Practical Brain Computer Interfacing

Diana Alexandra Valbuena Varon

Universität Bremen 2010

Practical Brain Computer Interfacing

Vom Fachbereich für Physik und Elektrotechnik
der Universität Bremen

zur Erlangung des akademischen Grades eines
Doktor-Ingenieur (Dr.-Ing.)
genehmigte Dissertation

von
Dipl.-Ing. Diana Alexandra Valbuena Varon
aus Ibague

Referent:	Prof. Dr.-Ing. A. Gräser
Korreferent:	Prof. Dr. rer. nat. habil. J. Peleska
Eingereicht am:	07.12.2010
Tag des Promotionskolloquiums:	14.06.2011

To Alvaro Alvira Rincón

Abstract

A brain-computer interface (BCI) is a communication system that enables users to voluntary send messages or commands without movement. The classical goal of BCI research is to support communication and control for users with impaired communication due to illness or injury. Typical BCI applications are the operation of computer cursors, spelling programs or external devices, such as wheelchairs, robots and neural prostheses. The user sends modulated information to the BCI by engaging in mental tasks that produce distinct brain patterns. The BCI acquires signals from the user's brain and translates them into suitable communication.

This dissertation aims to develop faster and more reliable non-invasive BCI communication based on the study of users learning process and their interaction with the BCI transducer. To date, BCI research has focused on the development of advanced pattern recognition and classification algorithms to improve accuracy and reliability of the classified patterns. However, even with optimal detection methods, successful BCI operation depends on the degree to which the users can voluntary modulate their brain signals. Therefore, learning to operate a BCI requires repeated practice with feedback that engages learning mechanisms in the brain. In this work, several aspects including signal processing techniques, feedback methods, experimental and training protocols, demographics, and applications were explored and investigated. Research was focused on two BCI paradigms, steady-state visual evoked potentials (SSVEP) and event-related (de-)synchronization (ERD/ERS). Signal processing algorithms for the detection of both brain patterns were applied and evaluated. A general application interface for BCI feedback tasks was developed to evaluate the practicability, reliability and acceptance of new feedback methods. The role of feedback and training was fully investigated on studies conducted with healthy subjects. The influence of demographics on BCIs was explored in two field studies with a large number of subjects. Results were supported through advanced statistical analysis. Furthermore, the BCI control was evaluated in a spelling application and a service robotic application. This dissertation demonstrates that BCIs can provide effective communication for most subjects. Presented results showed that improvements in the BCI transducer, training protocols, and feedback methods constituted the basis to achieve faster and more reliable BCI communication. Nevertheless, expert assistance is necessary for both initial configuration and daily operation, which reduces the practicability of BCIs for people who really need them.

Kurzfassung

Ein Brain Computer Interface (BCI) ist ein Kommunikationssystem, das Benutzern die Möglichkeit gibt, nach Belieben Nachrichten oder Befehle ohne Bewegung zu versenden. Das klassische Ziel der BCI-Forschungsarbeit ist die Unterstützung von Kommunikation und Kontrolle für Benutzer mit beeinträchtigter Kommunikation, die durch eine Krankheit oder Verletzung verursacht wurde. Typische BCI-Anwendungen sind die Kontrolle von Computer-Zeigern, Schreibprogrammen oder externen Geräten, wie z.B. Rollstühlen, Robotern und Neuroprothesen. Der Benutzer sendet dem BCI modulierte Informationen, indem er durch die Durchführung von mentalen Aufgaben bestimmte Gehirnwellen-Aktivitätsmuster erzeugt. Das BCI erfasst Gehirnsignale des Benutzers und setzt sie in passende Kommunikation um. Das Ziel dieser Dissertation ist die Entwicklung einer schnelleren und zuverlässigeren nicht-invasiven BCI-Kommunikation basierend auf der Erforschung des Lernprozess der Benutzer und deren Interaktion mit BCI-Transducern. Bislang hatte die BCI-Forschungsarbeit die Entwicklung verbesserter Mustererkennung und Klassifizierungsalgorithmen als Ziel. Trotzdem, sogar mit optimalen Detektierungsmethoden hängen erfolgreiche BCI-Operationen von den Möglichkeiten des Benutzers ab, mit denen er bewusst Gehirnsignale erzeugen kann. Deswegen ist es notwendig, um zu lernen, ein BCI effizient zu benutzen, wiederholt die Benutzung zu üben, was wiederum Lernprozesse im Gehirn anstößt. In dieser Arbeit wurden mehrere Aspekte, wie Signalverarbeitung, Feedback-Methoden, Experiment- und Trainings-Protokolle, Demographie und Anwendungen untersucht. Die Forschungsarbeit war dabei auf zwei BCI-Paradigmen ausgerichtet: ,,Steady-State Visual Evoked Potentials" (SSVEP) und ,,Event-Related (De-)Syncronization“ (ERD/ERS). Es wurden Signalverarbeitungsalgorithmen für die Erkennung der beiden Gerhirnwellen-Aktivitätsmuster angewendet und entwickelt. Außerdem wurde eine allgemeine Anwendungsschnittstelle für BCI-Feedback-Aufgaben entwickelt, um die Anwendbarkeit, Zuverlässigkeit und Akzeptanz von neuen Feedback-Methoden zu bewerten. Die Rolle von Feedback und Training wurde in diversen Studien mit gesunden Probanden untersucht. Der Einfluss von Demografie auf BCIs wurde zusätzlich in zwei Feldstudien mit einer großen Anzahl von Probanden erforscht. Die resultierenden Ergebnisse wurden durch fortschrittliche statistische Methoden gestützt. Zusätzlich wurde die BCI-Kontrolle in einer Schreib- und Service-Roboter-Anwendung untersucht. Diese Arbeit zeigt, dass BCIs für die meisten Benutzer eine effektive Kommu-

nikationsart bieten können. Die Ergebnisse zeigen, dass Verbesserungen im BCI-Transducer, in den Training-Protokollen und in den Feedback-Methoden die Basis bilden, um eine schnellere und zuverlässigere BCI-Kommunikation zu erlangen. Trotz aller positiven Ergebnisse ist noch eine Unterstützung durch Experten für die anfängliche Konfiguration und den täglichen Gebrauch zwingend erforderlich, was wiederum die Verwendbarkeit, für Menschen die wirklich BCIs benötigen, stark einschränkt.

Acknowledgments

This dissertation presents the results toward the development of an effective communication interface that connects the human brain with a computer to provide disabled users with communication and control, so called Brain Computer Interface (BCI). Over the last two decades, there has been a rapidly increase of laboratories that began to explore BCI technology. At the Institute of Automation (IAT) of the University of Bremen, BCI research started with the BRAINROBOT project in 2005.

I was first involved in the BCI field by absolving a student project at IAT in summer 2006. The project aimed to investigate the signals from the motor cortex for the control of computers and robots. In November 2006, I started working toward the doctoral degree in engineering with the project *Practical Brain Computer interfacing* under the supervision of Prof. Axel Gräser, head of the Institute of Automation, University of Bremen. In 2007, we had the opportunity to present our research work at the International Conference on Rehabilitation Robotics IEEE/ICORR, where our team got the prize for the best interactive presentation with the demonstration of the care-giving robot FRIEND-II controlled via BCI. This work is presented in chapter 4. At the Colloquium of Automation, I presented the results of chapter 3 (2007 and 2010), 5 (2008), and chapter 7 (2009). In 2008, at the International BCI Workshop and Training Course in Graz, Austria, part of the results of chapters 5 and 6 were disseminated. Later, this work was published by the IEEE Transactions on Neural Systems and Rehabilitation Engineering in April 2010. In the same year, the BRAINROBOT book was published, a collection with our most representative research from 2006 to 2009. As tutor, I was involved in the Robotics I, Process Automation II, and Brain Computer Interfaces lectures.

The studies in chapters 3, 4, 7, and 8 were accomplished in the Brain Computer Interfaces Laboratory at the IAT, University of Bremen. The experimental demonstrations at the international fairs CeBIT and RehaCare in 2008 were supported by a Marie Curie European Transfer of Knowledge grant BRAINROBOT. Data from BCI-inexperienced users recorded at both exhibitions were used for statistical analyses in chapter 6. The CeBIT team was composed by B. Allison, A. Brindusescu, H. Cecotti, T. Lüth, A. Moltsaar, I. Sapto-Condro, M. A. Spiegel, K. Stenzel, I. Sugiarto, A. Teymourian, D. Valbuena, I. Volosyak; and the RehaCare team by H. Cecotti, T. Lüth, K. Stenzel, D. Valbuena and I. Volosyak.

The work presented in chapter 4 was possible thanks to the active cooperation with colleagues of the AMaRob project, specially Marco Cyriacks. The Minimum Energy Combination algorithm was developed by Ola Friman. This algorithm was used for spatial filtering in chapters 4, 6, 7, and 8, and was continuously improved in our research group during the last years. Jan Ehlers was very helpful by coordinating the participation of the subjects in the study presented in chapter 7 and Tatsiana Malechka by the data collection during the training sessions in chapter 3. The Matlab function used for online ERD/ERS detection was developed by colleagues of the University of Warsaw within the European Community's Seventh Framework Programme under grant BRAIN.

Many thanks to my former colleagues Ola Friman and Brendan Allison for their support and collaboration during their stay at IAT, my colleagues Thorsten Lüth and Jan Ehlers for the support and cooperation along those years working together. I would like to thank my supervisor Prof. Axel Gräser for his support and giving me the opportunity to be part of the BCI research group at IAT, and Prof. Jan Peleska for accepting to be my second supervisor. Finally, I would like to thank my husband Johannes Feuser for his patience and incessant support.

Diana Valbuena
Bremen, Germany, 2010

Contents

1. Introduction

Many people in the world are unable to effectively interact with other people or operate assistive devices and communication technologies due to disabilities and functional impairments. Persons with amyotrophic lateral sclerosis (ALS), cerebral palsy, multiple sclerosis, traumatic brain injuries, spinal cord injury, and stroke are examples of groups that need a new communication channel to interact with the world [1]. When suffering from one of that diseases, people may lose control of their motor functions, and, therewith, the brain's normal communication channels. Most of these people would like to be able to communicate, but require an interface that does not rely on their impaired movement ability. They cannot use conventional interfaces, such as keyboards, mice or other interfaces that require greater muscular control. Alternative systems for less disabled users rely on eye-gaze shifting, electromyographic (EMG) activity and respiration [2]. Those most severely affected users may be completely locked in to their bodies and are unable to communicate in any way, they require a system that provides the brain with a new non-muscular communication and control channel. Brain computer interface (BCI) systems could address this need, since BCIs allow communication and control without requiring limb articulation nor any movement from the user [1]. The normal communication channels, such as speech and movement, are not used, but instead brain activity is directly recorded and transformed into control signals.

In the last years, BCI research have demonstrated proof of concept with healthy users in laboratory settings [3] and with severely disabled users in home environments assisted by scientific researchers [4, 5]. New BCI applications have been validated, such as wheelchair control [6, 7], electrical hand prosthesis control for the restoration of the grasp function [8], virtual smart home environment control [9] and control of assistive devices (e.g., the FRIEND-II system at the IAT lab [10, 11]). BCIs have been proven useful as communication systems for broader user groups than previously recognized [12–14]. BCI have been validated as tools for stroke [15, 16] and autism rehabilitation [17]. New software tools have greatly reduced the time and inconvenience of developing and testing new BCI signal processing methods [18]. However, BCI systems are still predominantly inflexible (long EEG preparation times are needed and unpleasant electrolytic gel is used), difficult to use (they require high mental load and concentration), unreliable (mostly less than 100% accuracy is achieved), and crucially unavailable to nearly all people who need them (high hardware costs and expert personal is re-

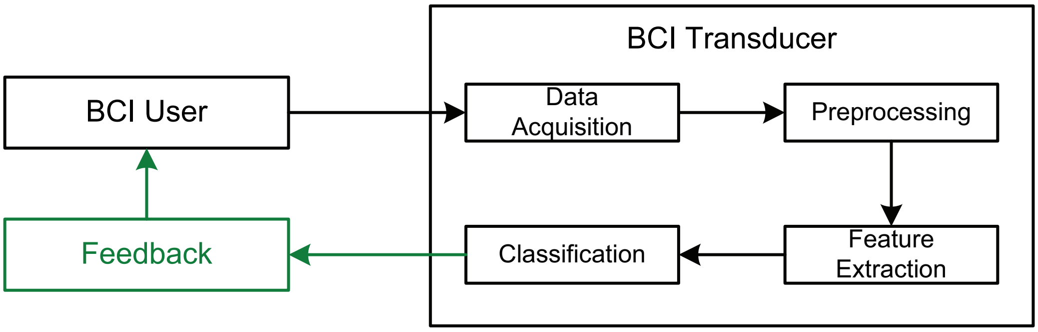


Figure 1.1.: Block diagram of a BCI as a real-time closed-loop system.

quired for initial configuration and operation). At their actual state, BCIs are research tools with limited practical function that might only be useful to some people with very severe physical disabilities [19]. Further BCI research aims to built more practical BCIs for much larger populations, i.e., systems that can easily identify and adapt to the needs, desires, and abilities of each individual user and operate effectively each day with little or no expert assistance.

The objective of this dissertation is to develop faster and more reliable non-invasive BCI communication based on the study of users learning process and their interaction with the BCI transducer using appropriate *feedback* methods. The hypothesis is that, when persons are trained with real-time feedback, they will generate more stable signals, and in this way the BCI control will be more reliable. Fig 1.1 shows a block diagram that explains BCI communication. A complete BCI system is a real-time closed-loop system that consists of three main components. The *BCI user* voluntarily modulates information and generates specific brain patterns by engaging in mental tasks (e.g., focusing attention to an oscillating stimulus or imaging movement of the hands). The *BCI transducer* acquires signals from the user's brain and translates them into suitable communication using efficient preprocessing, feature extraction and classification methods. The *feedback* provides information of the correct or incorrect response of the BCI and can be discrete or continuous, one- or more-dimensional, real or virtual, visual, auditory, or tactile. Successful BCI operation depends on how the BCI user and the system interact with each other. The link between both components is the user feedback to support the learning process.

The main contributions of this dissertation toward the development of more *Practical Brain Computer Interfacing* by focusing on the study of the BCI user with the analysis of the user's learning process and demographics research; the BCI transducer with evaluation of different signal processing methods; and the feedback with the implementation and evaluation of different feedback applications, are:

1. *Crucial parameters for the detection of the ERD/ERS brain patterns were identified and the relevance of feedback and training was investigated.* The event-related (de-)synchronization (ERD/ERS) paradigm is one of the most interesting strategies used for non-invasive BCIs because it requires no external stimulation and constitutes an endogenous BCI. However, effective endogenous BCI operation requires advanced signal processing tools that extract specific brain patterns from background noise and the user must learn to voluntarily modulate his/her brain signals. Chapter 3 presents the results obtained from two studies: An exploratory study that employs different existing signal processing tools to extract subject-dependent signal properties in the time, frequency and spatial domain from recorded EEG data from six healthy subjects; and a single-case study that investigates the learning effects of ERD/ERS training over several sessions. Both studies contributed to demonstrate online ERD/ERS control using three mental states (imagination of right hand, left hand and feet) on a virtual labyrinth application. 91.3% accuracy and 8.62 bit/min for a well trained subject after 12 sessions were achieved.

2. *A new application in the service robotics was validated.* Intelligent wheelchair mounted manipulators FRIEND-I/-II are being developed at the Institute of Automation, University of Bremen, since 1997 [20]. They were designed as assistive devices to support persons with disabilities in daily life activities as well as in working environments. The human-machine interface (HMI) of the FRIEND-II used a speech recognition system and a chin joystick as input devices. This excluded a wide spectrum of users with severe disabilities which could benefit from the system. The control via an steady-state visual evoked potential (SSVEP) based BCI was conceived as an opportunity to extend the range of users of the FRIEND-II system. The feasibility of controlling the FRIEND-II via BCI by focusing attention on four flickering lights was investigated on seven healthy subjects (see chapter 4). The user's task was to execute a predefined sequence of 10 commands to select high-level robot tasks from a menu system, such as pouring a liquid into a glass. Results demonstrated that goal-oriented control with a BCI is possible and that intelligent systems could compensate the unreliability of the BCI. The classification accuracy of the BCI was 96% in a group of five persons. Two subjects did not attain effective control of the system due to poor SSVEP performance.

3. *A general software framework for the evaluation of BCI feedback methods was developed and used to conduct several BCI studies.* Chapter 5 presents the design and implementation of a general software framework that enables

fast implementation of new BCI feedback tasks. The framework provides a set of cooperating classes that can be used to build applications that require appealing visual display, real-time feedback presentation, multiple frequency generation, presentation of sequences of stimuli, acquisition of BCI control signals and measurement of BCI performance. The result of this work was the successful implementation of two BCI feedback tasks: The speller task was used to investigate the effects of different kinds of SSVEP feedback on BCI performance and to evaluate SSVEP communication (see chapters 6, 7 and 8); and the labyrinth task was used to provide visual feedback for ERD/ERS BCIs (see chapter 3).

4. *The influence of subjects demographics on BCI performance in two field studies was investigated.* One of the most consistent observations in the BCI literature is considerable inter-subject variability, that often leads to the well-documented "BCI illiteracy" phenomenon (about 10–25% of users are unable to attain effective control) [21]. Chapter 6 investigates the causes of inter-subject variability and BCI illiteracy by analyzing data recorded in two field studies with a large number of test subjects. Results of both studies showed that most subjects, despite having no prior BCI experience, could use the Bremen SSVEP BCI system in a very noisy field setting. Performance data suggest that SSVEP BCIs may be better suited to younger and/or female subjects, though these trends did not attain statistical significance. Mean information transfer rate (ITR) was about the same for healthy subjects versus subjects with disabilities.

5. *The role of feedback and training for SSVEP-based BCIs was investigated.* Several articles have been argued that SSVEP BCIs generally require no training or just need a short training session to determine optimal parameters. This work supported the hypothesis that subjects can be trained to perform better on visual attention tasks and that feedback reflecting brain activity might improve performance. Chapter 7 presents the results of an SSVEP feedback study that uses feedback to train users to control a virtual keyboard. This study compares performance of two groups of subjects, one group that received only the discrete output of the BCI, and another group that additionally received real-time feedback of their SSVEP signals. Results proved that training with SSVEP causes positive effects on subjects and indicated that the type of feedback (continuous vs. discrete) exerts a measurable effect on the subject's performance, though continuous feedback requires more initial training than discrete feedback.

6. *Effective SSVEP BCI communication was validated.* Chapter 8 presents an SSVEP BCI that provides high information transfer rates. Effective SSVEP

> BCI communication was demonstrated in a study conducted on 27 subjects. Presented results demonstrated that improvements in the BCI transducer and the user feedback constituted the basis for achieving a mean ITR of about 50 bit/min. Also, BCI illiteracy could be reduced.

This dissertation is organized as follows: First, an overview related to basic concepts in present-day BCIs is presented in chapter 2. This comprises the definition of a BCI, its operation explained through four basic components: signal acquisition, signal processing, output devices and operating protocol; typical measures of BCI performance: accuracy and information transfer rate (ITR); and the three most effective approaches among non-invasive BCIs (SSVEP, P300 and ERD/ERS). The following chapters present materials and methods, results, discussion and conclusions of the studies mentioned above. Finally, chapter 9 summarizes major findings of this dissertation and points out future directions of research.

2. Present-Day BCIs

This chapter gives an overview of non-invasive brain-computer interfaces (BCI) and offers an introduction to an exciting and active field of research. In particular, this chapter starts with the definition of the term brain-computer interface and describes the process to translate brain signals into device commands through the components of a BCI: signal acquisition, signal processing, output devices and operating protocol. Furthermore, the measures of BCI performance are explained and finally the most effective approaches among non-invasive BCIs are presented.

2.1. Definition of a BCI

BCI research was pioneered by Dr. Jacques Vidal, Director of the Brain-Computer Interface Laboratory at the University of California, in the early 1970's. One of the results was the first successful attempt to include brain signals into human-computer communication. *Vidal* attempted to clarify the definition of direct brain-computer communication and established their possibilities and limitations [22]. Later, he presented a communication channel with what a human could control the movement of a cursor in four directions using visual evoked potentials [23].

The definition of the term BCI was given in 1999 during the first international meeting on BCI research and development [24]: "A brain-computer interface is a communication system that does not depend on the brain's normal output pathways of peripheral nerves and muscles." Brain computer interfaces allow users to communicate without movement. Instead, direct measures of brain activity are translated into messages or commands. BCI systems were initially developed in laboratory settings, and have begun providing communication to people who could not otherwise communicate due to severe motor disabilities [1, 4, 15].

BCI research is based on the development of complete systems that can provide communication and control by directly acquiring information from the brain and using it to perform actions operated by the user. This a real-time closed-loop system which involves feedback to the user [25]. The most heavily cited BCI review (Wolpaw *et al.*, 2002) describes the four main components of any BCI system. Like other communication and control systems, a BCI has an input, which is the brain activity from the user; an output, which are the commands to control computers or external devices; algorithms that translate the input into the output; and a protocol that governs how these components interact [1]. This process is

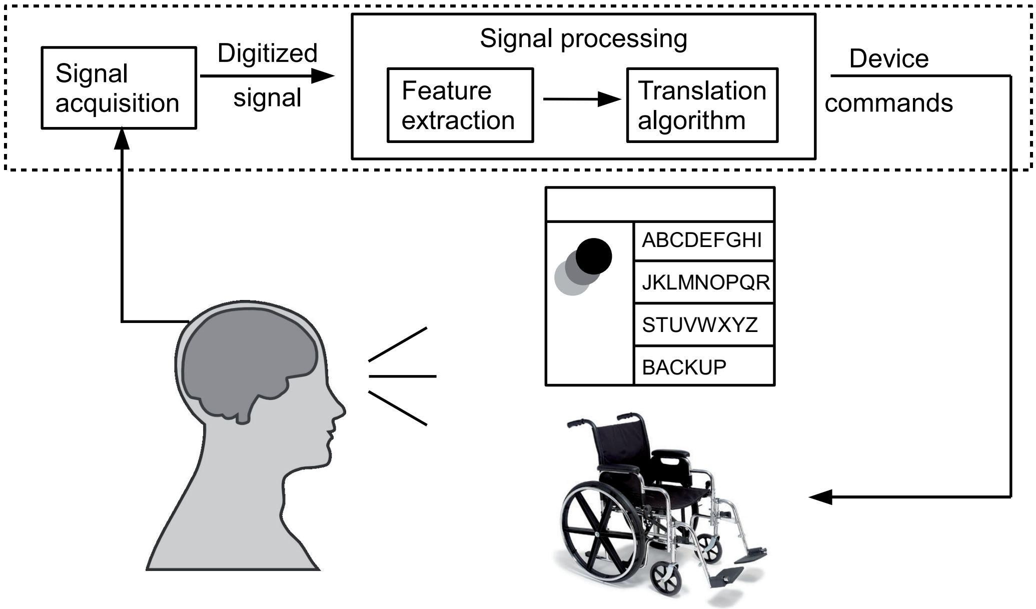


Figure 2.1.: The basic components of a brain-computer interface system. Reproduced from [2].

described through four components: signal acquisition, signal processing, output and operating protocol [1, 2]. Fig. 2.1 shows the basic design of any BCI system. The state-of-the-art of each of these components is reviewed in below. In summary, significant advances have occurred recently within the signal processing and operating protocol components [26]. Research has shown that subject performance may change dramatically with different BCI approaches (P300, ERD/ERS, SSVEP), and specific stimulus, signal processing, and feedback parameters within each approach. Within the signal acquisition and application components of BCIs, only minor to modest progress has been seen in recent years, and the greatest needs are simpler, more convenient sensors and greater application flexibility.

2.2. BCI Signal Acquisition

A variety of sensor modalities can detect brain activity [27]. While most BCI systems use electrical signals produced by the brain activity to derive user intent, a variety of magnetic or metabolic signals could be also used to drive a BCI [28]. Depending on the recording method to acquire electrical brain signals, BCIs can be invasive or non-invasive [2]. BCIs that do not require surgery to implant electrodes are termed non-invasive. BCIs that acquire signals from electrodes implanted in the brain or lying on the surface of the cortex are considered to be invasive. In general, there exist three recording alternatives depending of the grade of invasiveness of the recording system. BCI recording systems based on electrophysiological signals can be classified in noninvasive, cortical surface, and intracortical recording devices. Each method has advantages and disadvantages. Electroencephalography (EEG) [29] measures electrical signals from electrodes placed on the surface of the scalp. EEG recording is easy and noninvasive, but at the same time, it has relatively limited topographical resolution and frequency range. Also, EEG is susceptible to power line interference and other artifacts like electromyographic (EMG) signals or electrooculographic (EOG) activity [27]. Invasive methods are electrocorticography (ECoG), with electrodes on the surface of the dura or the surface of the brain or with microelectrodes implanted in the cortex or elsewhere in the brain [2]. At present, almost all non-invasive BCI communication rely on the EEG to measure brain activity (over 80% of BCI publications describe BCIs that use electrical signals recorded from the surface of the scalp [30]).

Methods for recording brain signals with sensors that are not in contact with the body are functional magnetic resonance imaging (fMRI), positron emission tomography (PET) or magnetoencephalography (MEG). Near-infrared spectroscopy (NIRS), functional near-infrared (fNIR) imaging measure changes in the brain's hemodynamic response. fMRI or NIRS provide good spatial resolution, but have poor temporal resolution. In addition, fMRI, MEG and PET are not currently suited for everyday use due to their technical demands, high expense, and/or limited real-time capabilities. MEG measures brain magnetic activity, might provide real-time control with excellent spatial and temporal resolution, but is expensive and impractical [26].

2.2.1. EEG Recording Systems

EEG recording systems provide the possibility to store and display information about brain current sources. The goal is to amplify potential differences between pairs of electrodes placed on the scalp such that the output voltage is proportional to scalp potentials generated within the body [31].

The recorded signals are the contribution of brain sources and any other current sources in the body (e.g., electrocardiogram, muscles, tongue, and eye movements) that produce scalp potential differences in frequency bands that overlap the EEG. All other signals different to brain sources are biological artifacts that can never be completely eliminated by amplifiers and filters. The amplifier-filter system can not distinguish artifacts from brain sources. Rejection of artifacts is accomplished by visual inspection or computer analysis, as it will be explained later in the signal processing section. Fig. 2.2 shows a simple schematic diagram of a typical EEG recording system. An EEG channel requires one electrode singled out as

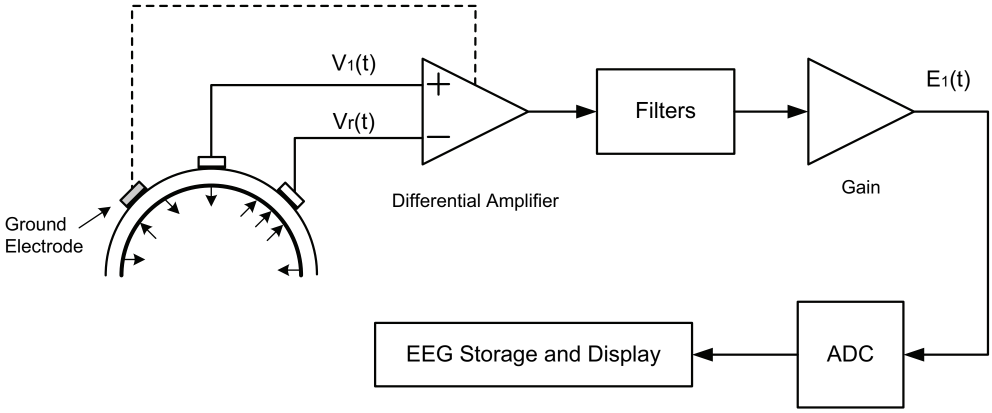


Figure 2.2.: The basic design of a typical EEG recording system. Modified from [31].

the reference electrode, one as the ground electrode, and all remaining electrodes are characterized as recording electrodes. Scalp signals acquired by a recording electrode $V_n(t)$ and the reference electrode $V_r(t)$ are passed through a differential amplifier. Electrode pairs are always require to measure scalp potentials because such recording depends on current passing through a measuring circuit. The ground electrode is connected to the internal ground of the differential amplifier, which is isolated from the power line ground. The measured signal is then filtered by a set of analog filters to reject artifacts. Low-pass filters typically remove frequency noise above 50 Hz to 100 Hz and high-pass filters remove frequencies below 0.5 Hz. A notch filter may or may not be used to remove power line interference (50 Hz in Europe). The output voltage proportional to scalp potential differences is

$$E_n(t) \cong A[V_n(t) - V_r(t)]; \quad n = 1, N \tag{2.1}$$

where A is the total system gain and N is the total number of recording channels with respect to one fixed location, the reference electrode. The scalp potential is substantially amplified and then pass through an analog-digital converter (ADC). The analog signal from each channel is sampled and numbers are assigned proportional to the amplitude of the waveform, as follows

$$E_n(k) \quad = \quad E_n(kT); \quad k = 1, 2, 3, \ldots \tag{2.2}$$

where $T = \frac{1}{f_{dig}}$ is the sampling period and indicates the time between samples and f_{dig} is the digitization rate or sampling rate (samples per second). The sampling rate is selected to avoid the misrepresentation of the recorded signal, that is without aliasing. The criterion for digitization used in time series acquisition is the Nyquist criterion

$$f_{dig} > 2f_{max} \tag{2.3}$$

where f_{max} is the highest frequency present in the EEG signal. EEG waveforms may then be displayed on the computer screen and stored for additional processing. In BCIs, EEG signals are acquired and processed in real-time to control external devices.

2.3. BCI Signal Processing

Once the signals are acquired, the signal processing unit extracts signal features and translates them into messages or commands. For BCI use the interesting signals are those that reflect the user's intentions, all other components are categorized as noise. The aim of this unit is to improve the spatial resolution and signal-to-noise ratio (SNR) of the recorded signals and then transform them into control signals. The signal processing has two parts: feature extraction and translation algorithm.

2.3.1. Spectral Filtering

The goal of the feature extraction is to analyze properties of the signals and isolate the features of interest that encode the user's intent. These features can be depending on the paradigm restricted to some frequency bands. A common approach is the use of digital frequency filters, such as finite and infinite impulse response filters, or for temporal filtering the Fourier-based filtering [32].

2.3.2. Spatial Filtering

Due to physical limits in spatial resolution of surface EEG, the discrimination of nearby located cortical areas represents a challenging problem for data analysis. Each single electrode acquires superposed data from within a certain neighborhood radius, where many originally different signals are superimposed. Therefore, spatial filtering techniques are required to get more localized signals. A spatial filter is a vector of weights specifying a linear combination of sensor outputs. The most common strategies for spatial filtering [32] used in BCI are bipolar filtering, common average reference (CAR), laplacian filtering, common spatial patterns (CSP), principal component analysis (PCA) and a more sophisticated one, independent component analysis (ICA).

The bipolar approach is a strategy to obtain a cleaner signal by canceling common nuisance signals. In practice, nuisance signals are strong and present in all electrodes. EEG data are measured with respect to a fixed reference using monopolar amplification, and later converted to bipolar recording digitally. Bipolar recordings are calculated as the voltage difference of two electrodes that are sufficiently close (1 to 3 cm) together. Typically, it offers much better spatial resolution than conventional reference recording.

The Laplace filtering is a practical and easily method to improve spatial resolution in EEG recorded with a small number of electrodes. The first method was first suggested by Hjorth (1975) [33]. The Laplace filter is estimated by averaging potential differences between a central electrode location and four surrounding electrodes. This filter eliminates volume conducted signals from distant regions and removes reference electrodes effects.

Common spatial pattern and its extensions are techniques to analyze multichannel data based on recordings from two classes (conditions) [34]. It allows to determine spatial filters that maximize the variance of signals of one condition and at the same time minimize the variance of signals of another condition.

2.3.3. Classification

The translation algorithm is basically a classifier that maps the input signals to classes in which each class corresponds with a control command. The most used classification algorithms used in BCI research are linear classifiers, neural networks, nonlinear Bayesian classifiers and nearest neighbor classifiers. Linear classifiers such as linear discriminant analysis (LDA) and support vector machines (SVM) are the most popular algorithms for BCI applications. They use linear functions to distinguish classes. The most widely neural network used for BCI is the multilayer perceptron (MLP). Classifiers that produce nonlinear decision boundaries are Bayes quadratic and hidden Markov model (HMM). Nearest neighbor classifiers consist in assigning a feature vector to a class according to its nearest neighbor(s), e.g., a feature vector from the training set (k nearest neighbors) or a class prototype (Mahalanobis distance). Both kinds of classifiers are discriminative nonlinear. BCI classification is achieved using a single classifier but the combination of several classifiers aggregated in different ways (boosting, voting or stacking) have been used as well. A complete review that presents the classification methods mentioned above and describes their critical properties can be found in [35].

2.4. BCI Output Devices

A BCI is primarily used to control assistive devices for people with severe motor impairments. After the brain signals have been extracted and translated into appropriate output classes, they can be used to drive a variety of output devices. BCIs have an extensive range of possible practical applications. The computer monitor is to date the most commonly used output device for a BCI. Most classic monitor-based applications are letter selection or cursor control, which are used for basic word-processing programs, sending e-mails, selecting items from a menu, accessing the Internet, or navigating a virtual environment. Other simple applications include managing basic environmental control, adjusting a television, or opening and closing a hand orthosis. More complex BCI applications include systems that require multidimensional control, e.g. wheelchairs, robotic arms, or neuroprostheses [8]. Intelligent devices that can compensate the unreliability of the BCI control signals are emerging applications. Also, neurofeedback tools, where the focus is not communication and control, but primarily to facilitate effective regulation and reorganization of brain structures, have recently been validated as therapy for stroke, autism, attention deficit hyperactivity disorder (ADHD), and other disorders [14, 15, 17, 36].

2.4.1. BCI-Driven Spelling Devices

Since the principal goal of a BCI is to provide means of communication and control for severely disabled people [1], BCI driven spelling devices are an important topic in BCI research. Several spelling devices controlled by a non invasive BCI system have been developed in the last years. They differentiate basically in the BCI approach, the number of commands and the selection strategy used. The first BCI spelling application was based on the P300 signal pattern [37]. The alphabet is typically arranged in a 6 by 6 matrix where each of the 36 cells contains a letter or a symbol. The characters in each row and column are randomly flashed and a P300 response is evoked every time the target letter is highlighted. Thus, in one trial of 12 flashes (6 rows and 6 columns), the target cell will flash only twice, a P300 is elicited for the row and other for the column. A number of other brain signals have since been successfully utilized for spelling. The system developed by the Tübingen group is based on binary decisions of the BCI [38]. The alphabet is split into two halves (letter banks) presented at the bottom of the screen. The user selects a letter bank by producing a Slow Cortical Potential (SCP), which is then split into two new halves. This procedure continues until each of the two letter banks had only one letter in it. When one of the final letters is selected, it is displayed in the top of the screen and the initial letter banks are shown again for a new selection. This system is know as the Thought Translation Device (TTD) and have been tested in lock-in patients demonstrating the usefulness of the device as an alternative communication channel [39, 40]. In two other studies that used a similar selection strategy but a different BCI approach, patients used motor imagery to modulate ERD and ERS changes. An ALS patient [41] and a patient suffering from severe cerebral palsy [42] learned to operate a virtual keyboard spelling application.

Another system based on binary decisions is the Hex-o-Spell developed by the Berlin group [43], which incorporates principles of Human-Computer Interaction into BCI feedback design. The mental text entry system Hex-o-Spell is controlled by the Berlin Brain Computer Interface (BBCI), which operates on spatio-temporal changes during different kinds of motor imagery [44, 45]. The Hex-o-Spell was designed to map a small number of BCI control states to a high number of symbols, it is controlled by two mental states (imagined right hand movement and imagined right foot movement). The Hex-o-Spell consist of six hexagonal fields surrounding a circle. By imagination of right hand movement, an arrow located in the center of the circle starts moving clockwise. An imagined foot movement stops the rotation and the arrow starts extending. If imagination continues, the arrow reaches the hexagon and selects it. The five symbols of the selected hexagon split into the individual hexagons. The arrow is then reset to its minimal length while maintaining it original direction. The same procedure is repeated to select a symbol. Splitting the alphabet into more that two parts might increase the information transfer rate. This approach is presented in [46], where the virtual keyboard is divided in three blocks (in a matrix of 3 rows by 9 columns), each associated to one motor imagery task. When a mental task is classified, the corresponding block split in three smaller blocks until a letter is selected. The process of writing a single letter requires always three commands. An asynchronously controlled three-class spelling device operated by motor imagery is proposed in [47]. Letters were arranged alphabetically on two moving vertical lines on the left and right half of the screen. Five items were visible on each side. By foot motor imagery the items scrolled from the bottom to the top of the screen.

2.5. Operating Protocol

The operating protocol [1,2] defines the real-time interactions between the user and the BCI system and governs how the other three components (signal acquisition, signal processing and application) interact with each other. It also determines the nature and timing of stimulus presentation, what selections are available to the user, details of user-system interaction, menu style, if the BCI is synchronous or asynchronous, and the type of mental strategy or approach used for control. Operating protocols must manage other details such as the type, location, and timing of feedback.

2.6. Measures of BCI Performance

The performance of a BCI system can be influenced by several factors: experimental paradigm, operating protocol, brain patterns, selected features, type of classifier, application, feedback presentation, etc. To compare different BCI systems, it is necessary to define consistent evaluation criteria.

2.6.1. The Confusion Matrix

The confusion matrix [48] describes the results of a classification problem by showing the relationship between the true classes (desired output) and the predicted classes (output of the classifier). The elements of the confusion matrix are denoted by n_{ij} and each element indicates how many samples of class i have been classified or predicted as class j. The number of correct classifications are represented by the diagonal elements n_{ii}, and the off-diagonal n_{ij} represents the number of incorrectly classified samples.

2.6.2. Classification Accuracy and Error Rate

The classification accuracy (ACC) and error rate (ERR) are the most popular measures of performance in BCI research [48]. Accuracy is easily to calculate and interpret by using the following formula:

$$ACC = p_o = \frac{\sum_{i=1}^{M} n_{ii}}{\sum_{i=1}^{M} \sum_{j=1}^{M} n_{ij}}. \tag{2.4}$$

The maximum accuracy that can be achieved is 1.0 (100%), which makes difficult to compare systems that are close to this limit. Another limitation of this measure is that the off-diagonal of the confusion matrix is not considered and all classes have the same weight. Chance accuracy is already $100/N$. For example, for a BCI that discriminates between two classes, 50% of the trials are correct just by chance. The error rate is defined as $1 - ACC$.

2.6.3. Information Transfer Rate

BCI systems differ greatly in their inputs, translation algorithms, outputs, and other characteristics and thus they are often difficult to compare. A standard performance measure was introduced by Wolpaw *et. al.*, (1998) to follow BCI development [49]. This general purpose benchmark is the information transfer rate (ITR). As derived from Pierce (and originally from Shannon and Weaver [50]), the bit rate for a communication system is the amount of information communicated per unit time [1]. This measure incorporates speed and accuracy in a single value and is calculated by,

$$B = \log_2 N + P \log_2 P + (1 - P) \log_2 \left[\frac{1 - P}{N - 1}\right], \tag{2.5}$$

where P is the classification accuracy and N is the number of targets.

2.7. Brain Patterns for EEG-based BCIs

Evoked potentials (EP), event-related potentials (ERP) and event-related changes measured on the scalp may be used as brain patterns for a BCI. Averaged evoked potentials are associated with specific sensory stimuli like repeated light flashes, auditory tones, finger pressure, or mild electric shocks. Single-stimulus waveforms are typically averaged to remove the spontaneous EEG. The number of stimuli required to produce an averaged evoked potential may be between ten and thousand, depending on the application. Event-related potentials normally occur at longer latencies from the stimuli and are associated with endogenous brain state. Most BCIs rely on either selective attention or motor imagery [51]. Commonly used brain patterns for non-invasive BCIs are the SSVEP (steady state visually evoked potential), the P300 (the 300-ms component of an evoked potential), and ERD/ERS (event-related desynchronization and synchronization). In a selective attention task, the user focuses attention on a particular stimulus. If the stimulus is presented in a constant face pace, SSVEP activity is produced at corresponding frequencies. Less frequent flashes may produce a P300 [52]. The P300 is a positive deflection in the evoked potential that typically develops about 300 ms after the eliciting stimulus. BCIs based on sensorimotor rhythms (SMR) can detect activity changes when a person imagines or performs a movement. Imagination of different movements produce ERD/ERS changes that convey user intentions [53]. When building a BCI, it is important to select the pattern according to the subjects capabilities (some tasks may be inappropriate for certain groups of subjects). For example, motor imagery may be difficult for a person who has been paralyzed for many years, or, indeed from birth. Visual tasks would probably be inappropriate for some visually impaired people, such as those who have been totally blind since birth [54]. Fig. 2.3 shows the mental strategies and brain patterns used in BCIs. These three approaches are explain in more detail in the following sections.

2.7.1. Steady-state Visually Evoked Potentials

Electrical potential changes in the brain following the presentation of a visual stimulus are known as visual evoked potentials (VEP). When the stimulus is presented in a constant fast pace (> 5 Hz [55]), resonance in the neuronal firing in the visual cortex of the brain will arise [56]. This phenomenon is called Steady-State Visually Evoked Potentials (SSVEP) [57]. Steady-state visual evoked potentials are responses elicited when cortical neurons of the visual cortex synchronize with the presentation of a periodic external stimulus. The brain response can be measured in a narrow frequency band containing the stimulus frequency. Flickering lights at different frequencies are usually used as stimuli. The frequency of the evoked SSVEP response matches that of the flickering stimulus exactly [58]. It

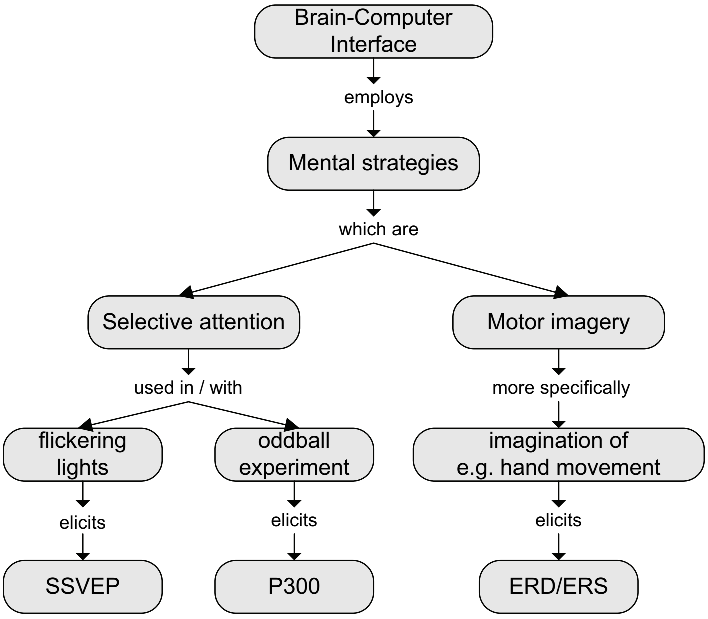


Figure 2.3.: Mental strategies used to control a brain-computer interface.

is possible to get an SSVEP response with a larger number of frequencies, from 1Hz to 100Hz [59]. SSVEP responses with maximum amplitude are obtained in three frequency bands: 5–12Hz (low), 12–25Hz (medium) and 30–50hz (high) [57]. However, the best responses are obtained for stimulation frequencies between 5 and 20 Hz [60].

The characteristic of the SSVEP response differs from the spontaneous activity of the brain and it can therefore be robustly detected. Signal processing approaches to isolate SSVEPs were pioneered by Regan (1989) [57], making use of the Fourier Analysis. Fig. 2.4 shows the spectra of an EEG signal from the visual cortex when a test person is looking at a light emitting diode (LED) flickering with 5, 7 and 9 Hz respectively. As can be seen, there are not only peaks at the stimulation frequencies, but also at the harmonic frequencies at 10, 14 and 18 Hz. Recent studies have been used the SSVEP phenomenon to build brain-computer interface (BCI) systems [55, 58, 61–70]. An SSVEP-based BCI translates brain activity patterns into control commands requiring the visual attention of the user. To elicit SSVEP patterns, an external stimulation is required with targets that flicker at different frequencies. Each target will produce a distinct SSVEP pattern. Hence, by analyzing the frequency content of the EEG signals, it is possible to infer the user's intent. With these systems, humans intentionally modulate their brain signals and their intentions can be mapped into interaction commands (e.g.,

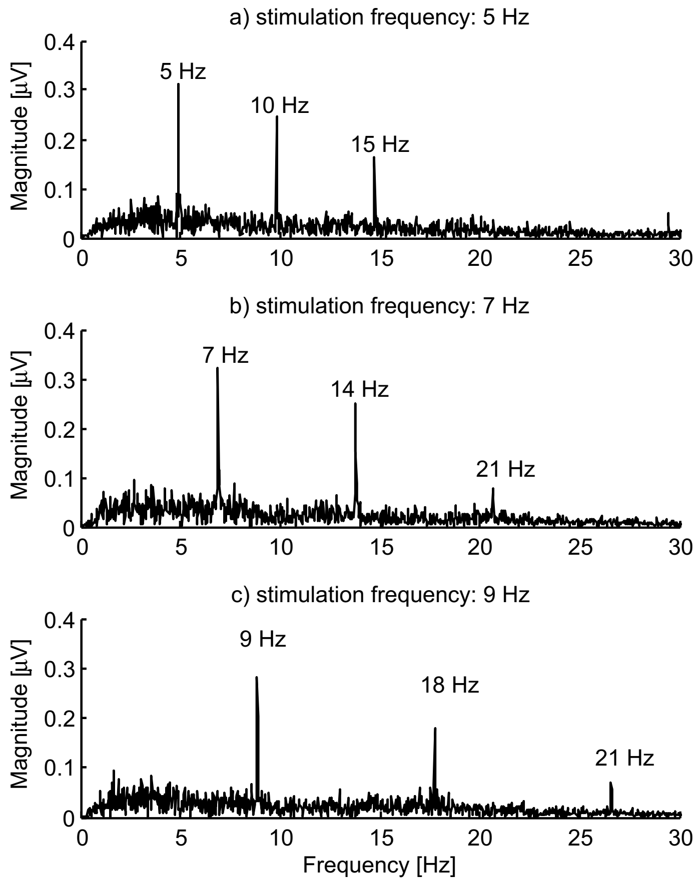
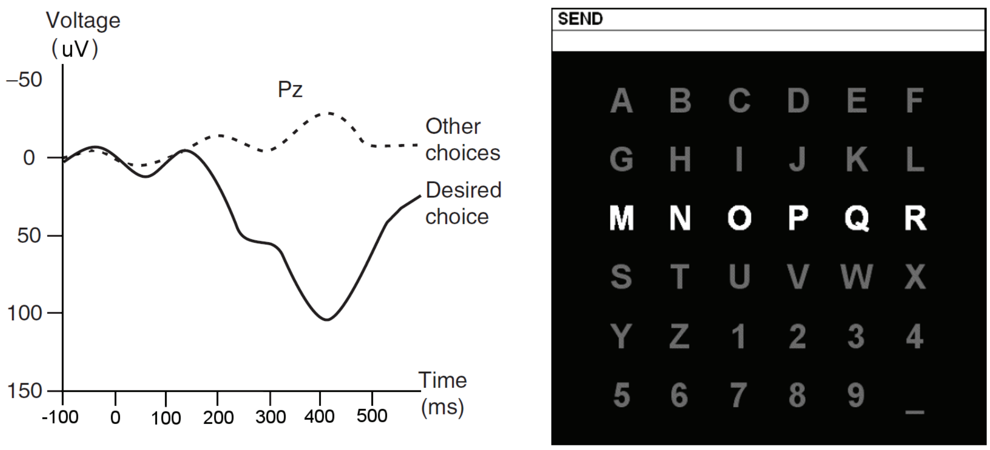


Figure 2.4.: SSVEP responses of an EEG signal acquired during visual stimulation with a light source flickering at 5 Hz, 7 Hz and 9 Hz.



