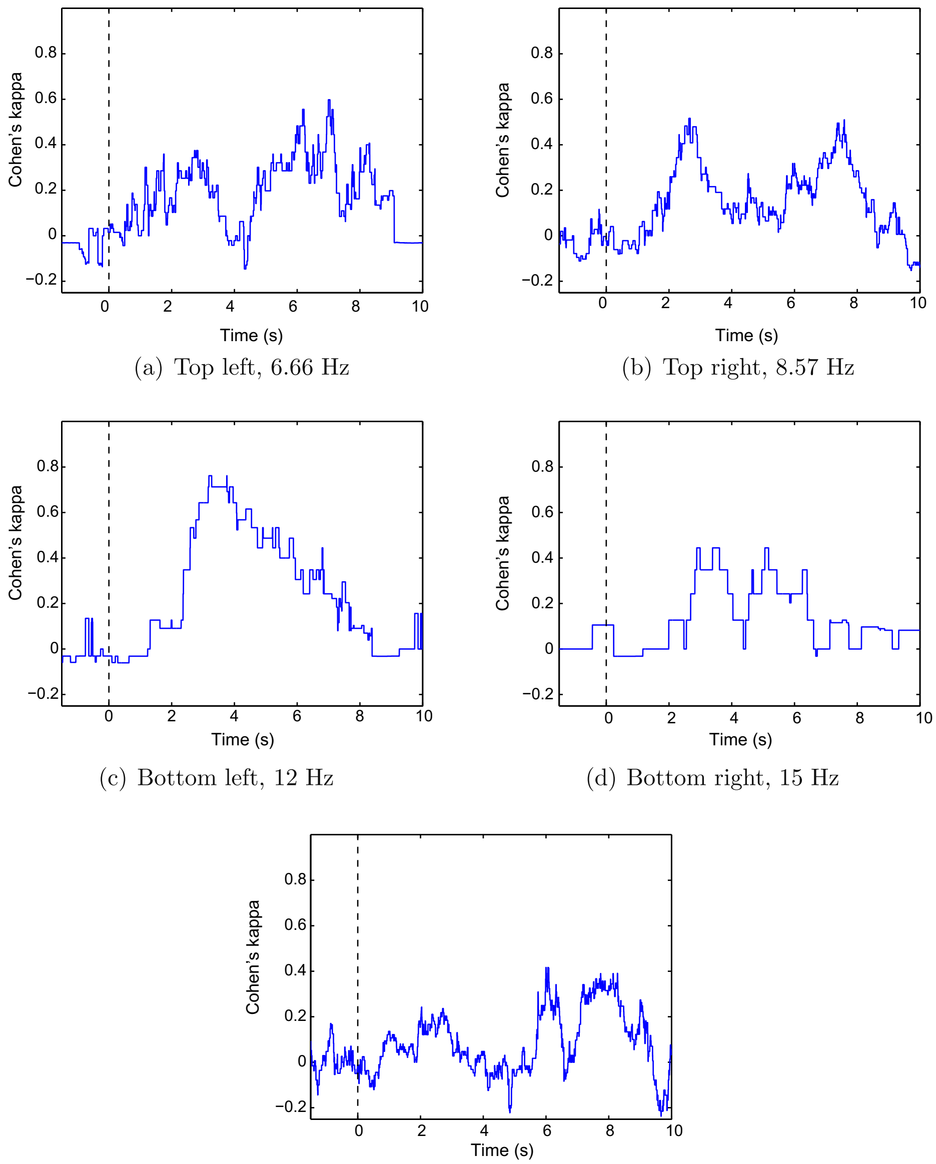
The active electrode system used has a better signal to noise ratio (SNR) on the cable between the electrode and the amplifier, potentially leading to less noise in the signal. However, in 2 users (user 6, 2 runs, user 12, 1 run) problems with the ground channel disconnecting due to large head movements introduced large line noise artifacts in some runs and rendered the signals un-usable. These runs were removed from the dataset prior to analysis and are not incorporated into the classification results.

3.5. Relationships between subject details and performance

The small number of subjects involved in this study means the impact of the statistical analysis of the relationships between subject details and their performance is limited and should be interpreted with caution. The results of the multi-linear stepwise regression analysis reveal a statistically significant ($p < 0.05$) relationship between the predictor variable subject gender and the criterion variable, the subjects performance at the SMR BCI with feedback provided ($r^2 = 0.501$, $p = 0.0136$). Further analysis reveals the accuracies achieved by male users and female users are seen to be significantly different (female user accuracies, mean ± SD (number of subjects); $0.849 \pm 0.112(5)$, male user accuracies; $0.681 \pm 0.071(5)$), with female users achieving significantly higher accuracies $p = 0.022$ when compared via a paired *t*-test.

4. Discussion

It has been shown that some users with CP are able to volitionally modulate their neurological activity in order to control a BCI at



(a) Top left, 6.66 Hz

(b) Top right, 8.57 Hz

(c) Bottom left, 12 Hz

(d) Bottom right, 15 Hz

(e) Null condition, the cross in the centre of the screen

Fig. 1. Online classification results achieved by the best performing user (user 5) when attempting online control of the SSVEP based BCI. Each plot illustrates the Cohen's kappa coefficient for each of the four SSVEP stimulation frequencies positioned in each corner of the screen and the null condition. Cohen's kappa is used due to the imbalance in class numbers entailed in reporting results for one class against the rest. The abscissa shows the time course over the trial starting from the onset of the visual cue (vertical, dashed line).

statistically significant levels of accuracy. Although the levels of accuracy are too low to demonstrate usability this result indicates that some individuals with CP can, with no prior training or experience, control a BCI and could potentially, in future, be able to use BCIs as assistive devices in selected circumstances.

The suitability of each BCI paradigm for each user depends on individual circumstances. Many users were observed to exhibit poor signal quality on occipital channels resulting from uncontrolled neck muscles and/or their head supports exerting pressure on the occipital electrodes. For this reason the suitability of SSVEP - and potentially also P300 - BCI control is limited and dependent upon either these users being able to control their neck muscles, and do without head support, or on suitable artifact removal methods being developed. By contrast SMR based BCIs could be controlled by 6 out of 14 users with task related SMRs observable in 12 users.

The SSVEP accuracies illustrated in Fig. 1 are observed to exhibit differences in granularity at different frequencies. Some explanation is needed for this. Inspecting the a posteriori probabilities for each stimulation frequency reveals large differences for different stimulation frequencies. The mean a posteriori probabilities are 0.49, 0.15, 0.29, 0.05 and 0.02 for the stimulus types null condition, 6 Hz, 8 Hz, 12 Hz, and 15 Hz respectively. Thus, the classifier is biased towards lower frequencies resulting in outputs at these frequencies being more frequently presented and finer grained plots resulting from greater numbers of switches at these stimulation frequencies.

The bias towards lower stimulation frequencies in the classifier may be physiological. Indeed in a pilot study performed on a small number of individuals with CP prior to the work reported here it was observed that the power spectrum of occipital EEG from individuals with CP exhibited larger spikes in response to lower stim-

Table 3
Columns two and three list peak online classification accuracies for control of the SSVEP based BCI by each user and the corresponding p-value against the null hypothesis of equal chance of each of the 5 classes (4 stimuli and the no-target condition) been classified. Asterisks (*) indicate users who achieved statistically significant ($p < 0.05$ adjusted via Bonferroni to $p < 0.0038$) accuracies as measured via the bootstrapping significance test. Columns four and five list mean accuracies during the stimulation period and the number of trials attempted by each user. Additionally, the HR (the percentage of trials for which the user was able to attain the correct feedback) is listed. Note, user 13 attempted SSVEP control but because of the position of their head rest was pressing on the occipital electrodes no usable signals could be recorded for this paradigm.

User	Peak accuracy	p		Mean acc.	Trials	HR
01	0.400	0.002	*	0.234	40	56.2
02	0.350	0.067		0.168	20	56.2
03	0.366	0.002	*	0.219	60	62.5
04	0.325	0.035		0.208	40	50.0
05	0.500	0.000	*	0.296	60	60.4
06	0.350	0.067		0.219	20	50.0
07	0.400	0.023		0.235	20	50.0
08	0.200	0.525		0.194	60	00.0
09	0.250	0.327		0.201	20	00.0
10	0.200	0.545		0.191	20	00.0
11	0.200	0.545		0.187	20	00.0
12	0.200	0.522		0.189	80	00.0
13	–	–		–	–	–
14	0.200	0.532		0.191	40	00.0

Table 4
Mean and standard deviation of balanced accuracies and Cohen's kappa related to attending to each SSVEP stimulation frequency and the null condition (attending to no stimuli).

Condition	Accuracy (mean ± std)	Kappa (mean ± std)
6.66 Hz stimuli	0.606 ± 0.112	0.191 ± 0.204
8.57 Hz stimuli	0.639 ± 0.165	0.209 ± 0.259
12 Hz stimuli	0.603 ± 0.135	0.176 ± 0.195
15 Hz stimuli	0.586 ± 0.116	0.202 ± 0.266
No stimuli	0.571 ± 0.090	0.176 ± 0.215

ulation frequencies then higher stimulation frequencies. Although it's important to note the well-known high inter-subject variability in EEG responses and the relatively small number of subjects in this study mean stronger conclusions cannot currently be drawn.

Peak accuracies, along with time courses of accuracy, are used to report performance at each of the BCI systems. This is common practice in BCI research and provides some measure of both the best performance and the performance over time (Treder et al., 2011; Fazli et al., 2012; Allison et al., 2010). However, it may be argued that peak accuracy alone does not provide a complete measure of statistically significant performance. To this end mean accuracies are also reported and their significance checked via a bootstrapping method. This reveals that users who achieve significant peak accuracies with the SSVEP BCI also achieve significant mean accuracies. However, two users (09 and 11) who achieved significant peak accuracies with the SMR BCI did not exhibit significant mean accuracies. This may be due to the small number of trials with user 09 (19 trials) or an unstable performance with a large period of false classifier results (user 11). By way of contrast, users 01, 02, 13, and 14 exhibit significant mean accuracies despite not exhibiting significant peak accuracies.

The hit rate (HR) records the percentage of trials for which the user achieves correct feedback. While correct feedback alone is not enough to indicate feasible BCI control it does give some measure of how successful control appears to be to the user and it is encouraging to see that for 7 of the SSVEP BCI users HRs of 50.0 and above are achieved. Although this must be contrasted with the remaining users who were not able to produce any correct feedback.

When inspecting the time courses of the classification accuracies achieved by each of the 6 users successful in controlling the SMR BCI at statistically significant levels of accuracy users 8, 9, and 11 achieve sustained levels of significant control. However, users 2, 3, and 14 only achieve significant control for transient periods of time or, in the case of user 3, the user attempted so few trials (9) that the impact of the results is very low. Users 2 and 14 completed 23 and 21 trials respectively. It's conceivable that with more trials a more sustained period of significant classification could emerge. However, this is currently only speculative and sustained, significant BCI control can currently only be seen to be achieved by 3 users.

The choice of which two out of the four classes are chosen for the online feedback condition over all users shows a slight preference for the feet motor imagery condition (chosen 8 times). Other classes are chosen similar numbers of times to one another (hand imagery 3 times, mental arithmetic 4 times, and word-letter association 5 times). The reason for this observed preference could be that the feet motor imagery condition produces an SMR pattern in these users which is more distinct and, therefore, differentiable then the other classes. However, this will require further research to verify due to the relatively small number of subjects involved in this study.

The users involved in this study received no prior BCI training. It is, therefore, interesting that a number of them were none-the-less able to achieve significant levels of control with one or other of the BCIs they attempted. Furthermore, it is interesting to note that this was achieved with BCIs which were not optimised for individuals with CP. Training sessions with the users – either BCI training or training at meditation – could improve the performance of BCI control with a number of users and, potentially, allow more users to achieve significant levels of control (Tan et al., 2009; Mahmoudi and Erfanian, 2006).

However, it's important to note that statistically significant levels of accuracy do not mean usable BCI control may be achieved. Useable BCI control may be defined as a sufficient level of control to allow users to complete a reasonable number of desired tasks. For binary control this is defined as 70% accuracy, based upon the results of two patients described in Kübler et al. (2001). During attempted online control of the two-class SMR BCI 5 out of the 6 users who achieved significant control are seen to produce either brief or sustained control above the 70% threshold. However, a larger number of trials would allow for further confirmation of this result.

Additionally, the use of more sophisticated signal processing methods, machine learning methods, and / or feature types may, potentially, also help to improve performance in a number of users with CP. It may be possible to allow some users who are not currently able to control a BCI at a statistically significant level of accuracy to do so. Investigations into improved methods are an on-going topic of research in BCI and have the potential to yield impressive results in future work.

The active electrodes used in this study have a considerably shorter setup time, when compared to the passive electrode systems more commonly used in BCI studies. However, this comes at the expense of potentially poorer signal quality due to the lack of an impedance measure in the particular amplifier system used. None-the-less, this was a successful decision as during online control no major problems with setup time were encountered and the proportion of usable signals is similar to that observed with passive electrode system used in other studies. In future work it may be possible to measure the signal quality during BCI operation via the use of alternative metrics which work in situations where impedance measures are not available, such as that proposed in Daly et al. (2012).

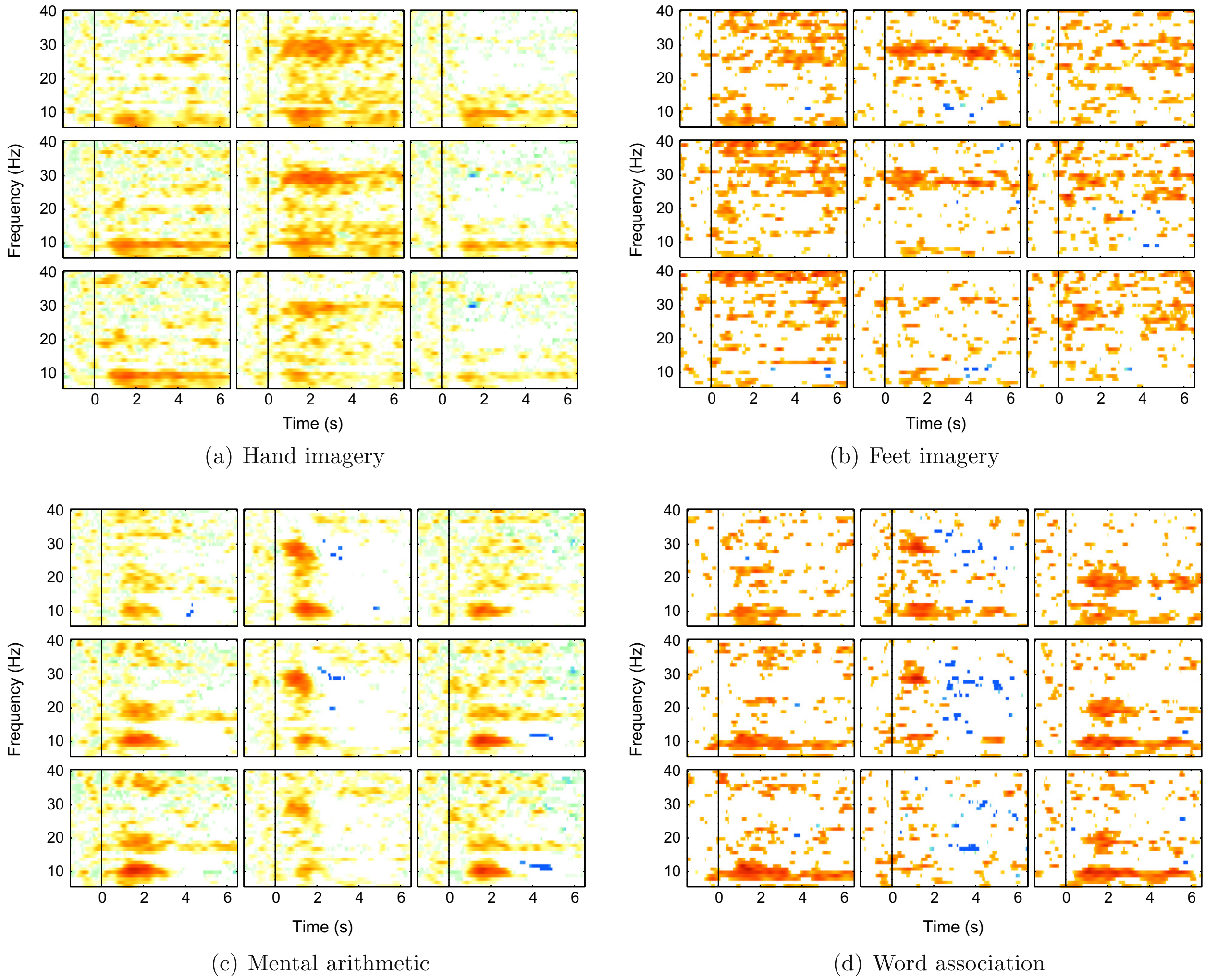


Fig. 2. Examples of SMRs, from a user with relatively clean EEG, relating to each condition, (hands/ feet imagery, mental arithmetic, and word association). Each plot is split into 9 subplots illustrating the common average referenced channels FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, and CP4. Red colours indicate significant periods of ERD and blue significant periods of ERS. Significance is determined via the bootstrapping approach described in Graimann et al. (2002). The vertical line at 0 s denotes the cue presentation time. (For interpretation of the references to colour in this figure caption, the reader is referred to the web version of this article.)

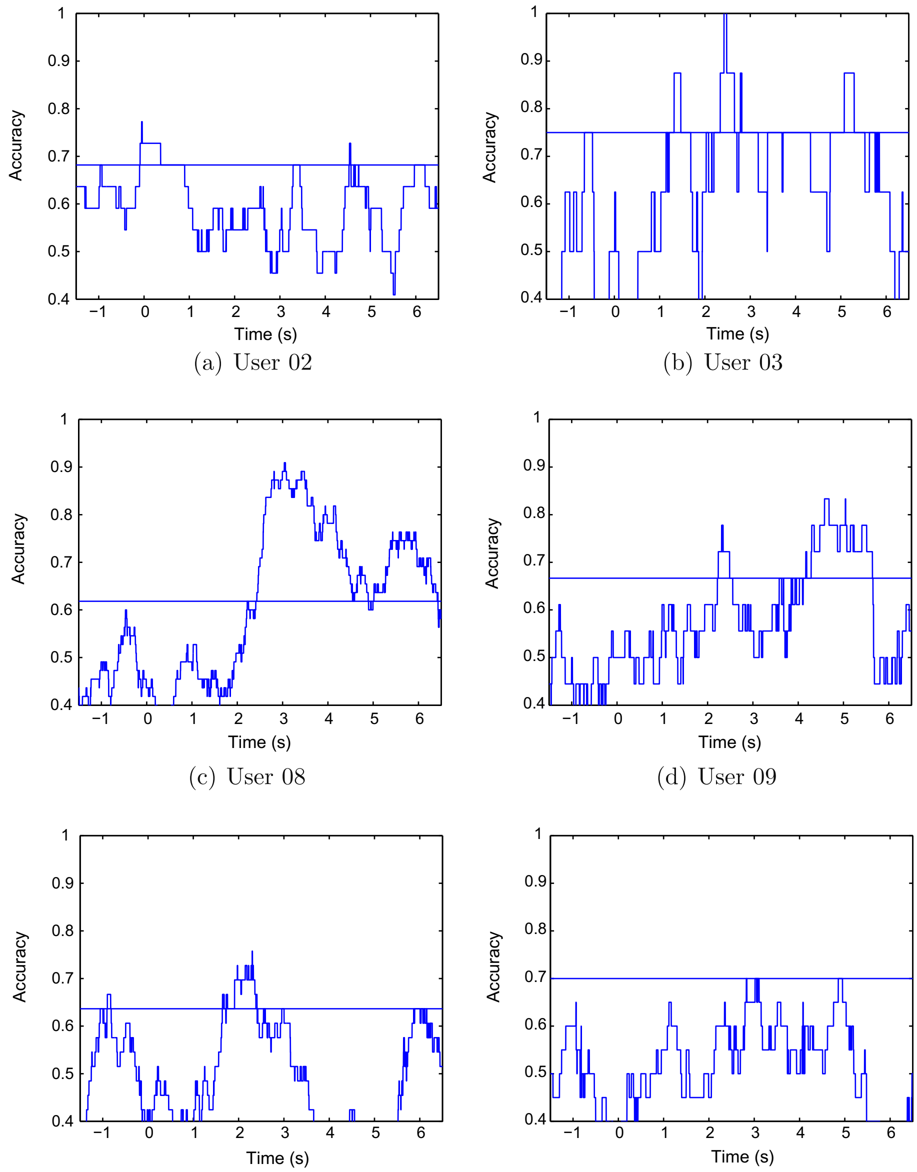
Other issues encountered during measurements include EMG, head movement, electrode pops (short lasting sharp amplitude changes caused by movement of the electrode), EOG, and eye blink artifacts, which are frequently observed, although this varies considerably between users. Users with spasticity exhibited considerably more EMG artifacts in their EEG than users without. However, correlation analysis between classifier outputs and automatically detected artifacts revealed statistically significant classification accuracy was based upon artifacts in only 1 case.

