# Embedded Brain Reading

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**Abstract**

Current autonomous robots and interfaces are far from exhibiting the adaptability of biological beings regarding changes in their environment or during interaction. They are not always able to provide humans the best and a situation-specific support. Giving the robot or its interface insight into the human mind can open up new possibilities for the integration of human cognitive resources into robots and interfaces, i.e., into their intelligent control systems, and can particularly improve human-machine interaction. In this thesis *embedded Brain Reading (eBR)* is developed. It empowers a human-machine interface (HMI), which can be a robotic system, to infer the *human's intention* and hence her/his *upcoming interaction behavior* based on the context of the interaction and the human's brain state. To enable eBR, an *automatic context recognition or generation* as well as *online, single-trial brain signal decoding*, i.e., *Brain Reading (BR)* for the detection of *specific brain states*, are required. The human's electroencephalogram (EEG) recorded from the head's surface is used in this work as a measure of brain activity. Experiments are conducted in controlled experimental setups, where subjects have to execute differently complex and demanding simple and dual-task behavior as it is performed during human-machine interaction. Using these experiments the applicability and reliability of BR is confirmed as well as training procedures for BR are improved. Furthermore, a formal model for eBR is developed and shown to be applicable for different implementations of eBR. The formal model is the first step to check implementations of eBR for their correctness and completeness. By means of robotic applications for tele-manipulation and rehabilitation it is further shown that eBR can be applied to either adapt or to drive HMIs, i.e., can be used to implement *predictive* HMIs for *passive* or *active support*. In case that eBR is applied for passive support, it is shown that *malfunction* of the whole system can be *avoided*. On the other hand, in case that eBR is applied for active support, i.e., to actively drive an HMI, it is shown that an *individual adaptation* of the support with respect to the requirements of different users can be facilitated by utilizing multi-modal signal analysis in eBR. Finally, it is shown that even in case of passive support eBR can measurably *improve human-machine interaction*.

**Zusammenfassung**

Autonome Roboter und Mensch-Maschine Schnittstellen sind heutzutage noch nicht so adaptiv und flexibel im Bezug auf Veränderungen in ihrer Umgebung oder sich ändernden Anforderungen ihres Interaktionspartners, wie es biologische Systeme sind. Aus diesem Grund erfüllen solche technischen Systeme nur eingeschränkt die Anforderung, Menschen situationsspezifisch und entsprechend wechselnden Gegebenheiten optimal zu unterstützen. Um dies zu ändern, ist es notwendig, dass robotische Systeme und ihre Schnittstellen Einsicht in die Gedankenwelt des Menschen erhalten. Dies ermöglicht es dem technischen System, menschliche kognitive Ressourcen zur Optimierung ihrer intelligenten Kontrolle und somit zur Optimierung der Interaktion zwischen Mensch und Maschine zu nutzen. In dieser Arbeit wird *embedded Brain Reading (eBR)* entwickelt. Es befähigt eine Mensch-Maschine Schnittstelle, die ein robotisches System sein kann, *Annahmen über die Absichten* des interagierenden Menschen aufzustellen und damit *zukünftiges Verhalten* im Kontext der Interaktion und basierend auf dem ermittelten Zustand des Gehirns *vorherzusagen*. Dementsprechend wird für die Realisierung von eBR eine automatische *Erkennung des Kontextes* der Interaktion als auch eine "online" fähige *Entschlüsselung von Gehirnaktivität* im sogenannten "single-trial" Verfahren, also die Erkennung spezifischer Gehirnzustände mittels *Brain Reading (BR)*, benötigt. Das menschliche, von der Kopfoberfläche gemessene Elektroenzephalogramm (EEG) wird in dieser Arbeit als Methode zur Messung der Gehirnaktivität genutzt. Experimente, in denen Probanden unterschiedlich komplexe und anspruchsvolle Verhalten, so wie sie auch bei der Interaktion zwischen Mensch und Maschine auftreten würden, ausführen müssen, werden in kontrollierten Versuchsumgebungen durchgeführt. Anhand dieser Experimente werden die Zuverlässigkeit von BR gezeigt und Trainingsverfahren für BR verbessert. Des weiteren wird in dieser Arbeit ein formales Model für eBR entwickelt. Für dieses wird gezeigt, dass es für verschiedene Implementierungen von eBR anwendbar ist. Das formale Modell erlaubt Implementierungen von eBR zu verbessern und auf ihre Korrektheit und Vollständigkeit zu überprüfen. Basierend auf Anwendungen aus der Robotik, genauer auf Basis von Telemanipulations- und Rehabilitationsanwendungen, wird außerdem gezeigt, dass eBR genutzt werden kann, um Mensch-Maschine Schnittstellen entweder in ihrer Funktionalität anzupassen, also auf die Anforderungen des Menschen zu optimieren und *passiv* zu unterstützen oder um die Schnittstelle selbst *aktiv* zu steuern. Die durch eBR adaptierte oder gesteuerte Schnittstellen werden *predictive HMIs* genannt. Für den Fall, dass sie für die passive Unterstützung eingesetzt werden, wird gezeigt, dass *Fehlfunktionen* des Gesamtsystems, welche durch Fehlinterpretationen der Gehirnaktivität potentiell möglich sind, *vermieden* werden können. Andererseits wird gezeigt, dass der Einsatz von eBR für die aktive Kontrolle von solchen predictive HMIs eine *individuelle Anpassung* dieser an die Anforderungen des Nutzers oder der Situation, wie z.B. dem Stand der Therapie, ermöglicht. Schlussendlich wird mittels eines Experimentes gezeigt, dass auch für den Fall, dass eBR für die passive Unterstützung eingesetzt wird, die *Interaktion* zwischen Mensch und Maschine *messbar verbessert* wird.

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# Introduction

In the last several decades different approaches have been pursued to support humans in their daily life and working environment or to restore their sensory and motor functions. The role of technical systems like intelligent, autonomous robotic systems in these approaches is steadily increasing with the increase of their ability to behave situation-specific and to support humans according to the current context. However, today's autonomous systems do not yet come close to the cognitive capabilities of humans regarding their ability to act correctly and appropriately in a given situation. Therefore, the application of autonomous robotic systems is to some degree restricted with respect to certain applications and/or environments and not always accepted by humans.

On the other hand, human-machine interfaces (HMI)s that are available today for the explicit or active control of technical systems or software allow to interact in a more flexible and intuitive manner. For example, by using an exoskeleton the control of a system like a robotic arm can be performed by intuitive, natural arm movement (Folgheraiter et al., 2012; Kirchner et al., 2013a). Further, novel HMIs are applied to intelligently interact with autonomous systems to compensate for their limitations. For example, interfaces are developed which cooperate with autonomous robots to request interaction only in situations which the robot cannot solve alone (Kaupp et al., 2010).

Although *explicit interaction* is improved by the application of such intelligent HMIs, most interfaces and robotic systems are not yet able to transfer or understand *implicit* information. However, for interaction between humans, implicit information is at least as relevant as explicitly sent information or commands. Implicit information is for example used by the interacting persons to *infer* the general state of the interaction partner, like the emotional state, involvement in the interaction or communication as well as the mental load. Moreover, implicit information can even be used to infer specific intentions or upcoming behavior, like to turn away and end a

conversation or to start a certain action. Therefore, implicit information can be used to *adapt future behavior* for the purpose of interacting better, i.e., more efficiently. Without making use of implicit information, at least the acceptance of an interaction partner will be limited or the interaction itself may even be affected.

## 1.1 Challenges in Human-Machine Interaction Research

To improve human-machine interaction and to increase the acceptance of robotic systems as supportive devices, as interfaces or as proper interaction partners, three of the main challenges that have to be solved in the current and future research will be addressed in this thesis and are discussed in the following:

- Challenge (1): robotic systems must *behave* more *like a human* to be better accepted as interaction partner or must - as assistive device - *restitute, substitute* or *expand human capabilities* without increasing the demands on the human interaction partner.
- Challenge (2): robotic systems, especially if their purpose is to enable or support human-machine interaction, must (better) *understand* the *intentions* of a human interaction partner to enable not only intuitive but *context-specific interaction*.
- Challenge (3): interaction between humans and robotic systems as well as the proper functioning of the robotic systems themselves must to some degree be *verifiable* and *predictable in their behavior* to reduce the risk in their application and to optimize their operation.

Note that challenge (3), i.e., correct functioning and the avoidance of failure of interaction has a strong impact on challenge (1), since systems that are malfunctioning will not be accepted as interaction partner or cannot reliably restitute, substitute or expand human capabilities. Moreover, only robotic systems that can infer intentions of the human interaction partner (challenge (2)) can support humans intuitively and efficiently (challenge (1)), as will be discussed later in more detail. Due to the close link among the three challenges, it is argued in this thesis that any approach that aims at improving the acceptance of robotic systems as supportive devices or as interaction partner has to consider at least the three challenges as given above.

### 1.1.1 Increasing the Acceptance of Robots and HMIs

To address challenge (1), research is conducted to improve the *appearance* of a robot for high acceptance (Saygin et al., 2012; Lemburg and Kirchner, 2011), to develop

interaction tools, i.e., interfaces, for explicit interaction, which allow the *intuitive control* of a robot, e.g., by gestures (Van den Bergh et al., 2011; Kim et al., 2013; Ma et al., 2013), and to establish *humanlike behavior* in humanoid robots (Or and Takanishi, 2005; Collins and Ruina, 2005; Huang and Mutlu, 2013).

#### 1.1.1.1 Humanlike Behavior

To achieve humanlike behavior of robots (Metzen et al., 2013; Sadeghipour and Kopp, 2011; Dindo et al., 2011), analysis tools for human behavior analysis and complex machine learning (ML) approaches that make use of imitation learning (Argall et al., 2009; Schaal, 1997), reinforcement learning (Abdenebaoui et al., 2007; Kober and Peters, 2012), and transfer learning (Taylor and Stone, 2009) with the goal of enabling robots to learn from humans and to optimize their behavior are applied. On top of this, robots should be equipped with *intelligent software architectures* that allow knowledge processing to autonomously infer suitable behavior of the robot in a specific situation and to learn about such suitable behavior from humans. For example, in (Tenorth and Beetz, 2013) it is discussed that the ability to infer a suitable behavior from incomplete human instructions is one prerequisite for future robotic agents.

Another approach that is able to tremendously increase the acceptance of robots as interaction partner is the application of *interfaces for speech generation and understanding* that may even imitate the learning of human's speech (Weizenbaum, 1966; Wahlster, 2000; Nöth et al., 2000; Herzog and Wazinski, 1994; Dindo and Zambuto, 2010). Already in the middle of the 20th century Joseph Weizenbaum (1923 – 2008), the developer of the computer program ELIZA (Weizenbaum, 1966) discovered that his simple natural language processing system, which was able to carry out humanlike conversations but actually not able to understand the meaning of human language, could be applied to substitute a human partner although this was never intended by his research. Psychiatrists even suggested to apply the program ELIZA as an acceptable substitute for human therapy (Weizenbaum, 1976). This shows that speech has a high relevance for the acceptance of robots, especially humanoid robots or virtual agents.

#### 1.1.1.2 Expanding and Restituting Human Capabilities

Besides the above referenced efforts in making the robot humanlike in its appearance, behavior and interaction capabilities, other approaches go in the direction of increasing the acceptance of robotic devices and agents by expanding or restituting human capabilities by their application. One main field for the application of robotic devices is the rehabilitation of disabled persons with the goal of *restituting human ca-*

*pabilities*. Especially exoskeletons are developed that restitute or substitute human capabilities like moving one's arm (Nef et al., 2005; Mihelj et al., 2007; Housman et al., 2009) or leg (Suzuki et al., 2007; Zoss et al., 2006).

Furthermore, robotic devices (like exoskeletons originally developed for military purposes) are able to increase the force a human can apply and thus *expand* her/his *capabilities* (Karlin, 2011). Similar approaches may also be applied in everyday tasks (Ugurlu et al., 2012), although special interest is given to specific applications that require permanent physically demanding work, like the care of sick or disabled people (Yamamoto et al., 2003). While surgical assistive devices, to give a further example, could be shown to support humans in a way that their performance is increased by, e.g., enhancing the speed of specific tasks performed during surgery, like tying a knot (Mayer et al., 2006), by taking over complicated tasks like catheter guidance (Riga et al., 2009), or by executing "superhuman" performance by adopting the best behavior from several surgeons (Van den Berg et al., 2010), results also showed that for the support of complicated surgical procedures the prediction of the surgeon's intention is essential to further improve a system's response (Weede et al., 2011). This shows that challenge (1) which has to be solved to develop future autonomous robots that are accepted as intuitive supportive device or as proper interaction partner is closely linked to challenge (2).

### 1.1.2 Transferring Intentions by Context-Specific Explicit and Implicit Interaction

To address challenge (2), i.e., to enable robotic devices or agents to infer human intention and behavior, *context-aware* HMIs have to be developed that are not only able to adapt their explicit behavior with respect to the context of interaction, e.g., actively request explicit interaction if required (Kaupp et al., 2010). They must further be able to transfer and make use of implicit information given a specific context of interaction and must be able to automatically identify changes in the context of interaction based on implicitly transferred information. To apply implicit information transfer between human and robot, the robot must be able to *transmit implicit information* by, e.g., gesture or facial expression, like a human (Sadeghipour and Kopp, 2011; Wimmer et al., 2008; Giorgana and Ploeger, 2011). Moreover, the robot or interface must in turn be able to analyze the human to *decode implicitly sent information*.

While *explicit* information is always transferred *actively*, since it is the main content of the information that is for a certain purpose transmitted to a second person or artificial system, *implicit* information is rather transferred *passively* often together with explicit information. To achieve high acceptance of an interaction partner, which is the main goal when improving human-machine interaction, it is highly relevant

that implicitly transferred information does *match* the explicitly transferred information, hence, matches the *context* of interaction to better transmit the *intention* of the interaction partner. For example, gesture can be used to implicitly support explicit information that is transmitted by speech (Bergmann et al., 2013). It was shown that the human interaction partner will likely not trust the information that is explicitly transferred or even the interacting system itself in case explicit and implicit transferred information do not match. When, however, explicitly transferred information is supported by implicitly transferred information, a human interaction partner will more likely accept a system as interaction partner (Bergmann et al., 2013).

#### 1.1.2.1 Physiological Computing for Explicit and Implicit Interfacing

To *passively* gain implicit information about a human besides *overt behavioral* data, like gestures, different *covert physiological* measures, like electrodermal activity or galvanic skin response, blood pressure, respiratory patterns, the electrooculogram (EOG) and pupillometry, the electromyogram (EMG), the electrocardiogram (ECG) and the electroencephalogram (EEG) can be recorded and analyzed. During human-machine interaction implicit information gained from covert and overt data of the interacting human can be used to *directly* adapt technical systems, like robots or interfaces, in their behavior or functionality or in their acceptance as an interaction partner for humans.

Physiological computing focusses on the *passive* adaptation of systems by *covert physiological* measures. However, it also covers approaches for direct, i.e., *explicit interfacing* between human and computer or machine based on the analysis of covert physiological data, as it can be done by applying brain-computer interfaces (BCI)s (see Section 2.2), as well as approaches for adapting the *human's psychophysiology* by giving biofeedback to the human (Schwartz and Andrasik, 2003; Allanson and Fairclough, 2004). For example, humans can be trained to regain muscle control by applying biofeedback on their muscle activity (Tim, 1997), or EEG- or neurofeedback can be applied to cure Attention Deficit Disorder (Pop-Jordanova et al., 2005). Biofeedback is further used to improve the performance of BCIs by enabling the user to learn the generation of optimal brain patterns (Chatterjee et al., 2007).

An adaptation of technical systems by passively conducted covert physiological data is in a more general sense also known as active *biocybernetic adaptation*. Biocybernetic adaptation is an application of physiological computing (Allanson and Fairclough, 2004), which is most relevant in the context of this thesis. By biocybernetic adaptation the interaction is enhanced or enriched by transforming physiological signals into, e.g., real-time computer input. Hence, implicit information is decoded from physiological data. It is usually used to change the functionality of a system regard-

ing, e.g., fatigue or frustration levels of a user and can enable *greater control* over complex systems (Woods, 1996).

Since covert physiological activity used for physiological computing is *continuously available* to a system, physiological measures allow a permanent access to the operators state even if overt behavior is absent. In (Gerson et al., 2006) it is shown that for some subjects information gained from covert physiological data, here the EEG, is *even more reliable* than information gained from overt behavioral data. In case of using physiological data passively for physiological computing, as for biocybernetic adaptation, a systems' user does not have to perform any additional task nor a higher mental or cognitive engagement is required. Hence, *workload* does not increase by implementing a passive approach of physiological computing or can even be subjectively *reduced*, while the *humans' performance is increased* (Prinzel et al., 2000). Furthermore, *task engagement* can be *increased* (Freeman et al., 1999).

It can be summarized that *passively applied* physiological computing is a suitable approach to gain implicit information about the interacting human and to make it available to a robotic system or its interface to improve interaction or performance, since the adapted system is optimized with respect to the requirements of the user.

#### 1.1.2.2 Brain Activity - an Implicit Covert Measure of Intentions

Measures of brain activity (see Section 2.1) must be considered to be of special interest for human-machine interaction in general, since they give insight into *brain states* and even allow to *uncover preconscious intention*, like early, preconscious movement intention (Libet et al., 1983; Shibasaki and Hallett, 2006). By means of the analysis of brain activity brain states and hence intentions of the human can be detected even before she/he is aware of it. EEG (see Section 2.1.1) is a direct measure of the electrical activity of the brain. Nowadays, it is quite clear that it is very hard to infer complex behavior with non-invasive EEG recordings alone, since with surface EEG it is only possible to investigate activity of the near-surface parts of the cortex and the source of the recorded activity is hard to determine (Zschocke, 1995; Luck, 2005). Moreover, the brain's activity is very complex since several functional brain processes overlay at a given point in time. Nonetheless, already early findings (Libet et al., 1983; Farwell and Donchin, 1988, 1991) gave the impression that the human EEG can serve as a *window into the human mind or brain* (Coles, 1989). Investigated patterns even allowed the development of BCIs (see Section 2.2) that could reestablish communication and motor function (Farwell and Donchin, 1988; Wolpaw et al., 2002; Guger et al., 1999; Pfurtscheller, 2000).

The analysis of *invasive* deep multi-electrode brain recordings (see Section 2.1 for discussion of different brain measures) showed impressive results in reading the

brains' electrical activity if compared to approaches that are based on the analysis of non-invasive EEG recordings. They allow for example to control a robotic arm just by "thinking" as it could be shown for monkeys and humans (Carmena et al., 2003; Hochberg et al., 2006). However, they are *not applicable* to healthy humans because of the high risk of complications during surgically implantation and during usage. Even for rehabilitation purposes fully implantable recording devices are not yet available without restrictions of their application because of the high risk that the brain tissue does reject implanted devices after a certain time of usage. Therefore, great significance is attached to the development of *new methods for the analysis of surface EEG* data to decode brain states and the development of easy to apply recording devices for the improvement or implementation of HMIs that make use of brain activity.

### 1.1.3 Correctness of Complex Systems and Interaction

When making use of both, overt and covert information for the purpose of establishing or improving human-machine interaction, one makes use of *uncertain* and *complex data* and *complex systems*. This and the implementation of complex interaction on different levels increases the *vulnerability* of such approaches *for errors* that might not be easy to be found. However, also the implementation of such approaches itself is very complex and demanding. Therefore, it is a challenge to guarantee that such systems are *correct* and *complete* when developed (Drechsler et al., 2012). To solve this issue, the first step is to assure correct functioning of complex systems with respect to specified application conditions and to make complex systems more predictive in their overall behavior.

However, to address challenge (3), new approaches are required that allow to describe complex human-machine interaction, i.e., to model the human or human data like physiological data and the interacting system(s) as well as the applied HMIs that are getting increasingly complex in their structure and behavior. Solutions how to best *formally describe* such complex systems and human-machine interaction have to be found in order to verify their correct functioning. This is a very challenging task. To enable a formal description of a complex system a *rigorous specification* of all parts and interfaces is required. Out of this a formal description (such as a finite state machine or a Kripke structure) can directly be derived, enabling to apply techniques such as *model checking* (Clarke et al., 1999). Alternatively, approaches can be studied that start with a formal specification, like Event-B (cf. (Abrial et al., 2010)). However, verifying those systems may fail due to their complexity itself as faulty dependencies between or interplay of processes are easily overseen when addressing the system as a whole. Thus, a possible solution is to focus on the *basic functions and processes* of

the system or interaction and verifying them in themselves, before addressing the formal verification of their interplay in a second iteration. At this point it is not yet clear which approach will be the best to solve this challenge. Extensive research in this field is required and of high interest to the research community.

## 1.2 Goals of the Thesis

The main goal of this thesis is to develop an approach that is mainly based on the analysis of the *human's brain activity* in order to *enhance implicit information flow* between human and interacting system to *improve interaction*. The developed approach has to be able to detect *specific brain states passively* without requiring extra involvement of the human and hence without increasing the workload. Furthermore, it should be applied to *adapt* a system to a *specific upcoming situation* to, e.g., support the start of a specific intended movement or to adapt a supportive system with respect to the individual perception of a specific information. Hence, the approach that is developed in this thesis enables an artificial system to infer intentions of the human interaction partner and by this to improve the support or to drive a specific upcoming, i.e., future, interaction task. To better describe and evaluate the approach, a *formal model* is developed and implemented in application scenarios. This formal model is a prerequisite for the application of *verification* methods.

It is still an open question how to make use of information about the human's brain states in an automatic fashion during complex interaction and how to avoid malfunction of the whole system caused by misinterpretation of the human's intentions. To solve these issues, *automated context generation* and *control mechanisms* have to be implemented to avoid or minimize the influence of misclassification of brain activity or to compensate for their possible negative influence on the whole system's functionality. Whether the implemented control mechanisms are able to facilitate *correct functioning* of the system or not has to be considered especially when *evaluating* the developed approach and its formal model on implementation examples.

To evaluate the formal model and to investigate whether the developed approach is able to measurably improve human-machine interaction, a *robotic telemanipulation scenario* is chosen as an application scenario. More specifically, the *passive adaptation* of an exoskeleton and of an operator monitoring system are chosen as implementation examples. By evaluating the approach with respect to its suitability to improve human-machine interaction for *rehabilitation purposes* it will further be shown that the developed approach can also be applied to *explicitly drive* an interface, e.g., exoskeleton or orthosis, while *enhancing the adaptivity* of the device to specific application requirements, i.e., the state of therapy of a patient. For

this active support of human-machine interaction, the intentions of the human are again *passively* decoded.

**The main goals of the thesis can be summarized as follows:**

**Main goal 1** Development of an approach for the *context-aware* passive or active support of an operator or user of a robotic system or interface based on the contextual *passive* analysis of brain signals (like the human EEG).

**Main goal 2** Analysis of the developed approach to show that it can be implemented to function *error-free* in a complex application, i.e., can adapt an HMI while *avoiding malfunctioning* of the whole system.

**Main goal 3** Analysis of the developed approach to prove that it does qualitatively and quantitatively *improve human-machine interaction* even in case of only passive support.

To achieve the above mentioned main goals, the following **subgoals** have to be fulfilled:

**Subgoal 1a** Development of *training and application scenarios* to investigate brain activity during complex and demanding human-machine interaction tasks.

**Subgoal 1b** Identification of *stable brain activity* that allows the detection of *specific* and *known brain states* of an interacting operator or user.

**Subgoal 1c** Development of *methods* that allow to *deal with only few training examples* for *online* applicable, *single-trial* ML-based brain signal analysis.

**Subgoal 2a** Development of a *formal model* that describes how *covert information from brain activity* can be used together with *overt information* in application scenarios in an *automated fashion*, while considering that misclassification of brain states are possible and their influence on the functioning of the system must be avoided, minimized or automatically corrected by implementing *control mechanisms*.

**Subgoal 2b** Investigation of the ability of the developed formal model to *cover differences in implementations*.

**Subgoal 2c** Analysis of the correct and *error-free* functioning of the developed approach even in cases of misclassification of brain states.

**Subgoal 3a** Implementation of the approach for the *online support* of applications.

**Subgoal 3b** Validation that the approach does *improve interaction* when applied for the passive adaptation of an HMI.

## 1.3 Contribution of the Thesis to Research Challenges

As stated in Section 1.2 the approach developed in this thesis does passively analyze brain activity - here the humans' EEG that is recorded non-invasively on the surface of the head - as it is done in passive approaches of physiological computing. However, this approach is not only able to detect a general state of the human, like her/his general task engagement (Pope et al., 1995), the task difficulty and lapses in the attention (Makeig and Inflow, 1993), but a *specific brain state* at a specific point in time with respect to a given context. To achieve this, brain activity has to be analyzed in single trial, i.e., for each relevant point in time. Given these requirements, the developed approach makes use of *Brain Reading (BR)* (see Section 2.3) to detect specific brain states. However, BR has to be implemented in a fashion that allows an *online* detection which is usually not required in most BR approaches. Thus, online capable BR for the detection of specific brain states is required for the approach and must be shown to be *feasible* to be applied in complex and demanding interaction scenarios.

To infer on the intention or upcoming behavior of the subject, the developed approach must further enable to *embed* BR into an application in a situation- and context-specific way. Therefore, the approach emerged from this thesis is called *embedded Brain Reading (eBR)*. It *combines* the analysis of *overt behavior* for context generation and the analysis of *covert physiological data*, to *passively* decode covert *implicit information* from the brain's activity and optionally other physiological measures. The goal for applying eBR is to *infer specific intentions* or *specific upcoming behavior* of the user to adapt HMIs to better support future interaction or to drive HMIs, while enhancing its adaptiveness to specific interaction requirements. The work does therefore contribute to challenge (1).

By developing eBR this thesis contributes to *challenge (2)* of the above defined research agenda, since eBR is able to passively infer on intentions and upcoming behavior of an interacting human, i.e., to gain and make use of covert *implicit* information about the interacting human by implementing *predictive HMIs*.

Moreover, by developing a *formal model* for eBR the work of this thesis contributes to *challenge (3)*, since it lays the foundation for the development of *formal verification approaches* that are *applicable for complex systems* and can be applied to *detect implementation errors*, which may otherwise be invisible. Furthermore, challenge (3) is addressed by investigating how the application of eBR can *avoid malfunctioning* of the whole system and human-machine interaction or is able to *minimize* most critical *false behavior*.

Besides the main contribution of the work in this thesis to the challenges defined for improving human-machine interaction, this thesis does further address *basic questions* in the field of interdisciplinary neuroscience and computer science research by investigating brain activity, i.e., the human's EEG, during complex and demanding human-machine interaction and by systematically analyzing the *correlation* between the characteristics of "known" activity of the brain and performance of ML analysis to show that BR is able to detect specific brain states. The work of this thesis supports the *usage of ML methods* for the *analysis of complex physiological data*, like the EEG. Moreover, results of this thesis show that knowledge about underlaying brain processes can help to optimize procedures in ML analysis, i.e., to *choose* appropriate *training data* or to *cope* with a *small amount of training examples*.

In summary, this thesis contributes to all three challenges of human machine interaction by *developing eBR*. By applying eBR, *predictive* HMIs can be implemented that either actively enable or reestablish interaction or passively improve interaction, both in a more situation- and context-aware fashion with respect to the *upcoming* requirements of the interacting human, if compared to the same HMI that is not adapted by eBR. Therefore, *by applying eBR*, the *interface* or robot does implicitly gain insight into the human's intentions, behaves accordingly and will therefore be *easily accepted as interaction-partner* or *supportive device* by the interacting human. Furthermore, by the interdisciplinary work of this thesis it contributes some basic findings about the improvement of ML analysis of single-trial EEG recordings and about the brain's activity and functioning during demanding human-machine interaction.

## 1.4 Structure of the Thesis

Based on the addressed general research challenges and the defined goals of the thesis as motivated in Part I, the work is divided into three further parts. In Part I an overview of the theoretical background of the thesis is given in Section 2. Thereafter in Part II and in Part III the results of this thesis, which are partly published as stated in Section C and at the beginning of each section of Part II and in Part III, are presented and discussed.

In Part II *Brain Reading (BR)* based on single-trial analysis of the human's EEG during human-machine interaction is investigated. This Part of the thesis addresses the **main goal 1** with the corresponding subgoals as well as the **basic questions** in neuroscience and computational science as defined in Section 1.3. In Section 3, experiments are presented that investigate event-related potentials (event-related potential (ERP)s) that are evoked by different brain processes, i.e., processes related to (1) *movement preparation* and (2) *target recognition and task set changes*, and can

be *detected* in the human's EEG by *BR* while the human is performing demanding interaction tasks that require dual-task performance. The results are published in (Kirchner et al., 2009; Kirchner and Kim, 2012; Kirchner et al., 2013b) and are currently under review (Kirchner et al., 2013c). The applied method for the detection of EMG-onset is published in (Tabie and Kirchner, 2013). In Section 4, it is shown that *brain patterns*, which are detected by ML analysis, are *related to ERPs* and that BR is hence able to detect *specific* brain states. Different problems and challenges that arise in applications, especially the *low amount of training data* for the training of the applied ML algorithms are discussed and solutions are presented here as well. It is further shown that two different brain states can be *simultaneously* detected by BR in an application scenario. Presented results are published in (Metzen and Kirchner, 2011; Kirchner et al., 2013d).

Part III of the thesis presents *embedded Brain Reading (eBR)* and how it is implemented to support applications, i.e., interaction during *tele-manipulation*, and that it allows to safely drive robotic devices for *rehabilitation purposes*. Therefore, this part of the thesis addresses the **main goals 2** and **3** with the corresponding subgoals as defined in Section 1.2. In Section 5, the *formal model* for eBR is presented, which is *evaluated* in Section 6. The results are published in (Kirchner and Drechsler, 2013b,a). Furthermore, in Section 6 results for the *online* application of eBR are briefly discussed. Correspondingly the results are published in (Kirchner et al., 2009, 2010; Wöhrle and Kirchner, 2014; Folgheraiter et al., 2011; Seeland et al., 2013b). In Section 7, the *relevance of multimodal signal analysis* for robotic-based rehabilitation and the direct control of robotic devices is discussed. It is shown that multimodal signal analysis, as supported by eBR, has the potential to improve human-machine interaction by enhancing its adaptiveness to application requirements. Presented results are published in (Kirchner et al., 2013a; Kirchner and Tabie, 2013; Kirchner et al., 2014). In Section 8, results of a study are presented that show that eBR can *improve human-machine interaction* even in case it is not used to drive an interaction but to adapt HMIs, i.e., for the *passive support* of an active exoskeleton that is applied for teleoperation. The results of this study are published in (Folgheraiter et al., 2012).

Finally *conclusions* are drawn in Part IV in Section 9 and an outlook is given for *future work* in Section 10.

# Chapter 2

# Theoretical Background

In this chapter an overview is given about relevant background information about physiological signals (Section 2.1), the used signal processing (SP) and ML framework and procedures for single-trial ML analysis (Section 2.4), as well as relevant work in related fields (Section 2.2 and 2.3).

## 2.1 Suitable Brain-Activity Measures

In the following an overview and comparison is given about different methods that allow to record brain activity. Furthermore, the suitability for their application in humans to support human-machine interaction in robotic application scenarios is discussed. To measure the activity of the brain two principle approaches are possible:

1. the *direct* approach, i.e., to measure the electrical activity of the brain and
2. the *indirect* approach, i.e., to measure changes in other measures that are correlated with the electrical activity of the brain.

Correlated measures that are applied for the *indirect* approach are for example electromagnetic activity measured by magnetoencephalography (MEG) or changes in blood flow or blood hemoglobin concentration measured by functional magnetic resonance imaging (fMRI), positron emission tomography (PET) or functional near-infrared spectroscopy (fNIRS).

MEG signals were first recorded by Cohen (1968). By this method magnetic fields are measured that are generated by electric currents. Magnetics fields are naturally produced by the brain, i.e., by ionic current flowing in the dendrites of neurons during synaptic transmission (Okada, 1983). They are counted as indirect measure of brain activity. However, they are of very low power and, hence, require very sensitive magnetometers to be detected and extensive magnetic shielding from external magnetic fields, including the Earth's magnetic field. Due to its *demanding requirements* on

the *recording equipment* and *environment*, MEG is not well-suited to be applied in robotic applications.

Like MEG signals, fMRI, PET and fNIRS are also indirect measures of the brain's activity. With these methods *changes of blood flow* and the *brain's metabolism* are measured. Both fMRI and fNIRS measure changes in blood hemoglobin concentration, i.e., the hemodynamic responses that are associated with neuron behavior also known as Blood-Oxygenation-Level-Dependent (BOLD) response (Arthurs and Boniface, 2002; Logothetis, 2002). While fMRI techniques allow to record these changes also in deep brain areas, fNIRS is limited to the upper cortical tissue. Compared to fMRI, fNIRS is very easy to apply and recording can take place while the subjects are moving without distorting the signal. Hence, fNIRS would therefore in general be applicable for the support of robotic application scenarios and is already applied for BCIs (Birbaumer, 2006; Pfurtscheller et al., 2010; Birbaumer et al., 2006). PET is a nuclear medical imaging technique that makes functional processes visible by the help of radionuclide tracers (Phelps et al., 1975). This method can be applied for neuroimaging based on the assumption that higher radioactivity is caused by an increase in blood flow which again is correlated with an increase of brain activity. Since *radioactive substances* have to be used and, similar to fMRI, *highly complicated* and *oversized measuring equipment* is required, this method similar to fMRI cannot be applied on-site or mobile for the support of robotic devices, although it was shown that fMRI recordings can be used to remotely control a robot (Cohen et al., 2012). Moreover, compared to MEG, only a very *low resolution in time*, i.e., in the range of seconds (Huettel et al., 2009), can be achieved by fMRI, PET and fNIRS, caused by the fact that the indirect signal of changes in blood flow is *measured after the neurons were active*. Therefore, they are less suitable if upcoming interaction behavior shall be inferred.

The *electrical activity* of the brain can by means of the *direct approach* be measured in two ways:

1. invasively, i.e., inside the brain or on the surface of the cortex, and

2. non-invasively, from the surface of the head.

Invasive measurements can either be performed intracellularly or extracellularly. *Intracellular* measurements are usually restricted to experiments on cellular level, in brain slices or in anesthetized animals (Hubel and Wiesel, 1962). For intracellular recordings a very fine (and sharp) micro electrode must be inserted into the cell to measure the membrane potential and the generation of action potentials (Hodgkin and Huxley, 1939) in neurons. Action potentials are very short changes in the membrane potential and allow information transfer between neurons.

Invasive *extracellular* measurements allow to measure both high-frequency action potentials in form of spikes as well as extracellular field potentials, i.e., low frequency electric current. The field potential is a signal of the sum of post synaptic potentials that are generated by synaptic transmission (Zschocke, 1995). While intracellular recordings are restricted to the field of basic research, especially since they cannot be applied in conscious and freely behaving animals, extracellular recordings can be applied in conscious animals.

For extracellular recordings, usually not just one electrode but several electrodes (Gray et al., 1995) or multi-electrode arrays (Taketani and Baudry, 2006; Cheung, 2007) are implanted. Compared to single intracellular recordings the temporal order of neuronal activity can be analyzed (Louie and Wilson, 2001) and hence the coordinated activity across many neurons can be investigated (Lee and Wilson, 2004). With multi-electrodes it is not only possible to record the activity of several neurons of one brain area but also of *different brain areas simultaneously* (Siapas et al., 2005; Gray et al., 1995) to investigate their interaction. For applications, information about motor movements, such as positioning or velocity, can be acquired from recordings in the motor cortex. This information can be used to *drive prothetic devices by neuromotor protheses* as shown in monkey (Carmena et al., 2003) and human (Hochberg et al., 2006). However, the application of such systems that make use of invasively recorded brain signals is strictly limited to basic research questions in animal studies or for clinical purposes in human (Ulbert et al., 2001) and hence not suited to support healthy humans in robotic application scenarios.

The synchronized postsynaptic potentials (local field potentials) (Zschocke, 1995) can further be measured invasively but on the surface of the brain by *electrocorticography (ECoG)*. For this method the brains' electrical activity can be recorded on the surface of the brain either epidural (outside the dura mater) or subdural (below the dura mater on the surface of the cortex). Hence, it is not required to implant electrodes into the brain matter. However, by means of ECoG it is no longer possible to record single spikes, i.e., action potentials, of neurons, but synchronized postsynaptic activity of pyramidal cells of the cerebral cortex. Compared to the EEG (see Section 2.1.1), which is recorded at the surface of the head, it allows to acquire signals with a rather high spatial resolution of about 1 cm (Asano et al., 2005). The ECoG is mainly used for *signal source localization* in clinical applications, e.g., to better identify and localize regions in the cortex that generate epileptic seizures (Palmini, 2006). Due to its invasive nature it is not suited for application in healthy humans in order to support human-machine interaction.

### 2.1.1 Electroencephalography

Similar to ECoG, EEG allows to record low frequency electric current of the brain that is generated by synaptic transmission. However, compared to ECoG EEG can be recorded *non-invasively*. Since local field potentials can due to the similar spatial orientation of the pyramidal cells orthogonal to the surface of the brain sum up to strong synchronous activity that spreads through the extracellular milieu by volume conduction, EEG can be measured even *outside the skull* on the heads' surface.

EEG is recorded by measuring *differences in voltage between two electrodes* over time. Several of such recordings over time result in EEG. Electrodes for the recording of EEG are usually positioned in a standardized way the 10-20 system (Society, 1991) or an extended system with fixed relative distance to each other and to reference points on the skull, i.e, the nasion and both inions (an example for an extended 10-20 system see for example Figure 3.8 in Section 3.2) to allow the comparison of results of different studies. Today, mainly electrode caps are used for an easy positioning of the electrodes. Since EEG is always measured as a difference between two electrodes, a reference electrode has to be defined. Different *references* are used, like the nose, the ear lobs, electrodes at position Cz or other electrodes of the (extended) 10-20 system. Today it is common to calculate an average or common reference as mean EEG activity over all signals to again make results of different studies more comparable, since the shape of the signal depends very much on the choice of reference (Zschocke, 1995).

Compared to most of the above mentioned methods, EEG is a comparably old method for the recording of brain activity. Historically, for a long time it was unclear that the brain is indeed the organ which is the source for consciousness and the humans capability of mental planning and reasoning as well as for the weighting of possible consequences. Only briefly after the renaissance of autopsy and experiments with live animals and humans, methods and experiments were developed far enough to investigate the structure and function of the brain in more detail. At that time huge amounts of knowledge about the brain's function and structure was gained in relatively short time. Paul Broca ($1824 - 1880$) showed by his systematic research that different functions of the brain can be allocated to certain regions of the cortex. Richard Caton ($1842 - 1926$) first reported in $1875$ on electrical activity of the brain recorded from exposed hemispheres of mammals. Only five decades later in 1924 Hans Berger ($1873 - 1941$) recorded the first human EEG and published his results in his work "Über das Elektroenkephalogramm des Menschen" (Berger, 1929).

One of the first finding was that EEG, which is recorded over time, does differ depending on whether the subject is relaxed or concentrated. Under relaxed conditions, especially if the eyes were closed, the frequency of EEG waves is lower and the am-

plitude of EEG is higher ($\alpha$ frequency band) compared to conditions under which the subjects have to concentrate where EEG activity is dominant in $\beta$ frequency band. Table 2.1 gives an overview over different *frequency bands* as they can be found in normal EEG.

Table 2.1: Frequency bands of EEG. Boarders of frequency bands are reported as defined in Figure 3.1. of (Zschocke, 1995). Values in brackets report on alternative borders of frequency bands used by some authors.

| **name of frequency band** | **frequency range** |
|---|---|
| $\beta$ | $12.5(13) - 30(30)$/s |
| $\alpha$ | $7.5(8) - 12.5(13)$/s |
| $\theta$ | $3.5(3) - 7.5(8)$/s |
| $\delta$ | $0.5(0.5) - 3.5(4)$/s |
| sub-$\delta$ | $< 0.5$/s |

### 2.1.2 Event Related Potentials

With the introduction of simple averaging techniques, ERPs, which were first recorded from 1935 to 1936 by Pauline and Hallowell Davis in awake humans, could be found to be evoked by external or internal events (see Figure 2.1 for an illustration of the averaging technique and characteristics of raw EEG and averaged ERP signals). External events could for example be visual or auditory stimuli, whereas internal events are for example the planning of movements. Besides visually evoked ERPs, some early described ERPs were the contingent negative variation (CNV) (Walter et al., 1964) and the P300 component (Sutton et al., 1965). Most ERP components are referred to by the letter "N" or "P" for negative or positive, respectively indicating the *polarity* of the component and a number indicating the *latency* of the component in milliseconds or the ordinal position in the observed pattern, like N200 for a negative ERP at about 200 ms. However, the latencies for some of the potentials are quite variable. The P300 is such an example. This potential can occur under different conditions with a latency of 250 to 900 ms (Verleger, 1997).

While earlier externally evoked potentials mainly depend on the characteristics of the evoking stimulus itself and reflect the *physical processing* of it, later ERPs are caused by *internal processes* like attention, memory or expectations as well as mental states, to name some of them. Thus, ERPs can be used to investigate the physical processing of stimuli as well as the internal state of a human. Furthermore, ERPs can be used for clinical purposes. Some ERP components show abnormalities under some neurological conditions. For example in subjects with increased risk for

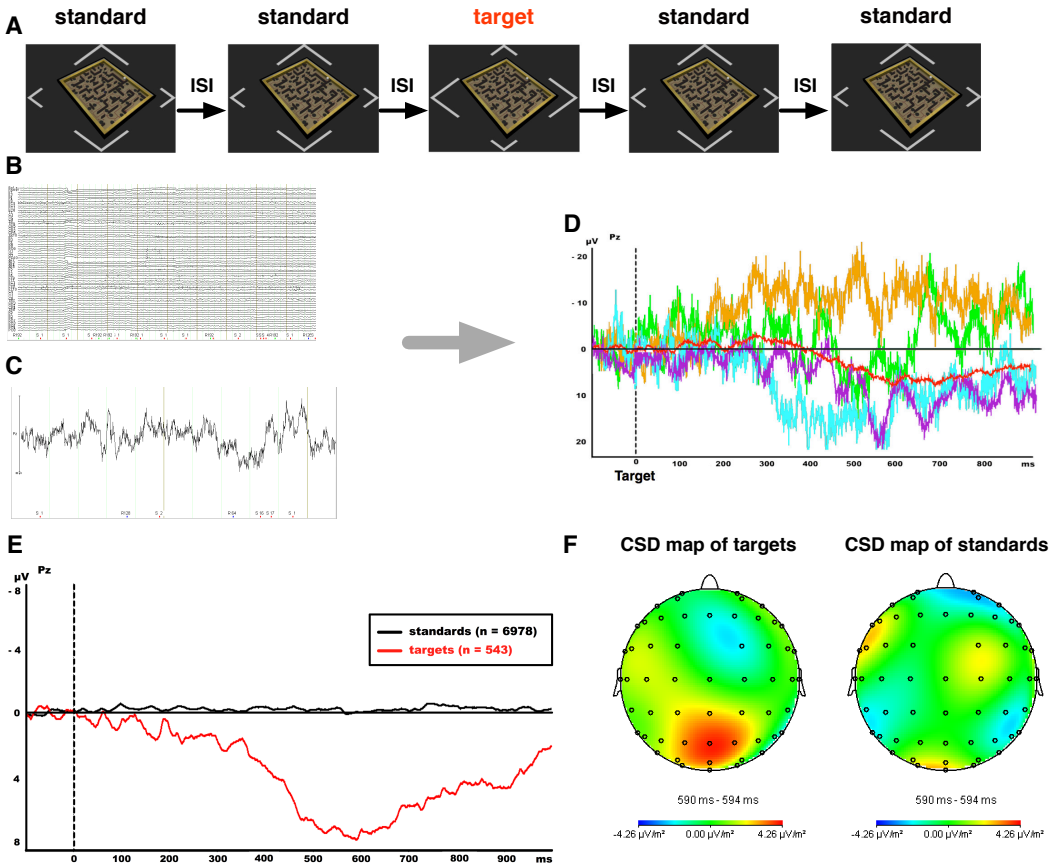


Figure 2.1: Event-related potentials and averaging. A: oddball paradigm: frequent stimuli (standards) are interleaved with infrequent stimuli (targets) that require a response of the subject (see Figure 4.3 for more details on the experimental *Virtual Oddball* setup). B: raw data: ongoing 64 channel EEG recording labeled with markers ("targets" and "standards") for the onset of the different stimuli. C: raw EEG data at electrode Pz, D: EEG epochs after segmenting the ongoing data with respect to the added *stimulus onset* markers. Only epochs containing the P300, i.e., epochs after the stimulus of type "target" are shown as raw signal compared to the averaged signal (red line). The small amplitude of the ERP that is contained in each epoch is overlaid by "background activity" and can only be seen after averaging the epochs of each type ("target" and "standard"), since correlated activity gets preserved, while unrelated activity is averaged out. E: Grand average activity in segments after standard and target stimuli. Average was calculated over all artifact free segments from all data of all subjects that took part in the *Virtual Oddball* experiment (see Section 4.1.1.1). Infrequent, task-relevant stimuli ("target", n = 543) evoke a stronger ERP P3 (Polich, 2007) than frequent stimuli ("standard", n = 6978) stimuli. F: current source density (CSD) map for averaged activity evoked by target and standard stimuli (red means positive, blue negative voltage). ISI: time between stimuli.

developing Alzheimer's disease, the amplitudes of the P50 on frequent stimuli and the P300 on infrequent stimuli in an oddball paradigm are significantly increased

compared to a control group (Boutros et al., 1995).

Like EEG, ERPs provide a *very high temporal resolution* especially if compared with fMRI, PET or fNIRS. Moreover, the temporal order of their appearance is directly correlated with underlying neuronal activity. Thus, based on the *temporal order* of ERP components statements about the temporal order of brain processes can be made and it can also be determined which stages, e.g., during the processing of stimuli, are affected by a specific experimental manipulation. Compared to behavioral measures, ERPs provide a measure even in case that no behavioral change can be observed or is not yet observed (Coles, 1989). However, since ERPs are usually of very small size, i.e., 10 to 100 times smaller in amplitude compared to "background" EEG (see Figure 2.1D), a large sampling size is usually required to measure them correctly by means of *averaging analysis* (Luck, 2005).

Opposite to the very high resolution of 1 ms or better, the *spatial resolution* of EEG as well as ERPs is very low, especially if compared to fMRI where a spatial resolution in millimeter range can be achieved. Due to this, it is extremely difficult to isolate a single ERP component from a complex of ERP components (Luck, 2005) or to localize their source, although source localization methods are available (Seeland et al., 2013a). Without making use of the averaging method, i.e., in case of single-trial analysis ERPs are extremely difficult to identify. Single-trial EEG activity in the ERP range cannot easily be distinguished for different classes. This is even true for a very stable ERP like the P300 as illustrated in Figure 2.1E and F. Even for the P300 individual single trials can by means of visual inspection not clearly be assigned to a specific class, i.e., standard or target, as illustrated in Figure 2.2.

Today, many *low cost* EEG recording systems are available and the application of electrode caps and recording of EEG is comparatively easy and fast. New electrode systems with active electrodes[1] that provide active shielding against artifacts allow an even shorter preparation while providing high quality data. Although artifacts, like movement, cardiac, eye or glossokinetic artifacts as well as environmental artifacts are a main issue in EEG recordings, *advanced SP* techniques like independent component analysis (Hyvärinen et al., 2001) and technical improvements of the recording system can minimize the problem to a degree that the recording of EEG is even possible during strong movements like sport activities. This and the possibility to apply supervised ML methods (see Section 2.4) for *single-trial ERP analysis* make EEG a very interesting method for the implementation of BCIs (Section 2.2) and BR (Section 2.3) and their application in robotics as further discussed in the following sections.

[1] see for example `http://www.brainproducts.com/productdetails.php?id=4`

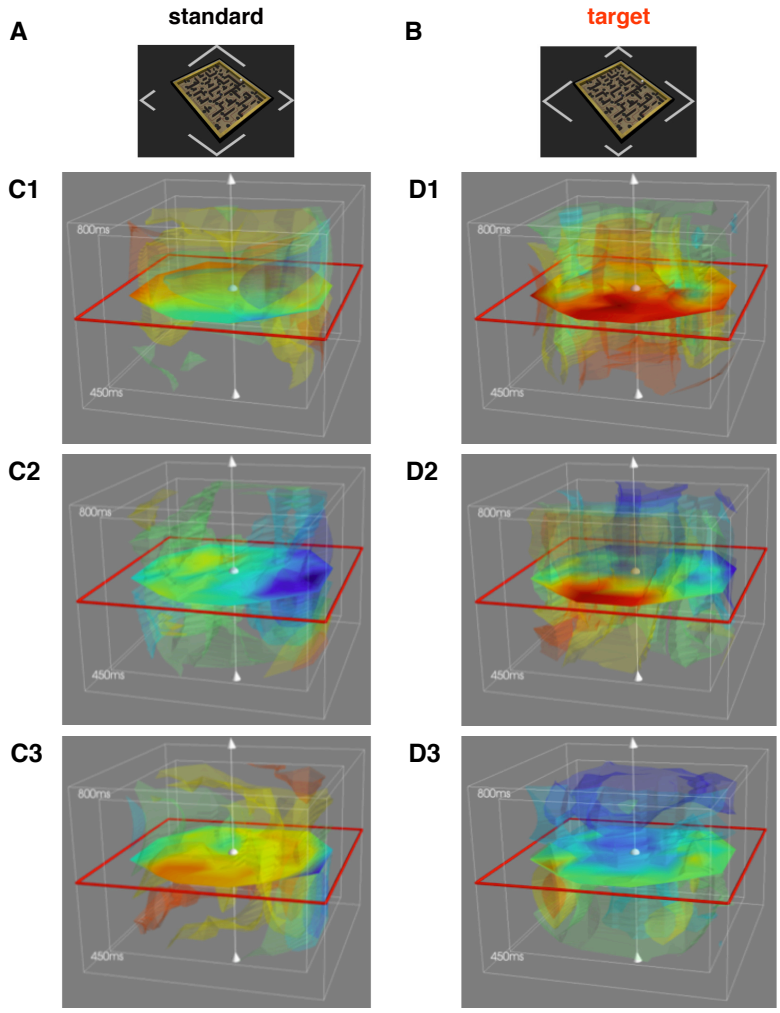


Figure 2.2: Single-trial event-related activity. A: frequent stimulus (standard) B: infrequent stimulus (target) (see Figure 4.3 for more details on the experimental *Virtual Oddball* setup). C: single-trial activity evoked by standards; D: single-trial activity evoked by targets; note that the third example for each condition C3 and D3 appears as if it would belong to the other class although this is not the case. EEG in C and D recorded by 64 electrodes is bandpass filtered with an FFT filter between 0 Hz and 4 Hz to concentrate the main energy of the P300 (discussion see Section 4.1.1.3). Data is illustrated for the time range of 450 to 800 ms after stimulus onset. The red square in each example indicates 650 ms after stimulus onset to highlight the point in time at which on average max. amplitude of the P300 is expected (see Figure 4.3E). The front side of the cube that bounds the filtered EEG signal refers to the back of the head of the subject, the side in the back to the front side of the head. Red means positive amplitude, which is on average maximal at parietal electrode sides, blue refers to negative amplitudes. Average activity at Pz as illustrated in Figure 4.3E is best matched by single-trial activity displayed in example D1.

## 2.2 Non-Invasive Brain Computer Interfaces

BCIs are often applied as an alternative to physical interaction and to *reestablish communication* (Wolpaw et al., 2002; Guger et al., 1999; Pfurtscheller, 2000; Birbaumer, 2006; Leeb et al., 2006; Enzinger et al., 2008; Blankertz et al., 2006a). The first BCIs were developed in the 1970s at the University of California Los Angeles (UCLA) (Vidal, 1973, 1977) and the expression "brain-computer interface" was defined. In the 1980s Lawrence Farwell and Emanuel Donchin developed their "mental prosthesis" that made use of the ERP P300 (Farwell and Donchin, 1988). This BCI, often referred to as "P300-speller" allows subjects, including paralyzed Locked-In syndrome patients (Kübler et al., 2001a), to communicate words, letters and simple commands. The P300-speller is implemented as follows: all 26 letters of the alphabet and some symbols are presented on a monitor. The letters and symbols are arranged in rows and columns which are repeatedly and alternately highlighted by changing, e.g., the brightness of the letters. A subject can choose a letter by focussing his attention on it. Whenever a row or a column gets highlighted that contains the chosen letter a P300 is evoked. The evoked ERP P300 can then be detected in the subject's EEG. This is usually done after enhancing the signal pattern, i.e., the P300, and reducing noise by *averaging* over several trials. In more recent years, *highly complex P300-based interaction* could be established, for example, to control elements in a virtual world, including turning lights on and off and stopping a mock-up car (Bayliss, 2003). Even *single-trial* detection of the P300 ERP component was shown to be possible and discussed to be applicable for BCIs (Li et al., 2011).

Other brain data than EEG data can also be used for the implementation of BCIs, like invasively recorded brain activity, MEG, fMRI or fNIRS data (Sitaram et al., 2007; Peplow, 2004; Birbaumer, 2006; Pfurtscheller et al., 2010). From those measurements EEG is used most often since it can be recorded non-invasively with comparably low cost and small recording devices with a high temporal solution. The latter makes EEG signals very suitable to be applied for *fast communication* (see Section 2.1). However, as stated before EEG data has a low spatial resolution and is very noisy, i.e., has a low signal-to-noise ratio. Due to the lack of advanced SP methods, early BCIs required the averaging of many trials (i.e., of signal instances that contain the hidden pattern) before the relevant pattern could be identified. Even by applying averaging methods, not all tested subjects were able to control a BCI by brain activity. To improve this situation, *biofeedback* was applied. By means of biofeedback a subject was able to adapt her/his brain activity to the requirements of the system (Barlow and Durand, 2004). The principle of biofeedback is to gain greater awareness of physiological functions (Schwartz and Andrasik, 2003), like the own brain activity. To enable biofeedback, instruments have to be applied that pro-

vide information about the physiological function that one is usually not aware of. For this reason, classical BCIs required biofeedback training sessions. During these feedback-sessions the subject gets a feedback about her/his brain activity and can *train her/his brain activity* to "produce" better, i.e., more suitable patterns, that can more easily be detected by the applied system. The drawback of the application of biofeedback is that the training sessions (i.e., feedback-sessions) that were required for this process could be very time consuming. Sometimes, days or even months of training were required (Kübler et al., 2001b). Moreover, not all subjects were able to learn to modulate their brain activity. People that show no or very poor performance in using a BCI are called *BCI illiterates* (Vidaurre et al., 2010).

With the introduction of ML methods it is now possible to implement BCIs that in principle no longer require biofeedback, i.e., to train to produce suitable brain pattern. Instead, learning takes place on the side of the algorithm that is later (after training) classifying the data. Thus, *training of the subjects is no longer required* but training data has to be recorded prior to each BCI application to train a classifier, unless online training is applied. However, the time that is required for training could massively be reduced from days and weeks to hours or even minutes. Furthermore, it could be shown that the number of BCI illiterates can be reduced by the application of special ML approaches (Vidaurre et al., 2010).

BCIs have not only been used for explicit information transfer in human-machine interaction, i.e, to implement interfaces for explicit communication and control, but recently also for implicit information transfer to improve man-machine interaction (Blankertz et al., 2002; Grimes et al., 2008; Zander et al., 2009; Haufe et al., 2011). Depending on whether a BCI is applied for explicit control purposes or to implicitly gain information about the user a categorization of BCIs into *active* and *reactive* BCIs for the control of devices and *passive* BCIs that are not used for the control of devices but to *passively* gain information about the user during interaction, which can then be used to change a device's or other HMI's function (Cutrell and Tan, 2008; Zander et al., 2010). While this definition focuses on the question of the BCIs' *purpose*, other definitions differentiate BCIs with respect to the question whether the user is *voluntarily controlling her/his brain activity* or not. If they control it actively, the BCI is defined as an *explicit* BCI, otherwise it is defined as an *implicit* BCI (George and Lécuyer, 2010). The definitions are not 100% equivalent as discussed later. However, in most cases active and reactive BCI are equivalent with explicit BCI and passive BCI are equivalent with implicit BCIs.

*Active* and *reactive* BCIs, which can also be referred to as *explicit* BCIs can for example be utilized to reestablish the ability of individuals that cannot use their motor system to communicate or are otherwise handicapped to interact explicitly with the environment. They can replace classical HMIs for the explicit control of devices like

a keyboard, a mouse or a joystick and are mainly developed to open up new ways of communication for disabled persons (Farwell and Donchin, 1988; Pfurtscheller, 2000; Guger et al., 1999; Wolpaw et al., 2002). The P300 speller from Lawrence Farwell and Emanuel Donchin (Farwell and Donchin, 1988) is an example for an active BCI that reestablishes communication. Recently, active and reactive BCIs are also used by healthy people (Allison et al., 2007), e.g., in BCI controlled computer games (Reuderink, 2008; Nijholt et al., 2008). The main drawback of this kind of BCIs is that the user has to *concentrate on the task of controlling* the device or his brain activity. Hence, the application of such BCIs typically requires a high amount of cognitive resources of the user. However, training can improve, even automate the control of such BCI and thus reduce the effort.

To extend the usage of EEG activity for physiological computing (Allanson and Fairclough, 2004) *passive* or *implicit* BCIs were developed (Zander et al., 2010; George and Lécuyer, 2010). They have their roots in several approaches in the past that focus on *user-state detection* (Zander et al., 2010). One well-known and controversially discussed application is the polygraphic lie detection (Committee to Review the Scientific Evidence on the Polygraph, 2003). Besides other physiological measures, like skin conductance, a lie detector can also be based on the detection of the ERP P300 (Farwell and Donchin, 1991) in EEG data. Here, implicit information is gained about the subject, i.e., it is distinguished between two user-states: (i) the user tells the truth or (ii) the user lies. The function of the "P300 lie detector" is based on the assumption that information, which is important to a potential lier, does evoke a P300 while other information that is unimportant does not. Hence, in case a person is asked, e.g., whether she/he knows a specific person, and she/he would answer "no" although the given information, like a photograph of a person or her/his name, evokes a P300, it can be assumed that she/he lies.

Since users of passive or implicit BCIs do not actively influence their brain activity, i.e., do neither voluntarily control a device by brain activity nor voluntarily produce brain activity, passive and/or implicit BCIs seem to be an appropriate tool to enable or improve *implicit information flow* in human-machine interaction. Recent approaches make use of such types of BCIs in this respect (see for example (Parra et al., 2003; Blankertz et al., 2002; Zander et al., 2009)). It was further proposed that passive BCIs can be integrated into more complex and realistic control systems, like emergency braking assistance in cars to improve its functionality (Haufe et al., 2011).

Finally, for a better support of humans it might be useful to combine different interfaces. It was already shown that an HMI, which can be a BCI, can be combined with a (second) BCI. The resulting interfaces are called *hybrid* BCIs (Pfurtscheller et al., 2010; Allison et al., 2012). In comparison to active or reactive BCIs, passive BCIs are discussed to be more easily applicable for hybrid BCI approaches than active

or reactive ones (Pfurtscheller et al., 2010; Zander et al., 2010) are.

## 2.3 Brain Reading

Brain Reading (BR) was introduced as a method to gain information about hidden processes and states of the brain, i.e., the *function of the mind* (Coles, 1989). While in (Coles, 1989) it is more generally discussed that brain activity can be related by BR to psychological and physiological events, it is further argued that BR can help to understand how brain activity relates to the sensory world (Cox and Savoy, 2003) or can help to understand how individual experiences are decoded in the brain (Haynes and Rees, 2006) as well as what a subject's conscious perception is (Haynes and Rees, 2005). One can summarize, that there is no uniform definition of BR. However, in all cases brain activity is analyzed with respect to questions of two main categories, i.e., to (1) questions about the *perception* of the external world or to (2) questions about *internal* (hidden) states and processes.