(a) (b)

Figure 2.5.: P300 component of an event-related brain potential and a matrix of possible selections.

move a cursor, click buttons, control external devices or computer-based applications). This ability to interact between the user and the outside world through a BCI system has a high impact for subjects with reduced or non muscular capabilities. These interactions can substitute the brain's normal neuromuscular interactions or even augment them, establishing a new non-muscular possibility for communication and control [71].

The SSVEP approach provides up to date the fastest and most reliable communication paradigm for the implementation of a non-invasive BCI system. The performance of the BCI can be assessed as the information transfer rate (ITR) as discussed in [1] and reported in several studies. This measure depends of factors, such as, speed, accuracy and number of targets, which can variate from two [61, 63, 64] up to 48 [55]. In a six target SSVEP-based BCI, an average accuracy of 95.3% and an information transfer rates of 58 ± 9.6 bit/min for 12 healthy participants were reported [69]. Other studies have reported classification accuracy of more than 90% [64–66]. Using a the code based SSVEP modulation technique, where pseudorandom sequences are presented to the user, a mean ITR value of 92.8 ± 14.1 bit/min for ten subjects was reported [72].

2.7.2. P300 Potentials

A P300-based BCI detects the P300 component of an event-related brain potential, which appears in the EEG over the central areas. The P300 is a wave that corresponds to a positive deflection in voltage at a latency of about 300 ms after

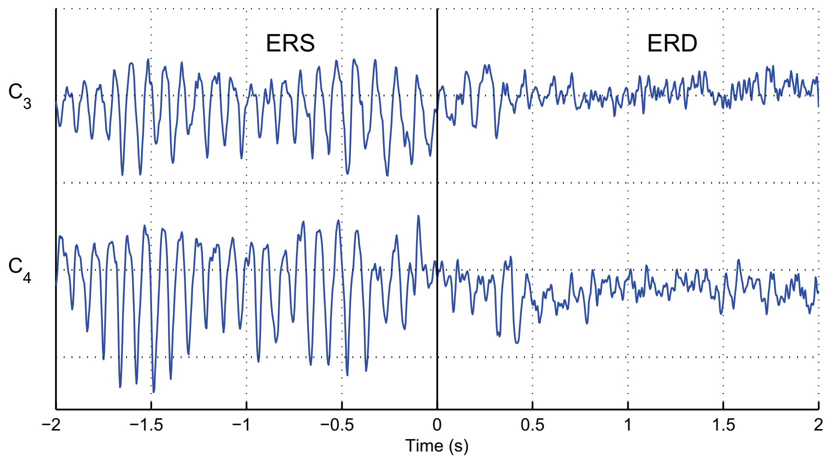


Figure 2.6.: Ongoing EEG signals recorded from electrodes C_3 and C_4 during right hand motor imagery. Imagination-onset was at $t = 0$ s.

the presentation of auditory, visual or somatosensory stimuli, see Fig. 2.5(a). In most P300-based BCIs described to date the stimulus is visual. However, in people with visual impairment, auditory or tactile stimuli might be used. Farwell and Donchin developed a P300-based BCI, which presents the user with a matrix of 6×6 letters or other elements on a computer screen [37], as shown in Fig. 2.5(b). The individual rows and columns of the matrix flash rapidly in a random sequence and the user is instructed to silently count flashes that include the letter or symbol that he/she wants to select, while ignoring other flashes. Only the row and column that contain the letter that the user wants to select evoke large P300 potentials.

2.7.3. Event-related Synchronization and Desynchronization

Since EEG signals are time series that are composed of mixtures of multiple frequency components, EEG is often labeled in a number of frequency bands that have been named after Greek letters: delta ($\delta = 1 - 4$ Hz), theta ($\theta = 4 - 8$ Hz), alpha ($\alpha = 8 - 13$ Hz), beta ($\beta = 13 - 20$ Hz), and gamma ($\gamma > 20$ Hz). There are different α rhythms depending on brain area and behavioral state [73]. The alpha rhythm is the classical brain rhythm, which is usually identified as near-sinusoidal oscillations at frequencies near 10 Hz, and occurs in a state of relaxed wakefulness, particularly evident when the eyes are closed. Normal resting alpha rhythms may be substantially attenuated, or even blocked in amplitude by opening the eyes, drowsiness, and in many subjects, by moderate to difficult mental tasks. Alpha rhythms, like most EEG phenomena, typically exhibit an inverse relationship between amplitude and frequency. The alpha rhythm is attenuated as the state of alertness is enhanced, such as sensory stimulation or mental activities. The term μ (mu) is used for a special rhythm occurring over the rolandic or central area within the alpha range. Contralateral movement, or even the mental intention to perform a movement can block or desynchronize the ongoing mu activity [73, 74]. These types of event-related changes represent frequency specific changes which consist of either decreases (ERD or event related desynchronization) or increases (ERS or event-related synchronization) of power in given frequency bands [53]. The term ERD is referred to the decrease of power relative to the baseline recorded seconds before the event, as shown in Fig. 2.6. The baseline represents a clear peak in the power spectrum. This paradigm is explained in more detail in the following chapter.

3. Sensorimotor Rhythm-based Brain-computer Interface

Sensorimotor rhythms (SMR) based BCI analyzes and classifies dynamics of single frequency component, such as the mu or beta rhythms, or multiple components of sensorimotor rhythms. Sensorimotor rhythms are 8–13 Hz (mu) and 13–20 Hz (beta) oscillations in the EEG recorded over sensorimotor areas. Normally, changes in mu and/or beta rhythm amplitudes accompany sensory stimulation, motor behavior, and mental imagery [53]. To enable communication between man and machine without movement, a popular class of BCI is based on the modulation of sensorimotor rhythm amplitudes. In the absence of any movement or sensation, mu and beta amplitudes increase. By imagination of movement, those amplitudes decrease. Motor imagery produces patters over sensorimotor areas similar to planning and execution of real movements. In this chapter, two studies are presented. The first study is an exploratory study that aims to find spatial and time-frequency properties of EEG signals recorded from the motor cortex during three classes of motor imagery (right hand, left hand and feet), and to evaluate the proposed experimental protocol through subjective report. The second is a single-case study that investigates the effects of training with motor imagery by analyzing recording EEG data, estimated BCI performance, and subjective report. Results showed that, consistent with other studies, different types of motor imagery produced noteworthy effects. Established and new signal processing techniques were utilized to find motor imagery patterns and to investigate pattern changes across training sessions.

3.1. Motor Imagery

Motor imagery (MI) corresponds to a subliminal activation of the motor system, which is involved not only in producing movements, but also in imaging actions, and learning by observation [75]. According to *Jeannerod* and *Frak* [75], motor imagery is the mental phenomenon of simulating an action. Mental representation of actions can be consciously (imagine self running or raising the hand) or unconsciously (visually presented hand) simulated and relies, at least partly, on brain mechanisms common with those for motor execution [75]. Studies based on patients with severe motor impairment demonstrated that conditions affecting the motor system leave intact the ability to generate motor imagery [4, 42].

It has been shown that this paradigm represents an efficient mental strategy to control a brain-computer interface. Mental imagination of movements involves similar brain regions as when a real movement is performed. The main difference between performed and imagined movements is that in the latter case the execution will be blocked in some cortical level but programming and preparation of both actions are similar. Several EEG studies confirm that motor imagery can activate primary sensorimotor areas. Also, similar cortical activity over the contralateral hand area during execution and imagination of hand movement have been found.

Two oscillations are important for the BCI: the Rolandic mu rhythm in the range 8-13 Hz and the central beta rhythm above 13 Hz [74]. Sensory stimulation, motor behavior, and mental imagery can change the amplitude of the EEG signals. Preparation and planning of self-paced hand movement results in a short amplitude suppression of mu and beta rhythms. This amplitude suppression or enhancement is called event-related desynchronization (ERD) and event-related synchronization (ERS), respectively [53]. Through neurofeedback training, users learn to voluntary modulate specific patterns in the brain. The length of the training is subject-dependent but it also depends of the mental strategy used [76].

Differences in performance between the users have been widely reported [76, 77]. The reasons are not well know, it has been speculated that motivational or emotional factors or the use of different mental strategies are responsible for this effect. Subjects interpreted instructions differently. Although the request to imagine moving a hand may seen straightforward, it is not. For example this task can be understood in several ways [54]:

(a) remember the feeling of hand moving

(b) visualize own hand moving

(c) visualize another's hand or abstract hand performing the movement

(d) combine remembered feeling and visualization of hand moving

(e) intent to move the hand while avoiding movement

Different ways of performing an imagery task involves different mental processes in the brain and therefore may produce different brain patterns. Some cognitive tasks may produce stronger brain patterns and other different characteristics. But which mental strategy generate the best brain patterns for a BCI is still not known.

A recent study compared the effects to instruct the participants to imagine the kinesthetic experience of movement instead of visualizing the movement [76]. In particular, the instruction how to imagine motor actions can be distinguished in the following kinds of imagery: Kinesthetic motor imagery involves a first-person process, where subjects are asked to imagine the kinesthetic experience of movement. The subject creates an "interior view" of the scene. Kinesthetic motor imagery results in detectable ERD/ERS patterns over sensorimotor areas, as confirmed in [76]. Visual-motor imagery involves a third-person process, where subjects imagine seeing himself or other person performing the motor action. In this kind of imagery, contrary to the kinesthetic mode, the subject has an "exterior view" of the scene.

3.2. Event-related Synchronization and Desynchronization

ERD/ERS can be quantified in the time, frequency and spatial domains, and can be used to study sensorimotor functions. An amplitude decrease of rhythmic brain activity can be found for example prior to hand or foot movements, and an amplitude increase for instance after termination of the movements [74]. It is also possible to distinguish between imagined right and left hand movements based on EEG signals and ERD/ERS analysis.

For the calculation of ERD/ERS, many event-related EEG trials are required, which are time-looked to a trigger event. Because event-related changes need time to develop and recover, the interval between two consecutive trials should last some seconds. Standard ERD/ERS calculation is done by bandpass filtering of each trial, squaring the samples and averaging over the trials and over the sample points. The ERD/ERS is then defined as the proportional power decrease (ERD) or power increase (ERS) in a given frequency band in relation to a reference interval several seconds before the task was performed [53]. Mathematically, ERD/ERS can be expressed as follows:

$$ERD_f(t) = \frac{P_f(t) - \langle P_f(t) \rangle_{ref}}{\langle P_f(t) \rangle_{ref}} \tag{3.1}$$

The classical procedure of ERD/ERS calculation is displayed in Fig. 3.1 with an example of dominant ERD in the alpha band during imagination of the right hand movement and ERS after the termination of the imagination. The method to compute ERD/ERS includes the following steps [53] [78]:

1. Bandpass filtering of all event-related trials. Event-related phenomena represent frequency specific changes of the ongoing EEG activity and therefore, these signals should be filtered in given frequency bands of interest. These frequency bands are obtained from time-frequency maps.

2. Subtracting the mean of the data for each sample. It is often useful to subtract the mean of the data for each sample before squaring because evoked potentials can mask induced activity.

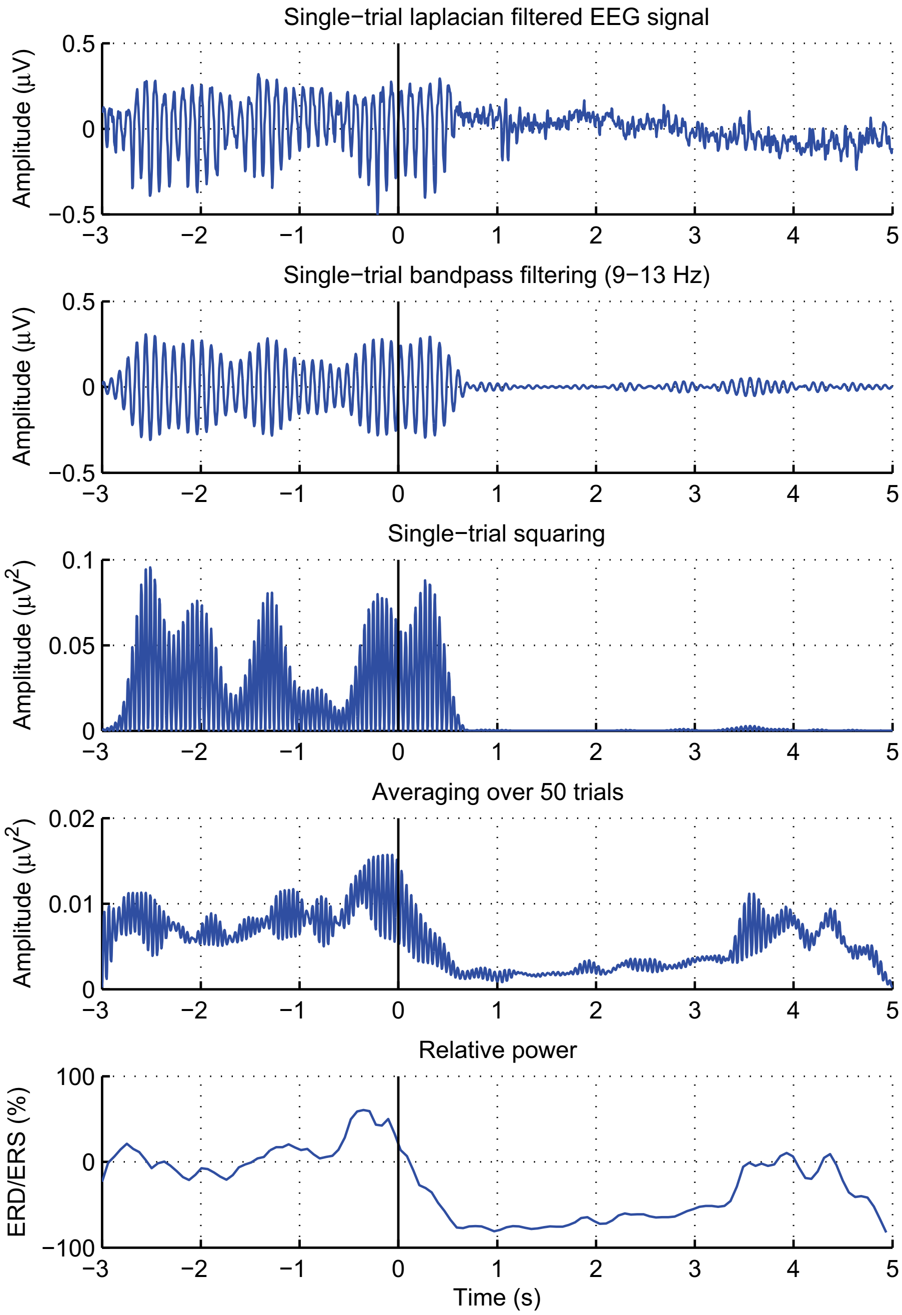


Figure 3.1.: Principle of ERD and ERS signal processing.

3. Squaring of the amplitude samples to obtain power samples. S_{ij} is the j^{th} sample of the i^{th} trial of the bandpass filtered data and $\bar{S}_j$ is the mean of the j^{th} sample averaged over all bandpass filtered trials.

$$Y_{ij} = (S_{ij} - \bar{S}_j)^2 \tag{3.2}$$

4. Averaging of power samples across all trials. N is the total of number of trials and P_j the average power.

$$P_j = \frac{1}{(N-1)} \sum_{i=1}^{N} Y_{ij} \tag{3.3}$$

5. Averaging of power in the reference interval $[r_0, r_0 + k]$. This epoch should reflect the normal state, i.e. stationary properties of the signal. In Fig. 3.1, the chosen interval was $[-2.5, -0.5]$ before the imagination was performed.

$$R = \frac{1}{(k+1)} \sum_{r_0}^{r_0+k} P_j \tag{3.4}$$

6. Obtaining percentage values for ERD/ERS.

$$ERDS_j = \frac{P_j - R}{R} \times 100 \tag{3.5}$$

7. Averaging over time samples to smooth the data and reduce the variability. In this example, the average over 32 samples was calculated with 50% overlapping.

3.3. ERD/ERS Exploratory Study

This study explores the frequency bands, temporal and spatial properties of electrical brain signals measured via EEG over the motor cortex during three classes of motor imagery (left hand, right hand and feet imagery). The objective of this study was to explore the signal characteristics of imagined movement with the aim to establish a communication channel between brain and computer. Additionally, the proposed experimental protocol for ERD/ERS screening was evaluated to determine best timing parameters of the stimulus presentation by collecting the impressions of the subjects. Analyses were conducted offline (evaluation of technology with pre-recorded signals). Dependent variables were optimal window length (time domain), relevant electrode positions (spatial domain) and most reactive frequency bands (frequency domain) for the recognition of each imagery task. The physical environment in which the experiments were conducted was the Brain Computer Interface Laboratory of the Institute of Automation. This location is a normal office room susceptible to noise and interferences. Subjects sat in reclined chair facing a computer screen 80 cm away.

3.3.1. Data Collection

This section describes the methods used for collecting data from subjects in an ERD/ERS screening session. Signal were collected in a synchronous mode, i.e., subjects respond to an internal response modulation to an external stimulus (modulated response). The biorecording technology used was EEG over the motor cortex. The specific electrode configuration proposed for this study for the classification of right hand, left hand and feet imagery tasks is shown in Fig. 3.2. EEG signals were recorded from 15 channels corresponding to central electrodes C_3, C_4, C_z and four electrodes around them using the extended $10-20$ system of electrode placement [79]. Data were referenced to the right ear lobe with a ground at site AF_z. This configuration was selected based on classification results from other studies which indicated that the most important electrode locations for differentiation between different motor imagery tasks are the electrode positions C_3, C_z, and C_4 [80]. Also, optimal spatial filtering of multichannel EEG single-trial data revealed electrode positions in the close neighborhood of C3 and C4 as the most important ones for discrimination between different motor imagery tasks [81].

Data were digitized with a sampling rate of 256 Hz and amplified through a gUSBamp amplifier. The software used for signal acquisition was the source module of BCI2000 (gUSBampSource.exe), which included a bandpass filter of $0.1 - 60$ Hz and a notch filter at 50 Hz. The stimulus presentation application of BCI2000 was used to present the sequences of stimuli. Additionally to the 15 EEG channels, a `StimulusCode` signal that indicated the numerical identifier of the stimulus being presented was recorded. `StimulusCode` was equal to 1 when the subject was responding to the instruction to imagine right hand movement; 2 to the instruction to imagine left hand movement; 3 to the instruction to imagine both feet movement; and 0 to the instruction to rest.

3.3.2. Subjects

Six able bodied subjects (age 24–32, 6 females) participated in the study. There was no selection criteria or screening of subjects. They participated voluntary without receiving any fee for their participation. All subjects were students at University of Bremen and had no experience with motor imagery tasks. Only Subject 3 and 4 had experience with another kind of BCIs.

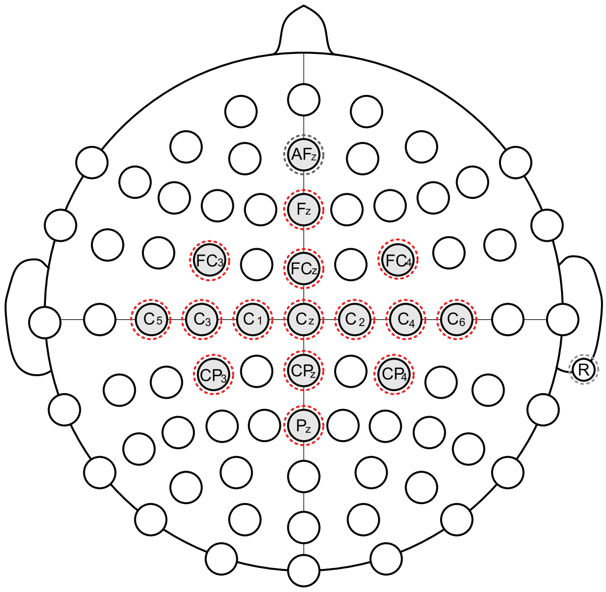


Figure 3.2.: Electrode locations over the motor cortex for an ERD/ERS screening session.

3.3.3. Experimental Protocol

The experimental design used in this study consisted of a single ERD/ERS screening session. The complete session lasted about one hour including electrode placement, subject preparation and recording. Each session consisted of two 20-min runs (150 trials) separated by 5-min break. In the first run, subjects were instructed to perform right hand, left hand and feet movements (motor execution - ME condition) followed by a second run where subjects where asked to imagine making that movements (motor imagery - MI condition) in response to an external stimulus. The first run was used as training for the subjects before the motor imagery tasks, which require high cognitive load and therefore are more difficult to perform. The subjects' task was to fix their attention on the computer monitor and perform the desired task as soon as a cue (text message) appeared on the screen. When the message "right hand" or "left hand" was displayed, the subject was instructed to imagine (MI condition) or move (ME condition) the respective hand depending on the condition. Specifically, subjects were instructed to imagine continuous opening and closing of the hand (e.g., squeezing a soft ball) at a rate of about one opening/closing per second. When the "feet" message was displayed, the subject was instructed to execute or imagine feet movement. The imagination of feet movement was similar to the one described for the hand, e.g, to imagine opening and closing both feet as when trying to grasp an object. Subjects were

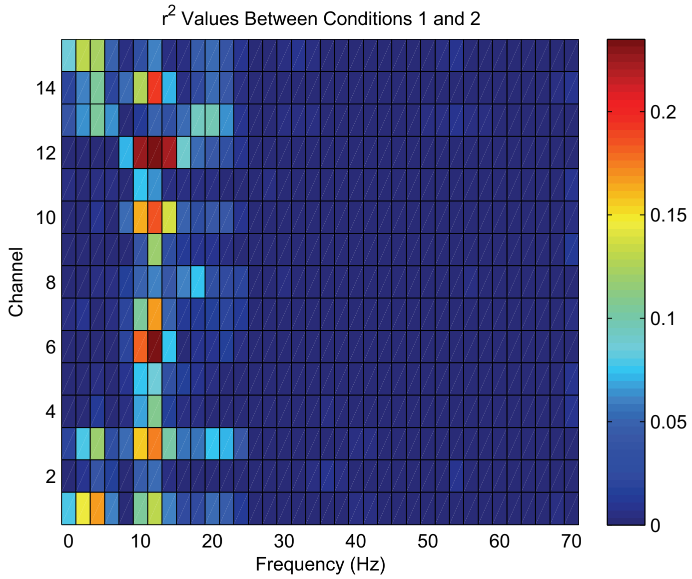


Figure 3.3.: Feature plots for right hand imagery of subject S1.

requested to maintain motor imagination as long as the message remained visible on the screen. The duration of the stimulus was five seconds. Between the trials a blank screen was presented, subjects were instructed to relax and stop any movement or imagery of movement (resting period). The inter stimulus interval (ISI) was randomized between three and five seconds. Stimuli were presented in a certain sequence, which consists of the presentation of each stimuli (right hand, left hand, and feet) in random order. A total of 50 sequences were defined.

3.3.4. Analysis

Recorded EEG data were analyzed in the frequency, time and spatial domain to find useful features that could discriminate three mental states: right hand, left hand and feet imagery. Offline analyses from 15 EEG channels were performed to find relevant subject-dependent activation patterns using different signal processing tools.

Frequency Analysis

The goal of analysis was to find patterns that distinguish imagery from resting state in the frequency domain, that is, in regard to the prominence of the difference in signal values between multichannel EEG recorded during imagery and EEG recorded during resting. In this study, 15-channel EEG data from the ERD/ERS

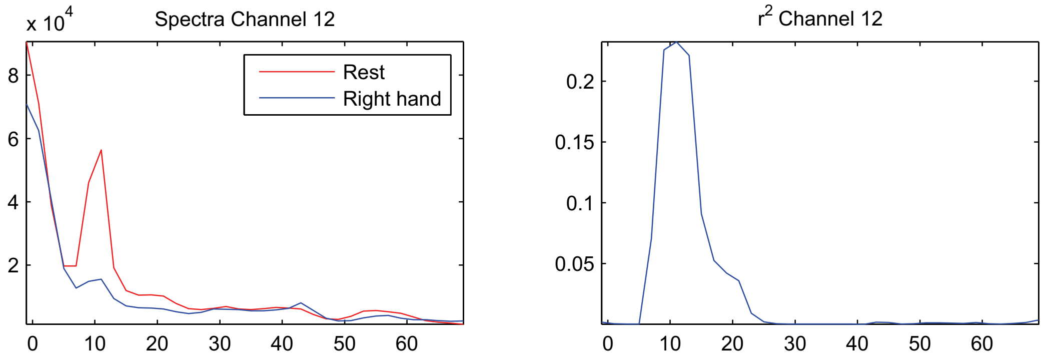


Figure 3.4.: Average voltage spectra (left) and average spectra r^2 (right) for right hand imagery at channel CP_3 for subject S1.

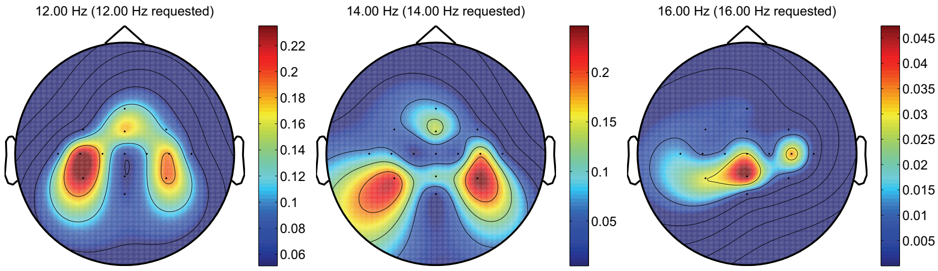
screening session from each of the six subjects were analyzed with the BCI2000 offline analysis tool [18]. First, for each electrode location, common average reference (CAR) filtering was applied. The CAR was computed according to the formula [82]:

$$V_i^{CAR} = V_i^{ER} - \frac{1}{n}\sum_{j=1}^{n} V_j^{ER} \tag{3.6}$$

where V_i^{ER} is the potential between the i^{th} electrode and the reference, and n is the total number of recorded electrodes. The waves resulting from CAR filtering were then subjected to an autoregressive (AR) spectrum analysis using the maximum entropy method (MEM) [83]. The average voltage spectra was calculated from 50 trials obtaining the spectra for each channel. The results were evaluated in terms of the average voltage spectra values for condition 1 (imagery) versus condition 2 (resting), and also in terms of the values of r^2 for the imagery/resting comparison. The r^2 measures the proportion of variance of two distributions, x and y, and was calculated by:

$$r^2 = \frac{\frac{1}{n_1}\left(\sum_{i=1}^{n_1} x\right)^2 + \frac{1}{n_2}\left(\sum_{i=1}^{n_2} y\right)^2 - \frac{1}{n_1+n_2}\left(\sum_{i=1}^{n_1} x + \sum_{i=1}^{n_2} y\right)^2}{\sum_{i=1}^{n_1} x^2 + \sum_{i=1}^{n_2} y^2 - \frac{1}{n_1+n_2}\left(\sum_{i=1}^{n_1} x + \sum_{i=1}^{n_2} y\right)^2} \tag{3.7}$$

These analyses can be displayed as feature, spectra and topography plots. Feature plots provides an overview of the data by displaying the r^2 values between two distributions as a function of frequency and channel. Fig. 3.3 shows the feature plot obtained from the data recorded from subject S1 during right hand imagery in the ERD/ERS screening session. From these feature maps, it is possible to determine those frequencies and electrode locations whose amplitude is maximally correlated with the subject's task. Fig. 3.4 shows spectra and r^2 plots that provides more detail information for selecting features. They show how data behave



(a) (b) (c)

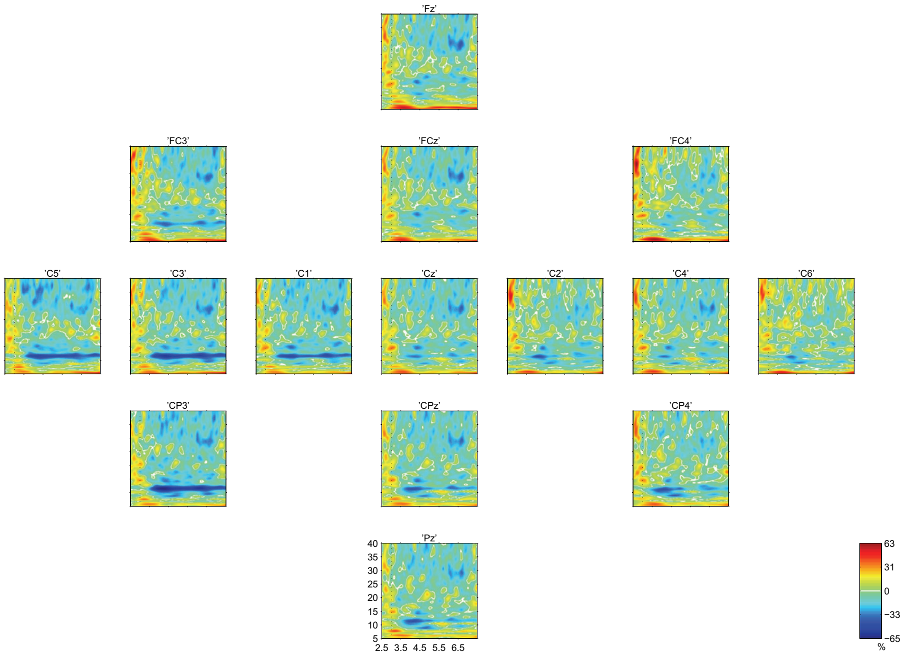
Figure 3.5.: Average voltage topographies of r^2 for the imagery of (a) right hand, (b) left hand and (c) feet movement of subject S1.

at a specific electrode channel. The plot on the left compares the frequency spectra for both conditions (right hand imagery vs. resting), and the plot on the right shows the r^2 reflecting the imagery/resting difference at the selected electrode channel.

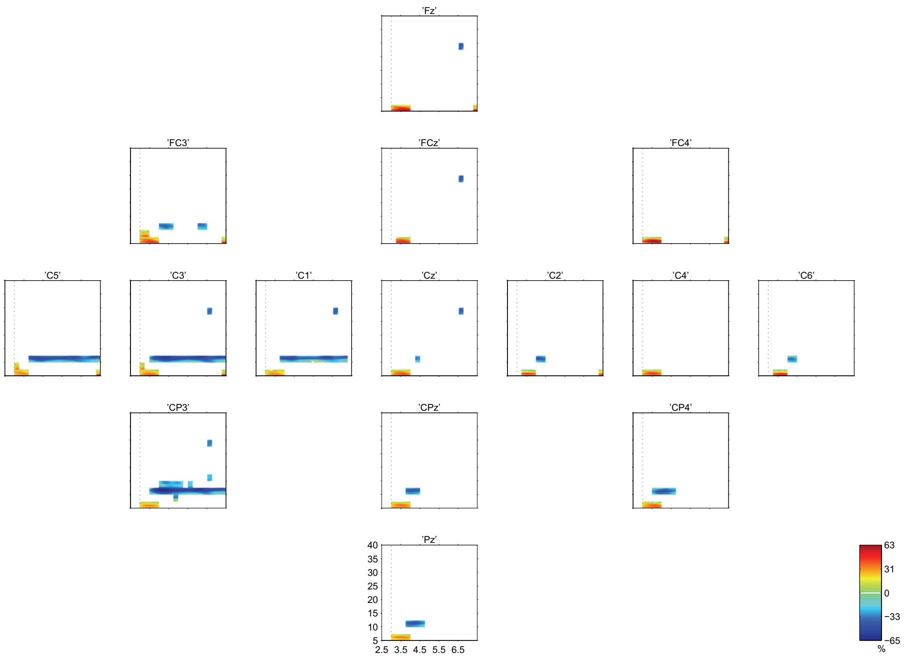
Topography plots show the r^2 values at a specific frequency. From the topography plot, it is possible to see how the data behave at a specific frequency. Fig. 3.5 shows the topographies during three imagery tasks at 12, 14 and 16 Hz. Red areas indicate most relevant electrode positions for the recognition of the respective task, whereas recording locations coded in blue do not provide essential information.

Time-frequency Analysis

Another method used to find relevant features during motor imagery tasks is the time-frequency analysis. This is an effective method for the visualization of event-related changes in oscillatory brain activity [78]. Time-frequency maps were useful for the selection of frequency bands and electrode locations with the most significant band power increase or decrease during motor imagery tasks. They provided an overview of the activity over broad frequency ranges and facilitates the finding of important subjects features. Typical ERD/ERS analysis requires the investigation of various channels and frequency bands that are dependent of the subject. The analyses were computed with algorithms described in [84], from 15-channel EEG and 50 trials of 8-second epochs. For each channel, a time-frequency map was calculated using the classical approach of quantification of ERD/ERS (Pfurtscheller and Lopes da Silva, 1999) for frequencies between 5 and 40 Hz as explained in section 3.2. First, the power of the signals was calculated by means of continuous wavelet transform and the absolute value at each point of the transform was squared. ERD/ERS changes were then computed as the power in relation to a reference period. The reference period corresponds to some seconds



(a)



(b)

Figure 3.6.: (a) ERD/ERS time-frequency maps and (b) significant ERD/ERS changes for right hand imagery of subject 1.

before the imagination was performed, that means when the subject was resting. Fig. 3.6(a) shows the ERD/ERS map calculated from 15 channels during imagery of right hand movement and Fig. 3.6(b) shows significant ERD/ERS changes. ERD values are colored blue, while ERS values are shown in red. The maps cover the frequency range from 5 to 40 Hz, which is sufficient to detect important ERD/ERS patterns such us mu and beta rhythms. The reference period was 0.5 to 2.5 seconds.

Temporal Analysis

The goal of the analysis was to find the optimal time window that better discriminates between each imagery class and the resting state. The results are computed with the algorithm described in [85]. First, data from resting state were used to estimate frequency bands of interest by FAD-parametric description of EEG time series, that is, by estimating the parameters: frequencies, amplitudes and damping coefficients (FAD) that characterize the basic EEG waves [86]. FAD decomposition detects the peaks within 7 and 30 Hz by calculating AR model coefficients, estimating the transfer function and finding the impulse response function parameters. Common spatial patterns (CSP) filtering was applied to the acquired EEG signals and the resulting waves were then subjected to bandpass filtering around the spectral peaks found in the first step. The mahalanobis distance was used to compare differences between different epochs, and to select the window, which maximizes differences between both classes. In this case, the inter-group mahalanobis distance [35] was applied to distinguish imagery from resting state using different epochs. The mahalanobis distance between two sets A and B is defined as:

$$d\left(\vec{A},\vec{B}\right)=\sqrt{\left(\vec{\mu}_A-\vec{\mu}_B\right)^T C^{-1}\left(\vec{\mu}_A-\vec{\mu}_B\right)} \tag{3.8}$$

where $\vec{\mu}_A$ and $\vec{\mu}_B$ represents the means of the vectors derived respectively from the class A and B, and C is the joint covariance matrix.

3.3.5. Results

Results of the frequency analysis

Table 3.1 summarizes the individual selected features for each subject that were visually found from the resulting BCI2000 frequency analysis plots. Results of the frequency analysis are explained only for data from a representative subject (S1) during imagery of right hand as example how those features were obtained. Fig. 3.3 shows the feature plot during right hand imagery of subject S1. As can be observed, there are two clusters at channel 6 and 12 corresponding to electrode positions C_3 and CP_3 at 11 Hz. These two electrodes correlate more with the imagination of right hand movement than the other 13 electrodes. To estimate the effectiveness of these features and exact frequencies, it is necessary to look at them in more detail using the spectra and topography plots. Fig 3.4 presents the average spectra and r^2 at channel location 12 (CP_3). The power spectrum at each condition clearly shows a peak at 11 Hz and 21 Hz while other frequency peaks are reduced. Changes in spectral power at 11 and 21 Hz during the imagination of the right hand movement can be observed. As expected, the power at these frequencies during the imagination of movement is less than when the subject is resting. There is a clear desynchronization (ERD) of the mu and beta components during the imagery, even stronger for mu than for the beta band. The r^2 plot shows also a clear peak at 11 Hz and a weak peak at 21 Hz. Fig. 3.5(a) shows the topography plot at 12 Hz for the imagery of right hand. A clearly focused contralateral activation can be observed as important classification feature. The time-frequency plot shown in Fig. 3.6(a) confirms the significance of the activation patterns of electrodes C_5, C_3, C_1 and CP_3 at 11 Hz.

Results of the temporal analysis

Results were obtained from imagination and resting periods extracted from the continuous EEG recorded in the ERD/ERS screening session. Windows of 2.0 and 3.0 seconds length were used for the analysis. The overlapping windows were calculated as the duration of the stimulus in the ERD/ERS screening session divided by four. In this study, the stimulus duration was five seconds. Thus, for a window length of 2.0 seconds, the overlapping was 0.5 seconds, and for 3.0 seconds, the overlapping was 0.75 seconds. That results in six epochs of 2.0 seconds length, and three epochs of 3.0 seconds length. Because the selection of the autoregressive model order is important to determine BCI performance [87], the results using four model orders 9, 11, 13 and 15 were also compared. Table 3.2 presents the results of analysis conducted on data from subject S2 for AR model orders 9 and 15 and window lengths 2.0 and 3.0. The mahalanobis distance was used as criteria for the selection of parameters. The parameters with the highest mahalanobis distance for each imagery class are highlighted in the table. The columns next to the mahalanobis distance show the probability of classification of the imagery and resting trials using the corresponding epoch and window length. The results of subject S2 suggest that the resting state classification is more accurate than the imagery classes. This observation was confirmed on the results of all subjects.

Table 3.3 shows the selected signal properties for each subject based on the highest mahalanobis distance: model order, frequency peaks and their bandwidth, and the window length of each imagination task. The probability of classification was evaluated by applying the classifier (constructed with the selected parameters)

Subject	Age	Imagery	Frequency [Hz]	Location	Features
S1	24	Right hand	10 – 14	C_3, CP_3	$\mathrm{CP_3}$(11 Hz)
		Left hand	10 – 14	C_4, CP_4	$\mathrm{CP_4}$(11 Hz)
		Feet	15 – 20	CP_Z	$\mathrm{CP_z}$(15 Hz)
S2	27	Right hand	16 – 22	C_3, CP_3	$\mathrm{C_3}$(19 Hz)
		Left hand	16 – 22	CP_4	$\mathrm{CP_4}$(19 Hz)
		Feet	22 – 28	CP_Z	$\mathrm{CP_z}$(25 Hz)
S3	27	Right hand	14 – 18	C_3, CP_3	$\mathrm{CP_3}$(15 Hz)
		Left hand	14 – 18	CP_4	$\mathrm{CP_4}$(15 Hz)
		Feet	24 – 32	C_Z	$\mathrm{C_z}$(25 Hz)
S4	29	Right hand	8 – 12	C_3	$\mathrm{C_3}$(11 Hz)
		Left hand	8 – 12	C_4	$\mathrm{C_4}$(11 Hz)
		Feet	18 – 22	CP_z	$\mathrm{CP_z}$(19 Hz)
S5	28	Right hand	12 – 18	C_3, CP_3, C_1	$\mathrm{C_3}$(17 Hz)
		Left hand	12 – 18	C_4, CP_4	$\mathrm{C_4}$(17 Hz)
		Feet	18 – 22	C_2	$\mathrm{C_2}$(19 Hz)
S6	32	Right hand	10 – 14	CP_3	$\mathrm{CP_3}$(11 Hz)
		Left hand	10 – 14	CP_4	$\mathrm{CP_4}$(11 Hz)
		Feet	14 – 18	C_Z	$\mathrm{C_z}$(15 Hz)

Table 3.1.: Results of the frequency analysis from the ERD/ERS screening session.

over all trials. The ratio between the correct classifications and the total number of trials is shown in the last column.

3.3.6. Discussion and Conclusion

This study confirmed previous findings in the literature that motor imagery produces changes in the mu and alpha bands and that the involved signal parameters are highly subject dependent. From the results of the time-frequency analysis it was possible to infer that most pronounced power variations may occur at different time points after cue onset and that those variations were different across the imaginations. Results of the temporal analysis confirmed this observations, the epoch in which one imagination was better classified differed from the epoch of other imaginations. That leads to the conclusion that the time window is also an important parameter to find relevant features and that it is dependent on the imagination. Some subjects needed more time to generate a particular imagination. Another observation was that the AR model order 13 and 15 provides better differentiation between the classes. Therefore, for the implementation of an online ERD/ERS classifier, it is always necessary to calibrate subject-dependent parameters, such as model order, frequency bands, electrode locations, and time window that differentiate best imagery classes from resting state.

Additionally, subjects impressions about the experimental protocol were collected by interviewing each subject after the testing phase. Some impressions are summarized as follows:

- The imagery tasks required significant commitment and concentration.
- The resting time between the imagery tasks (inter-trial interval) may be too short.
- The screening session lasting approx. 20 min was tiring and tedious.
- It was difficult to know if the imagination was performed well, there was no feedback.
- Electrode preparation lasted almost 20 minutes (15 electrodes), the overall session was over one hour. There is a need to reduce the overall duration of the screening session.

This issues will help to improve the experimental protocol for future ERD/ERS screening sessions.

Subject	Window length	Epoch	Imagery	Model order 9			Model order 15		
				Mahalanobis distance	Imagery	Resting	Mahalanobis distance	Imagery	Resting
S2	2.0 s	0.0 - 2.0	Right hand	1.451	0.74	0.83	1.385	0.72	0.86
			Left hand	1.402	0.78	0.80	1.757	0.82	0.83
			Feet	1.196	0.68	0.76	1.026	0.60	0.81
		0.5 - 2.5	Right hand	1.404	0.68	0.82	1.444	0.66	0.88
			Left hand	1.365	0.82	0.78	1.525	0.72	0.82
			Feet	1.755	0.74	0.87	1.811	0.74	0.86
		1.0 - 3.0	Right hand	1.155	0.68	0.82	1.198	0.70	0.79
			Left hand	1.301	0.80	0.74	0.891	0.44	0.79
			Feet	2.117	0.82	0.90	2.228	0.78	0.92
		1.5 - 3.5	Right hand	1.068	0.78	0.73	1.307	0.70	0.87
			Left hand	1.154	0.68	0.73	0.656	0.68	0.71
			Feet	1.948	0.80	0.88	2.028	0.74	0.86
		2.0 - 4.0	Right hand	0.975	0.80	0.70	1.150	0.64	0.85
			Left hand	1.306	0.78	0.70	0.993	0.72	0.68
			Feet	2.046	0.78	0.91	1.749	0.76	0.82
	3.0 s	0.0 - 3.0	Right hand	1.319	0.66	0.89	1.208	0.60	0.84
			Left hand	1.650	0.86	0.84	1.643	0.78	0.82
			Feet	1.770	0.84	0.83	1.667	0.78	0.86
		0.75 - 3.75	Right hand	1.443	0.64	0.89	1.392	0.70	0.89
			Left hand	1.100	0.70	0.73	1.631	0.70	0.86
			Feet	2.345	0.88	0.90	2.224	0.82	0.91
		1.5 - 4.5	Right hand	1.143	0.56	0.86	1.296	0.70	0.87
			Left hand	1.496	0.80	0.82	0.985	0.74	0.79
			Feet	2.146	0.84	0.91	2.045	0.76	0.95

Table 3.2.: Analysis of the temporal properties for right hand imagery of subject S2.

Subject	Model order	Frequency patterns f [Hz]	BW [Hz]	Temporal patterns Imagery	Window	Probability of Classification
S1	15	$f_1 = 10.10$	2.16	Right hand	0.75 - 3.75	0.84
		$f_2 = 22.73$	4.03	Left hand	0.0 - 3.0	0.90
				Feet	1.5 - 4.5	0.98
S2	15	$f_1 = 9.43$	1.82	Right hand	0.5 - 2.5	0.76
		$f_2 = 21.79$	3.74	Left hand	0.0 - 2.0	0.88
				Feet	1.0 - 3.0	0.80
S3	15	$f_1 = 8.92$	2.02	Right hand	0.5 - 2.5	0.66
		$f_2 = 21.44$	3.62	Left hand	0.5 - 2.5	0.84
				Feet	0.0 - 2.0	0.86
S4	13	$f_1 = 10.46$	1.18	Right hand	0.5 - 2.5	0.58
		$f_2 = 20.78$	5.38	Left hand	0.5 - 2.5	0.72
				Feet	0.0 - 2.0	0.90
S5	15	$f_1 = 9.87$	2.34	Right hand	1.0 - 3.0	0.60
		$f_2 = 19.85$	3.03	Left hand	1.0 - 3.0	0.50
				Feet	0.0 - 2.0	0.78
S6	13	$f_1 = 8.78$	1.56	Right hand	0.75 -3.75	0.66
		$f_2 = 21.38$	3.88	Left hand	0.75 -3.75	0.68
				Feet	0.75 -3.75	0.68

Table 3.3.: Selected frequency and temporal patterns for the classification of imagination of movements.

3.4. ERD/ERS Training Study

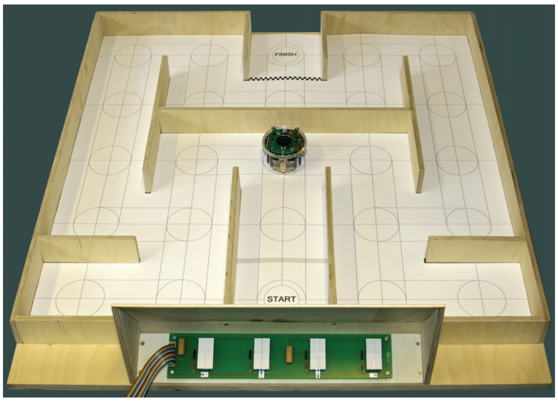
This study aims to investigate the relevance of ERD/ERS training across the sessions. One of the subjects from the previous study (S4), who accepted to undergo training for several weeks was the test subject (29 years old, female, right-handed). This subject learned to generate specific brain patterns by imaging movements of the right hand, left hand and feet. The training period was two months (13 training sessions).

3.4.1. Data Collection

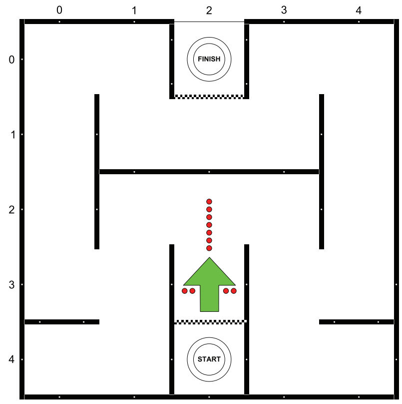
Each training session consisted of an ERD/ERS screening session and a feedback session [88]. The screening session records continuous EEG signals while the subject imagines left/right hand movement or feet movement depending on the presentation of a visual cue, then the best signal parameters are calibrated and a subject-dependent classifier is set up. The feedback session detects motor imagery patterns in ongoing EEG signals and provides the user with feedback about the correct or incorrect classification of the brain patterns. The electrode locations used in the previous study showed to be a good choice for ERD/ERS detection. Thus, the EEG signals were acquired for both sessions using 15 electrodes placed over the motor cortex as shown in Fig. 3.2. Electrodes and caps were provided by Easycap. Data were amplified through a Porti32 amplifier (Twente Medical Systems International, Netherlands) and sampled at 256 Hz.

