Utilizing Brain-Computer Interfaces for Human-Machine Systems

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2. Abstract

Human-Machine Systems (HMS) can read aspects of human brain activity if linked to this by means of Brain-Computer Interface (BCI). This connection can be established by a combination of methods of machine learning and given knowledge about the interpretation of the electroencephalogram (EEG). The resulting technology allows for automated analyses of brain activity in real time and can also be utilized to provide input commands for a technical system. In the past two decades, researchers have investigated BCIs mainly for the purpose of defining assistive technology for people with severe disabilities, leading to new channels for communication and control. This thesis is dedicated to a new endeavor in this field – the application of BCIs in HMS that are operated by users without disabilities. Based on a detailed description of the state-of-the-art in BCI research I identify unreliability, limited bandwidth of information transfer, high cognitive effort and cumbersome and time-consuming preparation as the main problems BCIs have to face in real world applications outside the laboratory. To address these problems, I introduce a newly developed framework extending a categorization of contemporary BCI systems with passive BCIs. Contrary to classic BCI systems, these do not aim at directly controlling a system by commands sent intentionally by the user. Passive BCIs access information about covert aspects of user state and making it available to the machine, with the aim of enhancing the given interaction. Combining it with recently introduced hybrid BCIs leads to the introduction of context-aware BCI-systems, incorporating larger portions of the available information space to increase the reliability of the global system. I validate these concepts with four studies that are embedded in current HMS research topics. Firstly, I give examples showing that passive and context-aware BCIs can indeed deliver valuable information about the user state, like information about intentions or internal interpretations, even if the bandwidth and reliability of the given BCI channel is restricted. Secondly, I show that passive BCIs can be added to a given HMS without increasing the effort of using the system, as such information channels inherently do not need attention of the user. Especially, I introduce a passive BCI for error detection that is universally applicable for any user, without the need for time consuming individual calibration. In combination with the last study investigating dry EEG sensors I finally demonstrate that the effort needed to prepare a BCI system can be reduced significantly. These studies also show that BCI technology can indeed be valuable for contemporary research in the field of HMS. I show that problems in safety and automated adaptation, as well as the well known Midas-touch problem in touchless interaction can be solved in an efficient way by utilizing the BCI concepts presented here. This thesis provides and validates novel concepts showing that BCI technology can indeed be used to significantly enhance Human-Machine Systems.

Zusammenfassung

Verbindet man ein menschliches Gehirn über eine Hirn-Rechner-Schnittstelle (BCI) mit einer Maschine, so kann das resultierende Mensch-Maschine-System (MMS) Informationen über die Hirnaktivität des Nutzers ableiten. Um diese Verbindung aufbauen zu können, werden Methoden aus dem Bereich des Maschinellen Lernens und Grundlagenwissen über die Interpretation des Elektroenzephalogramms (EEG) miteinander verknüpft. Dieser Ansatz erlaubt automatisierte Analysen der Hirnaktivität in Echtzeit, deren Ergebnisse insbesondere dafür genutzt werden können das technische System anzusteuern. In den letzten 20 Jahren lagen die Hauptziele der BCI-Forschung darin, Unterstützungssysteme für Menschen mit starken Behinderungen zu definieren, die eine Kontrolle über ein technisches System erlauben oder als Kommunikationsmedium genutzt werden können. Diese Doktorarbeit widmet sich jedoch einem anderen Ansatz: Ziel ist es, BCIs auch in MMS nutzbar zu machen, in denen gesunde Menschen interagieren. In einer detaillierten Analyse der aktuellen BCI-Forschung stellt sich heraus, dass die Unzuverlässigkeit, der schmalbandinge Informationstransfer, der hohe kognitive Aufwand bei der Nutzung sowie die umständliche und zeitraubende Kalibrierung eines BCI-Systems die Hauptprobleme bei dessen Nutzung in einer realen Anwendung darstellen. Um diese Probleme angehen zu können, führe ich eine neue Theorie ein, welche die Kategorisierung aktueller BCI-Technologie um passive BCIs erweitert. Im Gegensatz zu klassischen BCI-Systemen zielen passive BCIs nicht auf eine direkte Steuerung des Systems durch intendierte Befehle des Nutzers ab. Passive BCIs leiten Informationen über versteckte Aspekte des Nutzerzustands ab, die der Maschine bereitgestellt werden können, um die zugrundeliegende Interaktion zu verbessern. In Kombination mit der kürzlich neu eingeführten Kategorie der hybriden BCIs lassen sich so kontextsensitive BCIs definieren. Diese nutzen größere Anteile des im gegebenen MMS verfügbaren Informationsraums, um das Gesamtsystem zuverlässiger zu machen. Diese Konzepte werden über vier Studien validiert, die in aktuelle Fragestellungen der MMS-Forschung eingebettet sind. Einerseits gebe ich Beispiele dafür, dass passive und kontextsensitive BCI-Systeme wertvolle Informationen – wie Intentionen oder interne Interpretationen des Nutzers – liefern können. Dies ist sogar möglich, wenn die Bandbreite und Zuverlässigkeit des gegebenen BCI-Kanals eingeschränkt ist. Des Weiteren zeige ich, dass passive BCI-Kanäle sinnvoll zu einem MMS hinzugefügt werden können, ohne dass der Nutzungsaufwand ansteigt, da solche Informationskanäle inhärent keine Aufmerksamkeit des Nutzers benötigen. Insbesondere stelle ich ein passives BCI zur Fehlererkennung vor, welches universell für jeden Nutzer einsetzbar ist, ohne zuvor zeitraubend individuell kalibriert werden zu müssen. Zusammen mit der letzten Studie, in der trockene EEG-Elektroden untersucht werden, zeige ich, dass der Aufwand ein BCI-System einsatzfähig zu machen, drastisch gesenkt werden kann. Somit kann BCI-Technologie sinnvoll in zeitgemäßer Forschung im Bereich der MMS eingesetzt werden. Als Beispiel dafür präsentiere ich effiziente Lösungen von Problemen im Bereich der Systemsicherheit und der automatisierten Adaption, sowie für das wohlbekannte Midas-Touch-Problem in der berührungsfreien Interaktion, die auf den hier vorgestellten Konzepten aufbauen. Die in dieser Arbeit vorgestellten und validierten Konzepte neuer BCI-Technologien können also in der Tat dafür genutzt werden Mensch-Maschine-Systeme relevant zu verbessern.

3. Introduction

A Brain-Computer Interface (BCI) is a technical system deriving information directly from activity of the human brain. It can be used to send commands to a technical system without any muscular activity. So far, this has been used in applications like typing text or sending binary control commands to a technical system.
The main goal of this thesis is to evaluate how technologies derived from BCI research can be applied in Human-Machine Systems (HMS) in general. While research in the field of BCI has strongly focused on assistive technologies for people with severe disabilities, the main question here is how healthy users could benefit from a BCI system in their daily life. After taking a close look at the outcome of BCI research so far, I identify several research questions that need to be addressed to reach the above mentioned goal. These questions address the general applicability of BCI-technology, as well at technical issues and also the usability of BCI based systems, including factors like efficiency, effectiveness, and joy of use.

Based on these research questions and a review of contemporary methods from BCI research derived from computer science and the neurosciences, I will provide several extensions of the definition of BCI in a theoretical first part of this thesis. As previous BCI research led to a great variety of applications, I will first give a categorization of BCI-technology. It is derived from previous research done in the field of HMS, and shifts the description of BCI systems from the signals that can be decoded by the technical system to the interaction provided by the BCI from the perspective of the user. This includes a categorization of existing BCI systems into active and reactive systems, and a suggestion for a novel type of BCI system, namely passive BCIs. Furthermore, I will discuss the extension of BCI technology by hybrid systems. Contemporary BCI research focuses on BCI commands as singular input. In hybrid BCI systems this can be extended by additional modalities, like an additional (passive) BCI, standard input devices like mouse or keyboard, or additional psycho-physiological measures, e.g. eye-movements. Finally, I introduce the concept of context-aware BCI systems, unifying the presented extensions into one framework.

The last two parts of this thesis are dedicated to applications. Several experiments demonstrate the consistency and applicability of the concepts introduced earlier. This includes studies on the detection of human intentions, as well as usually covert interpretations and reactions of the user. These studies are embedded in the fields of shared control, automated adaptation and contact free interaction. The final section of this part is dedicated to the applicability of BCI technology in general, focusing on a convenient dry EEG sensor.

Part I.

Building up a theoretical background for Brain-Computer Interface based applications in Human-Machine Systems

From an abstract perspective, this thesis aims at a fusion of two fields of research – Human-Machine Systems and Brain-Computer Interfaces. A proper foundation of this work can only be achieved by developing a perspective into both fields and establishing an understanding for the goals, the methodology and problems of each field. I start with giving a brief introduction to both fields. Firstly, I define the terms Human-Machine System and interaction (see 4.1), followed by an overview of contemporary research directions (see 4.2). Then I will give a brief overview of the field of Brain-Computer Interfaces (see 5), stating issues that are intended to be resolved in this thesis. These descriptions form a basis for the following first part of this thesis giving a more detailed description of the research previously conducted in the field of Brain-Computer Interfaces (see 6.1), connecting it to Human-Machine Systems in general (see 6.6), resulting in the main research questions of this thesis (see 6.6.1). This leads to a theoretical part that aims at categorizing and extending the research field of Brain-Computer Interfaces, followed by studies validating concepts and answering research questions.

4. Human-Machine Systems

4.1. Definition

With the development and increasing deployment of complex tools for information processing, industrial processes, transportation or entertainment, the technical part of those systems is becoming more and more complex and sophisticated. But every technical system has a user who has to cope with it. Hence, a perspective on such systems should include both the user and the technical component. The field of Human-Machine Systems (HMS) investigates the *interaction* between a technical system and its user in general [1].
The term interaction describes an information flow between the technical system and the user. It not only includes a description of singular commands sent from the user to the machine or information presented by the machine to the user via output modalities, but also adaptive effects resulting from cycles of information exchange. Hence, the term interaction is only used in the following when I want to address at least one complete interaction cycle, containing the sending of a command, the influence of this action on the technical system and the perception of the overt changes of the technical system by its user. This refers to common forms of interaction, e.g. the programming of a VCR, driving a car or using a personal computer, as well as working with machines in industrial context.
From an initial description of the system, containing information about the user, the technical system and the environment, a closed loop interaction usually is derived allowing inference on the information exchange between all parts of the system. The field of HMS develops methods and approaches for optimizing the interaction regarding the factors of usability, efficiency, effectiveness, safety, and joy of use.

4.2. Directions

User-friendly design of HMS has become an important part of current research. New approaches evolve such as adaptive or interpretative HMS heading for optimal support of the user [2, 3]. This includes the fields of automated adaptation, shared control and safety assurance. Automated adaptation aims at designing a technical system that can interpret the current user state accurately and change properties of the interaction towards an optimized information flow. An application could also shut down automatically if the user notices they have opened it erroneously. Or a computer could show the information the user was looking for, if it knew what it was. Unfortunately, current applications of automated adaptation are not accepted well by its users. The adaptation is based on interpretations of the user's

behavior. This carries some information about the user's intentions or situative interpretations, but the correlation between behavior and cognitive state is only weak. The actual cognitive state of the user is usually not accessible by the machine.

The field of shared control develops technical subsystems for performing an automated decision making that transfers control over the given system between the user and a technical sub-system to optimize safety and efficiency of the overall system. One possible scenario is the adaptive reallocation of actions between operator and machine e.g. according to fatigue or attention. Here again, it is very difficult to derive an accurate estimation of the actual user state by means usually available in a HMS.

Research taken towards safety assurance focuses on concepts that increase the safety of a given HMS by evaluating the current state of distinct parts of the system and predicting its development. One example could be the preparation of specific crash safety systems in a car. The key information for the design of such context-sensitive systems is knowledge of current user state explicitly stated or implicitly generated by the user, like arousal, fatigue, workload. Here it is most valuable to access information about the current context of the HMS as soon as possible. A major problem is the interpretation of the situation by the machine – this can usually be achieved after the event, but then it might be too late.

One major achievement of this thesis is the presentation of valid examples of how HMS could also be improved by incorporating information about aspects of the user state that are usually hidden. This includes the user's internal interpretations of the actual context as well as user intentions. Especially, the use of the natural abilities of the human brain to interpret situational factors correctly can be utilized for HMS. The human cognition could serve as a sensor for the technical system. Furthermore, emotional user states like surprise, satisfaction, or frustration provide interesting information.

Another branch of current research of HMS is the investigation of multimodal in- and output. Multimodal input refers to the use of several signals emitted by the human body as commands for the machine. Usually input is generated by the tactile modality, pressing buttons or sliding on touch screens. Another known input modality is that of speech. But also aspects of physiological user state, like heart rate or the human gaze could be used as input modalities. Multimodal output refers to feeding back information from the machine so that it can be perceived well by its user. Visual information can be processed in detail, but needs an attention focus, while auditory information, like an alarm, can be processed in parallel and even if the user is preoccupied with other parts of the interaction, for example.

With this definition, HMS research gives the main point of view taken in this thesis of the field of Brain-Computer Interfaces.

5. Brain-Computer Interfacing in a nutshell

I now will give a brief overview of the field of BCI research, its technologies and methods, and also its main goals. This section is intended to give you a rough idea about the technology of BCI and the terminology that is related to it. Each statement of this section is discussed in more detail in later sections of this thesis. Hopefully, this will help readers who are unfamiliar with BCI research to develop a first impression of the research presented here.

5.1. BCI research

A Brain-Computer Interface (BCI) is a direct link between a human brain and a technical system. It detects patterns in brain activity and translates them into input commands given to the machine. Usually, brain activity is recorded using an EEG system and is interpreted by a conventional personal computer using machine learning and signal processing techniques. The initial, principal goal of BCI-based applications has been to provide communication and control channels for users who have lost their ability to communicate naturally. These are mainly patients suffering from amyotrophic lateral sclerosis (ALS) or tetraplegia (see section 6).
From the perspective of Human-Machine Systems (the science of interaction between humans and machines), a BCI defines a new input modality for the active or passive transmission of commands. Active commands are intentional and focused, like a mouse click, while passive commands can, for example, be derived from the brain's reaction to the perception of an error or other aspects of cognitive user state (see Chapter 9).

5.2. Why EEG?

Most of BCI research is based on the electroencephalogram (EEG) (see section 7.2). This is the technology of choice for most BCI researchers, because it provides high temporal resolution, is comparably easy to use and is not too expensive. Apart from these basic characteristics, the main advantage of using EEG for BCI is that it has been thoroughly researched. Numerous studies have been conducted based on analyses of EEG features corresponding to cognitive processes. This offers vast possibilities for BCI research. The drawbacks of EEG are its limited spatial resolution (see section 6.3 and figure 6.1) and vulnerability to artifact sources. These factors potentially limit current BCI research. However, they may

soon be resolved using powerful methods derived from engineering and mathematics, like Independent Component Analysis (ICA) or novel sensor designs (see Chapter 14).
Other measures too can be utilized for BCI research. These can be categorized as invasive versus non-invasive technologies. Relevant non-invasive measures are functional magnetic resonance imaging (fMRI), magnetoencephalogram (MEG) and functional near-infrared specotrography (fNIRS). fMRI and MEG share the major drawbacks of being complex in application and being unsuitable for long-term use. These technologies are also comparatively expensive. fNIRS and fMRI share the drawback of having a low temporal resolution, since both rely on the blood-oxygen-level-dependent (BOLD) component. The spatial resolution of fNIRS is also low; its greatest potential therefore lies in being a secondary measure used in conjunction with EEG to provide additional information on brain activity through the BOLD component. Potential invasive techniques are represented by the use of electrocorticogram (ECoG) and microelectrode arrays. Apart from being invasive, microelectrode arrays have one major drawback: once placed they can only be switched to other spatial areas with great difficulty and it is not possible to cover the whole cortex with sensors. They can therefore only be used for certain applications (see section 6.3).

5.3. Goals of BCI research

Attaining the primary goal of providing a channel for communication and control that relies on no other human bodily activity besides that of the brain requires the attainment of several sub-goals (see section 6.4).

5.4. Optimizing signal acquisition

The first step in Brain-Computer interfacing is to acquire information on brain activity. As a BCI is intended for long-term use, a proper sensor is needed that is quick and easy to apply, is as unobtrusive as possible, provides reliable information on brain activity, and operates without harming the user. EEG partially fulfills these criteria, but there is scope for optimization. The use of gel for impedance reduction is time consuming, limits the length of time that a BCI can be used continuously, and means that the user's hair needs to be washed afterwards. Also, the gel can cause uncomfortable skin irritations. Sensor technology therefore needs to be improved. Dry electrodes are being developed. These could provide a quality of data that is similar to that of the EEG systems in common use, but without the need for any liquids.

5.5. Defining features in EEG

Another important BCI research issue involves the identification of distinctive EEG features that can provide useful information about the user's current cognitive state. The term

'Features in EEG' refers to characteristic task- or state-related EEG patterns that can be used to infer information about the current state of the subject's brain. One major criterion for the usefulness of such features is that the user must be able to generate the features easily. But, as EEG is no one-to-one mapping of brain activity (mostly because of volume conduction and the reduction of the signal to two spatial dimensions) it is vital to minimize the likelihood of interference from features that may be generated by other cognitive processes and projected in a similar manner. Last but not least, the selected features should be easy to detect using automated methods. Typically, it is important to ensure a good signal-to-noise ratio; this can be achieved with signals that display low variance and strong coherence across trials, as well as high amplitudes in the time or frequency domains. In this respect, BCI research benefits from previous research in the neurosciences, providing a lot of information about features possibly suitable for BCI applications.

5.6. Detecting BCI-features

Another main task for BCI research is the development of efficient algorithms for translating brain activity into input commands. From an abstract perspective, these algorithms select and transform those portions of EEG data that best reflect a previously-selected brain activity pattern. This results in BCI features that do not necessarily retain the structure of EEG data and are consequently more abstract than the standard features. This is usually done in a three-step process. EEG produces a lot of data that conveys no information about the process being investigated and must be filtered out. Accordingly, a first step is to apply restrictive filters – that are implemented respecting the temporal structure of the data (retaining causality), in contrast to the signal processing typically used in EEG analyses. This restricts the temporal, spatial and oscillatory bandwidth of the EEG recording. Subsequently, features will be extracted based on knowledge derived from the neurosciences. In this step, particular components of the data will be selected, combined and attenuated by further processing. The final step is to calibrate a classification algorithm based on prototypical features that are usually generated in a separate training session. The resulting algorithm is used in the final application to derive information about the cognitive user state from the EEG. It is therefore highly important that BCI research has proper tools at its disposal that enable the optimal selection of features.

5.7. Ingredients of BCI research

Research in the BCI field is usually highly interdisciplinary (see Figure 5.1), and has its foundation chiefly in the neurosciences, psychology, mathematics and computer science. However as more BCIs are being incorporated in non-laboratory applications, BCI research has also been influenced by the fields of human factors, cognitive science, engineering and human-computer interaction (HCI). The neurosciences supply valuable information regarding the

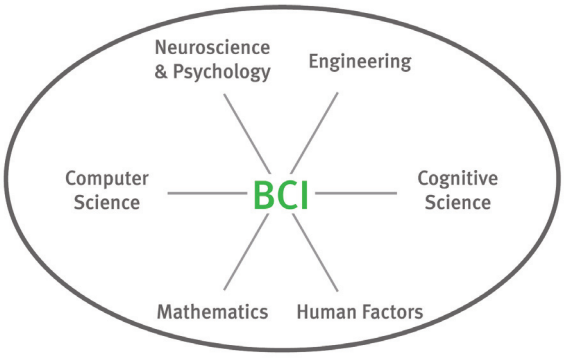


Figure 5.1.: Disciplines influencing BCI research.
BCI research is influenced by many disciplines. Neurosciences, psychology, computer science and mathematics are a substantial part of basic BCI research, while cognitive science, engineering and human factors became more relevant for building up BCI based applications.

structure and functionality of the human brain.

Psychology and cognitive science contribute to the analysis of the results and the setting-up of experimental designs in which the factor of investigation could be modulated while other factors are controlled, as well as the drawing of accurate inferences from a given set of results. Mathematics and computer science are usually consulted for building up a system for automating predefined steps of inference on EEG data. The knowledge and techniques derived from human factors, engineering and HCI are invaluable for setting up a usable and effective application that is based on BCI input. The systems constructed must make efficient use of the limited bandwidth available in a BCI system. This can be done by optimizing the interface design, incorporating as much automation as possible and including information about the environmental, user-related and technical state of the system being used.

5.8. Possible areas of application

The initial application of BCI systems has been to provide a mechanism for communication and control that can be used by severely disabled people. However, as the reliability and usability of BCI systems has improved over the past decade, their applicability and appeal for other applications has also grown. With the introduction of passive and hybrid BCI systems, this technology could also be of interest to other user groups. In particular, users in specialized working environments, such as astronauts, surgeons and people interacting in augmented environments, might benefit from being able to use additional input mechanisms (see section 9.4). This leads to the main theme of this thesis: the application of BCI technology for healthy users.

6. An overview of current research in the field of BCI

6.1. Introduction

In his 1973 publication 'Towards direct brain-computer communication' [4] Jacques J. J. Vidal outlined the notion of communication between a human being and a technical system based directly on neural activity. Since then many ideas, approaches and publications have been inspired by his proposition, and the term Brain-Computer Interface (BCI) has entered into common use. Some other terms, like Brain-Machine Interface (BMI), Direct Neural Interface (DNI) and Brain/Neuronal Computer Interaction (BNCI), are also used to describe this approach. One of the best known BCI-based systems is the P300 Speller developed by Farwell and Donchin [5]. It is described in section 7.2.5.

Until now, research in the field of BCI has mainly focused on applications to provide severely disabled users with new channels for communication and control [6]. Here, we are going to evaluate the capabilities of currently available BCI technology in a broader context – in general Human-Machine Systems, namely also for healthy users. I will start with an overview of recent developments in the field of BCI research.

6.2. Timeline of BCI research

Research into BCI can be divided into two successive phases. The first was chiefly influenced by researchers working in psychology and neuroscience who established the main purpose of classical BCI research. This consisted of building up communication channels based solely on brain activity for the purpose of supporting patients. The second phase has been shaped by the introduction into the BCI field of modern signal processing and machine learning techniques. The great efforts made by researchers in the fields of mathematics and computer science have enabled a major breakthrough in the applicability and performance of BCI systems.

6.2.1. The era of user trained BCI systems

This era started in the early 1980s with work by several researchers on BCI projects focused mainly on defining new communication channels for severely disabled people [6]. Some research groups achieved major advances. In the following I will briefly discuss the results and

approaches of three groups that have significantly influenced the direction of BCI research, and especially the directions of this thesis.

One research group was led by Gert Pfurtscheller at the Technical University of Graz, Austria. It is currently being led by Christa Neuper. Their investigation of changes in frequency bands induced by imaginary limb movements [7] were inspiring for several parts of this thesis (see Chapters 10, 11, 13). Their approach was initially based on the use of a small number of electrodes and simple data processing [8] but was later extended to larger and more complex sets [9]. Its main assumption is that motor imagery leads to a change in frequency recorded at specific electrode sites which is consistent across subjects and is easy for any subject to control [10].

A second group, led by Niels Birbaumer at the University of Tuebingen, Germany, trained their subjects to control the polarity of the EEG signals produced by specific areas of their brains. The resulting slow waves were used as input for a spelling device [11]. The approach involving the utilization of features from EEG time series as input commands has subsequently led to three main studies of this thesis (see Chapters 10, 11, 12)

A third group, led by Jonathan R. Wolpaw of the Wadsworth Center, USA, has utilized several BCI technology-based approaches for developing communication and control systems for application in the clinical context. The theory emerging from BCI research has been strongly influenced by the work on definitions carried out by Jonathan Wolpaw [6].

In principle, all these approaches have given the users basic control over the respective systems. However, this could only be achieved through a tremendous effort on the part of the user that required months of training [11].

6.2.2. The era of machine learning based BCI systems

The end of the 1990s saw the emergence of a new approach to BCI-based applications. The main change was the introduction of more complex data analysis methods that allowed subject-specific patterns in the brain to be detected. This made it possible to detect patterns induced by natural brain states in a highly reliable way. The main drawback of these methods is that the calibration of the system requires a significant amount of data for the generation of the prototypes of the expected signals. Due to the high degree of variance between data sets from different EEG recording sessions – even for the same subject – this calibration procedure usually has to be repeated at the beginning of every BCI session. However, once the system has been calibrated, the effort needed from the subject to control a device via a BCI channel is greatly reduced. In this way, the burden involved in realizing reliable BCI communication has switched from the user to the machine [12].

The above-mentioned group led by Gert Pfurtscheller has developed and implemented

several algorithms for detecting specific patterns connected with the imagination of limb movements. The most familiar of these is the optimization method known as Common Spatial Patterns (CSP, [9]) which has given rise to several more complex derivates [13].

Using this method, Pfurtscheller's group has focused on applications for severely disabled persons. The newest approach is known as hybrid BCI (see Chapter 9.5.6) and combines BCI with at least one additional input stream.

The group led by Prof. Jose del Milan in Martigny, Switzerland has also utilized several methods for machine learning-based BCI approaches that have mainly focused on event detection and Gaussian Mixture models (see section 8.1). His group too has focused on new applications, like shared robotic control, adding a secondary BCI channel (e.g. for error correction, see Chapter 9.5.6), or concepts for non-medical applications of BCI.

The largest input into the development of machine learning-based BCIs has come from Klaus-Robert Mueller's, the Berlin Brain-Computer Interface. Here, multiple methods have been developed and applied in various application scenarios (see `www.bbci.de`).

6.3. Different approaches for accessing data on brain activity

The basic principle of BCI research can be described as inferring information from recordings of physical parameters – that reflect brain activity – by technical system in real time and use it to enhance a given Human-Machine Interaction. This information is interpreted automatically and a reaction is initiated in the technical system with feedback to the human being. This theory defines a closed loop Human-Machine System with a control modality based on data reflecting brain activity.

Hence, the acquisition of physical parameters reflecting brain activity is one of the most relevant components of a BCI. Acquisition methods for brain activity used in neuroscientific research can be differentiated by several parameters, described below:

1. **Invasiveness** Invasiveness describes whether the application of this method damages the user's body. Invasiveness is especially a crucial factor when this damage is irreversible.

2. **Spatial resolution** The human brain is a three dimensional structure consisting of billions of neurons. As the activity of neurons and relations of these activities are the basis of the brains functionality, the perfect acquisition method would reflect any single neuron activity. So far, this is not possible. Spatial resolution is restricted by the number of neurons which are accumulated to one source of activity and by areas of the brain which are not or only partially observed by the used method.

3. **Temporal resolution** The activity of the human brain changes over time. Current neuroscientific research draws the conclusion that meaningful changes in activity can be recorded in very short intervals, lower bounds of three milliseconds are reported [14], and it might even be faster. Hence, the speed with which changes of the investigated physical parameters related to brain activity are recorded is highly relevant.

4. **Portability** Possible methods for recording correlates to brain activity differ strongly in technical and physical complexity. Regarding the usage of BCI in HMSs it is of relevance how much effort has to be taken to carry the system, or whether the system is portable at all.

5. **Acquisition cost** Cost is of course also a relevant factor for building up Human-Machine Systems. Referring again to the technical complexity of a method, the cost of data acquisition systems could actually be very high.

In the following I will give brief descriptions of relevant methods of data acquisition and their benefits and drawbacks regarding the above mentioned factors. See Figure 6.1 for a comparison of the presented methods regarding the parameters of spatial and temporal resolution.

Firstly, I will start with the group of methods that are inherently invasive. They share the big drawback of not being applicable for healthy users at the moment. Currently, it is being actively discussed in workshops, conferences and meetings [15, 16], whether these methods might be accepted by broad sections of the population within the next decades. But it is still unclear whether this discussion is driven by wishful thinking of some researchers of the BCI community or whether there are realistic arguments indicating the changes in society that would be necessary for a broad acceptance of this technology.

There are two irreversible invasive methods involving intracranial implantations:

Microelectrodes either single (ME) or bundled to arrays of 5 to 100 mm in diameter (MEA) are implanted in the tissue of the cortex to record single cell activity. Experience from animal studies show that with this method a very high spatial and temporal resolution can be achieved at selected areas of the brain, but as it damages the cortex itself a full coverage of the brain will not be possible. Also, a high risk of infection over time has been reported. This technology is portable, but it is very difficult to estimate costs. [17]

Electrocorticography (ECoG) is a method for which a flexible foil covered with electrodes is implanted under the skull to record electrical activity of groups of neurons. It is quite similar to the technique of EEG (see below) but the signal-to-noise ratio is much better, as the electrodes are closer to the origin of the signal. Here, very similar to the approach of microelectrodes, only a designated part of the brain can be observed and there is a risk of

infection. ECoG is portable and costs are hard to calculate. [18, 19]

Positron Emission Tomography (PET) is an invasive method, which not necessarily induces irreversible damage. Radioactive tracer isotopes are combined with metabolically active molecules, which are absorbed by brain cells at high activity [20]. It is a non-portable measure with a low temporal resolution and a good spatial resolution. Due to the scanning mechanism and the radioactive material it is costly. The main drawback is the radiation load to the human body. [21]

The non-invasive measures do not harm the user in an irreversible way. It might be that repeated application of such a method causes irritations of the skin, but they will not penetrate the tissue.

Magnetoencephalogram (MEG) With the magnetoencephalogram, changes of ionic currents within the dendrites of neurons (see Figure 7.1) can be recorded. This allows for a high spatial and a high temporal resolution. The recording device is not portable and requires a shielded room. Costs for acquisition and recordings are high. [22, 23]

Functional Magnetic Resonance Imaging (fMRI) As active nerve cells consume oxygen the blood oxygenation in the brain is a reliable indicator for brain processes. Blood oxygenation can be traced with magnetic resonance imaging, which measures specific reaction of oxygenated hemoglobin on a powerfully induced magnetic resonance pulse (BOLD component). This method has a high spatial resolution but a low temporal resolution, as significant changes in the BOLD component can only be recorded after a variable time lag of several seconds. The system is not portable and the costs for acquisition of the system and for each recording are high. [24, 25, 26]

functional Near Infrared Spectrography (fNIRS) Near infrared spectrography also traces the BOLD component similar to fMRI but uses differences in reflections of near-infrared light between oxygenated and deoxygenated hemoglobin. As each sensor also needs an emitter only a few sensors can be placed on the human head, resulting in a low spatial resolution. As with fMRI the time lag results in a low temporal resolution. The system is portable but costly. [27]

Electroencephalogram (EEG) The electroencephalogram records changes in ionic currents of neurons. It only can trace changes reliably, if a population of neurons of several cm^2 of the cortex (see section 7.1.1) behave similar [28]. The EEG signal is recorded always relative to a reference, so that no absolute values of electric potentials are shown. This is sufficient to distinguish functional different processes mapped onto the two dimensional cortex surface (see section 7.2 for details), but suffers from a phenomena called volume conduction that makes it hard to localize the source of a process precisely in the three dimensional brain.

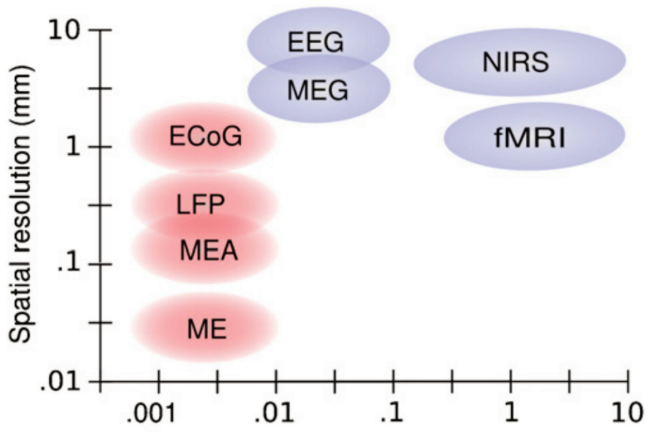


Figure 6.1.: Temporal and spatial resolutions provided by invasive and non-invasive measures.
Local Field Potentials are also shown. Invasive methods (red) clearly outperform non-invasive methods. But, as the benefit is not large and there is still room for improvement in algorithms and sensors, it is unclear how long the advantages of invasive methods will last. Figure taken from [32].

With this EEG allows for a high temporal but only a poor spatial resolutions. The spatial resolution can be enhanced by applying methods for source localization, like Independent Component Analysis (ICA) [29] or Beamforming [30]. It is portable and easy to apply but suffers from the necessity of applying a conductive gel between electrode and scalp surface to reduce impedances. The costs for the recording device are moderate and a single recording is cheap. [31]

EEG is the method of choice for applying BCI technology in general Human-Machine Systems. It is non-invasive, portable, cheap, makes it possible to trace cognitive processes, has a high temporal resolution, and if the spatial resolution is not sufficient it can be enhanced by methods for source localization. Another big benefit is that many studies on identifying EEG patterns related to cognitive processes have been conducted. This provides a large base for cognitive processes which might also be detected in single trial (see section 8.1), and, hence be utilized for BCIs. The major drawback of EEGs – especially for healthy users – is the effort needed for applying the electrodes to the users' scalp. This is mostly dependent on the time needed for minimizing the impedance between electrode and skin, which usually is realized by the application of a conducting gel.

All research in this thesis is based on EEG. This is in line with results from state-of-the-art research on accessing brain data in real world environments (as described in section 9.7). A description on the materials and setup can be found in section 9.1.

A 32-electrode setup usually takes up to 30 minutes of preparation time. Until this is reduced drastically, any application which might emerge from the results of this study has to deal with this drawback in usability. But, as the last chapter of this thesis shows, new types of electrodes might reduce the time needed for application to an acceptable level.

6.4. Main goals of current BCI research

From the time it was first defined, BCI research has focused on the development of systems for supporting severely disabled patients suffering from conditions like amyotrophic lateral sclerosis (ALS), quadriplegia with impairments to natural communication channels. The main goal has been to restore some independence.

An important challenge is to construct systems that provide asynchronous communication [6] which allows a user to decide when information is exchanged. In contrast, most laboratory equipment operates at the pace of the system: stimuli are presented at given points in time, and corresponding responses are required from the subjects. In typical Human-Machine Interactions the user can set the pace by manually pressing buttons that initiate interaction cycles. But this becomes difficult when it is limited to BCI communication. Some signals, like event-related potentials (ERPs, see section 7.2.4), relate directly to external events. Additionally, not all signals are reliably detectable, leading to delays in interaction or to false-positive selections.

For long-term use, a so-called 'brain switch' is needed. This consists of a secondary BCI-based input channel defined in relation to one of the most reliably detectable signals that indicates whether or not the subject wants to communicate via the main BCI channel [34]. The main issue is the definition of the underlying accurately detectable signal.

Additionally, most algorithms used are predicated on the assumption that the underlying data are stationary, i.e. that their statistical properties do not vary over time. But partly due to the human brain's plasticity – in other words, its capability for learning and adapting – it generates highly non-stationary data, which leads to the need for adaptation [35]. Fortunately, the data produced by an EEG system in a given working scenario is stepwise stationary, i.e. changes in the statistical properties are bounded in a particular, restricted timeframe.

Another branch of BCI research focuses on developing new kinds of data acquisition. The main goals here are to reduce the effort needed for implementing the sensor system, improving the quality of the recordings, and improving the acceptance of the equipment by users [16, 36].

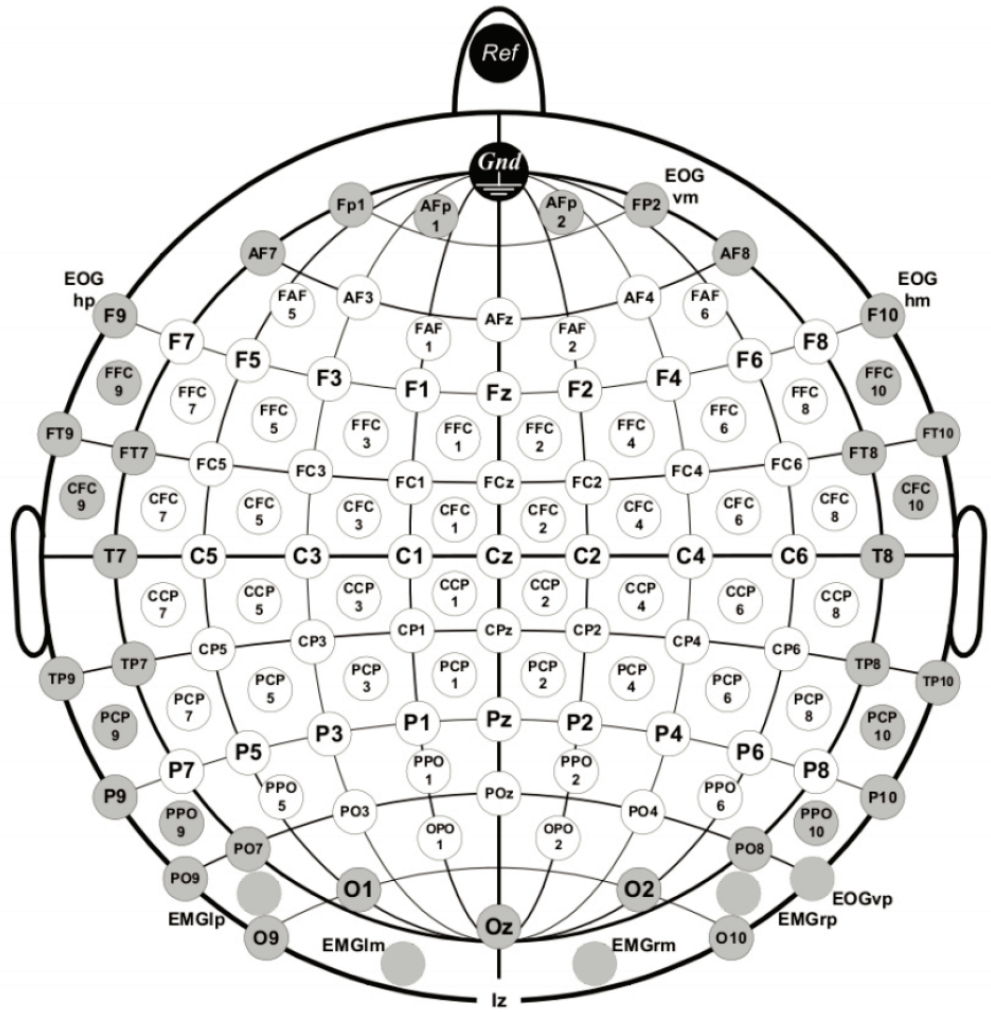


Figure 6.2.: Positioning of EEG electrodes along the extended international 10-20 system. The *topographic plot* shows the top of a human head. Its orientation can be determined by the sketched nose in the front and ears on the sides. Taken from [33]

6.5. The state of the art

To what degree have the goals of BCI been achieved in the past three decades? Currently, a few locked-in patients are working with BCI-based systems. Some of these systems use invasive techniques, while others rely on EEG-based methods – even fMRI, MEG and NIRS have been used. But applying a BCI to those individuals who most stand to benefit, namely completely locked-in patients, is still the most complicated challenge [37]. Advances in combining BCI-based input with robotic support or prostheses can potentially be achieved [38, 39]. But there is still a huge difference between laboratory studies with mostly healthy volunteers and real-world applications involving patients.

In this connection, the definition of a proper 'brain switch' would be very helpful. Most of the initial steps towards such a system have been taken by Gert Pfurtscheller's group. A novel hybrid approach combining a NIRS-based brain switch with a motor imagery BCI has recently been presented [40]. However, its applicability in real-world scenarios still has to be proven.

Even though a BCI-based system might work, there are still major drawbacks to be overcome. The fastest systems provide bitrates of several dozen bits/min for non-invasive-systems. It might be multiples of that in an invasive scenario. While this represents a big step away from a total lack of communication, it is still very limited compared to standard communications systems. One reason for this is that each BCI channel is usually limited to binary communication. Approaches developed in user-trained BCI systems have led to the possibility of three-bit communication, but these have been felt to be very exhausting [6] and would therefore only be feasible for short-term use.

Additionally, the wrong assumption that BCI data is statistically stationary, which is a prerequisite for most machine learning algorithms used, leads to the problem that the accuracy of a BCI system is not robust over time. Fluctuations in the performance require recalibration. A different solution to this problem could involve employing an auto-adaptive system [35] that continuously learns while it is in use. The resulting Human-Machine System would consist of at least two learning systems: the BCI classifier and the human brain. It would be necessary to ensure the convergence of their learning, as otherwise the result could be a vicious circle that produces a downward spiral in terms of performance and effort (see Chapter 11).

Even with non-invasive data acquisition, long-term use might lead to disadvantages for the user. The gel used with EEG electrodes could lead to skin irritation. One solution to this problem might be to develop dry electrode systems. This will be discussed in Chapter 14.

6.6. Broadening the approach to general human-machine systems

The approach I developed in Team PhyPA (see section 9.2) over the past five years aims for the application of BCI-based technology for Human-Machine Systems in general. This changes the evaluation criteria for such systems in several ways. We will leave highly controlled environments, leading to reduced signal-to-noise ratios and the capability to control and deal with influencing factors (see section 9.7 for more details). Over time, the user might face unpredictable stimuli, and the context of the given Human-Machine System might be altered. Additionally, the BCI-system will be compared to a higher variety of competing approaches of interaction.

Compared to standard communication and control methods, a BCI based system is no match. The usage is more cumbersome and less effective. Using a BCI needs a very long preparation phase due to the sensors and the calibration of the system. Also, common interaction channels provide a very high reliability. Even an extremely high accuracy for BCI based communication of 99 percent would not be acceptable for driving a car or typing.

6.6.1. Research questions

These facts lead to the main research questions of this thesis:

- Can the functionality of a BCI based system be decoupled from its bitrate?
- Can BCI-technology be used to provide novel or better solutions to complex or unsolved problems in HMS research?
- Can BCI-technology be combined beneficially with existing HMS?
- Can BCI technology be utilized beyond communication and control?
- Can the time needed to prepare and calibrate a BCI be reduced significantly?

With this thesis I address these research questions (see figure 6.3 for a visualization.) and give results from several studies (see Parts II and III). The context of BCI-based applications is broadened (see Chapter 9) and some possible applications outside the field of medical supporting systems are outlined. Most of the presented studies are first steps into directions opening new fields of research, connecting to other fields of research, and providing more precise research questions. The highly interdisciplinary field of BCI research would become more versatile.
The following two chapters of this thesis (7 and 8) give an overview of two theoretical cornerstones of the BCI technology used in the abovementioned studies. I start with an overview of the neuroscientifc background and will continue with a descriptions of techniques from the field of Machine Learning.

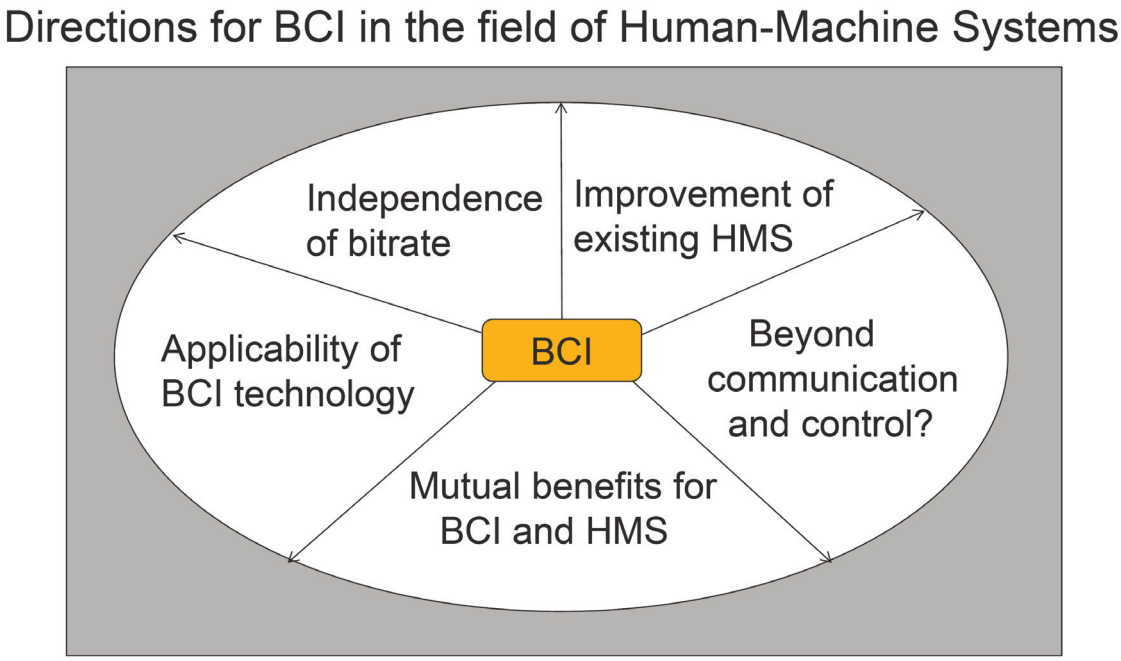


Figure 6.3.: Proposed directions for BCI research.
Classical BCI based applications can be seen as a specific part of the field of Human-Machine Systems. The research questions addressed in this thesis point at an extension of the field of BCI research to inlcude applications that are also valuable for users with no disabilities. This figure shows the direction in the field of HMS that are proposed for realizing this goal.