Most BR studies investigate fMRI data by means of multivariate statistical pattern recognition methods that include linear discriminant analysis (LDA) and support vector machine (SVM) to classify patterns of fMRI activations (see for example (LaConte et al., 2005) and (LaConte et al., 2003) for the application of LDA and SVM on fMRI data, respectively). Most BR studies on fMRI data do investigate *visual perception*. In these studies BR is applied to answer more basic questions like the perception of edge orientation (Kamitani and Tong, 2005) or questions that are related to more higher level processes like object recognition (Cox and Savoy, 2003). Furthermore, even whole image reconstruction can be done (Naselaris et al., 2009; Miyawaki et al., 2008). In (Cox and Savoy, 2003) it is shown that complex discrimination like 10-way discrimination of objects, i.e., categorization of objects into 10 possible categories, is possible by analyzing fMRI activity of the visual cortex by means of the above mentioned statistical pattern recognition algorithms. Besides answering questions about perceptual states in the visual domain, some studies can also be found to investigate related questions, like mechanism in the retrieval of visual memory (Polyn et al., 2005). Furthermore, in (Haynes and Rees, 2005, 2006) it could even be shown that BR can be applied to detect different *conscious perceptual experiences* of the human.

Not only fMRI data can be analyzed by BR but also EEG data. For example, in (Coles, 1989) it is already discussed that ERPs can be used as *markers for psychological and physiological events*. For example the LRP that precedes contralateral hand or arm movements can be used as a marker for the preparation of arm movements. To give another example for the usage of EEG data for BR, in (Suppes et al., 2009) it is investigated whether patterns in brain waves that are evoked by visually

or auditory presented words can be analyzed to answer questions about the hierarchical structure of language.

Consistently, for all given examples it can be stated that BR is a *passive* approach. It is a method that allows to investigate brain activity that is expressed under certain conditions to answer more fundamental but also specific questions about the *functioning of the brain*. The application of this method itself does not require extra cognitive resources from the user.

## 2.4 Machine Learning Methods for the Analysis of Brain Activity

In the field of artificial intelligence, supervised and unsupervised ML (Bishop, 2006) play an important role. ML allows to construct and study systems that can learn from data. For example, ML is applied to analyze and model raw sensor data (Langosz et al., 2011), to estimate internal states of robots (Thrun et al., 2005) and external states of the environment as it is, e.g., required for mapping and self-localization (Schwendner et al., 2013), to perform substrate classification (Kassahun et al., 2006), or to identify objects by learning of proprioceptive and exteroceptive data that is recorded while manipulating objects (Kassahun et al., 2006, 2007). Thus, ML deals with *representation and generalization*. A strength of ML methods is that they can be applied to analyze huge amounts of data to identify specific patterns while non-relevant data gets blinded out. However, the *performance*, i.e., effectiveness, of ML methods massively depends on at least two factors: (1) the distribution of training examples and (2) the ability of the chosen ML methods as well as SP methods to find and describe a complex spatial and temporal pattern (see Section 2.4.2). To achieve a high quality of training data, the chosen examples must be *representative* for the class. To choose the best SP and ML methods a systematic investigation of different methods and parameters has to be performed if relevant features are unknown. Since such systematic investigations can become quite extensive and time consuming even in case that an appropriate data processing and classification framework is applied (see Section 2.4.1), it is often useful to not just "blindly" analyze the data but to make the analysis dependent on assumptions about the data of the different classes and their features as it will be discussed and investigated in this thesis (see Chapter 3 and Chapter 4). This procedure does not only help to speed up the search, but to *learn* about the data and underlying brain processes.

A successful application of ML methods for the analysis of complex brain activity data requires sophisticated SP to remove artifacts and/or to reduce the dimensionality of the data. SP methods that are applied for the analysis of brain data, like

EEG data, were developed and applied for other purposes first, as for the localization of sound sources (Krim and Viberg, 1996; Sawada et al., 2003). Different SP methods were later developed for *artifact removal* in EEG data, like the regression method (Hillyard and Galambos, 1970; Verleger et al., 1982; Whitton et al., 1978) or the principle component analysis (PCA) (Berg and Scherg, 1991). Later, more advanced SP were applied in combination with ML methods for other areas in EEG analysis than artifact removal. For example, an approach for the analysis of human event-related brain dynamics (Makeig et al., 1996) combines a logistic infomax approach to perform independent component analysis (ICA) (Bell and Sejnowski, 1995) and an unsupervised neural network algorithm. In the recent years ML methods were increasingly used to search for *hidden information* in complex brain signals, as it can be recorded by, e.g., fMRI. For example, in (Haynes and Rees, 2006) ML was applied to answer questions about the conscious perception of humans by a method called "Brain Reading" (see Section 2.3). The application of ML methods for the analysis of brain data does not only increase in importance because of the advances in the development of measuring devices that allow to record increasingly complex data but also because of the todays understanding that all cortical areas of the brain are deeply interconnected via subcortical areas and their function can not be investigated und understood independently from each other. Hence, ML methods are increasingly applied to answer basic research question in neuroscience research about the functioning of the brain.

Besides their application to answer questions about the brains functioning, ML methods are applied to translate brain activity for machines as done by, e.g., implementing BCIs (see Section 2.2). The gained information can be quite complex and can even allow to control an artificial arm by the analysis of intracranially recorded brain activity in three dimensional space (Carmena et al., 2003; Hochberg et al., 2006). A further requirement for the choice of SP and classification algorithms for human-machine interaction purposes can be their *online* capability. This is especially relevant if an interacting system, i.e., an HMI or robotic system, should be adapted online with respect to a brain state, intention or upcoming behavior of the interacting human based on, e.g., classified EEG instances. Online capability does not only require a fast analysis and classification but often also the detection of specific brain patterns in individual EEG epochs, i.e.,single trials. Average analysis that is often applied in BCIs, e.g., for P300-based spellers (Schalk et al., 2004), has the advantage that the signal-to-noise ratio is increased, since the noise in the individual EEG epochs is not correlated and largely cancelled out by averaging (see Figure 2.1C). In contrast, *single-trial* analysis must deal with low signal-to-noise ratios, since the relevant information is typically significantly weaker (10 to 100 times (Luck, 2005)) than background activity and noise. Hence, sophisticated pre-processing and classification

methods are required to achieve good performance in single-trial classification.

In the following sections the SP and classification framework pySPACE (Section 2.4.1), which was used for all ML analysis that were performed in this work, typical single-trial SP and classification flows (Section 2.4.2) as well as performance metrics (Section 2.4.3) are described and discussed.

### 2.4.1 Classification and Evaluation Framework for EEG Analysis

The software framework (see Figure 2.3) used in this thesis for data acquisition and analysis consists of two main parts: an *EEG acquisition* infrastructure and the SP and classification framework *pySPACE* (Krell et al., 2013)[2]. The output of pySPACE is sent to an application via a transmission control protocol (TCP)-based protocol. Figure 2.4 illustrates the components of the software framework pySPACE in more detail. The software pySPACE allows automated comparisons of processing algorithms for offline time series data analysis and classification as well as online analyses. Hence, it is designed to suite both *online* processing of EEG data and *offline benchmarking* of SP and ML methods. The acquisition of data and its processing, as depicted in Figure 2.3, can take place on two different machines. Online capability is enabled by the application of fast algorithms and parallel processing of data segments or of individual EEG channels on multicore processors and/or graphics processing unit (GPU)-based architectures as well as on field programmable gate arrays (FPGA)s. Although pySPACE is a Python-based software framework, performance impairment of a scripting language[3] does not account here significantly since the computationally intensive algorithms are coded in a language that can directly be compiled in binary code, e.g., C++ (Kirchner et al., 2010).

The whole data processing in pySPACE can be defined in individual specification files (using YAML (Ben-Kiki et al., 2008)). Furthermore, the framework can be executed with the respective operations on several datasets at once. For the basic SP algorithms implemented in pySPACE, the node and flow concepts of the modular toolkit for data processing (MDP) software (Zito et al., 2008) were adopted. For example, pySPACE allows to specify a data processing procedure by means of a *data flow*, in which every processing step is modeled as a node. A sequence of nodes constitutes a (data-) flow. This allows to easily "plug together" different algorithms and to exchange one component of a flow by another in order to compare their relative performance. This is particularly useful for the empirical comparison of different preprocessing, feature selection, and classification methods. For evaluation purposes, different evaluation schemes (e.g., cross validation and metric calculation) are provided

[2]available at `http://pyspace.github.com/pyspace`

[3]see `http://raid6.com.au/~onlyjob/posts/arena/` for a comparison of performance of different scripting languages with C++

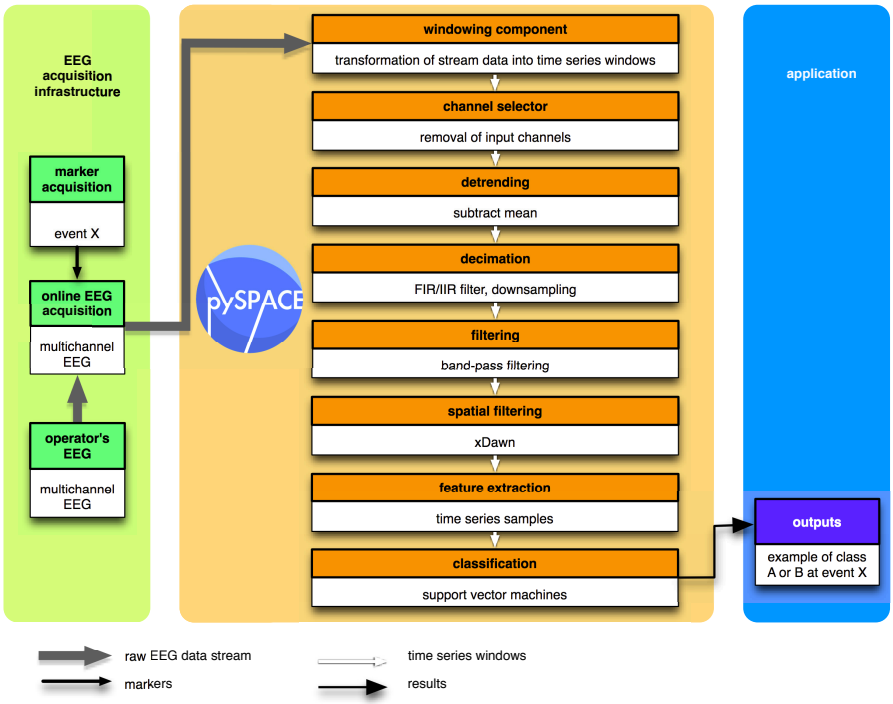


Figure 2.3: The data acquisition and processing framework pySPACE. Illustration of the structure of the data acquisition and processing framework and a typical example for a data processing flow in pySPACE that is used for single-trial ERP detection. Data can be streamed from the EEG acquisition infrastructure (or from data storage for offline analysis) to pySPACE as well as from pySPACE to an application over a TCP-based protocol.

in the framework and different evaluation results can be combined to one output file. This output file can then either be explored using external software or a graphical user interface provided within pySPACE.

### 2.4.2 Single-Trial Data Processing and Classification

In this thesis, single-trial classification of EEG instances is performed. EEG instances are segments of EEG data of a specific length that are obtained by windowing (see below). For data processing it must be distinguished between training and testing. In the *training* phase, a classifier is trained. This requires training examples, which are instances of EEG data that are labeled to belong to a specific class. In the *testing* phase, i.e., application, the trained classifier is applied. In the *testing* phase, data processing is structured as follows: (1) data acquisition, (2) windowing, (3) channel selection (4) signal preprocessing and feature generation, (5) classification and (6) possible post processing steps (see Figure 2.3).

EEG data is a continuous stream of the raw signal data, to which markers can be

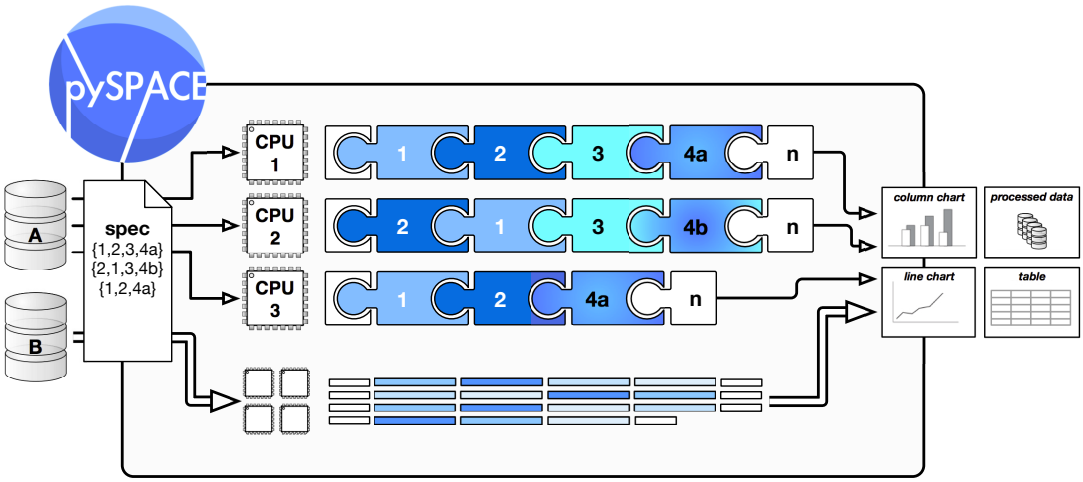


Figure 2.4: Processing scheme of a node chain operation in pySPACE. A and B are two different datasets, which shall be processed as specified in a simple specification file to allow automatic processing. Result of the analysis are new data or visualizations and performance charts. To speed up processing the different processing tasks can be distributed over several central processing units (CPU)s. The puzzle symbols illustrate different modular nodes, e.g., a cross-validation splitter (1), a feature generator (2), a visualization node (3), and two different classifiers (4a, 4b). They are concatenated to a node chain. Figure is based on Figure 3 of (Krell et al., 2013).

added to *label* specific events, such as stimulus presentation and subject's response. In an event-based analysis exactly one decision has to be made for each relevant event. All information that can be used for this decision is usually contained in a certain fixed time-range around the stimulus presentation. In this thesis, the process of extracting time windows, i.e., instances, from the continuously recorded EEG data is called *windowing*. Windowing simplifies computation, since it allows to work on instances of the same shape (length of the signal window). The windowing component can be configured by means of a configuration file, in which rules are defined that specify when to extract a window. For instance, whenever an important message is issued to the operator, a *marker* is inserted into the EEG. A typical rule for the windowing component would be to extract 1 second of EEG that follows such a marker. The marker does hence label the window, i.e., instance to belong to one class. Individual windows can overlap. The windowing of the recorded EEG data is relevant since instances of EEG data have to be processed and classified.

Before the instances are further processed an optional *channel selection* can be performed. For example it is possible to reject EOG or EMG channels that may be recorded together with the EEG or very noisy channels that may influence performance. Sometimes channels are removed for evaluation purposes, as depicted in Figure 10.3 in Section 10. After this optional channel selection step, data processing

can be subdivided into preprocessing, spatial filtering, feature generation and post processing. *Preprocessing* refers to operations aimed at increasing the signal-to-noise ratio. This is highly relevant for classifications based on single trials, where averaging cannot be performed since a prediction for each individual relevant point in time must be made. However, it requires some assumptions on which components of the time window are considered useful and which are considered as noise. In the thesis the recorded data is preprocessed as follows: usually the data is *detrended* first by the channel-wise subtraction of the mean signal value of the given window. This is followed by a *decimation* with an anti-aliasing filter to reduce the sampling rate. Afterwards, a *band pass filter* is applied to remove unwanted frequencies while retaining the sampling rate.

For example, for the detection of ERPs (see Section 2.1.1), only frequencies in the low range, i.e., below 4 Hz, are required to achieve best classification performance (Jansen et al., 2004; Ghaderi et al., 2014). Such filtering, eliminates or at least strongly reduces artifacts of higher frequency like muscle artifacts and noise induced by technical devices. On the other hand, eye artifacts contribute to the recorded signal in this low frequency range and can therefore not completely be removed by the applied filtering methods. To avoid eye artifacts in general, subjects usually have to focus on a fixation cross presented by, e.g., a monitor, while the EEG is recorded. Using this, the occurrence of eye artifacts can be reduced, so that the classifier cannot reliably base its prediction on these (Ghaderi et al., 2014). However, such controlled conditions are not always possible and *eye artifact removal* may be applied as an additional preprocessing step (see (Ghaderi et al., 2014) for a survey on eye artifact removal methods for single-trial classification).

After the above mentioned preprocessing steps, often *spatial filtering* is applied. Spatial filters (SF)s operate in the spatial domain to reduce noise, i.e., to combine relevant information contained in all channels in pseudo or virtual channels that then contain relevant information from different sources or sensors. Depending on which characteristic of the data should be amplified, different SF can be applied. The common spatial pattern (CSP) filter (Koles, 1991) is usually applied to amplify time-frequency dependent characteristics, while the xDAWN (Rivet et al., 2009) amplifies certain spatio-temporal properties of signals and is therefore especially designed for enhancing the synchronous response of ERPs. Alternatively, a spatial filter ($\pi$SF) can be applied to improve the detection of, e.g., the ERP P300 (Ghaderi and Kirchner, 2013a,b). The $\pi$SF was developed based on the assumption that brain responses to the same stimulus are of very similar shape. Hence, the sequence of all EEG responses that are evoked by the same kind of stimulus has a hidden periodicity that can be enhanced. The transformation that is performed by the $\pi$SF allows to project the relevant data into a lower dimensional subspace. More information about

methods that can be applied for signal analysis of electrophysiological measures can be found in (Bashashati et al., 2007).

Since classification algorithms typically operate on *feature vector data*, the preprocessed instances have to be transformed with at least one feature generator to a feature vector. Finding features that are not strongly influenced by variances in the data is important since it increases the probability that a classifier trained on these features achieves a good performance also under conditions that have not been tested during training. Possible types of features are the power of a certain frequency band in a certain channel, the correlation of two channels within a certain time interval, or - for the detection of ERPs - the voltage of a channel at a certain point in time (as for example applied in (Metzen et al., 2011b,a)). Alternatively, local straight lines, a special form of local polynomial features (Grabocka et al., 2013), that are obtained by fitting short segments of the filtered signal of each channel's data and using their slopes as features can be applied for the detection of ERPs (Ghaderi and Straube, 2013; Feess et al., 2013).

Finally, during the test phase a *classifier* is transforming the obtained feature vectors to *predictions*. For example, a SVM as implemented in LIBSVM (Chang and Lin, 2011) (SVC-C with a linear kernel), or an online classifier like the Passive Aggressive (PA) algorithm (Crammer et al., 2006), which can also be used in FPGAs (Wöhrle et al., 2013c), can be applied. Additionally to the above mentioned processing steps, postprocessing can be applied before and after classification, like the normalization of feature vectors before classification or score mapping to predictions scores after classification (see for example (Straube et al., 2013)).

### 2.4.3 Performance Metrics

The performance of a classifier has to be evaluated to determine whether, for example, a change in parameter space, different choices of training data, or the application of adaptive methods improves classification. When evaluating preprocessing and feature extraction methods in combination with a classification algorithm on test data, a confusion matrix (Ting, 2010) can be calculated showing the frequencies of true and false positive ($TP, FP$) and true and false negative ($TN, FN$) predictions on the test data. A straightforward and often used metric is the *accuracy (acc)*, i.e., the rate of correct decisions, defined as:

$$\text{acc} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{2.1}$$

The accuracy is, however, only an appropriate metric, if the class distribution is balanced. Quite often this is not the case: especially in natural environments, but often also in experimental setups like the oddball paradigm (see Section 4.1.1.1), the

class distribution is unbalanced as discussed in (Straube et al., 2011; Straube and Krell, 2013). For *unbalanced classes* metrics that are sensitive to class distribution, like accuracy, F-measure and mutual information (MI) should not be applied, if the classifier was trained on a classes with class distribution that differs from the class distribution during test. Alternatively, measures like balanced accuracy (BA) or the

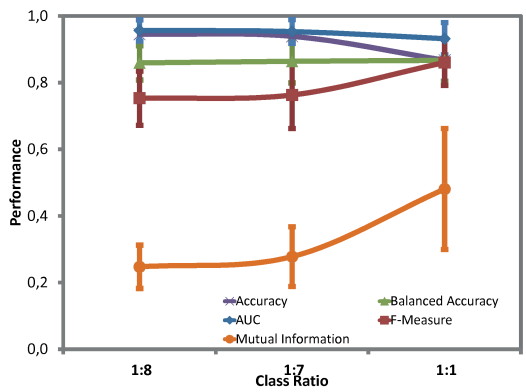


Figure 2.5: Comparison of different performance metrics with respect to their class distribution sensitivity. It can be seen that AUC and BA are not sensitive to changes in class distribution between training and test, while accuracy, MI and F-measure are. Source: (Straube et al., 2011).

area under the receiver operating characteristic curve (AUC) should be applied (see Figure 2.5 for comparing sensitivity of performance measures with respect to class distribution).

The AUC (Hanley and McNeil, 1982) is an indicator of *general separability*, i.e., of how well the classifier can separate the two classes. The AUC maps the different true positive rates (TPR) and false positive rates (1-TNR) obtained when the decision boundary is varied from $-\infty$ to $\infty$ onto a single scalar value. The AUC is then computed as the integral of the resulting function.

The BA (Brodersen et al., 2010) is the arithmetic mean of true positive rate (TPR) and true negative rate (TNR) and therefore calculated by

$$\mathrm{BA} = \frac{1}{2}\left(\mathrm{TPR} + \mathrm{TNR}\right). \tag{2.2}$$

It is used for evaluating the performance of a specific classifier. For both metrics, AUC and BA, a value of $0.5$ means guessing and $1$ means perfect classification.

# Part II

# Brain Reading - Detection of Specific Brain States

Brain Reading (BR) is in this thesis defined as the decoding of brain activity into information on the user's brain state, independent of whether this brain state is correlated with conscious or unconscious processes (Kirchner et al., 2009, 2010; Kirchner and Drechsler, 2013a; Kirchner et al., 2013d). The detected brain states are not artificially produced by the interacting human for, e.g., communication purposes, but naturally or passively "evoked" during normal interaction behavior.

Given this definition, it can be argued that BR is implemented in passive BCIs. For example the detection of error-related potentials is often used for passive BCIs to, e.g., correct commands that were likely wrong since after their execution an error-related ERP could be detected in the EEG of the interacting human (Zander et al., 2010). Hence, for such BCIs the brain state of "error detection" is detected by means of ML methods. Moreover, it can further be argued that also in most active BCIs, BR is applied. For example in a P300-based speller the brain state of "target recognition" is detected in the EEG in case a letter that a user wants to choose gets visually highlighted (see Section 2.2, P300 speller (Farwell and Donchin, 1988)). The difference between both given examples, the P300-based speller and the passive BCI for error detection, is that the relevant brain state is either actively produced for the purpose of communication or control as it is the case for active BCIs, or not as in the case of passive BCIs. Furthermore, the current brain state may be detected by single-trial analysis (as in the case of the passive BCI for error detection) or after averaging of several trials of EEG data (as often the case in active BCIs). Besides these differences, in both BCI classes specific brain states are detected.

Thus, BR can be seen as the basis for both BCI approaches, if defined as above. Only some active BCI approaches such as BCIs based on steady state visually evoked potentials (SSVEP)s (see for example (Valbuena et al., 2007)), where specific frequencies in the EEG recorded over visual areas are detected that are evoked by visual stimuli of the same frequency, may be considered to be not based on BR. In case of SSVEP-based BCIs the characteristic of visual areas of the brain to spontaneously adapt their frequency (in a determined frequency range) to specific frequencies of presented visual stimuli is plainly used to implement an interface but no specific brain state, that would usually be evoked under certain natural conditions, is detected. SSVEP-based BCIs simply make use of an intrinsic characteristic of visual areas.

Although for some applications where BCIs are used to establish or reestablish communications, like in medical applications for people that are otherwise unable to communicate (Birbaumer, 2006), the artificial production of brain activity for communication is expedient. Such an approach is not suited for most applications with healthy subjects in complex application scenarios (Izzo and Rossini, 2009), unless for some applications where subjects do not care about extra cognitive load, as for gaming purposes (Nijholt et al., 2008). To support complex interaction in robotic applications

only the detection of brain activity that is naturally produced during interaction is useful, since this would not increase cognitive load on the subject. It is shown that understanding the brain's functioning is important to *passively*, i.e., without extra involvement of the interacting human, detect specific brain states that are naturally involved or evoked during interaction by means of BR. The knowledge that is gained by BR about relevant brain states can then be used to support interaction.

Before showing how BR can be integrated into a robotic application scenario to support interaction (see Part III), in this part of the thesis it is shown that specific brain states can indeed be passively detected while a person is interacting in complex and demanding scenarios (see Chapter 3). Since for a robotic application scenario we want to detect a specific brain state at a relevant point in time, and not only a general state of the human as it is often done by physiological computing (see Section 2.2), BR must furthermore be applicable online and in single trial as discussed in Chapter 4. In summary, both chapters contribute to the **Main goal 1** of this thesis: "Development of an approach for the *context-aware* passive or active support of an operator or user of a robotic system or interface based on the contextual *passive* analysis of brain signals (like the human EEG)". Furthermore, since in both chapters training scenarios are developed to investigate brain activity during complex and demanding human-machine interaction they both contribute to **Subgoal 1a**. While Chapter 3 focusses on **Subgoal 1b** by investigating whether known brain states are reliably evoked during complex human-machine interaction tasks, Chapter 4 contributes to **Subgoal 1b** by showing that these known brain states are related to brain activity which can be detected in single trial. Chapter 4 does moreover contribute to **Subgoal 1c** by developing training approaches for BR that can handle few training examples.

# Chapter 3

# Event-Related Potentials Correlated with Brain States

Some challenges for applying BR for the detection of specific brain states during human-machine interaction in complex robotic application scenarios must be addressed to enable single-trial based BR as described in Chapter 4. Two main challenges are investigated here:

1. BR must be applied on EEGs recorded from subjects that are interacting in *complex and demanding robotic application scenarios*. The recorded EEG will, therefore, likely be very noisy due the artifacts from the interacting robotic system and control computers as well as motor activity of the operator caused by the interaction. Hence, in the following sections it will be evaluated, whether it is at all possible to reliably detect specific, known brain activity in the operators' EEG under such conditions.

2. The operator will likely perform *several tasks at once* within a given application scenario. To support different tasks, it must not only be detectable which task an interacting human is currently addressing or will perform to better support him, but furthermore whether she/he is changing her/his task. Hence, brain activity that is correlated with the intention of a subject or a change in task will be investigated with respect to their reliable occurrence in complex and demanding interaction scenarios in Section 3.1 and with respect to the effort and amount of intention that the subject invests into her/his task in Section 3.2.

## 3.1 Recognition of Task-Relevant Stimuli and Task Coordination Processes

A successful execution of multiple tasks during human-machine interaction in a demanding robotic application scenario requires an efficient strategy of attention division, the detection and evaluation of important, *task-relevant* information, retrieval of intended action from long-term memory, post-retrieval monitoring, and task-coordination processes characterized by several overlapping ERPs (West, 2011). Brain states that are related to target recognition processes and processes that are involved in task set changes are of special interest since strong and widespread ERPs are expected to be evoked by these processes as shown by investigations of target recognition (see (Polich, 2007) for review) or dual-task performance (Isreal et al., 1980; Bisiacchi et al., 2009) as well as retrieval of prospective memory (PM) and configuration of PM tasks (Bisiacchi et al., 2009; West, 2011).

Compared to "classical" EEG studies that investigate brain processes, under controlled conditions with the goal to understand underlying processes the study presented in Section 3.1.2 focuses on the detection of differences in ERP activity under simple-task and dual-task condition that are less controlled and copy the interaction of a human in a robotic tele-manipulation scenario. The goal is to identify relevant and (even more important) stable patterns in the EEG that are related to specific brain states and can likely be detected by BR. In Section 3.1.1 an overview of ERPs that give insight into the capabilities of the brain to identify *task-relevant* stimuli, to remember tasks and to switch between tasks is given. It is further discussed which ERP components might be relevant for human-machine interaction in demanding interaction scenarios and why they might be detectable in single trial by BR (see Chapter 4).

### 3.1.1 Positive Parietal Event-Related Potentials

It is well known that the ERP P300 is evoked whenever the brain detects stimuli that appear infrequently in the user's subjective perception. The P300 is a very stable ERP complex with strong amplitudes often applied in classic BCI applications (Farwell and Donchin, 1988) but also used to control very complex interaction scenarios (Bayliss, 2003). The P300 is evoked independent of stimulus modality, although some differences between P300 potentials evoked by different modalities, i.e., between visual and auditory evoked P300 potentials (Shelley et al., 1996; Duncan, 1988), can be found.

Several sub-components of the positive P300 are identified, like the novelty P3, the P3a and the P3b (Squires et al., 1975; Verleger et al., 1994; Polich, 2007). While

the novelty P3 was found to be evoked by stimuli that are *novel* and *unexpected* by the subject, the P3a was found to be evoked by *subjective infrequent* stimuli, and the P3b component was found to be evoked by infrequent *task-relevant* stimuli. Based on these findings, the P3a is thought to be "produced" by early attentional processes (Polich, 2007), while for the P3b it is assumed that this ERP component is not only an indicator for attentional, but also for early cognitive processes. It is evoked by processes that involve memory (Polich, 2007), i.e., target evaluation and target recognition processes (Kutas et al., 1977; Salisbury et al., 2001; Kirchner et al., 2009; Polich, 2007). In accordance to the involved brain processes, the novelty P3 and the P3a are frontally pronounced, while the P3b has its maximum amplitude at parietal central electrode sites. Peak latency for the P300 and especially for the P3b is not exactly at 300 ms as suggested by the name of the potential but shifts with respect of the complexity of the cognitive task that is required to evaluate the task relevance of a stimulus (Kutas et al., 1977).

The amplitude of the P3b does not only depend on the subjective impression of the frequency of occurrence of stimuli, but also on the importance, i.e., task relevance, is further supported by studies that show that a reduction of the amplitude of P3b can be found in case of ambiguous stimuli for which relevance and importance might not be clear. These results suggest that the P3b can be used to predict whether the subject understood the meaning (task-relevance) of a stimulus or given information (Johnson, 1986). In case that a subject misses an important stimulus it is further assumed that no P300 is expressed (Rolke et al., 2001).

The P300 was further shown to be applied as a measure of workload under dual-task conditions. It was shown that the amplitude of the P300 decreases with the increase in importance of the other task, i.e, the increase in the subjects' attentional and cognitive resources that were requested by the other task. For example Isreal and colleagues (Isreal et al., 1980) combined a visual monitoring task and an oddball discrimination task (Picton, 1992) and found that the P300 amplitude in the oddball task decreases the more difficult it became to solve the monitoring task. Further, many studies that compared the P300 that is evoked under single and dual-task conditions found a reduction in amplitude of the P300 from single to dual-task condition (see review in (Kok, 1997)).

Under dual-task condition besides the P300 other ERP activity is evoked in case that a *task-relevant* stimulus is recognized and requires the subject to remember to perform an intended action, i.e, a specific self-initiated task, that is embedded in the ongoing task and hence requires a change of task set (Bisiacchi et al., 2009; West et al., 2003; West, 2011). The additionally evoked ERP components are related to brain processes involved in PM. In PM-task experiments a specific ongoing task is usually performed that requires for example to respond to ongoing stimuli in a cer-

tain way, i.e., by pressing predefined keyboard keys. A second task, the PM task, also requires a specific but different response from the subject. This second task has to be performed whenever a specific stimulus, the PM cue, is presented that reminds the subject to perform the PM task. The PM task differs from the ongoing task, but both usually require a response or at least some performance of the subject. For example, the ongoing task could be rating words into categories by pressing different, predefined keyboard keys, while the PM task could be to press another key whenever a specific word (PM cue) that is different to the ongoing word stimuli is presented (Bisiacchi et al., 2009).

Dual-task performance is highly relevant for human-machine interaction in real robotic applications. For example, during the teleoperation of, e.g., a robotic arm, the teleoperation itself can be considered as an ongoing task, while responding to, e.g., warnings, as second task can be considered as the PM task. When a warning is presented, the operator has to remember what has to be done as a response. Further, he has to initiate the appropriate response. In contrast to most experimental PM task settings the ongoing task in the given example, i.e., tele-manipulation scenario, does not require specific predefined ongoing responses to specific predefined ongoing stimuli. The ongoing task, i.e., the teleoperation of the robotic arm, is to a very high degree uncontrolled and depends on the specific interaction task that is performed. But also other conditions might differ from a classical PM-task paradigm or at least cannot be kept controlled under natural interaction conditions. For example in (Bisiacchi et al., 2009) it is discussed that in PM-task experiments it is in most experimental settings not controlled, whether a subject has to perform the PM task right away as soon as a PM cue appears, or not. Hence, it is not defined whether the subject has to switch the task (perform a task switch), or is allowed to first perform or finish the ongoing task. However, the experiments performed in (Bisiacchi et al., 2009) showed that it does make a difference which task is performed first. A miss match negativity was only evoked if a task switch was required (i.e., the PM task has to be performed right away).

Such restrictions in the order of the subjects' behavior cannot be assumed under natural interaction conditions. During tele-manipulation one can think of the ongoing task, i.e., to manipulate the robot, to consist of many smaller tasks, such as to take control of the robot, lead it to a certain position, grasp an object and so on. It depends on the operator, whether he will right away respond to the PM cue (warning) or finish one of the subtasks first. This example points out that during natural behavior some conditions that might be kept controlled in a specific experimental setting and evoke certain differences in EEG activity, like the expression of a miss match negativity (Bisiacchi et al., 2009), might not be reproducible and hence not detectable during natural interaction behavior.

The given example points out that besides choosing known brain activity that is relevant with respect to the interaction behavior, it is further important to search for stable and characteristic brain activity. Such reliable known brain activity should always be evoked in case a certain interaction condition is present and should be insensitive to smaller changes in behavior. Only then it can be correlated with a specific brain state that is involved in natural interaction behavior. In case of target recognition, the P3b is not only relevant but should always be evoked by task-relevant stimuli and can be considered as a stable ERP. During interaction, and as prerequisite of target recognition processes, other earlier ERP activity like the N2 and their sub-components (Patel and Azzam, 2005) may also be evoked depending on specific conditions. For example, an N2a with an anterior cortical distribution might be evoked by either conscious attention, or ignoring of a deviant stimulus, while an N2b with a central distribution can only be found in case of conscious stimulus attention and appears usually in association with a P3b. But also other sub-components like the N2c at frontal and central electrode sides which are evoked during classification tasks, or the N2pc which is evoked in visual search task as index of attentional shift and can be found at occipital-temporal regions lateralized to the side contralateral to which the visual attention is shifted, can be differentiated. While in complex interaction tasks several of these sub-components can be evoked which may even overlay and thereby cannot clearly be used to define specific brain states, the P3b is a good indicator for target recognition processes and should hence be usable for detecting the brain state of "target recognition" by BR.

EEG activity that is a reliable indicator for PM-task related processes must also be identified: compared to ongoing activity trials, in PM trials an N300 is evoked that is thought to be associated with the detection of the PM cue. It is usually associated with a frontal positivity and can be distinguished from the N2b that is often evoked in oddball tasks (see above). However, differentiation from the N2b is not easy and only possible under very controlled conditions (see for example (West, 2011) for discussion of differences in both early potentials). Especially if both, target recognition and PM-related processes are involved at the same time as it is the case in the given example, i.e., the tele-manipulation scenario, it is likely not possible to differentiate between both potentials. Consequently, this early activity is not suited to differentiate between both discussed brains states, i.e, "target recognition" and "task set change" which are related to PM processes.

Besides the N300 and associated frontal positivity a parietal positivity can be found to be elicited in PM trials. This parietal positivity has at least two subcomponents, the P3b and the prospective positivity. Although more components can be found under certain conditions (see (West, 2011) for an overview and discussion), for our application case, i.e., teleoperation of a robotic arm, these two components are

most relevant. The P3b (discussed above) is evoked by processes that are involved in the recognition of target stimuli while the prospective positivity is discussed to be related to later processes, i.e., the configuration of the PM-task set (West, 2011). In (West and Wymbs, 2004) it could clearly be shown that both processes are distinguishable from each other under controlled experimental conditions. It was shown that the P3b begins at 300 to 400ms after the stimulus onset and is therefore clearly earlier in time than the prospective positivity which starts at 600 to 800ms (West, 2011). Since the prospective positivity is thought to be related to the configuration of the PM-task set, it can be seen as an indicator of the brain state of "task set change". This again is relevant during interaction to infer whether an operator might respond to a recognized PM cue (here equivalent to a target stimulus, e.g., warning) or not.

In summary, it can be concluded from literature that in a robotic application like the teleoperation of a robotic arm it can be expected that both, "target recognition" as well as processes involved in "task set changes" are reflected by pronounced ERP activities at parietal electrode sites. These pronounced ERP activities should be detectable in single trial by BR. That the above mentioned ERP components, P3b and prospective positivity, are indeed evoked during demanding and less controlled dual-task performance during human-machine interaction and that they can be differentiated to potentially allow to distinguish between both brain states "target recognition" versus "task set change" by BR is investigated in the study presented next.

### 3.1.2 Experimental Part - P3b and Prospective Positivity under Dual-Task Condition

To simulate a dual-task condition under less controlled conditions the experimental setting *Labyrinth Oddball* was developed in this thesis (see Section 3.1.2.1). The task in the experimental setting that requires target recognition, like the recognition of warnings that might be presented in a tele-manipulation scenario, was simulated by a visual oddball discrimination paradigm (Picton, 1992), where frequent stimuli are randomly mixed with infrequent stimuli. The infrequent stimuli, might, depending on the experimental setting, be task relevant. The oddball discrimination paradigm is not only well investigated and understood with respect to underlying brain activity, cognitive processes and evoked ERPs (Polich, 2007), but also widely used for EEG-based interaction, like the P300 speller (Farwell and Donchin, 1988). The experiments were performed under two conditions: first, the visual oddball was performed without a second task (*simple task*: visual discrimination oddball task) or, secondly, subjects were performing an additional continuous sensor-motor, i.e., manipulation task (*dual task*: oddball task while playing a labyrinth game (a modified BRIO® labyrinth was used, see information given below)). It is not clear whether EEG ac-

tivity that is evoked during dual-task performance under controlled conditions can be identified in the EEG which is recorded while a subject is performing in a demanding application scenario and hence is investigated in the presented study. Text, figures and tables of the following sections are taken and partly changed or adapted from (Kirchner et al., 2013c) (under review). A preliminary study in a similar setting as used here and its results is published in (Kirchner et al., 2009). Preliminary results of the study presented here are published in (Kirchner and Kim, 2012; Kirchner et al., 2013b).

#### 3.1.2.1 Experimental Setup and Procedure

The developed experimental setup *Labyrinth Oddball* is depicted in Figure 3.1. The experimental setting is designed to emulate a robotic human-machine interaction scenario, like a tele-manipulation scenario. Therefore, it is not completely comparable to classical PM-task or dual-task designs (see for example (Bisiacchi et al., 2009; West, 2011; Isreal et al., 1980)). It has hence to be stressed that a *direct* comparison of EEG activity evoked in this experimental design with EEG activity evoked in other dual-task or PM-task studies is only possible to a limited extent.

Thirteen subjects (age: 27 to 39 years; right-handed; normal or corrected-to-normal vision) participated in the study (see Figure 3.1). Subjects performed two experiments: a *simple-task* and a *dual-task* experiment within two counterbalanced sessions that were performed on the same day. In each experiment, subjects performed a visual discrimination *oddball task* and responded to infrequent, *task-relevant target* stimuli (randomly mixed among frequent, *task-irrelevant standard* and infrequent, *task-irrelevant deviant* stimuli, i.e., distractor stimuli which were similar to the task-relevant stimuli but required no response and did therefore also not interfere with the main task (playing the modified BRIO® labyrinth game). Stimuli were presented for 100 ms on a monitor that was placed right behind the game with a ratio of 1:12:1 and an ISI of 900 and 1100 ms. The required response was to press a buzzer that was positioned at the left side of the game. To press the buzzer, subjects have to stop playing the game with their left hand. The visual appearance of stimuli and number of stimuli presented per stimulus type and per task condition is illustrated in Figure 3.1.

During the *simple-task* condition, subjects were asked to hold both knobs of the labyrinth game while focusing on a ball placed in the middle of the game board. This behavior was requested to keep both conditions (simple-task and dual-task condition) and hence the behavior of the subjects as similar as possible. Tasks that had to be performed by the subjects under *dual-task* conditions were the following: playing the labyrinth game as an *ongoing task* that requires continuous senso-motor activity of

the subject, namely to keep moving a ball through the maze, while avoiding holes that were placed at regular distance on the track. Hence, the ongoing task is a very complex and demanding task, requiring sensor-motor coordination. However, all subjects knew the game and were well trained on a different day to play the game. They were hence comfortable with this task. As a second task the subjects had to watch visual stimuli to recognize *task-relevant* ones, i.e., had to again perform the visual discrimination *oddball task*. In case that a target was recognized, subjects had to remember and perform a PM task (press a buzzer for response).

Under both conditions (simple-task and dual-task condition) responding to the target stimuli was the more relevant task. Subjects were competing with each other. Missing a target event resulted in a high loss of points that could be gained by reaching subgoals, marked by numbers in the maze of the BRIO® labyrinth game and by reaching the final goal of the maze. Detailed information about the labyrinth game test bed can be found in (Metzen et al., 2009a).

**Ethics Statement:** The study has been conducted in accordance with the Declaration of Helsinki and approved with written consent by the ethics committee of the University of Bremen. Subjects have given informed and written consent to participate.

#### 3.1.2.2 Hypotheses

Demanding dual-task behavior (as performed by the subjects under dual-task condition) that involves a complex sensor-motor coordination task and a visual discrimination task are often given as examples when explaining PM tasks under natural conditions, e.g., stopping in front of a post office (PM task) while driving to work (ongoing task) since the driver discovered a post sign (PM cue), remembered that he has to stop (PM retrieval to stop to send a letter) and will prepare to stop and to fetch the letter from the bag (configuration of PM-task set) and finally will stop and take the letter out of the bag to bring it to the post office (PM-task execution). Hence, the natural complex dual-task behavior (driving and looking for the letter in the back) can often not only be defined as a dual task but *also* as a PM task.

Based on the literature referred to in Section 3.1 we expect that a broad parietal positivity is evoked under both conditions (simple-task and dual-task condition) by infrequent, *task-relevant* target stimuli (*targets*) and infrequent, *task-irrelevant* deviant stimuli (*deviants*) compared to frequent, *task-irrelevant* standard stimuli (*standards*) and can also be detected while the subject is performing a complex and demanding dual task. Under *both* conditions the P3b will mainly contribute to this parietal positivity evoked by infrequent stimuli (deviants and targets) that are either

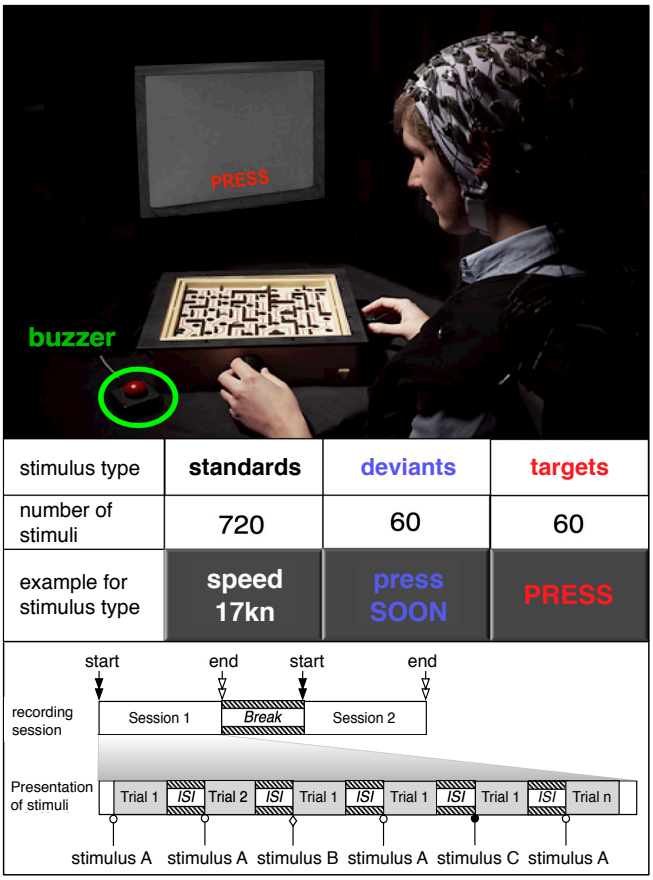


Figure 3.1: Experimental design of the *Labyrinth Oddball* setup. The upper part of the figure shows a subject performing in the experimental setup. Types and number of stimuli presented, session and run design are indicated in the lower part of the figure. Source: (Kirchner et al., 2013c).

task relevant (targets) or likely mistaken to be task relevant (deviants), while under *dual-task* condition (compared to simple-task condition) it is expected that *additionally* a later, prospective positivity will contribute to the broad positivity that is evoked by *task-relevant* target stimuli but not by task-irrelevant deviant stimuli. Due to the expected overlay of the P3b and prospective positivity evoked by target stimuli under dual-task condition the evoked parietal positivity should, in an *early* time window, be more pronounced on target stimuli than on deviant stimuli if compared to the simple-task condition. Further, we expect that a *later* part of the evoked parietal positivity should *only* under *dual-task* condition be more pronounced on *targets*, compared to deviant stimuli. Hence, the *prospective positivity* (that contributes most to the later part of the parietal positivity) should, under dual-task condition, *only* be evoked by infrequent *task-relevant target* stimuli but *not* by infrequent *task-irrelevant deviant* stimuli, since only under dual-task condition a change of task set is required, in case

that a target is recognized. Therefore, the specific characteristic of the parietal positivity is not only a *sign* for "target recognition" processes but also for processes that are involved in "task set changes".

Since in the experiments presented here the motor response required after targets interferes with the ongoing task, a task switch might further be required. However, the ongoing task might individually be divided into sub-tasks by the subjects. It is expected that subjects will finish a subtask first before answering the target (PM cue) event. A task switch is rather expected under artificial conditions, where a task switch is either forced by the experimental requirements (see (Bisiacchi et al., 2009) for a definition of task switch condition and discussion above) or caused by an urgent response request, i.e., in case of an emergency situation. Hence, it is not expected to detect task-switch related ERP components here.

#### 3.1.2.3 Methods

In the following information about data acquisition and analysis in the study described under Section 3.1.2.1 are given.

**Data Recording:** EEGs were recorded with 64 active electrodes (extended 10-20 actiCap system) and amplified by two 32 channel BrainAmp DC amplifiers [Brain Products GmbH, Munich, Germany]. Electrodes were referenced to electrode FCz. Impedance was kept below 5 kΩ. The sampling rate was set to 2500 Hz and data was band-pass filtered between 0.1 Hz to 1000 Hz.

**Behavioral Data:** The subjects' performances on correct and incorrect behavior (commission error, i.e., response on deviant stimuli and standard stimuli and omission error, i.e., missing response on target stimuli) were analyzed. In case of correct behavior (response on target stimuli) response time was analyzed for both simple and dual-task condition as time between onset of stimulus presentation and buzzer event. Furthermore, the absence of a response after target stimuli (amount of missed targets) was analyzed.

**Statistics on Behavioral Data:** To evaluate the response time on target stimuli, the median of response time for each subject was estimated based on buzzer events. Note that the median of response time had to be calculated, since the response times within a subject were not normal-distributed. The median value of each subject was averaged across subjects for each task and the between task difference was tested by paired t-test.

**ERP Average Analysis:** EEGs were analyzed off-line with BrainVision Analyser Software Version 2.0 [Brain Products GmbH, Munich, Germany]. First, EEGs were re-referenced to an average reference and filtered between $0.2$ Hz and $30$ Hz. Segments from $100$ ms before to $1000$ ms after stimulus onset were averaged based on stimulus of interest. Segments containing artifacts were rejected semi-automatically (amplitude $> 100\,\mu$V and $< -100\,\mu$V, gradient $> 75\mu$V). Target trials required a response within $200$ to $2000$ ms after stimulus onset to be counted as successful target trials. Only signal instances from successful target trials were used for calculating the average activity on target stimuli.

**Statistics on ERP Data:** To investigate the topography of the expected parietal positivity for each task, and, furthermore, to find out how the two different tasks (simple task and dual task) influence the expected parietal positivity, the average amplitude values across subjects were analyzed by repeated measures ANOVA with *stimulus type* (standards, targets, deviants), *time window* (early: $350$ ms-$600$ ms vs. late: $600$ ms-$850$ ms), *electrode* (CPz, Pz, POz) and *task* (simple task and dual task) as within-subjects factors [SPSS, version 20, SPSS Inc., Chicago, IL, USA]. If necessary, Greenhouse–Geisser correction was applied. For pairwise comparisons Bonferroni correction was applied.

#### 3.1.2.4 Results

In the following, results for behavioral and ERP data analysis are presented.

**Behavioral Data:** When analyzing response behavior we found only two commission errors on deviant stimuli for two subjects in total under the dual-task condition and none for the simple-task condition. Further, we found no omission error (*no* "missed targets"). This means that all target stimuli were recognized and answered by the subjects and subjects were able to perfectly distinguish between target and deviant stimuli. Figure 3.2 illustrates the median of response time on target stimuli for each subject in both tasks (simple versus dual task). First, the median of response time was calculated for each subject and each task. The median values of each subject were normally distributed for each task. To compare between both tasks the median values were averaged across all subjects resulting in an averaged median value of $0.77$ s for the labyrinth oddball task (dual task) and $0.79$ s for the simple oddball task (simple task). There was no significant difference in response time between both tasks [$t(12) = -1.25$, $p = 0.23$].

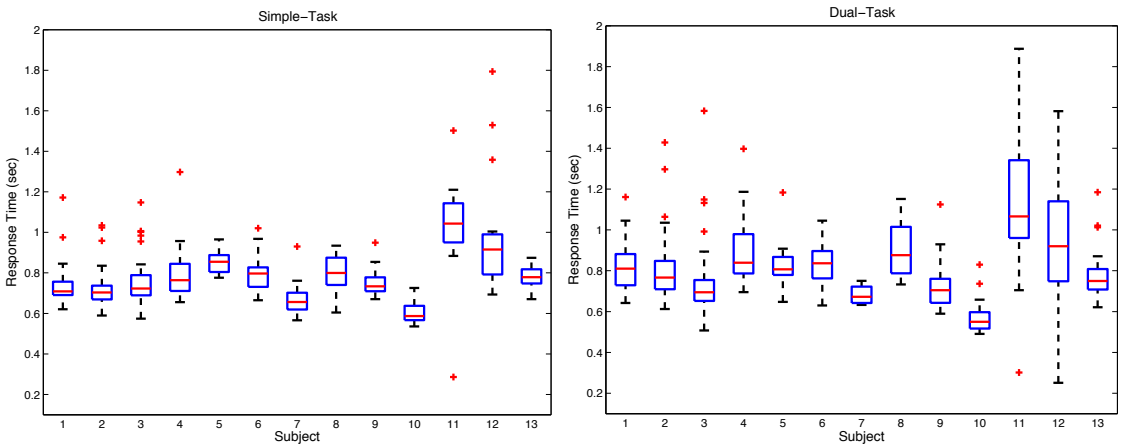


Figure 3.2: Response time under simple-task and dual-task condition. Left: Response time on targets under simple-task condition. Right: Response time on targets under dual-task condition. Figure is based on Figure 1 and 2 of (Kirchner et al., 2013c).

**ERP Average Analysis:** Figure 3.3 and Figure 3.4 illustrate the grand average ERPs on the three different types of visual stimuli at parietal electrode sites across all subjects for each task (*simple task* versus *dual task*). We observed a maximum positive broad ERP complex at parietal sites under *dual-task* and *simple-task* condition for all three electrodes (*CPz*, *Pz*, *POz*) and for both time windows (*early*, *late*) [interaction of *stimulus type* with *task*, *time window* and *electrode*: $F(4, 48) = 9.28$, $p < 0.001$, pairwise comparison, see Figure 3.6A]. Differences in ERP grand average waveforms recorded at electrodes CPz, Pz, and POz are illustrated in Figure 3.5.

For the early time window, a stronger positivity on targets compared to deviants was observed under both task conditions except for the electrode CPz for the simple task [dual task: $p < 0.002$ for CPz, $p < 0.002$ for Pz, $p < 0.002$ for POz; simple task: $p = 1$ for CPz, $p < 0.037$ for Pz, $p < 0.002$ for POz]. For the late time window, however, such stronger positivity on target versus deviant was only shown for the dual-task condition, but not for the simple-task condition [dual task: $p < 0.001$ for CPz, $p < 0.001$ for Pz, $p < 0.10$ for POz; simple task: $p = 0.961$ for CPz, $p = 0.082$ for Pz, $p = 0.434$ for POz]. For more details see Figure 3.6A.

The positivity on targets was stronger for the dual-task compared to the simple-task condition. Positivity on targets differed between the dual and simple task for all electrodes, but only for the late time window [POz: $p < 0.001$, Pz: $p < 0.003$, POz: $p < 0.005$]. Such differences in the late time window were not observable for deviant stimuli (more details, see Figure 3.6B).

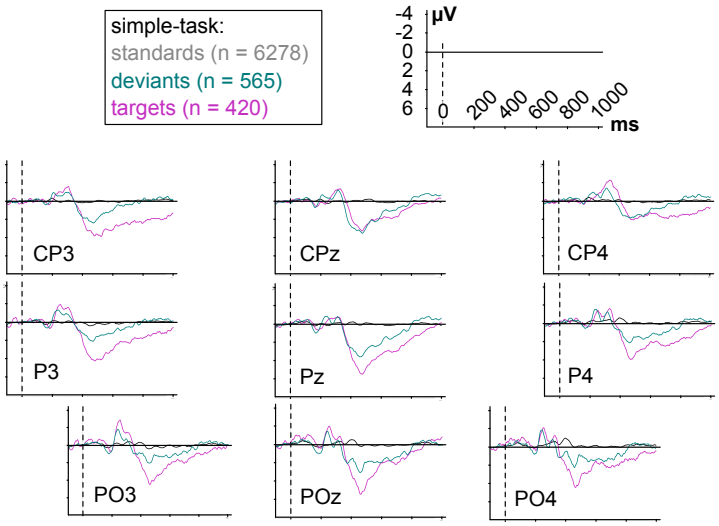


Figure 3.3: Grand average of parietal ERPs on different types of visual stimuli under simple-task condition. A broad, sustained parietal positivity starting at 300 ms could be observed on deviants and targets. Number of artifact free trials, i.e., signal instances, per stimulus type are indicated in the inserted box. Figure is based on Figure 3 of (Kirchner et al., 2013c).

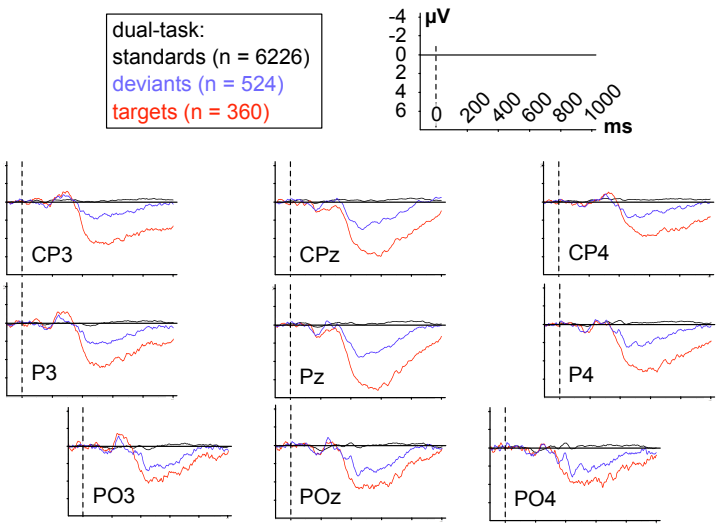


Figure 3.4: Grand average of parietal ERPs on different types of visual stimuli under dual-task condition. A broad, sustained parietal positivity starting at 300 ms could be observed on deviants and targets. Number of artifact free trials, i.e., signal instances, per stimulus type are indicated in the inserted box. Figure is based on Figure 4 of (Kirchner et al., 2013c).

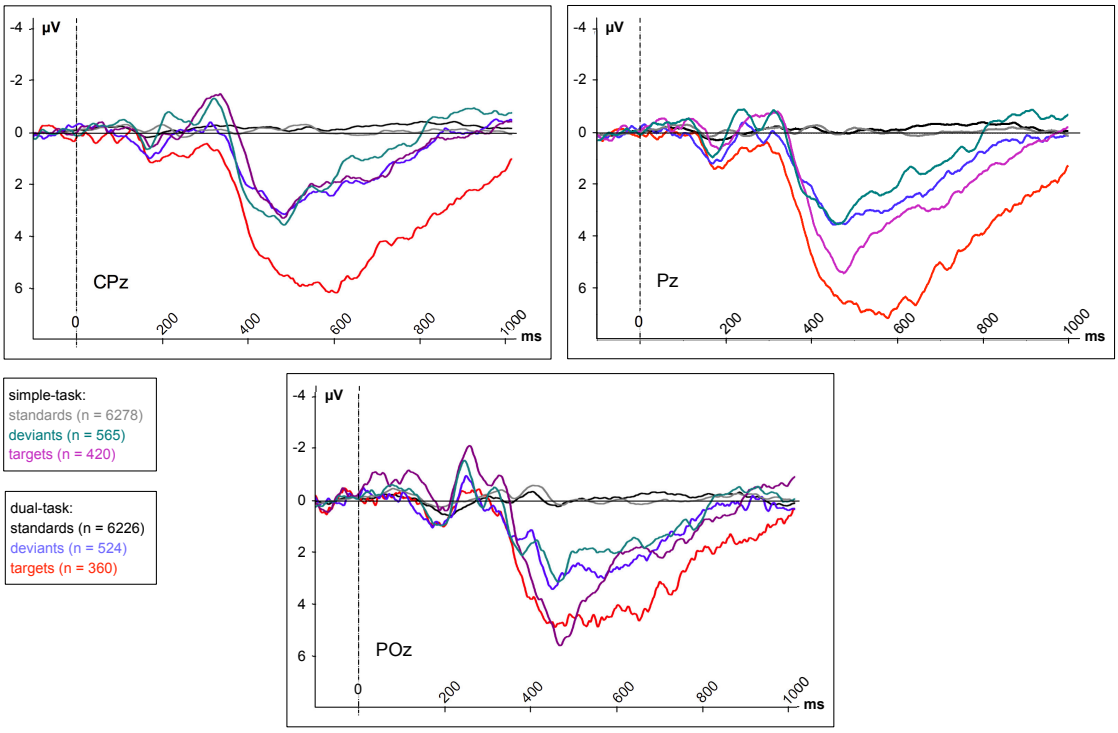


Figure 3.5: ERP activity at electrode CPz, Pz and POz. Curves show the broad sustained ERP activity on deviant and target stimuli under both conditions (simple and dual-task condition) starting at 350 ms. Prominent differences in the amplitude of the parietal positivity on targets compared to deviants can be seen in the late time window (starting at 600 ms). Numbers of artifact-free trials, i.e., signal instances, per stimulus type are indicated in the inserted box. Figure is based on Figure 5 of (Kirchner et al., 2013c).

