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ELECTROMAGNETIC SIGNALS IN NONINVASIVE BRAIN-COMPUTER INTERFACES

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TEKNILLINEN KORKEAKOULU
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Abstract

A brain-computer interface (BCI) translates task-related brain activity into computer commands. Detecting this activity is difficult, as the measured brain signals are generated by multiple sources and also include task-irrelevant brain activity. Using conventional methods such as signal averaging is not possible, because subjects should receive online feedback of their performance. BCI users usually either learn to control some components of their brain activity with the help of feedback or are presented with some stimuli that produce detectable signals in the brain.

This thesis reviews BCI research, basic principles of electroencephalography (EEG) and magnetoencephalography (MEG), the sensorimotor cortex, and then describes experimental BCI studies. The thesis comprises of five publications studying 1) sensorimotor cortical activation for BCI, 2) use of MEG for BCIs, 3) single brain signal trials during (attempted) finger movements for online BCI classification and 4) vibrotactile feedback in comparison to visual feedback. Participants were 45 healthy, 9 tetraplegic, and 3 paraplegic subjects.

First our results of tetraplegic subjects show that their 10- and 20-Hz rhythmic activity is more widespread and less contralateral than that of healthy subjects, providing a poorer control signal for two-class movement classification. For separating brain signals during right and left attempted movement, we selected features from the low-frequency bands. Second, our results show that for classification, MEG is not superior to EEG for two-class BCI, despite being a more localised measurement technique. Third, brain signals during finger movements could be classified online with high accuracy after basically no training. However, results from the tetraplegic subjects are much worse than those of the healthy subjects. Fourth, we show that vibrotactile feedback can be used as an alternative feedback channel during training and is especially useful when visual attention is needed for application control.

On the basis of these and earlier findings, it is concluded that accurate control of noninvasive BCI is possible but requires some training. Future important research involves more work with motor-disabled patients, especially when testing new signal processing methods. Better performance may also be achieved using different feedback modalities.

Keywords	Brain-computer interface, brain signal analysis, tetraplegic, EEG, MEG, feedback
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Tiivistelmä

Aivokäyttöliittymä kääntää tehtäväkohtaisen aivotoiminnan tietokonekomennoiksi. Tämän aktivaation tunnistaminen on hankalaa, koska mitatut aivokäyrät ovat lähtöisin useista lähteistä ja niihin sisältyy myös tehtävän kannalta epäolennaista aivotoimintaa. Tavallisesti aivokäyttöliittymän käyttäjät joko oppivat hallitsemaan jotain aivotoimintansa osatekijää palautteen avulla tai heille esitetään ulkoisia ärsykkeitä jotka tuottavat havaittavan aivosignaalin.

Tämä väitöskirja sisältää kirjallisuuskatsauksen aivokäyttöliittymiin, elektroenkefalografian (EEG) ja magnetoenkefalografian (MEG) perusteisiin sekä sensorimotorisesta aivokuoreen. Väitöskirja koostuu viidestä julkaisusta, joissa tarkastellaan aivokäyttöliittymien yhteydessä: 1) sensorimotorisen aivokuoren toimintaa, 2) MEG signaalien käyttöä, 3) yksittäisten liikkeiden tuottaman aivosignaalin käyttöä komentona, ja 4) tuntoaistipalautetta näköaistipalautteen sijasta. Kokeisiin osallistuivat 45 tervettä sekä yhdeksän neliraajahalvaantunutta ja kolme kaksiraajahalvaantunutta henkilöä.

Ensimmäiseksi tuloksista näemme, että neliraajahalvaantuneiden aivosignaalit antavat terveisiin verrattuna huonompia tuloksia kahden luokan liikkeen luokittelulle, sillä heillä 10- and 20-Hz rytminen aivotoiminta on levinnyt laajemmalle ja se on myös vähemmän unilateraali. Erottaaksemme vasemman ja oikean yritetyn liikkeen tuottamat aivotoiminnan valitsimme piirteitä matalilta taajuuskaistoilta. Toiseksi, tuloksemme näyttävät, että kahden luokan luokittelussa MEG ei ole EEG:ta parempi, vaikka onkin paikallisesti tarkempi mittausmenetelmä. Kolmanneksi, pystymme luokittelemaan yksittäisten sormenliikkeiden aiheuttamaa aivotoimintaa hyvällä tarkkuudella reaaliaikaisesti. Neljänneksi, näytämme että tuntoaistipalautetta voi käyttää vaihtoehtona näköaistipalautteelle, etenkin kun tarkkaavaissuutta tarvitaan visuaalisen sovelluksen hallintaan.

Näiden tulosten ja aikaisempien löydösten perusteella päättelemme, että aivokäyttöliittymä voidaan ohjata tarkasti kajoamatta aivoihin mutta siihen tarvitaan harjoittelua. Tulevaisuudessa tutkimuksen tulisi keskittyä liikuntakyvyttömien henkilöiden testaamiseen, etenkin kehittäessä uusia signaalinkäsittelymenetelmiä. Parempaan suoritukseen voimme myös yltää käyttämällä eri palautemodaliteettejä.

Asiasanat Aivokäyttöliittymä, aivosignaalianalyysi, EEG, MEG, neliraajahalvaantunut, palaute

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List of abbreviations

ALS	amyotrophis lateral sclerosis
AR	autoregressive
BCI	brain-computer interface
BP	bereitschaftspotential
CAR	common average reference
CNV	contingent Negative Variation
CSP	common spatial patterns
EOG	electro-oculargram
ERD	event-related desynchronization
ERS	event-related synchronization
EEG	electroencephalography
EMG	electromyogram
ERF	event-related field
ERP	event-related potential
FFT	fast fourier transform
fMRI	functional magnetic resonance imaging
ISI	interstimulus interval
KS	kolmogorov-smirnov
MEG	magnetoencephalography
MRPs	movement-related potentials
NIRS	near-infrared spectroscopy
PCA	principal component analysis
PSD	power spectral densities
PSP	postsynaptic potential
SNR	signal-to-noise ratio
SCP	slow cortical potentials
SSVEP	steady-state visual evoked potentials
SCI	spinal-cord injury
SQUID	superconducting quantum interference device
TFR	time-frequency representation
VEPs	visual evoked potentials

Preface

This thesis is the result of my research carried out at the Laboratory of Computational Engineering at Helsinki University of Technology during the years 2003-2008. In the beginning of 2008 the Laboratory integrated with the Laboratory of Biomedical Engineering and the work was completed at the new Department of Biomedical Engineering and Computational Science. My work was funded by the Graduate school of Electronics, Telecommunications and Automation (GETA). Additional funding has come from both the Academy of Finland through our Centre of Excellences and the EU FP6 project MAIA. In addition to these, my research has been supported financially by the Finnish Cultural Foundation, the Jenny and Antti Wihuri Foundation, and the Technology Promoting Foundation. I am grateful to all of these parties who have made the completion of this thesis possible.

I wish to thank my instructor and supervisor Prof Mikko Sams for his encouragement and support during my studies but especially for teaching me everything I know about scientific writing. I've had the pleasure to work with you since 2001, and our long discussions on scientific work will be remembered. First of my other co-authors, I wish to thank Pasi Jylänki for the crucial part you played in my work, I'm grateful for all the hours you spent making me understand how the algorithms work. For an honest man from middle Finland, it must have been a challenge to share a room with a (at times pregnant) woman: thank you for being a great room-mate and giving me *empathy* when I most needed it. I am also grateful to my other co-authors: Janne Lehtonen for implementing our online BCI system; Tommi Nykopp for helping me in the beginning of my studies; Dr Pekka Rantanen for initiating our work on tetraplegics and particularly Prof Hannu Alaranta for making work at the Synapsia rehabilitation centre possible. I also wish to thank my co-authors from our EU project MAIA for the collaboration. In addition to these, many people from the Lab helped me with my work and I am especially thankful to Dr Toni Auranen, Iina Tarnanen, Jaakko Kauramäki, Tapio Palomäki, Dr Ville Ojanen, Dr Riikka Möttönen and Dr Vasilj Klucharev for their help. Outside the Lab, I am truly grateful to Prof Riitta Hari for making MEG measurements possible, Prof Steven Roberts for making my stay in Oxford fruitful and to Dr Theresa Vaughan for the promotion of my work. Finally, I wish to

thank Prof Christina Krause and Prof Veikko Surakka for acting as pre-examiners and giving me valuable comments.

Moving on from Thesis related work, first I wish to thank all present and former personal for making LCE such a great place to work. Especially I wish to thank Prof Jouko Lampinen and Prof Kimmo Kaski for making the atmosphere so relaxed. I also wish to thank Eeva Lampinen, Kaija Virolainen and Aino Järvenpää for taking care of the endless bureaucracy. The still present voice of the Lab Dr Aapo Nummenmaa deserves a special thank you, besides your help, you are an invaluable friend outside work. Most of my best friends are personal of Lab (does this say something about my personal life or the really great people I've had the opportunity to work with?). For the utmost great times we've spent within and outside the borders of our country, I especially, wish to thank Dr Toni Tamminen, Dr Ilkka Kalliomäki, Dr Sebastian von Alfthan, Anne-Mari Seppola, the above mentioned Pasi Jylänki and Dr Aapo Nummenmaa and not forgetting the others who at times joined us for, perhaps, even *a glass of wine*.

Beyond work, I am privileged to have such a wonderful group of close friends and family that have supported me - thank you all! I am especially grateful to my parents for the encouragement you've given during all my studies. Dad, your continuous interest in my work has kept me going. Furthermore I am indebted to my in laws for their help and support. Tuula, you are the best mother-in-law one could hope for. Finally, I thank my husband Antti for everything - this wouldn't have been possible without you - as well my son Mikael for being such a positive sunshine in my life; the two of you make me the happiest person on earth. And not to forget, thank you Baby Kauhanen for, as your older brother a year ago, "kicking me forward" when finishing this work!

Espoo, May 2008

Laura Kauhanen

List of publications and author's research contributions

This dissertation consists of an overview and the following publications:

I Kauhanen, L., Nykopp, T., and Sams, M. (2006) Classification of single MEG trials related to left and right index finger movements. *Clinical Neurophysiology*, 117(2):430-439.

II Kauhanen, L., Nykopp, T., Lehtonen, J., Jylänki, P., Heikkonen, J., Rantanen, P., Alaranta, H., and Sams, M. (2006). EEG and MEG Brain-Computer Interface for Tetraplegic Patients. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 14(2):190-193.

III Lehtonen, J., Jylänki, P., Kauhanen, L., and Sams, M. (2008). Online classification of single EEG trials during finger movements. *IEEE Transactions on Biomedical Engineering*, 55(2):713-20.

IV Kauhanen, L., Jylänki, P., Lehtonen, J., Rantanen, P., Alaranta, H., and Sams, M. (2007). EEG-based brain-computer interface for tetraplegics. *Computational Intelligence and Neuroscience*, Volume 2007, Article ID 23864, 11 pages doi:10.1155/2007/23864.

V Cincotti, F., Kauhanen, L., Aloise, F., Palomäki, T., Caporusso, N., Jylänki, P., Mattia, D., Babiloni, F., Vanacker, G., Nuttin, M., Grazia Marciani, M., and del R. Millán J., (2007). Vibrotactile Feedback for Brain-Computer Interface Operation. *Computational Intelligence and Neuroscience*, Volume 2007, Article ID 48937, 12 pages doi:10.1155/2007/48937.

I was the principal author in Publications I, II and IV, and had the main responsibility for experimental design, measurements and data analysis as well as writing and preparing the manuscripts. The methods used for feature extraction and classification are work of the second authors. In publications II and IV the

third author helped with the measurements. All co-authors contributed by revising text. In Publication III, I assisted the first author with the measurements and participated actively in all stages of the study.

Publication V is a result of team work in the EU project MAIA. The publication is a collection of three studies. I was the principal author for Studies I and II which were done in our laboratory. The fourth and sixth authors designed the models used for feature extraction and classification and helped with the measurements. Study III was done at the Fondazione Santa Lucia institute in Rome, Italy, and I have only contributed to discussions on experimental design and results. I contributed equally with the first author in writing of the manuscript. All co-authors contributed by revising the manuscript.

Contents

Chapter 1

Introduction

1.1 Overview

A brain-computer interface (BCI) translates task-related brain activity into computer commands. BCIs could be used by anybody for device control. However, as we presently can only separate a few different tasks, i.e. commands, those most benefiting from BCIs are severely motor disabled persons who are not able to move their hands, including persons with tetraplegia, Multiple sclerosis and Amyotrophic Lateral Sclerosis. Most of these subjects can move e.g. their heads and eyes enabling also other ways of communication than BCIs. The group benefiting most from BCIs would be totally locked in patients incapable of moving any voluntary muscles. Unfortunately this is a very difficult group to study as it is impossible to know what their intentions are. The few studies on this patient group are reviewed in this thesis. The work in this thesis starts by developing methods with healthy subjects and moves on to testing these methods with tetraplegic subjects, who can benefit from a well-working BCI as movement of their head and eyes is freed for other purposes.

A BCI can be regarded as a system that translates the measured brain activity into device commands, not only the interface between the brain and the computer. The task-related brain activity can be measured with various methods, electroencephalography (EEG) being the most common. Before BCI use, a model has to be trained to distinguish the task-related activity patterns. Usually, an initial calibration session is required, during which subjects perform examples of different control tasks and the model is trained with samples measured during these tasks. Subsequently, during BCI use, the model categorises the brain activity measured during different tasks performed by the subjects, and a command is executed. The subjects receive feedback of their performance, which helps them try to improve. Signal processing methods and models are usually evaluated offline before online use, i.e. the models are trained and tested with previously gathered data.

During BCI use, subjects perform some control tasks that are either exogenous or endogenous. In the endogenous approach, control is independent of any muscle activity or external stimuli, and subjects usually imagine some simple action such as hand movement. Gradually subjects can learn to control their brain activity and BCI without any explicit commands. In the exogenous approach, external stimuli such as flickering rows of letters are presented to subjects who choose commands by directing their attention and usually gaze at the stimulus of interest.

Determining task-relevant activity is difficult, as the measured brain signals are generated by multiple sources and also include task-irrelevant brain activity. An increase of the signal-to-noise ratio (SNR) using such conventional methods as signal averaging is not possible, as subjects should receive online feedback of their performance within tens of milliseconds.