7. Neuroscientific Background

In this Chapter, I will give an overview of the relevant knowledge and principles of neuroscientific research. The first section focuses on knowledge from the neurosciences that formed the basis of the studies discussed in this thesis. I then consider different perspectives on EEG I have accommodated while working on this topic. A brief description of specific aspects of EEG signals follows, features reflecting interpretable brain activity that are well known from the neurosciences. Finally, I discuss the differences between classic neuroscientfic research and the approaches in BCI research.

7.1. Basic principles of neuroscientific research

7.1.1. Basic facts on the human brain

The human brain is a complex structure which is fascinating in many ways. Though it has been a topic for scientific investigations for hundreds of years, it is still understood only superficially. Principles how information is encoded, processed and distributed in the human brain, as well as meaning and functionality of specific areas are still under investigation. Novel approaches and methods are developed continuously, identifying new principles and structures in the human brain, and leading to complex mathematical models (see [41] for an example). One reason for the difficulty of developing a detailed understanding of the brain lies in its physical complexity. The human brain contains about 100 billion neurons (see [42] and figure 7.1). These are connected by electrophysiological processes and biochemical reactions and build up a complex network.

7.2. The measure of EEG

The EEG technique was described in section 6.3. In the following I discuss perspectives on the resulting data, its structure and introduce common analytical tools. I then compare these (classic) methods with tools developed for BCI research.

7.2.1. Information space

The method for accessing brain activity for our studies is the measure of EEG. It was introduced by Berger [31] in 1929 and is a method relying on electrical activity of the brain. This thesis follows the wide spread approach of inferring information on ongoing cognitive

processes from the EEG. In EEG changes of electrical currents over specific location of the human scalp are recorded. It does not record continuous signals, but takes samples in short, equally spaced cycles. If the time in seconds between samples is given by the sampling interval T, the sampling frequency of an EEG recording is $\frac{1}{T}$.
EEG does not reflect absolute values of current but relative values referenced to a system of reference and ground electrodes. The ground electrode ensures independence of EEG recordings from electrostatic charging accumulated in the human body. To eliminate global electrical current induced by external sources electrodes at the scalp are referenced to the reference electrode – which basically means that values recorded at the reference electrode are subtracted from the signal from each single data electrode. Also, reference and ground can be used to estimate the actual impedance between data electrodes and the human skin. External currents can be recorded by EEG due to volume conduction (see figure 7.2). An electrical field spreads in space at the speed of light, attenuating proportionally to the squared distance from its initial source [44]. Hence, an EEG electrode records the summation of signals from many sources of electrical fields in their environment. Especially, close sources emitting a field that is strong compared to the signal emitted by the cortex disturb EEG recordings. These sources can be found at different locations, including the human body or any technical equipment.

I divide sources contributing to EEG recordings into three categories:

1. **The human brain (Signal)** Changes in activity of the human brain lead to changes in electrical current in neurons. This activity can be recorded on the human scalp where it usually varies by $\pm$ 100 μV relative to a baseline current taken from the reference electrode. Potentials can be recorded if several cm^2 of cortex act synchronously [28]. Many processes in the human brain involve enough coherently acting neurons leading to patterns in time and space domain of EEG recordings (see section 7.2.5 for details). If a correspondence of patterns in EEG and cognitive processes can be established, the detection of such patterns leads to valuable information on the current cognitive state of the subject [46]. This concept is used in BCI research.

2. **Internal artifacts (First order artifacts)** EEG also records data from other physiological processes in the human body. Any muscle activity builds up current that is also recorded at electrodes on the scalp due to volume conductance. Movements of the human eyes adds another portion of data to EEG recordings, as here also muscles are involved and the human eye is a (relatively) powerful dipole itself. Due to these facts and their proximity to EEG electrodes, human eyes are a major source of artifacts in EEG recordings.

3. **External artifacts (Second order artifacts)** Our modern environment includes multiple sources of electrical current and magnetic fields. These sources also induce current to electrodes during EEG recordings. Any movement of the human head is a movement in a electrical field, adding noise. Externally triggered electrical activity, like fields induced by technical devices or power line noise, also add to the current.

EEG data usually reflects a summation of brain activity and artifacts, that defines problems for inference about human cognition from EEG data [46].
One major problem is that muscle or eye activity generates much higher currents than brain activity (mV instead of μV) adding a relevant portion of noise to an EEG recoding by volume conduction, which could influence the signal-to-noise ratio badly. Activity of eyes usually is recorded with the electroocculogram (EOG) while that of muscles can be accessed by the electromyogram (EMG) [47]. Another, even more crucial, major problem is the fact that this activity might be related to cognitive processes as well and, hence, coincide with information inferred directly from brain activity. Resulting patterns recorded in EEG are then a summation of internal artifacts and brain activity.

A basic principle of BCI research is to exclude or at least control artifact sources during experiments. The most prominent reason for this is the preliminary that patients intending to use a BCI usually lack of most of related artifact sources. Hence, a BCI for patients should strictly rely on brain activity. Another reason, more relevant for potential healthy BCI users, is the common assumption that artifact related patterns in EEG have a weaker correlation to cognitive processes as they are implicitly connected to these processes [48]. Brain activity itself should have a stronger correlation as the human brain is supposed to be the home of cognition.

7.2.2. Spatial configuration of EEG electrodes

Electrodes are positioned on areas on the human scalp that should reflect specific brain areas for all subjects. The electrodes are clipped into mounts that are distributed in specific patterns on a cap. Dependent on the shape and size of the subject's head the cap has to be placed so that the mounts are placed over designated brain areas. One common approach is the extended international 10/20 system [49] (also see figure 6.2). Here, electrodes are positioned relative to the center of the subjects scalp, where distances between adjacent electrodes are either 10% or 20% of the total distances bewteen the front and back (indicated by nasion and inion) or right and left (indicated by the left and right preauricular point) of the skull. Each electrode is labeled with a combination of letters and numbers. Letters indicate the part of the cortex and numbers identify the hemispheric location. Main areas are labeled by the initial letter of their names – Frontal, Temporal, Central, Parietal and Occipital. The midline is labeled by a following z and the hemispheric deflection is indicated by ascending numbers – odd numbers (1,3,5,7) for left hemisphere and even numbers (2,4,6,8) for right hemisphere, respectively. See figure 7.5 for details.

7.2.3. General domains of information in EEG

When inferring information from EEG signals, generally three domains are considered.

1. **Temporal Domain** A major portion of brain activity can be described by patterns in electrical activity of neurons [50]. Hence, it is of interest to investigate changes in neural activity or activity in populations of neurons over time that is reflected by the time course of values recorded at an EEG electrode, when the underlying effect is coherent enough. Hence, the most common perspective on EEG is the time course of electrical currents recorded at single electrodes. This is usually displayed by a graph of current against time, as shown in figure 7.3.

2. **Frequency Domain** Another perspective on brain activity is that activity is encoded by repeated discharging of single neurons or populations of neurons. Given sufficient synchronicity of a patch of cortex, this activity can be recorded by EEG electrodes leading to frequent homogeneous changes in amplitude of the time course signal. This phenomena is referred as *bursts in a specific frequency band*. A more general perspective on properties in diverse frequency bands can be accessed by calculating the frequency power spectra of a given EEG time course. This can be attained by generating the Fourier transform (see section 8.2.3) that is mainly based on the assumption that a given (finite) piece of EEG data is a linear combination of a finite number of sine and cosine functions with frequencies equaling multiples of one base frequency. The finiteness of this linear combination is ensured by the finiteness of the sampling frequency of the EEG and the Lemma of Nyquist and Shannon [51]. The frequency spectra of a given piece of EEG can be displayed by a graph of frequency against power (figure 7.4). The granularity of the x-axis is determined by the length of the analyzed piece of EEG and its sampling frequency [52].

3. **Spatial Domain** EEG also displays information in its spatial occurrence. Usually 32 to 256 electrodes distributed over the skull along the extended international 10/20 system [49], record a two dimensional projection of brain activity. As the brain is a three dimensional structure, generating electrical activity not only on its surface, the recorded projection can not represent a one-to-one mapping, as it inherently is not injective [53]. This is one reason leading to a *functional approach* in interpreting EEG data [54, 55] (see also sections 7.3 and 9.7.1). One major assumption in neuroscientific research is that the organization of the human brain contains regions processing information for specific tasks. If activity of the brain can be traced back to one or more of these centers its meaning coud be inferred, which would lead to a true one-to-one mapping between EEG data and the three-dimensional activity of the brain. There are several algorithmic approaches for identifying sources in all spatial dimensions of brain activity, bringing EEG research one step further forward to a bijective information transfer from brain activity to EEG patterns [53]. One major approach is the use of statistically independent components for reconstructing the source space [29]. The identification of spatial sources of brain activity leads to a combination of temporal and spatial patterns, resulting in networks of sources connected over time [56].

Each domain provides a perspective on information in EEG data that is at least partially disjunct from the others. Hence, combining information inferred from each domain to a joint information space often is a valuable approach. In BCI research this is reflected by the introduction of feature extraction methods which take several domains into account. Take a look at the comparison of Common Spatial Patterns (section 8.3.2) with logarithmic Bandpower Estimates (section 8.3.1) in section 8.1 for an example.

7.2.4. The approach of standard EEG analyses

In standard EEG analyses a correlation of brain activity and EEG patterns is developed and mapped to an external interpretation giving a more abstract meaning to brain activity. In figure 7.6 activity of specific regions in the motor cortex is mapped onto activations of specific areas of the human body, for example. Usually this mapping is restricted to areas on the cortex, the surface of the brain, as deeper structures of the brain are hard to access. Of course, this does not mean that there is no activity in deeper areas of the brain. More advanced analyses of EEG data – for example ICA – also allow for identifying sources lying in deeper structures of the brain [29].

With the projection of three-dimensional brain activity onto a discrete two-dimensional EEG space and the summation of electric currents resulting from brain activity and artifact sources makes it difficult to correlate patterns in EEG with activity of specific areas in the human brain. This is a major problem for giving a well-defined meaning to patterns in EEG.

In EEG research this problem has been approached with several mechanisms. Following the functional approach [54, 55] it is difficult to find a one-to-one mapping between brain activity and its meaning. Hence, a valuable approach is determining a specific factor under investigation by experimental conditions and relate resulting brain activity to it. Here, it is necessary to focus on one single factor under investigation, as multiple factors would lead to a conglomerate of relations which are hard to identify with single factors.
The definition of a proper experimental paradigm therefore includes strict control over factors influencing the experiment. The variation of factors should include all environmental, subjective and technical factors related to the (more abstract) factor under investigation and should fix all factors not related to it. With this the factor under investigation can be isolated and manipulated giving an external meaning to the resulting EEG recordings.

Due to volume conduction it still might be unclear which portion of the signal recorded by the EEG is related to relevant brain activity and what results from artifacts or unrelated activity of the human brain. Hence, it is also relevant to minimize *noise* influencing the EEG data. The term 'noise' describes the summation of signals from first and second order artifact sources including brain activity not related to the factor under investigation. Practically, this can be achieved by minimizing activity of the investigated subject's body

as well as possible to activity only directly related to the factor under investigation and vital functions. Another tool is focusing on patterns occurring only coherently over trials. The basic idea behind this approach is the assumption that in strictly controlled experimental environments noise related data occurs randomly while data related to the factor under investigation should be structured similarly. If data resulting from multiple trials of the experiment are averaged in a proper way, the outcome should reflect the *core pattern* related to the factor under investigation. With the term 'core pattern' I refer to the fact that variances in the data resulting from modulations in the factor under investigation are only weakly represented in the outcome of this approach.

This approach can be applied to data from time domain EEG. Here, the structure of the experiment usually contains markers indicating specific events, which can be overtly related to the factor under investigation, hence, on an abstract level of observation. Trials can then be averaged aligned to these events, canceling out unwanted artifact sources and also incoherent portions of data related to the factor under investigation, while emphasizing its core patterns. Usually, the outcome is corrected to a baseline generated from data mainly not influenced by the factor under investigation but strictly related to it in time. This approach is called the generation of *Event-Related Potentials* (ERP) [58, 47]. An ERP usually consists of peaks at certain latencies and (relatively) negative and positive amplitudes. See figure 7.8 for an example.

A similar approach can be applied to data from the frequency domain. Here, power spectra are averaged over trials and also aligned to dedicated events, so that changes in certain frequency bands can be correlated to the factor under investigation. Changes in frequency bands recorded by EEG result from decreases or increases in synchronicity of neuronal populations. This approach is called the mapping of *Event Related Synchronizations* (ERS) – if an increase of Bandpower is recorded – and *Event Related Desynchronizations* (ERD) – if Bandpower decreases – in certain bands [10]. See figure 7.7 for an example.

7.2.5. Relevant patterns in electroencephalography

This section gives an overview of the features of scalp EEG that are most frequently used for BCI purposes. Starting with ERPs I introduce the P300, the readiness potential and responses on perceived errors. Then, I present features based on ERD, such as the amplitude modulation of the Sensomotoric Rhythm (SMR) and the α-rhythm over parietal areas of the cortex (Parietal α-Rhythm). These patterns share the characteristic of being detectable quite easily in EEG and show a relatively low variance within and partially also between subjects – as we will see later in Chapter 12.

Novelty Potential

The perception and interpretation of novel and unexpected events is a relevant skill for human beings. In EEG it is reflected by the so called *novelty potential* [59]. It is an ERP with one negative component usually around 200 ms after perception of the event and a very prominent positive potential following 100 ms later. Dependent on the type of stimulus and how it is perceived, it is recorded in central-central, central-parietal and/or temporal electrodes [60, 61, 62], with generators proposed in the Anterior Cingulate Cortex (ACC), visual cortex and temporal lobes. Main electrodes usually record amplitudes of around 5 μV for the negative component and 10 μV for the positive component. Factors like attendance, task relevance, presentation in visual, auditory or tactile modality modulate the coherence and amplitude of both components. See figure 7.8 for an example of a typical topography and temporal series.

Novelty Potentials are usually evoked with so-called Oddball paradigms. Several derivates have been developed in recent decades [63]. They share the structure that stimuli are presented frequently to the subject in one modality. Most of the stimuli – usually 90% – share a similar structure or are identical and are called 'standards' while the remaing stimuli show an obvious difference in structure and are called 'deviants'. The observing brain reacts with a novelty potential to the perception of deviants.

The approach used by the P300 Speller is very common in BCI research [64, 65, 66]. Usually a matrix of 6 rows and 6 columns displaying all 26 letters of the alphabet plus the 10 numerals is presented to the subjects (see figure 7.9). While the subject focuses on a single letter or numeral, the rows and columns are randomly highlighted several times. The highlighting of the symbol being focused on evoke (at minimum) a more pronounced novelty-related potential than the subject's peripheral perception of the other flashes. Taking this assumption as its starting point, the BCI system then selects the symbol corresponding to the highest amplitude in the averaged positive component. The P300 Speller's approach utilizes brain signals indirectly via a reaction to an external stimulus. Hence, the signal detected by the BCI is not directly generated by the user. Other approaches that involve a BCI-based speller use directly generated brain signals, often involving motor imagery. A example is the Hex-O-Spell [67] developed by the Berlin Brain-Computer Interface group[1].

Though, most of research has focused on visually presented P300-Spellers, it seems inapproprtiate to utilize the visual modality for locked-in patients as they also lose control over their eye-movements in later stages [6]. And, if they still have control over their gaze, it might be more efficient to use an eye tracking system as input. Recent studies [66] have shown that the assumption that covert attention [68] also evokes a potential which is reliably detectable by common BCI approaches is untrue. Hence, it seems to be more reasonable to

[1] `www.bbci.de`

focus on P300-Spellers based on other domains, like the auditory [69, 70] or even tactile [71] modality.

Readiness potential

The preparation of motor actions usually evokes a Slow Cortical Potential (SCP)– which is a subtype of the class of ERPs – relative to the event of the action. When focusing on hand movements, e.g. movements of the index finger, one can find a slowly evolving negativity over the contralateral motor cortex. This SCP is called *readiness potential* – or Bereitschaftspotential – see figure 7.10 for an example. The coherence and the shape of the readiness potential and its amplitude are strongly dependent on factors like type of action, time available for preparation and task relevance. See Chapter 10 for an example of an experimental paradigm inducing readiness potentials.

In 1999 Niels Birbaumer and colleagues published an inspiring study on the utilization of SCPs for ALS patients in a BCI driven spelling device. The presented user-trained BCI detected a slowly modulated potential in central electrodes. Subjects learned over a period of four years to generate a negative or positive SCP artificially, which means that this ability can be seen as a newly learned skill. It was not necessarily related to a cognitive process that was established naturally in earlier stages of the subjects' life, and also was not coherent over subjects. Besides its practical relevance this study is also a beautiful example for plasticity of the human brain.

Error Responses

Current research suggests that the human brain has a general error monitoring process [73] evaluating events related to the humans actions [74, 75, 73]. It has been investigated in different approaches. Falkenstein [75] and Gehring [74] simultaneously investigated the brains' reactions to self inflicted errors – meaning that an acting human evaluates a previous decision as wrong in their own interpretation. In both studies a negativity roughly 100 ms after muscular motion onset was found which had highest attenuation in fronto-central electrodes, it is called Error Related Negativity (ERN). It is associated with a first alarm on erroneous behavior [76]. Falkenstein also investigated a later positive component, following the ERN about 300 ms, displayed well in response-locked difference wave-shapes (Miss-minus-Hit plots). He suggests a relation to a conscious error awareness [77]. See figure 7.11 for an example ERP. Miltner et al. [73] investigated responses to externally evaluated actions. The responses of the subjects brain that can be found 650 ms after feedback to the subject show a high similarity to the ERN and are called Feedback ERN (fERN) [73]. As described by Holroyd [63] and also Nieuwenhuis [78] the fERN occurs in response to a negative feedback referring to incorrect performance, a punishment or negative reward.

Both ERN and fERN are mainly localized in (dorsal) ACC [73].

In BCI research, the utilization of error responses of the human brain seem to be valuable, but has not been proven to be applicable. Schalk et al. [80] investigated error responses firstly in a BCI context. It was based on a positivity following response errors. As reported by Gehring and Falkenstein, it is unclear whether the positivity after response errors reflects error processing. Hence, it is doubtful whether this approach really is based on error responses. Blankertz et al. [81] showed theoretically that validated responses to self-inflicted errors could be used to improve classification accuracy in a BCI-driven system. Ferrez et al. [82] implemented an error correction system in a simple BCI-controlled setup. They showed that the overall accuracy could be improved. However, as there is a strong correlation between an error and the type of stimulus color and movement, it is still unclear whether the resulting ERP is related to error processing of the brain or to the simple perception of a moving and color changing stimulus as presented in [83]. The topography and morphology of ERPs from [82] and [83] indeed show a strong similarity. In Chapter 12 a first study utilizing validated error processes for enhancing Human-Machine Interaction will be presented.

Changes in synchronicity related to motor imagery and actions

One major feature used in current BCI research is the frequency state over motor cortex during motor imagery. If the subject imagines a movement of an extremity – like the left or right hand – motor neurons in the related part of the motor cortex (see figure 7.6) should lose synchronicity resulting in a decrease in the band power (ERD) of the μ-rhythm recorded in near electrodes. In contrast, the band power over other electrodes over the motor cortex should stay stable as the synchronicity of unactivated neurons should be kept (ERS) [10]. This pattern can be utilized for BCI approaches, as it defines a binary information channel which can be modulated by most users quite easily and naturally as the movement (and also its imagination) of extremities is a natural concept. See figure 7.12 for an example of ERD/ERS. This has been utilized in numerous studies for establishing a BCI-based channel for communication and control (e.g. [8, 84, 13, 85, 86, 57, 48, 87, 40]).

Parietal α-Rhythm

The concept of ERD/ERS can also be adopted for BCI purposes in detecting other states of the human brain than those related to motor imagery, as the restoration of synchronicity in populations of related neurons while not performing on a specific task is a basic principle of the human brain [88, 10]. It can also be found in processes related to sensory-semantic processing, memory, visual processing, fatigue and attentional state, see [88] for details. Here, the most discriminative frequency band is usually the α-band, mostly located in areas over the frontal lobe or parietal areas. In BCI related applications this process has mainly been used for detecting a correlate to mental workload or vigilance [89, 90, 91].

7.3. What is different in BCI research?

The interdisciplinary field of BCI research is partially based on results generated in neurosciences. Relations between brain patterns and external processes are utilized to define a communication channel based on brain activity. Therefore, basic principles of neurosciences (like the principle of functionality – see sections 7.2.3 and 9.7.1 for a description) are shifted or simply overwritten. Additionally, theories from neurosciences have to be extended because in BCI research the brain is observed while interacting more intensely with its environment than in standard laboratory experiments. This leads from laboratory experiments to the challenges of the moment in realistic scenarios.

7.3.1. Methodological shifts in BCI research

The above mentioned change in context leads to changes in personal motivation of the subject. Still it is unclear to what degree the level of motivation influences brain activity and patterns, but any impact should also influence features taken for BCI. Chapter 11 shows a study on shifts in context which also have an impact on the motivation of the subject. Other studies on motivational aspects of BCI performance can be found in [79] and [92].

In BCI experiments, the degree of complexity of the task to be resolved also changes. Standard neuroscientific experiments are usually restricted to simple and controllable factors of investigation. BCI experiments are usually more realistic, and hence more complex tasks are investigated and utilized. This implies less control over factors which requires more effort for analyzing and validating investigated patterns in EEG. Section 8.1 provides an overview of methods used for this in this thesis.

The most prominent principle from neuroscientific research that is not transferred to BCI research is functionality. While in neuroscientific experiments the controlled context usually evokes specific patterns in the activity of the subject's brain, in BCI experiments brain patterns are utilized to influence the given context. Hence, the information flow is reversed (see section 9.7.1).

From an algorithmic point of view the main advance in BCI research is the analysis of single trial events. BCI commands should be analyzed in realtime to provide a closed loop interaction between the user and the machine, so methods used for inferring the commands could hardly rely on averages of larger amounts of data. This leads to a shift from methods usually used for generating ERPs and ERDs/ERSs to methods from machine learning, which once calibrated could identify patterns in single trial data. See section 8.1 for a description of methods used in this thesis.

7.3.2. Methodological problems in BCI research

The shifts in methods used for BCI research imply questions and problems extending those already known from neuroscientific research. As EEG signals cannot usually be mapped one-to-ne to their sources, effort has to be made to ensure that BCI commands are clear enough to avoid interference with other cognitive processes while interacting through a BCI. This reaches the limits of current BCI research, as it focuses on the application of BCI systems in realistic scenarios. Hence, there are few studies available dealing with this set of problems. One detailed approach to feature validation in a BCI based application can be found in [93].

Another problem is the interdisciplinarity of BCI research. Adding the field of machine learning and advanced signal processing to neuroscientific research requires a BCI researcher to have extended knowledge in at least two highly complex fields of research. As this level of expertise can not be expected from every researcher in the field of BCI, workarounds are needed. The field tends to establish toolboxes with simplified user interfaces. This *black box approach* raises the danger of unsupervised analyses leading to a lack of validation in results [94]. For analyses presented in this thesis a toolbox has been developed which is easy to use and allows for proper validation. A simple syntax and advanced visualisations have been combined with proper statistical tests. See [95] for details and Parts II and III for a description of the application of this toolbox in this thesis. As it will now be released with the well-known toolbox EEGlab [96] it might be a first step for a solution of the above mentioned black-box problem.

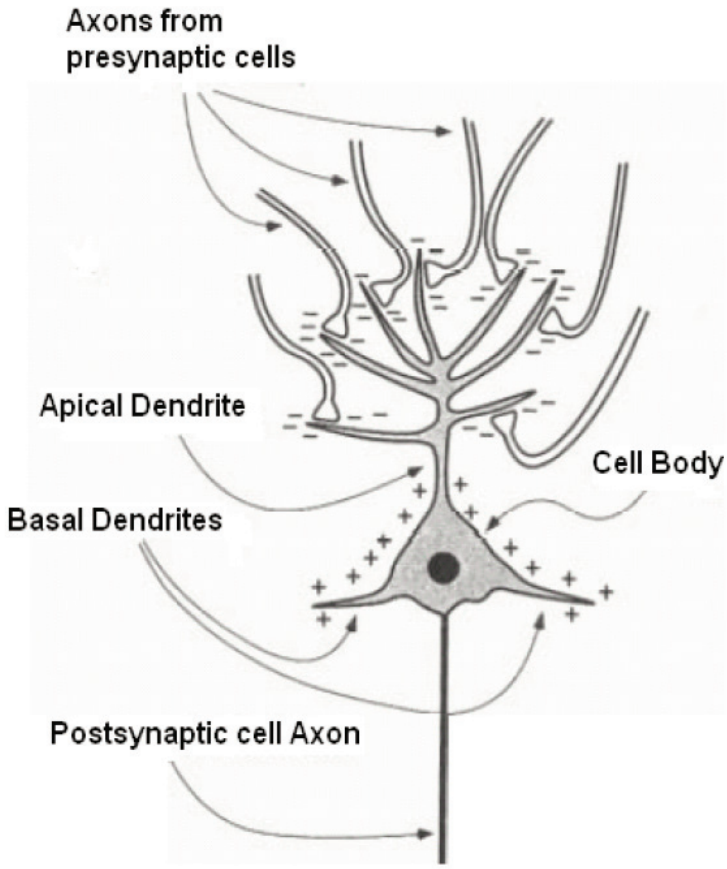


Figure 7.1.: Description of a neuron.
The human nervous system consists of a complex structure formed by neurons. A neuron is a cell capable of transmitting information through chemical and electrical processes. Junctions are established via synapses, exchanging electrical current or neurotransmitters between cells. Presynaptic neurons, the signal-passing cells, are connected to synapses via axons while postsynaptic neurons, which receive information, are connected through dendrites or the cell body of the neuron. EEG detects changes in electrical activity of neurons. If numerous neurons, oriented orthogonally towards the scalp surface, act synchronously, they induce potentials which can be picked up at electrodes outside the skull. Taken from [43]

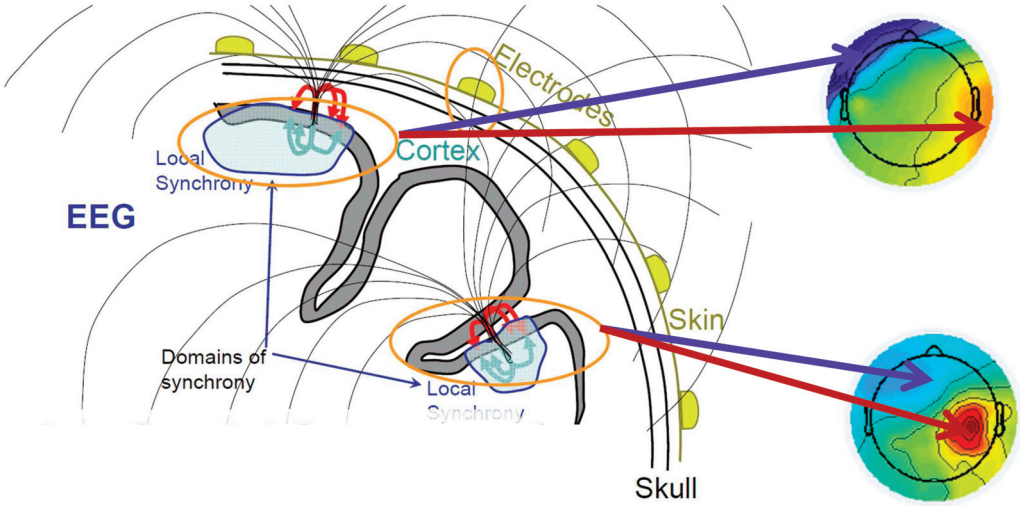


Figure 7.2.: Volume Conduction.
Due to volume conduction, EEG electrodes on the human scalp record summations of signals from different sources in the human brain. Each source projects in a dipolar way onto the human scalp. The figure shows the projections from the poles of two sources located nearby each other. The map of the resulting electrical field that is recorded at the electrodes is similar in both cases. The differences result from the spatial properties of the sources and the orientation of the related dipoles. Blue colour indicates a negative electrical field while red indicates a psoitive. See [45] for details. Taken and modified from [45]

Figure 7.3.: Ten seconds of EEG.
Ten seconds of a time series of a 32 channel EEG. Each row shows an electrode labeled on the left hand side along the nomenclature of the extended international 10/20 system. The sampling rate is 200 Hz, values for spaces in between are intFFFolated.

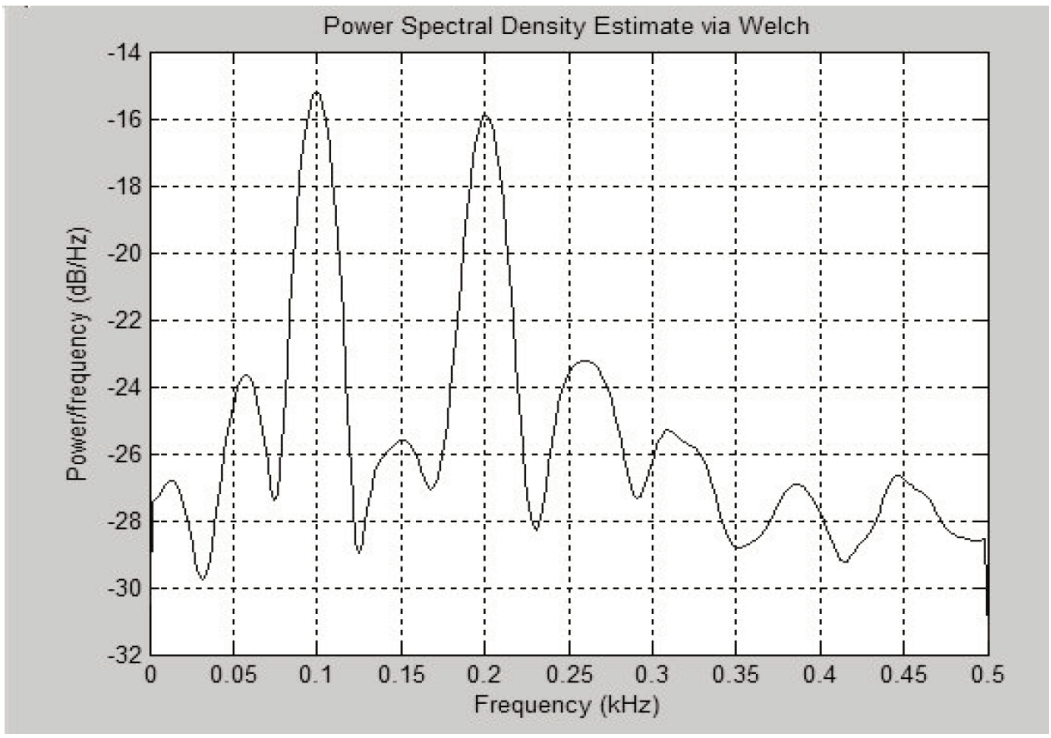
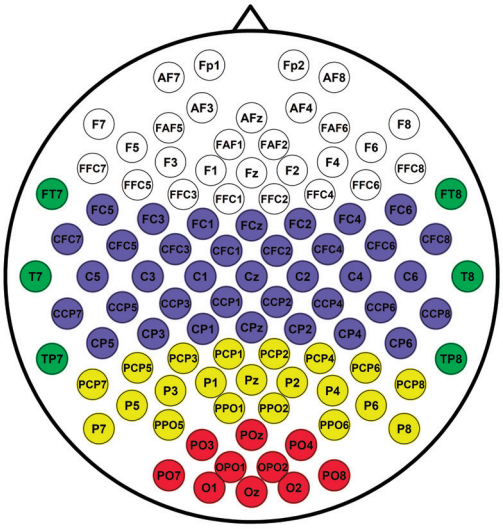
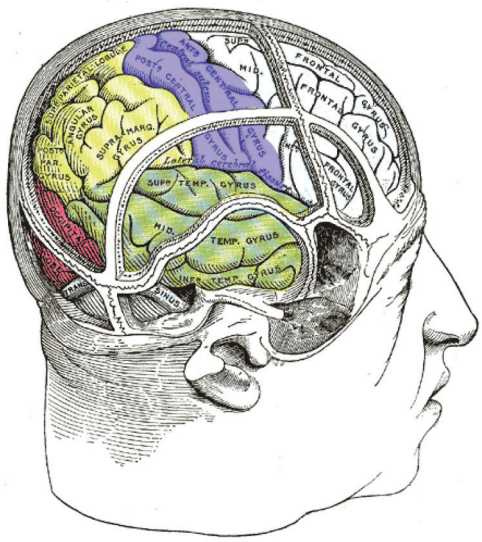


Figure 7.4.: Example of a power spectra.
An artificially generated power spectra of a signal sampled at 1000 Hz. The graph plots frequency (x-axis) against relative power (y-axis). See two major peaks at 100 and 200 Hz.



(a)



(b)

Figure 7.5.: Electrode positions and the lobes.
(a) The extended international 10/20 system. Colors encode lobes to which the underlying positions correspond: frontal (white), central (blue), parietal (yellow), occipital (red) and temporal (green) lobes. (b) The major lobes of the brain, colored as well. Taken from [57]

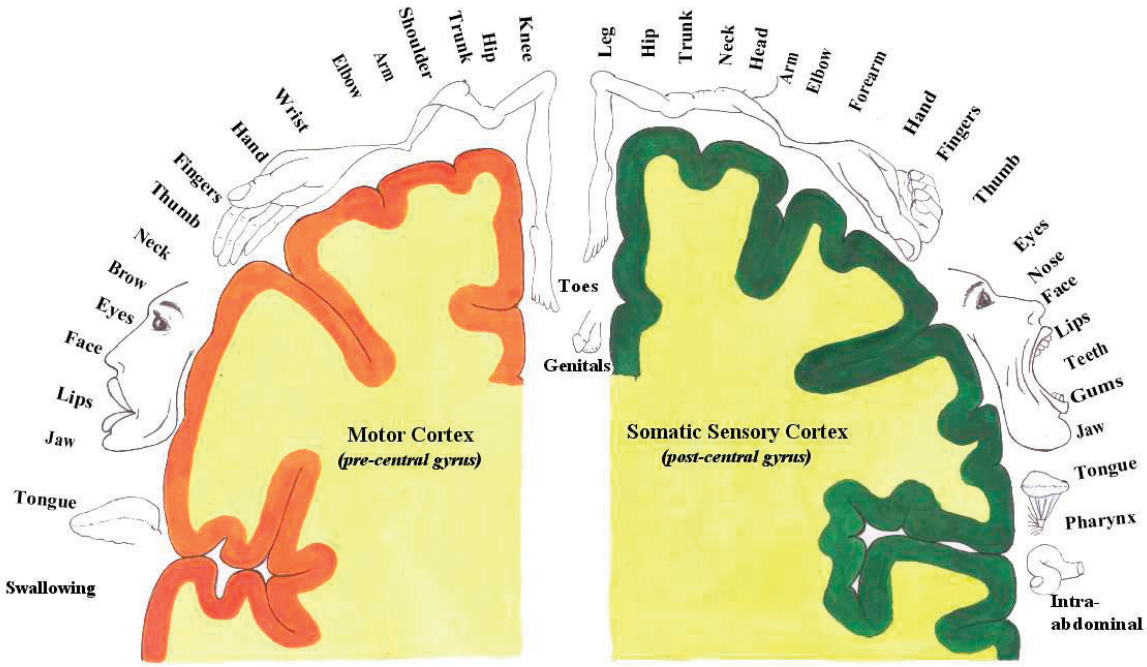


Figure 7.6.: The homunkulus.
Two lobes of the brain (blue color in figure 7.5). With the motor cortex, left, and the somatic sensory cortex right. A sketch of the human body is morphed on the parts of these lobe representing the specific parts of the body. This mapping is called 'homunculus'.
Taken from [57].

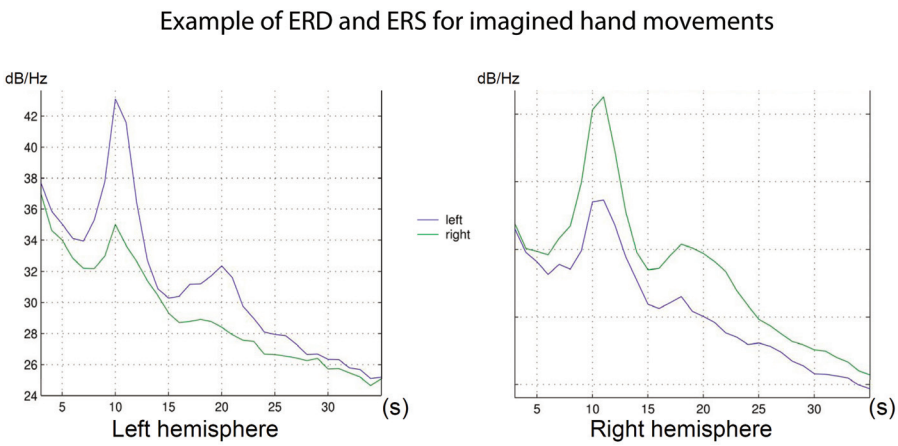


Figure 7.7.: An example of ERD and ERS.
Example for spectra over C3 and C4 while motor imagery of left and right hand movements. Blue curves indicate spectral power for left hand movements and green curves for right hand movements. In α and β bands a significant difference can be found in the spectra between laterality of movements.

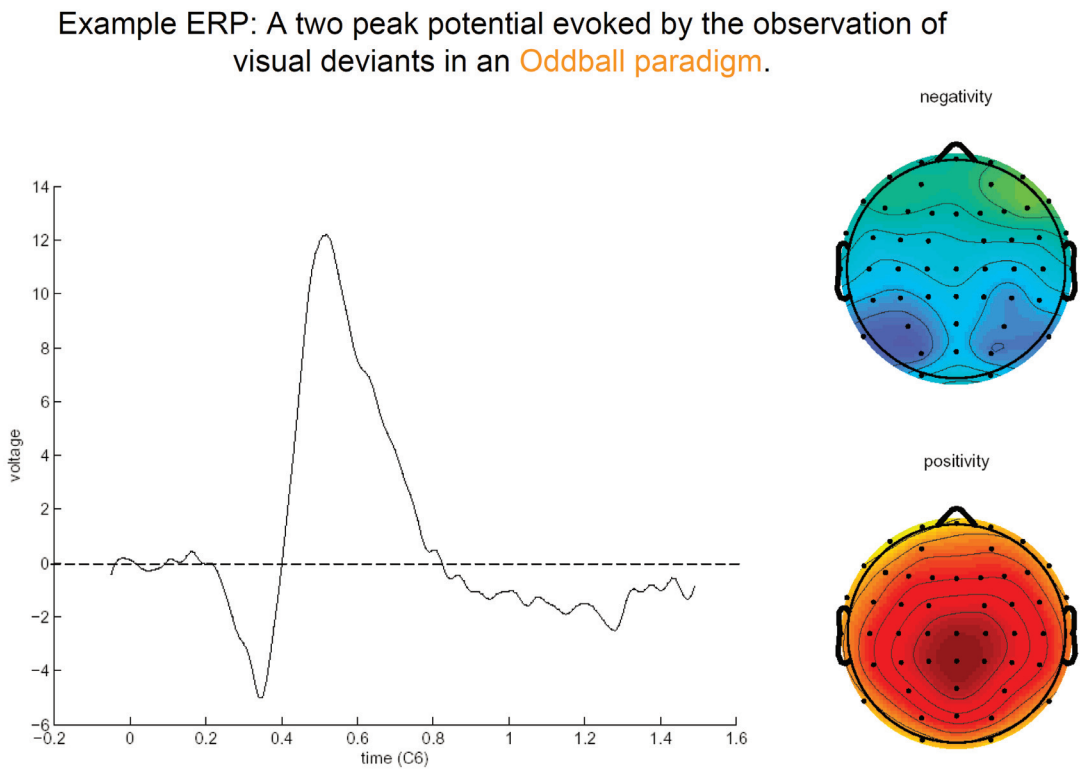


Figure 7.8.: The Novelty Potential.
A Novelty Potential as an example of an ERP at channel C6. This graph plots time (x-axis) against voltage (y-axis). Time 0 indicates the occurrence of a visually perceived deviant stimulus. At roughly 380 ms you see a negativity followed by a positivity peaking around 150 ms later. The topographic plots on the right show the distributions of the intensity of the negative peak (top) and the positive peak (bottom).

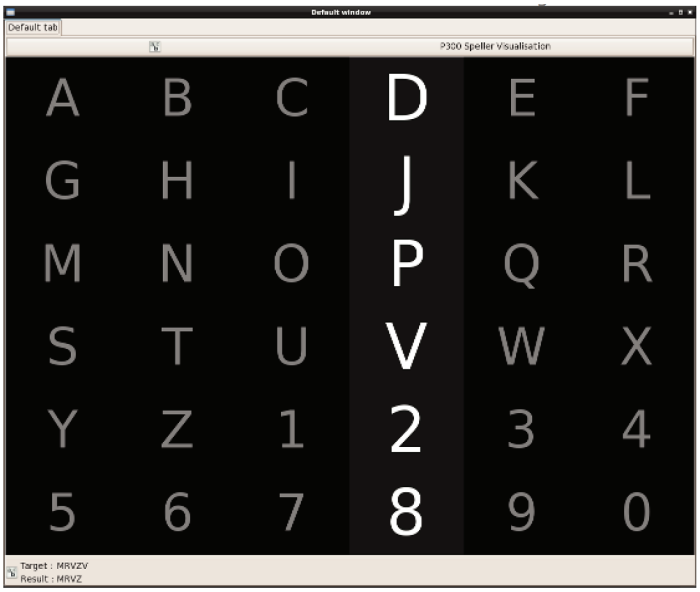


Figure 7.9.: The P300 speller.
A sceenshot of Brain Products' P300 speller. A flashing column in the 6x6 matrix containing letters and numerals. The voluntary perception of a letter in a flashing column or row evokes an accentuated P300. After random repititions of flashing rows and columns, the selected letter can be inferred from EEG signals.

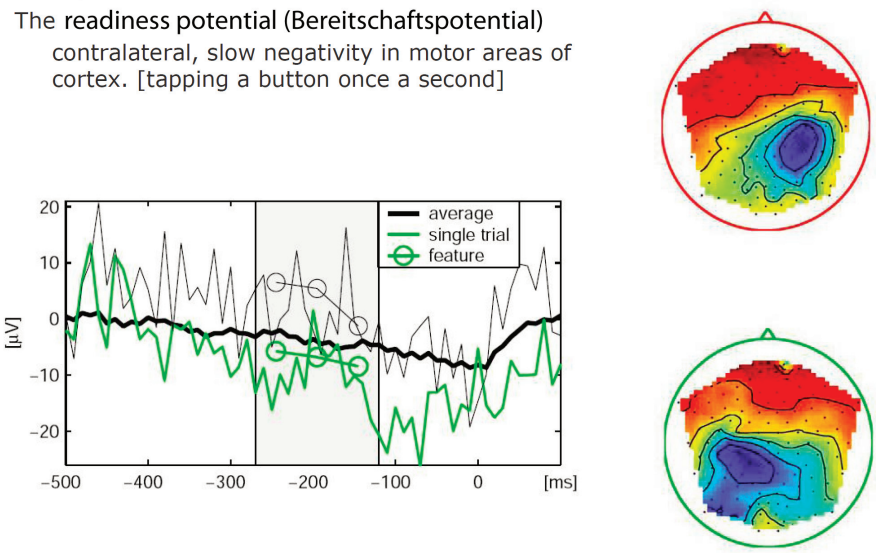


Figure 7.10.: The readiness potential.
The readiness potential in preparation of a paced hand movement. Here, the negativity starts evolving roughly 500 ms before the actual hand movement. Thin lines show two single trials while the bold line indicates an ERP averaged over several hundreds of trials. The circles indicate reasonable features for single trial detection of the negativity. On the right hand side the spatial topography of this negativity is displayed. Blue indicates a negative peak while red is positive. On top in the red circle you can see an average for left hand movements, below in the green circle a topography for averaged right hand movements. Adapted from [72]

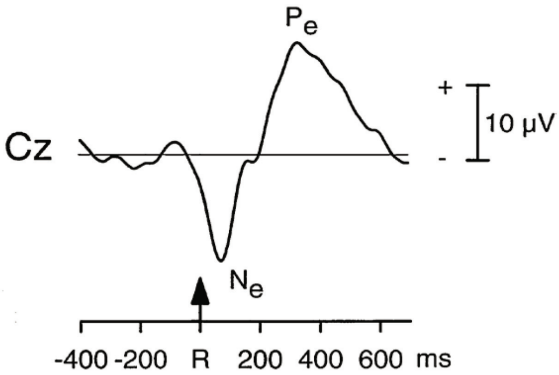


Figure 7.11.: The Error-Negativity.
Grand average of response-locked difference waves (errors minus correct) induced by self inflicted errors. Taken from [79].