#### 3.1.2.5 Discussion

Results show that deviant and target stimuli elicit visual discrimination and target recognition processes in the brain since they differ in appearance compared to standard stimuli. Both types of stimuli were under both task conditions successfully evaluated by the subjects with respect to their task-relevance, shown by very high performance in response behavior and they induced a P3b under both task conditions, i.e., during simple and dual-task condition. While performing complex sensor-motor behavior during human-machine interaction (dual-task condition) a broader parietal positivity is elicited on target stimuli compared to deviant stimuli with higher amplitude at parietal electrodes in both investigated time windows. The stronger expression of the parietal positivity in the *early time window* on *target* stimuli compared to non-target *deviant* stimuli is likely caused by differences in P3b expression due to differences in task-relevance of the stimuli, which is supposed to influence the

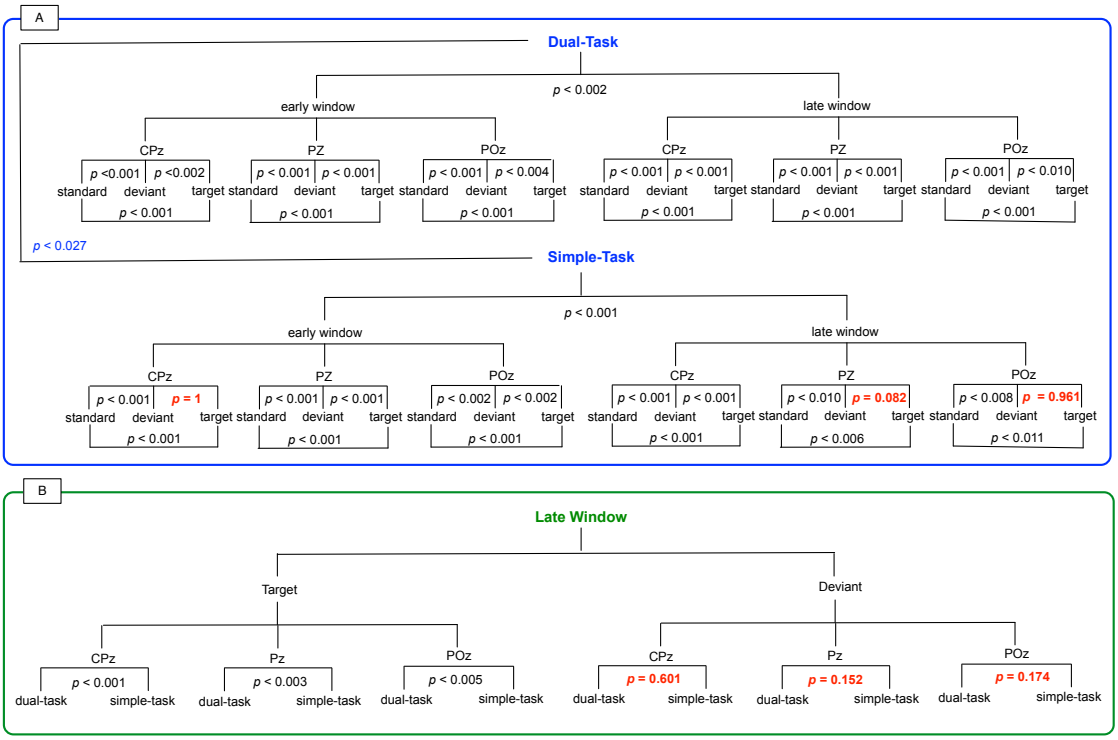


Figure 3.6: Overview on relevant parts of the results of statistical analysis. Most prominent differences are marked in red. Figure is based on Figure 6 of (Kirchner et al., 2013c).

amplitude of the P3b (Kok, 2001; Polich, 2007).

Under most conditions in which ERP activity evoked by *task-relevant* stimuli is investigated, it is difficult to assure that activity that is evoked by *task-relevant* stimuli is caused by target recognition processes solely and not by others like motor preparation that is evoked by preparing motor-response behavior. If comparing ERP activity evoked by infrequent task-relevant stimuli versus infrequent task-irrelevant stimuli compared to task-irrelevant frequent stimuli this is of special difficulty, since motor-response behavior is only executed after *infrequent task-relevant* stimuli and has to be considered when interpreting the results. However, although it is known that response behavior does influence the P3b amplitude, this effect should not have caused the observed differences since it would have reduced the amplitude of P3b on targets (Salisbury et al., 2001). Further, a major impact of motor-related activity on the P300 amplitude differences is only expected in case that a very fast response time is requested, since under such conditions a correlation can be found and response preparation and P300 overlap in time (see (Salisbury et al., 2001) for discussion). Since no fast response time was requested from the subjects a high correlation can

be ruled out and is supported by behavioral results (see Figure 3.2). Furthermore, since no significant difference in response time could be observed between both task conditions, a possible reduction of the P3b amplitude by motor response preparation should be similar in strength under both conditions. Moreover, it can generally be stated that possible differences related to motor activity are most prominent at frontal and central electrodes (Santucci and Balconi, 2009) and should not heavily influence ERPs at electrode Pz, where highest amplitudes for P3b are shown. However, motor preparation activity might be the reason for the missing difference in ERP amplitude in the early time window under the simple-task condition at electrode CPz (see Figure 3.6A). The most central parietal electrode CPz is closest to the cortical sites that evoke negative motor preparation activity (Santucci and Balconi, 2009) and is therefore more strongly influenced by this preparing activity than other electrodes are.

Differences in the late positivity on *targets* versus *deviant* stimuli in the *late* time window were only observed under the dual-task condition. This late positivity effect is likely caused by the required task set configuration and preparation of PM-task execution when switching the task from the complex senso-motor behavior (playing the labyrinth game) to response behavior (responding to target stimuli by motor response, i.e., buzzer press). In accordance with the literature PM-task and dual-task related activity at parietal sites is expressed in a later time window than ERP activity that is related to target recognition processes (West et al., 2003). However, since both processes evoke overlapping activity, the later PM-task or dual-task related activity will, to some degree, also influence ERP activity and differences between stimuli types in the early time window as discussed above. Nevertheless, highly significant differences in ERP activity on target versus deviant stimuli between both task conditions could be shown (Figure 3.6B) which confirm that additional brain processes are involved during dual-task condition.

Results indicate that complex behavior in natural scenarios not only involves visual discrimination and target detection, processes that evoke a P3b (Kok, 2001; Polich, 2007) (and earlier components not investigated here), but additional, later in time partly overlapping processes. Due to the complex behavior and required task set changes under dual-task performance (recognition and response to important stimuli and playing the labyrinth game) these additional processes are likely related to dual-task performance and preparation of PM-task performance (Bisiacchi et al., 2009; West, 2011). We showed that under both task conditions ERP activity (P3b) that is typical for the cognitive processing of important, possibly *task-relevant* stimuli is evoked and that dual tasking during complex human-machine interaction elicits a more prominent parietal ERP pattern resulting from overlapping ERP components.

Results of this study clearly show that the human EEG contains strongly ex-

pressed patterns faithfully representing well-defined brain states even if the human is heavily involved in different tasks. The stronger expression of the late parietal positive complex on targets observed under the dual-task condition should be more easily detected in single-trial analysis than the parietal positivity that is evoked by targets under the simple-task condition. Based on the results conducted here, in Chapter 4 it is investigated whether target recognition processes can be detected in single trial by BR. Results of this study further indicate that the significant difference of the later part of the parietal positive ERP complex might be detectable by a classifier in single trials to infer a change in task set. In the future, this may allow to infer whether an operator does not only recognize a task-relevant stimulus but may allow to infer whether she/he will indeed perform a second task, e.g., will respond to a *task-relevant* stimulus and pause the main task, like the teleoperation of a robot. This investigation is, however, not part of this thesis and left for future work.

## 3.2 Movement Preparation Processes

In robotic application scenarios that involve the activity of the motor system of the human for interaction, the level of involvement of the motor abilities depends on the actual tasks that have to be performed. The more demanding and important motor activity gets, the more brain resources are required by the motor system. For example, it is known that the expression of patterns in EEG which are related to movement preparation, depends on the motivation of a subject and on how much effort she/he invests (Shibasaki and Hallett, 2006). A high movement speed does require a higher effort from the subject than performing the same movement in slow speed. Thus, it can be expected that patterns evoked by motor preparation of the same kind of movement may differ in shape and characteristics depending on the amount of resources given to these brain processes. This might be critical for single-trial detection of movement intention during human-machine interaction as investigated in Section 4.2. Therefore, in Section 3.2.2, average ERP activity evoked by movement preparation of self-induced intentional arm movements with different speeds is first analyzed to estimate the effect of different requirements on the execution of movements (like different movement speeds or higher discreteness of movement), which may naturally occur during interaction, on the shape and characteristics of the ERPs. The goal of the study was to investigate the changes in the characteristics of the evoked pattern. Further, the presented study was performed to investigate the effect of different methods for the labeling of movement onset. Depending on the accuracy of the method that generates the required labels (markers) as well as different effects of movement speed on different kinds of markers, differences in average ERP activity are expected and investigated here. These differences might be relevant for the appli-

cation of single-trial BR. A reduction in average ERP signal strength might lead to a reduced performance in single-trial detection of movement preparation processes by BR. Furthermore, the effect of using different kinds of markers for movement onset detection on the characteristics of the ERP potentials is investigated. An overview over movement-related cortical potentials is given next in Section 3.2.1.

### 3.2.1 Pre-Motor Related Cortical Potentials

Kornhuber and Deecke could - by applying averaging methods - for the first time show that a complex of ERP potentials precedes intended movements (Kornhuber and Deecke, 1965). Most prominent are the Bereitschaftspotential (BP), also called early BP or readiness potential (RP), and the lateralized readiness potential (LRP), also called late BP or negative slope (NS) (Kornhuber and Deecke, 1965; Deecke et al., 1969; Shibasaki and Hallett, 2006).

The BP, which can be recorded up to at least two seconds before voluntary movement onset, is reported as bilateral and widespread potential with maximum amplitudes at medial central electrode sides (Santucci and Balconi, 2009; Deecke et al., 1976; Paradiso et al., 2004; Shibasaki and Hallett, 2006). The BP is thought to be evoked by early preparatory processes for movements and might reflect subconscious readiness for the forthcoming movement (Deecke et al., 1976; Libet et al., 1983; Shibasaki and Hallett, 2006). Its maximal amplitude over medial-central electrode sides is caused by the summation of electrical fields originating from bilateral premotor cortices and bilateral supplementary motor areas (SMA) (Shibasaki and Hallett, 2006). The amplitude of the BP is positively correlated with its onset time and shows intra-subjects constancy (Deecke et al., 1976; Kukleta et al., 2012). However, both onset time as well as magnitude of the BP, are found to be very task-dependent. This is especially true for the early BP (Kukleta et al., 2012). The BP onset time differs with respect to the experimental condition. If a subject is requested to perform movements at a self-paced rate with long breaks in between (i.e., every 5 s), the BP starts much earlier than under more natural conditions (Shibasaki and Hallett, 2006). Moreover, the onset of BP begins closer to the movement onset the faster the movement is executed (Masaki et al., 1998; Shibasaki and Hallett, 2006). The BP recorded at midline central region above SMA was found to start earlier and to be of greater magnitude for complex movements compared to simple movements (Simonetta et al., 1991; Shibasaki and Hallett, 2006). Other important influencing factors are task complexity, subjective difficulty, level of intention, or force. The larger the level of intention and the bigger the force, the larger is the early BP (Shibasaki and Hallett, 2006). The BP is, further, only seen before voluntary movements and not before involuntary movements and can thus be used to differentiate between voluntary

and involuntary movements (Shibasaki and Hallett, 2006).

The LRP is investigated in unilateral movement studies and derived by subtracting the averaged activity recorded at contra- and ipsilateral sites above motor-areas of the hand and arm (Coles et al., 1988; Eimer, 1998; Shibasaki and Hallett, 2006). Hence, the LRP is a special form of visualization of the lateralization of the late BP. The late BP can be distinguished from the early BP by the abrupt increase of the gradient, i.e, steeper slope of the curve. The late BP has an asymmetric distribution with maximal amplitude contralateral to the side of movement above sensorimotor areas of the brain and will occur at about 400–500 ms before movement onset (Shibasaki and Hallett, 2006; Deecke et al., 1976). Opposite to the findings in (Simonetta et al., 1991) in some studies only the late BP but not the early BP is found to be enhanced by the complexity of the movement that is planned to be performed (Kitamura et al., 1993; Shibasaki and Hallett, 2006). Beside the complexity of the movement, the precision as well as the discreteness of a movement do influence the late BP by enhancing its amplitude (Shibasaki and Hallett, 2006).

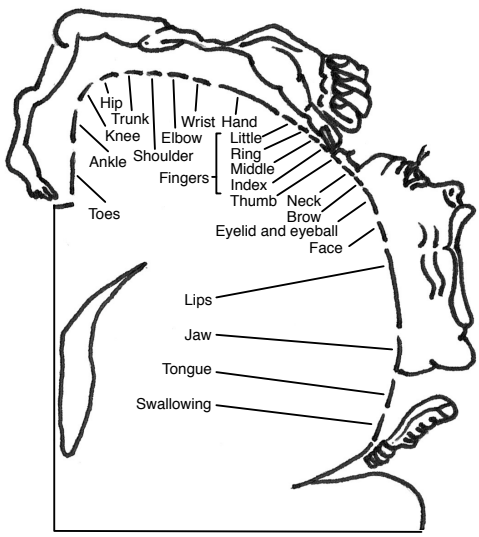


Figure 3.7: Motor homunculus. Somatotopic map of the primary motor cortex of one hemisphere (reproduction based on Figure 18-6 of (Kandel et al., 2000)).

Since the primary motor cortex is somatotopically organized, i.e., certain brain areas are directly mapped to certain body parts (see Figure 3.7), it is possible to differentiate between body parts to be moved by analyzing maximum amplitude shifts of the LRP over the head's surface. For example, EEG activity of brain areas involved in motor planning of the right hand and arm can best be recorded with electrodes C3 and FC3 (extended international 10-20 system electrode placement (Homan et al.,

1987)). Figure 3.8 shows average ERP activity recorded before movements of the right arm and hand at electrodes C3/C4, which are located above the hand areal.

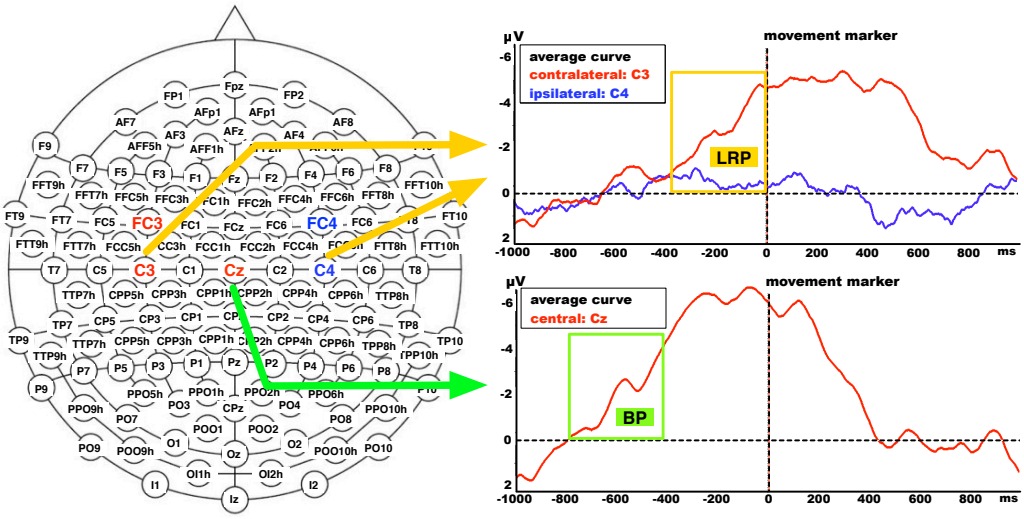


Figure 3.8: Electrode positions for recording the BP and the LRP. Left: electrode position of extended international 10-20 system (128 electrodes). Right: average EEG activity of one subject before arm and hand movement (movement marker); both components of the BP are shown: The early BP is defined as central non-lateralized negative activity recorded at electrode over the SMA. The late BP shows asymmetric distribution over the primary motor cortex contra and ipsilateral to the side of movement. Figure is based on Figure 6 of (Folgheraiter et al., 2012).

Besides early and late BP, pre-motion positivity (PMP) (or P-50) as well as the motor potential (MP) can further be found to be evoked before the movement onset (Deecke et al., 1969; Shibasaki et al., 1980). The PMP is a positive component that is only evoked before unilateral movement at the ipsilateral site of movement and is thought to be related to the suppression of movement of the opposite hand or arm (suppression of physiological mirror movements). Its physiological significance is not yet shown (Shibasaki and Hallett, 2006). On the other hand, the MP has a clear physiological significance, i.e., is most likely correlated with the activity of pyramidal tract neurons in the primary motor cortex, which is supported by its good localization to small areas at the contralateral central scalp that are precisely corresponding to the movement site (Shibasaki and Hallett, 2006). Both the peak latency of the PMP as well as the MP is defined with respect to the peak in EMG activity. Hence, the peak of MP occurs briefly, i.e., about 10ms, before the peak of correlated EMG activity.

### 3.2.2 Experimental Part - the BP and the LRP in Self-Initiated Arm Movements

In the following a study is presented that investigates ERP components, i.e., the BP (also called RP or early BP) and the LRP, i.e., the differential curve of the contra- minus ipsilateral late BP, that are evoked by self-initiated movement preparation processes. The effect of movement speed on the expression of movement preparation related average ERPs is investigated in the *Arm Movement* scenario. Further, it is investigated how different markers that label the onset of movement differ in their timing depending on the requested movement speed and what influence they have on the characteristics of the investigated ERPs. Results of the average ERP analysis are not yet published, but recorded EEG and EMG data was used for other publications (Tabie and Kirchner, 2013; Kirchner et al., 2013a; Kirchner and Tabie, 2013; Kirchner et al., 2014). Text and figures presented in the following are partly based on work presented in (Tabie and Kirchner, 2013) and (Kirchner et al., 2014).

#### 3.2.2.1 Experimental Setup and Procedure

Eight healthy male subjects (age: $29.9 \pm 3.3$ years; right-handed; normal or corrected-to-normal vision) participated in the study. Two of the $8$ subjects had to be excluded from data analysis, since a very high amount of artifacts in the EEG made average analysis impossible. To sustain comparability, these subjects were also removed from behavioral analysis. All experiments were performed in a shielded cabin to reduce the impact of external non-physiological artifacts as much as possible (see (Ghaderi et al., 2014) for discussion of artifacts in EEG and their sources). The subjects were seated in a comfortable chair in front of a table. A monitor was used to give feedback to the subjects. The subjects executed self-initiated and self-paced movements of the right arm (Figure 3.9). Further, two input devices containing micro switches were used to monitor the beginning and end of performed movements. The input devices were placed at a distance of approximately $30$ cm from each other. Events that were detected by the devices (pressing/releasing) were labeled in the EEG/EMG data.

In the first session of the experiment subjects were asked to move their hand from one input device to the other and back at their own speed in oder to produce natural movements. This condition is called *moderate* movement speed condition. In the second and third session the subjects had to perform fast and slow movements. Both movement speed conditions (*slow* and *fast*) were counterbalanced. All sessions contained $3$ runs with $40$ correct movements each and were recorded at the same day. In the *slow* movement speed condition each movement from the flat board to the buzzer (see Figure 3.9) had to take at least $1$ s. Since maximum movement speed differed between subjects, a preliminary investigation was performed to determine

the individual maximal movement speed for the *fast* condition. Each subject was asked to perform the movement to the buzzer and back starting from the flat board as fast as possible. This movement had to be repeated 10 times. Based on the recorded 10 movements the mean time, which was required to move from the flat board to the buzzer was calculated for each test person. The calculated mean times plus an offset of 10 ms were used as the maximum required time for fast movements. It varied from 120 to 275 ms between subjects.

During the entire experiments a green circle with a black fixation cross was shown to the subjects on the monitor. Executed movements were self-initiated and the only constraint for two consecutive movements was a resting time of at least 5 s between two consecutive movements. Movements that were carried out too early were reported to the subjects by changing the color of the green circle to red for 100 ms. Such wrong movement trials were not used for later data analysis and were not counted as correct movements. The same accounts for too slow movements during the *fast* condition and too fast movements during the *slow* condition. The experiment was designed with Presentation [Neurobehavioral Systems, Inc., Albany, USA]. Figure 3.9 illustrates the experimental setup and procedure.

**Ethics Statement:** The study has been conducted in accordance with the Declaration of Helsinki and approved with written consent by the ethics committee of the University of Bremen. Subjects have given informed and written consent to participate.

#### 3.2.2.2 Hypotheses

Based on the referred literature we expect that a broad early BP is evoked before movement onset as a sign for motor preparation processes. In case that a high speed for movement execution is requested the BP is expected to be larger in amplitude since it is expected that the execution of the movement at high speed requires a higher level of intention of the subject compared to movements that are performed in normal and slow speed. Hence, more resources are used by the involved movement preparation processes during the *fast* condition compared to the *moderate* and *slow* condition where movements are performed in slower speed and for the *moderate* condition compared to the *slow* condition, respectively. For the LRP, a similar effect is expected. However, regarding the characteristics of the LRP discreteness and precision of the planned movement are more relevant. Therefore, for the fast condition that requires higher precision in performing rather discrete movements, LRP activity with higher magnitude is expected compared to the slow and moderate movement speed condition. It is further expected that movement preparation processes that

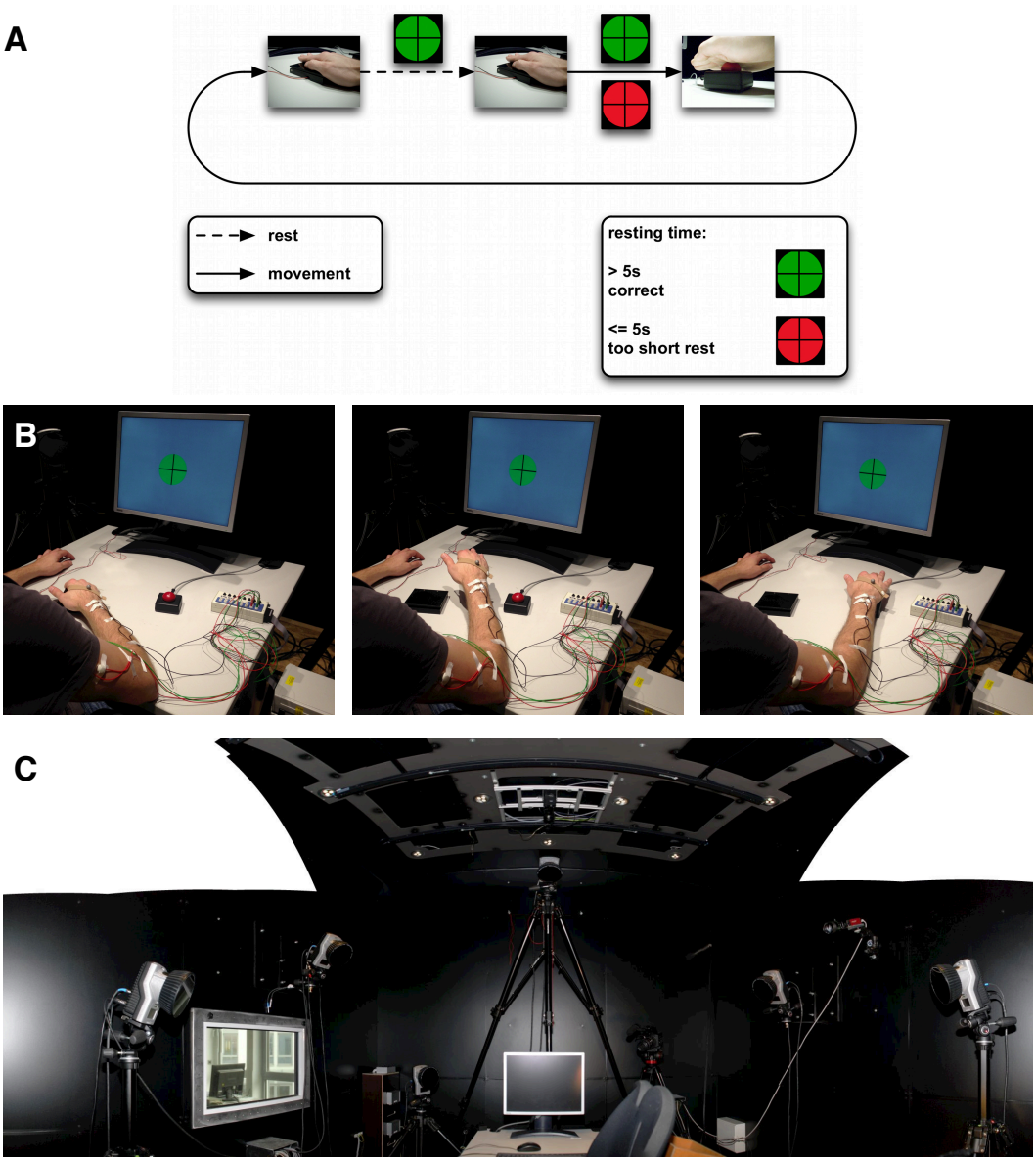


Figure 3.9: Experimental design of the *Arm Movement* setup. A: experimental procedure is shown. Between two consecutive movements a minimum resting time of 5 s had to be maintained. Movements between both input devices (microswitch and buzzer) were performed in different speeds, i.e., slow, moderate and fast. B: experimental setup is shown. Subjects were asked to move their right hand from a flat microswitch board to a buzzer, while looking at a green fixation cross presented on a monitor. C: experimental setup within the shielded cabin is shown. Figure is based on Figure 1 of (Tabie et al., 2014).

evoke the BP and LRP will occur before EMG onset, which can be detected before the physical movement onset, while the physical movement onset will be detected before the release of the input device on which the subjects hand is resting. Finally,

differences in the timing of markers for movement onset, i.e., the event of the release of an input device as well as the physical movement onset labeled by the Qualisys motion analysis system (in the following also called Qualisys marker), with respect to the EMG onset under the three different movement speeds are expected.

#### 3.2.2.3 Methods

**Data Recording:** EEGs and EMGs were acquired with 5 kHz, filtered between 0.1 to 1000 Hz using BrainAmp DC (EEG) and BrainAmp ExG MR (EMG) amplifiers [Brain Products GmbH, Munich, Germany] and saved to a computer. EEGs were recorded with a 128-channel actiCap system (reference at FCz) synchronized with EMGs that were measured bipolar with Ag/AgCl gel electrodes at four muscles of the right arm: M. brachioradialis, M. bizeps brachii, M. triceps brachii, and M. deltoideus. EEG and EMG data were recorded by synchronized recording devices. Events from both input devices were labeled in the recorded data. A motion capturing system was used to detect the physical movement onset of the subject's right arm. The system consisted of three cameras (ProReflex 1000) [Qualisys AB, Gothenburg, Sweden] and a passive infrared marker mounted on the back of the test person's right hand. Motions of the right hand were recorded with a sampling frequency of 500 Hz. The recorded motion data can be synchronized with the EEG/EMG data by means of introduced trigger events.

**Behavioral Data Analysis:** The subjects performance, i.e., correct behavior, were analyzed by determining the mean number of errors for each movement condition (slow, moderate, fast).

**Statistics on Behavioral Data:** To evaluate the error-rate, i.e., number of false movements (incorrect speed) or too short breaks between movements, the number of errors was analyzed by one-way repeated measures ANOVA with *movement speed* as a within-subjects factor [SPSS, version 20, SPSS Inc., Chicago, IL, USA]. If necessary, Greenhouse–Geisser correction was applied.

**Estimation of Physical Movement Onsets:** In an offline analysis the EEG/EMG data were synchronized with the motion data based on the introduced trigger events. The time points of the physical movement onsets were extracted from the tracking data as described in the following. The beginning of each movement was labeled in the EEG/EMG data by a microswitch. When this label was set, the subject was already in the movement phase, since the switch had been released by lifting up the hand from the input device. Therefore, the data from the motion tracking system

was analyzed in order to find the accurate physical movement onset. First, the movement speed of the subject's hand was calculated from the motion tracking data by computing the euclidean distance of consecutive samples. The unit of this speed is in mm/sample; the sampling period is 2 ms. Then, starting from each microswitch label, the movement speed for each movement trial was analyzed backwards. The physical movement onset was set as soon as the movement speed was below a threshold of 0.15 mm/sample, since this is the given accuracy of the tracking system. The determined time points were labeled in the EEG/EMG data and called *Qualisys marker*. They were used to label the *physical* begin of a movement. Figure 3.10 presents an example for a Qualisys maker, its relation to the recorded EMG activity and its distance in time to the input device marker.

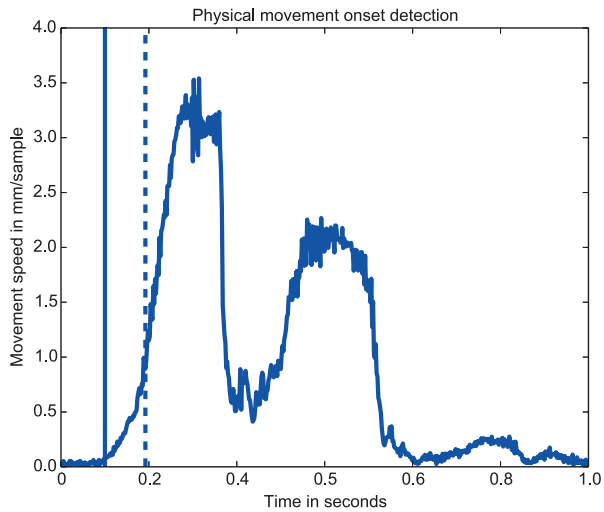


Figure 3.10: Example for the detection of the physical movement onset. The movement speed is shown, the dashed vertical line indicates the marker from the microswitch (of the input device) and the solid one the estimated physical movement onset. Source: Figure 1 of (Tabie and Kirchner, 2013).

**EMG Analysis for Automated EMG Onset Detection:** To estimate the EMG onset all four recorded channels and additionally the mean of all channels were used as different possible input sources. The data was preprocessed with a variance filter, defined as

$$v(t) = \frac{1}{N-1} \sum_{i=-N}^{0} x^2(t+i) - \left( \frac{1}{N-1} \sum_{i=-N}^{0} x(t+i) \right)^2 , \tag{3.1}$$

with, $N$ the length of the window used for filtering and x the raw EMG Signal. The variance was chosen for preprocessing, since it incorporates filtering and feature generation abilities (see Figure 3.11 for comparison of different preprocessing methods).

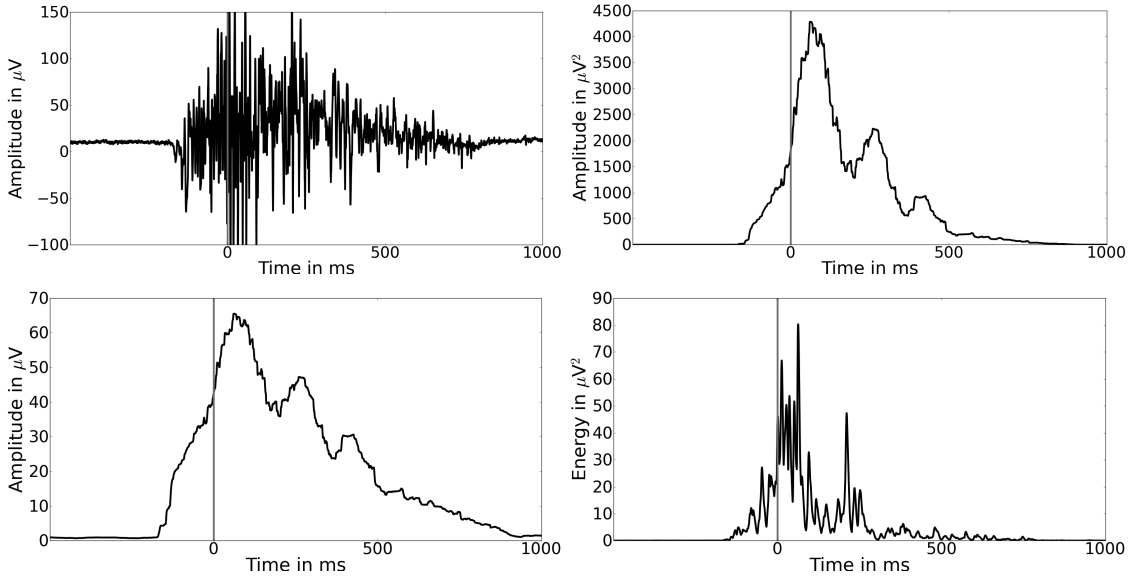


Figure 3.11: Resulting signals after different preprocessing methods on an arbitrary EMG burst. Upper left: original EMG signal; Upper right: variance filter applied; Lower left: SD applied; Lower right: Teager Kaiser Energy operator (TKEO) applied. Figure is based on Figure 2 of (Tabie and Kirchner, 2013).

Classification was done using an adaptive threshold, defined as

$$T(t) = \mu(t)_N + p\sigma(t)_N, \tag{3.2}$$

with $\mu$ the mean value, $\sigma$ the standard deviation (SD), $N$ the length of the window for the mean and SD and $p$ the sensitivity factor of the threshold (Semmaoui et al., 2012). The adaptive threshold is used due to its capability of compensating slow drifts in the EMG signals or possible higher noise level in the signal caused, for example, by resistance changes at the electrode side.

Cross validation was performed for training and testing the adaptive threshold. During the training phase the parameters for the variance filter and the adaptive threshold were optimized and the best EMG channels were chosen subject-specifically. For the optimization a grid search was used. For estimating best parameter values for the variance window sizes of $100, 250,$ and $500$ samples and for the adaptive threshold window sizes of $5000, 10000, 15000,$ and $20000$ samples and p values of $0 - 19$ were investigated. As performance measures for optimizing the preprocessing methods, prediction performance values of the prediction of movements based on the EMG data (using BA, see Section 2.4.3) and prediction time were used as performance metrics. In case that two or more combinations of parameters resulted in the

same BA value, prediction time was used to chose the best parameter combination.

For calculating the BA for parameter optimization, EMG onset was allowed in the range of $-500$ ms to $0$ ms before the physical movement onset. This lower bound ($-500$ ms) was chosen since EMG activity could be detected quite early in case of a pre-load of muscle activity during rest.

**Statistic on EMG Onset Detection:** To evaluate the number of misses in EMG onset detection the number of misses were analyzed by one-way repeated measures ANOVA with *movement speed* as a within-subjects factor [SPSS, version 20, SPSS Inc., Chicago, IL, USA]. If necessary, Greenhouse–Geisser correction was applied. For pairwise comparisons Bonferroni correction was applied.

**Analysis of Marker Timing:** The differences in time between EMG onset markers and markers for movement onset (i.e., Qualisys markers and markers from the microswitch input device) for each correct movement trial under all conditions were calculated. Mean values were estimated for each subject under all three movement conditions.

**Statistics on Marker Timing:** To investigate how the distance in time between the three different markers (EMG/Qualisys/Input device) varies in respect to movement speed (fast/moderate/slow), the distance in time between EMG and Qualisys, between EMG and input device, and between Qualisys and input device were compared by repeated measures ANOVA with two within-subjects factors: *movement speed* and *type of marker onset* [SPSS, version 20, SPSS Inc., Chicago, IL, USA]. If necessary, Greenhouse–Geisser correction was applied. For pairwise comparisons Bonferroni correction was applied.

**ERP Average Analysis:** EEGs were analyzed off-line with BrainVision Analyser Software Version 2.0 [Brain Products GmbH, Munich, Germany]. EEGs were re-referenced to an average reference and filtered between $0.1$ Hz and $30$ Hz. EEGs were segmented from $-1500$ ms before and ending $500$ ms ms after stimulus onset. Segments containing artifacts were rejected semi-automatically (amplitude $> 100\mu$V and $< -100\mu$V, gradient $> 75\mu$V). To count as correct trial, requirements on movement speed and duration of breaks between movement (see Section 3.2.2.1) had to be fulfilled. Artifact free segments from correct trials starting $-1500$ ms before and ending $500$ ms after stimulus onset were averaged for each subject individually over all runs of one condition based on stimulus of interest. For calculating the LRP, differential curves between averaged ERP activity from contralateral electrode sides of movement minus ipsilateral electrode sides of movement over the primary motor cortex ar-

eas of the hand (electrodes (contralateral/ipsilateral): FFC3h/FFC4h, FC3/FC4, and C3/C4) and the arm (electrodes (contralateral/ipsilateral): FFC1h/FFC2h, FC1/FC2, FCC1h/FCC2h, and C1/C2) were generated. To investigate the BP, ERP activity on electrode positions FCz and Cz were investigated. For visualization purposes grand averages over subject-wise averages were generated for each condition using BrainVision Analyser Software Version 2.0 [Brain Products GmbH, Munich, Germany]. Averages and grand averages for the electrode positions mentioned above were exported to MATLAB R2010b [The MathWorks, Inc.] to generate plots for subject-wise averaged EEG activity and grand averaged EEG activity.

**Statistics on ERP Data:** For statistical analysis, peak amplitudes were exported by BrainVison Analyzer Software Version 2.0 [Brain Products GmbH, Munich, Germany]. For analysis of the BP, maximum negative amplitudes before the respective movement marker (generated by detecting the EMG onset, or the movement onset either by means of the Qualisys system or the input device) at electrodes Cz and FCz were determined. For analysis of the LRP, maximum negative amplitude before the respective movement marker (generated by detecting the EMG onset, or the movement onset either by means of the Qualisys system or the input device) at electrode sides ipsilateral and contralateral to the movement were determined separately for the hand (contralateral/ipsilateral: FFC3h/FFC4h, FC3/FC4, and C3/C4) and arm area (contralateral/ipsilateral): FFC1h/FFC2h, FC1/FC2, FCC1h/FCC2h, and C1/C2).

To investigate how the amplitude of BP and the LRP varies depending on movement speed (slow/moderate/fast), amplitude differences between three different movement speeds were compared by repeated measures ANOVA with *movement speed* as within-subjects factor [SPSS, version 20, SPSS Inc., Chicago, IL, USA]. To determine whether the difference in amplitude is differently affected depending on the choice of marker that was chosen to label the movement onset, the analysis was performed for each type of movement onset marker (EMG/Qualisys/input device) separately. If necessary, Greenhouse–Geisser correction was applied. For pairwise comparisons Bonferroni correction was applied.

#### 3.2.2.4 Results

In the following results for behavioral, EMG onset, marker timing and ERP data analysis are presented.

**Behavioral Data:** In Table 3.1 mean values of the number of errors conducted in each run under each condition are given. Statistical analysis revealed that the

speed affects the number of errors [F$(2, 34) = 6.038$, $p < 0.014$]. Multiple comparisons showed that the *moderate* movement speed condition resulted in less errors compared to the *fast* movement condition [$p < 0.008$]. The same holds true for *moderate* compared to *slow* movements [$p < 0.038$], while no significant difference in error-rate was found between fast and slow [$p =$n.s.].

Table 3.1: Mean of number of errors. Mean is calculated over errors conducted in each run for each condition of movement speed. Three runs were performed by each subject for each movement speed condition.

| **movement condition** | **mean value** | **SE of mean** |
|---|---|---|
| slow | 6.11 | 1.52 |
| moderate | 4.17 | 1.08 |
| fast | 9.33 | 1.49 |

**EMG Onset Detection:** In Figure 3.12 examples for averaged EMG activity of slow (A), moderate (B) and fast (C) movement conditions are illustrated for subject 1 (see Section A.1 in the appendix of this thesis for the results of all subjects illustrated in Figure A.1, Figure A.2, Figure A.3, Figure A.4, Figure A.5, Figure A.6). It was not possible to detect the EMG onset for each of the correctly performed movements by the applied method. Table 3.2 displays the results for all subjects for EMG onset detection. Even though EMG onset detection seemed to perform quantitatively worst for the slow condition, the large difference in total missed between conditions was caused by the weak performance of EMG onset detection for some individual subjects (see subject 2 and subject 3 as well as a high SD in Table 3.2). No effect of *movement speed* on the number of misses in EMG onset detection could be found by statistical analysis [F$(2, 10)= 0.796$, $p =$ n.s.].

**Marker Timing:** Table 3.3 displays the calculated distance in time between marker types under all three movement conditions, slow, moderate and fast, respectively. It can be seen that the distance in time between the markers EMG onset and Qualisys decreases with increasing speed of movement. The same pattern can be observed in Figure 3.15 (see Section A.1 in the appendix of this thesis for the results of all subjects illustrated in Figure A.1, Figure A.2, Figure A.3, Figure A.4, Figure A.5, Figure A.6).

The observed differences could be supported by statistical analysis. Statistical analysis showed that the speed of movement has an effect on the distance in time between marker onsets [main effect of movement speed: F$(2, 10) = 4.561$, $p < 0.04$]. The distance in time between the EMG onset marker and the Qualisys marker did

Table 3.2: Total number of non-detected EMG onsets. Misses in EMG onset detections for all subjects over all runs for each movement condition are given. In total 120 movements were executed per condition over three runs.

| **subject** | **number of misses: slow** | **number of misses: moderate** | **number of misses: fast** |
|---|---|---|---|
| subject 1 | 5 | 27 | 13 |
| subject 2 | 31 | 9 | 15 |
| subject 3 | 59 | 14 | 47 |
| subject 4 | 6 | 10 | 1 |
| subject 5 | 15 | 16 | 3 |
| subject 6 | 15 | 4 | 10 |
| **total** | **131** | **80** | **89** |
| **mean** | **22** | **13** | **15** |
| SD | 20 | 8 | 17 |

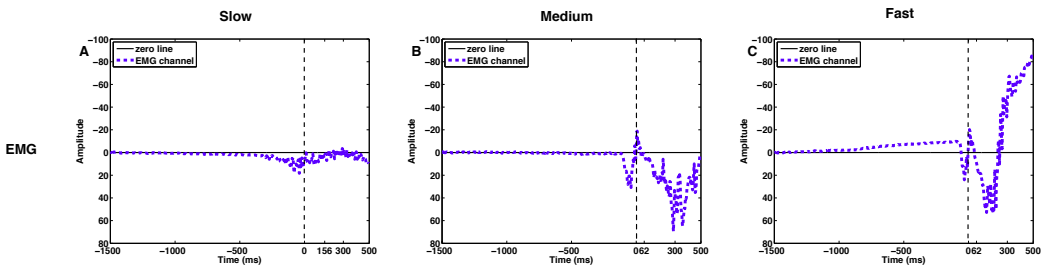


Figure 3.12: Effect of movement speed condition on averaged EMG signal. Averaged EMG activities based on the detected movement onset (dotted vertical line) for different movement speeds (A: slow; B: moderate, C: fast) for Subject 1 are shown.

linearly decrease, i.e., the distance was biggest for slow movements, smaller for moderate movements and smallest for fast movements [slow vs. moderate: $p < 0.011$, slow vs. fast: $p < 0.008$, fast vs. moderate: $p < 0.022$, see Figure 3.15]. In contrast, the distance in time between the EMG onset marker and the input device marker was stable with respect to movement speed [slow vs. moderate: $p =$ n.s., slow vs. fast: $p =$ n.s., fast vs. moderate: $p =$ n.s.]. Hence, no shift of the input device marker with respect to the EMG onset marker was observed.

**ERP Average Analysis:** Averaged ERP activity that is related to movement preparation processes preceding movement onsets is visualized in Figure 3.13, Figure 3.15 and Figure 3.14. Differences in amplitudes of BP and LRP were observed depending on the movement speed condition. This effect varied depending on move-

Table 3.3: Mean difference in time of occurrence between different marker types. Results are given for all subjects over all runs for each movement condition. Marker types were: EMG Onset (EMG), physical movement onset detected by Qualisys (Qualisys), marker generated by the input device when lifting the hand (taster).

| **subject** | **difference EMG/Qualisys** | **difference EMG/taster** | **difference Qualisys/taster** |
|---|---|---|---|
| **subject 1** | | | |
| cond. slow | 156 | 160 | 4 |
| cond. moderate | 62 | 104 | 42 |
| cond. fast | 45 | 110 | 65 |
| **subject 2** | | | |
| cond. slow | 145 | 155 | 10 |
| cond. moderate | 87 | 150 | 62 |
| cond. fast | 68 | 152 | 84 |
| **subject 3** | | | |
| cond. slow | 72 | 76 | 4 |
| cond. moderate | 52 | 82 | 30 |
| cond. fast | 41 | 76 | 34 |
| **subject 4** | | | |
| cond. slow | 135 | 140 | 5 |
| cond. moderate | 58 | 108 | 50 |
| cond. fast | 47 | 102 | 45 |
| **subject 5** | | | |
| cond. slow | 194 | 198 | 2 |
| cond. moderate | 83 | 98 | 15 |
| cond. fast | 46 | 98 | 52 |
| **subject 6** | | | |
| cond. slow | 150 | 157 | 7 |
| cond. moderate | 98 | 122 | 24 |
| cond. fast | 60 | 156 | 96 |

ment onset marker (see Table 3.4 for maximum amplitude values for BP and LRP).

In case that the EMG marker was used to label the movement onset, the amplitude of BP at FCz was smaller for slow movements compared to fast and moderate movements [F$(2, 10)$= $15.23$, $p < 0.002$, slow vs. fast: $p < 0.030$, slow vs. moderate: $p < 0.032$, fast vs. moderate: $p =$ n.s.]. At Cz, a smaller amplitude of BP was observed only in comparison of slow to fast movements [F$(2, 10) = 13.32$, $p < 0.003$, slow vs. fast: $p < 0.034$, slow vs. moderate: $p =$ n.s., fast vs. moderate: $p =$ n.s.]. Opposite to this finding, no significant effect of movement speed on the amplitude of LRP was found in both arm and hand area [Arm area: F$(2, 10) = 2.46$, $p =$ n.s.; Hand area: F$(2, 10) = 0.72$, $p =$ n.s.].

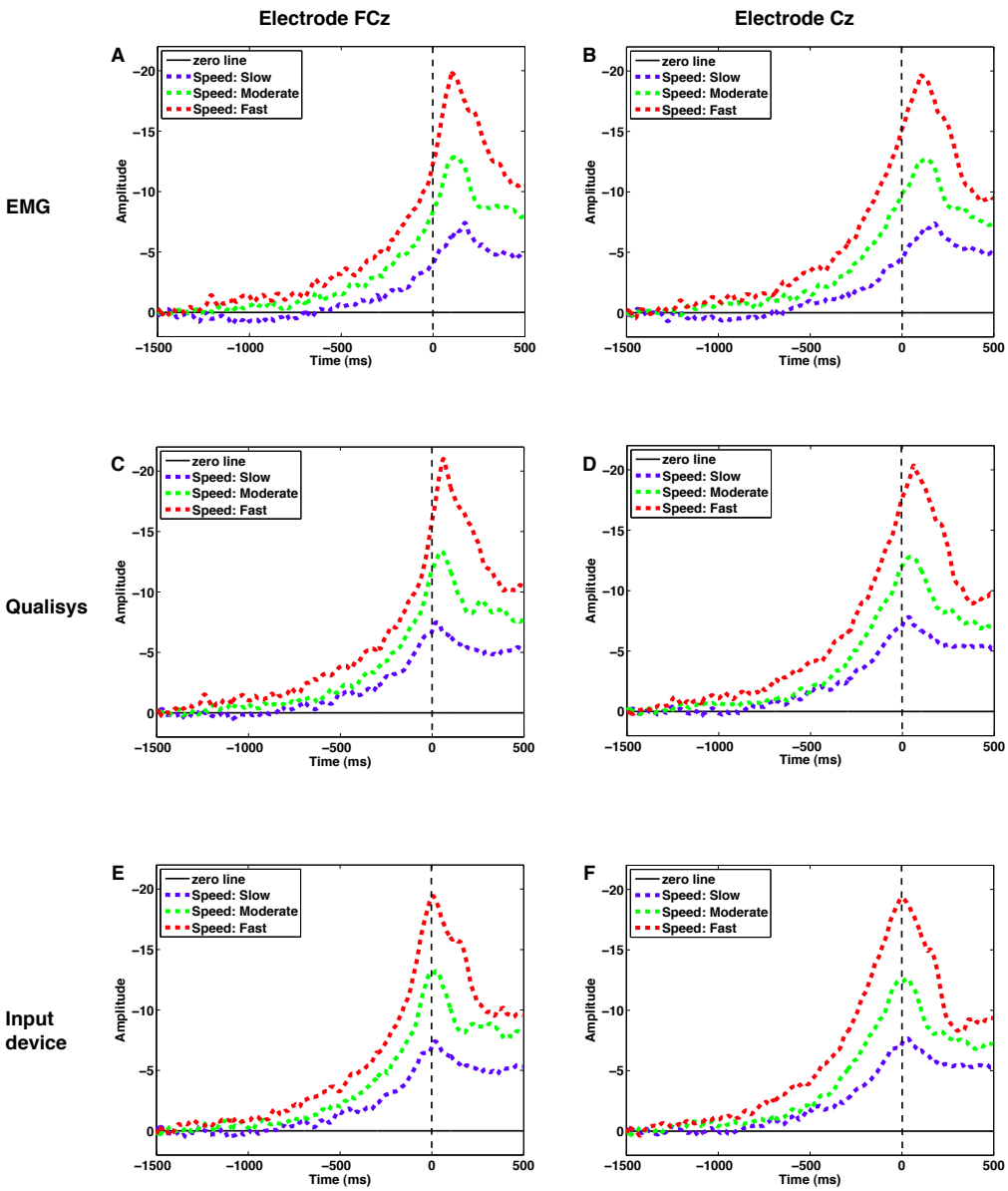


Figure 3.13: Effect of movement speed on characteristics of the BP under the different movement speed conditions. Grand averaged ERP activity evoked by movement planning and execution recorded at electrodes FCz (A, C, E) and Cz (B, D, F) are shown. For generating grand averages different markers were chosen: EMG onset marker (A, B), Qualisys (C, D), and input device (E, F). Dotted line labels the point in time as detected by the three methods, EMG onset detection, movement onset detected by Qualisys, movement onset detection as detected by the input device, respectively.

In case that the Qualisys marker was used to label the movement onset, the smallest amplitude of BP was observed at FCz for slow movements compared to fast and moderate movements [$F(2, 10) = 21.01$, $p < 0.001$, slow vs. fast: $p < 0.015$, slow vs. moderate: $p < 0.012$, fast vs. moderate: $p < 0.05$]. At Cz, a significantly smaller

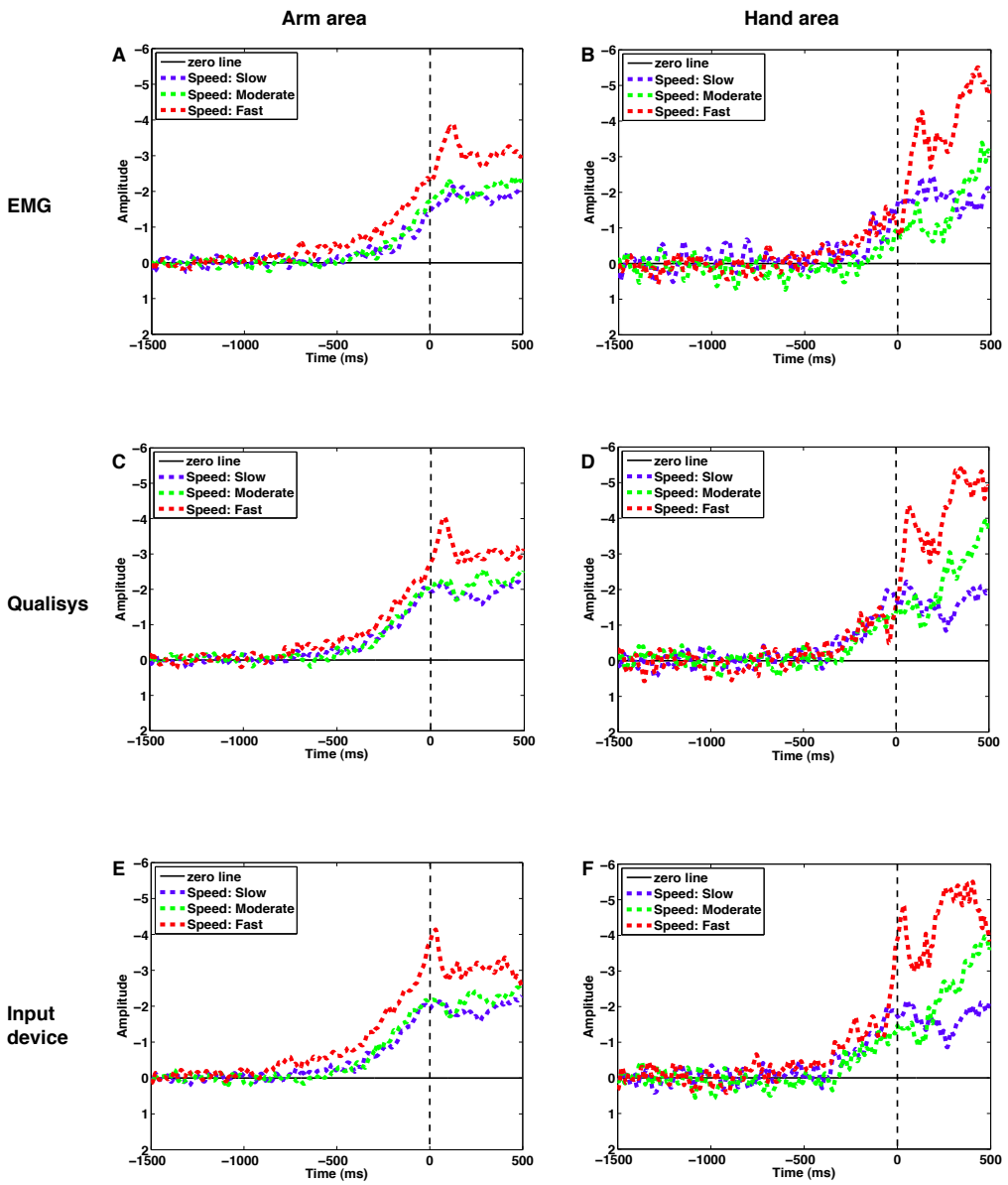


Figure 3.14: LRP calculated from recordings above arm and hand areas under the three movement speed conditions. A, C, E: LRP activity above arm areas of the primary motor cortex. B, D, F: LRP activity above hand areas of the primary motor cortex. Activity is calculated from average ERPs based on: A, B: EMG onset marker; C, D: Qualisys marker; E, F: input device marker. Dotted line labels the point in time as detected by the three methods, EMG onset detection, movement onset detected by Qualisys, movement onset detection as detected by the input device, respectively.

amplitude of BP was only observed in slow movement speed condition compared to fast movement speed condition [F$(2, 10) = 14.71$, $p < 0.002$, slow vs. fast: $p < 0.026$, slow vs. moderate: $p =$ n.s., fast vs. moderate: $p =$ n.s.]. Again, no significant effect of movement speed on the amplitude of LRP was found in both arm and hand area

Table 3.4: Maximum amplitude of BP and LRP. Amplitude values conducted at Cz and FCz are described for BP and above hand and arm area for LRP under all three movement speed conditions.

| **EMG onset marker** | BP at **Cz** | BP at **FCz** | LRP above **arm area** | LRP above **hand area** |
|---|---|---|---|---|
| cond. slow | $-7.66\mu$V | $-7.53\mu$V | $-1.91\mu$V | $-1.29\mu$V |
| cond. moderate | $-12.25\mu$V | $-11.88\mu$V | $-2.09\mu$V | $-1.29\mu$V |
| cond. fast | $-17.78\mu$V | $-15.97\mu$V | $-2.70\mu$V | $-1.20\mu$V |
| **Qualisys marker** | BP at **Cz** | BP at **FCz** | LRP above **arm area** | LRP above **hand area** |
| cond. slow | $-5.20\mu$V | $4,98\mu$V | $-1.02\mu$V | $-0.41\mu$V |
| cond. moderate | $-9.86\mu$V | $8.97\mu$V | $-1.70\mu$V | $-0.52\mu$V |
| cond. fast | $-15.32\mu$V | $12.43\mu$V | $-2.32\mu$V | $-1.25\mu$V |
| **Input device marker** | BP at **Cz** | BP at **FCz** | LRP above **arm area** | LRP above **hand area** |
| cond. slow | $7.74\mu$V | $-5.20\mu$V | $-1,91\mu$V | $-1.35\mu$V |
| cond. moderate | $12.97\mu$V | $-13.39\mu$V | $-2.61\mu$V | $-1.24\mu$V |
| cond. fast | $19.77\mu$V | $-19.96\mu$V | $-3.68\mu$V | $-3.12\mu$V |

[Arm area: F$(2,10) = 0.94$, $p =$ n.s.; Hand area: F$(2,10)= 0.07$, $p =$ n.s.].

In case that the input device marker was used to label the movement onset, the strongest amplitude of BP was found at FCz under fast movement condition compared to slow and moderate movement conditions [F$(2,10) = 47.92$, $p < 0.001$, fast vs. slow: $p < 0.014$, fast vs. moderate: $p < 0.001$, slow vs. moderate: $p < 0.003$]. At Cz, the stronger amplitude of BP was observed compared to fast and moderate movements [F$(2,10) = 21.46$, $p < 0.001$, fast vs. slow: $p < 0.044$, fast vs. moderate: $p < 0.042$, slow vs. moderate: $p =$ n.s.]. This time the same pattern could be observed for the maximum amplitude of LRP recorded above the arm area [Arm area F$(2,10) = 7.962$, $p < 0.012$, fast vs. fast: $p < 0.011$, fast vs. moderate: $p < 0.024$, slow vs. moderate: $p =$ n.s.], while again no significant effect of movement speed on the amplitude of LRP was found in data recorded above the hand area [Hand area: F$(2,10) = 3.55$, $p =$ n.s.].

In summary, while differences between the maximum amplitude of BP recorded at electrode Cz and FCz under *fast* and *slow* movement condition could be found to be significantly different irrespectively of what kind of marker was chosen, the difference between *fast* and *moderate* movement speed and *moderate* and *slow* movement speed showed different patterns. At electrode Cz, the difference between amplitudes of BP under slow and moderate movement conditions was never significant. When choosing the Qualisys marker and the input device to label movement onset, significant differences were found at electrode FCz for all conditions, while the difference

between amplitudes of BP under fast versus moderate condition at Cz was only significant if the input device was chosen to label the movement onset. For the LRP, differences between amplitudes evoked under the three movement speed conditions were only found to be significantly different for data recorded above the arm area in case that the input device was chosen to label the movement onset.

#### 3.2.2.5 Discussion

In Figure 3.13 and Figure 3.14 it can be seen that the latency of the maximum amplitude of the complex of movement-related cortical potentials MRCP (Shibasaki and Hallett, 2006) (i.e., the ERP complex at central electrode positions, which precedes and accompanies the execution of movements) differs depending on the kind of the marker used to label the movement onset. The observed difference in latency is similar for all movement speed conditions. When choosing the EMG onset or the Qualisys marker to label movement onset the peak of the average movement-related cortical potentials (MRCP) has a positive latency while the max. amplitude of the MRCP average curve based on the input device marker has a latency around "0", i.e., around the point in time of the input device marker. Therefore, the maximum value of the BP amplitude, if measured as maximum peak before the movement onset marker does differ between all three marker types (see results of ERP analysis) and is highest if the input device marker is chosen to label movement onset. A similar effect could be found for the LRP. However, when discussing the results of BP and LRP analysis, it must be stressed that the BP, or RP, and LRP are defined as maximum activity above areas of the primary motor cortex *before* EMG onset (Shibasaki and Hallett, 2006). Therefore, only Part A and B of Figure 3.13 and Figure 3.14 visualize the BP and LRP as defined in (Shibasaki and Hallett, 2006). If the movement onset is labeled by markers that detect the physical onset of a movement (Qualisys or input device), one has to be careful interpreting the results in case that maximum activity before the movement onset label was measured as maximum amplitude of BP. Likely not the BP but already the MP is detected in such a case. This has also to be considered in the case that a movement onset label is used to evaluate the performance in the detection of movement planning (see Chapter 4). In such a case, a time period before the respective movement marker has to be removed for evaluation (see Figure 4.12 in Section 4.2.1.3) to assure that movement planning is detected and not the execution of movements.

The results conducted by using EMG onset as marker nicely support the known findings from literature. It can be seen that the amplitude of BP does increase with movement speed, hence with the level of intention that the subjects puts into the movement while the movement speed has no effect on the LRP. Based on the be-

havioral analysis, it was more difficult for the subjects to perform the arm movement correctly under slow and under fast condition compared to moderate condition, i.e., no significant difference in the number of errors under slow versus fast movement speed condition was found. This result was expected. Although the LRP over arm areas was higher, if subjects had to perform more precise movements under fast movement speed condition under which the amount of errors did not differ from slow movement speed condition, this difference in amplitude of the LRP between slow and fast movement speed was not significant. Hence, the results of ERP analysis failed to show an effect of the precision of movement on the amplitude of LRP at the same level of effort. It is possible that movement performed under fast movement speed condition was not yet precise enough or subjects performed the movements too differently. Also, a possible difference in LRP between movement conditions might be affected by the observed huge difference in the lateralized MP component after EMG onset, that is not further investigated here (see Figure 3.14). Further analysis and investigations are required.