No formal survey of user experiences was conducted in this study. This was due to two reasons (1) many of the users became tired quickly and an additional survey conducted before, during, or after the measurements would have been an additional source of fatigue and (2) the users exhibited widely differing abilities to communicate (from normal speech to eye gaze communication via letter boards) which were prohibitive to attempts to administer a formal survey.

Many users became fatigued during use of the BCIs. This could, in part, be resolved by a more engaging paradigm. In particular some users complained that the mental arithmetic task was particularly difficult and the SSVEP stimuli were "annoying". This may be contrasted with the motor imagery tasks which were described by some users as "enjoyable". A proposed solution is the use of context aware BCIs, as proposed in Zander and Jatzev (2012) and Scherer et al. (2012), in which the BCI is augmented by additional information relating to the subject and/or environment (e.g. measures of subject engagement).

Analysis of the relationship between subject details and performance with the SSVEP and SMR BCIs reveals a significant relationship between subject gender and their performance with the online SMR BCI. However, it's worth noting that only 10 of the 14 subjects were able to attempt online control of the SMR BCI. Of these 10 users 5 were male and the females achieved higher classification accuracies. However, with only 10 subjects and differing numbers of trials over subjects (no significant difference was found in the number of trials between males and females, ($p = 0.852$), paired t-tests) it is not, at this stage, clear how generalisable this finding is to a wider population of individuals with CP. Future work will explore whether further statistical relationships emerge with more subjects.

The results reveal that not all approaches work for every user. Indeed, 6 of the 14 users can control the SMR BCI at above significant levels of accuracy and 3 can control the SSVEP BCI at above significant levels of accuracy, with one user overlap. This leaves 6 users who could not control either BCI at a statistically significant level.



(a) User 02 (b) User 03 (c) User 08 (d) User 09 (e) User 11 (f) User 14

Fig. 3. Online classification accuracies achieved by users who were able to achieve statistically significant ($p < 0.05$) classifier accuracies when attempting online control of an SMR based BCI and for whom there is not a significant correlation betwen classifier results and artifacts. Times are listed relative to the cue presentation time (denoted by the veritical dashed line) and the horizontal solid line illustrates the significance level at ($p < 0.05$). Note, the position of this line varies dependent upon how many trials each user completed in the feedback phase.

This finding may be considered alongside a large meta-analysis performed by Kübler and Birbaumer (2008) in which the efficacies of three different types of BCI for use as communication and control devices with a range of patient populations were assessed. The three BCIs assessed were SMR, slow cortical potential, and ERP based BCIs. Individuals with spinal cord injury, amyotrophic lateral sclerosis, brain stem stroke, multiple sclerosis, traumatic brain injury, and post-anoxic encephalography were considered. Subjects were ranked in terms of impairment and no statistical relationship was found between their performance and their degree of impairment when completely locked in subjects were excluded from the analysis.

Our results also show that for the individuals with CP involved in our study no statistical relationship was found between the degree of impairment and their ability to control a BCI. Thus, our findings add to and support those reported in Kübler and Birbaumer (2008).

When considering the performance of the SSVEP paradigm the result is somewhat surprising. SSVEP accuracies are generally relatively high when compared to other BCI paradigms. For example, Allison et al. (2010) reports a mean accuracy of 91.85% over 106 healthy subjects using an SSVEP BCI. However, when one considers the particular conditions of individuals with CP, in particular that a number of individuals exhibit spasticity and have problems controlling their neck muscles or require head rests, it is not so surprising that this particular user group exhibits considerably lower accuracies with the SSVEP task then might be expected from healthy subjects, or even other BCI target user groups.

Ultimately, the large degrees of differences in individual needs and results achieved indicate that BCIs need to be tailored to meet each user's needs and requirements. Doing so offers the possibility of producing BCIs which could be controlled by a number of individuals with CP. However, the results at this stage ultimately indicate that providing BCIs that are useful as assistive devices to this

Table 5
Online peak classification accuracies (Peak acc.), in the period 2–6 s relative to the cue, for control of the SMR based BCI by each user and corresponding *p*-values against the null hypothesis of equal chance of each of the 2 classes selected for online control been classified. Statistically significant peak accuracies are indicated via asterisks (*). Note, after application of Bonferroni correction the statistical significance threshold is adjusted from $p < 0.05$ to $p < 0.005$. Mean accuracies and their significance, as evaluated via the bootstrapping method, are also listed. The Pearson's correlation coefficient, and corresponding significance level, between the classifier output and automatically identified artifacts are also listed. HR denotes the hit rate; the percentage of trials for which the user achieved the goal of displaying a smiley face on screen. The trials column lists the numbers of trials performed by each user in the feedback condition. The final column lists which classes were selected for use in the online feedback phase, feet (F), hands (H), word association (W), or mental arithmetic (M). Note, rows left empty indicate users who elected to halt BCI training before sufficient artifact free trials had been gathered to train the classifier.

	Classification					Correlation				
User	Peak acc.	*p*		Mean acc.	$p < 0.01$	R	*p*	HR	Trials	Selected classes
01	0.667	0.008	*	0.541	*	−0.144	0.000	48.9	46	F/ M
02	0.727	0.008	*	0.568	*	0.004	0.168	63.6	23	F / W
03	1.000	0.000	*	0.695	*	0.004	0.319	87.5	9	F/ W
04	–	–	–	–	–	–		–	–	–
05	0.571	0.192		0.464		0.002	0.405	38.1	22	F/ W
06	–	–	–	–	–		–	–	–	–
07	–	–	–	–	–		–	–	–	–
08	0.909	0.000	*	0.699	*	0.002	0.152	100.0	56	H / M
09	0.833	0.001	*	0.627		0.003	0.238	27.8	19	F/ M
10	–	–	–	–	–		–	–	–	
11	0.757	0.001	*	0.498		0.002	0.284	48.5	34	F/ M
12	0.806	0.000	*	0.621	*	−0.022	0.000	100.0	32	H/ W
13	0.682	0.067		0.489	*	0.000	0.902	45.5	23	F/ H
14	0.700	0.021	*	0.520	*	0.002	0.547	65.0	21	F / W

user group presents a significant challenge. Nevertheless, the fact that BCI control was achieved by some naive untrained individuals with CP is an encouraging initial finding.

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Appendix D

Core publication (4)

A Co-Adaptive Brain-Computer Interface for End Users with Severe Motor Impairment

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Abstract

Co-adaptive training paradigms for event-related desynchronization (ERD) based brain-computer interfaces (BCI) have proven effective for healthy users. As of yet, it is not clear whether co-adaptive training paradigms can also benefit users with severe motor impairment. The primary goal of our paper was to evaluate a novel cue-guided, co-adaptive BCI training paradigm with severely impaired volunteers. The co-adaptive BCI supports a non-control state, which is an important step toward intuitive, self-paced control. A secondary aim was to have the same participants operate a specifically designed self-paced BCI training paradigm based on the auto-calibrated classifier. The co-adaptive BCI analyzed the electroencephalogram from three bipolar derivations (C3, Cz, and C4) online, while the 22 end users alternately performed right hand movement imagery (MI), left hand MI and relax with eyes open (non-control state). After less than five minutes, the BCI auto-calibrated and proceeded to provide visual feedback for the MI task that could be classified better against the non-control state. The BCI continued to regularly recalibrate. In every calibration step, the system performed trial-based outlier rejection and trained a linear discriminant analysis classifier based on one auto-selected logarithmic band-power feature. In 24 minutes of training, the co-adaptive BCI worked significantly ($p = 0.01$) better than chance for 18 of 22 end users. The self-paced BCI training paradigm worked significantly ($p = 0.01$) better than chance in 11 of 20 end users. The presented co-adaptive BCI complements existing approaches in that it supports a non-control state, requires very little setup time, requires no BCI expert and works online based on only two electrodes. The preliminary results from the self-paced BCI paradigm compare favorably to previous studies and the collected data will allow to further improve self-paced BCI systems for disabled users.

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Introduction

Performing specific mental tasks such as movement imagery induces spatio-spectrally specific power decreases (event-related desynchronization, ERD) and increases (event-related synchronization, ERS) in oscillatory bio-electrical activity as measured by the electroencephalogram (EEG) [1,2]. ERD-based brain-computer interfaces (BCIs) use machine learning techniques to translate patterns of such power changes into control signals [3]. This form of direct communication between brain and environment does not rely on the typical muscular output pathways of the body and can hence serve as assistive technology for individuals with severe motor impairment [4–7]. Intuitive, on-demand BCI control, independent of system cues has previously been demonstrated in healthy [8] and disabled users [9,10] using self-paced BCI systems. For self-paced operation, the BCI ideally detects whether the user is in a state where s/he intends to convey commands ("control state") or not ("non-control state"). The BCI then triggers commands only in the control state.

ERD-based BCIs can be a promising assistive technology. Their operation, however, is a skillful action that can require a varying amount of training [11]. The typical approach to setup ERD-based BCIs is to first (1) record EEG while the user performs specific mental tasks in a cue-guided paradigm. A BCI expert then (2) trains a statistical classifier based on the collected data. This classifier is then used to (3) provide feedback during an online training session. To attain effective BCI control using a small number of electrodes (e.g. less than 16), it is common to analyze the data from online sessions and to re-train classifiers over multiple sessions. Through this feedback training, the user ideally learns to produce better discriminable patterns of brain activity. This method has been shown to be effective ([4,5,7,9]), but takes time and can be strenuous for the user. Using a high number of electrodes with this conventional training approach can lead to highly effective ERD-based control in only one day of training in able-bodied users ([12]), but is slightly less practical due to the longer setup time.

Co-adaptive ERD-based BCIs on the other side, typically provide feedback for the user's brain-activity as early as possible and continuously adapt the underlying classifier model. In healthy individuals, co-adaptive ERD-based BCIs have proven highly effective both using a low (c.f. [13–15]) and a high number of EEG electrodes (c.f. [16]). To a limited extent, co-adaptive ERD-based BCIs have also been shown to be effective for users with severe motor impairment [5,17,18].

As of yet, there is no previous work that evaluates the suitability of auto-calibrating and co-adaptive training approaches, to establish ERD-based BCI control for a representative sample of novice users with severe motor impairment. In particular, no previous work in this research direction involved a non-control state which is an important step toward intuitive self-paced operation. Leeb and colleagues ([7]) trained 24 users with motor impairment in a conventional cue-guided paradigm over a maximum of ten sessions, so that half of the users were eventually able to control a spelling application or a tele-presence robot. Among other things, the authors identified auto-calibration and a non-control state especially for self-paced operation as important future research directions. Previous publications about self-paced operation in users with motor impairment were mostly case-studies using conventional, non-automated setup protocols, that required a BCI expert and training over a number of sessions [9,10,19].

Our primary aim in this work is to evaluate the effectiveness of a cue-guided, auto-calibrating and online re-calibrating ERD-based BCI training paradigm with a large group of 22 (20 novice) users with severe motor impairment. The BCI requires only six scalp electrodes overlaying the sensorimotor cortex and provides real-time feedback based on only two of these electrodes. The system starts collecting cue-guided mental activity for movement imagery of left and right hand and a non-control class. After approximately five minutes the system auto-calibrates and proceeds to provide visual online feedback for classifying the non-control state against the movement imagery of the particular hand that allowed for higher statistical discriminability. As a secondary aim we want to present preliminary results from a specifically designed self-paced training paradigm that is based on a low-bandwidth user interface adapted from literature [20].

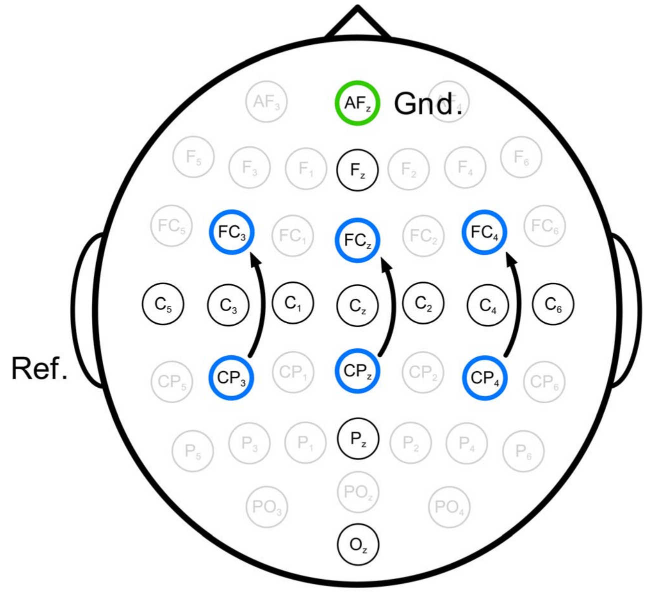

Figure 1. Recorded scalp electrode positions. The three bipolar derivations, indicated by the arrows were considered by the co-adaptive BCI. Feedback was provided from only one of these bipolar derivations. The bipolar derivation selected in the last re-calibration, was also used for the self-paced paradigm. The black circles mark electrodes, recorded for future analyses. The reference electrode was at the left ear-lobe (Ref.) and the ground electrode at AFz (Gnd.).
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Methods

Recording setup

Six EEG channels were recorded for the BCI. Ten additional channels were recorded for later offline analysis (not presented in this paper). The active electrodes were placed according to the 10/20 System of Electrode Placement (see Figure 1). The signal was sampled at 256 Hz with a band pass filter between 0.5 and 100 Hz and a notch filter at 50 Hz. A biosignal amplifier (g.tec Medical Systems, Graz, Austria) was used for recording.

Participants

Twentytwo volunteers with severe motor impairment participated in our study (age 37.8 $\pm$ 16.0 (SD) years; six female). All participants suffered from motor impairment in all four extremities. The medical conditions were either cervical spinal cord injury (SCI; ASIA A to D according to [21]), polyneuropathy, traumatic brain injury (TBI) or multiple sclerosis (MS). See Table 1 for details. Participant P18 suffered from paralysis of the right eye. All other end users had normal or corrected to normal vision. Participant P17 was in "Locked-in State" according to the definition in [22]. All measurements were conducted at the Institut Guttmann Neurorehabiliation Hospital (Barcelona, Spain). The study, including the measurement protocol and the consent procedure were approved by the local ethics board, "Comitè d'Ètica Assistencial de l'Institut Guttmann". All participants gave informed, oral consent. In addition, written consent was obtained for every participant. The signed consent forms are stored with the participants' clinical files. In many cases, written consent had to be provided by the participants' legal representatives as many participants were not able to write due to tetraplegia. The participants were instructed in person by caregivers with the support of presentation slides as briefing material.

Data collection

We recorded all EEG data in segments ("runs"). One run lasted one to seven minutes. See Figure 2 for an overview. For the co-adaptive paradigm we collected four runs of data (six minutes per run). There were 36 trials per run and 144 trials total for two classes per participant. For the self-paced paradigm, we recorded three runs of data. The first of these three runs was one minute long and was used to automatically adapt the bias of the classifier. The other two runs were seven minutes long. Two participants (P04 and P10) did not participate in the measurements for the self-paced paradigm.

Co-adaptive BCI paradigm

The co-adaptive paradigm started collecting data trials for one non-control class and two movement imagery classes (see Figure 3, Panel (A) and (B)). Cues were presented as audio-playback of spoken words and large, well discernible visual shapes, to make the paradigm usable for individuals with visual impairment. Every trial started with a reference period where a white cross was displayed from second zero to two. For this time, participants were instructed to visually fixate the white cross and relax with eyes open.

The visual and audible cue for one of initially three classes was presented at second two. The sequence of cues was random: The class *non-control* was indicated by a white cross and the spoken word "relax". For this class, participants were instructed to continue to relax with eyes open and to focus on the white cross. For class *left* and *right*, the participants were instructed to sustain kinaesthetic movement imagery (palmar grasp, [23]) of the left or the right hand over the whole imagery period until second seven. The two

Table 1. Information about the severely impaired participants.

User	Age	Sex	Hand dominance	Months since injury	Medical Condition	Disability
P01	66	F	Right	8	Guillain-Barré syndrome	Tetraparesis
P02	21	M	Right	2	SCI C4, ASIA A	Tetraplegia
P03[a]	46	M	Right	24	SCI C4, ASIA A	Tetraplegia
P04	19	M	Right	6	SCI C3, ASIA A	Tetraplegia
P05	39	M	Right	19	SCI C6, ASIA A	Tetraplegia
P06	45	M	Right	3	SCI C7, ASIA C	Tetraplegia
P07	60	M	Right	4	Brain Anoxia	Tetraplegia
P08	25	M	Right	11	SCI C4, ASIA A	Tetraplegia
P09	19	M	Left	5	SCI C4, ASIA B	Tetraplegia
P10[a]	43	F	Right	280	SCI C4, ASIA A	Tetraplegia
P11	21	M	Right	6	SCI C5, ASIA B	Tetraplegia
P12	65	F	Left	4	SCI C1, ASIA C	Tetraplegia
P13	38	M	Right	3	SCI C4, ASIA D	Tetraplegia
P14	19	M	Right	66	SCI C4, ASIA A	Tetraplegia
P15	47	M	Right	12	SCI C7 and TBI, ASIA A	Tetraplegia
P16	42	M	Right	147	SCI C6, ASIA A	Tetraplegia
P17	23	M	Right	6	TBI	Locked-in state
P18	34	F	Right	74	Multiple Sclerosis	Tetraplegia
P19	28	M	Left	5	TBI & brachial plexus injury	Tetraparesis
P20	24	F	Right	64	SCI C2, ASIA A	Tetraplegia
P21	41	F	Right	9	Hemorrhagic stroke	Tetraplegia
P22	66	M	Right	15	Polyneuropathy	Tetraparesis
Mean	37.8			35.1		
SD	16.0			64.9		

The participants are sorted by co-adaptive BCI performance. The superscript "a" marks the two participants who had used ERD-based BCIs before. TBI stands for traumatic brain injury. Functional scoring for spinal cord injury (SCI) is according to the American Spinal Injury Association (ASIA, [21]).
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classes were indicated by a left and right pointing arrow and the audible cues were the spoken words "left" and "right". No feedback was provided during the "initial calibration phase". In the background the system continuously identified artifact-congested trials in two steps: First by thresholding amplitude, kurtosis and probability of the band-filtered EEG [24] and second, by identifying trials where at least one feature is an outlier to the distribution of the values for all other trials [15].