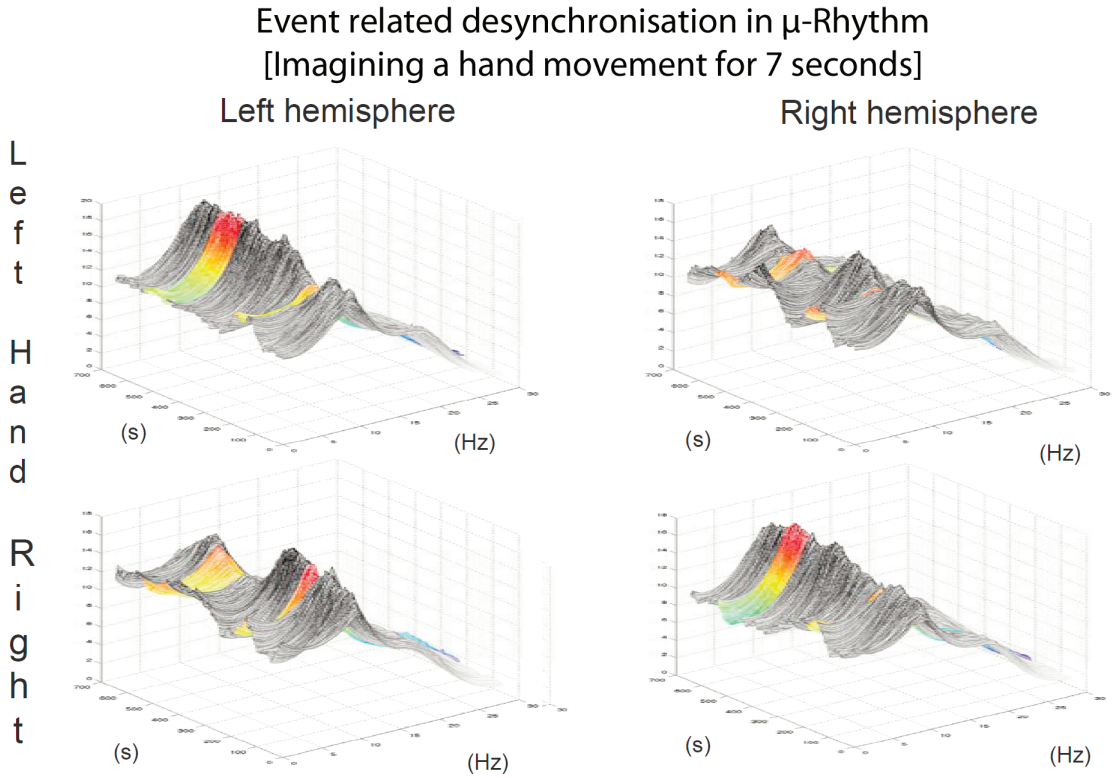


Figure 7.12.: ERD during imagined hand movements.
An example of an ERD and ERS while imagining hand movements. Each of the four subplots show a series of power spectra during 7 seconds of motor imagery. Rows show spectra for left and right hand movements in electrodes C3 and C4 representing left and right hemisphere. For BCI a simultaneous problem has to be solved. Colored areas indicate portions of data that reflect an ERD/ERS complex for right hand movements and an ERS/ERD complex for left hand movements simultaneously.

8. Techniques from Signal Processing and Machine Learning

In this Chapter I give an overview on the algorithmics used for the studies presented in this thesis. I will not give detailed insights into the underlying mathematics as all approaches are already been published and described in other publications. Hence, I try to avoid formulas as the resulting formality is not needed as no new formulas will be deduced, no strict logical implications are derived. All relevant literature is cited. Also, I do not focus on the implementation of the algorithms for application in this experiments as the description of the PhyPA Toolbox (see section 9.3) can be found detailed in [95]. I give a summary of the basic principles of algorithms used in machine learning based BCI research. When talking about specific algorithms I will give details about the capabilities and restrictions as well as an overview of factors influencing their applicability, like the number and complexity of free variables.

8.1. Prerequisites for the algorithms

The initial approaches of Brain-Computer Interfacing were based mainly on effort taken by the user. Users were trained to generate patterns in the recordings of their brain activity that were expected by the technical part of the given HMS. Though this approach proved to be successful [11], the burden on the users is a major drawback. Especially for users in a normal state of health this effort seems unacceptable. Another approach, mainly based on machine learning techniques, overcomes this drawback by transferring most of the learning effort to the technical part of the system.

Machine learning is a sub-field of computer sciences that adopts methods from optimization, probability theory, and signal processing and combines these in a framework for recognizing regularities, e.g. patterns in the data. See [97] for an interesting overview and introduction to the field of Machine Learning. The basics of the machine learning approach for BCIs are easily described. Patterns in EEG activity that are used as commands for the BCI are generated by the user through performing tasks (mentally), that already have been learned earlier in life. The user initially generates *prototypes* of data that are used to calibrate the machine learning algorithm for reliable detection in the intended application. There, the EEG data is processed and analyzed in real time for detecting the previously learned patterns and interpret them as commands. This can be used to discriminate the

presence or absence of distinct *classes* that can be seen as specific cognitive states, or to allocate the extend to which a specific state is present at that moment. The outcome of this analyses is a classification of the given data, that is usually an assignment to specific numeric values or given discrete classes. The resulting information can then be used to change the state of the technical system or the whole Human-Machine System (see Figure 8.2).

Thus, the user can directly generate BCI commands without time consuming learning. The reduction of the effort required to learn the skill of controlling a BCI is a major step in BCI research. In the last decade many researchers focused on the development of novel machine learning methods for BCI research and also on fine tuning of existing approaches. But this approach also includes drawbacks. Due to changes in basic properties of the EEG signals, mostly related to differences in electrode positions, in electrode impedances and changes in user state between sessions that might influence brain activity substantially, the prototype signals that the detection algorithms are calibrated on, usually have to be generated before each session. Also, the adaptation of the algorithms to the user introduces a second adaptive factor, in addition to the adaptive human brain, to the HMS. If the adapting processes do not converge, a downward spiral of positive feedback might lead to a significant decrease in performance of the given HMS. This will be discussed more in detail in Chapter 11.

8.1.1. Offline and Online Analyses

In principle there are two ways of processing EEG data for BCI approaches. In *offline analyses* recorded data is processed to indicate, what information can be expected in this type of data and what might be a good way to extract it. This is necessary for tuning detection algorithms to the specific subject in a given task. There are three possible outcomes of offline analyses. The first is insight into the data which might be related to already validated knowledge from the neurosciences or other sciences. The second is a detection algorithm that is able to detect chosen patterns in the given data, and hopefully as well in new sets of data from the same type. And third is an estimation of the performance of the BCI based part of the given HMS (see section 8.1.2). The validity of these outcomes depends strongly on how the analyses are performed and what portions of data are used for this. The best way is to mimic as closely as possible an *online analysis*, i.e. the real application of the BCI in realtime and in a realistic application. These so called *causal analyses* respect the following three rules:

1. Only take data into account that really is available at the time point you would like to analyze. This is especially relevant for filter methods which inherently might access future data, e.g. through forward-backward filtering.

2. Don't forget that the processing time of the algorithms influences the real time appli-

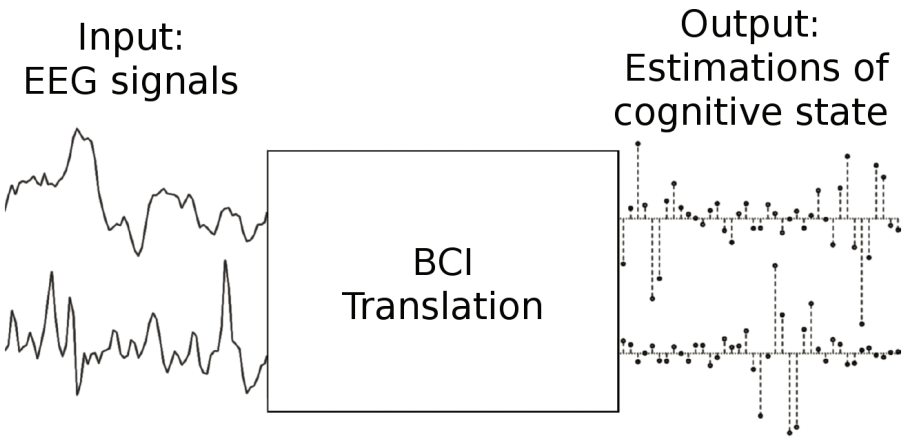


Figure 8.1.: Scheme of the BCI translation.
A BCI translates EEG into estimates of the extent to which an aspect of cognitive state exists. This can be done continuously or on request. The outcome can be binary (yes / no) or scaled ($[-1:1]$). Modified from [95]

cability of the given system. This is also strongly dependent on the hard- and software used.

3. Make sure that any processed data and information is available in online scenarios as well.

From an abstract perspective a machine learning based BCI estimates extent to which a cognitive process can be detected in a given set of EEG data. Hence, it translates EEG data into statements about the cognitive state of the user (see Figure 8.1). But how can such *translation algorithms* be defined? First of all it is necessary to determine which aspect of cognitive user state shall be detected. Then, based on knowledge from the neurosciences, specific properties of EEG that correspond to that aspect of cognitive user state have to be selected. Following this, an algorithmic model will be defined. This model should be capable to extract and identify patterns from the EEG that are related to the selected cognitive process. This method will be optimized such that a reliable prediction about the investigated aspect of cognitive user state is possible. The resulting recipe is called *classification scheme*, and is contained in step two of figure 8.2. Usually, this is derived in four steps, structured as follows:

1. **Signal Processing** The processes in this stage aim for two goals. The data has to be restructured so that it reflects the investigated information as well as possible. Usually

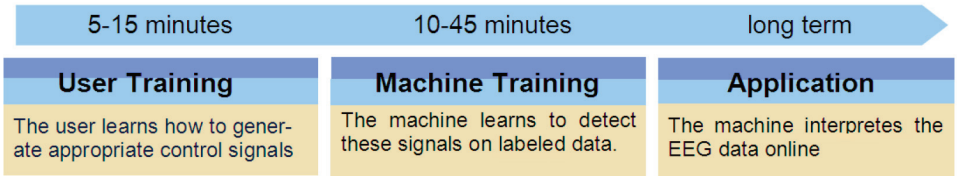


Figure 8.2.: The classical Training Sequence.
The classical Training Sequence used in machine learning based BCI research. In the first stage the user trains generating the command signal. In the second stage the user generates prototypes of the two classes that shall be discriminated. Based on this a discrimination algorithm is calibrated. In the last stage this algorithm is applied on online data for generating input commands to the HMS.

this is done by sub-dividing it along reoccurring processes resulting from the experimental structure. This results in a segmentation of the data into so-called *epochs*. Each epoch contains at least one *label* carrying information of the experimental design, and accordingly about the intended meaning of this portion of the data (see section 7.2.4 for details). The second goal is the restriction of the data to a relevant bandwidth. This can be achieved by using methods from signal processing to select specific frequency bands or to filter the data along spatial or temporal properties. The outcome of this stage are epochs, containing data that is focused on relevant parts of the signal.

2. **Feature Extraction** The main purpose of this stage is to build up a data structure that can be used to discriminate between the chosen classes best as possible. Therefore, portions of the data that seem to carry no information about the chosen classes are discarded. Also, data can be transformed, e.g. averaged, concatenated, condensed with the intention of increasing the correlation between the data and the classes. Here, the structure given by the EEG is usually destroyed leading to a new, more abstract data space, the so-called *feature space*. It can differ strongly from the initial structure, especially in its dimensionality. The outcome of this stage is a structure of feature vectors, containing data which should be highly related to the given classes, hence, to the factor under investigation.

3. **Classifier Definition** In this stage, a classification algorithm is calibrated on feature vectors extracted from data of prototypes generated for the given classes. The parameters for the feature extraction are learned and tested in an offline analyses, leading to estimates of the performance of the given classifier in application.

4. **Classifier Application** In this stage, the previously defined classifer is applied to new feature vectors in an online analysis. The outcome of the classification process is

used to interpret the given data, leading to estimates of the occurrence of changes in user state, and finally to input commands for the given HMS.

8.1.2. Performance measures

There are several measures available for estimating the performance of a given system. The most common is *crossvalidation* (CV) (figure 8.3).

The data will be randomly allocated to partitions. Each partition is used to calculate the accuracy of the classifier that has been calibrated on features extracted from the remaining partitions, yielding a sub-classification result. The average of the resulting sub-classification results give a quite accurate estimation of the classification accuracy in subsequent online application. To avoid *overfitting* [97] of the classifier to coincidental patterns in the data, free parameters of the classification scheme have to be selected carefully. For each free parameter a classification has to be developed and evaluated on an independent run of a crossvalidation on the current training set, leading to a set of new sub-partitions. This procedure is called *inner crossvalidation-run of a nested crossvalidation*. There are several derivates of this approach which might improve this estimate, as they take care of dependencies within the trial structure (see [95]).

Another measure for the performance of a BCI is *Kullback-Leibler Divergence* (KLD) [35], which reflects differences in the feature distribution of the initial training set to that from another portion of data - e.g. taken from an online recording.

Thirdly, the quality of the feature extraction can be estimated by calculating the *class correlation coefficient* R^2, where R indicates Pearson's Correlation Coefficient [98]. It calculates the correlation between a binary vector indicating the class type for each trial and a matrix containing the extracted features for each trial. Higher class correlation coefficients indicate that the feature extraction worked well.

8.2. Preprocessing

8.2.1. Spatial filters

Spatial filters are functions transforming the relationship *between* data recorded at different electrodes. In this thesis only linear spatial filters are used, meaning that the filter is represented by a matrix SF and the transformation of the EEG signal E at time t is described by $ET(t) = SF * E(t)$. IF SF is invertible, the application of spatial filters can easily be reversed by applying the inverse of SF.

In the following two spatial filters will be used.

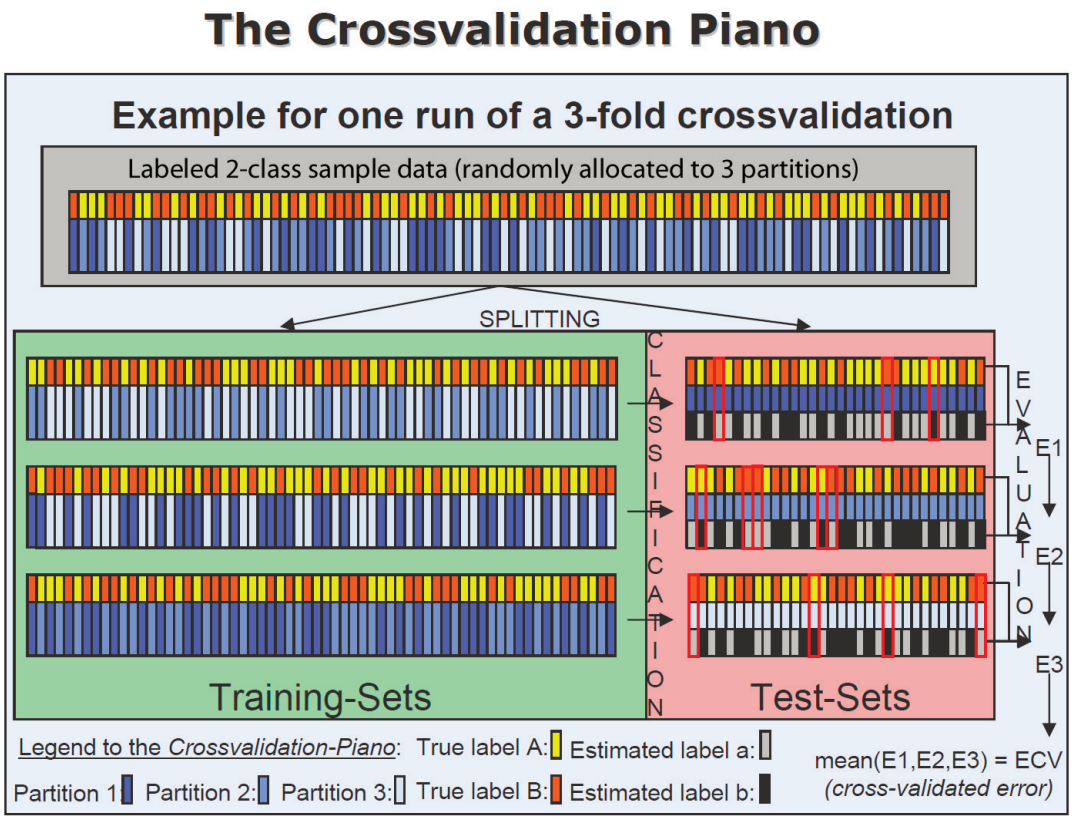


Figure 8.3.: The Crossvalidation-Piano.
Here an example of a 3-fold crossvalidation is shown. The sample data is randomly allocated to three partitions, independent of their class-membership. Then features are extracted from the union of two partitions (training set) and a classifier is trained on the resulting features. This classifier is then applied to all trials from the remaining partition (test set). The outcome is an estimation of the error rate of the derived classifier. This is repeated for all possible training sets (here 3). The resulting crossvalidation error is the average of all calculated error estimates.

1. **Channel selection**
   Knowledge derived from the neurosciences might imply that cognitive processes are represented mostly in specific EEG channels. For computational reasons it might also be valuable to reduce the amount of data processed in a classification scheme to the most discriminative parts of the EEG data stream. In that case, a channel selection could be applied, reducing the channels used to that suggested by the neurosciences.

2. **Laplacian filter**
   In cases where the examined process is focused on single electrodes that are spatially distant from each other, a *Laplacian filter* can be used to enhance the signal-to-noise ratio. From the data recorded at each electrode the averaged value of adjacent electrodes in the 10/20 system is subtracted. With the assumption that noise induced by artifact sources is represented in each electrode at almost at the same intensity – which makes sense as the intensity of artifact sources is usually higher by some orders of magnitude and distributed by volume conduction – a Laplacian filter should eliminate noise while retaining the spatially focused process of interest. See [99] for details.

8.2.2. Temporal filters

Temporal filters transform the relationship of the data *within* EEG channels, hence, they modify the time course of an EEG signal relative to itself. This weighting of the signal over time can be seen as being orthogonal to that of spatial filters.

In this thesis two temporal filters are used.

1. **Resampling**
   The resampling filter reduces the sampling rate of the recorded signal. This is done by skipping samples equally distributed over time. This method is non-causal and should only be used for offline analyses. In online analyses the sampling rate has to be set to a proper value from the beginning of the recording.

2. **Baseline correction**
   In ERP analyses it is helpful – often necessary – to see amplitudes of peaks relative to the basic level of the recorded EEG signal. The basic level is usually determined from segments of EEG data which are intended not to be influenced by cognitive processes, but only by noise. The average of samples recorded in this segment should reflect the baseline of the EEG signal. Practically, this filter only is applied in epochs relative to event markers, to ensure a consistent baseline.

8.2.3. Spectral filters

Spectral filters are subtypes of temporal filters. They transform spectral characteristics of the recorded EEG signal. Spectral filters are powerful tools focusing on specific aspects of EEG recordings, as many cognitive aspects are found in the frequency domain. Though there are many ways to define spectral filters, like infinite impulse response (IIR, [97]) or finite impulse response (FIR, [97]) filters, I will focus on Fourier Transformation (FFT, [97]) in this thesis, as it provides a causal filter which is invertible and has properties which can be determined only on characteristics of the given signal, such as the size of frequency bins is related to the number of trials and sampling frequency.

In this thesis four types of frequency reductions through spectral filters are used.

1. **High Pass Filtering**
   This filter preserves all frequencies above a selected threshold.
2. **Low Pass Filtering**
   This filter preserves all frequencies below a selected threshold.
3. **Band Pass Filtering**
   This filter preserves all frequencies between two thresholds.
4. **Notch filter**
   This filter keeps all frequencies but those between two thresholds.

8.3. Feature extractors

In the following I will give a brief description of the feature extractors used in this thesis. Feature extractors are the algorithmic core components of each BCI system. From my experience a classification can only work well if features are extracted properly, meaning that even complex classifiers could not help on features carrying little information.

8.3.1. Logarithmic Bandpower Estimates

The first feature extractor used for the detection of ERD/ERS phenomena is the determination of logarithmic bandpower estimates (Log-BP) [103, 102]. It can easily described by the following: Take the variance of a bandpassed and Laplacian filtered signal and calculate the logarithm. The variance of a bandpassed signal represents the accumulated bandpower of the remaining frequencies. Hence, if the signal is bandpassed to a frequency band representing a selected ERD/ERS phenomena, the selected features reflect the investigated process. A non-linear relation between signal amplitude in time domain and bandpower in frequency domain leads to a relatively higher variance in stronger signals than in weaker signals. To

retain Gaussian feature distributions, which is a relevant characteristic for many classifiers as described in [97], features are transformed logarithmically. See Figure 8.4 for an example.

8.3.2. Common Spatial Patterns

Common Spatial Patterns (CSP) is a powerful tool that can be applied for feature extraction in spectral and temporal domain – a spatio-temporal filter. Its main function is generating weights for each EEG electrode describing their relevance for discriminability. A set of weights is called a CSP pattern. By optimization along EEG features in the time domain given by a specific neurophysiologic paradigm it generates pairs of CSP patterns, one CSP pattern optimized for each class. This adds an adaptation to the specific spatial distribution for the current user. This is often helpful as there is evidence for user specific differences in brain topology. Another benefit is the reduction of the feature space dimensionality to a selection of meta channels calculated as linear combinations of the EEG channels weighted by the pattern weights. Details on the CSP optimization process have been described and discussed in numerous publications, e.g. [9, 100, 101, 13, 102]. Figure 8.5 shows a typical distribution of CSP patterns optimized for ERD as described below.

In the following I will describe the CSP derivates used in this thesis.

- **CSP for ERD**
  CSP optimizes for the discrimination between differences in ERD of two classes, along the same criteria as in Log-BP [9]. Patterns are generated by maximizing variance for one class and simultaneously minimizing variance for the other class. See Figure 8.6 for a detailed description. It leaves two free parameters for calculating the logarithmic bandpower estimates. Firstly, the frequency bands optimally reflecting the ERD/ERS phenomena for the specific subject have to be chosen. Secondly, a time window has to be chosen for calculating the variance of the bandpassed signal. In calibration this window is chosen relative to the beginning of each training epoch reflecting the time span that is most discriminative along all epochs and electrodes and between both classes. This is a complex parallel decision problem. See figure 7.12 for an example. The width of the chosen time window is very relevant. It defines the lag between the start of the command signal and its detection. Usually, this window moves over the continuous EEG and the probability of detection rises once half of the window contains the appropriate ERD/ERS complex.
  Hence, half of the width of the detection window is a good estimate for the lag of the system. This defines an optimization criteria between the accuracy of the system and the lag. The accuracy rises with the width of the detection window as the equality of estimating the actual bandpower is depending on it and the usability of the system is degraded by the width of this window as it increases the lag.

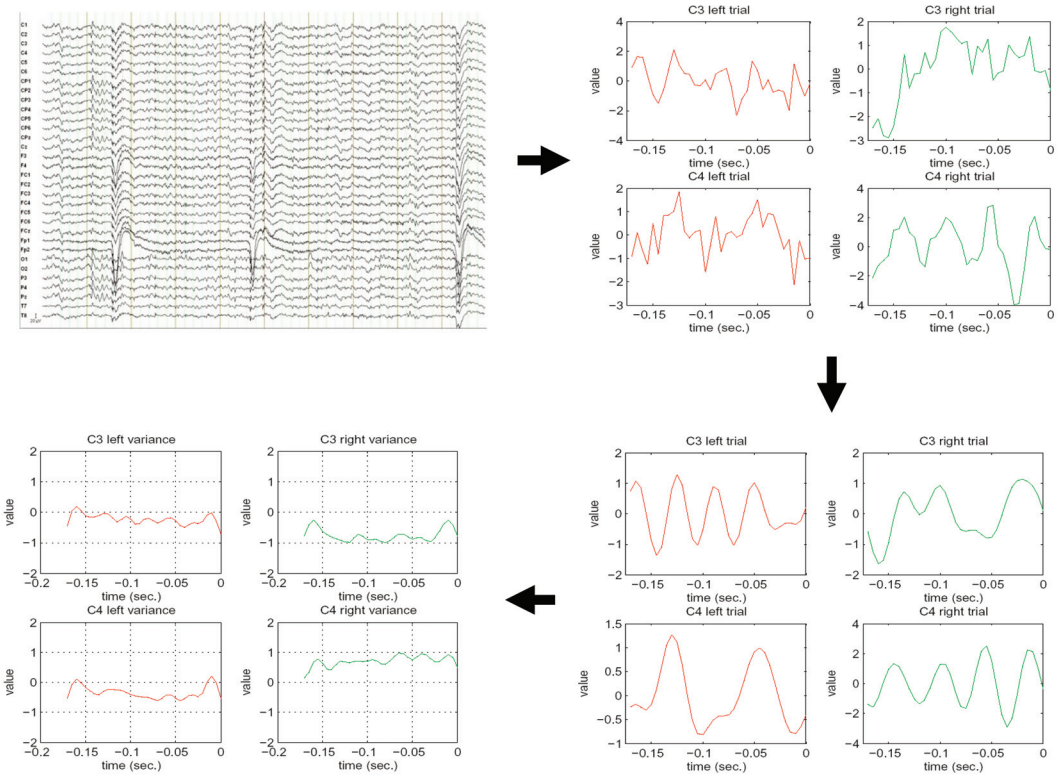


Figure 8.4.: Generating Logarithmic Bandpower estimates.
The first figure of this cycle (upper left corner) shows a standard EEG transformed by a selection of Laplacian filtered channels (C3 and C4) to epochs for left hand (green) and right hand (red) movements, shown in the next figure. Below the same data is shown after bandpassing to 7–30 Hz. The last figure shows the variance calculated for each sample of the time series. The result reflects a standard ERD/ERS complex. A digital version of this figure can be found at www.phypa.org.

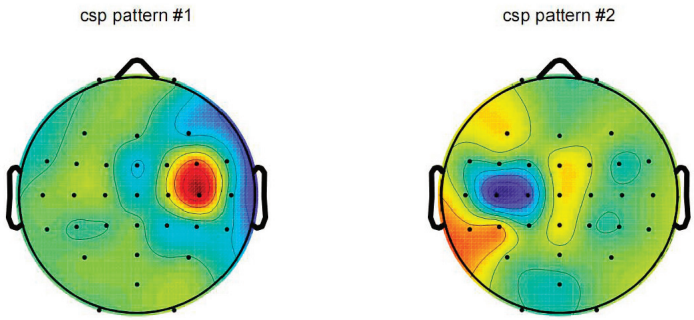


Figure 8.5.: A pair of CSP patterns.
A typical pair of CSP patterns. The pattern on the left hand side shows weights that are optimized for imagined left hand movements. The other pattern is optimized for right hand movements. Blue indicates negative weights, positive weights are shown in red.

- **SpecCSP**
  Spectrally weighted common spatial patterns (SpecCSP) were introduced in [13] solving the selection of frequency bands automatically. In an iterated sequence a frequency selection is optimized for a given CSP for ERD solution and vice versa. See [13] and Figure 8.7 for details. This method of feature extraction only has one free parameter, the time window for variance calculation. This leads to the same constraints as described in the previous paragraph. In this thesis it is the method of choice for the detection of ERD/ERS complexes as it usually outperforms Log-BP and CSP for ERD [13]. See Figure 8.7 for a description of the selection of frequency bands.

- **CSP for SCP**
  CSP can also be utilized for extracting features directly from the time domain. The approach described in [103] works as CSP for ERD but changes the optimization criteria from logarithmic bandpower estimates to deflection from a selected baseline. The free parameters of this approach are the selection of the time window and that of the baseline. Estimates for both parameters are usually given by previous neuroscientific research and show a low variance between subjects.

8.3.3. Pattern Matching Method

A general method for extracting features for SCPs, the Pattern Matching Method (PMM), was described in [81]. After a strict bandpass filtering to low frequencies the dimensionality of the signal is reduced by taking averages of sequential 50 ms second windows of data for each channel relative to the investigated event. This series of windows should cover the time span in the epoch where the occurrence of the potential is expected. It was initially introduced for

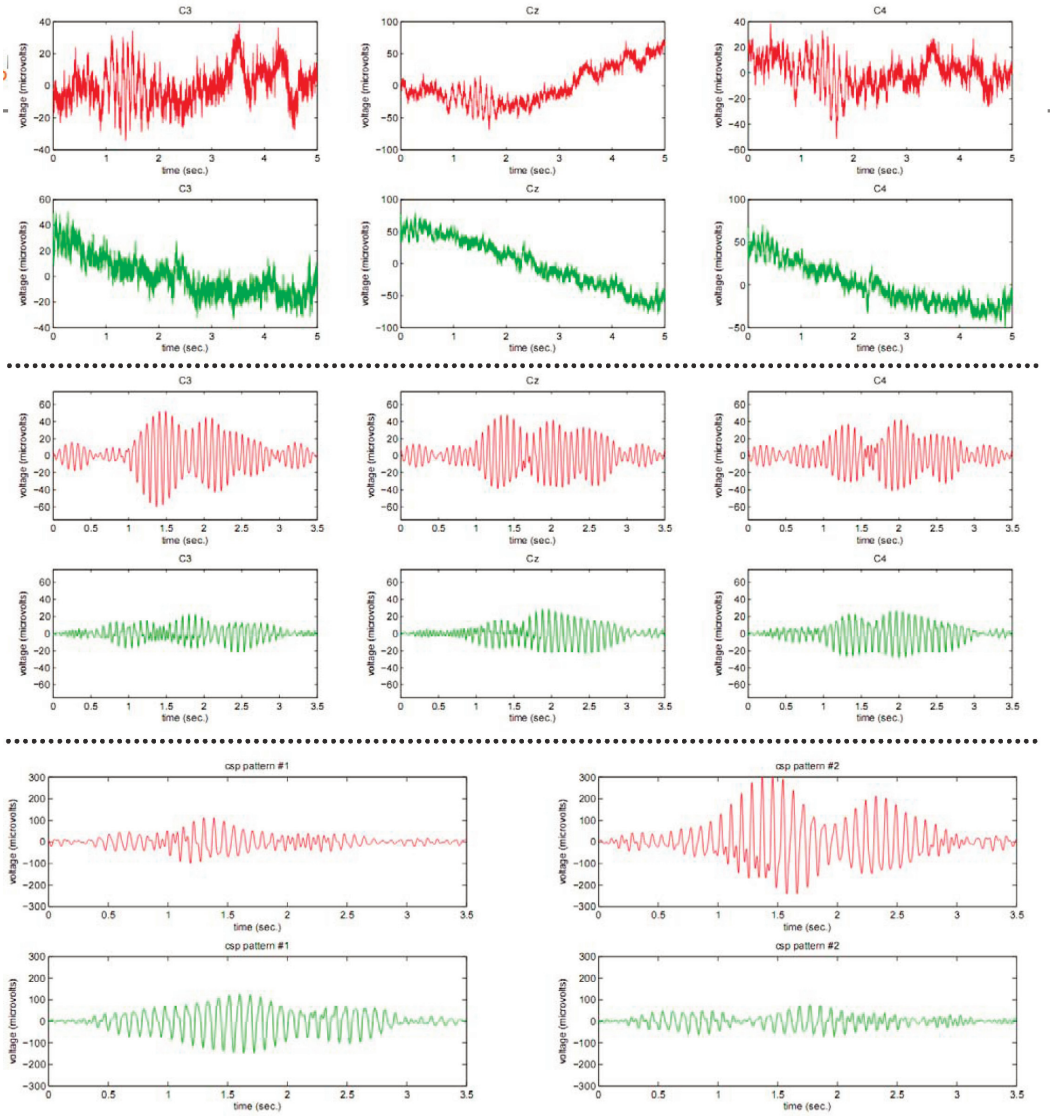


Figure 8.6.: Generating Common Spatial Patterns.
The processing of CSP for ERD feature extraction. The first two rows show single trial epochs of 5 seconds from raw EEG channels C3, Cz and C4. Data from left hand motor imagery is drawn in red and in green for that of the right hand. Rows 3 and 4 show the data after bandpassing it to 7-30 Hz. The last rows show two CSP meta channels. The first shows a linear combination with weights optimized for left hand movements, the second is optimized for right hand movements. From these meta channels two feature vectors are derived by calculating the logarithmic variance. $fv1 = [6.7, 7.8]$ and $fv2 = [8.9, 6.4]$. A digital version of this figure can be found at www.phypa.org.

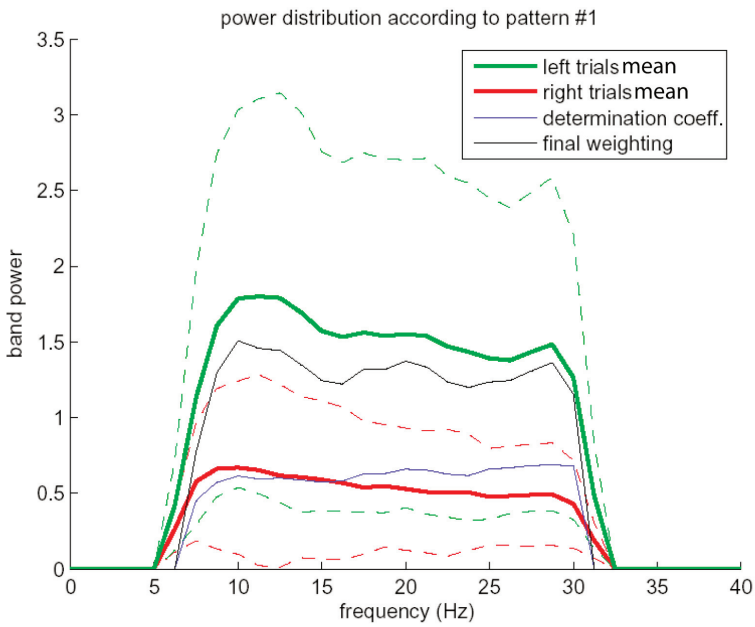


Figure 8.7.: Additional parameters for SpecCSP.
This figure shows the result of the spectral optimization and the related parameters by SpecCSP.

the detection of readiness potentials [81] but could be adapted for the detection of general ERPs, as seen in [104]. The only free parameter is the series of time windows selected for averaging. This method leads to a high dimensional feature space of multiples of the number of electrodes. As the ratio between number of trials and feature dimensions is a relevant factor for a successful calibration of classifiers – due to the Curse of Dimensionality as described in [97] – another implicit free variable is the selection of the electrodes. See Figure 8.8 for an example of selecting features of the detection of readiness potentials on channels C3 and C4.

8.4. Classification algorithms

Given a feature space, classifiers are required to perform the final inferential step from feature vectors to the binary decision values. In the following I will briefly describe methods used here. In almost every study, the simplest classifier – the *Linear Discriminant Analysis* – performed best. See Figure 8.9 for an example based on Log-BP. More information on this classifiers can be found in [95] and the specific references.

Linear Discriminant Analysis (LDA) [105] is the simplest model, which is optimal as long as two requirements are met: First, the noise projected into the feature space must be Gaussian and uncorrelated to the class membership of each trial. And, there must be a sufficient number of data points, which is dependent on the feature space dimension, because LDA relies on the estimation of covariance matrices for the feature distributions.

Quadratic Discriminant Analysis (QDA) [106] separates the data by a quadratic hyper surface and can be used if noise is class-correlated. Its downside is that it requires at least twice as many trials as LDA to work properly.

Regularized LDA or QDA (rLDA, rQDA) is often used when the number of trials is critically low [107], since the chance of overfitting, i.e. that the classification model is describing random patterns in the noise part of the data, instead those underlying the signal, is minimized.

Gaussian Mixture Models (GMMs) [108] model each class by a weighted mixture of different Gaussians. Therefore, they require an even higher number of trials than QDA. The implementation is based on the open-source toolbox GMMBAYES.

Support Vector Machines (SVMs) [109] do not estimate the full covariance matrices for both classes. Therefore, they are relatively robust for a limited number of training trials. Also, they can be used in combination with the kernel trick [110], leading to non-linear classification. The polynomial kernel, specifically, is referred to as SVM-P in the following. The SVM implementation is based on the open-source toolbox LibSVM.

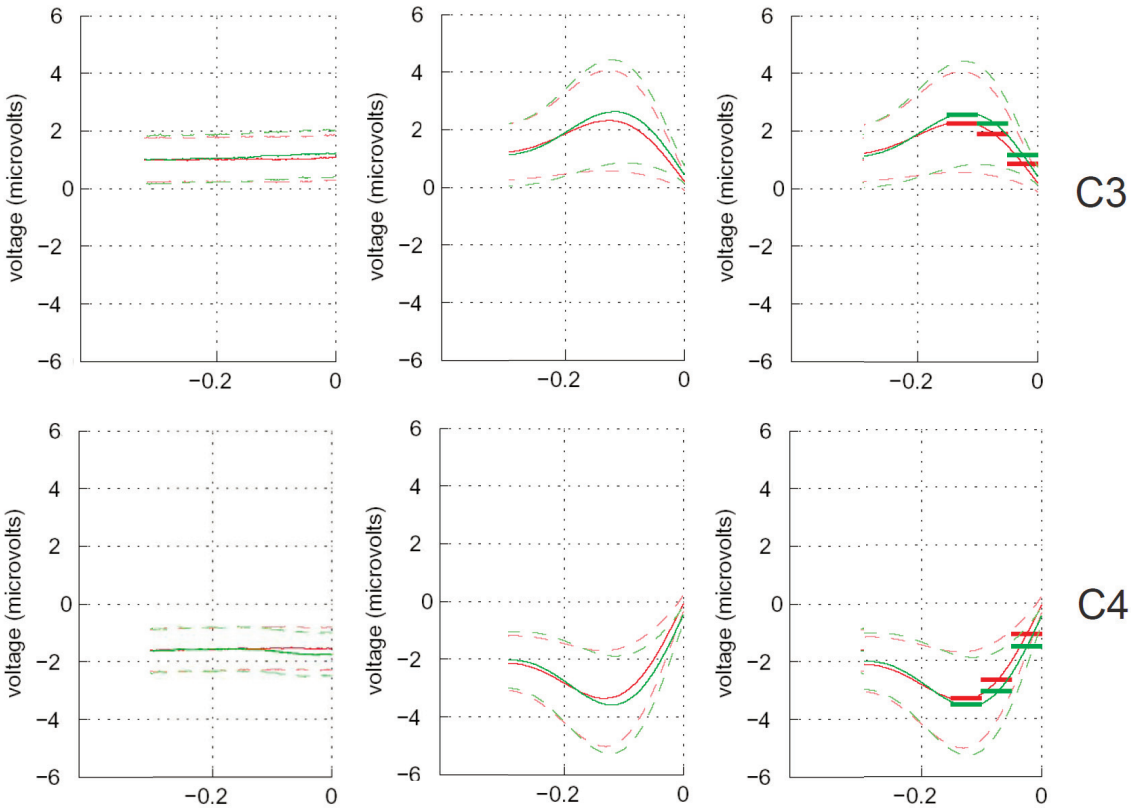


Figure 8.8.: The Pattern Matching Methods.
The processing of the Pattern matching feature extractor. The x-axis shoes time, while the voltage in each channel is displayed on the y-axis. The first column shows the averaged EEG time domain after filtering between 0.1 and 15 Hz for channels C3 and C4 and classes left hand movements (red) and right hand movements (green). The second column shows the data after weightening it with a cosine function. In the last rows three 50ms time windows are selected and averaged to features (bars).

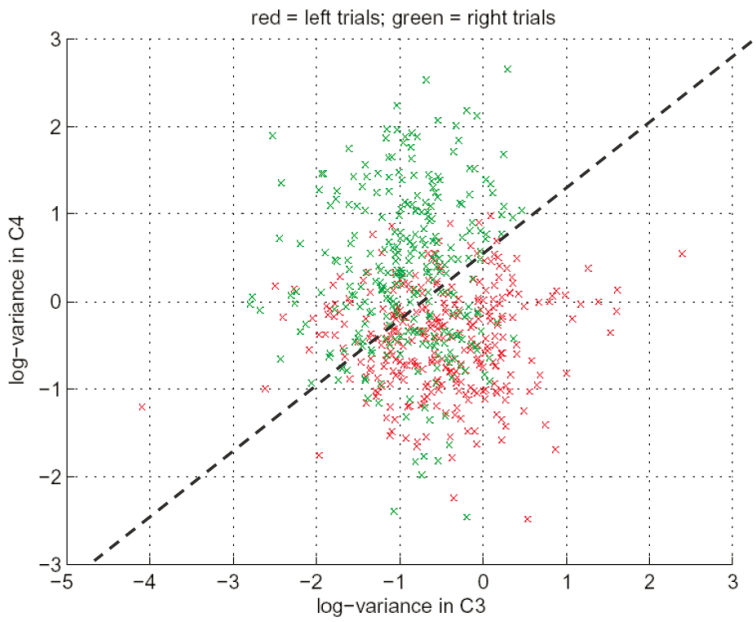


Figure 8.9.: Example of classification.
Two feature distributions are selected for imagined left (red) and right (green) hand movements by LogBP. The left axis indicates the logarithmic variance of channel C4 and the down axis shows it for Channel C3. The distributions are separable with LDA (black dotted line) with an accuracy of 90%.

In Chapter 9 I define and discuss a new approach to BCI research utilizing the above mentioned methods for a broad range of applications. It is motivated from the perspective of HMS research and embeds the classical approach of BCI research into a more flexible but also precise theory, also applicable for healthy users. The methodology of machine learning based classification as described above will be one cornerstone for the application of this theory in the experiments described in the second part of this thesis.

9. A broadened approach to Brain-Computer Interfaces

In order to tackle the research questions defined in section 6.6 one main hurdle was the development of an appropriate set of tools for building up BCI based applications. This includes a technical framework for running experiments and also a theoretical framework allowing for a precise definition and categorization of tasks and also for shortcomings in the current framework. Also, as BCI is a highly interdisciplinary field it is necessary to gather knowledge and principles of operation from several fields of research in one place. This leads to building up an interdisciplinary working group. Last but not least it is necessary to use proper material and technical resources. In the following sections of this chapter I give an overview of the concept of Team PhyPA, a research group founded on novel concepts, which gave proper background for running and evaluating studies. Also I talk about a MATLAB based toolbox which has been developed in Team PhyPA and is built for the purpose of BCI research for general Human-Machine Systems as well as for a good usability, allowing researchers from almost any field to use it easily. Following this I introduce the material used for studies presented later. In the last sections I go into detail on the theoretical framework – introducing the approach of passive BCI [111] and the concept of context-aware BCIs – I have developed for framing the research packaged in this thesis.

9.1. Materials used

We have used a Brain Products[1] BrainAmp system with a reference electrode placed on the nasion and the grounding electrode on Fz, Fpz or Pz, depending on the actual setup of the cap (see figure 6.2 for details). In each study a specific number of electrodes (32 to 96) has been applied to selected positions on the international extended 10-20 system shown in figure 6.2. The actual number of electrodes will be stated in the detailed description of the appropriate study.

For peripheral physiology we recorded electromyogram (EMG) and electroocculogram (EOG) using a Brain Products ExG system providing 4 bipolar channels. The grounding electrode was placed on the forehead.

The data from both Brain Products amplifiers were recorded with the Brain Vision Recorder software which was provided Brain Products on loan without any fee.

[1] Brain Products GmbH, Gilching, Germany

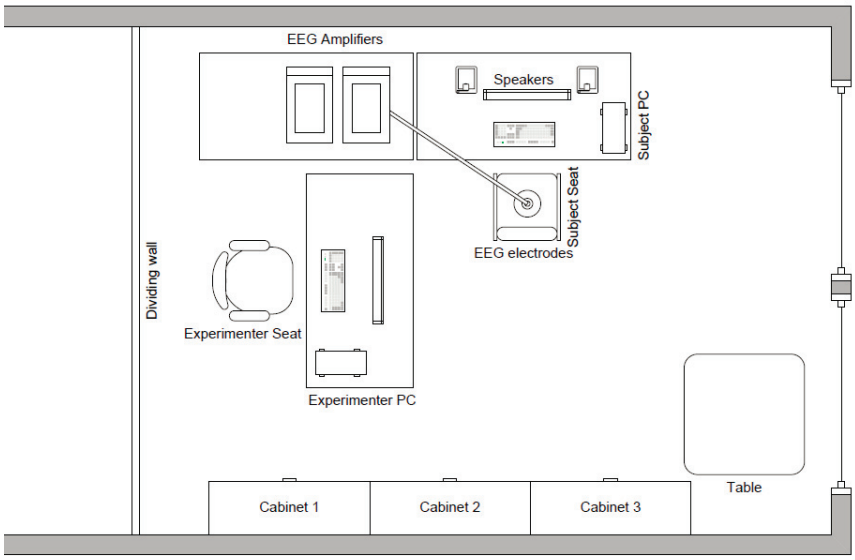


Figure 9.1.: The PhyPA laboratory.

In each experiment one experimenter (leader) was responsible for interacting with the subject and an assistant dealt with the equipment. Details about the recruitment of subjects can be found in the descriptions of the studies presented in Parts II and III. Subject and assistant were equipped with a standard personal computer (PC), running Windows XP (Service Pack 3). The PCs were connected to a standard keyboard, to stereo speakers, a standard mouse and a display. The displays had a 19 inch standard TFT panel and were connected digitally (DVI-I). Each PC was connected to a local area network (100 MBit) with access to the World Wide Web (WWW). Markers from the subject PC were sent to the Brain Products systems via a parallel port connection. As the PCs did not include a native parallel port we added a USB to parallel adapter, allowing for a full parallel port emulation [2]. The configuration of the PCs and working places in experiments are displayed in figure 9.1.

