HELSINKI UNIVERSITY OF TECHNOLOGY
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EEG-based Brain Computer Interfaces

In partial fulfillment of the requirements for the degree of Master of Science

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TEKNILLINEN KORKEAKOULU **DIPLOMITYÖN TIIVISTELMÄ**

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Tässä työssä käsitellään EEG-pohjaisia aivokäyttöliittymiä. Erityisesti keskitytään Adaptive Brain Interface (ABI) -nimiseen aivokäyttöliittymään, jota käytetään työn kokeellisessa osassa. Kokeissa käytettiin uutta ABI-laitteistoa, joka saatiin Teknillisen korkeakoulun Laskennallisen tekniikan laboratorioon marraskuussa 2001.

Aivokäyttöliittymissä on kaksi päälähestymistapaa: ajatustehtäviä käyttävä EEG hahmontunnistus ja EEG:n itsesäätelyyn perustuvaan väline-ehdollistuminen. EEG:n mittaaminen ja aivokäyttöliittymän komponentit esitellään. Erityisesti tarkastellaan käyttäjälle annettavaa palautetta ja harjoittelua. Aivokäyttöliittymien suorituskyvyn mittaaminen esitellään monipuolisesti. Työssä esitellään tarkemmin ABI:a ja viittä muuta aivokäyttöliittymää, joita myös verrataan useista eri näkökulmista. Aivokäyttöliittymien suorituskyvyn vertaaminen osoittautui vaikeaksi tulosten erilaisista raportointimenetelmistä johtuen.

Työssä raportoidaan tulokset kokeista, joissa kolme koehenkilöä harjoitteli ABI:n käyttöä noin tunnin päivässä viitenä peräkkäisenä päivänä käyttäen kolmea ajatustehtävää. Jokaisesta mittauksesta esitetään tulokset yhteisesiintymämatriisina ja kanavakapasiteettina. Lisäksi kunkin koehenkilön tuloksista esitetään kuvaajat, joissa voi nähdä ajatustehtävien oikeiden ja väärien luokitusten osuuksien kehittymisen 5 päivän aikana.

Tuloksissa oli suuria yksilöllisiä eroja. Suorituskyky vaihteli paljon mittauksesta toiseen eikä varsinaisesta kehitystä tapahtunut viiden päivän aikana kenelläkään koehenkilöistä. Tulokset olivat huonompia kuin aikaisemmalla ABI-laitteistolla saadut. Mitään yksittäistä syytä tulosten heikkenemiselle ei löydetty.

Avainsanat: aivokäyttöliittymä, EEG, ajatustehtävä, biopalaute

HELSINKI UNIVERSITY OF TECHNOLOGY | **ABSTRACT OF THE MASTER'S THESIS**

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This work deals with EEG-based brain computer interfaces, concentrating on the Adaptive Brain Interface (ABI), which is used in the experimental part of this work. The new ABI equipment, obtained in the Laboratory of Computational Engineering of the Helsinki University of Technology in November 2001, was used in the experiments.

Brain computer interfaces (BCIs) are divided into two main approaches: the EEG pattern recognition approach based on different mental tasks and the operant conditioning approach based on the self-regulation of the EEG response. The measurement of the EEG and components of a BCI are presented. Feedback and training the user receives are especially studied. The measurement of the BCI performance is reviewed extensively. The ABI and five other BCIs are examined and then compared from different viewpoints. The performance comparison of the different BCI systems proved to be difficult because the different methods of reporting results.

The results of the experiments in which three subjects trained to use the ABI during five consecutive days about an hour per day using three mental tasks are reported. The results of every recording are presented as confusion matrices and channel capacities. In addition, graphs showing the development of the correct and false classifications for all mental tasks are displayed.

There were substantial individual differences in the results. The performance varied a lot between the recordings and no actual development occurred during the five days with any of the subjects. The results were worse than those obtained with the older ABI equipment. No single reason for the weakening of the results was found.

Keywords: brain computer interface, EEG, mental task, biofeedback

Vanhemmilleni

Foreword

This work was done in the Laboratory of Computational Engineering in the Helsinki University of Technology as a part of the project called “Adaptive Brain Interfaces” funded by the ESPRIT Programme of the European Commission. The supervisor of this work was Professor Mikko Sams and the instructor Academy Fellow, Dr. Tech Jukka Heikkonen.

I would like to thank Dr. Tech Jukka Heikkonen for his guidance. I thank also Prof. Mikko Sams and all the personnel here in the Laboratory of Computational Engineering with whom I have had the pleasure to work with. Especially, I would like to thank Tommi Nykopp for his help on things related to feature extraction, classification and channel capacity. Finally, I would like to thank José del R. Millán for his help with issues related to the Adaptive Brain Interface.

Espoo, May 3, 2002

Janne Lehtonen

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Nomenclature

Abbreviations

AR	AutoRegressive model
ABI	Adaptive Brain Interface
ALN	Adaptive Logic Network
ALS	Amyotrophic lateral sclerosis
API	Application Programming Interface
BCI	Brain Computer Interface
CC	Channel Capacity
ECG	Electrocardiography, Electric activity in the heart
EEG	Electroencephalography, Electric brain activity
EEP H11	Electro Encephalo Processor model H11
EMG	Electromyography, Electric activity in the muscles
EOG	Electrooculography, Electric activity in the eyes
EP	Evoked Potentials
ERD/ERS	Event Related Synchronizations/Desynchronizations
ERP	Event Related Potentials
FFT	Fast Fourier Transform
GSR	Galvanic Skin Response
fMRI	functional Magnetic Resonance Imaging
MEG	Magnetoencephalography
MMLD	Man-Machine Learning Dilemma
MLP	Multi Layer Perceptron
OC	Operant Conditioning
P300	Event related Potential occurring 300 ms after stimulus
PET	Positron Emission Tomography

PR	Pattern Recognition
RP	Readiness Potential
SCP	Slow Cortical Potential
SL	Surface Laplacian
SPECT	Single Photon Emission Computer Tomography
TTD	Thought Translation Device
VEP	Visually Evoked Potential

Symbols

α	alpha band EEG frequencies
β	beta band EEG frequencies
δ	delta band EEG frequencies
μ	mu band EEG frequencies
Θ	theta band EEG frequencies
σ^2	standard deviation of a normal distribution

Chapter 1

Introduction

There are two aims in this work. The other is to provide a comprehensive review and comparison of the most important Brain Computer Interface (BCI) systems developed to this day. The other is to test the performance of the new Adaptive Brain Interface (ABI) device obtained in the laboratory of the Computational Engineering in November 2001.

Brain-Computer Interface (BCI) is a communication system, which enables the user to control special computer applications by using only his or her thoughts. Different research groups have examined and used different methods to achieve this. Almost all of them are based on electroencaphalography (EEG) recorded from the scalp. The EEG is measured and sampled while the user imagines different things (for example, moving the left or the right hand). Depending on the BCI, particular preprocessing and feature extraction methods are applied to the EEG sample of certain length. It is then possible to detect the task-specific EEG signals or patterns from the EEG samples with a certain level of accuracy.

First signs of BCI research can be dated back to 1960's, but it was in 1990's when the BCI research really got started. Faster computers and better EEG devices offered new possibilities. To date there have been over 20 BCI research groups. They have taken different approaches to the subject, some more successful than others. Less than half of the BCI research groups have build an online BCI, which can give feedback to the subject. None of the BCIs have yet become commercial and only a couple have been tested outside laboratory environments.

Despite the technological developments numerous problems still exists in building efficient BCIs. The biggest challenges are related to accuracy, speed and usability. Other interfaces are still much more efficient. If a disabled person can move eyes or even one muscle in a controlled way, the interfaces based on eye-gaze or EMG switch technology are more efficient than any of the BCIs today. However, BCI could provide a new communication tool for people suffering from so called locked-in syndrome. They are completely paralyzed physically and unable to speak, but cognitively intact and alert. Locked-in syndrome can be caused, for example, by amyotrophic lateral sclerosis (ALS), high-level spinal cord injure or brain stem stroke. In its severest form people are not able to move any muscle in their body.

Adaptive Brain Interface (ABI) is a BCI which has been developed under the project “Adaptive Brain Interfaces” financed by European Commission. The project started in 1998 and ended in 2001. The ABI is based on the pattern recognition approach. In this approach the user concentrates on different mental tasks, for example, moving the left hand or visually rotating a cube. The classifier is trained with EEG data containing the different mental tasks. The trained classifier can then classify EEG online and provide feedback for the user.

In this work basics of Brain-Computer Interface (BCI) are explained. Six different BCI systems (including ABI) are reviewed and then compared with each other. One week training with three subjects was carried out with a new ABI device in the Laboratory of Computational Engineering. Test results are presented and discussed.

In the second chapter, the basics of brain computer interface are described. Functional areas of the brain, EEG and its measurement are described. BCIs are divided into two main approaches called pattern recognition and operant conditioning approaches. BCI components are described briefly. Feedback, training and BCI performance are described in more detail. Finally, several BCI categories are introduced.

The third chapter provides the review and comparison of the six BCI systems, which are BCIs developed at the Alberta and the Oxford universities, a BCI developed at the Wadsworth Center, a Thought Translation Device and a Graz BCI and the ABI. The ABI is covered in more detail than other five.

The fourth chapter introduces the new ABI system. It presents the experimental methods and the results from five days training with three subjects. It also describes subject reports of mental task strategies and feedback experiences. Finally, it provides discussion on the results, mental tasks and feedback. The fifth chapter provides the conclusions of this work.

Chapter 2

Brain-Computer Interfaces (BCIs)

In the first international meeting devoted to BCI research held in June 1999 at the Rensselaerville Institute near Albany, New York, it was defined as follows: *"A brain-computer interface is a communication system that does not depend on the brains normal output pathways of peripheral nerves and muscles"* [66].

According to this definition, a BCI should be able to detect the user's wishes and commands while the user remains silent and immobilized. In order to do this, the brain activity must be monitored. Today there exists various techniques to do this. These include, for example, functional Magnetic Resonance Imaging (fMRI) [26], magnetoencephalography (MEG) [23], Positron Emission Tomography (PET), Single Photon Emission Computer Tomography (SPECT) [18], optical brain imaging, single neuron recording (with microelectrodes) and electroencephalography (EEG) [43].

From these methods, MEG, EEG and single neuron recording give continuous and instantaneous recordings of the brain activity (time resolution about 1 ms), which is required for real-time BCI. However, MEG is not practical to be used with BCI. The MEG measurements are made using a large device inside a magnetic shielded room. The single neuron recording, on the other hand, requires that the electrodes are inserted *inside* the skull. Therefore, almost all of BCIs reported to date have been based on EEG.

How can BCI then detect the user's commands from the EEG? There are two main approaches in achieving this. In the first approach the subject concentrates on a few mental tasks (for example, imagining the left hand movement or the cube rotation). Concentration on these mental tasks produce different EEG *patterns*. The BCI (or the classifier in particular) can then be trained to classify these patterns. The ABI and several other BCIs

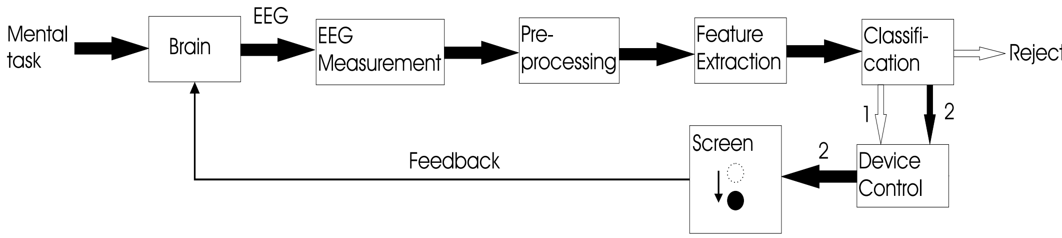

Figure 2.1: A BCI based on the classification of two mental tasks. The user is thinking task number 2 and the BCI classifies it correctly and provides feedback in the form of cursor movement.

(see e.g. [16, 58, 48, 32]) are based on this kind of *pattern recognition approach*.

In the second approach the user has to learn to self-regulate his or her EEG response, for example change the μ-rhythm amplitude [65]. Unlike in the pattern recognition approach, the BCI itself is not trained but it looks for particular changes (for example higher amplitude of a certain frequency) in the EEG signal. This requires usually a long training period, because all the training load is on the user. This kind of approach can be called an *operant conditioning approach*.

According to Allison [1] there are at least five components necessary for effective BCI system: 1) Knowing what to look for; 2) Knowing the relevant physiological signals; 3) Gathering the data from the user; 4) Extracting useful information from the raw signal; 5) Interface design.

Figure 2.1 shows a schematic picture of a BCI, which is based on pattern recognition approach. The BCI can classify two mental tasks and provides feedback in the form of cursor control. It has also “reject” option, if the probability of the classification does not exceed some predefined level.

The purpose of this chapter is to explain the concept of the BCI. First, the other part of the interface, the human brain, is examined. Then, the basic principles of electroencephalography (EEG) are explained. BCIs are divided into two above mentioned approaches. Then, the EEG measurement and the components of BCI system are defined. Feedback, human training issues and BCI performance measurement are explained after that. Finally, in the last section, BCIs are classified to different categories.

2.1 The human brain

The average human brain weights around 1400 grams. The brain can be divided into four structures: cerebral cortex, cerebellum, brain stem, hypothalamus and thamalus. The most relevant of them concerning BCIs is the *cerebral cortex*. The cerebral cortex can be divided into two *hemispheres*. The hemispheres are connected with each other via *corpus callosum*. Each hemisphere can be divided into four *lobes*. They are called *frontal*, *parietal*, *occipital* and *temporal* lobes. Cerebral cortex is responsible for many “higher order” functions like problem solving, language comprehension and processing of complex visual information [12]. The cerebral cortex can be divided into several areas, which are responsible of different functions. These areas can be seen in Figure 2.2. The functions are described in Table 2.1. This kind of knowledge have been used when with BCIs based on the pattern recognition approach. The mental tasks are chosen in such a way that they activate different parts of the cerebral cortex.