As soon as nine artifact-free trials per class (TPC) were available, the system trained one linear discriminant analysis (LDA) classifier for class *left* against class *non-control* and another one for class *right* against class *non-control*. For each classifier, the system chose one of six logarithmic band power features ($\mu=[9,13]$ Hz and $\beta=[16,26]$ Hz from the bipolars at C3, Cz and C4). The BCI then selected the one MI class with higher cross-validation classification performance against class *non-control* and proceeded to provide continuous, real-time visual feedback only for these two classes for the rest of the measurement (see Figure 3, Panel (C)).

In this "online phase", the system continued to perform trial-based outlier rejection and re-calibrated the system whenever five new artifact-free TPC were available (see Figure 3, Panel (A)). In every calibration step, the system also trained an autoregressive (AR) filter model (order 11) on all artifact-free trials. See Appendix A for more details on the calibration procedure and how the

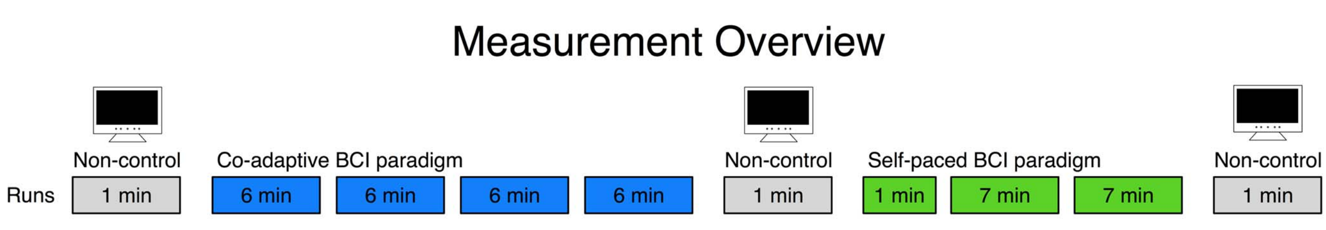

Figure 2. Overview of the measurement procedure. The runs colored in blue were recorded with the co-adaptive paradigm (see Figure 3). The runs colored in green were recorded with the self-paced paradigm (see Figure 4). During the non-control runs, we recorded EEG while participants relaxed with eyes open looking at a black screen. These non-control runs are not analyzed in this paper.
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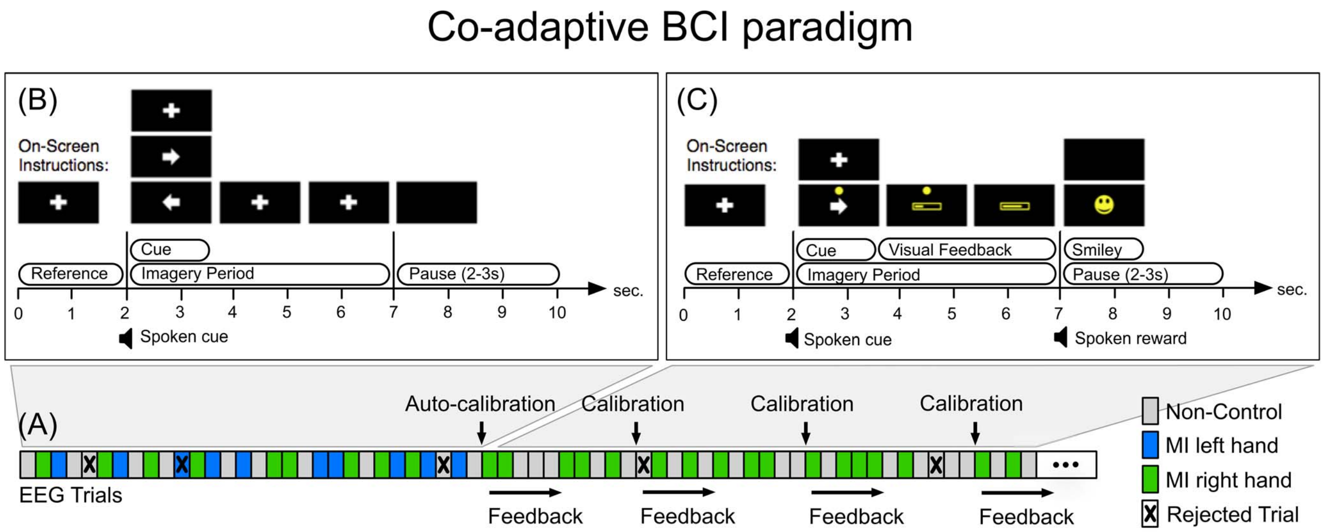

Figure 3. Schematic description of the co-adaptive BCI paradigm. Panel (A) shows how the system initially collected trials for three classes *non-control*, *left* and *right* hand movement imagery (MI left/right hand). Panel (B) shows the trial structure for the "Initial calibration phase". After nine "artifact-free" trials per class (TPC) were collected the system auto-calibrated, selected one of the hand MI classes and continued to provide visual, real-time feedback. Panel (C) shows the trial structure for the "Online phase". The system re-calibrated whenever five new artifact-free TPC were available.

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created classifier model was used in the self-paced BCI training paradigm.

During online operation, the system then applied the inverse transfer function of the AR filter to the EEG and thresholded the residual (prediction error) to detect artifactual activity in real-time [25]. Whenever artifactual EEG was detected, the system displayed a yellow dot (see Figure 3, Panel (C)). The yellow dot, remained on display for 0.5 s after offset of artifact detection. The end users were instructed to try to avoid any activity that would produce EEG artifacts.

To maximize the training effect and motivation in our group of mostly novice users, we only provided positive feedback between second 3.75 and 7 [15,26,27]. Specifically, only when the class-label predicted by the LDA matched the true class-label, a yellow feedback bar was displayed within the yellow rectangle seen in Figure 3, Panel (C). The yellow bar extended in length from left to right in proportion to the LDA distance. The users were instructed to try to extend the bar as far as possible. Whenever the predicted class-label did not match the true class-label of the cue, the yellow rectangle stayed empty.

If the predicted class-label and the true class-label matched for longer than a total time of two seconds between second three and seven, the system displayed a smiley and played an audio recording saying "excellent" starting with the pause at second seven. The length of the pause was random between two and three seconds.

Self-paced BCI paradigm

The self-paced paradigm was based on a validated low-bandwidth input user interface (UI) used in a very similar form in the assistive technology prototype BrainAble [20,28,29] (see Figure 4). It typically displays around six menu items in a circular arrangement of segments. An arrow points from the center of the user interface toward one segment at a time. The head of the arrow rotates clockwise around the center so that it takes four seconds to rotate over one segment. The length of the arrow stays at a fixed short length in case the non-control class is detected. The arrow grows proportional to the LDA distance in case movement imagery is detected. When the arrow length exceeds a predefined threshold, the arrow turns red. Keeping the arrow above the threshold for a certain uninterrupted period of time would usually trigger a selection of the menu item in the segment that the arrow is pointing at.

To evaluate the efficacy of this self-paced BCI training paradigm in a reliable and controlled way, we had to instruct the participants as to which menu items to select. We therefore displayed dynamically updated instructions in a dialog box above the UI (see Figure 4). The next target was determined randomly to be two to five segments clockwise after the last target item or the position of the arrow at the beginning of the run. We found this setup to be closest to the real-world case where the user decides autonomously which item to select. The participants were instructed to look at the screen and do nothing, whenever the arrow was pointing to a segment other than the target. For when the arrow was pointing to the target segment, participants were instructed to perform the previously trained movement imagery (either right or left hand).

To improve motivation [15,26,27] and to avoid inducing EEG non-stationarities as a result of "perceived loss of controllability" [30], we displayed the actual feedback only when the arrow was pointing to a target segment. When the arrow was pointing at non-target segments we displayed artificially generated feedback, where arrow length varied with gaussian noise around a length below the activation threshold. For target segments, the users always had full control. For every uninterrupted full second users managed to extend the arrow beyond the activation threshold they scored one point (maximum of four possible). If the users scored at least one point, the paradigm stopped for three seconds at the end of the segment and displayed the points in the instruction panel as seen in Figure 4, Panel (C).

Evaluation

For the co-adaptive paradigm we computed the accuracy for every sample point between second three and seven in the trial and

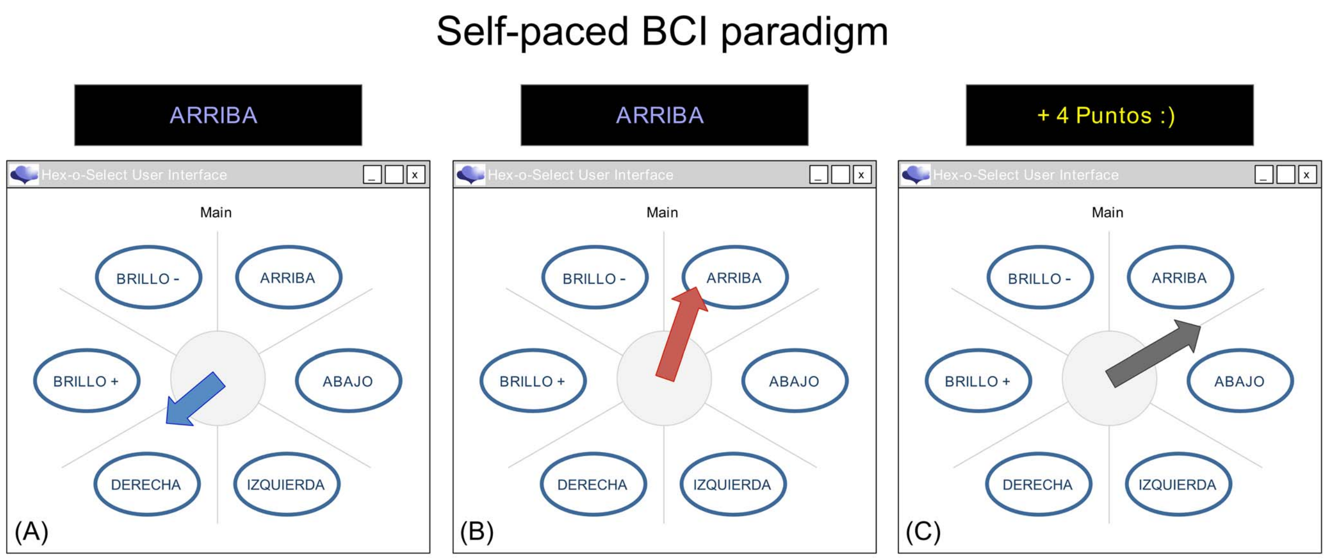

Figure 4. The self-paced BCI paradigm in different states of operation. The head of the arrow was generally rotating clockwise around the center. Panel (A) shows how the arrow is short and colored in blue, whenever class *non-control* is detected. The dialog above the window indicated the next target item. Panel (B) shows how the arrow changed its color to red, when movement imagery was above the activation threshold. The user scored one point for every second the arrow stayed above this threshold in a target segment. Panel (C) shows how the user received feedback if s/he scored at least one point. In this case the arrow stopped rotating and turned grey. After a refractory period of three seconds the paradigm returned back to the initial state depicted in Panel (A).
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report the peak value. To compare with results in literature, we also computed the Youden index [31] as the difference between true positive and false positive rate at an optimized threshold and dwell-time (range 0.5 to 4 s in steps of 0.5 s). The Youden index ranges from -1 (all targets missed, all non-targets hit) to +1 (all targets hit, all non-targets missed). We identified better than chance performance by comparing to confidence intervals around the theoretical chance level [32]. The threshold level of chance accuracy was 61.0 % (54 TPC; $p = 0.01$) for the co-adaptive paradigm.

For computing accuracy in the self-paced paradigm we considered true positive (TP), false positive (FP), true negative (TN) and false negative (FN) events. We counted one activation whenever the arrow was continuously extended above threshold for one second. Activations that were triggered while the arrow was pointing at the current target segment were counted as TP. All other activations were counted as FP. Notice, FP activations were not displayed to the user during online operation. If there was no activation throughout a segment, we counted one FN activation in case of a target- and one TN activation in case of a non-target segment. From all segments on average 31.2% were targets, the rest were non-targets. For computing accuracy we corrected the confusion matrices for this class imbalance so that the theoretical chance level was 50%. We conservatively computed the level of statistically significant ($p = 0.01$) chance accuracy based on the number of target segments for every end user. For statistical comparisons with results from literature we used undirected t-tests for independent samples.

Results

The co-adaptive paradigm worked with a peak online accuracy of 68.6 $\pm$ 8.2 (SD) %. The performance for 18 of 22 participants was significantly better than chance ($p = 0.01$). Figure 5 shows the overall peak accuracies as blue dots and the peak accuracies within the session as grey dots. In addition, the figure shows the evolution of feature separability as measured by the Fisher criterion over the recording session for every end user. The system auto-selected the classes *left* and *right* hand movement imagery equally often. From the 50% of end users who scored the highest online accuracy 8 of 11 were using *right* hand movement imagery. Figure 6 shows which features were most dominant in the final calibration step. We found Beta-Cz to be most dominant, followed by Beta-C3, Mu-C3, Beta-C4, Mu-C4 and Mu-Cz. Figure 7 shows exemplary power spectra for the three users, for whom the system worked most effectively. Two end users did not participate in the measurements for the self-paced paradigm. For the other 20 participants, we individually corrected the confusion matrices for class imbalance and found an overall accuracy of 64.4 $\pm$ 11.0 (SD) %. The accuracies were significantly higher than chance ($p = 0.01$) in 11 of 20 end users. Table 2 shows detailed results for both paradigms including the accuracies from the corrected confusion matrices for the self-paced paradigm.

Discussion

Effectiveness of the cue-guided, co-adaptive paradigm

The co-adaptive paradigm effectively provided better than chance online feedback for the majority (81.8%) of a representative sample of mostly novice severely disabled end users diagnosed with SCI, TBI, polyneuropathy or MS. The system used only two electrodes for online control. At least in healthy users, we previously found that scalp locations with relevant features tend to stay the same between sessions for the same individual [15]. Future training protocols could hence use six electrodes in the first session and mount only the two most relevant electrodes in consecutive sessions. As to feature relevance: Beta features were dominant for most of the users in the final calibration step. Mu features were mostly relevant at position C3; less at the positions C4 and Cz. Features from position C4 were dominant least frequently. We speculate that the factor handedness (19 from 22 users were right handed) might have influenced this outcome. The

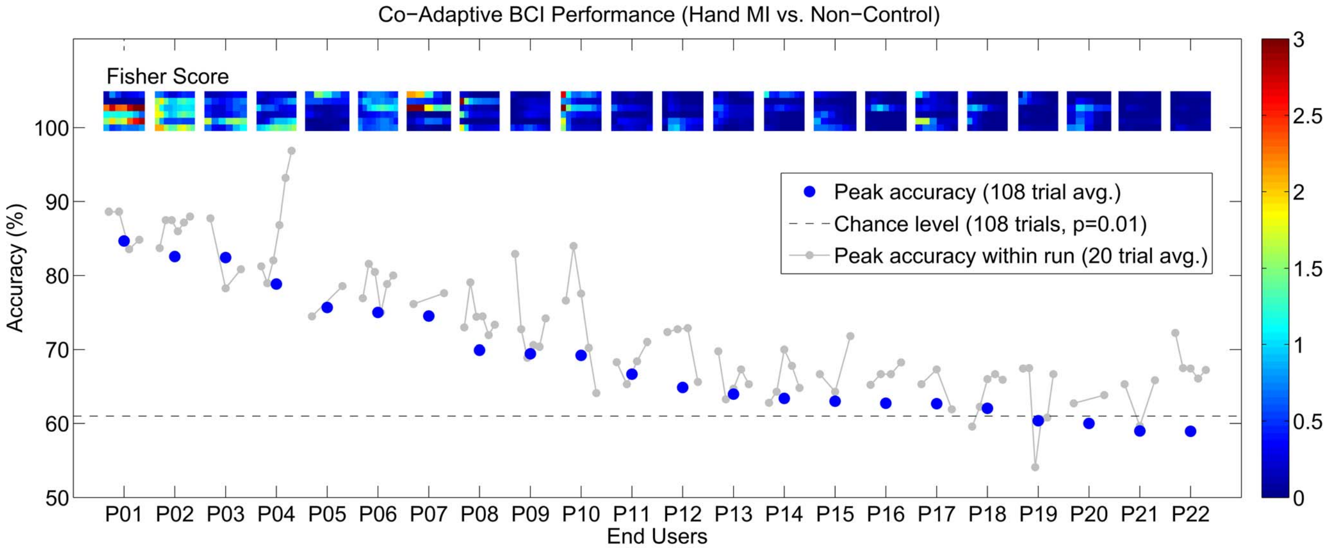

Figure 5. Online performance for all 22 end users. The blue dots show the overall peak accuracy, while the grey dots depict within session performance. The color coded maps show the Fisher criterion [48] over time (left to right) for the features μ_{C3}, β_{C3}, μ_{Cz}, β_{Cz}, μ_{C4} and β_{C4} (bottom to top).
doi:10.1371/journal.pone.0101168.g005

exemplary spectra for the three most successful users in Figure 7 look as expected, and show how decreases in sensorimotor rhythm power were used to control the BCI systems.

Comparing to cue-guided, co-adaptive paradigms in healthy users

Vidaurre and colleagues ([13]) presented a highly effective, co-adaptive ERD-based BCI that used 6 electrodes in tests with 12 healthy, novice volunteers. Correcting for statistical chance ($p = 0.01$) [32] we found our co-adaptive paradigm to work on average 6.7% better than chance (22 end users, none rejected, 20 BCI-novice). The BCI of Vidaurre and colleagues worked on average 11.6% better than chance (12 users, 3 rejected). Even though, this rejection of participants likely skewed the results in favor of the BCI in Vidaurre et al., there is still no significant difference between the results ($p = 0.099$). This result is highly encouraging, as it indicates that a co-adaptive BCI that supports a non-control state and uses only two electrodes online can work in severely disabled end users with an accuracy comparable to a slightly more complex system in healthy users.