Additionally, there were two server computers also connected to the local area network which could be accessed for time-consuming calculations. Both server computers were equipped with multiple processors (2 and 8 processors, Intel Opteron) and several gigabytes of Random Access Memory (RAM) (8 gigabyte and 24 gigabyte). The servers were running Suse Linux 10 until 2009 and subsequently Suse Linux 11.

For experiments involving the human gaze we used a remote eytracker[3] with a sampling

[2]USB2LPT, Henrik Haftmann, TU Chemnitz, Germany
[3]SensoMotoric Instruments, iView X RED

Figure 9.2.: Logo of Team PhyPA.

rate of 60 Hz and an accuracy of <0.4°, mounted directly under the bottom of the display.

Before the start of each experiment, subjects were asked to complete the FAL questionnaire[4] [112] to store information on the actual condition of the subject. Subjects were instructed with an appropriate and detailed text on the screen which they could browse self paced. This was part of the Feedback framework developed by Christian Kothe, which also merged data streams from each technical component of the presented framework. After this presentation subjects were encouraged to ask questions to the leading experimenter.

Subjects received EUR 20 per session.

9.2. Team PhyPA

When I started my work on this thesis at the Department of Human Machine Systems, Technical University of Berlin, Germany (FG MMS) I was aware of the fact that BCI research is highly interdisciplinary and also hard to start from the scratch. The Institute for Ergonomics and Psychology, where the FG MMS is embedded in, allocated funding for a 32-channel EEG system and other necessary equipment was already available at the FG MMS. Hence, mostly human resources and knowledge were missing, which could only be solved by building up a working group. As the FG MMS had no background at all in BCI research at that time it was hard to get funding from official funding agencies or industry for building up a new working group. Especially, as there was a successful working group at the Fraunhofer Institute FIRST (Intelligent Data Analyses) in Berlin.

I developed a concept for a minimum funding working group together with Prof. Matthias Roetting, head of the FG MMS, to support the formation of such a working group with funding provided by the FG MMS. This was the beginning of Team PhyPA.

The basic idea of Team PhyPA is to reduce spending on funding on human resources and substituting monetary reward for participating in the working group with the possibility of doing free research, to publish the results and to present it at conferences. I am con-

[4]Fragebogen zur Ausgangslage, developed by Janke in 1976

vinced from my previous experience, and Team PhyPA has shown, that students are capable and should already start working in a realistic research environment even before they have reached their masters degree. This conflicts with the general opinion in German scientific communities and universities. My opinion grew with the experience that many students in my social environment seemed to feel unhappy with repeating scientific steps in their studies. Also many faculties were focusing their teaching on theory. As BCI research is a very rewarding work, allowing for proof of concepts immediately in online experiments and offering realistic experience in offline analyses of appropriate data, my hope was that this could be a perfect match: To bring students of psychology, mathematics, human factors and engineering together and let them cooperate in Team PhyPA. They would get the chance to apply their knowledge, extend it to other fields of research and also gain practical experience. Additionally, they would get insight into the progress of a new and growing research community.

Obviously, this approach would only successful if aims would be defined that would motivate every single member of such a working group and would support convergence. These goals would have to be defined by the working group leader, who was me in this case.

Students at Team PhyPA got the chance to participate in current BCI research. Each student was assigned to a project and could contribute ideas to the experimental setup, running experiments and figuring out how to analyze the data. Equipment and resources were provided by the FG MMS. If results from one of these studies were interesting and novel enough, students were motivated to submit manuscripts to relevant conferences or workshops.

Also, a certain level of basic knowledge would be needed to be accessible to each member for starting up Team PhyPA. At the starting time of Team PhyPA I was already able to provide fundamental knowledge on BCI research itself, as I had the opportunity to learn a lot at the BCI working group of Benjamin Blankertz at Fraunhofer FIRST, Berlin (`www.bbci.de`). Also I could provide algorithmic understanding from my studies in mathematics and mathematical logic at the Westfaelische Wilhlems Universitaet in Muenster. I developed a lecture course (4 hours a week) for communicating basic knowledge and principles of BCI research. It was held first in spring 2006. I focused on conveying this in an interdisciplinary way, such that no specific pre-knowledge was necessary to follow the lectures. To my knowledge it was the first lecture course on BCI research worldwide.

As a follow up to this lecture course I developed a seminar project course aiming at participants from the initial BCI lecture and providing them with skills and knowledge to run BCI experiments and do valid analyses on BCI data. The structure was quite simple. The main goal was writing a scientific paper on a relevant research question from the field of BCI. In two sessions at the beginning I presented the current state of the art for a topic in BCI research. Then I divided the students into two groups with the task to develop a research question with an appropriate experimental plan to run the experiments and analyses

in the given time frame. The resulting plans were discussed and merged. In the following month the students were working on this plan with loose supervision. The outcome of this plan were then written into a seminar report and later on – under stronger supervision – condensed to a scientific paper.

But, as the task of Team PhyPA was to apply BCI research to general HMS, especially to applications for healthy users, we would have to augment the principles of BCI research which would need also fundamental knowledge in psychology and computer science. Hence, Matthias Roetting agreed to add funding for two more long term student positions in Team PhyPA for a computer scientist and a psychologist.

Almost for the whole time span of the last 5 years Christian Kothe worked as computer scientist and Sabine Jatzev worked as psychologist. They have provided most valuable input to the research at Team PhyPA. For me it will not be possible to disentangle their input from and to assign their contribution clearly to the work I present here. But I will do my best and provide references at parts where their input was salient.

Team PhyPA had a flat hierarchy – it was intended that there was a strong relationship and co-working.

Over the last 5 years 19 students joined Team PhyPA, compiling 17 theses and 42 publications in conference bands and books, winning 7 awards at conferences.

9.3. PhyPA Toolbox

One very important tool for BCI research is a set of online capable algorithms for preprocessing data, extracting features from it and classifying instances of existing or new features (c.f. 8.1). Also, it is very helpful to have routines which allow for a proper visualization of the data and its features. In the case of a setup aiming for interdisciplinary research another factor comes into play. It is not obligatory that each researcher from any discipline has major skills in programming. Hence, it is of great importance that tools provided for data analysis and online classification are easy to apply.

The only toolbox which was available in 2005 which could have fulfilled these properties was BCI2000 [113] developed by Schalk. But as this toolbox is focused on providing tools for standard BCI research and only is extendable with much effort by an expert in programming `C++` it was not an option for using it in Team PhyPA. It was necessary that tools could be adapted easily to new approaches.

Hence, I decided to develop a new toolbox for novel BCI research, fulfilling all above mentioned requirements. In cooperation with Christian Kothe I designed a framework for building up a toolbox in MATLAB[5], as this programming language is command line based. Hence, the code does not have to be pre-compiled for execution and is easy to apply, to understand and to modify. Over the past 5 years this framework was extended and redefined

[5]The Mathworks, Natick near Boston, USA

several times, always in close cooperation between Christian Kothe and myself. The implementation of the PhyPA-Toolbox was mainly done by Christian Kothe. But also Sebastian Welke, Till Klister and Fabian Bachl, as well as Matti Gaertner and I myself contributed code. A detailed description of this toolbox can be found in the Diplom thesis of Christian Kothe [95] which was supervised by Prof. Olaf Hellwich at the Department for Computer Vision and Remote Sensing, TU Berlin, and me.

The following text will give a rough overview of the capabilities of this toolbox.

The PhyPA-Toolbox uses the concept of BCI classification schemes (see section 8.1.1) for modularizing the steps needed for extracting information from an EEG data stream which is relevant for a given BCI approach. A classification scheme consists of a mixture of components from the following three categories: signal processing, feature extracting and machine learning.

It contains the following signal processing tools, feature extraction methods and general machine learning algorithms:

- Channel selection [95]
- Resampling [95]
- Deblinking [95]
- Envelope extraction [95]
- Epoch extraction [95]
- Baseline filtering [95]
- Re-referencing[95]
- Surface Laplacian filtering [114]
- ICA methods (Infomax, FastICA, AMICA) [29, 115]
- Spectral filters (FIR, IIR) [95]
- Spherical spline interpolation [116]
- Multi-window averaging for detection based on slow cortical potentials [72, 81]
- Logarithmic Bandpower estimates (logBP) [117]
- Common Spatial Patterns (CSP) [9]
- Spectrally-weighted Common Spatial Patterns [118]
- Adaptive Autoregressive Modeling, from BioSig [119]

- Linear Discriminant Analysis (LDA) [105]
- Quadratic Discriminant Analysis (QDA) [120]
- Regularized LDA and QDA [120]
- Linear Support Vector Machines [110] (implemented using LIBLINEAR)
- Kernel Support Vector Machines [110] (implemented using SVMPerf, with LibSVM fallback)
- Gaussian Mixture Models (three methods [121, 122, 123], implemented using GMM-BAYES)
- Variational Bayesian Logistic Regression [124] (contributed by T. Klister, [125])
- Deep Restricted Boltzmann Machines [126] (contributed by F. Bachl, [33])
- Relevance Vector Machines [127] (implemented using SparseBayes)

A BCI classification scheme has to be designed specifically for a given BCI approach. The PhyPA Toolbox allows for pre-defining BCI paradigms for commonly used approaches. With theses paradigms a very simple method of applying a BCI is introduced, as only free parameters have to be assigned.

Due to its modularity it provides a very simple way of adding new paradigms to the Toolbox.

The PhyPA-Toolbox contains a paradigm for each classification scheme defined in section 8.1, hence, there is a paradigm for CSP for imagined movements with LDA [9], Spec-CSP for imagined movements with LDA [13], logarithmic band-power estimates with Hjorth surface Laplacian filter [117], common spatial patterns for slow cortical potentials [103], multi-segment averages with LDA (for using the Lateralized Readiness Potential) [72, 81]. Each of the studies presented in Part II of this thesis has used these paradigms for analyses or online processing of the appropriate data.

But it also contains several paradigms not used in this thesis, such as adaptive autoregressive models on band-pass filtered channels, with LDA [119], multi-band CSP, ICA-decomposed logarithmic band-power estimates, and, as meta-algorithms, feature combinations [128] as well as multi-class classification by panels of experts.

This Toolbox is public domain (GNU public license V2) and can be downloaded at the Team PhyPAs Website[6]. Currently, Christian Kothe works at the Swartz Center for Computational Neuroscience, UCSD, USA, for integrating the PhyPA-Toolbox as a plug in into EEGLAB [96]. EEGLAB is a MATLAB based toolbox for EEG analyses. It has become

[6] `http://www.phypa.org`

a widely used platform for processing biophysical time series and sharing new techniques. At least 28 plug-in functions have been implemented by user groups. BCILAB will use the EEG dataset format of EEGLAB. Thus BCI applications in either environment may make direct use of EEGLAB data processing functions.

In the following section I present a novel framework for interweaving BCI technology into HMS. I will start with a change of perspective from medical applications to general HMS, focusing on healthy users, continuing then on new types of information which could be made accessible with BCI technology, resulting in a novel categorization of BCI applications, including an extension with *passive BCIs* as well as *hybrid BCIs*. Concluding, I will discuss the reflection of this perspective back to classical BCIs leading to the definition of *context-aware BCIs*.

9.4. BCI technology from a HMS perspective

9.4.1. Interpreting brain activity in single trial – different approaches

For decades, it has been of high interest to infer information on ongoing brain activity and its meaning. Apart from behavioral measures, like eye tracking, researchers used physical parameters that relate directly to physiological processes within the brain to accomplish this task [129]. Much of neuroscientific research is based on the EEG. The reason why so many researchers choose EEG is because of its high temporal resolution, ease of use and the comparatively low cost. Apart from these basic characteristics, the main advantage of EEG is that it has been thoroughly researched, since is first application by Berger in 1929 [31]. In the last century numerous studies were conducted that were based on analyses of EEG features corresponding to cognitive processes. The drawbacks of EEG – its limited spatial resolution and vulnerability to artifact sources – are factors that potentially limit current research. However, these may be resolved in the near future using powerful methods derived from engineering and mathematics, like ICA [29], beamforming [30] or novel sensor designs (see Chapter 14 and [130]).

Other measures too can be utilized for assessing brain activity. These can be categorized as invasive versus non-invasive technologies. Relevant non-invasive measures are fMRI, MEG and fNIRS, as described in section 6.3. fMRI and MEG share the major drawbacks of being complex in application and being unsuitable for long-term use. These technologies are also comparatively expensive. fNIRS and fMRI share the drawback of having a low temporal resolution, since both rely on the BOLD component. The spatial resolution of fNIRS is also low; its greatest potential is therefore as a secondary measure used in conjunction with EEG to provide additional information on brain activity. Potential invasive techniques include by the use of ECoGs and MEAs, allowing for a very good signal-to-noise-ratio. Apart from being invasive, microelectodes have a major drawback: once placed they can only be switched to other spatial areas with great difficulty and it is not possible to cover the whole cortex with sensors. They can therefore only be used for certain applications.

I focus on EEG-based research. It is our method of choice for gaining information on the ongoing state of the human brain as it occurs and identifying the underlying processes, which we will call Realtime Brain Signal Decoding (RBSD)[7] in the following.

From this perspective RBSD has been applied in several research endeavors within the past decades. One application for RBSD is gaining information about the ongoing user state, including intentions, situational interpretations and emotions. As this is encoded in human cognition, this approach is called *Cognitive Monitoring* [131, 132, 133, 134, 135]. Cognitive Monitoring focuses on posthoc analyses of events and conditions related to human cognition, as defined in section 9.5. The outcome of this type of analyses can be used to give a situational evaluation of a human interaction, which can be utilized for neuroergonomics, usability tests or a user state detection related to experimental conditions [135]. Besides Cognitive Monitoring and user state detection RBSD can be utilized in another valuable field of application – in Brain-Computer Interfaces. Here, the user voluntarily generates specific patterns of brain activity which can be detected by an automated RBSD, so that the resulting information can be used as a realtime input modality for controlling a technical device by thought or communicating through it (as described in section 6.4).

Very different approaches have been developed in the past two decades, e.g. [5, 136, 11, 137, 138], defining new communication channels for people with severe disabilities, which can be used reliably and independently from any activity outside the central nervous system [6].

9.4.2. Towards implicit interaction – Accessing covert aspects of user state and adding context-awareness to the system.

A BCI defines a new input modality for Human-Machine Interaction which could substitute or add up to [40] other input modalities like manual input. But from the perspective of Human-Machine System research, a given system could also benefit from information on the actual user state [3], which would define an implicit input modality, carrying information about the user state not sent intentionally by the user.

This would provide valuable information about the ongoing context of a given Human-Machine System, which will be defined more precisely in section 9.7. I propose to use RBSD as well for an automated inference of this information, hence, for combining the approach of cognitive monitoring for accessing the actual cognitive user state with that of BCI for detecting it automatically and feeding the resulting information back to the technical system. It can be seen as modifying the general approach of BCI and substituting the usually voluntary and directed command with *passively conveyed implicit information*. In section 9.5.3 I will give a framework which connects this approach to the definition of BCI and embeds it into a broader framework. The resulting approach of implicit input based on information on human cognition opens up the field of applications based on BCI technology to a broader

[7] thanks to Jeremy Hill, MPI for Biological Cybernetics, Tuebingen, Germany for a hint on this terminology

context, especially for using it for healthy users. In sections 9.5.7 and 9.5.8 I will give an overview on previously done research, connect it to the definition of BCI and embed it into a broader framework of definitions.

This approach allows for realtime access to the actual user state, which especially includes parts which are usually hidden, and will be named *Covert Aspects of User State* in the following. This information can be utilized for enhanced Human-Machine Interaction, including automated adaptation (see Chapter 12 for an example). But, in a more general concept, it allows for augmenting the accessible information space in a given Human-Machine System by valuable information on the context. This allows for implementing *context-awareness* into a given HMS, especially into a BCI based system. In section 9.7 I will describe the concept of context-awareness more in detail and in section 11 I will show results from a study utilizing passive BCI for adding context-awareness to a system.

9.5. Utilizing user state for Human-Machine Interaction

Relevant information in Human-Machine Systems includes the state of the technical system and of the system environment, as well as state of the user. In particular, cognitive processes like the user's internal interpretation of the situation are of great interest. This can be made clear by taking a look at another type of interaction – that between humans. Part of social interaction is explicit – by intentionally sending a message to another actor. In addition, there is an implicit information flow. By observing aspects of user state accompanying the explicit interaction, such as gestures, mimics, or body posture, actors gain access to information about inner states of each other. Reading interpretations and intentions of others is an important ability that involves representing and embedding the mental states of others in one's own mind, as, for example, postulated by the 'theory of mind' [139]. Such information might also be relevant for a more intuitive HMI [129, 140]. Consequently, integrating information on aspects of user state into HMI could lead to a more natural interaction between human and machine. Here, cognitive aspects are of special interest, as they might reflect highly complex information on the actual user state – which is mainly encoded in the human brain.

One can divide these aspects of user state roughly into two distinct groups, both of which can carry relevant (and implicit) information. First, there are latent processes, called *cognitive conditions* in the following, such as arousal, fatigue and more complex examples like the perceived loss of control, which will be described in more detail in the following parts of this paper. Second, there are time-bounded cognitive processes that I will call *cognitive events*. Investigated examples from this area include perception and processing of errors [81, 141, 142, 143], moments of bluffing in a game context [144] or surprise [145]. These examples of cognitive events and conditions could be utilized for enabling a more 'intelligent' interaction, as the system learns about the user state.

In a system which captures user state for implicit communication, this information flow can

be seen as input from the user to the BCI system which is not sent intentionally; in other words, as implicit commands [3]. Due to the fact that such implicit commands are generated automatically in the course of interaction, there is an increase in information flow, while at the same time the mental effort of the user does not increase. Hence, the use of information on cognitive user state is a highly efficient way of enhancing BCIs or HMS in general. Unfortunately, these aspects are difficult to observe by technical systems, as will be explored next.

9.5.1. Accessing user state with psycho-physiological measures

In the following I will give formal definitions of the concepts of hidden information about the user and implicit interaction. User state has covert parts, which are hard to access from the outside. Examples for these parts are physiological processes within the human body or the afore-mentioned processes of cognition. There are approaches to utilize overt measures, like the user's behavior, and of extracting information correlated to aspects of user state [146]. Further, physiological measures like haptic data [147] or eye gaze [129, 3] have been shown to provide useful information on user state. Yet, the scope of these methods is limited, as they can only generate information which is weakly correlated to the actual user state [48]. This gives the basis to define these parts as *covert aspects of user state* (CAUS), analogous to covert attention [68].

Covert aspects of user state
A covert aspect of user state is a process occurring within the user which can only be detected with weak reliability by using behavioral measures.

As the user's cognition is inherently hard to access by overt measures, a large proportion of cognitive processes are CAUS. Hence, we need an elaborate and continuous measure of accessing and providing those as input to HMI as proposed in the previous section. Since the electroencephalogram gives insight into the processes of the human brain, the source of all cognition, in high temporal resolution, it is a potentially suitable measure. With technology from Brain-Computer Interfacing, EEGs could be used for online detection and interpretation of distinct cognitive events and conditions. Applied in a broader context, such BCI based systems provide a powerful tool for enriching research on HMS in general with information on CAUS. Also, BCI input can be combined with other input modalities, common or newly defined, pointing to the definition of hybrid BCIs introduced by Pfurtscheller et al. in 2010 [40]. In the next sections, a detailed description of classic BCI technology from the perspective of HMS will be given, followed by an overview of broader definitions of Brain-Computer Interfaces, including passive and hybrid BCIs, and extending their use from medical applications to HMS in general.

9.5.2. Classical BCIs from an HMS Viewpoint

BCIs are primarily considered to be means of communication and control for their users (e.g. [6]). These 'classical' BCIs can be divided into two subgroups, which we now summarize from the perspective of HMI.

Directly controlled BCIs
Some BCIs allow for direct communication with a technical system, by mapping consciously controlled mental activity onto a new artificial output channel. Thereby, they can bypass the natural outputs of the brain, which is integral for their clinical applications. Examples are BCIs based on sensorimotor imagery [137], where the type of mental imagery is mapped to a multi-valued control signal. Despite its power and novelty, applying this type of control to general Human-Computer Interfaces is a challenge. The user's resources for parallel conscious communication are limited, creating a conflict between BCI and conventional control. Second, brain activity which can be both consciously controlled and at the same time measured with present non-invasive equipment largely overlaps with the brain's primary output modality – muscular control – creating another resource conflict. This limitation may eventually vanish with further advances in detecting more subtle cognitive processes and commands. Finally, if taken as a replacement to manual control instead of a complement, BCIs are currently slower, more prone to errors, and more difficult to use.

Indirectly controlled BCIs
BCIs in the second group rely on conscious modulation of brain activity, as it arises in response to external stimulation. In these, the modulated activity is mapped to an artificial control signal. Examples are P300 spellers (see section 7.2.5 and [5]): systems which detect a characteristic brain response, the P300, which is elicited whenever an on-screen letter focused by the user lights up. Thus, brain activity is indirectly controlled by shifting attention.

In this interaction technique, another resource of the user-the attention focus in visual, auditory, or tactile perception is modulated for the purpose of communication, and thereby occupied. For this reason, this subgroup of BCIs is not easily applied meaningfully in Human-Machine Interfaces.

Also, it might be more easy and more reliable to track overt and strong correlates of the users attention directly – maybe with an eye-tracker system – instead of inferring it from measures of brain activity.

9.5.3. Generalized notions of BCIs

We can re-express the previously identified groups in a framework which captures additional types of BCIs by shifting the perspective from the user side to the application side. This shift allows for the following definition of BCIs, which covers a broader spectrum of Human-

Machine Systems.

A BCI based system is a system to provide computer applications with access to real-time information about cognitive state, on the basis of measured brain activity, with the purpose of enhancing a given interaction between the user and the technical system.

Further, in this context, it is beneficial not to restrict the information available to BCIs to brain activity alone. Instead, context parameters may be used by BCIs to help improve the accuracy of their predictions, leading to hybrid BCIs (see [40] and section 9.5.6) and more generally to context-aware BCIs, as described in section 9.7. Specifically, when moving from controlled laboratory conditions to highly varying real-world situations, context parameters help to factor out variations in brain activity which could otherwise bury features of interest under noise and hence lead to difficulties in reversing the principle of functionality (see sections 7.3.1 and 9.7.1). These parameters may include the state of the application, such as program events, state of the environment, or state of the user as acquired by other physiological measures, such as body posture, voice tone, or gaze direction. Chapter 13 gives a complete example of how careful hybridization makes it possible to successfully integrate otherwise impractical BCI control (see Chapter 11) into HMIs. The classic BCI occupies, in the framework of the definition given above, the role of providing information which is actively messaged or modulated by the user in order to control the application. What is not covered by classical notions, however, is information which is not consciously sent by the user, spanning a large proportion of the implicit user state. BCIs which sidestep voluntary control are clearly restricted, but they have several benefits which are critical for their effective use in Human-Machine Interfaces. These will be outlined in the following.

BCI Categories

I propose the following three-fold categorization of applications resulting from BCI-technology. This includes applications already defined in classical BCI research as well as prospected applications for a more general context. Please keep in mind that by definition a BCI system has the main purpose to enhance a specific interaction cycle. Henceforth, the definition of a BCI system has to include a precise definition of the given interaction.

Active BCI
An active BCI is a BCI which derives its outputs from brain activity which is directly consciously controlled by the user, independently from external events, for controlling an application.

Reactive BCI
A reactive BCI is a BCI which derives its outputs from brain activity arising in reaction to external stimulation, which is indirectly modulated by the user for controlling an application.

Passive BCI
A passive BCI is a BCI which derives its outputs from arbitrary brain activity without the purpose of voluntary control, for enriching a human-computer interaction with implicit information.

Active and reactive BCIs match the subgroups of classical BCIs for direct and indirect control, respectively, and passive BCIs account for all other BCIs, especially those for implicit control. These three categories form a partitioning of the space of BCIs, since first, conscious control either depends on external influences, rendering it reactive, or works independently from it, making it active, and second, passive BCIs are defined as complementary in purpose to this conscious control (see Figure 9.3. However, the boundaries between the categories are not distinct.

9.5.4. Passive BCIs

Restricted forms of passive BCIs have been proposed in the past, for example for detecting forms of mental workload [89] and the perception of self-induced errors [81]. The description of these systems usually do not include a precise definition of the underlying interaction cycle – mostly they only describe the information flow from the user to the machine. Such applications have been referred to as "BCI as a measure", which is more connected to Cognitive Monitoring, than to passive BCI, but points in the direction of the concept of passive BCI, since they give rise to physiological measures of the user's cognitive state (specifically of CAUS). They have, however, not been analyzed and evaluated with respect to an ongoing Human-Machine Interaction, and focus on user-state detection without feedback, and hence on cognitive monitoring, alone. More recent cases include measuring working memory load [132], and detecting and correcting machine-induced errors. A complete example, the first cases of using passive BCIs to enhance a broad section of human-computer interaction, is found in Chapter 12.

Passive BCIs can also be seen as secondary communication channels in Human-Machine Systems: a Human-Machine System linked by some primary communication channel (e.g. manual input) can be complemented by an optional secondary channel formed by a passive BCI, influencing and enriching the ongoing primary interaction with implicit user information [148]. The performance of passive BCIs is therefore best measured by the cost or benefit of their use in a particular scenario, rather than in terms of their bit rate. Hence, I will not focus on bitrates in studies on passive BCIs discussed here.

Key Properties

Passive BCIs have the following three distinguishing aspects which account for their practical prospects in Human-Machine Interfaces:

Complementarity
Passive BCI is complementary to other Human-Machine Interaction, in the sense that it does not interfere with it, in contrast to most forms of active or reactive BCIs, for reasons mentioned earlier. A passive BCI can be reliant on either the presence or the absence of an ongoing Human-Machine Interaction, or be invariant under it.

Composability
An application can make use of arbitrarily many passive BCI schemes in parallel with no conflicts, which is more difficult for active and reactive BCIs due to the user's limited ability to consciously interact with them. The only limiting factor is the identification of processes under the constraint of reversed functionality.

Controlled Cost
Since no conscious effort is needed for the use of passive BCIs (besides preparation), their operational cost is determined by the cost of their mis-predictions. Passive BCIs producing probabilistic estimates, together with the a priori probability of predicting correctly, are sufficient for arbitrary cost-optimal decision making at the application level, with zero benefit in the worst case.

Since passive BCIs are so easily applicable in real-world systems, the only remaining cost factors of preparation and calibration come much more into focus. Therefore, calibration and related issues are considered in section 9.6 and a study on dry electrodes (minimizing application effort) is presented in Chapter 14.

9.5.5. Accessible state and potential applications

A broad spectrum of cognitive states can be accessed with passive BCIs, including latent cognitive conditions such as arousal [149], fatigue [150], vigilance [151], working memory load

[132], visual/auditory/tactile/cross-modality attention focus [152], and possibly some emotional states, etc. Temporary cognitive events such as surprise, perception of user/machine errors [81, 142, 143], or decision-making load [153], etc. can also be accessed. Significantly more subtle states could be accessed with better, but this is not easily deployable, measurement equipment [154]. For EEG or Near Infrared Spectroscopy, a simple rule of thumb is: what is represented in a large and compact area of the cortex and is close to the scalp should also be detectable. Thus, brain atlases [155] give a useful overview of what could potentially be accessed by passive BCI. EEG patterns found in studies presented in this thesis (Part II) are well known phenomena and their functionality as well as their localization have already been reported. Each pattern can be localized in specific areas of the cortex. But, as BCI systems are indeed also capable of detecting previously unknown or weakly reported patterns, like patterns related to bluffing in a game context [144], the analyses based on the passive BCI approach also could lead to learning on new patterns or networks [156] in the human brain.
Various potential applications arise from this data, such as for augmenting or improving existing systems, e.g. by improving safety and usability via operator monitoring, see [157] for an example. In this role, they make it easier to respect the human factor in a Human-Machine System. Another application is for creating highly interactive and sensitive Human-Machine Interfaces: having information about the ongoing activity profile of the user, the system can adapt to avoid cognitive overload, and further, information about the interpretation of events by users can serve as a better basis for making decisions. As a third example, passive BCIs could help to connect multiple users by accounting for more aspects of user state, both in professional multi-operator scenarios as well as in recreation environments.

9.5.6. Hybrid BCIs – combining BCI input with other input modalities

From the perspective of using BCI as an input modality arises the idea of combining BCI input with other input channels. Especially in Human-Computer Interaction (HCI) it is common to combine input from several sources. This can be done sequentially – think about using a mouse and a keyboard one after another – or simultaneously like giving speech input while driving a car. Interestingly, this approach took quite a while to reach research on BCIs. In 2010 hybrid BCIs were introduced by Pfurtscheller et al. [40], defining the combination of BCI-based input with other input modalities.

BCI input can be combined with other types of input in three different ways. It could be a mixture of several BCI-based input channels, this can be done simultaneously [158] or sequentially [159, 40]. Another possibility is the combination of a BCI-channel with input from other physiological measures, like heart-rate [160, 161]. In Chapter 13 I will present a study on combining an active BCI input stream with a gaze controlled stream in an simultaneous way. The third version of hybrid input is the combination of BCI commands with standard input modalities, like key strokes, mouse control or voice input. To my knowledge

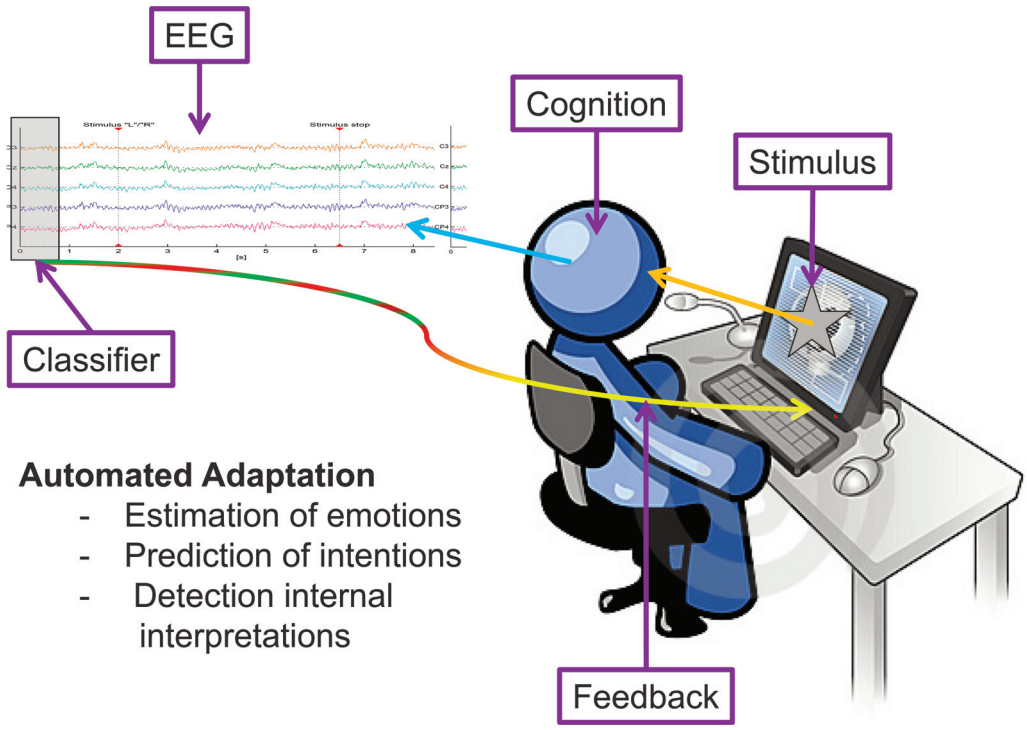


Figure 9.3.: The passive BCI interaction cycle.
This figure shows the principle behind passive BCI. It adds an implicit interaction channel that carries information about the current user state. The technical system gets access to information about Covert Aspects of User State like the users emotions, intentions and interpretations – usually as reactions on perceived information/stimuli – and adapts its state to it for enhancing a given primary interaction in a HMS.

there is no study on this type of hybrid BCI including an active BCI stream in the literature. All studies on passive BCI presented here (see Part II) could be seen as a form of hybrid passive BCI, contradicting the definition of hybrid BCI given in [40], which states that the BCI-input has to be voluntary. More details on hybrid BCIs and their application can be found in [40].

With the experience gained from research on hybrid BCIs, this new approach will prospectively lead to applications which are hard to realize solely based on BCI input. Similarly to the previously discussed approach of passive BCI, there is also a high potential for hybrid BCIs in applications for healthy users, thus for HMS in general. In Chapter 13 I will give an example in detail on how a hybrid BCI could be used to significantly enhance Human-Computer Interaction.

Hybrid BCIs could be seen as sub-types of BCI systems from a more general definition. They use specific aspects of context information – other inputs conveyed by the user – to enhance the current interaction. But as there is definitely more useful information on the context of a specific HMS I will present the definition of context-aware BCIs in section 9.7.

Next to here presented studies, other researchers worked on BCI for general HMS applications. In the next sections I give an overview of what happened in the past decade.

9.5.7. Applications resulting from BCI technology for healthy users

Technologies developed in recent decades of BCI research have become more and more interesting for a broader community of researchers. From its relatively broad definition in the early 1970s [4], the past decades have seen BCI applications focus strongly on providing new channels for communication and control for severely disabled persons [6].

Due to the considerable improvements in reliability and usability of EEG-based BCI systems, BCI technology for healthy users has become highly interesting for new types of applications [142, 104, 48, 162, 163] since the beginning of this millennium. This change of focus of part of the field from disabled to healthy users led to a concurrent shift in demands and defines new requirements for resulting applications based on BCI technology. Additionally, it should be taken into consideration that BCI for healthy users aims at partly different applications than BCIs for disabled users. In particular, direct input primarily for communication and control seems not to be the most promising BCI related application for healthy users, due to the low reliability of current BCI systems compared to standard communication channels, such as manual input or even speech. Similarly, the high effort usually required by a user for communication via a BCI is a drawback, if the same information could be provided through more common communication channels. Direct and primary input solely based on BCI can be expected to be far outperformed using conventional input methods, with the exception of gaming and special working environments.
In the case of gaming, the acquisition of a new skill and the interaction with a somehow unre-

liable system could indeed be the core purpose and challenge of the application. At present, gaming applications still mostly have the character of neurofeedback training, ranging from controlling the level of relaxation [164], to training the level of concentration ability [165] as well as to training reaction time [166] or timing of motor imagery [167].
The use of BCIs might be advantageous, hazardous environments come into mind, that limit the users' interaction capabilities (e.g., an astronaut in a space suit [168, 169]), or for the interaction with virtual objects [170, 171], lacking common unobtrusive and intuitive interaction channels.

9.5.8. Impact of passive input based on BCI technology

Passive input based on brain signals seems to be a valuable approach for enhancing Human-Machine Interfaces. Cutrell and Tan [172] suppose a BCI-like systematic approach for this new form of input. This goes in line with the framework presented here (section 9.5.3) originally presented at the same workshop [142] as Cutrell and Tan's idea [172]. The concept of passive BCIs provides a formal integration of passive input into BCI research. With this the space of possible applications based on BCI technology is extended widely. These additions could improve the state-of-the-art human-machine interaction by enabling the technical system to adapt to the user automatically [3, 104]. A prototype study on this is presented in Chapter 12 which is partially inspired by earlier work on error related potentials in the context of BCIs [141, 143]. This study provides evidence that this concept is indeed capable of enhancing the interaction between humans and technical systems with regard to efficiency, effectiveness and usability.
Other studies showed that the performance of a given BCI system could be enhanced by implementing an additional passive input [143]. We investigated this firstly in a study on the perceived loss of controllability which will be presented in Chapter 11. Team PhyPA also ran experiments on the interpretation of other humans' movements, error responses on auditory stimuli or bluffing in a game context, which will not be presented here but are reported in [173], [174] and [144].

BCI technology can also reveal valuable information about the user state in safety-critical applications, such as driving [157], industrial environments, or security surveillance. With respect to driving assistance applications, recent studies have explored the use of BCI systems in a driving simulation for assessing driving performance and inattentiveness [175] as well as for robustly detecting emergency braking or steering intention before movement onset in a real car and a simulator [157, 176]. Also, BCI systems can potentially be used for cognitive monitoring in real-time the mental workload of a driver and employing this information to switch off secondary tasks when the current level of workload reaches a critical level [89]. In a different context, initial steps have been taken towards assistive technologies that use the current mental state of a user for avoiding accidents in industrial environments [177]. Similarly, a pilot study showed the potential of BCI systems to recognize and predict mental

states of a user correlated with concentration [177], using the example of a simulated security surveillance system [48].

9.5.9. Research on BCI-based HMS, beneficial for healthy and disabled users

Several approaches have been proposed for employing the wide range of possibilities offered by BCI based technology for a broad community of healthy users. It is important to note that just as these new approaches benefit from the past decades of substantial research on BCIs for disabled users, these novel efforts targeted at healthy users can in turn be expected to contribute to and enrich efforts focusing on disabled users as well. Passive BCI streams are also valuable additions to classic or hybrid BCIs providing input for communication and control.
If the gaming industry adopted BCI systems, e.g a Sony 'Playstation 5' were equipped with additional input from the brain, one might be able to access not only dozens of datasets, as possible in current studies, but data from hundreds of thousands or even millions of gamers. This might give much more detailed insights into the interacting brain than is possible today. Also, it could provide a much better modeling of the human brain, enhancing the effectiveness of BCI systems and making it possible to adapt their functionality to special cases in medical support. With that, expanding the scope of BCIs to include healthy users might be helpful for patients with severe conditions such as locked-in patients. Also, gaming applications can be an excellent motivation for patients to train the use of a BCI using neuro-feedback, for instance with respect to speed and timing.

With some of the above mentioned approaches steps have been taken towards the proposed fusion of cognitive monitoring and BCI technology to passive BCI. Major parts have been realized by studies run in Team PhyPA. I give a detailed description of the main experiments in Parts II and III of this thesis. In the following sections I present a unified workflow for utilizing BCI technology in general Human-Machine Systems.

Applying BCI-technology in a broader sense – as proposed in the previous sections – poses new challenges. This is especially the case regarding the acceptance by healthy users [172, 3]. The time-consuming preparation phase of EEG systems and the calibration of BCI classification schemes limit the scope of possible applications. In Chapter 14 I discuss a new sensor type for accessing EEG data that allows for a quicker preparation, stepping towards a solution for one major problem of BCI research. In the following section I address the remaining problems, starting with an introduction of concepts, followed by a proposal for a calibration phase, extending that shown in figure 8.2, that is optimized for usability and efficiency in Human-Machine Interaction.

How can the remaining problem of time consuming calibration phases be solved? A first concept is the introduction of universal classifiers. In spite of the strong variability between EEG sessions, there are approaches for porting information between sessions [57]. In line

with this, there might even be the possibility of defining *universal classification schemes* applicable to users or groups of users with little or no recalibration. However, a prerequisite would be the existence of an aspect of cognitive state which is consistent and represented invariantly across subjects. I give an example of such universal processes and their applicability in Chapter 12.

Another problem is defined by the increasing number of artifacts recorded in the EEG data in a more complex context. These can be divided (see section 7.2) into those resulting from the environment (second order artifacts) or uncorrelated user state and those resulting from correlated user state (first order artifacts), such as dependent eye blinks and other types of behavior. As second order artifacts and uncorrelated first order arifacts always decrease the signal to noise ratio, these should be filtered out for BCI applications. In contrast, related first order artifacts may be used as features, but it is unclear whether these signals are as robust as cognitive events and states, with respect to context variation. In section 9.7 I also go into detail on that by defining how to use such information for augmenting the information state in Human-Machine Systems and BCIs.

The third problem is applying BCIs in a valuable way, in spite of their limited bandwidth and relatively low reliability. Shifting BCI applications into the context of general HMI leads to a more complex, and hence noisier, environment, and diversified user state induced by rich forms of interaction. This contradicts the concept of reversed functionality (see sections 7.3.1 and 9.7.1) in interpreting EEG patterns. But, the available rich information space could also be utilized to interpret the meaning of a given interaction, specifically. In Chapter 9.7 I provide a definition of a BCI based HMS which combines context information and emerges context-sensitivity.

9.6. Refining the BCI training sequence

Well known researchers from the field of BCI [6, 48] have already proposed unified workflows for BCI training and an application scheme (see figure 8.2). But these are all optimized for the very specific application environment of BCIs for communication and control in clinical setups. There is a high variability in the signals recorded between sessions or between subjects, and even within sessions (mostly due to changes in context), so an initial system calibration is necessary.

In classic BCI applications, this calibration and the user's learning of the task presented in the application are the only steps taken for learning about regularities in the given interaction cycle. This defines the first stage of adaptation.
With that, we address the adaptation of the machine to the user as well as the adaptation of the user to the machine. But it is very likely that the user will still be learning while

interacting within the application. Hence, the user state will change over time which might lead to later performance drops. Then, a re-adaptation of the classifier can be of use [35], defining the second stage of adaptation. In general, one faces the problem of two adaptive systems which may diverge over time. Both machine and user have to be trained to let their adaptations converge. To cope with the previously defined problems, the definition of procedures defining BCI applications has to be more elaborate. In Chapter 11 I will discuss the problem of divergence and will give an example how to utilize passive BCI for an heuristic approach to detecting non-stationarities, which can be used as an indicator for the necessity of adapting the classifier. Therefore, I propose the following sequence consisting of five stages, for structuring a BCI session:

User Training
In this stage the user becomes familiar with the task of the Machine Training stage. This task could be generating BCI detectable signals, mostly in active or reactive BCIs, or a predefined Human-Computer Interaction usually independent from BCI input, for generating passive signals.

Machine Training
In a standardized paradigm the user is guided to generate prototypes of brain activity which can be used as input for the proposed BCI application. In this stage all artifacts should be controlled. The outcome of this stage is a classification scheme, a combination of feature extraction and classifier, able to distinguish the intended commands or to infer an aspect of cognitive state.

Confluence Stage
Here, a simple BCI application is defined which can be controlled by the outcome of the previously defined scheme. Depending on the performance of the classification scheme in the initial application, parameters of the classification scheme might be adjusted or, in active BCIs, the user can learn how to interact with the system.

Validation Stage
This stage is the first test of the intended BCI application. Its outcome is a performance estimate of the defined classification scheme. Depending on this, it can be decided to repeat some of the previous three stages to obtain better results.

Application Stage
The defined and validated classification scheme is applied for generating input to the technical system resulting from brain activity of the user. Methods capable of online

adaptation might be used to (continuously) adjust parameters of the classification scheme to relevant changes of user state.

9.7. Towards context-awareness in BCI based applications

When dealing with a technical system many factors contribute to the development and the meaning of the interaction between user and machine. The user interprets information dependent on their current state, taking into account its relevance for the environment in which the interaction is embedded. The same information might have a completely different meaning if evaluated in a different *context*.

Humans easily deal with this ambiguity as their brain has evolved in a complex environment, where context-awareness is of high relevance. Technical systems such as personal computers do not have this ability. One reason for this is that technical systems usually interact in a rule based fashion and while it is feasible to develop a sound rule system it is very hard to establish a system which sufficiently models any use case, any configuration of system state.
Another problem is that technical systems lack a highly developed cognition which could help to adapt the rule system based on experience. One major fact is that quite often the technical system lacks information which would be necessary to react properly. In contrast, information flows to human beings are very rich in general, several senses providing realtime information on the actual interaction and its environment. Additionally, the human body provides valuable self monitoring which gives necessary information about the user.

A technical system usually relies on direct information provided intentionally by the user or originating from a rather simple self monitoring system. Information about the environment or on details about the state of the user is usually hidden for the machine. Hence, it is often difficult to build up a reliable and intuitive interaction. This is like interacting with the world without real time access to the information provided by your senses, and just relying on, say, written text provided by someone you do not know.

In the following I propose a systematic approach for enriching the information space of a technical system with psycho-physiological data. This can be understood as utilizing the human brain as a sensor for the technical system. Changes to the human cognition resulting from its context-awareness could be detected and interpreted by the technical system, adding also context-awareness to this part of the system.

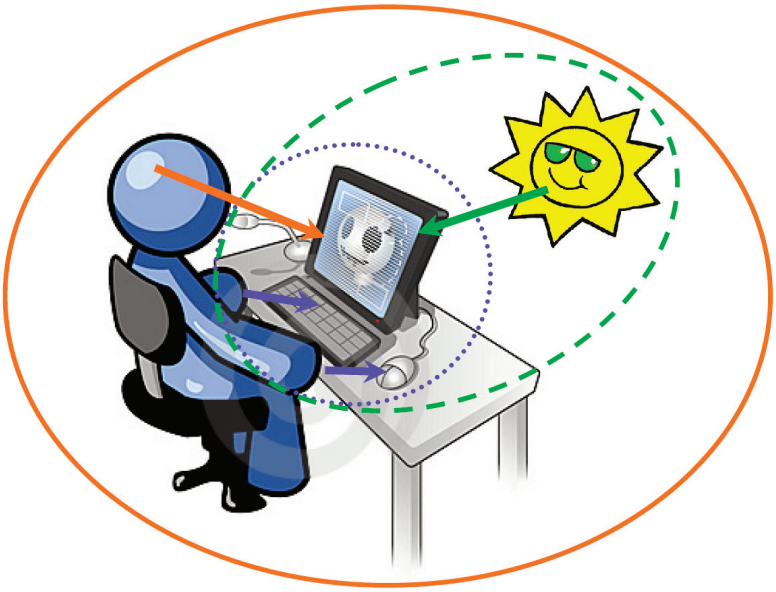


Figure 9.4.: Examples of information used in HMSs.
Different stages of available information spaces in Human-Machine Systems. Stage 1 (dotted line) shows an usual interaction. The user provides any information manually – usually using input methods like mouse, keyboard or voice control. Stage 2 (dashed line) adds information on the related environment to the system. For example this could be the implementation of light sensor to a notebook, adapting the brightness of the screen to the environmental light condition. And finally, in stage 3 (solid line), information on the user state is added to the system, leading to an interaction based on a holistic information space.