Even though the discussed results support to use EMG onset as marker, for BR this method of marker generation might not be the best choice, since the applied methods for automated EMG onset detection might not always perform well. In this study the detection of EMG onset performed especially worse for some subjects under the slow movement speed condition compared to both the other movement speed conditions (see Table 3.2). By analyzing the EMG by the applied method, many movement trials would not have been detected for those subjects and hence would not have been labeled under the slow movement speed condition. Also, some more advanced methods for the estimation of movement onset must be evaluated carefully. For example the detection of the physical movement onset performed with the motion tracking system Qualisys resulted in rather unreliable movement onset labels across movement speed conditions. For the slow movement speed condition, the Qualisys marker was closer in time to the input device marker, while for the fast movement speed condition the Qualisys marker was closer to the EMG onset marker (see Table 3.3). On the other hand, the marker that was added by the input device was quite stable over all movement speed conditions with respect to the EMG onset marker. However, the marker from the input device was suited worst to label the end of the BP or LRP and the begin of the MP as discussed above.

It can be summarized that the choice of method to label specific events in the EEG as discussed for the movement onset must be considered carefully. Results presented here show that none of the investigated markers is suited best over all conditions. It is important to consider what the pros and cons of the applied methods for labeling EEG data with respect to events or context of activity are and what the most important goal is, as to detect most movements (here marker generation by means of

EMG onset detection performs worse compared to movement onset detection by the simple technical device, i.e., the input device) or to label the data best with respect to known pre-motor potentials (here markers generated by means of EMG onset detection is best suited even if compared with a more advanced method for movement onset detection, like motion analysis using a motion tracking system), when choosing an appropriate method.

## 3.3 Summary

In Chapter 3 of the thesis four experimental setups were developed to investigate brain activity that is evoked by tasks that are commonly performed by humans during human-machine interaction. The *Arm Movement* setup is also used to generate training data and does therefore also serve as training scenario. Therefore, by the work of Chapter 3 **Subgoal 1a**, i.e., to develop training scenarios, is addressed. Investigations that were performed in this chapter and the presented results do further show that specific known ERPs, i.e., ERPs that are known to be evoked by "target detection" processes and processes that are involved in "task set changes", can be detected while a human is performing demanding interaction tasks (Section 3.1.2). The reliable expression of such patterns in EEG is prerequisite to apply single-trial BR for the detection of specific brain states, i.e., "target recognition and task change" under dual-task and PM-task condition. Conducted results do therefore partly fulfill **Subgoal 1b** by showing that known brain states are evoked during complex interaction tasks. However, results also show that BR might be sensitive to the subjects effort on a specific task and how much intention the subject gives to the task, as shown for the planning and execution of self-initiated movements. Further, BR may to some degree be sensitive to the correct labeling of training data, as the investigation of the effect of the timing of markers in the movement study (Section 3.2.2) indicates. Hence, for applying BR in robotic applications, training data must be labeled carefully and the kind of marker that is chosen must be chosen with respect to the main goals of BR to evaluate the performance of single-trial BR in a meaningful way. The presented results are all based on average ERP analysis, therefore, in the next chapter of this thesis it will be shown that BR can indeed be applied on single-trial EEG data and that patterns, which are detected by single-trial analysis, can be correlated to specific brain states that were shown here to be present during complex human-machine interaction in the *Labyrinth Oddball* setup and during the controlled movement study in the *Arm Movement* setup.

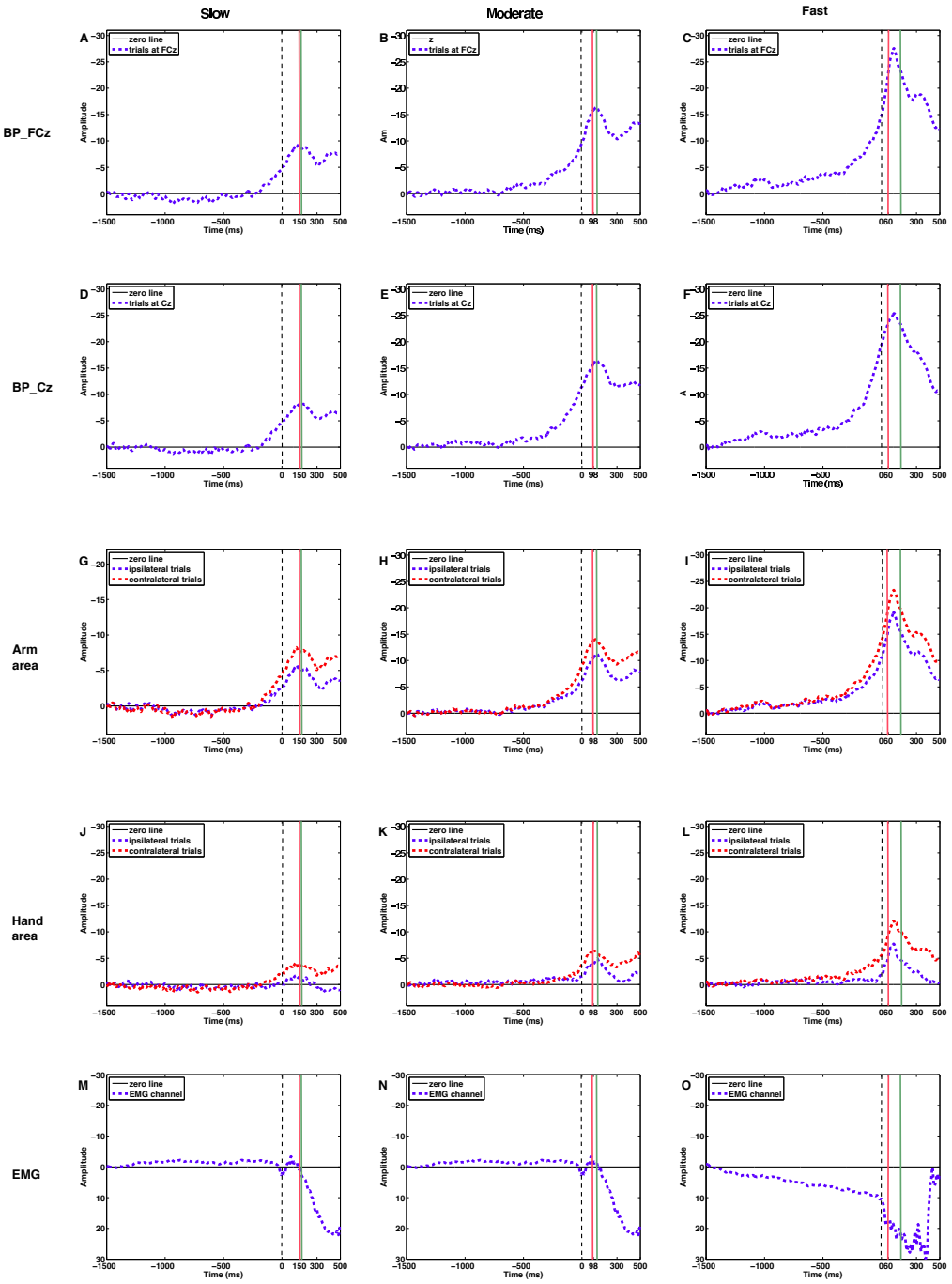


Figure 3.15: EMG activity and averaged ERP activity preceding arm movements based on EMG onset for Subject 6. A,B,C: BP at electrode FCz; D, E, F: BP at electrode Cz; G, H, I: ipsilateral and contralateral activity over arm areas; J, K, L: ipsilateral and contralateral activity over hand areas; M, N, O: averaged EMG activity for all three movement conditions, slow, moderate, and fast movement speed condition (A, D, G, J, M: slow ; B, E, H, K, N: moderate; C, F, I, L, O: fast), respectively. Dotted vertical line labels EMG movement onset. Red vertical line labels mean distance from EMG onset to movement onset as detected by Qualisys and green vertical line the mean distance to movement onset labeled by the microswitch input device.

# Chapter 4

# Brain Reading for Single-Trial Brain State Detection

To apply BR in application scenarios for the detection of (certain) brain states in specific situations, EEG data must be analyzed in single trial by SP and ML methods as described in Section 2.4. A first goal of the experiments presented in this chapter was to show that the strength in expression of investigated average ERP activity is "predictive" for the performance of BR. If true, this would support the hypothesis proposed in this thesis that by means of single-trial BR specific brain states can be detected.

In this thesis it is further hypothesized that new approaches for handling application-related challenges, like the reduced amount of training examples, can be solved by better understanding and characterizing involved brain processes. To support this hypothesis, a new approach of classifier transfer is presented that was developed based on the knowledge gained from average ERP analysis presented in the following sections and in Section 3.1.2. Classifier transfer is applied to cope with the issue that often only a few examples of training data can be recorded in an application scenario, given a reasonable training time. To successfully apply classifier transfer, it is relevant to better understand which conditions or brain processes are involved and contribute to classification performance. In oder to achieve this, results of classical average ERP analysis and results of ML analysis must be related to each other. To avoid a restriction in signal space and thus avoid to restrict the ML analysis of the signal sources expected from ERP analysis, data from electrode locations all over the surface of the head were used. The presented investigations will support the assumption that BR does indeed not just detect *any* difference between classes but *specific* brain states of the interacting human.

Finally, the simultaneous detection of two different brain states by BR will be investigated in an experimental set up that copies the conditions of a robotic tele-

manipulation scenario. This experiment supports the assumption that *dual* BR can indeed be applied on single trial while subjects perform complex and demanding interaction-task in a robotic application scenario as discussed in Part III of this thesis. Hence, BR can be applied to detect different brain states simultaneously.

## 4.1 BR Enabled by Classifier Transfer and Optimization of Training Data

It is known, as discussed in Section 3.1.1 and shown in the study presented in Section 3.1.2, that no P300 is expected to be evoked after frequent task-irrelevant stimuli (*standards*), while a P300 is evoked by infrequent *task-relevant* stimuli (*targets*). Further, it is hypothesized that *missed targets* will also not evoke a P300. The behavioral data of the experiments presented in Section 3.1.2 suggest that very well trained subjects will only rarely miss a target stimulus. Therefore, it will be hard to record a high enough number of training examples for the class of *missed targets*. If too few training examples are available, the performance of a trained classifier is very low since performance of ML methods strongly depends on the amount and quality of the training examples.

One option to cope with the problem of small amounts of training examples is to substitute the underrepresented training class by a training class for which more examples can be recorded. The examples of the alternative training class must of course be similar to the examples of the relevant class. If this is the case, classifier transfer can be applied. Such approaches are already applied with success. While in (Pan and Yang, 2010) an overview is given on when and how transfer learning can be applied, other studies more specifically evaluate classifier transfer for the detection of brain patterns. In (Iturrate et al., 2013) it could be shown that the so called observation error-related potential (ErrP) (observation ErrP) can be detected in a task in which the applied classifier was not trained. Here a transfer of a classifier for the same type of ErrP (observation ErrP) was performed between two different tasks. Opposite to this in (Kim and Kirchner, 2013) it could be shown that a classifier which was trained on one type of ErrP, i.e., *observation* ErrP, can be used to classify another type of ErrP, i.e., *interaction* ErrP, while the same interaction task was passively supervised or actively performed by the interacting human. The chosen approach was based on the hypothesis that although given the different kinds of interaction (active or passive interaction) similar patterns are expressed in the EEG when detecting an error. This hypothesis was supported by average analysis of the evoked ErrPs.

Based on the hypothesis stated above classifier transfer between *standard* and *missed target* stimuli is proposed in this thesis to be possible and to result in high

prediction performance. The complete procedure of substituting training examples is illustrated in Figure 4.1: During a *training* session a classifier was trained on two classes of EEG data: (i) data recorded after infrequent *task-relevant, perceived* target stimuli, i.e., *targets*, and (ii) data recorded after infrequent *task-irrelevant* standard stimuli, i.e., *standards*. In the application (test) the classifier that was trained as explained above was used to distinguish between (i) *task-relevant, perceived* target stimuli, i.e., *targets*, and (ii) *task-relevant, not perceived or missed* target stimuli, i.e., *missed targets*. Thus, the class with infrequent examples (*missed targets*), that is classified later, was substituted during training by the class with frequent examples (*standards*) resulting in a classifier that is "partly" transferred from training to test. In summary, it is systematically investigated here whether it is possible to transfer a classifier between classes used for training and testing that are similar with respect to the fact that the individual ERPs do not contain a specific component, i.e., a P300. For the other class that does contain the relevant pattern, i.e., P300 ERP, no classifier transfer takes place.

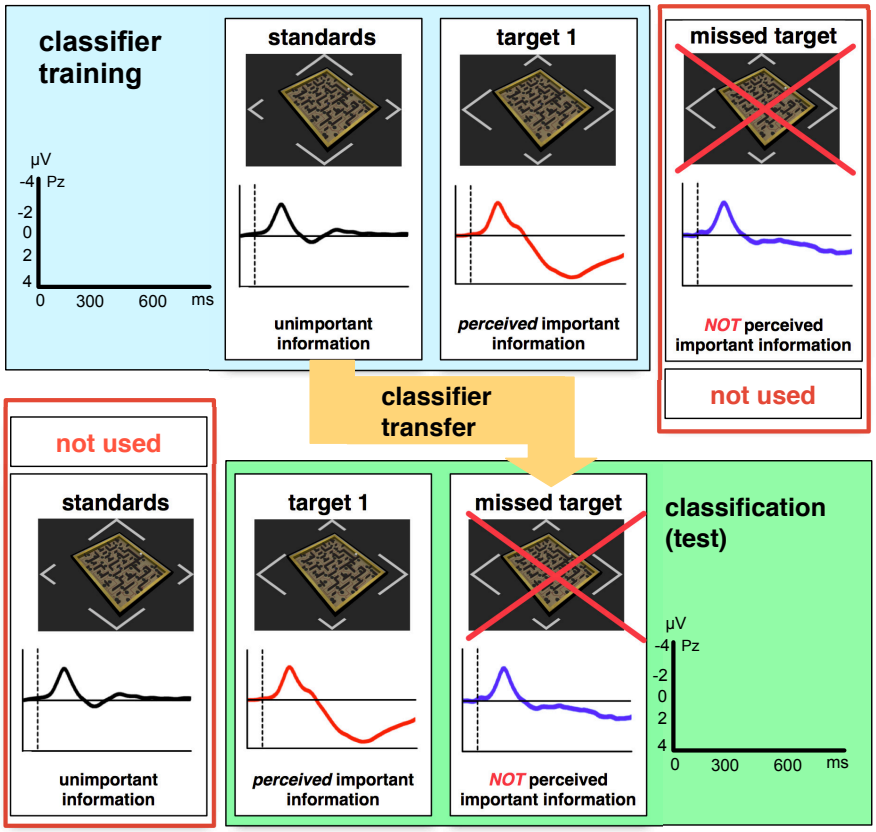


Figure 4.1: Transfer of classifier between the classes *standard* and *missed target*. For training the class *missed target* was not used, in test the class *standard* was not used. Figure is based on Figure 8 of (Kirchner et al., 2013d).

Preliminary investigations in the later described experimental setup (see Section 4.1.1) support the hypothesis that classifier transfer can be applied between *standards* and *missed targets* to cope with small amounts of training data for the *missed target* class. Results show that class separability is reduced in case that direct training is applied on an underrepresented class (see Figure 4.2, "Standards" refers to *standards*, "Rec. Targets" refers to *targets* and "Miss. Targets" refers to *missed targets*). This indicates that classification performance should be higher when training takes place on two well-represented classes and classifier transfer is performed to classify the underrepresented class, in comparison to training performed directly on an underrepresented class.

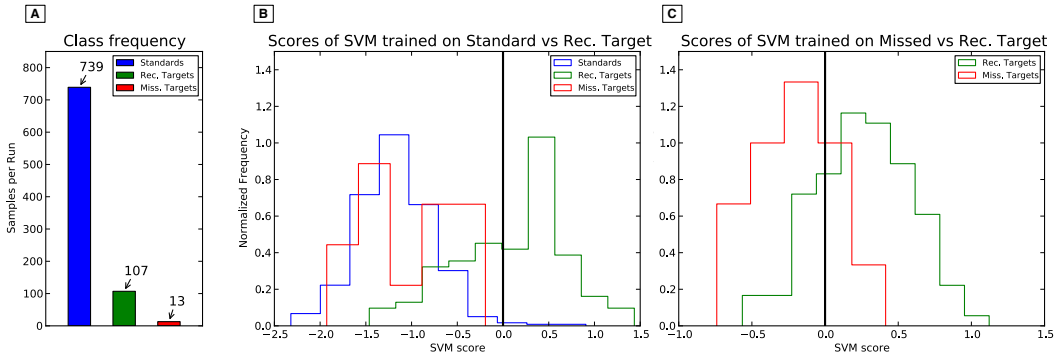


Figure 4.2: Separability of classes. A: class frequency is shown. B: a classifier (SVM) is trained on two highly represented classes "Standards" and "Rec. Targets" to later classify an underrepresented class "Miss. Targets". SVM scores are given to illustrate class separability. C: a classifier (SVM) is directly trained on the highly represented classes "Rec. Targets" and the underrepresented class "Miss. Targets" that are later classified. SVM scores are given to illustrate reduction in class separability, i.e., class separability between "Rec. Targets" and "Miss. Targets" is higher in case that classifier transfer was applied (B compared to C). Figure is based on figures of (Metzen and Kirchner, 2011).

Since the proposed approach of classifier transfer should only be successful in case that *missed targets* as well as *standards* both do not evoke a P300, while *targets* do, an average ERP analysis is performed in the following.

### 4.1.1 Experimental Part - Averaged ERP Analysis Supporting Classifier Transfer

In this section results of an average ERP analysis investigating whether a P300 is elicited by *target* stimuli but not (or weaker) by *standards* and *missed targets* under dual-task conditions are presented. Text, figures and tables of the following sections are taken and partly adapted from (Kirchner et al., 2013d). The data set

recorded as described below served for the development of a high number of SP and ML approaches and is hence used in a number of publications (Kirchner et al., 2010; Metzen et al., 2011a,b; Metzen and Kirchner, 2011; Straube et al., 2011; Ghaderi and Straube, 2013; Ghaderi, 2013a; Feess et al., 2013; Ghaderi, 2013b; Ghaderi and Kirchner, 2013a; Straube and Feess, 2013; Wöhrle et al., 2013a; Ghaderi and Kirchner, 2013b).

#### 4.1.1.1 Experimental Setup and Procedures

An ERP study was conducted in the *Virtual Labyrinth Oddball* scenario (Figure 4.3), which was developed in this thesis and has a similar setting compared to the one used in Section 3.1.2. The scenario again allows to investigate EEG activity common in scenarios where an operator is controlling a device while reacting to incoming infrequent information at the same time. It can be described as follows: A subject plays a virtualized BRIO® labyrinth game wearing an head mounted display (HMD). As input device (for the control of the simulated game) a real, modified BRIO® labyrinth game is used (see (Metzen et al., 2009b) for a description of the simulated game). Besides performing the demanding senso-motor task the subject again had to perform a second task, namely to react to infrequent task-relevant first ("Target 1" in Figure 3.1), second ("Target 2" in Figure 3.1), and third (in the shape of the second target but in red color) *target* stimuli by pressing a buzzer. Subjects were asked to respond immediately and not to ignore any target stimulus. Target stimuli were mixed up with frequent, task-irrelevant *standard* stimuli that required no response (see "Standards" in Figure 3.1; the corner with the longer sides points upwards instead of sidewards if compared with the first targets) in a ratio of $1 : 6$. The ISI was $1000$ ms with a random jitter of $\pm 100$ ms. All stimuli except for the third target stimuli (see below) were presented for a duration of $100$ ms. There were no infrequent, task-irrelevant deviant stimuli presented to the subject as it was the case for the experiments presented in Section 3.1.2. Since the manipulation task was very demanding, a rather long response time of $200$ ms to approximately $2000$ ms (approximately due to a $200$ ms jitter in inter stimulus intervals, i.e., $1800$ ms - $2200$ ms) after first target stimulus presentation was allowed during the recording of training data. Only in case there was no response within the given time period, the former "first target" trial was labeled as *missed target* and a second target was presented after two stimulus periods, i.e., after about $1800$ ms to $2200$ ms after the presentation of the first, missed target stimulus. After the second target stimulus a response time of $200$ ms to $1000$ ms was allowed before a third target was presented in the shape of the second target stimulus, but in red color. The third target stimulus was not shown briefly but continuously until response of the subject.

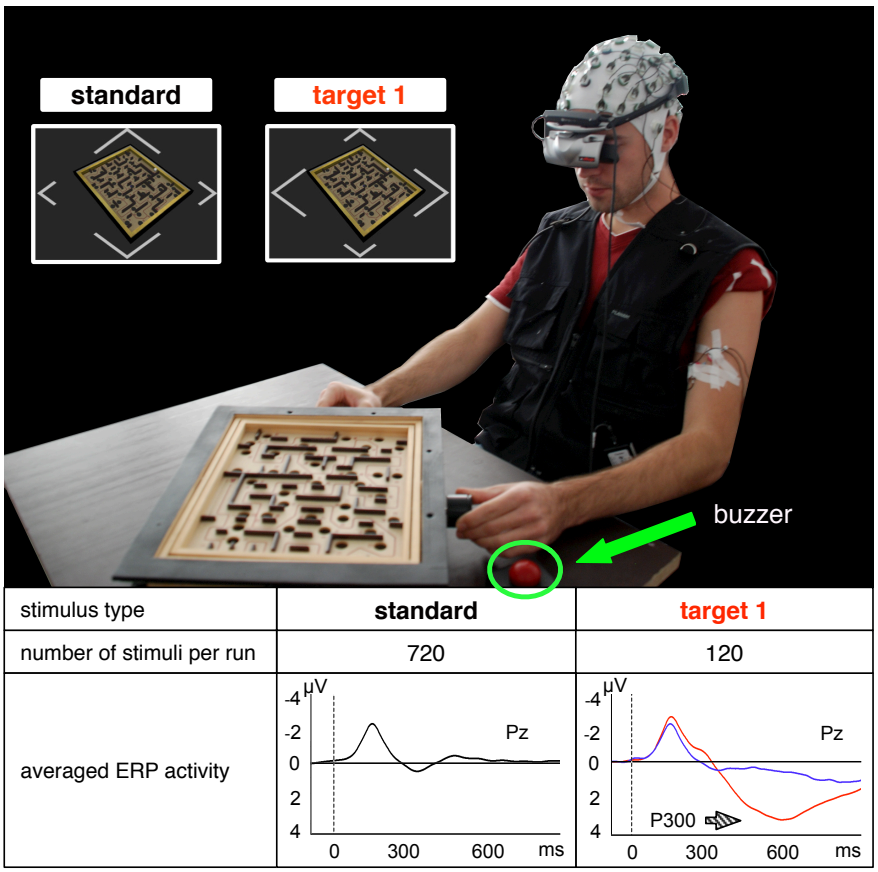


Figure 4.3: Experimental design of the *Virtual Labyrinth Oddball* setup. A subject is playing a virtualized BRIO® labyrinth game and reacts to less frequent first and second target stimuli by pressing a buzzer. The second target is presented in case that the first target was missed. Brain activity recorded after the different stimuli was averaged over all subjects, sessions, and runs (total number of trials after artifact removal: *target 1* (red ERP curve, right side): $n = 1623$; *missed target 1* (blue ERP curve, right side): $n = 439$; *standards* (black ERP curve): $n = 13598$). Figure is based on Figure 4 of (Kirchner et al., 2013d).

The use of the head mounted display in the *Virtual Labyrinth Oddball* setup allows for an easier and undisturbed playing of the game. For example in case of a loss of the ball, it can automatically be replaced at the start of the game. Further, the speed of the ball was artificially reduced to allow also less trained subjects to play. Moreover, performance of the subjects in the game was increased, which lead to an increased motivation in subjects to play the game. Even more important was that by using the HMD stimuli that were presented to the operator will always be shown at the same place in the subjects' field of view and with the same size, ensuring the player cannot miss a stimulus due it not being in his field of view, which could po-

tentially be the case in the setting used in Section 3.1.2. Furthermore, the gaming field, i.e., location of the ball will always be kept at approximately the same location with respect to the field of view and position of the presented stimuli. Additionally, since the visual presentation (shape and color) of standard stimuli that require no response and first target stimuli that require a response were kept very similar (see Figure 3.1), a strong difference in early visual processing of the stimuli was likely avoided. This assures that differences in the EEG recorded after the presentation of both stimuli types were mainly caused by processes of higher cognitive processing.

Six healthy subjects (males; mean age $27.5 \pm 2.1$; right-handed, and normal or corrected-to-normal vision) took part in the experiments. Subjects were instructed to respond to all *target* stimuli even in case they were uncertain. By this procedure, we ensured that *missed targets* were indeed missed and consciously not perceived as important and task-relevant stimuli. Subjects were in a competition to miss as few as possible *targets* while achieving good performance in the game. Recognizing and responding to all targets was rated higher. One subject had to be excluded in retrospect due to extensive eye blinks which made average ERP analysis impossible. The experiment was split into two sessions with at least one day of rest in between. In each session, each subject performed 5 runs with 120 *target 1* stimuli (important information) and about 720 *standard* stimuli (unimportant information, shape of stimuli see Figure 4.3). Stimuli were presented in random order.

**Ethics Statement:** The study has been conducted in accordance with the Declaration of Helsinki and approved with written consent by the ethics committee of the University of Bremen. Subjects have given informed and written consent to participate.

#### 4.1.1.2 Hypotheses

The hypothesis is that EEG activity evoked by frequent task-irrelevant information (*standards*) in the *Virtual Labyrinth Oddball* setup is very similar to EEG activity evoked by infrequent task-relevant stimuli that were either completely missed or somehow not properly processed by the brain and were therefore not recognized as task relevant and missed a response (*missed targets*). In both cases, i.e., after standard and missed target stimuli, the subject will not respond by buzzer press, because they are not task relevant (*standards*) or they are *not perceived* as task-relevant stimuli (*missed targets*). The expected similarities between EEG activity evoked by unimportant stimuli (*standards*) and by *missed target* stimuli are essentially caused by the lack of target detection and processing by the brain, either because of a failure (for *missed targets*) or because it is not required (for *standards*). Since target recog-

nition processes are correlated with the expression of a P300 and might be overlaid by other activity in the ERP range, like the prospective positivity that is evoked by task change processes, ERP analysis will be focused on data recorded at electrode positions at which main expression of these potentials is expected, i.e., at central to parietal medial electrode sites.

#### 4.1.1.3 Methods

**Data Recording:** While the subjects were performing the task, EEG was recorded continuously (62 electrodes, extended 10-20 system with reference at FCz) using a 64 channel actiCap system (Brain Products GmbH, Munich, Germany). Two electrodes were used to record the EMG of muscles of the lower arm related to the buzzer press in order to monitor muscle activity. Impedance was kept below 5 kΩ. EEG and EMG signals were sampled at 1000 Hz, amplified by two 32 channel BrainAmp DC amplifiers (Brain Products GmbH, Munich, Germany) and filtered with a low cut-off of 0.1 Hz and high cut-off of 1000 Hz.

**Behavioral Data:** For behavioral analysis we investigated the performance of the subjects in the oddball task. For this, we analyzed the subject's correct behavior and incorrect behavior (commission error, i.e., response on standard stimuli and omission error, i.e., missing response on target stimuli).

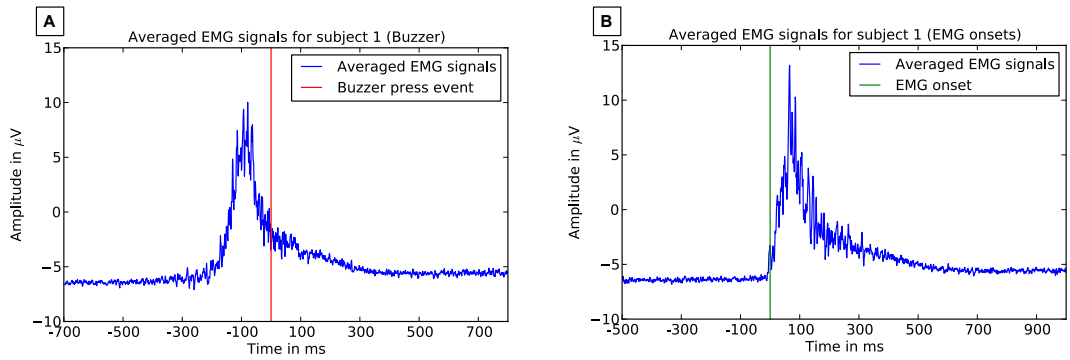


Figure 4.4: Averaged EMG activity for subject 1. A: Averaged activity based on buzzer press event. B: Average activity based on EMG onset. Figure is based on Figure 6 of (Kirchner et al., 2013d).

Further, we investigated the response times and jitter in response times based on buzzer events and EMG onsets (see Figure 4.4 for averaged EMG activity based on EMG onset and buzzer event). The onsets in the EMG signal had to be labeled manually, due to poor signal quality and constant movement of the subject an automated onset detection as described in (Tabie and Kirchner, 2013) was not possible. For the analysis of EMG onset the signals from the two unipolar EMG channels were

subtracted from each other to calculate a bipolar signal. The raw bipolar signal was preprocessed using a variance based filter with a window length of 1 s (Tabie and Kirchner, 2013). The resulting signals were visually inspected and each onset was marked in the EEG data. The single response time was then measured as interval between the target onset and the corresponding EMG onset. Single response times on buzzer events were measured as time between the onset of stimulus presentation and the onset of buzzer press. Further, the median of response time over all sets (3 sets $\times$ 2 sessions) for each subject and the minimal response time and maximal response time were calculated. Afterwards, the mean of subjects' medians were calculated.

**ERP Average Analysis:** ERP analysis was focused on EEG activity occurring 300 ms after stimulus onset, since earlier EEG activity is stronger related to visual stimulus processing and attentional processes rather than to higher cognitive processing. For average ERP analysis we used a low-pass filter with an untypical low cutoff frequency. The reason was that results of ERP analysis should be comparable with results of ML analysis (see Section 4.1.2). Although different pass bands are reported in P300 classification (see (Kaufmann et al., 2011; Jansen et al., 2004)), a study on the important factors of P300 detection concluded that the main energy of this type of ERP is concentrated below 4 Hz (Jansen et al., 2004). Our own investigations support this conclusion (see for example (Ghaderi et al., 2014)).

Average ERP analysis was performed off-line with the BrainVision Analyser Software Version 2.0 [Brain Products GmbH, Munich, Germany] on EEGs from runs 2, 3 and 4 of both sessions. Run 1 and 5 were not used for analysis to reduce the amount of data and thus processing time for the ML analysis presented in Section 4.1.2. Middle runs were chosen to minimize side effects due to training or exhaustion.

EEGs were re-referenced to an average reference (excluding electrodes Fp1, Fp2, F1, F2, PO9, PO10, FT7–FT10 due to artifacts and electrodes TP7 and TP8 which were used to record EMG activity) and filtered (0.2 Hz low cutoff, 4.0 Hz high cutoff). Artifacts (e.g., eye movement, blinks, muscle artifacts, etc.) were rejected semi-manually (maximal amplitude difference in 200 ms intervals was 50 $\mu$V, gradient 75 $\mu$V/ms, low activity was 0.1 $\mu$V over 100 ms). EEGs were segmented into epochs from 100 ms before to 1000 ms after stimulus onset. Epochs were averaged separately for each stimulus type. Only segments in which a stimulus of type *first target* was followed by a response within the given response time contributed to mean ERP curves on the stimulus type *target*. Segments in which no response followed after a stimulus of type *first target* were defined as *missed target* trials and were used to generate mean ERP curves on the stimulus type *missed target*. Baseline correction was performed before averaging (pre-stimulus interval: $-100$ to 0 ms). In case of missed target events a second target (Target 2 in Figure 3.1) was presented. In this study

the ERP activity evoked by stimulus type *second* target and *second* missed target 2 was not investigated.

**Statistics on ERP Data:** Amplitude differences were analyzed using repeated measures ANOVA with the within-factors *stimulus type*, *electrode*, and *time window* and between-factor *subject* [SPSS, version 20, SPSS Inc., Chicago, IL, USA]. To find the expected P300 effect, the difference between amplitudes of the ERPs that were evoked by the three stimulus types (*standards*, *targets*, and *missed targets*) was compared. Additionally, the factor *electrode* (Cz, Pz and Oz) was used to investigate spatial differences in the P300 effect. *Time window* was used as factor since visual inspection of the subject-wise post *target* epoch averages revealed multiple peaks in each subject within the time range of 300–900 ms. Therefore, the 300–900 ms window was divided into two separate windows (300–600 ms and 600–900 ms after the stimulus) to cover early and late parts of the broad peak (as seen in grand average in Figure 4.3), accounting for multiple, possibly overlapping positive ERP components. To investigate subject-specificity of the effects, *subject* was used as a between-subjects factor. Where necessary, the Greenhouse–Geisser correction was applied and the corrected $p$-value is reported. For pairwise comparisons, the Bonferroni correction was applied.

#### 4.1.1.4 Results

**Behavioral Data:** In total 724 omission errors ($575.2 \pm 82.23$) occurred, thus 724 *missed targets* were observed and 2876 *targets* stimuli were found with correct responses. No commission errors (i.e., responses on *standards* stimuli) could be found.

Figure 4.5 shows the median response time for each subject across two sessions. Based on the buzzer press events, responses occurred 837 ms after the target stimuli (mean of subject's medians). The median of minimal response time was 597 ms and the median of maximal response time was 1783 ms. The difference between the minimal and maximal response time was between 686 ms and 1657 ms (median: 1131 ms). EMG onsets began even earlier in time (mean of subject's medians: 551 ms). The median of minimal response time was 336 ms and the median of maximal response time was 1466.5 ms. The difference between the minimal and maximal response time was between 563 ms and 1621 ms (median: 1130.5 ms). No difference exists between median difference in response time based on the buzzer event (median: 1131 ms) and median difference of response time based on the EMG onset (median: 1130.5 ms).

**ERP Average Data:** The grand average over all subjects of the standard, target and missed target ERP pattern in the centro-parietal electrode (Pz) is depicted in

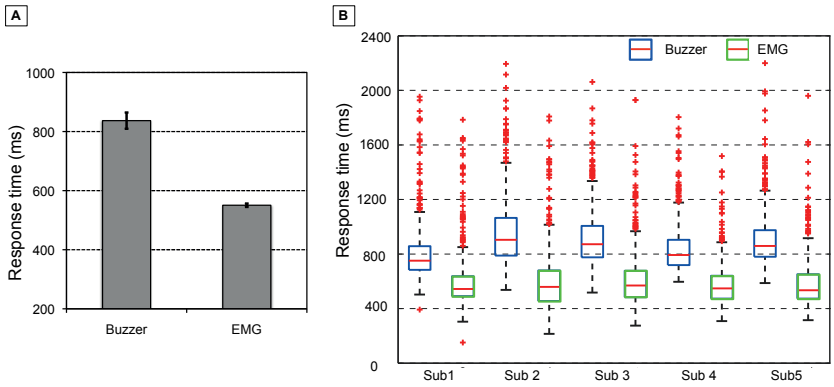


Figure 4.5: Response time for each subject across two sessions. A: Mean response time based on buzzer press event and EMG. B: Median of response time for each subject. Figure is based on Figure 7 of (Kirchner et al., 2013d).

Figure 3.1. Significant differences between standards and targets (i.e. P300 effect) were observed [$F(2, 50) = 65.27, p < 0.001$, pairwise comparisons: standards vs. targets: $p < 0.001$]. The P300 effect was stronger at the Cz and Pz electrodes compared to the electrode Oz [P300 effect at Cz: $p < 0.001$, P300 effect at Pz: $p < 0.001$, P300 effect at Oz: $p < 0.045$]. The significant amplitude difference between the ERPs evoked by targets and missed targets stems from a higher positive amplitude on targets for both time windows [$p < 0.001$]. This higher positivity elicited by targets was significant for four subjects [targets vs. missed targets: $p < 0.02$ for four subjects, $p = n.s.$ for one subject (subject 1), see Figure 4.6)]. Furthermore, no subject showed differences between ERPs evoked by missed targets and standards in the 300–600 ms time range recorded over central electrodes [standards vs. missed targets: $p =$ n.s.]. However, in the 600–900 ms window, amplitude differences between missed targets and standards are more subject-specific [standards vs. missed targets: $p =$ n.s. for subject 4 and 5, $p < 0.029$ for subject 1, 2, and 3, see Figure 4.6 for comparison of ERP activity recorded in subject 1 and subject 5)].

#### 4.1.1.5 Discussion

To summarize, a P300 effect elicited by targets was observed for both time windows and in all subjects with a maximum amplitude intensity at the central and parietal electrodes (Cz and Pz). The morphology of the ERP form elicited by missed targets is, especially in the 300–600 ms time window, similar to ERP forms elicited by standards and supports our hypothesis that EEG instances evoked by standard stimuli can potentially be used to substitute EEG instances evoked by missed targets during training. For the later time window results differed. Only two subjects showed no differences between standards and missed targets.

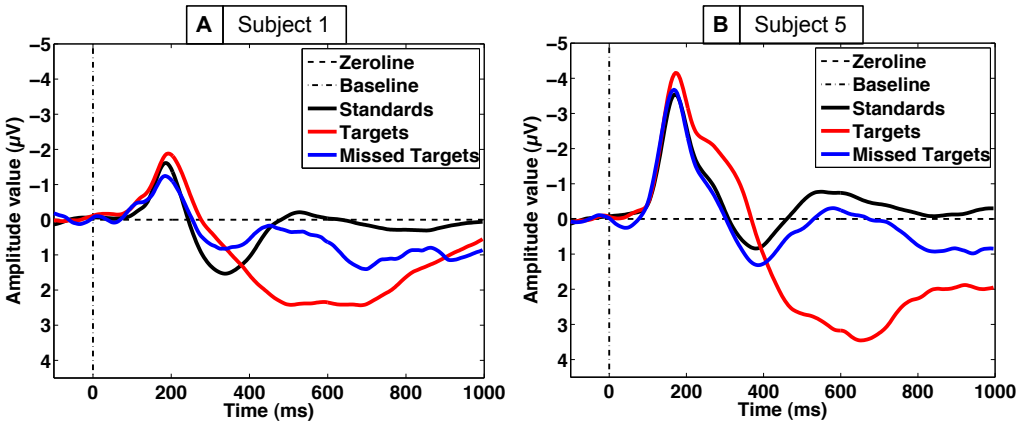


Figure 4.6: Averaged ERP activity in the *Virtual Labyrinth Oddball* scenario. Averaged ERPs of standards, targets, and missed targets are shown for two subjects with different ERP patterns. A: subject 1: no significant difference in ERP amplitude between targets and missed targets but significant difference in ERP amplitude between standards and missed targets for the late window was found. B: subject 5: a higher P300 effect on targets compared to both standards and missed targets and no significant difference in ERP amplitude between standards and missed targets for the late window was found. Figure is based on Figure 8 of (Kirchner et al., 2013d).

### 4.1.2 Experimental Part - Optimization of Training Data

To further investigate whether the similarity in shape of the investigated ERPs (see Section 4.1.1.4) indicates that a transfer of a classifier between classes is possible, we performed an ML analysis that systematically investigated best suited training windows for classifier training. The ML analysis presented in the following shows that classifier transfer results in high performance in detecting the states: *success in target recognition* versus *failure in target recognition*. Since the results of the average ERP analysis regarding the P300 effect (see Section 4.1.1.4 and Figure 4.6 illustrating two ERP curves of two subjects on all three types of stimuli) indicate that different time points in the ERP might contribute differently to the success of classification a classifier was systematically trained on different sub-windows to evaluate how well the transfer works for different windows. It was investigated which window size (with respect to results from average ERP analysis, see Section 4.1.1) is most important and which performance can be achieved after optimization of preprocessing and classification. A reduction of window size contributes to lower computational costs and is therefore desirable for online analysis. In contrast to the average ERP analysis described above (see Section 4.1.1) the early time window of 0–300 ms was included in ML analysis. This was done because it was expected that the early time windows may still contribute to the classification of the different classes (*standards*, *targets*, *missed targets*) even though the hypothesis (see Section 4.1.1.2) was that

main differences are caused by the P300 effect (see Section 4.1.1.4). To include this window into the investigation further serves as a control of the hypothesis. Text, figures and tables of the following sections are taken and partly adapted from (Kirchner et al., 2013d).

#### 4.1.2.1 Experimental Setup and Procedure

For a description of the experimental setup and experimental procedure see Section 4.1.1.1.

#### 4.1.2.2 Hypotheses

The hypothesis for the investigations presented in the following was, that due to the similarities in average ERP activity found in the analysis presented in Section 4.1.1 that were evoked at central parietal sites after the presentation of standard stimuli compared to missed targets, a classifier transfer between the classes standards and missed targets is possible and a classifier trained on the classes standard and target will show a high performance in classifying examples of the classes missed target and target. Further, it is expected that the performance of the classifier for different subjects can be predicted by the strength of the P300 effect found in the average ERP analysis, supporting the hypophysis that BR does indeed detect concrete brain states, i.e, the brain state of *target recognition and task change* in this example. This should moreover be supported by similarities found between ERP activity of the early and late window as well as achieved performance after training of data from early and late windows.

#### 4.1.2.3 Methods

**Data Recording:** Data recording is explained under Section 4.1.1.3.

**Data Processing for Single-Trial BR with Classifier Transfer:** Data processing was as follows: windowing and preprocessing were performed directly on the raw data from the recording device. In order to avoid that preprocessing artifacts such as, e.g., filter border artifacts, influence classification performance, we performed the complete preprocessing (including decimation and filtering) on a larger window between $-200$ and $1400$ ms relative to the stimulus onset. The following preprocessing based on the rationale issued mentioned above (see Section 4.1.1.3 and (Jansen et al., 2004)) were chosen: the data were baseline-corrected (with $100$ ms window prior to stimulus onset), decimated to $25$ Hz and subsequently lowpass filtered with a cut-off frequency of $4$ Hz.

As in the ERP analysis, trial runs 2, 3 and 4 of both sessions were used for training and testing. Different windows were cut by varying starting point (0 ms-700 ms) and window size (200 ms-800 ms) in steps of 100 ms. Data used for training and testing were different, as outlined above: training was performed on *standards* and *targets* of one experimental run and testing was performed on *missed targets* versus *targets* of another run within one session. All possible combinations of the above mentioned runs within one session were tested. Classifier features were the preprocessed time-channel values, i.e., the amplitudes.

To determine classification performance that can be achieved under optimized conditions, a final analysis with the goal to get a better estimate of the applicability of our approach of classifier transfer between the classes *standard* and *missed target* was performed. The processing window was chosen based on the results of ML analysis (Section 4.1.2.4). Classifier optimization of the SVM parameter complexity using a 5-fold cross validation in combination with a pattern search algorithm (Nocedal and Wright, 1999) to evaluate the overall performance in the application with an adjusted classifier was performed.

**Statistics on Single-Trial BR Performance after Classifier Transfer:** For statistical inference, three time windows from the temporal segmentation mentioned above, that match the later time windows which had been chosen for ERP analysis (300–600 ms, and 600–900 ms see Section 4.1.1) and the early time window of 0–300 ms were chosen. This procedure relates the results of the classifier performance-based approach to the results of the ERP analysis. Classification performances for the different window sizes were statistically analyzed using repeated measures ANOVA with the within-subjects factors *time window* (0–300 ms, 300–600 ms, and 600–900 ms) and *subject* [SPSS, version 20, SPSS Inc., Chicago, IL, USA]. Classification performance after optimizing the classifier were analyzed using repeated measures ANOVA with *subject* as within-subjects factor [SPSS, version 20, SPSS Inc., Chicago, IL, USA]. Where necessary, the Greenhouse–Geisser correction was applied and the corrected $p$-value is reported. For multiple comparisons, the Bonferroni correction was applied.

#### 4.1.2.4 Results

The results in Figure 4.7 illustrate how the separability of the two classes *missed targets* versus *targets* varies when different time windows are used for classification. For small and early windows (before 300 ms) the performance is lowest but above random guessing. For small window sizes (200–400 ms) the performance reached a maximum when used with windows starting after 300 ms. With increasing window

size performance also increases, which is yet impacted with the increased dimensionality of the data (more dimensions imply more information for the classifier) and has therefore to be considered carefully.

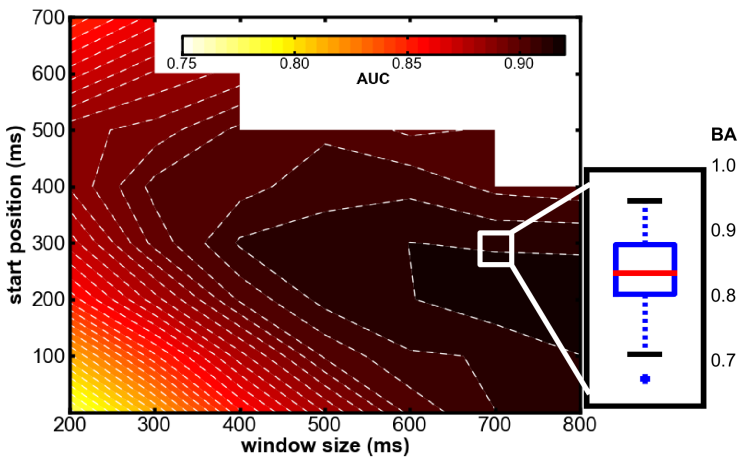


Figure 4.7: Classification performance in the *Virtual Labyrinth Oddball* scenario for missed targets versus recognized targets for different windows. The start position (y-axis) is given relative to stimulus onset. The inset on the right indicates the optimized performance using the window from 300 to 1000 ms. The different windows are compared using the AUC, while the optimized performance is given as BA. Figure is based on Figure 9 of (Kirchner et al., 2013d).

To investigate the amount of information in each time range, performances after training on fixed window sizes of 300 ms were compared as illustrated in Figure 4.8. The statistical analysis of the AUC values shows that performance is clearly affected by the choice of the time window [main effect of *time window*: $F(2, 22) = 82.43, p < 0.001$] and that classification of the middle window (300 ms–600 ms) and the late window (300 ms–600 ms) clearly yields higher performance compared to the early window (0 ms–300 ms) [early window: mean AUC of 0.82, middle window: mean AUC of 0.90, late window: mean AUC of 0.88, multiple comparisons: 0–300 ms vs. 300–600 ms: $p < 0.001$, 0–300 ms vs. 600–900 ms, $p < 0.001$, 300–600 ms vs. 600–900 ms: $p = 0.10$].

In a further analysis the possibility to improve classification performance by the combination of information of two windows was investigated. The middle time window (300 to 600 ms) that shows the highest classification performance for most subjects (see Figure 4.8) was combined with both other time windows (early: 0 to 300 ms and late: 600 to 900 ms time window) separately. The main result was that classification performance could be improved by the combination of the *middle* and *late* time window compared to the combination of the middle and early time window [main effect of *combined time window*: $F(1, 11) = 13.03, p < 0.005$, combination of the middle and early window: mean of AUC of 0.89, combination of the middle and late window:

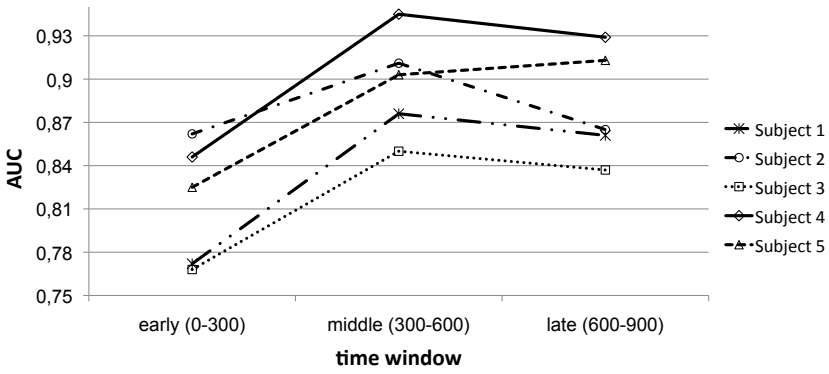


Figure 4.8: Classification performance for early, middle and late time windows. Mean classification performance is shown for each time window and each subject. Figure is based on Figure 10 of (Kirchner et al., 2013d).

mean of AUC of 0.92, pairwise comparison: combination of the middle and early window vs. combination of the middle and late window: $p < 0.02$] again supports our hypothesis that later cognitive activity is most important for the prediction of the success of cognitive processing.

As depicted in Figure 4.7, the best results in single-trial BR were obtained when starting the windows 300 ms after the stimulus was presented. This supports the hypothesis that P300-related processes contribute substantially to class separability. Based on these findings, a processing window in the time range between 300 ms and 1000 ms was chosen for single-trial detection of the *success* or *failure* of target recognition. As described in the methods section, an investigation with an optimized preprocessing procedure and classifier was performed next for this window. On average, a BA of 0.85 was obtained. While the measure of the AUC served for finding the interesting window ranges, this performance measure now reflects what the particular classifier is able to achieve under optimal conditions with the chosen signal and classification procedures. The distribution of the results is illustrated in the inset in Figure 4.7 and the classification performance for each subject is depicted in Figure 4.9. A significantly higher classification performance compared to all other subjects (except for subject 5) was shown for subject 4 [main effect of *subject*: $F(8, 88) = 2.97, p < 0.03$, details, see Figure 4.9 lower right].

It is worth to point out that average ERP analysis for subjects 4 and 5 (with better classification performance) in contrast to all other subjects could not reveal any significant differences in amplitude of ERP forms evoked by *standards* and *missed targets* (see Section 4.1.1) in both time windows (300 to 600 ms and 600 to 900 ms). This supports the thesis that the found P300 effect in ERP analysis is correlated with the performance achieved in single-trial BR for detecting the success in target recognition.

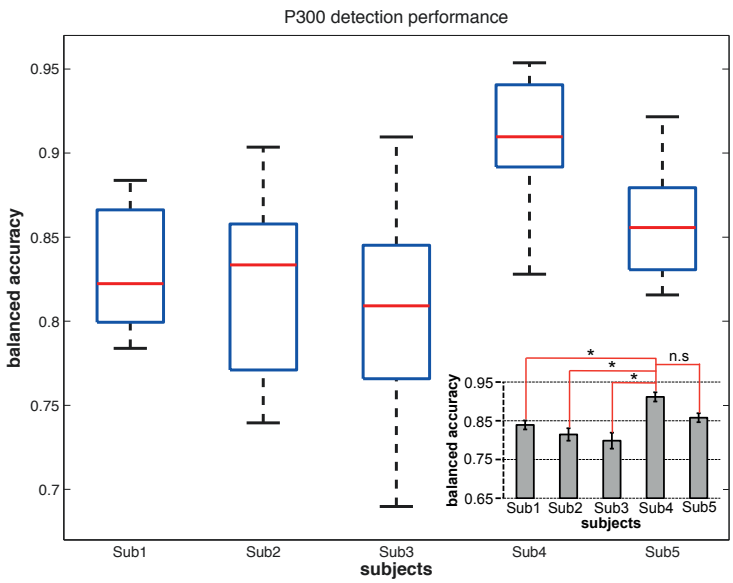


Figure 4.9: Classification performance in the *Virtual Labyrinth Oddball* scenario for the optimized case. For each subject the evaluated classification performance is shown for a window between 300 to 1000 ms (red line denotes median value of obtained classification performances). The inserted diagram shows the highest classification performance for subject 4 and 5 (mean classification performance and SE of mean are depicted). Figure is based on Figure 11 of (Kirchner et al., 2013d).

#### 4.1.2.5 Discussion

Results of ERP and ML analysis confirm that ERPs evoked by stimulus recognition and subsequent processes, e.g., change of task and preparation of response, are most important to detect the state of target recognition by BR. This is a basic prerequisite for eBR (see Part III) to infer response behavior of the operator. It was shown that a classifier trained on the classes *standards* versus *targets* can be successfully transferred to classify the classes *missed targets* versus *targets*. Results of ERP analysis of ERPs evoked in the middle time window that were found to be maximally expressed on central and parietal electrodes (Cz and Pz) were used to infer on classification performance. Thus, it is likely that the signal that is maximally expressed at these electrodes contributes most to the differences and similarities of the overall signal on all three types of stimuli.

The hypothesis that ERP activity evoked by frequent task-irrelevant *standard* stimuli is similar in shape and characteristic to ERP activity evoked by task-relevant stimuli that were not recognized as such (*missed targets*) was supported by the results. Further, results indicate that this similarity, which is especially strong in the middle time windows, is mainly caused by the absence of target recognition processes, since the P300 is either missing or massively reduced in amplitude. Certainly, pro-

cesses later than the evaluation and classification of stimuli (evoking a P300) that are related to task set preparation or response preparation and execution will also be involved (see Section 3.1 and (Kirchner and Kim, 2012; Kirchner et al., 2013b)). For example, for some of the subjects ERP activity evoked by unimportant standard stimuli and by missed target stimuli shows significant differences in the later time window, which may be related to late task set preparation processes (West, 2011) or late P300 activity that did not lead to a successful stimulus evaluation as discussed in (Kutas et al., 1977) and requires further investigation (see Figure 4.6, e.g. subject 1). Although a prominent similarity between *standards* and *missed targets* is the missing of a response of the subject, the results show that response related activity should not have a major influence on transferability of the classifier, since response time to individual target stimuli does vary widely (see Figure 4.5).

Results of ML analysis finally show that early stimulus processing in the time window 0–300 ms was not equally important as EEG activity in the later time range ($> 300$ ms) investigated here. However, early brain activity contributed as well. This might be caused by differences in attentional processes which have to be investigated in future experiments and analysis.

To summarize, conducted results allow to conclude that brain activity evoked by infrequent, unimportant stimuli (*standards*) in the investigated low frequency range is highly similar to brain activity evoked by *missed targets*, which are task-relevant stimuli that were not successfully processed, i.e., not recognized as task-relevant stimuli or completely missed. To substitute infrequent examples of *missed targets* by frequent examples of *standards* during training is possible and supports the hypothesis that transfer between classes is a feasible approach for applying BR in scenarios in which the amount of training data is way too small to implement methods that can handle few training data (Krauledat et al., 2008; Fazli et al., 2009; Lotte and Guan, 2010; Metzen et al., 2011a). Hence, the problem of few training examples in realistic scenarios can be solved by the proposed approach of classifier transfer with high classification performance, and can be improved by choosing appropriate window combinations. The choice of window, samples used for transfer and combination of windows was first defined by knowledge about underlying brain activity gained from average ERP analysis and confirmed by systematic ML analysis. Hence, it is shown that average ERP analysis can be a useful method to choose appropriate training data, especially if processes are involved that evoke pronounced patterns in EEG like the P300.

## 4.2 Simultaneous Detection of Brain States

Since in applications that require extensive human-machine interaction it may not only be required to detect just one specific brain state but two or even more, in this section it is investigated whether the simultaneous detection of two different brain states by BR is possible. To enable this evaluation, a second test scenario, the *Armrest* setup, was developed in this thesis. Experiments were conducted to test whether a simultaneous classification of two different brain states is possible by analyzing EEG data. The developed *Armrest* scenario covers several aspects of interaction in a robotic tele-manipulation scenario, and requires dual-task performance. However, the setting comes closer to a robotic application than the dual task performed in the *Labyrinth Oddball* and *Virtual Labyrinth Oddball* scenarios investigated before (see Section 3.1.2.1 and Section 4.1.1), because in the *Armrest* scenario the user is not always able to respond to information (responses to target events were *not* allowed during a defined rest period - see below). Instead, the subject has to postpone his response in such situations. This restriction was important to prove that BR still works under realistic conditions in which two performed tasks may influence, i.e., inhibit, each other in some situations. Further, it is expected that trained operators of application scenarios, like a tele-manipulation scenarios, have a low rate of *missed targets*. Hence, to investigate whether it is indeed possible to detect very few instances of *missed targets* by single-trial BR, the test scenario was designed such that subjects would not miss too many *target* stimuli. In the Armrest scenario two brain states were detected simultaneously by single-trial BR:

- "target recognition and task set change" (P300 and PM-task related activity, see Section 3.1.1) and

- "movement preparation" (late BP or RP and LRP activity, see Section 3.2.1).

### 4.2.1 Experimental Part - Dual Brain Reading

In the following a study is presented that analyses the performance of single-trial BR in an experimental setup developed in this thesis to investigating the simultaneous detection of two brain states and performance of classifier transfer under extreme conditions, i.e., very few examples of the relevant *missed target* class. Text, figures and tables of the following sections are taken and partly changed or adapted from (Kirchner et al., 2013d). The data set conducted in the *Armrest* scenario as described below was also used in (Kirchner et al., 2013a).

#### 4.2.1.1 Experimental Setup

The *Armrest* setup can be described as follows: Participants of the experiments wore an HMD and stood in a dimly lit room while performing two tasks in a virtual environment. The first task was to move the right arm from a rest position in order to reach a virtual target ball which was presented in the upper right corner marking a possible object which could be manipulated in a final application (Figure 4.10A and D). A hand tracking system was used to detect the point in time when the hand left the armrest. Whenever subjects moved their arm 5 cm away from the rest position, a marker for movement onset was sent and stored together with the EEG (movement marker was set at time point "0", see Figure 4.10B). After entering the target ball (see Figure 4.10D-2), the subject returned to the rest position (Folgheraiter et al., 2012). To support the rest state of the arm, an armrest was designed as part of the testbed. This armrest was integrated into the setup to imitate the strong support of the arm by the exoskeleton while the user is in a rest position. The arm and hand of the participant had to stay in the rest position for at least 5 seconds. In case the subject left the rest position too early, the target ball would disappear. This served to avoid too rapid changes between rest and movement which was necessary to assure sufficiently long non-movement periods for training of the classifier.

As second task, infrequent task-relevant versus frequent task-irrelevant information were presented at a ratio of 1:20. Three different types of task-relevant stimuli (target 1) were presented requiring three different responses, namely touching one of three virtual target objects in the virtual scenario as shown in Figure 4.10B-1, whereas each kind of warning required touching a particular one. Unimportant stimuli were similar in shape and required no response. In case the user missed an important stimulus (target 1), i.e., did not respond within 10 s after stimulus onset, a second stimulus (target 2), visually highlighted with a different color (orange instead of green), appeared. As for the *Labyrinth Oddball* and *Virtual Labyrinth Oddball* setups, task-relevant stimuli were expected to evoke a P300 and overlapping later ERP components while task-irrelevant stimuli should not (see Figure 4.10C). All three virtual response objects were presented at a fixed position in the HMD that followed the head movement to assure that all three response objects were always visible on the left side of the visual field. Again subjects were instructed to always respond to the target stimuli. Responding to the target stimuli was defined as the more important task, however was not allowed during rest.

Four healthy male subjects (between 25 and 31 years, right-handed, with normal or corrected-to-normal vision) took part in the experiments which were divided into three runs conducted on the same day. In each run, the subject had to respond to 60 target 1 stimuli. The number of intentional movements from the rest position

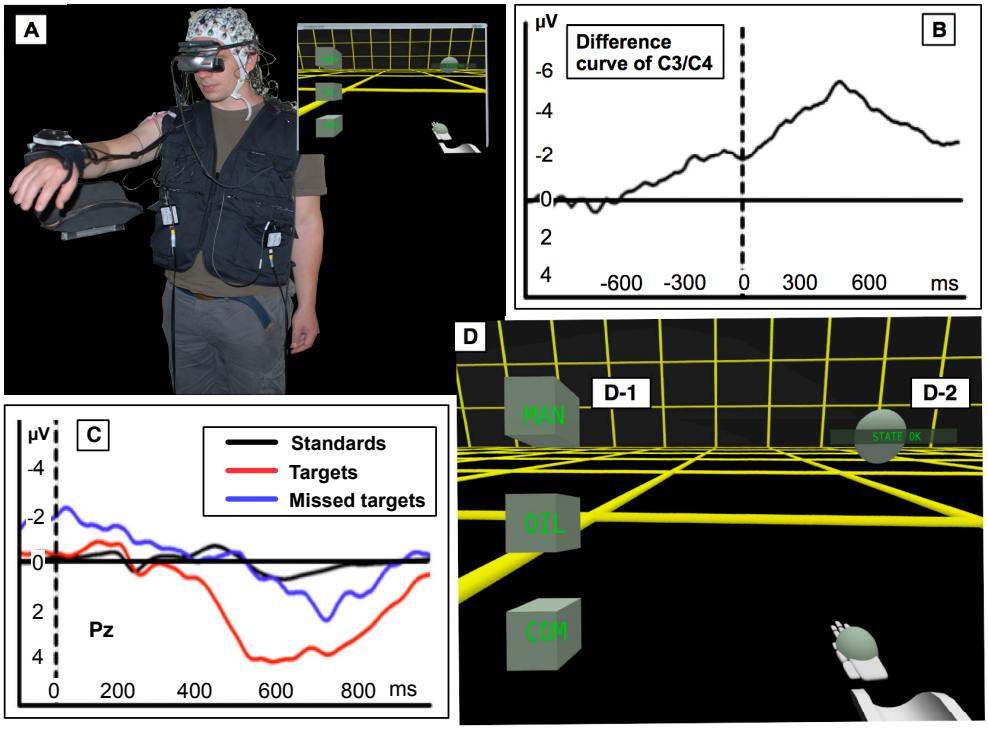


Figure 4.10: Experimental design of the *Armrest* setup. A: experimental setup: Armrest scenario; B: averaged difference curve between electrodes C3 and C4 (number of trials for movement events: 279) shows differences recorded over the primary motor cortex ipsilateral and contralateral to the side of movement (movement onset marker at dashed line); C: averaged ERP pattern at electrode Pz on different stimulus types (number of *standards*: 2968, number of *targets*: 156, number of *missed targets*: 9); D: three types of virtual response cubes (D-1) and virtual target ball (D-2). Figure is based on Figure 12 of (Kirchner et al., 2013d).

differed from 116 to 159. The shorter subjects rested (rest period had to last at least 5 seconds) the more lock-out trials they were able to perform in each run.