The first study on brain control of a computer was published by Vidal in 1973 (Vidal, 1973). It was not until the increase of computational speed in the mid-nineties that allowed growth of research in this area. During the last couple of years, hundreds of articles on BCIs have been published, and in 2005, scientists from more than fifty laboratories attended the international BCI meeting in Albany, USA, (Vaughan et al., 2006).

BCI research is multidisciplinary. Medical doctors are needed for research with patients, neuroscientist and psychologists for understanding brain function, and engineers and mathematicians for development of signal processing methods and software. Different research groups have specialised in different aspects of BCIs. Some concentrate on developing BCIs based on different brain imaging methods, others on developing better signal processing methods. Research groups use various electrophysiological signals for control, which differ, e.g., in the time needed to learn BCI use. Many different applications and feedback systems are under development. Some groups test their methods with motor-disabled patients, others with healthy subjects. There is also some research being conducted in home environments.

In 2002, when the research described in the present thesis was started, we hypothesised that if we can carefully characterise the signals we want to classify, classification accuracies will improve. Our approach has been more neuroscientific than mathematical. We started by characterising brain signals during real finger movements of healthy subjects (Publication I). We chose using single finger movements due to their good spatial separability into left and right movements as well as their large neural representation on the contralateral sensorimotor cortices. Instead of EEG, we employed magnetoencephalography (MEG), which, as explained in Section 1.2.5, has higher spatial resolution. For our first aim, we aimed at characterising movement-related signals for future use in motor-disabled patients. In the following publication (II), we studied tetraplegic patients and measured EEG and MEG simultaneously. Again, our aim was to characterise the signals before classification, especially as the rhythmic activation of the sensori-

motor cortex of patients with spinal-cord injury had not been investigated previously. In Publications I and II, we also addressed our second aim of comparing the accuracy of EEG and MEG classifications.

To reach our third aim of testing single (attempted) movements for BCI use, we proceeded to online measurements. We constructed our own Matlab-compatible EEG-BCI system (Lehtonen et al., 2004). We developed online classification methods that we first tested by classifying single brain trials related to finger movements in Publication III. Our hypothesis was that subjects could gain control of the BCI more quickly when performing single movements than when training to control their rhythmical brain activity. The latter is the most common method in BCIs (for a review see Wolpaw et al., 2002). Brain signal control is usually obtained after several weeks of training during which subjects perform continuous movements for 5-10 s. However, fast initial learning is an important factor that might increase motivation and willingness to use BCIs. The experiment in Publication III was designed so that it would also work with motor-disabled patients. In Publication IV we studied six tetraplegic subjects. Again, we aimed for good performance with a short training time.

Deviating from Publications I-III in Publication IV instead of finger movements, the tetraplegic subjects attempted to perform the hand movement they felt easiest to do. For tetraplegics, it is difficult to try perform special instructed movements. Based on experience from Publication II, we allowed the subjects themselves choose the movements they wanted to perform, giving them examples such as finger and hand movements.

Feedback plays an important role when learning to use a BCI. Feedback is usually visual. However, vision, visual attention, and gaze can be needed to perform everyday tasks during BCI use. Vision may also be compromised in some patients. There is some research on auditory feedback (Nijboer et al., 2008; Pham et al., 2005; Hinterberger et al., 2004). However, no previous work had studied the use of vibrotactile feedback during BCI learning. Our fourth aim was to determine if vibrotactile feedback could be used in addition to or instead of the visual one. In Publication V, we compared visual and vibrotactile feedback during short-term learning.

In addition to the five peer-reviewed articles and their summaries, this thesis comprises a short review of BCI research. The remaining sections of the first chapter explain the basic principles of EEG and MEG measurements and review recent research on sensorimotor cortical activation with an emphasis on spinal-cord injured patients. The last section explains BCI operation and reviews the current state of the most developed systems.

To increase readability, textbook references on elementary facts are not included in the text. Main general neuroscience references are Kandel et al. (2000) and Purves et al. (2001). A basic EEG reference is Niedermeyer and Lopes Da Silva (1999) and MEG basics are from Hämäläinen et al. (1993).

Research aims are presented in Chapter 2 and the material and methods of experimental studies in Chapter 3. Chapter 4 presents the results of each publication and focuses on critical discussion of the expected results. Chapter 5 includes the final discussion and future perspectives.

1.2 Measuring brain activity

1.2.1 Source of the measured signals

The human brain is mainly built of neurons and glial cells. The glial cells mainly keep the chemical environment stable and transport nutrition and waste material. The neural networks process information with action potentials and postsynaptic potentials (PSP). A neuron consists of three parts: a dendritic arborisation, a soma or cell body, and an axon. The dendrites receive excitation from other neurons and conduct it to the cell body. When the voltage across the neuron's membrane at the axon hillock, situated between the soma and the axon, reaches a firing threshold, an action potential is generated. The action potential moves through the axon towards the synapse, the connection to another cell, where the pre-synaptic cell frees neurotransmitters into the space between the cells. When reaching the postsynaptic cell, these neurotransmitters cause a change in potential across the membrane by opening up either sodium or chloride channels. This results in a potential difference over the membrane, causing either an excitatory PSP or an inhibitory PSP respectively. The post-synaptic cell becomes depolarised (or hyperpolarised), and this current flows through the dendrite to the soma, creating a current sink at the end of the dendrite and a current source by the soma.

The synaptic current flow can be modelled as a current dipole and the action potential by two oppositely oriented current dipoles, a quadrupole. These dipoles produce electric and magnetic fields. The dipolar field of a quadrupole decreases with distance (r) as $1/r^3$ and of a dipole as $1/r^2$. Due to of the greater attenuation of the quadrupoles, the measured electric and magnetic field signal is mainly produced by the PSP. Furthermore, because the current dipole generated by a single PSP is of the order 10^{-14}A, tens of thousands of similarly orientated synapses have to be active simultaneously before the magnetic field produced by the current dipole can be detected. Most of the magnetic fields and electric potentials measured outside the head are generated by the parallel cortical pyramidal neurons that are approximately perpendicular to the scalp.

1.2.2 Electroencephalography

The electrical fields in the brain can be recorded with three types of electrodes: depth, cortical, and scalp. Electroencephalography is the registration over time of the potential difference between scalp electrodes. These voltage registrations are

always bipolar, i.e., either the activation is measured between two electrodes, or multiple electrodes are referred to a common reference electrode. The electrodes are placed on the scalp according to a montage. In the most common International 10−20 system montage, the nasion-inion distance is measured and 23 electrodes are placed 10% or 20% of this distance apart from each other. Many other systems have evolved from the 10−20 system allowing the placement of more electrodes. The 10% system proposed by the American EEG foundation allows the placement of 64 electrodes (Fig. 1.1). The electrode locations are referred to by names, such as Fp1 and O2, which are derived from the lobes of the brain: occipital, parietal, temporal, frontal; numbering increases laterally from midline towards the ears: uneven numbers on the left and even numbers on the right hemisphere.

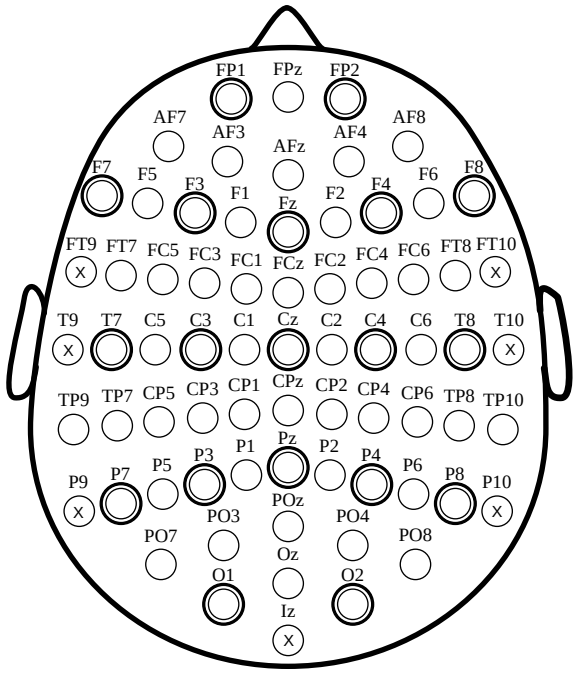

Figure 1.1: The standard electrode positions according to the international 10−10 system. The electrodes included in the 10−20 system are marked with a darker ring. The marked ones are usually not included in the 10−10 system.

The electrodes for EEG measurements are usually made of noble metals such as gold and silver and are covered with a chloride layer. The silver-silver chloride electrodes are the most commonly used. Preparation of the skin (cleaning and removal of dead skin) before attaching the electrode is important. For good signals, the impedance between electrodes should be below 5 kOhm. The voltage changes in a single neuron are in the order of millivolts. Due to attenuation of the signals by intervening layers of tissue and bone, the EEG amplitude is 5−300 μV.

The recorded signals are influenced by the choice of reference site. Ideally, the site should be inactive; in reality, this is impossible. A common reference electrode is often placed on the tip of the nose, the mastoid(s), or the vertex (top of the head). In BCI recordings, it is convenient to use fewer electrodes to reduce preparation time. For BCIs, different references can be used to better detect different sorts of activity. Dipole sources that are tangential to the skull show up as a potential difference across neighbouring electrodes. Bipolar recordings, where the electrode pairs are placed close to each other, measure local changes in the potential field and show tangential dipoles. Radial dipoles show up more diffusely and can best be detected with, for example, the Laplace method (Hjorth, 1975).

The Laplacian is calculated by combining the value at each commonly referenced electrode with the values of the neighbouring electrodes. With this method, the spatial voltage distribution is dependent on the neighbouring electrodes' distance. The small Laplacian uses the neighbouring electrodes and emphasises focal sources whereas the large Laplacian uses the next-neighbouring electrodes. In BCI research, the Laplacian can be used to detect focal activity over the sensorimotor cortex (McFarland et al., 1997).

Another spatial filter, the common average reference (CAR), provides an estimate of almost reference-free EEG by subtracting the average of all electrodes from the signals of interest. This method assumes that the electrode mean is neutral (Bertrand et al., 1985), an assumption that is only met if the electrodes are placed uniformly and completely covering the head, which is not optimal for BCI research. CAR recordings emphasise highly focal sources as the widely distributed activity is present in a large proportion of the electrodes and thus subtracted. CAR may also cause unwanted "ghost potentials" if activity is present in most of the other electrodes except the ones of interest.

The EEG includes both the signal of interest, artefacts, and noise. The subject can produce artefacts by moving, sweating, tensing muscles, or blinking. These artefacts are easier to prevent than compensate for by providing the subjects with good instructions. Computers and other electrical devices induce 50- or 60-Hz noise, which can be reduced by attaching the electrodes well and measuring EEG in an electrically shielded room. Also, modern electrode caps with preamplifiers in the electrodes provide good signal-to-noise ratios. The 50- and 60-Hz noise is easy to filter as long the activity of interest is not in this frequency range. In addition, the brain itself produces "noise", i.e., signals that we are not interested in. The above-mentioned Laplacian and CAR spatial filters can help to distinguish the signals of interest from other cerebral activity.

1.2.3 Magnetoencephalography

Currently, MEG instruments are based on Superconducting Quantum Interference Devices (SQUIDs) that allow recordings of small biomagnetic fields (Hämäläinen

et al., 1993). The magnetic field is brought to the SQUID sensor by a superconducting flux transformer. The most common flux transformers are magnetometers as well as planar and axial gradiometers. The magnetometers are composed of a single pick-up coil and are equally sensitive to both the magnetic field from the brain and artefacts. The gradiometers contain a compensation coil wound in the direction opposite to the pick-up coil, which decreases the influence of distant activity as the same magnetic flux is linked into both coils. Thus, gradiometers are sensitive to the inhomogeneous magnetic fields produced by a source situated nearby and insensitive to a homogenous magnetic field, e.g., produced by a noise source. Due to the configuration of the coils, planar gradiometers give the strongest response over the current source, whereas the axial gradiometer gives the maximum response on both sides of the source.

Present-day helmet-shaped magnetometers consist of hundreds of channels (e.g. 306, Neuromag Vectorview) to cover the whole head. The diameter of the sensor coil is approximately 2 cm. Larger coils provide better sensitivity but average the field more, decreasing spatial resolution. To keep their superconductivity, the SQUIDs have to be immersed in liquid helium. The liquid helium is kept in a Dewar container that must be filled regularly.

Before the MEG measurement, the position of the head is defined with respect to the MEG device. With the Neuromag Vectorview MEG device (Elekta Neuromag Oy), a few small coils are placed on the head and the positions of these coils are measured in relation to known landmarks on the head (nasion, inion, and the preauricular point). When a subject's head is inside the MEG device, current is passed through these loops to obtain the position of the head relative to the sensors.

The largest artefact for MEG recordings is generated by the geomagnetic field, which is eight or nine orders of magnitude greater than that produced by the brain (Hämäläinen et al., 1993). Good signal quality requires a magnetically shielded room. This shielding also helps against artefacts from electrical devices. MEG is also sensitive to any moving magnetic objects; therefore subjects must remove all magnetic materials in their clothing that could move during breathing. As with EEG measurements, the subjects can cause artefacts by eye blinking, tensing their muscles, or moving. The movement artefact is more severe than in EEG as the MEG sensors are not attached to the head. The subjects should sit immobile during the recording. The magnetic field generated by cardiac activity produces another source of artefacts.

1.2.4 Spontaneous and event-related activity

The spontaneous MEG and EEG consist of rhythmical activity which can best be measured in the frequency range of $0.5-70$ Hz. The oscillatory activity is mainly due to feedback loops of the complex neural networks in the brain. These fre-

quency patterns are commonly categorised into four groups: alpha waves (8−13 Hz) are found over the occipital and parietal areas in almost all normal persons when awake; beta activity (13−30 Hz) occurs when the subject is alert and engaged in a task; theta waves (4−7 Hz) are associated with relaxed states; and delta waves (0.5−4 Hz) occur mostly during deep sleep.