9.7.1. Information flow in BCIs

When analyzing a given system it is often useful to model the information flowing within that system and from that system to its environment. This can include a detailed description of the type of information or the amount of information flowing, [178], or an abstract network of subsystems and information streams in between.

A description of a Human-Machine System models the interaction between a user and a technical system. It usually contains several information streams between the technical component, the human component and the environmental component of the given system. When considering a BCI based Human-Machine Interaction, the BCI usually models one of these streams, an input modality solely based on brain activity.

The mapping of EEG signals to distinct brain processes is usually ambiguous, as only

superpositions of processes can be recorded – due to volume conduction (see figure 7.2 and [29]). This leads to the fact that EEG patterns which are generated by different processes might look very similar – the meaning of a specific pattern depends on its generation [63]. This concept of functionality (as introduced in section 7.3.1) is the basis for inferring information on brain processes and results from concepts of neurosciences. The aim is to learn how the brain works. In BCI research this principle is reversed – the aim is to infer the underlying functionality from observed brain patterns. The occurrence of a specific EEG pattern leads to interpretations of the intentions of the user. An ERP, e.g. P300, see section 7.2.5, indicates that the user has focused on specific stimuli [5], or ERD, shows that the user intends to give the command to move a cursor to one side by imagining a hand movement [136]. In most cases this works because the system has information of most intervening factors as these systems are usually working in a highly controlled environment, like a laboratory or a clinical setup. In typical HMS, like a PC in an office, while interacting with the input panel of a machine in industrial environments or while manipulating a virtual object in an augmented environment, the surrounding information space gains complexity. Hence, it becomes more difficult to keep up the principle uf functionality in interpreting EEG signals, which is of great importance for the reliability of a given BCI input.

Especially, for application of BCI systems in more complex environments, for patients who use their BCI at home [179] or even for healthy users in special working environments [48, 3, 157], I propose to use as much information on the actual context as possible to ensure reliability of the BCI input. I suggest augmenting a BCI system to a context-aware system, including as much information on the actual state of the user, the technical system and their environment as possible for retaining functionality.

9.7.2. Adding context-awareness to BCI systems

From the perspective of information flow taken on actual BCI research it is obvious that only a limited amount of available information is used for interpretation of signals and optimization of interaction. Usually, the utilized information space consists of the following three categories.

1. Input – Information on the state of the user's brain. It usually carries binary commands sent explicitly and voluntarily, or implicitly by the user. It defines an information flow from the user to the machine.

2. Output – Displays information on the state of the technical system and gives feedback on previous commands. It defines an information flow from the machine to the user.

3. Implications – This is information inferred from relations between input and output. It results from logical combinations and gives meaning to specific events. Usually it is represented as annotations (markers) in the recorded brain data

These categories of course reflect major aspects relevant for a given BCI system, as proven by many successful BCI experiments. But they only describe a small portion of the holistic space of available information. Much information resulting from the context of the given system, consisting of the human user, the technical system and their environment, is usually not included (see figure 9.4).

The context of a given human-machine system is defined by the following three types of information:

1. Information on the state of the user. This includes information on the body but also about cognitive aspects like intentions, emotions or situational interpretations.

2. Information on the state of the machine. This includes information on technical aspects of the system as well as on the available information space which can be accessed by the machine. Especially, it is of interest whether this space is sufficient for rule based decisions.

3. Information on the state of the environment. The environment usually carries multiple factors which are capable of altering a given Human-Machine Interaction. It contains any related factor which is not explicitly modeled in the given HMS.

As BCI systems are mostly used in simple contexts, allowing for control over factors and hence for retaining functionality, it is often sufficient to restrict the available information space to input and output and related implications. But when the complexity of the context rises it is to access a broader context space.

Information about the environment and the technical system can be gained by incorporating available sensors in the feature space of the BCI system. For example, if the BCI is used in the context of driving a car, information about the vehicle is represented in the CAN bus [180] and environmental information is available from several sensors. Combining features from this information with the existent BCI feature space could be utilized for enhanced feature classification [157]. Also other information on the environment in general HMS could be utilized [181].

But, information on the user state might be highly relevant for adding context awareness to the BCI system. Additional information could be accessed by physiological data, like electromyogram, electrocardiogram or skin conductance (see section 9.5.6), as well as information on the human gaze ([182] and Chapter 13). However, as data on the brain state is inherently part of a BCI system it should also be utilized to gain more information on the user state. In later parts of this thesis I will follow the approach of adding another, inherently passive, BCI based information channel to the system, which provides information on the actual cognition of the user. Changes in the actual context of a given HMS could be protocoled in that way without any explicit action of the user.

9.8. Applying the previously defined schemes and frameworks

The theoretical part of this thesis is now completed. A framework has been presented which is intended to apply BCI-technology in a broader sense. This is especially of interest when taking a look at the goals of this thesis as stated initially in section 6.6. Studies presented in the next two Parts of this thesis, are based on the previous provided framework and give answers to the research questions.

In a first study I introduce an approach of applying passive BCIs for the detection of intentions of the user. I investigate which classification scheme is best suitable for detecting the planning of finger movements, that is usually a CAUS, allowing for classification before onset of muscle activity.
I then give two examples of how a context-aware BCI approach can be defined utilizing information on CAUS. With changes to the context, changes in the cognition of the users are induced by introducing new states of the technical system. This leads to a perceived *loss of control* which induces non-stationarities in the given feature space, decreasing the estimated performance of the proposed system. With information on that CAUS, one can gain insight into the inherent covert aspect of the user state of perceived loss of control over the system. This could be used to adapt the state of the technical system to occurrences of loss of control, for example, with shifting more control to the machine in shared control scenarios [183].
Additionally, the passive BCI presented here can be used for a heuristically based approach for adapting the classifier to changes in the properties of the features over time. It could provide indicators for a relevant change in the feature space which can hardly be detected by overt measures.

The third study on passive BCIs shows how a given Human-Machine Interaction can be improved regarding the factors of efficiency and reliability by incorporating information about the user's internal interpretation, shortly after its occurrence, when it inherently is a CAUS. It focuses on the detection of responses of the human brain to perceived errors in the given interaction. It provides evidence that the process is indeed universal for any user as well. A universal classifier can be defined, replacing an individually trained classifier and canceling the necessity of a machine training stage (see section 9.6). These results lead to improved usability of specific BCI-based applications.

In the third Part I focus on hybrid BCIs by presenting a study about the combination of an active BCI with gaze based input. Here, the Midas touch problem, as defined by Pausch and colleagues in 1993 [184, 185], is solved. This leads to an improvement of Human-Computer Interaction as indicated by the results of the presented study, as well as indicated by the fact that many problems in touchless interaction with gaze control are connected to the Midas touch problem.
In a final report I present a validation study of a novel EEG system based on dry electrodes.

Data recorded with this system shows only minor differences to data recorded with a standard EEG system. This gives a realistic hope for a major improvement in usability of BCI-based applications in near future.

Part II.

Studies about passive BCIs

In this part of the thesis I introduce examples for the application of the concept of passive BCI by presenting and discussing three studies. The first study (see 10) is connected to a project (which will not be discussed in detail here) for the benchmarking of algorithms commonly used in BCI research. In the first stage of this larger project we investigated BCI classification schemes for the classification of executed hand movements. Of course it is of more interest to detect such movements before they are detectable from the outside world. Keeping that in mind, this approach leads to the detection of the *intention* to perform a movement, introducing a passive BCI. The second study describes a passive BCI for the detection of the loss of control (see 11) a user might perceive in a unreliable system. This occurs in many systems based on input by active BCI, as this is still highly inaccurate, or, for example, during technical or environmental problems while driving a car. The third and final study (see 12) aims at the application of passive BCIs in the field of automated adaptation. Applications including automated adaptation often suffer from a poor reliability of the adaptation system – examples of this are auto-adaptive menu structures in Windows XP and the talking paper clip 'clippy' in Word (both are products of Microsoft). I will present a passive BCI based approach for automatically correcting such adaptation errors by utilizing the human perception and its evaluation in the brain as a sensor for a technical system, detecting the occurrence of the errors.

10. Benchmarking classification schemes for movement related brain activity

A core subject in contemporary BCI research is the discrimination of EEG patterns related to hand movements, both executed and imagined. Besides developments on P300 spellers most of the research focused on motor imagery improving the accuracy of detection, c.f. [186, 137, 187, 101, 103, 39, 57, 188, 38, 33, 10, 189, 35, 167, 13, 190]. Yet, the field is still lacking a large-scale objective comparison of available classification schemes. Thus, we decided to set up a platform for this comparison, which can be extended by everybody in future [102]. In this thesis, I start with the comparison of classification schemes suitable for the detection of executed hand movements, as this seems to be more relevant than the detection of motor imagery for applications in the given scope. This can especially be used to set up a passive BCI for detecting the intention of movement even before movement onset – which is a CAUS in most cases. The study presented in the following was supported by several members of Team PhyPA, namely Christian Kothe, Sabine Jatzev, Sebastian Welke, Anne Mann, Matti Gaertner, and Klas Ihme.

10.1. A passive BCI for predicting movements

As described in section 7.2.5 the readiness potential precedes movements by several 100 milliseconds. Several studies showed that a readiness potential can be detected by a BCI, see [81] as an example. Seen as a passive BCI system, this input channel could be used in numerous HMS to optimize safety or usability. One example would be the detection of intentions to steer a car in a specific direction or to change speed. If that information were accessible by modern cars it could be used to give warnings or to prepare for a crash, where each millisecond might be valuable. This approach is discussed by Sebastian Welke in his dissertation [176]. It shows that the application of passive BCI technology for the detection of movements might be very relevant for HMS in general. As mainly motor imagery has been investigated in BCI research, it is still unclear how to set up such a passive BCI system. The results of the above mentioned benchmarking approach about executed hand movements can be used to learn which classification scheme might be best suited for solving this problem. Due to the significant inter- and intra-individual variability in observed EEG patterns, this benchmarking survey was conducted with a large number of subjects. To date, few methods have been tested with data from more than a dozen subjects, so most of them are not supported by statistically significant and representative results.

10.2. Motivation for Team PhyPA's benchmarking approach

Researchers developing new algorithms for BCI research encounter problems finding publicly available EEG data to test their methods [191]. Also, there is still a lack of publicly available results derived from controlled experimental designs for valid method comparisons [187]. Our approach has a first goal to provide EEG data recorded in a highly controlled and homogeneous environment to the BCI community, so that different researchers can train and test their algorithms on comparable data and without the hassle of the recording procedure. The second goal of the Benchmarking Study is providing information about the performance, capabilities and restrictions of different algorithmic approaches. On the one hand we compare different feature extraction methods on one selected classification algorithm and on the other hand an exemplary comparison of different classifiers is given for the most prominent feature extractors. Besides the high number of algorithms, there is also a relevant variety of experimental setups which influence the outcome of experiments. This makes it even harder to compare given algorithms.

Therefore, we recorded 32-channel EEG, EOG and EMG of 36 participants accomplishing a standard button press task in two blocks with 650 trials each. Electrodes were placed along the standard extended international 10/20 system, reference was placed at nasion, ground at Fz and impedances of all electrodes were kept below $20k\Omega$. In addition to this, room temperature and noise levels were recorded. No data in the subsequent results had to be discarded due to artifacts, for providing data reflecting online scenarios best possible. All data and detailed instructions about the procedure are available at `http://www.phypa.org/benchmarking.html`. The page should serve as a data hub for benchmarking different algorithms. We encourage researchers to download the data, test their algorithms and upload their results.

As the experimental setup clearly also has an impact on the human cognition and hence on extracted features, it is necessary to compare classification schemes using data from different experimental setups. We provide the first step with datasets from 36 participants on a single experimental setup and also the infrastructure for further steps. Researchers are encouraged to contact me for uploading their data on executed hand movements to our website and to enrich the proposed benchmarking approach. For the purpose of fairness in scientific cooperation we propose a license on our website including rights of usage, citation policy and possible co-working on publications.

The following section first presents a short description of the task, followed by examples of different types of specific evaluations of the classification scheme approaches.

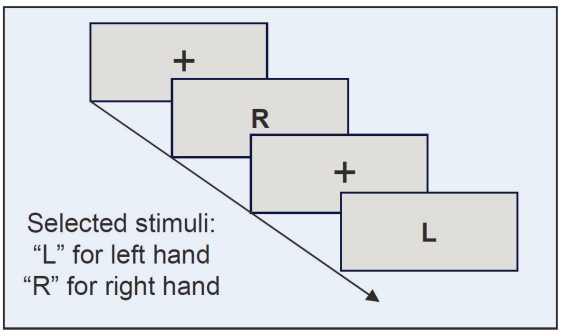


Figure 10.1.: A sequence of the LR-paradigm.
Each stimulus – selected from L,R – is displayed for $700ms$ and interleaved by a cross for $300ms$.

10.3. Experimental task – the LR paradigm

The LR-Paradigm, introduced in [128] was used, as experimental task. One session in the experimental design consisted of two blocks with 650 trials each. During each trial, a black letter randomly chosen from the set {L,R} was displayed on a grey background for $700ms$ followed by a pause of $300ms$. Participants were textually instructed to press the left (or right) CTRL-key when an L (or R) was presented. They were asked to react as quickly and accurately as possible. The inter-trial interval (ITI) lasted $1000ms$. Each block was divided into two parts with a two minute break in between. There was a longer interval (14 minutes) between the blocks. See figure 10.1 for a visualization.

10.4. Benchmarking procedure

We followed an offline approach. This lends itself well to method comparisons, since the subject's behavior is not influenced by the performance of a particular algorithm, and methods can later be compared on the basis of identical data. Also, chaotic effects like loss of control, are avoided (see chapter 11).

The idea is to compare the capability of different classification schemes to discriminate between movements of the right and left hand solely on EEG data. Therefore, the first block should be used as a training data set, while the second block should be taken to test the performance of the algorithms on unseen and unlabeled data. To compare different algorithms, either the classification error on the unseen data of block 2 or the cross validation error on block 1 shall be reported. Considering different application scenarios it is of interest to learn at which time relative to the button press which detection accuracy is possible. Hence, we propose three different time ranges (categories) on which the feature extraction and classifier training should be based. Category 1 comprises data from $-500ms$ to $-200ms$

relative to the button press, category 2 ranges from $-500ms$ to button press and category 3 from $-500ms$ to $+200ms$. For each category any subset of the data can be used.

Of course, the implementation of classification schemes also influences the effectiveness of BCI systems as well as the type of evaluation method – namely the type of cross validation. Therefore, we suggest using the PhyPA-Toolbox as a framework for testing novel algorithms on the datasets. As we have set priority on ease of usage and a simple modularity while developing this toolbox, it will be easy to implement any new classification scheme. With this a standard is given for comparison on the level of implementation.

The offline evaluation is followed a cross validation, in which a classifier is repeatedly trained and tested on disjoint trial sets as described in section 8.1.1. Out of the several data partitioning variants, such as randomized CV, blockwise or chronological CV, we chose randomized 10x repeated 10-fold CV as it is the most widely used method in the BCI field. For the estimation of meta-parameters, e.g. for regularization, we performed a 10x repeated 10x10-fold nested CV.

10.5. Analysis and results

The EEG features that enable the discrimination of left- and right-hand finger movements fall into two categories: ERD/ERS complexes and SCPs, in our case the lateralized readiness potential [192]. All algorithms were implemented as given in the reference and in the description in sections 8.3 and 9.3.

10.5.1. Feature extraction

The used feature extraction methods are based on neurophysiologic knowledge.

10.5.2. ERD feature extraction

Idle (sensori-) motor neurons tend to exhibit locally synchronous polarity oscillations which can be observed in the EEG channels above the motor cortex. Preparing motor actions causes this synchrony to break down, like when executing the action, and the measured amplitudes in the affected EEG channels drop accordingly [28]. This can be used to infer the laterality of the ongoing motion.

ERD based feature extractors as described in section 7.2.5 were compared. In figure 10.2 it can be seen that the measured ERD effects are in fact emitted from the motor cortex, and take place within some subband of $7-30Hz$, as is predicted by neurobiology.

The Log-BP algorithm

In this ERD-based feature extractor, the EEG data is first Laplacian-transfomed, and then the logarithmic bandpower in the frequency sub range within $7-30Hz$ is calculated for each channel. The time is determined by the full length application of the given window sets. This gives a feature space of 32 dimensions for each window set.

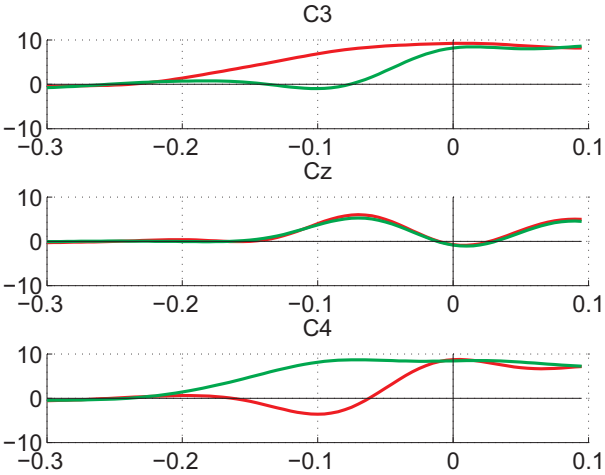


Figure 10.2.: Prepocessed readiness potentials.
Event-related potentials (here: readiness potential) for both classes (red: left, green: right) over channels C3, Cz and C4. Y axis is in microvolts. Time (on the x-axis, in seconds) is relative to the keypress.

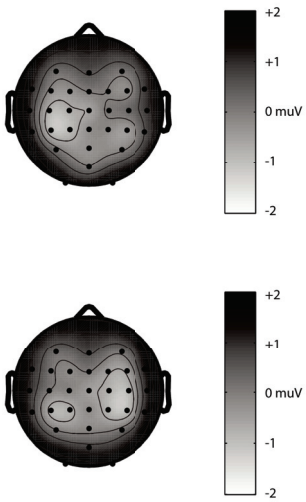


Figure 10.3.: Cortical topography of the readiness potential.
Left (top) and Right (bottom) class at $-0.08s$ relative to keypress. Taken from [193]

The CSP for ERD algorithm
A more complex feature extractor for ERDs is the Common Spatial Patterns algorithm, as described in 7.2.5. The idea of CSP here is to find 6 patterns such that the variance in each trial projected according to them is most discriminative (i.e. maximum difference between the two classes of left and right motor preparation). Subsequently, the full EEG data of each windowset for each trial is projected according to each of these patterns and then Log-BP is calculated similar to the above method, leading to a 6 dimensional feature space for each windowset.

The SpecCSP algorithm
Spectrally Weighted CSP [13] not only learns spatial patterns, but also frequency filters for each pattern, with bands weighted according to how much each band contributes to the discrimination of the classes, but it leads to a similarly structured feature space.

Other common spectral variants of CSP, like CSSP and CSSSP have basically been superseded by SpecCSP, as was shown in [13].

Moreover, hand-movement-related EEG can be discriminated according to SCP. It is well known that hand movements are preceded by a lateralized readiness potential, i.e., a local low-frequency negativity over electrode sites contra-lateral to the moving hand, as described in section 7.2.5.

10.5.3. SCP Feature Extraction

The SCPs, the local low-frequency polarity changes ($1 - 5Hz$) in the EEG that were of interest are typically located above the motor cortex. In these channels, a slow negativity (the readiness potential) can be observed prior to a movement. From the spatial distribution of this negativity the laterality of the upcoming movement can be inferred [72]. Figure 10.2 shows that the measured SCP features are in fact mainly driven by the motor cortex. Its location (figure 10.3) is also consistent with neurobiological predictions [194].

The Pattern Matching Method
SCP features are the basis of the PMM as proposed in [72] and described in section 8.3.3. Each channel is preprocessed by a short raised-cosine windowed FFT filter and then the average potentiation over four consecutive $50ms$ windows prior to the key press is retained. In total, the features extracted by this method are represented in a $4x32 = 128$ dimensional space for each window set.

The CSP for SCP algorithm
This algorithms attempts to reduce the complexity of the SCP feature space by first projecting the EEG channels down to a small set of meta-channels. This is done by a modified

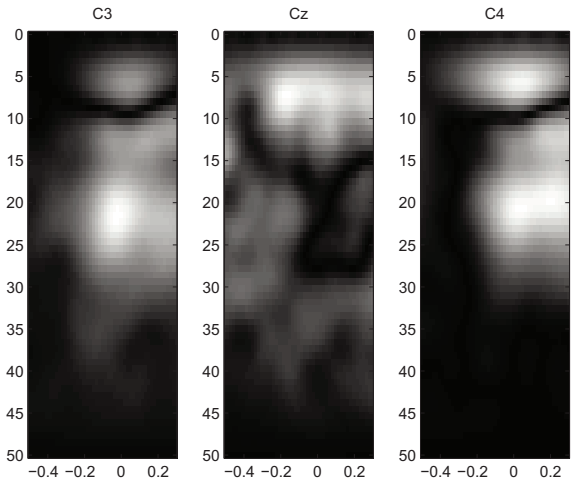


Figure 10.4.: Spectral differences during motor imagery.
Grandaverage of spectral difference between left/right movements over time (x-axis) for channels C3, Cz and C4. The y-axis goes from $0Hz$ (top) to $50Hz$ (bottom). Brighter indicates a stronger difference (not directed) between classes. Taken from [193]

CSP algorithm which optimizes for maximum discriminability according to deflection from zero, instead of variance (as described in section 8.3).

Feature extraction was accomplished in all three categories. The resulting feature vectors were classified using LDA, which was trained on the data of block 1 and tested on the unseen data of the second block.

Figure 10.5 summarizes the classification errors (training and test error) based on the different feature extraction methods in the three categories. It shows that the plain PMM delivered the lowest classification error (both training and test) for all three time ranges. Moreover, feature extraction methods based on SCPs perform better than methods based on ERD-related features. For ERD features, the third category provides the lowest classification error, while for SCP features it is lowest in the second category. CSP and SpecCSP perform on a similar level. For all feature extraction methods, the test error is higher than the training error. However, it seems that the difference increases with lower training error. Differences were tested using a 4 (feature extraction method) x 3 (category) x 2 (training/test) repeated-measures ANOVA [98]. All main effects were significant (feature extraction method: $F(3, 105) = 246.3$, $p < .01$; category: $F(2, 70) = 7.346$, $p < .01$; training/test: $F(1, 35) = 24.6$, $p < .01$).

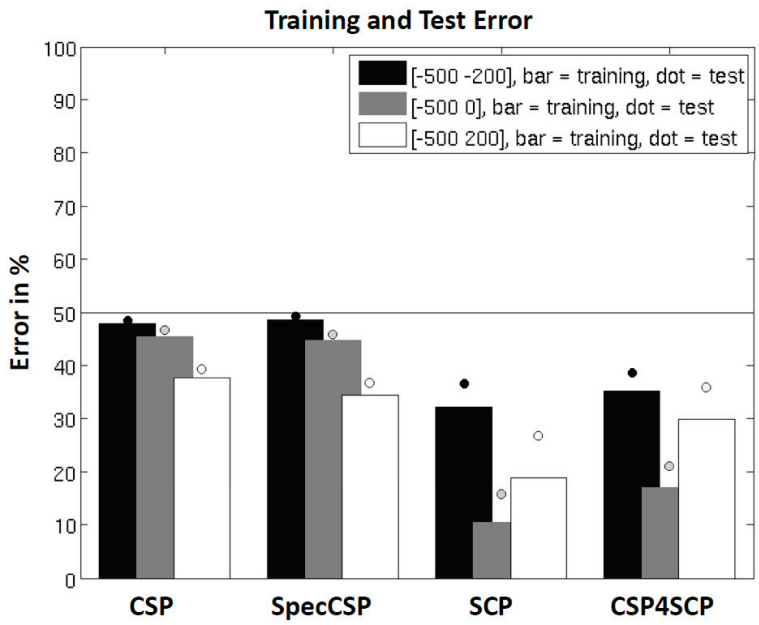


Figure 10.5.: Training- and Test-Error of the Benchmarking study.
Training (bar) and test error (dot) accomplished based on the different feature extraction methods CSP, SpecCSP, SCP and CSP for SCP in the three different categories.

10.5.4. Classification

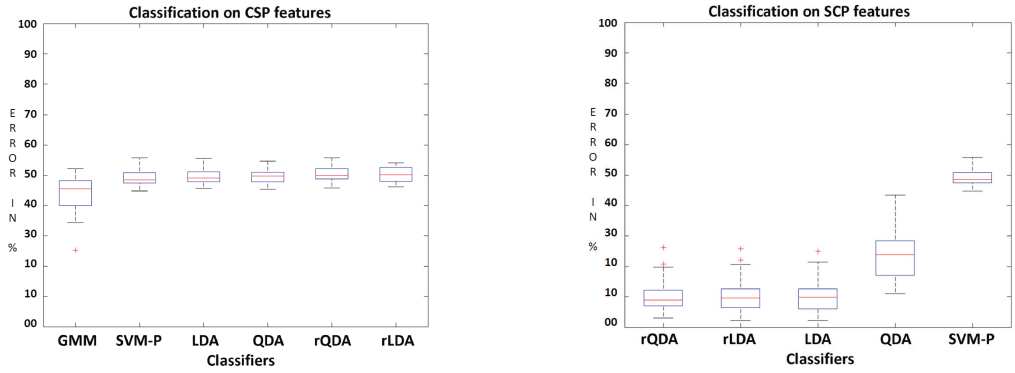
Different classifiers were compared by means of the cross validation error of a randomized 10x repeated 10-fold CV. For the estimation of meta parameters, e.g. for regularization, we performed a 10x repeated 10x10-fold nested CV. Data of the first block were taken into account for this. Classifiers were compared at the basis of features extracted by the PMM and CSP. The following classifiers, as described in section 8.4, were tested:

1. Linear discriminant analysis [105]
   LDA assumes that the covariance matrices are equally shaped between the classes.

2. Quadratic discriminant analysis [106]
   QDA allows for classification without the assumption of equally shaped covariance matrices between the classes.

3. Regularized LDA and regularized QDA [120]
   Regularization followed a sparsity criteria for the estimated covariance matrices. The regularization parameters were selected by an inner cross validation.

4. Support Vector Machines with polynomial kernel (SVM-P) [108]



(a) Classification on CSP features

(b) Classification on SCP features

Figure 10.6.: Performance estimates for the classifiers of the Benchmarking study. Classification results of different classifiers based on CSP features (a) and SCP features (b).

This SVM is trained with a polynomial kernel of order 3 and a kernel function parameter (coef0) of 0.

5. Gaussian mixture models [109]
   The GMM is trained along the greedy expectation-maximization method with a maximum number of three full components.

Figure 10.6a shows the mean cross validation error on CSP features. Here SVM-P and GMM delivered the best classification results; still the simple LDA outperformed QDA. For SCP features (see figure 10.6b), the simplest classification model, LDA, performs almost on a par with rLDA and rQDA and outperforms SVM-P and QDA (GMM is not presented because it failed to converge for many participants.).

10.6. Results

The ERD-based algorithms generally performed significantly worse than the SCP-based ones (figure 10.5). Log-BP features were outperformed by the more complex CSP and SpecCSP methods, as was expected. For SCP feature extractors, CSP for SCP, performed slightly worse than the PMM. Figure 10.6, which compares classifiers on SCP and CSP features, shows that the simplest classifier model, LDA, was not significantly worse than any other tested classifier. On the other hand, there are commonly used classifiers which failed badly, especially plain QDA. Also, GMM failed to converge for too many subjects, so it could not be presented here.

10.7. Conclusion and outlook of the first step towards the benchmarking approach

According to figure 10.5, CSP significantly outperformed Log-BP. The former learns the subject-specific spatial projection of the signal, while the latter only has a static mapping between channels and features. This shows that there is critical inter-individual variability in how the motor brain rhythms are projected across the cortex and onto features. Interestingly, the benefit of SpecCSP with respect to CSP, namely that it learns the frequency spectrum of the relevant brain rhythms, is hardly reflected in the results (see figure 10.6). This can be attributed to the difficulty of measuring the frequency spectra precisely when the number of oscillations is small, as is the case here.

From the comparison of classifiers on SCP features, two important observations can be made. Firstly, none of the non-linear classifiers could outperform linear discriminant analysis, which is strong evidence that the data is in fact linearly separable (see figure 10.5). Secondly, the danger of overfitting is high with these features, as proven by the failure of QDA (see figure 10.6), and of GMM, which was unable to build models on SCP but worked comparatively well on ERD. Some regularized non-linear methods, such as SVMs with polynomial kernel, and rQDA, however, handle the features expectedly well.

On ERD features it can be seen that non-linear models did in fact perform better than linear models on SCP features. Also, since the feature space dimensionality is much lower at 6 dimensions, no method overfitted as dramatically as in the SCP case. However, ERD-specific results suggest that for the majority of subjects the key-pressing movements are too fast to allow for discriminative ERD. A recent offline study [186] comparing multiple tap rates ($0.5s, 1s, 2s$) over six subjects shows similar results for self-paced movements.

This work gave an overview about the benchmarking approach of Team PhyPA for testing BCI algorithms. It presented information about the acquired data, the task as well as the procedure. Moreover, two benchmarking examples were given. These showed that the simple PMM for feature extraction combined with an LDA classifier performed on a par with or even outperformed more complex classification schemes for the discrimination of hand-movement-related features.

I hope to encourage other researchers to use the framework of a public data hub and a standardized toolbox to continue this benchmarking approach. Results on novel classification schemes and also new data from other experimental designs will be published at the benchmarking website. The next step will be to extend the approach to data from experiments from imagined hand movements and from experiments on the evaluation of errors by the human brain.

10.8. Discussion of the passive BCI approach based on the readiness potential

This study shows that a classification scheme based on the PMM and LDA provides a method capable of discriminating between the intention to move the left and the intention to move the right finger. The reliability increases with data taken closer to the actual button press. But even at $500ms$ before the button press a quite reliable detection is possible. This proves that the proposed passive BCI might be applicable for real world applications. Especially, it might be very valuable for intention detection in cars, which might be used for increasing traffic safety. Details about this idea and possible applications can be found in the thesis of Sebastian Welke [176].

A major drawback of the concluding approach is its dependency on specific events that arises from the use of ERPs. The classification scheme that performed best, is only valuable to applications where knowledge about the timing of events is available – restricting its applicability. This might be the reason why the rather simple feature extractor PMM performed unexpectedly well. Other feature extractions, like CSP and SpecCSP, are not restricted to a specific time frame. They should keep their performance regardless to what segment of the data they are applied. Unfortunately, their performance in this study is rather bad.

Hence I conclude that further steps in the development of classification schemes have to be taken to dissolve dependencies or increase classification accuracies. PMM is basically a specialized version of Symbolic Aggregate Approximation (SAX) [195][1]. It might be useful to apply derivates or extensions of SAX [196] to extracting features from ERPs. I have taken first and promising steps towards this direction by applying a toolbox based on [197] and implemented by Tim Mullen to our data.

Nevertheless, the combination of PMM and LDA can be applied in specific scenarios delivering valuable information, e.g, it may show whether a driver intends to steer to the left or right in an upcoming maneuver, even though it will be difficult to predict an unexpected maneuver.

With this study I gave the first example of a passive BCI system, that can be seen as a first proof of concept. The passive information extracted is still strongly related to an active command, the button press. The next step into the direction defined by the passive BCI approach would be the detection of an aspect of the user state that is somehow tangential to the current behavior of the user.

[1] Thanks to Tim Mullen, UCSD, San Diego, USA for a hint on this.

The studies in the following two sections will exactly do that. I first consider the detection of the covert aspect of user state related to the feeling of losing control over a device. Accessing this portion of the user state allows for an augmentation of the information about the current context of a specific HMS, that otherwise would be hard to achieve. Hence, this study also provides a first example of context-aware BCI systems.

11. A passive BCI for detecting perceived loss of control

11.1. Introduction

As the user's cognition is inherently hard to access by overt measures, a large portion of highly relevant cognitive processes are CAUS (as defined in section 9.5.1). This might be of high importance for an HMS based on BCI input, as changes of the cognitive state might influence the features extracted by the BCI. But as EEG is recorded in a BCI system we might utilize it to gain information about CAUS for extracting relevant context-information with a passive BCI.

In this section an example of a context-aware BCI approach is given, utilizing information about CAUS. Here, the context induces a change in cognition by introducing the user to new and unexpected states of the technical system. This leads to a perceived *loss of control* which induces non-stationarities in the given feature space, decreasing the estimated performance of the proposed system. This information about the context, accessed by an additional information channel based on passive BCI, could be utilized for a heuristically based approach for adapting the classifier to changes in the properties of the features over time. Also, one can gain insight into the inherent covert aspect of user state of the feeling of losing control over the system. This could be used to adapt the state of the technical system to losses of control, for example, with shifting more control to the machine in shared control scenarios [183]. This study shows that there is much more valuable information in the EEG stream than is usually incorporated to set up a BCI based control. I was supported during this endeavor by the following members of Team PhyPA: Christian Kothe, Sabine Jatzev and Sebastian Welke.

While allowing for control over a feedback device via brain activity, BCIs still suffer from performance decrements during an online session. As a possible cause for the BCI classification problem, non-stationarities in the statistical properties of the extracted feature distributions were identified [35]. Numerous studies note that new methods of adaptation have to be found [101, 190, 35, 198, 38], in order to limit the influence of statistical non-stationarities on the classification accuracy, but so far no heuristic-based approaches have been developed.

A major difference of heuristic approaches for adaptation compared to automated ap-

proaches is that information about the context drawn from the heuristic approach can be used to control the process of adaptation. Adaptation based only on the classification process itself could lead to divergence effects – if the adaptation process is disturbed by factors not modeled by the adapting function these factors might attract the adaptation leading to a downward spiral of decreasing performance. Especially, additional cognitive processes are good candidates for inducing non-stationarities, as they could be connected to the factor under investigation in the dynamic brain. But it is unclear whether such processes exist and how they should be identified.

With this study I was able to isolate one cognitive factor responsible for statistical non-stationarities in EEG data: user's perceived the loss of control. Loss of control refers to the perceived control the user has over a feedback device. My hypothesis is that the perception of loss of control could lead to adaptation processes in the human brain, inherently leading to changes in properties of extracted features. See figure 11.1 for a hypothetical description based on the Basket Paradigm (see figure 11.3 and [84]).

11.2. Backgound

11.2.1. Subject of investigation - non-stationarities:

In recent years non-stationarities in statistical properties of BCI feature distributions have become an increasingly relevant issue in BCI research. These statistical non-stationarities are likely to occur in the course of time of an experimental session causing drastic changes in BCI relevant features, leading to a serious decline in the classification accuracy. Several studies claim that they have to be further investigated to find new solutions of online adaption e.g. [101, 190, 35, 198, 38]. In a first systematic quantitative study, Shenoy et al. [35] found evidence for non-stationarities in the statistical properties of the relevant extracted features. They called for the need of an investigation of neurophysiological and psychological causes. Various adaptation methods have been developed, following a data based approach. Here some of the parameters of the translation algorithm (see 8.1) are updated during an online session [198, 38, 190, 199]. Nevertheless, apart from [35], none of these studies investigated possible *causes* for statistical non-stationarities. The resulting procedures are therefore vulnerable to overfitting [108]. Likewise in this study we want to investigate non-stationarities on a new theoretical basis, adopting a heuristic approach. Causes for these effects have to be identified at first, in order to find relevant indicators. As a result, a new adaptation scheme could be followed by changing parameters of the classification scheme, whenever the crucial factor indicates the need for adaptation.

11.2.2. Factor of interest - loss of control:

This study investigated the factor of perceived loss of control. By control, we refer to the perceived controllability the user has over a feedback device. Perceived loss of control could cause a change in the cognitive state of the subject, and therefore change the context with

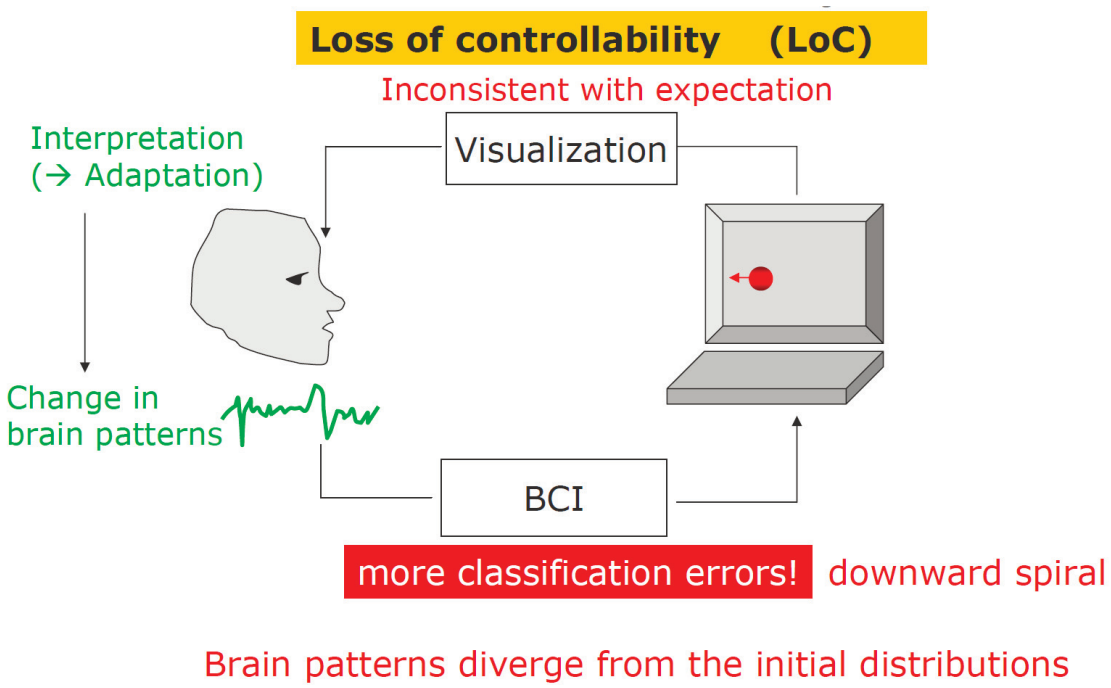


Figure 11.1.: The cycle of losing control.
Perceived loss of control: In a typical system based on active BCI control in the Basket paradigm (as described in figure fig:BasketParadigm) a feedback cycle emerges. The user reacts on current feedback (position of the falling ball) sending commands changing the feedback state. Misinterpretation of brain signals (ball moves in the wrong direction due to a classification error) might lead to a feedback state that is not expected. The user could think that they had not sent proper input signals or made a mistake. This could lead to adaptation processes in the user's brain – the user wants to send correct signals. But such a situation is unlikely in the calibration session, the BCI system is not calibrated for the adapted signals. This leads to more classification errors, causing even stronger adaptation effects in the human brain. Two adaptive systems diverge from each other – a downward spiral of decreasing classification accuracy has been established.

severe impact on the extracted features. The idea of perceived control has been used before, to refer directly to the classification accuracy of a BCI system [84, 35]. Data based methods face the problem of complexity of online BCI systems, consisting of two strongly interacting components, namely the user and the machine, which creates a closed feedback loop. The user and the technical system have to optimize for the same goal – hence, ideally, adaptations of both systems should converge. However, both systems could also diverge from one another, as demonstrated here (see figure 11.1). Hence, knowledge on the occurrence of a change in the perceived loss of control could be used to readjust the technical system – for instance by adapting or retraining the classifier in BCI systems. In general HMS, the detection of loss of control based on a passive BCI could be used to change responsibilities in the given system. This could be done by transferring more control to the technical part in shared control systems.
Loss of control is a result of the static translation algorithms confronted with the variable brain trying to optimize during phases of classifier errors. Hence, loss of control is induced because the classifier output is inconsistent with the expected feedback. Here, we present a new experimental setup called the RLR paradigm (Rotation-Left-Right paradigm), which is controlled by manual key presses. For investigating loss of control, we manipulated the rate by which the user was able to predict the feedback under controlled conditions by artificially introducing machine errors. We recorded EEG data while people were playing this game and analyzed BCI features offline (for details see the following methods section) to control possible intervening factors. Moreover, this setup avoids phases of loss of control over the feedback device occurring in online sessions. In this study, I found evidence that changes in the loss of control have an impact on BCI performance.

11.3. Methods

An offline analysis approach was utilized, replacing the usual online session following initial calibration measurement. Thereby subjects performed a series of clearly defined control actions, while the EEG was only recorded and not fed back to the user. Hence, the subject is not influenced by the performance of a particular algorithm and multiple algorithms can later on be compared on exactly the same data.

11.3.1. Experimental Task and setup

Experimental task
The experimental task was to rotate a stimulus with left or right key presses until it corresponded to a target figure. The stimulus was either the letter L or R, indicating left or right key press (Ctrl key, standard keyboard) and direction of rotation (left or right) (see figure 11.2). Change of stimulus color indicated different angles of rotations: red indicated 90 degrees, yellow 60 degrees, and green 30 degrees. Every $1000ms$, the letter changed color, indicating the possibility of rotation. The stimulus would not rotate automatically, but only

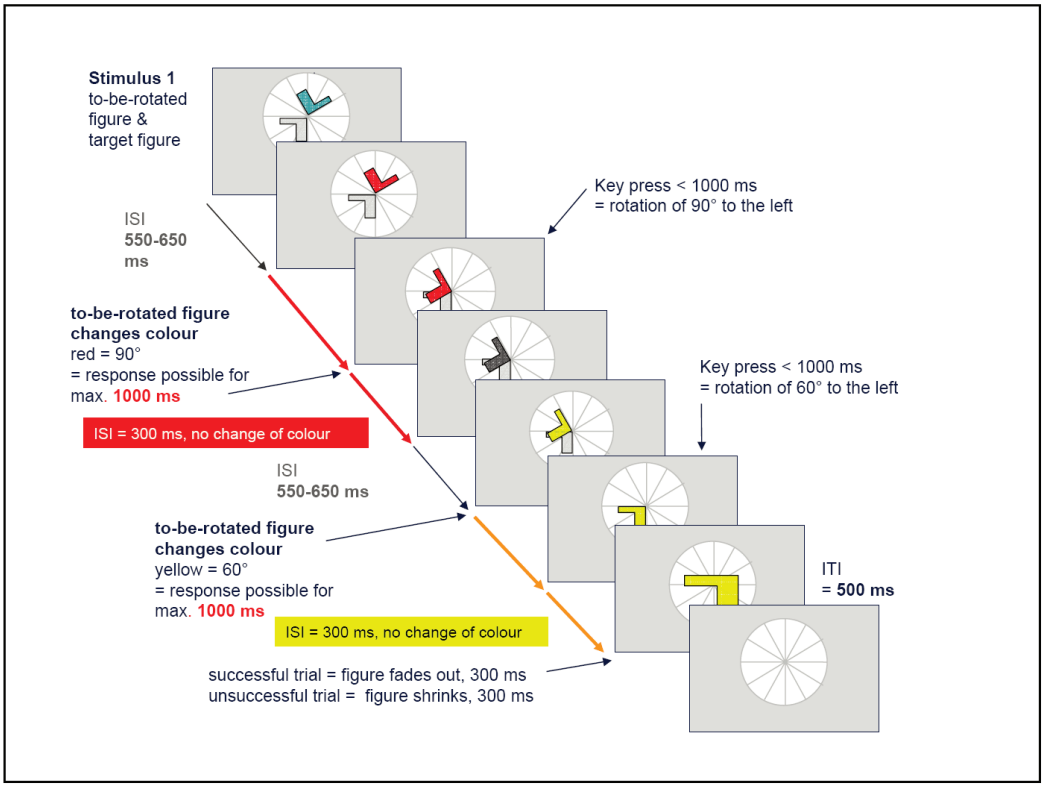


Figure 11.2.: The RLR paradigm.
Experimental task of the RLR paradigm, section of a sample trial.

if a key was pressed. Therefore, participants were able to build up a strategy to achieve the following goal: to rotate the initial stimulus as fast as possible to match the orientation of the target stimulus. After rotation, the letter remained in its color for $300ms$, changed to gray for a variable inter-stimulus interval (ISI) of 550 to $650ms$; during that time, no key press was possible. The inter-trial interval (ITI) was $1000ms$. Failed trials were defined as rotating the stimulus too far or pressing the inappropriate key. Mapping rules of colors and degrees of rotation were kept constant until loss of control was introduced and a wrong mapping of colors and angles occurred, leading to machine errors and wrong trials.