**Ethics Statement:** The study has been conducted in accordance with the Declaration of Helsinki and approved with written consent by the ethics committee of the University of Bremen. Subjects have given informed and written consent to participate.

#### 4.2.1.2 Hypotheses

Our hypotheses was that BR is able to simultaneously detect two different brain states in parallel. This is a main requirement for applying BR in applications that would benefit from the simultaneous supervision of two different brain states that

may be predictive for different behavior, which can be supported by eBR (see Part III). In the *Armrest* setup we re-tested the substitution of training examples and, hence, partly classifier transfer in a scenario that is similar to a robotic tele-manipulation scenario as described in Section 6 and produces even less training examples than the *Labyrinth Oddball* and *Virtual Labyrinth Oddball* scenarios do. The goal was to confirm the applied approach of classifier transfer and to show that it still works in a scenario in which both classified brain states may influence each other.

#### 4.2.1.3 Methods

**Data Recording:** For reasons of future data analysis and method development not presented here EEG was continuously recorded with a high density of sensors, i.e., with a 128 electrode system (extended 10-20 system, actiCap, Brain Products GmbH, Munich, Germany), referenced to FCz. Four electrodes of the 128 actiCap system served to record the EMG of muscles of the upper arm (M. biceps brachii and M. triceps brachii) in order to monitor muscle activity. All signals were amplified using four 32-channel BrainAmp DC amplifiers (Brain Products GmbH, Munich, Germany) and filtered with a low cutoff of 0.1 Hz and high cutoff of 1 kHz. Signals were digitized with a sampling rate of 5 kHz. Impedance was kept below 5 kΩ.

**Behavioral Data:** As for the *Virtual Labyrinth Oddball* scenario the subject's performance in the oddball task in terms of the amount of target stimuli with response and false reactions (omission and commission errors) as well as response times and jitter in response time based on the movement marker were analyzed. It was further analyzed how many movements from the rest position were valid, i.e., followed five or more seconds of rest. EMG data was analyzed to determine EMG onset with the method described earlier (see Section 4.1.1.3).

**Data Processing for Single-Trial BR with Classifier Transfer:** Data processing to detect the brain state "target recognition and task change" in EEG by ML analysis was performed as for the *Labyrinth Oddball* scenario in the optimized case (see Section 4.1.2.3). Due to the reduced amount of training examples that could be recorded here, three runs that were recorded in one session per subject performing the task were joined to a single data set, which was used for performance estimation based on a $5 \times 2$-fold cross validation. For performance estimation we had to use a modified cross validation strategy to estimate the classifier's accuracy due to the low number of missed targets. The partitioning of *standard* and *target* examples for training as well as the partitioning of *target* examples for testing was performed as usual to generate mutually exclusive splits, but all *missed target* examples of the

whole dataset were used in every test split for estimating classification performance. Note that due to the classifier transfer the classifier was *not* trained on missed targets and thus *all* missed target examples were *unknown* to the classifier during testing as it also holds true for all targets examples that were used for testing.

**Statistics on BR Performance in the Armrest Scenario and Comparison with the Virtual Labyrinth Oddball Scenario:** To evaluate subject-specific differences in classification performance in the *Armrest* scenario, the data were analyzed by one-way repeated measures ANOVA with *subject* as within-subjects factor [SPSS, version 20, SPSS Inc., Chicago, IL, USA]. For multiple comparisons, the Bonferroni correction was applied. To compare classification performance between Virtual Labyrinth Oddball scenario and Armrest scenario, Mann-Whitney U test [SPSS, version 20, SPSS Inc., Chicago, IL, USA] was performed. Note that different subjects participated in both experiments (*Virtual Labyrinth Oddball* / *Armrest*) except for one subject (coded as subject 1 for the *Virtual Labyrinth Oddball* and subject 3 for the *Armrest* scenario).

**Data Processing for the Detection of Movement Preparation Processes by Single-Trial BR:** To detect movement intention BR classifies two classes: (i) *no* movement preparation and (ii) movement preparation. Since movement intention is neither locked to a certain stimulus (i.e., command) nor happens after a fixed time of delay, it is necessary to *continuously* analyze the EEG stream. This continuous analysis is based on a sliding window approach, i.e., a window of a fixed length extracts instances of 1000 ms every 50 ms from the EEG stream (see Figure 4.11). For correct

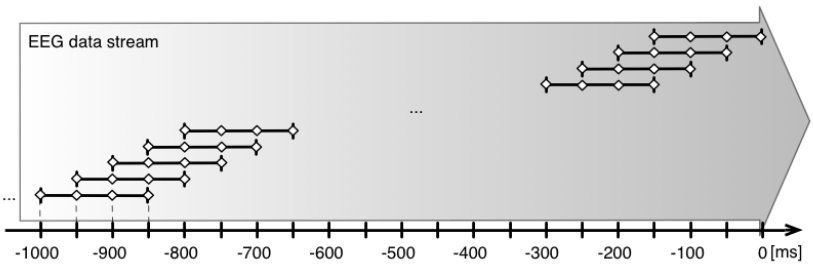


Figure 4.11: Sliding window approach for continuous classification of movements. Segments of a fixed length are cut out every 50 ms until the movement marker occurs (time point zero). Note that the time reference is unknown until the movement happens. Figure used with kind permission of Anett Seeland.

labeling during training and for performance evaluation the problem of *ambiguous* instances emerges here, i.e., windows that neither clearly belong to the movement preparation nor to the no movement preparation class. To deal with this problem,

training is performed time dependent on the lock-out event, i.e., only specific windows were used for training.

During online prediction the classifier should to some extent be time shift invariant, hence should not only be able to detect the EEG pattern at the time point it was trained on, but also at adjacent instances. To obtain such a time shift invariant classifier, in (Blankertz et al., 2006c) the classifier was trained on two rather than just one window per movement marker. In (Kirchner et al., 2013a) it is systematically analyzed whether the number of training windows per movement influences classification performance. It was found that two training windows significantly improve classification performance, while a higher number of training windows per movement does not significantly improve classification.

In the investigation that is presented next, the question of *which* combination of two training windows (labeled by their end time with respect to the movement marker) provides the best results across subjects is addressed. The two identified windows can subsequently serve for all subjects and an exhaustive re-optimization or re-analysis is unnecessary. This is highly relevant for an online application.

To predict upcoming movements from single trials the following procedure was applied. Similar to the approach presented in (Folgheraiter et al., 2011), windows for the "movement preparation" class had a length of $1000$ ms and were cut out with respect to the movement marker. During training, $13$ different training windows for that class that ended between $-600$ to $0$ ms relative to the movement marker, i.e., $[-1600, -600]$, $[-1550, -550]$, $\ldots$, $[-1000, 0]$ were analyzed for each movement trial. For the "no movement preparation" class, training windows of an equal length were cut out every $1000$ ms, if no other marker was stored in the data stream $1000$ ms before or $2000$ ms after that window. Since the duration of a rest period was not fixed, the number of instances per data set differed for that class (from $359$ to $520$).

Data processing in both cases (training and test) was done as follows: All trials were standardized ($\mu = 0$, $\sigma = 1$), decimated to $20$ Hz and band pass filtered ($0.1$-$4.0$ Hz). Only the last $200$ ms were used for feature generation: $124$ channels $\times$ $4$ time points $=$ $496$ features. Finally, an SVM was trained on the feature vectors of the training data. To obtain classification performance for each subject a $5 \times 2$-fold cross validation was used on the merged data of one session ($3$ concatenated sets). In each training run, SVM parameters were optimized with an internal 5-fold cross validation using a pattern search algorithm (Nocedal and Wright, 1999).

Since the training windows overlapped in time, similar performances could be expected. Hence, overlapping windows were analyzed for each subject in order to find time points which lead to significantly different performances to define borders of clusters. Based on this analysis, 13 training windows were grouped in three *clusters*: early $[-600, -450]$ ms, middle $[-400, -250]$ ms and late $[-200, -0]$ ms. Across all

subjects, the middle cluster (cluster B) provided a significantly better classification performance compared to both the early (cluster A) and late cluster (cluster C): B vs. A: $p < 0.001$, B vs. C: $p < 0.001$ (see also first three columns of Figure 4.14). Further, classification performance using training windows of the late cluster was significantly higher than that of the early cluster (C vs. A: $p < 0.001$).

To calculate a performance measure (here BA, see Section 2.4.3) for performance evaluation, labeling the sliding windows was required. Since the onset of the LRP cannot exactly be determined for single trials, we defined a time range from $-600$ to $-350$ ms based on average ERP analysis (see Figure 4.12) as an uncertain area, i.e., as a time range in which we could not be certain (for each single trial) whether or not the brain was already preparing a movement. Sliding windows ending in this time domain were left out for performance calculation. Also, predictions based on windows ending at $-150$ to $0$ ms (see Figure 4.12) were excluded due to the fact that the actual movement onset happens before the movement marker is stored (see estimation of movement onset in Section 4.2.1.4).

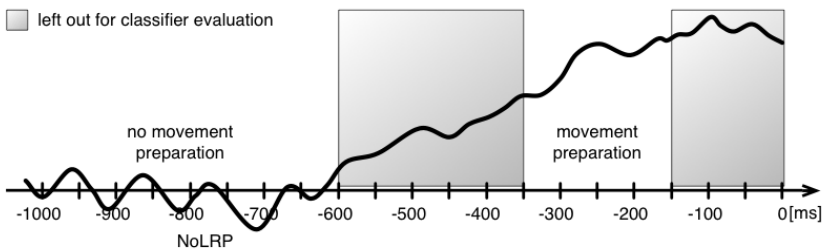


Figure 4.12: Classifier evaluation for sliding windows. Evaluation depends on the end time of a sliding window: less than $-600$ ms with respect to the movement onset label: true label "no movement preparation"; between $-300$ to $-200$ ms with respect to the movement onset label: true label "movement preparation"; in gray shaded area: left out for evaluation due to unknown true label or already started movement. The black line illustrates the average ERP difference curve for channels C3/C4 over all subjects. Figure is based on Figure 13 of (Kirchner et al., 2013d).

**Statistics on Data Processing for the Detection of Movement Preparation Processes by Single-Trial BR:** To evaluate *which* combination of two training windows is optimal, performance of all possible combinations of two training windows were computed, i.e., combinations within the same cluster (within-cluster, e.g. $-500$ ms combined with $-450$ ms) and between clusters (between-cluster, e.g. $-500$ ms combined with $-300$ ms). The mean performance of all within–cluster combinations and all between-cluster combinations for each defined cluster, the mean performances of the single training windows in each cluster, and the performance of all training windows were finally compared using repeated measures ANOVA with *combination*

(10 levels) as a within-subjects factor [SPSS, version 20, SPSS Inc., Chicago, IL, USA]. The performance that can be achieved in case of training takes place on all 13 training windows served as a baseline, representing the case that no specific training windows were chosen.

#### 4.2.1.4 Results

**Behavioral Data:** In the whole experiment, subjects responded in total to $720$ target stimuli and missed $33$ target stimuli (mean and SD across subjects for omission errors: $8.25 \pm 2.63$). This low amount of omission errors, i.e., *missed targets*, was expected due to the low effort of the main task. In total $7$ commission errors on standard stimuli occurred (subject $2$: one commission error, subject $4$: $6$ commission errors). The response time was on average $4.7$ sec (mean of subject's median), with a median minimal response time of $1.5$ sec and the median maximal response time of $15.3$ sec The difference between minimal and maximal response time was between $7.4$ sec and $19.1$ sec (median $13.8$ sec). A rest period of at least $5$ s preceded on average $89\,\% \pm 9\,\%$ of the performed movements. For EMG onset detection only the data from M. biceps brachii contained usable information. However, we observed a preload in muscle activity of one subject resulting in an onset of around $-1.7$ sec relative to the movement marker. Therefore, based on the analysis of motion tracking data recorded during intentional movements of the right arm with normal speed (see Section 3.2.2) we calculated the time it took to move the arm by $5$ cm from the rest position. For the subjects recorded in the arm movement study in Section 3.2.2 such movement took on average $154$ ms. Hence, we assumed that the physical movement onset in this very similar setup was around $-150$ ms relative to the movement marker.

**Performance of BR after Classifier Transfer:** The resulting BA values are shown in Figure 4.13. Best classification performance was obtained for subject 1. Mean classification performance was slightly lower compared to the *Labyrinth Oddball* scenario (see, Figure 4.13 vs. Figure 4.9). However, classification performances between both scenarios did not differ significantly [median for *Labyrinth Oddball*: $0.839$, median for *Armrest*: $0.791$, mean ranks of *Labyrinth Oddball*: $6.2$, mean ranks of *Labyrinth Oddball*: $7.8$, $U = 4$, $Z = -2.11$, $p = 0.19$, $r = 0.494$)]. These results show that the classifier transfer approach can be applied to realistic scenarios in which the subject is performing several tasks but is not always allowed to respond to an important stimulus right away. Moreover, it is shown that a highly underrepresented class can successfully be classified.

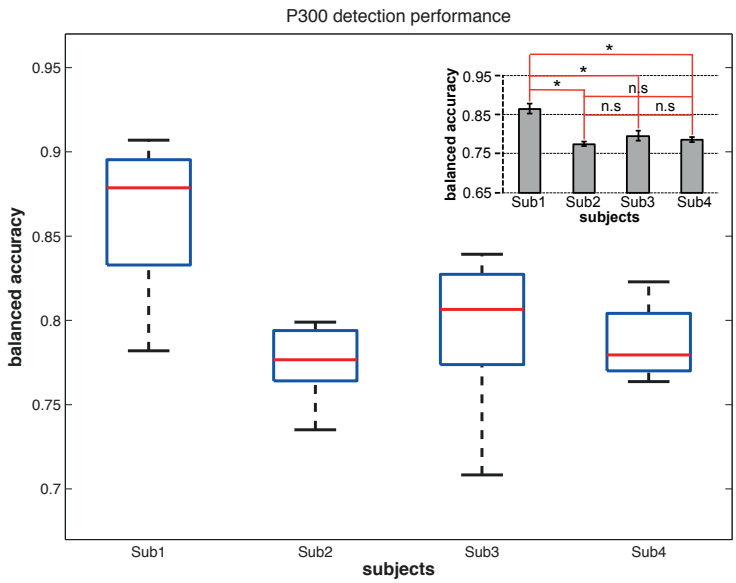


Figure 4.13: Classification performance in the *Armrest* scenario. Results for the performance of the classifier trained in the dual BR scenario for classification of *missed target* vs. *target* instances after classifier transfer are shown for all subjects individually (red line denotes median value of obtained classification performance). The inserted diagram shows mean classification performance and SE of mean. Highest classification performance is observed for subject 1. Figure is based on Figure 14 of (Kirchner et al., 2013d).

**Detection of Movement Preparation Processes by Single-Trial BR:** Figure 4.14 depicts a comparison of classifiers trained on one, two or else all 13 training windows. Results showed that the combination of two training windows increased classification performance (A+A vs. A: $p < 0.001$, B+B vs. B: $p < 0.001$, C+C vs. C: $p < 0.001$, A+B vs. A: $p < 0.001$, B+C vs. B: $p < 0.001$, B+C vs. C: $p < 0.001$, C+A vs. A: $p < 0.001$, C+A vs. C: $p < 0.001$) except when combining training windows from B and A in comparison to the performance when using single windows from B (A+B vs. B: $p = n.s.$). The best overall performance was obtained when combining training windows from cluster B and C, although there was no significant difference compared to window combinations within B (B+C vs. B+B: $p = n.s.$). The average TPR from training window combination of cluster B and C at time point $-200$ ms (latest time point of movement preparation class and before estimated movement onset at $-150$ ms, see Figure 4.12 was on average $0.85 \pm 0.066$. Performance of a classifier trained on all 13 training windows was worse than that of the classifier trained on the best pair of windows (All vs. B+C: $p < 0.001$).

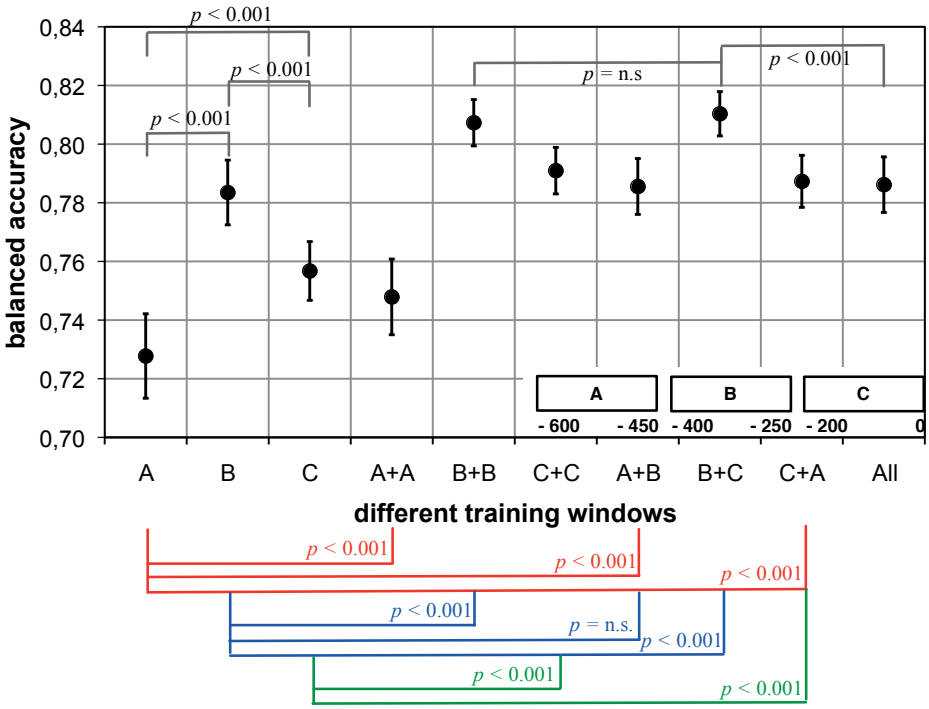


Figure 4.14: Illustration of cluster combinations and performance for different combinations of training windows. Training time combinations: two windows were combined using the previously found clusters (see methods description for details). Classification performance of a $5 \times 2$-fold cross validation for four subjects quantified with mean balanced accuracy and standard error. The x-axis shows different training settings: A, B, C – one training window per movement marker ending at different times with respect to the movement; A+A, B+B, C+C, A+B, B+C, C+A – two training windows per movement marker, combined within the same cluster or with other clusters; "Al"l – 13 training windows were used to train a classifier. Figure is based on Figure 15 of (Kirchner et al., 2013d).

#### 4.2.1.5 Discussion

By the experiments performed in the *Armrest* scenario it was shown that the BR approach to detect the brain state "recognition of important information", which was developed in the *Virtual Labyrinth Oddball* scenario, can be transferred into a new setup in which two mutually influencing tasks had to be performed while still achieving similar classification performance. The results from Section 4.1.1 that substitution of training examples and hence, partly classifier transfer between two different classes in training and test is possible were confirmed. Results indicate that the supervision of trained operators in a tele-manipulation scenario is possible, since *trained* operators will miss only few examples of target stimuli similar to subjects that are performing a simple task in the *Armrest* scenario (compared to the more

difficult *Virtual Labyrinth Oddball* scenario). Especially in the *Armrest* scenario only very few examples for missed target stimuli were available. These few examples could not have been sufficient for alternative training methods that allow direct training with few training examples as shown for the *Virtual Labyrinth Oddball* setup above (see also (Metzen et al., 2011a)).

Besides the detection of the success of information recognition it was shown that the detection of movement intention based on EEG data in the ERP range (Bai et al., 2011; Ibáñez et al., 2011; Wang and Wan, 2009; Blankertz et al., 2006c) is also possible under dual-task conditions in which the subjects are not solely concentrating on movement preparation. Within the sliding window analysis, the influence of different training windows on the performance on the continuous prediction of upcoming movements was investigated. Subject-independent time intervals, which provide different detection rates depending on which interval the training window belongs to, were found. This allows to make more general suggestions for classifier training on data of new subjects, like using a first training window ending between $-400$ to $-250$ ms before movement marker (cluster B) and a second one between $-200$ to $0$ ms (cluster C).

The choice of the training windows critically depends on the point in time when the movement has to be predicted (e.g., in a range from $-300$ to $-200$ ms relative to the movement marker (Figure 4.12)). If the application requires an earlier prediction, this may have an influence on the choice of the optimal training window. Exact interval boundaries for choosing appropriate training windows for movement prediction remain to some degree subject-specific. However, based on the results obtained here, large subject-specific differences are not expected.

In this study the performance of the classifier given as BA the TPR (True Positive Rate) is most relevant, since by means of the control mechanism explained in Section 6.1, FPR (False Positive Detections) do not lead to a failure in behavior. The TPR of $0.85$ (SD: $0.066$) that was computed from the training window combination of cluster B and C at a point in time close to the actual movement onset ($-200$ ms) indicates that in case of applying the approach online $85$ out of $100$ movements would have been predicted by detecting movement preparation processes. These results further indicate that single-trial classification performance of BR should be sufficient for adapting an exoskeleton in an application scenario (see Section 6.1).

To summarize, with the experiments conducted in the dual BR scenario *Armrest*, it was shown that: (i) the intentional state "movement intention" as well as (ii) the cognitive state "recognition of important stimuli and task coordination" can be detected in single trial by BR while a subject is performing a dual task that is similar to a dual task which has to be performed during complex interaction with a robotic system, like to teleoperate a robotic arm (see Chapter 6). The single-trial classification

of different brain states by BR resulted in high performance. Reliability of the detection of movement preparation processes could be improved by combining appropriate training windows. Classification of missed target instances versus recognized target instances was made possible by applying the developed approach of classifier transfer. The reliable and high performance in single-trial prediction of the dual BR that was obtained is an important prerequisite for adapting or driving different HMI's during human-machine interaction in robotic applications as discussed in Part III of this thesis with respect to the changing requirements of the user.

## 4.3 Summary

In Chapter 4 of the thesis two further training scenarios were developed that allow the investigation of brain activity by average ERP analysis as well as ML analysis. The work conducted here does therefore together with work conducted in Chapter 3 fulfill **Subgoal 1a** by developing training scenarios. The development of application scenarios has still to be done. Results conducted in experiments presented in Chapter 4 show that one or even two different specific brain states can (simultaneously) be detected by single-trial BR while a subject is performing complex and demanding tasks. Supported by the finding that performance of ML analysis for P300 detection is predictive for results of average P300 analysis and vice versa it was shown that knowledge about EEG activity that is correlated with a specific cognitive state or intention of a human can be used to develop new approaches for training, i.e., classifier transfer, which can cope with disadvantageous conditions in the training data, i.e., too few training examples. These findings together with the results mentioned above fullfil **Subgoal 1b** of the thesis, i.e., to show that specific and known brain states can be related to brain activity that can reliably be detected while subjects perform complex interaction task.

Results further indicate that with the help of average ERP and ML analysis it is possible to identify relevant brain patterns involved during complex human-machine interaction behavior. To detect relevant brain patterns by single-trial BR, appropriate training data has to be identified for training the applied classifier. Knowledge gathered from ERP analysis was used to improve classification performance significantly by, i.e., combining relevant training windows that were identified to contain important information about cognitive processes. By optimizing the choice of training data, the effect of subject specificity for both described cases of brain state detection could further be reduced resulting in stable and reliable BR performances. Hence, **Subgoal 1c** of the thesis could be fulfilled in this chapter.

To conclude, the results of this thesis presented in Chapter 4 strongly support the proposed hypothesis that BR can be applied during complex human-machine in-

teraction, since brain patterns that are detected by single-trial ML analysis can be correlated to specific known activities of the brain, i.e., ERP activity, and hence can be correlated to specific (intentional and cognitive) states of the operator. The findings are supported by online applications of BR for the online detection of the brain states "target recognition" and "task set change" in the *Virtual Labyrinth Oddball* scenario as documented in the Video B.2. **Main goal 1** of the thesis is, besides the development of application scenarios (as part of **Subgoal 1a**), fulfilled by work of Chapter 3 and Chapter 4. The gained knowledge about the occurrence of such states can then be used to infer upcoming behavior by means of eBR as shown next in Part III of the thesis.

# Part III

# Embedded Brain Reading - Support of Interaction Behavior

In Part II of this thesis **Main goal 1** of the thesis was addressed. It was shown that specific brain states that are relevant for interaction are present under demanding interaction conditions and can passively be detected in single trial by BR as it is defined in this thesis. In Part III of the thesis it is investigated how BR can safely be embedded in robotic applications. The goal of *embedded BR* (eBR) (Kirchner and Drechsler, 2013a) is to infer the intention of the interacting human, i.e., to correlate brain states, detected by BR, with upcoming interaction behavior. By applying eBR, *predictive HMIs* (Kirchner et al., 2013d) can be developed that are able to (better) support upcoming interaction behavior.

When discussing what the differences between such *predictive HMIs* compared to BCIs are, the characteristics of different kinds of BCIs with respect to their capability to infer upcoming behavior and to detect "naturally" involved brain activity have to be specified first. When comparing passive and active BCIs there are strict differences in the goal of both types of BCIs with respect to inferring the human's upcoming behavior and the requirements on the human to "produce" specific brain activity. Passive BCIs are defined to only require to detect a specific brain state that is "naturally" evoked during interaction. On the other hand, it is not necessarily required to infer the upcoming behavior of the user. For example, passive BCIs that are applied for the detection of interaction errors usually correct or reverse a command just dependent on the detected brain state but independent on whether the human has the intention to correct a possible error or not. Hence, upcoming behavior of the user is not necessarily relevant for passive BCIs or at least not required to be inferred.

On the other hand, an active BCI is applied for the sole purpose to decode the intention of the user in order to substitute behavior that would otherwise be performed by the motor or communication system. To enable this, brain activity is "used" like a tool to explicitly transmit intentions. Although the detected brain state or brain pattern (in case of steady state visually evoked potential (SSVEP)-based BCIs) highly correlates with the intention of the user, this brain state or pattern is in most cases "produced artificially" by the interacting human for the purpose of communication and control, i.e., as a substitute of such behavior. For example, brain activity that is evoked by the imagination of hand movements can be used to drive a speller (Blankertz et al., 2006b). The speller substitutes for speech behavior. Hence, a specific brain state "movement imagination" is artificially coupled to an intention "choosing a letter". Should a user not know about the functioning of the BCI it would be impossible for her/him to control it.

Other active BCIs are less artificial. For example a classical speller that makes use of the ERP P300 detects the letter that the user of the BCI wants to choose by detecting the P300 that is evoked in case the relevant letter is visually highlighted (Far-

well and Donchin, 1988). Here, the connection between the subjects' intention and the brain state is more direct, since the brain state of target recognition is correlated with the intention to choose a letter. A more natural approach would however allow the user to think of the letter "a" and by this choose an "a". There are some approaches in active BCIs that allow such natural transmission of intention. However, they are often limited to invasive methods like intracranial recorded brain activity (Carmena et al., 2003; Hochberg et al., 2006) (see Section 2.1). Surface EEG is, in most cases, too noisy and vague to allow such direct relations between brain state and intention of the human for explicit communication.

In this thesis eBR is developed, which is able to cope with the above mentioned issues, since:

- BR, as the basis for eBR, does always only detect brain states that are naturally evoked during interaction and
- by eBR the detected brain states are correlated with intentions of the user, i.e., are used to predict upcoming behavior.

The latter is however only possible, if the context of interaction is used to adapt or drive a predictive HMI by eBR. Thus, eBR is not defined as a specific kind of BCI, but is rather defined by the way it makes use of brain activity, i.e., by passively gaining covert information about the brain state with respect to a specific context, and by the way it is using this information to infer upcoming behavior with the goal to enable a predictive HMI to support (or drive) this upcoming behavior context-specifically. To drive and control BR context-specifically, i.e., to enable context-specific eBR and to implement predictive HMIs the following components are required:

1. an HMI that can be adapted or controlled by eBR,
2. additional supportive systems, and
3. other physiological than the EEG data or other data, like technical data.

The role of these components is discussed in Chapter 5 in general and in Chapter 6 and in Chapter 7 on examples.

Furthermore, while in Chapter 5 a formal model for eBR is developed to present a general description, this formal model is then evaluated in Chapter 6. The work conducted in Chapter 5 and Chapter 6 does therefore address **Main goal 2** of the thesis. While work in Chapter 5 does by the development of the formal model mainly contribute to **Subgoal 2a**, work in Chapter 6 contribute to **Subgoal 2b** and **2c** by evaluating the formal model on implementation examples and by analyzing the correct and error-free functioning of eBR in application scenarios. Furthermore, work

in Chapter 6 does further contribute to **Subgoal 1a** and **Subgoal 3a** by developing application scenarios and by the online application of eBR in those scenarios.

In Chapter 6 and Chapter 7 **Main goal 2** of the thesis is further addressed by showing that upcoming behavior can be supported by eBR in two different ways, by either implicitly making use of the gained information by adapting an HMI to better support the user in his interaction with a robotic device (see Chapter 6) or by generating explicit commands based on the inferred behavioral intention of the user that is naturally defined by the brain state and context of the interaction, i.e., by driving the interaction supported by a robotic device (see Chapter 7). For both approaches, it is shown that eBR is safe to be applied in real robotic applications. Controls can be integrated in an approach to avoid malfunction of the system as discussed for the adaptation of the HMI (Chapter 6). Such controls are not easily implemented in case that eBR is used to drive an HMI (see Chapter 7). Here, false behavior of the system, which may be caused by misclassification of the human's brain state by the BR, can be minimized or the outcome of BR can be weighted and controlled by multimodal signal analysis, so that the functioning of eBR is manipulated in a way that false behaviors of the HMI, which are annoying for the user, are avoided (see Chapter 6).

Chapter 8 does finally address **Subgoal 3b** of **Main goal 3** of the thesis. It is shown that the application of eBR in a robotic application to adapt an HMI, i.e., an exoskeleton, does measurably improve certain aspects of human-machine interaction in order to enhance the operators' support. In this investigation, the required force to interact with the exoskeleton was used as a measure.

# Chapter 5

# A Formal Model for Embedded Brain Reading

To implement eBR in an application for supporting human-machine interaction, the context of the interaction must be known. Only then it is possible to infer upcoming interaction behavior via eBR by safely making use of information about brain states that are detected by BR. The way eBR is implemented must avoid or minimize the risk of malfunctions of the *predictive HMI*. To enable context generation and supervision for a safe adaptation of the HMI by eBR, complex rules and requirements, like communication rules, application rules, robotic control mechanisms, system design and rules for labeling EEG data to allow an interpretation of the brains activity have to be considered and implemented. Giving a good description for such a complex system is challenging and especially difficult if scientists from different fields are involved. Errors in implementations are hard to avoid under such conditions.

In this thesis it is therefore not only argued that eBR is an appropriate method to enhance and enrich human-machine interaction, but it is further stated that a general, formalized model for eBR (Section 5.1) must be developed. Such a formal model is a primary requirement for the application of formal modeling and verification techniques on system level (Drechsler and Große, 2005; Tabakov et al., 2008). In the future, it may be possible by applying formal modeling and verification techniques on system level to verify the correct functioning of complex human-machine interaction and the involved systems in an automatic fashion during their development and, even more important, during their application.

In the following sections the rather general formal description of eBR developed in this thesis is presented. Text, figures and tables of the following sections are taken and partly adapted from (Kirchner and Drechsler, 2013a). Preliminary results can be found in (Kirchner and Drechsler, 2013b).

## 5.1 The General Model and Definition of Rules for BR and eBR

Figure. 5.1 presents the developed model for eBR: eBR requires HMIs that not only control the application or robotic system but also control and supervise eBR. These HMIs must be adaptable with respect to detected brain states and then inferred behavior of the interacting human. Further, the required HMIs must themselves be able to identify behavior or situations that are relevant for the interaction to drive eBR. An HMI that is adapted by eBR is called *predictive HMI* as it makes use of information gained from brain state analyses by BR and other behavioral and situational analysis required for eBR (see below) to generate knowledge about upcoming, i.e., future, behavior of the interacting human.

For the application of eBR the generation of context is highly relevant. To generate behavioral or situational context and to supervise or correct eBR, other systems should be integrated as well. They should allow the analysis of other data, like other psychophysiological (e.g., EMG and eye movement) or technical data that is acquired during interaction to detect situations or human behavior that is relevant to the interaction. For behavioral or situational context generation these supportive systems are mainly applied to label the EEG by generating markers for BR (bold lines from "MG" (marker generation) in Figure 5.1). For supervision or control of eBR they can be applied to give feedback to the HMI, to, e.g., approve the behavior that was inferred (dotted lines pointing towards the HMI in Figure 5.1).

To apply eBR in a specific application, two rules have to be defined: (1) $R^{BR}$ that defines the way of processing of brain activity and prediction of the brain state by BR and (2) $R^{AdaptHMI}$ that defines how to infer future behavior (based on the predicted brain state) and how to adapt (or drive) the HMI to better support the inferred behavior, i.e., how to embed BR into an application for *predictive HMIs*. While the BR rule $R^{BR}$ can, in most cases be kept the same for different applications, as long as the same brain states have to be detected and the same labels are provided by the HMI, supportive systems or the BR system itself (see Section 5.1.1), the adaptation rule $R^{AdaptHMI}$ is likely different for different applications to better support their specific requirements.

### 5.1.1 Sources and Labeling of Brain Activity Data for BR and eBR

In general, any method that allows fast recording and analysis of brain activity can be used for BR. For the reasons given in Section 2.1 the following explanations focus on EEG as source for brain activity.

The analog brain signal $A$ ($A \in \mathbb{R}^c$), which is recorded with standard recording de-

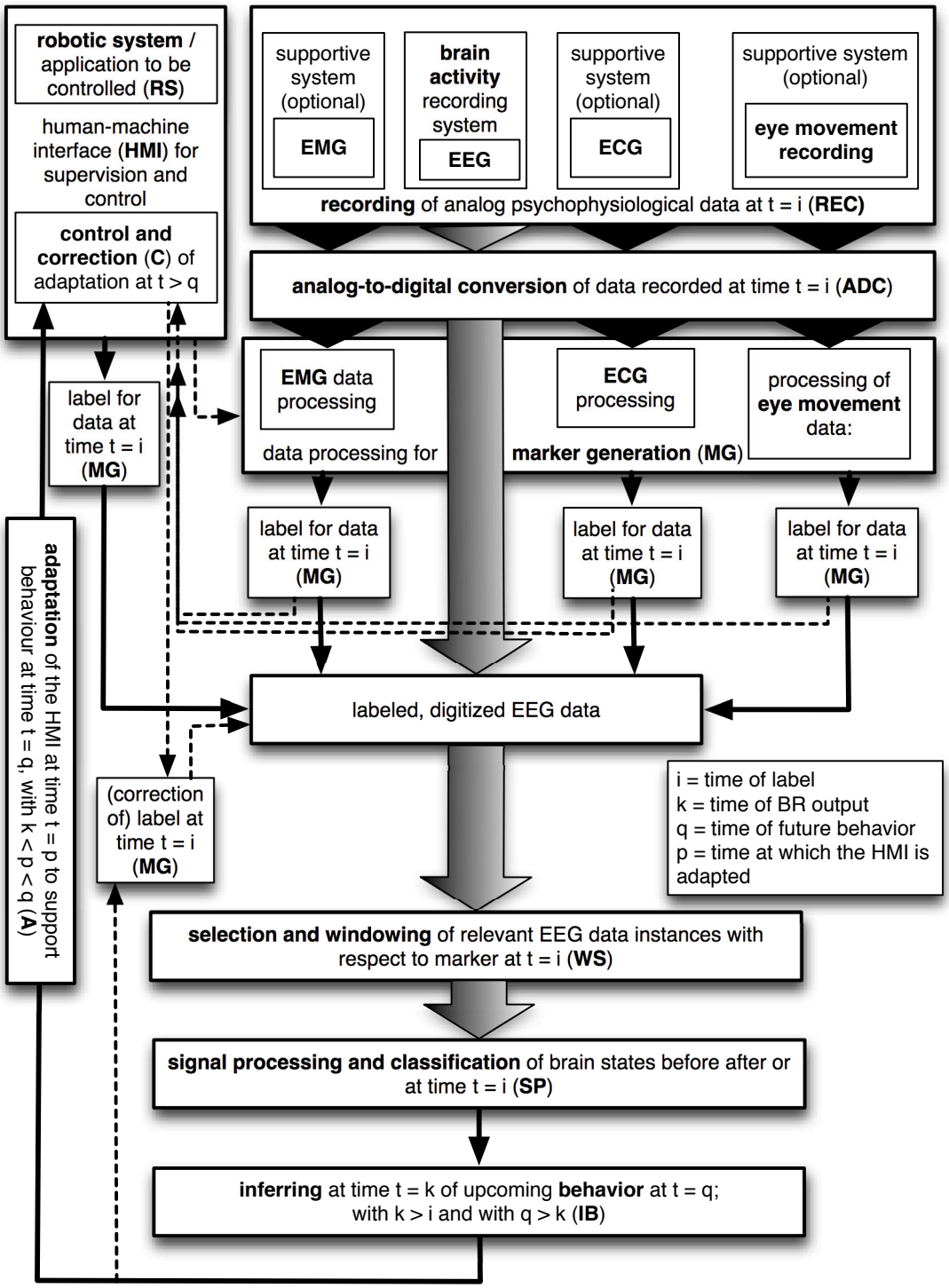


Figure 5.1: Model for eBR in a formal structured form. Source: Figure 3 of (Kirchner and Drechsler, 2013a).

vices with $c$ channels (electrodes) from the brain at time $t$ ($t \in \mathbb{R}$), is first transferred into a digital output signal

$$O(t) = \begin{bmatrix} d_1(t) \\ d_2(t) \\ . \\ . \\ d_c(t) \end{bmatrix}, \tag{5.1}$$

with $d_l \in \mathbb{N}', \mathbb{N}' \subset \mathbb{N}, l \in [1, c]$ and $\mathbb{N}' = \{-2^u, -2^u + 1, ..., 2^u\}$, with $u \in \mathbb{N}, u = z - 1$, with $z \in \mathbb{N}$, where $z$ is the bit width and $c$ is the number of channels, $t = n\Delta t, n \in \mathbb{Z}$ and $\Delta t$ is the sampling interval.

Since the analog-to-digital (AD) conversion (referred as "ADC" in Figure 5.1) takes place on the hardware side, the characteristic of the digitized signal depends on the specifications of the hardware that is used, e.g., bit width $z$ of the AD-converter. Further, the analog signal is sampled with a hardware-specific sampling frequency $f = 1/\Delta t$. For a certain time point $i$ the output of the AD-converter is

$$o(i) = \begin{bmatrix} d_1(i) \\ d_2(i) \\ . \\ . \\ d_c(i) \end{bmatrix}. \tag{5.2}$$

After analog-to-digital conversion it is then possible to generally apply SP and classification methods on the digitized data. However, since human EEG is very complex data (see Section 2.1.1), especially if recorded from many sites of the brain as sum of activity, the generation of *specific context* is highly important to allow the analysis of the EEG data with respect to specific questions. This is even more relevant if, as in this work, supervised learning methods are applied. Supervised ML methods require training examples that are *labeled* to belong to a specific class. Labels are often provided by human experts that manually label training examples. However, for eBR an *automated* labeling of EEG data is required for its online application in robotic interaction scenarios. In Figure 5.1 labeling of data is referred to by "MG" for marker generation.

By online labeling an *automated generation of context* can be enabled. Context information can hereby be used differently, i.e., to label training data as stated above, to trigger EEG analysis, to confirm or correct classification results, i.e., for adapting BR analysis (see Section 10 and (Wöhrle et al., 2013a)), or to properly, i.e., context-specifically, make use of the gained information about brain states and inferred be-

havior. Examples can be given: if the goal is to generate training data, e.g., instances of EEG evoked by task-relevant or task-irrelevant stimuli (see Section 4.1.2), both, the presentation of task-relevant and task-irrelevant stimuli have to be labeled differently to divide the examples in two training classes based on the two different types of context. Is the goal to determine whether a task-relevant stimulus is recognized by the user online during test, i.e., application, only the event of the presentation of a task-relevant stimulus (but no longer the event of a task-irrelevant stimulus) has to be labeled online. If the goal is to evaluate whether BR was correct in detecting a specific brain state and whether eBR was correct in inferring a specific behavior, the inferred behavior must be confirmed. If, for example, the brain state of movement preparation was detected by BR and the behavior of movement onset inferred by eBR (based on the given context of interaction), the event of movement onset can be detected to supervise and potentially correct the functioning of eBR. Furthermore, the inferred behavior can also be evaluated against the actual behavior performed by the subject in order to apply feedback to the classifier, i.e., it is validated, whether the inferred behavior was correct in respect to the subjects' executed behavior, which is then fed back to the classifier in form of a positive or negative feedback and may then also result in a re-training of the classifier in case of a false prediction.

Generation of context can be supported and triggered by different systems that allow the analysis of other data, like other physiological data than EEG. For example, the EMG can be analyzed for the detection of movement onset. But also non-physiological signals, like technical signals recorded by the interacting system, e.g., pressure on force sensors to detect a subjects' movement, or other signals recorded by other supervising systems in the setup can be used (e.g., motion tracking data, see Section 3.2.2). To summarize, for automated EEG analysis and automated adaptation or control of an interacting system the context must automatically be defined and labeled. In most cases it makes sense to label recorded data, like EEG data, directly by adding markers to the digitized data stream at specific time points. This has, as explained above, to be done in an automated fashion to allow online data analysis. In summary, markers have to be introduced to label a specific context and hence enable SP and classification by BR, adaptation of the SP or classification algorithm applied for BR as well as supervision and control of eBR.

To label relevant behavior or situations at time point $t = i$ in the EEG stream, the digital signal $o(i)$ is labeled by a marker $m(i)$ of a certain type. Markers $m(t)$ are specific for the relevant brain state (that will be detected by BR) and the kind of application for eBR. They are defined as

$$m(t) \in M^{Apl}, M^{Apl} = \{-2^u, -2^u + 1, ..., 2^u\}, \tag{5.3}$$

with one type of $m(t)$ for *no* marker.

Adding markers to each output $o(i) \in O$ results in the signal $o_m(i)$ defined as

$$o_m(i) = \begin{bmatrix} d_1(i) \\ d_2(i) \\ . \\ . \\ d_c(i) \\ m(i) \end{bmatrix}, \tag{5.4}$$

with $m(i) \in \{-2^u, -2^u + 1...2^u\}$.

### 5.1.2 Brain State Detection by BR

To allow eBR to infer on upcoming behavior of the human specific brain states can be detected by BR. This requires the application of single-trial ML methods for classification and prior SP to enhance the signal to noise ratio. This requires the labeling of EEG data as explained next.

#### 5.1.2.1 Labeling and Windowing of Relevant Training and Test Instances for BR

To analyze the digital signal by BR for the detection of specific brain states, certain segments or windows of the signal $O(t)$ have to be defined for further processing based on the introduced labels. In Figure 5.1 the process of windowing is referred to as "WS" for *window segmentation*.

For processing, these windows must have a certain length depending on the characteristics of the hidden signal. In this thesis for the sake of simplicity we use rectangular windows, although other types of windows might in principle be possible and suitable and will not be excluded from the general model. Based on the markers and a predefined BR rule $R^{BR}$ the signal $O(t)$ is cut into instances, i.e., windows $W_x^{m(t)}$ defined as

$$W_x^{m(t)} = \{O(t) \mid R_{low}^{m(t)} < t < R_{up}^{m(t)}\}, \tag{5.5}$$

with $x$ is the number of windows chosen with respect to one marker type $m$ at a certain time point $i$, $R_{low}^{m(t)}$ for the start of the window and $R_{up}^{m(t)}$ for the end. For a certain marker $m(i)$ several windows can be cut. These windows can overlap over a certain time period, start and end before or after the time $t = i$. Moreover, different windows of different types $W' \subset W$, where $W$ is the space of windows, may be of interest during training or test of eBR as defined by the BR rule $R^{BR}$.

#### 5.1.2.2 Processing of Windows for the Detection of Brain States by BR

After windowing, all relevant windows are processed within an SP chain: $SP_f \circ SP_{f-1} ... SP_1$ referred to as "SP" in Figure 5.1 (see also Section 2.4.2). This transfers $W' \subset W$ to $Y$ as output of SP and classification. The output for processing a relevant $W^{m(t)}$ is $y_i \in Y$. Each output $y_i$ can be correlated to a prediction score for the likelihood of a brain state that was present in the past, since $y_i$ is only available at time $t = k$, with:

$$k = R_{up}^{m(i)} + j, \text{for } R_{up}^{m(i)} > i \tag{5.6}$$

or

$$k = i + j, \text{for } R_{up}^{m(i)} \leq i,$$

with $j$ is the time required for all steps of SP.

### 5.1.3 Inferring Intentions and Future Behavior by eBR

The mapping between the output $y_i \in Y$ as the likelihood for a certain brain state $s_i \in S$ as defined by the BR rule $R^{BR}$ and the likelihood of the inferred behavior $b_q \in B$ which may require an adaptation of the HMI is defined by the adaptation rule $R^{AdaptHMI}$. Based on the output $y_i$ a possible *future* behavior ($b_q$) at time $t = q$, with $q > k$, can thus be inferred to adapt the HMI *before* the inferred future behavior is expressed. The process of *inferring future behavior* by eBR is referred to as "IB" in Figure 5.1.

#### 5.1.3.1 Dependencies between Prediction Time and Adaptation Time

The prediction time $p$, i.e., the time interval between the point in time at which the behavior is inferred and the point in time at which this inferred behavior is executed, is defined as $p = q - k$ and must be positive ($p > 0$). Further, to adapt the HMI at $t = p$ for the future behavior some adaptation time $r$ is required which depends on the adapted system and its control mechanism. To adapt an HMI early enough $p > r$ must be fulfilled. Thus, it is not enough to predict a certain behavior $b_q$ before it is executed but it must be predicted early enough to enable the adaptation of the HMI before the predicted behavior $b_q$ is expressed at time $t = q$. Hence, an effective prediction time $p_e$ is required which can be defined as

$$p_e = p - r, \tag{5.7}$$

with $p_e > 0$.

### 5.1.4 Adaptation of Predictive HMIs by eBR

The *adaptation* of an HMI by eBR (referred by "A" in Figure 5.1) results in a *predictive HMI* (definition see above and (Kirchner et al., 2013d)). It does always take place with respect to the inferred behavior. Further, adaptation of the predictive HMI requires a certain time $r$ (see above) and takes place between time $t = k$ and $t = k + r$. The adaptation time $r$ must further be smaller than the prediction time $p$ ($r < p$) to enable eBR to infer on behavior before it is executed. The kind and strength of adaptation may not only depend on the predicted behavior $B$ but also on the output of systems that control the adaptation, e.g., the HMI itself or other supportive systems (Figure 5.1, see also Chapter 7).

The kind of adaptation of the HMI depends on the application and the purpose of the *predictive HMI* and is also defined by the adaptation rule $R^{AdaptHMI}$. The HMI can, for example, be adapted in a way that integrated sensor data is differently evaluated to, e.g., increase sensitivity. For example, as explained more deeply in Chapter 6, sensor data recorded by integrated sensors of an exoskeleton to detect movement onset might be differently evaluated to detect smaller changes in case that movement onset is inferred by eBR. On the other hand, the HMI can be adapted by eBR in a way that it is leaving a support position to drive a movement in case that movement onset behavior is inferred by eBR. Such an approach might be chosen in case of, e.g., the support of patients that cannot move their arm during rehabilitation by an upper limb exoskeleton or orthosis (see Chapter 7). In the first example, the *support* is more *passive*, i.e., an executed behavior is eased (see Chapter 8). In the second example, the *support* of the predictive HMI is more *active*, i.e., behavior of the human is enabled.

### 5.1.5 Integrated Supervision and Self-Correction of eBR

BR analysis and thus the detection of specific brain states $S$ by single-trial EEG analysis can, due to the high complexity and low signal to noise ratio of brain data in general (which is even worse for EEG data if compared to other brain activity as discussed in Section 2.1) not always be correct. Moreover, the mapping between the detected brain state $S$ and the inferred behavior $B$ might be wrong or contain uncertainties (i.e., a different behavior $b_q^* \in B^*$ might be executed than it was inferred ($b_q^* \neq b_q$)). Therefore, it is important to implement supervision and automated correction mechanisms into the eBR approach that either minimize or even prevent false adaptations of the HMI and/or correct them. The process of *supervision and correction* is referred as "C" in Figure 5.1.

To correct incorrect adaptation, the expressed behavior $b_q^*$ of the human has to be monitored and compared with the inferred behavior $b_q$ to search for discrepancies.

If such discrepancies are detected, the HMI can be adapted again (or readapted) to better meet the detected behavior $b_q^*$. By implementing automated control and correction, a malfunction of the whole system in case of misclassification of the brain state $S$ by BR or misprediction of the behavior $B$ can be avoided in case that the HMI is rather *passively supported* by eBR. Examples for this will be given in Chapter 6.

Is eBR, however, applied to adapt an HMI in a more active fashion (see Chapter 7) a malfunctioning of the predictive HMI is possible, if there is no chance to control the inferred behavior by the detection of the later executed behavior. This can be the case if supporting disabled persons that cannot move their arm by an orthosis that is rather *actively supported* by eBR. The subjects do not show own behavior. Thus, there is no behavior that can be detected to correct for falsely inferred behavior (intention). For such cases, it is better to combine the detections made by BR on specific brain states with predictions or detections made by other psychophysiological measures on other behavior that can be used to confirm the inferred behavioral intention of the supported human. By this it is possible to implement a more robust eBR approach as discussed in Chapter 7.

## 5.2 Summary

In Chapter 5 a general model for eBR in a formal structured form was developed and presented. It was described and discussed that for eBR context generation is highly relevant for different steps or phases, e.g., for generating training data, labeling of relevant events, or adapting BR as well as for the supervision and control of eBR. Furthermore, it is stated that two different rules should be defined for each application. The first one describing the procedure for BR, the second for embedding BR into the application. While the first rule mainly depends on the brain states that have to be detected by BR, the second depends on the application of eBR. It was further discussed and shown on the model what must be considered with respect to timing to facilitate predictive HMIs by applying eBR. Finally, while considering different options for the supervision and control of eBR, it was differentiated between the application of eBR for predictive HMIs that enable an either passive or active support of the interacting human. It can be summarized that the work of this chapter fulfills **Subgoal 2a** of this thesis.

# Chapter 6

# Evaluation of the Model on Implementations for Passive Support

As stated in Chapter 5 there are two possible main applications for brain activity in robotics. First, brain activity can be analyzed to control a device, like a prothesis or exoskeleton. Hence, brain activity could be used to drive a predictive HMI to actively enable communication or reestablish motor control. One emerging application for robotics is the rehabilitation of the human sensor-motor system. Here, the analysis of brain activity can be used to drive a prothesis or exoskeleton to bridge the gap between brain and skeletal and muscular system. Thus, eBR can be applied to establish or reestablish communication or motor function. Second, brain activity could be interpreted to learn about the state of the human in a specific situation to adapt a predictive HMI with the goal of better supporting upcoming interaction behavior. By this approach information is gained about processes that may not be "visible" by other measures. The given support is rather passive. Interaction is enriched or eased by making use of the "cognitive" capabilities of the human during interaction. It is highly relevant to stress that any brain activity that is used is passively, i.e., naturally produced. There is, as the definition of BR states (see Chapter 3), no artificial communication between human and system by "producing" certain brain activity for interaction purposes. The advantage of such an approach is that a machine or robot can gain insight into a human to better support her/him without having the operator perform an extra task or putting him under higher workload due to the application of eBR.

While the application of eBR for an active support and its challenges are discussed in Chapter 7 in this chapter the passive support approach will be explained on two examples in a robotic application. The main goal of this chapter is, however, to eval-

uate the formal model for eBR as defined in Chapter 5 on two application examples for the passive support of interaction in a robotic application scenario, i.e., for the tele-manipulation of a robotic arm. Both examples are then used to evaluate the developed formal model with respect to its general applicability and completeness and to show that the formal description of both applications can already be used to verify the functioning and to detect implementation errors that were hard or impossible to detect without this formal description. In summary, by the performed evaluation of the formal model for eBR it is shown that the formal model improves the application of eBR by (1) contributing a detailed description of the system, (2) optimizing underlying procedures, (3) enhancing general reproducibility and (4) improving comparability with similar approaches, (5) pointing out small but relevant differences between approaches that cannot be derived otherwise, and by (6) facilitating the detection of errors in implementations. It is further discussed why the application of formal modeling and verification techniques on system level (Drechsler and Große, 2005; Tabakov et al., 2008) is important for different fields of application and for pursuing new paths in advanced human-machine interaction. Text, figures and tables of the following sections are taken and partly adapted from (Kirchner and Drechsler, 2013a; Folgheraiter et al., 2012) and (Kirchner et al., 2013d). Results of online application of eBR in the tele-manipulation scenario can be found in (Wöhrle and Kirchner, 2014) and (Seeland et al., 2013b).

## 6.1 Passive Support of Predictive HMIs in a Robotic Tele-manipulation Scenario

By an operators' behavior we cannot determine his brain state is, e.g., whether he recognized a presented information or warning. He may for example not respond to a warning since he is performing a more urgent task or does not want to interrupt a task or interaction with the robot he is currently performing for other reasons. An interface is further not able to infer whether an operator will start an interaction out of a rest situation. The system must rather react quickly to a started interaction by first detecting it and second changing its mode with respect to the new behavior of the interacting human. In both cases interaction between an interface and the human operator would be enhanced and facilitated if the system knew about the operators brain state and intended behavior. Hence, interaction could be improved by applying eBR and thus implementing predictive HMIs.

The recognition of important information can be detected in brain activity even if the operator does not respond right away to the important measure and overt behavioral data is hence missing. Since operators of complex systems are well trained and

know that they have to respond to urgent warnings, it would be reasonable to infer by eBR that an operator will respond in case it is known that he recognized a warning by detecting the relevant brain state of "target recognition and task set change" (see Chapter 3) by BR. With respect to the other example it was already shown in Chapter 3 and Chapter 4 that the preparation of arm movements can be detected in the EEG by BR. Hence, by detecting the brain state of "movement preparation" it can be inferred that a human operator will start a movement. However in both cases there are uncertainties in inferring the upcoming behavior, e.g., the operator might be disturbed and forget to answer to the important information or the operator might imagine to start to move but might actually not execute this behavior. Brain activity that is evoked by imagining a movement or the actual planning of the same movements' execution is very similar and cannot easily be distinguished (Kornhuber and Deecke, 1965; Deecke et al., 1969). Imagination of movements is even used in active BCI for communication that requires no execution of movement activity, such as the control of a speller by imagination of hand movements (Blankertz et al., 2006b). Hence, in both given application examples eBR can be applied for predictive HMIs to infer upcoming interaction behavior based on the embedded analysis of brain states by BR, but must be supervised and controlled closely to avoid malfunctioning of the whole system.

During teleoperation of a robotic arm (see Figure 6.1) an operator is not only required to tele-manipulate a robotic device like a robotic arm but she/he has to recognize and understand *task-relevant* information about the general situation or possible hazards, e.g., a person entering the operating area of the robot, a malfunction of the exoskeleton or robot, or requests for communication from outside, as a second task. It is known that under such conditions of high workload attention to a second task can be impaired (Isreal et al., 1980; Woods, 1996). This impairment can lead to failure in one of the tasks, most likely the subjectively less important one. Since manipulation of the exoskeleton requires a very high amount of the user's cognitive resources, it is likely that she/he misses important information. In Chapter 4 it was already shown that the recognition and failure of recognition during a demanding dual task can be detected in single trial by BR. This knowledge about this cognitive state of the interacting human can be used to implement an HMI that passively supports human-machine interaction with respect to adjusting the strategy of information presentation to the operator by eBR.

The functioning of the HMI that passively supports interaction can be described as follows. Instead of having a second person to assist the operator the implemented OMS is adapted by eBR to better assist the operator under both conditions, i.e., if she/he recognized an important warning or did not recognize it. The adaptation of the OMS is visualized and documented by the Video B.3 provided as supporting video. In

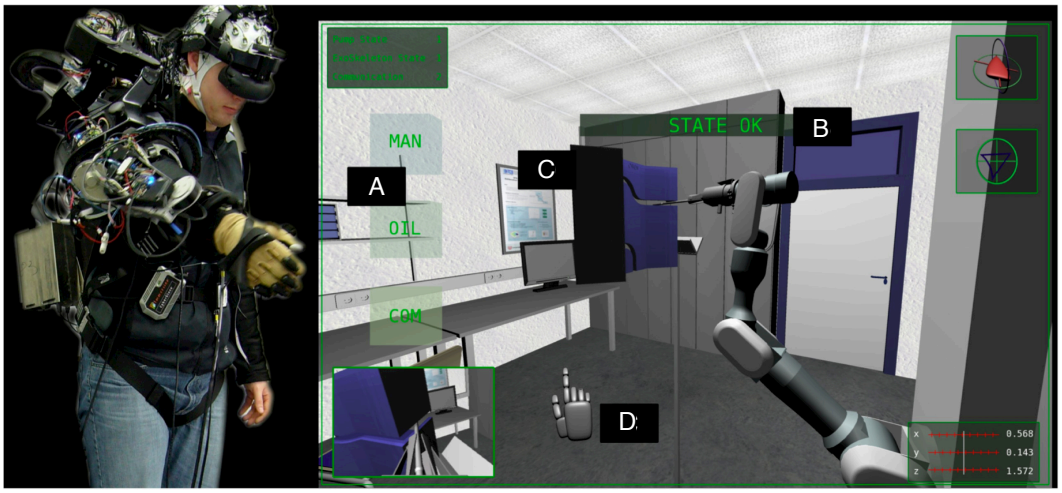


Figure 6.1: Experimental setup for the *Tele-manipulation* scenario - a holistic feedback control of semi-autonomous robots. In the *Tele-manipulation* scenario an operator is wearing an exoskeleton and, with the support of a virtual scenario, is tele-manipulating a robotic arm. A: three kinds of virtual response cubes (different responses are required for different types of warnings); B: different kinds of stimuli: unimportant stimulus (STATE OK - no response required), warning (first target - response required), repeated and enhanced warning (second target - response required), third warning (response is critical, e.g., exoskeleton control is disabled); C: labyrinth that the robot has to be moved through; D: virtual hand. Figure is based on Figure 1 of (Kirchner et al., 2013d).

the following the approach will briefly be explained.

The task of BR is to detect different brain patterns, i.e., patterns that are evoked by the recognition of *task-relevant* stimuli (that contain a P300 and a prospective positivity, see Section 3.1 and Section 4.1) and patterns that are evoked by *task-relevant* stimuli that were *not recognized*, i.e., missed (containing *no* P300 and no prospective positivity, see Section 4.1), hence, to detect the brain state of "target recognition and task set change" or its absence. The gained information on this brain state is then used by eBR to infer whether or not the operator would respond to a presented *task-relevant* stimulus. Depending on the inferred behavior the repetition time for warnings presented by the OMS is finally adapted. For example, if eBR infers that the operator will respond (in case BR detected brain patterns related to the recognition of important stimuli) the tolerated response time is extended. On the other hand, if eBR infers that the operator will *not* respond (in case BR did *not* detect brain patterns related to the recognition of important stimuli) the allowed response time is reduced or the important information is repeated immediately (see Figure 6.2). However, the OMS will always keep track on the response behavior of the opera-

tor. Hence, in case BR *falsely* detected the state of "target recognition and task set change" and the operator will hence not respond to the *task-relevant* stimulus, the OMS will repeat the warning after a predefined time. On the other hand, does the operator respond although this was not inferred by eBR the OMS will *not* repeat the warning. Experiments for the online adaptation of the predictive HMI, i.e., the OMS, by eBR that were conducted so far in the above described robotic tele-manipulation scenario support our approach (Wöhrle and Kirchner, 2014). Subjects reported that an adapted OMS can reduce stress by avoiding to force fast responses and emphasizes important information by repeating them at a higher frequency in case the subject was distracted.