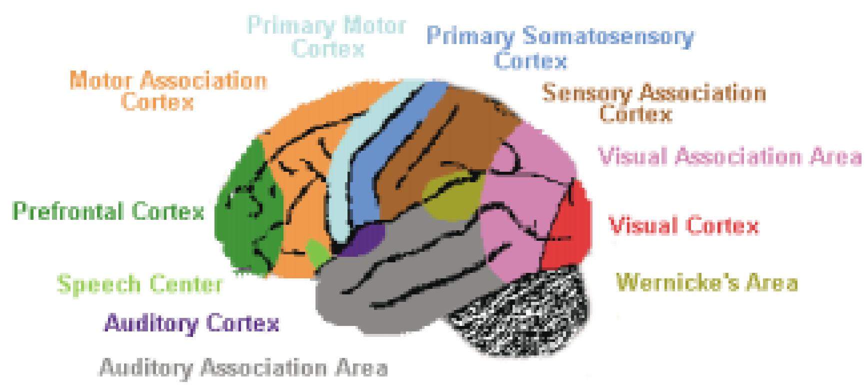

Figure 2.2: Functional areas of the brain [12]

Cortical Area	Function
Auditory Association Area	Complex processing of auditory information
Auditory Cortex	Detection of sound quality (loudness, tone)
Speech Center (Broca’s area)	Speech production and articulation
Prefrontal Cortex	Problem solving, emotion, complex thought
Motor Association Cortex	Coordination of complex movement
Primary Motor Cortex	Initiation of voluntary movement
Primary Somatosensory Cortex	Receives tactile information from the body
Sensory Association Area	Processing of multisensory information
Visual Association Area	Complex processing of visual information
Wernicke’s Area	Language comprehension

Table 2.1: Cortical areas of the brain and their function [12]

2.2 Electroencephalography (EEG)

Electroencephalography (EEG) is a method used in measuring the electrical activity of the brain. This activity is generated by billions of nerve cells, called *neurons*. Each neuron is connected to thousands of other neurons. Some of the connections are excitatory while others are inhibitory. The signals from other neurons sum up in the receiving neuron. When this sum exceeds a certain potential level called a *threshold*, the neuron fires *nerve impulse*. The electrical activity of a single neuron cannot be measured with scalp EEG. However, EEG can measure the combined electrical activity of millions of neurons [25].

The temporal resolution of EEG is very good: millisecond or even better. However, the spatial resolution is poor. It depends on the number of electrodes, but the maximum resolution is in centimeter range whereas, for example, in MEG, PET or fMRI it is in millimeter range [21]. The ongoing EEG is characterized by amplitude and frequency. The amplitudes of the EEG signals typically vary between 10 and 100 μV (in adults more commonly between 10 and 50 μV) [47].

The electrical activity goes on continuously in every living human's brain. We may sleep one third of our life times, but the brain never rests. Even when one is unconscious the brain remains active. Much of the time, the brain waves are irregular and no general pattern can be observed [62].

Allison [1] lists four prerequisites, which must be met for the activity of any network of neurons to be visible in EEG signal: 1) The neurons must generate most of their electrical signals along a specific axis oriented perpendicular to the scalp; 2) The neuronal dendrites must be aligned in parallel so that their field potentials summate to create a signal which is detectable at a distance; 3) The neurons should fire in near synchrony; 4) The electrical activity produced by each neuron needs to have the same electrical sign.

All this means that an overwhelming majority of neuronal communication is practically invisible in EEG. However, there exists various properties in EEG, which can be used as a basis for a BCI:

1. Rhythmic brain activity
2. Event-related potentials (ERPs)
3. Event-related desynchronization (ERD) and event-related synchronization (ERS).

Band	Frequency [Hz]
Delta (δ)	< 3.5
Theta (θ)	4-7.5
Alpha (α)	8-13
Beta (β)	>13

Table 2.2: Common EEG frequency ranges [47]

2.2.1 Rhythmic brain activity

Depending on the level of consciousness, normal people's brain waves show different rhythmic activity. For instance, the different sleep stages can be seen in EEG. Different rhythmic waves also occur during the waking state [62]. These rhythms are affected by different actions and thoughts, for example the planning of a movement can block or attenuate a particular rhythm. The fact that mere thoughts affect the brain rhythms can be used as the basis for the BCI.

The EEG can be divided into several frequency ranges as displayed in Table 2.2. They are named after Greek letters (δ, θ, α, β, γ). These ranges set the limits in which the different *brain rhythms* (named according to same letter as the frequency range) can be observed. The order of the letters is not logical and can be understood only in the historical view [47].

Figure 2.3 illustrates examples of the brain rhythms. These rhythms (*alpha, beta, delta and theta*) are explained later in this section according to Niedermayer [47]. Note that the list in Table 2.2 is not the definite list of the brain rhythms. Many other rhythms have been proposed in EEG literature. One of them is the *mu rhythm*. It is also included in this section, because it has significance in BCI research.

Delta rhythm. EEG waves below 3.5 Hz (usually 0.1-3.5 Hz) belong to the delta waves. Infants (around the age of 2 months) show irregular delta activity of 2-3.5 Hz (amplitudes 50-100 μV) in the waking state. In adults delta waves (frequencies below 3.5 Hz) are only seen in deep sleep and are therefore not useful in BCIs.

Theta rhythm. Theta waves are between 4 and 7.5 Hz. Theta rhythm plays an important role in infancy and childhood. In normal adults theta waves are seen mostly in states of drowsiness and sleep. During waking hours the EEG contains only a small amount of theta activity and no organized theta rhythm. Niedermayer lists some studies in which the theta activity of 6-7 Hz over frontal midline region had been correlated with mental activity such as problem solving. However, he did not find it in his own studies.

Alpha rhythm. The International Federation of Societies for Electroencephalography and Clinical Neurophysiology proposed the following definition of alpha rhythm: *Rhythm at 8-13 Hz occurring during wakefulness over the posterior regions of the head, generally with higher voltage over the occipital areas. Amplitude is variable but is mostly below 50 μV in adults. Best seen with eyes closed and under conditions of physical relaxation and relative mental inactivity. Blocked or attenuated by attention, especially visual, and mental effort.*'

The posterior basic rhythm increases in frequency during the childhood and reaches the frequency 8 Hz (the limit of the alpha rhythm) at the age of 3 years. At the age of 10 years the frequency reaches a mean of about 10 Hz, which is typical mean adult alpha frequency. The frequency tends to decline in elderly individuals and in dementia.

The alpha rhythm is temporarily blocked, i.e, its amplitude decreased, by eye opening (see an example in Figure 2.3), other afferent stimuli or mental activities. The degree of reactivity varies. Usually, eye opening is the most effective manipulation.

Mu rhythm. Mu rhythm frequency is around 10 Hz and amplitude mostly below 50 μV. Although the frequency and the amplitude of the mu rhythm are similar to the alpha rhythm, the mu rhythm is topographically and physiologically different from the alpha rhythm. Mu stands for motor and the mu rhythm is strongly related to the functions of the motor cortex, but also to the adjacent somatosensory cortex. The mu rhythm is blocked by movements or light tactile stimuli. The fact that the thoughts about performing movements and readiness to move can also block the mu rhythm, have made it important in BCI research.

Beta rhythms. Any rhythmical activity in the frequency band of 13-30 Hz may be regarded as a beta rhythm. Beta rhythm amplitudes are seldom larger than 30 μV. Beta rhythms can mainly be found over the frontal and central region. A central beta rhythm is related to the mu rhythm. It can be blocked by motor activity and tactile stimulation.

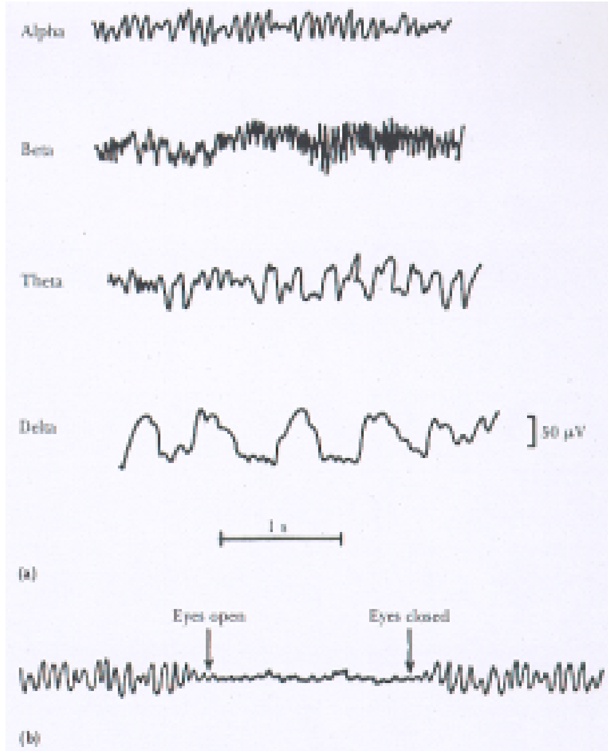

Figure 2.3: (a) Examples of alpha, beta, theta and delta rhythms. (b) Effect of eye opening in the alpha rhythm [62].

BCIs based on the rhythmic activity

Many BCI researches have considered about using the imagination of hand or foot movements as the basis of the BCI. Therefore, the mu rhythm plays an essential role in them. Pineda et al. [57] studied the use of the mu rhythm in BCI and concluded that "mu rhythm is not only modulated by the expression of self-generated movement but also by the observation and imagination of movement." Wolpaw et al. [65] have used the self-regulation of the mu rhythm or central beta rhythm amplitude in their BCI (see also section 3.1.3). To my knowledge, no other rhythmic activity have been used in BCIs. However, in EEG biofeedback, self-regulation of, for example, alpha or beta rhythms, has been used extensively [24].

2.2.2 Event-related potentials (ERPs)

Event-related potentials is a common title for the potential changes in the EEG that occur in response to a particular "event" or a stimulus. These changes are so small that in order to reveal them, EEG samples have to be averaged over many repetitions. This removes the "random" fluctuations of the EEG, which are not stimulus-locked.

Event-related potentials can be divided into exogenous and endogenous. Exogenous ERPs occur up to about 100 ms after the stimulus onset. They depend on the properties of physical stimulus (intensity, loudness etc.). The potentials from 100 ms onward are called endogenous. They depend largely on psychological and behavioral processes related to the event. Figure 2.4 A demonstrates examples of event-related potentials to visual stimulus and Figure 2.4 B to an auditory stimulus [42].

The most commonly studied ERP is *P300*. This positive deflection in the EEG occurs about 300 ms after the stimulus onset. P300 is commonly recorded during an "odd-ball paradigm". In it the subject has been told to respond to a rare stimulus, which occurs randomly and infrequently among the other, frequent stimuli [42].

Evoked potentials (EPs) is a subset of the ERPs, that rise in response to a certain physical (visual, auditory, somatosensory etc.) stimulus. A typical evoked potential is the *Visual evoked potential* (VEP) that reflects the output features of the entire visual pathway. The EEG over the visual cortex varies at the same frequency as the stimulating light [44].

BCIs based on ERPs

The DC-shifts presented in Figures 2.4 A and 2.4 B are also called slow cortical potentials (SCPs) by Birbaumer et al. [7]. Birbaumer et al. also describe a BCI called Thought Translation Device (TTD), which is based on the self-regulation of the SCPs. See section 3.1.4 for more information about the TTD.

The Air Force Research Laboratory have implemented and evaluated two BCIs based on the VEP detection [40]. In the other BCI the user is trained to control his or her VEP amplitude while watching a visual stimulus, which is modulated at a fixed frequency. In the other BCI the user can select "virtual" buttons. Two virtual buttons modulated at different frequencies are displayed at the same time. The user selects the button simply by looking at it.

A couple of BCIs have been based on the detection of the P300 [6, 17]. Donchin et al. [17] describe a BCI in which the user is presented with a matrix of 6 by 6 cells, each containing one letter of the alphabet. The user concentrates on the cell containing the letter which he or she wants to select, while each row or column is intensified in a random sequence. This

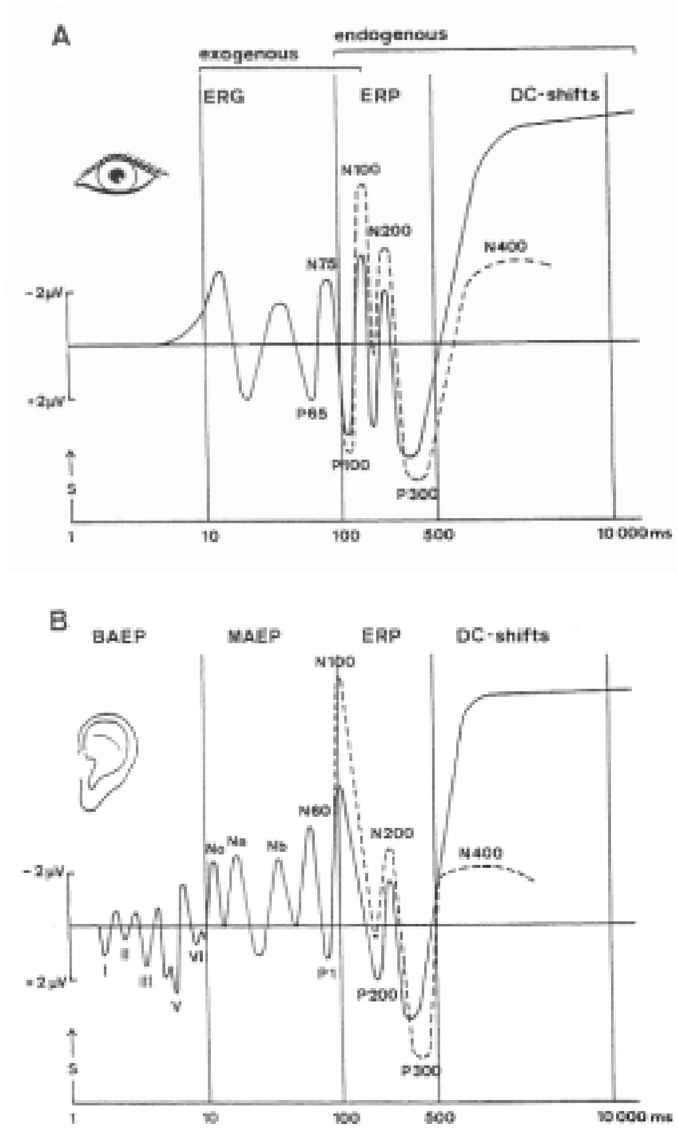

Figure 2.4: Averaged event-related potentials to visual (A) and auditory (B) stimuli [42].

produces an oddball sequence where the row or the column containing the attended cell are “rare” items and elicit a P300. In the online experiments, four subjects could select the letter of their choice in 56 % of the trials, when the maximum communication speed was 4.8 characters/min.