Experimental setup

In the initial calibration measurement, participants performed the LR paradigm (as described in 10.3 and [128]) (five minutes) by pressing a key with right/left index finger depending on the letter (R/L) appearing in the middle of the screen for $1000ms$. Afterwards, a short practice block (P) of two minutes duration was introduced (RLR paradigm). The following sessions were divided into three blocks (A1, A2, B). For each block, the RLR task had to be performed. A pause of 5 minutes was inserted between blocks. The first two blocks (A1, A2; 12 minutes duration each) were identical. During the third block (B; 29 minutes duration), loss of control was introduced. After 7 minutes, loss of control was introduced by gradually increasing the probability of error from 0 to 30 percent (transition time of four minutes). This probability of error was held constant for another 7 minutes (Buc) and decreased to 0 in a second transition phase. Another final phase of 7 minutes of correct feedback followed (Ba2). Data from blocks A1 and A2 could be used to investigate the influence of time on feature distributions and BCI performance. This could then be compared to data from block B, where loss of control was introduced in a controlled way.

Experimental paradigm

The new RLR paradigm parallels features of typical online feedback scenarios in BCIs (e.g. Basket Paradigm (see figure fig:BasketParadigm, [128])). It mimics an asynchronous BCI (internally paced, user-driven) [200]. There is an iterative decision process within each trial which has a defined goal and therefore provides motivation for participation in the game. Also, the factor of loss of control is represented equally in both paradigms, Basket and RLR. The benefit of the RLR paradigm is that while all other factors are kept constant, the factor of loss of control can be modulated. We chose to use no BCI control for our paradigm, because this would introduce a second source of possible loss of control since BCIs can be unreliable. Furthermore, we chose not to use a manually controlled version of the basket paradigm, because the task of that paradigm is extremely simple when controlled with reliable input devices such as a mouse or keyboard, and might therefore lead to underchallenged subjects. One solution for making a manually controlled basket paradigm more challenging would be to increase speed. However, this would make it difficult to estimate features in an appropriate way as described in Chapter 10 and [193].

Recording

For this study 22 healthy subjects (age range $19 - 40$) took part. EEG was recorded from scalp with 32 channels of EEG in standard extended international 10/20 distribution with

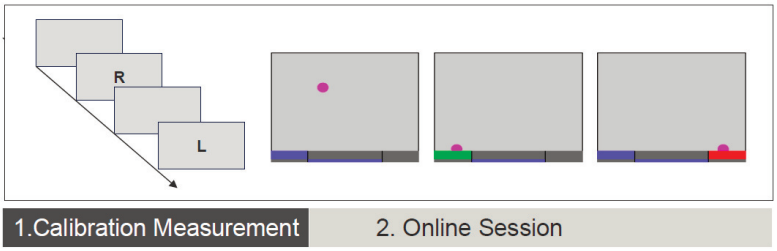


Figure 11.3.: The Basket paradigm.
The Basket paradigm: A classifier is calibrated for motor imagery on the LR paradigm (left hand side). The BCI is used to steer a ball, that is falling with constant speed, into one corner of the screen, that is highlighted by a blue field, the 'basket'. Classification is performed stepwise – every $50ms$ a classification is requested leading to a small movement of the ball into the proposed direction.

reference at nasion, sampled at $1000Hz$, with a band pass from 0.05 to $200Hz$. Impedances of all electrodes were kept below $20k\Omega$. EMG and EOG data, as well as ambient temperature and noise level, were recorded, controlling for – but not removing – external effects such as measurement artifacts and class-related eye movements.

11.3.2. Analysis of EEG data

The data was analyzed in a two-step process. First, classifiers were trained on the initial data set generated with the LR paradigm. This was done using a cross validation (see 8.1.2 and [108]) on the given dataset. The continuous EEG data for a session is segmented into a set of blocks, one for each trial. The recorded trials were repeatedly part of disjoint training and corresponding testing sets. An instance of a classifier was trained on the training set and its performance was then estimated on the unknown data of the test set. Here, a 10x(10,5)-fold nested CV was used, which means that we repeated 10-fold CV with a nested 5-fold CV (for the sake of an unbiased selection of free parameters of the used methods) for ten times. Second, features were extracted from data of blocks A1, A2, and B, and the previously trained classifier was applied on these features. In this study, two different types of feature extraction were used, one type reflecting the readiness potential and another type for event-related desynchronization. BCI features for SCPs and ERD were extracted following the SpecCSP and CSP for SCP approach (see section 8.3). The development of the α-band component in the spectral domain has been protocoled by FFT over a moving window.

11.3.3. Dependent measures of non-stationarities

Two methods were used to measure the impact of loss of control on BCI performance. First, changes in feature distribution were tracked by calculating the Kullback-Leibler divergence (KLD) (see 8.1.2) of data taken from a moving window over blocks A1, A2 and B compared to data from the initial calibration data. Second, changes in the performance of the application of the initially trained classifiers over the progress of blocks A1, A2 and B were checked. Significant changes in KLD indicated the occurrence of non-stationarities in the feature space, while simultaneous decreases in classification accuracies showed the impact of these non-stationarities and, hence, the impact of loss of control on BCI performance.

To assess the impact of loss of control on the classifier performance in an offline analysis, pseudo online classification rates (POC) were calculated over time. POC was determined as follows: The appropriate CSP derivate was used (with a time window of $300ms$, six patterns, and a band-pass filter of $7 - 30Hz$ for SpecCSP and $0.5 - 15Hz$ for CSPfSCP). A classifier was trained on the initial LR block. Then, this classifier was applied to every key press, over the course of the main experiment (i.e. blocks A1, A2, and B). An average of approximately 100 gradual classifier outputs in a one-second window before each key press was averaged and taken as the classifier's decision for this key press. The sign of this decision value (left keys, on average, assigned -1, right keys $+1$) was remapped according to the key actually pressed, such that correct decisions were assigned positive values and wrong decisions were assigned negative values. By this, I obtained a real number for each key that was pressed by the subject. This was necessary because we have no pre-defined time points in the experiment where keys were pressed. Subjects could freely chose when to press a key for each color change, hence, within a time window of $1000ms$. To provide a plot showing coherent changes in classification accuracy over the whole time scale of the experiment, we needed to implement POC. Plots in figure 11.5 show the aggregation of all values over all 22 subjects. The data was forward-backward-filtered with a moving average window of 25 seconds. Therefore, positive values in the plot indicate overall correct classifier decisions, while values close to zero or negative indicate overall wrong decisions.

The KLD (see section 8.1.2) of the classifier's feature distributions was also calculated. All measures were calculated relative to the training data distribution of the initial calibration measurement (the LR block). KLD was used to measure the divergence of the CSP feature distributions as they build up over the course of the main experiment. Note that these KLD results were determined in a classic offline fashion, i.e. one for each key press, as KLD reflects distributions of trials.
KLD itself shows changes in distributions of features – these could lead to increasing or decreasing performance. The measure of POC shows estimates of actual classification accuracy expected in online application – but do not indicate possible reasons. In combination, the measures of POC and KLD make it possible to identify and track back non-stationarities on

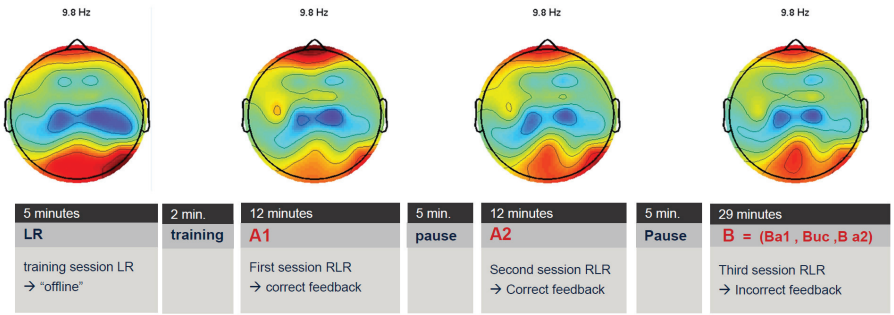


Figure 11.4.: Topographical development of the α-rhythm during the RLR paradigm. Topographical plots: spatial distribution of $10Hz$ activity over all blocks

BCI features relative to the initial calibration measurement.

11.4. Results

Class correlation of eye movements during the RLR sessions were all below $r = 0.012$, showing no significant difference to the class correlation of the LR design. This ensures that the result of the classifier output in the RLR design does not strongly depend on class-correlated eye movements and might be seen as an indicator for an underlying cortical process. T-tests [98] were calculated for the average over blocks (A1, A2, and B) of KLD and POC on CSPfSCP and SpecCSP features. Neither KLD nor POC showed a difference between blocks A1 and A2. For the SpecCSP features based on Event-Related Desynchronization, phases including loss of control (block B) showed a significant ($p < .05$) increase in KLD of the SpecCSP features. Also, the pseudo-online classification rate shows a decrease over time and correlates significantly ($p < .05$) to that of the KLD in block B (see figure 11.5: 1/3). For CSPfSCP, there was no significant change for the phases with loss of control (see figure 11.5: 2/4). Hence, there is a causal relationship between phases of loss of control and the combination of decrease in POC and increase of KLD for ERD-based features. This indicates that loss of control induces relevant non-stationarities to the feature space. We found no evidence for a similar effect on SCP features.

In RLR-designed sessions the overall α-rhythm is less pronounced than in the standard LR-Training. It slightly increases over time, see figure 11.4.

11.5. Discussion

Due to the new experimental design of the RLR paradigm, I was able to isolate one factor responsible for BCI relevant non-stationarities. With increasing loss of control the KLD

increases, disclosing non-stationarities in the feature space. No influence of time on the loss of control could be found, as no significant changes in any measure between blocks A1 and A2 were found. However, loss of control has a significant impact on features extracted with SpecCSP. This effect could not be found in features based on CSP for SCP. Hence, the choice of feature extraction methods is crucial for controlling the impact that non-stationarities have on BCI performance and how they reflect changes in the context. This information can reliably be detected with the measure of KLD, and verified with the measure of POC. The combination of both measures applied on adequate features gives insight in the CAUS correlating to the factor of loss of control. The KLD could be used as an indicator for detecting increases in loss of control. Unfortunately; the classification accuracy will only be accessible, if it were possible to gain the true labels of each trial – what is hardly feasible in most application scenarios.
It was possible to replicate the change in background activity of the brain, typically occurring in the transition from offline to online session. This change manifests itself in a less pronounced α-rhythm during the online session than in the calibration measurement (e.g. LR-Training). Shenoy et al. [35] identified this shift of data in feature space as a main cause for statistical non-stationarities and traces this change back to the fact that the calibration measurement is more monotonous than the online session. This results ensure that the RLR design mimics typical online sessions, showing also a less pronounced α-rhythm.

The BCI system defined here suffers, like most EEG-based systems, from the ambiguity of the signal. Nevertheless, when looking at this from a more abstract perspective, adding this secondary information channel increases the information ratio available, which should lead to more reliable decisions. Consequently, the ambiguity of the primary input channel, e.g. the BCI input, decreases.
Even though these results are based on offline analyses, they could be used as an additional information channel based on a passive BCI for enriching the information space of a given motor-controlled BCI systems as well as for adaptation in partially automated HMS, which could be primarily BCI-controlled or not.

11.6. Conclusion

The loss of control study reveals that the two systems involved in BCI sessions – the translation algorithm and the brain – can diverge while trying to optimize for better results. Here, simulated errors of the computer lead to an attempt by the subject to adapt, causing a change in brain patterns. As an unavoidable consequence, with proceeding interaction, classification becomes more and more complicated, leading to even more errors by the computer. Hence, this loop contains a significant portion of positive feedback, which leads to steadily increasing classification errors once a certain threshold is passed. Identifying starting points for this vicious circle will open up new possible solutions for online adaptation. Loss of control

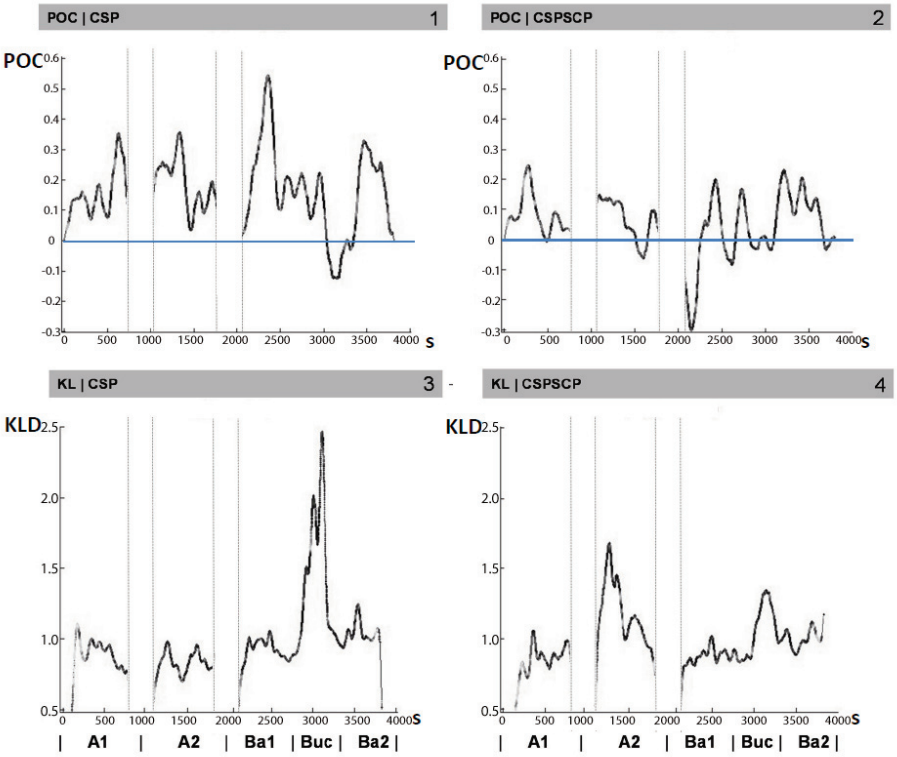


Figure 11.5.: POC and KLD for different classification schemes used in the loss of control study.
(1,2,3,4): Smoothed variations of the grandaverage. Figures 1 and 2 show POC accuracy, figures 3 and 4 show KLD. Left hand is ERD based, right hand is SCP based.

should serve as an indicator for statistical non-stationarities, and thereby overfitting would be avoided while making a content reasonable adaptation. This adaptation is characterized by a passive approach with no need for an active action of the subject directed towards the BCI. Anyhow it provides relevant information about the current mental state of the user, making an improved interaction possible. The RLR paradigm can be utilized for recording signals from movements without generating a parietal α-rhythm. It gives the opportunity to manipulate BCI relevant factors, since there are other possible influences, which still have to be investigated.
One indicator for loss of control, the Kulback-Leibler divergence, was found and possibly a second one, the classification accuracy, if available. Here, I have not discussed whether specific features in the EEG can be found resulting from the perceived loss of control in this study. Future studies and experiments will examine this more closely.
This study on loss of control shows that it is indeed possible to gain relevant context information about the cognitive user state by implementing a new information channel based on passive BCI technology and adding this channel to an existing BCI system. As the loss of control has a crucial impact on the efficiency of a system, the newly gained information can be used to adapt to the new context, adding more context awareness to the system. This is only one of many possible ways of how passive BCIs can be utilized to augment the information space of a given HMS. Neuroscientific research provides a great diversity of cognitive events or conditions that may be detectable with passive BCI channels and could provide valuable context sensitive information.
More generally, this approach is not only applicable to BCI systems. An additional passive BCI channel could also be established in almost any other HMS, provided that it is possible to access data reflecting current brain activity. Moreover, it might be of high value to add other physiological measures as additional information channels. For example, I see a high potential in eye tracking systems and the combination of these with passive BCI technology. This work is a first step towards more elaborate Human-Machine Systems – specifically, BCI-based systems – incorporating significantly more information about the context. Combined with other approaches such as automated adaptation, complex inference, and a variety of environmental sensors as well as additional physiological measures, it might lead to context aware systems allowing for intuitive and intelligent interaction between human beings and technical systems.

Following up on this, the next sections will provide more elaborate examples of how BCI technology can be utilized to augment context information in more complex applications. Firstly, I present an application for a passive BCI in the context of automated adaptation. It will show that responses of the brain following the perception of an erroneous adaptation of the system can be used to set up an automated error correction system.

12. A passive BCI for automated adaptation based on error responses

The rapid development of automation technology has increased the precision and efficiency of HMI, but has also been shown to be a source of errors in such systems. These systems have even been referred to as 'clumsy automation' [201], causing additional cognitive workload for the human instead of reducing it. One example is the user assistance program "Clippy" of Microsoft Word. Based on inference on behavioral measures it provides an automated adaptation that is not accepted because it is too erroneous [202]. Here, the opposite of the intended optimization of a given HMS was accomplished, leading to a crucial decrease in performance when the system is accepted by the user. This example shows that the potential of a user assistance based on automated adaptation is constrained by its error rate. One possible solution for that problem could be automated error correction.
We developed an Error BCI [142, 203] that enables single trial detection of brain responses to machine errors as caused by erroneous automation processes. The passive BCI investigated here, however, could reduce the user's cognitive workload and the error-proneness of automated systems. This can be achieved by augmenting the context information available to the machine, and by supplying continuous information about related CAUS of perceiving an error via passive input, leading to automated error correction. The perceived errors are fed back to the system and thus enable a correction or adaptation. The proposed direct access to the cognitive state results in more suitable and context-sensitive adaptation compared to other automation technologies that have to rely on behavioral or other implicit data [201]. Since BCI error detection is based on reaction of the brain to the environmental context, a passive BCI is defined with no additional cognitive effort for the user. In addition, it defines a secondary input channel that does not conflict with the primary mode of interaction.

12.1. Experimental design

The applicability of the Error-BCI to enhance HMI efficiency was investigated by utilizing a game as the experimental task, in order to simulate a realistic situation and to ensure clear setting of goals, proper user motivation, and understandable and controllable rules. We adapted the RLR paradigm (presented in Chapter 11) to the RLR Game, by restricting it to two colors and to reductions of rotation angles. This game simulates the situation of faulty adaptation. The goal of the player is to rotate one of two letters from the set $\{L, R\}$ displayed in front of a circle, until a given target position is reached. The letter L is rotated

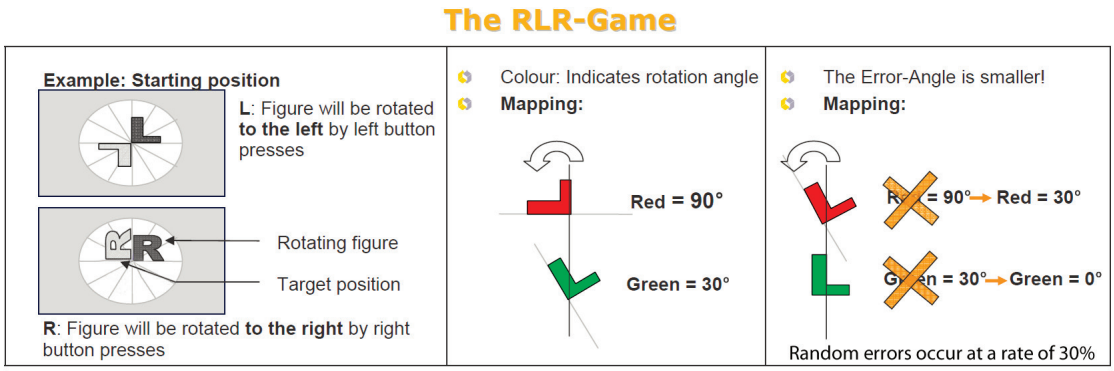


Figure 12.1.: The RLR Game.
Left: Examples of rotation. Both possible target positions at 180 and 270 degrees are shown. Middle: Full Control mode. Both possible rotation angles (30 and 90 degrees) are shown. Right: Reduced Control mode. Both reductions of rotation degrees (from 90 to 30 and from 30 to 0 degrees) are shown. These reductions occur with a probability of 30%. In Reduced Control mode button presses can be interpreted in two ways. In *expected interpretation* letters would rotate as intended, while in *unexpected interpretation* angles would be reduced. From the perspective of the machine both interpretations are correct states, they just occur with a different probability. Of course, the user has a different perception of this. Expected interpretations are in line with their own interpretation, while unexpected interpretations result are surprising. It also destroys previously generated strategies, implying a negative valence.

anticlockwise by a left key press and the letter R clockwise by a right key press. A round of the game is completed when the target position is reached. The letters automatically change color in $1000ms$ intervals, where color indicates the degrees of rotation upon key press – this, so far, is identical to the RLR design. The following mapping rules hold for the RLR Game: Letters can light up in two different colors. Red indicates rotation of 90 degrees and green indicates rotation of 30 degrees upon key press. Only one press is possible per color phase, and there is an intermittent gray phase, where no rotation is possible. Players are free to choose the time point of the key press, and therefore have the chance to build up an efficient strategy, in order to achieve the goal of the task: to be as fast and accurate as possible. See figure 12.2 for examples of strategies. In a first mode, the subject has full control over the game (Full Control Mode). During the second mode (Reduced Control Mode) false rotation angles (machine errors) appear randomly. In these, rotation angles are smaller than expected: in 30% of all key presses, red letters would rotate by 30 degrees instead of 90 degrees and the green letter would not rotate at all (see figure 12.1). To increase motivation, a second player competes in the RLR game. Performance is measured and fed back to both players by presenting the score after each round. A player wins a round by reaching the target first. Hence, the artificially induced machine errors have a negative valence for the user, since they decrease the performance and also lead to frustration. Faulty trials are defined as rotating the stimulus too far (beyond the target positions) or pressing the wrong button (left versus right). In these cases the opponent wins the point automatically. Four different experiments were performed using the RLR game, presented next.

12.2. Theoretical Background

Adaptation Errors in Human-Machine Systems are bad for the performance of the whole system. They disturb devised strategies and call for additional actions correcting the cause or the result of an error. Errors are usually unexpected, as HMS in general are designed for reliable operation. The RLR Game includes each of these factors. Hence, the resulting reactions of the brain should be to some degree comparable to those resulting from adaptation errors. We expect a mixture of a novelty potential (see section 7.2.5), as errors can be seen as deviants in the normal operation of the game, and feedback negativity (see section 7.2.5), as it has a bad valence for the user.
The Error-BCI should discriminate two classes of conditions: (1) erroneous rotations and (2) correct rotations. The classification scheme is aimed at detecting the ERP of the above mentioned mixture of Novely Potential and fERN.

12.3. Structure of experiments

In the following sections I briefly present the results of four experiments. The first aims at a theoretical proof of the existence and detectability of the proposed ERP. It also introduces

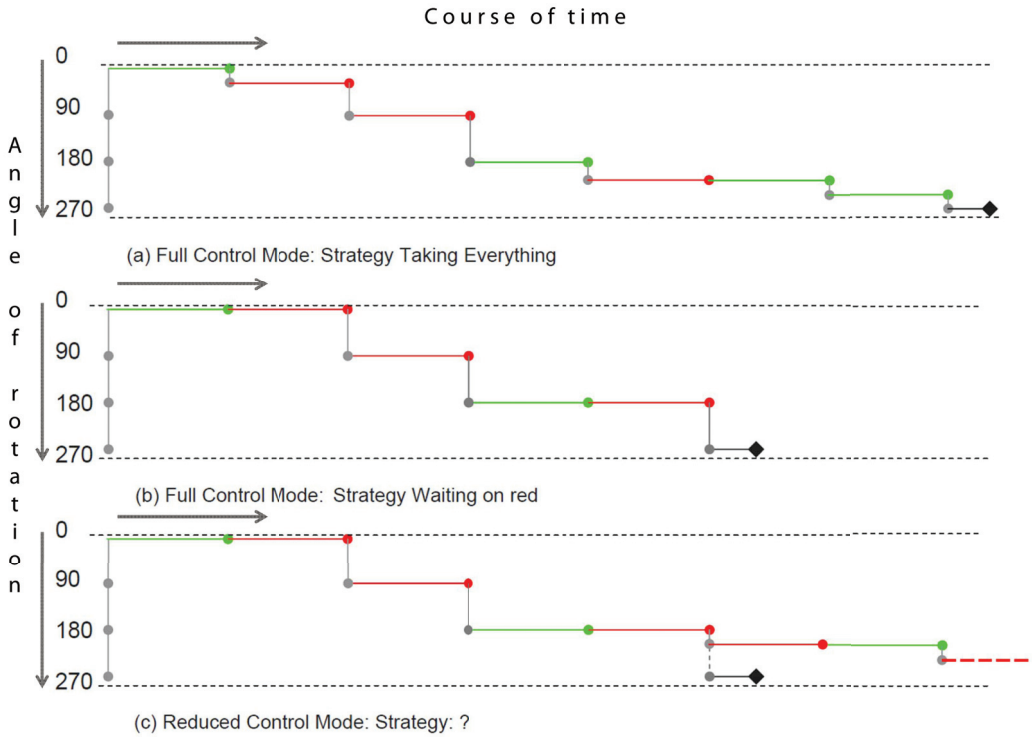


Figure 12.2.: Strategies developed during the RLR Game.
Strategies developed by subject while playing the RLR Game. On the left axis the angle of rotation is shown, while time is indicated on the x-axis. The color of the line codes the possible rotation angle. In 'taking everything' strategy the player takes an rotation angle offered. 'Waiting on red' in the second row is more efficient. The player reaches the target faster. Most of the subjects learned this strategy during game. The last row shows the possible behavior of a player who previously learned the "waiting on red" strategy and applies it to a session in reduced Control Mode. In this example, "taking everything" would be more efficient. The player has to develop a new, probably more complex strategy.

and validates a derivate of the classification scheme that performed best in Chapter 10 for detecting more complex ERPs. The second study involves an online version of the first offline experiment, while the third study leaves the laboratory and examines the setup in a real world environment. The final experiment of this study introduces and investigates the concept of *universal classification*, It shows in an offline analysis that a classifier can be defined that can be transferred between sessions and even between subjects and henceforth is universally applicable.

12.4. Offline experiment

This initial study was intended to prove the existence of BCI classifiable ERPs in the context of the RLR Game. Relying on the results of offline crossvalidations a classification scheme could be designed also applicable in online experiments.

12.4.1. Experimental setup

The first experiment took place in Team PhyPA's EEG laboratory under controlled experimental conditions, involving 14 participants (8 male, 6 female, age: $21 - 30$ years). During the user training, participants learned the rules of the game by practicing it without an opponent. In this first session they played in the Full Control Mode. In a second session, the Reduced Control Mode was introduced, generating machine errors. During a third session, participants played against a trained opponent in the Reduced Control Mode. The experimental task of this machine training phase was identical to the user training, except for the opponent, sitting nearby. In one session, approximately 40 rounds were played in both modes. No online feedback by BCI was given, but EEG was recorded at 54 electrode positions, with Brain Products EasyCap electrodes, according to the 10/20 system for offline analysis, with reference at nasion and ground at FPz. EMG and EOG were recorded additionally. All electrode impedances were kept below $20k\Omega$.

12.4.2. Feature extraction and classification

For BCI feature extraction, the data was resampled at $100Hz$, epoched from $0 - 800ms$ relative to stimulus rotation, and an FFT bandpass filter was applied using a frequency range of $0.1 - 15Hz$. Subsequently, the PMM was utilized [81] (see section 8.3.3). Averages of 7 sequential time windows of $50ms$ length were extracted relative to the event of pressing the button and used for the PMM (see section 8.1 and figure 12.3). A classifier was trained on these features, using regularizeed Linear Discriminant Analysis. In this study, classification results were obtained offline by 10-fold outer and 8-fold inner nested cross validation on the data of the Reduced Control Mode with opponent.

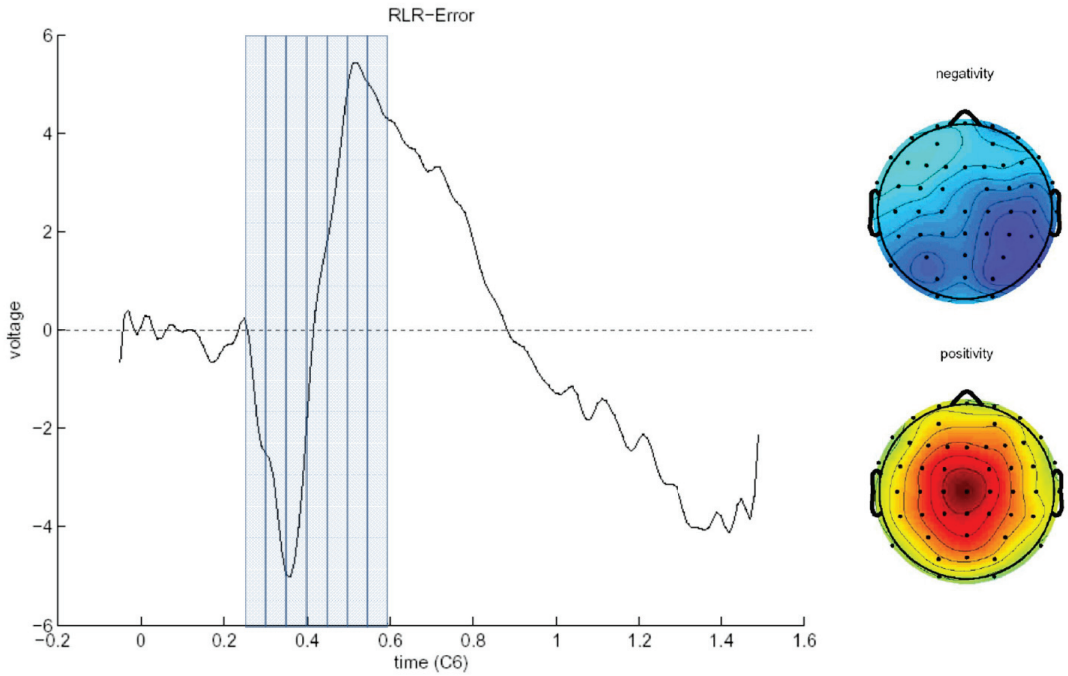


Figure 12.3.: ERP of the RLR Game.
Left: Grandaverage (14 subjetcs, 80 trials per class and subject, difference between both classes (error - correct)) at channel C6 of the ERP evolving after button presses (x-axis, in seconds) following error trials. First there is a negative component, with a minimum around 380ms, followed by a positive component with maximum between 550 and 580ms. The boxes indicate timewindows from which the features are drawn. Right: Scalp distributions of the negative and positive component. Red indicates positives values, blue negative. Intensity reflects amplitude.

Subject	Classification Error (%)
1	16.00
2	14.51
3	15.88
4	10.25
5	13.02
6	19.67
7	23.51
8	18.35
9	10.16
10	20.96
11	24.35
12	18.60
13	19.85
14	10.90
Mean	**16.86**

Table 12.1.: Classification results of Experiment No. 1 for the Error-BCI.

12.4.3. Results of the offline experiment

Figure 12.3 shows the grandaverage of the resulting ERP relative to the button press. It is characterized by a negative wave with a peak latency of $350ms$ and a positive wave $150ms$ later, very similar to the feedback Error Related Negativity (see section 7.2.5). The topography of the positivity shows a strong similarity to that of the Novelty Potential (see section 7.2.5). In figure 12.4 the class correlation coefficient (see section 8.1.2) is shown for each subject and feature. It shows that both negativity and positivity are relevant and equivalent features for classification. The average classification accuracy is 83.1% (table 12.1). Figure 12.4 also shows that respective topographic maps of the LDA weights do not indicate a dependence on artifacts. The independence of artifacts is supported by figure 12.5 as well.

12.5. Laboratory Online Experiment

The previously elaborated results will be applied in an online experiment. The user receives support from the Error-BCI. See figure 12.6 for details. If the detection is reliable this could lead to an enhancement of the given interaction.

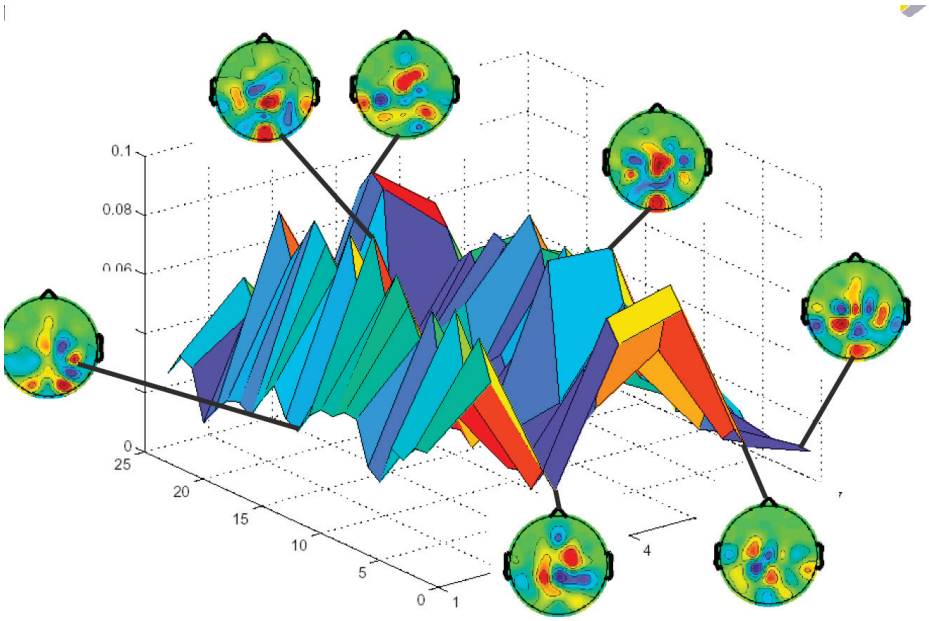


Figure 12.4.: Class correlations of the classification scheme used for the RLR Game. R^2 values for each feature over subjects. Right axis indicates the order of each $50ms$ window taken for feature extraction. The upper axis shows the resulting class correlation coefficient for each subject (left axis, from off- and online experiments). The negativity of the ERP (window no. 2) shows high coefficients for all subjects. The positivity (windows no. 4 and 5) seems to be relevant for most subjects (not for subjects 5 or 18). Topoplots show grandaverages of LDA weights for each time window. They indicate that frontal electrodes are not relevant for classification i.e. eye movements are not of high relevance for classification. See figure 12.5 for more information about eye movements.

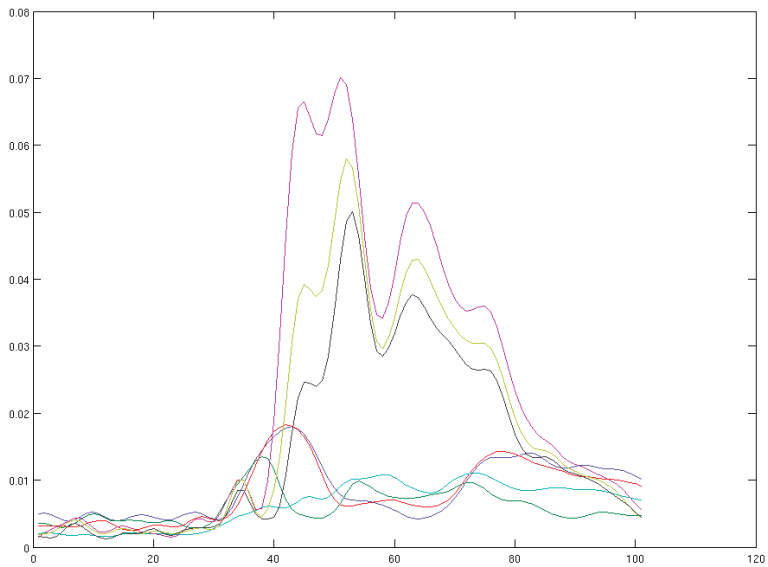


Figure 12.5.: Independence of eye movements for the classification in Experiment No. 1 for the Error-BCI.
Class correlations over time in channels Cz (pink), CPz (yellow), Pz (black) and four channels showing EOG. Red and blue show vertical eye movements while blue and light blue indicate horizontal movements. Clearly, the preprocessed EEG data contains more information about the classes – in the relevant time span – than the EOG channels. Nevertheless, vertical eye movements show a relevant correlation.

Subject	Classification Error (%)
1	16.23
2	9.93
3	12.84
4	7.01
5	4.17
6	26.49
7	18.32
8	23.23
9	14.41
10	15.22
11	20.14
12	16.92
13	15.91
14	11.64
Mean	**15.18**

Table 12.2.: Classification results of Experiment No. 2 for the Error-BCI.

12.5.1. Experimental setup

This experiment also took place in Team PhyPA's EEG laboratory. We invited the same subjects as in Experiment No. 1 and repeated the experiment controlling factors in the same way as described above (section 12.4). In addition to the sequence of games described in the first experiment, subjects played one round supported by the Error-BCI. The opponent was not supported.

12.5.2. Feature Extraction and Classification

Features were extracted as described in the previous experiment description (section 12.4.2). The resulting LDA classifier was then applied relatively to the markers for button presses in the online experiment (12.6).

12.5.3. Results of the online experiment

In the online experiment the classification accuracy averaged over subjects was 84.83%. Details can be found in table 12.2.

Figure 12.8 shows the improvement in gaming performance achieved by supporting with the Error-BCI. It clearly indicates benefits. In similarity to the offline experiment artifacts seem to be irrelevant for classification, as well (see figure 12.7).

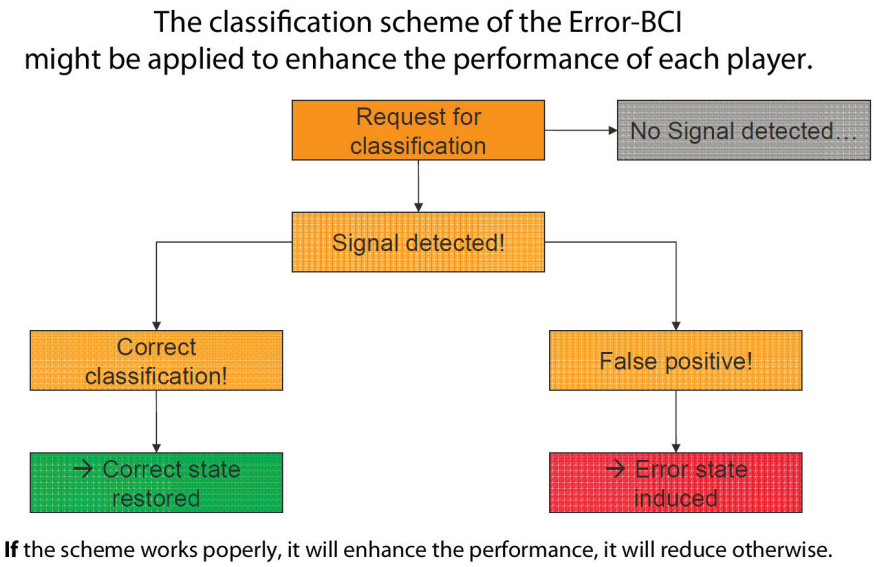


Figure 12.6.: Request for classification.
After each button press a classification is requested. If the Error-BCI does not detect an error response in the data, the game continues as usual. If it found an error response, the game could be influenced in two ways. If the detection was correct, the button press was interpreted in a false way by the game (unexpected interpretation, see figure 12.1 for details.). In this case the system switches to the state of expected interpretation, restoring the expected rotation angle. If the detection was wrong, the users did not perceive an error, but the BCI assumes they did. The classification was erroneous. In this case the letter was rotated as expected, the system is in the expected interpretation state, and will switch now to the state of unexpected interpretation, reducing the rotation angle accordingly, as described in the right part of figure 12.1

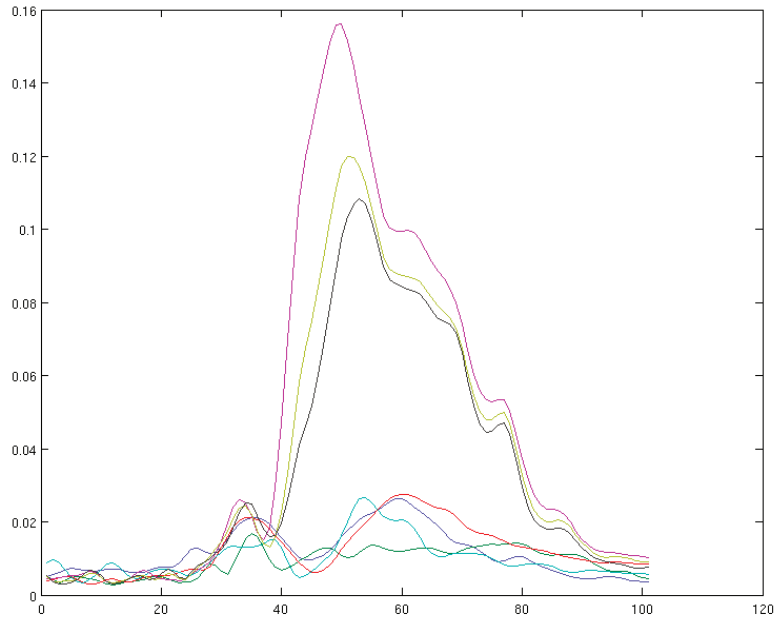


Figure 12.7.: Independence of eye movements for the classification in experiment No. 2 of the Error-BCI.
Class correlation coefficients (R^2, y-axis) for the online experiment over time (x-axis, time in centiseconds, alligned to stimulus presentation at 0 centiseconds) – basically, the results are very similar to that of the offline experiment. Cz (pink), CPz (yellow), Pz (black) and four channels showing EOG. Red and blue show vertical eye movements while blue and light blue indicate horizontal movements.

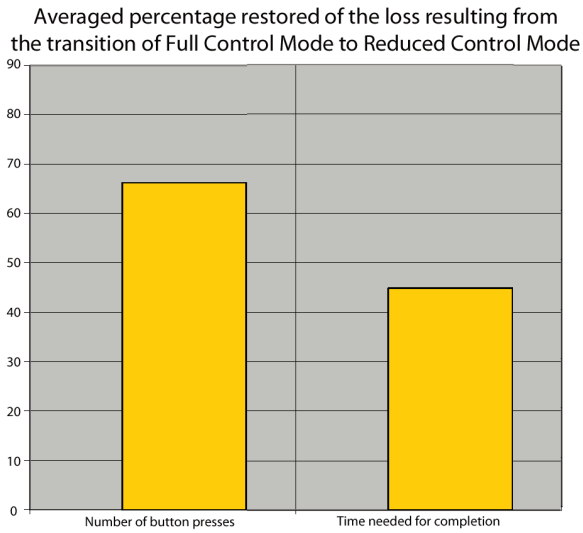


Figure 12.8.: Improvement achieved with the Error-BCI.
Benefits resulting from automated error correction based on the Error-BCI. The introduction of error trials in the transition from full control to reduced control led to a decrease in performance. Subjects needed more button presses and took longer to reach the target position. Bars in this figure show how much (y-axis, in percent) of the lost performance could be restored by the Error-BCI support. Baselines for the values of time needed to reach target and number of button presses were taken from stages of Full Control. Then differences between baseline and Reduced Control and baseline and supported Reduced control were compared.

12.6. Real world online experiment

(see Section) The third experiment was conducted at the 'Long Night of Science' at the TU Berlin (LNdW 2007) with the aim of showing that this approach is capable of being applied in real world scenarios.

12.6.1. Experimental setup

Four times two different players from the audience played the RLR game against each other. The setting at the LNdW served as an uncontrolled environment to test whether the classifier is robust enough to work properly in such situations. Each pair played three sessions, consisting of 40 trials per class, and lasting for about 15 minutes. First, the user training included one session without error states. The machine training stage followed, introducing machine error trials with a probability of 30%. EEG was recorded for one player (Player A). A classifier was trained based on the sample trials of the machine training. Automatic error detection and adaptation via Error-BCI was applied in the last session, but only for Player A. EEG was recorded at the 13 electrode Brain Product ActiCap positions, which had proved most discriminative in Experiment No. 2. The Brain Products ActiCap system was used, with reference at nasion and ground at FPz. EMG and EOG were recorded additionally. All electrode impedances were kept below $30k\Omega$.

12.6.2. Feature Extraction and Classification

For BCI classification, the same method (PMM) as in the offline experiment were utilized.

12.6.3. Results from the real world experiment

While points were equally distributed between session 1 and 2, the performance of the BCI supported players (Players A) increased strongly during the third session. This is indicated by a substantially higher score of the BCI-supported player, compared to the opponent and to their own former sessions, plotted in figure 12.9 as difference in points between players. The classifier had an accuracy of 81.2% with error ratios equally distributed over both classes.