ERD/ERS screening session

During the screening session, the subject was requested to imagine right hand, left hand and both feet movement in a predefined sequence. The stimulus presentation application of BCI2000 was used to present sequences of stimuli. With the experiences collected from the first exploratory study, it was possible to establish an improved experimental protocol to train subjects. Three important changes were done. First, each motor imagination cue was indicated by an arrow that signalized the respective task instead of text messages to reduce the cognitive load of the user. The inter stimulus interval (ISI) varied randomly between five and eight seconds to give the user the opportunity to rest and prepare for the next mental task. In the previous study, it was found that time windows between zero and three seconds after cue onset were enough to classify the imaginations, and also subjects could not produce imaginations for longer time periods. Therefore, the stimulus duration was changed to three seconds. Each training session consisted of 150 trials (50 for each class).



(a) Intermediate trainer



(b) Advanced trainer

Figure 3.7.: BCI trainer applications used at different learning stages.

ERD/ERS feedback session

The feedback session makes use of an online ERD/ERS transducer and a feedback application (BCI trainer). The ERD/ERS transducer analyzes segments of EEG data and detects if they correspond to the imagination of "right hand," "left hand," "feet," or "resting." The ERD/ERS transducer no only deals with the discrimination between distinct motor imagery patterns (active classes), but also the main challenge is to handle the resting state. The software framework used for the communication between the acquisition, signal processing and application modules was BCI2000 [18]. The source module acquires EEG signals with a sampling rate of 256 Hz and applies a high pass filter at 0.1 Hz and a notch filter at 50 Hz. Blocks of 32 samples (125 ms) are transmitted to the signal processing module. This sample block size defines the timing of the complete system. The signal acquisition module processes the data coming from the source module and outputs a control signal that can be "right hand," "left hand," "feet," and "resting" depending on the classifier decision. The signal analysis is conducted on windows of the same length as used in the calibration. For example, for a window length of 2 seconds the module collects the EEG data into a matrix of 15×512 samples. At each signal processing cycle, old data is shifted and the incoming 32 samples are located at the end of the buffer matrix. Then, the classification is performed. Control signals from the signal processing module are received by the BCI trainer via UDP (user datagram protocol). The mode of operation of the signal processing is independent of an external cue stimulus. The time windows in which the subject performs a mental task are unknown for the system, and therefore the signal is processed continuously.

The BCI trainer is a software tool that provides several applications and helps users to improve their BCI skills. It transforms the output of the BCI transducer into a visual representation on the computer screen to show the user how successful he/she is in modulating a desired brain pattern. The goal of the BCI trainer is to support learning. In this work, three different applications were used to provide feedback to the user at different learning stages. In the initial stage, a window showing the result of the classification was used (session 1 to 6). Subjects were trained for about 15 minutes in a free mode (no cues were presented). In the intermediate stage, subjects task was to navigate a miniature robot out of the labyrinth (see Fig. 3.7(a)). For this task, three control signals were used. With the "move forward" command the robot moved forward to the next position in the labyrinth. With the commands "turn left" and "turn right" the robot rotated 90 degrees to the left and to the right. Imagination of feet movement corresponds to "move forward," left and right hand imagery to "turn left" and "turn right," respectively. A feedback session started with the robot placed at the START position and ended when the robot reached the FINISH position. The time was measured at the exact time point when the robot left the start position until the last command to reach the final position was received. If the robot was facing a wall, and a "move forward" command was classified, the command was counted as incorrect, but the robot did not move forward. Accuracy and information transfer rate were calculated based on the time, hits and trials information. In this application, the signal processing module counted the number of repetitions of each command in eight consecutive commands (1000 ms). The command with more repetitions was send to the robot control program. Additionally, when the robot was moving from one position to another all incoming commands were rejected. This lowered the level of difficulty of the application. From sessions 1 to 6, the subject trained with the simple trainer and immediately after the subject was given the opportunity to train with the intermediate trainer. Up session 7 until 11, the subject trained only with the intermediate trainer.

In the advanced stage, a virtual instead of a real labyrinth was used to train the subject (see Fig. 3.7(b)). The layout of the labyrinth remained unchanged, but instead of a robot, an arrow simulated the robot movements. The subject's task was to navigate the cursor (green arrow) from the start to the final position. The control and performance calculation were done in the same way as in the real labyrinth. With the virtual labyrinth the level of difficulty was increased because the processing of commands was faster (every 125 ms). The application processed every incoming command and provided feedback by showing a red circle on top (for feet imagery), left (for left hand imagery) or right (for right hand imagery) of the cursor. Only when eight commands were collected, the cursor performed a movement. In this work, the virtual labyrinth was used in the last two feedback sessions.

3.4.2. Analysis

The ITR was calculated on the basis of the stages necessary to reach the goal, i.e., the low level commands sent to the transducer. This lead to an N of 3, based on the 3 movement commands ("turn left," "turn right" and "move forward"). The BCI performance was calculated using the variables: *hits*, *trials* and *time* that were calculated as follows:

1. The total time (*time*) was measured as the elapsed time since the robot abandoned the START position after the first classification of the "forward" command (this command was not counted for the ITR calculations, this command was used to mark the start of the experiment).

2. Each executed command was rated as correct or incorrect based on the actual robot position. The column and row starting from top left corner represented the actual position as shown in Fig. 3.7. Thus, the FINISH position was marked as (2, 0) and the START position as (2, 4). The current direction of the robot was indicated by a numerical value that could be 0°, 90°, 180° or 270°. A value of 0° indicated the forward direction. For example, at the beginning of the experiment after the first classification of the "forward" command, the robot is located at position (2, 3) and has a direction of 0°. In this position, only the command "forward" is correct, all other commands are treated as incorrect for the calculation of accuracy.

3. After each command, the evaluation of the position and direction starts again. For example, in position (1, 1, 90°), any of the commands "left"or "right" would be incorrect, only the "move forward" command would be correct.

4. At position (2, 2), the user could use one of the two possible paths to reach the goal, left or right. Both ways were rated as correct. But, once the subjects had chosen one of the paths, they should follow it. If later this position was reached again, a new choice was possible.

5. If the robot was facing a wall, and a "forward" command was executed, the classified command was counted (as incorrect), but the robot did not move forward.

6. Accuracy was then calculated as the number of all correct commands (*hits*) divided by the total number of executed commands (*trials*).

3.4.3. Results

Fig. 3.8 presents the probability of classification for each motor imagery task across the training sessions. These results were obtained with offline analysis

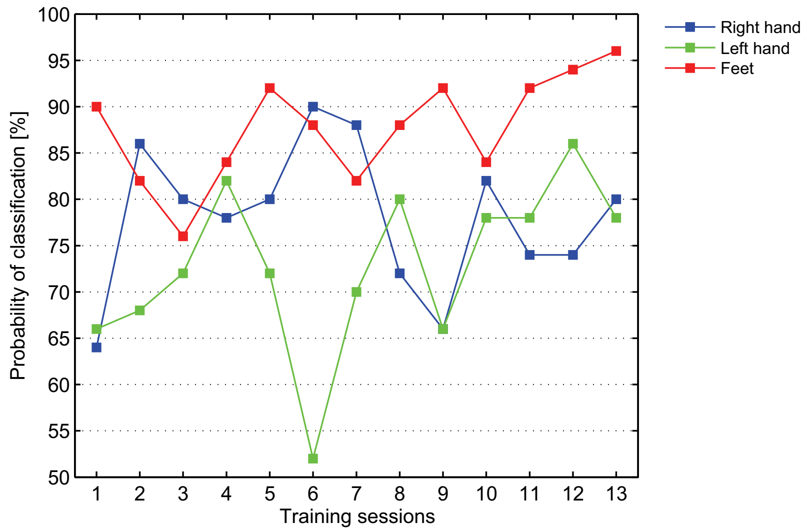


Figure 3.8.: Probability of classification for the calibration data.

from the EEG recorded in the screening session (50 trials per task). The analyses of the calibration data were conducted using a window length of 2 seconds and an AR model order 13. The classification parameters were found by selecting the highest mahalanobis distance between different overlapping windows. Each training session required a calibration session to set up the classifier.

Table 3.4 shows the results from the feedback sessions. Initially, the subject trained with a simple window that showed the output of the classification (session 1 to 6). That training was done in a free mode, in which the subject decided when to perform a task. From session 1 to 11, the intermediate feedback application was used. The task was to navigate a robot out of the labyrinth. Only since session 7, the subject was able to navigate the robot from the start to the goal position. Therefore, no classification results are shown for the initial six sessions. The results show that the subject could control the robot movements with an accuracy of 73.91% already after six training sessions. After five training sessions, the level of difficulty was increased by letting the user to control the advanced trainer. Results were even better than with the intermediate trainer, an accuracy of 91.3% could be achieved, and the number of total trials and total time was decreased.

3.4.4. Discussion and Conclusion

These results demonstrated that online ERD/ERS control using three mental states (imagination of right, left hand and feet) is possible. ERD/ERS patterns

Feedback session	Hits	Trials	Time [s]	Accuracy [%]	ITR [bpm]
7	34	46	551.08	73.91	2.484
8	30	42	562.84	71.43	1.953
9	24	77	715.72	31.17	0.001
10	29	41	560.25	70.73	1.845
11	35	53	680.00	66.03	1.450
12	21	23	171.60	**91.30**	**8.622**
13	30	39	354.20	76.92	3.798

Table 3.4.: Results obtained from the feedback sessions.

related to three types of motor imagery could be recognized successfully in real-time. The optimal selection of the most relevant features from the EEG of the user together with feedback training made possible to successfully complete a very difficult control task (navigate a robot/cursor out of the labyrinth) by using three independent control signals derived alone from ongoing EEG signals. These results are promising because the level of difficulty of the control task was very high, three different patterns were recognized in an asynchronous mode (allows the user to operate the BCI independently of an external cue stimulus), and a lot of experience in ERD/ERS training was gained.

Users' progress depends on development of improved training methods in relation to the learning stage. It was found that the instructions given to the user played an important role. In this study, the BCI protocol asked the user to produce imagination of movements by opening and closing the hand. User's report about the strategies employed showed that the subject changed constantly her strategy, and the most effective one was imagine playing piano. Once the subject identified the best strategy, BCI control was more accurate. That may explain why at the first six training sessions, no effective control over the robot movements could be achieved. More extensive work to determine effective mental strategies and to optimize the user training is needed [89,90]. The subject also reported more difficulties to keep control of the resting state than the imagination of movements. That suggests than some kind of mental training or experience with relaxation techniques may further contribute to better BCI performance.

4. High-level Control of Semi-autonomous Assistive Devices via BCI

A brain-computer interface transforms brain activity into commands that can control computers and a wide range of assistive technologies for severely disable users. Although advanced signal processing methods are used in BCI research, the output of the BCI is still unreliable and its information transfer rate is lower compared with conventional human interaction interfaces. Therefore, BCI applications have to compensate the unreliability and low information content of the BCI. Direct control of a robot arm or a wheelchair would be not only slow and frustrating, but even dangerous if the control solely relies on the BCI output. Assistive devices that autonomously conduct goal-oriented tasks and independently detect and resolve safety issues are more suitable for being controlled via BCI.

This chapter presents the rehabilitation robot FRIEND-II controlled by the Bremen-BCI based on SSVEP. The complete system is operated following the high-level or goal-selection control approach. The role of the BCI is to translate high-level requests from the user into control commands that are executed by the FRIEND-II system. The BCI is used to navigate a menu system and to select high-level commands such as pouring a beverage into a glass. The low-level control is executed by the control architecture MASSiVE, which in turn is served by a planning instance, an environment model and a set of sensors (e.g., machine vision) and actors. The BCI is introduced as a step towards the ultimate goal of providing disabled users with at least 1.5 hours independence from care givers.

4.1. High-level Control Approach

Most BCIs have been used to control computer applications such as spelling devices [52], simple computer games [63, 91], virtual environmental control [92], and cursor control applications [41]; but only a limited number of systems have been also used for controlling more sophisticated applications, including protheses [8], robotic arms, and mobile robots [46]. These are complex applications that require the control of all details of the process that accomplishes the user's intents. In this process-control approach [93], BCIs are not well suited for controlling more complex details of demanding applications because of two reasons [94]: (a) complex applications increase the mental workload of the user and can thus negatively affect BCI performance, and (b) complicated tasks require a number of sub-tasks, which, when controlled on a low-level basis, can be time consuming, fatiguing and frustrating. This underscores the importance of reducing the burden on BCI users through effective goal-oriented protocols. Goal-oriented or high-level BCI control means the BCI simply communicates the user's goal (the task) to the intelligent application device that manages the process. Once the system knows the task, it can autonomously performs all necessary sub-tasks to achieve the goal. In contrast, low-level control means the BCI manages all the intricate interactive process involved in achieving the goal, and therefore requires high-speed interactions with the device as the task proceeds. Thus, goal selection is easier and appears to be a more realistic strategy for BCI control. Furthermore, the goal-oriented strategy provides a more natural control, is more similar to normal motor control because it distributes the operation of actions by delegating lower-level aspects of motor control to another structures [93].

In any interface, users should not be required to control unnecessary low-level details of system operation. This is especially important with BCIs; allowing low-level control of a wheelchair or robot arm, for example, would not only be slow and frustrating but also dangerous. Therefore, developing robust BCI applications capable of providing effective real world control requires developing intelligent mechanisms that can mediate between the user's goals and the individual actions needed to implement those goals.

An intelligent BCI system should, however, also provide the user with the option of implementing lower level commands if desired. This is necessary if the high-level commands do not contain the exact goal that a user seeks to attain. An assistive robotic system that automatically pours water if the user conveys thirst may not satisfy a user who instead wants soda, juice, or wine. In these cases, the user might not mind the additional time required to perform tasks that are not preprogrammed. An ideal intelligent system would identify frequently issued command sequences and adapt accordingly, perhaps developing a new option to get juice if the user often does so. Many current BCI applications that only provide low-level control would benefit if they would provide high-level control as well.

4.2. Rehabilitation Robot FRIEND-II

The term rehabilitation robot describes a broad range of assistive devices that are designed to meet the requirements of and address the problems confronted by people with disabilities. The scale of disabilities can range from slightly disabled to most severely disabled people. Depending on user's impairment (scale of

Figure 4.1.: Rehabilitation robot FRIEND-II controlled by the Bremen-BCI.

disability) various forms of input mechanisms are used to control rehabilitation robots. Joystick, keyboard, and mouse are typical input devices for less severely disabled people. Sip/puff switches, interpretation of voice or head position, eye gaze, and electromygraphic activity are input modalities for people with disabilities that prevent them from using other interfaces. Control by BCIs is usually the last resort for the most severely disabled people. BCIs can control any application that other interfaces can control but with a lower information throughput.

The rehabilitation robot FRIEND-II (**F**unctional **R**obot Arm with User Fr**ien**dly Interface for **d**isabled People) developed at the Institute of Automation of the University of Bremen is a semi-autonomous system designed to assist disabled people in activities of daily living [95]. The main components of FRIEND-II are a conventional wheelchair, a 7 degrees-of-freedom dexterous manipulator (robot arm), a gripper with force/torque sensor, a stereo camera system mounted on a pan-tilt head, a smart tray with tactile surface and weight sensors, a TFT monitor, and a computing unit consisting of three independent industrial PCs [20]. The stereo camera system and the smart tray form together a robust and redundant system that is able to reliably localize objects on the tray largely independent from lighting conditions. Fig. 4.1 shows the FRIEND-II system and an able-bodied user who controls the system with a BCI.

FRIEND-II is able to perform certain operations completely autonomously. An example of such an operation is a "pour in beverage" scenario. In this scenario, the system detects the bottle and the glass both located at arbitrary positions on the tray, it grabs the bottle, moves the bottle to the glass while automatically avoiding any obstacles on the tray, it fills the glass with liquid from the bottle while continuously controlling the fill level of the glass, and finally puts the bottle back in its original position.

Besides this goal-oriented, high-level control approach for autonomously performed tasks, FRIEND-II also provides the option to perform low-level control. This is necessary because the system operates in an unstructured environment, and uncertainties in sensor data can, in rare cases, result in slightly erroneous estimation of the position of objects. In such cases, the user can take over the control of the manipulator and adjust the gripper location. This is done in an intuitive manner using Cartesian commands and with support from the system, which controls the redundancy of the manipulator in parallel to simplify the task for the user. After gripper adjustment by the user, the system can proceed with the execution of the remaining tasks in an autonomous mode [11].

4.2.1. Multi-layer Architecture for Semi-autonomous Service Robots

The control of the FRIEND-II is facilitated by the multi-layer architecture MASSiVE (**M**ultilayer **A**rchitecture for **S**emi-Autonomous **S**ervice Robots w**i**th **V**erified Task **E**xecution) [96]. This architecture provides high-level control approach for autonomously performed task, and the option to perform low-level control. In order to enable user involvement in the task processing, the MASSiVE architecture consist of four modules, as shown in Fig. 4.2. The reactive-layer abstracts the hardware specific functionality from sensors and actuators. The sequencer is responsible for task planning. The human-machine interface (HMI) governs user interactions and provides feedback. The world-model is used to store symbolic and sub-symbolic data of the system and user environment.

A task is selected and started via input devices available to the user. All possible input devices and their degrees of freedom are managed by the HMI. At present, keyboard, mouse, joystick, voice, and BCI control are supported input devices. The chosen high-level task, e.g., "Pour in a beverage," is forwarded from the HMI to the sequencer, which plans the task on the basis of pre-defined task knowledge and petri-nets. The result of the planning process is a list of sub-tasks that must be executed by the reactive layer. In the context of the MASSiVE control architecture, these sub-tasks are called *skills.* If a problem would occur during the execution of these sub-tasks and the user has to be involved, the sequencer invokes a special *user interaction skill* using its interface to the HMI. The situation can be then addressed by the user [96]. From the sequencer's point of view, these *user interaction skills* are like normal *skills* executed by hardware components. This approach leads to a reduction of the planning complexity and a semi-autonomous

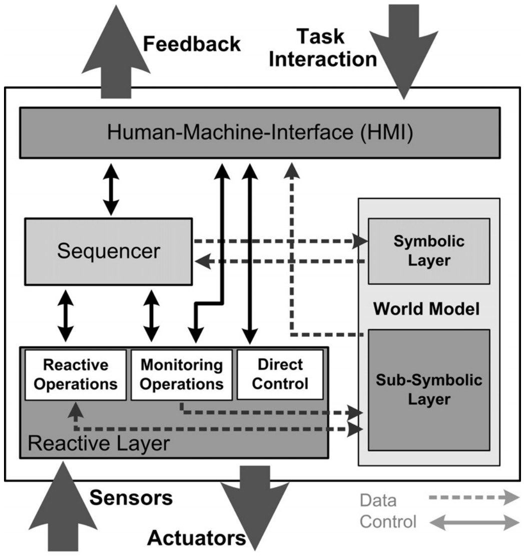


Figure 4.2.: Overview of the robot control architecture MASSiVE.

system [97].

In the context of planning and execution, the world model plays the role of a knowledge base. The division into symbolic and sub-symbolic part originates in the need to store different kinds of data for different levels of abstraction. On one hand, the sequencer needs data describing objects during the task planning process (e.g., what kind of objects are involved in the task scenario) without further knowledge about them (symbolic data). On the other hand, detailed information about those objects is needed during execution of an already planned task in the reactive layer (sub-symbolic data). Hence, the sequencer operates on the symbolic, the reactive layer on the sub-symbolic part of the world model. The connection between both kinds of data is established via object anchoring, as presented in [98]. The directed connection of the world model with the HMI evolves from the necessity of giving feedback to the user during execution of a *user interaction skill*. Thus, the HMI only operates on the sub-symbolic part of the world model.

4.2.2. Human-machine Interface

The HMI consists of multiple modules with different functions. These modules are the graphical user interfaces, the input devices, the HMI model, the command mapper and the interaction component. The HMI and its components are shown in Fig. 4.3. The interaction component is responsible for the interaction between the user and the system and vice versa. It forwards the tasks to be processed to

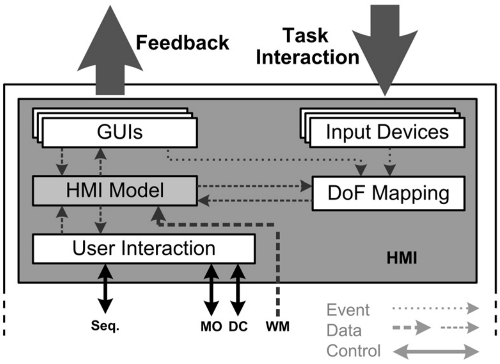


Figure 4.3.: Overview of the human-machine interface.

the sequencer, it is able to initiate additional environment monitoring, it has the possibility of direct hardware control (used for special user interactions) and it offers user interaction skills as methods to the sequencer. The model component manages a representation of the graphical user interfaces, the data necessary for the communication with the user (e.g., textual usage hints in different languages and data from the world model used to give feedback) and processes incoming HMI commands. Following the observer design pattern [99], each HMI command that is received and processed results in a change of the model that is forwarded to all graphical user interfaces, the command mapper and the interaction component. The communication between all components is implemented using CORBA (Common Object Request Broker Architecture) [97].

To integrate the BCI application into the HMI of the control architecture an input device application was implemented. This application acts as a TCP/IP client. It receives the BCI commands and forwards them as asynchronous events to the command mapper. The latter maps the BCI commands into HMI commands in correspondence to Table 4.1 and forwards them to the model, which is then updated. In this case, the current selection is changed in a list. The list contains possible system tasks and folders used to group system tasks. The graphical user interface of the HMI offers a control panel, a list with the offered system tasks, a log window and a window with the currently running tasks. The last two windows are used to provide feedback to the user, who can follow the current state of the system. The list with the offered system task is independent of the number of commands used for the BCI to control the HMI. That means that more tasks can be added without any changes in the BCI system and without adding new flickering lights. The user can navigate the MASSiVE HMI main menu by looking the associate light sources as follows. The light flickering at 13 Hz encode the command "move to the left" and the previous folder is highlighted. If the user

Frequency [Hz]	BCI command	HMI command
13	BCI_RIGHT	Select next
14	BCI_LEFT	Select previous
15	BCI_SELECT	start task/open task folder
16	BCI_CANCEL	one directory level back

Table 4.1.: Stimulation frequencies and their corresponding control commands

wants to go to the next folder, she/he has to focus on the light with 14 Hz ("right" command). To start the execution of a task or to open a task folder she or he has to focus on the 15 Hz light encoding the command "select." The 16 Hz flickering light is used to go back one directory level ("cancel" command).

4.3. A Robust BCI Based on SSVEP

The Bremen-BCI is based on the detection of SSVEP patterns. As mentioned previously, SSVEP are potentials elicited in a visual selective attention task in which BCI users focus their attention on light sources that flicker with frequencies above 5 Hz. External flickering lights are used as stimuli. Each flickering light and its corresponding SSVEP are associated with a certain control command. The Bremen-BCI detects SSVEP and also discriminates between different SSVEP patterns evoked from different stimulation frequencies. The basic components of this BCI system are the signal acquisition and signal processing components. The signal acquisition module is based on a biosignal amplifier, which records brain signals from the visual cortex, connected to the USB port of a regular laptop computer, on which the signals are processed. The signal processing component includes the software that extracts the features of the brain signals and the translation algorithm that translates the extracted features into device commands.

The Bremen-BCI implements a robust signal processing methodology that provides high information transfer rates. Recorded signals are processed to find SSVEP signal-to-noise ratios (SNR) calculated with the minimum energy combination method described in [100]. The algorithm to detect SSVEP frequencies is outlined in the following sections.

4.3.1. SSVEP Modeling

For a visual stimulation with a frequency f, the recorded brain signals are modeled as a composite of SSVEP response, background activity and noise. The measured brain signal $y_i(t)$ is the voltage proportional to scalp potential differences between a reference electrode and a signal electrode i. This model is linear and decomposes the electrode signal into three parts:

$$y_i(t) = \sum_{k=1}^{N_h} a_{i,k} \sin(2\pi k f t + \phi_{i,k}) + \sum_j b_{i,j} z_j(t) + e_i(t). \tag{4.1}$$

The first part is the evoked SSVEP response signal modeled as a number of sinusoids with frequencies given by the stimulus frequency f and a number of harmonic frequencies N_h, and the corresponding amplitude $a_{i,k}$ and phase $\phi_{i,k}$. The second part describes the background brain activity and nuisance signals $z_j(t)$, which are added to each electrode signal and scaled with the weight factor $b_{i,j}$. The nuisance signals are concurrent brain processes or external disturbances such as breathing artifacts and power line interference. The last part $e_i(t)$ describes a noise component in the measurement, which is specific for electrode number i.

Assuming a time segment of N_t samples and a sampling frequency F_s, the model can be expressed in vector form

$$\mathbf{y}_i = \mathbf{X}\mathbf{a}_i + \mathbf{Z}\mathbf{b}_i + \mathbf{e}_i, \tag{4.2}$$

where $\mathbf{y}_i = [y_i(1), \ldots, y_i(N_t)]^T$ is a vector with N_t elements, and $\mathbf{e}_i$ is a similar vector with noise. The SSVEP model matrix $\mathbf{X}$ is of size $Nt \times 2N_h$

$$\mathbf{X} = [\mathbf{X}_1\, \mathbf{X}_2 \ldots \mathbf{X}_{N_h}], \tag{4.3}$$

where each submatrix $\mathbf{X}_k$ contains a sine and cosine pair in its columns. Finally, assuming that brain signals are acquired from a number of electrodes $i = 1, \ldots, N_y$, the model can be further generalized to

$$\mathbf{Y} = \mathbf{X}\mathbf{A} + \mathbf{Z}\mathbf{B} + \mathbf{E}, \tag{4.4}$$

where $\mathbf{Y} = [\mathbf{y}_1, \ldots, \mathbf{y}_{N_y}]$ is a $N_t \times N_y$ matrix with the electrode signals as columns, and $\mathbf{Z}$ is the background activity. $\mathbf{A}$ and $\mathbf{B}$ contain the corresponding amplitudes, and $\mathbf{E}$ is the noise matrix.

4.3.2. Minimum Energy Combination

The minimum energy combination method is used to create a spatial filter that linearly combines the signals of all electrodes into channel signals in a way that the SSVEP response is magnified and strong interferences are minimized. A channel signal is denoted by $\mathbf{s}$ and consists of a combination of the signals measured by different electrodes $\mathbf{y}_i$'s. The detection of an SSVEP response is improved by considering several channels $\mathbf{S} = [\mathbf{s}_1, \ldots, \mathbf{s}_{N_s}]$, where N_s is the number of channels.

A channel $\mathbf{s}$ is obtained by combining the original electrode signal using a weight vector $\mathbf{w}$ of size N_y

$$\mathbf{s} = \sum_{i=1}^{N_y} w_i \mathbf{y}_i = \mathbf{Y}\mathbf{w}. \tag{4.5}$$

More generally, the spatial filter creates several channel by making different combinations of the original electrode signals

$$\mathbf{S} = \mathbf{Y}\mathbf{W}, \tag{4.6}$$

where $\mathbf{Y}$ is a given number of electrode signals and $\mathbf{W}$ is a $N_y \times N_s$ matrix containing the weights for each combination in its columns.

In order to minimize as much of the nuisance signals as possible, the first step is to remove any potential SSVEP components from all electrode signals by projecting them onto the orthogonal complement of the SSVEP model matrix $\mathbf{X}$

$$\tilde{\mathbf{Y}} = \mathbf{Y} - \mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{Y}. \tag{4.7}$$

The remaining signal $\tilde{\mathbf{Y}}$ contains approximately only background activity and noise, i.e., $\tilde{\mathbf{Y}} \approx \mathbf{Z}\mathbf{B} + \mathbf{E}$.

The next step is to find a weight vector $\hat{\mathbf{w}}$ that minimizes the resulting energy of the combination of electrode signals $\tilde{\mathbf{Y}}\hat{\mathbf{w}}$. The linear combination for minimizing the variance of $\tilde{\mathbf{Y}}$ is found by optimizing

$$\min_{\hat{\mathbf{w}}} \left\| \tilde{\mathbf{Y}}\hat{\mathbf{w}} \right\|^2 = \min_{\hat{\mathbf{w}}} \hat{\mathbf{w}}^T \tilde{\mathbf{Y}}^T \tilde{\mathbf{Y}} \hat{\mathbf{w}}, \tag{4.8}$$

which has the solution in the eigenvector $\mathbf{v}_1$ that corresponds with the smallest eigenvalue λ_1 of the covariance of $\tilde{\mathbf{Y}}$. Since the matrix $\tilde{\mathbf{Y}}^T\tilde{\mathbf{Y}}$ is symmetric, a combination of electrode signals produces channel signals that are uncorrelated and have an increasing energy stemming from nuisance signals. The weight matrix $\mathbf{W}$ is created by choosing the eigenvectors as follows

$$\mathbf{W} = \begin{pmatrix} \frac{\mathbf{v}_1}{\sqrt{\lambda_1}} & \cdots & \frac{\mathbf{v}_{N_s}}{\sqrt{\lambda_{N_s}}} \end{pmatrix}, \tag{4.9}$$

where $\lambda_1 \leq \lambda_{N_s}$. Each eigenvector is normalized with the square-root of the corresponding eigenvalue, therewith the resulting channel signals will have the same energy. The number of eigenvectors included in the weight matrix determine the number of channels. N_s is chosen so as to discard as close to 90% of the nuisance signal energy as possible using the following approach:

$$\frac{\sum_{i=1}^{N_s} \lambda_i}{\sum_{j=1}^{N_y} \lambda_j} > 0.1. \tag{4.10}$$

The denominator is the total energy in the nuisance signals and noise, and the numerator is the total energy retained when N_s combinations are used.

4.3.3. SSVEP Detection

Since the SSVEP response is a periodic signal with energy only in the fundamental stimulation frequency and its harmonic frequencies, the presence of this signal can be quantified as the power in the SSVEP response frequencies divided by the estimated noise power in the same frequencies, that is, an SSVEP signal-to-noise ratio (SNR). The SNR indicates how many times larger the SSVEP response is compared to the case when no stimulation frequency is present. The average of the SNR over all N_s spatially filtered signals and all N_h SSVEP harmonic frequencies is a test statistics and is calculated by:

$$T = \frac{1}{N_s N_h} \sum_{l=1}^{N_s} \sum_{k=1}^{N_h} \frac{\hat{P}_{k,l}}{\hat{\sigma}_{k,l}^2}. \tag{4.11}$$

$P_{k,l}$ is the power in the kth SSVEP harmonic frequency in channel signal $\mathbf{s}_l$ and is estimated as follows

$$\hat{P}_{l,k} = \left\| \mathbf{X}_k^T \mathbf{s}_l \right\|^2. \tag{4.12}$$

$\hat{\sigma}_{k,l}^2$ is an estimate of the noise power in the same frequency. To estimate the noise power in the SSVEP frequencies, an auto-regressive model is first fitted to the channel signals, and the fitted models are then used to interpolate the noise power in the SSVEP frequencies. The energy in the SSVEP frequencies is removed before fitting the $AR(p)$ model

$$\tilde{\mathbf{S}} = \mathbf{S} - \mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{S} = \tilde{\mathbf{Y}}\mathbf{W}. \tag{4.13}$$

The AR(p) models are efficiently fitted by invoking the Wiener-Khinchin theorem for computing the autocovariance of each channel signal and then solving the Yule-Walker equations using a Levinson-Durbin recursion. This yields the $AR(p)$ model parameters $\alpha_1, \ldots, \alpha_p$, as well as an estimate of the variance $\hat{\sigma}^2$ of the white noise driving the $AR(p)$ process. The noise level at SSVEP harmonic frequency number k can be interpolated via the following formula for the power spectrum of the $AR(p)$ process

$$\hat{\sigma}_{l,k}^2 = \frac{\pi N_t}{4} \frac{\hat{\sigma}^2}{\left| 1 + \sum_{j=1}^{p} \alpha_j \exp\left(-2\pi i j k f / F_s\right) \right|^2}. \tag{4.14}$$

where i is the complex $\sqrt{-1}$.

4.4. High-level Control Study

In order to investigate the feasibility of controlling the rehabilitation robot FRIEND-II by a brain-computer interface, the Bremen SSVEP BCI was connected to the

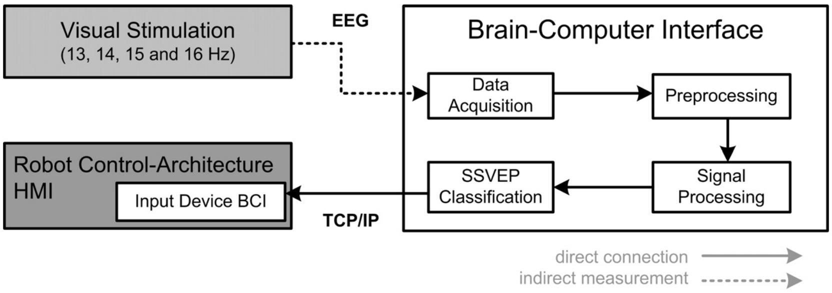


Figure 4.4.: Diagram of the SSVEP-based BCI system application.

robot control architecture. Communication between the BCI system and MASSiVE was established using the TCP/IP communication protocol. Four flickering lights with frequencies 13, 14, 15, and 16 Hz and encoding four commands (select next, select previous, start task and cancel task) were used to select goal-oriented, high-level tasks performed by the FRIEND II. Fig. 4.4 shows the block diagram of the complete system. An external visual stimulation in form of an array of light sources was presented to the user. Each frequency corresponds to a command "right," "left," "select," and "cancel" that controls the HMI main window. The BCI can detect the frequencies of the light sources by analyzing the frequency contained in the measured EEG signals and extracting the SSVEP from multiple electrodes placed over the visual cortex. When the user focuses her/his attention on one of the flickering lights, the signal-to-noise ratio corresponding to that frequency increases in amplitude. The BCI sends a command every time this signal exceeds the threshold and is transmitted to the HMI in the robot control-architecture for further processing.

4.4.1. Data Collection

All data were recorded with gold electrodes attached at the locations P_z, PO_3, PO_4, O_z, O_9, and O_{10} from a customized 65 channel montage based on the standard 10–20 system electrode placement. Data were referenced to a ground electrode placed at AF_z. Electrodes and caps were provided by g.tec (Guger technologies, Austria). EEG paste was applied to bring impedances below 5 KΩ. An EEG amplifier from g.tec was used to acquire the electrode signals. An analog bandpass filter of 2–30 Hz was used in the amplifier, and the signals were digitized with a sampling rate of 128 Hz. For visual stimulation, a custom made array with four red light emitting diodes (LEDs) was used and connected to a controller with which the flickering frequency of the diodes was generated. Each LED covered an area of about 2×4 cm^2. The LED controller is based on a PIC16F877 microcontroller that allows driving up to 16 LED's with individual blinking frequencies

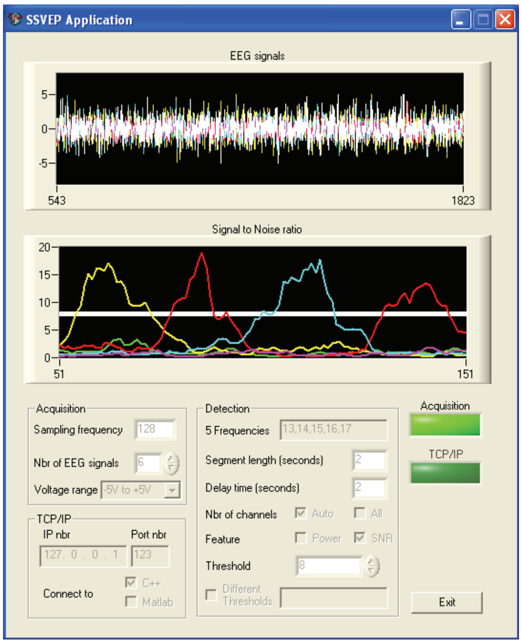


Figure 4.5.: Bremen-BCI real-time data acquisition and processing software.

in the range from 0.2 to 1000 Hz. The controller internally works with a timing signal of 204.8 μs. The flickering frequencies of the LED's were set to 13, 14, 15 and 16 Hz and duty cycle of 50%. The Bremen-BCI software system was used for all aspects of data acquisition and processing. Fig. 4.5 shows a screen-shot of the acquisition and real-time signal processing software which detects SSVEP responses, a period of 10 seconds of data is shown. In the top graph, the acquired EEG signals are plotted with a voltage range between -5 to 5V. In the bottom graph the detected SNR for each stimulation frequency is displayed. The SNR signals from six EEG channels are calculated by spatial filtering with the minimum energy combination and AR modeling methods explained in sections 4.3.2 and 4.3.3. The SSVEP detection algorithm takes a window length of 2 seconds of EEG data to calculate the SNR of the incoming signals. This calculation is executed every 100 ms (13 samples). For each frequency the SSVEP detection software shows a different SNR signal color (13 Hz $\hat{=}$ green, 14 Hz $\hat{=}$ yellow, 15 Hz $\hat{=}$ red and 16 Hz $\hat{=}$ blue). The detection threshold is drawn in the bottom plot (white line). By default this threshold was set to 8, meaning that a command is issued when the power in one of the visual stimulation frequencies exceeds 8 times its normal value. When the user focuses her/his attention on one of the flickering lights, the SNR corresponding to that frequency increases in amplitude. In the SNR plot, it can be seen how the SNRs for different frequencies increase and exceed the threshold four times, i.e., the user is able to issue four commands during this period by looking at different LED's. A result code is available for each frequency (13 Hz $\hat{=}$ '01', 14 Hz $\hat{=}$ '02', 15 Hz $\hat{=}$ '03' and 16 Hz $\hat{=}$ '04') and indicates which light source the person is focusing on. This result code is issued each time the signal with the largest SNR exceeds the threshold, then is transmitted to the application interface via the standard network protocol TCP/IP for further processing. Only if two seconds have passed since the last command, and a signal exceeded the threshold, result code is not '00'; otherwise the result code is '00', indicating that no frequency was detected or that the subject is resting.

4.4.2. Results

In a first evaluation, a healthy person known to have strong SSVEP responses was chosen as test subject. The user's task was to navigate the HMI main window by focusing on the light sources. The array of four diodes was fixed at the top of the TFT monitor of the FRIEND-II system, where the HMI application was displayed. While seated in the wheelchair (Fig. 4.1), the subject was given 9 specific menu navigation tasks to execute. Each task consists of a sequence of commands. For example, task 1 was to follow the sequence *right-right-right-select* to execute the task "Pour in beverage." The second task was to open a folder and to start a robot task following the sequence *right-right-select-right-right-right-select.* Task 3 was to go back in a folder and then select the task "serve beverage" following the sequence *cancel-right-right-right-select.* To evaluate the performance of the system, the time needed to complete each task was recorded. Moreover, the impact of the distance to the flickering LEDs was also investigated by repeating the 9 tasks both with a distance of 0.5 m and with a distance of 0.7 m to the LEDs. The times necessary to navigate the main menu using the BCI with different distances to the light sources and the number of commands for each task are shown in Table 4.2. The user was able to navigate the HMI main menu with an average speed of 2.38 and 2.69 seconds per command for the distances 0.5 and 0.7m from the light sources respectively. A paired t-test gives the statistical significance $p = 0.24$, i.e., no significant difference between the distances 0.5 and 0.7 meters could be found.

Seven subjects in the age range of 25 to 35 years, and without previous BCI experience participated in this study. Each user was asked to perform a predefined sequence to select high-level robot commands. The experiments were conducted in an office-like environment without any special shielding or other precautions to avoid or reduce external noise or interferences from other electronic devices, power lines, or routine background activity such as people talking or performing common work tasks. The given task was to navigate the HMI main menu by executing 10 commands. In order to evaluate the performance of the system, errors made and the time required to complete the command sequence were measured. An error

		Distance = 50 cm	Distance = 70 cm
Task	# of commands	Time (s)	Time (s)
Task 1	4	10:2	25:7
Task 2	6	17:9	19:0
Task 3	5	12:5	13:0
Task 4	5	15:9	12:5
Task 5	5	12:8	12:5
Task 6	5	13:0	17:2
Task 7	5	12:0	11:1
Task 8	5	12:2	09:5
Task 9	5	22:4	21:3

Table 4.2.: Times to navigate the HMI main menu with the BCI using two different distances to the visual stimulation.

was counted when the BCI made a classification that did not correspond with the user's intention. The test paradigm was as follows: The subjects were asked to look at each of the light sources and to perform some random commands to get used to the system for a few minutes. The SSVEP response was measured and the threshold for each participant was adjusted before the actual test began. The time required to execute the task, the number of errors and the estimated seconds per command for the 7 test subjects are reported in Table 4.3. Subjects #6 and #7 were not able to produce a sufficiently strong SSVEP response and thus were not able to perform the task. With subject #6 strong response was only obtained at 13 Hz. For subject #7 strong responses were obtained for 13 Hz and 14 Hz. The other five subjects achieved on average a classification rate of 96% and selection speed of 4.61 seconds per command. After the experiment, all participants were asked if the task was fatiguing, if the flickering lights caused any inconvenience, and if the selection task required considerable mental load. All participants found the task non-fatiguing. None reported about any inconvenience concerning the flickering lights, and none found that the task required a high mental load [10].

4.4.3. Discussion

In this chapter, an application of Brain-Computer interfaces in the service robotics area was presented. The MASSiVE software structure and the FRIEND-II system support the daily activities of people with severe disabilities by, among other things, controlling a seven degrees of freedom lightweight manipulator mounted on a commercial wheelchair. A large number of tasks such as pouring in a beverage or serving a beverage can be executed on a high level of abstraction using an SSVEP-based BCI, as shown in Fig. 4.6. This is done by detecting four distinct

Subject	Errors	Time (s)	# of commands	Seconds per command
1	0	18:8	8	2.35
2	0	38:9	10	3.89
3	1	72:3	10	7.23
4	0	49:7	10	4.97
5	1	46:2	10	4.62
6	-	-	-	-
7	-	-	-	-

Table 4.3.: Time required to execute the experimental task, the number of erros and the estimated seconds per command for 7 test subjects.

patterns in the brain activity of the user, who must be able to move the eyes to focus on the different light sources. It means that patients who have no voluntary muscle control of any sort including no control of eye movement cannot control this system. Potential users of this BCI application are those who have only a very limited capacity for neuromuscular control but can still control eye movement to operate the system. This group includes people with brain stem stroke, severe cerebral palsy and spinal cord injuries [1]. A BCI based on SSVEP is an alternative to, or can be used in combination with, an eye-tracker. The only disadvantage of an SSVEP-based BCI system is that the user is constantly confronted with visual stimuli, which can become exhaustive after longer usage.

An advantage of BCIs based on evoked potentials is that they can achieve higher information transfers rates compared to systems that do not use external stimuli. However, current BCIs are still too slow for controlling rapid and complex sequences of movements. Instead, the user has to execute control on a higher level. With the system presented in this work, the user can initiate the execution of a robot arm task by simply executing five consecutive commands, which is done in less than 15 seconds. Another advantage of the presented SSVEP-based BCI system compared to other non-invasive BCIs based on slow cortical potentials or motor imagery is that no training is required before using the BCI. SSVEP responses are strong inherent brain signals which can be well detected. With BCIs based on motor imagery, users need an initial training period that can take a couple of hours or a few days. They learn to control some mental task, for example, imagination of left and right hand or foot movement. With the proposed SSVEP-based BCIs, the only parameter that needs to be adjusted is the user-defined threshold. It is important to note that there are some subjects for which the SNR signals are not strong enough to be detected. The percentage of the population for which BCI control does not work well enough to control applications has been

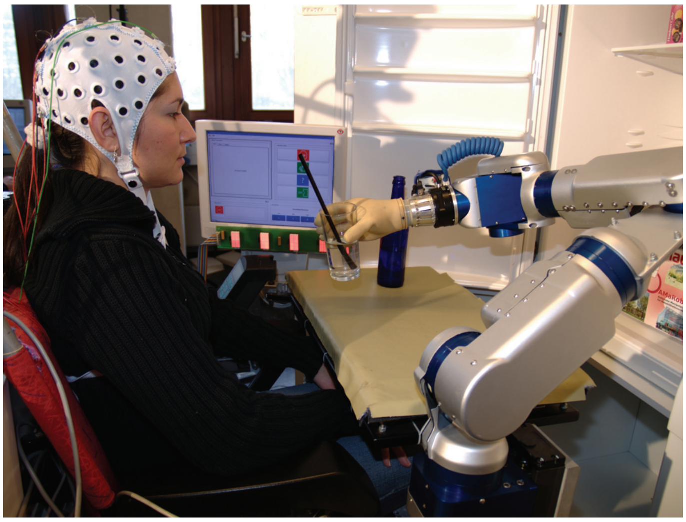


Figure 4.6.: Pouring beverage into a glass and serving a beverage scenario.

investigated in chapter 6.

4.4.4. Conclusion

The aim of this work was to integrate an SSVEP-based BCI into a semi-autonomous architecture that controls a robot arm to provide disabled users independence from care givers. With 4 commands the user navigates the main menu of the robot architecture, which in turn controls the manipulator. These commands are generated by the BCI system which detects 4 frequencies, 13, 14, 15 and 16 Hz, when the user is focusing his/her attention on the flickering LEDs. The number of tasks that can be executed by the robot arm can be increased without adding new flickering lights. It has been show that this control system provides effective navigation times for high level control. An average speed of 2.38 seconds per command was achieved with a distance of 0.5 meters from the LEDs providing the visual stimulation. Additionally, the classification accuracy of the SSVEP-based BCI was 96% in a group of 5 persons. These results demonstrate that goal-oriented control of a rehabilitation robot with a BCI is possible. It also demonstrates the robustness of the Bremen-BCI system, because the test environment was (unlike most other BCI studies) not a shielded room with ideal conditions for EEG recording. The fact that two out of seven subjects were not able to produce SSVEP cannot be accounted to the inefficiency of the BCI system. Rather, this is a result of using untrained subjects for this study. Although many subjects can perform selective attention tasks without any training, some subjects need training to learn to perform the task of selective attention effectively.

5. Software Framework for BCI Feedback Tasks

This chapter presents the development of a general software framework that enables the implementation of BCI feedback tasks. The novelty of the interface is the control via brain computer interface (BCI). The user communicates intentions through a BCI, which translates brain signals into control commands. The motivation for the development of this interface was the need to give feedback to the user. A first implementation of the feedback interface was a spelling device [101], which is described in section 5.5. The spelling device consisted of a matrix of characters, and its operation was based on 2-dimensional cursor control, four commands for navigation and one for selection. The effectiveness and robustness of the spelling program controlled via an SSVEP-BCI was demonstrated at the CeBIT 2008 (world's largest information technology fair) on 106 subjects [102], and at the RehaCare 2008 (leading international trade fair for rehabilitation) on 36 subjects [103]. Results of both studies are presented in chapter 6. The second implementation of the feedback interface led to a more general design, which included not only a BCI spelling application but a set of cooperating classes that can be reused to build any BCI application or feedback task. This chapter describes the technical realization of both implementations. After giving an overview about the software requirements of the speller task and visual stimulator, the design and implementation of a general purpose application interface that provides real-time frequency generation and feedback for the user is presented.