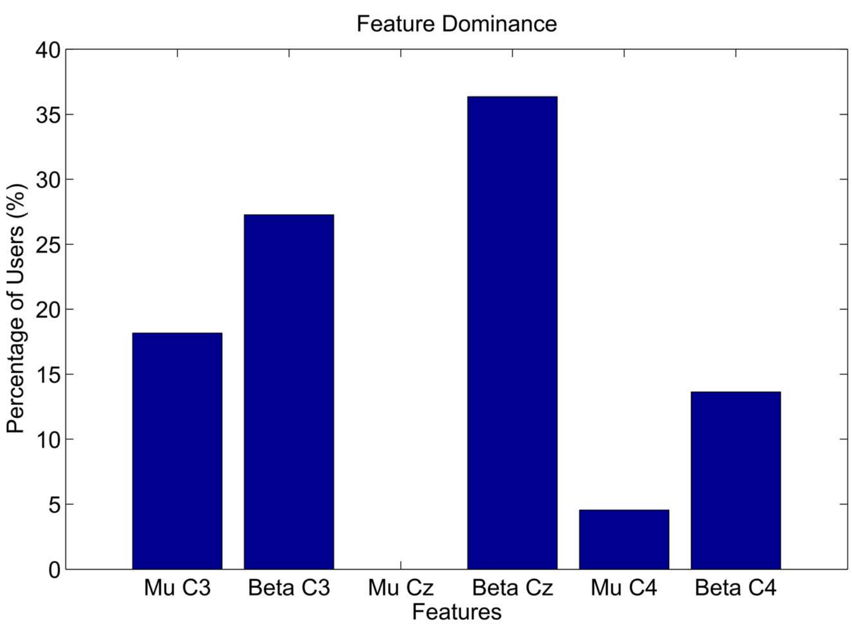

Figure 6. Feature dominance after calibration. Shows for what percentage of users, the different logarithmic band-power features were selected in the final classifier calibration step.
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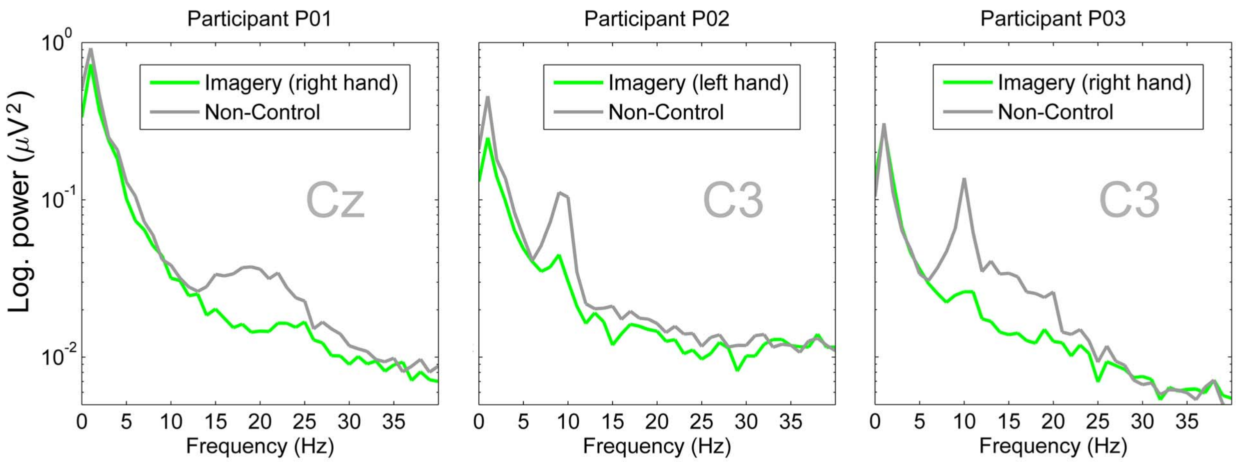

Figure 7. Overview of power spectra. The three panels show power spectra for the three participants for whom the BCI system worked most effectively. For participant P01 and P03, the system selected the β-feature and for participant P02 the α-feature. Here, all three users control the system by causing oscillatory power of the sensorimotor rhythms to decrease (event-related desynchronization, c.f. [2]).
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Table 2. Detailed results for both paradigms.

	Co-adaptive BCI				Self-paced BCI
User	**Acc. (%)**	**Youden index**	**Selected MI**	**Feature**	**Acc. (%)**
P01	84.7*	0.773	Right	β_{Cz}	94.2*
P02	82.6*	0.715	Left	μ_{C3}	75.6*
P03[a]	82.4*	0.686	Right	β_{C3}	82.1*
P04	78.8*	0.573	Right	μ_{C3}	61.8*
P05	75.7*	0.373	Left	β_{C4}	50.2
P06	75.0*	0.542	Left	β_{Cz}	
P07	74.5*	0.518	Right	β_{Cz}	
P08	69.9*	0.252	Right	μ_{C4}	58.5
P09	69.4*	0.356	Right[b]	β_{Cz}	73.4*
P10[a]	69.2*	0.401	Right	β_{Cz}	69.8*
P11	66.7*	0.218	Right	μ_{C3}	75.1*
P12	64.9*	0.227	Left[b]	β_{C3}	51.8
P13	64.0*	0.258	Left	β_{C4}	63.4*
P14	63.4*	0.268	Right	β_{C4}	62.9*
P15	63.0*	0.120	Right	μ_{C3}	59.4
P16	62.7*	0.286	Left	β_{C4}	53.3
P17	62.7*	0.152	Left	β_{C3}	55.3
P18	62.0*	0.048	Left	β_{Cz}	58.2
P19	60.4	0.188	Left[b]	β_{C3}	63.3*
P20	60.0	0.299	Left	β_{Cz}	59.2
P21	59.0	0.130	Right	β_{C3}	61.2*
P22	58.9	0.144	Left	β_{C3}	58.8
Mean	68.6	0.342			64.4
SD	8.2	0.208			11.0

The accuracies for the self-paced paradigm were corrected for class imbalance, so that results are comparable. The superscript "a" marks the two end users who had previously used ERD-based BCIs. The asterisks indicate significantly better than chance (p = 0.01) accuracy. The superscript "b" marks left-handed users. MI stands for motor imagery and Acc. abbreviates accuracy.
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Comparing to cue-guided paradigms in users with motor impairment

Leeb and colleagues ([7]) validated a conventional ERD-based BCI training protocol with 24 end users (11 with tetraplegia) in a maximum of ten training sessions. The authors discuss, how auto-calibrating and co-adaptive training approaches could expedite BCI setup. Based on their findings, the authors continue to explain how allowing for a non-control state "becomes essential for mentally operating devices over long periods". Our system implements these thoughtful propositions in that it offers a non-control state, automatically selects the most effective class-combination during auto-calibration and regularly re-calibrates online. The system presented by Leeb and colleagues reached a high Youden index above 0.4 for 41.7% of end users after a maximum of ten training sessions. Our co-adaptive system performed above the same threshold for 31.8% of end users after 24 minutes of training. That means less users reached the same performance threshold with our system in the first session. Still, our system advantageously complements this existing, effective approach, as it offers a non-control state and completely removes the requirement for a BCI expert (even for calibration). After the caregiver mounts the six electrodes and starts the system, users can typically train with real-time feedback based on two electrodes after less than five minutes. Based on literature we would also expect performance of the co-adaptive paradigm to improve over multiple training sessions [5,13,15].

Comparing to cue-guided paradigms in users with SCI

Pfurtscheller and colleagues ([33]) recorded 16 EEG channels from 8 para- and 7 tetraplegic individuals with SCI at lumbar ($N_L = 1$), thoracial ($N_{Th} = 7$) and cervical ($N_C = 7$) level who were instructed to perform three types of movement imagery in a cue-guided paradigm. Using manual outlier rejection and common spatial patterns (CSP, [34]), the authors found the highest offline classification accuracy between movement imagery of the left hand and both feet. We used these results for comparison. Correcting for statistical chance [32] we found the system in Pfurtscheller et al. to perform 8.2% better than chance (80 TPC; $p = 0.01$), while our co-adaptive system performed 7.9% better than chance (15 users with SCI; 54 TPC; $p = 0.01$). We found no significant performance difference ($p = 0.943$). This result is encouraging as Pfurtscheller and colleagues discuss how their approach was successful with only one of the tetraplegic users. Our co-adaptive system worked better than chance for 14 of 15 tetraplegic end users. Our system classified based on 2 instead of 16 electrodes and automatically provided online feedback after less than five minutes. Our system did further not require manual artifact rejection, feature selection, classifier training or any other interaction of a BCI expert. Most importantly our system supports a non-control state which is important for intuitive, self-paced interaction.

Conradi and colleagues ([35]) calibrated an ERD-based BCI using CSP on 30 minutes of high density EEG (64 electrodes) from 7 BCI-novice individuals with cervical SCI at ASIA levels A or B. The authors found discriminable ERD patterns in four of the participants, computed classifiers and proceeded to record online feedback runs. In the condition "cursor on", which is most similar to our setup the system worked at 67.7% accuracy (computed as the weighted average of accuracy values in Table 1 in [35]). For our sample of 15 users with SCI (13 BCI-novice; none excluded, ASIA A or B, three with C or D) we found a comparable average online accuracy of 69.9 $\pm$ 7.4 (SD) %. In comparison, our system does not deliver much higher performance, but our implementation complements the existing, effective approach in other ways: Our system does not require BCI expert interaction and provides online feedback automatically after less than five minutes. The caregiver needs to mount only six electrodes of which only two are used for control, which may be more practical for some applications. Finally, our system offers a non-control state, which is important for self-paced BCI operation.

Rohm and colleagues ([36]) showed how 9 of 10 end users (one rejected due to a classifier problem) with cervical SCI (ASIA A or B) achieved an overall accuracy of 65.7% in a high number of training sessions. While the online accuracy with our co-adaptive system at 69.9 $\pm$ 7.4 (SD) % is not much higher, there are some ways how our system complements this existing approach: Instead of more than 13 electrodes, our system requires only six electrodes, from which it only uses two online. Instead of offline training and manual calibration, our system provides feedback automatically after less than five minutes. Most importantly our system supports a non-control state which is important for self-paced operation.

Effectiveness of the self-paced BCI training paradigm

Several previous case studies ([10,19,37]) demonstrated successful self-paced BCI control in individuals with SCI. A recent study showed successful and reasonably flexible control of a spelling application and a tele-presence robot in a large group of users with motor impairment [7]. All of these end users had undergone extensive BCI training typically over multiple sessions and in most cases these systems did not support a non-control state. In our first, simple attempt we found the present self-paced paradigm to work significantly better than chance ($p = 0.01$) in 11 of 20 end users (majority with SCI; 18 BCI novice). With the exception of P19 and P21, the end users, who achieved better than chance accuracy with the self-paced paradigm had generally also achieved better than chance accuracy previously with the co-adaptive paradigm. Our present approach can complement the effective, existing approaches in that it allows for comparably fast (24 minutes) and fully automatic setup and training without any BCI expert interaction. Typical training protocols to improve performance, like selecting optimal task combinations ([12,38–40]) were performed automatically. Finally, the present self-paced paradigm supports a non-control state and uses only two electrodes during operation.

Limitations

A limitation of the present setup was that the self-paced paradigm did not work better than chance for as many end users as the co-adaptive paradigm. This was anticipated and can be explained by the fact that in favor of stability we did not yet use fully automatic optimization of the threshold but chose a fixed value for all users. The threshold was fixed to a value which allowed to easily trigger activations with the predefined activation dwell-time of 1 s in the self-paced paradigm. By allowing the users to trigger activations in the target segments, while suppressing erroneous feedback in the non-target segments we were aiming to make this training paradigm more enjoyable and motivating for our mostly novice end users ([27]). In addition we wanted to avoid, that the users' perception of mistakes would introduce additional non-stationarities in the EEG ([30]). Based on the clean data we collected from these end users we can do further analyses and simulations in the future to find system configurations that can automatically optimize threshold, dwell-time and features to allow for more robust self-paced operation.

Future prospects

In this work we used a co-adaptive BCI paradigm to quickly establish a communication and control channel for users with SCI, TBI, polyneuropathy or MS. The co-adaptive paradigm already supported a non-control state and the generated classifiers worked well in the presented self-paced paradigm. Additional workload measurements in future experiments could help to objectively quantify the merit of supporting a non-control state. Based on the collected data we are working to improve our signal processing methods to attain higher system efficacy. In addition we plan to explore the impact of using non-motor tasks and multi-session training. The present system selected a user-specific control strategy automatically based only on cross-validation accuracy and feature separability. Future implementations could also consider physiological markers in the decision process. In addition to the user population in the present study, future research could also target individuals in minimally conscious state [41]. Finally, co-adaptive BCI training paradigms could also be evaluated for their efficacy as tools in neuro-rehabilitation [42] after neural injuries like stroke [43,44] or SCI [45,46].

Conclusions

We presented a cue-guided, auto-calibrating and online co-adaptive ERD-based BCI training paradigm that allowed for significantly better than chance ($p = 0.01$) control in 18 of 22 severely disabled users (20 BCI-novice). After only 24 minutes of co-adaptive training, 11 of 20 end users were able to control a self-paced BCI training paradigm with a control proficiency significantly better than chance ($p = 0.01$). Comparing with literature we found our co-adaptive BCI to well complement existing, effective approaches in that it requires no BCI expert, supports a non-control state and provides feedback based on only two electrodes automatically after less than five minutes.

Appendix A. Details on classifier calibration and use

For initial class selection, the typical calibration was performed for both class combinations *left* vs *non-control* and *right* vs *non-control* to select the one class combination that showed higher median leave-one-out cross-validation (LooCV) test accuracy. Such choosing of a user-specific task combination had been previously shown to improve ERD-based BCI control proficiency [12,38–40]. The calibration procedure always worked in the following steps on all collected artifact-free trials: First the BCI extracted a total of six logarithmic band-power features (1 second averaging) in the bands 9 to 13 and 16 to 26 Hz ([15,47]) from bipolar derivations at C3 (FC3 - CP3), Cz (FCz - CPz) and C4 (FC4 - CP4). The system proceeded to select the single feature with maximum discriminability according to the Fisher criterion (cf. [48]) in the classification period from second three to seven within the trial. The BCI then split the classification period into eight adjacent 0.5 s windows and computed LooCV accuracy for every one of theses windows. Specifically the system trained an LDA classifier for the logarithmic band-power values in the 0.5 s time window and then applied the classifier sample-wise to the feature of the whole classification period of the test-trial. Averaging across all test-trials resulted in one accuracy curve of 4 s length for every training window (eight total). The training window, whose LooCV accuracy curve yielded the highest median accuracy over these 4 s was used to finally train the classifier. As a last step the system trained the AR filter model (order 11) of the real-time artifact detection method on all artifact free trials [25]. The system re-calibrated seamlessly in the background whenever five new TPC were available and the most recently trained classifier model was always immediately used in the online system. The last classifier generated in the co-adaptive paradigm was automatically used in the first run of the self-paced paradigm. With an LDA output ranging approximately from -1 to 1, the activation threshold was set statically to 0.5 for all participants. An activation was triggered whenever participants produced above threshold classifier output for a fixed dwell-time of at least 1 s. The system automatically adjusted the bias term of the classifier based on the data recorded in the first run of the self-paced paradigm.

Author Contributions

Conceived and designed the experiments: JF RS EO. Performed the experiments: JF UC EO JM. Analyzed the data: JF. Contributed reagents/materials/analysis tools: JF RS. Wrote the paper: JF RS EO GM. Implemented and tested the co-adaptive and self-paced brain-computer interface: JF.

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Appendix E

Core publication (5)

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Prototype of an auto-calibrating, context-aware, hybrid brain-computer interface*

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Abstract— **We present the prototype of a context-aware framework that allows users to control smart home devices and to access internet services via a Hybrid BCI system of an auto-calibrating sensorimotor rhythm (SMR) based BCI and another assistive device (Integra Mouse mouth joystick). While there is extensive literature that describes the merit of Hybrid BCIs, auto-calibrating and co-adaptive ERD BCI training paradigms, specialized BCI user interfaces, context-awareness and smart home control, there is up to now, no system that includes all these concepts in one integrated easy-to-use framework that can truly benefit individuals with severe functional disabilities by increasing independence and social inclusion. Here we integrate all these technologies in a prototype framework that does not require expert knowledge or excess time for calibration. In a first pilot-study, 3 healthy volunteers successfully operated the system using input signals from an ERD BCI and an Integra Mouse and reached average positive predictive values (PPV) of 72 and 98 % respectively. Based on what we learned here we are planning to improve the system for a test with a larger number of healthy volunteers so we can soon bring the system to benefit individuals with severe functional disability.**

I. INTRODUCTION

Electroencephalography (EEG) based brain-computer interface (BCI) systems can establish a channel of communication for individuals with severe functional disabilities (cf. [10], [5], [1]). Sensorimotor rhythm (SMR) based BCIs generate control signals based on the dynamics of oscillatory brain activity in the EEG. Such SMR based BCIs use machine learning techniques to detect decreases (event-related desynchronization, ERD, [7]) and increases (event-related synchronization, ERS) of the amplitude of specific frequency bands within the SMR, which the user can voluntarily influence by performing certain mental tasks (e.g. motor imagery).

However, modulating these brain patterns to create a reliable control signal is a skill-full action that, with traditional training paradigms, can require extensive training over weeks or even months [5]. Recent studies showed that co-adaptive online training paradigms effectively lead to high control accuracy, even in participants that could not achieve control with conventional training paradigms [9]. In the simplest case, the user can, after training, produce a one dimensional signal, that can be used to interact with the environment.

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SMR based BCI systems can be complimented with other BCI or non-BCI input signals, where both signals are used either simultaneously or in a sequential manner. This by definition constitutes a Hybrid BCI [6]. Such Hybrid BCI setups can increase the number of available classes, the stability and/or speed of the BCI system. Another way to increase reliability of the interaction is to implement the concept of context-awareness, which means that the system adapts according to the current status of user and environmental variables [4].

A hybrid system of an SMR BCI and a conventional assistive technology device integrated with an optimized Graphical User Interface (GUI) to a Context-Aware Environmental Control System has the potential to vastly increase social inclusion and independence of users with severe functional disabilities, since the combination potentially brings up synergies and balances out shortcomings that the components might have in standalone configurations. This is an improvement over existing systems, which often implement only one or some of the abovementioned technologies or concepts, which we think might leave considerable potential in interaction efficacy unused. Other systems require expert interaction during calibration and are therefore more difficult to operate for non-expert caregivers.

We integrate a Hybrid BCI (SMR BCI and Integra Mouse® mouth joystick), a simulated Workload Detector, a specialized GUI based on [2] and a Context-Aware Environmental Control System in an intuitive framework that allows the user to trigger actions in the outside world. The paradigm for this first proof of concept involving 3 healthy volunteers very loosely resembles a potential real-world use-case, where we (1) auto-calibrate the SMR BCI, then (2) let the user remotely control a camera via ERD, then (3) simulate that the Workload Detector deactivates ERD and at last (4) let the user post a message on Twitter® using the Integra Mouse.