12.7. Discussion

The studies presented in this Part show that it is possible to enhance the efficiency of HMI via passive BCI, constituting an additional information channel. By providing the technical system with information about the perceived errors, the system was able to adapt the actions to the user's covert cognitive state of perceiving an error. Especially the second study shows that this significantly optimizes the Human-Machine Interaction in real-world environments. The Error-BCI assesses an aspect of the user state that is connected to an inherently covert

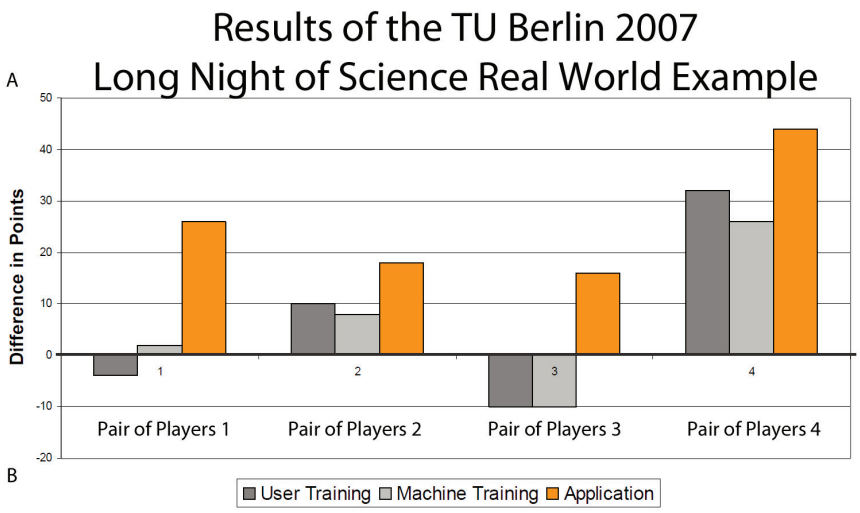


Figure 12.9.: Results from the LNdW.
Bars indicate differences in points in each of the three sessions for all four pairs of players. Positive bars indicate that Player A got more points. Orange bars indicate the supported sessions. In these sessions Player A obviously got more points than in the previous sessions, while his opponent stayed at the same performance.

cognitive process, the internal evaluation of external events, leading to an interpretation based on subjective experiences of the player. As this CAUS can be accessed quite reliably it extends the available information space, leading to higher context-awareness in the system. The classification results combined with the outcome of the restoration of efficiency lost due to the introduction of errors to the game (see figure 12.8) and the performance of supported players in the LNdW scenario (see figure 12.9) show that this extension of the context-awareness indeed leads to better performance of the given HMS. The application of this concept is a first step of validating the novel framework of context-aware BCIs outside the laboratory. Clearly, this validation has to be extended to other scenarios. Especially it is important to show the applicability of this approach in different applications, leaving the RLR Game. Additionally, it will be of high interest to see whether an Error-BCI is also applicable for other sensory modalities of the user, like interactions based on auditory or tactile information. A major drawback of the Error-BCI presented here is the need for calibration before it can be applied. This clearly hinders an application in real-world applications. The following sections will provide an initial step towards a solution for this problem.

Subjects	Error Individual (%)	Error Group (%)
1	16.00	16.33
2	14.51	14.2
3	15.88	13.00
4	10.25	20.51
5	13.02	13.33
6	19.67	31.38
7	23.51	17.24
8	18.35	14.56
9	10.16	7.46
10	20.96	16.45
11	24.35	26.22
12	18.60	18.57
13	19.85	11.83
14	10.90	7.11
Mean	**16.86**	**16.30**

Table 12.3.: Comparison of the group classifier with Experiment No. 1 of the Error-BCI. Results of the classifications from Experiment No.1 and the group classifier crossvalidated over subjects.

12.8. Towards universal classification

Another approach I followed on the data collected in the previous described experiments is the generation of a universal classifier for the detection of the investigated potential. With the term 'Univesal Classifier' I refer to a classifier that works universally between subjects and sessions.

12.8.1. Transferring classifiers between subjects

I performed an offline analysis on the data from experiment No. 1 in the following way: First, I merged the data from all subjects but one. On the merged data set I applied the same feature extraction scheme as described above (see section 12.4.2). I then applied the resulting classifier on the trials of the excluded subject. I repeated this procedure for each of the 14 subjects in turn, and calculated the classification accuracy. In table 12.3 I compared the results of this approach with the classification accuracies from standard, cross validated, individually trained classifiers. The results show that both classifiers performed equally over subjects. The differences were only marginal and not significant (t-test $t(13) = 0.37$, $p > .1$, see section 14.4.8 and [98] for selection of alpha level and controlling for the beta error).

Subjects	Error Individual (%)	Error Group (%)
1	16.23	13.01
2	9.93	14.72
3	12.84	12.80
4	7.05	13.45
5	4.17	11.43
6	26.49	24.15
7	18.32	20.00
8	23.23	22.70
9	14.41	15.30
10	15.22	11.00
11	20.14	16.67
12	16.92	14.07
13	15.91	9.54
14	11.64	9.62
Mean	**15.19**	**14.89**

Table 12.4.: Comparison of the group classifier with Experiment No. 2 of the Error-BCI. Result of the classification from Experiment No.2 and the group classifier transfered from Experiment No.1 to Experiment No.2.

12.8.2. Transferring classifiers between sessions

In a second approach I trained a classifier on features extracted from a dataset merged from all 14 datasets from Experiment No.1. Then I applied this classifier on the data from each subject from Experiment No.2. As I reinvited the subjects from Experiment No.1 for Experiment No.2 I transfered this classifier only between sessions. In table 12.4 I compared the classification accuracies from individually trained classifiers with the results of this approach. Here, again no significant differences were found (t-test: $t(13) = 0.26$, $p > .1$, see section 14.4.8 and [98] for selection of alpha level and controlling for the beta error).

12.8.3. Discussion

With these offline analyses I showed the investigated ERP could be detected between sessions and between subjects with a classifier trained on groups of subjects. The reason could be that the variance of the extracted features is not bigger between sessions and subject than within an individual subject. Also, it is beneficial for optimizing a classifier to have more data available. The trained group classifiers had 13/14 times more data than the individually trained classifiers. With this approach I introduce the theoretical concept of a universal classifier applicable in online scenarios. This will be a task for future investigations.

Part III.

Studies on the optimization of applicability of current BCI systems

Part III of this thesis includes two full studies not based on passive BCI. These studies are presented in more detail than those in Part II. The first (see 13) will be an example of a hybrid BCI. The system presented provides a new solution to a well defined problem from the field of touchless interaction – the Midas touch problem. It is an example how a BCI could counter-balance a weakness of defined HMS, based on only one input modality. It shows that weaknesses of BCIs, here its limited bandwidth and lack of accuracy that would not allow for an accurate 2D cursor control, could be counter-balanced by adding a modality that is suitable for this approach.

The second study (see 14) is more general. It leaves the theoretical framework developed here and focuses on a more practical issue: the application of sensors for BCI systems – that is also a very relevant issue for using BCI technology in HMS. The experiment presented evaluates convenient dry EEG sensors in terms of their signal quality. This is further analyzed towards the quality of standard EEG analyzes and the accuracy of BCI classification. This is achieved by comparing it to data simultaneously recorded with wet electrodes. The results show that, indeed, these dry electrodes can be used with only a small decrease in signal quality.

13. A hybrid BCI combining gaze and BCI control for touchless HMI

As described in Chapter 6, classic (active and reactive) BCIs provide new communication channels for people with severe disabilities. But it is questionable whether a BCI is the best choice for controlling a device if partial muscular activity is still available. For example, gaze-based interfaces can be utilized for people who are still able to control their eye movements. Anyhow, such interfaces suffer from the lack of a natural degree of freedom for the selection command, e.g. a mouse click. One workaround for this problem is based on so-called dwell times, which easily leads to errors if the users do not pay close attention to where they are looking. In the following study I present a multimodal interface we developed in Team PhyPA [182] combining eye movements and a BCI to a hybrid BCI (as defined in section 9.5.6), resulting in a robust and intuitive device for touchless interaction. This system especially is capable of dealing with different stimulus complexities. Matti Gaertner and Christian Kothe supported me in this endeavor.

13.1. Motivation

Referring again to [6] a classic EEG based BCI is as system which gives the user communication and control channels that do not depend on the brain's normal output channels of peripheral nerves and muscles. Its main purpose is to provide assistance in communication to severely paralyzed patients – especially those who suffer from ALS as described in section 6.4. Applications for BCI based systems have also been proposed for patients who are not completely locked-in – e.g. controlling wheelchairs [39]. It has to be questioned whether a BCI should be the method of choice for patients who still have some control over parts of their peripheral nervous system. For these patients, other physiological parameters might provide a more efficient information channel for interaction. Especially when being able to control eye movements, an eyetracker seems to be a promising option because the achievable bitrate in communication is higher, as the information is not restricted to binary commands. Furthermore, the preparation time is definitely lower and eye gaze based systems are in the same price range as EEG systems. Nevertheless, some crucial problems remain to be solved in eye gaze based interaction in order to make it an efficient communication channel. One major problem that is tackled in the work presented here is the definition of a proper selection command.

Among others, Bolt [204] introduced the use of eye movements as an input modality for search-and-select tasks as early as 1982. His idea of 'eyes as output' was intended to facilitate HMI. Since then, numerous studies have shown that the user's gaze can be used to efficiently solve search tasks, c.f. [205, 206, 207, 208]. However, whereas moving the mouse cursor with eye movements is quite intuitive, it is more difficult to find a proper mechanism for performing the click operation. Most solutions today are based on so-called dwell times, i.e. the user has to fixate an item for a pre-defined period of time in order to activate it. This technique faces the inherent problem of finding the optimal dwell time. If it is too short, click events will be carried out unintentionally and thus lead to errors. If the dwell time is too long, fewer errors will be made but more experienced users will get annoyed and demotivated. Especially, in scenarios where the complexity of the provided stimuli varies over time, there is no possibility of defining an optimal dwell time. Adding a BCI to eye gaze based interaction could solve the problem by providing an additional binary communication channel. A BCI command is under voluntary control and it is independent from stimulus complexity. Even though the dipolar properties of human eyes have a strong impact on the EEG signal [209], modern machine learning based algorithms are able to extract features independent from the user's eye movements. By combining BCI with eye gaze control we implemented a hybrid BCI (see section 9.5.6 and [40]) which allows for an intuitive and efficient device for touchless interaction in HMI. Such a hybrid BCI can be a useful tool for both medical application and healthy users as well.

13.2. Gaze controlled user interfaces

With certain restrictions eye gaze interaction can be a convenient and a natural addition to the interaction with technical systems. The eye gaze is basically an indicator of a person's attention over time [210]. For Human-Computer Interaction this means that the mouse cursor and visual focus usually correspond to each other, which implies an intuitive substitution of the conventional mouse control by eye movements.

However, this rule does not always apply. The design of gaze-based systems has to consider unintentional fixations and sporadic dwellings on objects that typically occur during visual search or when people are engaged in demanding mental activity [211]. This fact is known as the 'Midas Touch' problem: Although it may be helpful to simply look at an object and have the corresponding actions occur without further activity, it soon becomes annoying as it becomes almost impossible to let the gaze rest anywhere without issuing a command [206]. The problem directly points to the challenge of defining the mouse click operation in gaze-controlled environments.

Dwell-time based solutions were found to be the best technique that can establish an even faster interaction process than using a mouse [212]. However, choosing a dwell time duration is always a trade-off between speed and accuracy. Furthermore, a well defined

feedback informing the user about the current state of the activation progress is crucial, but can be difficult to design [213]. Even with adaptive algorithms, e.g. shortening the dwell time period with growing user experience [214], the system can not tell whether the user fixates a command button to trigger an action or for a different reason. For example the user could also have difficulties to read the description on the button, or reflect about the corresponding systems action, or could be trying to understand the meaning of a complex icon. It is not possible to find a perfect relation between gaze duration and user intention. Additionally, for the user the activation of an item is inherently a different action than searching for it. From the perspective of distributed cognition [215], it is reasonable to define orthogonal input methods for these tasks. As dwelling is an inherent part of searching, this might lead to a high workload induced by dwell time based systems. Thus, it would be beneficial to replace this implicit way of issuing a command with a concurrent and directly controllable user action.

13.3. Combining eye gaze input and BCI

The research reported here evaluated the combination of a selection command through a BCI and spatial navigation through eye gaze input, which defines a hybrid BCI. A two dimensional cursor control is realized by tracking the user's eye gaze and a dedicated control thought detectable by a BCI is mapped on the activation of objects. This investigation focused on learning more about the potential of the hybrid BCI as a multimodal BCI/Eye Gaze Interface. Which problems are addressed in that approach?
In typical Human-Computer Interaction the information presented by technical systems varies in complexity over time. One example is the complexity of the information encoded in icons displayed on a computer screen. Some are simple and easy to understand while others are ambiguous or complex. This is also influenced by subjective factors depending on experience of users or physiological factors, like quality of eyesight. Hence, in these scenarios the choice of a proper dwell time gets even harder and might be even impossible, resulting in a suboptimal performance. The performance of such a system is depending on the underlying stimulus complexity.
In the approach presented here, the dwell time selection is replaced by a BCI command, which should resolve the dependence on stimulus complexity. But to ensure that, we would have to prove the independence of the BCI command from any eye movements. It could be dependent, as the eye itself is a powerful dipole influencing EEG recordings. Hence, we have to verify that the detection algorithm used for BCI is robust against eye movements.

From this perspective, the system presented here would clearly outperform a dwell time based system, if the following requirements on the performance can be fulfilled. The replacement of dwell times by BCI need to prove to be a promising solution to the Midas touch problem by not yielding higher error rates in the selection tasks. Also, task completion times of the BCI selection method should also be lower or at least comparable to dwell times. Fi-

nally, using the new interface must at least be as convenient as a solely gaze-based interface. Thus, the workload associated with the presented hybrid BCI should not be higher and its usage should be preferred in comparison to conventional eye tracking interfaces.

13.4. Experimental evaluation

This study evaluates a search-and-select task in a 2D environment. We intend to mimic an everyday HMI. Therefore we use a typical personal computer setup and display a number of different items on the screen. As the quality of the gaze tracking is not a factor under investigation we decided to minimize its influence, by minimizing the chances of erroneous input.

This experiment compares a BCI based activation of targets in an eye controlled selection task against two conventional dwell time solutions with different activation latencies. The study aims to determine the degree to which a BCI can match or even outperform dwell time activation with respect to effectiveness, efficiency and demands on cognitive resources for 'clicking' the target stimulus. Task difficulty in the selection task was varied by showing either simple visual stimuli with only a few random characters or by presenting more complex visual stimuli featuring a higher number of characters. Two dwell times, a short one and a long one, were chosen for a better representation of the range of typical interaction situations with gaze-controlled applications. Assuming that generating the activation thought and processing feature extraction and classification still require a minimum duration, it does not seem very likely that subjects will be able to complete tasks with the BCI more quickly. The question here is whether they are significantly slower with a BCI than with dwell times. Additionaly we investigated the impact of stimulus complexity on the different activation types. Here, we expect a clear advantage for the BCI based solution.

The activation thought via BCI is a conscious, explicit command – in contrast to the implicit commands of dwell time solutions. Thus, the error rate in the BCI condition should be substantially lower, especially for difficult selection tasks. Also, this fact should lead to a lower workload and higher acceptance of the user, as the interaction should be more intuitive.

13.5. Methods

13.5.1. Participants

Ten participants (five male, five female) took part in the present study. They were monetarily compensated for their participation. Their ages ranged from 19 to 36 years. Before engaging in the experiment, subjects were screened for shortness of sleep, tiredness, and alcohol or drug consumption. All participants reported normal or corrected-to-normal vision.

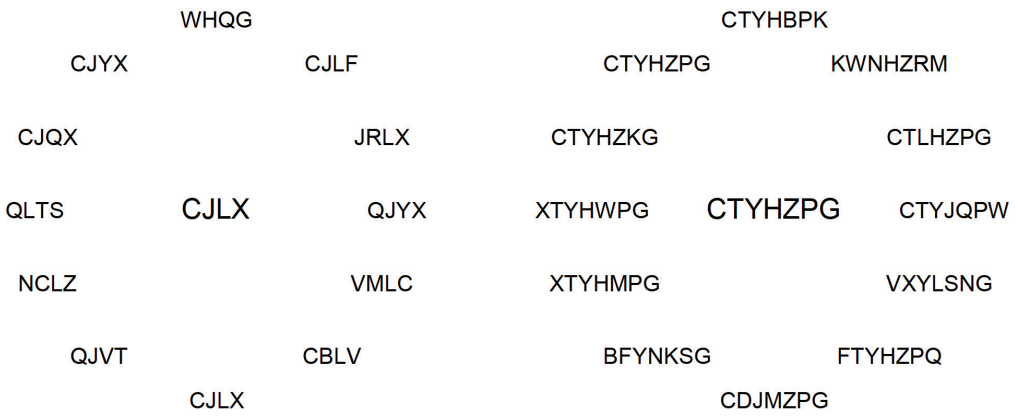


Figure 13.1.: Tasked used in the Midas touch study.
Examples for easy (left) and difficult (right) search tasks.

13.5.2. Tasks

The participants had to perform a search-and-select task. They were presented with stimuli consisting of four characters in the 'easy' condition and seven characters in the 'difficult' condition. The reference stimulus was displayed in the center of the screen. Around this item twelve stimuli were shown in a circular arrangement, eleven distractors and one target stimulus, which was identical to the reference stimulus. The radial arrangement of search stimuli ensured a constant spatial distance to the reference stimulus. Strings of consonants were presented to avoid similarities to known words. The distractors shared a constant number of characters with the target. Examples of the search screens are shown in figure 13.1.

Subjects had to select the target stimulus by either fixating it for the given dwell time or by thinking the activation thought. It was not possible to use standard suggestions for dwell time durations from literature (e.g. [206]), because the difficulty levels of the search task are not directly comparable to search tasks on a graphical user interface (GUI) in terms of absolute time needed for identification. The stimuli were chosen to be easily kept in working memory in the 'easy' condition and to almost exceed its storing abilities in the 'difficult' condition. To make sure that the dwell times match stimulus complexity, various versions were tested in pre-experiments. The selection criterion was that the short version is still well controllable and that the long activation latency is not perceived as slowing down the user. The short dwell time was 1000 milliseconds, the long dwell time 1300 milliseconds. To keep control over the duration of the experiment, a trial terminated automatically after 15 seconds if the user was not able to select an item during this time. These trials were excluded from further analysis.

13.5.3. Apparatus

Brain activity was recorded by a 32 channel EEG system, positioned along the standard extended international 10/20 system sampled at $1000Hz$, later band pass from 0.05 to $200Hz$. Grounding was established with electrode Fz, the reference electrode was placed on the nasion. Eye movements were tracked with a remote eye tracker (SensoMotoric Instruments, iView X RED, as described in section 9.1), relying on cornea reflex measurement. The gaze direction was sampled at $60Hz$ and saccades were identified using the GUIDe algorithm [216]. Lighting was kept constant during the experiment.

13.5.4. BCI classes for binary control

In the BCI session of this experiment the task for the user was to select an object on the screen by an imagined hand movement. This defines a binary problem for the BCI: to discriminate the user's motor imagery from its absence. After user and machine training an appropriate feature extractor and classifier has to be trained to be applied in the test scenario, as described in section 8.1.

During the user training, subjects were assisted in how to imagine this movement. Many of them found the imagination task easier after they were given the hint to try to feel sensations on their hands instead of visually imagining the movement. We instructed the users to imagine wringing out a towel with both hands by turning them into opposite directions. We chose this type of imagined hand movements because it represents a targeted activity, which seemed to be reasonable from the perspective of embodied cognition [217].

When the users had learned to perform the imagination task, the machine training started. The training session lasted approximately 15 minutes and 40 trials of training data for each condition were recorded. Here, most importantly, the chosen paradigm has to be as similar as possible to the experimental condition to provide well-defined prototypes for training the detection algorithm. Nevertheless, it can only be similar to a certain degree, as there is an inherent difference between training phase and application phase. The training phase does not contain a feedback from the system to the user's behavior. Additionally, data from the training phase should not contain too much task-relevant noise.
In the case of this experiment these two constraints have been fulfilled by adopting the search-and-select task of the experimental condition for the training paradigm. Subjects were viewing the same circle of strings as in the application phase. The intention was to mimic the user's behavior in the application phase as closely as possible while keeping control over it. Therefore – in contrast to the application phase - a box containing the word 'search' was jumping randomly from string to string while covering the letters behind. Subjects were instructed to follow the box with their eyes until the word 'select' appeared. When this occurred, they were instructed to perform the imagined hand movement for three seconds (figure 13.2). With that we guided the user to generate data for two classes. One class was

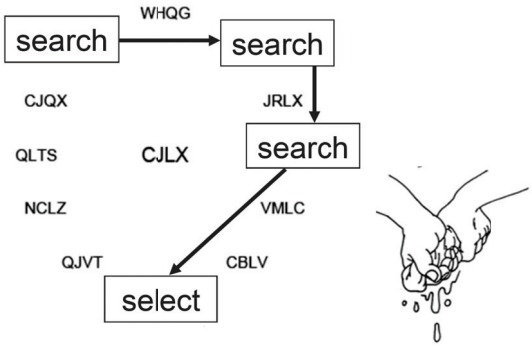


Figure 13.2.: Calibration during the Midas touch experiment.
A sample of a calibration sequence. The subject follows the box labeled 'search' till it stops with label 'select'. Then the subject performs motor imagery of both hands for 3 seconds – imagining wringing out a towel.

chosen as the period of time when subjects were following the 'search-box' with their eyes. The other class was defined as the period of time when subjects were instructed to perform the imagined hand movement.

The first class is defined as noise in the search condition, which should not be dependent on any specific process. This preliminary is hard to control, as there might be factors in the search condition inducing specific class relevant features which are detectable by SpecCSP (see section 8.3.2 for details on SpecCSP). Hence, it has to be checked by validating the features selected by the classifier, which will be done in section 13.6. The second class of features is based on ERD over the motor cortex. The mean electrode and frequency weighting over all subjects is shown in figure 13.3.

In the second step, an LDA was generated from the extracted features. The classification accuracy was validated via a 10-fold cross validation.

13.5.5. Design and procedure

After making sure that all EEG electrodes were in place and working, additional EMG electrodes were attached to the participant's arms to monitor for muscular activity which might correlate to activation command. Before and during the technical preparations subjects received a general overview on the procedure of the experiment and their tasks. A complete and summarized presentation of the test setting was given afterwards. A 9-point eye tracker calibration, user training and machine training stages followed. To finalize this preparation phase, subjects practiced using the BCI command and the experimenter re-adjusted the bias of the classifier's hyperplane in the confluence phase. When the training was successful, a short calibration of the eye tracker followed and the experiment started.

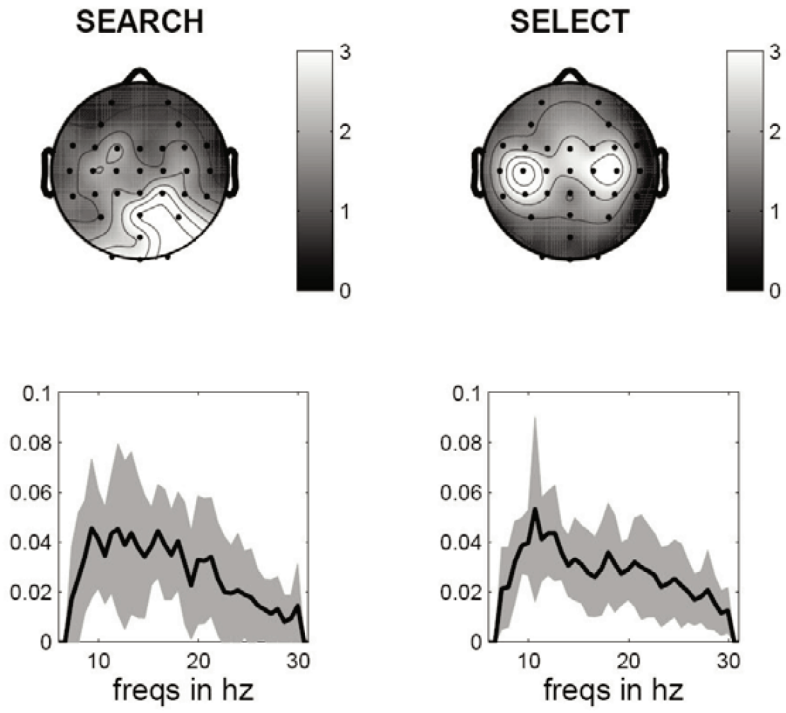


Figure 13.3.: SpecCSP parameters for classification during the Midas touch experiment. Mean electrode and frequency weighting over all subjects calculated by the SpecCSP optimization (see section 8.3.2). The units of all weights shown are arbitrary. The gray area in the lower two plots shows the variance between subjects.

Two different levels of search difficulty (easy, difficult) and three levels of activation technique (dwell time short, dwell time long, BCI) were varied in a 2x3 factorial design, with repeated measurements on both factors. Participants went through the levels of the factor activation technique in separate blocks. The order of these blocks was counterbalanced across subjects. Subjects completed 30 trials per condition. The experiment itself took about one hour, the whole test procedure about 2.5 hours. Effectiveness was measured in terms of errors in task completion. Efficiency was defined as the time needed to complete a search task. Mental workload was assessed with the unweighted version of the NASA Task Load Index – the so-called Raw Task Load Index, RTLX [218]. The NASA TLX was completed by the participants after each condition. At the end of the experiment the participants had the opportunity to discuss their experiences with the experimenter and were asked to rate the activation techniques according to their preferences.

13.6. Results and discussion

The crossvalidated accuracy of the classification during the training phase lies at 89.0% (chance level at 50%) averaged over all subjects. The standard deviation is 10.3%. One subject stated clear doubts on the functionality of BCI based systems and could be identified as an outlier, due to questionable motivation for this experiment. Consistently, the crossvalidation showed an accuracy of 60.9% for that subject. The averaged crossvalidation accuracy without the outlier lies at 92.1% ($SD = 3.1\%$). The recorded EMG shows no significant correlation to the classification relevant classes.

Time needed for task completion and accuracy (data on errors) were averaged across all subjects for each selection method and level of search difficulty. Trials with errors were not included in the analysis of response time. First, an analysis of variance was conducted on the results. The alpha level for significance was chosen to be 5%. In a second step, the data of the easy and difficult condition were pooled for each selection method. This makes it possible to take a closer look in pairwise comparisons between BCI vs. long dwell time and BCI vs. short dwell time. To avoid the problem of multiple comparisons, the alpha level was Bonferroni corrected for these tests.

The accuracy data are summarized in figure 13.4. The 'easy' condition yielded 88.0% correct selections when using the BCI. In 93.8% of all tasks correct answers were produced in the 'dwell time long' (dwl) condition, and in 83.8% in the 'dwell time short' (dws) condition. Fewer correct selections were made in the 'difficult' condition. Remarkably, the BCI leads to the best results with 78.7% correct selections, although the difference to the long dwell time, 75.6%, is only marginal. The short dwell time condition, however, leads to a strong negative effect on performance as the percentage of correct answers dropped to 51.1%. This change in the result pattern in the difficult condition is reflected in a significant search condition activation technique interaction ($F(2, 18) = 13.30$, $p < .001$). An analysis of the main effects

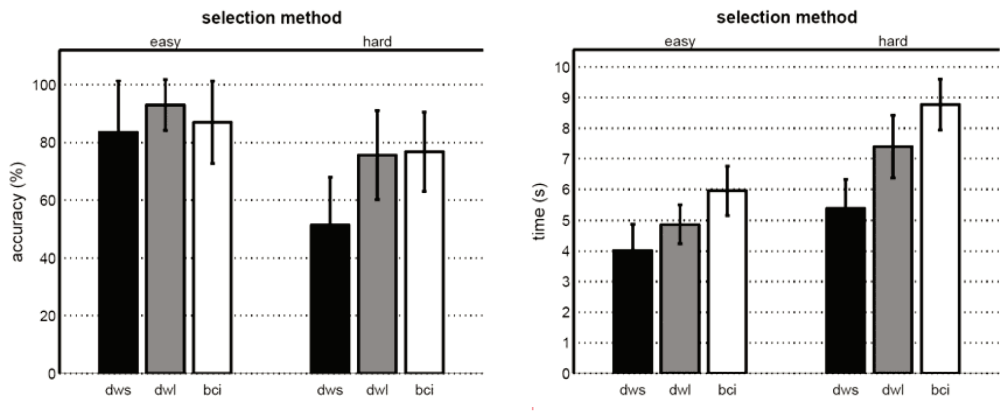


Figure 13.4.: Estimates for classification accuracy in the Midas touch experiment. Left: Percentage of correct selections: Short dwell times (dws), long dwell times (dwl) and Brain-Computer Interface (bci). Right: Task completion times: Short dwell times (dws), long dwell times (dwl) and Brain-Computer Interface (bci).

confirms general differences between the activation techniques ($F(2, 18) = 12.47$, $p < .001$) and that the difficult search condition leads to more errors ($F(1, 9) = 38.37$, $p < .001$).

The pooled BCI accuracy average is 83.3% correct selections, the corresponding values for dwell time long and dwell time short are 84.7% and 67.4%. Pairwise t-tests [98] reveal that the better performance of the BCI compared to 'dwell time short' is significant ($t(9) = 3.66$, $p = .005$). The small differences between BCI and 'dwell time long' is not reliable ($t(9) = 0.33$, $p = .75$). As expected, the BCI allows users to activate (click) GUI items more precisely than a dwell time solution with short latencies. Long dwell times are suited for precise object activation but do not prove to be substantially better than BCI based selection.

Task completion was fastest in both search conditions with short dwell times (easy: $3.98s$; difficult: $5.38s$). Next was dwell time long ($4.79s$; $7.37s$), leaving BCI the slowest method of activation ($5.90s$; $8.84s$). This general difference between the input methods is statistically significant ($F(2, 18) = 56.25$, $p < .001$). The results are depicted in figure 13.4.

Looking at these results the data also shows that the difficult search task leads to longer search times, which is only of minor interest ($F(1, 9) = 102.38$, $p < .001$). The significant interaction of the factors 'search condition' and 'activation technique' reflect larger differences in the 'difficult' compared to the 'easy' condition ($F(2, 18) = 7.46$, $p < .01$). The pairwise comparisons support the view that BCI selection was slowest (bci: $7.37s$; dwell time long: $6.08s$; dwell time short: $4.68s$). These differences are significant (bci - dwl: $t(9) = 4.31$, $p = .002$; bci - dws: $t(9) = 13.57$, $p < .001$).

The overall TLX results show no differences in workload between the activation techniques. Nevertheless, in one subscale of the NASA RTLX – the question that was concerned about the amount of frustration of the users – the BCI method was rated significantly lower ($p < .05$) than both dwell times. This finding is consistent with the preference ratings at the end of the experiment. Here, nine out of ten participants preferred using the combined BCI/Eye Gaze Interface over the standard gaze-based interface. In the concluding questionnaire, many subjects stated that they followed an avoidance strategy in the dwell time approach. They moved their eyes shortly on an item and then quickly into a 'safe area' at the border of the screen to avoid any false selection. Then they recalled the previously seen image from memory and decided whether this item was a target or not.

As stated in section 13.5.4 the paradigm of the machine training stage has to be quite similar to the task in the application stage, but may be contaminated by artifacts. Hence, it is necessary to evaluate on which type of features the classification is based on. In this case, the question is whether the BCI classification was based on the intended features of the EEG signal or whether it was influenced by artifacts. As some of the features were chosen automatically by the SpecCSP feature extractor, it would be possible that these do not reflect the intended aspects of the EEG signal, namely imagined hand movements and absence of imagined hand movements. The definition of the machine training stage also induces another class relevant factor which is recorded by the EEG, namely not moving the eyes and moving the eyes. If features induced by eye movements are more relevant for classification than those resulting from motor imagery, one class will be defined by the existence of eye movements while the other is defined by the absence of eye movements. Hence, the resulting selection method would behave similar to the dwell time based approach. This has to be investigated.

There is strong evidence to support the assumption that classification was based on the imagination task. On the one hand the SpecCSP frequency- and electrode weightings (see figure 13.3) show that for the selection-class electrodes over the motor cortex have the highest weights. Also the frequency range with the highest weights lies in the α-band, which is frequently associated with activity of the sensorimotor system. A classification on features reflecting the absence of eye movements would induce higher weights on frontal electrodes and on a broader frequency band. The same holds for a classification based on corrugator electromyogram. For the search-class frontal electrodes are not weighted high either. These facts support the assumption that classification was not based on eye movements.
From a practical point of view, classification on the absence of eye movements would face the same problems as the dwell time approach. An item is activated if there are no eye movements. Hence, we asked the subjects to fixate a string of letters without imagining the activation command during the confluence phase (stage 3, see section 9.6). In nine out of ten subjects the strings were not selected until subjects were asked to perform the imagination task. Taken together, these findings support the independence of the BCI from eye movements.

13.7. Conclusions and outlook

We could show that the Midas Touch problem of gaze based systems can be resolved by adding a BCI channel for selection. With the benefit of voluntary controlling of the activation command, this approach is especially applicable in environments with fluctuating stimulus complexities. Fixed dwell times are not applicable in such environments because the time needed for object selection varies from trial to trial. Our results show that it is possible to perform more accurate selections with the BCI activation command than with the solution that is based on short dwell times. Also the strong user preference for BCI instead of dwell times for the activation of selected objects and the lower rating in the frustration scale of the BCI method are quite remarkable results.

However, using BCI is still somewhat slower. Nonetheless, although statistically significant, the magnitude of the difference between BCI and the dwell time solutions is notably small. But this need not be a drawback. With the change from an implicit to an explicit activation command, subjects could take the time they needed for solving the task and did not have to choose an avoidance strategy as in the dwell time approach. The aforementioned findings of user preference and low frustration ratings also indicate that the users appreciate having the time they needed for task completion during the BCI selection without being in a rush because of a restricted dwell time. Taken together, these findings show that a BCI has successfully proven to outperform dwell time activations.

However, the long preparation time for a standard EEG system is a major drawback for using BCI in Human-Computer Interaction. This problem might to be solved in the near future with the rapid ongoing development of dry electrode systems (as described in Chapter 14), which would reduce the setup time for an EEG system to some minutes.

This fact, as well as the other results suggest that the presented approach for activation is a promising technology for multimodal interfaces that may help to optimize touchless interaction for healthy users as well as for medical applications.

With this study it is proven that hybrid BCI systems can be used to enhance HMS in the domain of touchless interaction. Hence, both concepts introduced in the theoretical part of this thesis, passive BCIs and hybrid BCIs, are validated.

14. A validation study of dry electrodes

14.1. Abstract

Although it ranks among the oldest tools in neuroscientific research, EEG still forms the method of choice in a wide variety of clinical and research applications. In the context of BCI, especially in that of utilizing BCI for healthy users, EEG is the most prominent sensor technology, as described in section 7.2. By this, EEG applications could be employed in a wider range of working environments. However, the use of EEG in the context of HMI is impeded by the cumbersome preparation of the electrodes with conductive gel that is necessary to lower the impedance between electrodes and scalp. Dry electrodes could provide a solution to this barrier and allow for EEG applications outside the laboratory and clinical context.

This study evaluates a prototype of a three-channel dry electrode EEG system, comparing it to state-of-the-art conventional EEG electrodes. It answers the last of the research questions defined in section 6.6.1. Moritz Lehne, Klas Ihme, Sabine Jatzev and Christian Kothe supported me during this study.
Two experimental paradigms were used. First, ERPs were investigated with a variant of the oddball paradigm. Second, features of the frequency domain were compared by a paradigm inducing occipital α frequencies.
Furthermore, both paradigms were used to evaluate BCI classification accuracies of both EEG systems. It was found that amplitude and temporal structure of ERPs as well as features in the frequency domain did not differ significantly between the EEG systems. Regarding the frequency domain, BCI classification accuracies were equally high in both systems. With respect to the oddball classification accuracy, there were slight differences between the wet and dry electrode systems. Following the experimental results, the tested dry electrode EEG system seems to perform on par with conventional systems and might – due to its easier handling – help to foster the use of EEG among a wider range of potential users.

14.2. Introduction

As already briefly described in section 7.2, EEG is one of the oldest imaging techniques used in clinical diagnosis and cognitive neuroscience. It was first described in the 1920s [31] and a large share of neurophysiogical studies still use EEG as method of choice, because

recording is non-invasive and has a high temporal resolution superior to other non-invasive methods. With the emergence of the research field of BCI, EEG applications entered new fields such as the rehabilitation of people with complete loss of control over muscle activity [6] or Human-Machine Interaction as mainly discussed in this thesis. However, to start migrating BCI technologies from laboratories into work context and everyday life, some restrictions concerning the practicability of the EEG method have to be overcome. These include the long preparation time of conventional EEG systems and the use of electrode gel necessary for lowering the impedance between the electrodes and the participants' scalp. Depending on the number of channels used, EEG preparation time can take up to an hour or longer. Moreover, participants can suffer skin irritation due to long-term use. Since BCIs often remain as the last communication device for patients with almost no control over their muscle activity, these barriers were accepted in clinical applications. In order to integrate BCI applications into Human-Machine Systems for healthy people, EEG systems need to become easier to use with a reduced configuration phase. The application of dry electrodes could lower preparation time to only a few minutes, since electrode gel is omitted.

A search of the literature shows there are three prototypes of such dry electrode systems. Popescu et al. [86] designed an array of specially coated contacts comprising six electrode channels. The system was evaluated in an online BCI experiment where participants had to accomplish a motor imagination task to control a computer cursor. Performance of the dry system was compared to a traditional wet one, recorded in alternation, resulting in a degradation of the bit rate by 30%. Oehler et al. [219] developed a capacitive EEG system with 28 channels. In a BCI experiment using steady state visually evoked potentials (SSVEPs), they compared their electrode system to a conventional one. Transferring the same information took three times longer with the dry system. A third system using multi-walled carbon nanotube arrays was introduced in 2007 by Ruffini and coworkers [220]. The system was evaluated comparing it to a wet system in a standard EEG paradigm in a few trials with one human participant. Therefore, general conclusions about the system's performance could not be made so far.
Consequently, none of these three dry electrode systems can ensure an EEG measurement that is comparable to standard EEG measurements, which is a necessity for an application of dry electrode systems in a wider context.

Another dry electrode system has been developed by Brain Products (Gilching, Germany) and was evaluated by Team PhyPA [130]. This system contains three electrodes that can be placed over the occipital lobe at the electrode positions PO7, Oz, and PO8 of the standard extended international 10-20 system. There is no need for electrode gel, so preparation time is reduced to roughly five minutes. The system does not pose any health risk for the user. The aim here is to show the applicability of the dry electrode system for EEG analysis in a neuroscientific context and for BCI application in rehabilitation and HMSs. The performance of the dry electrodes was compared to a conventional wet electrode cap (ActiCap,

BrainProducts) containing three electrodes at comparable positions, ensuring simultaneous signal acquisition of both systems.

Two experiments were conducted employing neuroscientific standard paradigms, inducing ERPs and spontaneous EEG. In order to investigate ERP features, a variant of the oddball paradigm was used [63], eliciting an ERP similar to the well known N2P3 complex (see section 7.2.5). P300 ERPs have already been used successfully in BCI applications, e.g. the P300-speller [5]. Spontaneous EEG features were investigated by an experimental task inducing alternating concentration (cognitive engagement) and relaxation, thus causing different levels of band power in the α-band ($7-13Hz$) over occipital electrode sites [221]. Like ERPs, these variations of frequency power can be used in BCI applications, e.g. in the context of gaming [222]. The averaged signals of both experiments were analyzed with standard neuroscientific EEG methods. Besides, they were analyzed and classified offline on single-trial basis to evaluate their possible applicability in the field of BCI.

14.3. Dry electrode system

The dry electrode system used in this study is essentially a modified version of the BrainProducts actiCAP system with electrodes adapted so as to establish a direct contact with the skin without relying on conductive gel. For this, electrodes were manufactured as a comb-like structure with a diameter of 10 mm featuring 12 small pins of 4 mm length and 2mm diameter. For the frontal electrodes applied to the forehead, cup electrodes of 10 mm diameter were used (see figure 14.1).

Both, digital and analog methods are employed for signal processing. Digital signal processing is responsible for impedance matching and LED control, while signal transmission from the recording site to the amplifier is realized by analog methods. An optional noise suppressor is available (however, this option was not used in this study). The two frontal electrodes of the system are used as reference and ground. Signal electrodes can be positioned on the adjustable headband. When attaching the headband, reference and ground electrodes exert a slight pressure on the forehead thus forming contact with the skin. For the signal electrodes, a conductive connection to the scalp is realized via the electrode pins that penetrate through the participants' hair.

14.4. Experiment 1 – Oddball

14.4.1. Participants

Twelve students of the Technical University of Berlin (aged $20-28$ years, 5 male) took part in the experiment. All of them were neurologically healthy and reported normal or

Figure 14.1.: Sketch of the dry electrode cap.
Sketch of the dry electrode cap. The three comb-like electrodes are placed inside in the back of the cap. Ground and reference are placed laterally in the front.

corrected-to-normal vision. They were paid Euro 10 and gave informed written consent to participate.

14.4.2. Procedure

Participants were seated comfortably in front of a monitor, wearing the two different electrode caps simultaneously. The task was explained to participants by written instructions on the screen. A typical oddball paradigm was used including four blocks, each of two minutes duration. In each block the stimulus had a different starting position. After each block, participants were instructed to name the number of deviants.

14.4.3. Paradigm

The experimental task was similar to classical oddball paradigms, presenting rare deviants in a sequence of standards (frequent stimuli). At the beginning of a trial a circle divided by lines into 30° angles appeared on the screen (similar to the marks on a clock, see figure 14.2). The standard stimulus was a bar appearing at one of four possible starting positions (3, 6, 9 or 12 o'clock) rotating 90° (standard condition). This frequent stimulus was interrupted by a rare rotation (deviant condition), performing a snap movement. The bar rotated in a 60° angle, followed by a snap movement back to the 45° position after $100ms$ later. Odd rotations occurred with a probability of $p = .1$. Rotation of the bar was instantaneous; the ISI between two starting figures was $1000ms$. Hence, this paradigm resulted in a 2 (tasks) x 2 (electrode system) x 3 (channels) factorial design.

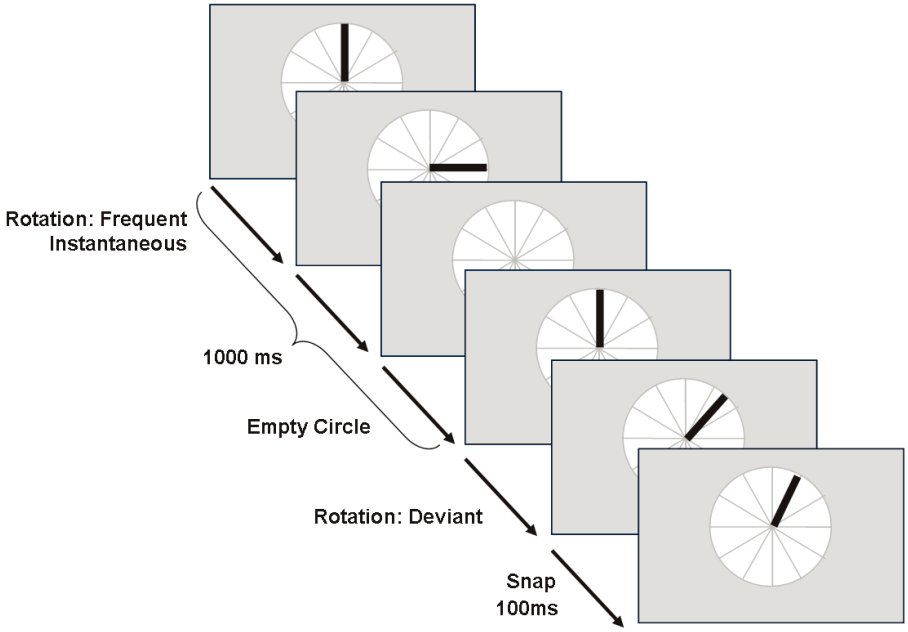


Figure 14.2.: The Oddball task of the validation study.
Example trials for the experimental task of the Oddball paradigm showing the standard and deviant condition.

14.4.4. EEG recording

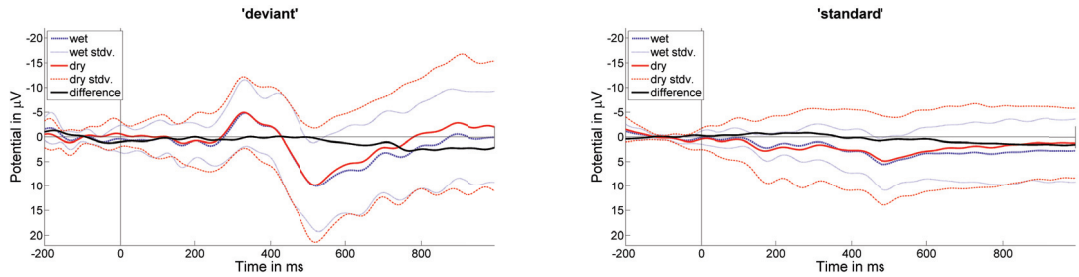
EEG was recorded with two different electrode types:
An ActiCap (Brain Products) with three standard active electrodes at occipital positions (PO7, Oz, PO8), an active ground and reference electrode at frontal positions (Fp1, Fp2). The dry electrode system described above (equipped with three dry active electrodes at the corresponding occipital positions, plus a dry active ground and reference electrode at the same frontal positions).
Electrodes were placed at positions PO7, PO8 and Oz, according to the standard extended international 10-20 system. Since both electrode caps were used simultaneously for EEG recoding, one cap was placed at standard positions and the other cap approximately 1.5 cm above these positions. Upper and lower positions of the electrode sets were counterbalanced across participants. EEG data was recorded at a sample rate of $500Hz$. Impedances of all electrodes were kept below $20k\Omega$, which is a standard calibration according to the specifications of the ActiCap. The standard ActiCap electrodes were connected to a 32-channel-amplifier BrainAmp DC by BrainProducts. For the dry electrodes the 8-channel-amplifier V-Amp (BrainProducts) was used.