Event-Related EEG Potentials (ERPs) or the corresponding MEG Fields (ERFs) are sudden changes in the brain's activity time-locked to a specific physical or mental event. These responses are small and often difficult to detect in single trials. However, a stimulus which is presented to the subject several times produces a similar response every time. To acquire an ERP or ERF, the time-locked signals from several trials are averaged. If the time-locked rhythmical brain activity is not phase-locked over trials, then ERF/ERP signals might cancel each other (Pfurtscheller and Lopes da Silva, 1999). Typical ERPs are characterised by components named by their polarity and latency from the stimulus onset, such as N100 and P300. N100 is a negative potential peak that reaches a maximum at about 100 ms after the stimulus is presented; P300 is a positive potential peak at 300 ms. The corresponding evoked fields are often named only by their latency, e.g., M20. The magnetic counterparts of common ERPs such as N100 are called N100m.

1.2.5 Comparing MEG and EEG

Despite the close relation of EEG and MEG, there are some differences. MEG and EEG measure different components of the currents. MEG is mostly sensitive to the tangential currents in sulci, whereas EEG also detects the radial currents in gyri, making the interpretation of the EEG signal origin more difficult (Hämäläinen et al., 1993). EEG also detects deep current sources better than MEG. For comprehensive information on the source of the activity, one should measure both EEG and MEG. Optimally, these two should be recorded simultaneously, which is possible if EEG is measured with nonmagnetic electrodes.

The electrical fields measured by EEG are distorted by the extra cerebral tissues and the skull. Magnetic fields produced by currents in the macroscopically rather homogenous intracranial space and the irregular and weak currents in the bone, which conduct electricity poorly, can be neglected (Hämäläinen et al., 1993). Thus, magnetic fields are not affected by extra cerebral tissue and are more locally distributed on the head surface than the corresponding EEG; this may facilitate selection of those sensors which contain most information. Furthermore, the need for reference complicates the interpretation of the EEG signals. When interested in the origin of the signals, precise knowledge of the conductivities of the head tissues is needed more in the interpretation of the EEG than MEG origin.

MEG instrumentation is much more expensive than EEG equipment. The MEG SQUIDs have to be kept at an ultra-low temperature, which also makes the

MEG device rather immobile. EEG electronics, in contrast, can be quite small, and several different portable EEG systems are available. In addition, even though both MEG and EEG yield better signals when measured in shielded rooms, EEG is less sensitive to noise and can also be obtained outside a shielded room. Due to these features, EEG is certainly better-suited for BCI measurements. However, as technology progresses, we may have access to portable MEG devices (see e.g. BabySquid, Tristan Technologies).

Subject preparation is quicker in MEG. If the source of the activity is not of interest, as often is the case in BCI research, the MEG measurement can be started very quickly. Depending on the amount of electrodes it can take over 20 minutes to put the EEG cap on. During long measurements, the signal quality of EEG may decline as the electrode gel dries, which is not a problem with MEG. Development of dry electrodes can provide quicker preparation times for EEG and better long-term signal quality (Popescu et al., 2007).

1.3 Movement related activity

1.3.1 Anatomy

The sensorimotor cortex, also known as the Rolandic cortex, consists of the motor and somatosensory cortices which are located anterior and posterior to the central sulcus in the frontal and parietal lobes, correspondingly. Both the primary motor and somatosensory cortices are organised somatotopically so that regions of cortex represent different parts of the body. Each part of the body is represented in brain volume in proportion to its relative importance in motor and sensory behaviour. The sensorimotor pathways of the brain are crossed; the left side of the cortex relates mostly to the right side of the body and right side to the left. For example, the left side motor cortex predominantly controls right limbs.

1.3.2 Activity of the sensorimotor cortex

The sensorimotor cortex exhibits spontaneous rhythmical activity in the $10-20$ Hz range that can be detected with both MEG and EEG. This so-called mu-rhythm is known for its comb-like form and consists of 10-Hz and 20-Hz components (Hari and Salenius, 1999). Other researchers have decided to name only the 10-Hz component mu and 20-Hz component central beta rhythm (Pfurtscheller et al., 1998). Pfurtscheller et al. (1998) have mainly studied the mu-rhythm using EEG. The source of the 10-Hz component is situated more posterior than the source of the 20-Hz component. It is believed that the former originates in the somatosensory cortex and the latter in the motor cortex (Salmelin and Hari, 1994b). The source of the 20-Hz component follows the somatotopic organisation of the motor

cortex whereas the 10-Hz component is clustered close to the hand region in the somatosensory cortex (Salmelin and Hari, 1994b).

The sensorimotor neuron population either decreases or increases its synchrony in response to an event, which results in an amplitude suppression (event-related desynchronisation or ERD), or an amplitude enhancement (event-related synchronisation or ERS) of the mu-rhythm. Both frequency components are suppressed by movement execution (Pfurtscheller, 1981; Salmelin and Hari, 1994b,a). In an experiment with self-paced finger movements, the 10-Hz ERD began 2.5 s before movement onset and lasted for a couple of seconds before returning to the baseline level (Pfurtscheller et al., 1996). The corresponding 20-Hz ERD began just before movement onset, lasted only for a short while and was followed by an ERS that reached its maximum just after the end of the movement. In general, the contralaterally dominant suppression of the mu-rhythm begins $1-2$ s before movement, becomes bilateral just before movement onset, and is followed by a contralaterally dominant rebound of the 20-Hz component (Nagamine et al., 1996; Stancak and Pfurtscheller, 1996; Salenius et al., 1997; Salmelin and Hari, 1994b,a; Toro et al., 1994). Also similar post-movement patterns were found with EEG for foot-movement, localised close to electrode Cz (Neuper and Pfurtscheller, 1996)

Motor related potentials (MRPs) can be detected before, during, and after movements showing the highest amplitudes over electrodes C3, C4, and Cz (Cui and Deecke, 1999). Self-paced movements are preceded by the Bereitschaftspotential (BP), also called the lateralized readiness potential (Kornhuber and Deecke, 1965). It starts 1.5 s before the movement onset, and largest amplitudes are detected over the central electrodes C1, C2, C3, C4, Cz, and FCz (Cui et al., 1999). BP becomes more contralateral just before movement onset. Externally cued movements are preceded by a Contingent Negative Variation (CNV) (Walter et al., 1964). The scalp distribution of the late CNV resembles the distribution of the late BP. The contralaterally dominant movement related magnetic fields are divided into three components: the readiness field, the motor field, and the movement-evoked fields (Nagamine et al., 1996).

Mental imagination of movements involves similar brain activation as when one is preparing such movements (Crammond, 1997; Pfurtscheller and Neuper, 1997). However, the ERD during imagination of movement is almost entirely detected contralaterally, not bilaterally as during movement execution (Pfurtscheller, 2000). The activity patterns are also different for kinesthetic and visual-motor mode of imagery: only Kinesthetic experiences produces similar patterns (Neuper et al., 2005).

1.3.3 Brain activity of paralyzed patients

Even though paralyzed patients cannot move their extremities, their sensorimotor cortices are activated during attempted movements. A functional magnetic reso-

nance imaging (fMRI) study with five tetraplegic patients with spinal-cord injury (SCI), paralyzed for 1−5 years, showed that the patients' sensorimotor cortices are activated during attempted hand and foot movements (Shoham et al., 2001). Similar activations were found in healthy control subjects during real movements. The patients' motor cortex activation closely follows the normal somatotopic organisation in the primary and non-primary sensorimotor areas. The patients were instructed to genuinely try to move their body parts, not just to imagine doing so.

In another fMRI study with nine paraplegic patients having complete spinal-cord injury between T6 and L1 for 1 mo−33 yrs, activation patterns during motor attempts resemble those of the control group performing the corresponding movements, but activations were weaker in the patients (Sabbah et al., 2002). The activation patterns differed between motor imagery *vs.* motor attempts.

Green et al. (1999) measured 120-channel EEG while 24 tetraplegic patients attempted cued (ISI 7−10 s) middle finger and toe movements. EEG was also measured from 20 paraplegic patients during real finger movements and attempted toe movements. Contralateral motor potentials were recorded from the motor cortex during attempted finger movements. In both patient groups, these potentials (modelled by dipolar sources) were located more to the posterior than those of the healthy controls. However, this finding is subject to controversy. In a more recent study using fMRI Turner et al. (2001), in agreement with Sabbah et al. (2002), did not find any reorganization of hand motor representation in paraplegic patients.

1.4 Brain-computer interfaces

The following provides an overall and critical review of BCI literature. A comprehensive survey on BCI designs prior to January 2006 is provided by Mason et al. (2007). Figure 1.2 shows how the following sections are related to BCI development and design.

1.4.1 Measurement of brain activity

BCIs can be either noninvasive or invasive. Invasive recordings can provide signals with higher spatial resolution and fewer artefacts but involve a high level of risk as subjects undergo surgery. Invasive recordings also involve problems of tissue damage and the questionable stability of the electrodes during long-term recordings. During short experiments, epileptic subjects have controlled an invasive electrocorticography (ECoG)-based BCI (Leuthardt et al., 2004; Hill et al., 2006). ECoG measures brain activity on the surface of the cortex with a small grid of electrodes and helps evaluation of patients before epilepsy surgery. Wessberg et al. (2000) were the first to translate intracortical neuronal activity into robot commands. Microwires, recording the activation of only 50−100 neurons,

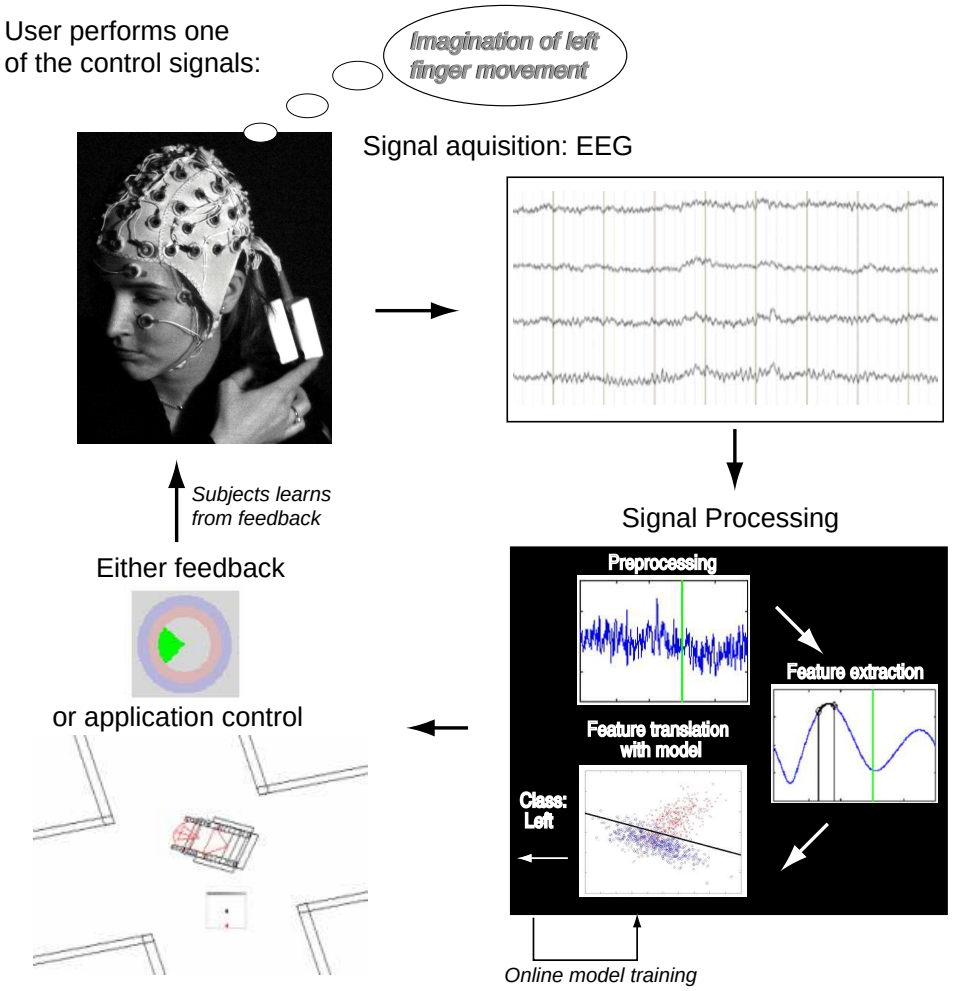

Figure 1.2: BCI function. The users perform one of the control signals while the brain activity is measured. The signals are processed and a classifi cation result is derived. The user is then given feedback of the classifi cation result or an application is controlled.

were implanted in a rhesus monkey motor cortex. The monkey, after training of the algorithms, was able to control a robot arm by moving a joystick. The computer predicted the movement 50−100 ms before it even happened and the robot moved in the same way as the monkey arm. Since then, several monkeys have obtained BCI control with signals from implanted electrodes in their sensorimotor cortex (for a recent review see Lebedev and Nicolelis, 2006). A few studies have implanted electrodes into the brain's of human subjects for BCI investigation (Kennedy et al., 2000; Hochberg et al., 2006; Donoghue et al., 2007). These

subjects have controlled a cursor on a computer screen by imagining hand movements, for example. The performance has been variable both across and between subjects and has been comparable with noninvasive studies.

Brain activity for BCIs has been measured noninvasively with functional magnetic resonance imaging (Weiskopf et al., 2003; Yoo et al., 2004; Weiskopf et al., 2003), near-infrared spectroscopy (NIRS) (Coyle et al., 2007), MEG (Mellinger et al., 2007), and EEG (for a review see Wolpaw et al., 2002). Due to its portability and relative inexpensiveness, most BCIs are presently based on EEG measurements. Nonetheless, EEG signals are a sum of all brain activity, some of which might cancel out, distorted by the skull. It is challenging to distinguish the patterns of interest from the background activity. Functional MRI provides signals with much better spatial resolution but is feasible for BCI use only in very special circumstances. NIRS measures the same changes in the blood oxygen level as fMRI and has better spatial resolution than EEG. NIRS devices are also less expensive and more portable than fMRI. As with fMRI, the main drawback is speed of operation, i.e., a temporal resolution of several seconds.

MEG measures partly the same currents as EEG, but the currents are less distorted. Thus, MEG could act as a pre-processing tool for EEG measurements by showing more accurately the subject-specific features used for BCI control. Subjects could also train to use a BCI with MEG to get more accurate feedback during the training session and then change to EEG-BCIs when accurate control is obtained. Despite their better spatial resolution, MEG-based BCI systems are impractical for widespread clinical use because they are large and expensive.