5.1. Introduction

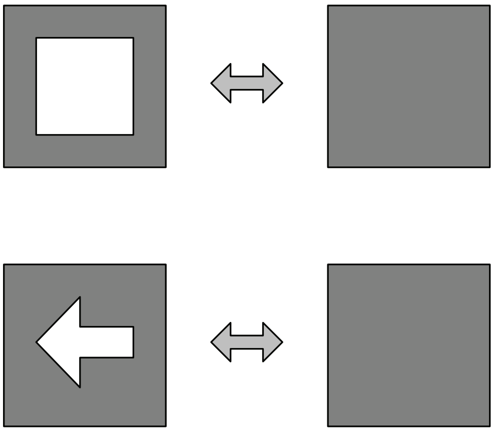
BCIs have an extensive range of possible practical applications, from very simple to very complex. The eventual practical importance of such applications depend on their capabilities, practicability, and reliability, on their acceptance by specific kinds of users, and on the extent to which they have important advantages over conventional methodologies. The practicability of BCI applications require thorough evaluation to demonstrate their long-term reliability, their functionality and acceptance across a large range of people. Particularly in the first stages of their development, the implementation of a general application interface able to configure applications that match each user's unique needs, desires and physical and social environments is needed. This chapter presents the development of such general interface for BCI applications, whose output is the feedback that the brain uses to maintain and improve the accuracy and speed of communication. The idea to create a more general software than the solution presented in 5.5.3 for a speller task was initiated after several analyses of the results obtained from conducted studies on healthy subjects as well as on disabled users (see chapter 6). The initial goal was to produce a more reliable frequency generation and improve the feedback presented to the user. Those considerations led to the design and implementation of a software framework that is be the basis for the implementation of new BCI applications, which can adapt to the users' preferences and different signal processing methodologies. The software presented here is developed to be as general as possible and to provide real-time feedback to the user. Feedback provides information of the correct or incorrect response in a synchronous (cue-based) or asynchronous (uncued) BCI. This feedback can be discrete or continuous, one- or more dimensional, real or virtual. Feedback is not only important during the training period but also during the operation of the BCI application. Therefore, several feedback tasks were implemented for testing new paradigms or stimulus characteristics (stimulus presentation task), for BCI training (speller, labyrinth, robot control task) or for communication purposes (speller task). One of the main features of the software is the visual stimulation for SSVEP-based BCIs, which includes the difficult task to generate frequencies and the display of stimuli on the computer screen in real-time.

5.1.1. Repetitive Visual Stimuli

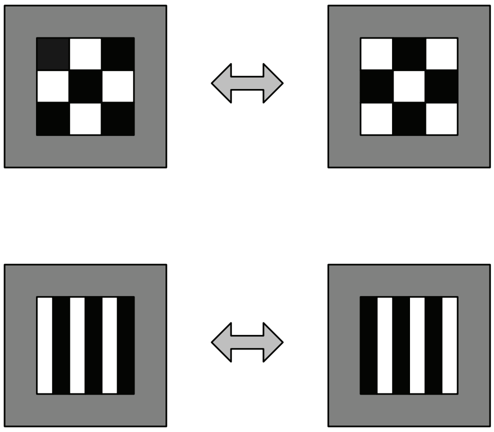
Exogenous BCI systems rely on activity elicited in the brain by external stimuli, such as BCIs based on Steady-state Visual Evoked Potentials (SSVEP). To elicit an SSVEP, a repetitive visual stimulus is presented to the user. Each command is associated with a repetitive visual stimulus. If users direct attention to one such stimulus, activity over occipital areas at corresponding frequencies can be used to infer user intent [23]. The stimulus may oscillate at a frequency from 1 to 100 Hz [59]. The properties of the visual stimulator such as frequency, contrast, color, are dependent of the rendering device and influence the SSVEP response (amplitude and phase). This section presents the three properties of the repetitive visual stimuli that have a significantly effect on the strength of the SSVEP signal, the rendering device, color, and frequency.

Stimulus Type

In SSVEP-based BCIs research, visual stimulators are typically displayed on two types of devices, light sources and computer monitors [104]. The repetitive visual



(a) single graphic stimuli



(b) pattern reversal stimuli

Figure 5.1.: Stimuli rendering options for visual stimulation on a computer screen. From [104].

stimulus can be rendered on a computer screen by alternating graphical patterns, or with external light sources able to emit modulated light. Stimulus presentation for SSVEP-based BCIs is typically rendered using either single graphic stimuli or pattern reversal stimuli, as shown in Fig. 5.1.

Light stimuli are rendered using light sources such as light emitting diodes (LED) [105], fluorescent lights [106], or Xenon lights [107], which are modulated at a specific frequency. The frequency of the light sources are typically controlled by electronic circuits, which internally used microcontrollers for frequency generation. These kind of circuits provides accurate waveform generation.

Single graphics stimuli are rendered on the computer screen in form of rectangles, square, images or arrows (see Fig. 5.1(a)). The single stimuli appear and disappear from the background at a specific rate.

Pattern reversal stimuli are rendered by alternating at least two graphical patterns, for example, checkerboxes or lineboxes, as shown in Fig. 5.1(b).

Stimulus Color

Color is other characteristic that may affect the quality of the SSVEP response with different displays. Regan (1966) reported the effect of stimulus color on average SSVEP potentials by showing the relationship between the peak-to-peak amplitude of the potentials evoked by red, yellow, and blue stimuli [108]. He found an interesting dependency on the frequency of the stimuli. For both blue and red light the low-frequency flank of the amplitude peak was very steep, but for the high-frequency flank was less steep for blue than for red. Red stimuli had the most selective amplitude peak, and yellow the least. In other study, chromatic (isoluminant red and green sinusoidal gratings) and achromatic (black and white sinusoidal gratings) VEPs were compared [109]. The second and four harmonic of the SSVEP were affected by the chromaticity of the visual stimuli. For SSVEP-based BCIs that use LEDs for stimulation, red, green, and white color have been used, whereas red color is the most used. For pattern reversal and single graphic stimuli, the white and black combination is the most popular. Nevertheless, at present there is no study that addresses how color influences the performance of SSVEP-based BCIs [104].

Stimulus Frequency

The stimulation frequency is one of the most important properties of the repetitive visual stimuli. When a subject gazes at the stimulus, SSVEP is induced in the brain. The fundamental frequency of the evoked SSVEP matches exactly the frequency of the target. Boundaries of SSVEP are often defined in the 3–50 Hz range. However, flickering stimuli at very low frequencies ($\ll 3\,\mathrm{Hz}$) can induce SSVEPs [110]. Also, other investigations have shown that SSVEP can be elicited up to 80 Hz [59]. Those frequencies can be classified into three frequency bands as suggested by Regan (1989) [57]: low (1–12 Hz), medium (12–30 Hz), and high (30–60 Hz). The frequency resolution of the SSVEP is about 0.2 Hz and the bandwidth in which the SSVEP can be effectively observed is between 6 and 24 Hz (empirically determined values) [55].

5.2. Software Specifications

The problem was specific to the design and implementation of a spelling application with the following requirements:

- Graphical representation of a spelling layout with the possibility to adjust values and properties of the targets (letter and symbols).
- Graphical representation of SSVEP visual stimulation, and configuration of stimuli parameters such as color, frequency, size, etc.
- Real-time frequency generation.
- Discrete feedback presentation in form of 2-dimensional cursor control and mapping of BCI commands for cursor directions and target selections.
- Continuous feedback representation.
- Control via a brain computer interface.

- Network connections for the acquisition of control signals from any BCI signal processing module.

5.3. Software Design

The software design based on the requirements described above led to the design and implementation of a more general application interface able to configure BCI applications and provide real-time feedback to the user. The aim was to evaluate the practicability, reliability and acceptance of new applications and feedback methods for BCI.

The solution was designed specific to the problem at hand but also general enough to address future problems and requirements. The idea was to avoid re-design in the case of the implementation of new feedback tasks, which were not necessary known at the time of software creation. This important issue led to consider the use of a design pattern. As defined in [99], a design pattern explains a general design that addresses a recurring design problem in object-oriented systems. It describes the problem and gives a solution as a general arrangement of elements (objects and classes in this case) that solve the problem. Design patterns make easier to reuse successful designs and architectures. The design pattern used in this work focuses on the creation of BCI feedback tasks and real-time frequency generation.

5.3.1. BCI Feedback Tasks

BCI feedback tasks are basically user interfaces that translate data coming from the signal processing unit of the BCI into a visual representation on the screen to provide visual feedback to the user. Any BCI application consists of the following elements (see Fig. 5.2). The *control signal* is the output of the signal processing module of the BCI and reflects user's intent, the *view* is its screen representation, and the *parameters* define application-wide settings that is constant during a run. A run is the time period when the application is started, and ends when the application is suspended. The application view must ensure that its appearance reflects actual user's input. If the control signals change, the view updates itself. Besides the graphical representation of the feedback tasks, their configuration is also of high relevance. A BCI application have to be constantly tested and parameters have to be adjusted in regards to subject's skills and preferences. Each feedback task should be configurable in a modern and convenient way by means of a graphical user interface (GUI). Between configuration dialogs and feedback tasks exist a high cohesion, because configuration dialogs configure or parametrize the tasks. In general, any feedback task follows five states of operation:

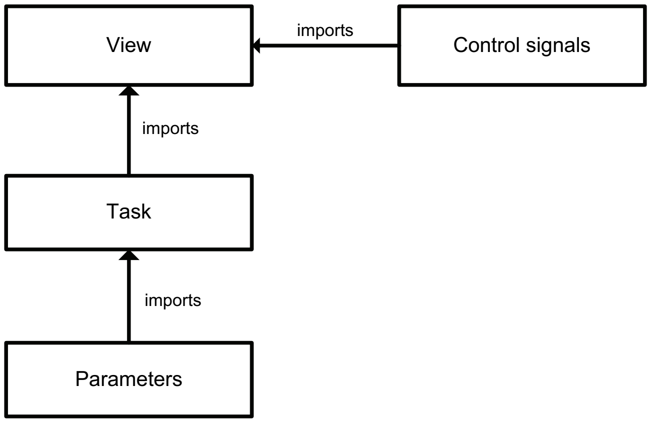


Figure 5.2.: BCI feedback task elements and their relationship.

1. *Start-Up*: instantiates the task.
2. *Initialization*: set application parameters.
3. *Suspended:* The task is suspended at the end of the initialization phase, the task is fully configured.
4. *Running:* processes all incoming control signals.
5. *Termination:* closes the application window.

5.3.2. Real-time Frequency Generation

This section is dedicated to the frequency generation for repetitive visual stimuli that are displayed on the computer screen. The basic principle of a repetitive visual stimuli is the alternation of a single graphical object that appears or disappears into the background at a specified rate. The stimulation rate is reported as the number of full cycles per second, normally simply referred to as the frequency of the stimulus [104]. Single graphics stimuli elicit an SSVEP response at the frequency of one full cycle (i.e. two alternations). Thus, the period of one alternation for any single graphic stimulus is given by

$$T = \frac{1}{2f} \tag{5.1}$$

The timing of the graphical alternations is a real-time task that needs a special design and implementation. The first version of the software made use of multimedia timers (see section 5.5). This approach showed that the usage of timers did not produce the best scheduling for the repetitive visual stimuli because of their accuracy and resolution. Timers do not have the possibility to check if the requested number of timer clicks could be delivered or not. For example, if a timer is unable to deliver the requested number of clicks, it will silently discard some. Moreover, they are not guaranteed to time out at the exact value specified. In many situations, they may time out late by a period of time that depends on the accuracy of the system timers. Most platforms support a resolution of 1 millisecond, though the accuracy of the timer will not equal this resolution in many real-world situations [111].

To minimize problems experimented with timers, the solution proposed here makes use of a worker thread. The thread operates at a sampling time T_s, from which the stimulation frequencies are calculated. The number of frequencies that can be generated depend on the number of alternations and the sampling time T_s, in this case, two alternations are used. Thus, the period T_n for a single stimuli n in function of the thread sample time T_s is defined by

$$T_n \in \{2mT_s\}\,; m = 1, 2, 3, \ldots ; n = 0, 1, 2, \ldots \tag{5.2}$$

Using the relation between period and frequency, all possible stimulation frequencies f_n that can be generated using two alternations are calculated by

$$f_n \in \left\{\frac{f_s}{2m}\right\}; m = 1, 2, 3, \ldots ; n = 0, 1, 2, \ldots \tag{5.3}$$

where f_s is the sampling frequency of the worker thread. Table 5.1 shows an example of all possible frequencies that can be generated with a worker thread operating with a sampling time of 20 ms and two alternations (a total of 25 frequencies can be generated). The number of generated frequencies could be increased up to 50 by using different number of alternations, but that would influence the duty cycle of the stimulation frequency and thereby the SSVEP response to the stimulus. With two alternations the duty cycle is kept at 50%.

For the implementation of this approach, the system parameter T_s is crucial and must be selected respect to several constraints, e.g., the hardware (microprocessor, graphic card) and the operating system. From (5.3), it can be also deduced that the maximum possible frequency for a virtual LED (VLED) that can be generated using this approach is half of the sampling frequency f_s of the worker thread, that is

$$\max f_n = \frac{f_s}{2}. \tag{5.4}$$

If the stimulation frequency is produced in form of a square wave, there exist two states. Each VLED v_n has an active or ON state ($v_n = 1$) that shows a single graphic item, and a passive or OFF state ($v_n = -1$) that hides the graphic item,

$$v_n \in \{1, -1\}\,; n = 0, 1, 2, \ldots \tag{5.5}$$

n	m	$T_n(ms)$	$f_n(Hz)$
f_0	1	40	25.00
f_1	2	80	12.50
f_2	3	120	8.33
f_3	4	160	6.25
f_4	5	200	5.00
f_5	6	240	4.17
...	...	...	...
f_{24}	25	1000	1.00

Table 5.1.: Stimulation frequencies generated using $T_s = 20\,\mathrm{ms}$ ($f_s = 50\,\mathrm{Hz}$).

The flickering frequency is then produced by changing the state of the VLED. To determine when a VLED must change its state v_n, a counter c_n is introduced for each VLED. The counter c_n describes how many times the worker thread is executed before the corresponding state v_n changes. The value of the counter is calculated in relation to the period T_n by

$$c_n = \frac{T_n}{2T_s}. \tag{5.6}$$

In general, for each sample point k in which the worker thread is executed,

$$\begin{aligned} t &= kT_s; t \geq 0 && (5.7) \\ \Leftrightarrow k &= \frac{t}{T_s} && (5.8) \end{aligned}$$

all counters c_n are subtracted by 1:

$$\forall n : c_{n,k} = c_{n,k-1} - 1 \tag{5.9}$$

At sample point $k = 0$, the initial value for all counters is first calculated as indicated by (5.6)

$$\forall n : c_{n,0} := c_n = \frac{T_n}{2T_s}. \tag{5.10}$$

Then, the state $v_{n,k}$ of the VLED is changed only if the corresponding counter $c_{n,k}$ is equal to 0:

$$\forall n : v_{n,k} = \begin{cases} c_{n,k} = 0 & (-1)v_{n,k-1} \\ c_{n,k} \neq 0 & v_{n,k-1} \end{cases} \tag{5.11}$$

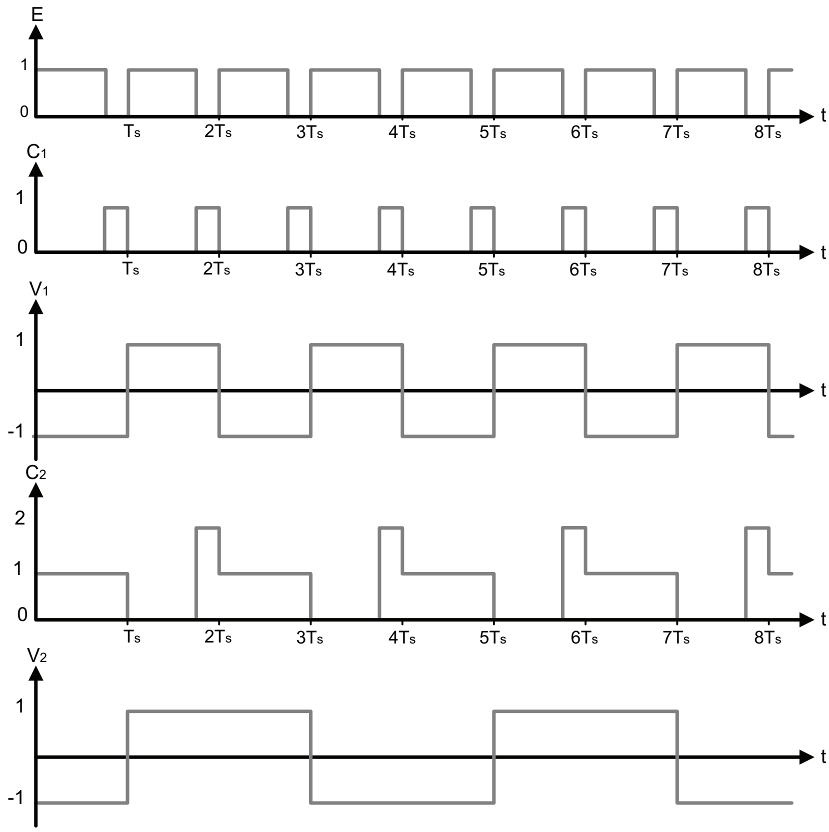


Figure 5.3.: Example of the generation of two stimulation frequencies with $T_1 = 2T_s$ and $T_2 = 4T_s$.

When a counter $c_{n,k}$ reaches zero, its current value is reset to its initial value calculated as in (5.6) to be ready for the next state change, as follows:

$$\forall n : c_{n,k} = \begin{cases} c_{n,k} = 0 & \frac{T_n}{2T_s} \\ c_{n,k} \neq 0 & c_{n,k-1} \end{cases} \tag{5.12}$$

Fig. 5.3 shows an example of the generation of two different stimulation frequencies using the worker thread approach. E represents the execution state of the worker thread. $E = 0$ means that the worker thread is suspended, and $E = 1$ that the thread is running or executed. For simplification of this example it is assumed that the thread is not interfered by other threads or processes. v_1 and v_2 are VLEDs with flickering periods $T_1 = 2T_s$ and $T_2 = 4T_s$, respectively. c_1 and c_2 are the corresponding counters for each VLED.

For a stimulation frequency with period $T_1 = 2T_s$, the initial value of the counter

c_1 is calculated by

$$c_1 = \frac{T_1}{2T_s} = \frac{2T_s}{2T_s} = 1 \tag{5.13}$$

The initial value of c_1 is 1, meaning that the counter c_1 only can switch between the values $\{0, 1\}$. The VLED v_1 changes its state every sample point $k = \frac{t}{T_s}$, which results in the maximal possible flickering frequency $f_1 = \frac{f_s}{2} = \frac{1}{2T_s}$.

For a frequency with period $T2 = 4T_s$, the initial value of the counter c_2 is calculated by

$$c_2 = \frac{T_2}{2T_s} = \frac{4T_s}{2T_s} = 2 \tag{5.14}$$

This counter c_2 switches between the values $\{0, 1, 2\}$ and the state v_2 of the VLED only changes every second sample point $2k = \frac{2t}{T_s}$. This results in a flickering frequency $f_2 = \frac{f_s}{4} = \frac{1}{4T_s}$, which is shown in the time diagram as v_2.

5.4. Software Implementation

The programming language used for the implementation of the design pattern was C++ [112], and the Qt4 [111] framework was selected for graphical representation. The proposed design pattern bundles base functionality which is useful for any BCI application into a base class. This functionality comprises the acquisition of signals, parametrization of application view position and dimensions, maintaining an application log and application messages to the user, initialization and processing events that occur during system start-up and operation, evaluation methods of user performance (time, accuracy and information transfer rate). Each specific feedback task consists of a set of common operations defined by its interface. New tasks can be defined in terms of existing classes using class inheritance. When a task class inherits from a parent class, it includes the definitions of all data and operations that the parent class defines.

Fig. 5.11 shows an unified modeling language (UML) [113] class diagram with the participants of the design pattern. Four different tasks for representing BCI signals were implemented. All tasks have identical interface but different implementations. The classes defining a stimulus presentation, speller, labyrinth, and robot feedback tasks are the concrete BCI applications.

The following classes are the participants in the design pattern:

`ApplicationBase` is the base class from which all feedback task classes inherit.

`StimulusTask` is a base class for application modules that require the presentation of stimulus flickering with a desired frequency. It implements real-time frequency generation using a worker thread (see section 5.3.2).

`FeedbackTask` is a base class for application modules that provide feedback in a trial-based paradigm.

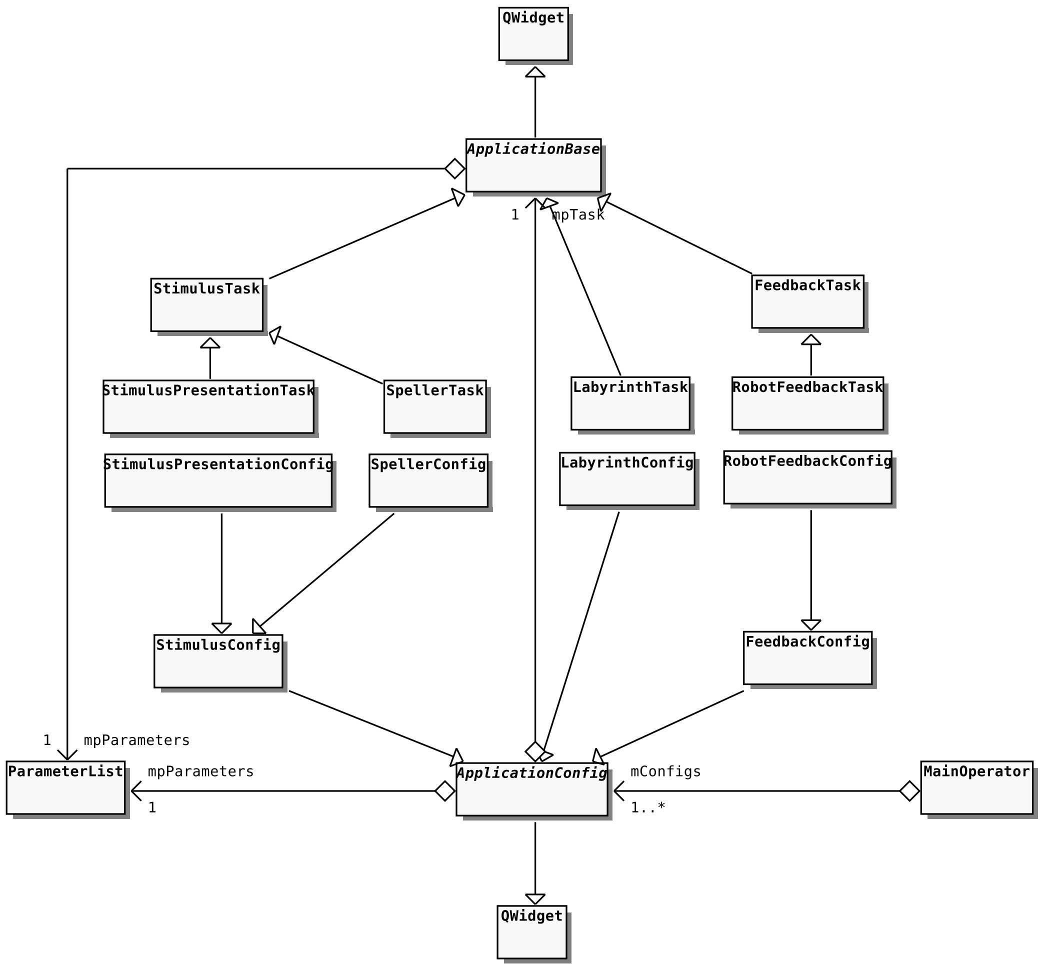


Figure 5.4.: UML class diagram for BCI feedback tasks and their configuration dialogs.

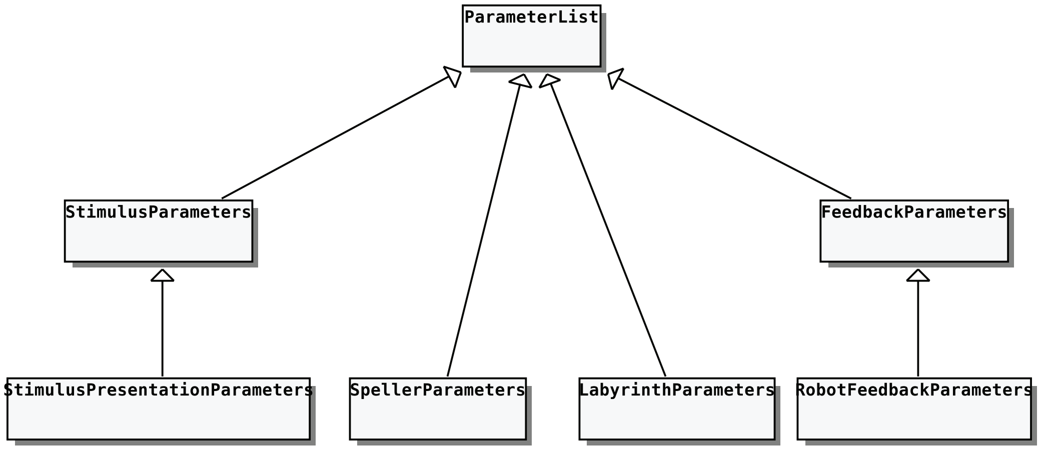


Figure 5.5.: UML class diagram for parameter lists.

Objects of type FeedbackTask or StimulusTask are not use directly; rather, subclasses inherit from it, and implement specialized behavior building on the base functionality provided by this classes.

`StimulusPresentationTask`, `SpellerTask`, `LabyrinthTask`, and `RobotFeedbackTask` are the concrete products or concrete task classes.

`ApplicationConfig` is the task creator. It instantiates the concrete task object and is the base class for configuration dialog classes.

`StimulusConfig`, `StimulusPresentationConfig`, `SpellerConfig`, `LabyrinthConfig`, `FeedbackConfig` and `RobotFeedbackConfig` are the concrete creators, which means here the concrete configuration dialog implementations.

`MainOperator` is the experimenter's user interface, determines the system configuration and which task should be started.

`ParameterList` is used to hold and transfer information between the tasks and its configuration. It holds all information needed by every task class to represent the model.

`StimulusParameters`, `StimulusPresentationParameters`, `SpellerParameters`, `LabyrinthParameters`, `FeedbackParameters` and `RobotFeedbackParameters` are the concrete task parameters holding specific information for each task class.

5.4.1. Classes Description

ApplicationBase Class

`ApplicationBase` is the base class for all concrete products or concrete task classes. It declares pure virtual methods [112], other methods and attributes. `ApplicationBase` is not a pure virtual class [112]. The reasons are of practical

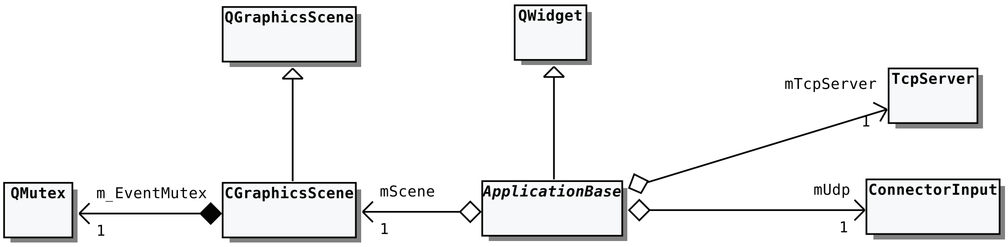


Figure 5.6.: UML class diagram for `ApplicationBase` class.

nature, because in this way `ApplicationBase` can provide to its children general methods and attributes. `ApplicationBase` inherits from `QWidget` because all concrete BCI tasks should be graphically represented as widgets [111]. It has also an aggregation to `CGraphicsScene`, which is a simple reimplementation of the original Qt4 class `QGraphicsScene`. `CGraphicsScene` aggregates a `QMutex` object to provide access serialization between threads [111]. A mutex avoids parallel accesses to the graphical representation (scene), which could cause undesired graphical artifacts. Fig. 5.6 shows a detailed UML class diagram of this class.

Additionally, `ApplicationBase` has an aggregation to `TcpServer`, which holds an implementation for listening on a TCP socket, and an aggregation to `ConnectorInput`, which is an implementation for incoming UDP packets. `TcpServer` is used for the general interaction with other BCI software like signal processing modules, whereas `ConnectorInput` is a concrete implementation for interaction with the BCI2000 framework [18]. Both aggregations are static [112], because for different instances of `ApplicationBase` children only one concrete TCP and UDP socket can be used.

StimulusTask Class

The `StimulusTask` class is a cooperating class that makes up a reusable design for the implementation of BCI tasks based on stimulus presentation. `StimulusTask` is parent class from which another classes inherit. Its responsibility is the frequency generation and presentation of stimuli within the framework. This design provides the advantage that common methods and attributes can be provided by only one implementation and do not have to be reimplemented several times. `StimulusTask` can not instantiated directly, because it holds pure virtual methods which must be implemented by its children. Fig. 5.7 shows a UML class diagram of this class and other related classes for stimuli presentation. `StimulusTask` is the parent class for all task classes that require stimulus presentation, e.g., speller task and stimulus presentation task. `StimulusTask` holds an aggregation to the nested class [112] `StimulusThread`.

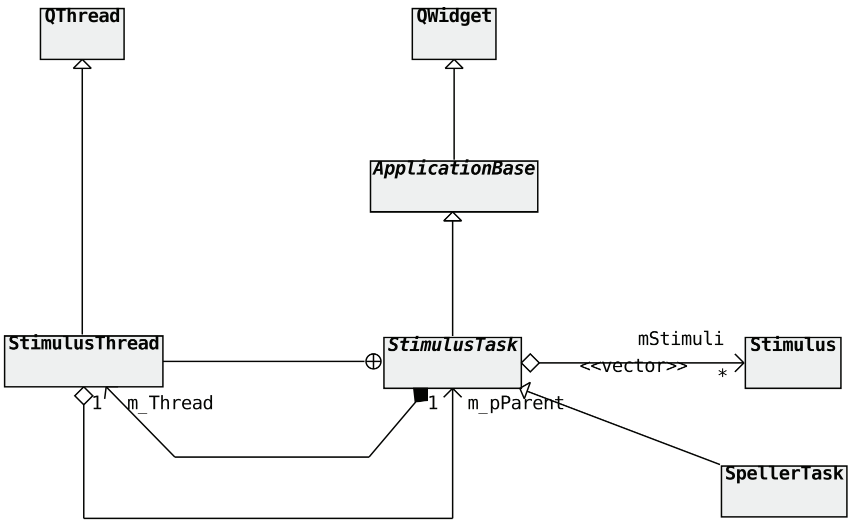


Figure 5.7.: UML class diagram of the `StimulusTask` class.

StimulusThread Class

The real-time frequency generation was also integrated in the design pattern. `StimulusThread` is the implementation of the worker thread approach presented in 5.3.2. To create the worker thread that controls the timing of the stimuli alternations, the subclass `StimulusThread` inherits from `QThread` [111]. The `QThread` class provides platform-independent threads. The sampling behavior of the worker thread is then realized by reimplementing the virtual method `StimulusThread::run()`, which is the starting point for the thread. After calling `start()`, the created thread calls `run()`.

`StimulusThread` is a nested class of `StimulusTask`, because it needs direct access to several members of its parent, which are private. This access is realized by the aggregation `m_pParent` of the type `StimulusTask*`, a pointer to its parent class. Stimuli counters and states are located in `StimulusTask::mStimuli`, an aggregation to the `Stimulus` class, which can be accessed by `m_pParent` pointer. `StimulusTask` always holds exactly one instance of `StimulusThread`, which is described by the composition `m_Thread`.

This methodology uses the soft real-time [114] methods existing in current operating systems. These are mainly sleep-statements, which suspend a thread for a certain amount of time. For the measurement of the execution time, the Advanced Communication Environment (ACE) [115] communication framework was used. The actual functionality of Qt4 does not provide the possible available accuracy under a Linux-kernel, which is currently in the range of nano seconds, and therefore ACE instead of Qt4 was used for this task. ACE is also platform-independent and

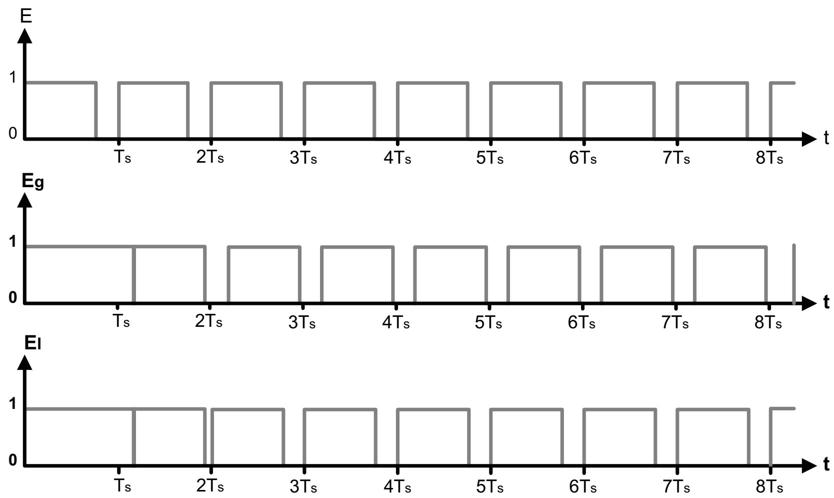


Figure 5.8.: Different drifts of sample points.

therefore presents no limitation for the running operating system of the software.

Soft real-time systems could produce drifts of sample points. If the execution of the thread for a sample point k is delayed about some Δt, the execution of the next sample point $k+1$ can not start at $t = (k+1)T_s$. The next sample point would start at $t = (k+1)T_s + \Delta t$ instead. If that occurs, it is said that the sample point $k+1$ has drifted. The consequence of a drift is that all following sample points will drift about Δt. Furthermore, any additional drifts Δt_n with $n = 0, 1, 2, \ldots$ will be added to the drift. The time of later samples points are calculated as $t = (k+1)T_s + \Delta t + \sum_{n=0}^{\infty} \Delta t_n$. This is called global drift of sample points. In general, drifts of sample points can not be avoided in soft real-time systems because of their definition, but it is possible to eliminate the influence of the drift of a single sample point. This can be done by calculating the time for the next sample point. That means, in the case that the sample point $k+1$ has drifted by $t = (k+1)T_s + \Delta t$, the following sample point $k+2$ will not drift, because its start time $t = (k+2)T_s$ is calculated. This is called local drift of sample points.

Fig. 5.8 shows the difference between global and local drifts as time diagrams. E is an ideal thread execution without any drift, E_g is thread execution with global drift and E_l is thread execution with local drift. To avoid general global drifts, the calculation of start points was implemented in `StimulusThread` and therefore only local drifts can occur. This is assumed to be the currently best solution for soft real-time systems.

To minimize the execution time of the thread, which directly influences the minimal possible sample time T_s, some parts of the thread method `StimulusThread::run()` were manually enhanced by the usage of inline assembly statements [112].

Although current compilers already provide a very good code optimization, it was necessary to optimize code parts, which were very often executed like elements of loops by manually written assembly parts with the aim to reduce the thread execution time. The calculation of counters and VLED states is the main execution part of the worker thread and was therefore enhanced by inline assembly statements. The minimal possible sample time T_s of the worker thread depends on the hardware of the executing system. On the main testing system, it could be observed that the enhancement with inline assembly reduced the minimal sample time about approximately 2 ms. Since the minimal sample time directly influences the possible frequencies for generation (see equation 5.3), this can assumed to be an important advantage.

A `StimulusTask` object can have a set of stimuli and therefore `StimulusTask` has an aggregation of multiplicity * to the class `Stimulus`. Objects of the class `Stimulus`, also shown in Fig. 5.7, are used for the graphical representation of VLEDs. Their sates (on, off) are modified by `StimulusThread` as already described above.

SpellerTask Class

`SpellerTask` is a concrete product in the design pattern because it can directly be instantiated. It provides all functionality needed for a typical BCI spelling application. This means on the one hand the graphical display of the virtual keyboard or speller, but also the generation of flickering VLEDs. The speller class inherits from `StimulusTask` to provide all visual stimulation functionality. `SpellerTask` uses the `mTcpServer` aggregation of its base class `ApplicationBase` to connect and interact with signal processing software. The speller class could be also the basis for the implementation of new communication functions such as sending/receiving emails, chatting, or surfing the web, which can effectively improve the quality of life of the disabled user. The primary used speller task configuration is presented in Fig. 5.9(a). It consists of a layout with 32 characters arranged in a rhombus layout and five stimuli used to navigate the cursor and select characters.

StimulusPresentationTask Class

This class presents sequential series of visual stimuli to the user. It implements evoked responses, and selective attention paradigms, or screening sessions. The sequence and characteristics of the stimuli can be parametrized though its corresponding configuration dialog. Fig. 5.9(b) shows an example of a stimulus presentation task. The subject's task is to focus attention to the stimulus flickering at a desired frequency while performing series of mathematical tasks.

LabyrinthTask Class

The `LabyrinthTask` class is the implementation of a training environment that navigates an object or a cursor through a 2D maze, the subject's task is to bring the cursor from the start position to the final position. The input signals can be control signals from a BCI or key events. The labyrinth task responds to four control commands: "move forward," "move backwards," "turn right," and "turn left." This task was already used to train users to modulate sensorimotor rhythms by performing three mental tasks (see chapter 3). Additionally, this task measures performance in terms of competition time (s), accuracy (%), and information transfer rate (bit/min). This information is updated every second and presented at the bottom of the display. Fig. 5.9(d) shows a screen-shot of the labyrinth display after the finalization of an experimental run. The cursor is represented by a green arrow. `LabyrinthTask` inherits from `ApplicationBase` and implements the following methods:

1. *Initialize()*: set application parameters. The cursor is located at the "start" position and waits for data to process. All counters are reset.

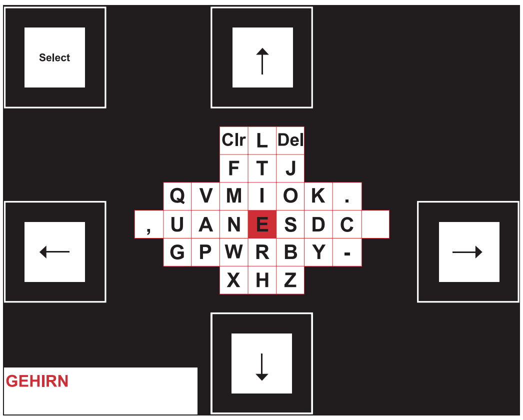
2. *StartRun():* the run is started only when a "move forward" command is received. The cursor will move forward to the next position in the labyrinth. At this time point the experimental run is started and the current time is measured.

3. *Process():* this method maps all commands received via TCP or UDP into cursor movements.

4. *StopRun():* the task is suspended at the end of the initialization phase, the task is fully configured, or when the "finish" position has been reached.

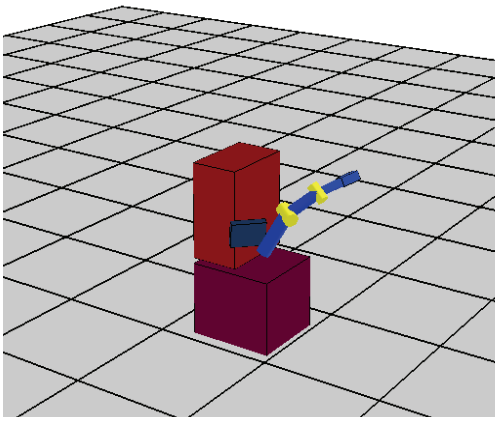
RobotFeedbackTask Class

The `RobotFeedbackTask` class is the implementation of a virtual training environment that shows the model of a robot manipulator mounted on a wheelchair in a 3D space (see Fig. 5.9(c)), similar to the FRIEND system at IAT. This task was included in the software to be used in further feedback studies or to train subjects before they operate the real system. This class includes the `libMVRGL` library that provides a set of classes to map objects using virtual reality (MVR) [116]. Real objects can be modeled by combining three simple shapes (cuboid, cylinder and sphere).

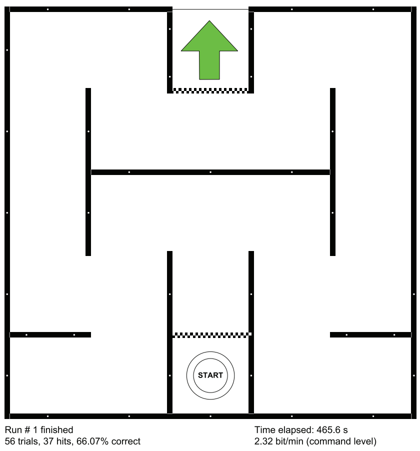


(a) Speller task

(b) Stimulus presentation task



(c) Robot feedback task



(d) Labyrinth task

Figure 5.9.: Visualization of four different BCI feedback tasks implemented in "Neurofeedback" using the classes of the BCI feedback framework.

MainOperator

The MainOperator class uses the framework elements to provide an application (executable) called NeuroFeedback.exe. The main operator is a window that shows an icon for each available feedback task.

5.5. Speller with Integrated Stimulator

This section presents the speller application with integrated SSVEP stimulator used in the experiments in chapter 6. The application consist of a matrix of 32 possible selections (letters and symbols) and five single graphics stimuli encoding five different commands (see Fig. 5.10). The matrix is navigated right, left, up and down to reach a character by focusing on the flickering lights. With this integrated system, the stimulus and the visual feedback are provided on the same screen and therefore the user's attention is kept on the same place, making the execution of tasks faster and avoiding error-classifications. The user does not need to switch attention between the stimulus and the feedback provided by the speller application to see if the output corresponds to what she/he wanted to spell. An earlier version of the system [10] (see chapter 4) had an array of LEDs, but subjects had to shift attention from the monitor to one of five LEDs to effect control. Subjects complained that switching attention from the monitor to another target, often located outside the fovea, impaired performance and ease of use. Therefore, the integration of stimulus sources and feedback in one application was more suitable.

5.5.1. Spelling Layout

The spelling layout was chosen depending on the strategy used for selecting characters and the available number of commands. When only binary decisions of the BCI are used to select letters, a procedure that employs partitioning the alphabet until the desired letter remains may be suitable. With the Bremen-BCI more than two commands can be robustly detected. Therefore, a selection strategy based on five commands was used for this spelling application. In prior work carried out at the IAT lab, two different spelling layouts and selection schemes were compared and evaluated to be controlled with five commands [117]. The Row-Column layout is similar to the design commonly used in P300 spelling programs, where letters are chosen by first selecting the row containing the desired letter and then the column. The Rhombus layout is that in which a cursor is navigated right, left, up and down to reach the desired letter. It was found that the row-column layout was faster, especially for strong performing subjects. For low performing subjects, the rhombus layout may be more suitable because accidental commands or error-

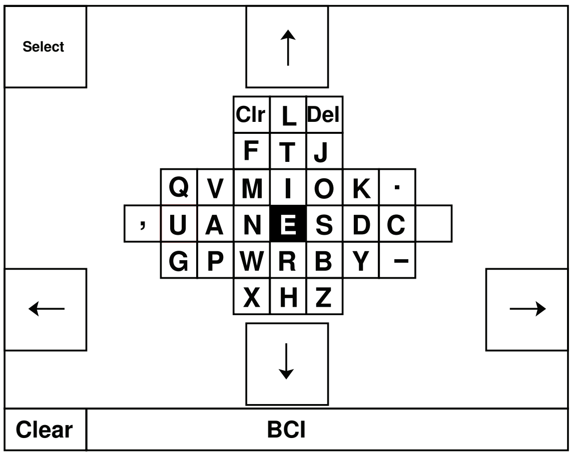


Figure 5.10.: Brain actuated spelling device with integrated visual stimulator.

classifications can easily be corrected by the user. An error only means that the cursor moves one step in the wrong direction. In the row-column layout, all commands are implicitly select-commands. Thus, with the Rhombus layout is easier to keep a constant visual attention and accidental commands or error-classifications can easily be corrected by the user. Therefore, the rhombus layout was selected as spelling layout for the Bremen-BCI application. Some modifications to the Rhombus layout were done. Delete and clear functions were implemented as additional characters and some other characters were added.

Fig. 5.10 shows the spelling layout used in this application to be controlled with five commands. The display consisted of a matrix with 32 letters and other characters that the subject could communicate. Delete and clear functions were elements that can be selected in the matrix. Letters were ordered depending on their occurrence in the English language. Except for the letter 'E,' which its occurrence is the most frequent in the English alphabet, two or more commands are needed to select a letter. Other frequent letters are ordered to be reached without any attention switches, e.g., the letter 'C,' can be reached just by using the "right" command three times. It is assumed that the sequence *right-right-right* is faster to execute than *left-up*. The selection of a letter requires navigating the cursor right, left, up and/or down until the desired letter is reached. Once a letter has been selected, the cursor starts over at the center position, the 'E' character.

5.5.2. Visual Stimulator

The SSVEP stimulator consists of single graphic objects that appear and disappear in the background at a specific frequency. Visual stimulators displayed on the computer screen implement virtual LEDs and its frequency is generated on software by alternating the graphics objects [101]. The stimulator for the spelling layout displayed in Fig. 5.10 requires five VLEDs that flicker to a desired frequency on the computer screen. For two dimensional control, four stimuli encode cursor movement commands (left, right, up and down) and one command for the selection of a character. Each VLED is alternated in constant intervals depending of the stimulation frequency.

5.5.3. Speller Program

The speller program is the software implementation of the spelling layout and visual stimulator described above. The object-oriented programming language C++ [112] was selected for this implementation. For the visualization of the speller and the visual stimuli, the cross-platform framework Qt4 [111] was used. Qt4 supports 2D graphics applications by incorporating a broad set of rendering, texture mapping, animations, special effects, and other powerful visualization functions. The speller application is a graphical interface that consist of rectangular elements that can be either *targets* or *stimulus*, and a status bar that shows the spelled text. Targets are objects that perform an action when they are selected; and stimulus are objects that can present or hide itself performing a flickering action. This application receives five commands from the BCI analysis software. Four commands correspond to cursor movements and the fifth command performs letter selection. The cursor moves by highlighting the current target and a letter is selected by appending the current target text to the status bar text. If "'Del" is selected, the last character is deleted from the status bar and for "Clr," the status bar is cleared.

An UML class diagram of the spelling application is shown in Fig. 5.11. The spelling program consists of the following classes:

`MainApplication` class is the application main window. It inherits from the `QWidget` class. A widget is the base element in Qt and the base class of all user interface objects. `MainApplication` is a window with a frame and a title bar. It contains an object of the `TcpServer` type for network connections and an object of the `Speller` type for showing the graphical interface for the speller application and the visual stimulator. Information about the state of the client connection is available on its title bar. It also receives mouse and keyboard events from the window system. Keyboard events are received by reimplementing `keyPressEvent()`.