II. MATERIALS AND METHODS

A. System Architecture

Our framework mainly consists of three loosely coupled parts that we show in the Architecture Overview Diagram in Fig. 1. Block (A) User Interface, includes the hybrid system consisting of an SMR BCI, a mouth joystick and a simulated Workload Detector. The color segmentation of block (A) depicts how the parts overlaying (A.1) are needed for auto-calibration and the parts overlaying (A.2) are

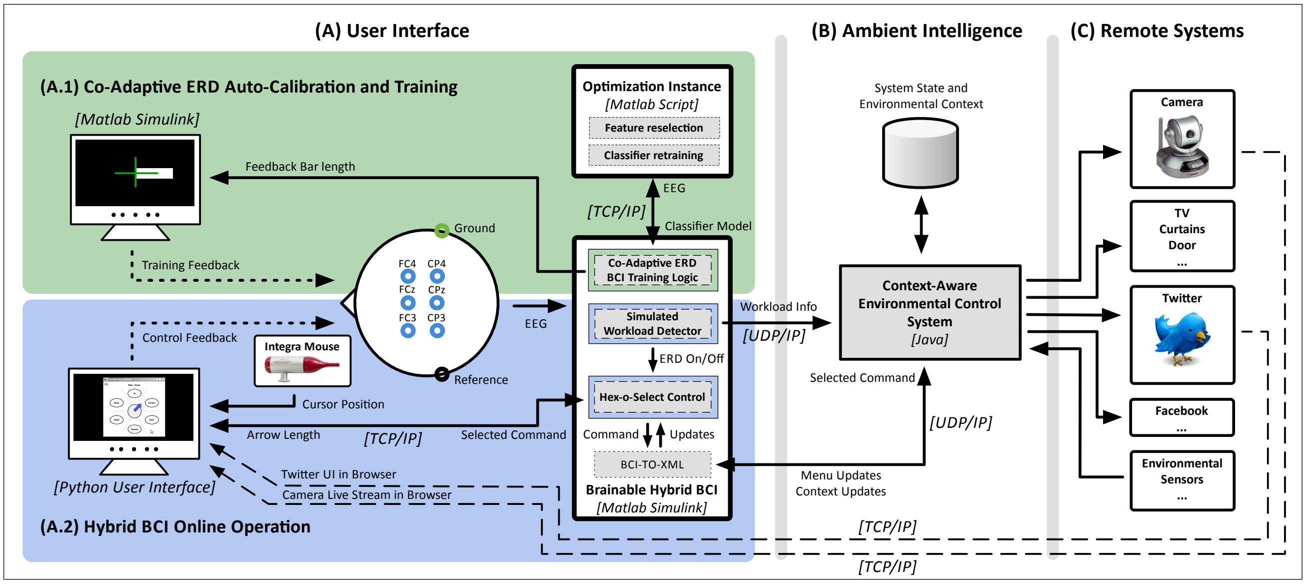

Fig. 1. Architecture Overview Diagram for the complete framework, excluding some supported input interfaces that are not the focus of this work. The framework mainly consists of three loosely coupled segments in the panels (A) User Interface, (B) Ambient Intelligence and (C) Remote Services. The components overlaying the green area (A.1) are used during Co-Adaptive ERD Auto-Calibration and Training while the components overlaying the blue area (A.2) are mainly used for Hybrid BCI Online Operation. (Twitter logo is the property of Twitter Inc., San Francisco, CA, USA).

needed for online operation. Block (B) shows the Context-Aware Environmental Control System that updates the GUI depending on the context, executes commands that the user selects and controls Remote Services in block (C) via an abstract interface called Universal Control Hub (UCH, [11]) which is based on ISO standard 24752, as promoted by the international OpenURC Alliance (http://www.openurc.org/).

B. EEG Setup for ERD BCI control

We recorded EEG at a sample-rate of 256 Hz with a bandpass filter between 0.5 and 100 Hz and a notch filter at 50 Hz. For signal acquisition we used g.GAMMAsys active electrodes, a g.USBamp biosignal amplifier and the g.HIGHspeed signal acquisition block (g.tec, Guger Technologies OEG, Graz, Austria). The positions for the 6 electrodes according to the 10/20 System for Electrode Placement were FC3, FCz, FC4, CP3, CPz and CP4. The three bipolar derivations FC3-CP3, FCz-CPz and FC4-CP4 (blue colored sensors in Fig. 1), were considered during ERD auto-calibration and one was used during online operation.

C. Co-Adaptive ERD Auto-Calibration

The system by default loads the ERD classifier configuration from the last training at startup and is then ready to use. With one double-click, a new co-adaptive online ERD training session can be started, where the user has to produce two different mental activities (right hand versus both feet movement imagery) in a cue guided training paradigm (see Fig. 2). The paradigm starts with offline data collection and then automatically calibrates and provides feedback after approximately 3 min (7 trials per class). During this online feedback operation the system continuously analyzes the data, reselects one best logarithmic bandpower feature (α, 10 to 13 Hz, or β, 16 to 24 Hz from C3, Cz or C4) and recalculates a new linear discriminant analysis (LDA) classifier whenever 5 new trials per class are available after trial based outlier rejection (see [3] for details). A total of 60 trials were collected during ERD auto-calibration procedure.

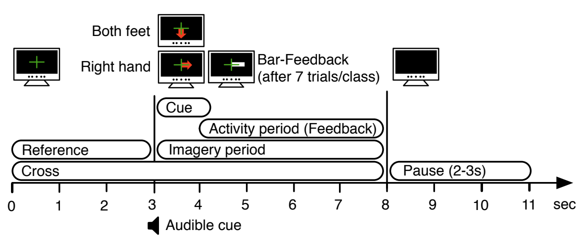

Fig. 2. The task for the user was to perform sustained right hand versus both feet movement imagery starting from the cue (second 3) to the end of the cross period (second 8). A trial started with 3 s of reference period, followed by a brisk audible cue and a visual cue (arrow right for right hand, arrow down for both feet) from second 3 to 4.25. The activity period, where the user received feedback, lasted from second 4 to 8. There was a random 2 to 3 s pause between the trials.

D. Hex-o-Select GUI and Control Logic

As GUI for our online ERD/Integra Mouse Hybrid BCI control, we use a customized implementation (see Fig. 3) based on [2]. This GUI that we refer to as Hex-o-Select displays a variable number (3 to 8) of menu items in layers that are organized in a tree structure. The menu items can represent either atomic actions or headlines that lead to sub-menu layers. The last element of every sub-menu layer is labeled 'Back' and leads to the menu-layer directly above.

The GUI is completely remote configured by the Context-Aware Environmental Control System and receives immediate updates whenever devices change their status (e.g. Twitter Logged On or Off). All this communication is mediated by the BCI-TO-XML Block (see Fig. 1 and [8]).

The GUI supports four different operation modes: (I) The arrow mode uses a one dimensional signal. In this mode, the length of an arrow can be increased by imagining right hand movement and decreased by imagining movement of both feet. The arrow is rotating at a slow pace and colored in blue when its length is lower than a certain threshold (see Fig. 3, Panel A). Whenever its length exceeds the threshold, the arrow stops rotating and turns its color to red (see Fig. 3, Panel B). The user can select the menu item in the segment where the arrow is pointing to by keeping the arrow length above the threshold for a dwell time of 3 s. After every successful activation the system would either execute an action or change to a sub-menu layer depending on the type of the item. After any activation, the arrow resets to the original position (pointing upwards), remains disabled, static and colored in black for a refractory period of 3 s.

The operation modes (II) and (III) use two dimensional input signals to guide a cursor to select items. Operation mode (II) allows for devices such as Joystick, eye-tracker or Wii-Remote whereas operation mode (III) enables the system mouse as an input device. The latter option allows to use assistive technology like the Integra Mouse but also allows an operator or care-giver to quickly interact using the system mouse. Operation mode (IV) allows for any simultaneous hybrid operation of the modes (I), (II) and (III).

E. Online Simulation of the Workload Detector

Our idea is that the system could try to detect whether the user is overwhelmed with workload and could then deactivate the ERD BCI so that no erroneous activations can be triggered. We mainly focus on testing the proposed Hybrid BCI for interacting with the Context-Aware Environmental Control System. Therefore we only simulate the functionality of the Workload Detector by having an experimenter trigger it manually at a defined point in the test protocol.

F. Mouth Joystick Setup

As the second active input signal next to ERD we used a mouth joystick (Integra Mouse, LifeTool Solutions GmbH, Linz, Austria, see Fig. 1), since it is a common assistive technology device. By moving the tip of the mouth joystick with their lips, users could freely control the system mouse cursor up, down, left and right. The tip of the joystick has the form of a small tube and the users could trigger a left-mouse click by briefly (less than 1 s) creating underpressure in the mouth piece by sucking out the air.

G. Experimental Paradigm and Evaluation

We tested our system in one session with 3 healthy volunteers (male, age 25 ± 3.5), who had previously used ERD BCIs but were not specifically trained for this experiment. The protocol of interactions was the same for every participant. First (1) the users completed the Co-Adaptive ERD Auto-Calibration and Training paradigm of our prototype (see Fig. 1, Segment (A.1)). From this we report the selected feature and the peak training accuracy from second 4 to 8 in the trial after leave-one-out cross-validation. We then start the system in Hybrid BCI Online Operation Mode (see Fig. 1, Segment (A.2)) where the GUI simultaneously runs (I) Arrow Mode based on ERD and (III) System mouse cursor mode relying on the signal from the Integra Mouse (see Section II-D).

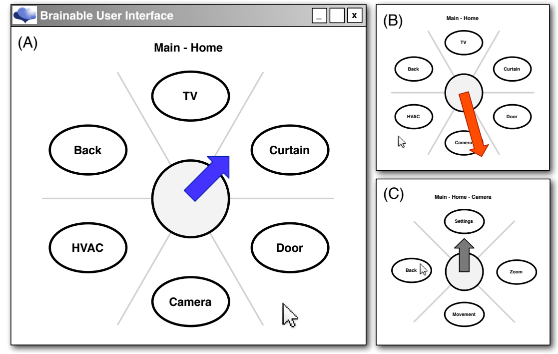

Fig. 3. The panels show different layers in the Hex-o-Select GUI (based on [2]). Arrow Mode (I) and System Mouse Cursor Mode (III) are activated in all the panels. In Panel (A) the arrow length is below selection threshold and the arrow is therefore colored in blue and rotating, whereas in Panel (B) the arrow is extended over the selection threshold and therefore colored in red and not rotating. Panel (C) shows the change to the sub-menu layer 'Camera' after a successful selection in Panel (B). The arrow is colored in black which indicates that the system is in refractory period.

The second step (2) concerned the ERD online operation and was divided in 3 subtasks: (2.a) 1 min idle, (2.b) actual selection of the 10 predefined menu-items in 4 layers to remote control a camera and again (2.c) 1 min idle. The camera is exemplary for a variety of supported devices, and could in practice be used by a disabled, potentially bed-bound user to perceive what happens in other localities. For the idle period the subjects were instructed to actively avoid triggering any activations. For this, we report the number of False Positive (FP, i.e. unintentional) activations. For (2.b) we report time-to-finish (TTF), False Negatives (FN, i.e. failure to trigger an activation) and Positive Predictive Value ($PPV = total(TP)/(total(TP) + total(FP))$, TP means True Positive, i.e. intentional activation).

We then (3) simulate that the Workload Detector triggers and deactivates the ERD input, so that in practice no unintentional commands could be sent by the ERD signal when the user is overwhelmed with workload.

At last (4) the participants had to select a predefined sequence of 20 menu items in 5 layers using the Integra Mouse to post the text 'Hello' to a configured account in the social platform Twitter (http://www.twitter.com). We report the same performance criteria as in step (2.b).

III. RESULTS

All three participants successfully completed the full test protocol and all systems worked as expected. We present

	(A.1) Calibration		(A.2) Online Operation							
	ERD - Calibration		ERD - Camera control					Integra - Twitter control		
	60 Trials LooCV		Idle	10 Selections			Idle	20 Selections		
	Feature	Acc. (%)	FP	PPV (%)	FN	TTF (s)	FP	PPV (%)	FN	TTF (s)
S01	α_{C3}	96.0	0	76.9	10	20:55	0	100.0	4	1:11
S02	α_{C4}	92.0	0	59.1	0	12:07	0	93.3	3	1:06
S03	α_{Cz}	88.0	2	80.0	3	10:39	1	100.0	2	1:05
Mean	-	92.0	0.67	72.0	4.3	14:33	0.3	97.8	3	1:07
SD	-	4.0	1.2	11.3	5.1	05:33	0.6	3.9	1	0:03

TABLE I

RESULTS OF THE (A.1) AUTO-CALIBRATION AND (A.2) HYBRID BCI ONLINE OPERATION PHASE.

all results in Table I. Based on the high average of 92 % over the peak training accuracies, the subjects were able to reach an average of 72 % PPV in the Hex-o-Select ERD online condition. As expected, the average PPV in the Integra Mouse condition was even higher, above 97 %.

IV. DISCUSSION

Three healthy volunteers successfully operated the prototype of our highly integrated context-aware system by means of a Hybrid BCI consisting of an SMR BCI and a mouth joystick to control a camera and to post a message on the social platform Twitter. The tested functionality is representative for a vast number of other compatible appliances (TV, Door, etc.) and internet services (Facebook, etc.).

Operating the system did not require any expert knowledge other than connecting the user and starting the system. In the beginning, the Co-Adaptive ERD Auto-Calibration and Training system successfully identified single features for the three users that led to an average peak training accuracy of 92 % after only 11 minutes of calibration. Also, the transition from cue-paced training to online ERD operation did not cause any problems. In online ERD operation, the users were able to effectively select the correct menu items using Hex-o-Select with an average PPV of 72 %. This was even though they had to orient themselves in the menu structure and were possibly distracted by the camera feedback. The number of FP activations was surprisingly low in the idle periods and the users effectively corrected their mistakes during online operation. The long TTF for Subject S02 can be attributed to the comparably high occurence of FNs, where often the time of the arrow-length being above threshold was slightly below dwell-time. Using subject-specific dwell-time or checking for the total time above threshold per segment could improve the system in this concern.

During informal interviews, subjects reported that operating the ERD BCI for 10 to 20 min was mentally straining. This supports the idea that a mechanism such as the Workload Detector that we simulated could be beneficial in combination with an ERD BCI. As expected, the control with the Integra Mouse was very fast and accurate, and only led to a low number of FNs.

The positive results of this first pilot study lead us to conclude that this system may potentially increase independence and social inclusion of users with disabilities by offering intuitive control over smart home devices and internet services. We are working to improve the efficacy of the Hybrid BCI based on what we learned here so that we can start tests on a larger number of healthy users with the aim to eventually deploy our system to create real-world benefit for users with functional disabilities.

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Appendix F

Core publication (6)

ORIGINAL RESEARCH ARTICLE
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Exploration of the neural correlates of cerebral palsy for sensorimotor BCI control

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Cerebral palsy (CP) includes a broad range of disorders, which can result in impairment of posture and movement control. Brain-computer interfaces (BCIs) have been proposed as assistive devices for individuals with CP. Better understanding of the neural processing underlying motor control in affected individuals could lead to more targeted BCI rehabilitation and treatment options. We have explored well-known neural correlates of movement, including event-related desynchronization (ERD), phase synchrony, and a recently-introduced measure of phase dynamics, in participants with CP and healthy control participants. Although present, significantly less ERD and phase locking were found in the group with CP. Additionally, inter-group differences in phase dynamics were also significant. Taken together these findings suggest that users with CP exhibit lower levels of motor cortex activation during motor imagery, as reflected in lower levels of ongoing mu suppression and less functional connectivity. These differences indicate that development of BCIs for individuals with CP may pose additional challenges beyond those faced in providing BCIs to healthy individuals.

Keywords: electroencephalogram (EEG), brain-computer interface (BCI), cerebral palsy, sensorimotor rhythm, event-related desynchronization (ERD), phase synchrony, phase dynamics

INTRODUCTION

Cerebral palsy (CP) can be a very debilitating life-long condition affecting activities of normal living. We explored a novel approach to the use of a brain-computer interface (BCI) to assist individuals with CP experiencing motor impairment. Given the difficulties people with CP have in using standard BCIs, we investigated alternative neural correlates of movement, which may allow better BCI control by this group.

CP describes a group of brain and nervous system disorders that can involve movement, learning, visual, and auditory perception, and cognitive processing (Miller, 2005). CP is caused by brain injury occurring pre- or peri-natally, or in the first 2 years of infancy (Holm, 1982; Odding et al., 2006). It may be induced by hypoxia to a particular brain area, or result from intracerebral hemorrhage, infection, head injury, or jaundice (Perlman, 1997).

CP can lead to difficulties in maintaining posture and coordinating movement. Problems include muscle tightening, abnormal gait, muscle weakness, tremors, spasms, and loss of coordination. Severity varies, and effects may be uni- or bilateral, involving upper, lower, or all limbs, occasionally resulting in almost complete paralysis (Krigger, 2006). Therefore, individuals with CP experience a range of challenges in their day-to-day lives for which they may require assistance.

BCIs offer a promising way of providing greater independence for individuals with CP (Wolpaw et al., 2002; Neuper et al., 2003; Millán et al., 2010; Sellers et al., 2010). BCIs base control of devices on direct recording and interpretation of brain activity. As such, they can enable control of a computer without activation of the efferent nervous system. BCIs can be used to control devices that could, for example, facilitate movement limited by weakness or poor coordination, or aid communication, establishing a direct, non-muscular, communication channel between a user and the environment (Wolpaw et al., 2002). Furthermore, although CP is a non-progressive condition, the associated symptoms may change over time as the individual's body grows and develops (Badawi et al., 2008). Such changes open the possibility of BCI-based neurofeedback approaches to alleviate motor impairments (Daly et al., 2013a). Moreover, it has been proposed that a motor imagery (MI) strategy could be beneficial in rehabilitation efforts to improve motor control in cases of cortical lesion induced movement impairments (reviewed by Zimmermann-Schlatter et al., 2008). Such an approach is encapsulated in a MI-BCI. MI-BCIs are based upon the detection of changes in sensorimotor rhythms (SMRs), oscillatory activity in the motor cortical regions (Pfurtscheller and Neuper, 2001), and have been suggested as effective communication devices for users with CP (Neuper et al., 2003).

One of the most common approaches to BCIs is based on event-related desynchronization (ERD), which is a modulation in cortical electrical activity before, during, and after attempted execution, or imagination, of active or passive movement, manifested in the electroencephalogram (EEG) (Pfurtscheller and Lopes da Silva, 1999; Müller-Putz et al., 2003, 2007), magnetoencephalogram and electrocorticogram (Hinterberger et al., 2008; Foldes, 2011). The corresponding representation area in the motor cortex exhibits suppression of on-going oscillatory activity in the alpha (8–13 Hz) and beta (13–30 Hz) frequency bands (Niedermeyer, 1999; Pfurtscheller and Lopes da Silva, 1999). After movement cessation, beta oscillatory activity increases over baseline event-related synchronization (ERS) then returns to baseline activity. This process is considered to correspond either to a motor cortex inhibition or a sensory reafference (Baker, 2007; Müller-Putz et al., 2007). Mu and beta activity are modified by limb movement and MI (Pfurtscheller et al., 1997; Neuper et al., 1999).

Despite promising results with ERD-based BCI control in healthy populations, previous studies have shown that users with CP were not able to control an MI-BCI based upon ERD/S at comparable accuracy levels (Neuper et al., 2003; Daly et al., 2013a). However, MI-BCIs offer a number of advantages over other BCIs, including not requiring any executed movement, e.g., eye gaze, which a number of other BCIs [such as steady state visual evoked potential (SSVEP)- and event related potential (ERP)-based BCIs] require. Furthermore, they are intuitive, and in a pilot exercise, participants reported using such BCIs to be enjoyable (Daly et al., 2013b), increasing motivation, which is advantageous when BCIs are being employed for rehabilitation purposes. We therefore investigated differences in SMR activity in participants with CP and healthy participants in order to explain the diminished performance in users with CP, as well as to explore other neural correlates of MI, which may be more useful for controlling BCIs in this group.

More recently, a new way of interpreting how the brain may process information, based on interactions between different brain areas rather than solely on their activations, has been gaining prominence in cognitive neuroscience. Human and animal studies indicate that transient episodes of long- and short-range phase synchrony, between distant and adjacent cerebral areas, as measured by pair-wise interactions between electrodes at micro- and/or macro spacings, correspond to perceptual and cognitive processes (Varela et al., 2001). Such synchrony has been proposed to underpin cognitive acts through the transient formation and dissolution of neural assemblies (Varela et al., 2001). The phase locking value (PLV), as introduced in Lachaux et al. (1999), provides a method for quantifying the degree of phase synchrony in a particular frequency band between different time series of electrical brain activity, such as recorded from EEG electrodes at different scalp locations. In contrast to coherence measurement, the PLV is strictly sensitive to the phase and not to the amplitude of the signals (Varela et al., 2001; Brunner et al., 2006). A PLV close to 0 indicates no synchrony, while a value close to 1 indicates perfect synchrony of the two compared time series at that point.