Unfortunately, none of the current brain imaging methods is optimal: invasive methods involve high risks, fMRI and MEG devices are large and expensive, NIRS signals have low temporal resolution, and EEG and MEG signals are noisy. NIRS and EEG also involve long preparation times, and assistance is needed to put on the sensors. However, both NIRS and EEG-based BCIs can provide help to severely motor-disabled persons, and a few working systems will be reviewed in the following sections.

Presently, it is impossible to know whether future BCIs will be noninvasive or invasive. Both have obvious drawbacks. Implanted electrodes in particular need to be developed further to improve compatibility with brain tissue. Also, more long-term invasive recordings are needed.

1.4.2 Different electrophysiological control signals

For BCI control, subjects can generate brain activity in two basic ways (Mason et al., 2007). In an endogenous BCI, subjects perform some mental task such as imagining hand movements. In an exogenous BCI, subjects are exposed to, e.g., visual stimuli that produce a measurable signal. Commonly used features or electrophysiological control signals for BCIs are *slow cortical potentials* (SCPs), *sen-*

sorimotor rhythms, P300 evoked potentials, cortical neuronal activity, movement-related potentials (MRPs), *visual evoked potentials* (VEPs), *steady-state visual evoked potentials* (SSVEP), and response to basic cognitive tasks (Wolpaw et al., 2002; Mason et al., 2007). Of these, P300, SSVEP and VEPs are exogenous, and all but cortical neuronal activity are recorded noninvasively.

The following section shortly reviews the currently used noninvasive electrophysiological control signals. Even though only EEG studies are reviewed, comparable signals can in principle also be detected with MEG. In addition, some state-of-the-art papers related to each control signal where especially motor-disabled persons were studied are presented.

Slow cortical potentials

Slow cortical potentials (0.1−2 Hz) are related to the overall preparatory excitation level of the cortex (Birbaumer et al., 1990). Increased cortical activity associated with movements or other cognitive functions generates negative SCPs, and reduced cortical activation generate positive SCPs. Subjects can learn to self-generate negative or positive SCP shifts and thus control a BCI with them (Kubler et al., 1999; Birbaumer et al., 2000).

SCPs were one of the first BCI control signals, and already in 1999, two locked-in patients with amyotrophic lateral sclerosis (ALS) were able to control a binary BCI using them (Birbaumer et al., 1999). Over the past 15 years, over 20 ALS patients have learned to select letters and write words with a binary BCI based on SCPs (Birbaumer and Cohen, 2007). As a drawback, the training usually takes several weeks.

Sensorimotor cortical rhythms

Contralateral changes in the rhythms are detected when subjects perform, imagine, or attempt a movement which can be used for computer control of, e.g., a cursor (see for example Wolpaw et al., 1991; Pfurtscheller et al., 2000; Hill et al., 2006) (for more details on the rhythms see Section 1.3.2). It is even possible for subjects to learn to control the rhythms with the help of feedback. These subjects initially imagine movements to control the rhythms but eventually only perform the task, e.g., think about the cursor moving left (Wolpaw and McFarland, 2004),

In a study by Wolpaw and McFarland (2004), four subjects including two paraplegics learned to control the two components of the mu-rhythm independently, resulting in two-dimensional BCI control. EEG was measured with electrodes C3 and C4. The four subjects could choose one out of 8 targets with an accuracy of 70−92%. The mean trial durations were 1.9−3.9 s. The different subjects trained between 22 and 68 daily sessions at a rate of 2-4 sessions per week.

In a similar but invasive study, one tetraplegic patient with complete spinal-cord injury at C4 also gained two-dimensional BCI control (Hochberg et al., 2006). A 4×4 mm grid of electrodes was implanted in his motor cortex. In this clinical pilot experiment, he was able to move a cursor on the screen with a target hit accuracy of $73-95$ % over six sessions. Mean reaction time to correctly hit targets was 2.51 ± 0.16 s. Despite nine months of use, the accuracy and speed of operation never exceeded the noninvasive study of Wolpaw and McFarland (2004).

Pfurtscheller and Neuper (2001) described the first tetraplegic who was able to control delivery of electrical stimulation to his hand which allowed him to grab a glass on the table. The subject had learned to control the synchronisation and desynchronisation of his mu-rhythm. Also, four ALS patients and one patient with severe cerebral palsy have operated a binary BCI by controlling their mu-rhythm (Kubler et al., 2005; Neuper et al., 2003).

Movement-related potentials

In addition to changes in mu-rhythm, performed, imagined, and attempted movements evoke slow potential shifts in EEG signals (for more details see Section 1.3.2). No subject training is needed. The MRP-related single trials are difficult to extract without knowledge of movement onsets. MRP-based BCIs use either button press or electromyogram (EMG) to reveal movement onset (Blankertz et al., 2003; Li et al., 2004) or presented an external trigger when the movements should be performed (Pfurtscheller et al., 1996). The former is not possible with motor-disabled patients. Single-trials related to MRPs have only been studied with healthy subjects performing movements.

P300

A P300 event-related potential occurs when a subject is presented with an infrequent or relevant stimulus among many frequent and/or irrelevant stimuli. In the first P300-based BCI, the user was presented with a 6×6 matrix of letters (Farwell and Donchin, 1988). The rows and columns of the matrix flashed in a random sequence as the user attended to a particular letter. The row and the column containing the wanted letter is the rare event and after several flash sequences it can be distinguished from the others based on the average of several trials of the elicited P300. The P300 BCI use does not require any training. However, it usually requires some eye gaze control.

Initial concerns that the P300 might habituate with repeated simulation (Kubler et al., 2001) were overruled by a study where three ALS patients controlled a P300-based BCI for a period of 6 weeks (Sellers and Donchin, 2006). The subjects were presented with a random sequence of four visual and/or auditory stimuli

(YES, NO, PASS, and END). The subjects were asked to attend to either the YES or NO stimuli. After several presentations of the stimuli, the attended stimulus could be distinguished based on the averaged elicited P300 response. An ALS patient has also used a P300-based BCI in his home for a longer period of time (Vaughan et al., unpublished).

Visual evoked potentials and steady-state visual evoked potentials

In a visual evoked potential (VEP) -based BCI, an alternating stimulus is detected from the VEP; the stimulus the user focuses on produces the strongest response (Sutter, 1992). This is similar to P300-based BCIs, except that different components of the visual evoked potential are used for discrimination. In a steady-state visual evoked potential (SSVEP) BCI, several visual stimuli on a screen flicker at different frequencies. The EEG over the visual cortex shows an increase in the amplitude of the frequency component of the signal that matches the frequency of the stimulus the subject is attending. The stimulus can be distinguished from the frequency content of the EEG. As with P300, (SS)VEP-based BCIs do not require any training. Subjects usually need gaze control to refocus on new objects.

Seventy normal subjects and one ALS patient with implanted electrodes could select a target from a 64-target visual array every $1-3$ seconds using VEPs. With SSVEP, four subjects could select between two buttons with a 92% mean accuracy. The average selection times were between $1.3-3$ s (Middendorf et al., 2000).

Response to cognitive tasks

Some BCIs are based on recognising the EEG patterns related to some cognitive tasks such as imagining a rotating object or solving a multiplication task (Millan Jdel and Mourino, 2003a; Penny et al., 2000). These tasks produce distinguishable EEG patterns that can be localised on different sites on the head. These tasks are not very natural control signals, as extra effort is required to imagine, e.g., a rotating object, and the task itself does not correlate with the intended command (e.g. go right). So far no patients have obtained BCI control with these cognitive tasks.

Comparison of methods

The different electrophysiological control signals each have advantages and disadvantages. Controlling SCP and the sensorimotor cortical rhythms takes a long time to learn but does not require any external stimuli as P300, VEP, and SSVEP. Also, MRPs require detection of the movement onset, which usually requires some external stimuli.

The implementation of the platform BCI2000 (Schalk et al., 2004), freely available to all researchers, has made it easier to compare different methods. Nijboer et al. trained eight severely paralysed ALS patients to control a BCI based on P300, SMR, and SCP (described in a review of Birbaumer and Cohen, 2007). Subjects trained with each method for 20 sessions. During the SCP training period, the subjects did not acquire over 70% classification accuracy, which is regarded as necessary control accuracy for a two-task BCI (Perelmouter and Birbaumer, 2000). Even though control was obtained with SMR, the shortest training times were needed for P300-based BCI. Also, letter selection with P300 was faster. None of these patients was fully locked-in, and they all had control of their eye movements. Totally locked-in patients cannot use a conventional P300-BCI based on visual stimuli where eye movements are needed. These subjects could be presented with auditory stimuli, but the bit rates would probably not be as high because it might not be as easy to distinguish between dozens of different auditory stimuli.

1.4.3 Biofeedback training

Subjects can learn to control their brain signals such as the mu-rhythm and SCPs with the help of feedback. The subject can be trained in two ways: operant conditioning and predefined imagery instructions (Curran and Stokes, 2003). In the imagery strategy, the subjects are instructed to imagine specific motor movements that produce well-known signal changes. In operant conditioning, control is achieved by learning from the feedback, regardless of the actual source of control; the mental tasks performed by the subjects vary greatly.

Kamiya (1968) reported the first operant training of EEG alpha waves. In a typical neurofeedback study, subjects are either shown a video-display of their brain waves or they are given auditory feedback and then try to self-regulate the waves (Kamiya, 1968; Nowlis and Kamiya, 1970). Neurofeedback training has proved to be useful in treatment of different neurological conditions such as attention deficit hyperactivity disorder and control of epileptic seizures (for reviews see Vernon et al., 2004; Sterman and Egner, 2006).

In BCI training, feedback is usually based on the performance of the classification algorithm and can be given at three different points in time during the trial (Wolpaw et al., 2002). First, continuous feedback, such as a moving cursor, is presented during the trial. Second, feedback of the trial outcome, such as reaching a goal, can be present when the trial ends. The third, less common type of feedback is positive enforcement like a "thumbs-up" after the trial. Neuper et al. (1999) have shown that continuous feedback during the trial is more effective than discrete delayed feedback. Even though some form of feedback plays an important role in initial skill learning, it can also distract the subjects. McFarland et al. (1998) have shown that feedback has in different subjects either disadvantageous

or beneficial effects on EEG control. Also, short-term removal of feedback from well-trained subjects did not significantly affect the overall performance (McFarland et al., 1998). Surprisingly, only the two studies mentioned above explored how feedback affects the learning process.

Presently, most BCIs utilise visual feedback. A few studies have also tested other feedback modalities. Both SCP-based (Pham et al., 2005; Hinterberger et al., 2004) and mu-rhythm based (Nijboer et al., 2008) binary BCI control was achieved with auditory feedback. Compared to visual feedback, however, the training times with auditory feedback were longer and the control accuracies worse. Auditory feedback control has not yet been tested with blind or motor-disabled patients.

As reviewed in the previous section, even some motor-disabled patients learned to control a BCI through feedback. Nevertheless, it seems that feedback training can be more difficult for motor-disabled patients. When learning to control their sensorimotor rhythms, patients with ALS required longer training times than healthy subjects (Kubler et al., 2005).

BCIs would be most helpful for fully locked-in patients, i.e. patients with no voluntary motor control. Unfortunately, according to a review by Birbaumer and Cohen (2007), not a single patient in a fully locked-in state has been able to obtain control of her brain signals. Birbaumer (2006) speculates that this can be due to "1) locked-in state being accompanied with a drop in cognitive abilities and attention or 2) locked-in state leading to extinction of goal-oriented thoughts which are needed for operant conditional training".

Adaptation

BCI systems consist of two learning components: *the brain* that learns and adapts with the help of the computer's feedback and *the computer* that should adapt to the user's changing brain activity. Wolpaw et al. (2002) describe three levels for BCI algorithm adaptation. In the first level, the algorithm is adapted to the user's features once after the first training session and never again. These algorithms are not useful before the subject has achieved stable control of his brain activity. The second level of adaptation employs periodic adjustments to the algorithms. Traditional BCIs work with these first two levels of adaptation. However, the model trained on past EEG data might not be optimal for following sessions. The third level is real online adaptation that also accounts for how activity in the brain changes due to feedback and other factors such as level of attention.

The need for online model training is acknowledged (see e.g. a review by Millan Jdel et al., 2007; McFarland et al., 2006), but to date there are no existing real-time adaptive BCI systems. Some BCIs are capable of online model training using supervised learning with correct information on the subject's intent (Buttfield et al., 2006; Vidaurre et al., 2005). However, when users autonomously

control an application, correct class labels are not available. The need for adaptive systems is obvious but a challenging task, especially as class information is difficult to infer from noisy and nonstationary EEG signals. Recent work on online predictability of error-related potentials (Buttfield et al., 2006) proposes a promising way of implementing models that can infer class-information from misclassifications using reinforcement learning.

1.4.4 Signal processing

From a machine-learning point of view, a BCI can be regarded as a pattern recognition process consisting of signal acquisition, pre-processing, feature extraction, and feature translation (Wolpaw et al., 2002). The purpose of the feature extraction process is to choose features that are computationally feasible, lead to a good classification rate, and reduce the measured data into a manageable amount of information. The purpose of the feature translation is to correctly categorise the different class-related features into classes.

BCI use consists of two steps. In the first training step, brain signals are acquired during different tasks, features are selected from this data, and a model is optimised with training samples from each class. In the second BCI step, subjects use the BCI and the model categorises the class related samples based on the training data. Feedback based on the classification result can be given to the user. The BCI can also be used to operate an application. Conventionally, data is first gathered in a training session, then the model is calibrated during the break and used in the following session; the two steps can also be performed sequentially online.

Numerous methods have been tested for the different stages of BCI signal processing. Several recent comprehensive surveys are available (McFarland et al., 2006; Mason et al., 2007; Lotte et al., 2007; Bashashati et al., 2007) and the following is only a short review of these.

As the recorded brain signals include much noise, pre-processing is important. Re-referencing methods, also known as spatial filters discussed in Section 1.2.2, are one of the most common pre-processing steps. Common average reference and the Laplace method are especially good for the local sensorimotor cortical signals. The second most common pre-processing method, Common Spatial Patterns (CSPs) (Muller-Gerking et al., 1999; Ramoser et al., 2000; Dornhege et al., 2003), also includes spatial information of the EEG signals. The disadvantage of these spatial filters is that they require a large amount of electrodes and require long preparation times, which is suboptimal for BCIs. CSPs are also sensitive to noise and artefacts in single trials as well as small changes in electrode positions (Muller-Gerking et al., 1999; Guger et al., 2000). In addition to these, independent component and principal component analysis (PCA) are applied.