`Speller` class is a widget responsible for displaying targets (letters or symbols) and stimuli objects. This class is based on the graphics view framework of Qt [111], which provides a surface for managing and interacting with a large number of 2D graphical items (scene), and a view widget for visualizing the contents of the scene. A `QGraphicsScene` object contains items of varying geometric shapes and serves

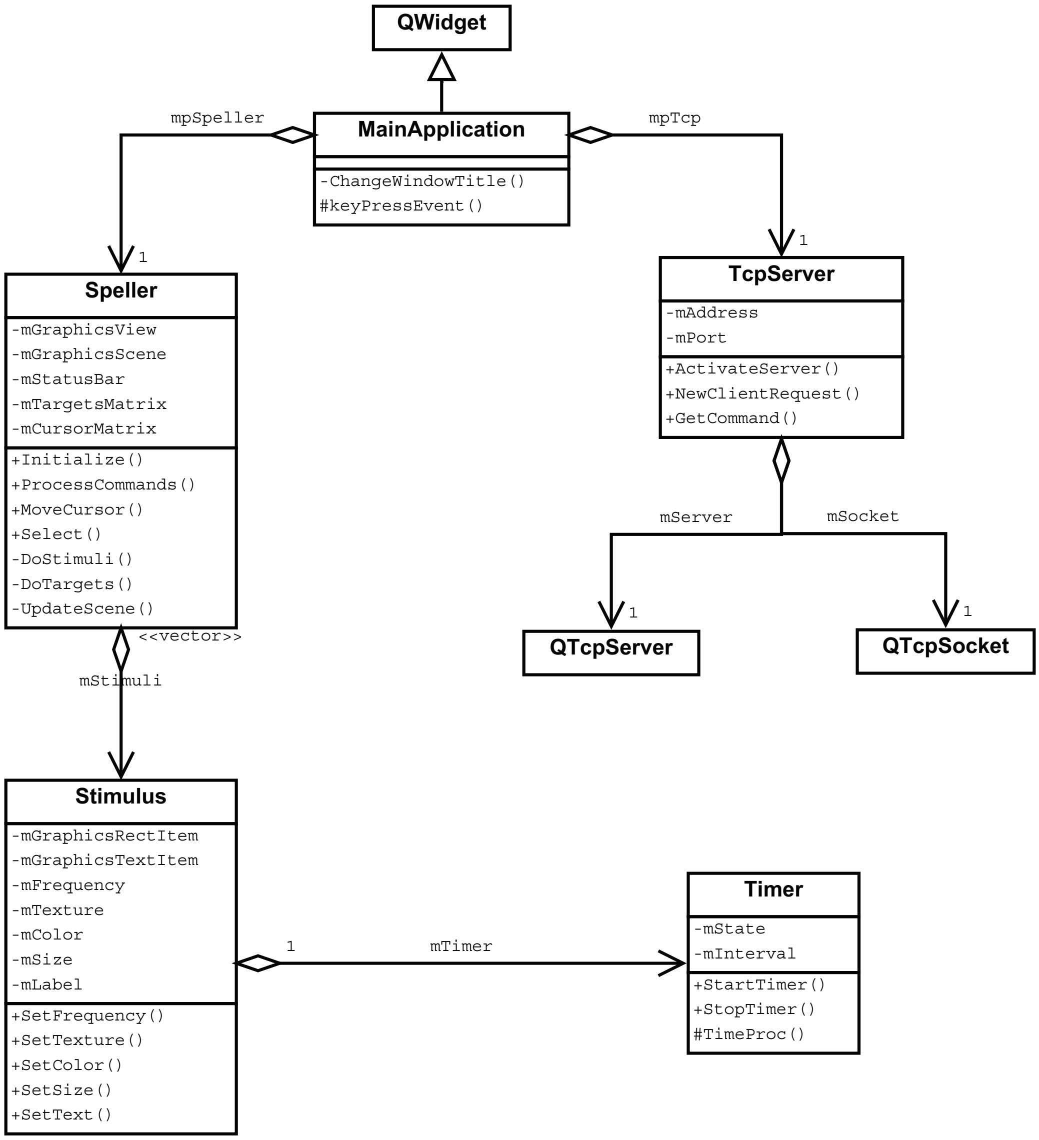


Figure 5.11.: UML class diagram of the spelling device with integrated visual stimulator based on multimedia timers for frequency generation.

as a container for `QGraphicsItem` objects. `QGraphicsScene` is used together with `QGraphicsView` for visualizing the items. Targets are represented by text items (`QGraphicsTextItem`) and the cursor matrix is represented by rectangle items (`QGraphicsRectItem`). The matrix of targets and cursor items are added to the scene by calling `QGraphicsScene::addItem()` in `DoTargets()`. The cursor initial postion is the target 'E.' The speller responds to four commands, "left," "right," "up" and "down" by highlighting the character at the current position. When the command "select" is received, the current character is displayed on the status bar, which is a `QLineEdit` object, located at the bottom of the application window. The `ProcessCommands()` method responds to BCI commands. The speller class also provides acoustic feedback when a character is selected and when the cursor is moved. Stimuli are objects of the `Stimulus` class and are added to the scene by calling `DoStimuli()`. The scene is updated as soon as all events in the window system's event queue have been processed.

`Stimulus` class represents the functionality of a flickering LED. In a typical SSVEP-based BCI application, a flickering light is associated with a certain control command and is needed for visual stimulation. The main functionality of this class is to perform a flickering action by changing the current visible state of the virtual LED. An object of the class `Timer` is needed for setting the intervals, in which the virtual LED is shown or hidden. A timer is started for each VLED and the timer interval is set depending of the desired flickering frequency. Timer intervals are calculated as half of the period. If the member variable `mState` is true the VLED is shown, otherwise it is hidden, when the scene is updated. In this way the flickering frequency is generated. An event is sent each time the timer finishes counting. The texture, stimulus frequency, and other display parameters can be adjusted to each user.

`TcpServer` class provides a TCP-based server. The Transmission Control Protocol (TCP) is a low-level, stream-oriented network protocol used for transmission of data. The `TCPServer` class makes possible to accept incoming TCP connections. The function `listen()` is called to have the server listening for incoming connections. The server listens on a specific address and port. The `newConnection()` signal is then emitted each time a client connects to the server. The `nextPendingConnection()` accepts the pending connection as a connected `QTcpSocket`. The spelling program is started as server and waits until the BCI connects to start flickering the VLEDs objects. When data is available on the listening port, a signal is emitted to the `Speller` class, which maps the commands into cursor movements or letter selections.

`Timer` class implements a multimedia timer that provides high-resolution timing. The `TimeProc` function is called once upon the expiration of periodic events changing the state member variable of the virtual LEDs.

5.6. Conclusion

In this chapter, the requirements, design and implementation of a general application interface for the presentation of BCI feedback tasks were described. The challenges of this software are the real time frequency generation to present visual repetitive stimuli on the computer screen, and the presentation of different types of feedback for the user (e.g., feedback that shows real time SSVEP activity) to investigate the feasibility of new feedback methods. These two aspects are the basis for the robustness of the feedback interface system presented in chapter 8, which used the classes of the framework. The motivation to build a more modern and general concept was the development of the speller program (see section 5.5) whose extension was very limited; and the necessity to provide a more reliable frequency generation for visual stimulation than the offered with multimedia timers. While in the speller program all classes were designed to accomplish the immediate goal unconcerned about future changes, the software framework presented in this work based on extendability and re-usability concepts to offer the possibility to develop others feedback tasks based on the exiting classes of the framework.

6. Influence of Subject Demographics on BCI Performance

Brain-computer interface systems provide severely disabled users with communication and control. This remains the principal focus of many research groups. However, there has been increasing attention to using BCIs to provide communication for new user groups, such as healthy users or persons with less severe disabilities. But before BCIs can become practical communication tools—for existing or new user groups—BCI demographics must be better explored and addressed. It is unclear why some BCI approaches or parameters are less effective with some users. One of the most consistent observations in the BCI literature is considerable inter-subject variability, and thus the need to customize various parameters according to each user [1, 21, 62, 118]. Inter-subject variability often leads to the well-documented "BCI illiteracy" phenomenon; across different BCI approaches (SSVEP, P300, ERD/ERS), about 10–25% of users are unable to attain effective control [5, 21, 58, 77, 119, 120]. While some of these (and other) articles have speculated about the causes of inter-subject variability and BCI illiteracy, there has been little applied research to study why they occur.

This chapter elucidates BCI demographics by exploring correlations among BCI performance, personal preferences, and different subject factors such as age or gender. Results of two studies conducted on two exposition fairs showed that most people, despite having no prior BCI experience, could use the Bremen-BCI system in a very noisy field setting. Performance tended to be better in both young and female subjects. Most subjects stated that they did not consider the flickering stimuli annoying and would use or recommend this BCI system. These and other demographic analyses may help identify the best BCI for each user.

6.1. BCI Demographic Work

BCI demographics research could help address why some people are better at BCI use than others, how genetic, background, and lifestyle differences affect performance and preferences with different BCI systems. It could also help to determine if it is possible that the best BCI approach and parameters could be anticipated without extensive testing and modification, or maybe if BCI illiteracy can be predicted. Demographic information could help to provide the best BCI for each user, ideally with little or no expert help to configure and adapt key parameters.

The first study that assessed a BCI with several dozen subjects was titled "How many people can use a BCI?" [121]. This article presented results from 99 untrained subjects who used a SMR BCI in a field setting. Subjects imagined moving either the right hand or both feet in response to cues provided on a monitor. About 70% of subjects attained accuracy between $60 - 80\%$ in this two-choice task, and about another 20% of subjects attained greater than 80% accuracy. This landmark paper made significant progress toward validating SMR BCI systems with untrained users in field settings, but did not record any demographic information nor subjective report. That is, while it helped to answer the question of how many people can use a BCI, it did not provide any guidance as to why some subjects were better than others. A very recent paper explored P300 BCIs across a similar number of subjects, 35 of whom received questionnaires to explore demographic issues [122].

The present work attempts to address BCI demographics through applied research with a large number of subjects. The results of two studies are presented, the CeBIT study [102], in which 106 subjects participated, and the RehaCare study [103], in which 37 subjects participated including eight handicapped users. The conduction of both studies was approved by the Ethics Commission of the University of Bremen. The principal goal was to assess SSVEP BCI performance and evaluate correlations between performance, preferences, and individual characteristics assessed with brief questionnaires both before and after BCI use. In addition to evaluating objective dependent variables involving spelling performance, also subjective information such as whether subjects found SSVEP BCI use fatiguing or unpleasant was assessed. Additional goals were to explore phrase length (the number of letters or characters spelled), path length (the number of consecutive instructions needed per letter), and free versus copy spelling.

6.2. CeBIT Study

CeBIT is the world's largest information and communications technology exhibition fair held every year in Hanover, Germany. This fair was very attractive for the BCI research group of the university of Bremen, as it is an excellent location for large data collection, since many people interested in new technologies can be found, and would likely participate in a quite long procedure ($45 - 60$ min) without reward. Apart from that, the noisy and busy setting meets the demands to test BCIs in realistic environments, and the potential risk of sampling errors due to technically biased subjects appeared reasonable. From the 4$^{\text{th}}$ to 9$^{\text{th}}$ of March 2008, subjects were randomly recruited from visitors to the Institute of

Automation booth. The team consisted of seven researchers and four assistant researches. The results of this study and statistical analyses are described in detail in the following sections. They may contribute to find relationships between human variables and BCI performance and, thus, may reduce time identifying the best BCI for each individual user. Defining variables that influence the communication between brain and computer is an important step for BCIs to become practical tools for heterogeneous user groups.

The principal goal of this study was to assess SSVEP BCI performance across a large number of subjects. Individual user characteristics were assessed with brief questionnaires both before and after BCI use and correlated with BCI spelling performance. Gender was assumed to be an interesting factor based on prior findings in other studies. Features may be significantly different in female subjects compared to male subjects. Skosnik *et al.*, (2006) found that female subjects demonstrated higher SSVEPs to both 18 and 25 Hz stimulation assessed via spectral power and phase-locking [123]. Kaufmann *et al.*, (2001) suggested gender differences in cerebral hemodynamics [124]. Some BCI studies have also observed differences across subjects. Allison *et al.*, (2008) found that female subjects produced greater differences than male subjects, but these effects were not significant. Also, they observed that subjects who play video games every day perform better on a visual attention task [119], which is consistent with other reports [125]. Other demographic variables like age and education as well as variables that potentially influence the ability to focus attention, like fatigue or substances (alcohol, nicotine, caffeine) are tested for statistical significance. BCI performance was measured as accuracy, efficiency and information transfer rate (ITR) during copy and free spelling tasks. In addition to evaluating dependent performance variables (accuracy, efficiency, and ITR), subjective information such as whether subjects found SSVEP BCI use fatiguing or unpleasant, was also assessed.

6.2.1. Data Collection

All data were recorded from sites P_z, O_z, $PO3$, $PO4$, $O9$, and O_{10} from a customized 74 channel montage based on the standard 10–20 system of electrode placement [126]. Data were referenced to site FC_z with a ground at site AF_z. Electrodes and caps were provided by Easycap. These electrodes required electrode gel, as is typical of conventional EEG recording systems. Data were digitized and amplified through a g.tec amplifier (Guger Technologies, Austria), which included a bandpass filter of 2–50 Hz. Data were stored on a PC compatible laptop running Windows Vista. The Bremen-BCI software system was used for all aspects of the SSVEP display, real-time data processing, feedback, and data storage. Fig. 6.1 shows an example of a screenshot when a subject successfully spelled "IAT." The center of the display contained 32 letters and other characters that the subject

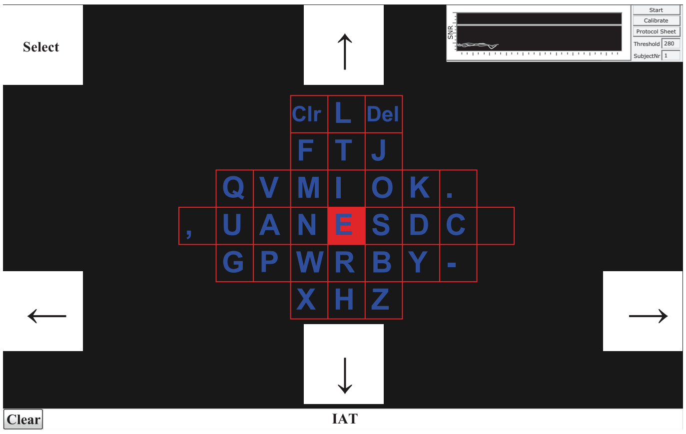


Figure 6.1.: The display used in the CeBIT study.

could communicate. The letters were arranged according to their occurrence in the English language in order to facilitate spelling and shorten the spelling time. Delete (erase last character) and clear (erase all letters) were available by moving the cursor to Clr or Del, respectively. At the beginning of each run, a cursor was presented over the 'E' character, and once a letter was selected, the cursor went back to the initial position. The bottom of the screen presented the character sequence that the subject already selected. Thus, the bottom of the screen contained no characters at the beginning of each run. Subjects spelled by focusing on one of five boxes presented on a laptop monitor. Each box contained either an arrow (left, right, up, or down) or the word "Select," and oscillated at a different constant frequency: 13, 14, 15, 16, or 16.5 Hz (respectively). They encoded a corresponding command by the flicker frequency of the particular box. When the user focused attention to a box, an SSVEP response of the same frequency as the stimuli and its harmonics was elicited and thus measurable over the occipital cortex. These frequencies, and the best arrangement of characters in the display, were determined through prior work [100, 117] and pilot work [101]. The box in the top right of Fig. 6.1 presented the real-time data processing of the EEG signals, the threshold, and some control buttons. The Bremen-BCI automatically determined the best spatial filter for each subject using the algorithm in [100] and then calculated the power at each of the five stimulation frequencies. The detection relied on a threshold based linear classifier. If the power at a specific frequency exceeded the predetermined threshold, the corresponding command was executed. If more than one signal exceeded the threshold, the frequency with the largest power was classified. To avoid multiple unintended executions of the same command, a simple command-selection algorithm was applied, which ensured an idle period of at least two seconds between subsequent commands. The spelling program was responsible for interpreting and mapping the commands (a detail description of this software is available in section 5.5). For example, if activity at 14 Hz exceeded the threshold, the command was send to the speller program and the cursor moved to the right. There was no "wraparound" feature; if the cursor could not move further to the left, then the cursor did not move if 13 Hz activity exceeded the threshold. If activity at 16.5 Hz exceeded the threshold, the character highlit by the cursor was selected. The EEG raw data and the executed commands were stored in a text file on the laptop for further offline analyses.

6.2.2. Subjects

In this study, subjects were people who went to an exposition and had no prior expectation of spending almost an hour following a protocol as a research subject. Subjects also had no prior or subsequent contact with the experimenters nor any incentive to complete the study. Test subjects were recruited from visitors to the Institute of Automation booth at CeBIT 2008. This booth featured a monitor display announcing that visitors might be able to participate as research subjects, and could ask booth personnel for more information. All persons who asked to participate in the study (after reading a consent form and subject information sheet) became research subjects. Potential subjects were asked if they were at least 18 years old or had a seizure, epilepsy, mental or physical disorders, or any skin allergies. Subjects would have been rejected if they had answered yes to any of these questions, but none of them did. A total of 106 subjects participated in this study. Subjects' mean age was 30.58 years and standard deviation was 11.863. Age range was between 18 and 79 years. Fig. 6.2 shows the age distribution separated by gender. The majority of the subjects were young males (76.42%) with mean age 31.94 ± 12.164 years. The normality of the distribution was checked with the Kolmogorov-Smirnov (K-S) test. Age may not be assumed to come from a normal distribution ($p > 0.001$).

6.2.3. Experimental Protocol

All subjects were randomly recruited from visitors to the IAT booth and were generally not chosen on the basis of gender or age. The subjects had the possibility to inform themselves about the study through subject-information sheets offered at the booth. If they were interested, they contacted a team-member. It was first assured that every subject was full age and healthy (no epilepsy, mental or physical disorders, or skin contact allergies). Then, the subject was given time to read the consent form and ask questions. After completing a consent form, each subject completed a brief electronic questionnaire and was prepared for EEG recording. Subjects were free to abandon the study any time and without giving

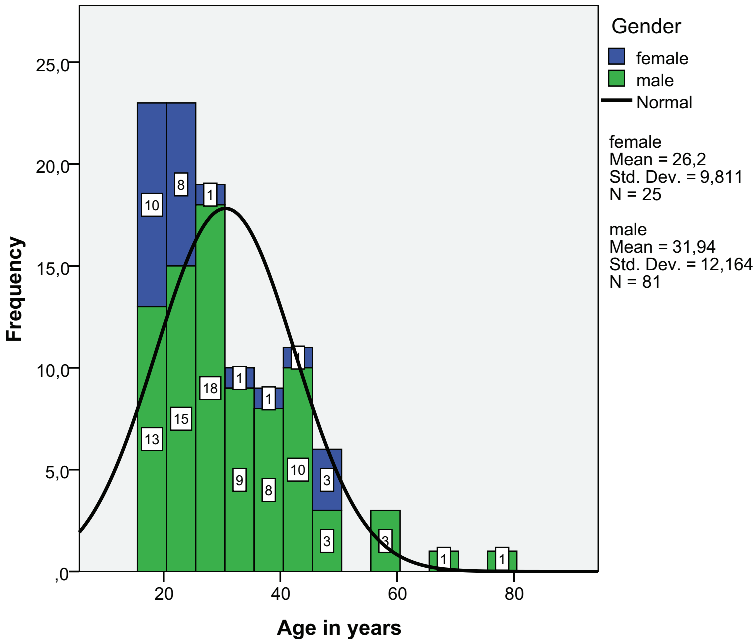


Figure 6.2.: Distribution of subjects' age separated by gender.

any reason. In that case, the cap was removed and the recording was canceled. The pre-questionnaire assessed subject information like gender, age, education level, etc. While completing the questionnaire, the subject was prepared for EEG recording. For each electrode, impedance was checked to be below 10 KΩ in order to get good signal acquisition. The subject was sitting in front of a laptop that displayed the SSVEP spelling program shown in Fig. 6.1.

Subjects participated in a practice run, in which they used the SSVEP BCI system to write the word "BCI." The experimenter used the resulting data to manually adjust subject parameters. Next, each subject used the SSVEP BCI system to spell five phrases. Four of these phrases were chosen by the experimenter (copy spelling), and the fifth was chosen by the subject (free spelling). The four copy spelling phrases were BCI, SIREN, CHUG, and BRAIN COMPUTER INTERFACE. Before the free spelling run, each subject verbally told the experimenter of the phrase that s/he intended to spell so spelling efficacy could be assessed. The order in which these five phrases were presented was determined randomly. Each run ended when the subject spelled the desired phrase, or a similar phrase with some errors, or made five consecutive errors, or chose to stop spelling. At the end of each run except the last run, each subject had a short break lasting about 30 seconds. It was sometimes apparent that subjects were not able to spell effectively. In such cases—specifically, if subjects made five consecutive errors in each

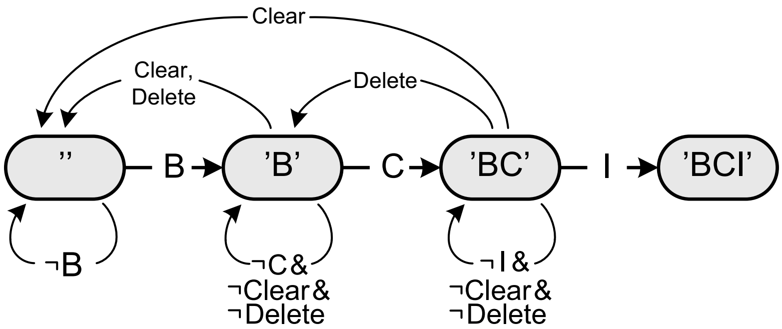


Figure 6.3.: Automaton used in offline data analysis. From [102].

of the five runs—additional manipulations were explored. An experimenter would manually adjust the threshold required to execute a command or the frequency used for the "select" button was changed. After the phrases were spelled, subjects completed a second electronic questionnaire to offer the possibility to evaluate the system and provide feedback to the developers and the procedure was complete. The entire procedure took about 40 minutes on average per subject, and never more than one hour. This time does not include the delay between when a subject asked to become a subject and when the above procedure began.

6.2.4. Offline Analyses

Offline analyses were conducted in order to assessed BCI performance defined as the amount of information communicated per unit time (ITR). To this end, the total of correct selections were counted, and the time needed to spell a phrase was determined from the stored file. Before calculating ITR, it was necessary to determine a set of rules to follow when interpreting the data. These rules were decided after extensive visual inspection of the letters that were spelled and consideration of different rulesets, then programmed in to an automaton (shown in Fig. 6.3) to automatically identify which trials would be counted in further analysis. ITR was then calculated based on the following formula:

$$B = \log_2 N + P \log_2 P + (1 - P) \log_2 \left[\frac{1 - P}{N - 1} \right]. \tag{6.1}$$

In this formula, B represents the number of bits per trial, N represents the total number of possible choices, and P represents the probability of correct selection. B was then multiplied by the number of selections per minute to obtain ITR in terms of bits per minute.

The calculations were focused on real world communication—the message that was actually sent, rather than the stages necessary to form that message. Thus, the automaton used the following rules:

1. ITR was calculated on the basis of the letters selected, rather than the low level commands sent to the transducer [30, 127]. This led to an N of 32, based on 32 letters, instead of an N of 5, based on 4 movement commands and select.

2. Clear and backspace commands were counted as such, rather than as letters. Thus, the message "Q DEL BCI" would be considered 100% accurate—that is, the same as "BCI." Since ITR was calculated based on the total time to convey each message, errors reduced ITR by increasing the time needed to correctly spell. Uncorrected errors were counted as such, so "BQCI" was 75% accurate.

3. Words were only counted if the entire word was spelled. Thus, "PUT" or "HUG" were ignored. That is, these messages would not have been counted as efforts to spell, and were not used in ITR calculations. This was done because it was often difficult to objectively judge whether such phrases represented legitimate efforts to spell the phrase defined in the protocol.

4. When analyzing "BRAIN COMPUTER INTERFACE," either separator (the dash or space) or no separator between those three words was allowed. Letters were not counted as separators.

5. Any additional selections after the word was spelled were ignored, but additional letters before the word were counted as mistakes. Thus, "QBCI" was 75% accurate, while "BCIQ" was 100% accurate. This was decided because the program did not immediately terminate after the message was spelled, since the word order was pseudorandom (including the free spelling run) and hence neither the experimenter nor the software knew ahead of time which word was intended. Thus, additional letters were sometimes accidentally spelled after the word was complete even though the subject was not paying attention to the BCI at all—a classic example of the Midas touch problem, when extraneous information is mistakenly translated into a command [128].

6. Similarly, speed was defined as the time from the beginning of the run until the run ended for one of the reasons listed above. If the software continued running after the word was spelled, the extra time (like any extra characters) was ignored.

7. Efficiency was defined as the minimum number of commands necessary to spell the target phrase divided by the number of commands issued during the run.

Pre-questionnaire		N	Mean	SD	Range
Age	Age in years	106	30.58	11.863	18–79
Gender	1 = Female	25	1.76	0.427	1–2
	2 = Male	81			
Need for vision correction	1 = Yes	46	1.48	0.502	1–2
	2 = No	42			
	Not answered	18			
Education level	1 = Junior high school	10	2.47	0.843	1–4
	2 = High school	37			
	3 = College or university	31			
	4 = PhD	10			
	Not answered	18			
Computer work (h/week)	answered	88	33.13	16.937	2–80
	Not answered	18			
Computer games (h/week)	answered	88	3.32	9.332	0–60
	Not answered	18			
Substances	Alcohol	23			
	Caffeine	21			
	Cigarettes	16			
	Not answered	18			
Hours of sleep last night	answered	88	6.22	2.323	0–13
	Not answered	18			
Do you presently feel tired?	answered	88	2.09	1.035	1–5
	Not answered	18			
Post-questionnaire					
Did the system work well for you?	answered	84	3.39	1.336	1–5
	Not answered	22			
Would you use or recommend this system to others?	answered	84	3.82	1.263	1–5
	Not answered	22			
Do you think the BCI was easier if you	1 = concentrated on LED?	54	1.36	0.482	1–2
	2 = gazed at LED?	30			
	Not answered	22			
Did you find it easy to switch attention?	answered	84	3.62	1.289	1–5
	Not answered	22			
Did you find the flickering stimuli annoying?	answered	84	2.55	1.274	1–5
	Not answered	22			
Do you presently feel tired?	answered	84	2.31	1.242	1–5
	Not answered	22			

Table 6.1.: Answers collected from pre- and post-questionnaires. In questions that could be answered in a 1–5 scale, 1 means no and 5 means yes.

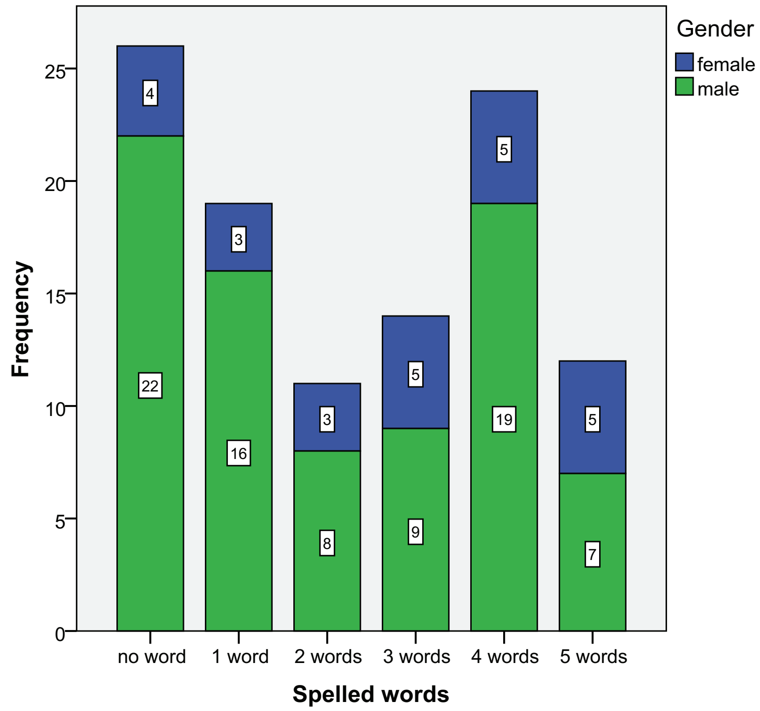


Figure 6.4.: Distribution of the number of words spelled by 106 subjects.

6.2.5. Results

Tables 6.1 and 6.2 present results from subjects, questionnaire replies, and BCI performance. All 106 subjects completed the consent form and answered at least the questions about age and gender, were prepared for EEG recording, and began using the BCI. 18 subjects did not answer any of the remaining questionnaire items and 22 subjects did not answer the post-test questionnaire. Subjects' task was to spell four words in copy spelling mode and one word in free spelling mode. The order in which these five words were spelled was determined randomly by the computer. Due to many uncontrollable variables experimented at CeBIT, this procedure was changed and some subjects did not complete the study for various reasons. Subjects were not committed to finish the study and were free to leave at any time. For example, some subjects' recording sessions ended because the subject decided to stop because of poor performance, or did not have more time to finish the protocol (wanted to see a specific CeBIT event, or had to meet a friend, etc.). Other subjects chose to spell phrases of their choosing rather than the "copy spelling" phrases suggested in the protocol, and thus some subjects' data are incomplete. No subjects stopped participating because they reported

Spelling task	N	Time [s] Range	Time [s] Mean±SD	ITR [bit/min] Range	ITR [bit/min] Mean±SD
BCI	65	21.53 – 463.63	126.11 ± 99.284	1.79 – 41.80	10.96 ± 7.697
BCILong	22	241.01 – 1029.54	455.94 ± 205.924	6.99 – 29.87	18.20 ± 6.653
SIREN	52	27.42 – 431.64	107.53 ± 79.002	3.48 – 54.70	19.73 ± 12.600
CHUG	43	43.57 – 435.20	133.46 ± 97.467	2.76 – 27.54	12.82 ± 6.649
Free	58	29.66 – 911.73	199.75 ± 173.828	2.96 – 50.58	14.66 ± 9.665
		Efficiency [%]		Accuracy [%]	
BCI	65	37.50 – 100	86.34 ± 20.802	37.50 – 100	91.85 ± 15.565
BCILong	22	57.14 – 100	86.02 ± 14.960	88.89 – 100	98.78 ± 2.944
SIREN	52	45.45 – 100	85.84 ± 17.227	62.50 – 100	93.45 ± 11.923
CHUG	43	33.33 – 100	91.42 ± 18.090	80.00 – 100	98.14 ± 5.878
Free	58	30.77 – 100	84.29 ± 20.693	60.00 – 100	96.65 ± 8.467

Table 6.2.: BCI spelling performance from subjects at CeBIT 2008. BCILong refers to the phrase “BRAIN COMPUTER INTERFACE.”

any pain, discomfort, fatigue, or similar problems. Fig. 6.4 shows an overview of the collected data according to the number of words spelled by the 106 subjects. On average subjects spelled 2.25 ± 1.784 words ($N = 106$). 26 subjects did not attain effective control or decided to stop the experiment. For these subjects (24.53%) no data were available for any of the words. In contrast, only 11.3% of the subjects completed the protocol by spelling the five words. From the figure, it is observed that data from female subjects were almost equally distributed across the number of spelled words, while for male subjects more variation is observed. Effects of age in BCI performance are analyzed in the following section.

Table 6.2 presents descriptive statistics for each spelling task and different measures of BCI performance: time in seconds, information transfer rate in bits transferred per minute, accuracy, and efficiency in percent. In that table, N represents the number of subjects that successfully spelled each word. Subjects performed best with the word “SIREN,” which had the shortest path to each letter (19.73 bit/min). Most subjects (79.25%) chose not to spell out “BRAIN COMPUTER INTERFACE.” But in terms of accuracy, BCILong was spelled with less errors than the other words (98.78%). Mean accuracy within the word groups was 95.77%, efficiency was 86.78%, and information transfer rate was 15.27 bit/min. A one-way repeated ANOVA was conducted to test differences between the spelling tasks with ITR as dependent variable for all subjects who could spell all words ($N = 12$). ANOVA revealed statistically significant differences in performance within the spelling tasks, $F(4, 44) = 2.724, p = 0.041$. Multiple comparisons showed significant differences between the performance for “BCI” and “SIREN,” $p = 0.046$, and between “BCILong” and “SIREN,” $p = 0.024$.

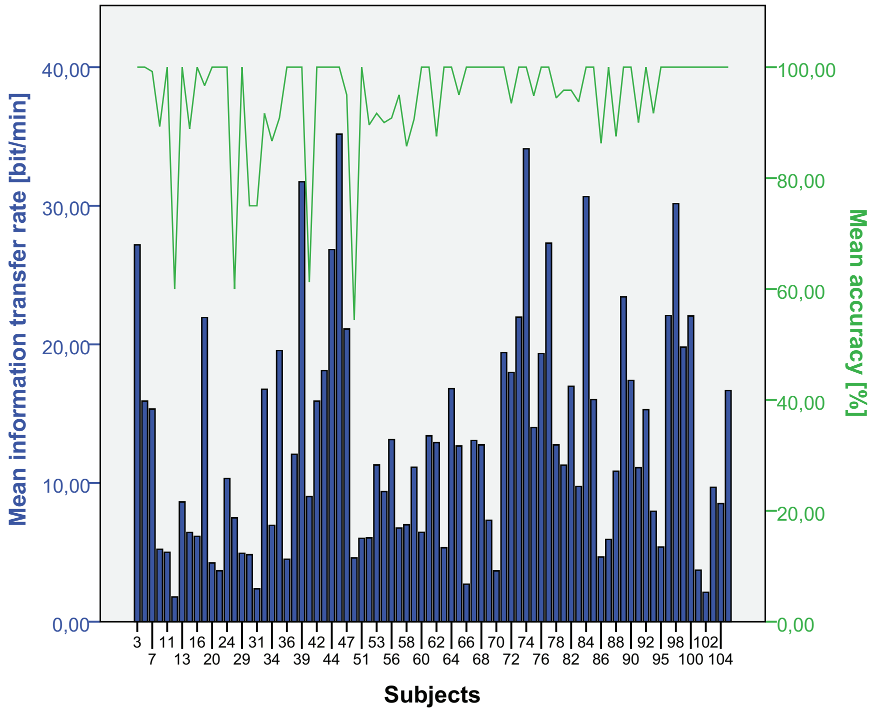


Figure 6.5.: Mean information transfer rate and accuracy for 80 subjects across all spelling tasks.

Fig 6.5 shows the mean individual BCI performance for each subject in terms of information transfer rate and accuracy. 80 subjects performed with a mean information transfer rate of 13.00±8.196 bit/min, accuracy of 94.54±9.935%, and efficiency of 85.26±14.851%. These values differed from the mean values presented above (ITR: 15.27 bit/min; accuracy: 95.77%; efficiency: 86.78%) because the number of words spelled by each subject differed. Visual inspection of Fig. 6.5 shows that there were considerable inter-subjects differences in the study, as widely reported in other BCI studies [93].

The following statistical analyses presents the results of the correlations between performance, preferences and individual characteristics. The BCI performance measure selected for the analyses was the information transfer rate, as this measure incorporates both time and accuracy in a single value. Efficiency was calculated to show that subjects normally executed more commands than the minimum number of commands to spell the target phrase. This happened because subjects had to correct each false classification. Preferences and individual characteristics were assessed with brief questionnaires both before and after BCI use.

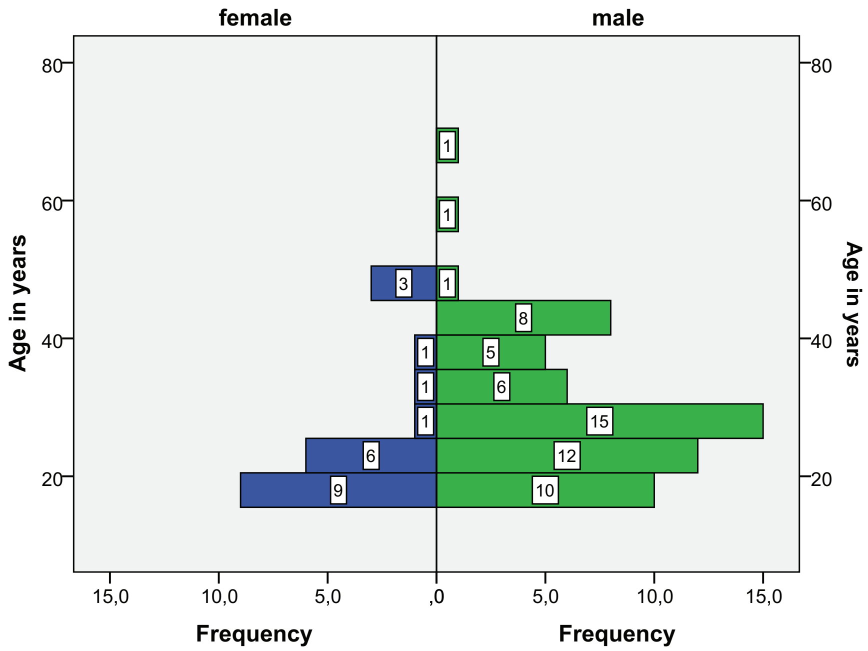


Figure 6.6.: Frequency of age for male and female BCI literate subjects.

Effects of Age and Gender

106 subjects participated in the study (30.58 ± 11.863 years), from which 25 (23.58%) were female (26.2 ± 9.811 years) and 81 (76.42%) were male subjects (31.94 ± 12.164 years). The oldest woman was 46 years old, while the oldest man was 79 years old. As stated before, 26 subjects (24.53%) did not complete the study for two reasons: either subjects were unable to spell with the SSVEP-BCI or they abandoned the study without having spelled the five words. From those 26 subjects, 15 subjects completed the post-questionnaire but did not successfully spell any word and 11 subjects left without filling out the post-questionnaire. Those subjects that tried to spell but attained poor control are referred as BCI illiterates. 11 subjects produced non-target data and ended the session because of different reasons as explained above. This means that from the initial population of 106 subjects, it is assumed that only 14.15% of the subjects were BCI illiterates (14 males and 1 female subject). Following this assumption, BCI illiteracy was higher in males than in females. For the 10.37% of the subjects that did not complete the study, the BCI literacy is unknown. Thus, following statistical analyses were performed for a population of 80 subjects, who could spelled at least one word. Mean ITR for each subject was used as dependent variable (mean performance value within the spelled words), see Fig. 6.5.

Gender	**Age**	N	ITR [bit/min]	Accuracy [%]	Efficiency [%]
female	18 – 24	15	17.59±9.315	95.23±11.731	83.60±17.403
	25 – 32	2	16.03±10.458	100.00±0.000	99.20±1.131
	33 – 49	4	12.97±6.731	93.75±7.217	79.65±7.350
	total	21	16.56±8.740	95.40±10.336	84.33±15.718
male	18 – 24	20	14.98±8.157	96.45±4.471	87.46±12.263
	25 – 32	20	12.48±8.219	94.85±10.286	86.86±14.653
	33 – 49	17	7.56±4.383	90.83±13.455	80.79±17.320
	59 – 66	2	7.39±2.829	95.00±7.071	95.00±7.071
	total	59	11.74±7.677	94.24±9.861	85.59±14.655
total	18 – 24	35	16.10±8.638	95.93±8.259	85.81±14.577
	25 – 32	22	12.80±8.211	95.32±9.900	87.98±14.405
	33 – 49	21	8.59±5.186	91.39±12.411	80.57±15.758
	59 – 66	2	7.39±2.829	95.00±7.071	95.00±7.071
	total	80	13.00±8.196	94.54±9.935	85.26±14.851

Table 6.3.: Descriptive statistics for ITR, accuracy and efficiency with two factors (gender and age).

Fig. 6.6 shows the age distribution for female and male BCI literate subjects ($N = 80$). BCI literates' mean age was 29.14 ± 10.381 years and ranged between 18 and 66 years. The female group age was 26.00 ± 9.793 ($N = 21$), while the male group age was 30.25 ± 10.435 ($N = 59$). From the figure, it can be observed that equal gender distribution is only given for $18 - 24$ years old subjects. Age was not a controllable variable in this field study. Subjects may not be reflective of the general population; they tended to be young men. For statistical calculations, four age groups were used: $18 - 24$ years, $25 - 32$ years, $33 - 49$ years, and $59 - 66$ years. The first group was chosen because the variable gender was almost equally distributed for that age. The second and third groups were chosen according to the size of the first group; and the last group includes only few male subjects older than 59 years. Table 6.3 shows the descriptive statistics for the four age groups. From the table, age and gender effects are observed. ITR tended to be higher for young subjects. Moreover, it seems that females, who spelled on average with 16.56 bit/min performed better than males, who spelled with a rated of 11.74 bit/min.

Fig. 6.7 shows the relationship between age and ITR for each gender. This figure indicates that the older the subject becomes, the lower is the ITR. This trend is similar for both genders. The independence of both factors is indicated by the parallel lines. By analyzing age and gender, it is important to notice that the age groups are not equal in size. In general, most users were between 18 and 24 years old. Also, few female uses were in the other age groups with ages greater than 24 years. For male users the groups are almost equally distributed,

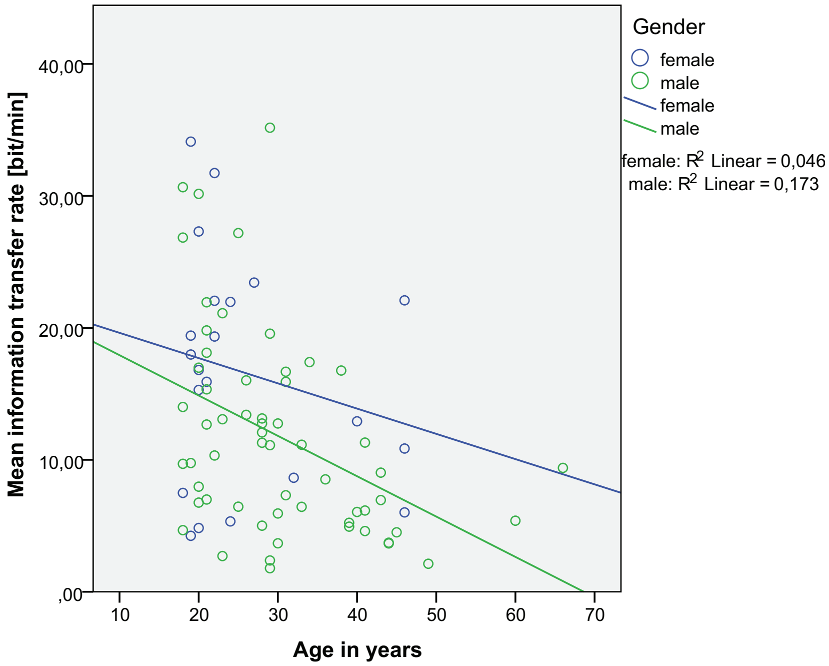
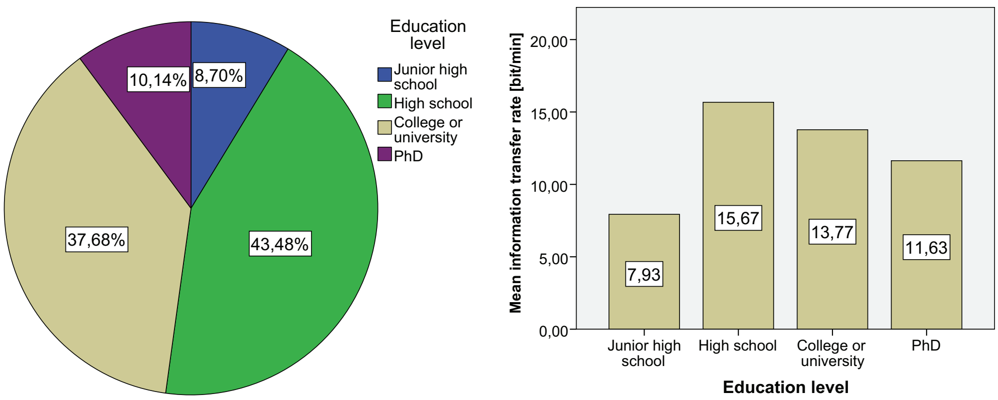


Figure 6.7.: Relationship between age and ITR for each gender.

except for the age group between 59 and 66 years. An one-way ANOVA was conducted on mean ITR with two factors (age and gender). Neither an effect on gender, $F(1,73) = 2.118, p = 0.132$, nor an effect on age, $F(3,73) = 2.129, p = 0.104$, was statistically significant, nor was their interaction, $F(2,73) = 0.156, p = 0.856$. Multiple comparisons (Tukey HSD) between the age groups indicated a significant difference in ITR between $18-24$ years old and $33-49$ years old users ($p = 0.004, \alpha = 5\%$). By analyzing the relationship between age and the ITR for each spelling task, only for the word “SIREN” significant effects of age, $F(1,46) = 5.402, p = 0.025$, and gender, $F(2,46) = 3.285, p = 0.046$, were found. Multiple comparisons showed differences between $18-24$ and $33-49$ years old users, $p = 0.032$.

Pre-test Questionnaire Results

The pre-test questionnaire collected answers to questions about need for vision correction, education level, use of the computer for working and playing computer games in hours per week, hours of sleep in the last night, ingested substances in the last 24 hours such as alcohol, caffeine or cigarettes, and level of tiredness. Table 6.1 presents the answers collected from this questionnaire. A total of 88 out of 106 subjects responded the pre-test questions. Subjects that could use the SSVEP-BCI



(a) (b)

Figure 6.8.: (a) Distribution of the education level and (b) ITR for subjects according their education level.

and answered the pre-test questionnaire were 69. Therefore, further results and statistical analyses were performed for a sample of 69 subjects. The need for vision correction could be answered as 1, that meant yes or 2 that meant no. 34 subjects need vision correction, whereas 35 did not need to wear any vision aid. A t-test failed to reveal a statistically reliable difference between the mean ITR of subjects that needed a vision correction (12.48 ± 6.624 bit/min) and the subjects that did not need vision correction (15.23 ± 9.450 bit/min), $t(67) = 1.395, p = 0.168$.

The education level could be answered on scale from 1 to 4, 1 meaning "junior high school" or the German "Realschule," 2 "high school" or German "Abitur," 3 "college or university" or German "Fachhochschule" or "Universität," and 4 "PhD" or German "Dr." degree. Fig. 6.8(a) shows the distribution of the groups; the majority of the subjects visited or were visiting either the high school or a college or university. Fig. 6.8(b) shows the performance achieved by subjects according to their education level. The highest ITR was achieved by subjects that visited the high school (15.67 ± 9.397 bit/min). An one-way ANOVA was conducted with ITR with education level as factor. No effect due education level was found, $F(3, 65) = 1.745, p = 0.166$. Multiple comparisons did not find any significant differences between the groups.