BCIs based on detection of *readiness potentials* (RP’s) have also been proposed by Barreto et al. [5] and Pineda et al. [57]. RP is an ERP which is time-locked to the performance or the imagination of the movement. It is most prevalent over cortical motor areas [57].

It should be noted, that the BCIs proposed by Middendorf [40] and Donchin et al. [17] need that the user is able to maintain attention on the “virtual” button or the cell containing the letter. It is unknown if the locked-in patient can do this long enough for these BCIs to work with them.

2.2.3 Event-related desynchronization (ERD) and event-related synchronization (ERS)

Event-related desynchronization (ERD) and event-related synchronization (ERS) can be defined as follows [51]:

1. Event-related desynchronization (ERD) is an amplitude *attenuation* of a certain EEG rhythm.
2. Event-related synchronization (ERS) is an amplitude *enhancement* of a certain EEG rhythm.

In order to measure an ERD or an ERS, the power of a certain frequency band (for example, 8-12 Hz) is calculated before and after certain “event” over a number of EEG trials. The event can be externally-paced (such as light stimulus) or internally paced (such as voluntary finger movement). The power (averaged over a number of trials) is then measured in percentage relative to the power of the *reference interval*. The reference interval is defined, for example, as 1 second interval between 4.5 and 3.5 seconds before the event (i.e. during the rest). The ERS is the power increase (in percents) and the ERD is the power decrease relative to the reference interval (which is defined as 100 %). To keep the power at the reference interval at the resting level, the interval between two consecutive events should be random and not shorter than a few seconds [45].

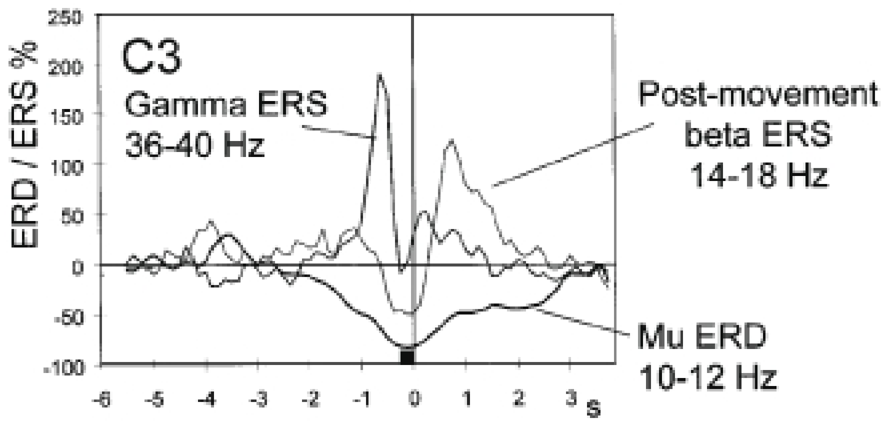

Figure 2.5: ERD time courses computed for three different frequency bands (10-12 Hz, 14-18 Hz, and 36-40 Hz) from EEG trials recorded from electrode position C3 during right index finger lifting [56].

ERD and ERS can be presented in time and space. Figure 2.5 presents power time courses for three different frequency ranges (10-12 Hz, 14-18 Hz and 36-40 Hz). EEG was recorded over the electrode position C3 during the right index lifting. Vertical line at t=0 presents the movement onset. Figure 2.6 displays ERD maps for the left and the right motor imagery obtained from a single subject. Using single trial-EEG data, distribution of the alpha band (9-13 Hz) ERD was calculated. The maps are shown at t=625 ms after the representation of the cue.

BCI based on ERD and ERS

Pfurtscheller and Aranibar first quantified ERD in 1977. Since then Pfurtscheller developed a BCI called Graz BCI in 1990s. The Graz BCI is based on detecting ERD and ERS of the different μ and β rhythm bands during the imagined left and right hand movements (see, for example, [55]). The operating of this BCI was performed in series of trials lasting 8 seconds each. The interval between the trials was randomized between 0.5 to 2.5 s (see section 3.1.5 for information about the trial and the newest developments of the Graz BCI).

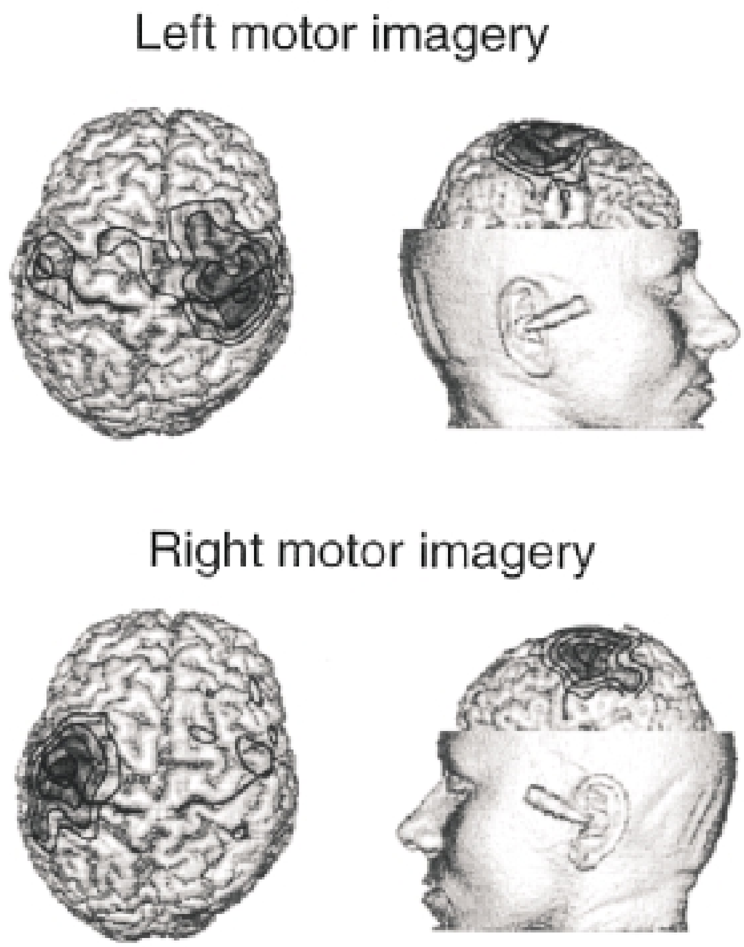

Figure 2.6: ERD maps for a single subject for the cortical surface of a realistic head model. The distribution of the alpha band (9-13 Hz) ERD was calculated for left and right motor imagery [55].

2.3 Two different BCI approaches

What are the thoughts the user thinks in order to control a BCI? An ideal BCI could detect the user's wishes and commands directly. However, this is not possible with today's technology. Therefore, BCI researches have used the knowledge they have had of the human brain and the EEG in order to design a BCI. There are basically two different approaches that have been used. The first one called a *pattern recognition approach* is based on cognitive mental tasks. The second one called an *operant conditioning approach* is based on the self-regulation of the EEG response.

2.3.1 Pattern recognition approach based on mental tasks

As discussed in the section 2.1 that different cortical areas have different functions. A few BCIs including the ABI are based on different mental tasks. These tasks should activate different cortical areas and produce different EEG rhythms. This approach can be called the pattern recognition approach. The BCIs based on the pattern recognition approach include the ABI [16] (see section 3.2), the Oxford BCI [58] (see the section 3.1.2) and the Alberta BCI [32] (see the section 3.1.1). Keirn and Anderson were to first to study the possibility of using classification of different mental tasks as a basis of a BCI [29, 2].

The mental tasks used in BCIs have included motor imagery, visual, arithmetic and baseline tasks. The principle of choosing the different mental tasks is that they produce easily detectable and different EEG patterns. Activation should occur close to the cortex so that it can be detected with scalp electrodes. In order to produce different EEG patterns, mental tasks should activate different parts of the brain. Therefore, the knowledge of cortical areas and their function (see section 2.1) has been used when choosing the mental tasks. For example, the imagination of the right hand movement should activate the left motor cortex and the imagination of the left hand movement the right motor cortex. The visual tasks should activate the visual association area, where as the arithmetic task should activate the prefrontal cortex.

It should also be noted that some mental tasks suit better to some people than others. For example, the kind of mental task in which the subject is instructed to imagine rotating cube around its axis (used for example in [16, 2, 29]) may be too difficult for some people. Therefore, the mental tasks used in BCI should be *individual*.

2.3.2 Operant conditioning approach based on self-regulation of EEG

In the section 2.2 different kinds of brain rhythms and event-related potentials were introduced. A couple of BCI research groups have based their BCIs on the *self-regulation* of one of these rhythms or potentials. This approach can be called the operant conditioning approach [31]. Birbaumer et al. [7] (see section 3.1.4) have based their BCI called a Thought Translation Device (TTD) on the self-regulation of the SCPs and Wolpaw et al. [65] (see the section 3.1.3) have based their BCI on the self-regulation of μ or β rhythms. This kind of approach differs from the pattern recognition approach in several ways. The users are not aware of any rhythms or event-related potentials happening in their brains unless they receive some kind of *feedback* (see section 2.6).

According to Kubler et al. [31] there are three elements important for successfully learning to self-regulate the EEG response:

1. Real-time feedback of the specific EEG activity
2. Positive reinforcement of correct behavior
3. Individual shaping schedule in which progressively more demanding tasks are rewarded

What are the instructions given to the user in order to acquire control of the specific EEG activity? Wolpaw et al. [65] report that new users are advised that various kinds of motor imagery are usually helpful in the beginning to acquire control. Wolpaw et al. also report that users have said that they use imagery less and less as the training continues.

In the TTD no instructions are given. Users are only instructed to be attentive to the feedback and to find most successful mental strategy. There are, however, subjective reports of mental strategies which have been used with TTD. In the study reported in [7] the patients used very different mental strategies. Patient 001 used imagery of “electrifying the brain”, patient 003 gave the “order” to the cursor to move to the bottom of the screen and patient 004 imagined himself carrying something heavy up a hill and letting it loose at the top. Patient 002 could not report any systematic mental strategy [31].

2.4 Measuring EEG

In the scalp EEG the electrical activity of the brain is recorded non-invasively, i.e. from the surface of the scalp using normally small metal plate electrodes. While the number of the electrodes varies from study to study, they are usually arranged according to an international 10-20 system. Recordings can be made either using reference electrode(s) or bipolar linkages. The EEG signal can be affected by many artifacts coming from the equipment or the subject.

2.4.1 Electrodes

The EEG is recorded with *electrodes*, which are placed on the scalp. Electrodes are small plates, which conduct electricity. They provide the electrical contact between the skin and the EEG recording apparatus by transforming the ionic current on the skin to the electrical current in the wires. To improve the stability of the signal, the outer layer of the skin called *stratum corneum* should be at least partly removed under the electrode. *Electrolyte gel* is applied between the electrode and the skin in order to provide good electrical contact. Usually small metal-plate electrodes are used in the EEG recording [63].

2.4.2 Electrode placements

In order to make patient's records comparable over time and to other patient's records, a specific system of electrode placement called *International 10-20 system* is used. The system is for 21 electrodes. The distance between the specific anatomic landmarks (nasion and inion, see Figure 2.7) is measured after which the electrodes are placed on the scalp using 10 and 20 % interelectrode distances. Each electrode position has a letter (to identify the underlying brain lobe) and a number or another letter to identify the hemisphere location. Odd numbers are on the left side and even on the right side. Z (for zero) refers to electrode placements at midline. The system allows the use of additional electrodes. As can be seen in Figure 2.7 midline (or zero) electrodes are flanked up by electrodes numbered 3 on the left and 4 on the right.

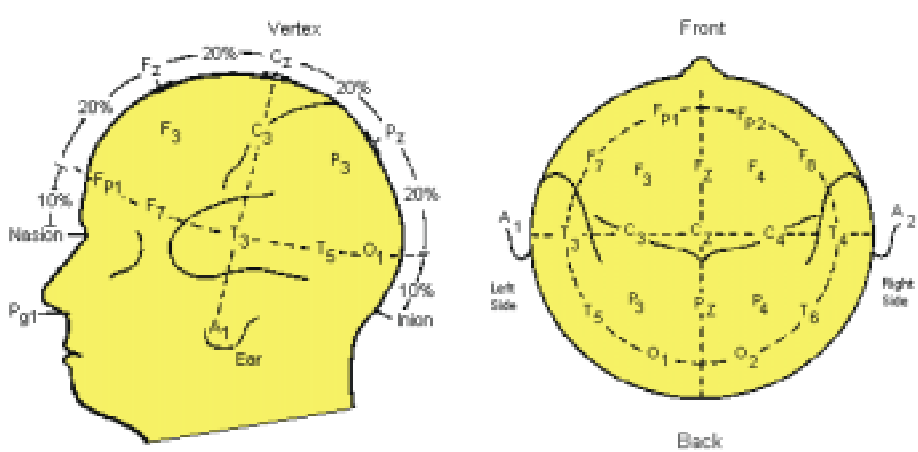

Figure 2.7: The international 10-20 electrode system: side and top views [11].