Current features extraction algorithms use time-domain, frequency, and time-

frequency domain features such as band powers, power spectral densities (PSDs), autoregressive (AR) parameters and wavelet features. PSDs are most commonly used. As the feature space often has high dimensionality, feature selection is usually performed before classification; PCA and genetic algorithms are the most common algorithms but feature selection very often is performed by a visual inspection of the signals. The choice of both pre-processing as well as feature extraction methods depends on which electrophysiological signals the subject uses as a control signal and the number of electrodes.

For classification, linear classifiers are generally more robust than nonlinear ones as overfitting can be more easily controlled. Linear classifiers define linear decision boundaries in feature space to distinguish classes; linear discriminant analysis and linear support-vector machines are most common for BCIs. Nonlinear methods such as neural networks are flexible classifiers, but care is needed when tuning the parameters as overfitting to the data is possible. Some groups have also used Bayesian inference for classifier models to determine classifier parameters such as Hidden Markov models and Bayes quadratic models. To date, the simpler the method, the more it is used, and usually the better it works. As an example, one of the state-of-art papers by Wolpaw and McFarland (2004) categorises the features based on difference in the amplitude of the power.

The choice of classifier depends on the nature of the features. Generally, BCI features are non-stationary and have non-stationary noise, the feature space has high dimensionality, and the data includes a limited number of training samples. These are all problems that create a real challenge for BCI signal processing methods. The need for online feedback preferably within milliseconds also limits the use of some computationally demanding methods.

1.4.5 Users and applications

BCI users can control assistive technologies enabling movement and communication. Presently the average output bit rate of BCIs, i.e. how many bits of information per time unit can be transmitted, on average is low and is best for simple applications that improve the quality of life of motor-disabled patients. Surprisingly, there is little documented information on what specific applications these users want (Kubler et al., 2006). Most systems focus on restoring and maintaining communication. Currently, subjects can select items from a computer screen with two or more choices, browse the internet or even operate control-switches, common appliances and medical devices (for a recent review see Allison et al., 2007).

For many locked-in patients, slow communication is better than no communication. However, with the growing field of intelligent appliances, such as intelligent wheelchairs, many of the present applications can be made more efficient. Dasher is a good example of intelligent text-producing software for potential BCI

use. It exploits a language model and a dynamic visual display to allow efficient entry of text (Wills and MacKay, 2006). Despite more efficient operation, some users may actually prefer slower and more reliable or otherwise simpler BCIs and find highly complicated interfaces too tiring.

BCI application design is also limited by other features. First, when using the exogenous electrophysiological control signals, the application depends on external stimuli. For example, visual stimuli require gaze to be directed to a display. Second, most current BCIs work synchronously requiring some external stimulus controlling the timing of the commands. An asynchronous BCI enables the users to perform the commands at their own pace but is also more vulnerable to unrelated brain activity being interpreted as commands (Scherer et al., 2007). Third, most BCIs have to be activated by an external helper. To overcome this, some BCI applications include the possibility to turn a BCI on and off with brain activity (Borisoff et al., 2006; Kaiser et al., 2001).

In principle, anybody could operate a BCI; it would free our hands and we could turn on a television while eating or transmit a message without anybody seeing. This scene, however, is highly optimistic. Imagine putting on the electrodes, starting up the software, performing motor imagery, and after all this effort achieving only a few bits per minute with modest accuracy. Present-day BCIs are not easy enough to operate or fast enough to be beneficial for individuals other than severely motor-disabled patients.

Whether less severely motor-disabled patients benefit from BCIs is still under investigation. As these patients can also utilise other more conventional assistive technologies based on, e.g., eye-, jaw and head tracking, BCIs can be too slow. However, as patients gain better BCI control, use without paying exclusive attention is possible. Some patients actually consider BCIs easier to use than eye-tracking (Vaughan et al., 2006).

Chapter 2

Aims of the study

The first aim of this thesis was to characterise and categorise the activation of the sensorimotor cortex during attempted and real movement. Other aims were 2) to examine use of MEG in BCIs, 3) to use single brain signal trials during (attempted) finger movements for online BCI classification and 4) to use vibrotactile feedback. The motivation for choosing these aims are specified at the end of chapter 1.1. Both healthy (I−IV) and motor-disabled (II, IV, V) subjects were tested with MEG and/or EEG. In Publications P I to P V the specific aims were:

P I: To characterise and classify single MEG trials during finger extensions of healthy subjects and examine the use of MEG for BCIs.

P II: To characterise and classify single EEG and MEG trials during attempted finger extensions of tetraplegic subjects and to compare EEG and MEG classification.

P III−IV: To test whether novice healthy subjects (P III) and tetraplegic patients (P IV) could achieve satisfactory online EEG BCI performance after an approximately 20-min training period with single-trial finger extensions (P III) or attempted hand movements (P IV).

P V: To compare visual and vibrotactile feedback for BCI training.

Chapter 3

Material and methods

3.1 Overview

The aim of this chapter is not to reprint all the corresponding chapters in the original Publications I-V. Instead this chapter aims to give an overview of the used methods and make it possible for the reader to compare the methods used in the different publications with each other. For more details on all sections the reader is referred to the original Publications.

The chapter is built around three tables that provide a general overview. Table 3.1 summarises the materials section of subjects (healthy or tetraplegic), recording device and measurement place. The three different studies (I-III), in Publication V are considered separately. Table 3.2. summarises how the subjects performed the task (i.e. if for example hand movements where performed, attempted, or imagined), what kind of feedback the subjects were given, and duration of the experiments. In Publications I-II, the aim was to study the nature of the signal used in BCIs. Therefore, no feedback of performance was given. In Publications III-V, the experimental setup is more complicated because BCI control is included. While the subjects' task is only to move an object on the screen by performing hand movements, the setup requires knowledge of when and how feedback is given to the subjects, what happens if the subjects' performs wrong and when the mathematical models should be updated. In all our BCI experiments, to facilitate learning we aimed to give our subjects feedback as quickly as possible. The experimental setup of Publication V, Study III, deviates most from all others as it was it was a psychophysical experiment and no brain activity was measured. The subjects' task was to navigate a visual corridor (Fig. 3.4) with a PC mouse. BCI derived noise was added to the control signal to make the control more realistic. All experimental setups are described in more detail in section 3.3.

Table 3.3 summarises the feature extraction and classification section. For the non-expert reader this section is the most difficult to understand. For more

information on what a feature, feature selection and classification the reader is referred to section 1.4.4. To summarise, task related signal parts i.e., features, are extracted from the brain signals. A mathematical model (classifier) is then trained with the signals to distinguish the two classes. The given feedback depends on the output of the classifier. The whole process is summarised in Figure 1.2. All the feature extraction methods are commonly used (e.g. FFT, AR) to extract either amplitude values from some movement related time-window or band power values from different movement related frequency bands. Also the used classifiers are commonly used in BCI research.

3.2 Subjects

Fifteen healthy and nine tetraplegic subjects in Publications I−IV were all novice BCI users. Table 3.1 summarises the methods and Table 1 in Publication IV provides further details on tetraplegic subjects. The healthy subjects were laboratory personal or university students. The tetraplegic patients were undergoing rehabilitation at the Käpylä Rehabilitation Centre, Helsinki. All patients were interviewed and the experimental procedure was explained to them before asking them to participate in the experiments. All subjects were volunteers and none of them was paid for participation. Publications II and IV were approved by the Ethical Committee of the Hospital District of Helsinki and Uusimaa. Those subjects that needed help in signing informed consent forms received that assistance.

Publication V is a collection of three different studies: I, II and III (Table 3.1). Five able-bodied and three paraplegic subjects participated in the preliminary experiments also described in the publication. Twelve healthy subjects, all novice BCI users, participated in the EEG Studies I and II. Eleven healthy and two paraplegic experienced BCI users participated in Study III.

Table 3.1: Subjects and Recordings. *BRU=Brain Research Unit, LCE=Laboratory of Computational Engineering, Synapsia=Käpylä Rehabilitation Centre, SL=Santa Lucia

Publication	Subjects	Recording: Sensors (BCI control)	Measurement device (Place)*
I	5 healthy	306 MEG	Neuromag (BRU)
II	3 tetraplegic	306 MEG; 58 EEG	Neuromag (BRU)
III	10 healthy	6 EEG (6)	BP (LCE)
IV	6 tetraplegic	14 EEG (6)	BP (Synapsia)
V (Study I)	6 healthy	12 EEG (2)	BP (LCE)
V (Study II)	6 healthy	13 EEG (6−12)	BP; active cap (LCE)
V (Study III)	11 healthy, 3 paraplegic	Psychophysics	(SL, Rome, Italy)

3.3 Recordings

Recordings for Publications I and II were made in a magnetically shielded room with a 306-channel whole-head helmet-shaped neuromagnetometer (Vectorview, Neuromag, Helsinki, Finland) in the Brain Research Unit of the Low Temperature Laboratory at the Helsinki University of Technology (Fig. 3.1). The device consists of 102 identical triple sensor units. Each unit consists of one magnetometer and two orthogonal planar gradiometers. For Publication II, simultaneous 58-channel EEG was also recorded, with a reference electrode placed on the nose. During the recordings, the subjects sat with their heads supported against the helmet-shaped MEG device. The tetraplegic subjects were lifted from their wheelchairs into the movable measurement chair outside the shielded room.

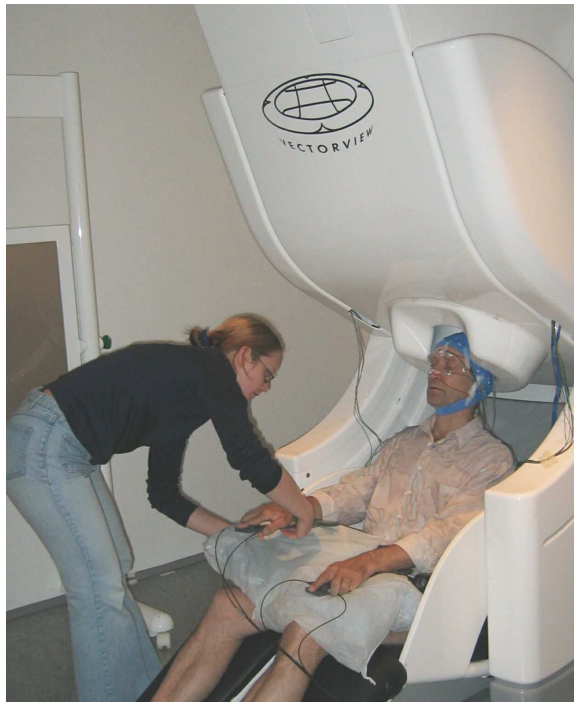

Figure 3.1: Subject is being prepared for simultaneous MEG and EEG measurement.

For Publications III, IV and V (Study I and II), EEG was measured with a 32-channel amplifier (Brain Products GmbH, Germany) with a reference electrode located between Fz and Cz. Horizontal and vertical eye movements were measured with three additional electrodes. Measurements for Publication III and V were conducted inside an electrically shielded room at the Laboratory of Computational Engineering and Publication IV in patient rooms at the Käpylä Rehabili-

tation Centre. The subjects sat in front of a computer screen during the measurements (Fig. 3.2). EEG was recorded with electrodes over the sensorimotor cortex placed according to the international 10−20 system. The number of electrodes used in each experiment is shown in Table 3.1. The EEG equipment in Study II of Publication IV was the same as in the other studies, except that an active electrode cap was used with electrodes that had built-in pre-amplifiers and impedance level indicators.

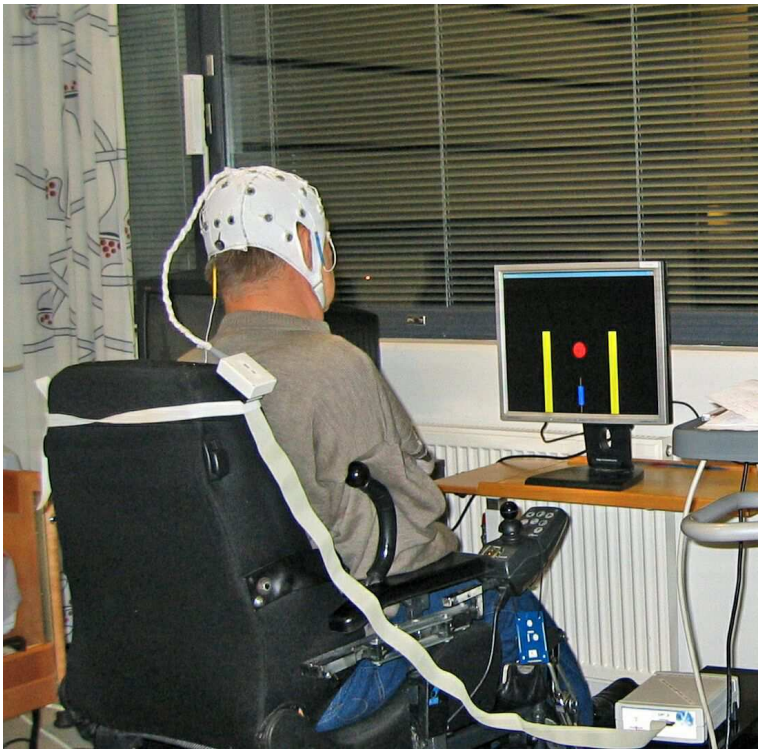

Figure 3.2: Subject sitting in front of the computer screen with EEG cap on. The subject's task is to move the red circle on the screen to the yellow target by attempting hand movements when the blue meter disappears.

No brain activity was measured in Study III of Publication V. More on this experimental design in section 3.4.

3.4 Experimental setup and feedback

In Publications I and II, the subjects were instructed to perform or attempt a brisk left, right, or both index finger extension after an auditory (P I) or visual cue (P II) (Table 3.2). Inter-cue-interval was 3 s. In P II, there was also a no-movement

condition where subjects saw the trigger but did not perform any movement. In P I, the subjects could themselves choose which movement they performed. Two 12-minute (P I) and two16-minute sessions (P II) were recorded. The subjects were not given any feedback of their performance; i.e., there was no online BCI operation.