Working on the computer or playing computer games was rated as the amount of hours per week that a subject spent doing these activities. On average subjects used the computer for working for about 32.93 ± 16.736 hours and played 3.34 ± 9.575 hours computer games. For analysis on the influence of the computer use, subjects were divided in three groups: subjects that spent less than 25 hours, between 25 and 40 hours, and more than 40 hours using the computer. 19 subjects used the computer less than 25 hours per week (12.75 ± 8.914 bit/min), 34 between 25 and 40 hours (15.74 ± 7.848 bit/min), and 16 more than 40 hours (11.26 ± 7.746 bit/min). An One-way ANOVA performed on ITR and computer use as factor revealed no influence of computer use between the groups on BCI performance, $F(2, 66) = 1.905, p = 0.157$. Subjects were separated in two groups according to the factor computer games: subjects that played and did not play computer games. 39 subjects did not play computer games (13.25 ± 7.135 bit/min), and 30 played computer games (14.69 ± 9.550 bit/min). No effect due computer games could be assessed, $t(67) = 0.718, p = 0.475$.

The questions regarding consumption of alcohol, caffeine, or nicotine in the last 24 hours were answered as yes or no. 31 subjects answered to having consume one or more of these substances (11.78 ± 6.472 bit/min), whereas 38 did not consume any of the substances (15.58 ± 9.171 bit/min). An independent t-test was used to compare the mean performance values of subjects who consumed vs. subjects who did not consume one or more of the above mentioned substances. Results of the t-test show only a mild evidence that the population mean performance for both groups are unequal, $t(67) = 1.942, p = 0.056$.

On average subjects slept 6.08 ± 2.373 hours the night before participating in the experiment and ranged between no sleep and 13 hours of sleep. To test the influence of sleep on BCI performance, two groups were used: Subjects that slept five or less than five hours, and subjects that slept more than five hours. 20 subjects slept five or less than five hours (12.76 ± 8.296 bit/min), and 49 slept more than five hours (14.33 ± 8.256 bit/min). The t-test failed to reveal a statistically significant difference between both groups, $t(67) = 0.761, p = 0.477$.

The level of tiredness before the experiment was reported on scale from 1 to 5, 1 meaning “not tired” and 5 “very tired.” 22 subjects answered “not tired” (16.02 ± 9.906 bit/min), 24 claimed to be “a little tired” (13.30 ± 8.947 bit/min), 18 answered neutrally (12.06 ± 5.393 bit/min), 3 subjects reported to be “tired” (15.67 ± 2.406 bit/min), and 2 subjects to be “very tired” (10.70 ± 2.909 bit/min). Subjects who reported not to be tired had the highest ITR, while subjects that felt tired had the lowest; it appears to exist a linear relationship between the ITR and the tiredness level. The Levene statistic rejected the hull hypothesis that the group variances are equal, $p = 0.009$. However, a nonparametric Kruskal-Wallis test that makes minimal assumptions about the underlying distribution of the data, failed to revealed a significant difference in the information transfer rate of the groups with tiredness as factor, $p = 0.691$.

Post-test Questionnaire Results

After the experiment, subjects completed a brief post-questionnaire that asked them about subjective opinion about the BCI system, if the SSVEP BCI system used here was generally perceived as annoying or difficult to use, and if it did produce significant fatigue. Also, subjects stated if they found it easier to concentrate on the target versus gaze at the target. The level of tiredness was reported on a 1 to 5 scale, as in the pre-test questionnaire. In comparison with the pre-test questionnaire, the SSVEP-BCI did not produced significant fatigue: level of tiredness before the experiment was 2.09 ± 1.035 ($N = 88$) and after the experiment 2.31 ± 1.242 ($N = 84$). Subjects evaluated subjectively, if the BCI system worked in general in a scale from 1 to 5, 1 meaning no and 5 yes. 10 subjects answered no, 24 answered yes, all other subjects answered between 2 and 4. Most subjects would use or recommend the system (65.48%).

6.3. RehaCare Study

The RehaCare study was conducted at the Institute of Automation booth on the 19$^{\text{th}}$ international rehabilitation fair RehaCare in Düsseldorf, Germany. One goal of the experiments described hereafter was to reach a large audience of potential BCI users from both the disabled and able-bodied population. Moreover, high level of background noise and inappropriate illumination conditions are predominant in such exposition fair. This is notably different to the usual EEG recording conditions in which an electrically shielded room with low background noise and luminance is used.

6.3.1. Data Collection

The EEG data was recorded in the same way as in the CeBIT study. Standard Ag/AgCl EEG electrodes were placed on sites $P_Z, PO_3, PO_4, O_Z, O_9, O_{10}$; AF_Z was used for ground, and C_Z was used for the reference electrode. Abrasive electrolytic electrode gel was applied between the electrodes and the skin in order to bring impedances below 15 KΩ. An EEG amplifier g.USBamp (Guger Technologies, Graz, Austria) was used and the sampling frequency was 128 Hz. During the EEG acquisition, an analog bandpass filter between 2 and 30 Hz, and a notch filter around 50 Hz (mains frequency in Europe) were applied directly in the amplifier. Subjects sat approximately 60 cm from the LCD (liquid crystal display) screen of the notebook running the Bremen-BCI software (see Fig 6.1).

The main difference with the CeBIT study was the selection of the stimulation frequencies. Although the same display was used, it was considered to change the stimulation frequencies into factors of the laptop monitor refresh rate. As the quality of the SSVEP response depends on the stability of the frequencies, the five frequencies that were used in this study were factors of the refresh rate of 60 that produces the stimulation frequencies: 7.50 Hz (“left”), 8.57 Hz (“right”), 10.00 Hz (“up”), 12.00 Hz (“down”) and 6.67 Hz for “select.” The chosen frequencies

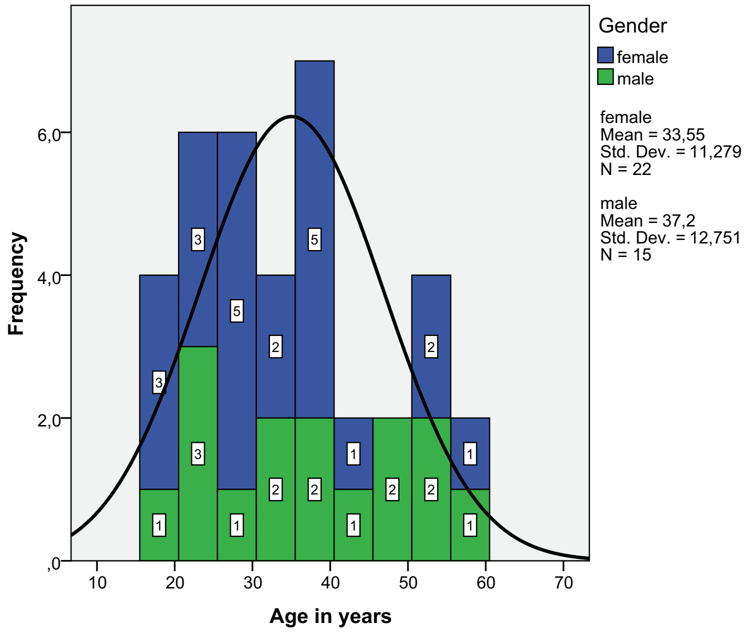


Figure 6.9.: Distribution of subjects' age separated by gender.

correspond to periods equivalent to 9, 8, 7, 6 and 5 frames on the LCD screen respectively. A fixed number of frames within one period assures the frequency stability [129].

6.3.2. Subjects

Experiments were performed on volunteer subjects recruited from visitors to the IAT booth at the rehabilitation fair RehaCare 2008. This study was approved by the local ethic committee of the University of Bremen, Germany, and all subjects gave informed consent. A total of 37 subjects participated in this study. Subjects' mean age was 35.03 ± 11.864 years. Age range was between 18 and 57 years. Fig. 6.2 shows the age distribution separated by gender. The majority of the subjects were females (59.46%) with mean age 33.55 ± 11.279 years. The other 40.54% were males with mean age 37.2 ± 12.751 years. Eight subjects from the 37 total subjects had different disabilities, 3 were unable to fill in the consent form by themselves. All participants were naive subjects with no prior experience with SSVEP based BCIs. 18 subjects required vision correction; four of them were not wearing their glasses during the experiment. Subjects did not receive any financial reward for participating in this study.

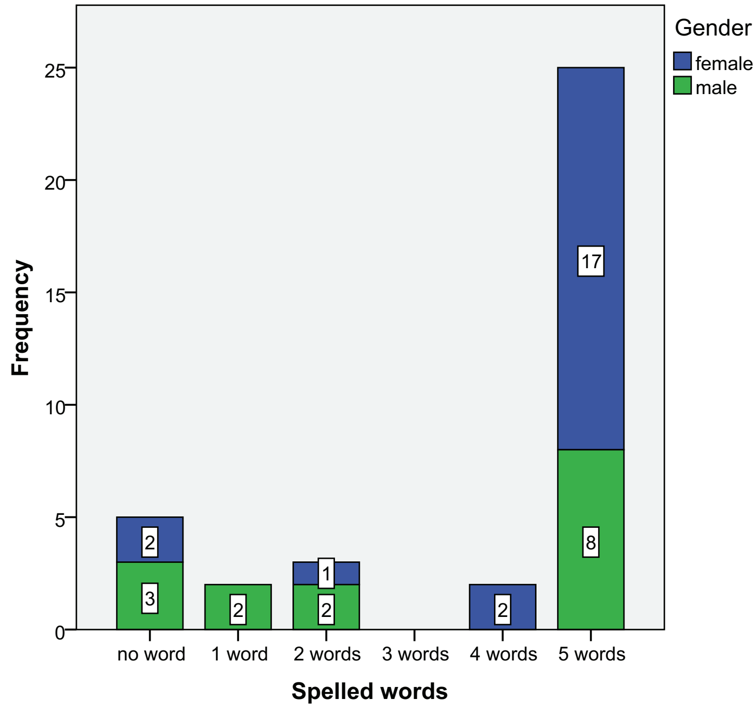


Figure 6.10.: Distribution of the number of words spelled by 37.

6.3.3. Experimental Protocol

Subjects were first asked if they were full age and ever had a seizure, mental disorders, or skin contact allergies with used electrolytic abrasive gel. Subjects would have been rejected if they answered yes to any of these questions. All subjects completed a written consent form and a pre-test questionnaire including some screening questions. For the case of users with disabilities, this form was completed by the care giver as dictated by the subject. A short familiarization run was carried out in order to introduce the experimental procedures and to manually set the subject-specific threshold for each subject. The subjects' task was to spell five messages with the SSVEP based Bremen-BCI system. Three of the messages were the same for all subjects and were chosen by the experimenter (copy spelling), and two words were chosen by the subject (free spelling). The copy spelling words were in sequence BCI, BRAIN, and GEHIRN. The first free spelling word should had five letters (Free1) and the second did not have any restrictions (Free2). Each subject verbally told the experimenters the first free spelling word that they intended to spell before each free spelling run. The experimental protocol was very strict in case of misspelling. The participants were advised to correct errors

Spelling task	N	Time [s]	Acc. [%]	ITR [bit/min]
BCI	28	102.50 ± 116.090	93.36 ± 8.878	23.42 ± 11.902
BRAIN	29	124.14 ± 77.479	90.97 ± 8.211	21.09 ± 8.839
GEHIRN	27	119.98 ± 59.239	93.73 ± 8.104	21.68 ± 9.940
Free1	28	103.47 ± 85.995	94.06 ± 7.829	26.68 ± 11.677
Free2	29	135.14 ± 142.706	93.27 ± 9.522	25.67 ± 10.671

Table 6.4.: BCI spelling performance from subjects at RehaCare 2008.

by using the special characters "Del" and "Clr." Performance for copy spelling tasks was calculated online. All data collected during the experiment were stored anonymously. After finishing the experiment the electrode cap was removed, the post-test questionnaire was answered and the experiment finished.

6.3.4. Results

Subjects' task was to spell three words in copy spelling mode and two words in free spelling mode. The order in which these five words were spelled was determined randomly by the computer. Fig. 6.4 shows an overview of the collected data according to the number of words spelled by the 37 subjects. On average subjects spelled 3.81 ± 1.927 words ($N = 37$). Five subjects did not attain effective control and decided to stop the experiment. For those subjects no BCI performance could be assessed for any of the words. The majority of the subjects 67.57% completed the protocol by spelling all five words.

Table 6.4 presents the average BCI performance for each spelling task across the subjects. Three different measures are displayed: time in seconds, information transfer (ITR) rate in bits transferred per minute and accuracy (Acc.) in percent. N represents the number of subjects that successfully spelled each word. Accuracies achieved in individual spelling tasks varied considerably (ranged from 66.13% to 100%) with the majority achieving $p > 90\%$ (see detailed results for each subject in Appendix B). The spelling time also varies between subjects, leading to ITRs in the range from 3.64 to 50.13 bit/min. Subjects performed best with the free spelling word 1 (word with five letters: 26.68 bit/min). In terms of accuracy, Free spelling 1 was spelled with less errors than the other words (94.06%). A one-way repeated ANOVA was conducted to test differences between the spelling tasks with ITR as dependent variable for all subjects who could spell all words ($N = 25$). ANOVA revealed statistically significant differences in performance within the spelling tasks, $F(4, 96) = 3.768, p = 0.007$. Multiple comparisons showed significant differences in performance between copy spelling tasks BRAIN and GEHIRN, and both free spelling tasks.

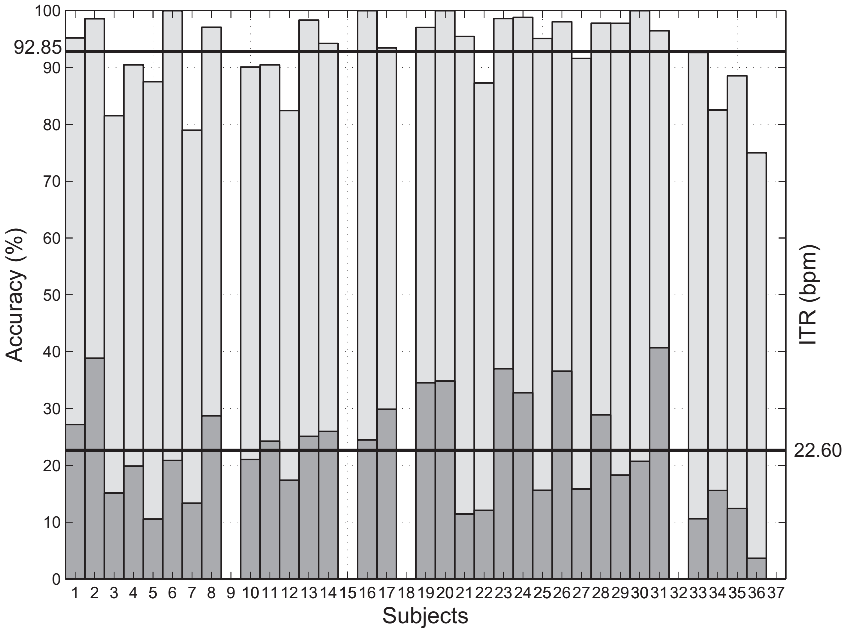


Figure 6.11.: Individual information transfer rate and accuracy achieved by each subject across five spelling tasks. From [103].

Fig 6.11 shows the mean individual BCI performance for each subject across the spelled words in terms of information transfer rate and accuracy. 32 subjects performed with a mean information transfer rate of 22.60 ± 9.648 bit/min and accuracy of $92.85 \pm 6.810\%$. The BCI illiterates were five subjects: two females and one male with disabilities, and two males without disabilities.

Fig. 6.12(a) shows the relationship between age and ITR for each gender. This figure indicates that the older the subject becomes, the lower is the ITR. This trend was similar for both genders. Moreover, mean ITR of female subjects (24.93 ± 8.455 bit/min, $N = 20$) was higher than there for male subjects (18.73 ± 10.617 bit/min, $N = 12$). An one-way ANOVA was conducted with ITR as dependent variable and gender as factor. The effect of gender on the ITR did not attained statistically significance, $F(1, 30) = 3.322, p = 0.078$. An one-way ANOVA was also conducted on ITR separated by two groups of BCI users. The group of healthy subjects could use the BCI with a mean ITR of 23.65 ± 9.923 bit/min ($N = 26$), whereas the group of subjects with disabilities achieved 18.09 ± 7.396 bit/min ($N = 6$). The ANOVA-test failed to reveal a statistically significant difference between both groups, $F(1, 30) = 1.654, p = 0.208$.

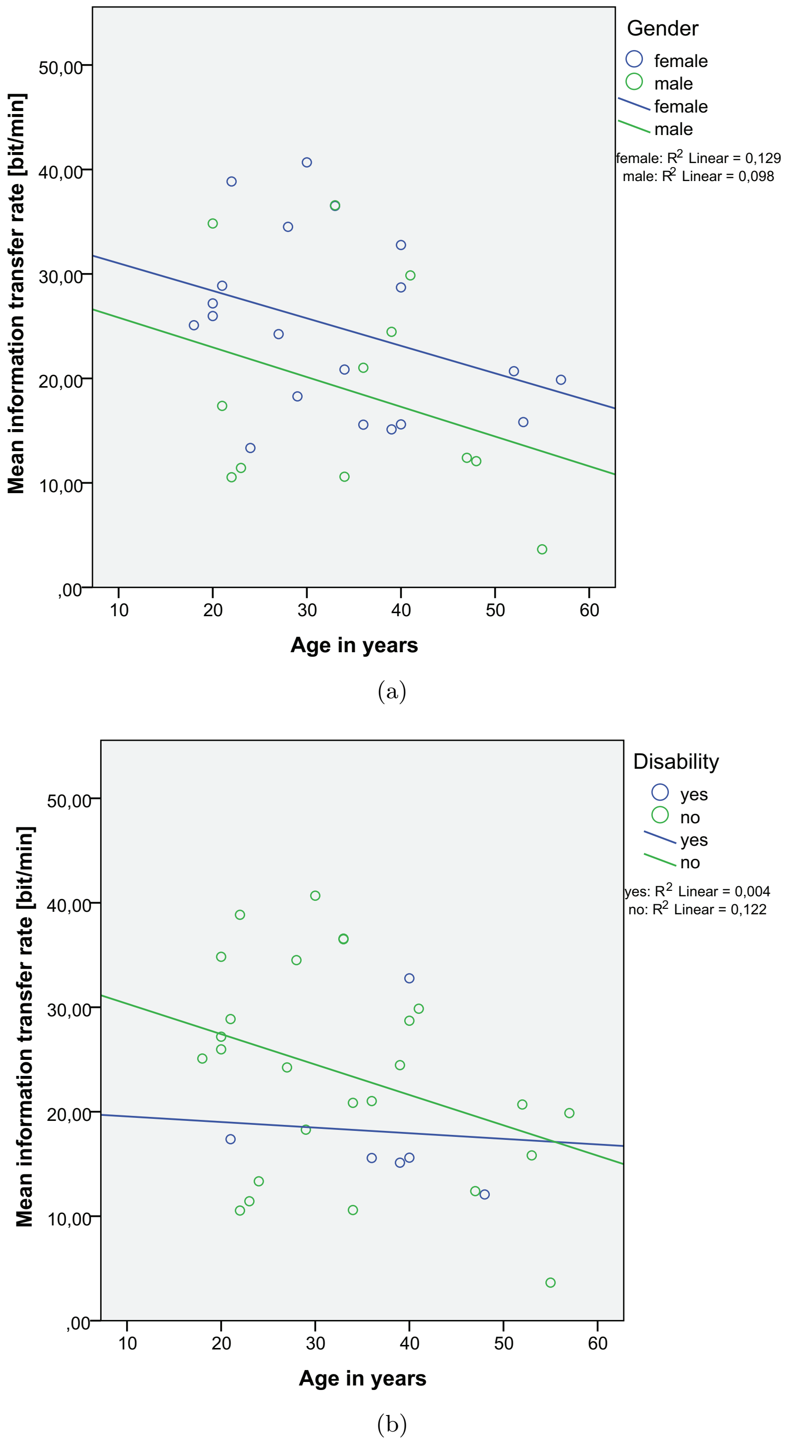


Figure 6.12.: Relationship between age and ITR separated by (a) gender and (b) disability of the subjects.

6.4. Conclusion

The performance data show that the Bremen-BCI system could provide effective communication for most subjects in both studies. These results elucidate which factors do (and do not) correlate with objective and subjective measures of SSVEP BCI performance, and help elucidate the best BCI for each user. The CeBIT study conducted on 106 healthy subjects resulted in an mean information transfer rate of 13.00 ± 8.196 bit/min and accuracy of $94.54 \pm 9.935\%$. Whereas, the RehaCare study conducted on 37 subjects including 8 subjects with disabilities resulted in a mean ITR of 22.60 ± 9.648 bit/min and accuracy of $92.85 \pm 6.810\%$. By comparing both results is evident that the RehaCare study produced much higher transfer rates that the CeBIT study. Nevertheless, it is important to note than the ITR calculation for the CeBIT study was done on the application level. That means, ITR was calculated on the basis of the letters selected ($N = 32$). The ITR in the RehaCare study was calculated on the basis of the low level commands sent to the transducer (command level). This led to an N of 5, based on five control commands. Performance at the transducer or command level would yield different results than at the application level. Therefore, analyzing performance at the same level would facilitate comparisons of both studies. However, a more important concern than the ITR values achieved is the BCI illiteracy response of both studies. At CeBIT a total of 26 subjects (24.53%) were unable to attain effective control, whereas at RehaCare 5 subjects (13.51%) were BCI illiterates. In conclusion, stable stimulation frequencies led to better performance and reduced illiteracy.

7. Role of Feedback and Training in SSVEP-based BCIs

This chapter addresses two important aspects of SSVEP-based BCIs, which are feedback and training. The main goal of this study was to determine whether feedback and training can help to increase BCI performance on subjects that learn to use an SSVEP BCI. The training protocol and feedback techniques used in this study were designed based on the target application, a spelling device. The subjects' task was to navigate a cursor into a matrix of characters and to select the desired character for communication purposes. This study compares performance of two groups of subjects, one group receives only discrete feedback, and the other group additionally received real-time feedback of their SSVEP signals. To determine if there is a significant improvement across the training sessions and how different types of feedback may affect BCI performance, information transfer rates and classification accuracies for 20 subjects were analyzed and statistical analyses were performed.

7.1. Introduction

Advances in cognitive neuroscience and signal processing techniques allow to interface computers directly with brain activity. Physical processes in the brain that correspond with certain mental tasks can be monitored and given in form of visual feedback in a computer screen. This technology is known as neurofeedback, and is used in brain-computer interface research to enable conscious control of brainwave activity to produce stable signals that control computers or other communication devices. Successful BCI control depends significantly on how the users can voluntary modulate their brain signals and not only on the signal processing algorithms used to translate brain signals into control commands [130]. Learning to operate a BCI requires repeated practice with feedback to engage learning mechanisms in the brain.

Neurofeedback provides information of the correct or incorrect response of the BCI. This feedback can be discrete or continuous, one or more dimensional, real or virtual. Discrete feedback can be e.g., a number, a letter, a sound or an icon. Continuous feedback is very often presented in form of a bar that represents the power of the brain signal. A realistic 3D feedback is e.g., hand movement realized

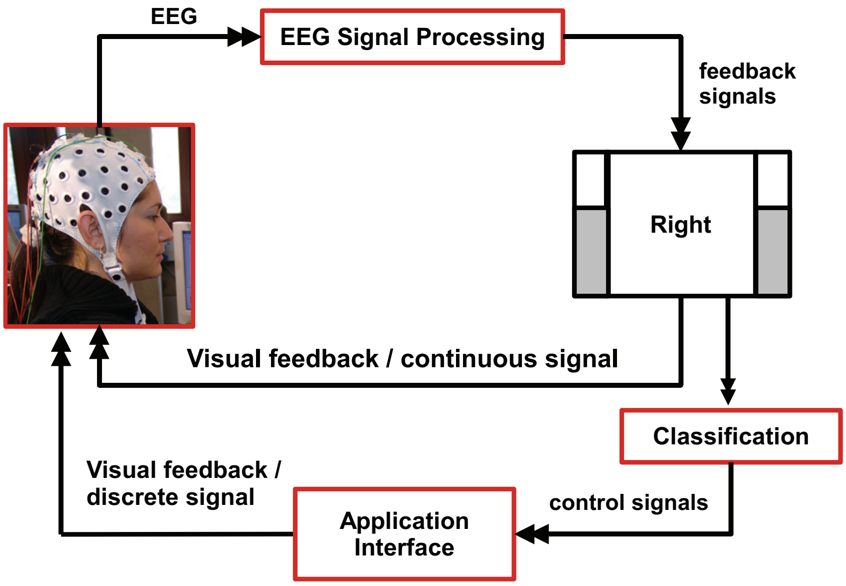


Figure 7.1.: Components of a BCI during feedback training.

by a virtual system, when the subject imagines hand movement. Feedback signals can be presented in a computerized game-like form. The aim is to maintain user's motivation and attention to the task. To keep the training period as short as possible, a well design training protocol and helpful real-time feedback are essential. A study that evaluates the role of feedback in EEG-based communication shows that continuous visual feedback can have benefits as well as negative effects on EEG control, and that theses effects vary across subjects [131].

During last years, many studies have shown that SSVEP-based BCIs generally require no training or reported that SSVEP systems need a little user training [55], which usually means a short familiarization session or a training phase to determine optimal system parameters [70]. Allison *et al.* (2008) suggested that subjects can be trained to perform better on visual attention tasks and that feedback reflecting SSVEP activity might improve performance [119]. For example, subjects who do not produce enough SSVEP activity for effective BCI control could be trained to perform better through neurofeedback training. Many articles have reported that visual feedback presentation may enhance performance in a BCI task, especially for modulation of mu rhythms [130, 132]. For SSVEP-based BCIs, only one study has addressed neurofeedback training for learning to control SSVEP amplitude [61]. However, the best feedback type and training protocols in a real BCI application are still not known.

7.2. SSVEP Feedback Study

7.2.1. Data Collection

EEG signals were recorded with eight sintered Ag/Ag-Cl electrodes from the surface of the scalp. Electrodes were placed at positions P_Z, PO_3, PO_4, O_Z, O_9, and O_{10}, from a customized 74 channel montage based on the standard 10-20 system of electrode placement [79]. All channels were referenced to the right ear lobe with a ground at the left ear lobe. Impedances were kept below $5\,\mathrm{K}\Omega$ by using electrolytic electrode gel, as is typical for conventional EEG recording. Data were digitized with a sampling rate of 128 Hz and amplified through a g.tec amplifier (Guger Technologies, Austria), which included a bandpass filter of 2–30 Hz, and a notch filter at 50 Hz.

Subjects were seated in a comfortable chair approximately 80 cm from an LCD monitor (22 Samsung SyncMaster 2233 with a vertical refresh rate of 60 Hz and resolution of 1680 × 1050 pixels), which displayed the graphical user interface (GUI) shown in figure 7.2. Two computers were used. PC1 (notebook) ran the signal processing software of the Bremen BCI system, including real-time EEG data acquisition and classification; and PC2 (desktop PC running Linux) implemented the application interface that provided the spelling interface and continuous feedback to the user (Neurofeedback interface described in section 5.4). Both programs communicated via the Transmission Control Protocol/Internet Protocol (TCP/IP). The implementation on two separate PCs was chosen for this study to facilitate meeting the different real-time requirements for the EEG and visual stimulation.

Signal Processing

Minimum energy combination (MEC) was used to create a spatial filter that linearly combines the signals of all electrodes in a way that the background activity and noise are minimized [100]. The BCI automatically determined the best spatial filter for each subject and then calculated the signal-to-noise ratio (SNR) at each stimulation frequency. Since the main SSVEP response is a periodic signal with energy only in the stimulation frequencies and their harmonics, a test statistic for testing the presence of an SSVEP response can be calculated. The test statistic averages the SNRs across all used harmonic frequencies and over all spatially filtered signals, and it calculates how many times larger the estimated SSVEP signal is compared to the case where no visual stimulus is present. The SNR was estimated every 13 samples (about 100 ms) from a signal length window of 2 seconds. If the SNR value at the specific frequency exceeded a predetermined threshold, the corresponding command was executed. For more technical details about the method used please see chapter 4.

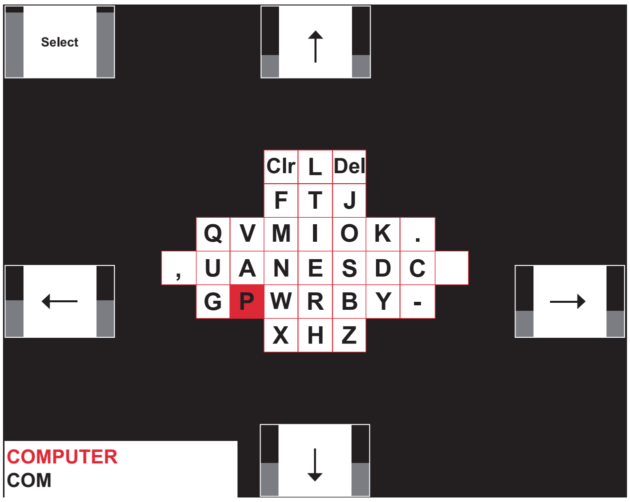


Figure 7.2.: SSVEP display with real-time continuous feedback.

Application Interface

Fig. 7.2 presents the display used in this study. The center of the display contains 32 letters and other characters that the subject could select. Subjects spelled by focusing on one of five flickering boxes presented on the display. Each box contained either an arrow (left, right, up, or down) or the word "select" and oscillated at a different constant frequency: 7.50, 8.57, 10.00, 12.00, and 6.67 Hz, respectively. These frequencies were determined through prior work [129], and were consistent with the monitor refresh rate of 60 Hz, which provides better quality of visual stimuli. The frequency generation was based on the approach presented previously in section 5.3.2. The signal processing algorithm calculated the SNR at each of the five stimulation frequencies every 100 ms. For example, if activity at 7.5 Hz exceeded the predetermined threshold, the corresponding command was executed and the cursor moved to the left. If activity at 6.67 Hz exceeded the threshold, the character highlighted by the cursor was selected. This character arrangement takes into account the probabilities of occurrence of every letter and was determined during previous work as described in [117]. At the beginning of each run and after each selection, the cursor was presented over the 'E' character. There was no "wraparound" feature; if the cursor reached the layout boundaries, e.g., at letter 'H,' then the cursor could not move further to 'L.' Possible misspellings should be corrected with the "Del" option located at the top-right of the matrix. During the experiment, if the feedback bars at the flickering boxes were activated, they varied in relation to the SSVEP amplitude. The maximum level that the feedback bars can reach is the subject-specific threshold.

7.2.2. Subjects

Two groups of participants (control group and experimental group) were trained to use the SSVEP-BCI to control the spelling device shown in Fig. 7.2. The control group received only discrete feedback from the spelling device. That is, the visual feedback was presented in form of discrete cursor movements (left, right, up, down), by highlighting actual letter background. These actions were received from the signal processing module, which detects the corresponding control commands from the EEG signals. Auditory signals played the name of the received navigation command or selected character simultaneously with cursor movements or letter selections. The bottom of the screen presented the character sequence that the subject already spelled.

The experimental group additionally received continuous feedback. That is, SSVEP amplitudes were displayed in form of dynamic vertical bars at each flickering box. The bars providing the real-time feedback were placed left and right of each flickering box and represented SSVEP signal strength with a lineal scale from zero to the predetermined subject-specific threshold. Thus, the corresponding control signals were generated, if the vertical bars were completely filled. Continuous feedback was realized by using the SNR calculation at each of the five stimulation frequencies and the state of the feedback bars were updated each 100 ms, which is the time set to calculate an SNR value.

7.2.3. Experimental Protocol

Each test person participated in series consisting of six training sessions. During every training session, each subject completed a brief questionnaire that included questions regarding actual level of tiredness and stress, and substances ingested in the last 24 hours prior to the experiment. Then, the subject was prepared for EEG recording. At the beginning of the first session, subjects participated in an additional practice run. In this run, subjects spelled the word "SIREN," and the experimenter used the resulting data to manually adjust a subject-specific threshold required for frequency detection. Next, subjects were instructed to spell five words as follows. Three of these words were chosen by the experimenter (copy spelling) and did not change in the course of the training sessions. These copy spelling tasks were "GEHIRN" (brain in German), "COMPUTER," and "NEUROWISSENSCHAFT" (neuroscience in German). Fourth and fifth words were chosen by the subject (free spelling) and changed over the sessions. Free spelling tasks are referred further as "FREE1," which consisted of a word composed of five letters, and "FREE2" for a word without restrictions. Before each free spelling task, each subject verbally told the experimenter the word that she/he intended to spell. The order in which these five words were presented to the user was randomly selected for each session. Each run ended, when the subject correctly spelled the specified word, or when the subject was not able to spell (that did not occur during this study). At the end of each session, after the five words were written, subjects completed a second questionnaire regarding tiredness and annoyance due to the flickering lights, and then the procedure was finalized. The entire procedure took on average about 40 minutes per subject for each of six sessions.

7.2.4. Analysis

For statistical analyses, the performance values obtained from five spelling tasks across six sessions were used. The goal was to find effects on training sessions, and differences between the two feedback types, discrete and continuous. BCI performance was assessed as information transfer rate, which is defined as the number of bits transmitted per trial. The calculation of information transfer rate for a brain-computer interface is described in [1] as follows:

$$B = \log_2 N + P \log_2 P + (1-P)\log_2\left[\frac{1-P}{N-1}\right] \tag{7.1}$$

where N is the number of possible choices ($N = 5$ commands) and P is the probability of identifying the target (accuracy). Bit rate in bits per minute can then be obtained by dividing B by the speed of the BCI system, which represents the number of commands per minute.

This study aims to find statistically significant effects of training across training sessions and to test the effectiveness of different kinds of feedback in SSVEP based BCIs. To this end, repeated measures analysis of variance (ANOVA) were used to determine whether there is a statistically significant difference in performances within the sessions and between both feedback conditions.

7.3. Results

The overall results obtained from 20 participants are summarized in Fig. 7.3. It shows the information transfer rate and accuracy for each subject averaged over all tasks and feedback sessions. Subjects achieved a mean information transfer rate of 36.51 ± 11.66 bit/min and accuracy of 97.66 ± 4.19%. Minimum and maximum ITR peaks were 7.51 and 63.28 bit/min and for classification accuracy 72.41 and 100%, respectively. As can be seen, considerable inter-subject differences in the information transfer rates were found. This observation was confirmed by one-way repeated measures ANOVA computed with subject as between-subjects factor and session as within-subjects factor. Table 7.1 summarizes the results of all conducted ANOVA tests for the whole sample and separated feedback groups.

	ANOVA effects for information transfer rate		
	Whole sample ($N = 18$)	Discrete FB ($N = 10$)	Continuous FB ($N = 8$)
	FB(2) x task(5) x session(6)	task(5) x session(6)	task(5) x session(6)
session	$F(5, 445) = 17.613^*$	$F(5, 245) = 11.087^*$	$F(5, 195) = 10.374^*$
session * subject	$F(85, 360) = 6.126^*$	$F(45, 200) = 5.169^*$	$F(35, 160) = 7.825^*$
session * task	$F(20, 425) = 0.609$	$F(20, 225) = 0.489$	$F(20, 175) = 0.426$
session * FB	$F(5, 440) = 3.279^*$		
session * task * FB	$F(20, 400) = 0.308$		

	ANOVA effects for correct selections		
	Whole sample ($N = 5051$)	Discrete FB ($N = 2649$)	Continuous FB ($N = 2402$)
	FB(2) x session(6)	session(6)	session(6)
FB	$F(1, 5039) = 6.893^*$		
session	$F(5, 5039) = 10.365^*$	$F(5, 2643) = 5.696^*$	$F(5, 2396) = 7.972^*$
session * FB	$F(5, 5039) = 3.530^*$		

* F-values 1% level

Table 7.1.: Significant F-values for repeated ANOVAs.

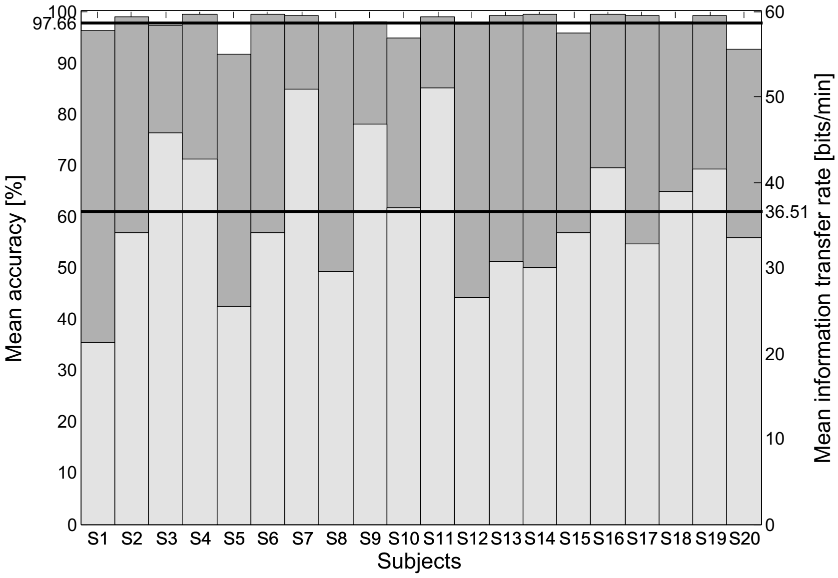
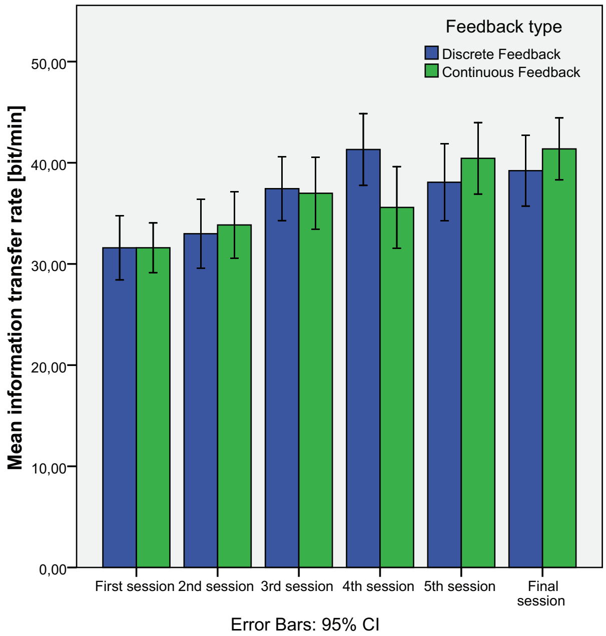


Figure 7.3.: Information transfer rates and accuracies for 20 subjects averaged over all training sessions.

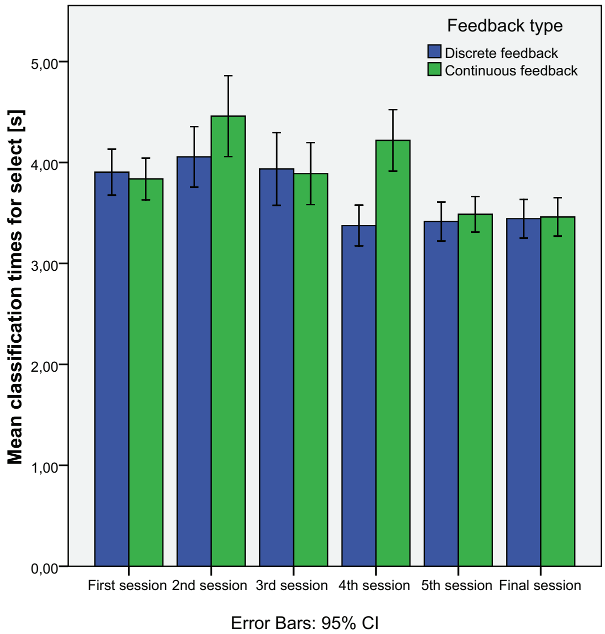
7.3.1. Performance during Feedback Sessions

Subjects were trained under two feedback conditions, one group received discrete feedback only (subjects S1 to S10), while the other group received additionally the continuous feedback (subjects S11 to S20). They participated on six training sessions, except for subjects S15 and S20 who participated only on the first four training sessions. Therefore, subjects S15 and S20 were excluded for further statistical analyses. Fig. 7.4(a) compares the information transfer rate of both groups across the sessions. Mean information transfer rates for discrete and continuous feedback conditions were 36.77 ± 12.48 and 36.23 ± 10.74 bit/min, respectively. To find significant differences in performance of subjects who received discrete versus continuous feedback across the six feedback sessions, a repeated measures ANOVA was computed with type of feedback as between-subject factor and session as within-subject factor. The results revealed a significant main effect between the feedback type, indicating that discrete feedback group performed better than the continuous group in the course of the sessions. A main effect of training within the sessions was found in the whole sample ($N = 18$).

Mean information transfer rates achieved for the group receiving discrete feedback ($N = 10$) were: session 1: 31.59 ± 11.17; session 2: 32.99 ± 11.97; session 3: 37.44 ± 11.10; session 4: 41.31 ± 12.49; session 5: 38.08 ± 13.40; session 6: 39.22 ± 12.31. User performance increased on average 7.62 bit/min after 6 sessions



(a)



(b)

Figure 7.4.: BCI performance under two feedback conditions, discrete and continuous feedback, over six experimental sessions. (a) Mean information transfer rates. (b) Mean classification times needed to perform a "select" command.

of training, and the peak was found in the fourth session. Analysis on the effects of training for the discrete feedback condition were performed. One-way repeated measures ANOVA was specified for performance (ITR) as the dependent variable and session number as within-subject factor. It was found that there were significant differences between the sessions. To learn more about the structure of the differences, pairwise multiple comparisons between the sessions were performed. Multiple comparisons revealed significant differences between the initial training session and sessions 3, 4, 5 and 6. The average increase of 7.62 bit/min was due to the training and improvement could be achieved already in session 3.

Data from subjects receiving continuous feedback ($N = 8$) revealed the following mean information transfer rates over six training sessions: session 1: 31.60 ± 7.68; session 2: 33.85 ± 10.28; session 3: 36.99 ± 11.14; session 4: 35.59 ± 12.62; session 5: 40.44 ± 11.05; session 6: 41.37 ± 9.58. To test the hypothesis that the increase of 9.78 bit/min was due to the training, a one-way repeated measures ANOVA was specified on the ITR for each training session as within-subject factor. Significant effects on performance were found. Pairwise comparisons showed significant differences between the initial session and sessions 5 and 6. The continuous feedback group performed best in the final session.

7.3.2. Classification Times

Classification time was measured as the time difference between the detection of the last navigation command and a letter selection command. All navigation commands such as "left," "right," "up," and "down" were discarded from this analysis because the goal was to find significant improvement in SSVEP training rather than the ability to find the letters on the matrix layout. To assess improvement over the sessions, analyses were conducted based on all correct selections. Information about session number and feedback type were used as factors, and the time needed to perform a "select" command was used as dependent variable.

Fig. 7.4(b) compares selection times for both groups across the sessions. Mean classification times for the "select" command was 3.69 ± 2.72 in the discrete feedback condition, and 3.89 ± 2.82 for continuous feedback. Mean selection times achieved by the group receiving discrete feedback were: session 1: 3.90 ± 2.43; session 2: 4.06 ± 3.18; session 3: 3.94 ± 3.87; session 4: 3.38 ± 2.17; session 5: 3.42 ± 2.06; session 6: 3.44 ± 2.05. For the continuous feedback condition, selection times were: session 1: 3.84 ± 2.13; session 2: 4.46 ± 4.06; session 3: 3.89 ± 3.12; session 4: 4.22 ± 3.07; session 5: 3.49 ± 1.80; session 6: 3.46 ± 1.94. ANOVA results for correct selections are shown in Table 7.1. Analyses on the whole sample revealed that the feedback type had significant effects on the selection times.

7.3.3. Copy versus Free Spelling

To analyze differences between copy and free spelling tasks, performance data from all subjects were separated by groups. Five groups were composed depending on the spelling tasks. To assess differences between spelling tasks, one-way repeated ANOVA was specified for ITR as dependent variable, and spelling task and session as factors. As shown in Table 7.1, ANOVA results were not significant, indicating that the performance was similar for all tasks. Subjects could switch from copy to free spelling without any decrement in performance. As expected, the phrase length did not have a noteworthy impact on performance results.

7.3.4. Questionnaire Results

Subjects preferences were evaluated by asking subjects that received continuous feedback, if they found the feedback bars distracting. They answered this question on a 1 to 5 scale, 1 meant not distracting and 5 very distracting. Mean answer was 2.05 ± 1.32. In general, subjects did not find the continuous feedback distracting. This answer and the information transfer rate were highly negatively correlated ($r = -0.482, p < 0.001$) by using Spearman bivariate correlation. Subjects who performed better did not find the feedback bars distracting and for bad performing subjects, the feedback bars were distracting. By comparing groups based on training sessions, the bivariate correlation showed that there is a significant and fairly strong negative correlation between performance and subjects preferences across sessions.

7.4. Discussion

The problem addressed in this work was to analyze the effects of SSVEP training and feedback type over several sessions. Brain-computer interfaces that operate with prior conditioning of EEG responses, that is the case of SSVEP, do not require a sophisticated learning procedure, but it is probable that long-term use of these signals can cause changes that may be adaptive or maladaptive [133].

A steady increase of the mean ITR that became significant after five (continuous feedback), respectively three (discrete feedback) sessions compared to the initial session values was found. Essential for this early improvement could be the acquisition of the speller's letter arrangement, which could reduce the duration of the subjects' visual search for a target character. For the continuous feedback condition, a marked slump in the learning curve shape during session four was observed. This suggested the assumption that an additional variable contributes to the overall performance in the ITR and occasionally may interfere with it. In contrast to the almost consistently rising trend of the mean ITR, a clear course of increasingly faster selection times could not be obtained in either one of the experimental conditions. According to the post-experimental surveys, it is assumed, that the ability of a subject to diminish it's selection times is the result of a short-term learning process. This process aims to find the optimal strategy to produce stable SSVEP signals, for example, the subject could try focusing at certain edges of the flickering squares or focusing the stimuli as a whole. In searching for the best possible system response, the subject tests and rejects cognitive strategies and produces a more inconsistent curve shape over the first training sessions. Only after an appropriate access to a reliable SSVEP processing has been discovered, the subjects' mean selection times level out at a stable state (session four to six for the discrete and five to six for the continuous feedback condition). The slope of the ITR curve in the fourth session of the experimental condition can therefore be ascribed to the effect of a less productive concentrative strategy indicated by the simultaneously high selection times. An overall difference between the two feedback groups was found, which suggest that discrete feedback supports more rapid initial training. Furthermore, this condition is accompanied by lower variances in the individuals mean selection times during the first three training sessions. Since, it can be adopted that positive feedback is particularly important in the period of evaluating one's individual SSVEP handling strategy; in conclusion, discrete feedback facilitates the effectiveness of SSVEP training during the early sessions and the stimulus flanking bars in the experimental condition may trigger a distracting effect that makes it even harder to come upon an early ideal response strategy.

7.5. Conclusion

This work proved that training with SSVEP causes positive effects on subjects and indicated that the type of feedback (continuous vs discrete) exerts a measurable effect on the subject's performance. There is evidence to suggest that discrete feedback supports more rapid initial training since subjects not only need to acquire the speller's letter arrangement but explore options to improve their SSVEP signals in a way the BCI could easily detect them. During this early period of mapping out cognitive strategies, the accompanying bars of the continuous feedback type have proved to be inappropriate to enhance the operator's convenience. Particularly with regard to these results a new advanced type of feedback has been proposed. Results of this more intuitive feedback type is shown in the following chapter.