2.4.3 Reference and bipolar recordings

The EEG recordings can be divided into two major categories: Reference recordings and scalp-to-scalp bipolar linkages. In the reference recording each electrode is referred to either distant *reference electrode*, one common electrode on each side of the head or to combined activity of two or more electrodes. The reference electrode(s) must be placed on the parts of the body where potential remains fairly constant. Usually reference electrodes are placed on the ear lobes or on the mastoid bones behind the ear. In addition to one single reference electrode two reference electrodes shorted together can be used. In bipolar recordings differential measurements are made between successive pairs of electrodes [46].

2.4.4 Artifacts

When measuring the EEG, all of the signals do not come from the electrical activity of the brain. Many potential changes seen in the EEG may be from other sources. These changes are called *artifacts* and their sources may be the equipment or the subject. These artifacts include [34]:

- **Technical artifacts**
  - *Mains interruption*. The surrounding electrical equipment may induce 50-Hz or 60-Hz component in the signal.
  - *Electrode artifacts*. If electrodes are improperly attached or in poor condition, their impedances may vary.
- **Physiological artifacts**
  - *Motion artifacts*. Subject's movements cause electrodes or electrode cables to move.
  - *EMG artifacts*. The tension of muscles (especially masticatory, neck and forehead muscles) causes EMG artifacts.
  - *Cardiac artifacts*. The heart causes many different artifacts: ECG, pulsation artifact, ballistocardiographic artifact, pacer artifact, respiration artifact
  - *Oculographic artifacts*. These include the eye blink artifact and the eye movement artifact.
  - *Sweating*. This can affect, for example, the impedances of the electrodes.

2.5 BCI components

A typical BCI device consists of several components. These include electrode cap, EEG amplifiers, computer and subject's screen. A critical issue is how the user's commands, i.e., the changes in the EEG, are converted to actions on the feedback screen or the application. This process can be divided into five stages:

1) Measurement of EEG This is done by using the electrodes. Many BCIs use a special *electrode cap*, in which the electrodes are already in the right places, typically according to the international 10-20 system (see section 2.4.2). It saves time because the electrodes do not have to be attached one by one. Typically, less than 10 electrodes are used in online (see section 2.9) BCIs with sampling rates of 100-400 Hz.

2) Preprocessing This includes amplification, initial filtering of EEG signal and possible artifact removal. Also A/D conversion is made, i.e. the analog EEG signal is digitized.

3) Feature extraction In this stage, certain features are extracted from the preprocessed and digitized EEG signal. In the simplest form a certain frequency range is selected and the amplitude relative to some reference level measured [65]. Typically the features are certain frequency bands of a power spectrum. The power spectrum (which describes the frequency content of the EEG signal) can be calculated using, for example, Fast Fourier Transform (FFT), the transfer function of an autoregressive (AR) model [61] or wavelet transform [36]. No matter what features are used, the goal is to form *distinct* set of features for each mental task. If the feature sets representing mental tasks *overlap* each other too much, it is very difficult to classify mental tasks, no matter how good a classifier is used. On the other hand, if the feature sets are distinct enough, any classifier can classify them.

4) Classification The features extracted in the previous stage are the input for the classifier. Different BCIs can classify different number of classes, typically 2 to 5 classes. The classifier can be anything from a simple linear model to a complex nonlinear neural network that can be trained to recognize different mental tasks. With the exception of a simple threshold detection [65, 7], the classifier can calculate the probabilities for the input belonging to each class (see e.g. [16]). Usually the class with the highest probability is chosen. However, in some BCI protocols none of the classes may be chosen, if the classification probability does not exceed some predefined level. This kind of classification result can be called “nothing” or “reject”.

5) Device control The classifier’s output is the input for the device control. The device control simply transforms the classification to a particular action. The action can be, e.g., an up or down movement of a cursor on the feedback screen or a selection of a letter in a writing application. However, if the classification was “nothing” or “reject”, no action is performed, although the user may be informed about the rejection.

2.6 Feedback

Feedback is an important factor in BCIs. In the BCIs based on the operant conditioning approach, feedback training is essential for the user to acquire the control of his or her EEG response. The BCIs based on the pattern recognition approach and using mental tasks do not definitely require feedback training. However, feedback can speed up the learning process and improve performance. Cursor control has been the most popular type of feedback in BCIs. Feedback can have many different effects, some of them beneficial and some harmful. Feedback used in BCIs has similarities with *biofeedback*, especially EEG biofeedback.

2.6.1 Biofeedback in general

Biofeedback can be defined as follows: “*Biofeedback is the process in which a subject receives information about his biological state. Usually a subject is not aware of his physiological functions, especially those controlled by the autonomic nervous system, such as heart rate and peripheral vasoconstriction. Biofeedback creates an external loop by which a subject can monitor one or more of his physiological states.*” [49].

The most popular types of biofeedback machines or techniques include: Electroencephalography (EEG), electromyography (EMG), skin temperature and galvanic skin response (GSR). Different feedback methods have been used in different clinical purposes, for example, treatment of anxiety and muscle tension [49].

2.6.2 EEG biofeedback

The history of the EEG biofeedback can be dated back to late 1960's and 1970's, when the self-regulation of the alpha rhythm and alpha biofeedback methods were popular. It was thought that with the help of biofeedback every individual could reach the same state as *yogis* or *zen buddhists*, who were observed to show well modulated alpha during meditation. This dream did not come true and the interest in the alpha biofeedback declined in 1980's [49]. However, since then the EEG biofeedback has made a "comeback". It is no longer concentrated on relaxation and alpha training. Today the EEG biofeedback (or the neurofeedback as it is sometimes called) is used for the treatment of numerous disorders, for example Attention Deficit Hyperactivity Disorder (ADHD), panic attacks, sleep disorders, epilepsy etc. in many countries [24]

The basic idea in the EEG biofeedback is the operant conditioning of certain EEG parameters. Typically, the goal of the training is to increase the activity on a certain frequency band and decrease it in another. This is possible by providing feedback for the subject. The feedback can be, for example, a car in the computer game. The speed of the car can be coupled with the desired condition. The car moves faster, if the patient's EEG gets closer to the desired condition and slower, if it gets farther [24].

Generally, biofeedback methods used in the clinical EEG biofeedback have been much more imaginative than in BCI systems. Whereas in the BCI systems the feedback is in the form of the cursor control in almost all cases, the feedback in EEG biofeedback has included various kinds of games and visual displays. In addition to visual feedback, auditory and tactile feedback have also been used [24].

Biofeedback in the form of games is especially important with children. EEG biofeedback requires attention and the session typically lasts around 30 min. Usually EEG biofeedback treatment requires tens of sessions. For this reason it is necessary to provide children with interesting feedback in order to keep them engaged in the treatment.

The EEG biofeedback is closely related to the operant conditioning approach in BCIs. In fact, the self-regulation of the slow cortical potentials (see the section 2.2.2) have been used with patients having neurological and psychiatric disorders, for example, untreatable chronic epilepsy (see e.g. [33]). Today, a BCI called Thought Translation Device is based on self-regulation of SCPs [7]. However, there is fundamental difference between the use of BCI and typical EEG biofeedback treatment. In biofeedback treatment the goal is to reach certain condition and maintain it, whereas in BCIs the goal is that the user learns to change his or her EEG between two or more conditions (classes).

2.6.3 Feedback in BCIs

In most BCIs some kind of feedback is provided to the user. The most popular form of feedback has been the cursor control (see e.g. [65, 7, 58, 32]). In a typical *trial*, the user tries to move the cursor to the target, which is located on one side of the screen by using two commands (i.e., up&down or left&right). At the start of the trial the cursor is at the middle of the screen. The trial ends when the cursor hits either the target or the opposite end of the screen. If the target side of the screen is hit, the target can be flashed to indicate the trial outcome. One trial typically lasts a few seconds. Figure 2.8 shows an example of the feedback display used in the TTD [8]. After the cursor has hit the target, it blinks and a smiley face saying “very good” appears as a *positive reinforcement*.

Why has the cursor control been such a popular type of feedback in BCIs? One reason may be that the goal of many BCI research groups is to give the user, a disabled person, an opportunity to operate an ordinary personal computer by thoughts. In addition to this, there may be other reasons. In Kostov’s et al. [32] words: “We chose cursor movement because it is objective, easily implemented, simple for the user to learn, and can serve as a prototype for control of a wide variety of applications.”

The cursor control is an example of *continuous* feedback. However, the classifications in BCIs are made in discrete manner. In order to make cursor movement to *look* continuous (i.e the cursor does not make “jumps”), the time between two classifications should be less than about 60 ms (consider that the film creates an illusion of movement by presenting still frames at 24 frames per second, i.e., a frame every 41,6 ms). The time steps used in six BCIs can be seen in Table 3.3.

Ideally continuous feedback would be instantaneous, i.e., *real-time*. However, this is not possible with the current BCI systems, which require that some finite sample of EEG data is analyzed and classified before the feedback can be presented to the screen. For example, in BCIs presented in Table 3.3, the shortest EEG sample (window in the table) is 200 ms (in the Wadsworth BCI).

Beside continuous, feedback can also be *discrete*. ABI uses this kind of feedback by presenting each mental task as a colored ball. The ball lights up when the EEG sample is classified as belonging to a corresponding task. With Graz BCI (see section 3.1.5) this

Figure 2.8: An example of feedback display used in the TTD. After the ball-like cursor has successfully hit the target, a smiley face appears as a positive reinforcements. Modified from [8].

kind of discrete feedback has also been used. In the experiment made in 1997 and reported in [52], the certainty of decision was shown to the user after each 8-second trial. If the requested movement could be correctly classified, '+' was shown. If the data of current trial was identified to other class than requested, '−' was shown. Ambiguous results were shown as 'o' .

Feedback can also be *graded*. Graded feedback is proportional to some variable. In the same experiment as described above, the size of the '+' and '−'-signs identified how well the classifier recognized the mental tasks (left and right hand movement in this case). Large signs identified "clear decision" and small signs "decision".

2.6.4 Effect of feedback

In BCIs using the operant conditioning approach (see section 2.3.2), the feedback about the performance is essential in *skill development*, i.e., in acquiring control over the EEG response. The subject needs to know which imagery moves the cursor up and which imagery down. However, at the same time the feedback from the cursor movement can have other effects, some of them beneficial and some of them harmful [39].

Beneficial effects

1. Furnishes continual motivation
2. Ensures attention to the task by maintaining the subject's interest

3. Improves performance by allowing rapid reaction to wrong classifications

Harmful effects

1. The feedback stimulus might prevent concentration on internal states
2. The false classifications can elicit frustration and thus affect the EEG response (for example, cause EEG desynchronization)
3. The correct classifications might lead to anticipation and thus affect the EEG response (for example, cause EEG synchronization)
4. The visual feedback stimulus might affect the alpha rhythm

McFarland et al. [39] studied the kinds of short-term effects the removal of cursor movement had on the performance of the subjects who were already trained with the Wadsworth BCI. They found out, that 2 out of 10 subjects performed significantly better when only the trial outcome was shown, while 4 other performed significantly worse. Also Kaiser et al. [27] studied the short-term effects of the feedback with subjects already trained with the TTD. They found out that the removal of the cursor movement resulted in an initial performance drop, but was quickly recovered. They suggested that the trial outcome feedback could be more important in maintaining the self-control over the EEG signal than continuous feedback (i.e., the cursor movement). However, they suggested that further research is needed to elucidate this question.

In BCIs using the pattern recognition approach, feedback is not essential, because they are based on predefined mental tasks (see the section 2.3.1). However, feedback can improve learning and performance, because the subject gets information on how the classifier classifies the mental tasks and can then try to perform the mental tasks in a way that they can be classified better. In other words, the subject and BCI are adapted to each other. This process can be called *mutual learning process* and it is explained in section 2.7.3.

2.7 Human training issues

To date, most of the BCI research has concentrated mainly on technical issues; how to measure, process and classify the EEG signal better and better. However, the producer of this EEG signal, the human being, may be as important or even a more important factor in a successful BCI than the technical developments. Therefore, the issues concerning the human training are worth considering. What is the training protocol used? How much time does the training require? How is the load divided between the user and the BCI system? This section tries to provide some answers to these questions.

2.7.1 Training protocol

How is the user trained to use the BCI system, i.e., what kind of training protocol is used? The protocols vary from one BCI to another. Typically, however, training is divided into series of *sessions* and each session is divided into a certain number of *trials*. One session typically consists of tens of trials and lasts 5-30 minutes. Using a BCI requires so much concentration that usually half an hour to one hour of training is enough for one day.

2.7.2 Training period

Some BCIs, which are based on the detection of the event-related potentials (namely the P300 or the VEP, see 2.2.2) require basically no training. The user can start using the BCI and its applications right away. Usually, however, more or less time for training is required in order to build an online BCI with a good level of accuracy.

The training period differs greatly among different BCIs, from days to months. The required training period is greatly dependent on how the *training load* is divided between the user and the system. As mentioned in the section 2.3, in BCIs based on the operant conditioning approach, the user has to learn to self-regulate his or her EEG response. On the other, in BCIs based on the pattern recognition approach, the emphasis on that the system is trained with the EEG data obtained while the subject is performing the mental tasks. The operant conditioning approach requires usually a much longer training period than the pattern recognition approach. This is largely because the training load between the user and the BCI is divided differently in these approaches.

In BCIs based on the operant conditioning approach all the training load is on the user (e.g., [7, 65]). The drawback of this approach is that it may take months of training before the user achieves the desirable level of performance. The users may be instructed what kind of mental imagery they should or should not use. In order for the user to acquire self-control of EEG response, some kind of feedback is essential at least in the beginning (see

2.6). Although the training load is on the user, the electrode positions or the amplitude thresholds can be adjusted individually for each user during the training.