Table 3.2: Subjects and Recordings. * L=Left, R=Right, B=Both, N=Nothing.

	Control Task*		Feedback	Experimental Setup sessions
I	Self-paced	L,R,B	none	Two 12 min
II	Triggered, attempted	L,R,B,N	none	Two 16 min
III	Triggered	L,R	visual	8−10 4 min
IV	Triggered, attempted	L,R	visual	6−10 4 min
V (I)	Continuous imagined	L,R	visual or tactile	Six 7 min
V (II)	Continuous imagined	L,R	visual or tactile	Nine 4.5 min
V (III)	Movement of PC mouse	-	visual or tactile	30 min + 2 min

In Publications III−V, trials were classified online and feedback was given to the subjects. In Publications III and IV, the subject's task was to play a game and move a circle from the centre of the computer screen to the target located on the left or right side of the screen by means of EEG signals related to real or attempted single right- or left-hand movements (Fig. 3.2). The circle moved proportionally to the output of the classifier, i.e., the probability of the appropriate class. The movement onsets were triggered with a visual cue every 2 s. Before the beginning of a game, the subjects where instructed which target they should try to hit (see Fig. 2, Publication III, for further details). Each movement was a trial, and each game consisted of 3−10 trials. The experiment was divided into 8−10 (P II) or 6−10 sessions (P III), depending on how quickly the subjects got tired. Each session lasted 3.5−4 minutes and consisted of 16−30 (P II) or 10−27 games (P III). The experiment in Publication III was shorter than the experiment in Publication II as the patients tired more quickly. We developed the online EEG-BCI system used in both P II and P III.

In Studies I and II of Publication V, subjects received every second either visual or vibrotactile feedback of the classifier performance. The experiment in Study I consisted of six 7-minute sessions, three with vibrotactile and three with visual feedback. The experiment in Study II consisted of nine 4.5-minute sessions: one training session, two sessions with both feedback modalities, three with vibrotactile and three with visual feedback. Visual feedback was an arrow pointing either to the left or right displayed on the computer screen for 200 milliseconds. The vibrotactile feedback was given for 200 milliseconds at 200 Hz with vibrating elements attached with tape to the left and right side of the lower neck. Subjects performed visually triggered continuous left or right hand movements for 10−15

s. In Study II subjects were also presented with a visual robot distracter on the screen in front of them (Fig. 3.3). The use of a distractor robot made the experiment more realistic as we are usually trying to perform some visual task ,like navigate in an environment, while simultaneously trying to learn from classifier feedback. The robot automatically navigated around a corridor in accordance with the task the subject was performing. The robot simulation program was developed by our EU project partners at the K.U. Leuven, Division of Production engineering, Machine design, and Automation (PMA), Leuven, Belgium.

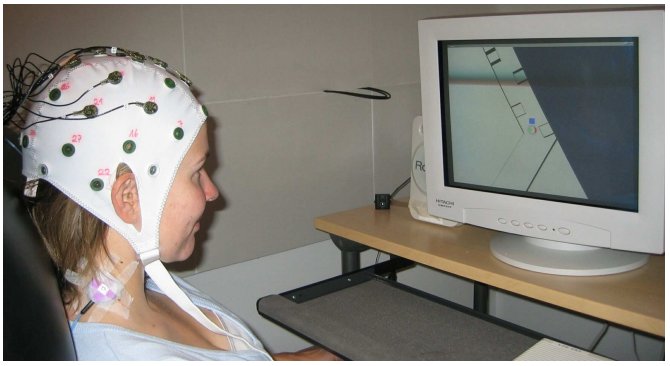

Figure 3.3: Subject sitting in front of the computer screen with the EEG cap on. She is trying to control the autonomous wheelchair robot by imagining hand movements. She received either visual feedback or vibrotactile feedback. The vibrotactile sensors are attached to the lower neck.

In Study III, the subjects received visual or vibrotactile BCI feedback while they navigated a visual corridor with a PC mouse. BCI-derived noise was added to the control signal to make the control signal more realistic(Fig. 3.4). Each room in the corridor included 4×4 steps and the following room could be accessed through a narrow gate. The visual task monitor (corridor) was updated discretely every 2 s. Continuous (updated every 100 ms) feedback of the classifier was either given visually on the screen or through vibrations to the upper back. Subjects had to attend to both the visual task monitor and the visual or vibrotactile feedback, i.e., the control monitor. To ensure visual attention to the application, the subjects were also asked to detect a visual stimulus before entering each new room. If they detected the stimuli incorrectly, they had to renavigate through the room. Performance was measured in several ways: the rate of steps in the ideal path, the rate of steps in an acceptable path, the time to complete the ten-room path, and the rate of correct answers to the task (key colour).

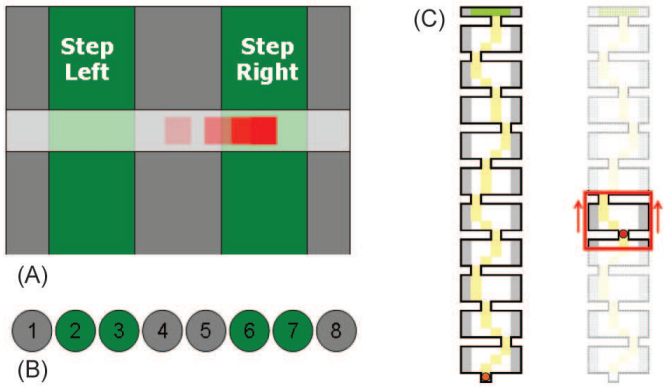

Figure 3.4: A) Visual feedback of the pseudo BCI controller. The subjects had partial control of the red cursor, whose postition was changed at discrete times (2 s). B) Vibrotactile feedback of the BCI controller. Each tactor of the stripe encoded the corresponding visual feedback in tactile form. C) The visual corridor the subjects navigated. Left: represents the whole maze, with the ideal path shown in yellow. Right: the scrolling red frame shows the portion of the maze visible during task performance.

3.5 Feature extraction and classification

The extracted features in Publication I were power spectral values calculated using the transfer function of an autoregressive model (for a summary of all features see Table 3.3). The power spectra were calculated for a period during which the post-movement rebound activation was detectable in all subjects in the 20-Hz range. We chose thies feature based on visual inspection of the average signals in the training sessions. The frequency with maximum energy and the corresponding sensor location were chosen individually for each subject and used as features in the classification. The feature vector consisted of power values of a band of 10 frequencies centred at the chosen peak frequency. Different feature combinations were inspected; features from both one and nine sensor locations on each hemisphere were used. This resulted in 10 frequencies $\times$ 2 sensors = 20 features or 180 features for 18 sensors.

In Publication II, MEG and EEG signals were filtered with passbands of 0.5−3 Hz and 3−7 Hz. These features were also chosen based on visual inspection of the signals in the training session. In EEG analysis, the signals were first filtered with the same passbands and the difference between the channels C3−C4, F3−F4, and P3−P4 was calculated. Each MEG sensor location has two orthogonal gradiometers. In MEG analysis, signals from six parallel gradiometers over the left and six over the right hemisphere were averaged separately. Also, the signals from the corresponding orthogonal gradiometers were similarly averaged. This formed two time series per hemisphere, one for the parallel and one for the

Table 3.3: Features and Classifi cation.

	Features	Signal of Interest	Feature selection	Classifi er
I	Spectral(AR)	20 Hz	Visual inspection	RBF
II	Filtered amplitude	0.5−3 Hz, 3−7 Hz	Visual inspection	Linear&Dynamic
III	-"-, instaneous: >3Hz	Selected: 1−45 Hz	KS test statistic	Linear
IV	-"-	-"-	-"-	-"-
V(I)	Spectral (FFT)	7−13 Hz	none	-"-
V(II)	Spectral (Gabor)	Selected:6−30 Hz	Bayesian inference	-"-

orthogonal gradiometers. For each EEG and MEG channel, six amplitude values were downsampled from a 200-ms time segment starting from movement onset. In total, there were 3 channels × 6 time points = 18 EEG features and 4 channels × 6 time points = 24 MEG features.

The features in Publications III and IV were similar to those in Publication II except that the bandpass filtering was done with the Fast Fourier Transform (FFT), by adjusting undesired components to zero and computing the inverse FFT. In addition, no channel differences were calculated. Several different time windows relative to the cue and frequency bands were inspected, in the band between 1 Hz −45 Hz. For bands above 3 Hz, the instantaneous amplitude of the signal was computed with the Hilbert transform (see Fig. 3.5, for further details). In total, seven different frequency-band and time-window combinations were included from six channels, resulting in a total of 42 features. In P II−IV, where the subjects performed single movements, the timing of the movements (cue) was utilised in feature calculation.

In Publication V Study I, the features were FFT components (7−13 Hz). These components were calculated from a one-second sliding time window, resulting in 2 channels × 7 spectral components = 14 features. In Study II, for each channel, one instant spectral/band power value was used as a feature; the features were calculated once every second by convolving the EEG signals with Gabor filters. The length of each Gabor filter was two seconds corresponding to a bandwidth of approximately 0.5 Hz. The centre frequency of each filter was determined in the feature selection from the 6−30 Hz frequency band. Depending on the subject, about 6 channels × one power estimate = 6 features.

The choice of features used in different studies depended on the inspected electrophysiological control signal. Power spectral estimates suited well for the 20-Hz post-movement rebound (P I), filtered averaged amplitude values for single trials (P II−IV) and in P V spectral power estimates (Study I and II) for continuous movements.

Subject-specific features were selected in Publications I, III, IV, and V (Study

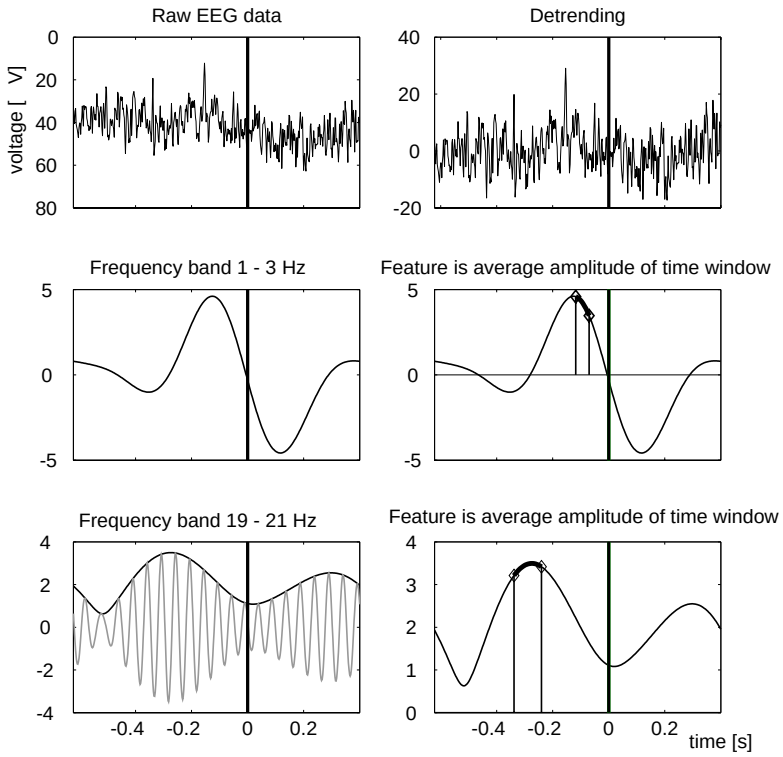

Figure 3.5: Computation of the features. The raw EEG signals were first preprocessed and detrended. The frequency components were extracted using fast Fourier transform. For frequencies over 3 Hz, the instant amplitude of the signal is taken using Hilbert transform. The feature is the average amplitude of some time window (second and third rows, right).

II). The best features, i.e. the exact frequency bands, time-windows and/or best sensors, were selected by visual inspection of the training data (Publication I and II), using the Kolmogorov-Smirnov (KS) test statistic as a difference measure between classes (P III and IV) or using Bayesian inference (Study II). The features used in Study I (P V) were chosen based on previous experience.

The features were classified with a Radial-Basis function network with a linear output (P I) or a linear classifier with logistic output function (P II−V). In the offline Study II, we also tried dynamic classification; the parameters of a linear classifier were updated with particle filters. In Studies I−II, the classifiers were trained with data from the first training session and tested with data from the second session. In Studies III−V, the classifiers were trained online labelled data. After classification of each movement, the classifier was trained with a sample history of approximately 400 s (P II and III), 60 s (Study I) and 300 s (Study II), always including an equal amount of samples from both classes. Except for

Study II, the classifiers were also tested in a separate testing sessions in which the classifier was kept static.

Chapter 4

Summary of studies

4.1 Classification of single MEG trials related to left and right index finger movements (P I)

4.1.1 Results

Using averaged time-frequency representations (TFRs) of the training data, we visually inspected the signals related to the index finger movement and decided to use the contralaterally dominant post-movement rebound in the 20-Hz range as a feature for offline classification. Through visual inspection, we chose the best channels and spectral (frequency) components for each subject. When the features were classified into two classes (left *vs.* right movements), classification accuracies in the five subjects were 80%−94%. The bit rates ranged from 5.6 to 13.2 bits/minute. When the signals in three consecutive trials were averaged, the classification accuracy improved in three subjects significantly to a mean over all subjects of 91%; but the bitrate/minute also decreased to a range from 4.6 to 7.3 bits/minute.

The averaged TFRs showed clear unilateral rebounds for unilateral movements and bilateral activation for movement of both fingers. However, three class (left *vs.* right *vs.* both) classification accuracies were only 57−67%, too low for practical BCIs.

4.1.2 Discussion

Contrary to our hypothesis, we did not obtain better classification accuracies using MEG as compared to similar studies using EEG (see e.g. review by Wolpaw et al., 2002), even when signals related to three different tasks were classified. One reason might be the simple finger-lifting task, which selectively activates the left and right sensorimotor cortex. Apparently, activities from these two cortical

areas can be picked up equally well by MEG and EEG. Whether the good spatial resolution of MEG is advantageous in more than two category classification, involving activity in spatially separate brain areas, needs further investigation.