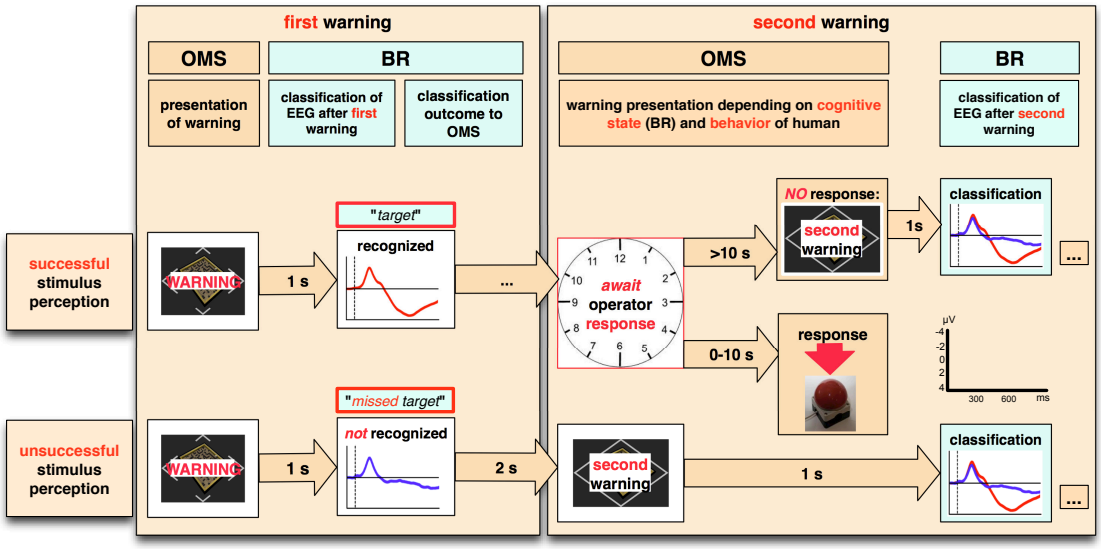


Figure 6.2: Adaptation of the operator monitoring system (OMS) by eBR. The currently implemented message scheduling procedure which is controlled by the OMS is shown. The OMS considers the cognitive state that is detected by BR and allows to infer the behavior of the human. The general procedure is described in the following: after a warning the operator's EEG is analyzed by BR. Detection of success versus no success in the recognition of important information by BR allows to infer future behavior (response or no response) by eBR. As a consequence, the behavior of the OMS is adapted, i.e., the tolerated response time is extended or a second warning is presented right away by the OMS. In case the operator does not respond to the second warning, a third warning follows. Approximate time required for predictions made by BR and predefined response times are given in the arrows. Figure is based on Figure 2 of (Kirchner et al., 2013d).

Besides the OMS, a central part of the tele-manipulation scenario (see Figure 6.1) is an exoskeleton developed by our group (Folgheraiter et al., 2009) to intuitively control different robotic arms or legs (Folgheraiter et al., 2008, 2012). The exoskeleton used for teleoperation both serves as a control device for a semi-autonomous robot as

well as an interface for controlling a virtual scenario. For control reasons switching between two operating modes of the exoskeleton:

1. a position control (PC) mode, where the exoskeleton supports the user by enabling him to rest in a self-chosen rest position that is kept by the exoskeleton, and

2. an free run (FM) mode, where the operator can move freely and control the virtual scenario (see Figure 6.3 adopted from (Folgheraiter et al., 2012))

is very interesting for an adaptation by eBR. During rest, the applied control mechanisms of the exoskeleton cannot make predictions about upcoming behavior as it is possible during interaction (Kirchner et al., 2013a) as visualized and documented by the Video B.4, which is provided as supporting video. Hence, to improve interaction it is relevant to know whether the operator wants to move again.

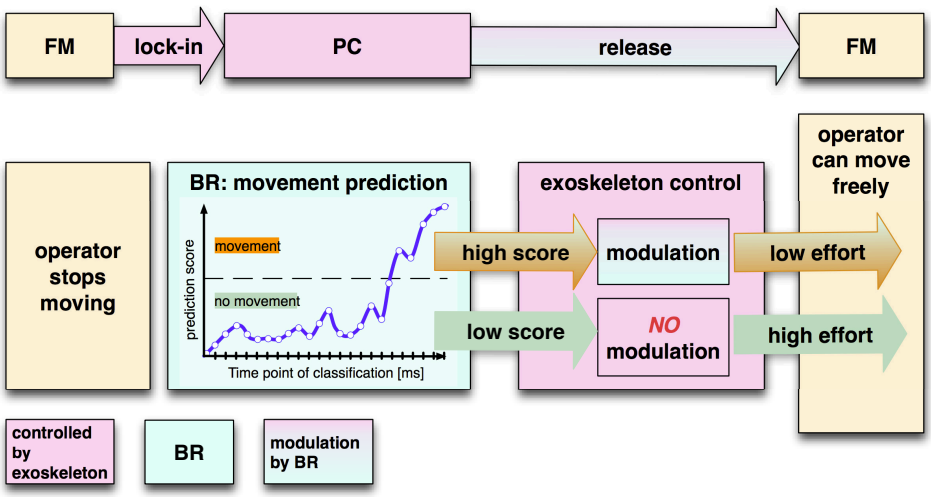


Figure 6.3: Adaptation of the exoskeleton's control by eBR. It is shown how eBR adapts the exoskeletons control. The exoskeleton supports the user while moving (FM mode). In case the user stops moving, the exoskeleton locks in to support the arm at a chosen position (PC mode). To release, the user has to press against sensors that are integrated into the exoskeleton. To ease that release, BR detects movement intention. The movement prediction score is then used to modulate the exoskeleton's control by eBR: the higher the prediction score (i.e., the more certain the classifier is) the stronger is the adaptation of the exoskeleton's control and the lower is the effort required by the user to transfer the exoskeleton from PC to FM mode. Pressure against the sensors is always required for release, which minimizes the risk of *false lock out* in case of possible false detection of movement intention by BR. Figure is based on Figure 3 of (Folgheraiter et al., 2012).

Movement intention (see Section 3.2) can be predicted from the user's EEG as shown for arm movements in the *Armrest* scenario in Section 4.2. By detecting brain

patterns via BR that are related to movement preparation processes, the onset of movement can be inferred by eBR and used to adapt the interface, i.e., exoskeleton, for an *easier lock out* from a rest situation (PC mode in Figure 6.3). However, since movement imagination evokes very similar brain activity as the planning of movement that will be executed, as discussed above, control mechanisms have to be applied to avoid *unwanted lock out* from a rest position. Therefore, movement intention that is detected by BR does not directly change the exoskeleton's mode. Any change from PC to FM mode will only happen after the inferred movement onset is confirmed by the force sensors that are integrated in the exoskeleton (see Figure 6.3). This prohibits faulty behavior of the exoskeleton while simultaneously improving interaction by reducing the force that is required for *lock out* in case the inferred behavior is indeed executed as shown in Chapter 8 of this thesis. Results from an online study in the tele-manipulation scenario show that eBR can be applied successfully to implement a predictive HMI, i.e., predictive exoskeleton (Seeland et al., 2013b).

**Ethics Statement:** Note that all experiments with human subjects published in (Seeland et al., 2013b) and (Wöhrle and Kirchner, 2014) that were performed to evaluate eBR in the robotic application scenario *Tele-manipulation* (see Video B.5) have been conducted in accordance with the Declaration of Helsinki and approved with written consent by the ethics committee of the University of Bremen. Subjects have given informed and written consent to participate.

## 6.2 Evaluation of the Formal Model for eBR on the Example of Passive Support

As explained above in detail two different implementations for eBR are applied in the tele-manipulation scenario to adapt two HMIs:

1. an exoskeleton in the implementation *AdaptExo* and
2. an OMS in the implementation *AdaptOMS*.

To improve the behavior of an exoskeleton during tele-manipulation in the implementation *AdaptExo* (Figure 6.1) eBR is used to predict the intentional state "movement intention", i.e., the brain states of movement preparation ($S^{MovPrep}$) and no movement preparation ($S^{noMovPrep}$) to prepare the HMI, i.e., exoskeleton, for the execution of self-induced movements ($B^{*MovOnset}$) in case of $S^{MovPrep}$. Predictions about the brain states $S$ are made based on the output $Y$ of the brain activity analysis as defined in the BR rule ($R^{Mov}$). Adaptation of the exoskeletons' control is made based on a mapping between $Y$ and the likelihood of an upcoming behavior $b_q^*$ ($b_q^* \in B^{*MovOnset}$)

as defined by the rule for adapting the HMI ($R^{AdaptExo}$). In this implementation, eBR does reduce the effort, i.e., required force, the user has to invest to *lock out* the system from a rest position and in doing so allows a smoother and more intuitive interaction (see Chapter 8 and (Folgheraiter et al., 2012)).

To improve the operators' support by an OMS (Figure 6.2) in *AdaptOMS* we implemented an approach that automatically analyses the operators' cognitive state "target recognition and task set change" to predict whether he recognized important, *task-relevant* information (i.e., detected the brain state of $S^{CorrPercept}$) and will thus likely respond to them (show response behavior $B^{*CorrResp}$) or whether he did not recognize important, *task-relevant* information ($S^{InCorrPercept}$) and will likely not respond. The rules for detecting the occurrence or missing of the cognitive states "target recognition and task set change" are defined in the BR rule ($R^{Percept}$). The predictions made about the execution of the inferred behavior $B^{*CorrResp}$ are used to adapt the OMS with respect to the allowed response time, i.e., only a short response time is allowed in case that no response is predicted and a long response time is allowed in case a response is predicted as defined in the adaptation rule ($R^{AdaptOMS}$).

When formally comparing the implementations *AdaptExo* and *AdaptOMS* important differences exist with respect to, e.g. the windowing procedures, the rules for adding makers by BR and the type of performed control and correction. These differences must be considered and become very important when both implementations should be integrated in one flow, i.e., to adapt the OMS and the exoskeleton within one application and by one eBR flow as it is the case in the scenario displayed in Figure 6.1 and it was shown to work for the similar *Armrest* Scenario in Section 4.2. In the following it is shown that those differences can be covered by the developed general formal model for eBR (see Chapter 5 and Figure 5.1) as explained on some examples.

### 6.2.1 Coverage of Differences in Implementations by the Model

In both implementations the analog signal $A \in \mathbb{R}^{124}(t)$ was recorded with $124$ channels. After digitization with $16$ bit it was sampled with $f = 5000\,\text{Hz}$ as defined in the BR rules $R^{Percept}$ and $R^{Mov}$.

The output of analog-digital conversion is defined as

$$o(i) = \begin{bmatrix} d_1(i) \\ d_2(i) \\ . \\ . \\ d_{124}(i) \end{bmatrix}, \tag{6.1}$$

Table 6.1: Implementations of part "WS" of the model for *training* of eBR. WS is defined in Figure 5.1. Source: Table 1 of (Kirchner et al., 2013d).

| AdpatExo ("WS" in *training*) | AdaptOMS ("WS" in *training*) |
|---|---|
| $W_x^{m(t)}$ as defined in BR rule $R^{Mov}$: | $W_x^{m(t)}$ as defined in BR rule $R^{Percept}$: |
| **windows for training of BR**: In *AdaptExo* windows are chosen before windowing. Same is true for instances of type $S^{Ignore}$ in *AdaptOMS*. In *AdaptOMS* instances for $S^{CorrPercept}$ are chosen after windowing (Wöhrle and Kirchner, 2014) since response time varies widely with respect to the application and work load of the user and allows no selection by time, whereas movement preparation in *AdaptExo* takes always place just before movement onset (Seeland et al., 2013b) and allows selection based on time points. | |
| Instances of the rest period are chosen to train for the class $S^{noMovPrep}$:<br><br>Only markers of type $m_{noMovPrep}$ are considered that occur within the rest period between the markers $m_{offset}$ and $m_{onset}$ in case there is no other marker 2000 ms before and after $m_{noMovPrep}$.<br><br>$W_1^{m_{noMovPrep}} = \{O(t) \mid (i - 1000\,ms) < t < i\}$, with $m(i) = m_{noMovPrep}$.<br><br>To select instances of the cognitive state $S^{MovPrep}$, two windows within each rest period with respect to one $m_{onset}$ marker are chosen:<br><br>$W_1^{m_{onset}} = \{O(t) \mid (i - 950\,ms) < t < (i + 50\,ms)\}$, with $R_{low}^{m_{onset}} = i - 950\,ms$ and $R_{up}^{m_{onset}} = i + 50\,ms$.<br><br>$W_2^{m_{onset}} = \{O(t) \mid (i - 1100\,ms) < t < (i - 100\,ms)\}$, with $R_{low}^{m_{onset}} = i - 1100\,ms$ and $R_{up}^{m_{onset}} = i - 100\,ms$. | Instances of the class of behavior $B^{*CorrResp}$ are defined as:<br><br>$W_1^{m_{response_x}} = \{O(t) \mid i\}$, with $m(i) = m_{response_1}$, or $m(i) = m_{response_2}$, $R_{low}^{m_{response_x}} = i\,ms$, and $R_{up}^{m_{response_x}} = i + 1\,ms$.<br><br>$W_1^{m_{relevant_x}} = \{O(t) \mid i\}$, with $m(i) = m_{relevant_1}$, or $m(i) = m_{relevant_2}$, $R_{low}^{m_{relevant_x}} = i\,ms$, and $R_{up}^{m_{relevant_x}} = i + 1000\,ms$ are chosen for the class $S^{CorrPercept}$, if followed by $W_1^{m_{response_x}} = \{O(t) \mid i\}$. The rule makes sure that after an instance $s_i^{CorrPercept}$ an instance of type $B^{*CorrResp}$ follows (the target was perceived).<br><br>$W_1^{m_{irrelev}} = \{O(t) \mid i\}$, with $m(i) = m_{irrelev}$, $R_{low}^{m_{irrelev}} = i\,ms$, and $R_{up}^{m_{irrelev}} = i + 1000\,ms$ are chosen for the class $S^{Ignore}$ in case there is no marker of type $m_{response_x}$ or $m_{relevant_x}$ 2000 ms before or after a marker $m_{irrelev}$. |

with $d_j \in \mathbb{N}', \mathbb{N}' \subset \mathbb{N}$ and $\mathbb{N}' = \{-2^{15}, -2^{15}+1, ..., 2^{15}\}$.

Further, in both implementations markers are defined as

$$M^{AdaptOMS} = M^{AdaptExo} = \{-2^{15}, -2^{15}+1, ..., 2^{15}\} \tag{6.2}$$

and $m(t) = -1$ for *no marker*.

Markers for training of BR are generated by different systems as allowed by the formal model (Figure 5.1). For example, in *AdaptExo* the HMI, the BR system, and a position tracking system (PTS) as a supportive system generate the required markers, whereas in *AdaptOMS* only the HMI generates the markers.

For the implementation of *AdaptOMS* it was important to understand the rules for choosing training examples (Table 6.1). The formalization of eBR was used here to better understand procedures. In this particular application (Figure 6.1 and (Wöhrle and Kirchner, 2014)), it was not possible to generate enough training examples for $S^{InCorrPercept}$. To solve this issue, the underrepresented class was substituted by examples of the class that were expected to evoke similar brain activity (see Section 4.1). Moreover, threshold adaptation was developed to later cope with the fact that the built classifier is not optimal to classify in the test case (Metzen and Kirchner, 2011). In detail, in *AdaptOMS*, brain activity present during the brain state $S^{Ignore}$ that is evoked by ignored, *task-irrelevant* stimuli (labeled by $m_{irrelev}$) was expected to be similar to brain activity present during the brain state $S^{InCorrPercept}$ that was is evoked by important stimuli (labeled by $m_{relevant}$) to which the user did not respond (see Table 6.1). Therefore, windows $W_x^{m(t)}$ as defined in BR rule $R^{Percept}$ with $W_1^{m_{irrelev}}$ were chosen to *train* for the brain state $S^{InCorrPercept}$, while windows defined by $W_1^{m_{relevant}}$ were chosen to train for the brain state $S^{CorrPercept}$ in case there was a response on the important warning, i.e., $W_1^{m_{relevant}}$ is followed by an instance of type $W_1^{m_{response}}$.

While instances for the *training* classes $S^{CorrPercept}$ in *AdaptOMS* are, as described above, chosen *after* windowing just by defining an *order of instances*, those for the class $S^{MovPrep}$ in *AdaptExo* are *not* chosen *after* windowing but with respect to their distance in time to the marker $m_{onset}$ within the rest period that is labeled to start at the point is time that is labeled by $m_{offset}$ *during* windowing (Table 6.1). The marker $m_{onset}$ labels the movement onset of the user's arm after a rest period. The marker $m_{offset}$ is added to label the time points of *lock in*, i.e., start of a rest period, which is detected by the exoskeleton. Note, that two windows are defined for each $m_{onset}$ (see Section 4.2 and (Kirchner et al., 2013a,d). Although both implementations show differences in the procedure for choosing relevant instances (windows), both implementations are covered by the formal model for eBR (Figure 5.1). This shows that the model is general enough to cover differences in implementation, while

Table 6.2: Implementations of part "WS" of the model for *test* of eBR. WS is defined in Figure 5.1. Source: Table 2 of (Kirchner et al., 2013d).

| AdpatExo ("WS" in *test*) | AdaptOMS ("WS" in *test*) |
|---|---|
| $W_x^{m(t)}$ is defined in BR rule $R^{Mov}$. | $W_x^{m(t)}$ is defined in BR rule $R^{Percept}$. |
| **windows for test of BR**: In *AdaptExo* windows are chosen independent of the state of the HMI. In *AdaptOMS* they are chosen with respect to the state of the HMI, i.e., in case that a warning was presented. | |
| Instances of class $S^{noMovPrep}$ or $S^{MovPrep}$ are defined as:<br><br>$W_1^{m_{BRwin}} =$<br>$\{O(t) \mid (i - 1000\,ms) < t < i\}$,<br>with $m(i) = m_{BRwin}$,<br>$R_{low}^{m_{onset}} = i - 1000\,ms$,<br>and $R_{up}^{m_{onset}} = i$. | Instances of class $S^{CorrPercept}$ or<br>or $S^{InCorrPercept}$ are defined as:<br><br>$W_1^{m_{relevant_x}} = \{O(t) \mid i\}$,<br>with $m(i) = m_{relevant_1}$, or<br>$m(i) = m_{relevant_2}$, $R_{low}^{m_{relevant_x}} = i\,ms$,<br>and $R_{up}^{m_{relevant_x}} = i + 1000\,ms$. |

still allowing a detailed description of relevant parts of the implementation.

More examples for the capability of the model to cover differences in the implemented procedures can be given for the *test* phase, i.e., application of eBR. The main difference between both implementations during *test* is, that in *AdaptOMS* it is known when to classify EEG instances $W_1^{m_{relevant}}$, since only after a *task-relevant* information (warning) is presented to the user a classification of the cognitive state "target recognition and task set change" (classification of $S^{CorrPercept}$ and $S^{InCorrPercept}$) is required (see Table 6.2 and (Wöhrle and Kirchner, 2014)). On the other hand, in *AdaptExo* it is *not* known at what time classification by BR is important, since it is unknown at what time the operator wants to start to move (to leave a rest position). Here, instances $W_1^{m_{BRwin}}$ are therefore cut continuously, i.e., every 50 ms (see Table 6.2, Figure 4.11 in Section 4.2 and (Seeland et al., 2013b)) based on the marker $m_{BRwin}$ that is automatically added by the BR system to label the end of each instance.

Moreover, for adapting the exoskeleton in *AdaptExo*, the adaptation time $r$ is more relevant than for adapting the OMS in *AdaptOMS* and continuous prediction of rel-

Table 6.3: Implementations of part "A" of the model for adapting the HMI. A is defined in Figure 5.1. Source: Table 3 of (Kirchner et al., 2013d).

| AdpatExo ("A" by eBR) | AdaptOMS ("A" by eBR) |
|---|---|
| The output $Y$ modulates the time threshold $T_{th}$ of the force sensors in the exoskeleton, i.e., in case of $B^{CorrResp}$ the user has to press shorter against sensors to *lock out* the system from rest while executing $B^{*CorrResp}$ as defined in the adaptation rule $R^{AdaptExo}$. | The output $Y$ modulates the allowed response time (RT) for the user that is controlled by the OMS as defined in $R^{AdaptOMS}$. |
| $T_{th}(k) = (T_{th}^{Max} - (1 - 2(y - 0.5)) + T_{th}^{Min}$<br><br>with $y_i = 1$ for minimal time threshold $T_{th}^{Min}$ and maximum movement prediction impact here: $T_{th}^{Min} = 10$ ms, since control frequency is $100$ Hz and with $y_i \leq 0.5$ for maximal time threshold $T_{th}^{Max}$ experimentally determined to avoid *unwanted lock out* (Folgheraiter et al., 2012). | For $y_i = 1$ the allowed RT is increased from $2$ s to $RT_{max} = 10$ s<br><br>for $y_i = -1$ *no* adaptation of RT takes place ($RT_{min} = 2$ s) (Wöhrle and Kirchner, 2014). |
| The time that is required for each adaptation $r$ depends on the frequency of predictions made by BR (here every $50$ ms) and the time required to adapt the time threshold $T_{th}$ (here $10$ ms).<br><br>The adaptation time $r$ for a certain time point $i$ is in the worst case $r_i = 60$ ms. An effective prediction $p_e = (q - k) - r$ can be as early as $190$ ms before a movement onset ${b_q}^{*MovOnset}$ since a high classification performance can be achieved at $250$ ms (Folgheraiter et al., 2011) before $B^{*MovOnset}$ at $k = q - 250$ ms, with $q = 0$ ms. | The time that is required to adapt RT $r$ takes $r \approx 12$ms and can be neglected since adaptation is only required before $RT_{min}$ reduced by $R_{up}^{m_{relevant}}$ and $j$.<br><br>The OMS requests predictions of the cognitive state by eBR only after the presentation of important information (targets) to adapt RT if ${b_q}^{*CorrResp}$ is not executed before $RT_{min}$<br><br>The HMI controls the eBR system and its own adaptation. |

evant behavior is only required in *AdaptExo* (Table 6.3). Here, the BR continuously provides values for $Y$ and sends them to the HMI while the exoskeleton makes only use of an output $y_i$ in case it is locked in for some time ($4\,s$ in this implementation), i.e., is in a rest period. Thus, during test the HMI does control its adaptation by eBR as defined in the model but has no influence on BR, while the OMS in *AdaptOMS* actively requests predictions from the BR system after warnings and thus controls both the BR system and its own adaptation by eBR. Finally, the HMI does control correction procedures. For both implementation it controls whether the predicted behavior, $B^{*MovOnset}$ or $B^{*CorrResp}$, respectively, is actually executed. However, in *AdaptExo*, the behavior of the HMI is only changed in case the beginning of the execution of it is detected as explained above, while in *AdaptOMS* the behavior of the OMS is changed first by extension of the allowed response time in case that $B^{CorrResp}$ is predicted (Table 6.3). This adaptation is then only controlled afterwards by monitoring the response behavior $B^{*CorrResp}$ of the user. In case that no $B^{*CorrResp}$ is detected by the HMI within the extended allowed response time a second warning is presented. The here given example emphasizes that different parts of the model may be more or less relevant for different implementations and may also be implemented by different procedures, but still fit the model.

### 6.2.2 Detection of Implementation Errors by Formalization

After formalizing both implementations we found errors that were not detected before, since these errors would not lead to malfunction of the HMIs but just worsen the performance. For example, by formalizing the implementation *AdaptExo* with respect to the general model of eBR (Figure 5.1 in Chapter 5) we could uncover an implementation error that was caused by misinterpreting the outcome $Y$ of SP. On the exoskeletons' control side it was expected that in the case of no movement preparation no value, i.e., $y_i = 0$ should be the output of BR. However, Table 6.3 shows that eBR was not just predicting the brain state of movement planning $S^{MovPrep}$ (in case of $y_i > 0.5$) but also the brain state of *no* movement planning $S^{noMovPrep}$ (in case of $y_i \leq 0.5$), which is not relevant for this application. In this example in case of $y_i \leq 0.5$, the exoskeleton would erroneously have been adapted for a *faster lock out* although *no* movement preparation was predicted by BR if the error would not had been found. Finding the error was only possible after formalizing this implementation.

In the implementation *AdaptOMS* an error was found within the implementation of the part "SP" of the formal model for eBR as displayed in Figure 5.1. Here, training of eBR should take place on instances of type $W_x^{m_{relevant_1}}$ and $W_x^{m_{relevant_2}}$ (see Table 6.1). Instances of type $W_x^{m_{relevant_1}}$ are first warnings and instances of type $W_x^{m_{relevant_2}}$ are repeated second warnings that are better visible (by changing the

color). During test eBR does detect the cognitive state after both types of warnings to allow the prediction of response behavior. However, in the setting a third type of warning was used ($W_x^{m_{relevant_3}}$) to enhance the number of training examples. This third warning was very strong. We expected that the user would in all cases respond to this warning, especially since the control of the robot was removed from the user after the warning was shown for 1000 ms. Thus, BR was not required to detect the cognitive state after the presentation of the third warning and eBR was not required to infer the respective behavior since this was quite clear due to the forced response on the third warning. Further, EEG patterns evoked by the third warning were quite different compared to EEG patterns evoked by the warnings of type 1 and 2. Thus, by training the classifier on instances of type 3 performance in the classification of the cognitive state for instances of type 1 and 2 might have dropped. By formalizing this implementation *AdaptOMS* the error could be found.

## 6.3 Summary

In Chapter 6 the general, formal model for eBR that was developed in this thesis and presented in Chapter 5 was evaluated on two implementation examples, *AdaptOMS* and *AdaptExo*, that were described in detail in Section 6.1. By developing an application scenario for eBR this chapter contributes to **Subgoal 1a** of the thesis, i.e., to develop a robotic application scenario for tele-manipulation. It further contributes to **Subgoal 3a** of the thesis by implementing eBR for online support in this application scenario, as it is documented by Video B.5 provided as supporting video. By means of the implementation examples it was further shown that (1) the developed formal model fits different implementations, (2) covers differences in the implemented procedures of different parts of the model, and (3) could uncover errors that are difficult to find without formalization. Hence, the work fulfills all subgoals of the **Main goal 2** of the thesis.

The presented work of this chapter indicates that formal models for complex systems, as presented here, enable a very detailed as well as clear description of procedures. This becomes more important as more interdisciplinary research is required to develop complex systems for advanced human-machine interaction, since it can ease their implementation for different applications as explained on the examples.

Results of the evaluation of the model further indicate that the formalization of eBR is important for the introduction of this approach in complex practical use cases, since it allows to verify that eBR works error-free while being adaptive to different requirements as shown on both implementation examples in the tele-manipulation scenario. One application of growing interest is robotic-based rehabilitation (see Chapter 7). To apply robotic systems for rehabilitation, it has to be assured that (1) such

systems are correct and complete when developed (Drechsler et al., 2012) and work error-free while being adaptive to different requirements of different groups of patients and their state in rehabilitation (Kirchner et al., 2013a, 2014) as it was shown in the application of eBR in the tele-manipulation scenario in this chapter.

# Chapter 7

# Multimodal Signal Analysis for Adaptive Active Support by eBR

In this chapter it is described how eBR can be used to actively support a predictive HMI for the purpose of rehabilitation or to reestablish motor function of the upper limbs. It is shown by experiments on the data set described in Section 3.2 that additional physiological data, here EMG, can not only be used to support eBR by generating context as discussed in Section 5.1.2.1 or to control the correct functioning of BR as discussed in (Kirchner et al., 2013a; Kirchner and Tabie, 2013; Kirchner et al., 2014) (instead of using sensor data from the HMI for movement onset detection as discussed in Section 6.1, see also (Folgheraiter et al., 2011, 2012; Seeland et al., 2013b; Wöhrle and Kirchner, 2014)), but to adapt the support of the predictive HMI with respect to the state of therapy by combining predictions made on the basis of BR analysis of EEG data and analysis of EMG data. Text, figures and tables of the following sections are taken and partly adapted from (Kirchner et al., 2014). Preliminary results can be found in (Kirchner et al., 2013a; Kirchner and Tabie, 2013).

## 7.1 Active Support of predictive HMIs by eBR in a Rehabilitation Scenario

To enhance human-machine interaction for the purpose of rehabilitation, it is not enough to develop highly accepted assistive technology devices (definition see (United States Congress, 2004)) that do not restrict the person who is wearing it, are comfortable and intuitive to use, not fixed to a special support mechanism but are worn by the patient to allow natural behavior, while multiple contact points to the patient's body avoid pressure points and allow the reflection of complex force patterns for accurate guidance (Kirchner et al., 2013a; Folgheraiter et al., 2012). It must, in addition, be as-

sured that intentions of the patient are communicated and translated into supported behavior. By inferring the patients' behavioral intentions it is possible to reestablish functions of patients that are disabled, like motor behavior, by a technological device like an active exoskeleton or orthosis. The more intuitive the communication of intentions is implemented and executed, the more natural will the patient be supported and the less cognitive resources will be required by the patient to enable this support. Based on the listed requirement, eBR would be an appropriate approach to infer motor intention, since it allows to passively detect brain states that are evoked naturally during interaction or interaction intention by BR and can be used context sensitively to support a specific interaction task.

For rehabilitation of the motor system movement intention of the patient can be detected by her/his brain activity, e.g., the EEG, as shown in Section 4.2 and in (Pfurtscheller, 2000; Folgheraiter et al., 2011; Bai et al., 2011; Ibáñez et al., 2011; Kirchner et al., 2013a; Seeland et al., 2013b) for healthy subjects and in (Lew et al., 2012) even for stroke patients whose brain, i.e., its motor control function, is to some degree impaired. However, most studies request the patient to imagine a certain movement quite artificially. For example in (Novak et al., 2013) movement onset was triggered by cues given by the experimental setup (i.e., auditory cues). In this study subjects do not perform self-initiated movements, but movements on command. In a natural application such commands are, however, missing. Movement intentions must be detected to support self-initiated movements. In Section 4.2 it was already shown that BR is able to detect the onset of intentional movements and in (Kirchner et al., 2013a) it was shown that the onset of self-initiated, self-paced movements can be predicted from EEG data presented in Section 3.2 independent of the movement speed.

The integration of EEG-based movement onset predictions in the control of an assistive technical device has one great advantage: the earliness of prediction that can be achieved based on EEG analysis allows to close the gap between movement planning and execution for natural behavior, and may thus boost rehabilitation since the patient gets the feeling as if she/he and not the assistive device, like an exoskeleton, is controlling the limb (Muralidharan et al., 2011). This effect should especially be supported in case that EEG activity is not artificially produced for the control of a device, as for example by imagining movements of ones "right" and "left" arm to open and close a hand prothesis (Guger et al., 1999), but when it is detected passively (as it can be enabled by BR), i.e., the patient imagines the same movement that should be supported by the device. Further, certain event-related activities in EEG are a reliable indicator that a patient wants to execute a *self-initiated, voluntary* movement. Especially the Bereitschaftspotential (BP) (or readiness potential (RP)) is evoked before voluntary movements and not before involuntary movements and can

thus be used in clinical practice to differentiate between voluntary and involuntary movements as they might often be detected in EMG data recorded from patients with spasm (Shibasaki and Hallett, 2006).

EMG activity on the other hand can also be used to predict movement onset (Kirchner et al., 2013a) and is also quite often solely used to trigger an orthosis or a prosthesis (Rosen et al., 2001; Fleischer et al., 2006; Cavallaro et al., 2006; Benitez et al., 2013b). However, also other physiological signals, like gaze direction as well as technical signals can be used alone or in combination with EMG and EEG data to detect movement intention or to detect the target of a movement to support reaching the movements' goal (Hayashi et al., 2005; Novak et al., 2013; Tabie and Kirchner, 2013; Kirchner et al., 2013a; Kirchner and Tabie, 2013; Kirchner et al., 2014; Benitez et al., 2013a). A prediction of movement onset that was made based on EEG analysis can, for example, be confirmed by (i) a simultaneously detected fixation of manipulable objects by the eyes, (ii) the detection of muscle activity or by (iii) measuring pressure against force sensors of the device. By analyzing the context of behavior even complex interaction, like grasping a certain object (Novak et al., 2013), can be triggered and executed by the device (Figure 7.1).

What sources of physiological data should be combined depends on the requirements, e.g., the kind of disability and neuromuscular disorder (Corbett et al., 2012) as well as the state and progress of the patient in rehabilitation. Further, the correctness of a prediction can, in principle, be improved by combining several sources of physiological data or even other information, like preferences of the patient (Novak et al., 2013; Corbett et al., 2012; Huang et al., 2011). Moreover, it is important to evaluate which effect a combination has on the control of the device. The usage of certain data may prohibit an early prediction. For example, the EOG or eye tracking can be used to improve the detection performance of EEG-based predictions (Novak et al., 2013). However, a controlled eye movement that can be detected by eye tracking takes place after the subject's decision to move. Hence, it does not allow the detection of preconscious movement intention (Shibasaki and Hallett, 2006), but conscious movement intention which is "communicated" by eye movements. Still, to add this signal can be a good choice for patients whose EEG does not allow good prediction performance or who show no other movement-related activity, like EMG, at all, but it does no longer support the positive effect of a fast, almost preconscious control where the subject gets the impression that the device "knows" what her/his intention is. Which signals are relevant at which state of movement planning and execution has been systematically investigated for the prediction of movement targets. For example, in (Novak et al., 2013) it was shown that different measures should be combined for different states, e.g., for movement planning, start of movement and movement execution. When different objects were shown to the subject but move-

ment did not yet start, EEG and EOG were found to be most predictive, while eye tracking and EMG could be used best to predict the choice of the target after the movement started.

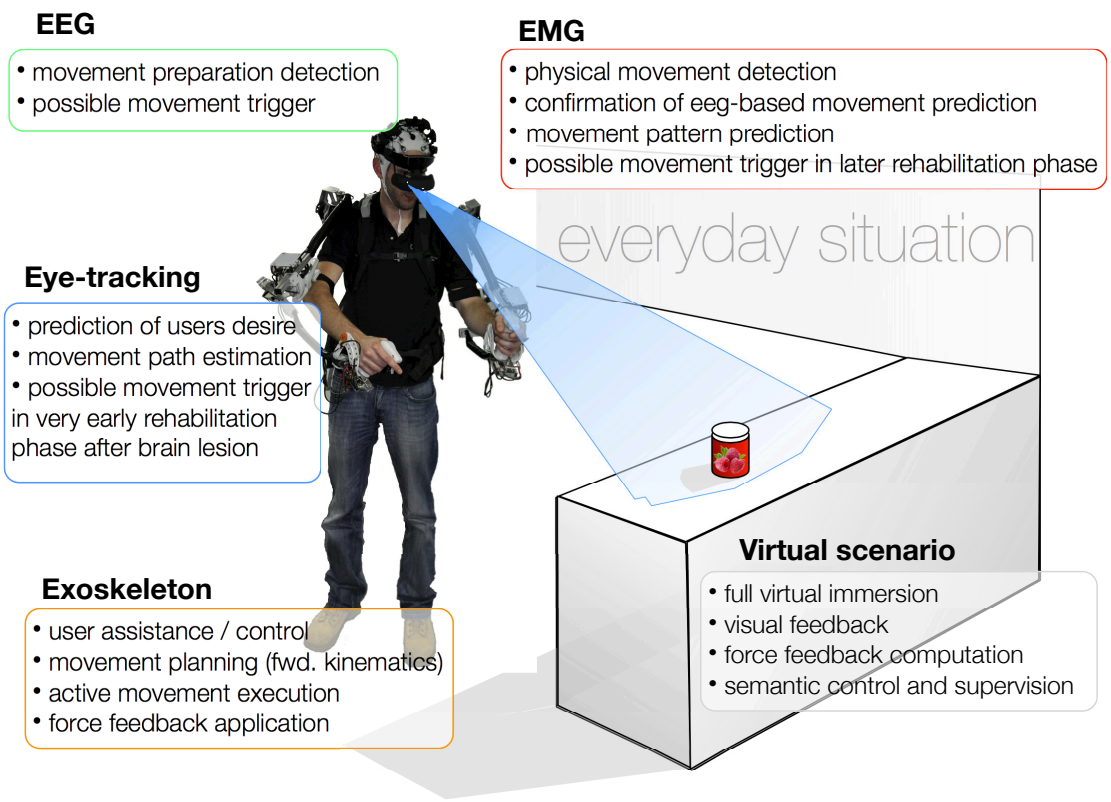


Figure 7.1: Schemata of a subject assisted by an exoskeleton within a possible rehabilitation scenario. The exoskeleton is controlled online via signals directly recorded from the user and an eye-tracking system. The support is context driven and can be realized in the real world or a virtual scenario. Figure is based on Figure 1 of (Kirchner et al., 2014).

With the investigation presented in the following it is shown that eBR can make use of other psychological data, here EMG data, to potentially adapt a predictive HMI in a way that a more individual support of patients with respect to their state in therapy is enabled. It is shown that the reliability of movement predictions as well as the true positive rate in movement predictions made based on EEG analysis by BR and EMG analysis can be adapted by eBR, if brain activity data , i.e., EEG data, and supportive signals, i.e., EMG data, are combined differently.

### 7.1.1 Experimental Part - Adaptive Support of Arm Movements by eBR based on Multimodal Signal Analysis

In this section it is investigated whether it is possible to infer that a subject wants to start a self-initiated movement based on EEG and EMG data recorded during movements of the right arm (see Section 3.2). It was not the goal to show that multimodal analysis improves absolute prediction performance but that a different combination of multimodal data, i.e., EEG and EMG data, can help to better adapt an assistive technical device, like an exoskeleton or orthosis, to different states in rehabilitation. Thus, the goal was to show that the functionality of the whole system can maximally be optimized with respect to two different types of errors that have different relevance in different states of rehabilitation. This can be achieved by applying two different approaches for combining both kinds of physiological data. The scope of this work was not yet to show a working approach to support patients nor an online application but an offline analysis of general feasibility. Results presented here were achieved in an offline combination and comparison of both physiological signals. To assure that the results will not be affected by implications of different neuromuscular disorders, the feasibility of the above explained approach was investigated by conducting experiments with healthy subjects (see Section 3.2).

#### 7.1.1.1 Experimental Setup and Procedure

The experimental setup is described in Section 3.2. However, only data that was recorded under the "normal" speed condition was used here since the goal was to investigate not only self-initiated but also self-paced movements. Such movements, rather than really fast or slow movements, are expected to be performed during natural interaction and training of movements for rehabilitation.

**Ethics Statement:** The study has been conducted in accordance with the Declaration of Helsinki and approved with written consent by the ethics committee of the University of Bremen. Subjects have given informed and written consent to participate.

#### 7.1.1.2 Hypotheses

In the following investigations it is hypothesized that a different combination of EEG and EMG analysis can either enhance (i) the reliability of movement detection, i.e., decrease the false positive rate (*FP-rate*) (error type I), by combining both signals in an "AND" fashion, or (ii) improve the positive detection rate of self-initiated move-

ment detection, i.e., decrease the false negative rate (*FN-rate*) (error type II), by combining both signals in an "OR" fashion.

#### 7.1.1.3 Methods

EEG and EMG data acquisition and the estimation of physical movement onset based on EMG data were performed as described in Section 3.2.

**EEG Analysis:** For EEG data analysis, 64 of the 128 recorded channels (extended 10-20 system) were used. The analysis of the EEG data was optimized to detect event-related potentials (ERPs) in single trial. Movement planning evokes several movement-related potentials as discussed in Section 3.2. An early detection of these components allows the prediction of movement onset (Folgheraiter et al., 2011; Lew et al., 2012).

For preprocessing, the data was standardized channel-wise (subtraction of mean and division by SD) and decimated to 20 Hz. Next, an FFT band-pass filter with a pass band of 0.1 to 4 Hz and xDAWN, an spatial filter (SF) (Rivet et al., 2009), were applied. After spatial filtering, four pseudo-channels were used for further processing. The data were processed window wise on windows with a length of 1000 ms. The last four samples of the windows were used as time domain features and a Gaussian-feature-normalization (features have zero mean and variance one) was performed. For later classification, a support vector machine (SVM) (Vapnik, 1995) was trained.

Training windows were defined for both classes: ”movement intention” and ”resting state”. For ”movement intention” the windows $[-1100, -100]$ ms and $[-1000, 0]$ ms before each physical movement onset were used. For ”resting state” windows were cut every 1000 ms, as long as no movement occurred 1000 ms before and 2000 ms after a window.

In the test case, overlapping windows were cut every 50 ms (see Figure 4.11) in a range from $-4000$ ms to 0 ms before a movement ($[-5000, -4000]$ ms, $[-4950, -3950]$ ms, ..., $[-1000, 0]$ ms). A prediction of a movement was allowed in a range of $-1000$ ms to 0 ms before movement onset. As border between classes $-1000$ ms with respect to the physical movement onset was chosen, although it is known that the BP or RP (Kornhuber and Deecke, 1965; Deecke et al., 1969) that is detected by the performed analysis can be expressed way before $-1000$ ms or later (Santucci and Balconi, 2009). For the choice of the class border a) the signal properties and b) a possible application were considered. In the application the assistive device should actively supported by eBR start the movement simultaneously with the patient’s conscious will to move. Hence, detection of unconscious movement intention is only useful if the device needs time for reaction. Very early detections of

movement intention might lead to triggering movement onset by the assistive device before the patient is ready. The obtained SVM scores were transformed to a movement probability with a sigmoid function (Platt, 2000). A probability greater than $0.5$ corresponded to movement preparation. For each subject individually a 3-fold cross validation analysis of the data was performed, in which each fold corresponded to one experimental run. During the training phase the complexity parameter of the SVM was optimized using a grid search. The grid contained 7 values: $10^{-6}, 10^{-5}, \ldots, 10^{0}$.

**Definition of Conditions:** Four different conditions were investigated:

**A:** EEG-based prediction. In this condition prediction of movement onset is based *only* on EEG analysis.

**B:** EMG-based prediction. In this condition prediction of movement onset is based *only* on EMG analysis.

**C:** "OR" combination of A and B. Here A and B are combined in a way that a movement onset counts as predicted, if either EEG *or* EMG-based analysis or both predicted a movement.

**D:** "AND" combination of A and B. Here A and B are combined in a way that a movement onset counts as predicted, if both EEG *and* EMG-based analysis predicted the movement.

For all conditions the *TP* and *FP-rates* as well as the BA (see Section 2.4.3) and the mean prediction times were calculated.

**Used Metrics for Performance Evaluation:** As performance metrics the true positive and false positive rate used, defined as

$$\textit{TP-rate} \stackrel{\text{def}}{=} \frac{TP}{TP+FN} \tag{7.1}$$

and

$$\textit{FP-rate} \stackrel{\text{def}}{=} \frac{FP}{FP+TN}, \tag{7.2}$$

where TP is the number of correctly classified ”movement intention” windows, FN is the number of wrongly classified ”movement intention” windows, TN is the number of correctly classified ”resting state” windows and FP is the number of wrongly classified ”resting state” windows, respectively. Note that for calculating the *TP-rate* one correctly classified window based on EEG analysis in the range of $-1000\,\text{ms}$ to $0\,\text{ms}$ and for EMG in the range of $-500\,\text{ms}$ to $0\,\text{ms}$ was sufficient. For the *FP-rate* each

window from the ”resting state” that wrongly predicted a movement was counted as FP.

**Statistics on Error Rates:** Note that from a statistical point of view it is more intuitive to compare two error types, rather than an error type (FP-rate) with a success type (TP-rate). However, due to the relation between the *TP* and *FN-rate* (error type II is defined as *FN-rate* $= 1 -$ *TP-rate*) the statistical results obtained by using the *TP* and *FP-rate* is equivalent to that provided by using the *FN-* and *FP-rate*. Thus, to compare the two different signal types and their combinations, the error rates obtained were analyzed by repeated measures ANOVA with error type (*FP-rate*: error type I / *FN-rate*: error type II) and signal type and their combinations (EEG/EMG/"AND"/ "OR") as within-subjects factors [SPSS, version 20, SPSS Inc., Chicago, IL, USA]. Where necessary, the Greenhouse–Geisser correction was applied and the corrected $p$-value is reported. For multiple comparisons, the Bonferroni correction was applied.

**Common Metric for Performance Evaluation:** To evaluate the performances obtained from the two types of signals (EEG/EMG) and their combinations (AND/OR) together, the BA (for definition see Section 2.4.3) was used as a common metric. The BA is calculated as balanced classification rate (i.e., the BA considers the accuracy of the positive class and accuracy of the negative class independently) and thus the BA is insensitive to unbalanced class ratios. Such unbalanced ratios between the positive and negative class have to be considered, since in this study 40 ”movement intention” and 2400 ”resting state”examples occurred per run. It is important to show that the approach of combining both EEG and EMG signals for adapting an assistive technical device with respect to the requirements of therapy does not influence absolute prediction performance too negatively. However, it should be noted that the two methods (EEG- and EMG-based movement prediction) behave differently concerning the ratio between *FP-rate* and *FN-rate*. More specific, similar levels of both error rates for the EEG could be observed, while these levels were very different for the EMG signal (see Table 7.1). Hence, it is not straightforward to compare the two different signal types (EEG/EMG) and their combinations (AND/OR) with a single metric that does not take into account these observed differences. To still enable a direct comparison BA values are provided. Other metrics can be calculated based on the given performance rates.

**Prediction Time:** The prediction time is defined as the earliest point in time (under the above defined conditions, i.e., interval boundaries) where a physical movement start could be predicted. Since the distributions of prediction times differ a

lot for EEG and EMG-based classification and especially the combination (condition C, see above) is not Gaussian distributed, median and quartiles are reported. For EMG-based predictions of movement onset (condition B, see above) the point in time was marked at which the adaptive threshold is exceeded. For EEG-based detection of movement intention (condition A, see above) the earliest time window (furthest away from movement onset) that was classified to belong to the class of movement intention was used to estimate the EEG-based prediction time.

#### 7.1.1.4 Results

**Prediction Time:** In Figure 7.2 the distribution of prediction times for EEG and EMG-based predictions of movement onset is shown (see also Table 7.1). For visualization purposes a video is provided that visualizes the earliness in prediction of the different movement prediction conditions (see Video B.2). For EEG-based detection of movement intention the median of the prediction time was 450 ms (with lower 25%-quartile $Q1$: 200 ms and upper 25%-quartile $Q3$: 900 ms), for EMG-based predictions of movement onset the median of the prediction time was 61 ms ($Q1$: 36 ms, $Q3$: 90 ms). Note that for EEG-based predictions the prediction times are clustered in lines with a spacing of 50 ms due to the windowing procedure explained above. In

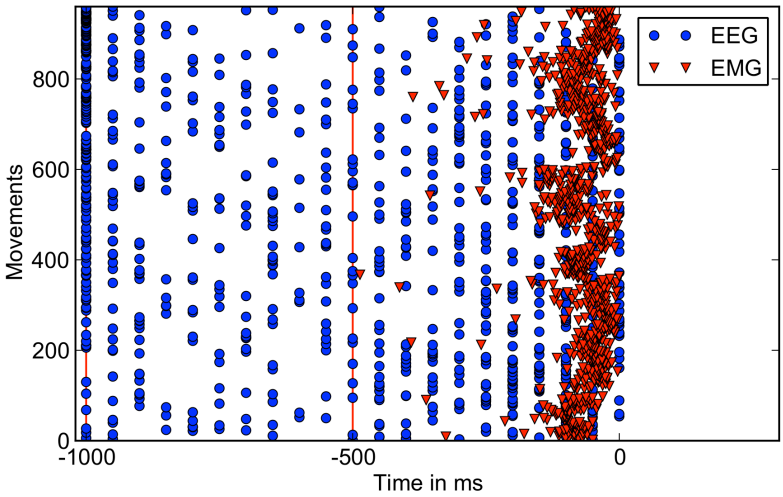


Figure 7.2: Distribution of prediction times for EEG-based and EMG-based movement prediction. Time point zero corresponds to the physical movement onset, the red line at time −500 ms indicates the range up to where predictions based on EMG (red) were allowed, for EEG predictions (blue) up to −1000 ms before physical movement onset were allowed, again marked with a red line. Figure is based on Figure 3 of (Kirchner et al., 2014).

Figure 7.3 all windows classified as ”movement intention” are plotted to better visualize the distribution of false and true positive classification. The plot shows that for

EEG based predictions, instances (windows) recorded before $-1000$ ms were sometimes also classified as movement intention. In the plot, all individual movements (independent of subject and run) are ordered in the way that the ones with the highest *FP-rate* are displayed at the top of the figure. The differences in performances were highly dependent from the performance of individual subjects as shown in Figure 7.4. It is obvious that for single movements for which EEG-based movement prediction was too early, the general performance in separating classes ("movement intention" and "resting state") was weak. In the lower part of Figure 7.3, 27.2 % of the whole 960 movements that were analyzed in this study contain no FPs (no positive predictions before $-1000$ ms with respect to the physical movement onset). For the combination of both signals in an ”OR” fashion (condition C) the median of the prediction time was 110 ms ($Q1$: 50 ms, $Q3$: 500 ms) and for the ”AND” combination (condition D) the median of the prediction time was 57 ms ($Q1$: 33 ms, $Q3$: 88 ms).

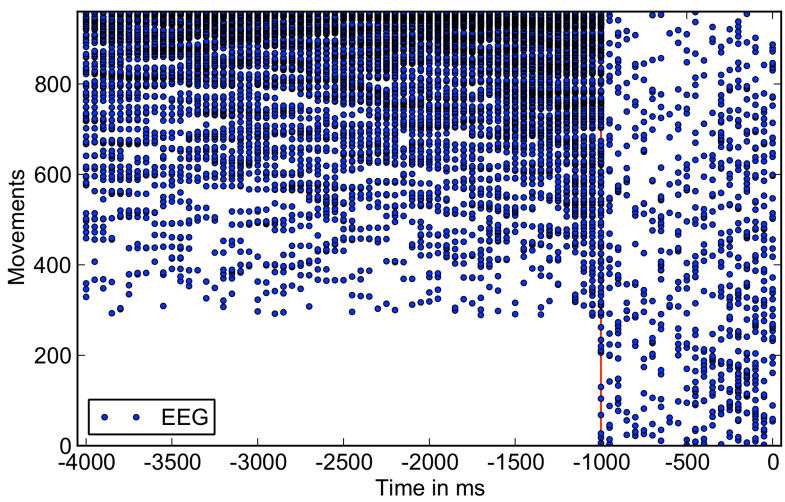


Figure 7.3: Distribution of prediction times for EEG-based movement prediction including the non movement range. Time point zero corresponds to the physical movement onset, the red line at time $-1000$ ms indicates the range up to where predictions based on EEG were allowed, the range from $-4000$ ms to $-1050$ ms corresponds to the no movement class, hence all predicted windows in that range count as FPs. Figure is based on Figure 4 of (Kirchner et al., 2014).

**Prediction Performance:** The classification results are summarized in Table 7.1 and visualized in Figure 7.5 (*TP* / *TN-rates* and *FP* / *FN-rates*) and Figure 7.6 (balanced accuracy). Statistical analysis revealed that the signal types and their combinations (EEG/EMG/ "AND"/ "OR") affect the error rate for both types of error (*FP-rate*: error type I / *FN-rate*: error type II) [interaction between error type and type of signal combinations: $F(3, 21) = 28.46, p < 0.001$]. For error type I, the "AND" combination is the best combination of signals, i.e., reduces error of type I most, with

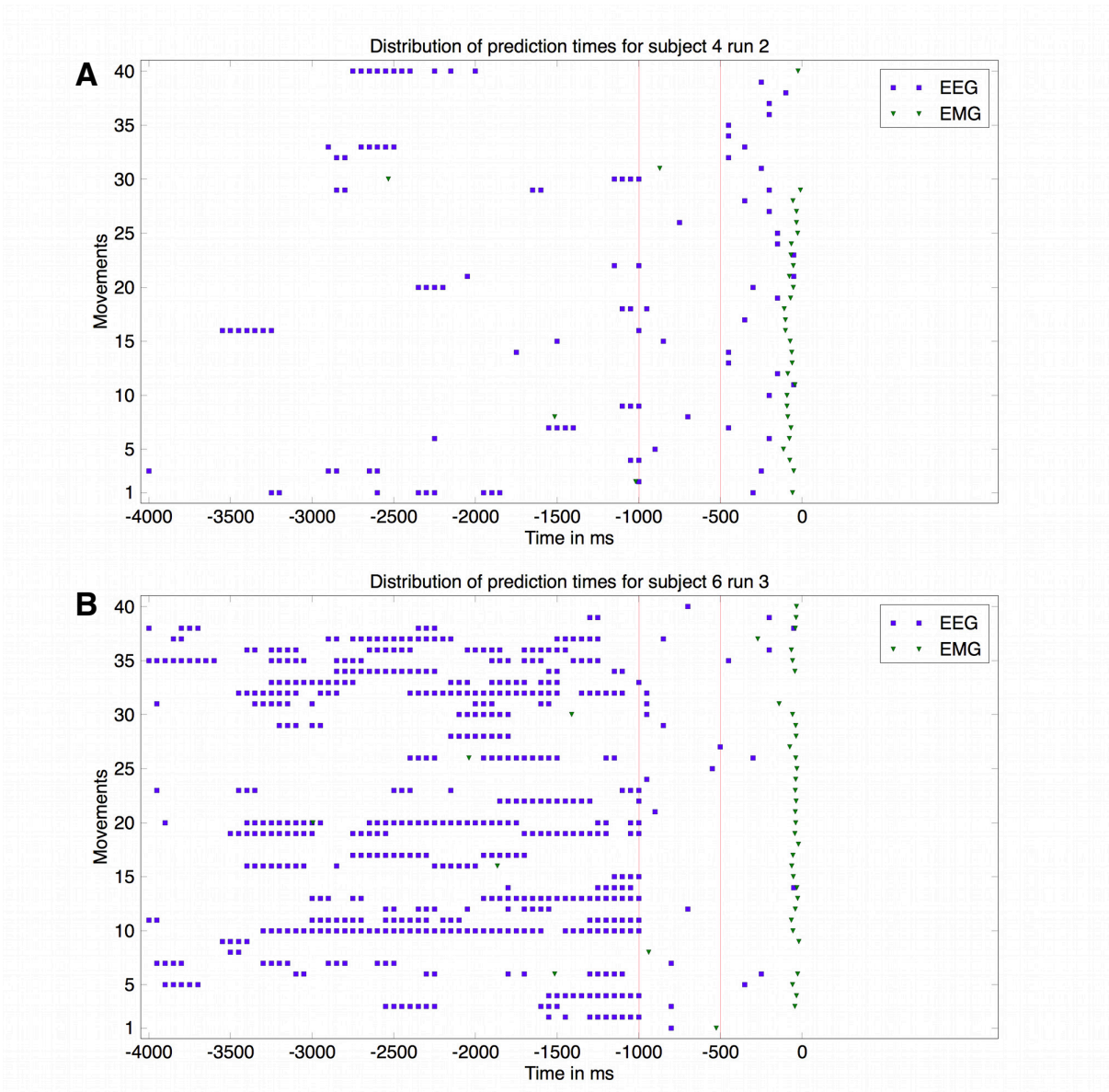


Figure 7.4: Distribution of prediction times for EEG-based and EMG-based movement prediction including the non movement range for two subjects. A: Example for good performance in EEG-based prediction. B: Example for bad performance in EEG-based prediction. Source: Supporting Information Figure S1 of (Kirchner et al., 2014).

significant differences to all other types of signals and their combinations [AND vs. EMG: $p < 0.003$, AND vs. EEG: $p < 0.008$, AND vs. OR: $p < 0.007$]. The type of signal "EMG" is better than the type of signal "EEG" [$p < 0.008$] and the "OR" combination [$p < 0.008$]. The type of signal "EEG" is better than the "OR" combination [$p < 0.003$]. For error type II the "OR" combination is the best combination of signals,

Table 7.1: Classification results for all 4 combinations of signals. Results for different classification conditions (from left to right: EEG only, EMG only, combination of both with "OR" and with "AND"): The mean classification results with SD are shown in TP, FP, TN, FN-rate and balanced accuracy. The prediction time is given in 25 %-, 50 %- and 75 %-quantiles, respectively. Source: Table 1 of (Kirchner et al., 2014).

| **Condition** | **A (EEG)** | **B (EMG)** | **C ("OR")** | **D ("AND")** |
|---|---|---|---|---|
| TP-rate | $0.88 \pm 0.1$ | $0.86 \pm 0.1$ | $0.98 \pm 0.03$ | $0.76 \pm 0.16$ |
| FP-rate | $0.1 \pm 0.06$ | $0.001 \pm 0.001$ | $0.1 \pm 0.06$ | $0.0002 \pm 0.0004$ |
| TN-rate | $0.9 \pm 0.06$ | $0.999 \pm 0.001$ | $0.9 \pm 0.06$ | $0.9998 \pm 0.0004$ |
| FN-rate | $0.12 \pm 0.1$ | $0.14 \pm 0.1$ | $0.02 \pm 0.03$ | $0.24 \pm 0.16$ |
| balanced accuracy | $0.89 \pm 0.07$ | $0.93 \pm 0.07$ | $0.94 \pm 0.04$ | $0.88 \pm 0.08$ |
| prediction time (ms) | $200, 450, 900$ | $36, 61, 90$ | $50, 110, 500$ | $33, 57, 88$ |

i.e., reduces error of type II most, with significant differences to all other types of signal and their combinations [OR vs. EMG: $p < 0.022$, OR vs. EEG: $p < 0.037$, OR vs. AND: $p < 0.007$]. The type of signal "EMG" is better than the "AND" combination [$p < 0.037$], but not better than the type of signal "EEG" [$p =$ n.s.]. The type of signal "EEG" is better than the "AND" combination [$p < 0.022$].

#### 7.1.1.5 Discussion

Results show that both signals, EEG and EMG, can be used to reliably predict movements before a physical movement onset. Thus, both signals can potentially be used to control a device with high performance. In case a fast control algorithm for the assistive device is used (Folgheraiter et al., 2012) the evaluated prediction time would, for both conditions A and B, allow to support movements in a way that subjects would possibly not notice a delay between their intention and the execution by the device. Since EEG-based predictions can be made much earlier than EMG-based predictions, EEG might be more suitable to give the user the feeling that a device is delivering support on time and without delay. However, whether there is indeed a subjective difference between both methods has to be investigated further.