The opposite approach would be a BCI based on the pattern recognition approach, in which the whole training load is on the system. No feedback would be given. Usually, however, some kind of feedback is given. In this kind of approach, both the user and the BCI system are trained (see e.g. [58, 32, 16]). This can be called a *mutual learning process* where both the system and the user learn from each other. The idea is that the BCI system (classifier) learns the individual EEG patterns while the user learns to better produce these patterns with the feedback training [16].

2.7.3 Mutual learning process

In BCIs based on the mutual learning process, both the user and the BCI system (classifier) are trained. Since no fixed pattern is searched within the EEG data, the system must be trained first. This is typically done by recording the EEG while the subject concentrates on each mental task a few times. This first recording is done offline and no biofeedback can be given. The first classifier is then trained with this EEG data.

After the first classifier is trained, feedback can be given in the next session. This makes it possible for the user to see how the system classifies the mental tasks he or she performs. The user may then be able to learn to produce these mental tasks in such a way that the system recognizes them better. In addition, the user may improve in performing the mental tasks, for example, by being able to concentrate on them better or by learning a new mental strategy to perform them. Therefore, it is necessary that the system is *re-trained*, i.e., a new classifier is trained. This procedure of re-training can be done over and over again. However, ideally the user would be able to produce relatively *stable* EEG patterns and there would be no need to train a new classifier over and over again. If it is possible remains a question.

Pfurtscheller and Neuper [56] discuss *man-machine learning dilemma* (MMLD): “MMLD implies that two systems (man and machine) are strongly interdependent but have to be adapted independently. The starting point of this adaptation is the training of a “machine” to recognize certain EEG patterns of a subject. During this phase, no feedback is given. As soon as feedback is provided, each feedback results in an adaptation of man to machine: man tries to repeat success and avoid failure.” Feedback can then change the EEG patterns (see section 2.6.4). The changed EEG patterns require “the adaptation of machine to man", or in other words, the re-training of the classifier with the data obtained from the last session(s) with the feedback.

2.8 BCI performance

To this day, none of the BCIs have achieved the communication *speed* or the *accuracy* of the other interfaces. In addition, there is a problem of evaluating BCI performance. The results are reported differently from one BCI paper to another. This makes it difficult to compare different BCIs.

2.8.1 Measurements of accuracy in BCIs

There have been many different measurements. One method of reporting accuracy is to give a *correct classification rate*. This parameter tells the percentage of the classifications the BCI system classifies correctly. It does not take into account that individual classes usually have different classification rates and that some of the EEG data may be rejected (see the section 2.5).

More comprehensive way to report accuracy is to present a *confusion matrix*. The confusion matrix tells not only the correct classification rates of each class, but also in which classes the false classifications were classified. If rejection was used, it shows the percentage of the classifications that were rejected. Examples of confusion matrices can be found in Tables 2.3 (no rejection used) and 2.4 (rejection used). The correct classifications are in the diagonals of the confusion matrices.

Unfortunately, confusion matrices are displayed only in a few BCI papers. The correct classification rate is found in most papers, but sometimes only a *hit rate* is reported. The hit rate tells how many times the user managed to hit the target with a cursor (see 2.6). The hit rate is not a good way to report results because the number of the cursor steps required to reach the target influences the hit rate. Therefore, two hit rates are only comparable if the number of the steps is equal. Furthermore, the hit rate tells very little about what the actual classification accuracy of the BCI is. It is possible, for example, that the hit rate is close to 100 %, but the classification rate is below 60 %.

Rejection is used in some BCIs. It is related to the classification method used. The idea is that uncertain classifications are rejected. If rejection is used and the mental task is still classified to a wrong class, the wrong classification can be called *false positive* (FP). The number of false positives should be kept minimal or nonexistent, if a robust functioning of a BCI is wanted. Rejection can increase BCI performance.

2.8.2 Bit rate and channel capacity

An information transfer rate, a *bit rate*, can be used in order to take into account both accuracy and speed of a BCI. The bit rate is a standard measure of any communication system (which a BCI basically is). It tells the amount of information communicated per time unit. The highest bit rate a noisy communication system can theoretically have, is called a *channel capacity* [59]. The classification errors produce noise in the BCI system.

The channel capacity can be calculated in a closed form if the following conditions are met: 1) Classes have equal classification rates; 2) Errors are distributed symmetrically; 3) The rejection is not used. Table 2.3 displays an example of a confusion matrix, in which all of these conditions are met. The equation for calculating the channel capacity in a closed form is:

$$C = \log_2 N - P \log_2 P + (1 - P) \log_2 \left(\frac{(1 - P)}{(N - 1)} \right) \tag{2.1}$$

where N is the number of classes and P is the correct classification rate. The unit is *bits/s* or *bits/trial*. Maximum information transfer rate for an errorless BCI with N commands is $\log_2 N$ (all the classifications are correct, i.e., P=1).

The channel capacity as a function of accuracy for a different number of choices (i.e, 2, 4, 8, 16, 32) can be examined in Figure 2.9. The curves are based on the Equation 2.1. As can be seen from the figure, accuracy (i.e., the correct classification rate) affects greatly on the channel capacity. For example, when number of selections (N) is 2 (the most common in today's BCIs) and the accuracy increases from the 80% to 90%, the channel capacity is almost doubled $(0.5301/0.281 = 1.91)$ in bits/trial.

The correct classification rate is used in the Equation 2.1. Therefore, it is presumed that the false classifications are distributed evenly. Furthermore, it is assumed that no rejections are made. If this is not the case, as in confusion matrices presented in Table

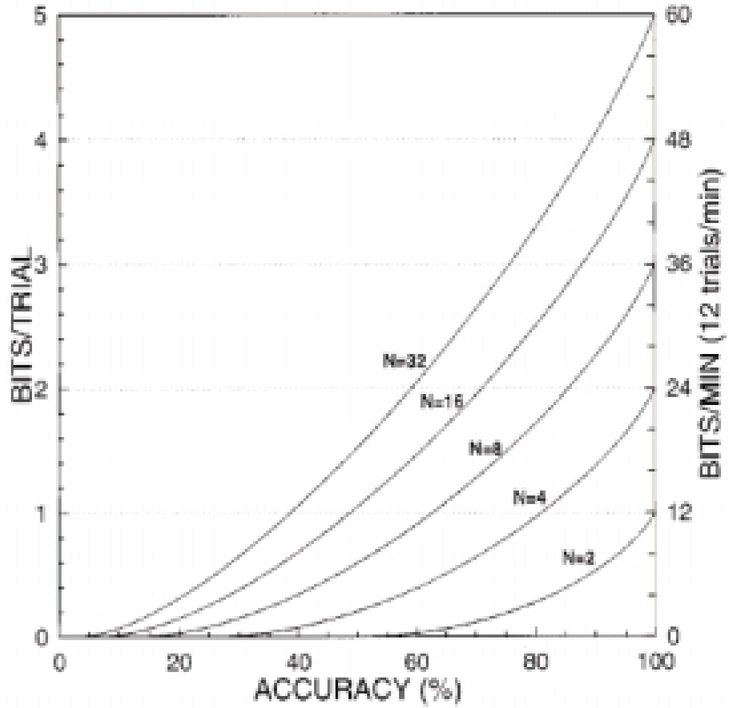

Figure 2.9: Bit rate in bits/trial (i.e., bits/selection) and in bits/min (assuming 12 trials/min), when the number of possible selections (N) is 2, 4, 8, 16 or 32 [66]

2.4, the channel capacity is calculated using Arimoto-Blahut algorithm [10]. The result of this algorithm convergates to the channel capacity of the system. The channel capacities for matrices presented in Table 2.4 are calculated in Table 2.5.

CM (%)	Class 1	Class 2	Class 3
Class 1	60	10	30
Class 2	30	60	10
Class 3	10	30	60

Table 2.3: An example of a confusion matrix, from which the channel capacity can be calculated analytically using the Equation 2.1.

CM 1 (%)	Class 1	Class 2	Class 3	Reject
Class 1	91	0	2	7
Class 2	1	74	12	13
Class 3	4	1	73	22

CM 2 (%)	Class 1	Class 2	Class 3	Reject
Class 1	92	0	0	8
Class 2	0	51	5	46
Class 3	0	9	56	35

CM 3 (%)	Class 1	Class 2	Class 3	Reject
Class 1	100	0	0	0
Class 2	0	42	0	58
Class 3	0	0	36	64

Table 2.4: Three different confusion matrices

Confusion Matrix	1	2	3
C	1.03	1.01	1.21

Table 2.5: Channel capacities of the confusion matrices in Table 2.4. The third matrix has the biggest channel capacity, the two other are almost equal.

2.9 Categorizing BCIs

Previously, in this chapter, BCIs were divided into those using the pattern recognition approach and those using the operant conditioning approach. However, BCIs can be categorized differently, which is done in this section.

Invasive and non-invasive BCIs Non-invasive BCIs are based on EEG measured with the scalp electrodes. Almost all todays BCIs are based on this. In invasive BCIs, the electrical activity of the brain is recorded from *inside* the head (e.g., from the cerebral cortex). The recordings are made, for example, with one or more *microelectrodes*. In addition, macroelectrodes are used in electrocorticogram (ECoG) recordings. The microelectrodes can record activity of a single neuron. Kennedy has successfully used this kind of approach [30]. Levine et al. have studied the use of ECoG as a signal source for a brain computer interface [35]. Wessberg et al. [64] recorded activity from multiple cortical areas and large population of neurons from two owl monkeys during different arm movements. They were able to make accurate real-time prediction of the arm movement trajectories in real-time.

Synchronous and asynchronous BCIs Many BCIs work in a synchronous mode, i.e., in a externally paced mode. The user must produce specific mental states in a predefined time window. In other words, the system initiates the period of control, i.e., the control is *system-initiated*. In an asynchronous mode, the brain activity is analyzed continuously. The user can freely initiate the specific mental task(s) used as the control signal(s), i.e., the control is not system-initiated but *user-initiated*. This requires that BCI can detect when the EEG control is intended and when it is not. Birch and Mason have tried to implement this kind of an asynchronous BCI [37].

Universal and individual BCIs Universal BCI relies on assumption that by gathering EEG data from few users it is possible to find a classification function that should be valid for everybody. So the BCI is the same for all users. In individual BCI the fact that no two people are the same, both physiologically and psychologically is taken into account. Therefore, the BCI is different with different users, i.e., *individual* [14].

Online and offline BCIs Online BCIs are the actual working BCIs. The signal processing, features extraction, classification, and device control (see 2.5) are done in *real-time* (or at least relatively close to it). This makes it possible to provide feedback for the user. This is not possible in the offline BCIs. The EEG is typically recorded as in online BCI, but using more electrodes. The recordings are then stored and the actual BCI research is done later. This makes it possible to examine, for example, different electrode positions, preprocessing and feature extraction methods, classifiers etc. The performance of the offline BCI can be evaluated using, for example, *cross-validation test*. The results are comparable with the same kind of online BCI (without biofeedback), if all the recorded EEG data are used. However, if some of the recorded data is removed (for example containing EMG or EOG artifacts) the results are not comparable.

EEG features Usually BCIs are categorized according to what EEG feature or features they try to detect. These features include: SCP, μ or β rhythm amplitude, P300, RP, EEG power spectrum features and action potential of single cortical neuron.

Imagery and mental tasks From the user's point of view, BCIs can be categorized according to what kind of imagery they require. Motor imagery has been used in many BCIs (e.g. [52]). Other mental tasks (e.g., arithmetic and visual tasks) have been used in e.g. [58]. Other BCIs may leave the choice of imagery up to the user [32, 7].

Chapter 3

BCI systems

This chapter describes six different BCI systems. Five of them are included in the literature review. The sixth, used in the present study, *Adaptive Brain Interface* (ABI), is described in more detail. After the BCIs are introduced they are compared to each other.

3.1 Different approaches to BCI

This section provides an overview of five BCI systems based on the scalp EEG. Three of them (BCIs developed in the universities of Alberta and Oxford and the Graz BCI) are based on the pattern recognition approach like ABI. The other two use the operant conditioning approach. The BCI developed at the Wadsworth Center uses the self-regulation of the μ or β rhythms where as the Thought Translation Device is based on the self-regulation of the slow cortical potentials (SCPs).

3.1.1 BCI research at the University of Alberta

Alexandar Kostov and Mark Polak started their BCI research at the University of Alberta, Canada, in 1995. Their BCI system was based on the pattern recognition approach. In the study reported in [32] EEG data was recorded with 28 electrodes arranged according to the international 10-20 electrode system. Signal amplification and the initial filtering were done by Brain Imager, a device manufactured by Neuroscience Inc. The EEG signals were digitized at a sampling rate of 200 Hz. Features were extracted for electrodes C3, C4, P3 and P4 using the 4th order autoregressive (AR) feature extraction method. The EEG patterns were classified with an adaptive neural network called Adaptive Logic Network (ALN) [3] in on-line experiments.

Training was done in 30-min sessions. The subject was seated in front of the feedback monitor while the EEG signals were recorded. Feedback was provided in the form of the cursor control. The subject was instructed to move the cursor to the target located at top or bottom (1-D setup), or at top, bottom, left or right (2-D setup) sides on the screen. When the cursor reached the target or missed it by reaching the edge of the screen, a new target position was chosen. The position of the cursor was updated every 50 ms. The speed of the cursor was affected by the number of the steps required to hit the target, which was set by the operator.

The first half of the training session was used to train the new ALN classifier as the subject was attempting to move the cursor towards the target. When the subject achieved control of the cursor, the training of the ALN was halted and the second half of the session was used to evaluate the performance.