At the same time as the present study, the BCI group in Tubingen developed an online MEG system (Lal et al., 2005; Mellinger et al., 2007). The online system was first presented in Lal et al. (2005) where five subjects trained to control a BCI. The subjects imagined either tongue or left little finger movements for three seconds during an eight second trial. The trial also included cue and relaxation periods. After achieving over 70% classification accuracy, the subjects tried to spell their name with the "thought translation device", a computer program with which one can select letters from a virtual keyboard (Birbaumer et al., 1999). Training took 6−8 blocks of 50 trials. The results are not better than in corresponding EEG studies, and bit rates are lower than ours due to the eight-second-long trials. In a more recent MEG study, six subjects learned to control the power of their mu-rhythm (Mellinger et al., 2007). The performance obtained after 30−40 minutes of training was similar to a state-of-the-art EEG-based mu-rhythm BCI (Guger et al., 2003).

In classification of the single trials, we defined the feature extraction window based on actual finger movement onsets, which is not possible in studies with attempted movements of paralysed subjects. We hypothesized that it would be possible to pace the attempted movements based on, e.g., a visual cue; a hypothesis we tested in P II−IV.

For BCIs, it is natural to use signals generated in the sensorimotor cortex by, for example, hand movements to control spatial movements on a computer screen. The use of real movements instead of imagined ones was justified by several fMRI studies, which show that the activation of tetraplegics attempting hand movements resembled the activation of healthy subjects performing real movements, more than when the tetraplegics just imagined movements (Sabbah et al., 2002; Shoham et al., 2001). Despite these justifications, it is impossible to know for sure whether single attempted movements of motor-disabled patients evoke similar responses. This consideration led us to conduct the following study P II.

4.2 EEG and MEG brain-computer interface for tetraplegic patients (P II)

4.2.1 Results

The 10- and 20-Hz rhythmic activity was recorded over the sensorimotor cortex in the three tetraplegic patients with both EEG and MEG. Contrary to that found in healthy subjects, the TFRs in Figure 4.1 display how the 10 and 20 Hz activity over the sensorimotor cortex is suppressed bilaterally during the unilateral

attempted movement tasks. In addition, no contralateral post-movement rebound can be detected. Both the activity and suppression were also more widely distributed than in healthy subjects. The slow movement related fields and potentials were contralaterally dominant, and we tested them as features for classification.

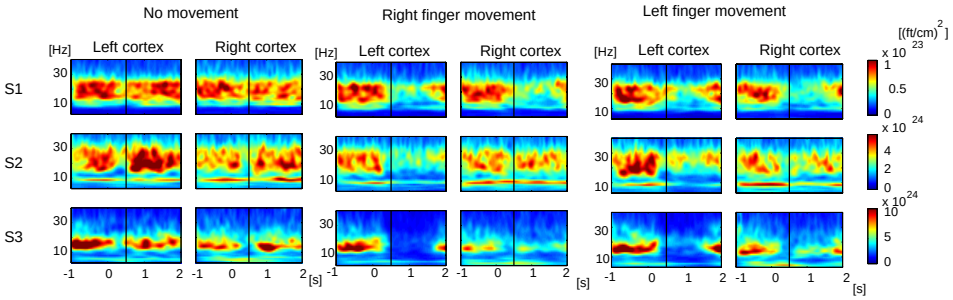

Figure 4.1: Time-frequency representations of all subjects over two sensors over the left and right sensorimotor cortex. Subjects either performed left, or right hand movement, or did not move at all. Movement onset at black line.

The classifiers were trained with data from the first 16-minute session and tested with the second. Two-class classification was performed using both a conventional batch trained classifier and a dynamic classifier that is updated sequentially after each trial. Nykopp et al. (2004) presents more information on the sequential classifier. We tested two frequency bands, of which the lower 0.5−3 Hz gave slightly better accuracies than the higher 3−7 Hz. Even though the EEG and MEG classification accuracies were comparable, the best results were obtained with the dynamic classifier with 0.5−3 Hz EEG features. Classification accuracies were 75%, 89% and 91% for the three subjects. More specific details can be found in Tables I and II in Publication II.

Table 4.1: Offline classification accuracies of both MEG and EEG data tested with both a batch trained and dynamically trained classifier (PII)

Data and Classifier	Feature	S1	S2	S3	Mean
EEG	0.5−3 Hz	87	85	69	**80**
Batch trained	3−7 Hz	67	66	63	**65**
MEG	0.5−3 Hz	81	79	79	**80**
Batch trained	3−7 Hz	77	75	80	**77**
EEG	0.5−3 Hz	91	89	75	**85**
Dynamically trained	3−7 Hz	70	72	69	**70**
MEG	0.5−3 Hz	81	83	81	**80**
Dynamically trained	3−7 Hz	80	75	85	**80**

4.2.2 Discussion

Contrary to our hypothesis, which was based on several fMRI studies described in more detail in Section 1.3.3, the brains of the spinal-cord injured subjects and especially the rhythmic activity did not respond to movement in a similar manner as those of healthy subjects. The activation was more widespread and less contralateral, providing a poorer control signal for two-class movement classification. Fortunately, it might be possible to enhance the contralaterality of the mu-rhythm by training. Pfurtscheller et al. (2000) show that one tetraplegic subject after several weeks of training could produce larger contralateral differences in the rhythms.

It would be interesting to compare our results to a similar study in which subjects imagined single movements. Previous studies also show contralateral activity during movement imagination (Pfurtscheller, 2000) which we did not see but experimental design can affect the results. Because only three subjects were studied, the present results should be regarded as tentative.

Good classification accuracy was achieved with the lower frequency band features. As we hypothesised, the accuracies were similar for both EEG and MEG. We did not measure EOG, but as the subjects were asked to focus their gaze in the middle of the screen where all the stimuli were presented, no stimulus-related eye movements were present that could influence the lower band features. When using single movement attempts, good classification accuracies were possible after basically no training. However, both P I and P II were offline studies, and to address the effect of feedback on the single trial control we conducted studies P III and P IV.

4.3 Online classification of single EEG trials during finger movements (P III)

4.3.1 Results

The subjects' task was to move a circle on the screen to a target on either side of the screen by performing left and right finger lifts. We used subject-specific features selected from the $1-45$ Hz range. These features were chosen automatically using the KS-static as a difference measure after the first three training sessions and the best frequency bands varied among subjects. In five subjects, the best features were around 10 Hz, in four subjects around 2 Hz, and in one subject in the $18-20$ Hz band. The time window for feature extraction did not allow for post-movement features, as these were not found in the patients in P II.

During training, the classifier was updated online, giving up-to-date feedback to the subjects. However, the results are presented from the testing part where the classifier was kept static. This corresponds to real BCI use where we cannot

the classifier based on class labels as the intent of the subject is not known. EEG trials related to externally cued movements (ISI=2s) could be classified with 80% accuracy in 7/10 subjects after 20 minutes of feedback training. The subjects hit the correct target in 84−100% of all games; 6/10 subjects chose no wrong targets, which is important in many practical applications. The speed of the application use was quite good for S1−S7, who were able to make a choice, i.e. hit the target on average, every 8-17 s.

4.3.2 Discussion

According to our hypothesis, we obtained good classification accuracies in same order of the accuracies obtained during mu-rhythm training, with the advantage of a short training period. Unfortunately, our experimental design had some shortcomings, making comparison of our results to those of others difficult. First, we restricted each game to a maximum of ten trials. We used this maximum to prevent subjects' frustration and to have an equal amount of trials from both classes for classifier optimisation during the training sessions. Second, we did not realise that even though the subjects were performing single movements every 2 s, the application itself required several consecutive movements of the same finger before the target was reached. Activation related to movements could be correlated, and control might not be possible without several activation-related consecutive movements. To check this possibility, we performed offline analyses showing that classification related to the first trial also was possible. Third, if it would have been available at the time of the experiments, the use of BCI2000 (Schalk et al., 2004) and its experimental setups would have guaranteed comparable experiments with other research groups.

Our results are outperformed by a more recent study by Blankertz et al. (2007). In their study, ten untrained healthy subjects controlled a two-class BCI by imagining either left or right hand or foot movements basically after no training. Only a calibration session was needed to gather data for the classification algorithm. The classified CSP features are based on the reactivity of the mu-rhythm. They reach bit rates as high as 37.1 bits/min. Surprisingly, subjects were able to change their mental task, i.e. limb of imagination, as fast as every 1.8 seconds. It is not clear if the subjects imagined single movements or continuous movements. One drawback of their study is the large amount of electrodes that are needed: 128 channels. Long preparation times are needed before use.

Nonetheless, their methods need to be verified with motor-disabled subjects before they are declared useful for assistive technologies (Blankertz et al., 2007). As a merit, a bit rate of 37.1 bits/min is almost high enough for a healthy subject to control some easy application, if having 128 electrodes on his head is not considered a problem. Based on the experience from study P II, we doubt that untrained motor-disabled patients will achieve bit rates even close to those of Blankertz

et al. (2007) if control is based on the mu-rhythm. To our knowledge, they have not yet tested their methods on motor-disabled patients. We tested our methods on tetraplegic patients in P IV.

Despite updating the classifier online, our experimental design and short training periods do not allow for discussion on the effects of online training of both the algorithm and the user. Comparison is difficult especially since we have not conducted a comparable study with a static classifier.

4.4 EEG-based brain-computer interface for tetraplegics (P IV)

4.4.1 Results

The experimental setup was the same as in P III, except that the subject's task was to move a circle on the screen by attempting hand movements. Based on P II, we used the amplitudes of the slow cortical brain activity (1−3 Hz), sub-sampled from seven time-intervals around the cue, as initial features. For S1, we used the initial features throughout the experiment because he performed well with them during the initial training session. Individual features were selected for S2−S6 during the first break. Several time windows for the low frequency band were also chosen by the feature extraction algorithm for subjects S2 and S3. The features of S4−S6 were widely distributed from 6 to 38 Hz, showing little separability between the classes according to the Kolmogorov-Smirnov statistic.

Three out of six subjects (S1−S3) with complete tetraplegia could control a BCI after five to seven 4-minute training sessions. They moved a circle several times from the centre of the computer screen to the correct target on one of its sides. Results are presented from a testing period when the classifier was not trained any further. S1−S3 hit the target with an accuracy of 94%, 67%, and 57% (every game included), respectively. Despite the relatively low hit accuracy due to high number of games ending unfinished (ten trials were exceeded), these subjects made few or no mistakes. The average correct hit rates were 2.2−3.8 hits/min. Assuming that the single EEG trials are independent, attempted left- versus right-hand movements could be classified with mean accuracies of 79%, 69%, and 61%. The transmitted information rate for the best subject (S1) was 8 bits/min.

To be able to exclude the possibility of BCI control based on eye movements, we simulated the experiment using only the EOG channels. In the individual subjects, the offline single-trial classification accuracies were from 46% to 61% (mean 52%) for all subjects. S2 showed the highest classification accuracies of 61% in the last two testing sessions. These numbers are lower than the classification accuracies of the EEG channels.

4.4.2 Discussion

Three subjects obtained moderate BCI control. S1 showed good separability between the classes based on the low frequency band already during the first training session. In addition, two other patients could control the application. However, an additional offline analysis showed that the moderate discriminability of S2 was also obtained with the EOG channels. The classification accuracy of S2 was 61%, lower than the 67% obtained on the basis of EEG channels. It is quite possible that the same features which were used in EEG trial classification were also picked up by the EOG channels. However, we cannot exclude the possibility that eye movements influenced the classification of his data.

All subjects were highly motivated and gave a genuine effort. Presently, it is impossible to know whether the failure was due to a too short training period or the possibility that one or several of these subjects might not be able to produce separable signals over the sensorimotor cortex by single movement attempts. A follow-up study exploring the effects of learning on single trials is needed.

We developed methods for online classification of single trial movements and tested these on 10 healthy subjects in P III. The classification accuracies were high enough for accurate control. The experimental design of this study was similar to P III, except that the experiment was generally shorter as the patients tired more quickly. The results of the tetraplegic subjects are much worse than those of the healthy subjects. This means that methods developed and tested with healthy subjects do not necessarily work as well with motor-disabled patients.

Our offline study P II showed that slow movement-related potentials of left and right attempted hand movements of three tetraplegics could be classified accurately whereas the present online results are much worse. A couple of factors can account for these differences. First, online results are usually worse than in offline analysis as the task of following the feedback is more difficult, which influences the concentration and the visual view of the subjects affecting the measured signals. Second, as there are large differences between subjects and so few patients were available, the subjects in P II might have been better due to sheer chance.

Work with motor-disabled patients, though rewarding, is much more difficult than working with healthy subjects. They cannot help the experimenter fit the cap comfortably or move themselves into better sitting positions. Some patients also tire quickly of sitting for too long. Unfortunately, because outside personnel is needed for cleaning the skin and washing the hair, it was more difficult to get good impedances for the measurements. Furthermore, patient rooms and wheelchairs include electrical devices that interfere with the signals. Spasticity is also a common problem, causing jerking movements and artefacts especially in the MEG signals.

4.5 Vibrotactile feedback for brain-computer interface operation (P V)

4.5.1 Results

In our preliminary experiments presented in the beginnng of PV, we found that five able-bodied and three paraplegic subjects were able to discriminate between vibrotactile stimulations of slightly different intensities or at slightly different locations (see Fig. 3, Publication V, for further details). Studies I−III compared vibrotactile and visual feedback in three short experiments. We investigated whether vibrotactile feedback can improve BCI performance instead of or in addition to visual feedback (Study I and II). Furthermore, we tested whether BCI control during a disturbing visual task (Study II) and visual application control (Study III) is possible with vibrotactile feedback and how it compares with control during visual feedback.

In Study I, six subjects practised for three 7-minute sessions with visual and three sessions with vibrotactile feedback. The order of the given feedback modalities was counterbalanced across subjects. No differences were found between training with vibrotactile or visual feedback during the 42-minute experiment. With both feedbacks, the average classification accuracy over sessions and subjects was 68%. The results were confirmed with six other subjects in a similar 41-minute long study (II) where the corresponding accuracies were 67% (vibrotactile) and 68% (visual). Study II also included a robot simulator program as a visual distractor. When asked, most of the subjects (10/12) felt that vibrotactile feedback was more natural. In the case of conflicting feedback, i.e., when the classification went wrong, the vibrotactile vibration disturbed more.

In both Study I and II, the stimulation caused vibrotactile responses in the measured EEG signal, appearing in 0−8 Hz and 30−40 Hz bands in synchrony with the onset and end of the stimulation. The ERP during left- and right-side vibrotactile stimulation, low-pass filtered below 10 Hz, shows in both hemispheres a response peaking at around 200 ms. Both this low- and high-band artefact did not interfere with our mu-rhythm control signals.