On the other hand, it was shown that EEG analysis can lead to more false positives than EMG analysis does (Figure 7.5). There are different explanations for this. First, one of the most important reasons for higher $FP$-$rates$ in EEG-based predictions is that movement planning (movement intention) might be detected, which may not result in movement execution (Kornhuber and Deecke, 1965; Deecke et al., 1969). Second, for some subjects EEG-based predictions did not work that well, as can be seen in Figure 7.4. Therefore, some subjects might have worsened the overall error rates. In this study this subject-specific effect was not evaluated, since the investigation focused on a general evaluation of the potential of combining different methods

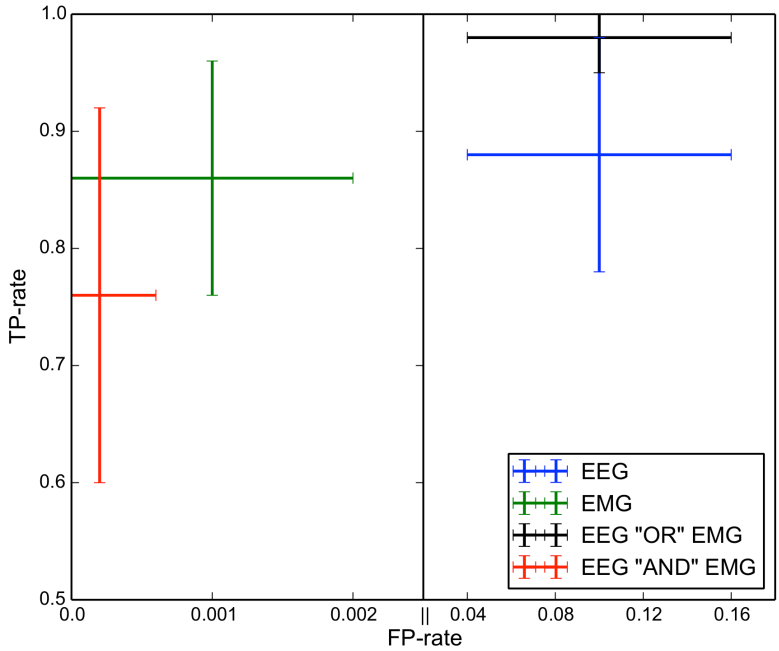


Figure 7.5: Prediction results in TP and FP-rate for different combinations of signals. Following combinations of signals are shown: condition A (EEG) (blue), condition B (EMG) (green), condition C (EEG ”OR” EMG) (black) and condition D (EEG ”AND” EMG) (red). The mean TP-rate and FP-rate for all subjects is shown; the bars indicate the SD. Note for the x-axis two scales are used, since the FP-rates for condition B (EMG) and condition D (EEG "AND" EMG) are very small compared to the other two conditions. The two vertical dashes within the x-axis label highlight the scale change. Figure is based on Figure 5 of (Kirchner et al., 2014).

for adapting an assistive technical device with respect to the state of therapy.

It was already shown by other studies that the combination of different measures can improve the performance of detections of subjects intentions, e.g., in the case of movement target prediction (Novak et al., 2013; Corbett et al., 2012). To detect the intention of patients is highly relevant to support them appropriately. A device can best support a movement if, for example, the target of the movement is known. Here it was investigated which methods and combination of methods can best be used to predict *when* a patient wants to execute such a movement with respect to different therapy states. To detect movement intention is highly relevant to support self-initiated, voluntary movements by assistive technology devices like active exoskeletons. Conducted results show that all classification modalities have a high performance in a range of 0.88 to 0.94 BA. The best result was achieved using the ”OR” combination and EMG as a single modality. Slightly worse results were obtained from EEG-based classification and the ”AND” combination. With respect to the small differences in

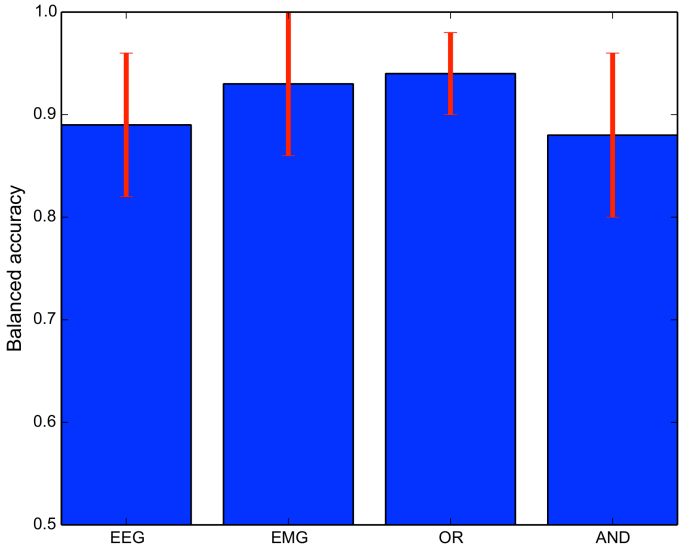


Figure 7.6: Prediction results in balanced accuracy for different combinations of signals. Following combinations of signals are shown: condition A (EEG), condition B (EMG), condition C (EEG "OR" EMG) and condition D (EEG "AND" EMG). The mean balanced accuracy for all subjects is shown; the bars indicate the SD. Figure is based on Figure 6 of (Kirchner et al., 2014).

the absolute performance, it is hard to decide which signal or combination of signals is best to be used to detect movement intention. The most intuitive idea would be to use the "OR" combination because of the highest performance. However, the EEG-based classification has only a slightly worse accuracy, but movements can be predicted 4 times earlier. Results show that the signals or combination of signals always have to be chosen according to the application and goals in rehabilitation, as investigated in this work, and are not always solely based on the absolute prediction performance.

During the rehabilitation process the importance of avoiding false movement onset predictions (*FP-rate*; error type I) and thus inappropriate triggering of movements can differ. If the goal of the therapy is to start rehabilitation of patients, who likely produce no strong signals, it is more relevant to detect most movement intentions, hence to reduce the occurrence of type II errors (*FN-rate*). Thus, a combination of signals in an "OR" fashion could be the best choice, since it results in a high $TP$-$rate$ (close to 1 in healthy subjects) and reduces the *FN-rate*, i.e., type II error. By an "AND" combination of both signals on the other hand the $FP$-$rate$, i.e., error type I, can be strongly reduced resulting in a very reliable detection performance. This is desirable as soon as rehabilitation progresses and more precise behavior together

with better performance can be expected from the patient. Since the $TP$-$rate$ is also reduced (error type II is enhanced) and the patient's effort will hence less likely result in true positive behavior, she/he must try harder to trigger the movement and as a result the engagement of the patient is enforced. Since the expression of the BP is highly dependent on the motivation of a subject and on how much intention she/he puts into the movement or the planning of a movement (Shibasaki and Hallett, 2006), a higher engagement in the task allocates more brain resources to the motor task as could be shown by an increased motor-related BP activity in Section 3.2. Furthermore, an "AND" combination can help to distinguish voluntary from involuntary movements since only in case of the detection of a BP the assistive device is triggered. Thus involuntary movements will not be supported by the device or could even be diminished by appropriate control mechanisms. Moreover, the "AND" combination reduces the variance in prediction times observed for EEG-based movement prediction, since the variance in EMG-based prediction times was very small. This could enhance the subjective reliable performance of a predictive technology device that is actively adapted by eBR.

## 7.2 Summary

The work in Chapter 7 makes use of the training scenario developed in Chapter 3 and contributes to **Subgoal 3a** by defining an application scenario for *home rehabilitation*. However, the online application of such a scenario is not topic of this thesis but current research task of the RIC. Besides this contribution, the work of this chapter mainly contributes to all subgoals of **Main goal 2** by investigating in detail, how multimodal signal analysis and supportive systems can improve the functioning of eBR, i.e, are essential parts and features of the approach. In summary, results presented here support the hypothesis that the integration of multimodal analysis of physiological data in eBR has the potential to support patients by predictive technology devices more individually to their kind of disease and state of rehabilitation. It is expected that for patients this effect will be even more dominant, but this has to be evaluated further, especially with respect to acceptable prediction performances and applicability.

# Chapter 8

# Improvement of Human-Machine Interaction by eBR

Whenever there are physiological data used for the control or support of a technical device one has to consider the extra effort on the users and possible constrains that are put on them. Thus, the benefit of such an approach has to be analyzed thoroughly. As discussed earlier, the approach of eBR does not put extra cognitive or attentional demands on the user. However, preparation time (to set up on the EEG system and to train the classifier) is increased and the EEG system might possibly constrain the user with respect to her/his freedom to move (depending on which system is used). Therefore, it is highly relevant to evaluate the benefit of the integration of eBR. This is straight forward for applications were eBR does reestablish the functioning of parts of the body, like the limbs for rehabilitation purposes. For passive support as explained in Section 6.1, where eBR was applied to implement two different predictive HMIs for the support of subjects that are controlling and supervising a robotic tele-manipulation scenario, this question can, however, not be answered straight away. The question of benefit remains often disregarded when passive approaches are applied, although it is especially here most important to show a measure of the users' and the systems' benefit, since a passive approach does usually not establish or reestablish functions of the human (body) and is, hence, not indispensable for the interaction.

In some studies simulations are used to evaluate the modification of the system (Rao et al., 2010), but in principle one should analyze experimental data from the user and the robotic system recorded during interaction. For example, interaction force can be measured and a reduction of it can be taken as a sign for the improvement of human-machine interaction. Studies that measure interaction force

can be performed using the interface itself as measuring instrument, as shown for an one-arm exoskeleton (Ronsse et al., 2011), or they utilize a commercial haptic interface (Ott et al., 2005; Feyzabadi et al., 2013). In the following an experiment is presented that investigates whether eBR does indeed improve the interaction between a human and the applied exoskeleton in a measurable fashion to achieve not only a perceptual but also a measurable improvement in interaction for the human. Text, figures and tables of the following sections are taken and partly adapted from (Folgheraiter et al., 2012).

## 8.1 Measuring the Improvement in Interaction Effort

As described in Section 6.1, the exoskeleton that is used for tele-manipulation can be adapted by eBR resulting in an improved transition from one exoskeleton mode to another (see Figure 6.3) without the risk of malfunctioning of the whole system. The major advantage of the described approach is that the user maintains the executive power in every situation. Moreover, if either no or a wrong prediction about a possible movement onset is made by BR, most likely nothing noticeable for the user will happen due to the control mechanisms that are applied in eBR. However, it is not clear how strong an adaptation of the exoskeletons control does improve interaction. The threshold of the integrated force sensor for triggering a release of the exoskeleton of the rest position is adapted by eBR with respect to the time that a user has to press against the force sensor. It is expected that the interaction force is reduced in case of a correct adaptation of the exoskeleton by eBR, i.e., in case that eBR correctly inferred movement onset. Thus, in the experiment described in the following, interaction force is measured by a force sensor that is integrated in the exoskeleton. A systematic evaluation of the reduction in interaction effort is performed by simulating a stepwise adaptation of the exoskeleton by eBR.

To measure the reduction in interaction force that is caused by eBR, the system has to be calibrated to the users demands first to conduct comparable results. The proposed calibration procedure can be performed before each teleoperation session to minimize the required interaction force *before* the predictive HMI, i.e., the exoskeleton, gets adapted by eBR. It is therefore independent of eBR (see Figure 8.1) and guarantees a baseline behavior of the whole system that is maximally adapted and optimized to the current user. Any reduction of interaction force can then be counted for the application of eBR.

The general flow of the experiments conducted inclusive preparation is shown in Figure 8.1. In the context of this work *effort* is defined as the integral over time of the interaction force (see Equation 8.3) at the wrist contact point during the switch phase. In general, the bigger this integral is, the larger is the momentum that the

user needs to transfer the interface in order to initiate the movement. This is clearly correlated with the energy that the user has to spend to change control mode and has significant influence on the fatigue and comfort feeling in using the interface.

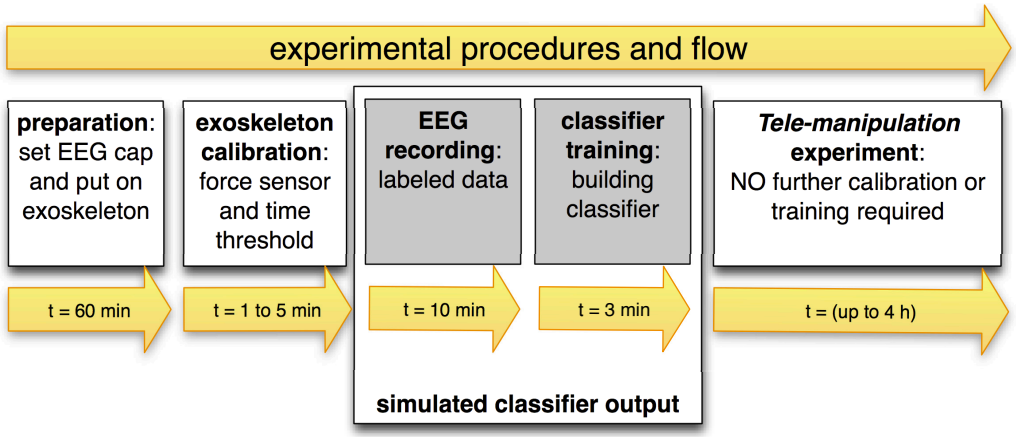


Figure 8.1: Experimental procedure and preparation for the adaptation of the exoskeleton by eBR. In the performed experiments, EEG was not recorded and analyzed (marked as grey box). To measure the effect of modulating the exoskeleton control by eBR, fixed values for movement prediction (simulated classifier output), representing three different values for certainties in predictions, were used. Figure is based on Figure 7 of (Folgheraiter et al., 2012).

In the following section first the calibration strategy is explained and evaluated before the effect of eBR on the interaction force, i.e., on the reduction of the users *effort* will be investigated.

### 8.1.1 Experimental Part - Calibration of an Exoskeleton

The goal of the conducted experiments was to calibrate the system so that it behaves optimal with respect to different users before eBR is applied. By the calibration procedure the effort of the user to *lock out* the system from a rest position should be minimized as much as possible while avoiding malfunctioning, i.e., *false lock out*, of the system due to movements of the user's upper body during rest.

For the calibration of the exoskeleton the following requirements had to be fulfilled:

1. The minimal *force* threshold ($F_{th}$) and *time* threshold ($T_{th}$) for the integrated force sensor of the exoskeleton that avoid the occurrence of a *lock out* due to the eventual interaction forces generated at the wrist by a rotation of the upper body have to be found.

2. Above mentioned values have to be estimated for different users individually.

3. An experimental protocol is required designed in order to assure an unified calibration procedure.

4. For a real application the calibration must be performed in a reasonable amount of time. Therefore, too complicated or too restrictive operative conditions have to be avoided.

#### 8.1.1.1 Experimental Setup and Procedure

Experiments were performed on five male subjects that had different anthropometric characteristics. Table 8.1 reports these characteristics, i.e., height, weight, upper-arm length, forearm length, and distance between the shoulders, for each subject. To avoid additional stress to the subject due to the weight of the interface, a special tutor was developed that allows to sustain the exoskeleton without restricting the mobility of the body (see Figure 8.2 A).

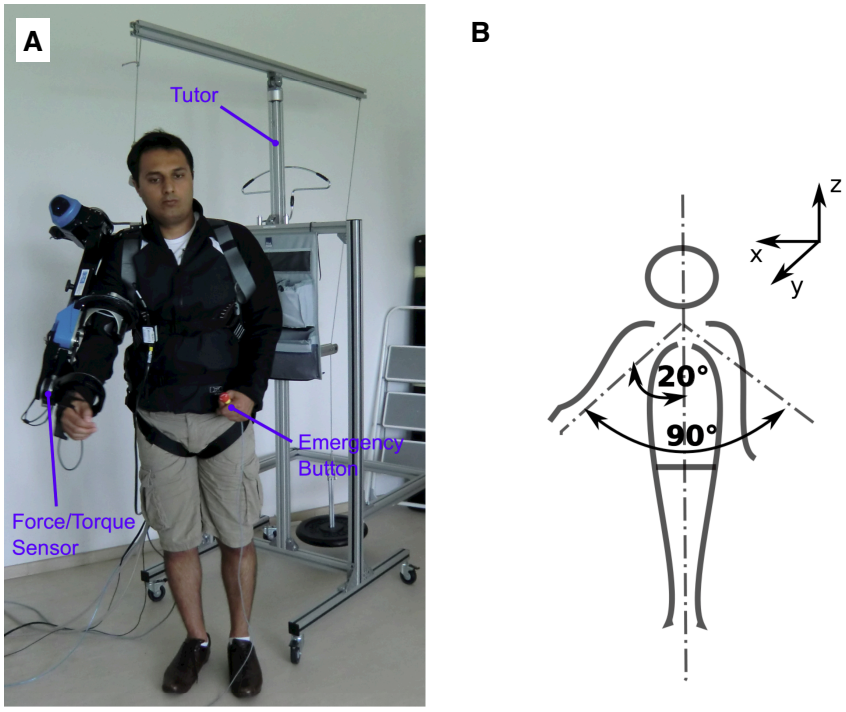


Figure 8.2: Experimental setup and calibration procedure. A: The weight of the exoskeleton is sustained via a cable connected to a tutor. B: The user is rotating the upper body for $90°$, while the arm was hold by the exoskeleton in a $15 - 20°$ position with respect to the third joint of the exoskeleton. Figure is based on Figure 8 of (Folgheraiter et al., 2012).

Table 8.1: Anatomical parameters of the five subjects involved in the experiment. Table is based on Table 2 of (Folgheraiter et al., 2012).

| subject | height [m] | weight [Kg] | length upper arm [m] | length forearm [m] | shoulders distance [m] |
|---|---|---|---|---|---|
| subject 1 | 1.80 | 78 | 0.3 | 0.3 | 0.38 |
| subject 2 | 1.79 | 85 | 0.33 | 0.28 | 0.43 |
| subject 3 | 1.86 | 85 | 0.32 | 0.27 | 0.44 |
| subject 4 | 1.85 | 84 | 0.3 | 0.29 | 0.39 |
| subject 5 | 1.70 | 64 | 0.26 | 0.23 | 0.42 |

**Ethics Statement:** The study has been conducted in accordance with the Declaration of Helsinki and approved with written consent by the ethics committee of the University of Bremen. Subjects have given informed and written consent to participate.

#### 8.1.1.2 Hypotheses

It is expected that subject-specific but reliable values for the minimal *force* threshold ($F_{th}$) and the minimal *time* threshold ($T_{th}$) can be found for the individual subjects that assure that the exoskeleton can support the position of the users' arm even during upper body movements.

#### 8.1.1.3 Methods

In the following the calibration procedure and applied methods are described.

**Calibration Procedures:** With the first experiment the minima for both thresholds, $F_{th}$ and $T_{th}$, were determined for each subject by applying an iterative method. Thanks to the iterative approach, it can be guaranteed that the minimal thresholds can correctly be estimated.

The calibration was done as follows: the user was asked to perform a predefined rotational movement of the upper-body keeping the lower extremities fixed. In order to have the same experimental conditions in different sessions, a prerecorded video was displayed to the user that shows the exact movement sequence and timing. A video was chosen since human learn new motor skills faster by imitation (Mataric, 1994). As initial pose, the forearm was completely extended and the shoulder was flexed forward in order to bring the third joint of the exoskeleton in an angular range between $15 - 20°$ (see Figure 8.2 A). The user was then asked to repeat a rotational movement of the upper body. By this movement the upper body was turned by about $90°$ (see Figure 8.2 B). Each movement was performed with a regular speed as it was shown in the video.

The rotational movement of the upper body simulates the case in which the user, whose arm is kept by the exoskeleton in a rest position, is involved in other activities

Table 8.2: Optimal *lock-out* parameters for five subjects. Source: Table 3 of (Folgheraiter et al., 2012)

| Parameter | Subj.-1 | Subj.-2 | Subj.-3 | Subj.-4 | Subj.-5 | Average | SD |
|---|---|---|---|---|---|---|---|
| $T_{th}^{Max}$ | 0.3 | 0.2 | 0.3 | 0.3 | 0.3 | **0.28** | 0.04 |
| $F_{th}^{Min}$ | 8 | 10 | 5 | 4 | 4.5 | **6.3** | 2.59 |

that require him to orient his upper body into a certain direction. Such tasks could be required to be performed by the user during monitoring activities in the virtual scenario.

At the beginning of each experimental session, the force threshold was set to a maximum value $F_{th}^{Max}$ and the time threshold to a minimum value $T_{th}^{Min}$ (smallest possible value depending on the control frequency of the system, i.e., $10\,$ms for the control frequency of $100\,$Hz). The chosen procedure assures that no movement can cause the system to *lock out* right from the beginning of the calibration procedure. The user performed the described rotational movements for a specific $F_{th}$ value $10$ times. In case that no *unwanted lock out* occurred, $F_{th}$ was decreased stepwise by $10\%$. This procedure was performed until the user locked out due to the rotational movement. The value for $F_{th}$ that was used while the user locked out was then kept constant while the time threshold $T_{th}$ was increased until the rotational movement no longer caused an *unwanted lock out* of the system. The so found values are later refereed as $F_{th}^{Min}$ and $T_{th}^{Max}$, respectively.

#### 8.1.1.4 Results

In the following the results of the calibration procedure are presented.

**Results of Calibration Procedure:** In total the calibration procedure required on average $63$ movements for each subject. Each movement lasted on average $2.6\,$seconds. The determined set of optimal thresholds for each subject are summarized in Table 8.2. Figure 8.3 A depicts an exemplary trajectory of the wrist movement and the corresponding velocity, as it was recorded during the experiment (Figure 8.3 B). The velocity of the recorded movements is projected on the transversal plane. Note that the trend is quite regular supporting a good repeatability of the calibration movement.

#### 8.1.1.5 Discussion

Results conducted in the experiments for the calibration of the exoskeleton that were conducted with five users of different anthropometric characteristics show that the

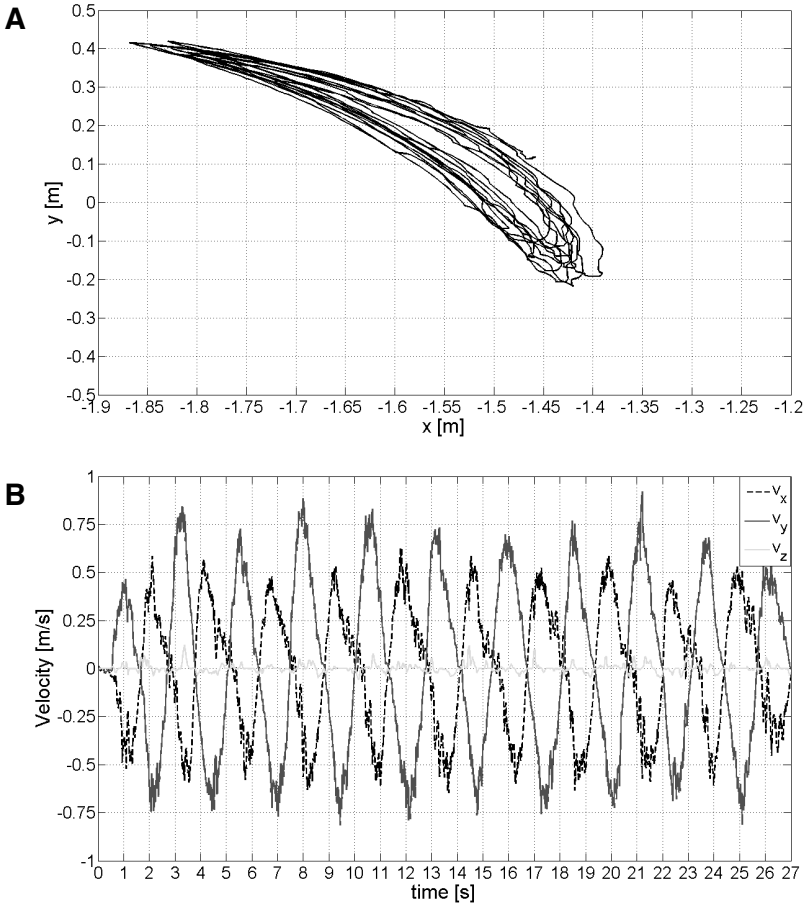


Figure 8.3: Example for trajectory and velocity of the movements during calibration. A: wrist trajectory projected on the transversal plane. B: velocity trend along the X,Y,Z coordinates. Figure is based on Figure 9 of (Folgheraiter et al., 2012).

minimal values for $F_{th}$ and $T_{th}$ were more similar for the time threshold $T_{th}$ compared to the force threshold $F_{th}$. The higher individual difference for the force threshold might have been caused by the different anthropometric characteristics of the users or differences in their muscular strength. Further, the fact that the force was measured by just one sensor might have influenced this result as well. Depending on the accurate positioning of the sensor, the force may have measured differently well, while the time that the sensor was triggered was not affected that much by this circumstance. Based on the conducted results, it can be concluded that it is more reasonable to change the time threshold by eBR than the force threshold, since the time threshold shows lower differences between subjects and a stepwise or proportional reduction of the time threshold should have more comparable effects.

### 8.1.2 Experimental Part - Reduction of Interaction Force by eBR

For the experiment presented next, the detection of movement-related ERPs was simulated with three representative prediction values that were transferred into three threshold $T_{th}$ values as if it would be supported by eBR. Three predefined and fixed values were used for all subjects in order to allow a systematic and comparable analysis. Not only a high certainty in movement prediction was evaluated but also lower ones to mimic uncertainties in the movement prediction and its impact on the control of the exoskeleton. The time thresholds directly correspond to different classifier outputs here: while a minimal time threshold corresponds to perfect detection of brain activity related to movement planning, the maximal threshold represents the situation where no brain activity related to movement planning has been detected (corresponding to a normalized classification score of $0.5$). Therefore, a *maximum movement prediction impact* with a time threshold ($T_{th}^{Min}$) corresponds to the minimal possible value with respect to the exoskeleton's control frequency (i.e., with $100$ Hz every $10$ ms) and *no movement prediction impact* corresponds to the time threshold that was experimentally determined as minimal time threshold needed to avoid *unwanted lock out* ($T_{th}^{Max}$). Further, a *realistic movement prediction impact* with a middle time threshold ($T_{th}^{Mid}$) corresponding to a situation where the classifier predicts an upcoming movement with a normalized classification score of $0.75$ was chosen. The experimental procedure is explained in the following.

#### 8.1.2.1 Experimental Setup and Procedure

The same subjects that performed the calibration procedure performed this experiment right after the calibration experiment. At the beginning of the experiment the user is first asked to bring the arm in a starting configuration (arm was held parallel to the body). He was requested to keep the arm in this position until the exoskeleton enters the "full user support mode" due to a decrease in the activity level of the user and supports the arm. Afterwards, a signal was presented to the subject which advised him to initiate an extension movement of about $90°$. During the movement, the interaction force between the exoskeleton and the user's wrist was measured via a 6-axis force/torque sensor (ATI nano 25). The subject had to perform this procedure $30$ times. For each repetition, the time threshold was changed randomly unnoticeably to the user to one of the three predefined values for $T_{th}$:

$$T_{th} \in \left\{T_{th}^{Min}, T_{th}^{Mid}, T_{th}^{Max}\right\} \tag{8.1}$$

with

$$T_{th}^{Mid} = \frac{T_{th}^{Max} - T_{th}^{Min}}{2} \tag{8.2}$$

Following this random procedure, the user is not aware of the policy adopted to regulate the *lock-out* mechanism. This is particularly important to avoid that a priori knowledge affects movement preparation and by this the amount of force delivered by the user to the exoskeleton.

**Ethics Statement:** The study has been conducted in accordance with the Declaration of Helsinki and approved with written consent by the ethics committee of the University of Bremen. Subjects have given informed and written consent to participate.

#### 8.1.2.2 Hypotheses

It was hypothesized that a reduction in the time threshold would result in a reduced effort of the user, i.e., reduction in the measured force integral, that is required for *lock out*. It is expected that the force integral is smallest for $T_{th}^{Min}$, highest for $T_{th}^{Max}$ and in between for $T_{th}^{Mid}$. It was further expected that a medium time threshold that corresponds to a mean certainty in movement onset prediction and hence medium adaptation of the exoskeletons control by eBR would still result in a significant reduction of the effort for the user to *lock out* from a rest position.

#### 8.1.2.3 Methods

In the following methods for the investigation of the reduction of interaction force by eBR and statistical analysis of results are described.

**Calculation of the Force Integral across Time Thresholds:** For calculating the effort required to pass from the *lock-in* to the *lock-out state*, the force was integrated according to equation 8.3.

$$I = \int_{T_0}^{T_{Lout}} F_{int}(t)dt \tag{8.3}$$

Where $T_0$ is the time when the force starts to rise due to the limbs movement, and $T_{Lout}$ is the time where the transfer of the system to the *lock-out* state is finished. To demonstrate the advantages of the integration of the movement prediction in controlling the device, it is necessary to verify the disequation 8.4, where $I_{Min}, I_{Mid}, I_{Max}$

correspond to $T_{th}^{Min}, T_{th}^{Mid}$, and $T_{th}^{Max}$, respectively.

$$I_{Min} < I_{Mid} < I_{Max} \tag{8.4}$$

Doing that it can be stated that a decrease in the threshold $T_{th}$, due to a correct movement prediction, will also bring a decrease in the correspondent $I$ and therefore a reduction of the user's effort needed to change the control modality.

**Statistics on Force Integral across Time Thresholds:** Since the effect of the three different values for the time threshold were repeatedly measured within each subject, the data were for statistical evaluation analyzed by repeated measures ANOVA with time threshold (3 levels: $T_{th}^{Min}$, $T_{th}^{Mid}$, $T_{th}^{Max}$) and subject (5 levels: 5 subjects) as within-subjects factors [SPSS, version 20, SPSS Inc., Chicago, IL, USA]. For pairwise comparisons, the Bonferroni correction was applied.

#### 8.1.2.4 Results

In the following recorded data and statistical results of the effect of eBR on the reduction of interaction force are presented.

**Reduction in Interaction Force:** Figure 8.4 shows the wrist trajectory generated by a user during the *Lock-out* experiment. It can be seen that the individual movements are very similar.

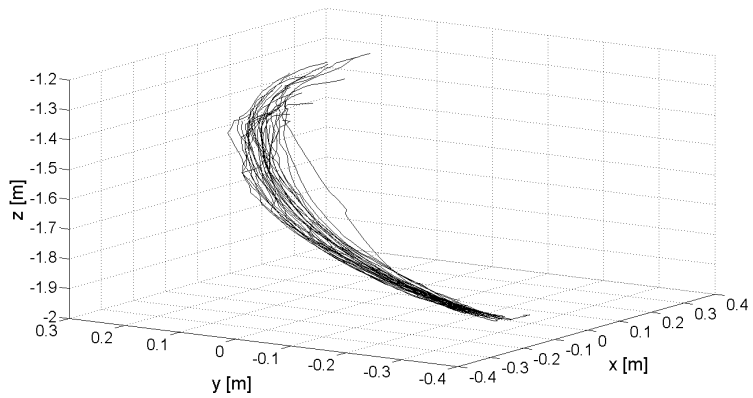


Figure 8.4: Wrist trajectory of a subject acquired during the *Lock-out* experiment. Figure is based on Figure 12 of (Folgheraiter et al., 2012).

Interaction force values conducted in the *Lock-out* experiment for subject 3 and subject 5 are presented in Figure 8.5 and Figure 8.6. The upper graph reports the normalized values $(0\ to\ 1)$ for the chosen $T_{th}$ threshold, the lower graph indicates

the integral of the force calculated among the interval $[T_0 \ T_{Lout}]$. In detail, each line represents an exemplary instance of the *Lock-out* experiment, in total $30$ values are reported. The additional three horizontal lines in the lower graph indicate the averages of a set of $10$ trials that share the same time thresholds. Note that there is a clear distinction between the three cases. This confirms that the time threshold has a strong impact on the interaction force and therefore on the effort that the user to transfer the exoskeleton from the "full user support mode" to "transient mode".

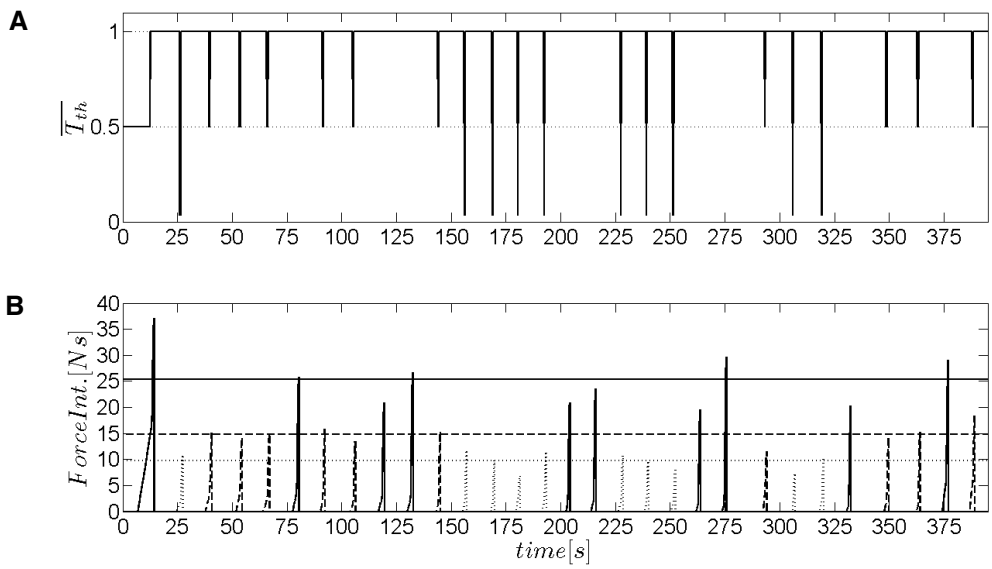


Figure 8.5: Data recorded in the *Lock-out* setup for subject 5. A: for each of the 30 trials, the chosen time threshold among the three possible values $\{0, 0.5, 1\}$. B: interaction force measured at the wrist contact point is reported. Figure is based on Figure 10 of (Folgheraiter et al., 2012).

It can be observed that the values for the force integrals are on average different for both subjects with respect to the three chosen time thresholds. More precisely the difference between the three average values appears to be reduced for subject 3 compared to subject 5. Comparing the two subjects it can further be observed for both subjects that the averages of the force integrals if $T_{th}^{Mid}$ was applied are not centered between the averages for the force integrals for $T_{th}^{Min}$ and $T_{th}^{Max}$, but are shifted toward the bottom, i.e., show a lower average force integral as would be expected in case of linear correlation. This can generally be confirmed by the data of the other three subjects. For all subjects a non-linear dependence between the threshold value and the force integral (see Figure 8.10) was found. For four of the five subjects (all subjects but subject 1), $T_{th}^{Mid}$ had an over-proportional effect on the reduction of the force integral.

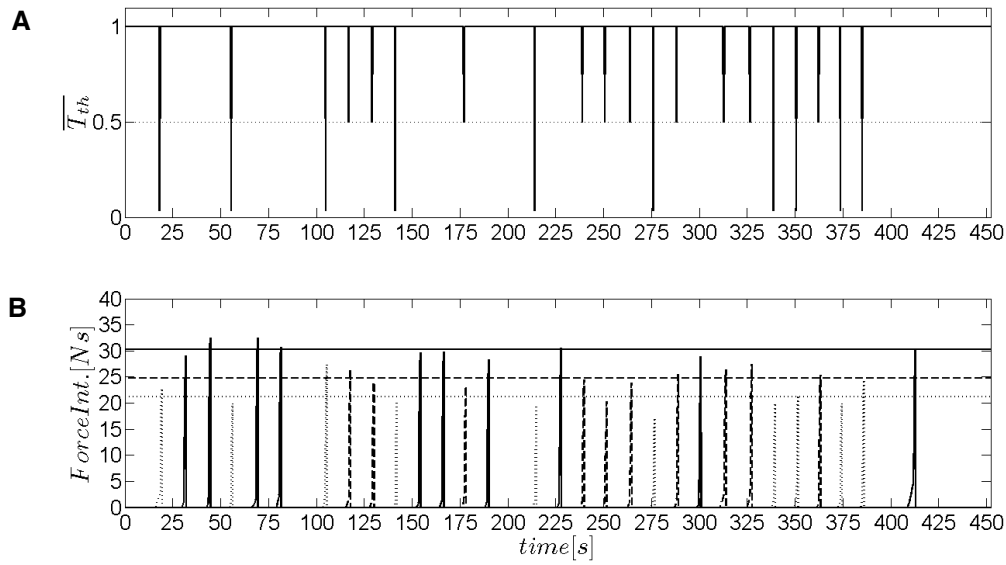


Figure 8.6: Data recorded in the *Lock-out* setup for subject 3. A: for each of the 30 trials, the chosen time threshold among the three possible values $\{0, 0.5, 1\}$ is shown. B: interaction force measured at the wrist contact point is reported. Figure is based on Figure 11 of (Folgheraiter et al., 2012).

Table 8.3 and 8.4 reports in detail the results of this experiment for all subjects. The average of the force integral is indicated for each threshold class together with other descriptive measures. On one hand, the descriptive measures in Table 8.3 are summarized in Figure 8.7 which depicts the average of the force integral calculated by averaging the means of 5 subjects across 10 measured movements for each time threshold to show the *subject-specific differences* in threshold values (e.g., high SD).

On the other hand, the average of the force integral is calculated by averaging the means of 10 measured movements across 5 subjects to show the *difference in values between threshold classes* (Table 8.4 and Figure 8.8).

As indicated by the results displayed in Figure 8.8, statistical analysis revealed that the force integral was significantly affected by the time threshold [main effect of *time threshold*: $F(2, 18) = 280.13, p < 0.001$]. As shown in Figure 8.9, the force integral associated with both the middle and lowest time threshold were significantly distinguishable from the force integral associated with the highest time threshold [$T_{th}^{Max}$ vs. $T_{th}^{Min}$: mean difference = 12.57 standard error = 0.63 $p < 0.001$; $T_{th}^{Max}$ vs. $T_{th}^{Mid}$: mean difference = 7,39 standard error = 0.49 $p < 0.001$]. Further, a significant difference between the measured force integrals associated with the middle and lowest time threshold [$T_{th}^{Mid}$ vs. $T_{th}^{Min}$: mean difference = 5.17 standard error = 0.45 $p < 0.001$] was found.

Table 8.3: Descriptive measures of the force integral for 5 subjects across 10 movements. Table is based on Table 4 of (Folgheraiter et al., 2012).

| | **force integral** [Ns] | $T_{th}^{Max}$ | $T_{th}^{Mid}$ | $T_{th}^{Min}$ |
|---|---|---|---|---|
| **subject 1** | mean | 32.59 | 26.21 | 17.84 |
| | SD | 2.20 | 4.32 | 3.23 |
| **subject 2** | mean | 26.09 | 20.35 | 15.98 |
| | SD | 5.10 | 3.69 | 3.60 |
| **subject 3** | mean | 30.24 | 24.70 | 21.25 |
| | SD | 1.39 | 2.01 | 2.93 |
| **subject 4** | mean | 28.00 | 19.19 | 14.64 |
| | SD | 2.37 | 1.85 | 3.39 |
| **subject 5** | mean | 25.34 | 14.82 | 9.68 |
| | SD | 5.53 | 1.73 | 1.74 |
| | **mean across 5 subjects** | **28.45** | **21.05** | **15.87** |
| | **SD across 5 subjects** | **2.99** | **4.55** | **4.26** |
| | **SE across 5 subjects** | **1.34** | **2.03** | **1.91** |

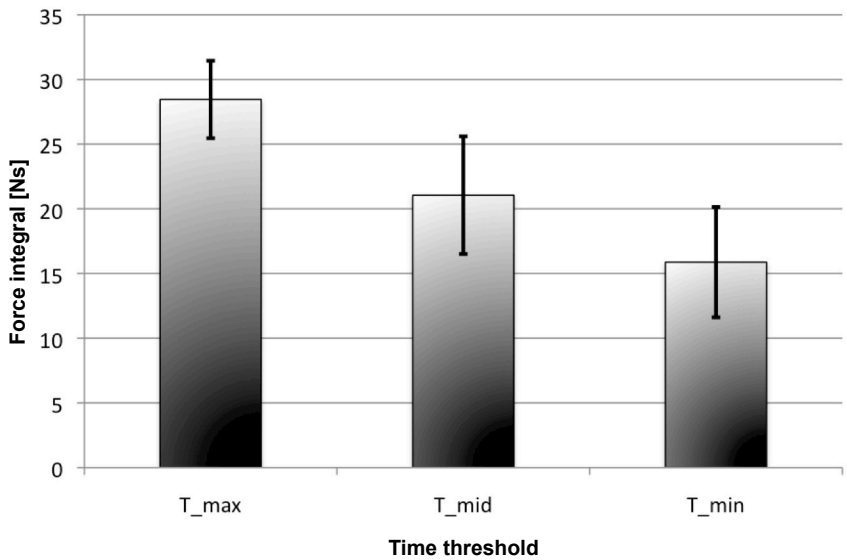


Figure 8.7: Average and SD of the means of the measured force integral for different time thresholds across movements. Values are calculated for 5 subjects across 10 measured movements at different normalized time thresholds. SD reports subject-specific differences. Figure is based on Figure 13 of (Folgheraiter et al., 2012).

Table 8.4: Descriptive measures of the force integral for 10 movements across 5 subjects. Table is based on Table 5 of (Folgheraiter et al., 2012).

| **force ntegral** [Ns] | mean $T_{th}^{Max}$ | mean $T_{th}^{Mid}$ | mean $T_{th}^{Min}$ |
|---|---|---|---|
| movement 1 | 30.51 | 21.50 | 15.51 |
| movement 2 | 29.29 | 19.84 | 14.78 |
| movement 3 | 28.57 | 21.18 | 17.29 |
| movement 4 | 28.51 | 21.77 | 16.21 |
| movement 5 | 28.55 | 21.35 | 15.13 |
| movement 6 | 29.07 | 21.06 | 16.49 |
| movement 7 | 25.26 | 19.95 | 17.46 |
| movement 8 | 28.58 | 19.48 | 14.92 |
| movement 9 | 27.82 | 20.92 | 15.33 |
| movement 10 | 28.39 | 23.57 | 15.70 |
| **mean across 10 movements** | **28,46** | **21.05** | **15.87** |
| **SD across 10 movements** | **1.33** | **1.17** | **0.95** |
| **SE across 10 movements** | **0.42** | **0.37** | **0.30** |

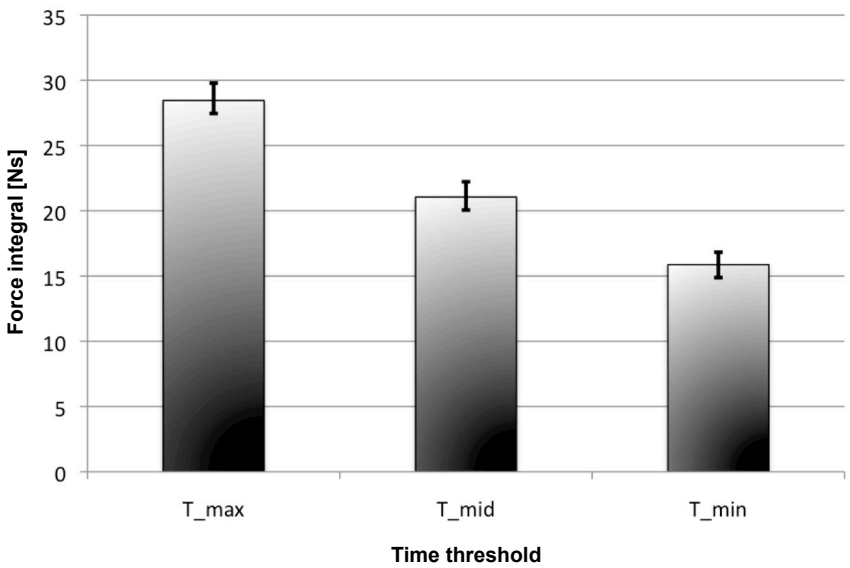


Figure 8.8: Average and SD of the means of the measured force integral for different time thresholds across subjects. Values are calculated for 10 measured movements across 5 subjects. SD report threshold-specific differences. Figure is based on Figure 14 of (Folgheraiter et al., 2012).

Further, we found that the threshold values have different impact on the different subjects [main effect of *subject*: $F(4, 36) = 34.37, p < 0.001$]. Measured differences in force integral for each threshold value among the subjects are due to different reasons. At first, for a fixed limb trajectory, the interaction force is strongly depending on the dynamics of the combined arm-exoskeleton system. This in turn depends on the physical properties of the limb (e.g., mass and geometry) as well as the way the exoskeleton is worn by the user. The contact points between the limb and the interface may have been positioned differently for the five users affecting the force distribution. Furthermore, the force applied by the subject together with the level of muscle co-activation may also have influenced the amount of energy that was exchanged during the movement. However, although the threshold values were differ-

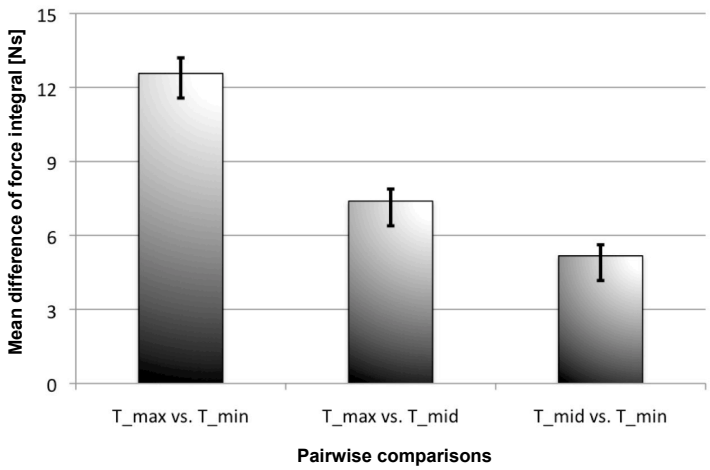


Figure 8.9: Mean difference and SE for each pairwise comparison of interaction force. Note: mean difference of force integral in Ns is calculated by averaging the difference between two different levels of time threshold (so-called *time threshold-pair*) within the subject. Figure is based on Figure 15 of (Folgheraiter et al., 2012).

ent among the subjects, all subjects showed the same pattern regarding the effect of time threshold on the force integral [interaction between *time threshold* and *subject*: $F(8, 72) = 27.88, p < 0.02$]. This can obviously be seen in Figure 8.10 which illustrates the pattern of time threshold for each subject.

In summary, although the minimal required threshold value to avoid false *lock out* was subject-specific (i.e., different threshold values for $T_{th}^{Max}$ were measured depending on individual subjects) an equivalent effect of the three time thresholds on the force integral was observed. This finding suggests that the exoskeleton and its modulation by eBR works very stable for individual subjects. Hence, the presented results support the advantages of using movement prediction by BR to modulate the

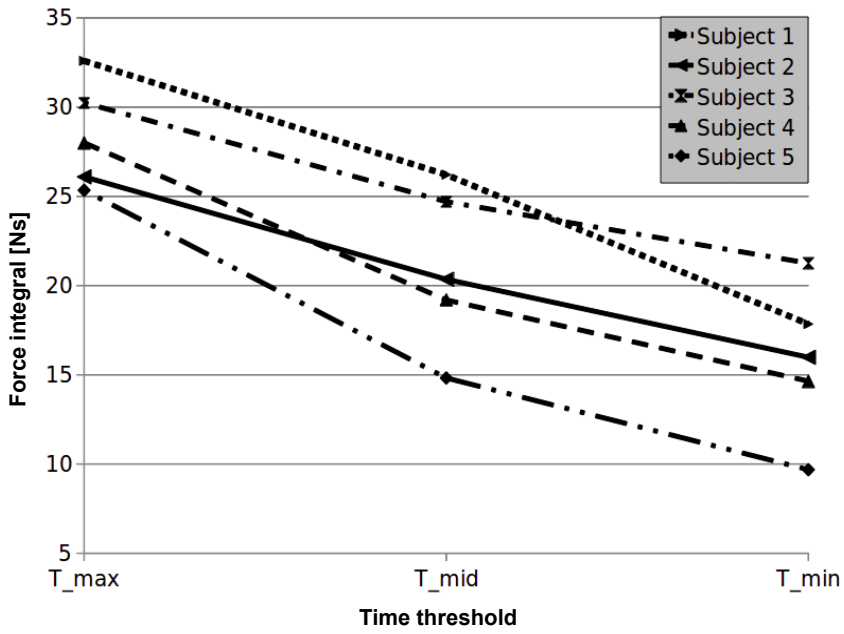


Figure 8.10: Pattern of relation between time threshold and force integral for each subject. Figure is based on Figure 16 of (Folgheraiter et al., 2012).

transition from "full user support mode" to "transient mode" by eBR. Further, as can be seen in Figure 8.9 the impact on the reduction of the time threshold does not seem to linearly modulate the force integral, meaning that a reduction of the time threshold has in most cases an over-proportional effect on the force integral.

#### 8.1.2.5 Discussion

Results clearly demonstrate how eBR can, by inferring on movement onset (based on the detection of movement preparation processes by BR), be applied to improve the comfort of the user by decreasing the effort that is required from the user to *lock out* the exoskeleton from a rest-position. The approach presented here requires short calibrations per session to identify individual minimal time and force thresholds. However, the finding that users with different anthropometric characteristics applied similar forces to achieve the transition from *lock in* to *lock out* in each experimental condition implies that an overall force and time threshold may be sufficient for all subjects. The overall threshold might rather be dependent on the interfacing system and sensors used. This is also supported by the finding that the different time thresholds effected the force integral similarly and by the over-proportional effect of the adaptation of the exoskeleton by eBR even in case a suboptimal parameter ($Th_{Mid}$). The over-proportional effect that could be found for 4 of 5 subjects does fur-

ther support a high impact on the improvement of human-machine interaction by adapting the technical device by eBR.

## 8.2 Summary

With the experiments presented in Chapter 8 it is shown, that eBR does improve human-machine interaction *even* in case of a passive support. It is further shown that this improvement is independent of other measures that improve human-machine interaction. Although the exoskeleton was adapted to the users' individual requirement, the simulated adaptation of the system by eBR did in all cases result into a further reduction in the users' effort. Thus, the positive perceptual effort that was reported by subjects during online experiments as published in (Seeland et al., 2013b) could be supported by quantitative measures, i.e, by measures of the force integral. Hence, the presented results show that eBR does not only improve human-machine interaction if it is applied for active support, but also if it is applied for passive support and does therefore fulfill **Subgoal 3b** of the thesis. Besides this main contribution, it does further contribute to **Subgoal 1a** of the thesis by developing the *Lock-out* training scenario.

# Part IV

# Conclusions and Outlook

# Chapter 9

# Conclusions

In this thesis, *embedded Brain Reading (eBR)* was developed and formalized. It passively makes use of *covert* information from the *humans' brain activity* by *Brain Reading (BR)* and *overt* information from behavioral and situational data for *automatic context generation* to enable *passive* or *active* support of *predictive HMIs* in, e.g., robotic application scenarios like tele-manipulation or rehabilitation. In case of active support eBR enables *explicit* communication by making use of naturally evoked brain activity, i.e., by decoding brain activity to infer intentions of the user for the generation of control signals to enable interaction with a robotic device. In case of passive support, eBR is used to *implicitly* make use of brain activity, i.e., decodes the users' inferred intention to adapt an interface that takes care of the explicit interaction. In Figure 9 the passive support of eBR is explained on the example of the *Tele-manipulation* application. It has to be stressed that, whether the support is active or passive, brain activity is never artificially produced for communication purposes. Only naturally evoked brain activity is decoded by BR and used by eBR to infer on intentions of the user to either drive or improve interaction. Using this approach, any extra cognitive load on the user is avoided.

**Reliable Detection of Brain States:** In Chapter 3 it was shown in two experimental setups that were developed in this thesis that specific brain states can be detected based on average ERP analysis, while a human is performing demanding interaction tasks or self-initiated arm movements. To be more precise, in Section 3.1 it was shown in the *Labyrinth Oddball* scenario that the brain state of "recognition of important stimuli and task coordination" can reliably be detected during dual-task behavior. The correlation between brain activity and specific brain states was possible, since well-known and understood parietal ERP activity, mainly the P300 and the prospective positivity, were detected by average analysis during interaction, i.e., dual-task performance. These ERPs are strong and reliable indicators for the cog-

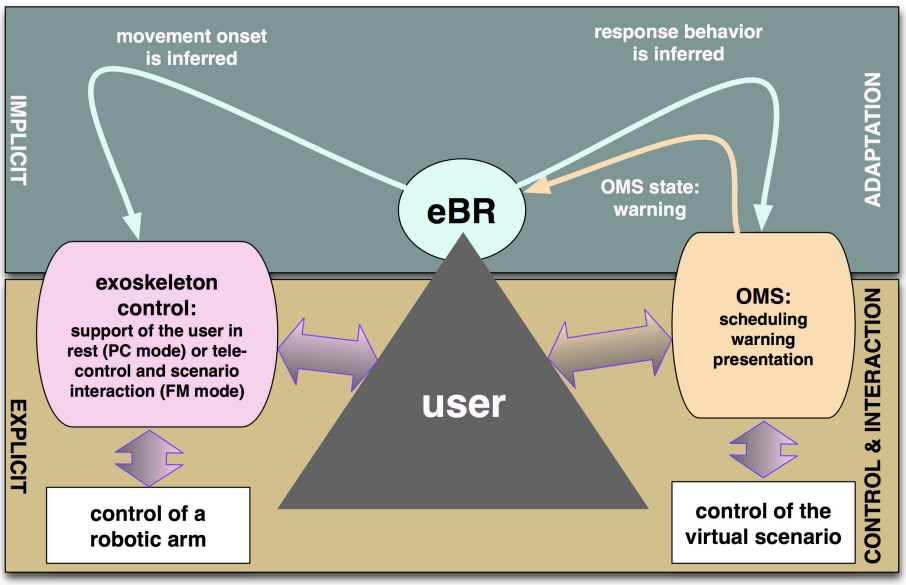


Figure 9.1: Implicit adaptation of HMIs by eBR during passive support. Explicit interaction between HMI and, e.g., a robotic device is adapted based on passively gained information about the users intention by eBR. While the user is aware of her/his active, i.e., explicit, control of the robotic arm or virtual scenario via both HMIs, i.e., the OMS and the exoskeleton, the support provided by eBR is implicit, hence not actively controlled by the user. The user is not even aware of it but does feel the improvement in interaction in case that the passive support is successful.

nitive state of "recognition of important stimuli and task coordination". To detect the covert brain state of "recognition of important stimuli and task coordination" is highly relevant for human-machine interaction, since it can be used as an indicator for the recognition of important, i.e., *task-relevant*, information that are given to an operator during demanding interaction tasks. Results furthermore indicate that it is possible to even distinguish between "target recognition" and "task coordination" processes by the analysis of average ERP activity over parietal sites.

In the *Arm Movement* scenario, it was investigated in Section 3.2 whether movement intention is affected by the effort and intention a user invests into a motor-task, i.e., into the execution of arm movements. It was shown that the BP is affected by the requested movement speed. Opposite to this finding the LRP was not affected by movement speed. However, it is known from literature that the discreetness, precision and complexity of a movement has an effect on the size of the amplitude of the LRP. Here, further investigations are required. Highly relevant for applying single-trial eBR for rehabilitation purposes is the correlation found between movement speed and the expression of the BP, since it is suggested that movement speed

is correlated with the amount of intention that is involved in the planning and execution of the movement. Hence, by increasing the amount of intention, the BP should be easier to be detected by single-trial BP. This finding is probably similar relevant for rehabilitation purposes than the finding that the kind of movement, i.e, which body part is moved, has an effect on the LRP. To know what kind of change in a movement planning or execution evokes stronger ERPs can help to improve procedures for the detection of the brain state of "movement planning" by BR as prerequisite to infer movement intention by eBR. Further, it was shown that the kind of markers that are chosen to label EEG data is very relevant to consider with respect to the goals of the application of eBR.

The results of both studies confirm that specific brain states can be detected during complex and rather natural behavior as it can occur during human-machine interaction. The investigated brain states were found to be reliably represented by the above mentioned ERPs. While Chapter 3 mainly contributes to **Subgoal 1a**, i.e, to investigate brain activity during complex and demanding human-machine interaction, the above summarized findings contribute to **Subgoal 1b** of the thesis.

The finding that well-known ERPs are evoked under different interaction conditions and the understanding of their simultaneous occurrence as well as their strength of expression depending on different interaction conditions (i.e., dual-task performance and speed as well as timing effort during the execution of arm movements) does further contribute to the understanding of brain functioning during complex, natural behavior of humans and hence contributes to basic research questions in the field of *neuroscience research*.

**Single-Trial Brain Reading:** In Chapter 4 it was shown that averaged ERPs are related to predictions made by single-trial BR analysis and that with the help of knowledge about underlying brain activity it is possible to choose appropriate training data and to develop a new approach for classifier transfer. These findings indicate that single-trial BR can detect the brain states investigated before that are related to the well-known averaged ERP activity (see Video B.2 provided as supporting video). Hence, it is shown that single-trial BR can be applied to make use of covert information about brain states. The findings of Chapter 4 together with Chapter 3 do therefore fulfill **Main goal 1** of the thesis. In these two Chapters most *test and training* scenarios were developed to fulfill **Subgoal 1a** of the thesis, i.e., the:

- *Labyrinth Oddball* scenario
- *Arm Movement* scenario
- *Virtual Labyrinth Oddball* scenario, and

- *Armrest* scenario.

A further *test* scenario, i.e., the

- *Lock-out* scenario

was developed later in Chapter 8 and the *application* scenarios, i.e., the

- *Tele-manipulation* scenario and
- *Home Rehabilitation* scenario

were developed in Chapter 6 and Chapter 7, respectively, to allow to optimize and test the approach of single-trial BR in complex interaction scenarios and to develop and test eBR as summarized later. The development of these test and application scenarios does further contribute to **Subgoal 1a** of the thesis.

When summarizing the work with respect to the relevant gained knowledge about underlying brain activity by *averaged ERP analysis* for the improvement of single-trial BR and its application for the detection of *specific brain states* in more detail, the following findings and results are worth to be highlighted: in the developed *Virtual Labyrinth Oddball* scenario it was shown in Section 4.1 that the results of the conducted average ERP window study was predictive for the relevance of data from different time windows. To be more precise, by a systematic BR single-trial window study and the performed average ERP window study it was found that EEG activity from a time window, in which most P300 activity is contained, is most predictive for the outcome of single-trial BR analysis. These results show that knowledge about average ERP activity can help to choose relevant time windows and features for training of classifiers for BR. The systematic BR single-trial window study further showed that during dual-task interaction behavior later brain processes that are related to P300 and prospective positivity are more relevant for the detection of the brain states "recognition of important stimuli and task coordination" than earlier processes that are more related to early stimulus processing and attentional processes. Hence, it was shown that BR is indeed able to detect brain processes in single trial that are related to the above mentioned brain state of "recognition of important stimuli and task coordination".

Moreover, in Section 4.1 an approach for classifier transfer was developed to handle a situation in which only a small amount of training data might be recorded during interaction. This was only possible by applying the knowledge about expected average ERP activity. The developed approach of classifier transfer was further shown to be transferable to the *Armrest* scenario, where for the one class only very few examples were available that would have made direct training impossible. Furthermore, the *Armrest* scenario was used to show that BR is able to detect two different

brain states, i.e., "recognition of important stimuli and task coordination" and the intentional state of "movement intention", that are influencing each other simultaneously. Results supported the *dual* BR approach (see Section 4.2). This finding is highly relevant for supporting the approach of eBR in real applications, since the *Armrest* scenario is very similar to the later described robotic tele-manipulation scenario where eBR is applied for passive support of interaction. The *Armrest* scenario requested quite natural behavior of the subjects like to delay a response to a stimulus that was presented to the user with very high inter stimulus intervals as it would be expected to occur during realistic interaction.

From the point of view of *neuroscience research* the findings again support that average ERP activity as it is investigated under controlled experimental conditions can also be evoked in more complex and demanding natural interaction scenarios. Furthermore, the findings indicate that results of single-trial activity conducted by means of ML methods can be related to results of average ERP analysis. Hence, by showing this correlation, it is supported that ML methods that can be used to investigate brain activity on single-trial basis can be applied for extending our principle knowledge about the brain's functioning.

**Embedded Brain Reading and predictive HMIs:** In Chapter 5 a formal model for eBR was developed. The model shows that eBR is not a direct interface but adapts HMIs with respect to behavior or intentions that are inferred by eBR. Behavior and intentions can only be inferred by an "embedded" analysis of covert brain states by BR. Embedded means that covert information is gained by BR and used by eBR in the overt context of interaction. The context of interaction is automatically generated or extracted by the analysis of overt behavioral and situational information. For the automatic context generation supportive systems can be used. The approach of automated context generation further allows to automatically control or correct eBR and hence is very important for:

1. an error-free functioning of eBR and the adapted HMI in case of a *passive support* in a robotic tele-manipulation scenario (see Section 6.1) or

2. for the reduction of the impact of error or the avoidance of certain errors, as it was explained in Chapter 7, where eBR is investigated with respect to its suitability to be applied for *active support* for the purpose of robotic-based rehabilitation.

Especially the results presented in Chapter 7 stress that supportive systems that make use of other physiological data are highly relevant for the concept of eBR: To not only rely on the passive detection of covert information from brain data, as it

is often the case for passive BCIs, but to make use of further overt behavioral data or even personal preferences as discussed in Chapter 7. In summary, as a main contribution eBR for passive support allows to avoid malfunctioning of systems, when brain activity is misclassified or a wrong behavior or intention is inferred, and allows to avoid certain error types if applied for active support to better adapt a systems to the requirements. By this, eBR is not only shown to be applicable in scenarios where brain activity is not required for the whole functioning of a system, i.e., where the goal is not to reestablish functionality but to enhance interaction comfort, but it is also shown that by means of eBR the reestablishing of functionality can be optimized with respect to the user's needs.