Every subject could choose the mental tasks he or she wanted to use to achieve the cursor control. One of Kostov's subjects, a multiple sclerosis patient (seen in Figure 3.1), imagined the hydraulic lift installed in his home going up and down to move the cursor. Other people have used relaxing thoughts to move the cursor up and stressful thoughts to move it down. [60]

Kostov and Polak give the results in the form of the hit rate (see the section 2.8). They report that once subjects are fully trained (giving no indication how long it will take to "fully" train the subjects), they can hit the target close to 100 % when 32 cursor steps are required to hit or miss the target (1-D setup). It is impossible to know what the actual classification rate was, when the results are given in this way. Furthermore, Kostov and Polak report that they have been able to train only two subjects to achieve 2-D cursor control. They achieved the hit rates of 70 % and 85%, respectively. The number of the steps required to hit the target was not reported.

The goal of this project was to develop a BCI capable of accurate two-dimensional (2-D) cursor control. In addition, the intention was to develop range of applications for the BCI. One application reported to date has been an environmental control device [28]. Unfortunately, the principal researcher, Alexandar Kostov, has died. It is not known if the project has continued after his death.

Figure 3.1: Alexandar Kostov (left) and Mark Polak (middle) with Jim Killick, a multiple sclerosis patient sitting in the wheelchair and wearing the electrode cap [60]

3.1.2 BCI research at the Oxford University

William Penny and Stephen Roberts started BCI research at the Oxford University, England, in 1996. Online experiments were done with seven volunteer subjects in 2000 [58]. The EEG was recorded from one *bipolar* channel with two electrodes located 3 cm behind C3 and C4 of the international 10-20 system. The ground electrode was placed on the right mastoid. The signal was bandpass filtered with 3 dB points set at 0.1 Hz and 100 Hz and digitized at 384 Hz. The EEG data was analyzed using the 8th order autoregressive (AR) model. This model was fitted to 1/3 second blocks of data (128 samples) which slid 32 samples (1/12 second) from one processing time step to next.

In the study made in 1999 Penny and Roberts [50] had found out that motor imagery vs. math task was more easily discriminated than motor imagery vs. baseline task. Therefore, in the most recent study (2000) [58] they used only motor imagery vs. math task. The classification was performed by using Bayes logistic classifiers. The first classification system was trained via the initial 10 second recording of each of the tasks without feedback. After the first recording, feedback was provided in the form of the cursor control. The upward movement of the cursor was associated with the math task and the downward movement with the motor imagery. Each up or down movement task lasted for some 10-15 seconds. The classification system was re-trained after each experiment, using the previous experimental data as a training data.

Penny and Roberts experimented with two methods in order to improve the performance of their BCI. The methods were a latent-space smoothing and a reject option. The latent-space smoothing means that the low certainty decisions may be rejected or "over-ruled" by the higher certainty decisions from the recent past. A two second window was used. In the reject option a third class called "reject" was added. Using Bayesian decision theory the certainty of the classification was calculated. If the certainty of the classification did not exceed a particular threshold then the EEG was classified to "reject" class.

Penny and Roberts reported the classification results for three scenarios: hard rejection, soft rejection and baseline (no rejection). The scenarios were explained as follows [58]:

- **Hard rejection**. The latent-space smoothing and reject option was used. If, however, more than 50 % of an experimental block was rejected then the entire block was removed from the data set as a "corrupted" data epoch
- **Soft rejection**. The latent-space smoothing and the reject option was once more applied but no removal of experimental blocks was performed.
- **Baseline**. No smoothing or rejection was performed and classification was made on a sample-by-sample (each 1/12 second) basis.

The mean correct classification rates for the three scenarios for all seven subjects are presented in Figure 3.2. They show that the hard and soft rejection scenarios improved considerably the classification accuracy. Overall mean classification rates (fraction correct) were 0.8648 (hard rejection), 0.7595 (soft rejection) and 0.5318 (baseline). This improvement of the accuracy came with a price. When the hard rejection scenario was used, 21 % of the data blocks were entirely rejected and of the remaining data samples an average of 28% were rejected. Using the soft rejection method, an average of 34 % of the data samples were rejected.

3.1.3 BCI research at the Wadsworth Center

Jonathan Wolpaw and his colleagues have done BCI research at the Wadsworth Center, the United States, since 1986. Their BCI is based on the self-regulation of the 8-12 Hz μ or the 13-28 Hz β rhythms. In the study made in 1998, 64 EEG channels were recorded from the surface of the scalp from 4 subjects (one with ALS) [41]. Each channel was referenced to the electrode in the right ear. 62 of 64 channels were digitized at 128 Hz and stored for later evaluation. Two remaining channels located over each hemisphere of

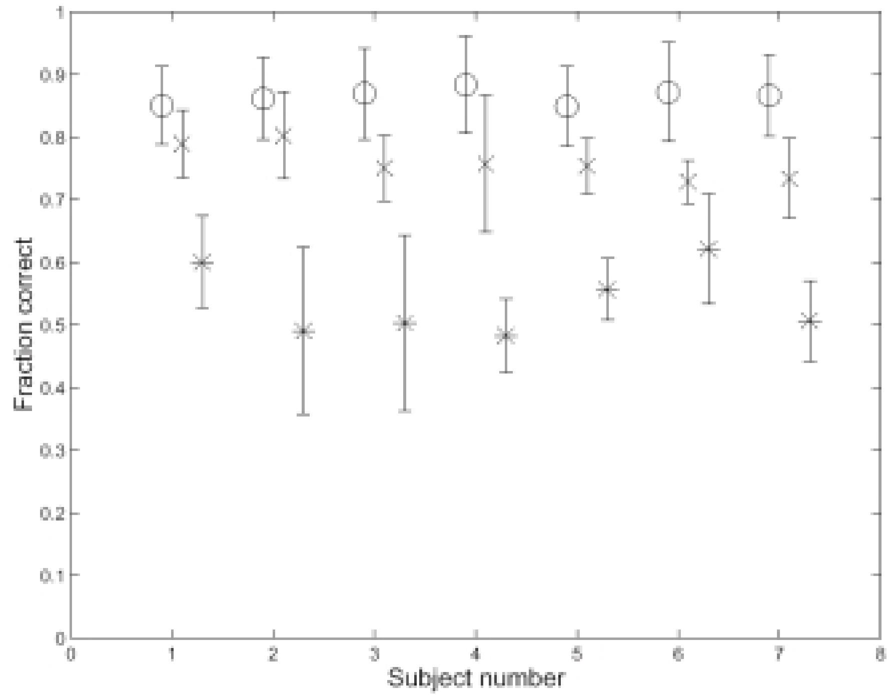

Figure 3.2: Mean classification results, $\pm$ standard deviation for all seven subjects in Oxford BCI. Performance for three scenarios is presented: hard rejection (o), soft rejection ($\times$) and baseline ($*$). Performance averaged over all subjects is 0.8648$\pm$0.0694(o), 0.7595$\pm$0.0667($\times$) and 0.5318$\pm$0.1153($*$) [58]

the sensimotor cortex (e.g., C3 and C4) were digitized at 196 Hz. They were converted to either a common average reference (CAR) derivation or a large Laplacian derivation [38].

The feature extraction and the classification were done as follows. The EEG data was analyzed using the autoregressive (AR) algorithm and an amplitude (i.e., the square root of power) was calculated in a 3-Hz wide frequency band. The frequency band corresponded to 8-12 Hz μ rhythm (2 subjects) or 18-24 Hz central β rhythm (2 subjects). The sum of the amplitudes from the two channels was calculated every 100 ms using the preceding 200 ms segment of the EEG data. This sum was the independent variable in a linear equation that determined a cursor movement.

The training was done in 30 min sessions divided into 8 runs lasting 3 minutes each and separated by 1 minute rest periods. Each run consisted of several trials. In each trial the user tried to move the cursor from the center of the screen to the target located at the top or bottom of the screen. The distance to top or bottom was 94 cursor steps. The cursor moved every 100 ms up or down according to the linear equation described above. The target location (top or bottom of the screen) varied in pseudo-random order resulting in equal number of each targets. If the cursor hit the target, it flashed for 1.5 s as a reward.

After the initial training the targets were replaced with words YES and NO and the subjects were asked simple questions like “is 2+2=4?” or “is a potato a mode of transportation?”. The subjects answered to the questions by moving the cursor to either YES or NO target. The answers were confirmed with a response verification (RV) procedure, in which the YES and NO targets were switched and the question was answered again.

Data was gathered from each subject from 5 consecutive sessions containing 333 to 401 questions. 4.0 to 4.6 question were asked per minute. 64 % to 87% of the answers were confirmed with the RV procedure. 93% to 99% of these answers were correct. 78% to 93% of separate parts of all the answers were correct (these percentages correspond the hit rates with 94 cursor steps). Miner et al. concluded that even though the subjects' attention was not solely focused on moving the cursor in the question-answer protocol, they achieved the same performance as they had previously achieved with the standard target format.

3.1.4 The Thought Translation Device (TTD)

Niels Birbaumer research interest over the years have been the slow cortical potentials (SCPs) (see the section 2.2.2). Birbaumer has used the self-regulation of the SCPs with the epileptic patients (see e.g. [33] and the section 2.6.2). During 1990's Birbaumer and his colleagues developed a BCI called the Thought Translation Device (TTD) at the University of Tűbingen in Germany. Over the years the TTD has been used by 12 ALS or other patients with severe or total paralysis. They have used it as a communication tool at their homes or in a nursing home [31].

Birbaumer and coworkers studied five patients using the TTD [7]. The EEG was recorded from the electrode Cz referred to mastoids at a sampling rate of 256 Hz. The EEG signal was filtered and corrected for the eye movement artifacts. SCPs were then extracted from the EEG signal. The training day usually consisted of 6-12 sessions, each of them consisting of 70-100 trials and lasting 5-10 minutes. The patients were trained several times a week.

In the initial training phase (slow wave training) the subjects were trained to produce either SCP negativity or positivity. The required SCP amplitude change was gradually increased from 5 μV to 8 μV during the training. Feedback was provided in the form of a cursor control. The cursor was a ball-like light, which the subject tried to move to the target located at the upper part of the monitor (when SCP negativity is required) or at the lower part of the monitor (when SCP positivity is required). Each trial consisted of 2 s baseline period and 2-4 s feedback period when SCPs were fed back. The EEG was averaged over a sliding window of 500 ms moving in steps of 63 ms. When the subject achieved stable performance of 75 % correct trials, he or she can began to work with a language support program.

In the language support program the alphabet was split into two halves (letter-banks). These letter-banks were shown successively at the bottom of the screen. The subject could choose the letter bank shown by producing a SCP shift (either SCP negativity or positivity according to subject's preference). If the subject produced the required SCP shift the letter bank was split into two new halves. This continued until each of the letter-banks contained only one letter. When the subject selected one of them, the selected letter was displayed in the top text field of the screen and a new selection began from the start. The program also included a "return function". If the subjects rejected two successive letter-banks the option to erase the last symbol in the textfield appeared.

The use of the language support program was divided to two or three phases. In the copy spelling phase the subjects used their preferred SCP response (negativity or positivity) to copy letters. In the free spelling phase subjects could select letters according to their wishes.

Two of the five subjects progressed to the free spelling stage. It required over 140 training sessions (including the slow wave training and the copy spelling) from the other patient and over 210 training sessions from the other. The training time is long considering that the TTD only detects (after initial training phase) either the SCP negativity or positivity. The speed of writing was slow. Subjects needed an average about 2 min for the selection of one letter (based on trial length of 4.5 s).

The results of the sessions are reported as percentages of "correct responses". This means that beside the slow wave training phase, the results are specific to the language support program. The results of the slow wave training correspond to the hit rate, but the number of the cursor steps is not reported. Each of the subjects achieved mean hit rates of about 70 %, but the variance between the sessions was high.

Beside the language support program the TTD has two other applications: The environment control unit and the Internet browser "Descartes" [22]. Birbaumer and his colleagues have now taken part in a project called "BCI 2000" (http://www.bciresearch.org). It will try to combine the slow cortical capacity of the TTD with the μ and β rhythm capacity of the Wadsworth BCI (see the section 3.1.3).

3.1.5 Graz brain-computer interface

Pfurtscheller and his group in the Graz University of Technology, in Austria, started the "Graz Brain-Computer Interface" project in 1991 [55]. The Graz BCI has moved through various stages of prototypes during 1990's. However, all this time it has been based on the detection of the ERD and the ERS patterns during the motor imagery (see e.g. [20] and the section 2.2.2).

In the study made in 2001, the Graz brain-computer interface (BCI) was based on the classification of the EEG patterns during five different mental tasks [48]. One aim of the research was to study how the number of mental tasks affected the channel capacity. Classification was done *offline* (see the section 2.9. Three male subjects (S1, S2 and S3) took part in the study. They were all familiar with the Graz BCI [55].

The timing of the trial in this new study was the same that had been used in Graz BCI experiments before (see e.g. [55, 56]. A fixation cross was presented in the center of a monitor at the start of each trial. Two seconds later the subject heard a warning "beep". A symbol representing one of the five different types of mental tasks was then shown between 3 s and 4.25 s. These mental tasks were left-hand movement (L), right-hand movement (R), foot movement (F), repeated subtraction of a constant number from a randomly chosen number (A), and tongue movement (T). After the presentation of the symbol, the subjects performed the mental tasks according to the symbol until the end of the trial (8 s). The time to the next trial was randomized between 0.5 to 2.5 s to avoid adaptation. Each session included 200 trials divided into four 50 trial runs (15-min break between runs). Each mental task was performed 40 times in one session, but the sequence of the mental tasks was randomized.

The EEG was recorded with 29 gold electrodes (see Figure 3.3). The ground electrode was placed on the forehead. The EEG signals were filtered between 0.5 Hz and 30 Hz and digitized at the sampling rate of 256 Hz. EMG and EOG artifacts were excluded from the data sets. After the artifact removal, datasets included 545 trials for subject S1, 507 for subject S2 and 449 for subject S3.