8. Practical SSVEP-based Brain-computer Interface

This chapter describes how the final goal of this thesis was achieved toward the development of a practical BCI. A practical BCI can be defined as an effective and usable communication tool for a wide range of users, one that can be used outside the laboratory and with little expert assistance. The first though to make BCIs more practical from the Engineering point of view is to make BCIs faster and more reliable, that means increasing the information transfer rate (ITR). But to achieve the goal of increasing the ITR of actual BCI systems, three parameters are closely related: the accuracy of the detection, the speed of the detection, and the number of patterns that can be discriminated [94]. For example, shorter window lengths may speed up the detection time but also may reduce accuracy, or accuracy may be also affected with the number of patterns that can be differentiated. In this work, the case study to increase the ITR of BCIs was the Bremen-BCI. The Bremen-BCI is a BCI transducer that implements a robust signal processing approach to detect SSVEP patterns in ongoing BCI signals. BCI control with the Bremen-BCI was confirmed with the results of the studies presented in chapters 4 and 6, in which most subjects attained effective control of a robot arm and a spelling device, respectively. Results of chapter 7 showed the importance of feedback to increase performance of subjects. Based on those results, a method used for increasing the ITR of the Bremen-BCI was proposed. This method was based on two principal concepts, first improving the SSVEP detection algorithm, and second improving the frequency generation of the visual stimuli and the presentation of intuitive feedback. Both used in combination helped users to be more accurate and thereby increased the performance of the BCI. Improvements in the BCI translation algorithm were focused on the timing of the detection using an adaptive mechanism and the classification using a softmax activation function. The adaptation of the window length used for each signal processing cycle was used to speed up BCI communication. A novel control interface that provides real time feedback of the SSVEP signals by changing the size of the visual stimulus was the major improvement of the spelling device. A study using the improved Bremen-BCI signal processing methodology and the new control interface was conducted on 27 healthy subjects. Results showed a peak information transfer rate of 117 bit/min and mean ITR of 49.93 bit/min. In comparison with online

SSVEP-based BCI systems that have exhibited performance up to 70 bit/min [70], the results achieved with the improved Bremen-BCI are challenging. The Bremen-BCI signal processing chain is presented in section 8.1, then details of the control interface are presented in section 8.2, and finally the methods and results of the high ITR study with 27 subjects are described in section 8.3.

8.1. BCI Transducer

8.1.1. Spatial Filtering

The first step of the signal processing module is to create a spatial filter that linearly combines the signals of all electrodes in a way that the background activity and noise are minimized. The spatial filter creates several channels by making different combinations of the original electrode signals using the minimum energy combination (MEC) [100]. This filter was already described in detail in section 4.3.2. To extract discriminant features, the signals from the i electrodes need to be combined. This can be achieved by defining a channel vector s of length N_t which is a linear combination of the electrode signals, y_i,

$$s = \sum_{i=1}^{N_y} w_i y_i = Yw \tag{8.1}$$

where w is a vector of weights $[w_1, \ldots, w_{N_y}]$ associated with the individual electrode signals. The aim of the channel s is to enhance the information contained in the EEG while reducing the nuisance signals. Several channels can be created by using different sets of weights, depending on the nature of the SSVEP signal and the noise. Equation (8.1) can be generalized for N_s channels as

$$S = YW \tag{8.2}$$

with the set of channels $S = [s_1, \ldots, s_{N_s}]$ and the corresponding weight matrix $W = [w_1, \ldots, w_{Ns}]$.

8.1.2. SSVEP Power Estimation

The estimated signal power in the kth SSVEP harmonic frequency in channel signal s_l is given by

$$\hat{P}_{k,l} = \| X_k^T s_l \|^2 \tag{8.3}$$

where X contains the sine and cosine pairs with the SSVEP harmonic frequencies.

The test statistic, which is an average of the power over all N_s spatially filtered components and all N_h SSVEP harmonic frequencies, for testing the presence of an SSVEP response can be calculated by

$$T = \frac{1}{N_s N_h} \sum_{l=1}^{N_s} \sum_{k=1}^{N_h} \hat{P}_{k,l} \tag{8.4}$$

8.1.3. Normalization

In a BCI application with several stimuli, a test statistic for each stimulation frequency is calculated. The test statistic for each frequency is then normalized into a probability

$$p_i = \frac{T_i}{\sum_{j=1}^{j=N_f} T_i} \quad \text{with} \quad \sum_{i=1}^{i=N_f} p_i = 1 \tag{8.5}$$

The probability for each frequency is passed though a Softmax activation function to enhance SSVEP detection

$$p_i' = \frac{e^{\alpha p_i}}{\sum_{j=1}^{j=N_f} e^{\alpha p_j}} \quad \text{with} \quad \sum_{i=1}^{i=N_f} p_i' = 1 \tag{8.6}$$

where α is set to 0.25. Each probability p_i is compared with an empirically determined threshold. If the highest probability exceeds the threshold, then the corresponding frequency is detected, and the control command associated with this frequency is executed.

8.1.4. Classification

The classifier output R is determined as the number of the i-th frequency, if 1) this i-th frequency has the highest probability p_i', 2) p_i' exceed the pre-defined threshold β, and 3) the detected frequency belongs to one of the stimulating frequencies:

$$R = \begin{cases} argmax(p_i'), \\ p_i' \geq \beta, \\ i \leq N_c \end{cases} \tag{8.7}$$

where $1 \leq i \leq N_f$ and β is set to 0.35 (based on prior practical investigations and on the number of used frequencies N_f). N_c represents the number of commands (number of stimuli).

If R is classified as an undesired frequency ($i > N_c$) then this classification will be rejected (the detected frequency does not belong to the stimulation frequency set). To improve the overall reliability of the system, the commands corresponding to the stimulating frequencies are produced only if their probability is higher than the fixed threshold β.

The main advantage of the methodology outlined above is the fact that the pre-defined threshold β represents the relative probabilistic value and not the absolute value as in the original method [100,101], and as such it is independent of changes in the segment length T_s of the acquired EEG signal used for classification.

The classification has to take into account the moment when the subject does not focus on any stimuli. Therefore, the classifier output also detects a resting state or transition states between two stimuli and moments when the user's attention is not on a particular stimulus. These states where no SSVEP response should be detected is called zero class. If stimulation frequencies are located at the alpha band, this can produce false classifications in resting state.

8.1.5. Adaptive Mechanism

The signal processing algorithm proposed here is adaptive in two parts of the signal processing chain. First, in the online adaptation of the spatial filter MEC, in which the number of channels used is recalculated every signal processing cycle (100 ms for a sampling rate of 128 Hz), and second in the online adaptation of the time segment length T_s used for the classification. At the beginning of the trial, the first classification will be performed with the minimal time segment length of 750 ms (the values of 750, 1000, 1500, 2000, 3000 and 4000 ms were determined on previous work, for more details please refer to [134]). Similar to the original method, the classification is performed with the sliding window of T_s based on the last acquired EEG data approx. every 100 ms (every 13 samples with the sampling rate of 128 Hz used). In the case where no classification can be made and the actual time t allows the extension of the T_s to the next pre-defined value, this new value will be used instead:

$$\forall t : T_s = \begin{cases} 750\text{ms}, & t \leq 1000\text{ms} \\ 1000\text{ms}, & 1000\text{ms} \leq t \leq 1500\text{ms} \\ \dots & \\ T_{s_n}, & T_{s_n} \leq t \leq T_{s_{n+1}} \\ \dots & \\ 4000\text{ms}, & t \geq 4000\text{ms} \end{cases} \tag{8.8}$$

Further, after each performed classification, the EEG data used for the classification (T_{s_n}) will be empty. This ensures that no subsequent classification of the same frequency based on the buffered data can be done. In addition, the user of the BCI system will need some time for the gaze shifting. An additional 700 ms of the EEG data will not be utilized, they are usually contaminated by strong movement artifacts, therefore this data exclusion is helpful for the reliable classification. The next classification will be performed again with the minimal value $T_s = 750\,\text{ms}$.

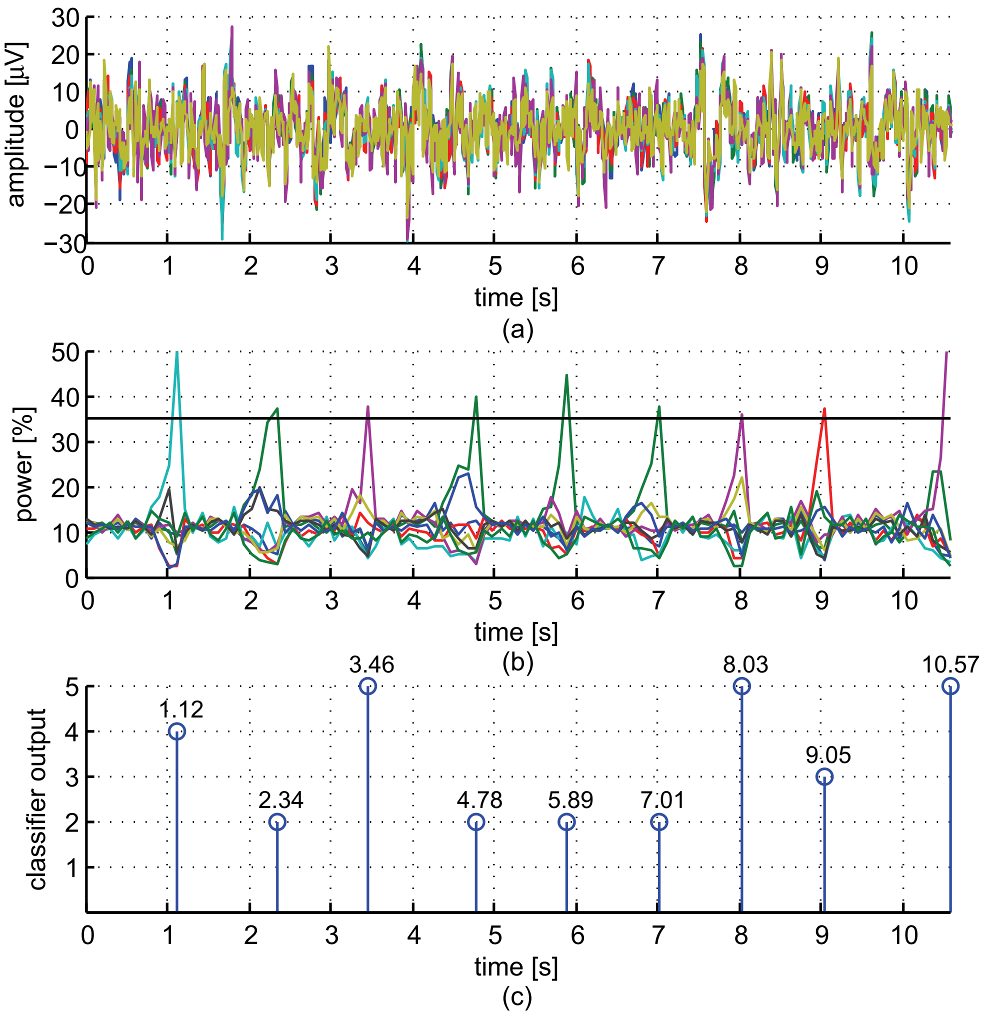


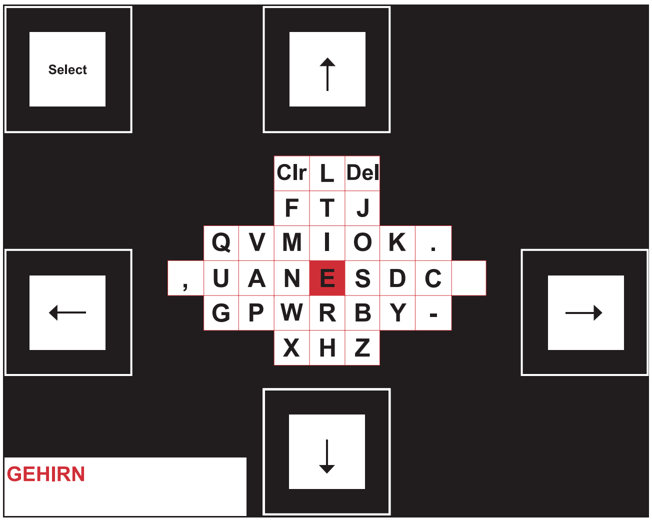
Figure 8.1.: Time courses and processing steps of the SSVEP signal detection for the word "BCI" spelled by subject 1. (a) EEG signals acquired from the visual cortex ($N_y = 6$). (b) Signal classification on the basis of a threshold ($\beta = 35\%$). Each signal represents the normalized power calculated for a specific frequency over all spatially filtered components (Ns) and all SSVEP harmonic frequencies ($Nh = 2$). A total of 9 (Nf) frequencies are processed but only 5 (N_c) encode a command (blue $\hat{=}$ left; green $\hat{=}$ right; red $\hat{=}$ up; light blue $\hat{=}$ down; magenta $\hat{=}$ select). Therefore only five frequencies are classified. (c) Result of the classification (1 $\hat{=}$ left; 2 $\hat{=}$ right; 3 $\hat{=}$ up; 4 $\hat{=}$ down; 5 $\hat{=}$ select). The numbers indicated the exact time of the classification.

Fig. 8.1 shows the output of the signal processing module of the Bremen-BCI for a subject that successfully spelled the word "BCI." Subject's task was to spell letters by navigating a cursor left, right, up, and down until the desired letter was reached. This letter could be then selected using the "select" command. The number of frequencies to detect was set to nine ($N_f = 9$), five stimulation frequencies ($6.66, 7.50, 8.57, 10.00, 12.00$ Hz) encoding five control commands and four additional frequencies ($7.08, 8.03, 9.28, 11.00$ Hz) for improving the robustness of the detection. The additional frequencies were calculated as the mean value between two target frequencies. Fig. 8.1(b) shows the power probability for each frequency and Fig. 8.1(c) the output of the classifier. For this spelling task, the user performed a total of nine commands. A command was executed when a signal exceeded the threshold of 35% (dotted line). After each classification, the signal processing module rejects 700 ms of EEG signals, because it is assumed that during this period the subject shifts gaze.

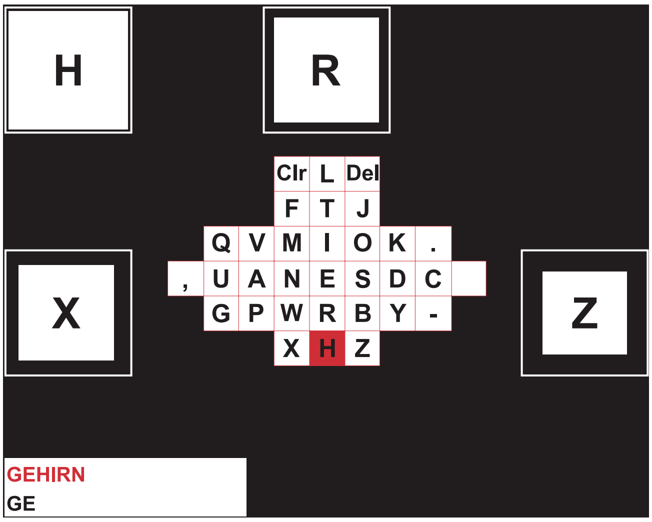
8.2. Control Interface

Users require effective interfaces that provide real-time feedback. The visual interface that interacts with the user is therefore very important to achieving high performance. The spelling interface toward a practical BCI is presented in Fig. 8.2. It consists of a keyboard and five stimulation boxes. These boxes contain the commands that can be sent: up, down, left, right, and select. Subjects spell by focusing on one of five boxes, which oscillates at a different constant frequency. Fig. 8.2(a) presents the speller display at beginning of a run. The cursor is presented over the 'E' character and the stimuli boxes in their default size (150 x 150 pixels). Each box contains either an arrow (left, right, up, or down) or the word "select" indicating the command it encodes. The white frame located around the stimulus box represents the maximum size that the stimuli can reach. This frame helps the user to know when a command is executed. The bottom of the screen contains the word to spell for the copy spelling case.

Fig. 8.2(b) shows an example of a screen-shot when a subject attempts to spell the German word "GEHIRN." After the subject had successfully spelled the sequence "GE," then the cursor is navigated until the next target character, the letter 'H.' Because at letter 'H' there is no possibility to move the cursor down, the stimulus encoding the corresponding command was deactivated. This rule was applied for all letters at boundaries of the layout. Continuous feedback is provided according to the power of the EEG signals. That is, the stimulus size increases or decreases depending on the actual power value at the corresponding stimulation frequency. Additionally, the next target for each stimulus is displayed on the box.



(a) At the beginning of the experiment



(b) During the experiment

Figure 8.2.: Spelling interface with feedback toward a practical BCI. (a) At the beginning of the experiment, all flickering boxes are represented in their default size of 150 × 150 pixels. (b) Subject trying to spell the target word “GEHIRN.” The actual letter ‘H’ is going to be selected. As no further “down” movement is possible, this stimulus box has been deactivated. The amplitude of the SSVEP responses control the size of the stimuli.

8.3. High ITR Study

This section describes a usability study aiming to demonstrate that the Bremen-BCI approach is controllable in a close-loop system with feedback (visual and auditory), and to investigate maximum and average information transfer rates that can be achieved with the system. The physical environment in which experiments were conducted was a normal office room in the Institute of Automation at the University of Bremen. This is different to the usual EEG recording conditions which is usually an electrically shielded room with low background noise and luminance. Subjects were seated in a comfortable chair approximately 60 cm from a LCD monitor with the control interface shown in Fig. 8.2.

8.3.1. Data Collection

EEG data were recorded from the surface of the scalp via eight sintered Ag/Ag-Cl EEG electrodes. They were placed on AF_Z for ground, right ear lobe was used for the reference electrode and $P_Z, PO_3, PO_4, O_Z, O_9, O_{10}$ as the input electrodes on the international system of EEG measurement. Standard abrasive electrolytic electrode gel was applied between the electrodes and the skin to bring impedances below $5k\Omega$. An EEG amplifier g.USBamp (Guger Technologies, Graz, Austria) was used for these experiments. The sampling frequency was 128 Hz. During the EEG acquisition, an analog bandpass filter between 2 and 30 Hz, and a notch filter around 50 Hz (mains frequency in Europe) were applied directly in the amplifier. The Bremen-BCI software system was used for all aspects of the real-time data processing and data storage. The SSVEP display was presented on a LCD screen (1680×1050 pixels) that presented a virtual keyboard and five white boxes, each one flickering at 7.5 Hz (“left”), 8.57 Hz (“right”), 10 Hz (“up”), 12 Hz (“down”), and 6.67 Hz (“select”). The size of each stimulus box was 150×150 pixels. Technical details of the software development of the control interface (speller and presentation of visual stimulation) used in this study is available in chapter 5.

8.3.2. Subjects

A total of 27 subjects participated in the study. Subjects mean age was 23.59 years, range 18-35 with standard deviation 4.73. This study included a total of 21 naive subjects who had never used any kind of BCI system before, subjects 1-3 had extensive SSVEP-BCI experience and were included in this study in order to form the reference value, subject 27 used the Bremen-BCI system once, and subjects 5 and 15 were “BCI illiterates” during the previous experiments. None of the subjects had neurological or visual disorders. Subjects did not receive any financial reward for participating in this study.

8.3.3. Experimental Protocol

Each subject completed a brief questionnaire including the age and gender information and was prepared for EEG recording. Next, a short familiarization run was carried out in order to introduce the experimental procedures and the letters arrangement. The assessment task was to spell five messages with the SSVEP based Bremen-BCI system. Three of the messages were the same for all subjects and were chosen by the experimenter (copy spelling), and two words were chosen by the subject (free spelling). The copy spelling words were "BCI", "GEHIRN" (German word for brain), and "INTERFACE." The subjects were told that their first free spelling word should be five letters long and their second word did not have any restrictions. Free spelling tasks are referred further as "FREE1", which means a word composed of five letters, and "FREE2" for a word without restrictions. Before the free spelling trial, each subject verbally told the experimenter the phrases that she/he intended to spell. The order in which these five phrases were presented to the user was determined randomly to avoid adaptations. Each trial ended automatically, when the subject correctly spelled the specified word (or when the subject chose to stop spelling due to any reason such as visual fatigue - this happened to subjects 15 and 20). Misspellings should be corrected with the "Del" option located at the top-right of the matrix. At the end of each session, after the phrases were spelled, subjects completed a second questionnaire and the procedure was complete. The entire session took on average about 40 minutes per subject.

8.3.4. Analysis

Analyses were based on the calculation of the information transfer rate (ITR) in bits per minute and the accuracy (Acc.) in percent for each spelling task. The following ITR formula presented in [49] was used for the computations:

$$B_t = \log_2 N + P \log_2 P + (1 - P) \log_2 \left[\frac{1 - P}{N - 1} \right], \tag{8.9}$$

where P is the classification accuracy and N is the number of targets. B_t is calculated in bits per trial. ITR was calculated on the command level, meaning that the number of targets is the number of flickering boxes and not the number of characters in the spelling layout. The reason was, none of the letters or special characters were flickering and therefore could not be directly selected by means of SSVEP communication channel. The number of commands required for each letter selection varied depending on its location on the layout (selection of the letter 'E' in the middle of the speller layout with just one "select" command) to maximum five commands (e.g., selection of the letter 'G', four movement commands and the selection).

In the case that one wrong moving command was detected, the user should correct this error first, e.g. the correction movement command "right" after the erroneously detected "left" command. Therefore, in this case the correction step is counted as correct command classification. So that, the number of commands can increase depending of the subject's performance. In case of incorrectly classified selection command, the wrongly spelled letter should be corrected, this results in five additional commands to select the special character "Del."

Classification accuracy P was calculated in the traditional way and was defined as the number of correct command classifications divided by the total number of classified commands. If some of the stimuli are deactivated, these frequencies still can be classified due to various reasons like e.g. background brain activity in the alpha range (8–12 Hz). Since all five frequencies can be (erroneously) classified independently of the actual cursor position, the assumption that all choices are equally probable still could be suggested.

The spelling time T (for the whole word) was considered in the calculation of the ITR in bits per minute (B_m). A very important issue was the value of N. Since some of the flickering boxes were deactivated when the current cursor position was on an edge of the speller layout, the ITR calculations considers $N = 2, 3, 4,$ or 5 depending on the cursor position. This leads to the modified ITR calculation:

$$B_m = \frac{60}{T} \cdot \sum_{N=2}^{5} [C_N \cdot B_t(N)] \tag{8.10}$$

where C_N is the number of classifications at N targets and T is the spelling time in seconds. B_t in this case is a function of N. It is worth noting that this at first sight quite complicated ITR calculation results only in very minor decrease of the ITR values. This could be easily explained with the selected speller layout: only the letters 'G', 'H', 'F' from altogether 18 letters of the three copy spelling words "BCI", "GEHIRN", and "INTERFACE" are located at the layout boundaries, where some stimuli will be deactivated ($N = 3$ for 'G', $N = 4$ for 'H', and $N = 4$ for 'F'). Since during the correct spelling of the word "BCI" the cursor is never located at the layout boundaries, the number of targets $N = 5$ during the complete spelling task "BCI", $C_2 = 0$, $C_3 = 0$, $C_4 = 0$, $C_5 = 9$, respectively, and the ITR was calculated in the conventional way:

$$B_m = \frac{60}{T} \cdot 9 \cdot B_t(5) \tag{8.11}$$

It is important to note that none of the 27 subjects during all spelling tasks ever reached the letters ',' and '␣' located at the left and the right boundaries of the speller layout, therefore, the minimal value of N was 3 in this study.

The highest theoretically achievable ITR can be achieved with this BCI system is 132.68 bit/min, assuming a minimal time between two consequent command classifications of 1050 ms (an idle period of 700 ms plus 350 ms enough to detect a frequency):

$$ITR_{max} = \frac{60}{1.05} \cdot \log_2 5 \tag{8.12}$$

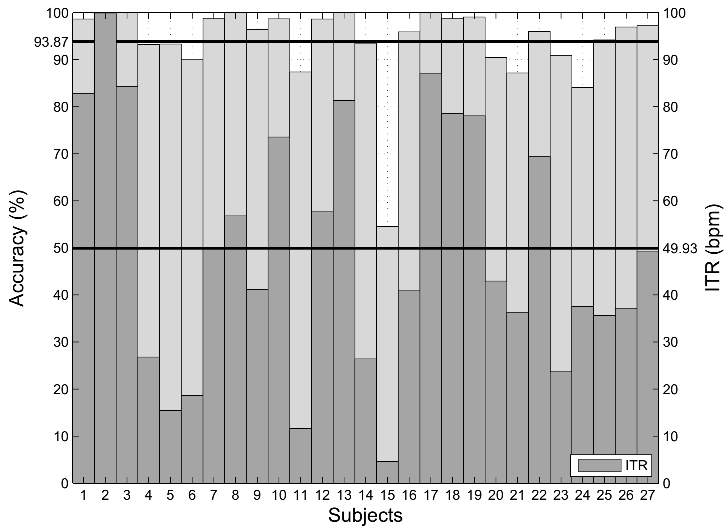
Since this is the ideal situation, the real ITR values will be always below this theoretical value because a subject needs some time to change focus between two stimuli or to look at the layout to find the characters.

8.3.5. Results

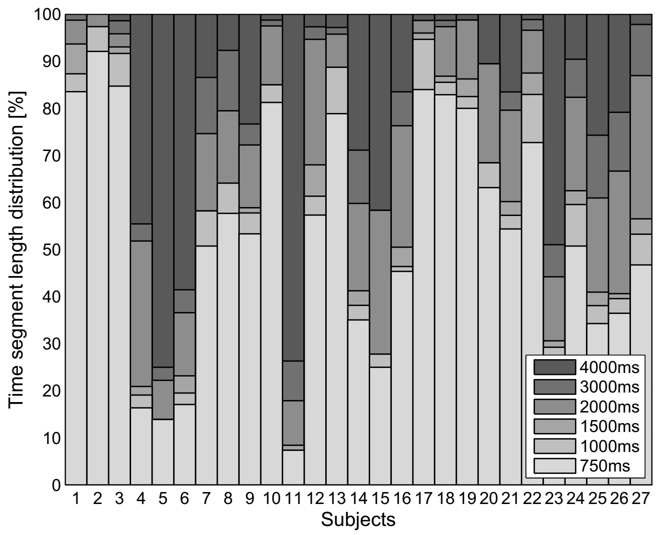
Three conventional BCI performances, spelling time, accuracy and ITR achieved, for five spelling words over all 27 subjects are summarized in Table 8.1. The format of this table allows a direct comparison to previous studies (see Appendix A and B). For every word the minimum (**Min**), maximum (**Max**), mean (**Mean**) and standard deviation (**S.D.**) for each measured variable are obtained by averaging over all subjects who completed the particular spelling task. Accuracies achieved in individual spelling tasks vary considerably, in the range from 54.55% to 100.00%. However, the majority of achieved accuracies are over 92%. The spelling time also varies between subjects, leading to ITRs in the range from 4.61 to 117.39 bit/min with the mean of about 50 bit/min.

Fig. 8.3(a) shows individual accuracies and information transfer rates achieved by 27 subjects. Mean information transfer rates across all tasks and subjects was 49.93 ± 26.44. Fig. 8.3(b) presents the normalized (by the total number of correct classifications) distribution of the time segment length for all correct classifications. This distribution is independent of the stimulus frequency.

Information transfer rates and accuracies were analyzed to find significant differences within spelling tasks using repeated measures analysis of variance (ANOVA). Data from the 25 subjects who successfully completed all tasks were used for this analysis. The results show that performance measured as ITR across five different spelling tasks differed significantly, $F(4, 96) = 20.373, p < 0.001$. Post hoc tests revealed that the word "BCI" was significantly different from all other spelling tasks ($p < 0.002$). In terms of accuracy, also spelling tasks were performed differently $F(4, 96) = 4.70, p < 0.002$. Post hoc tests show that the word "INTERFACE" differed from others two words: "BCI" ($p < 0.05$) and free spelling with five letters ($p < 0.05$).



(a)



(b)

Figure 8.3.: Results of BCI performance for 27 subjects. (a) Mean individual accuracies and information transfer rates. (b) Distribution of the time segment length for all correct classifications. From [135].

Subject	Word "BCI" Time [s]	Acc. [%]	ITR [bpm]	Word "GEHIRN" Time [s]	Acc. [%]	ITR [bpm]	Word "INTERFACE" Time [s]	Acc. [%]	ITR [bpm]	Free spelling 1 (5 letters) Time [s]	Acc. [%]	ITR [bpm]	Free spelling 2 Time [s]	Acc. [%]	ITR [bpm]
1	12.00	100.00	104.47	27.85	100.00	72.06	49.58	93.33	63.93	20.43	100.00	94.52	22.57	100.00	79.39
2	10.68	100.00	117.39	22.87	100.00	87.75	31.91	100.00	95.45	20.74	100.00	100.77	21.24	100.00	97.45
3	12.92	100.00	97.06	28.26	100.00	71.03	38.21	100.00	79.70	21.15	100.00	91.33	20.23	100.00	82.64
4	29.38	100.00	42.68	99.96	95.24	23.21	259.84	84.00	14.90	101.69	86.96	19.04	76.92	100.00	34.16
5*	69.51	100.00	18.04	154.94	88.89	10.43	228.36	87.88	12.96	55.78	100.00	22.48	74.79	90.00	13.26
6	65.12	83.33	21.21	134.60	89.47	13.77	169.86	86.11	17.81	47.98	100.00	23.23	71.52	91.67	17.53
7	26.22	100.00	47.81	49.58	100.00	40.86	71.12	100.00	42.82	41.66	94.12	44.23	9.36	100.00	74.39
8	15.46	100.00	81.12	43.18	100.00	46.47	56.08	100.00	54.31	41.05	100.00	55.21	44.10	100.00	46.95
9	19.72	90.91	56.91	74.57	100.00	27.17	100.17	91.43	34.56	51.92	100.00	37.20	52.43	100.00	50.12
10	13.63	100.00	92.01	32.62	100.00	62.12	48.37	93.55	68.66	32.32	100.00	71.48	18.93	100.00	73.61
11	85.14	78.57	10.96	155.44	89.47	11.11	264.62	90.91	12.24	128.01	94.12	14.40	202.86	84.00	9.47
12	21.85	100.00	57.37	40.14	100.00	50.48	48.16	100.00	63.24	34.46	100.00	58.24	26.94	93.33	59.81
13	11.90	100.00	105.35	27.44	100.00	73.13	38.51	100.00	79.08	31.50	100.00	65.72	16.68	100.00	83.54
14	46.96	100.00	26.70	114.70	87.10	23.42	116.52	86.11	26.27	60.66	100.00	29.54	75.71	94.44	26.11
15*	282.38	54.55	4.61	-	-	-	-	-	-	-	-	-	-	-	-
16	21.96	100.00	57.09	41.05	100.00	48.89	169.94	90.20	28.55	43.90	100.00	31.74	58.83	89.47	38.13
17	12.31	100.00	101.89	25.72	100.00	78.04	37.50	100.00	81.22	24.09	100.00	95.91	21.24	100.00	78.69
18	13.22	100.00	94.83	31.81	94.12	58.50	39.43	100.00	77.25	20.23	100.00	88.58	29.58	100.00	73.87
19	12.92	100.00	97.07	28.56	100.00	70.95	45.52	100.00	66.91	40.74	95.45	61.27	19.22	100.00	94.25
20	46.64	90.48	42.95	-	-	-	-	-	-	-	-	-	-	-	-
21	19.52	90.91	55.51	40.35	100.00	49.74	179.39	79.03	21.70	45.83	88.24	34.81	53.66	77.78	19.85
22	12.31	100.00	101.88	40.24	94.12	46.24	64.82	92.31	61.86	26.63	93.75	65.71	23.17	100.00	71.31
23	34.25	100.00	36.61	146.68	88.57	20.68	441.44	76.62	10.48	64.00	100.00	30.17	165.37	89.19	20.35
24	19.83	100.00	63.24	99.05	83.33	31.41	152.79	77.78	21.97	32.72	94.12	55.77	128.60	65.38	15.48
25	26.95	100.00	46.52	107.89	88.89	15.13	183.16	87.04	25.21	58.22	95.24	39.86	34.47	100.00	51.42
26	25.71	100.00	48.76	67.78	100.00	29.61	150.14	90.38	32.92	66.44	94.44	29.82	24.90	100.00	44.76
27	19.22	100.00	65.25	40.64	94.12	45.34	56.29	100.00	54.11	35.06	100.00	39.74	94.07	92.11	42.25
Min	10.68	54.55	4.61	22.87	83.33	10.43	31.91	76.62	10.48	20.23	86.96	14.40	9.36	65.38	9.74
Max	282.38	100.00	117.39	155.44	100.00	87.75	441.44	100.00	95.45	128.01	100.00	100.77	202.86	100.00	97.45
Mean	36.58	95.88	62.79	67.04	95.73	44.29	121.67	92.27	45.92	45.89	97.46	52.03	55.50	94.69	51.95
S.D.	52.82	10.00	32.57	45.24	5.46	23.14	99.82	7.72	26.39	25.33	3.89	26.50	48.80	8.61	27.65

* Subjects that participated in previous SSVEP experiments and were "BCI-illiterates."

Table 8.1.: Detailed results for each word and each subject.

8.4. Conclusion

Presented results demonstrated that improvements in the signal processing and new feedback modules of the BCI system constituted the basis for achieving ITRs in the order of 100 bit/min. The novel idea of adapting the processed signal values to the size of the stimuli to provide continuous real-time feedback was one of the keys to achieve high online performance, as well as the exact frequency generation. Further research should identify other factors that can relate with performance, such as, human factors, training procedures, time behavior of the complete system (the user can learn the time latencies and responses of the system), and error recognition and error correction at early stages of the BCI signal processing. In this work, the classification threshold was set to a constant value for all frequencies ($\beta = 0.35$). Further research might also consider a frequency dependent β to take into account the variation of the power of SSVEPs at different frequencies.

9. Summary and Future Directions

In this dissertation, the development of *practical Brain Computer Interfacing* communication was assessed by studying all components that are involved in the BCI closed-loop, i.e., the user, the transducer and the feedback. The objective was to improve the speed and the reliability of non-invasive BCI systems that acquire brain signals via EEG. In order to reach this main goal, this work focused on two BCI paradigms: the event-related (de-)synchronization (ERD/ERS) and the steady state visual evoked potential (SSVEP). The former is the amplitude increase or decrease of the brain waves during performed or imagined movement (e.g., hands or feet movement), and the latter reflects attention to a rapidly oscillating stimulus (> 5 Hz). Whereas the ERD/ERS constitutes an endogenous BCI (responds to internally generated signal), the SSVEP constitutes an exogenous BCI (responds to an automatic response to an evoked stimulus).

Concerning ERD/ERS communication, crucial parameters for the detection of ERD/ERS brain patterns were identified and the relevance of feedback and training was investigated (see chapter 3). Consistent with other studies, results of the ERD/ERS explorative study showed that the ERD/ERS patterns were subject-dependent and varied in frequency (around mu and beta bands) and space (electrode location). With the help of time-frequency analyses, it was found that another important parameter for the successful detection of ERD/ERS is the time window in which the imagination of movement can be better differentiated. These results were very helpful for the development of an online ERD/ERS detector, which first separates the data in classes (each imagery class and resting period), searches for the frequency peaks in the spontaneous EEG spectrum (resting period), builds frequency bands based on the found peaks, and finally searches for more prominent differences between the band pass filtered imagery classes and the resting state. The ERD/ERS feedback study showed a single-case study of a subject that trained motor imagery tasks over 14 training sessions. The results of this study led to an important conclusion, the feedback application (BCI trainer) used to train subjects should be implemented as a set of applications with different levels of difficulty, for instance, initial, intermediate, and advanced; and the training protocol should be adapted according to the learning process of the user to avoid frustration and low motivation. Both studies contributed to demonstrate online ERD/ERS control using three mental states (imagination of right hand, left hand and feet) on a real (intermediate trainer) and a virtual (advanced trainer) labyrinth application. 91.3% accuracy and 8.62 bit/min for a well trained subject after 12 sessions were achieved with the virtual labyrinth. Although the ERD/ERS paradimg provides an endogenous communication, it requires complicate signal processing methods and long training periods. Most subjects complained that motor imagery tasks were difficult to perform. The experience with this paradigm led to indeed ERD/ERS requires significant commitment and a lot of concentration for the user. Moreover, calibration sessions of 150 trials (20 minutes) are tiring and tedious. The reduction of calibration times would be vital for any further implementation that focuses on online ERD/ERS communication. Further ERD/ERS research should also concentrate to validate ERD/ERS as advanced neurofeedback tool, in which the goal is not communication but rehabilitation, for example as therapy for stroke, autism, ADHD, and other disorders.

Concerning SSVEP communication, a new application in the service robotics was validated, the role of training and feedback was investigated, and effective SSVEP communication was achieved. The high-level control study in chapter 4 demonstrated that the proposed goal-oriented approach for the control of a service robot via BCI is possible. This underscores the importance of reducing the burden on BCI users through effective goal-oriented protocols when controlling more complex applications than simple computer based applications. The goal selection approach was easier for the subjects and appears to be a more realistic strategy for the control of the complex systems than the low-level control. To allow users the low-level control of the robot arm would not only be slow and frustrating but also dangerous. New applications for communication and control should employ intelligent devices that can increase what users may accomplish with the limited control available with modern BCIs. With the aim to improve the accuracy and information transfer rate of SSVEP based BCIs, the role of feedback and training was investigated in an spelling application. The results of the feedback study that used real time feedback of the SSVEP signals to train subjects to control a virtual keyboard proved that training with SSVEP causes positive effects on subjects and indicated that the type of feedback (continuous vs discrete) exerts a measurable effect on the subject's performance, though continuous feedback requires more initial training than discrete feedback (see chapter 7). Based on performance results and subjective report of the test subjects, a more intuitive feedback for the SSVEP stimuli was developed by changing the size of the stimulus by means of the SSVEP signals (see chapter 8). Moreover, improvements in the signal processing algorithm used to detect the SSVEP responses to the stimuli contributed to achieve high information transfer rates (49.93 bit/min averaged over 27 subjects). Even the best information transfer rate for an experienced subject and a well-tuned BCI system as such one presented in chapter 8 is relatively low, in the vicinity of 2 bit/s. This is still too low for natural interactive communication (spoken English is about 40 bit/s, eye tracking 14 bit/s, mouse

12 bit/s, source: [136]), so researching ways of optimizing detection techniques, the exploitation of the learning skills of the users though feedback and incorporating prediction mechanisms to speed communication are still needed [137].

Already in the experiments conducted in chapter 3 and 4, there was a consistent observation: the considerable subject variability and the phenomenon than some subjects were unable to attain effective control. Aiming to answer the question if demographic information could help to understand why some people are better at BCI use than others, or if gender, age, background, and lifestyle differences affect performance, this dissertation also made an effort to address BCI demographics (see chapter 6). To this end, the causes of inter-subject variability and BCI illiteracy were investigated by analyzing data recorded in two field studies with a large number of test subjects. Results of both studies showed that most subjects, despite having no prior BCI experience, could use the Bremen SSVEP BCI system in a very noisy field setting. Performance data suggest that SSVEP BCIs may be better suited to younger and/or female subjects, though these trends did not attain statistical significance. Also, subjects with disabilities could use the BCI with a similar performance as healthy subjects. While those studies helped to validate effective SSVEP communication, they did not help to address BCI demographics. Demographics questions should be best addressed with a more equal distribution of key characteristics like age or gender, requirement that was no fulfilled at the CeBIT or RehaCare event. In future BCI studies that cannot recruit or screen subjects in advance, researchers might consider rejecting some subjects and encouraging others to attain a better mix of, for example, young versus old subjects [102]. Further demographic research should identify how individual subject factors relate to performance with other BCIs, and with other parameters such as the best frequencies, thresholds, tasks, mental imagery, training regimens, feedback, or other adjustable parameters. This research should facilitate BCIs that can adapt to each user, ideally with little or no expert help.

The spelling interface for SSVEP and the training environment for ERD/ERS were the result of the software development described in chapter 5. This software was designed following extendability and re-usability concepts, which showed to be an effective solution for software development in BCIs. The practicability of BCI feedback tasks require thorough evaluation to demonstrate their long-term reliability, functionality and acceptance based on experimental results and subjective report. Feedback tasks graphical representation change but the general concept remains constant. A feedback task presents a view, acquires BCI control signals and works based on configuration parameters. Therefore, the development of a general application interface to study different kinds of feedback types was the best solution to solve the software problem. Future research could extend this software concept to other parts of the BCI system to build a BCI general software framework.

Future progress in BCI research can be expected by the design of hybrid BCI architectures [138,139] that incorporates different BCI approaches with other biosignals or external devices such as an eye tracking system [140], new algorithms that can adapt together with the learning process of the user, exploitation of mental states, and incorporation of human-computer interaction concepts. The development of new electrodes, e.g., dry electrodes or electrodes that require water instead of electrolytic electrode gel, would make both daily setup and clean up much faster, easier and comfortable. A very recent study conducted at IAT [141] presents promising results that confirm the operational readiness of water-based electrodes for BCI applications. Advances can be expected by the development of dry electrodes, amplifiers, lightweight and portable equipment by the inclusion of industry partners in BCI projects.

A. CeBIT data set

This appendix contains detailed results of the experiments conducted at CeBIT 2008. Table A.1 presents a synopsis of the CeBIT study and Table A.2 displays the performance results assessed by 106 subjects. Subjects numbers 28 and 52 do not exist. A hyphen symbol (-) indicates that the task was not completed.

Table A.1.: Study synopsis

Synopsis		
Study description	Study class	(non-controlled) Usability study
	Objective(s)	Assess SSVEP BCI performance across a large number of subjects
	Online/Offline	Online (evaluation of technology with live biosignals)
	Subject class	Human
Experimental variable(s)	Dependent variable(s)	Information transfer rate of control interface [bpm] Correct selection of targets [%] Completion time of spelling task [s]
Assistive technology	Description	Virtual keyboard with 32 targets
	BI Technology design model	(2 component) Demonstration system - Transducer and Spelling Device
	Target population	Fully-paralyzed (locked in individuals) Partially-paralyzed individuals Individuals with other severe motor disabilities
	Target activity	Communication with people
	Target environment	Anywhere (indoors or outdoors)
Physical environment	Location	Field study: subjects sat in a chair facing a laptop monitor 50 cm away at an exposition fair.

Table A.2.: Detailed results of experiments conducted at CeBIT 2008.

Subject	Word "BCI" Time [s]	Word "BCI" Acc. [%]	Word "BCI" ITR [bpm]	Word "BCI Long" Time [s]	Word "BCI Long" Acc. [%]	Word "BCI Long" ITR [bpm]	Word "SIREN" Time [s]	Word "SIREN" Acc. [%]	Word "SIREN" ITR [bpm]	Word "CHUG" Time [s]	Word "CHUG" Acc. [%]	Word "CHUG" ITR [bpm]	Free spelling Time [s]	Free spelling Acc. [%]	Free spelling ITR [bpm]
1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
3	33.11	100.00	27.18	-	-	-	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
6	109.28	100.00	8.24	358.31	100.00	20.09	-	-	-	-	-	-	77.29	100.00	19.41
7	42.86	100.00	21.00	682.91	96.00	10.02	119.54	100.00	12.55	83.08	100.00	14.44	64.19	100.00	18.70
8	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
9	165.55	100.00	5.44	-	-	-	166.46	71.43	6.87	327.03	100.00	3.67	314.84	85.71	4.94
10	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
11	179.66	100.00	5.01	-	-	-	-	-	-	-	-	-	-	-	-
12	344.09	60.00	1.79	-	-	-	-	-	-	-	-	-	-	-	-
13	104.91	100.00	8.58	-	-	-	-	-	-	137.92	100.00	8.70	-	-	-
14	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
15	-	-	-	-	-	-	190.43	83.33	6.66	327.44	100.00	3.66	141.17	83.33	8.99
16	-	-	-	-	-	-	193.48	100.00	7.75	230.34	100.00	5.21	489.63	100.00	5.51
17	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
18	31.79	100.00	28.31	278.79	100.00	25.83	63.17	83.33	20.08	64.90	100.00	18.49	88.36	100.00	16.98
19	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
20	-	-	-	-	-	-	-	-	-	-	-	-	353.74	100.00	4.24
21	-	-	-	-	-	-	-	-	-	-	-	-	408.18	100.00	3.67
22	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
23	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
24	-	-	-	-	-	-	-	-	-	116.19	100.00	10.33	-	-	-
25	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
26	92.83	60.00	6.62	-	-	-	-	-	-	-	-	-	73.43	60.00	8.36
27	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
29	-	-	-	-	-	-	-	-	-	-	-	-	911.73	100.00	4.94
30	146.45	75.00	4.83	-	-	-	-	-	-	-	-	-	-	-	-
31	298.29	75.00	2.37	-	-	-	-	-	-	-	-	-	-	-	-
32	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
33	43.37	75.00	16.33	-	-	-	61.45	100.00	24.41	-	-	-	345.31	100.00	9.56
34	193.07	60.00	3.18	1029.54	100.00	6.99	-	-	-	-	-	-	309.05	100.00	10.68
35	47.84	100.00	18.81	-	-	-	40.12	83.33	31.63	73.13	80.00	13.49	167.78	100.00	14.30

Continued on next page...

Table A.2 – Continued

Subject	Word "BCI"			Word "BCI Long"			Word "SIREN"			Word "CHUG"			Free spelling		
	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]
36	199.67	100.00	4.51	-	-	-	-	-	-	-	-	-	-	-	-
37	63.07	100.00	14.27	-	-	-	92.42	100.00	16.23	-	-	-	261.63	100.00	5.73
38	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
39	51.09	100.00	17.62	-	-	-	27.73	100.00	54.10	51.39	100.00	23.35	65.91	100.00	31.86
40	85.52	60.00	7.18	-	-	-	96.59	62.50	10.87	-	-	-	-	-	-
41		-	-	-	-	-	-	-	-	-	-	-	-	-	-
42	327.44	100.00	2.75	-	-	-	51.59	100.00	29.07	-	-	-	-	-	-
43	62.36	100.00	14.43	392.03	100.00	18.37	80.74	100.00	18.58	71.40	100.00	16.81	80.44	100.00	22.38
45	-	-	-	-	-	-	43.98	100.00	34.11	51.19	100.00	23.44	65.30	100.00	22.97
46	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
47	-	-	-	-	-	-	-	-	-	-	-	-	34.13	100.00	35.16
48	47.84	75.00	14.80	300.12	100.00	23.99	45.30	100.00	33.11	73.94	100.00	16.23	568.55	100.00	17.41
49	87.45	37.50	5.21	-	-	-	286.30	71.43	3.99	-	-	-	-	-	-
50	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
51	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
53	157.52	100.00	5.71	-	-	-	-	-	-	-	-	-	189.92	100.00	6.32
54	129.39	75.00	5.47	-	-	-	210.34	83.33	6.03	344.60	100.00	3.48	163.01	100.00	9.20
55	204.95	75.00	3.45	-	-	-	70.38	100.00	21.31	131.12	100.00	9.15	-	-	-
56	71.40	100.00	12.61	-	-	-	-	-	-	-	-	-	159.86	80.00	6.17
57	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
58	67.44	100.00	13.35	-	-	-	55.05	83.33	23.05	158.44	80.00	6.22	151.13	100.00	9.93
59	148.99	100.00	6.04	-	-	-	184.54	100.00	8.13	202.62	80.00	4.87	262.64	100.00	8.00
60	231.16	42.86	2.15	-	-	-	84.70	100.00	17.71	299.20	100.00	4.01	658.84	100.00	4.10
61	104.71	100.00	8.60	-	-	-	165.65	62.50	6.34	106.03	100.00	11.32	65.51	100.00	18.32
62	-	-	-	-	-	-	157.83	100.00	9.50	244.66	100.00	4.90	243.04	100.00	4.94
63	-	-	-	465.77	100.00	15.46	-	-	-	105.73	100.00	11.35	245.98	100.00	13.42
64	72.11	75.00	9.82	707.69	100.00	10.17	59.31	62.50	17.70	91.81	100.00	13.07	130.20	100.00	13.82
65	392.13	100.00	2.30	-	-	-	-	-	-	-	-	-	322.46	100.00	8.37
66	61.14	100.00	14.72	281.94	100.00	25.54	-	-	-	95.88	100.00	12.52	82.98	100.00	14.46
67	75.66	100.00	11.89	-	-	-	79.12	100.00	18.96	83.38	100.00	14.39	361.66	80.00	5.45
68	463.63	100.00	1.94	-	-	-	431.64	100.00	3.48	-	-	-	-	-	-
69	60.63	100.00	14.84	551.69	100.00	13.05	107.45	100.00	13.96	86.94	100.00	13.80	246.90	100.00	9.72
70	50.38	100.00	17.87	-	-	-	196.32	100.00	7.64	-	-	-	-	-	-
71	147.88	100.00	6.09	-	-	-	175.50	100.00	8.55	-	-	-	-	-	-
72	245.48	100.00	3.67	-	-	-	-	-	-	-	-	-	-	-	-

Continued on next page...