In Chapter 6 it was shown that the developed formal model is general enough to cover different implementations of eBR (see Section 6.2.1) as explained in the example for the adaptation of two HMIs, i.e., the OMS and an exoskeleton, in the robotic *Tele-manipulation* scenario that was developed in this thesis and presented in Section 6.1. Furthermore, it was shown in Section 6.2.2 that the formalization of eBR enabled the finding of implementation errors that were otherwise impossible to identify. The problem in identifying implementation errors is caused by the passive support of eBR and its feature to avoid malfunctioning of the whole system or adapted HMI even in the case that eBR fails to infer behavior or intentions correctly.

By means of the work in Chapters 5, 6 and 7 the **Main goal 2** of this thesis is fulfilled. Further, by work in Chapter 6 and Chapter 7 the **Subgoal 3a** is fulfilled by developing and implementing two online applications for eBR in the *Tele-manipulation* scenario (Chapter 6, see Video B.5 provided as supporting video) and by defining a third application scenario *Home Rehabilitation* in Chapter 7.

**Improvement of Human-Machine Interaction and Contributions to Research Challenges:** Finally, it was shown in this thesis that *predictive HMIs*, i.e., HMIs that are adapted by eBR, can be applied for active or passive support of human-machine interaction as stated above. While for active support, as explained on the example of applying an exoskeleton for *rehabilitation* purposes, it is quite clear that eBR improves interaction since it can be applied to reestablish motor behavior as investigated in Chapter 7, this was not so obvious for the passive support. However, it was shown in Chapter 8 on the example of passive support of an exoskeleton in the presented *Lock-out* scenario that eBR actually improves interaction by reducing the required interaction force for changes in the modality of the exoskeleton. The work done in Chapter 8 does therefore fulfill **Subgoal 3b** of the thesis. By fulfilling this subgoal, all main and subgoals of this thesis as defined in Section 1.2 could be reached.

**Contributions to Research Challenges:** First of all, the development of embedded Brain Reading (eBR) contributes to solve research *challenge (1)*. To improve human-machine interaction it clearly enhances the acceptance of interfaces by gaining insight into brain states to reestablish interaction (by enabling active support) and by passively supporting interaction and improving it qualitatively but also quantitatively.

Secondly, the development of eBR further contributes to research *challenge (2)* of the defined research agenda. It improves the understanding of the human by a robotic systems since: eBR allows to infer intentions of the user, while brain activity that is detected by the passive BR approach is never produced artificially, the (cognitive) demands on the user are therefore never artificially enhanced by applying eBR, which works "in the background" and is not perceived as annoying or tiring as it was reported by users that participated in studies with online application of eBR (Seeland et al., 2013b; Wöhrle and Kirchner, 2014). Furthermore, a predictive HMI can by means of eBR support upcoming behavior and intentions of the interacting human. By giving a machine insight into the human's intention and by enabling it to infer on upcoming behavior that can then be better supported, eBR enables intuitive, context and situation-aware support by making use of overt and covert information about the user.

Finally, the work presented in Chapter 5 and Chapter 6 does support research *challenge (3)*, since it shows that complex human-machine interaction and the involved systems can be described by a formal structure model. Such a model is the prerequisite to make complex systems and human-machine interaction to some degree verifiable, predictable in their behavior, and to reduce the risk of their application, as well as to guarantee the improvement of interaction by their application and to optimize their functioning.

It can be summarized that the work of this thesis contributes to all three research challenges that were mentioned to be addressed to improve human-machine interaction. While knowledge about underlying brain activity from the neuroscientific point of view could be shown to help to improve approaches of ML, i.e, contributed to research in the field of computer science, the work of this thesis did also contribute to neuroscientific questions, like the understanding of brain functioning under natural, complex interaction and dual-task conditions and by supporting the usage of single-trial BR for neuroscience research. Hence, results and findings of the thesis strongly support the concept of interdisciplinary work and cooperation to approach and solve todays complex challenges in basic as well as application-close research.

# Chapter 10

# Outlook

For future work, the application of eBR as well as the approach itself can further be improved to enable and even enhance comfort of the user and performance of the approach. Besides further research in the field of neuroscience to better understand underlying brain processes and to optimize the detection of specific brain states by BR, SP and ML methods for BR should be developed that enable a more flexible and efficient analysis of the highly non-stationary brain activity or other physiological signals.

**Future Work on Improving SP and ML Methods:** *Adaptive* methods for SP and ML that enable online learning should be highlighted, since they allow to adapt SP and ML methods to the changes in the human's brain activity. For example, by applying sequential or online learning a CL that may first have been trained on few training examples can sequentially or online be adapted in its parameters to new incoming examples as it could be shown for the LDA classifier and Kalman filter (Vidaurre et al., 2008; Yoon et al., 2008). In the extreme case of sequential learning a CL is not pre-trained at all but trained from "zero" using incoming examples. For online learning the labeling of data after classification is required to give a feedback to the CL, whether the prediction was correct or not. Hence, labeling is performed with respect to the correctness of the outcome of classification (see (Wöhrle et al., 2013c) for an offline investigation of single-trial based adaptive CL training).

When online adaptation is applied to a processing flow, one has to consider that not only the CL but also the applied spatial filter (SF) must be adapted (Ghaderi and Straube, 2013; Wöhrle et al., 2013a). In Figure 10.1 it is shown that online learning of the SF and the CL does both contribute to overcome differences in EEG recorded in different sessions (DS) from different users (DU) within the same application (see Figure 10.2 from (Kirchner et al., 2010) for visualization of the effect of CL transfer on classification performance under different transfer conditions). In summary,

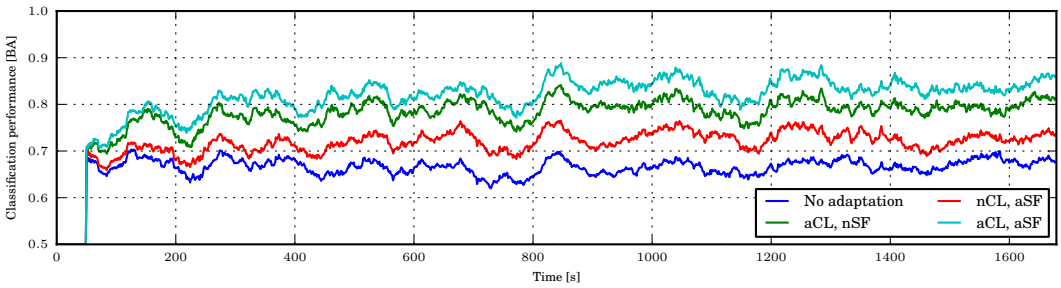


Figure 10.1: Performance in P300 detection in EEG data of the *Virtual Labyrinth Oddball* scenario over time for a Passive Aggressive 1 (PA1) CL. Performance is shown in the condition of CL transfer between different users (subjects) and different session (DUDS) for different adaptation strategies, where *CL* refers to classifier, *SF* to spatial filter and $a/n$ to recalibration/no recalibration. Figure is based on Figure 13 of (Wöhrle et al., 2013a).

by online learning it is possible to overcome even large differences between subjects. Hence, a method that was developed and trained for one subject can during its application be adapted to another subject's EEG data. Hence, tiresome training sessions for new subjects can completely be avoided. Remember that a worse performance at the beginning of an application for a new subject has no negative impact on the application due to the specification of eBR in case it is passively applied. For an active application of eBR for rehabilitation purposes, adaptive methods are extremely interesting, since they enable an online adaptation to changes in brain activity that may, after a disfunction of their brain and during recovery, be more prominent than "normal" changes in brain activity of healthy users.

**Future Work on Improving Acquisition and Analysis Hardware and Software:** Besides the online learning capability of the applied methods, the general online applicability is further highly relevant. To enable online processing, different approaches can be chosen and combined: (1) applying different general software optimization techniques, like preallocation of buffer variables, (2) choosing or developing real time capable algorithms for data processing and classification, like an appropriate anti-aliasing lowpass filter for the data decimation step, (3) applying parallelization techniques to speed up the SP of data recorded by several sensors, which can be performed in parallel (see (Kirchner et al., 2010) for further discussion).

For the purpose of parallel computing, the application of field-programmable gate arrays (field programmable gate array (FPGA)s), which are reconfigurable, application-specific hardware components, becomes increasingly popular for digital SP (DSP) techniques (Meyer-Bäse, 2007; Tessier and Burleson, 2001) in general.

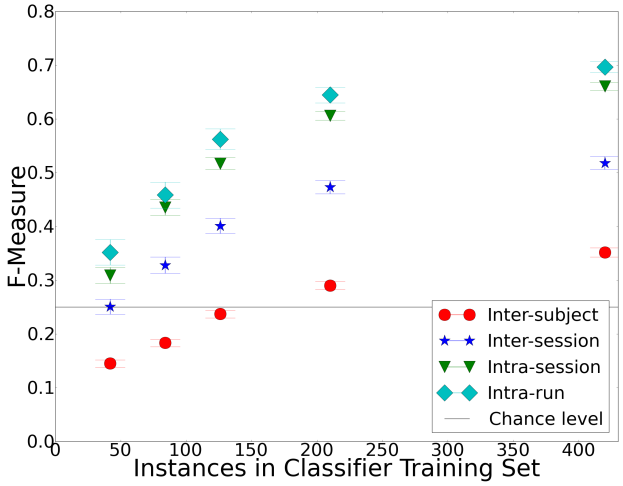


Figure 10.2: Effect of transfer type and training set size on classification performance in P300 detection in EEG data of the *Virtual Labyrinth Oddball* scenario. Inter-session (inter-session differences in EEG are caused by training effects or differences in electrode positioning for the same subject in different sessions on different days) and inter-subject transfer (transfer of CL trained on a data from a different subject) reduces classification performance significantly compared to intra-run transfer (transfer of CL between parts of data of one run: a CL is trained on a part of the data of one run and tested on another part of the data of the same run; intra-run is common condition), while intra-session (transfer between runs of one session: different runs that belong to one session are performed on the same day and are usually separated by breaks) transfer does not. Figure is based on Figure 4 of (Kirchner et al., 2010).

Some approaches have already been applied for the embedded analysis of physiological data, see for example (Shyu et al., 2010). FPGAs are characterized by high computing performance and low energy consumption, although they possess some disadvantages with regard to the required intricate software development and to the heterogeneity of the necessary algorithms (see discussion in (Kirchner et al., 2010)). However, many today's FPGA-based systems can only process a small number of channels of sensor data and can often only process data with low frequency rate or low complexity (see for example (Edlinger and Guger, 2005; Gargiulo et al., 2008; Lin et al., 2009; Bueno et al., 2013)). Since EEG data is of high complexity, standard EEG acquisition systems record EEG data with a high sampling rate of 1000 to up to 20000 Hz, and many applications require to record data from many electrodes distributed over the heads surface, FPGA-based systems have to be developed that are able to handle such complex and high amount of data in real-time (Wöhrle et al., 2013b).

The application of FPGA-based systems can further increase the comfort of the user, since they can, due to their small size and low energy consumption, be inte-

grated into the HMI that is adapted, e.g., the exoskeleton. This makes eBR mobile and avoids a possible negative impact of eBR on the human's interaction with the system or her/his comfort (Kirchner et al., 2013a).

Moreover, to improve the acceptance of eBR the simplicity of the acquisition of EEG data must be improved as well. Recently, EEG recording devices became much smaller[1] and the quality of the data was enhanced by different methods, like the usage of active electrode systems that are less sensitive to artifacts that are induced by movements of the subjects or environmental noise[2]. Dry electrodes, which can easily be applied for EMG data acquisition (Chan and Lemaire, 2010), can also be used for EEG data acquisition. Although with dry electrodes it is quite challenging to conduct high quality EEG recordings, some approaches are very promising to reduce the effort of EEG acquisition. For example, a low number of as much as 6 dry electrodes could be shown to be sufficient for the prediction of movement intention (Popescu et al., 2007).

Alternatively, for easier handling it would be very helpful to reduce the amount of electrodes required to record the physiological signals. For example, in (Kirchner et al., 2010) it could already be shown that 8 electrodes are sufficient to detect the P300 ERP in single trial (see Figure 10.3). For the detection of movement-related ERP potentials, an even lower amount of electrodes might be sufficient since the BP and LRP are local activities (see Section 3.2.1). In general it is, however, difficult to identify the most relevant electrode positions subject-independently. This is especially true if eBR is applied for the active support of patients, due to bigger differences resulting from, e.g., brain injury that leads to massive changes in the patients brain activity (Kirchner et al., 2014). Hence, sophisticated methods must be developed to automatically chose electrodes that contain most and unique information (see for example (Feess et al., 2013)).

**Challenges for the Application of eBR in Everyday Application Scenarios:** As explained in Section 6.1, eBR cannot only be applied for medical purposes to actively reestablish functioning of parts of the body of patients, but can also be applied in the fields of robotic and hence industrial applications. This new and advanced approach may in future for example be applied to support healthy subjects in demanding every day tasks by generally improving workflows by enabling a technical system to make use of human cognitive resources or by an individual and situation-specific support of elderly employees in, e.g., heavy physical work. Since the application of eBR that enables an advanced bidirectional human-machine interaction in

[1] see for example http://www.ant-neuro.com/products/eegosports_intro for a small and mobile EEG and EMG recording system

[2] see for example http://www.brainproducts.com/productdetails.php?id=4 for an active electrode system

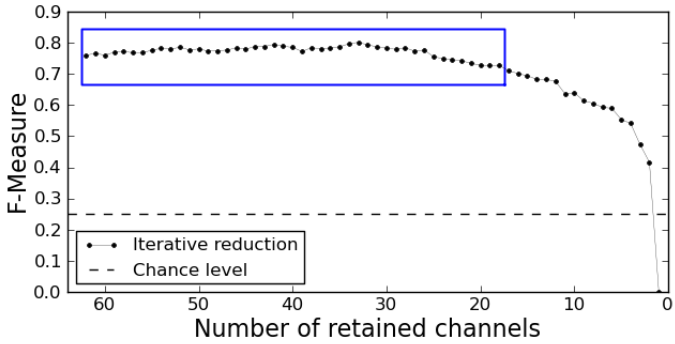


Figure 10.3: Effect of the number of EEG channels on single-trial classification performance in P300 detection. Blue rectangle highlights different numbers of electrodes used for training and testing that assure similar (not significantly different) classification performance. Figure is based on Figure 5 of (Kirchner et al., 2010).

domains that would not necessarily require active support, control mechanisms that avoid malfunctioning or a reduction of performance are essential. That eBR is able to provide such an error-free support was shown in this thesis. However, it was also discussed that especially passive support approaches by eBR are challenging to be automatically verified regarding their correctness in implementation and functioning. Therefore, in future work, new approaches for the formal verification of such complex systems must be developed, which is a challenging task but would increase the acceptance of eBR that is able to passively and safely make use of uncertain data to improve human-machine interaction.

# Appendix A

# Additional Figures

## A.1 Additional Figures Supporting Results of the *Arm Movement* Study

In the following some additional figures are provided that support results in Section 3.2.2.4. Results of Subject 6 as presented in Figure 3.15 are once more illustrated in Figure A.6 to allow easy comparison with the other five subjects.

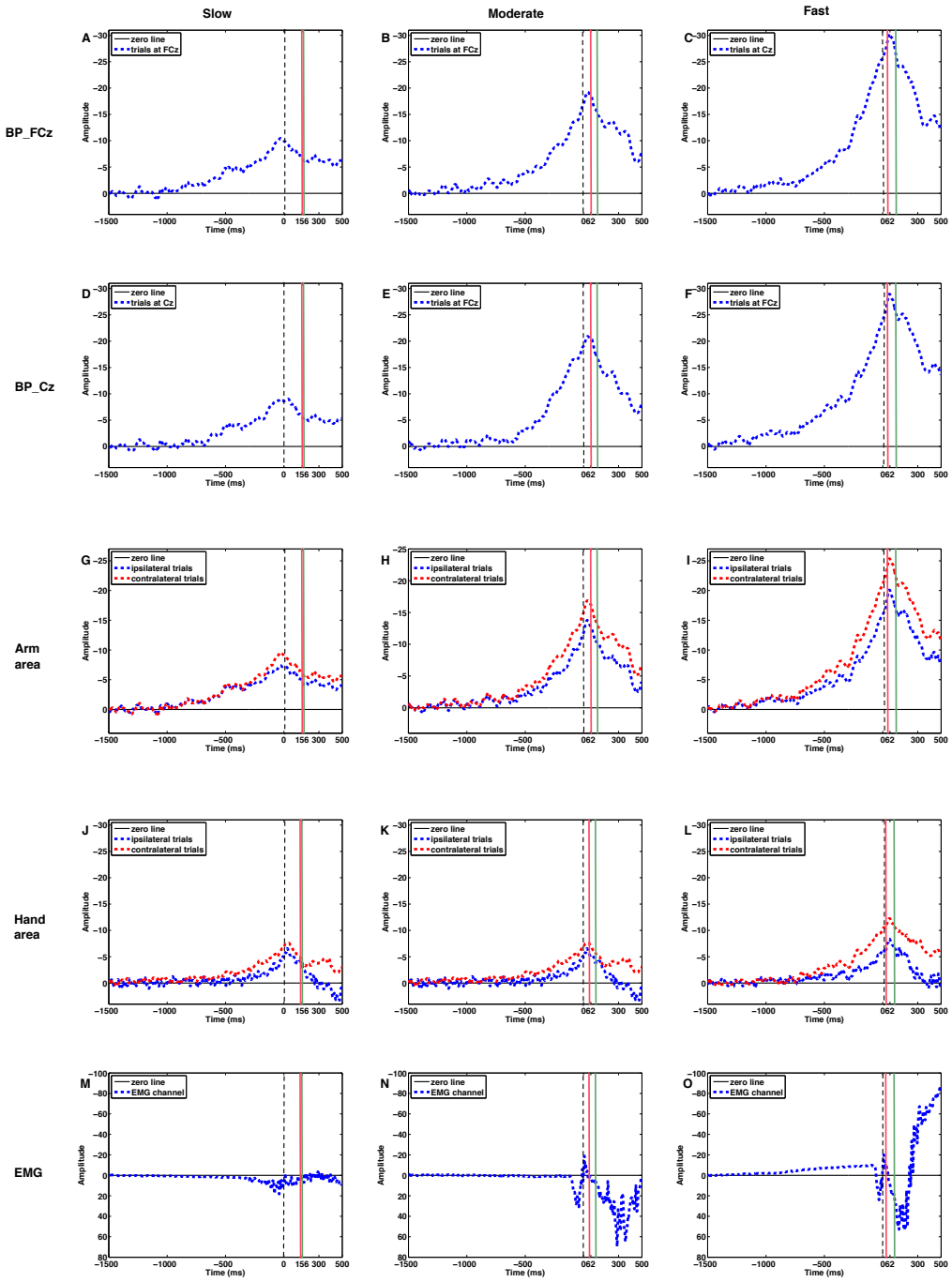


Figure A.1: EMG activity and averaged ERP activity preceding arm movements based on EMG onset for subject 1. A,B,C: BP at electrode FCz; D, E, F: BP at electrode Cz; G, H, I: ipsilateral and contralateral activity over arm areas; J, K, L: ipsilateral and contralateral activity over hand areas; M, N, O: averaged EMG activity for all three movement conditions, slow, moderate, and fast movement speed condition (A, D, G, J, M: slow ; B, E, H, K, N: moderate; C, F, I, L, O: fast), respectively. Dotted vertical line labels EMG movement onset. Red vertical line labels mean distance from EMG onset to movement onset as detected by Qualisys and green vertical line the mean distance to movement onset labeled by the microswitch input device.

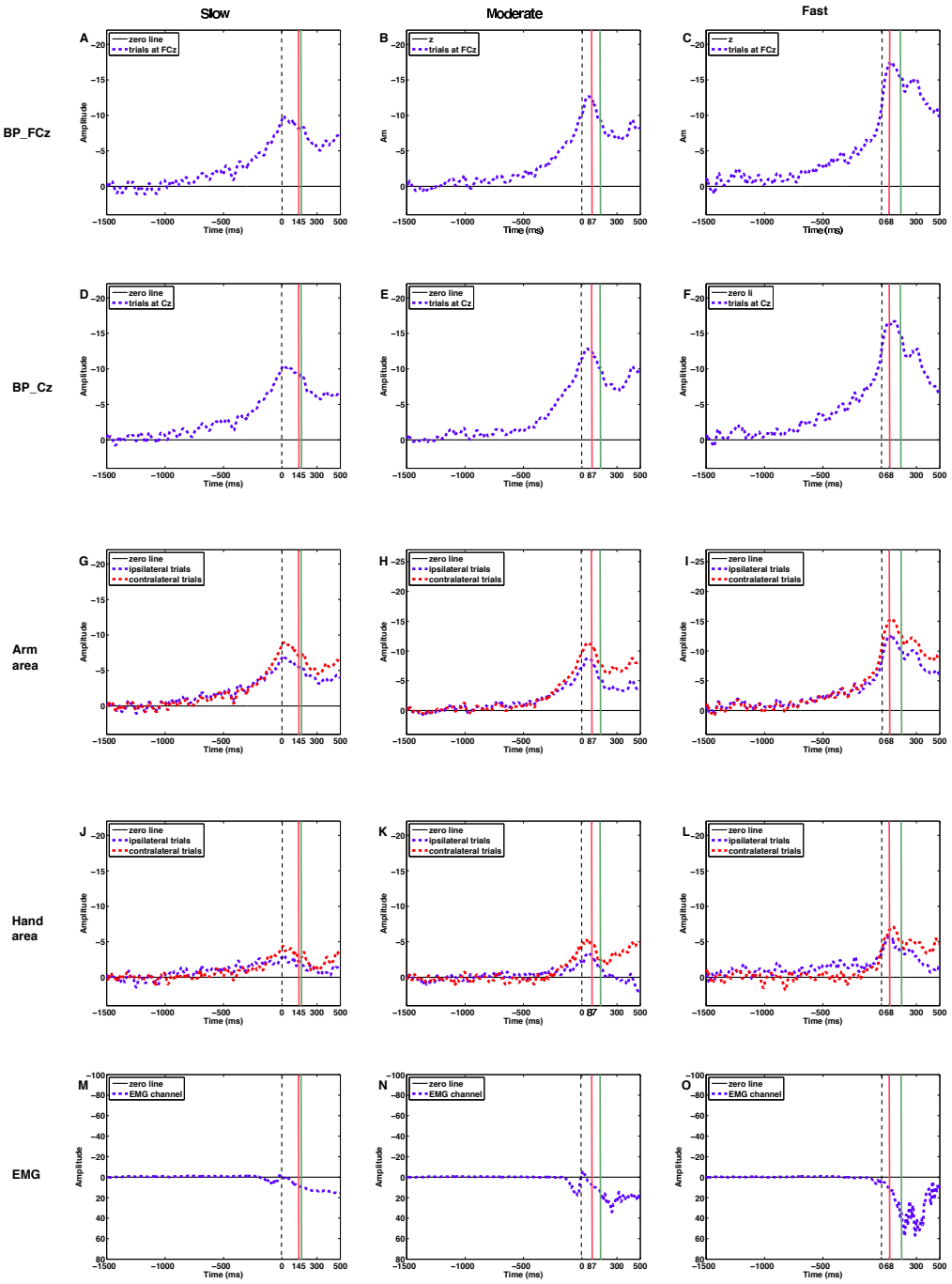


Figure A.2: EMG activity and averaged ERP activity preceding arm movements based on EMG onset for subject 2. A,B,C: BP at electrode FCz; D, E, F: BP at electrode Cz; G, H, I: ipsilateral and contralateral activity over arm areas; J, K, L: ipsilateral and contralateral activity over hand areas; M, N, O: averaged EMG activity for all three movement conditions, slow, moderate, and fast movement speed condition (A, D, G, J, M: slow ; B, E, H, K, N: moderate; C, F, I, L, O: fast), respectively. Dotted vertical line labels EMG movement onset. Red vertical line labels mean distance from EMG onset to movement onset as detected by Qualisys and green vertical line the mean distance to movement onset labeled by the microswitch input device.

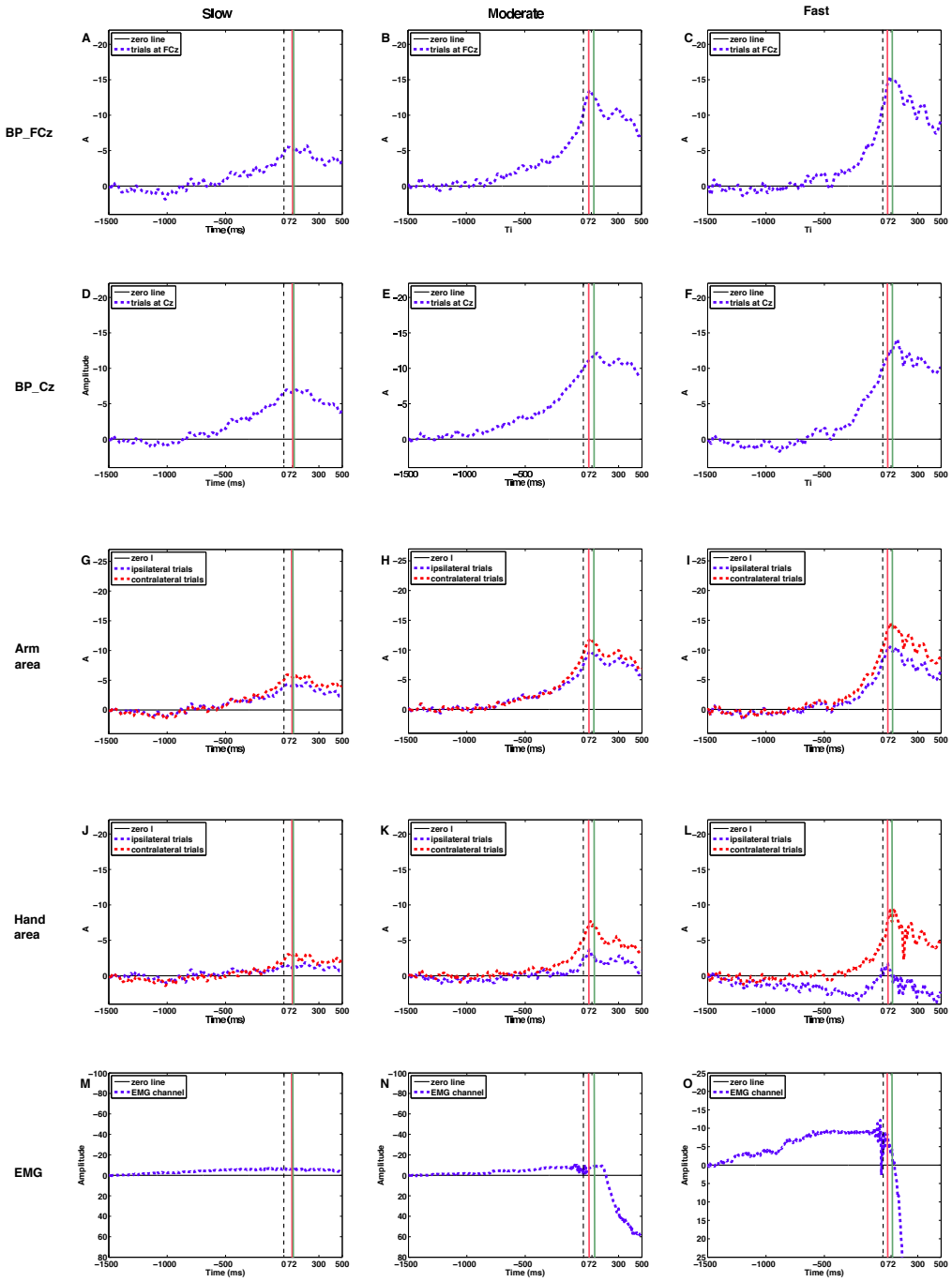


Figure A.3: EMG activity and averaged ERP activity preceding arm movements based on EMG onset for subject 3. A,B,C: BP at electrode FCz; D, E, F: BP at electrode Cz; G, H, I: ipsilateral and contralateral activity over arm areas; J, K, L: ipsilateral and contralateral activity over hand areas; M, N, O: averaged EMG activity for all three movement conditions, slow, moderate, and fast movement speed condition (A, D, G, J, M: slow ; B, E, H, K, N: moderate; C, F, I, L, O: fast), respectively. Dotted vertical line labels EMG movement onset. Red vertical line labels mean distance from EMG onset to movement onset as detected by Qualisys and green vertical line the mean distance to movement onset labeled by the microswitch input device.

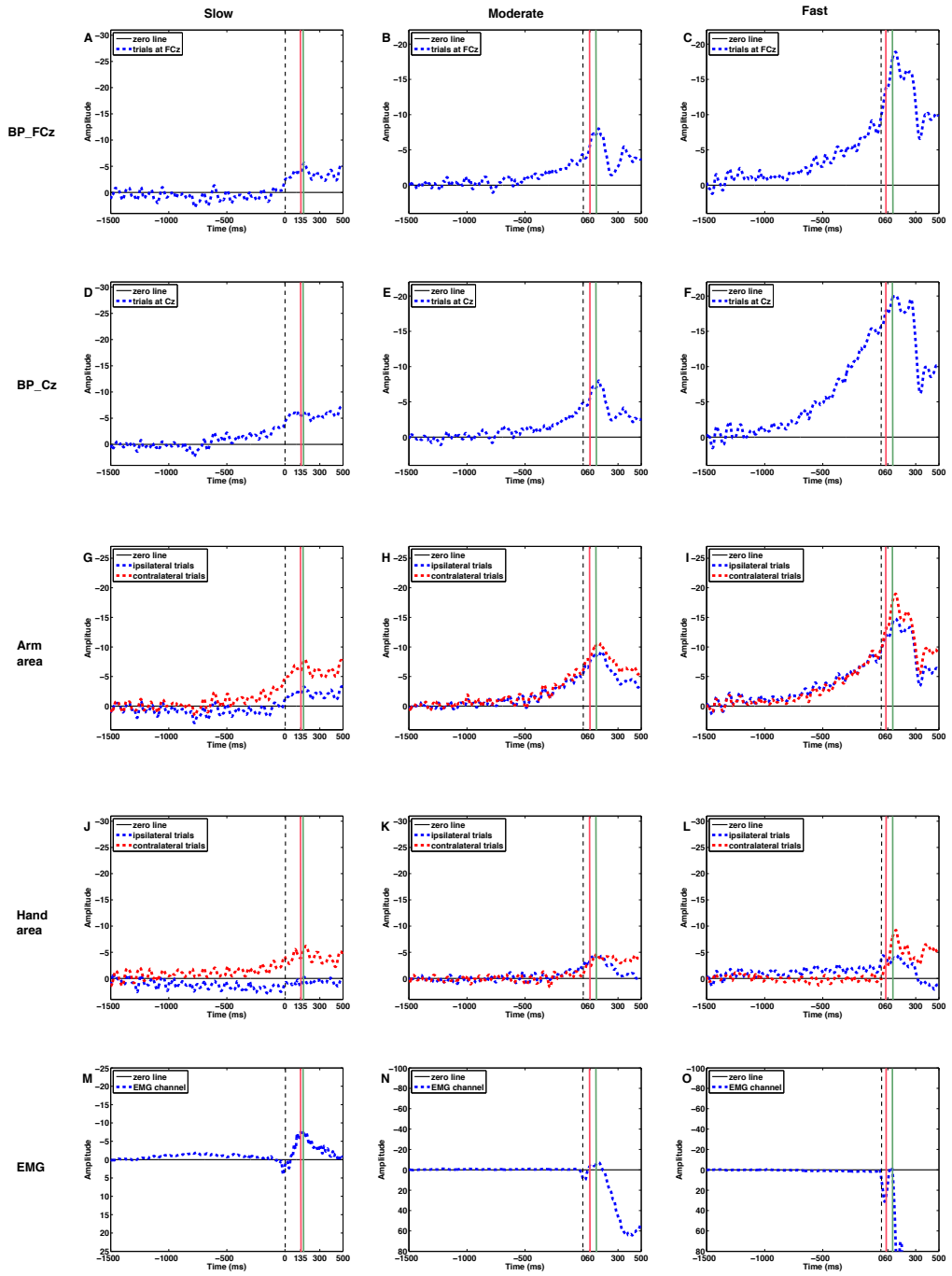


Figure A.4: EMG activity and averaged ERP activity preceding arm movements based on EMG onset for subject 4. A,B,C: BP at electrode FCz; D, E, F: BP at electrode Cz; G, H, I: ipsilateral and contralateral activity over arm areas; J, K, L: ipsilateral and contralateral activity over hand areas; M, N, O: averaged EMG activity for all three movement conditions, slow, moderate, and fast movement speed condition (A, D, G, J, M: slow ; B, E, H, K, N: moderate; C, F, I, L, O: fast), respectively. Dotted vertical line labels EMG movement onset. Red vertical line labels mean distance from EMG onset to movement onset as detected by Qualisys and green vertical line the mean distance to movement onset labeled by the microswitch input device.

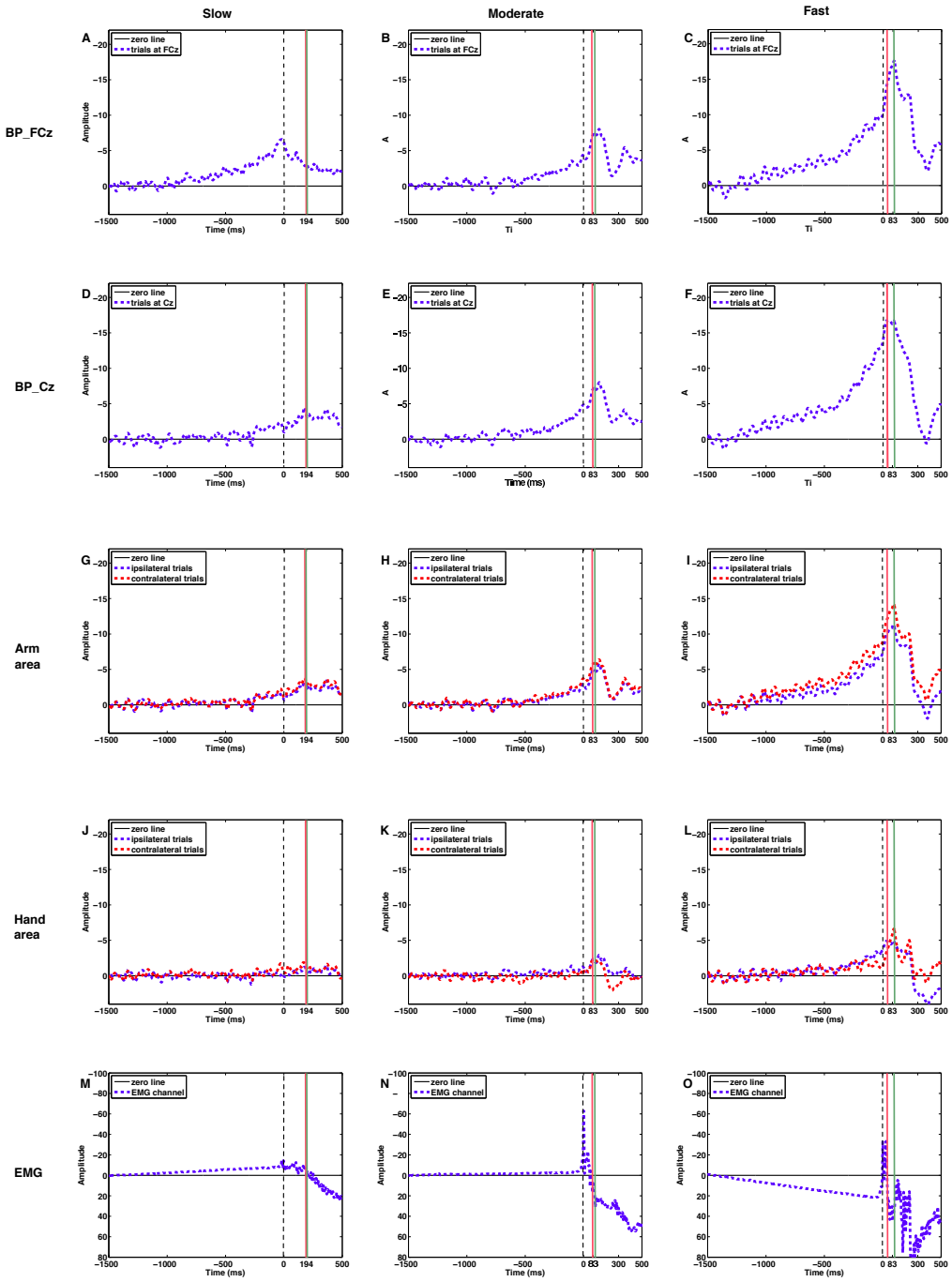


Figure A.5: EMG activity and averaged ERP activity preceding arm movements based on EMG onset for subject 5. A,B,C: BP at electrode FCz; D, E, F: BP at electrode Cz; G, H, I: ipsilateral and contralateral activity over arm areas; J, K, L: ipsilateral and contralateral activity over hand areas; M, N, O: averaged EMG activity for all three movement conditions, slow, moderate, and fast movement speed condition (A, D, G, J, M: slow ; B, E, H, K, N: moderate; C, F, I, L, O: fast), respectively. Dotted vertical line labels EMG movement onset. Red vertical line labels mean distance from EMG onset to movement onset as detected by Qualisys and green vertical line the mean distance to movement onset labeled by the microswitch input device.

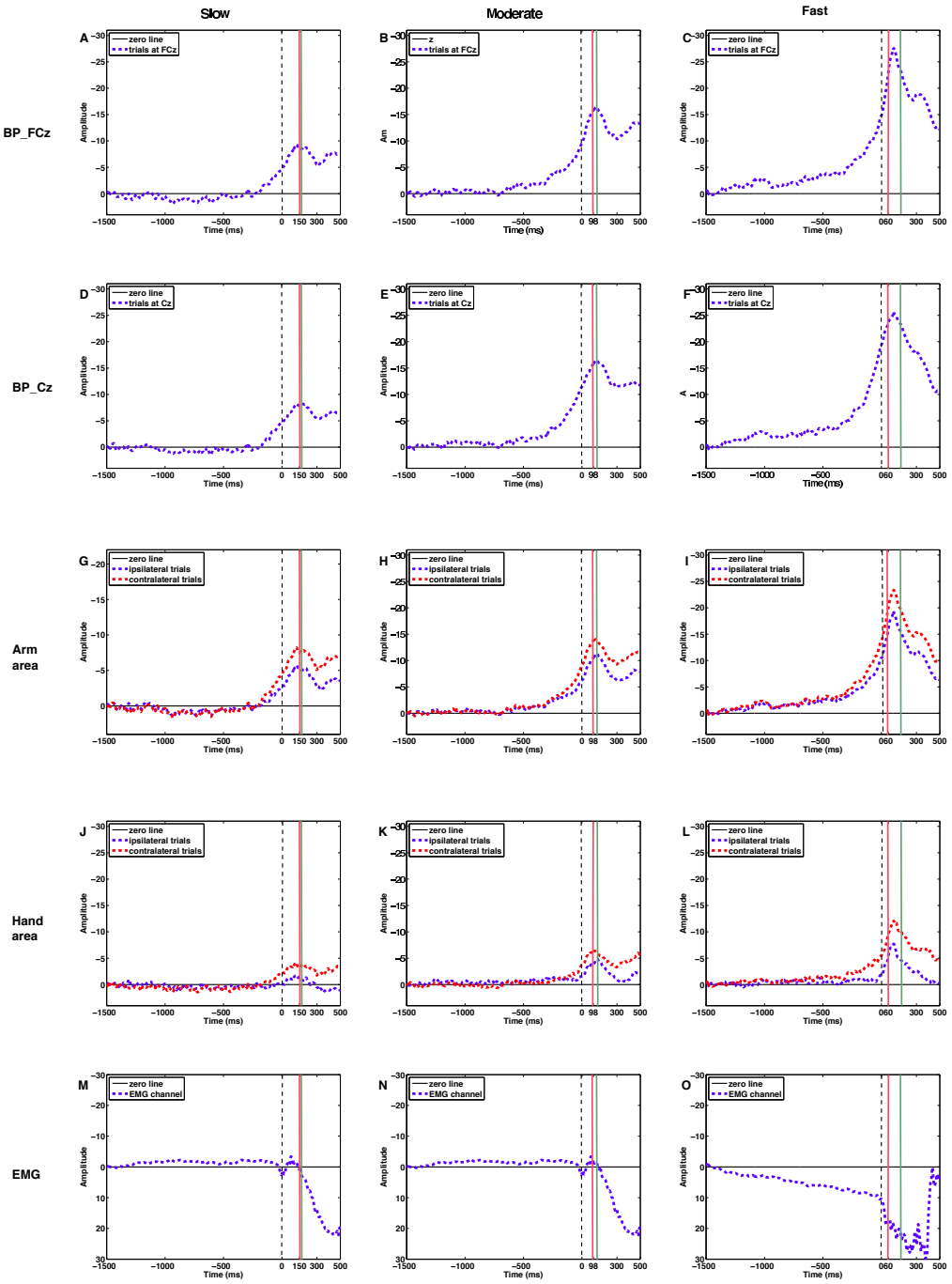


Figure A.6: EMG activity and averaged ERP activity preceding arm movements based on EMG onset for subject 6. A,B,C: BP at electrode FCz; D, E, F: BP at electrode Cz; G, H, I: ipsilateral and contralateral activity over arm areas; J, K, L: ipsilateral and contralateral activity over hand areas; M, N, O: averaged EMG activity for all three movement conditions, slow, moderate, and fast movement speed condition (A, D, G, J, M: slow ; B, E, H, K, N: moderate; C, F, I, L, O: fast), respectively. Dotted vertical line labels EMG movement onset. Red vertical line labels mean distance from EMG onset to movement onset as detected by Qualisys and green vertical line the mean distance to movement onset labeled by the microswitch input device.

# Appendix B

# DVD

## B.1 PDF version of the Thesis

On the DVD a PDF version of the thesis "Embedded Brain Reading" is provided, named "ThesisElsaAndreaKirchner.pdf".

## B.2 Supporting Videos

On the DVD supporting videos are provided as follows:

Video B.1: online detection of failure and success in the recognition of important information in the *Virtual Labyrinth Oddball* scenario. It is shown how BR is able to detect the success and failure in recognizing important, i.e., task-relevant, information. P300 related processes that are evoked by target recognition processes are detected online in the *Virtual Labyrinth Oddball* scenario.

Video B.2: simulation of the triggering of movements based on the analysis of different types of signals (EMG and EEG) and their combinations recorded in the *Arm Movement* scenario. The video shows both arms of the subject filmed from the top of the room. Three frames around the video with colors green (condition A), red (condition B) and yellow (condition D) indicate the detection of a movement intention of one particular condition. In addition, three animations are placed below the video, showing a mannequin doing a movement similar to the ones performed by the subject. These animations are again coupled to the three above mentioned prediction conditions and thus triggered by corresponding movement predictions. Condition C is implicitly contained in the video, due to the fact that any prediction made either by EEG or EMG is displayed.

Video B.3: online adaptation of the OMS by eBR in the *Tele-manipulation* scenario. It is shown how the OMS that is adapted by eBR supports the current state, i.e., success or failure in recognition of important information, of an operator who is teleoperating a robotic arm. In case a failure in recognizing important, i.e., task-relevant, information is detected, the important information is repeated after a short while. In case that success in recognizing important information was detected, the important information will not be repeated for a longer time during which a response of the subject is monitored. In case the response is missing within the extended response time the important information is repeated although BR detected success in the recognition of the important, i.e., task-relevant, information.

Video B.4: online adaptation of the exoskeleton by eBR in the *Tele-manipulation* scenario. It is shown how the exoskeleton's control is adapted by eBR to ease lock-out from a rest position. Online prediction values and the point in time at which sensors that are integrated in the exoskeleton detect the movement onset are visualized in an inserted diagram. Video and online prediction values for BR as well as movement onsets are synchronized in time. The video shows that too early or false movement predictions by BR are irrelevant for the control of the system. Only correct movement predictions ease the handling of the exoskeleton by the operator.

Video B.5: the *Tele-manipulation* scenario and adaptation of two HMIs by eBR. It is shown how an operator controls a robotic arm via a virtual scenario that is presented to him by an HMI. The control of the robotic arm is enabled by an exoskeleton. While controlling the robotic arm, the operator has to respond to important warnings. The implemented OMS is supporting the operator in this task. Both HMIs, the OMS and the exoskeleton, are adapted by eBR.

# Appendix C

# Contribution to Publications

Most results of this thesis are already published or under review. The referred publications are published in *international journals* (Kirchner et al., 2013b,d; Kirchner and Drechsler, 2013a; Kirchner et al., 2014; Folgheraiter et al., 2012) or *under review in international journals* (Kirchner et al., 2013c), published in the proceedings of *international conferences* (Kirchner and Kim, 2012; Tabie and Kirchner, 2013; Kirchner et al., 2013a, 2010; Wöhrle and Kirchner, 2014; Folgheraiter et al., 2011; Seeland et al., 2013b), *european conferences* (Kirchner and Tabie, 2013), in the proceedings of *national conferences* (Metzen and Kirchner, 2011) or *workshops* (Kirchner et al., 2009; Kirchner and Drechsler, 2013b). In the following the contributions of the authors to all publications that are referred as main results of the thesis are listed.

## C.1 Publications in International Journals:

**1. (Folgheraiter et al., 2012) (published)** Folgheraiter, M., Jordan, M., Straube, S., Seeland, A., Kim, S. K., and Kirchner, E. A.; "Measuring the improvement of the interaction comfort of a wearable exoskeleton." *International Journal of Social Robotics.*

Contribution of the author of the thesis:

- identification of relevant work from literature
- coordinated work for this publication
- design of experimental setup and experiments
- proposed and supported design of calibration procedure
- supported statistics (especially design)

- wrote parts of introduction, results and discussion
- improved text

Contribution of the main and the co-authors of this publication:

- performed experiments
- statistical design and analysis
- wrote parts of the paper related to the exoskeleton

**2. (Kirchner and Drechsler, 2013a) (*invited paper*, published)** Kirchner, E. A. and Drechsler, R.; "A Formal Model for Embedded Brain Reading." *Industrial Robot: An International Journal*.

Contribution of the author of the thesis:

- developed formal model
- wrote most parts of the paper
- evaluated formal model on implementation examples

Contribution of the co-author of this publication:

- supported the development of the formal model by discussion of concept and preliminary results
- contribution to the text and improvement of the text

**3. (Kirchner et al., 2013b) (published)** Kirchner, E. A., Kim, S. K., and Fahle, M.; "EEG in Dual-Task Human-Machine Interaction: On the Feasibility of EEG based Support of Complex Human-Machine Interaction." *Perception*.

Contribution of the author of the thesis:

- analysis of the state of the art
- identification of relevant work
- design of experimental setup
- conducted experiments
- performed average ERP analysis

- contributed to statistical design
- wrote most parts of the paper
- wrote most parts of the ethic proposal and presented it to ethic commission
- presented poster at the conference

Contribution of the co-authors of this publication:

- contributed to statistical design and analysis
- supported experiments
- wrote parts of methods and results
- supported the writing of the ethic proposal
- discussion of results in the context of the main topics of the journal and improvement of text

**4. (Kirchner et al., 2013c) (under review)** Kirchner, E. A., Kim, S. K., and Fahle, M.; "On the feasibility of EEG based support of multi-task human-machine interaction: Late positive parietal event-related potentials in simple-task and dual-task performance." *PLoS ONE*.

Contribution of the author of the thesis:

- analysis of the state of the art
- identification of relevant work
- design of experimental setup and experiments
- performed experiments
- analysed data
- supported statistical design and analysis
- wrote most parts of the paper

Contribution of the co-authors of this publication:

- supported experiments
- performed statistical analysis

- wrote parts of results
- discussed results
- corrected and improved text

**5. (Kirchner et al., 2013d) (published)** Kirchner, E. A., Kim, S. K., Straube, S., Seeland, A., Wöhrle, H., Krell, M. M., Tabie, M., and Fahle, M.; "On the applicability of brain reading for self-controlled, predictive human-machine interfaces in robotics." *PLoS ONE*.

Contribution of the author of the thesis:

- analysis of the state of the art
- identification of relevant work
- concept of the usage of BR for the improvement of human-machine interaction
- design of experimental setup and experiments
- conducted parts of the experiments
- performed averaged ERP analysis
- contributed to statistical design
- wrote most parts of the paper
- wrote most parts of the ethic proposal and presented it to ethic commission

Contribution of the co-authors of this publication:

- conducted parts of the experiments
- performed ML analysis and statistics
- wrote some parts of methods and results
- supported writing the ethic proposal
- corrected and improved text

**6. (Kirchner et al., 2014) (published)** Kirchner, E. A., Tabie, M., and Seeland, A.; "Multimodal movement prediction - towards an individual assistance of patients." *PLoS ONE*.

Contribution of the author of the thesis:

- analysis and summary of the state of the art
- identification of relevant work
- design of experimental setup
- proposed concept for multimodal ML analysis and different possibilities for the combination of signals
- wrote most parts of the ethic proposal and presented it to ethic commission
- supported the definition of statistical design
- wrote most parts of the paper

Contribution of the co-authors of this publication:

- conducted experiments (in the context of a Master thesis that was supervised by the main author)
- wrote parts of the ethic proposal
- performed ML analysis and statistics
- wrote parts of the paper and improved text

## C.2 Publications in Proceedings of International Conferences:

**1. (Kirchner et al., 2010) (published)** Kirchner, E. A., Wöhrle, H., Bergatt, C., Kim, S. K., Metzen, J. H., Feess, D., and Kirchner, F.; "Towards operator monitoring via brain reading - an EEG-based approach for space applications." *In Proc. 10th Int. Symp. Artificial Intelligence, Robotics and Automation in Space*, Sapporo, Japan.

Contribution of the author of the thesis:

- analysis of the state of the art
- identification of relevant work
- concept of brain reading for the support of tele-manipulation in robotics
- design of experimental setup
- design of experiments
- performed parts of experiments
- ethic proposal
- wrote most parts of the paper

Contribution of the co-authors of this publication:

- supported experiments
- performed ML analysis
- wrote parts of the paper related to ML analysis
- presented paper at the conference (talk)

**2. (Folgheraiter et al., 2011) (published)** Folgheraiter, M., Kirchner, E. A., Seeland, A., Kim, S. K., Jordan, M., Wöhrle, H., Bongardt, B., Schmidt, S., Albiez, J., and Kirchner, F.; "A multimodal brain-arm interface for operation of complex robotic systems and upper limb motor recovery." *Proceedings of the 4th International Conference on Biomedical Electronics and Devices (BIODEVICES-11)*, Rome, Italy.

Contribution of the author of the thesis:

- analysis of state of the art for the adaptation of assistive devices by biosignals

- developed concept of adaptation of exoskeleton by single-trial EEG signal decoding
- design of experimental setup "Armrest" to record EEG data with simulated support of an exoskeleton
- support of experiments in the "Armrest" scenario
- wrote parts of introduction, BR part, parts of discussion and contributed to experimental parts (methods and results) for ML analysis

Contribution of the main and the co-authors of this publication:

- wrote parts related to the design and the development of the exoskeleton
- state of the art for ML analysis
- performed ML analysis, wrote parts of methods and results of ML analysis
- presented paper at the conference (talk)

**3. (Kirchner and Kim, 2012) (published)** Kirchner, E. A. and Kim, S. K.; "EEG in Dual-Task Human-Machine Interaction: Target Recognition and Prospective Memory." *In Proceedings of the 18th Annual Meeting of the Organization for Human Brain Mapping*.

Contribution of the author of the thesis:

- analysis of the state of the art
- identification of relevant work
- design of experimental setup
- extended ethic proposal to cover experiments
- conducted experiments
- performed average ERP analysis
- contributed to statistical design
- wrote most parts of the paper
- presented poster at the conference

Contribution of the co-author of this publication:

- supported experiments
- contributed to statistical design definition
- wrote parts of results
- conducted statistical analysis

**4. (Tabie and Kirchner, 2013) (published)** Tabie, M. and Kirchner, E. A.; "EMG onset detection - comparison of different methods for a movement prediction task based on EMG." *In Proceedings of the 6th International Conference on Bio-inspired Systems and Signal Processing (BIOSIGNALS-13)*, Barcelona, Spain.

Contribution of the author of the thesis:

- identification of relevant work
- design of experimental setup
- design of experiments
- wrote parts of introduction and discussion
- wrote most parts of the ethic proposal and presented it to ethic commission

Contribution of the main author (master thesis student supervised by author of the thesis) of this publication:

- built experimental setup
- conducted experiments
- developed algorithm for EMG onset detection and analysis of state of the art
- performed analysis
- wrote most parts of the paper
- supported work for ethic proposal and wrote parts of it
- presented paper at the conference (talk)

**5. (Kirchner et al., 2013a) (published)** Kirchner, E. A., Albiez, J., Seeland, A., Jordan, M., and Kirchner, F.; "Towards assistive robotics for home rehabilitation." *In Proceedings of the 6th International Conference on Biomedical Electronics and Devices (BIODEVICES-13)*, Barcelona, Spain.

Contribution of the author of the thesis:

- analysis of the state of the art
- identification of relevant work
- concept for the application *Home Rehabilitation*
- general design of data analysis (most data was already available from other experiments and studies, which were designed by the main author and covert by an ethic proposal as mentioned above.)
- wrote most parts of the paper
- presented paper at the conference (talk)

Contribution of the co-authors of this publication:

- performed experiments with exoskeleton
- wrote parts of the paper with respect to the design of the exoskeleton and results of ML analysis and analysis of data from the exoskeleton
- improved text and supported analysis of the state of the art

**6. (Seeland et al., 2013b) (published)** Seeland, A., Wöhrle, H., Straube, S., and Kirchner, E. A.; "Online movement prediction in a robotic application scenario." *In Proceedings of the 6th International IEEE EMBS Conference on Neural Engineering (NER)*, San Diego, California, USA.

Contribution of the author of the thesis:

- design of experimental setup
- concept for the adaptation of the exoskeleton's control by BR during telemanipulation via a robotic arm
- ethic proposal
- support of experiments

- wrote parts of introduction and discussion and corrected text

Contribution of the main and the co-authors of this publication:

- performed experiments
- performed ML analysis
- wrote most parts of the paper
- presented paper at the conference (poster)

**7. (Wöhrle and Kirchner, 2014) (received *"best paper award"*, published)** Wöhrle, H. and Kirchner, E. A.; "Online Detection of P300 related Target Recognition Processes During a Demanding Teleoperation Task." *In Proceedings of the International Conference on Physiological Computing Systems, (PhyCS 2014)*, Lissabon, Portugal.

Contribution of the author of the thesis:

- design of experimental setup and experiments
- discussed design of ML analysis
- concept of BR for the support of teleopertation in robotic applications
- wrote parts of introduction, methods, discussion and ethic proposal

Contribution of main author of this publication:

- performed ML analysis
- wrote most parts of the paper
- will present paper at the conference

## C.3 Publications in Proceedings of European Conferences:

**1. (Kirchner and Tabie, 2013) (presented at conference)** Kirchner, E. A. and Tabie, M. (2013). "Closing the gap: Combined EEG and EMG analysis for early movement prediction in exoskeleton based rehabilitation." *In Proceedings of the 4th European Conference on Technically Assisted Rehabilitation - TAR 2013*, Berlin, Germany.

Contribution of the author of the thesis:

- analysis and summary of the state of the art
- identification of relevant work
- design of experimental setup
- proposed concept for multimodal ML analysis and different possibilities for the combination of signals
- wrote most parts of the ethic proposal and presented it to ethic commission
- wrote most parts of the paper
- presented paper at the conference (talk)

Contribution of the co-author of this publication:

- conducted experiments (in the context of a master thesis that was supervised by the main author)
- wrote parts of the ethic proposal
- performed ML analysis
- wrote parts of the paper and improved text

## C.4 Publications in Proceedings of National Conferences:

**1. (Metzen and Kirchner, 2011) (published)** Metzen, J. H. and Kirchner, E. A. (2011). "Rapid adaptation of brain reading interfaces based on threshold adjustment." *In Proceedings of the 2011 Conference of the German Classification Society (GfKl-2011)*, Frankfurt am Main, Germany.

Contribution of the author of the thesis:

- design of experimental setup
- design of experiments
- conducted experiments
- concept of classifier transfer
- contributed to abstract

Contribution of the main author of this publication:

- ML analysis
- concept of threshold adaptation for adjustment of the classifier after classifier transfer
- presented work at conference (talk)
- wrote most parts of the abstract

## C.5 Workshop Contributions:

**1. (Kirchner et al., 2009) (published)** Kirchner, E. A., Metzen, J. H., Duchrow, T., Kim, S. K., and Kirchner, F. (2009). "Assisting Telemanipulation Operators via Real-Time Brain Reading." *In Lohweg, V. and Niggemann, O., editors, Proc. Mach. Learning in Real-time Applicat. Workshop 2009, number 3 in Lemgoer Schriftenreihe zur industriellen Informationstechnik*, Paderborn, Germany.

Contribution of the author of the thesis:

- analysis of the state of the art
- identification of relevant work
- design of experimental setup
- concept of online single-trial BR
- conducted experiments
- performed average ERP analysis
- contributed to statistical design
- wrote most parts of the paper

Contribution of the co-authors of this publication:

- supported experiments
- contributed to statistical design and conducted statistical analysis
- concept for ML framework

**2. (Kirchner and Drechsler, 2013b) (presented at work shop)** Kirchner, E. A. and Drechsler, R. (2013b). "Towards formalization of embedded brain reading." *In the International Conference on Design, Automation & Test in Europe (DATE 2013) - Workshop on Neuromorphic and Brain-Based Computing Systems (NeuComp 2013)*, Grenoble, France.

Contribution of the author of the thesis:

- developed formal model
- wrote abstract

- prepared poster

Contribution of the co-author of this publication:

- supported the development of the formal model by discussion of concept and preliminary results
- presented work at the workshop

# Acronyms

**A** adaptation

**acc** accuracy

**AD** analog-to-digital

**ADC** analog-to-digital conversion

**ANOVA** analysis of variance

**AUC** area under the receiver operating characteristic curve

**BA** balanced accuracy

**BCI** brain-computer interface

**BOLD** Blood-Oxygenation-Level-Dependent

**BP** Bereitschaftspotential

**BR** Brain Reading

**eBR** embedded Brain Reading

**C** supervision and correction

**CL** classifier

**CNV** contingent negative variation

**CSD** current source density

**CSP** common spatial pattern

**CPU** central processing unit

**DC** direct current

**DFKI** German Research Center for Artificial Intelligence

**ECG** electrocardiogram

**ECoG** electrocorticography

**EEG** electroencephalogram

**EMG** electromyogram

**EOG** electrooculogram

**ERP** event-related potential

**ErrP** error-related potential

**FFT** fast Fourier transform

**FM** free run

**FPGA** field programmable gate array

**fMRI** functional magnetic resonance imaging

**fNIRS** functional near-infrared spectroscopy

**GPU** graphics processing unit

**HMD** head mounted display

**HMI** human-machine interface

**IB** inferring future behavior

**ICA** independent component analysis

**IMMI** Intelligent Man-Machine Interface - Adaptive Brain-reading for Assistive Robotics

**ISI** inter stimulus interval

**LDA** linear discriminant analysis

**LRP** lateralized readiness potential

**MDP** modular toolkit for data processing

**MEG** magnetoencephalography

**MG** marker generation

**MI** mutual information

**ML** machine learning

**MP** motor potential

**MRCP** movement-related cortical potentials

**NS** negative slope

**OMS** operator monitoring system

**PC** position control

**PCA** principle component analysis

**PET** positron emission tomography

**PM** prospective memory

**PMP** pre-motion positivity

**PTS** position tracking system

**RP** readiness potential

**RIC** Robotics Innovation Center

**SD** standard deviation

**SE** standard error

**SF** spatial filter

**SMA** supplementary motor areas

**SP** signal processing

**SSVEP** steady state visually evoked potential

**SVM** support vector machine

**TCP** transmission control protocol

**VI-Bot** Virtual Immersion for holistic feedback control of semi-autonomous robots

**WS** window segmentation

**YAML** yet another multicolumn layout

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