14.4.5. Pre-processing

To obtain ERP measures, EEG data was visually inspected for artifacts. EEG data containing muscle artifacts or eye blinks were excluded from further analysis. Artifact removal was performed on wet electrode data and then transferred automatically to the dry electrode data. A band pass filter of $0.1-15Hz$ was applied. Epochs of $1000ms$ length stimulus locked to standard stimulus rotation or deviant (odd) stimulus rotation were extracted. A $200ms$ pre-stimulus interval was used for baseline correction. This resulted in 40 trials for deviant conditions and 350 trials for standard conditions.

14.4.6. ERP measures

An ERP analysis was conducted on the data of the oddball paradigm in order to compare standard ERP measures as peak amplitude and peak latency between dry and wet electrode data. Grandaverage ERPs and difference curves (deviant-minus-standard) were calculated for dry and wet electrode EEG data to obtain time windows for oddball related potentials. According to the grandaverage ERPs (see figure 10.2), the time window for the negativity was defined as $250-400ms$ after stimulus onset; for the positivity a time window of $450-600ms$ was chosen. Difference curves were calculated and plotted for each participant individually. ERP peak amplitude and latency of the difference curves were determined for each participant by choosing the minimum amplitude value for the negativity in the expected time window ($250-400ms$) and the maximum amplitude value for the expected time window of the positivity ($450-600ms$). Difference peak latencies were calculated for each participant, subtracting mean minimum latency of the negativity by the mean peak latency



(a) ERPs of deviant trials

(b) ERPs of standard trials

Figure 14.3.: The ERP of the Oddball task.
Grandaverage ERPs (12 subjects) for deviant (a) and standard (b) trials are shown for channel PO8. ERPs for dry (red) and wet (blue) electrode data are plotted together with a difference curve (black) for different data (dry-minus-wet). Dotted lines show the standard deviations for the grandaverage ERPs.

of the positivity.

14.4.7. BCI analysis

The BCI single-trial analysis was conducted by calculating the offline classification error using a 10x5-fold cross validation (see section 8.1.2) to estimate BCI classification accuracy. EEG data were downsampled to $100Hz$, epochs were generated from 0 to $800ms$ relative to stimulus onset and a $0.1 - 15Hz$ FFT band pass filter was applied. For classification, a modified version of the PMM (see section 8.3.3) was utilized. Trials were partitioned into six time windows of $50ms$ according to the shape of the ERP. Calculating the mean of each time window and single trial for the three channels resultsin a 18-dimensional feature space (3 channels x 6 time windows). As a classifier, regularized linear discriminant analysis (rLDA) was used.

14.4.8. Statistical analysis

Differences of negative and positive peak amplitudes between dry and wet electrode data were tested for significance by conducting a 2 (electrode type) x 3 (channels) repeated-measures ANOVA, with two within-subject factors. An ANOVA was calculated for each dependent measure: the peak amplitude of the negativity and positivity of the according difference curve. Greenhouse-Geisser corrected degrees of freedom and significant values were used when the assumption of sphericity was not met. Since the goal was to fulfill the null hypothesis, i.e., to show that there are no differences in ERP measures between dry and wet EEG data, the alpha significance level was set to $p > .1$ to control for the beta error [98]. Correlations between dry and wet difference latencies were obtained by calculating bivariate

Amplitude	**Negativity (300 – 400 ms)**		**Positivity (500 – 600 ms)**		**Latency Difference (pos. – neg.)**	
	Mean (μV)	**Standard Deviation** (μV)	**Mean** (μV)	**Standard Deviation** (μV)	**Mean** (ms)	**Standard Deviation** (ms)
Dry: PO7	-8.53	8.47	5.98	7.43	171.33	47.82
Wet: PO7	-9.30	5.36	5.87	9.00	177.50	39.69
Dry: Oz	-7.46	8.61	3.53	8.32	158.33	52.56
Wet: Oz	-8.04	7.91	5.55	12.20	178.83	41.42
Dry: PO8	-8.28	7.35	6.88	5.79	174.17	35.78
Wet: PO8	-9.34	5.21	7.46	8.25	182.50	35.28

Table 14.1.: Results from the Oddball analyses.
ERP results. Mean values and standard deviation for peak amplitudes and latency differences for the negativity and positivity

correlations (Pearson correlation, see section 8.1.2), which were tested for significance by a one sample t-test against zero. The probability of getting a correlation as large as the resulting one by chance, if true correlation was zero, was evaluated against a significance level of 5% ($p = .05$). Classification accuracies were tested for significant differences between wet and dry electrode data by using a paired sample t-test.

14.5. Results

14.5.1. ERP measures

Figure 14.3 shows grandaverage ERPs for wet and dry electrode data for standard and deviant trials at electrode PO8. The difference curves are plotted to show differences in ERP shape for the two electrode systems. The morphology of the dry vs. wet mean ERPs is almost identical except for some differences in standard deviation revealing a higher standard deviation for the dry electrode data in the standard condition.

For the peak amplitude measure, analysis of variances revealed that neither the main factor of electrode type (dry vs. wet electrode system) (negativity: $F(11) = 0.2$, $p > .1$, positivity: $F(11) = 0.15$, $p > .1$), nor the factor channel (PO7, Oz, PO8) (negativity: $F(11) = 1.54$, $p > .1$, positivity $F(11) = 1.87$, $p > .1$) had significant effects on the peak amplitude. Accordingly, there were no significant differences between wet and dry electrode data or channels. Table 14.1 shows mean values and standard deviation for the peak amplitudes and difference peak latencies.

The mean difference peak latency (positive minus negative peak latency) was 171.33ms

Participants	Wet	Dry
1	73.0	69.6
2	76.8	68.2
3	79.6	83.9
4	72.8	73.8
5	77.9	83.2
6	79.4	69.1
7	72.5	64.5
8	80.4	72.6
9	79.0	73.3
10	79.5	78.2
11	80.7	66.5
12	82.4	62.4
Mean	**77.8**	**72.1**

Table 14.2.: Classification accuracies from the Oddball task.
Results of BCI analysis. Shown is the offline classification accuracy (%), calculated by cross validation for each participant for dry and wet electrode data.

for dry versus 177.50ms for wet electrode data at channel PO7, 158.33ms (dry) versus 178.83ms (wet) at channel Oz and 174.17ms (dry) vs. 182.50ms (wet) at channel PO8. Bivariate correlations for difference peak latencies between dry and wet electrode data were high and significant for all electrodes (PO7: $r = 0.64$, $p < .05$; Oz: $r = 0.65$, $p < .05$; $PO8 : r = 0.65$, $p < .05$).

14.5.2. BCI analysis

Classification results for all participants are shown in table 14.2, mean classification accuracy was 77.8% for the wet and 72.1% for the dry electrode data. Differences in classification accuracy between wet and dry electrode data ($t(11) = -2.64$, $p < .05$) were significant. The difference in classification accuracy was approximately 6% points.

14.6. Discussion

The grandaverage ERP morphology for dry and wet electrode data is almost identical except for a higher standard deviation for dry electrode data in the standard condition. This reveals that the signal to noise ratio for the dry electrode EEG data is not as good as for the wet electrode EEG data, still showing only slight differences in the grandaverage. Statistical analysis of standard ERP measures revealed no significant differences between wet and dry electrode EEG data with respect to peak amplitudes. In addition, mean difference peak latencies (positivity minus negativity) showed a highly significant correlation between wet

and dry electrode data across subjects. This indicates that there is no time lag induced by the dry electrode system. It can be assumed that the dry electrodes are suitable for standard ERP analysis with respect to ERP measures investigated here.

Statistical analysis of the results of the BCI classification accuracy revealed significant differences between dry and wet electrode data. Regarding BCI single trial analysis, the results of the dry electrode data were lower by approximately 6% classification accuracy with a mean of 72.1% (dry) compared to 77.8% (wet) classification accuracy. Still, both electrode types show a relatively high classification error, which is not satisfactory for this kind of paradigm. The reason for this could be the small number of trials for single-trial analysis, with only 40 trials for the deviant condition. In addition, this could be due to the fact that the utilized oddball paradigm is not as suitable for the detection of oddball ERPs at occipital sites as other oddball paradigms. A rotating stimulus paradigm was used, inducing an oddball ERP with a delayed timing and different morphology compared to standard oddball paradigms. Nonetheless, standard ERP peak amplitude and latency as well as BCI classification accuracy all revealed that both EEG systems lead to comparable analysis results in the ERP domain.

14.7. Experiment 2 – alpha paradigm

14.7.1. Participants

Like in Experiment 1 twelve students (some of them had already participated in the first experiment) of the Technical University of Berlin (age: $20 - 28$ years, 4 male) took part. All of them were neurologically healthy and reported normal or corrected-to-normal vision. They were paid Euro 10 and gave written consent to participate.

14.7.2. Procedure

Participants performed four blocks of the alpha paradigm, with a duration of five minutes each, including short breaks between blocks.

14.7.3. Paradigm

The experimental paradigm included two conditions ('relaxed' vs. 'engaged'). In the 'relaxed' condition participants were instructed to relax and close their eyes for six seconds, indicated by the german phrase 'Bitte entspanne Dich nun.' ('Please relax now.' in english.) appearing on the screen (see figure 14.4). The starting point for this period was signaled to them by a high tone, the end by a lower tone. The task of the 'engaged' condition was to find a word by concatenating letters appearing shortly at random locations on screen, indicated by 'Erkennst Du das Wort?' ('Do you recognize the word?' in english). These

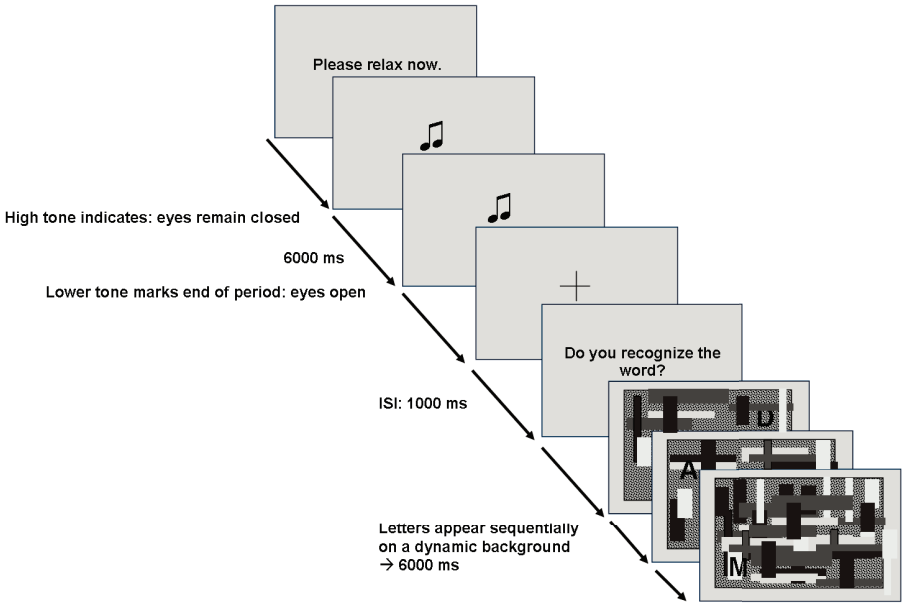


Figure 14.4.: The alpha paradigm of the validation study.
Example trials for the experimental task of the paradigm to induce α-activity. In the 'engaged' condition, participants had to recognize a word in a sequence of letters presented against a noisy background. In the 'relaxed' condition, participants had to close their eyes and relax, indicated by a high tone.

letters were lit up successively on a dynamic background with different gray-scaled shapes in a six second period. Shapes changed size and intensity making letter detection difficult and strenuous. In addition letters had to be memorized until a word was recognized putting load on working memory during this condition in contrast to the 'relaxed' condition. At the end of each trial, participants were instructed to name the recognized word. In sum, participants performed 52 trials of the 'relaxed' condition and 52 trials of the 'engaged' condition, randomly distributed across the four experimental blocks.

14.7.4. EEG recording

EEG recording was conducted in the same way as in Experiment 1.

14.7.5. Pre-processing

Artifact removal was identical to Experiment 1. Epochs extracted lasted six seconds from beginning of the task to the end of this period.

14.7.6. EEG frequency analysis

In order to determine whether the frequency characteristics of the dry electrode data are comparable to the wet electrode data, three different measures were used. First, power spectral densities of dry and wet electrode data were compared. For this, spectral densities in the range of 0.1 to $40Hz$ were computed using the EEGLAB function 'spectopo'. This was done separately for each electrode and experimental condition ('relaxed', 'engaged'), both for the spectral densities of individual subjects as well as for the densities averaged across all participants (grandaverage). Second, the mean band power in the α-band ($7 - 13Hz$), which was expected to be pronounced in the relaxed condition, was investigated more closely. Mean band power for each single trial of the 'relaxed' and 'engaged' condition was determined for each channel and participant. The resulting single trial band power values were normalized for each condition and participant by the band power mean of the corresponding data set. Normalized single trial band power values were averaged across trials and channels for each condition. Mean difference values between conditions were calculated ('relaxed' minus 'engaged') resulting in one normalized mean difference band power value per participant.
As a third dependent measure, the time course of the band power in the α-band range was examined. For each trial, a sliding window of 100 data points length was shifted over the signal with a window overlap of 99 data points for two successive shifts. The signal in each window was transformed by multiplying it with a Gaussian window of the same length to avoid leakage effects. Then, the normalized band power of the transformed signal was calculated. The resulting band power time courses were averaged across trials, yielding 12 vectors (3 channels x 2 conditions x 2 electrode sets) for each participant containing the time course information of the band power in the α-band.

14.7.7. BCI analysis

To assess the potential of the dry electrodes for BCI applications, classification accuracies between dry and wet electrode data were compared. For this, logarithmic band power values were used for feature extraction. Based on these features, classification was performed using a rLDA. Classification accuracies were estimated using 10x10-fold cross validation.

14.7.8. Statistical analysis

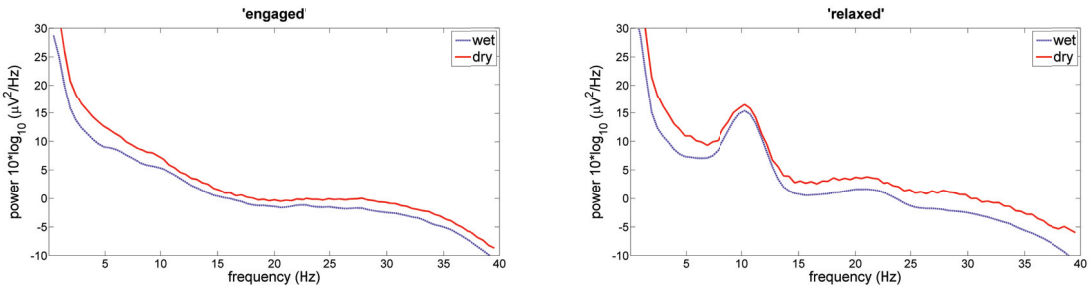
For power spectral densities in the range of $0.1 - 40Hz$, bivariate correlations (Pearson Correlation, see section 8.1.2) between dry and wet electrode data were calculated for each participant and electrode as well as for the grandaverage mean. For these individual and grandaverage correlations, one sample t-tests against zero were performed for each electrode, again at a significance level of $p < .05$. Mean difference band power values were tested for significant differences across participants between wet and dry electrode data using paired sample t-tests. The alpha significance level was again set to $p > .1$ to control for the beta error. For band power time courses in the α-band, bivariate correlations between wet and dry electrode data were calculated for each condition, channel, and participant. Classification accuracies of dry and wet electrode data were compared with a paired sample t-test. The significance level was raised again to $p = .1$ to control for the beta error.

14.8. Results

14.8.1. Frequency spectra

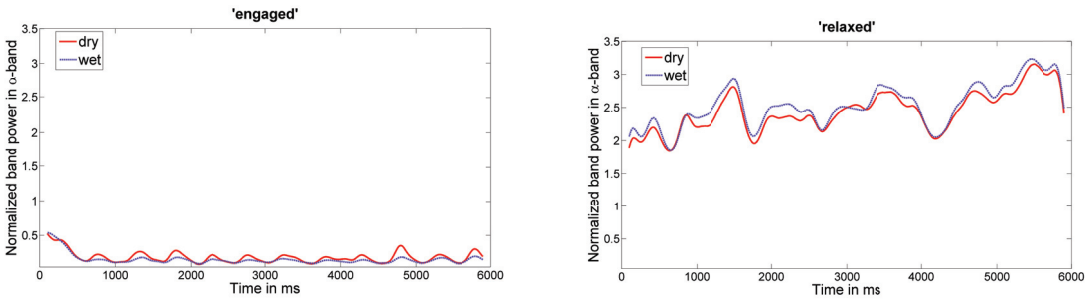
The mean of individual correlations (subjects x channels) between dry and wet electrode power spectral densities was $r = 0.97$ ($SD = 0.03$) with all individual correlation values above $r > 0.86$. For the grandaverage power spectral densities, the respective correlation coefficients were above $r > 0.98$ (mean: 0.99, $SD = 0.01$) for all three channels. All correlations reached a significant value of $p < .05$. Figure 14.5 shows two examples for grandaverage power spectral density plots for both conditions.

The grandaverage band power difference between conditions 'relaxed' and 'engaged' was $bp_{rel-eng} = 2.68$ ($SD = 1.20$) for dry electrode data and $bp_{rel-eng} = 2.54$ ($SD = 0.82$) for wet electrode data. The t-test for individual mean bandpower differences between conditions yielded no significant differences between wet and dry electrode data ($t(11) = .34$, $p > .1$). For α-band power time courses, mean correlation across participants and channels for the relaxed condition was $r = 0.74$ (PO7: $r = 0.72$, $Oz : r = 0.73$, PO8: $r = 0.76$). These correlations were significant for all participants (all values $p < .05$). For the 'engaged' condition the mean band power correlation was $r = 0.63$ (PO7: $r = 0.63$, $Oz : r = 0.66$, $PO8 : r = 0.61$). For two subjects, the correlation was not significant at PO7 and for one of these not significant at Oz. For all other participants and channels, correlations were



(a) Frequency power spectra of 'engaged' trials (b) Frequency power spectra or 'relaxed' trials

Figure 14.5.: Power spectral densities of the alpha paradigm.
Grandaverage power spectral densities at PO7. Data are averaged across subjects during (a) relaxation and during (b) mental engagement.



(a) Time course of α-power for 'engaged' trials (b) Time course of α-power for 'relaxed' trials

Figure 14.6.: Time course of α-band power in the alpha paradigm.
Time course of α-band power. Examples (participant 8) for the time course of the α-band power for the experimental conditions 'engaged' (a) and 'relaxed' (b).

significant. Figure 14.6 shows the time course of the α-band power of a participant with high correlations between the two EEG systems (participant 8).

14.8.2. BCI analysis

Table 14.3 lists the classification accuracies of individual participants for the different electrode sets. Mean classification accuracy for dry electrode data was 90.7% and 94.0% for wet electrode data. Comparing classification accuracies between wet and dry electrode conditions no significant differences were found between the two electrode systems ($t(11) = .67$, $p > .1$).

Participants	Wet (%)	Dry (%)
1	97.1	99.0
2	100.0	96.3
3	99.0	100.0
4	99.0	98.1
5	97.1	72.2
6	98.1	97.1
7	100.0	98.1
8	100.0	98.1
9	81.7	90.4
10	58.8	61.3
11	98.1	90.4
12	99.1	87.4
Mean	**94.0**	**90.7**

Table 14.3.: Classification accuracies of the alpha paradigm.
BCI results of the alpha paradigm. Classification results for all participants.

14.8.3. Discussion

The consistently high correlations between the frequency spectra of the dry and wet electrode data suggest that both electrode sets are equally capable of measuring spontaneous EEG. This is also supported by the band power analysis of the α-band. Band power differences between 'relaxed' and 'engaged' condition do not differ significantly. With respect to the time course of the α-band power, it was evident that there were significant correlations across all participants for the 'relaxed' condition and predominantly significant correlations in the 'engaged' condition. One possible explanation for the sporadic not significant correlations in the 'engaged' condition, for two participants could be the fact that the dry data was not preprocessed individually for artifacts. Artifact removal was performed by visual inspection on the wet electrode data. These rejection time windows were automatically transferred to the dry electrode data to make a comparison of both electrode systems possible and to rule out possible influences of manual artifact removal on the dry electrode data quality. Hence, artifacts occurring only in the dry electrode system, e.g. due to sweat or movement of individual electrodes remained in the data and could have contaminated experimental trials.
Mean classification accuracies were above 90 for the data of both electrode sets and the distributions did not differ significantly from each other. However, for some participants there were larger differences, varying in both directions.

14.9. General discussion

Two experiments with ERPs and spontaneous EEG show that the tested dry electrode set is capable of recording EEG signals for neuroscientific research and Brain-Computer Interfaces. Compared to a set of standard wet electrodes with the same number of channels, there was almost no difference in standard ERP and frequency measures. ERP peak latency measures revealed that there is no time lag induced by the dry electrode system. In addition, there was no significant performance degradation for the BCI classification with respect to the frequency domain. The slightly degraded classification results of the oddball paradigm for the dry electrode set remain to be investigated. It might be possible that the paradigm is not suitable for single-trial analysis at occipital sites. The effects could be due to the small number of trials or the new measurement method utilizing dry electrodes. In sum, the dry electrode system investigated here showed in most cases no performance degradation in EEG and BCI measures. This new dry electrode cap could open new opportunities to apply BCI in the context of HMI, e.g. for use in systems including passive BCIs or context aware BCIs in general. But also patients could benefit from this new technology because handling of the dry electrode system overcomes many of the restrictions of conventional EEG systems.

14.10. Conclusion and outlook

This study presented a prototype of a dry electrode cap which shows a high potential to be applicable in neuroscientific context and BCI research. This system represents a crucial step to move BCIs from laboratories to people's homes, which is a crucial part for applying BCIs in HMS in general. This offers hope for improving applicability and usability of systems that might result from the passive BCI systems proposed in Part II. Developing the current system further to a high-density electrode array and thus rendering possible broader EEG-studies is a challenge being approached at the moment.

Nevertheless, even if applicable, high density dry electrode systems will be available in future, they might not fulfill the requirements for every user. These systems would still require time for calibration and are overtly visible. Allthough cars are HMS that could benefit from passive BCI input in a significant way, it is hard to believe that drivers would set up a cap on their head in their daily life. Hence, it appears valuable to think about different ways to access information about the electrical activity of the human brain.

One possible solution would be the implementation of sensors into the environment which are capable of acquiring information about the current brain activity remotely. In cars these sensors potentially could be build into the seat or attached to the ceiling nearby the drivers head.

Another, from my perspective very promising variant would be the application of *subdermal electrodes*. Such electrodes would be implanted below the skin and above the bone of the skull, which should not be a high risk for the health of the user, and could potentially transmit their signals wirelessly while being powered by batteries or energy drawn directly

from the body of the user, e.g. by body heat. I would not expect that the signal quality of such electrodes would increase, but once they are implanted they would not need any setup and assumably could be used any time. One further benefit would be that electrode positions should not vary between sessions in the same way they do in classical EEG setups, as electrodes should not move once they are implanted. Taken together with the fact that subdermal electrodes potentially could be implanted in a way that they will be unseen in later application, these electrodes could leed to (passive) BCI applications that are seemlesly integrated into daily life. Users could interact with technical systems, they could be identified and their cognitive and emotional state could be recognized by the system without performing any conscious or time consuming action. Hence, with such electrodes passive BCI technology could lead to a highly efficient and more natural interaction between human beings and technical systems that seemlesly is integrated into daily life, similar to that we observe between humans everyday.

14.11. Acknowledgments

The author gratefully acknowledges the support by the company Brain Products with providing us the first prototype of the ActiCap Dry System.

Part IV.

Discussion, Conclusions and Outlook

15. Discussion

In this thesis, BCIs have been identified as possible means to access a particularly interesting states of a Human-Machine System – Covert Aspects of User State – which promises to enable a more intuitive and context-sensitive HMS. The canonical notion of BCI as control device was revisited from an HMS standpoint and its two main categories have been integrated into the definitions of active and reactive BCI. A third distinct type of BCI has been defined as passive BCI, with applications which are potentially far reaching but limited by present preparation and calibration procedures. As a way forward, a sequential structure for the entire process of BCI usage was proposed, followed by several complete examples of BCI based Human-Machine Interaction from the newly defined categories.
The first study utilizes existing classification schemes for the detection of readiness potentials. Its main results are twofold.
Firstly it shows that the classification scheme based on a straightforward feature extraction (see 8.3.3) and the simplest classifier (see 8.4) performs best. One reason for this unexpected result might be that more complex schemes could not play out their strength as they had to deal with a very limited number of prototypes of the investigated features. Due to the curse of dimensionality (see [97]) the complexity of methods needs to be satisfied with a sufficiently large set of training trials. This result leads to the question whether it makes sense to develop more complex classification schemes for BCI research, as from a practical perspective it is very useful to limit the number of trials generated in the calibration stage. With this result some of the main assumptions that led to the second era of BCI research (see 6.2.2 and [72]) might be contradicted – at least for this case of fast paced and hence short-term movements.
Secondly, the results of this study show that at least the well performing classification scheme can be used to set up a passive BCI for detecting the intention of moving. While the achieved accuracy of approximately 90% seems to be low for applications based on an active BCI – like steering a car – it is very valuable for setting up a passive BCI for time critical or safety sensitive HMS, like preparing safety systems before an accident. In such systems any information predicting a crucial event is extremely valuable, even if it is not 100% reliable. Of course this study is only the first step towards this direction of research and far from a real world application. But it shows the potential arising from a small shift in perspective on BCI technology.
Main drawbacks are still the accuracy of the passive BCI system, and the long time needed to set up a BCI. But the results of the studies in Chapters 12 and 14, especially in 12.6, 12.8 and 14.4, show that passive BCIs are applicable in real world scenarios, might be enhanced

with universal classification and can be set up with dry electrodes.

The second study also leads to two-fold results – again one relevant for BCI research and one for applications in HMS.
From the perspective of BCI research a context sensitive factor was identified inducing non-stationarities to the given feature space. On the one hand it is important as it shows that some classification schemes can indeed be influenced by changes in the context – here especially by changes in the current user state. On the other hand it delivers a practical tool for identifying at least one source of non-stationarities that might be used to initiate an adaptation or a re-calibration of the given classifier. The resulting heuristical method might be more robust in performance than methods based on data properties. This would define a passive BCI with the purpose of stabilizing classification accuracy in a given active BCI system. From the perspective of HMS, the introduced approach might also be used to set up another passive BCI.
The perceived loss of control over a system might occur in various HMSs and lead to critical changes in system state. This change in user state is dependent on subjective interpretations of the situation – that might even be erroneous. Hence, this information is hard to access with other means, defining it as CAUS. As this CAUS carries information about a malfunction, whether induced by the technical or human part of the system, its detection can be valuable to increase safety or to initiate an adaptation.
Especially, the resulting passive BCI is a first example of a context-aware BCI. Again the applicability of this system is limited by the limited reliability and usability of BCI systems in general, that might be resolved with further developments towards universal classification (see 12.8) and dry electrodes (see 14).
The results presented here do not identify the processes leading to the changes in the feature space. Hence, from a neuroscentific perspective it is unclear what the passive BCI defined here is exactly detecting. The measures of POC and KLD (see 11.3.3) are only indirect, and allow only for implicative reasoning. With this lack in knowledge it will be hard to refine the classification scheme and enhance the reliability of the given system. From the perspectives of both neurosciences and HMS research it seems to be valuable to continue the analyses of the data and identify processes and features more accurately.

The last study about passive BCIs presented here has shown that the user's subjective interpretations of a given situation is also accessible. The first two experiments (see 12.4 and 12.5) show in a laboratory setup that the passive BCI defined here is well defined and has an accurate performance. Furthermore, its applicability for adaptive systems is proven. A significant increase in reliability, speed and accuracy of the interaction in the given HMS has been found – a large portion of performance that was lost with the introduction of the Reduced Control mode could be restored with the supportive BCI.
The results show that features are well defined and that the given classification scheme is mostly independent from first order artifacts like eye movements. The independence of ar-

tifacts was ensured by the well chosen experimental design of the RLR Game (see 12.1). It was valuable for this study, as it ensured the validity of the assumption, that features are related to specific brain activity. Again, it is interesting that the classification scheme that has performed best in the study presented in Chapter 10 shows a high accuracy here as well.

This indicates that it seems to be a highly accurate scheme for the detection of general ERPs. The third experiment presented in this study (see 12.6) leaves the laboratory setup and enters real world application. It firstly proves that passive BCIs are indeed applicable in the intended context of uncontrolled, natural environment. The final analysis of this study 12.8 opens up a new direction for BCI research. The existence of a brain pattern that is universally detectable by a classification scheme unifies the benefits of both eras of BCI research (see 6.2.1 and 6.2.2). It combines the high accuracies achieved by utilizing methods from machine learning, does not need long term user training and no calibration phases before single sessions. From a theoretical perspective it shows that the investigated features are consistent in every human brain and that the variance of features between subjects is not higher than that within subjects. That is a very interesting result from a neuroscientific perspective. The investigated error processing of the human brain seems to be 'hard coded' in a very specific and coherent way.
In combination with easy applicable sensors, as introduced in Chapter 14, this approach solves one of the biggest problems of BCI technology: the time-consuming preparation phase that reduces the usability of these systems below the threshold of acceptance for most users. Nevertheless, this approach still has to be validated in an online scenario and in other experimental designs or applications. The results still might be very specific for the given RLR-Game. Also, its performance when using dry or potentially subdermal electrodes has to be investigated. But, first steps I have taken in that direction show very promising results, giving hope for a final solution of this problem.

In the first study of Part III, I present a first hybrid BCI combining gaze control and an input modality based on an active BCI. I show that it is indeed possible to counterbalance weaknesses of different input modalities in a hybrid BCI system. Here, especially, the major drawback of each is substituted by individual strength of the other modality: 2D cursor control was established by gaze input, which is a natural and intuitive modality for this kind of input. BCIs have proven themselves not to be suitable for this endeavor, mainly due to their limited bandwidth and high error rate in continuous control. Input by an active BCI perfectly meets the constraints of a selection command though. It is a discrete binary command that needs to be orthogonal and independent from the steering modality. Hence, this combination seems to be a perfect match from a theoretical perspective. It is finally confirmed by the results (see 13.6) of this study in a realistic search-and-select task (see 13.5.2).
I see a high potential for this kind of hybrid BCIs in further studies and real world applications. It should outperform any system that is already established for touchless interaction.

Again, the major drawback is the application of the BCI system and its sensors. A reduction of the number of electrodes and the use of dry sensors would be essential for real world applications. So, further investigations of classification schemes that might reduce the number of sensors needed for a proper detection of the selection command seem to be very valuable. Also, exchanging the active BCI with a passive BCI not depending on voluntary selections could reduce the effort taken by the user and improve the efficiency of the given HMS. First steps towards both directions have been taken in my lab and appear to be very promising.

The final study presented in my thesis had a high impact on the interpretation of the results of each of the other studies presented here and will hopefully influence ongoing research. For a long time the use of dry electrodes seemed to be the holy grail of BCI research. It was discussed in numerous papers and for a long time no significant progress was found. Even though the prototype is limited as it has only three data electrodes at restricted positions, its evaluation shows that the given type of sensor is capable of recording data suitable for EEG analyses and common BCI approaches. The major advantage of this prototype compared to other easily applicable sensor types is that it also can be applied at places on the head that are covered with hair.
Nevertheless, further investigations have to be made here as well. It seems to be problematic, from an engineering perspective, to build a mounting that is stable enough to provide enough pressure on each sensor if multiple sites at the scalp are assessed. Also, long term applicability and data quality on subjects that are on the move have to be checked. These investigations should be done easily in near future, and any problems appearing then can probably be solved quite easily. And maybe subdermal electrodes, as discussed in section 14.10. Nevertheless, the main problem, namely recoding data in a good quality without gel at hairy parts of the head, has been solved.

Hence, the question whether BCI technology could be applied in a useful way for a broader sense of HMS can thus be answered positively. At least the framework presented here of passive, hybrid and context-aware BCIs embedded in an elaborated training sequence leads to new and more efficient interaction between human and machine. Adding BCI-Technology to a given gaze-based interaction system leads to a more natural and less erroneous form of interaction. Access to the user's situational interpretation and also to user intentions allows for higher levels of automated adaptation and, hence, leads to highly efficient HMS. Combined with the dry sensor system evaluated here, this approach could lead to various types of novel applications. Especially the files of automated adaptation, shared control, task balancing and safety assurance could benefit from these approaches. But also applications or entertainment, like computer games, could benefit from the framework presented here. To date, most applications for computer games are based on direct input, implying the same restrictions as discussed here for general HMS. I would expect a high impact in this sector as well resulting from principles based on passive and context-aware BCI systems.

From a more abstract perspective the technology presented here allows for a better, more complex description of the user and their state, that is accessible for the technical part of a HMS. This new kind of 'understanding' that a computer system can develop for its user, could be seen as a new type of artificial intelligence. It is based on the utilization of information that is constantly emitted by the human body, including a preprocessing of environmental information perceived by the human and evaluated by their brain.
The technology that is derivable from these concepts could also be used for applications that would have to be discussed from an ethical perspective. It might find its application in military or intelligence, as there the optimization of work flows is highly important. Even though passive BCIs, and hence also context-sensitive BCIs, are by definition intended to improve a closed-loop interaction in a HMS, derived technology also could be used in terms of cognitive monitoring, e.g. lie detection. From my perspective an ethical discussion about the usage of this technology is unavoidable, and should be fostered actively.
It is clear that the potential that can emerge from BCI technology is far from being completely explored.

16. Conclusions

In the first part of this thesis I extended the theoretical background of BCI research by passive BCIs, and discussed the impact of hybrid BCIs to BCI research in general as well as with regard to HMS research. With the introduction of context-aware BCI systems I combined the presented concepts into a unified framework. In Parts 2 and 3 of this thesis I give several examples for the applicability of the building blocks of the theory of context-aware BCI systems. Taken together, these studies can be seen as a first proof of concept validating the main assumptions and ideas of the new framework. Furthermore, I report about a study validating the signal quality and BCI applicability of a novel EEG system based on dry sensors. With this last study I have addressed all the research questions defined in section 6.6 at the beginning of this thesis.

The main argumentation is summarized in the following list:

Can the functionality of a BCI based system be decoupled from its bitrate? Yes! The studies based on passive BCI, especially the Error-BCI described in Chapter 12 clearly show that BCI input with a very low bitrate can lead to a huge, beneficial impact on Human-Machine Interaction. But also the study describing a hybrid BCI (see Chapter 13) shows that high speed input is not necessary for a successful BCI-based interaction. This outcome motivates a shift of research effort from the increase of bitrates to the design of applications where BCIs can be implemented very specifically, counterbalancing weaknesses of a given HMS with the unique inference of information resulting especially from passive BCIs.

Can BCI-technology be used to provide novel or better solutions to complex or unsolved problems in HMS research? Also this question can be answered positively. Applications based on the concept of context-aware BCIs provide insight into parts of the information space of a given HMS that can hardly be accessed reliably with other measures. This potentially can be utilized for increasing safety in HMS, as described in Chapters 10 and 11. Here, user intentions and internal interpretations can be accessed and potentially be utilized for enhancing or preparing decisions made by the technical systems. But even if the system has made wrong decisions, a passive BCI can be used to correct them (Chapter 12). While these studies show only potential enhancements resulting from BCI technology, the study on gaze-based input (Chapter 13) solves a very specific problem of general HMS – the well known Midas touch

problem for gaze-controlled systems. All of these studies provide insight about where the potential of BCI systems for HMS lies.

Can BCI-technology be combined beneficially with already existing HMS? This thesis provides evidence that this indeed is possible. The studies in Chapters 12 and 13 give examples of applications from the fields of automated adaptation and touchless interaction that can be combined beneficially with BCI technology. Systems including automated adaptation usually suffer from a certain clumsiness (see 4.2 and 11.1. Gaze-controlled systems are dependent on specific dwell times resulting from stimulus complexity. Both restrictions can be resolved with the concepts presented here of novel BCI systems.

Can BCI technology be utilized beyond communication and control? This questions points at the focus of BCI research on exactly these applications over the past three decades. With the introduction of passive BCIs and their potential values (see 9.5.4 and 9.5.4) and especially context-aware BCI systems and the resulting accessible information space (see 9.5.5 and 9.5.8) this question also can be answered positively. All examples given here (see 10, 11, 12 and 13) show that this technology can be used to access a high variety of cognitive states carrying information that can be utilized, even quite easily, for diverse applications not restricted to communication and control.

Can the time needed for preparing and calibrating a BCI be reduced significantly? Results from both studies presented in 12 and 14 show that it can indeed be reduced. With the introduction of the concept of universal classification (see 12.8) and with theoretically validating the existence of a universally detectable feature in EEG signals (see 12.8.2) for the first time, it has been proven that time consuming calibration is not a necessity for setting up a reliable BCI system. The study investigating dry sensors shows that the evaluated system is capable of providing data that is suitable for BCI endeavors (see 14.5.2 and 14.8.2) as well as for standard EEG analyses (see 14.5.1 and 14.8.1). Hence, it is also proven that time consuming usage of gel or other fluids as well as cleaning of hair and scalp is also not a necessity for BCI based applications

Although these results show the possibility that BCI technology can be an valuable addition for human beings interacting with technical systems in general, they only are first step into a new field of research. A major goal is the decoupling of all results from specific experimental paradigms and embedding the systems into real world applications. Experience from these endeavors could then be fed back to research initiating a second stage of refinements. It has to be expected that in real world scenarios the impact of noise and the ambiguity of EEG signals will still increase, even though I have already lifted control over factors in parts of this thesis. Hence, the principle of inverse functionality (section 7.3.1) used in BCI systems is endangered even more. With this the impact that could be drawn from the implementation of context-aware BCI systems grows. It seems reasonable to focus more on the possibilities arising from that part of the framework presented here in future studies.

Finally, there are many factors regarding the usability and efficiency of BCI-based solutions for HMS that still can be (and have to be) investigated. One example is that statements on user experience are mostly not taken into account in the endeavors presented here. This could also lead to new tools for other directions of research, like psychology and usability research. Passive BCIs could be used for gaining insight into aspects of user state that are usually assessed post hoc by questionnaires. In the final section of this thesis, Chapter 17, I discuss ideas and plans for my future studies aiming in these directions. I give an outlook on my planned research aiming at the above mentioned goals, open questions and problems in the extended version of BCI research presented here. Nevertheless the major results of this thesis solve the previously identified major problems of applying BCI technology for HMS, and set a starting point for new and fascinating directions of research.

17. Outlook

In the scientific research I have done towards this thesis, I learned that the potential of BCI-technology is not limited to applications for severely disabled users. In a series of studies, I presented evidence that BCI can be applied usefully for healthy users, and that it could provide novel means to analyze neuroscientific data in general. Currently, several labs in Europe and the USA are beginning to share this perspective on BCI research – leading to a stronger support for the ideas of passive and hybrid BCIs; and hopefully as well for context-aware BCIs in near future. However, as these approaches have initially been investigated in the past three years, there still is a strong need and potential for elaborating and validating these approaches.
In the coming years, I would like to contribute to this development by focusing on three directions of BCI research, leading to more usable BCIs for applications in neuroscientific research and other domains.

17.1. Making BCIs more practicable

To date, research in BCI considers the low usability of BCI-technology as an acceptable drawback. But a shift to other domains, as well as a shift towards assistive technology for home use, demands a significant increase in usability. From my perspective, this could be achieved by developing BCI-systems based on fewer dry electrodes that require little or no calibration. Additionally, it will be beneficial to implement context information about the environment, the technical system and the user state to enhance the overall reliability of its usage. Hence, I would like to continue with ongoing studies on validating follow-ups on the prototype of a dry electrode system discussed in 14. I would follow this up with a thorough analysis of the approach I have followed on utilizing Restricted Boltzmann Machines (RBMs) for reducing the number of electrodes needed (not presented in this thesis). Finally, I would like to elaborate the theoretical framework introduced in Chapter 9. As it is intended as a novel tool for counterbalancing the high error rate of current BCI-systems, by adding supportive information, the correctness of decisions based on BCI-data could be validated with a-priori probabilities drawn from contextual information. Another perspective would be that information drawn from BCI could enhance decision making in existing systems.

17.2. BCI-technology as tool for neuroscientific research

The domain of neuroscientific research has developed from analyzing averaged data only towards single trial analysis. The reason for this is a stronger interest in leaving highly controlled laboratory setups for analyzing brain-functions in real world scenarios. Of course, this defines an interesting connection to the field of BCI research, as now both fields share more interests. I see a valuable contribution of BCI technology in two aspects of the neurosciences. Firstly, BCI-technology can be used to build up more complex experimental setups, like setups adapting to the current state of the subject or allowing single-trial insight into the data even in noisy environments. And secondly, the outcome of feature extraction or classification can be used to generate a more detailed insight into the data analyzed. Studies and perspectives are already available, but the methodology needs to be validated and applied.
For this I would like to continue my previous approach of combining methods from Computational Neurosciences, like ICA, with BCI technology. The toolbox that we recently developed in Team PhyPA will support me in combination with EEGLAB to follow this approach. I will use it for analyzing data that I have recorded in complex or neuroscientific experimental setups.

17.3. Solving open problems from other scientifc domains with BCI-based technology

Besides the neurosciences, other fields of research have also developed an interest in BCI-technology. In Human-Machine Systems, BCIs might be used as secondary and implicit input modalities, contributing to common input channels and leading to a more natural interaction. Insight into current aspects of the user state might also be relevant for human factors and psychological research. It could be used to replace currently common assessments like thinking aloud or questionnaires. Factors of interest could be the detection of intentions, internal interpretations and emotional factors.
In this branch of BCI research, I especially would like to continue focusing on the combination of gaze-based control and BCI-input to a hybrid BCI, which can be implemented as a novel input modality for human-machine systems. This could be used for touchless interaction in assistive technology as well as for professional environments, which induce situational disabilities. From my perspective, the most interesting step would be shifting from an actively conveyed BCI-command to a passively sent one.
Additionally, I would like to continue evaluating studies about covert aspects of user state, and investigate the whole scope of detectable aspects as well as the benefits resulting from including them into the available information space of already existing Human-Machine Systems.

There are a lot of fascinating things to be done. So, lets do it!

A. Appendix

A.1. List of abbreviations

Abbreviations

ACC ..... Anterior Cingulate Cortex
ALS ..... amyotrophic lateral sclerosis
BCI ..... Brain-Computer Interface
BMI ..... Brain-Machine Interface
BNCI ..... Brain/Neuronal Computer Interaction
BOLD ..... blood-oxygen-level-dependent
CAUS ..... covert aspects of user state
CSP ..... Common Spatial Patterns
CV ..... crossvalidation
DNI ..... Direct Neural Interface
ECoG ..... electrocorticogram
EEG ..... electroencephalogram
EMG ..... electromyogram
EOG ..... electroocculogram
ERD ..... Event Related Desynchronizations
ERN ..... Error Related Negativity
ERP ..... event-related potential
ERS ..... Event Related Synchronizations
fERN ..... Feedback Error Related Negativity
FFT ..... Fast Fourier Transformation
FG MMS ..... Department of Human Machine Systems
FIR ..... finite impulse response
fMRI ..... functional magnetic resonance imaging
fNIRS ..... functional near-infrared specotrography
GMM ..... Gaussian Mixture Model
GUI ..... graphical user interface
HCI ..... Human-Computer Interaction
HMS ..... Human-Machine Systems
ICA ..... Independent Component Analysis
IIR ..... infinite impulse response
ISI ..... inter-stimulus interval
ITI ..... inter-trial interval
KLD ..... Kullback-Leibler divergence
LDA ..... Linear Discriminant Analysis

LNdW	'Long Night of Science' at the TU Berlin
Log-BP	logarithmic bandpower estimates
LR-Paradigm	Left-Right Paradigm
ME	microelectrodes
MEA	microelectrode arrays
MEG	magnetoencephalogram
PC	personal computer
PET	Positron Emission Tomography
PMM	Pattern Matching Method
POC	pseudo online classification rates
QDA	Quadratic Discriminant Analysis
RAM	Random Access Memory
RBSD	Realtime Brain Signal Decoding
rLDA	Regularized Linear Discriminant Analysis
RLR Game	Rotation-Left-Right Game
RLR paradigm	Rotation-Left-Right paradigm
rQDA	Quadratic Discriminant Analysis
SAX	Symbolic Aggregate Approximation
SCP	Slow Cortical Potential
SMR	Sensomotoric Rhythm
SpecCSP	Spectrally weighted common spatial patterns
SSVEP	steady state visually evoked potential
SVM	Support Vector Machines
SVM-P	Support Vector Machines with polynomial kernel
WWW	World Wide Web

A.2. List of figures

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A.4. References

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Eidesstattliche Versicherung gemäss §5 (5) der Promotionsordnung für die TUB

Hiermit erkläre ich an Eides statt, dass ich die Dissertation selbständig verfasst habe; die von mir benutzten Hilfsmittel und Quellen sind aufgeführt und die Arbeit ist nicht in Zusammenarbeit mit anderen Wissenschaftlern oder Wissenschaftlerinnen erstellt worden.

Berlin, den 30. Dezember 2011