In Study III, the subjects received either continuous visual or vibrotactile feedback of the 'BCI' classification as they simultaneously tried to navigate a visual placeholder (updated every 2 s) through a corridor of rooms. To ensure visual attention to the application, the subjects were asked to detect a visual stimulus before entering the next room. If they detected the stimulus incorrectly, they had to renavigate the room. Performance was measured in several ways: rate of steps in the ideal path, rate of steps in an acceptable path, time to complete the 10-room path, and rate of correct answers to the task (key colour).

If we only consider the subjects' ability to guide the placeholder through the rooms, the accuracies obtained from visual and tactile feedbacks were comparable

(80.9% versus 83.7%, $p > 0.05$). The most notable difference was in the attentive resources that subjects were able to devote to the task. A significantly higher rate of mistakes (86.0% *vs.* 97.5%, $p = 10^{-4}$) occurred when visual attention was divided between the control and task monitors. Given the payload set for wrong answer, this yielded a significantly longer time to the destination in the same condition (182 seconds for visual and 131 seconds for vibrotactile feedback, $p = 2 \times 10^{-4}$).

4.5.2 Discussion

In this first publication introducing vibrotactile feedback, we found that tactile feedback permits an appropriate training of users to BCI operation, does not interfere with simultaneous visual stimuli, and may improve performance when the subject's attention is highly loaded by a simultaneous visual task. These results are, however, from three short studies; long-term effect of vibrotactile feedback needs more investigation.

In BCI applications, three ways of using vibrotactile feedback are possible. First, vibrotactile feedback could be used in addition to visual feedback, giving the subjects multimodal feedback. Second, tactile feedback could be given when visual attention is needed for application control, when the application itself, such as an intelligent wheelchair, is mostly controlled by an intelligent control unit. In these first two cases, feedback conveys the output of the BCI classifier. Also, feedback of the navigation environment, for instance, might be useful. Thus, third, vibrotactile feedback could inform the subject about parts of the environment the subject cannot see.

As a next step, subjects should be trained with vibrotactile feedback to control their mu-rhythm using e.g. the BCI2000 to allow for appropriate comparison with visually trained subjects. It would also be interesting to test if blind people prefer vibrotactile or auditory feedback. Tactile feedback can more easily be distributed spatially mimicking for example a moving cursor than auditory feedback.

Chapter 5

Discussion

The results of this study are discussed in the light of the four aims listed in section 2. These aims relate to results in several publications simultaneously. For more discussion of the results of each publication the reader is referred to section 4 where the discussion of the original publications is extended to the newest publications that were not available at the time of printing the original publication.

Our first aim was the characterisation of sensorimotor cortical activation to improve classification of single MEG and EEG trials related to real or attempted movements. We inspected this in several studies with healthy subjects in Publications I and III and with tetraplegic subjects in II and IV. By characterisation of the signals we achieved in healthy subjects high classification accuracies. These healthy subjects showed clear contralateral movement related activity patterns in the 20-Hz (mu-rhythm) range both pre- and post-movement. These patterns were not as clear in tetraplegic subjects and we used low-band activity instead. The characterisation of the brain signals show that the activation patterns of movement-disabled persons differ on critical aspects from those of healthy subjects. This finding suggests that all methods developed for motor-disabled patients should be tested with them. For example, in the first study demonstrating two-dimensional cursor control using noninvasive signals, none of the four subjects was severely motor-disabled (Wolpaw and McFarland, 2004). The applicability of the results depends on the success of a replication study with motor-disabled patients. Despite most research being done with healthy subjects, fortunately, in the last years there has been a clear increase in the research with severely disabled and locked-in patients (see, e.g., Pfurtscheller et al., 2000; Birbaumer et al., 2000; Neuper et al., 2003; Kubler et al., 2005; Vaughan et al., 2006; Sellers and Donchin, 2006).

The second aim of this thesis was the evaluation of MEG for BCIs, which we tested in Publication I and II. As described in section 1.2.5 MEG can provide more localised signals than EEG. MEG signals are also easier to interpret as no refer-

encing is needed, and MEG detects (in case of an ideal sphere) only the tangential sources. These features can make classification of MEG signals easier than EEG signals. Contrary to our hypothesis, we did not obtain better accuracies with MEG than with EEG. Our findings were recently corroborated by an online MEG study (Mellinger et al., 2007). As a conclusion, so far MEG has not proven superior to EEG. In addition, MEG devices are immobile, expensive, and sensitive to urban magnetic noise, features that certainly limit their usefulness in BCI applications. Still, improvements are possible with more research defining optimal tasks for MEG classification. MEG might prove useful in single-trial classification of multiple classes with spatially separate distributions. For example, three tasks with activation patterns in spatially separate areas such as foot movement in addition to left and right finger movement, could prove better than EEG. If its full potential is used, the spatially more accurate MEG could provide better feedback to the subjects during initial training and shorten training times.

There are not many online MEG systems available that can be used for BCI development, an additional problem that delays discovering the true value of MEGs for BCIs. At the time of our experiments, the platform BCI2000 (Schalk et al., 2004) was not compatible with our Neuromag MEG device. The platform was not compatible with our EEG Brain Products equipment either but we are able to develop our own Matlab-compatible online EEG system. Presently, BCI2000 is compatible with most systems and when possible its use is highly recommended; developing one's own real-time feedback system is time-consuming.

Our third aim was to inspect the use of brain signals related to externally cued single trial real or attempted finger movements for online BCI classification. Control with single-trial movements gave good results with practically no training in ten able-bodied subjects. Three of our six tetraplegic subjects gained moderate control. For two of these, two-class classification accuracy was higher than 70%. However, the accuracies were much worse than in healthy subjects. So far it seems that fast learning of an endogenous online BCI use to achieve good classification accuracies is possible in only some tetraplegic patients. Future research should investigate how the brain signals evolve in subjects who initially learn single-trial control and continue to train for some time. It is possible that the contralaterality of the sensorimotor activity will become more evident with training as shown in one subject by Pfurtscheller et al. (2000).

Unfortunately, our results cannot be generalised to other motor-disabled patients. Spinal-cord injury and ALS can affect the functioning of the sensorimotor cortex in different ways, and research on locked-in patients with ALS is needed before drawing conclusions about whether our single-trial approach would work with them. ALS patients that are not yet severely locked-in have been able to control a P300-based visual or auditory BCI (Sellers and Donchin (2006) and for a review see Birbaumer and Cohen (2007)), and so far this approach has provided the best bit rates for them.

Our fourth aim, studied in Publication V, was to compare visual and vibrotactile feedback. We showed in three short experiments that use of tactile feedback is feasible. Hopefully, this first publication on vibrotactile feedback, in addition to work with auditory feedback (Pham et al., 2005; Hinterberger et al., 2004; Nijboer et al., 2008), will increase research of different feedback modalities while also improving research on learning with feedback. As BCI training usually requires long training times, the need for more research on long-term effects of feedback is evident.

The four aims that were inspected relate more to basic brain research than real BCI use. Our research gave more insight in the functioning of the brain during attempted movements and learning during different feedback modalities than for designing BCI applications. In most experiments, we used a simple application of moving a circle on a screen. However, in Study II in Publication V, we did integrate our BCI algorithms with an intelligent simulated wheelchair program. For six healthy subjects, one-dimensional control (move left and right) was possible. A real version of this intelligent BCI-driven wheelchair is operational at the Mechanical Engineering Department at K.U. Leuven in Belgium (Vanacker et al., 2007).

The aim of the thesis was not to test various signal processing methods. The measured EEG and MEG signals are noisy and the task dependent activity patterns are difficult to differentiate. This poses several challenging signal processing tasks which include choosing the appropriate activation patterns for control (features, for example 20-Hz activity), choosing how the features are extracted (e.g. spectral features computed with FFT), and what model (classifier) is used to determine to which class a new sample (set of features) belongs. Different methods were used in different publications. This is partly because different methods are suitable for capturing different kind of activations, for example in frequency vs time-domain, but also because we developed and modified the methods during our research. A detailed evaluation of these methods is beyond the scope of this thesis as most of the work has been done by the co-authors but a short discussion follows.

Automatic feature selection is one of the biggest challenges in BCI research. In PI and PII we chose the features based on visual inspection of the averaged training data. In PIII and IV we used a simple automatic feature selection procedure based on the Kolmogorov-Smirnov test. Due to the large number of possible features and feature combinations we decided to compute a comprehensive set of both spectral as well as temporal features and to compare the class-conditional distributions separately for each of them. It worked well, if the subjects had well separable activation patterns but worked rather poorly for, e.g., the three patients whose activation patterns were not distinguishable. The biggest problem was the large dimensionality of the feature space compared to the amount of training samples. In Study II of Publication V we also tested a Bayesian approach to select the most relevant features for a linear classifier automatically. The results were

encouraging even with so few training examples and this approach should be developed further. Especially the MCMC approach for estimating the posterior distribution of the unknowns was too slow for online experiments.

In PI, the spectral features of the 20-Hz post-movement rebound were estimated with an autoregressive (AR) model. Unfortunately we could not proceed in this direction as our experiments with tetraplegics showed no contralaterally dominant activity in the 20-Hz range. In PII the features were amplitude values of the slow activity (1−3 Hz and 3−7 Hz) around a cue triggering the onset of the movement. This extraction method does not require difficult signal processing. These features are very easy to compute but correct timing of movements with respect to the cue is critical. In PII we used both low frequency amplitude values as well as higher frequency spectral features. We decided to include as many relevant features as possible also from higher frequency bands. The dimensionality of the feature space was kept manageable for classification by removing correlations among the features with whitening. This worked well when the subject had separable signals. The same method was used in PIV but it did not work as well as the patients showed less lateral movement-related activity. In this case, the problem was probably not in the method but in the inseparable signals. In PV we compared vibrotactile and visual feedback with healthy subjects imagining continuous movements. Spectral features suit best for continuous movements. The features in Study I were FFT components which captured the continuous desynchronizations on a 1-2 second time scale adequately. In Study II we extracted similar spectral features with gabor filters but these were more focused in time-domain.

The classifier used in PI was chosen based on previous work. In PII-V, the classifiers were linear. A dynamic classifier was also tested in PII but could not be applied in the online experiments as it was not possible to implement the required online signal processing methods in the online system. In PIII-PV the linear classifiers were trained online using correct class-labels. The need for online classifier training is widely acknowledged but not many online applications have been reported so far (see e.g. reviews by Millan Jdel et al., 2007; McFarland et al., 2006). PIII was one of the first attempts and unfortunately our experimental design made our results difficult to compare with other studies. Subjects performed several consecutive single trial movements before reaching the target, which made it impossible to know whether the activations related to these single trials were independent of each other. To ensure that the subjects played several games, i.e. they could try to hit several targets, and to maintain a balanced set of training examples from both classes, the subjects were given a maximum of only ten trials before the game ended. Future research comparing different signal processing methods should aim to find more general experimental setups that would make comparisons easier. When using online training it is difficult to select when the model should be trained and when it should be kept static. It is also difficult to know when the training should be done by the user and when by the model,

and what happens if both learn simultaneously. Longer experiments are needed to address this question. Furthermore, choosing the correct speed for adapting the classifier in a supervised framework is crucial since too quick updates can produce false results and erroneous feedback.

In future, BCIs can help motor-disabled patients communicate and control external devices without muscle movements. Unfortunately, so far BCI development has been more research than development of really useful systems. Presently, there are two main directions in BCI research. The first focuses on developing better signal analysis methods for classification of brain signals (see e.g. Blankertz et al., 2006; Hill et al., 2006; Li et al., 2004; Blankertz et al., 2004; Dornhege et al., 2004; Millan Jdel and Mourino, 2003b; Guger et al., 2000; Roberts et al., 1999)and the other on training subjects to use BCIs (see e.g. Wolpaw and McFarland, 2004; Cincotti et al., 2003; Elbert et al., 1980). Our research is located somewhere in between these two directions. Despite being focused on bit rates, we also aimed at testing our methods with the motor-disabled population and having short training times. Future research on BCIs should concentrate on issues most pertinent to developing new assistive systems for motor-disabled patients. While development of classification methods is important, more work with motor-disabled patients is needed, especially when testing new signal processing methods. In addition, further inspection of different feedback modalities would be valuable, as visual attention might be needed for application control. Also, other brain imaging techniques, especially near-infrared spectroscopy, perhaps combined with EEG, can provide better control signals.

The user group gaining most from BCI technology are locked-in patients – not tetraplegics. Our work with tetraplegics showed how well they use assistive technologies with other control sources such as their mouth. BCIs would be especially important for completely locked-in patients, who cannot move any voluntary muscles. Contrary to earlier beliefs, the incidence of depression in these patients given the possibility to communicate is not higher than that of the general population (e.g. Robbins et al. (2001)). Unfortunately, however, as discussed in the introduction, according to a review by Birbaumer and Cohen (2007), not a single patient in a fully locked-in state has been able to obtain control of her brain signals. Hopefully some of the obstacles of helping completely locked in patients communicate will be solved. Nonetheless, present BCIs offer tetraplegics and other motor disabled patients an additional or alternative control method in producing text, controlling one's environment, and using internet or email applications. Occasionally, these patients can even find BCIs less tiring to use (Vaughan et al., 2006).

Despite not yet creating prefect applications, BCI research has benefited other fields of science. As BCI researchers have intensively studied different electrophysiological control signals, this has increased understanding of, e.g., the murhythm, P300 and SCP (see e.g. Pfurtscheller and Lopes da Silva, 1999; Farwell

and Donchin, 1988; Birbaumer et al., 1990) . In addition, we know more about how the motor cortical areas of tetraplegics and other motor-disabled persons differ from those of healthy subjects. We also understand the disease pathology of especially ALS patients better. BCI research has also created a need for more easy-to-use, cheaper, and more portable brain measurement devices. In the future, portable NIRS devices look especially promising in BCI use. Noisy brain signals have inspired engineers and mathematicians to develop more robust signal processing methods. Also, the low bit rate output signals have created a need for the development of new, more intelligent assistive devices, such as BCI controlled wheelchairs. Finally, BCI research can also inspire the emergence of new feedback research directions to treat disorders like epilepsy and attention deficit disorder.

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