Changes in coordination of activity through timing have been identified in motor cortex activity during movement (Meinecke et al., 2005; Sweeney-Reed and Nasuto, 2009). Local phase synchrony in the motor cortex alpha band has been found to increase prior to movement, decreasing at movement, then increasing again afterwards in healthy participants (Sweeney-Reed and Nasuto, 2009). These electrical activity changes are also potential candidates for controlling an MI-BCI.

Furthermore, the temporal dynamics of synchrony exhibit changes during MI tasks (Daly et al., 2011). We recently proposed an approach to modeling phase synchronization dynamics in the EEG during a motor task in healthy individuals (Daly et al., 2013c). Differences in temporal dynamics of phase relations between participant groups could indicate a difference in timing of cortical integration resulting from CP lesions, offering another approach to BCI control.

A number of questions arise. It is currently unknown how CP-induced motor-cortical lesions affect ERD strength, MI efficacy, or other SMR-related activity such as phase relationships, despite the potential benefits to CP sufferers from the use of SMR activity to control a BCI. Crucial to the development of effective BCIs for this group is determination of whether CP-related impairment also results in alteration of the electrophysiological patterns usually detected during MI. The question is particularly important, as individuals with CP are among those who stand to benefit significantly from BCI use.

We therefore had two goals. First, we assessed how motor cortex SMR activity differs in individuals with CP compared with healthy individuals, in order to identify a useful approach to BCI control in users with CP. Second, we sought to further our understanding of the motor impairments in CP through detailed examination of electrical activity in the motor cortex during MI.

MATERIALS AND METHODS

Participants with CP and healthy controls attempted to control a BCI using MI. Institutional review board ethical approval was obtained prior to all measurements. We first provide details of the EEG recording and BCI paradigm, before describing the analysis methods and inter-group comparisons.

HEALTHY PARTICIPANTS

The first dataset was from 12 able-bodied BCI-naïve volunteers (5 female and 7 male, median age 26 ± 3.0 years). Details of these participants are listed in **Table 1**.

Table 1 | Summary of the healthy participants.

Participant	Age	Gender
1	32	F
2	21	M
3	26	F
4	27	M
5	26	M
6	22	F
7	28	F
8	26	M
9	28	M
10	26	M
11	22	M
12	25	F

Gender is indicated by either M (male) or F (female).

These data were recorded in a cue-guided, auto-calibrating and adaptive ERD-based BCI paradigm (see Faller et al., 2012 for details). EEG was recorded from electrodes FC3, FCz, FC4, C5, C3, C1, Cz, C2, C4, C6, CP3, CPz, and CP4 via a g.GAMMAsys active electrode system along with a g.USBamp amplifier (g.tec, Guger Technologies OEG, Graz, Austria).

In this study only EEG from the first training session was used to remove bias due to practice. In every trial, we displayed a fixation cross over the entire trial duration. Between 1.5 and 2.75 s, a visual cue indicated the required task. The participants were instructed to perform kinesthetic MI of their right hand (condition 1) or both feet (condition 2) from the time the cue appeared on the screen until the time the cross disappeared (**Figure 1A**).

The system collected data offline until 10 trials were available for each class (∼3.5 min). After enough trials had been recorded during the training phase, online positive reinforcement regarding the strength of the mental activity was provided to the participants for each trial during data measurement. As only trials from the training phase were considered in this work, we do not detail this here. Further details may be found in Faller et al. (2012).

It is important to note that one of the aims of this work was to investigate motor control processes during BCI control. BCI control is typically based on either a small number of averaged trials or single trials. Indeed results identified from averaging across a larger number of trials could be misleading when applied to BCI.

PARTICIPANTS WITH CP

The second dataset was recorded from 14 BCI-naïve volunteers with CP (7 female and 7 male, median age 36 ± 11 years). All participants exhibited upper limb disorders and 10 participants also exhibited lower limb disorders. Details of these participants are provided in **Table 2**.

EEG was recorded from electrodes AFz, FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4, PO3, POz, PO4, O1, Oz, and O2 via a g.GAMMAsys active electrode system along with a g.USBamp amplifier (g.tec, Guger Technologies OEG, Graz, Austria). Further details on the participants are reported elsewhere (Daly et al., 2013a).

A similar paradigm to that applied with the able-bodied participants was used. A cue-guided, auto-calibrating and adaptive SMR BCI paradigm was optimized for disabled users. The timing of the trials was adjusted based upon requests made by participants with CP, in a prior pilot study, for a longer MI period (see Daly et al., 2013a for details).

We presented a fixation cross from 0 to 1.5 s. From 1.5 to 3.5 s, a visual cue indicated the required task. From 3.5 to 8 s the system again displayed the fixation cross. The participants were instructed to perform four mental tasks, of which only kinesthetic MI of either hand (condition 1) or both feet (condition 2) were used for this analysis (see **Figure 1B**).

After the first auto-calibration, the system displayed feedback in the form of a bar, as with the control participants, from 3.5 to 8 s. Data were collected offline for the four conditions until a sufficient number of artifact-free trials were gathered for accurate estimation of the class boundaries. Thus, different numbers of trials were gathered per participant. Further details are provided in Daly et al. (2013a).

In this study, as with the control group, only EEG from the training period was used, to remove bias due to practice. Note that the length of the training period differed between participants, as some participants required more repetitions than others before sufficient class separation could be obtained by the classifier. Details on the feedback provided after the training phase may be found in Daly et al. (2013a).

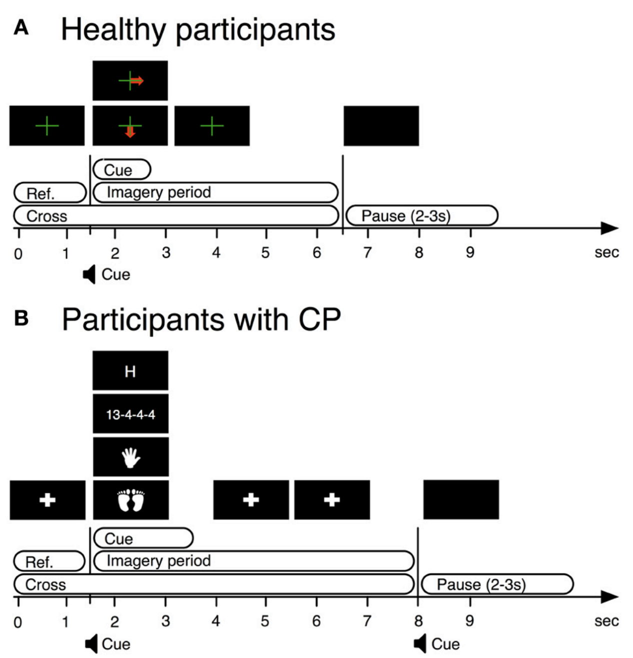

FIGURE 1 | BCI paradigms used in training stages of BCI operation by both users with CP and healthy users. (A) BCI paradigm used with healthy participants. **(B)** BCI paradigm used with participants with cerebral palsy.

Table 2 | Summary of the participants with CP.

Participant	Age	Gender	Orthopedic disorders
1	53	M	LLD, ULD
2	36	M	LLD, ULD
3	52	F	LLD
4	22	M	LLD, ULD
5	32	M	LLD
6	20	F	LLD, ULD
7	34	M	LLD, ULD
8	58	F	LLD
9	32	F	LLD
10	36	F	LLD, ULD
11	38	M	LLD, ULD
12	36	F	LLD, ULD
13	37	M	LLD, ULD
14	31	F	LLD, ULD

Gender is indicated by either M (male) or F (female). Orthopedic disorders are denoted by codes indicating lower limb disorders (LLD) or upper limb disorders (ULD).

PRE-PROCESSING

EEG from nine channels positioned over the motor cortex and common to the recording montage used with both participant groups was used (FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, and CP4). The data were then re-referenced to a common average reference (CAR) scheme before segmentation into trials.

Trials containing artifacts were then identified as any trial for which the amplitude exceeded $\pm 80\,\mu$V. These trials were excluded from subsequent analysis. From the healthy users 2.58 ($\pm$2.72) trials were removed and from the users with CP 8.07 ($\pm$7.49) trials were removed.

As we were only interested in trials relating to the 2 MI tasks common to both groups, this leaves a total of 17.33 ($\pm$2.77) trials remaining for healthy users and 19.92 ($\pm$7.49) trials remaining for users with CP.

We focused on four frequency bands of interest in subsequent processing steps. These were the alpha (8–13 Hz), lower beta (13–16 Hz), mid beta (16–20 Hz), and upper beta (20–30 Hz) frequency bands.

BANDPOWER FEATURES

Band-powers (BP) were calculated for all channels as the root mean squared amplitude of the EEG filtered into the frequency bands of interest. These frequency bands were chosen as they are well-known to contain the ERD/S response observed during motor planning and execution/imagery (Pfurtscheller and Lopes da Silva, 1999). The data were then baselined; the mean BP amplitude in the 1.5 s prior to cue appearance was subtracted from the data.

Our aim was to derive a representative BP response from the EEG for the participants with CP, in order to examine potential differences to healthy participants. Even within a specific CP subtype, CP inherently has significant variability, as lesions can occur at different locations or take different forms such as malformations, periventricular lesions or cortico-subcortical lesions (Wu et al., 2006; Korzeniewski et al., 2008). We therefore averaged the BP of the nine CAR channels described above to attempt to correct for inter-participant differences in spatial locations of greatest ERD/S manifestation.

Additionally, baseline BP in the 1.5 s pre-cue baseline period was also compared between groups.

PHASE LOCKING VALUE (PLV)

Following bandpass filtering to provide a narrow band signal, PLVs between channel pairs were calculated as per Lachaux et al. (1999). We filtered the channels into the four frequency bands of interest. We then extracted the instantaneous phase from each trial using the Hilbert transform and calculated the PLV pair-wise for all possible channel combinations according to the following formula (Lachaux et al., 1999)

$$\mathrm{PLV_t} = \frac{1}{N}\left|\sum\nolimits_{n=1}^{N} \exp(j\theta(t, n))\right|,$$

where N denotes the number of trials to average, t denotes the time point in the time series, and θ(t,n) denotes the phase difference between the two time series. The PLVs for all possible pairwise combinations were then averaged as per the approach taken in Sweeney-Reed et al. (2012).

Additionally, PLVs between the primary motor cortex (M1) and the supplementary motor area (SMA) were estimated by measuring the mean PLV between channels FPz-C3, FPz-Cz, and FPz-C4. This was based upon observed strong PLV between M1 and the SMA during MI-BCI control (Wang et al., 2006).

PHASE DYNAMICS

The temporal dynamics of the phase of the EEG across multiple EEG channels were compared using the method described in Daly et al. (2013c). First, the phase values from the preprocessed multivariate EEG time series from the channels over the motor cortex (FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, and CP4) were used to define a relative phase vector by taking their phase relative to the average phase on a set of reference channels. These reference channels were chosen to minimize the effect of specific phase dynamics on one channel biasing the results and are symmetrically arranged about the midline. Formally,

$$\Phi_i\,(t) = \theta_i\,(t) - \theta_R(t),$$

where $\theta_i(t)$ denotes the phase on channel i at time t and $\theta_R(t)$ denotes the phase on a reference channel R at time t. The following four channels were used as references FC3, FC4, CP3, and CP4. These were chosen as they surround the channels most often associated with MI (C3, Cz, and C4).

A relative phase pattern vector was then defined as

$$\Upsilon\,(t) = (\Phi_1\,(t)\,, \ldots, \Phi_N\,(t)\,),$$

where N denotes the number of channels for which relative phase Φ_i was calculated.

The relative phase pattern vector characterizes the phase across the multivariate time series at a given moment in time. Thus, its temporal evolution is informative about the temporal dynamics of phase across the motor cortex.

The time series of relative phase patterns were then segmented into regions of phase stability. This was done via the Instantaneous Instability Index (III) (Ito et al., 2007) of the relative phase pattern vectors, which is defined as

$$I\,(t) = \sqrt{\sum\nolimits_{i=1}^{N} d_i(t)^2},$$

with

$$d_i\,(t) = \frac{1}{N}\sum\nolimits_{h=1}^{N} \{1 - \cos\left(\Phi_i\,(t) - \Phi_h\,(t)\,\right)\}.$$

A period of phase stability may be defined as a period for which I falls below a certain percentile of its magnitude values; the fiftieth percentile—as used in Ito et al. (2007)—was used in this work. A Global Phase Synchronization (GPS) pattern vector was then defined across each of the periods of synchronization. Formally,

$$p^g = (\Xi_1^g, \ldots, \Xi_N^g),$$

defines the GPS pattern vector, where

$$\Xi_i^g = \tan^{-1} \frac{\sum_{t \in l^g} \sin \Phi_i(t)}{\sum_{t \in l^g} \cos \Phi_i(t)} ,$$

and where l^g denotes the gth GPS episode, with $1 \leq g \leq M$ and M is equal to the number of GPS episodes. Thus, the vector p^g gives the average phase pattern during a single episode of GPS.

The entire series of phase pattern vectors p^g was then clustered and labeled via a K-means clustering approach to produce a labeled GPS time-series, s^g. In this work $K = 6$, based upon the choice made in Ito et al. (2007) and Daly et al. (2013c).

The temporal dynamics of phase synchronization patterns (the labeled GPS time-series) were characterized by a Hidden Markov model (HMM) which attempted to capture the temporal dynamics of the process by assuming an underlying stochastic system modeled by a series of state transitions. Each of the k states within the HMM can generate observables, which comprise the values taken by the labeled GPS time-series.

HMMs may be used to model and classify the temporal dynamics of phase pattern vectors. Initial parameters were drawn from uniform distributions. Further details of how this may be done are reported elsewhere (Daly et al., 2013c). In this work the number of states in the HMM was determined by application of a summation of Akaike's information criterion and Bayesian information criteria (AIC + BIC) (Visser et al., 2002). The HMM toolbox provided by Murphy (1998) was chosen for implementation due to its low computational cost.

COMPARISON

Stepwise regressions were calculated with mean BP strengths and PLVs over all trials in the MI period used as the criteria. The time series of relative BPs and PLVs were first segmented into time windows of length 2 s from 0 s relative to the cross onset to 8 s. Thus, four time segments were created (0–2, 2–4, 4–6, and 6–8 s) and BP strengths and PLV values averaged over these time segments.

The predictors were group (healthy users vs. users with CP), age, gender, and number of artifact-free trials completed by each participant and included in the analysis. Separate regressions were performed for the classes hand and feet MI with mean ERD/S and PLV strengths in the alpha and beta bands.

Comparisons were made across four frequency bands and four time segments. It may be argued that a Bonferroni correction is required. However, subsequent time segments are not independent of one another, which is assumed by Bonferroni correction. Additionally, the frequency bands investigated were selected based upon their known involvement in motor-related activity (Pfurtscheller et al., 1997). Therefore, because of the lack of independence between time segments, and because we expect motor related responses at many of the investigated frequencies, we list all comparisons significant at $p < 0.05$ (uncorrected).

In order to assess the reliability of differing phase dynamics to differentiate between user groups, HMMs were trained and applied to classify the mean BP and PLV trials from each participant into either users with CP or healthy users in a leave-one-out train and validation scheme. This was done independently for the hand and feet MI conditions. Statistical significance of the resulting accuracy was then assessed against the null hypothesis of equal probability of each class label being assigned.

Additionally, to determine whether the HMM classification result was determined by the user group (users with CP vs. healthy users), or some other factor (e.g., age), stepwise regressions were calculated. The log-likelihood ratio between the two groups was entered as the criterion. The predictors were group (healthy users vs. users with CP), age, gender, and the number of artifact-free trials completed by each of the participants. Separate regressions were performed for the classes hand and feet MI.

Note, *t*-testing was used for *post-hoc* testing and assumes normality of each tested distribution. To check for this a one sample Kolmogorov–Smirnov test for normality was performed prior to each *post-hoc* *t*-test reported throughout this work.

RESULTS

During periods of MI both healthy BCI users and BCI users with CP exhibited ERD/S changes from baseline in the alpha and beta frequency bands. These were accompanied by increases over baseline in the degree of observed PLV. Background PLV levels were also observed to be higher in participants with CP compared to healthy participants. Finally, significant differences were observed in phase dynamics between participant groups, with healthy participants exhibiting greater levels of inter-channel phase differences than participants with CP. These findings are summarized in **Table 3** and detailed in the following sections.

SENSORIMOTOR RHYTHM ACTIVITY

Results are summarized in **Table 4**. In the alpha frequency band (8–13 Hz) larger ERDs were found for hand MI in healthy participants. A significant effect of group (healthy users vs. users with CP) was found for the hand MI task in time segments

Table 3 | Summary of key findings.

	Healthy		CP
Baseline PLV		$<$	
Relative PLV		$>$	
Relative ERD/S		$>$	
Ill dynamics		$>$	

Table 4 | Summary of significant ERD/S findings.

MI: hand/feet	Group with greater ERD	Frequency	Time (s)	Stepwise regression r^2-value	*Post-hoc* *t*-test *p*-value
Hand	Healthy	Alpha	4–6	0.148	=0.034
Hand	Healthy	Alpha	6–8	0.180	=0.033
Hand	Healthy	Mid beta	4–6	0.156	=0.048
Hand	Healthy	Mid beta	6–8	0.176	=0.043
Feet	Healthy	Mid beta	4–6	0.239	=0.004
Feet	Healthy	Mid beta	6–8	0.231	=0.017
Hand	Healthy	High beta	4–6	0.310	=0.005

4–6 s ($r^2 = 0.148$; $p = 0.0473$) and 6–8 s ($r^2 = 0.180$; $p = 0.0274$). Note, r^2 denotes the root mean squared fit of the model.

Post-hoc t-tests revealed a significantly larger (more negative) BP reduction in healthy users than users with CP (i.e., MI-related ERD was significantly less in the CP group) ($p = 0.034$ and $p = 0.033$). No other significant effects were observed in the alpha frequency band.

In all instances of *post-hoc* testing the test failed to reject the null hypothesis of normality ($p > 0.05$ and $p > 0.01$).

In the mid beta band (16–20 Hz) significantly larger ERDs were observed in healthy participants from 4 s onwards during both hand and feet MI. A significant effect of group was found during hand MI between 4 and 6 s ($r^2 = 0.156$; $p = 0.042$). *Post-hoc* testing (*t*-test) revealed a significantly greater ERD (more negative relative BP) in healthy users ($p = 0.048$). Additionally, between 6 and 8 s during hand MI, there was a significant effect of group ($r^2 = 0.176$; $p = 0.011$). *Post-hoc* testing revealed a significantly greater ERD (more negative BP) in healthy users. Between 4–6 s ($r^2 = 0.239$; $p = 0.009$) and 6–8 s ($r^2 = 0.231$; $p = 0.011$) significant effects of group were observed, with *post-hoc t*-tests revealing significantly more ERD (negative BP) in healthy users ($p = 0.004$) than users with CP ($p = 0.017$).

In the upper beta frequency band (20–30 Hz) larger ERD was observed during hand MI in healthy participants. A significant effect of group was observed during hand MI between 4 and 6 s ($r^2 = 0.310$; $p = 0.002$). A *post-hoc t*-test again revealed significantly more ERD (negative relative BP) in healthy users ($p = 0.005$). Note, no other significant effects of any predictors were observed in any frequency band. Also of note, is the observation that the lower beta frequency band (13–16 Hz) contained no significant effects of any independent variable within any time segments.

An example of mean BPs in the mid beta frequency band during hand MI tasks for each participant group is illustrated in **Figure 2**. Note the large negative BP fluctuation exhibited by healthy users when compared to users with CP.