The logarithm of the band power for five bands (7-10 Hz, 10-13 Hz, 16-20 Hz, 20-24

Hz, 24-30 Hz) was calculated for every channel using a fifth-order Butterworth filter in a window from seconds 4 to 8 of each trial. This formed a feature vector consisting of 145 components describing all EEG signals from all electrodes. A subset of features was calculated using step-by-step procedure. A hidden Markov model (HMM) was used as a classification method. Classification accuracy was evaluated using 5-fold cross-validation test.

The confusion matrices for the three subjects when a $N = 5$ classes classifier was used can be seen in Table 3.1. Each subject's confusion matrix was used to determine the class combinations for $N = 2, 3, 4$ classifiers by selecting the most distinguishable mental tasks. The performances of $N = 2, 3, 4, 5$ classifiers was then compared. It was found out that the classification accuracy decreased steadily with an increasing N with all subjects. However, the maximum channel capacities (calculated using Equation 2.1) for the subjects were S1: 0.42 ($N = 2$), S2: 0.81 ($N = 4$), and S3: 0.56 ($N = 3$) bits/trial.

3.2 The Adaptive Brain Interface (ABI)

The BCI system used in the experimental part of this work is called *Adaptive Brain Interface* (ABI). The ABI has been developed under the project "Adaptive Brain Interfaces" financed by European Commission. The project started in 1998 and ended in 2001. The project had 4 partners: 1) ISIS at the Joint Research Centre of European Commission, in Ispra Italy; 2) IRCCS Ospedale di Riabilitazione S. Lucia; 3) Fase Sistemi Srl; and 4) Laboratory of the Computational Engineering at the Helsinki University of Technology.

In this section the older version of the ABI is described, whereas a new ABI version was used in the experiments of this thesis (see the chapter 4). The ABI is based on the *mutual learning process* (see the section 2.7.3) where the system and the user *adapt* to each other. The system learns to classify each user's individual EEG patterns generated during the mental tasks. This is made possible by *neural network classifier* which learns these user-specific patterns. The other part of the learning process, the user, learns to undertake the mental tasks in a way that the system recognizes them better. The user may choose the mental tasks (see the section 3.2.2) he or she uses and the strategies to undertake those mental tasks (e.g., thinking of moving a finger, the hand or the whole arm). The learning process can be enhanced with *feedback*.

The ABI has been able to classify *three* mental tasks from online spontaneous EEG signals

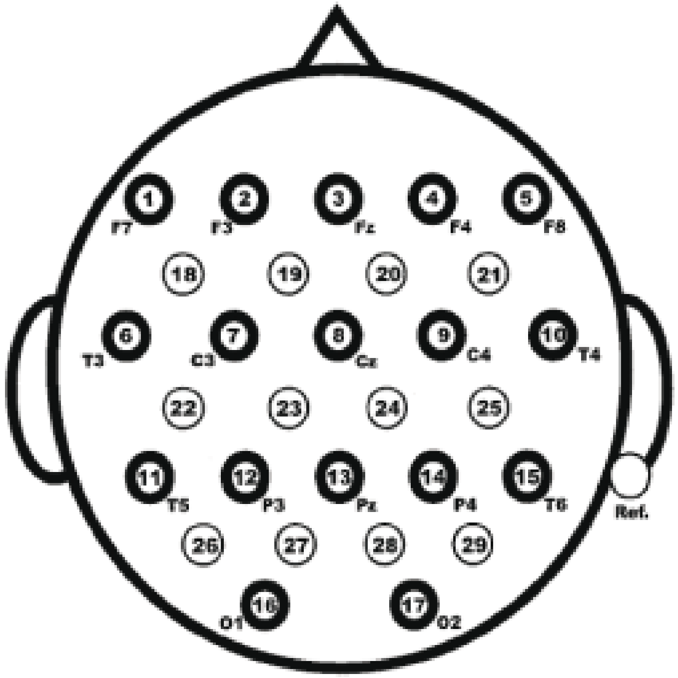

Figure 3.3: Positions of the 29 electrodes used in the Graz BCI. The 17 electrode positions with bold circles belong to the international 10-20 system. The rest twelve electrodes were inserted in between, in order to increase spatial resolution [48].

Subject/Task	L	R	F	A	T
S1/L	45.4	17.2	12.2	16.2	8.9
S1/R	22.2	26.8	21.0	18.5	11.5
S1/F	16.7	8.5	58.0	5.7	11.1
S1/A	6.5	7.1	6.3	61.0	19.0
S1/T	9.6	7.7	12.7	26.9	42.9
S2/L	68.1	15.6	7.1	6.1	3.0
S2/R	18.4	73.9	2.4	2.9	2.4
S2/F	9.8	4.7	58.4	11.7	15.4
S2/A	8.9	5.2	12.1	57.7	16.1
S2/T	0.8	2.4	15.0	10.4	71.4
S3/L	22.2	26.9	20.1	18.6	12.1
S3/R	24.1	29.0	20.1	18.6	12.1
S3/F	16.4	10.4	55.4	9.3	8.5
S3/A	16.5	23.1	10.0	40.1	10.3
S3/T	6.9	6.3	5.5	1.3	80.0

Table 3.1: Confusion matrices for subjects S1, S2 and S3 in the Graz BCI [48]. See text for details.

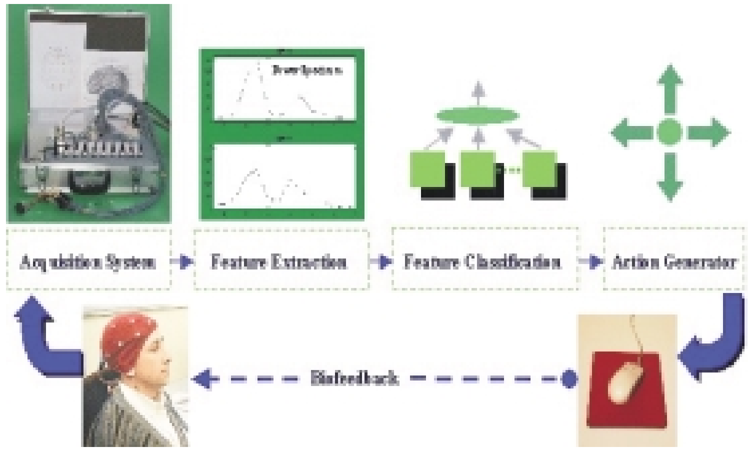

Figure 3.4: The key components of the ABI system [13]

with around 70 % accuracy [16]. The false classifications were kept below 5%, because uncertain classifications were *rejected*. Classification decision is made every 0.5 s. Also the training time required to achieve this level of performance has been short; only few days of moderate training (1 hour per day).

The performance of the ABI outside the laboratory environment was demonstrated in IST’2000 (the European conference of the information society community organized by the European Commission) in Nice, France. The ABI was used by the members of the project and by three visitors in an exhibition area containing electromagnetic fields, noise and people moving around. Particularly, one of the visitors managed to write something without errors and play the Pacman (see the section 3.2.5 after less than one hour training [13].

3.2.1 Overview of the system

The ABI system can be divided to components according to Figure 3.4. Each component is described below in more detail according to [16].

Acquisition system The portable EEG system has 8 scalp electrodes. They are placed on F3, F4, C3, Cz, C4, P3, Pz and P4 according to the international 10-20 system (see Figure 3.5). The sampling rate of the system is 128 Hz. A *surface Laplacian* (SL) [4] is estimated locally over the six electrodes (C3, Cz, C4, P3, Pz and P4) by using a finite

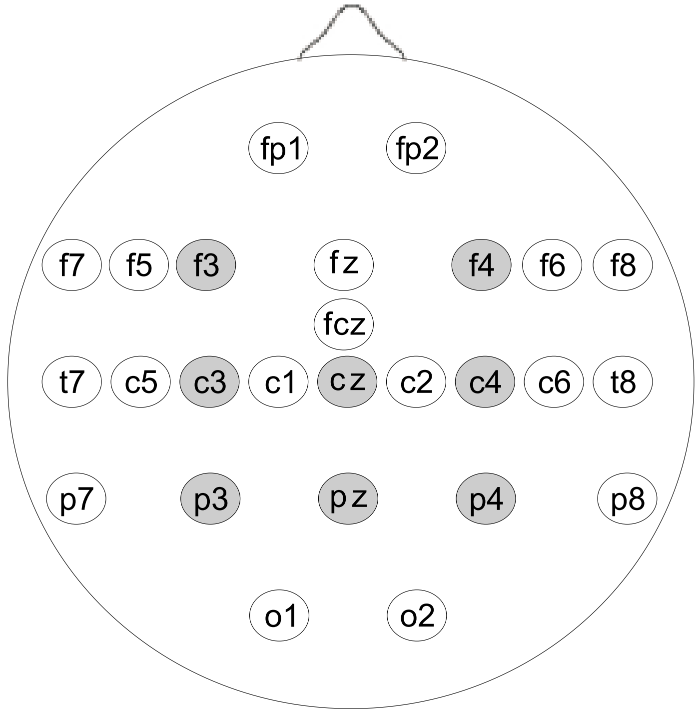

Figure 3.5: The electrodes used in the ABI are painted gray in this picture [16].

difference method in which the mean activity of the neighboring electrodes is subtracted for each position of interest. Then the signal is bandpass filtered with a second order 4-45 Hz *Butterworth filter*. In addition, the signals are referred to a baseline, which is the average of initial resting period. This period lasts 1 minute and the users are instructed to remain in resting state (eyes open). This baselining is done, because the brain activity is not stable over time.

Feature extraction The extracted features are power spectrum density components in the frequency band of 8-30 Hz within 1/2 second EEG segments averaged from 1 second sequences. The overlapping between the segments is 50%. As a result each EEG sample is represented by 72 features (6 channels times 12 components each). Thus, an EEG sample is computed every 1/2 second.

Feature classification Classification is done using a classifier called *local neural classifier*. In this classifier, every mental task (class) is presented by a *prototype* in a high-dimensional input space. The aim is to find the appropriate position of the prototypes in this space to differentiate the classes. Therefore, during training, the prototypes are pulled

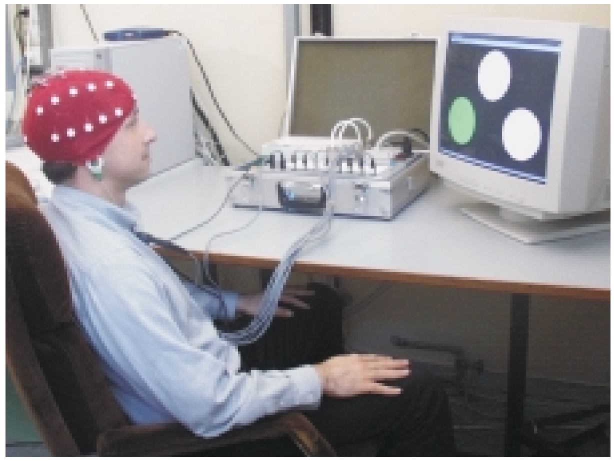

Figure 3.6: Biofeedback in the ABI system [15]

toward the EEG samples of the mental task they present and pushed away from the EEG samples of other tasks.

Biofeedback Biofeedback is provided in the form of colored buttons. If, for example, three mental tasks are used, three colored buttons are displayed each representing one particular mental task. The subject performs the mental tasks spontaneously and a button lights up if the arriving EEG data is classified to a corresponding mental task (see Figure 3.6).

3.2.2 Mental tasks

Mental tasks used in the ABI are chosen in a way that they activate cortical areas at different extents (see the section 2.1). The mental tasks used in ABI are:

- **Relax**. The subjects stays his or her eyes closed and tries to relax.
- **Subtractions**. The subject performs subtractions by a fixed number (e.g., 60-3=57. 57-3=54, 54-3=51,...).
- **Cube rotation**. The subject imagines a three dimensional cube rotating around one of its axis.
- **Right hand movement**. The subject imagines repetitive movements of the right arm or its fingers.

- **Left hand movement**. The subject imagines repetitive movements of the left arm or its fingers.
- **Word association**. The subject forms successive words in his or her mind in such a way that the next word starts with the last letter of the previous word.

Note that the eyes remain open in all the other mental tasks expect in the relax task.

3.2.3 Training

The first training session with the new subject is done *offline*. The EEG data recorded in this session is used to train the first individual neural classifier. Recording is done as follows.

The subject is instructed to remain in a resting state the first 60 seconds of the recording. In the resting state the subject keeps his or her eyes opened but does not undertake any particular task. The *average resting pattern* is computed over this initial period and used as a *baseline* for all the other tasks.

During the recording the subject performs the chosen mental tasks. The operator instructs the subject which mental task to perform next by saying it aloud (e.g., “right” or “relax”). The operator enters the label of the task manually. The subject concentrates on one mental task for 10 to 15 seconds before the operator chooses the next task. To remove artifacts caused by the communication between the subject and the operator and to avoid mislabeling of the mental tasks, data recorded 2 seconds before and 2 seconds after each transitions is removed. The neural classifier trained at the first session is embedded in the BCI and used in the second session. From this session onwards training can be done *online* and biofeedback can be used to enhance the learning process. Otherwise the training protocol is the same with or without biofeedback. The neural classifier can be tuned with the EEG data recorded in the second session. This classifier can then be used in the third session and so on. After the subject reaches the desirable level of performance, training is halted and the subject can start using the applications (see the section 3.2.5).

Last day of training	Subject		Confusion matrix (%) Relax	Left	Right
3	MJ	Relax	100	0	0
		Left	0	57	2
		Right	0	9	52
5	CGS	Relax	93	0	0
		Left	0	61	6
		Right	0	4	85
4	MC	Relax	76	0	1
		Left	0	24	6
		Right	0	9	21

Table 3.2: The online classification performances for subjects MJ, CGS and MC after 3-5 days of consecutive training with biofeedback [16].