Table A.2 – Continued

Subject	Word "BCI"			Word "BCI Long"			Word "SIREN"			Word "CHUG"			Free spelling		
	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]
73	112.73	100.00	7.98	307.02	100.00	23.45	68.55	100.00	21.88	57.38	100.00	20.91	65.71	100.00	22.83
74	61.14	75.00	11.58	439.05	92.31	15.02	83.69	100.00	17.92	52.00	100.00	23.08	53.83	100.00	22.29
75	35.95	100.00	25.03	308.55	100.00	23.34	-	-	-	74.75	100.00	16.05	51.19	100.00	23.44
76	21.53	100.00	41.80	241.01	100.00	29.87	29.35	100.00	51.10	89.38	100.00	13.43	104.81	100.00	34.35
77	54.84	100.00	16.41	626.74	96.00	10.91	78.10	83.33	16.24	96.38	100.00	12.45	-	-	-
78	77.09	100.00	11.68	382.28	100.00	18.83	89.88	100.00	16.69	-	-	-	99.43	100.00	30.17
79	-	-	-	264.06	100.00	27.27	37.38	100.00	40.13	58.80	100.00	20.41	70.08	100.00	21.40
80	69.57	100.00	12.94	820.02	88.89	7.80	116.39	100.00	12.89	107.86	100.00	11.13	66.73	83.33	19.01
81	55.05	100.00	16.35	-	-	-	75.77	100.00	19.80	283.16	100.00	4.24	265.08	83.33	4.79
82	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
83	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
84	48.45	100.00	18.58	545.09	100.00	13.21	77.70	83.33	16.33	-	-	-	106.03	100.00	19.81
85	156.51	75.00	4.52	-	-	-	127.66	100.00	11.75	81.76	100.00	14.68	148.69	100.00	8.07
86	-	-	-	323.27	100.00	22.27	67.44	100.00	22.24	43.57	100.00	27.54	29.66	100.00	50.58
87	81.76	100.00	11.01	-	-	-	109.18	100.00	13.74	55.76	100.00	21.52	84.20	100.00	17.82
88	212.47	75.00	3.33	-	-	-	155.70	100.00	9.63	435.20	100.00	2.76	534.32	70.00	2.96
89	161.79	100.00	5.56	-	-	-	322.66	100.00	4.65	232.58	100.00	5.16	179.26	100.00	8.37
90	62.97	100.00	14.29	-	-	-	93.64	62.50	11.21	-	-	-	212.47	100.00	7.06
91	40.83	100.00	22.04	348.46	100.00	19.80	47.02	100.00	31.90	61.14	100.00	19.63	113.55	100.00	23.78
92	92.42	100.00	9.74	376.39	100.00	19.13	48.14	100.00	31.16	99.23	100.00	12.09	80.54	100.00	14.90
93	158.84	100.00	5.67	-	-	-	67.54	100.00	22.21	127.46	80.00	7.74	111.72	80.00	8.83
94	71.50	100.00	12.59	-	-	-	73.53	100.00	20.40	93.03	100.00	12.90	-	-	-
95	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
96	226.38	100.00	3.98	-	-	-	106.13	83.33	11.95	-	-	-	-	-	-
97	167.07	100.00	5.39	-	-	-	-	-	-	-	-	-	-	-	-
98	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
99	45.40	100.00	19.82	-	-	-	62.66	100.00	23.94	-	-	-	80.03	100.00	22.49
100	65.51	100.00	13.74	-	-	-	27.42	100.00	54.70	50.78	100.00	23.63	63.07	100.00	28.54
101	46.11	100.00	19.52	-	-	-	54.54	100.00	27.50	80.13	100.00	14.98	69.67	100.00	17.22
103	99.63	100.00	9.03	-	-	-	34.43	100.00	43.57	-	-	-	88.56	100.00	13.55
104	-	-	-	-	-	-	-	-	-	-	-	-	322.66	100.00	3.72
105	423.92	100.00	2.12	-	-	-	-	-	-	-	-	-	-	-	-
106	-	-	-	-	-	-	-	-	-	-	-	-	371.31	100.00	9.70
107	105.63	100.00	8.52	-	-	-	-	-	-	-	-	-	-	-	-
108	-	-	-	-	-	-	-	-	-	-	-	-	107.96	100.00	16.67

Continued on next page...

Table A.2 – Continued

Subject	Word "BCI"			Word "BCI Long"			Word "SIREN"			Word "CHUG"			Free spelling		
	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]
Min	21.53	37.50	1.79	241.01	88.89	6.99	27.42	62.50	3.48	43.57	80.00	2.76	29.66	60.00	2.96
Max	463.63	100.00	41.80	1029.54	100.00	29.87	431.64	100.00	54.70	435.20	100.00	27.54	911.73	100.00	50.58
Mean	126.11	91.85	**10.96**	455.94	98.78	**18.20**	107.53	93.45	**19.73**	133.46	98.14	**12.82**	199.75	96.65	**14.66**
S.D.	99.28	15.57	7.70	205.93	2.94	6.65	79.00	11.92	12.60	97.47	5.88	6.65	173.83	8.47	9.67

B. RehaCare data set

This appendix contains detailed results of the experiments conducted at RehaCare 2008. Table B.1 presents a synopsis of the RehaCare study and Table A.2 displays the performance results assessed by 37 subjects. A hyphen symbol (-) indicates that the task was not completed.

Table B.1.: Study synopsis

Synopsis		
Study description	Study class	(non-controlled) Usability study
	Objective(s)	Reach a large audience of potential BCI users, specially disabled subjects
	Online/Offline	Online (evaluation of technology with live biosignals)
	Subject class	Human
Experimental variable(s)	Dependent variable(s)	Information transfer rate of BCI transducer [bpm] Correct selections of targets [%] Completion time of spelling task [s]
Assistive technology	Description	Virtual keyboard with 32 targets
	BI Technology design model	(2 component) Demonstration system - Transducer and Spelling Device
	Target population	Fully-paralyzed (locked in individuals) Partially-paralyzed individuals Individuals with other severe motor disabilities
	Target activity	Communication with people
	Target environment	Anywhere (indoors or outdoors)
Physical environment	Location	Field study: subjects sat in a chair facing a laptop monitor 50 cm away at an exposition fair.

Table B.2.: Detailed results of experiments conducted at RehaCare 2008.

Subject	Word "BCI"			Word "BRAIN"			Word "GEHIRN"			Free spelling 1			Free spelling 2		
	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]
1	39.03	100.00	32.12	115.69	85.71	20.98	69.69	100.00	29.99	71.21	100.00	27.39	122.20	90.32	25.41
2	25.01	100.00	50.13	47.55	100.00	35.16	55.16	100.00	37.88	41.05	100.00	37.34	135.00	92.86	33.75
3*	59.20	100.00	21.18	219.10	76.92	15.39	161.09	82.76	14.19	235.86	81.25	15.27	180.19	66.67	9.57
4	165.78	81.25	14.49	97.21	94.44	21.12	159.47	88.00	14.60	53.74	100.00	31.11	231.99	88.64	18.02
5	-	-	-	139.26	87.50	10.54	-	-	-	-	-	-	-	-	-
6	-	-	-	87.77	100.00	19.05	146.27	100.00	14.29	79.64	100.00	26.24	111.14	100.00	23.82
7	74.77	100.00	16.77	157.14	71.88	11.03	205.28	71.88	8.44	103.10	81.82	16.32	180.19	69.23	14.13
8	70.42	93.33	23.46	62.36	100.00	26.81	78.94	100.00	26.47	99.66	92.00	26.49	69.08	100.00	40.34
9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
10	57.51	93.33	28.72	245.01	79.03	17.64	85.64	100.00	24.40	116.42	86.67	11.51	104.02	91.30	22.84
11	74.25	88.24	21.49	80.77	94.44	25.42	168.32	88.89	20.49	100.69	92.31	27.53	93.57	88.46	26.26
12*	55.48	93.33	29.77	300.25	80.30	15.99	184.77	73.33	9.27	126.67	81.82	13.28	155.83	83.33	18.56
13	72.84	93.33	22.68	75.37	100.00	22.18	79.86	100.00	26.17	-	-	-	33.24	100.00	29.34
14	36.48	100.00	34.37	49.88	100.00	33.52	129.71	85.71	14.03	54.45	91.67	23.03	71.72	93.75	24.89
15*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
16	-	-	-	-	-	-	-	-	-	61.17	100.00	20.50	58.83	100.00	28.42
17	52.32	84.62	20.80	93.56	91.67	26.80	79.13	90.91	28.37	54.96	100.00	40.56	50.99	100.00	32.79
18	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
19	34.86	100.00	35.97	101.89	85.19	22.58	99.95	100.00	20.91	42.16	100.00	46.26	53.54	100.00	46.84
20	56.05	100.00	22.37	47.65	100.00	35.09	55.48	100.00	37.66	36.70	100.00	41.76	67.26	100.00	37.28
21	117.71	90.91	9.54	125.46	100.00	13.33	-	-	-	-	-	-	-	-	-
22*	173.11	83.33	8.35	272.74	91.18	12.83	113.28	94.12	16.94	319.16	89.36	14.32	827.49	78.35	7.98
23	32.42	100.00	38.68	63.39	94.44	32.39	61.56	100.00	33.95	48.68	100.00	42.93	104.63	100.00	34.62
24*	33.43	100.00	37.50	47.45	100.00	35.24	85.33	94.12	22.49	58.22	100.00	35.90	97.93	100.00	32.72
25*	58.21	100.00	21.54	225.80	87.50	6.50	279.42	88.00	8.34	62.17	100.00	24.65	114.92	100.00	16.97
26	38.71	100.00	32.39	53.64	92.86	28.31	51.01	100.00	40.97	49.78	100.00	41.98	121.81	97.37	39.19
27	112.45	84.62	9.68	96.01	92.86	15.82	135.62	94.12	14.15	225.50	86.36	17.26	56.50	100.00	22.19
28	64.11	93.33	25.77	52.22	100.00	32.01	83.00	100.00	25.18	88.07	100.00	31.64	91.75	95.65	29.74
29	56.59	100.00	22.16	138.35	92.86	10.98	146.78	100.00	14.24	69.90	100.00	25.91	165.46	96.00	18.13
30	-	-	-	-	-	-	-	-	-	48.16	100.00	23.14	68.77	100.00	18.23
31	29.27	100.00	42.84	53.77	82.35	24.60	53.65	100.00	38.96	43.20	100.00	48.37	45.83	100.00	48.64
32	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
33	273.63	93.33	6.04	201.32	86.36	9.67	238.59	95.24	10.30	136.00	88.24	11.73	210.76	100.00	15.20
34*	468.34	66.13	5.73	90.61	90.00	21.89	104.02	89.47	17.82	87.67	88.24	18.20	160.39	78.79	14.22

Continued on next page...

Table B.2 – Continued

Subject	Word "BCI"			Word "BRAIN"			Word "GEHIRN"			Free spelling 1			Free spelling 2		
	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]	Time [s]	Acc. [%]	ITR [bpm]
35	71.52	100.00	17.53	258.71	80.65	8.81	128.39	94.12	14.95	383.22	73.81	6.37	133.97	94.12	14.33
36	466.62	75.00	3.64	-	-	-	-	-	-	-	-	-	-	-	-
37*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Min	25.01	66.13	3.64	47.45	71.88	6.50	51.01	71.88	8.34	36.70	73.81	6.37	33.24	66.67	7.98
Max	468.34	100.00	50.13	300.25	100.00	35.24	279.42	100.00	40.97	383.22	100.00	48.37	827.49	100.00	48.64
Mean	102.50	93.36	**23.42**	124.14	90.97	**21.09**	119.98	93.73	**21.68**	103.47	94.06	**26.68**	135.14	93.27	**25.67**
S.D.	116.09	8.88	11.90	77.48	8.21	8.84	59.24	8.10	9.94	86.00	7.83	11.68	142.71	9.52	10.67

* Individuals with disabilities

References

[1] J. Wolpaw, N. Birbaumer, D. McFarland, G. Pfurtscheller, and T. Vaughan, "Brain-computer interfaces for communication and control," *Clin. Neurophysiol.*, vol. 113, pp. 767–791, 2002.

[2] B. Allison, E. Wolpaw, and J. Wolpaw, "Brain-computer interface systems: progress and prospects," *Expert Rev. Med. Devices*, vol. 4, no. 4, pp. 463–474, 2007.

[3] T. Vaughan *et al.*, "Brain-Computer Interface Technology: A Review of the Second International Meeting," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 11, no. 2, pp. 94–109, Jun. 2003.

[4] A. Kübler, F. Nijboer, J. Mellinger, T. Vaughan, H. Pawelzik, G. Schalk, D. McFarland, N. Birbaumer, and J. Wolpaw, "Patients with ALS can use sensorimotor rhythms to operate a brain-computer interface," *Neurology*, vol. 64, pp. 1775–1777, 2005.

[5] A. Kübler, V. Mushahwar, L. Hochberg, and J. Donoghue, "BCI Meeting 2005–Workshop on Clinical Issues and Applications," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 131–134, Jun 2006.

[6] J. Millán, P. Ferrez, F. Galán, E. Lew, and R. Chavarriaga, "Non-invasive Brain-Actuated Interaction," in *BVAI 2007, LNCS 4729*. Springer, 2007, pp. 438–447.

[7] C. Mandel, T. Lüth, T. Laue, T. Röfer, A. Gräser, and B. Krieg-Brückner, "Navigating a smart wheelchair with a brain-computer interface interpreting steady-state visual evoked potentials," in *Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Oct. 2009, pp. 1118–1125.

[8] G. R. Müller-Putz and G. Pfurtscheller, "Control of an Electrical Prosthesis With an SSVEP-Based BCI," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 1, pp. 361–364, Jan. 2008.

[9] G. Edlinger, C. Holzner, C. Guger, C. Groenegress, and M. Slater, "Brain-Computer Interfaces for Goal orientated Control of a Virtual Smart Home

Environment," in *Proc. 4th International IEEE/EMBS Conference on on Neural Engineering NER 09*, May 2009, pp. 463–465.

[10] D. Valbuena, M. Cyriacks, O. Friman, I. Volosyak, and A. Gräser, "Brain-Computer Interface for high-level control of rehabilitation robotic systems," in *Proc. IEEE ICORR'07*, Jun. 2007, pp. 619–625.

[11] T. Lüth, D. Ojdanic, O. Friman, O. Prenzel, and A. Gräser, "Low level control in a semi-autonomous rehabilitation robotic system via a Brain-Computer Interface," in *Proc. IEEE ICORR'07*, June 2007, pp. 721–728.

[12] B. Allison, B. Graimann, and A. Gräser, "Why Use a BCI If You Are Healthy?" in *Proc. ACE'07*, Jun. 2007, pp. 7–11.

[13] T. M. Vaughan, D. J. McFarland, G. Schalk, W. A. Sarnacki, D. J. Krusienski, E. W. Sellers, and J. R. Wolpaw, "The Wadsworth BCI Research and Development Program: at home with BCI," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 229–233, Jun 2006.

[14] B. Graimann, B. Allison, and A. Gräser, "New applications for non-invasive brain-computer interfaces and the need for engaging training environments," in *Proc. Int. Conf. Advances in Computer Entertainment Technology, ACM*, 2007, pp. 25–28.

[15] N. Birbaumer and L. G. Cohen, "Brain-computer interfaces: communication and restoration of movement in paralysis," *J. Physiol.*, vol. 579, no. 3, pp. 621–636, 2007.

[16] K. K. Ang, C. Guan, K. S. G. Chua, B. T. Ang, C. Kuah, C. Wang, K. S. Phua, Z. Y. Chin, and H. Zhang, "Clinical study of neurorehabilitation in stroke using EEG-based motor imagery brain-computer interface with robotic feedback," in *Proc. IEEE EMBC'10*, Sep. 2010, pp. 5549–5552.

[17] J. Pineda, D. Brang, E. Hecht, L. Edwards, S. Carey, M. Bacon, C. Futagaki, D. Suk, J. Tom, C. Birnbaum, and A. Rork, "Positive behavioral and electrophysiological changes following neurofeedback training in children with autism," *Research in Autism Spectrum Disorders*, vol. 2, pp. 557–581, 2008.

[18] G. Schalk, D. McFarland, T. Hinterberger, N. Birbaumer, and J. Wolpaw, "BCI2000: A General-Purpose Brain-Computer Interface (BCI) System," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1034–1043, Jun 2004.

[19] B. Allison, "The I of BCIs: Next Generation Interfaces for Brain-Computer Interface Systems That Adapt to Individual Users," in *Human-Computer*

Interaction. Novel Interaction Methods and Techniques, LNCS. Springer, 2009, pp. 558–568.

[20] O. Ivlev, C. Martens, and A. Gräser, "Rehabilitation robots FRIEND-I and FRIEND-II with the dexterous lightweight manipulator," *Technology and Disability*, vol. 17, pp. 111–123, 2005.

[21] A. Nijholt and D. Tan, "Brain-Computer Interfacing for Intelligent Systems," *IEEE Intell. Syst.*, vol. 23, no. 3, pp. 72–79, 2008.

[22] J. J. Vidal, "Toward Direct Brain-Computer Communication," *Annu. Rev. Biophys. Bioeng.*, vol. 2, pp. 157–180, 1973.

[23] ——, "Real-Time Detection of Brain Events in EEG," *Proc. IEEE*, vol. 65, no. 5, pp. 633–641, May. 1977.

[24] J. Wolpaw, N. Birbaumer, W. Heetderks, D. McFarland, P. Peckham, G. Schalk, E. Donchin, L. Quatrano, C. Robinson, and T. Vaughan, "Brain-Computer Interface Technology: A Review of the First International Meeting," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 2, pp. 164–173, Jun. 2000.

[25] D. J. McFarland, D. J. Krusienski, and J. R. Wolpaw, "Brain–computer interface signal processing at the Wadsworth Center: mu and sensorimotor beta rhythms," *Prog. Brain Res.*, vol. 159, pp. 411–419, 2006.

[26] J. N. Mak and J. R. Wolpaw, "Clinical applications of brain–computer interfaces: Current state and future prospects," *IEEE Rev. Biomed. Eng.*, vol. 2, pp. 187–199, 2009.

[27] G. Schalk, "Sensor modalities for brain-computer interfacing," in *Human-Computer Interaction, Part II, HCII 2009, LNCS 5611*, 2009, pp. 616–622.

[28] J. R. Wolpaw, G. E. Loeb, B. Z. Allison, E. Donchin, O. F. do Nascimiento, W. J. Heetderks, F. Nijboer, W. G. Shain, and J. N. Turner, "BCI Meeting 2005–Workshop on Signals and Recording Methods," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 138–141, Jun 2006.

[29] E. Niedermeyer, "The normal EEG of the waking adult," in *Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*, E. NiederMeyer and F. Lopes da Silva, Eds. Lippincott Williams and Wilkins, 1999, ch. 9, pp. 149–173.

[30] S. G. Mason, A. Bashashati, M. Fatourechi, K. F. Navarro, and G. E. Birch, "A Comprehensive Survey of Brain Interface Technology Designs," *Ann. Biomed. Eng.*, vol. 35, no. 2, pp. 137–169, Feb. 2007.

[31] P. L. Nunez and R. Srinivasan, *Electric Fields of the Brain: The Neurophysics of EEG.* Oxford University Press, Inc., 2006, ch. 7, pp. 275–312.

[32] G. Dornhege, M. Krauledat, K.-R. Müller, and B. Blankertz, "General Signal Processing and Machine Learning Tools for BCI Analysis," in *Toward Brain-Computer Interfacing*, G. Dornhege, J. del R. Millán, T. Hinterberger, D. McFarland, and K.-R. Müller, Eds. Cambridge, Massachusetts: The MIT Press, 2007, ch. 13, pp. 207–234.

[33] B. Hjorth, "An online transformation of EEG scalp potentials into orthogonal source derivations," *Electroencephalogr. Clin. Neurophysiol.*, vol. 39, pp. 526–530, 1975.

[34] M. Krauledat, M. Tangermann, B. Blankertz, and K.-R. Müller, "Towards Zero Training for Brain-Computer Interfacing," *PLoS one*, vol. 3, no. 8, p. e2967, 2008.

[35] F. Lotte, M. Congedo, A. Lecuyer, F. Lamarche, and B. Arnaldi, "A review of classification algorithms for EEG-based brain-computer interfaces," *J. Neural Eng.*, vol. 4, no. 2, pp. R1–R13, Jun 2007.

[36] G. Pfurtscheller and C. Neuper, "Future prospects of ERD/ERS in the context of brain-computer interface (BCI) developments," in *Event-Related Dynamics of Brain Oscillations*, ser. Progress in Brain Research, C. Neuper and W. Klimesch, Eds. Elsevier, 2006, vol. 159, ch. 28, pp. 433–437.

[37] L. A. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalogr. Clin. Neurophysiol.*, vol. 70, no. 6, pp. 510–523, Dec 1988.

[38] N. Birbaumer, N. Ghanayim, T. Hinterberger, I. Iversen, B. Kotchoubey, A. Kübler, J. Perelmouter, E. Taub, and H. Flor, "A spelling device for the paralysed," *Nature*, vol. 398, no. 6725, pp. 297–298, Mar 1999.

[39] A. Kübler, B. Kotchoubey, T. Hinterberger, N. Ghanayim, J. Perelmouter, M. Schauer, C. Fritsch, E. Taub, and N. Birbaumer, "The thought translation device: a neurophysiological approach to communication in total motor paralysis," *Exp. Brain Res.*, vol. 124, no. 2, pp. 223–232, Jan 1999.

[40] N. Birbaumer *et al.*, "The Thought Translation Device (TTD) for Completely Paralyzed Patients," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 2, pp. 190–193, Jun. 2000.

[41] G. Pfurtscheller, G. Müller-Putz, A. Schlögl, B. Graimann, R. Scherer, R. Leeb, C. Brunner, C. Keinrath, F. Lee, G. Townsend, C. Vidaurre, and C. Neuper, "15 years of BCI research at Graz University of Technology: Current Projects," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 205–210, Jun 2006.

[42] C. Neuper, G. R. Müller, A. Kübler, N. Birbaumer, and G. Pfurtscheller, "Clinical application of an EEG-based brain-computer interface: a case study in a patient with severe motor impairment," *Clin. Neurophysiol.*, vol. 114, pp. 399–409, 2003.

[43] B. Blankertz, M. Krauledat, G. Dornhege, J. Williamson, R. Murray-Smith, and K.-R. Müller, "A Note on Brain Actuated Spelling with the Berlin Brain-Computer Interface," in *Universal Access in HCI, Part II*, C. Stephanidis, Ed. Springer-Verlag Berlin Heidelberg, 2007, pp. 706–713.

[44] R. Krepki, G. Curio, B. Blankertz, and K.-R. Müller, "Berlin Brain-Computer Interface-The HCI communication channel for discovery," *Int. J. Human-Computer Studies*, vol. 65, no. 5, pp. 460–477, 2007.

[45] K.-R. Müller, M. Tangermann, G. Dornhege, M. Krauledat, G. Curio, and B. Blankertz, "Machine learning for real-time single-trial EEG-analysis: from brain-computer interfacing to mental state monitoring," *J. Neurosci. Methods*, vol. 167, no. 1, pp. 82–90, Jan 2008.

[46] J. Millán, F. Renkens, J. M. no, and W. Gerstner, "Brain-actuated interaction," *Artificial Intelligence*, vol. 159, pp. 241–259, 2004.

[47] R. Scherer, G. R. Müller, C. Neuper, B. Graimann, and G. Pfurtscheller, "An Asynchronously Controlled EEG-Based Virtual Keyboard: Improvement of the Spelling Rate," *IEEE Trans. Biomed. Eng.*, vol. 51, pp. 979–984, 2004.

[48] A. Schlögl, J. Kronegg, J. Huggings, and S. Mason, "Evaluation Criteria for BCI Research," in *Toward Brain-Computer Interfacing*, G. Dornhege, J. del R. Millán, T. Hinterberger, D. McFarland, and K.-R. Müller, Eds. Cambridge, Massachusetts: The MIT Press, 2007, ch. 19, pp. 327–342.

[49] J. R. Wolpaw, H. Ramoser, D. J. McFarland, and G. Pfurtscheller, "EEG-based communication: improved accuracy by response verification," *IEEE Trans. Rehabil. Eng.*, vol. 6, no. 3, pp. 326–333, Sep. 1998.

[50] C. E. Shannon, "A mathematical theory of communication," *Bell System Technical Journal*, vol. 27, pp. 379–423, 1948.

[51] B. Graimann, B. Allison, and G. Pfurtscheller, "Brain–computer interfaces: A gentle introduction," in *Brain–Computer Interfaces*, ser. The Frontiers Collection, B. Graimann, B. Allison, and G. Pfurtscheller, Eds. Springer-Verlag Berlin Heidelberg, 2010, ch. 1, pp. 1–27.

[52] E. Donchin, K. Spencer, and R. Wijesinghe, "The mental prosthesis: Assessing the speed of a P300-based brain–computer interface," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 2, pp. 174–179, Jun. 2000.

[53] G. Pfurtscheller and F. Lopes da Silva, "Event-related EEG/MEG synchronization and desynchronization: Basic principles," *Clin. Neurophysiol.*, vol. 110, pp. 1842–1857, 1999.

[54] E. A. Curran and M. J. Stokes, "Learning to control brain activity: A review of the production and control of EEG components for driving brain-computer interface (BCI) systems," *Brain and Cognition*, vol. 51, pp. 326–336, 2003.

[55] X. Gao, X. Xu, M. Cheng, and S. Gao, "A BCI-based environmental controller for the motion-disabled," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 11, no. 2, pp. 137–140, Jun. 2003.

[56] G. Burkitt, R. Silberstein, P. Cadusch, and A. Wood, "Steady-state visual evoked potentials and travelling waves," *Clin. Neurophysiol.*, vol. 111, pp. 246–258, 2000.

[57] D. Regan, *Human Brain Electrophysiology: Evoked Potentials and Evoked Magnetic Fields in Science and Medicine.* New York: Elsevier, 1989.

[58] G. Müller-Putz, R. Scherer, C. Brauneis, and G. Pfurtscheller, "Steady-state visual evoked potential (SSVEP)-based communication: impact of harmonic frequency components," *J. Neural Eng.*, vol. 2, pp. 123–130, 2005.

[59] C. S. Herrmann, "Human EEG responses to 1-100 Hz flicker: resonance phenomena in visual cortex and their potential correlation to cognitive phenomena," *Exp. Brain Res.*, vol. 137, no. 3–4, pp. 346–353, Apr 2001.

[60] M. A. Pastor, J. Artieda, J. Arbizu, M. Valencia, and J. C. Masdeu, "Human cerebral activation during steady-state visual-evoked responses," *J. Neurosci.*, vol. 23, no. 37, pp. 11 621–11 627, Dec. 2003.

[61] M. Middendorf, G. McMillan, G. Calhoun, and K. Jones, "Brain–Computer Interfaces Based on the Steady-State Visual-Evoked Response," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 2, pp. 211–214, Jun 2000.

[62] M. Cheng, X. Gao, S. Gao, and D. Xu, "Design and implementation of a brain-computer interface with high transfer rates," *IEEE Trans. Biomed. Eng.*, vol. 49, no. 10, pp. 1181–1186, Oct. 2002.

[63] E. C. Lalor, S. P. Kelly, C. Finucane, R. Burke, R. Smith, R. B. Reilly, and G. McDarby, "Steady-state VEP-based brain-computer interface control in an immersive 3D gaming environment," *EURASIP J. Appl. Signal Process.*, vol. 19, pp. 3156–3164, 2005.

[64] S. P. Kelly, E. C. Lalor, C. Finucane, G. McDarby, and R. B. Reilly, "Visual spatial attention control in an independent brain-computer interface," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 9, pp. 1588–1596, Sep 2005.

[65] L. J. Trejo, R. Rosipal, and B. Matthews, "Brain-Computer Interfaces for 1-D and 2-D cursor control: Designs using volitional control of the EEG spectrum or steady-state visual evoked potentials," *IEEE Trans. Neural Syst. Rehab. Eng.*, vol. 14, no. 2, pp. 225–229, June 2006.

[66] K. D. Nielsen, A. F. Cabrera, and O. F. do Nascimento, "EEG based BCI-towards a better control. Brain-computer interface research at aalborg university," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 202–204, June 2006.

[67] Y. Wang, R. Wang, X. Gao, B. Hong, and S. Gao, "A Practical VEP-Based Brain–Computer Interface," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 234–239, Jun 2006.

[68] P. Martinez, H. Bakardjian, and A. Cichocki, "Fully Online Multicommand Brain-Computer Interface with Visual Neurofeedback Using SSVEP paradigm." *Computational Intelligence and Neuroscience*, vol. 2007, pp. 94 561–94 570, 2007.

[69] G. Bin, X. Gao, Z. Yan, B. Hong, and S. Gao, "An online multi-channel SSVEP-based brain-computer interface using a canonical correlation analysis method," *J. Neural Eng.*, vol. 6, no. 4, p. 046002, Jun. 2009.

[70] S. Parini, L. Maggi, A. C. Turconi, and G. Andreoni, "A robust and self-paced BCI system based on a four class SSVEP paradigm: Algorithms and protocols for a high-transfer-rate direct brain communication," *Computational Intelligence and Neuroscience*, vol. 2009, pp. 1–11, 2009.

[71] J. R. Wolpaw, "Brain-Computer Interface," *Encyclopedia of Neuroscience*, vol. 1, pp. 429–437, 2009.

[72] G. Bin, X. Gao, Y. Wang, B. Hong, and S. Gao, "VEP-based brain-computer interfaces: time, frequency, and code modulations," *IEEE Comput. Intelli. Mag.*, vol. 4, no. 4, pp. 22–26, Nov. 2009.

[73] F. Lopes da Silva, S. Goncalves, and J. D. Munck, "Electroencephalography (EEG)," *Encyclopedia of Neuroscience*, vol. 1, pp. 849–855, 2009.

[74] G. Pfurtscheller and C. Neuper, "Motor Imagery and Direct Brain-Computer Communication," *Proc. IEEE*, vol. 89, no. 7, pp. 1123–1134, Jul. 2001.

[75] M. Jeannerod and V. Frak, "Mental imaging of motor activity in humans," *Curr. Opin. Neurol.*, vol. 6, pp. 735–739, 1999.

[76] C. Neuper, R. Scherer, M. Reiner, and G. Pfurtscheller, "Imagery of motor actions: Differential effects of kinesthetic and visual–motor mode of imagery in single-trial EEG," *Cogn. Brain Res.*, vol. 25, pp. 668–677, 2005.

[77] E. Friedrich, D. J. McFarland, C. Neuper, T. M. Vaughan, P. Brunner, and J. R. Wolpaw, "A scanning protocol for a sensorimotor rhythm-based brain-computer interface," *Biol. Psychol.*, vol. 80, pp. 169–175, 2009.

[78] B. Graimann, J. Huggins, S. Levine, and G. Pfurtscheller, "Visualization of significant ERD/ERS patterns in multichannel EEG and ECoG data," *Clin. Neurophysiol.*, vol. 113, pp. 43–47, 2002.

[79] G. H. Klem, H. O. Lüders, H. H. Jasper, and C. Elger, "The ten-twenty electrode system of the international federation," *Electroencephalogr. Clin. Neurophysiol. Suppl.*, vol. 52, pp. 3–6, 1999.

[80] G. Pfurtscheller, C. Brunner, A. Schlögl, and F. L. da Silva, "Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks," *NeuroImage*, vol. 31, pp. 153–159, 2006.

[81] H. Ramoser, J. Müller-Gerking, and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Trans. Rehabil. Eng*, vol. 8, no. 4, pp. 441–446, Dec 2000.

[82] D. J. McFarland, L. M. McCane, S. V. David, and J. R. Wolpaw, "Spatial filter selection for EEG-based communication," *Electroencephalogr. Clin. Neurophysiol.*, vol. 103, pp. 386–394, 1997.

[83] L. Marple, "A new autoregressive spectrum analysis algorithm," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. 28, no. 4, pp. 441–454, August 1980.

[84] J. Żygierewicz, P. J. Durka, H. Klekowicz, N. Crone, and P. Franaszczuk, "Computationally efficient approaches to calculating significant ERD/ERS changes in the time-frequency plane," *J. Neurosci. Methods*, vol. 145, no. 1–2, pp. 267–276, 2005.

[85] R. Kuś, J. Żygierewicz, J. Ehlers, and T. Lüth, "WP3 second prototypes with emphasis on improving flexibility, reliability, performance, and ease of use with ERD BCI systems," University of Bremen and University of Warsaw, Tech. Rep., 2010.

[86] P. J. Franaszczuk, P. Mitraszewski, and K. Blinowska, "FAD-parametric description of EEG time series," *Acta Physiol Pol.*, vol. 40, no. 4, pp. 418–422, 1989.

[87] D. J. McFarland and J. R. Wolpaw, "Sensorimotor rhythm-based brain-computer interface (BCI): model order selection for autoregressive spectral analysis," *J. Neural Eng.*, vol. 5, no. 2, pp. 155–162, 2008.

[88] T. Malechka, D. Valbuena, R. Kus, J. Zygierewicz, I. Volosyak, and A. Gräser, "ERD/ERS BCI training on the basis of a labyrinth application," *International Journal of Bioelectromagnetism*, vol. 13, 2011, accepted for publication.

[89] C. Neuper, G. Müller-Putz, R. Scherer, and G. Pfurtscheller, "Motor imagery and EEG-based control of spelling devices and neuroprostheses," *Prog. Brain Res.*, vol. 159, pp. 393–409, 2006.

[90] D. Valbuena and A. Gräser, "Mental Strategies to Operate a Motor-imagery-based Brain-computer Interface," in *Methods and Applications in Automation.* Aachen: Shaker Verlag, 2008, pp. 66–74.

[91] R. Krepki, B. Blankertz, G. Curio, and K. robert Müller, "The Berlin Brain-Computer Interface (BBCI) towards a new communication channel for online control in gaming applications," *Multimed. Tools Appl.*, vol. 33, pp. 73–90, February 2007.

[92] R. Leeb, D. Friedman, G. R. Müller-Putz, R. Scherer, M. Slater, and G. Pfurtscheller, "Self-Paced (Asynchronous) BCI Control of a Wheelchair in Virtual Environments: A Case Study with a Tetraplegic," *Computational Intelligence and Neuroscience*, vol. 1, p. 79642, 2007.

[93] J. Wolpaw, "Brain-computer interfaces as new brain output pathways," *J. Physiol.*, vol. 579, no. 3, pp. 613–619, 2007.

[94] B. Graimann, B. Allison, C. Mandel, T. Lüth, D. Valbuena, and A. Gräser, "Non-invasive brain-computer interfaces for semi-autonomous assistive devices," in *Robust Intelligent Systems*, A. Schuster, Ed. London: Springer, 2008, ch. 6, pp. 113–138.

[95] C. Martens, O. Prenzel, and A. Gräser, "The Rehabilitation Robots FRIEND-I & II: Daily Life Independency through Semi-Autonomous Task-Execution," in *Rehabilitation Robotics.* I-Tech Education Publishing, 2007.

[96] O. Prenzel, C. Martens, M. Cyriacks, C. Wang, and A. Gräser, "System Controlled User Interaction within the Service Robotic Control Architecture MASSiVE," *Robotica*, vol. 25, no. 2, pp. 237–244, 2007.

[97] C. Martens, O. Prenzel, J. Feuser, and A. Gräser, "MASSiVE: Multi-layer architecture for semi-autonomous service-robots with verified task execution," in *Proc. 10th Int. Conf. OPTIM'06*, vol. 3, 2006, pp. 107–112.

[98] O. Prenzel, "Semi-autonomous object anchoring for service-robots," in *Methods and Applications in Automation*, B. Lohmann and A. Gräser, Eds. Shaker Verlag, 2005, pp. 57–68.

[99] E. Gamma, R. Helm, R. Johnson, and J. Vlissides, *Design Patterns: Elements of Reusable Object-Oriented Software*, 1st ed. Addison-Wesley, 1995.

[100] O. Friman, I. Volosyak, and A. Gräser, "Multiple channel detection of steady-state visual evoked potentials for brain-computer interfaces," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 4, pp. 742–750, Apr. 2007.

[101] D. Valbuena, I. Sugiarto, and A. Gräser, "Spelling with the Bremen Brain-computer Interface and the Integrated SSVEP Stimulator," in *Proc. 4th Int. Brain-Computer Interface Workshop and Training Course*, Graz, Austria, Sep. 18–21 2008, pp. 291–296.

[102] B. Allison, T. Lüth, D. Valbuena, A. Teymourian, I. Volosyak, and A. Gräser, "BCI Demographics: How many (and what kinds of) people can use an SSVEP BCI?" *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 2, pp. 107–116, Apr. 2010.

[103] I. Volosyak, H. Cecotti, D. Valbuena, and A. Gräser, "Evaluation of the Bremen SSVEP based BCI in real world conditions," in *Proc. IEEE ICORR'09*, Jun. 2009, pp. 322–331.

[104] D. Zhu, J. Bieger, G. G. Molina, and R. M. Aarts, "A survey of stimulation methods used in SSVEP-based BCIs," *Computational Intelligence and Neuroscience*, vol. 1, p. 702357, 2010.

[105] L. Piccini, S. Parini, L. Maggi, and G. Andreoni, “A Wearable Home BCI system: preliminary results with SSVEP protocol,” in *Proc. IEEE EMBS’05*, vol. 2005, Jan. 2005, pp. 5384–5387.

[106] G. Calhoun and G. McMillan, “EEG-based control for human-computer interaction,” in *Proc. Annu. Symp. Human Interaction With Complex Systems*, 1996, pp. 4–9.

[107] M. Huang, P. Wu, Y. Liu, L. Bi, and H. Chen, “Application and Contrast in Brain-Computer Interface between Hilbert-Huang Transform and Wavelet Transform,” in *Proc. 9th International Conference for Young Computer Scientists ICYCS 2008*, 18–21 Nov. 2008, pp. 1706–1710.

[108] D. Regan, “An effect of stimulus color on average steady-state potentials evoked in man,” *Nature*, vol. 210, pp. 1056–1057, Jun. 1966.

[109] K. Arakawa, S. Tobimatsu, H. Tomoda, J. Kira, and M. Kato, “The effect of spatial frequency on chromatic and achromatic steady-state visual evoked potentials,” *Clin. Neurophysiol.*, vol. 110, pp. 1959–1964, 1999.

[110] F.-B. Vialatte, M. Maurice, J. Dauwels, and A. Cichocki, “Steady-state visually evoked potentials: Focus on essential paradigms and future perspectives,” *Prog. Neurobiol.*, vol. 90, pp. 418–438, Feb. 2010.

[111] J. Blanchette and M. Summerfield, *C++ GUI Programming with Qt 4*, 2nd ed. Prentice Hall, 2006.

[112] B. Stroustrup, *The C++ Programming Language. Second Edition.* Addision-Wesley Publishing Company, 1998.

[113] Object Management Group, “OMG Unified Modeling Language (OMG UML), Superstructure,” Jan. 2011, version 2.4. [Online]. Available: http://www.omg.org/spec/UML/2.4/Superstructure/Beta2/PDF/

[114] J. Liu, *Real-Time Systems.* Prentice Hall, 2000.

[115] S. D. Huston, J. C. Johnson, and U. Syyid, *The ACE Programmer’s Guide.* Addision-Wesley Publishing Company, 2002.

[116] J. Feuser, O. Ivlev, and A. Graser, “Collision prevention for rehabilitation robots with mapped virtual reality,” in *Proc. of the 9th Int. Conf. Rehabilitation Robotics IEEE ICORR*, 2005, pp. 461–464.

[117] O. Friman, T. Lüth, I. Volosyak, and A. Gräser, “Spelling with Steady-State Visual Evoked Potentials,” in *Proc. 3rd Int. IEEE/EMBS Conf. Neural Eng.*, May. 2007, pp. 354–357.

[118] D. J. McFarland, W. A. Sarnacki, and J. R. Wolpaw, “Brain-computer interface (BCI) operation: optimizing information transfer rates,” *Biol. Psychol.*, vol. 63, pp. 237–251, 2003.

[119] B. Allison, D. McFarland, G. Schalk, S. Zheng, M. Moore, and J. Wolpaw, “Towards an independent brain–computer interface using steady state visual evoked potentials,” *Clin. Neurophysiol.*, vol. 119, pp. 399–408, 2008.

[120] F. Nijboer, A. Furdea, I. Gunst, J. Mellinger, D. J. McFarland, N. Birbaumer, and A. Kübler, “An auditory brain-computer interface (BCI),” *J. Neurosci. Methods*, vol. 167, no. 1, pp. 43–50, Jan 2008.

[121] C. Guger, G. Edlinger, W. Harkam, I. Niedermayer, and G. Pfurtscheller, “How Many People are Able to Operate an EEG-Based Brain-Computer Interface (BCI)?” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 11, no. 2, pp. 145–147, Jun 2003.

[122] C. Guger, S. Daban, E. Sellers, C. Holzner, G. Krausz, R. Carabalona, F. Gramatica, and G. Edlinger, “How many people are able to control a P300-based brain-computer interface (BCI)?” *Neurosci. Lett.*, vol. 462, no. 1, pp. 94–98, Jun 2009.

[123] P. D. Skosnik, G. P. Krishnan, J. L. Vohs, and B. F. ODonnell, “The effect of cannabis use and gender on the visual steady state evoked potential,” *Clin. Neurophysiol.*, vol. 117, pp. 144–156, 2006.

[124] C. Kaufmann, G. K. Elbel, C. Gössl, B. Pütz, and D. P. Auer, “Frequency dependence and gender effects in visual cortical regions involved in temporal frequency dependent pattern processing,” *Hum Brain Mapp.*, vol. 14, no. 1, pp. 28–38, 2001.

[125] B. Allison and J. Pineda, “Effects of SOA and flash pattern manipulations on ERPs, performance, and preference: Implications for a BCI system,” *Int. J. Psychophysiol.*, vol. 59, pp. 127–140, 2006.

[126] H. Jasper, “The ten-twenty electrode system of the international federation,” *Electroencephalogr. Clin. Neurophysiol.*, vol. 10, pp. 371–375, 1958.

[127] M. M. Moore Jackson, S. G. Mason, and G. E. Birch, “Analyzing Trends in Brain Interface Technology: A Method to Compare Studies,” *Ann. Biomed. Eng.*, vol. 34, no. 5, pp. 859–878, May 2006.

[128] M. M. Moore, “Real-world applications for brain-computer interface technology,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 11, no. 2, pp. 162–165, Jun 2003.

[129] I. Volosyak, H. Cecotti, and A. Gräser, "Impact of Frequency Selection on LCD Screens for SSVEP Based Brain-Computer Interfaces," in *IWANN 2009, Part I, LNCS 5517*. Springer, 2009, pp. 706–713.

[130] C. Neuper, R. Scherer, S. Wriessnegger, and G. Pfurtscheller, "Motor imagery and action observation: Modulation of sensorimotor brain rhythms during mental control of a brain-computer interface," *Clin. Neurophysiol.*, vol. 120, pp. 239–247, 2009.

[131] D. McFarland, L. McCane, and J. Wolpaw, "EEG-based communication and control: Short-term role of feedback," *IEEE Trans. Rehabil. Eng.*, vol. 6, no. 1, pp. 7–11, Mar. 1998.

[132] J. Pineda, D. Silverman, A. Vankov, and J. Hestenes, "Learning to Control Brain Rhythms: Making a Brain-Computer Interface Possible," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 11, no. 2, pp. 181–184, Jun 2003.

[133] A. Kübler, B. Kotchoubey, J. Wolpaw, and N. Birbaumer, "Brain-Computer Communication: Unlocking the Locked In," *Psychological Bulletin*, vol. 127, no. 3, pp. 358–375, 2001.

[134] I. Volosyak, H. Cecotti, and A. Gräser, "Steady-state visual evoked potential response - impact of the time segment length," in *Proc. on the 7th international Conference on Biomedical Engineering BioMed2010, Innsbruck, Austria, February 17 –19*, 2010, pp. 288–292.

[135] I. Volosyak, D. Valbuena, T. Lüth, and A. Gräser, "Towards an SSVEP based BCI with high ITR," Institute of Automation, Bremen, Tech. Rep., 2010. [Online]. Available: http://nbn-resolving.de/urn:nbn:de:gbv:46-00102056-17

[136] G. Schalk, "Brain-computer symbiosis," *J. Neural Eng.*, vol. 5, pp. 1–15, 2008.

[137] D. Valbuena, I. Volosyak, and A. Gräser, "sBCI: Fast Detection of Steady-State Visual Evoked Potentials," in *Proc. IEEE EMBC'10*, Sep. 2010, pp. 3966–3969.

[138] G. Pfurtscheller, T. Solis-Escalante, R. Ortner, and P. Linortner, "Self-paced operation of an SSVEP-based orthosis with and without an imagery-based "brain switch": A feasibility study towards a hybrid BCI," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, pp. 409–414, Feb. 2010.

[139] G. Pfurtscheller, B. Z. Allison, C. Brunner, G. Bauernfeind, T. Solis-Escalante, R. Scherer, T. O. Zander, G. Mueller-Putz, C. Neuper, and N. Birbaumer, "The hybrid BCI," *Frontiers in Neuroscience*, vol. 2, pp. 1–11, 2010.

[140] D. Valbuena, T. Malechka, I. Volosyak, and A. Gräser, "A novel EEG acquisition system for brain computer interfaces," *International Journal of Bioelectromagnetism*, vol. 13, 2011, accepted for publication.

[141] I. Volosyak, D. Valbuena, T. Malechka, J. Peuscher, and A. Gräser, "Brain-Computer Interface using Water-based Electrodes," *J. Neural Eng.*, vol. 7, p. 066007, 2010.

Index