Significant differences were observed in the 1.5 s baseline period, with significant effects of group in most frequency bands and classes (hand-alpha: $r^2 = 0.351$; $p = 0.002$, foot-alpha: $r^2 = 0.286$; $p = 0.007$, hand-lower-beta: $r^2 = 0.235$; $p = 0.022$, hand-mid-beta: $r^2 = 0.275$; $p < 0.001$, foot-mid-beta: $r^2 = 0.236$; $p = 0.005$, hand-upper-beta: $r^2 = 0.269$; $p < 0.001$, foot-upper-beta: $r^2 = 0.264$ $p = 0.001$). In each case *post-hoc* testing (*t*-test) revealed significantly larger baseline (background) BP recorded from individuals with CP.

PHASE LOCKING VALUES

Results for PLVs are summarized in **Table 5**.

In the alpha frequency band a significant effect of group was observed during hand MI between 4–6 s ($r^2 = 0.268$; $p = 0.006$) and 6–8 s ($r^2 = 0.364$; $p = 0.001$). *Post-hoc* tests (*t*-tests) revealed relative PLV values to be significantly higher in healthy users ($p = 0.013$) compared to users with CP ($p < 0.001$).

When considering the PLVs between M1 and the SMA a significant effect of group was observed during hand MI between 4–6 s ($r^2 = 0.167$; $p = 0.034$) and 6–8 s ($r^2 = 0.232$; $p = 0.011$). *Post-hoc* testing revealed a significantly higher level of M1-SMA PLV in healthy users ($p = 0.034$ and $p = 0.009$). Additionally, a significant effect of gender was observed during feet MI between 0 and 2 s ($r^2 = 0.148$; $p = 0.047$). *Post-hoc* testing revealed significantly higher M1-SMA PLV for female participants ($p = 0.029$).

In the lower beta frequency band a significant effect of group was observed in the time window 6–8 s during hand MI ($r^2 = 0.239$; $p = 0.009$) and during feet MI ($r^2 = 0.183$; $p = 0.026$). A *post-hoc t*-test revealed a significant increase in PLVs in healthy users ($p = 0.012$ and $p = 0.009$). A significant effect of group was also observed for the M1-SMA PLV in the lower beta band during hand MI between 6 and 8 s ($r^2 = 0.225$; $p = 0.012$). *Post-hoc* testing revealed a larger PLV in healthy participants ($p = 0.016$).

In the mid beta frequency band a significant effect of Group was observed during hand MI in time segments 4–6 s ($r^2 = 0.336$; $p = 0.001$) and 6–8 s ($r^2 = 0.347$; $p < 0.001$). *Post-hoc t*-tests again revealed significantly larger PLVs in healthy users ($p =$

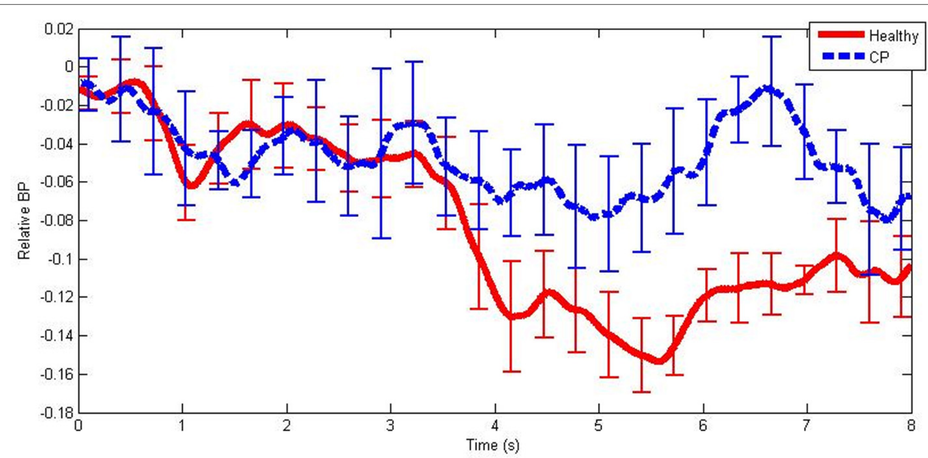

FIGURE 2 | An example of mean band-power differences from baseline from healthy users and users with CP in the mid beta frequency band during hand MI. The error bars illustrate ±1 standard deviation from the mean.

0.006 and $p = 0.004$). During feet MI significant effects of group were also observed during time segments 4–6 s ($r^2 = 0.202$; $p = 0.019$) and 6–8 s ($r^2 = 0.376$; $p < 0.001$). *Post-hoc* t-tests revealed significantly larger PLVs in healthy users compared to users with CP ($p = 0.025$ and $p = 0.015$).

Table 5 | Summary of significant PLV findings.

MI: hand/feet Region: MC/M1-SMA	Group with greater PLV	Frequency	Time (s)	Stepwise regression r^2-value	*Post-hoc* t-test p-value
Hand, MC	Healthy	Alpha	4–6	0.268	=0.013
Hand, MC	Healthy	Alpha	6–8	0.364	=0.001
Hand, M1-SMA	Healthy	Alpha	4–6	0.167	=0.034
Hand, M1-SMA	Healthy	Alpha	6–8	0.232	=0.009
Hand, MC	Healthy	Lower beta	6–8	0.239	=0.012
Feet, MC	Healthy	Lower beta	6–8	0.183	=0.009
Hand, M1-SMA	Healthy	Lower beta	6–8	0.225	=0.012
Hand, MC	Healthy	Mid beta	4–6	0.336	=0.006
Hand, MC	Healthy	Mid beta	6–8	0.347	=0.004
Feet, MC	Healthy	Mid beta	4–6	0.202	=0.025
Feet, MC	Healthy	Mid beta	6–8	0.376	=0.015
Hand, M1-SMA	Healthy	Mid beta	6–8	0.197	=0.014
Feet, M1-SMA	Healthy	Mid beta	4–6	0.196	=0.036
Feet, M1-SMA	Healthy	Mid beta	6–8	0.266	=0.011
Hand, MC	Healthy	Upper beta	0–2	0.214	=0.004
Hand, MC	Healthy	Upper beta	2–4	0.268	=0.003
Hand, MC	Healthy	Upper beta	4–6	0.511	<0.001
Hand, MC	Healthy	Upper beta	6–8	0.399	=0.002
Feet, MC	Healthy	Upper beta	4–6	0.169	=0.021
Hand, M1-SMA	Healthy	Upper beta	4–6	0.341	=0.005
Hand, M1-SMA	Healthy	Upper beta	6–8	0.303	=0.009

Region denotes the region of the motor cortex considered where MC denotes the whole motor cortex and M1-SMA denotes PLVs between the M1 and SMA regions.

When considering the PLV between M1 and the SMA in the mid beta band a significant effect of group was observed during hand MI between 6–8 s ($r^2 = 0.197$; $p = 0.001$) and during feet MI between 4 and 6 s ($r^2 = 0.196$; $p = 0.021$) and 6–8 s ($r^2 = 0.266$; $p = 0.006$). *Post-hoc* t-tests revealed significantly larger PLVs in healthy users compared to users with CP ($p = 0.014$; $p = 0.036$; $p = 0.011$). Additionally, significant effects of gender were observed during hand MI between 0 and 2 s ($r^2 = 0.191$; $p = 0.023$), with a *post-hoc* t-test revealing significantly larger PLVs in female users ($p = 0.027$).

In the upper beta frequency band, significant effects of group were observed in time segments 0–2 s ($r^2 = 0.214$; $p = 0.015$), 2–4 s ($r^2 = 0.268$; $p = 0.006$), 4–6 s ($r^2 = 0.511$; $p < 0.001$), and 6–8 s ($r^2 = 0.399$; $p < 0.001$) during hand MI. *Post-hoc* t-tests revealed that in each case there were significantly larger PLVs in the healthy users than in the users with CP ($p = 0.004$, $p = 0.003$, $p < 0.001$, and $p = 0.002$). Additionally, during feet MI a significant effect of user age was observed in the time segment 0–2 s ($r^2 = 0.195$; $p = 0.021$), with *post-hoc* testing (correlation) revealing a significant negative correlation with PLV strength decreasing with increasing age ($r = -0.442$; $p = 0.021$). Finally, during feet MI significant effects of group ($r^2 = 0.169$; $p = 0.009$) and participant gender ($r^2 = 0.364$; $p = 0.012$) were observed in the time segment 4–6 s, with *post-hoc* t-tests revealing larger PLVs in healthy users ($p = 0.021$) and larger PLVs in female users ($p = 0.032$).

Significant effects of group were also found for PLVs between M1 and the SMA in the upper beta band during hand MI between 4–6 s ($r^2 = 0.341$; $p < 0.001$) and 6–8 s ($r^2 = 0.303$; $p = 0.003$), with *post-hoc* t-tests revealing larger PLVs in healthy users ($p = 0.005$ and $p = 0.009$). Additionally, a significant effect of gender was observed during feet MI between 4 and 6 s ($r^2 = 0.212$; $p = 0.016$), with a *post-hoc* t-test revealing a larger PLV in female users ($p = 0.040$).

An example of mean relative PLVs in the mid beta frequency band during hand MI is illustrated in **Figure 3**. Note that there

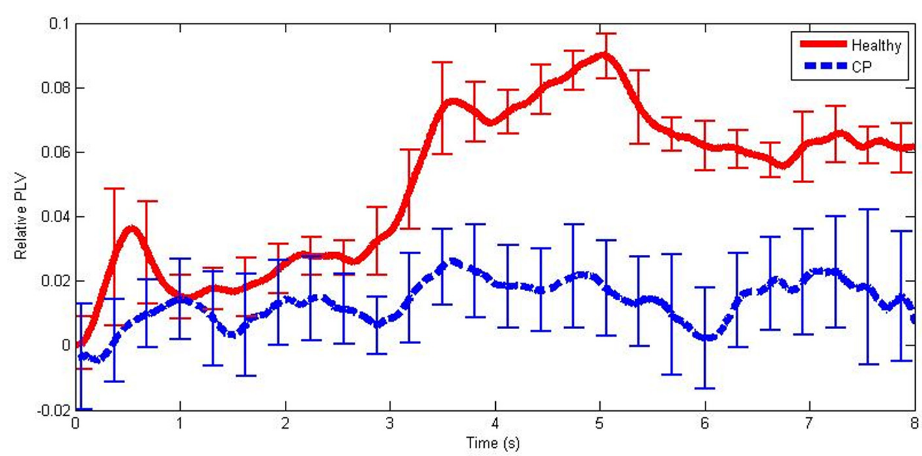

FIGURE 3 | An example of mean PLV differences from baseline from healthy users and users with CP in the mid beta frequency band during hand MI. The error bars illustrate ±1 standard deviation from the mean.

was a large increase in PLV in the healthy user group and only a very small increase in the group of users with CP.

PHASE DYNAMICS

Phase dynamics may be observed in the time series of III values. An example is illustrated in **Figure 4**. Note that healthy users exhibited greater III levels than users with CP. The higher levels indicate a greater amount of instability in the inter-channel phase differences in the healthy individuals.

Users may be differentiated by their group (either users with CP or healthy users) with an accuracy of 0.7143 ($p < 0.05$) for the hand MI condition and 0.7500 ($p < 0.05$) for the feet MI condition. Thus, a significant difference was observed in phase dynamics between users with CP and healthy users during both MI tasks.

The results of the stepwise regressions revealed a significant effect of group ($r^2 = 0.168$; $p = 0.046$) for hand MI.

Additionally, a significant effect of group ($r^2 = 0.179$; $p =$ 0.039) was also revealed for feet MI with no significant effects of any other predictors. This result indicates that the difference in log likelihoods of the phase dynamics of each user being generated by one or other of the HMMs was determined by the users' group rather than other potential factors such as their age. This result, therefore, further confirms a significant difference in phase dynamics between users with CP and healthy users.

DISCUSSION

Individuals with CP exhibited statistically significantly smaller ERD strengths and PLVs in channels recorded over the motor cortex than healthy individuals while performing two common BCI control tasks: hand MI and feet MI. Significant differences were observed most often between 4 and 8 s relative to fixation cross presentation time. There was also a larger BP in the baseline period in individuals with CP. Additionally, analogous differences were also observed in motor cortex PLV strengths and PLV strengths between the primary motor cortex (M1) and the SMA.

The observed differences were most frequently explained by the participants' group (whether they have CP or not), as compared to differences in age, numbers of trials performed, or gender, which only sporadically explained the observed differences. Furthermore, a significant difference was also observed in the phase dynamics exhibited by each participant group, with individuals with CP exhibiting smaller differences in moment-to-moment phase stability.

It is important to consider the time course of the trial when discussing these results. All the trials included for analysis are from the training runs for both the healthy users and the users with CP. During these runs, no feedback was provided to the users. Hence, it was not clear to users at which point MI should cease. This is reflected in the long periods of observed MI which extend up to 8 s from fixation cross presentation time.

The lesser degree of ERD coupled with higher baseline BP activity suggests impairment of motor cortical engagement during attempted motor control tasks in individuals with CP, resulting in reduced levels of suppression of the ongoing alpha and beta frequencies and different temporal dynamics. The latter was indicated by reduced short-range synchronization of motor cortex activity and differing rates of phase state transitions. High levels of local phase synchrony in motor areas have been shown to precede movement in healthy participants, possibly due to a participant involved in a motor-related task being in a continual state of readiness to move, followed by a phase-scattering which has been interpreted as preparation for the selection of the particular neural assembly required for the selected movement (Sweeney-Reed and Nasuto, 2009). The present results indicate that such a state of preparedness is reduced or absent in participants with CP, and we suggest that this may be a result of inadequate development of the ability to form relevant functional connectivity patterns during early developmental stages. Additionally, the higher levels of background activity in the alpha and beta frequency bands (as indicated via the differences in baseline activity) may indicate less motor cortical localisation and specialization in individuals with CP.

The smaller III fluctuations in the group of participants with CP are an interesting observation. III reflects the number of transitions between phase microstates (Ito et al., 2007), which represent short lasting periods of stability in the electrical activity in the brain. Such electrical activity is thought to follow a pattern of chaotic itinerancy in which the trajectory of phase activity wanders through a landscape of ruined attractors (Ito et al., 2007). A smaller level of III fluctuation therefore corresponds to longer time periods spent at each localized attractor and a potentially less reactive set of dynamics. This may be indicative of a more diffuse (unstructured) mode of inter-cortical communication in individuals with CP.

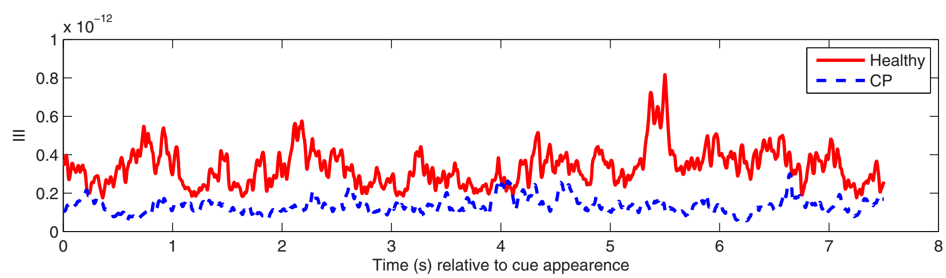

FIGURE 4 | An example of mean III time series over participants in the alpha (8–13 Hz) frequency band from healthy users and users with CP during hand MI.

A number of factors could explain why such differences were observed between users with CP and healthy users. One possibility is that the fetal brain damage experienced by individuals with CP prevents the learning of reliable motor control in the early developmental stages of childhood. As such, individuals with CP may experience more difficulty acquiring reliable control of their motor functions (Palisano et al., 1997) and, hence be unable to reliably produce the associated ERD responses.

It has been shown elsewhere that, in addition to impairment in motor planning, individuals with CP also exhibit impairment in MI as measured via rotation-related negativity by Parson's hand rotation paradigm (Crajé et al., 2010; Van Elk et al., 2010). As there is a known relationship between efficacy at hand mental rotation and ERD strength (Chen et al., 2013), it is reasonable to speculate that there may, therefore, be a relationship between CP-related impairment and ERD strength.

In contrast, individuals with severe stroke lesion induced impairments are seen to exhibit larger ERD/S strengths (Kaiser et al., 2012). Furthermore, the ERD strength may increase in the non-lesioned hemisphere (possibly as a compensatory neuroplastic change). While it is reasonable to hypothesize that lesions occurring in the fetal brain or during infancy will also induce changes in ERD strength, the lack of a compensatory increase in ERD strength elsewhere in the motor cortex may be, potentially, explained by recruitment of those cortical areas for other functions.

Additionally, post-stroke the ERD/S strength may reflect a re-learning process as the individual attempts to recruit other cortical areas to re-learn actions familiar pre-stroke. In the case of individuals with CP, such re-learning may not be possible, as the impairment was present from childhood, and motor cortical pathways are either damaged or have since been recruited for other tasks via neuroplastic processes.

Another factor that may explain the differences between individuals with CP and post-stroke individuals could relate to differences in learning processes. It has been reported that children with CP exhibit significantly slower rates of learning motor tasks than aged-matched healthy children (Hung and Gordon, 2013). Learning to use a MI-BCI may be described as akin to a motor learning task. Therefore, the lower ERD responses observed by individuals using our BCI may be a result of a slower learning process. Given further training, it is possible that individuals with CP may eventually learn to generate ERDs equivalent in strength to those generated by healthy individuals.

The effects on the analysis results of multiple comparisons should be discussed. Each set of features (ERD/S strengths and PLV values) was divided into four time segments and four frequency bands across two conditions. Therefore, 32 comparisons were made for each of the features (ERD/S values and PLVs). It should be noted, however, that many of the observed significant differences between the groups occurred in stable regions. For example, the majority of the significant differences in ERD/S strength occur in the time segments 4–6 and 6–8 s. Additionally, the investigated frequency bands are known to be involved with motor processes. We therefore suggest that application of a Bonferroni correction for multiple comparisons would be inappropriate here, as it takes no account of these regions of significant differences.

The findings that there are significant effects of age (upper beta) on the ability to separate ERD strength are of some interest. However, these effects are not reliably repeated across frequency bands, time segments, or conditions. The lack of repeatability suggests that these effects may be falsely positive, arising from the multiple comparisons made in the analysis.

The differing numbers of trials between participants and groups was hypothesized to be a significant factor. However, this was not observed to be the case. Additionally, it is important to note that it is common in BCI studies to attempt to determine motor control intention from a relatively small number of trials. Thus, the small number of trials used here represents a realistic challenge, while the larger number of participants adds robustness to the results.

Our findings may be contrasted with those in Pires et al. (2011), in which no differences were observed in P300-BCI performance when comparing between healthy users and users with CP. However, it is important to note that differences in profiles of P300 ERPs compared to SMR activity make comparison between these studies non-trivial. Furthermore, only three individuals with CP participated in the work described in Pires et al. (2011) and these were not differentiated from users with amyotrophic lateral sclerosis (ALS).

In contrast, Nam et al. (2012) compared functional integration, measured by coherence, during a P300 BCI control task performed by individuals with CP, ALS, and healthy controls. A lower BCI accuracy and information transfer rate was found for individuals in both the motor disabled groups (Nam et al., 2012). This was seen to occur alongside an increase in localized coherence during the task in healthy participants when compared to participants in the groups of motor impaired individuals. The difference between electrophysiological activity during MI when compared to P300 means a direct interpretation of these results against MI is not possible. However, they do indicate that some difference in performance at a BCI task may be observed in individuals with CP and that this may also relate to changing levels of connectivity.

Of particular note is that our work examines ERD (based upon the Fourier transform) and phases (based upon non-linear analysis) separately, as these have been shown to exhibit different time courses (Sweeney-Reed and Nasuto, 2009). Previous studies have investigated connectivity in the brain, during BCI control tasks, via the coherence measure (e.g., Krusienski et al., 2012). Coherence is a measure of amplitude and phase. By separating them, we have been able to reveal different aspects of neural processing and increase our understanding of the underlying physiology.

These findings have potential implications for research into the use of BCIs by individuals with CP. First, smaller ERD strengths are harder to differentiate reliably from on-going EEG activity. Hence, MI-BCI control accuracy may be expected to be lower for individuals with CP. Second, BCIs for neurofeedback rehabilitation efforts could, for example, be tailored to encourage greater ERD strength. On the one hand, a case study has already demonstrated improvement in ERD-based classification rates following neurofeedback (Neuper et al., 2003). On the other hand, we postulate that such neurofeedback may, additionally, increase the ability of this user group to accurately control their own motor functions.

Additionally, the lower ERD strength exhibited in individuals with lesions occurring in early childhood compared to lesions occurring in adulthood (e.g., stroke) suggests that delivering neurofeedback rehabilitation in childhood to individuals with CP may be one promising route of enquiry. This may encourage early neuro-plastic changes and allow acquisition of motor control, which would otherwise prove more challenging.

There are some limitations to our study: The heterogeneity of our CP participants means that we do not have enough participants to provide statistical evidence that the variation in the specific diagnoses of the participants with CP would explain the high variability of ERD/S strengths in that group. Another possible limitation was that the age of the participants was not matched. We did, however, find that this factor did not have a significant effect in our regression analysis.

In future work we intend to explore differences between individuals with CP and how this relates to their ability to produce ERD/S responses and control a BCI. We will also attempt to use the knowledge gained from this study to expedite the development of BCIs that work as effectively as possible for individuals with CP.

CONCLUSION

A significant difference was found between individuals with CP and healthy individuals in terms of the strength of the ERD response, PLV strength, and phase dynamics measured from them during hand and feet MI tasks. Individuals with CP produced significantly lower ERD strengths and PLVs. This suggests that efforts to develop MI-BCIs for individuals with CP must be tailored to the lower ERD response and differences in connectivity strengths expected in this population. Therefore, providing reliable BCI control to users with CP presents a greater challenge than providing BCIs to healthy users.

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This article was submitted to the journal Frontiers in Neuroengineering.

Appendix G

Author contributions

J. Faller, C. Vidaurre, T. Solis-Escalante, C. Neuper and R. Scherer (2012) **Autocalibration and recurrent adaptation: Towards a plug and play online ERD-BCI**. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 20(3), 313-319.*
Doi: 10.1109/tnsre.2012.2189584.

JF (70 %), CV (2 %), TS (3 %), CN (5 %), RS (20 %).
Conceived and designed the experiment: JF, RS; Performed the experiments: JF; Analyzed the data: JF; Contributed materials and/or analysis tools: JF; Implemented and tested the Adaptive BCI system: JF; Wrote the paper: JF, RS, CN, CV, TS.

J. Faller, R. Scherer, E. V. C. Friedrich, U. Costa, E. Opisso, J. Medina and G. R. Müller-Putz (2014) **Non-motor tasks improve adaptive brain-computer interface performance in users with severe motor impairment**. *Frontiers in Neuroscience, 8(320).*
Doi: 10.3389/fnins.2014.00320.

JF (70 %), RS (15 %), EF (5 %), UC (2 %), EO (2 %), JM (1 %), GM (5 %).
Conceived and designed the experiment: JF, RS, EF; Performed the experiments: JF, EF, UC, EO, JM; Analyzed the data: JF; Contributed materials and/or analysis tools: JF; Implemented the data acquisition system: RS; Wrote the paper: JF, RS, EO, JM, GM.

I. Daly, M. Billinger, J. Laparra-Hernández, F. Aloise, M. Lloria García, J. Faller, R. Scherer and G. R. Müller-Putz (2013) **On the control of brain-computer interfaces by users with cerebral palsy**. *Clinical Neurophysiology, 124, 1787-1797.*
Doi: 10.1016/j.clinph.2013.02.118.

ID (40 %), MB (20 %), JL (4 %), FA (3 %), ML (3 %), JF (10 %), RS (15 %), GM (5 %).
Conceived and designed the experiment: ID, MB, RS, JF; Performed the experiments: ID, MB, JL, FA, ML; Analyzed the data: ID, MB; Contributed materials and/or analysis tools: ID, MB; Implemented the visual attention based BCI: MB; Implemented the adaptive BCI system: JF; Wrote the paper: ID, MB, RS, GM, JF.

J. Faller, R. Scherer, U. Costa, E. Opisso, J. Medina and G. R. Müller-Putz (2014) **A co-adaptive brain-computer interface for end users with severe motor impairment**. *Public Library of Science (PLOS) One, 9(7), e101168.*
Doi: 10.1371/journal.pone.0101168.

JF (70 %), RS (20 %), UC (2 %), EO (2 %), JM (1 %), GM (5 %).
Conceived and designed the experiment: JF, RS, EO; Performed the experiments: JF, UC, EO, JM; Analyzed the data: JF; Contributed materials and/or analysis tools: JF, RS; Implemented and tested the Adaptive BCI system: JF; Wrote the paper: JF, RS, EO, GM.

J. Faller, S. Torrellas, F. Miralles, C. Holzner, C. Kapeller, C. Guger, J. Bund, G. R. Müller-Putz and R. Scherer (2012) **Prototype of an auto-calibrating, context-aware, hybrid brain-computer interface**. *Proceedings of the 34th Annual International Conference of the IEEE Engineering in Medicine and Biology (EMBC), 1827-1830.*
Doi: 10.1109/tnsre.2012.2189584.

JF (55 %), ST (20 %), FM (1 %), CH (1 %), CK (1 %), CG (2 %), JB (5 %), GM (5 %), RS (10 %)

Conceived and designed the experiment: JF, RS; Performed the experiments: JF; Analyzed the data: JF; Implemented and tested the Adaptive BCI training paradigm: JF; Implemented and tested the online BCI application and the Python User Interface: JF; Implemented Environmental Control System: ST, FM, CH, CK, CG, JB; Wrote the paper: JF, RS, GM.

I. Daly, J. Faller, R. Scherer, C. M. Sweeney-Reed, S. J. Nasuto, M. Billinger and G. R. Müller-Putz (2014) **Exploration of the neural correlates of cerebral palsy for sensorimotor BCI control**. *Frontiers in Neuroengineering, 7(20), 1-11.*
Doi: 10.3389/fneng.2014.00020.

ID (40 %), JF (35 %), RS (10 %), CS (5 %), SN (3 %), MB (2 %), GM (5 %).
Conceived and designed the experiment: ID, JF; Performed the experiments: ID, JF, MB; Analyzed the data: ID, JF; Contributed materials and/or analysis tools: ID; Wrote the paper: ID, JF, CS, RS, SN, GM.

Appendix H

Curriculum vitae

Curriculum Vitae

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Personal Information

Date of Birth January, 12th, 1985
Nationality Austrian

Summary

I studied computer science at Vienna University of Technology and for my dissertation I worked on adaptive brain-computer interfaces for motor impaired users at Graz University of Technology. I recently acquired temporary funding at Berlin Institute of Technology, where I currently write collaborative research proposals on how to use brain-computer interfaces to passively and unobtrusively improve human-machine interaction for both, disabled and healthy users.

Education

Since 2009 **PhD Student, Computer Science, Graz University of Technology**

Thesis: *"Adaptive Brain-Computer Interfaces for users with severe motor impairment."*
Advisors: Prof. G. R. Müller-Putz, Dr. R. Scherer and earlier Prof. C. Neuper

2005 – 2009 **M.Sc., Computer Science, Vienna University of Technology** (w. honors)

Thesis: *"A virtual reality framework for controlling an avatar via an SSVEP BCI."*
Advisors: Dr. R. Leeb, Prof. D. Schmalstieg and Prof. G. Pfurtscheller

2005 – 2009 **B.Sc., Computer Science, Vienna University of Technology** (w. honors)

1999 – 2004 **Higher Engineering School, Computer Science, St. Pölten**[1] (w. honors)

1995 – 1999 **Grammar School (BRG), St. Pölten** (w. honors)

[1] This was followed by one year civilian service, which is mandatory in Austria.

Professional Experience

Since Oct. 2014	**Berlin Institute of Technology**	Research in Neuroadaptive Technology

With my contract at TU Graz ending, I applied for a seven month start-up grant at TU Berlin. As the proposal received funding, I started working on multiple collaborative research proposals surrounding Neuroadaptive Technology, where we propose to use brain-computer interface technology to passively and unobtrusively improve human-machine interaction to benefit both, disabled and healthy users.

2008 – 2014	**Graz University of Technology**	Brain-Computer Interface research

For brain-computer interface (BCI) research, I used signal processing and statistical machine learning techniques during data analysis in Matlab, and for implementing real-time systems in Matlab Simulink, C++ and Python. I tested BCI systems in over 150 measurement sessions (over 60 with severely motor impaired users), presented scientific findings at numerous international conferences, published in peer-reviewed engineering journals and contributed to chapters in scientific text books.

2007	**MAGNA Steyr Engineering**	Software development: Car control software

Summer internship: I developed and successfully tested a Matlab Simulink based control software for a prototype-car at the Magna Steyr electronics pre-development department.

2007	**Siemens AG**	Software development: Satellite communication

Besides education: I developed a Linux-based, multi-threaded C++ application that was successfully used to test the network protocols of a modem for satellite communication.

2006 – 2007	**MAGNA International AG**	IT and System Administration

During summer and besides education: I was assuring correct and uninterrupted operation of the IT infrastructure of the Magna headquarter and other company buildings on the campus.

2000 – 2006	**Vinosoft Computer**	Software and Network Engineering, IT
2003	**EVN AG**	Summer Intership: High voltage electrician
2000 – 2002	**Festspielhaus St. Pölten**	Summer Internship: Software Engineering, IT

Involvement in International Cooperations

2013 – 2014 EU Project *"BackHome"* (Brain-neural computer interfaces on track to home - Development of a practical generation of BNCI for independent home use; FP7-STREP-288566, 2012-2015). Function: Project Assistant.

2009 – 2012 EU Project *"BrainAble"* (Autonomy and social inclusion through mixed reality Brain-Computer Interfaces: Connecting the disabled to their physical and social world; FP7-STREP-247447, 2010-2012). Function: Project Assistant.

2008 – 2009 EU Project *"PRESENCCIA"* (Presence: Research Encompassing Sensory Enhancement, Neuroscience, Cerebral-Computer Interfaces and Applications; FP6-IST-IP-27731, 2006-2009). Function: Student Project Assistant.

Research Stays and Visits

2014 Research visit at Schölkopf Lab, Max-Planck Institute, Tübingen, Germany

Found better than chance common spatial pattern based BCI classification on alpha and beta but not gamma EEG from an individual with late stage ALS. (1 week).

2014 Research visit at van der Helm Lab, TU Delft, Delft, Netherlands

Evaluated Transfer Entropy based causality analysis in source space of human EEG, recorded whilst applying robot-mediated, multisine wrist-perturbation. (1 week).

2014 Research visit at Fernandez Lab, Donders, Radboud University, Nijmegen, Netherlands

Computed preliminary results for Random Forest based searchlight classification on fMRI data, recorded during audio-visual stimulation in a memory task. (1 week).

2013 Research visit at Schalk Lab, Wadsworth Center, Albany, NY State, USA

Found canonical correlation analysis to be more efficient, but equally effective as regularized classification for detecting auditory attention from human ECoG. (1 week).

2012 EEG Measurements with Patients, Ability Net, Liverpool, UK
2010 – 2012 EEG Measurements with Patients, Guttmann Institute, Barcelona, Spain
2010 Visit to Scott Makeig Lab, UC San Diego, CA, USA
2010 Visit to John Polich Lab, Scripps Research Institute, San Diego, CA, USA
2010 Visit to software company Blizzard Entertainment, Irvine, CA, USA
2010 – 2014 Project related travel to collaboration partners in Spain, Germany and UK

Conference Participation[2]

2014 6th International Brain-Computer Interface Conference, Graz, Austria
2014 Austrian Computer Science Day 2014, Graz, Austria
2013 IEEE EMBS Neural Engineering Conference, San Diego, CA, USA
2013 Society for Neuroscience Conference, San Diego, CA, USA
2013 Society of Biomedical Engineering (Austria, Germany and Switzerland), Graz, Austria
2012 Recent Advances in Assistive Tech. & Eng. Conference (RAatE), Worwick, UK
2012 Berlin Brain-Computer Interface Workshop 2012, Berlin, Germany
2012 3rd Tools for BCIs (TOBI) Workshop, Würzburg, Germany
2011 5th Int. Brain-Computer Interface Workshop 2011, Graz, Austria
2010 Styrian Brain-Research Initiative (INGE St) Congress, Graz, Austria
2010 Future BNCI Conference, Graz, Austria
2010 Int. Conf. on Applied Bionics and Biomechanics (ICABB), Venice, Italy
2010 4th International BCI Meeting 2010, Asilomar, CA, USA
2010 Real Actions in Virtual Environments (RAVE) conference, Barcelona, Spain
2010 1st Tools for BCIs (TOBI) Workshop, Graz, Austria

Reviewer Activity (selected)

- Journal of Neural Engineering
- Journal of Neuroengineering and Rehabilitation
- IEEE Transactions on Biomedical Engineering
- International IEEE EMBS Conference on Neural Engineering
- SigCHI Conference: Human Factors in Computing Systems

[2] Please see the publications section for a full list of accepted conference work.

Workshop Participation

2014	Summer School on Brain Connectivity, Radboud University, Nijmegen, Netherlands
2013	17th EEGLab Workshop 2013, San Diego, CA, USA
2012	Berlin Brain-Computer Interface Summer School 2012, Berlin, Germany
2011	Future BNCI Workshop, Graz, Austria
2010	Student Colloquium, 4th International BCI Meeting 2010, Asilomar, USA
2010	BCI 2000 Workshop, 4th International BCI Meeting 2010, Asilomar, USA
2008	Workshops at Accenture, McKinsey and Boston Consulting Group, Vienna, Austria

Grants, Awards and Honors

2014	Start-up funding to write proposals, granted by Berlin Institute of Technology (7 months)
2014	Travel Grant (Connectivity Workshop), awarded by Styrian Brain Initiative (INGE St.)
2014	Travel Grant (Stay at Donders), awarded by Austrian Research Association (ÖFG)
2014	Travel Grant (Stay at MPI), awarded by Graz University of Technology
2014	Travel Grant (Stay at TU Delft), awarded by Styrian Government (Land Steiermark)
2013	Travel Grant (Stay at Wadsworth), awarded by Styrian Government (Land Steiermark)
2013	Travel Grant (EEGLab Workshop), awarded by Styrian Brain Initiative (INGE St.)
2013	Finalist, Best Student Poster, Biomedical Engineering Conference, Graz, AT
2012	Finalist, Best Paper Award, Styrian Brain Initiative (INGE St.)
2010	National Science Foundation Stipendium, BCI Meeting 2010, Asilomar, USA
2008	Research Grant for diploma thesis work, Vienna University of Technology
2004	Award for excellent academic achievement, Government of Lower Austria
1999 – 2004	Small Scholarships for exc. academic achievement, Higher Engineering School

Membership in Scientific Societies

- Member of the Austrian Society for Biomedical Engineering (OeGBMT)

Other Qualifications

Certifications	Cisco Certified Network Associate, CCNA
	Sun Certified Java Programmer, SCP
	Sun Certified Web Component Developer, SCWCD
	European Computer Driving License, ECDL
	Cambridge Business English Certificate (Level Vantage), BEC
Languages	German, *native speaker*
	English, *business fluent in spoken and written language*
	Spanish, *good comprehension skills*
Driving License	Categories A (motor cycle), B (car), C (truck), E (heavy trailer)
Manual craft	Basic knowledge in carpentry, basic knowledge in wine growing
Music	Concert Trumpet (Performance Award-Levels Bronze and Silver), Guitar

References

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Publications

Journal Articles

Faller, J., Scherer, R., Costa, U., Opisso, E., Medina, J., and Müller-Putz, G. R. (2014). A co-adaptive brain-computer interface for end users with severe motor impairment. *PLOS One*, 9 (7), e101168.

Faller, J., Scherer, R., Friedrich, E. V. C., Costa, U., Opisso, E., Medina, J. and Müller-Putz, G. R. (2014) Non motor tasks improve adaptive brain-computer interface performance in users with severe motor impairment. *Frontiers in Neuroscience,* 8 (320).

Daly, I., **Faller, J.**, Scherer, R., Sweeney-Reed, C. M., Nasuto, S. J., Billinger, M., Müller-Putz, G. R. (2014) Exploration of the neural correlates of cerebral palsy for sensorimotor BCI control. *Frontiers in Neuroengineering,* 7 (20).

Daly, I., Billinger, M., Laparra-Hernandez, J., Aloise, F., Lloria Garcia, M., **Faller, J.**, Scherer, R. and Müller-Putz, G. R. (2013). On the control of Brain-Computer Interfaces by users with cerebral palsy. *Clinical Neurophysiology*, 124 (9), p.1878-1897.

Faller, J., Vidaurre, C., Solis-Escalante, T., Neuper, C., and Scherer, R. (2012). Autocalibration and recurrent adaptation: Towards a plug and play online ERD-BCI. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 20 (3), p.313-319.

Scherer, R., **Faller, J.**, Balderas, D., Friedrich, E.V.C., Pröll, M., Allison, B., Müller-Putz, G. (2012). Brain-Computer Interfacing: More than the sum of its parts. *Soft Computing*, 17 (2), p.1-15.

Faller, J., Müller-Putz, G. R., Schmalstieg, D., and Pfurtscheller, G. (2010). An application framework for controlling an avatar in a desktop based virtual environment via a software SSVEP brain-computer interface. *Presence: Teleoperators and Virtual Environments.*, 19 (1), p.25-34.

Under Review

Pinegger, A., **Faller, J.**, Wriessnegger, S. C. and Müller-Putz, G. R. (in Press). Control or non-control state: That is the question! An asynchronous visual P300-based BCI approach. *Journal of Neural Engineering*.

Scherer, R., **Faller, J.**, Friedrich, E. V. C., Opisso, E., Costa, U., Müller-Putz, G. R. (under Review). Bring mental activity into action! Self-tuning mental imagery-based brain-computer interfaces. *PLOS One.*

Turconi, M. M., Wriessnegger, S. C., **Faller, J.**, Pinegger, A. and Müller-Putz, G. R. (under Review). Effects of a complex hybrid brain-computer interface protocol on the P300 response. *International Journal of Human Computer Studies.*

Steyrl, D., Scherer, R., **Faller, J.** and Müller-Putz, G. R. (under Review). An online sensorimotor rhythm Brain-Computer Interface utilizing a Random Forest classifier. *Frontiers in Neuroscience.*

Halder, S., Pinegger, A., Käthner, I., Wriessnegger, S., **Faller, J.**, Antunes, J. B. P., Müller-Putz, G. R. and Kübler, A. (under Review). Brain-controlled applications using dynamic P300 speller matrices. *Artificial Intelligence in Medicine.*

Schwarz, A., Scherer, R., Steyrl, D., **Faller, J.** and Müller-Putz, G. R. (under Review). A random forst classifier and common spatial patterns in a co-adaptive brain-computer interface quickly allow for accurate control. *Sensors.*

Conference Talks

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