3.2.4 Performance

In the study [16] the recognition of three mental tasks was studied. Table 3.2 reports the *online* performances of the local neural classifiers at the last day of the training for three subjects. The subjects (MJ, CGS and MC) were trained in the presence of biofeedback for 3 to 5 consecutive days (sessions). Subject MJ was familiar with the ABI before, whereas subjects CGS and MC had no previous experience. Subject CGS achieved the most impressive results: 93 %, 61 % and 85 % for relax, left and right, respectively, whereas the false classifications were only 0 %, 6% and 4 %. The channel capacities can be calculated from the confusion matrices using the Arimoto-Blahut algorithm [10]. They are 1.19 (MJ), 1.20 (CGS), and 0.64 (MC) bits/trial.

The evolution of the online performance for subject CGS can be seen in Figure 3.7 and for subject MJ in Figure 3.8. As can be seen from the graphs, the evolution of the performance for subject CGS is not linear while with subject MJ it is. This can be due the fact, that subject MJ was familiar with the ABI before, while for subject CGS this was the first time he used the ABI [16].

3.2.5 Applications

Today, there exist two applications: the *Virtual keyboard* and the *Pacman game*. ABI has also been used to control a *robot* [13]. The user controls Pacman with two commands to make it turn left or right. Pacman stops when it reaches the wall. The goal of the game is

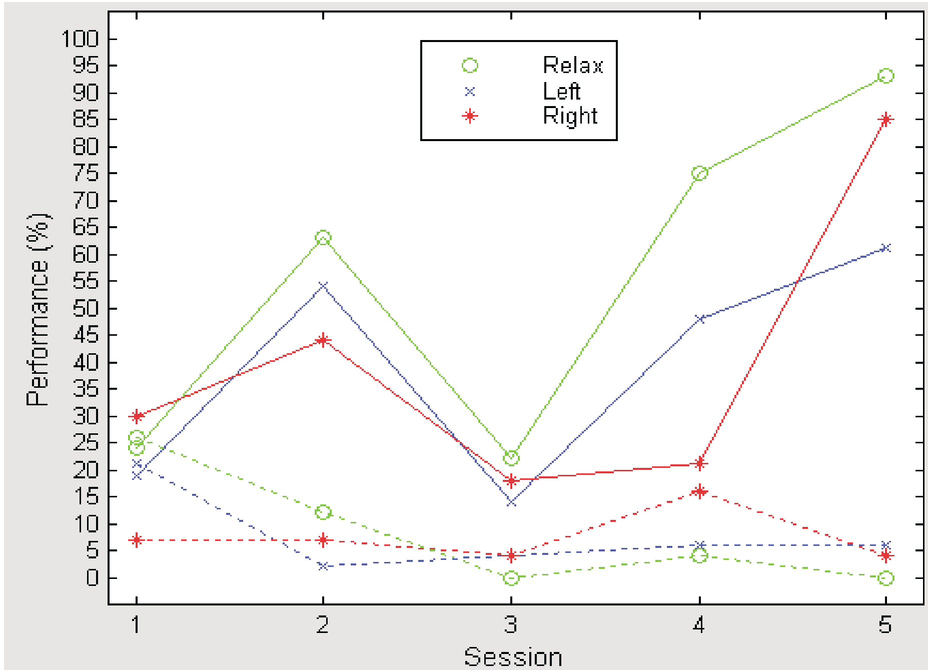

Figure 3.7: The evolution of online performance for subject CGS during five consecutive days. The solid lines represent correct classifications and dashed lines wrong classifications for corresponding tasks [16].

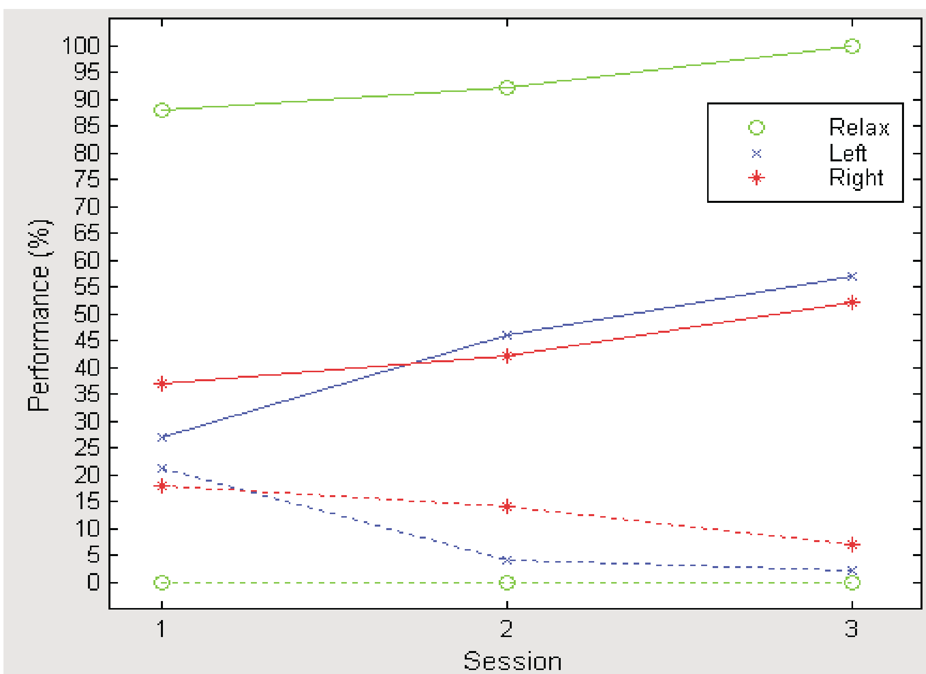

Figure 3.8: The evolution of online performance for subject MJ during three consecutive days. The solid lines represent correct classifications and dashed lines wrong classifications for corresponding tasks [16].

Figure 3.9: ABI's Virtual keyboard

to collect all the dots (euro coins in this case) from the maze. There are no ghosts in this version of the Pacman game.

The Virtual keyboard works as follows. The keyboard is first split into three areas each containing 9 letters (see Figure 3.9). The areas are indicated by colored frames. Each color is configured to one of the three mental tasks used. Classifications are made every half a second, as usual, and the flashing of the colored area gives the feedback for the user.

In order to select the letter of his or her choice, the user must concentrate on the task which corresponds to the color of the area where the letter is. After a successful selection, the selected area is split into three further parts each containing three letters. If the user is able to select one of these three areas, the actual letter to be written can then be selected from three remaining letters.

The program can be configured in a way that three consecutive classifications belonging to the same mental task must be made before the area is selected. This reduces the error rate. It is possible to go back one step. The program can be configured to wait for few seconds for a particular mental task to performed a certain number of times. With these settings one letter can be selected in 14 seconds if no false classification occur. In practice, speed of 20 seconds per letter has been achieved.

3.3 Comparing BCI systems

In this section the six BCIs described before in this chapter are compared. The comparison is made for training duration, EEG measurement, preprocessing, feature extraction and classification methods. In addition, mental tasks, imagery and applications used in BCIs are compared. Finally, the performances of the six BCIs are reviewed, but that comparison proved to be difficult, because the results are reported in differently in different BCI papers. Summary and discussion is provided in the end of this chapter.

3.3.1 Training duration

In order to compare the training duration of the six BCIs explained in this chapter, answering the following questions would be helpful: What is the training duration needed to reach the stage after which no considerable improvement can be achieved? How long does it take to reach a certain level of performance (for example, classification rate of 80 %)? How does the performance vary between trials, sessions or days? What are the individual differences in the training duration, i.e., do some people learn to use a BCI significantly faster than others?

However, at present, it is not possible to answer properly to these questions. There simply is not enough research and results reported. Answering the first question would require the same subject to use the same BCI for a long time (over a month). However, in the majority of the published papers there are reports only from short experiments lasting only a few days. Some BCI researches may have used the same subject(s) in two or more experiments, but the BCI itself (classifier, signal processing methods etc.) has changed between the experiments.

The six BCIs described before can be divided into two categories. Two of the BCIs (the TTD and the Wadsworth BCI) are based on the operant conditioning approach, i.e., the self-regulation of the EEG response. The system itself does not learn, so all the training load is on the user. These BCIs require *always* that the subject is trained with biofeedback. The training duration can be very long as is the case with the TTD. It required from several weeks to over a year of training for the subjects to reach the "free spelling phase" (see the section 3.1.4) [31]. Wolpaw et al. report in a paper published in 2000 [65] that the users of the Wadsworth BCI "develop substantial control (of the cursor movements) within 5-10 half-hour practice sessions and continue to improve with further practice". However, there is no information about what "the substantial control" means and how long the users will continue to improve after that. In a paper published in 1998 [39] McFarland et al report that "high accuracy (i.e., >90%) usually takes several months to develop and the subjects vary greatly in their learning rates.

The BCIs in the other category (Alberta, Oxford, Graz BCI and ABI) rely on the pattern recognition approach. It means that the BCI system (or the classifier in particular) learns to classify individual EEG patterns during the different mental tasks. The training load is more on the BCI system than on the subject. The subject does not even have to be trained, which is not possible with the BCIs based on the operant conditioning approach. This was the case with the most recent Graz BCI [48] experiment. However, the experiment was done offline and it is therefore not known how well the classifier would have performed in an online situation. Kostov et al. [32] (the Alberta BCI) report only that "Acquiring control with our BCI takes some training, but most of our subjects were able to demonstrate some control even after only two 30 min sessions". This does not tell much about the actual training duration. Roberts et al. [58] (the Oxford BCI) gave the results as a mean classification accuracy over all experiments. Therefore, there is no information whether the performance improved from one session to another. With the ABI the online results of one week training period with two subjects are reported in [16]. The evolution of online performance for subject CGS can be seen in Figure 3.7 and for subject MJ in Figure 3.8.

Even though the newest experiment with the Graz BCI was done offline, online experiments have been done before, see e.g. [52, 19]. A study lasting as long as four months has been reported in [53, 56]. In that study a tetraplegic patient was trained to control hand orthosis by mental imagination of specific motor commands. The subject of the experiment was able to move only his biceps in upper limbs. The initial classification accuracy was about 65%. In the first 30 sessions the mental tasks were left and right hand movement and no substantial improvement could be seen. Only after the other mental task was replaced from left hand to movement of both feet, accuracy improved sharply to about 95%. In the last session all 160 trials were correctly classified.

3.3.2 EEG measurement

The BCI researchers have to decide the number and the placements of the electrodes. The number of the electrodes is always a compromise. Increasing the number of the electrodes makes more precise localization of the EEG activity possible. On the downside, computing time increases as the number of the electrodes increases. In addition, from the

Figure 3.10: Tetraplegic patient used the Graz BCI to control the electrical driven hand orthosis in his left hand [54].

user's point of view, more electrodes means more cumbersome electrode cap, and more time goes to the preparation of the measurement. For this reason many BCI researches aspire to use as few electrodes as possible.

The positions of the electrodes depend on the BCI itself and the EEG responses which it tries to detect and classify. If, for example, motor imagery is used, electrodes above the motor cortex (C3 and C4) are typically used to measure EEG. Sometimes BCI researches do offline research with large number of electrodes in order to solve which electrode positions would be most effective in the online BCI.

In the Alberta BCI 24 electrodes were used in the measurements, but only the electrodes at positions C3, C4, P3 and P4 were used in the actual online BCI. Linked ears reference was used. In the Oxford BCI, the EEG was measured from only single *bipolar* channel. Difference between two electrodes located 3 cm behind C3 and C4 was measured. In the Wadsworth BCI, two electrodes were also used, located in C3 and C4 while the reference electrode was on the right ear. In the TTD, only one electrode was used, located in Cz. In the latest offline experiment with the Graz BCI , 29 electrodes were used [48]. The reference electrode was on the right ear (see Figure 3.3). In the online Graz BCI, the EEG was measured from two *bipolar* channels 2.5 cm anterior and 2.5 cm posterior to the electrode positions C4, C3 and Cz, respectively [53]. In the ABI, 8 electrodes were used in positions F3, F4, C3, Cz, C4, P3, Pz, and P4. Reference electrodes in both ears were linked together. Electrodes used in each of the six BCIs are presented in Table 3.3.

BCI	Electrodes	Sampling rate	Freq. range	Feature extr.	Window	Step	Classifier
Alberta	C3, C4, P3 and P4	200 Hz	2-30 Hz	4th-order AR	0.50 s	0.05 s	ALN
Oxford	C3' & C4' (bipolar)	384 Hz	0.1-100 Hz	8th-order AR	0.33 s	0.08 s	Bayes
Wadsworth	C3 and C4	196 Hz	8-12 or 18-24 Hz	AR+amplitude	0.20 s	0.10 s	threshold
TTD	Cz	256 Hz	No infor.	amplitude	0.50 s	0.06 s	threshold
Graz	29 (see Figure 3.3)	256 Hz	0.5-30 Hz	Band power[1]	4.00 s	5.75 s	HMM
ABI	8 (see Figure 3.5)	128 Hz	8-30 Hz	Power spectrum	1.00 s	0.50 s	Local

Table 3.3: Preprocessing and feature extraction methods in the six BCIs. 1) The logarithm of the band power for frequency bands of 7-10 Hz, 10-13 Hz, 16-20 Hz, 20-24 Hz and 24-30 Hz was calculated for every channel. Then a subset of a feature vector was calculated

3.3.3 Preprocessing, feature extraction and classification

Different preprocessing, feature extraction and classification methods are applied to the raw EEG signal in the six BCIs. They can be seen in Table 3.3 as well as electrodes used in each BCI. In the table the frequency range means the range from which the features are calculated. Window means the length (in seconds) of the time window which is used to calculate the features. Step is the movement of the window in time. For classifiers, see sections 3.1 and 3.2.

3.3.4 Subjects

Today's BCIs could provide a communication tool for severely disabled people who cannot use any other interface. In the future BCI could be used, for example, to control hand orthosis. Therefore, any BCI should be tested with disabled subjects to see how they can use the interface and if there are differences compared to healthy subjects. A disabled person may be better motivated than a healthy subject. However, BCI researches must be careful not to rise too high expectations within the disabled subjects. Furthermore, acquiring disabled subjects can be a problem if one does not work in a hospital or other such environment. All the six BCIs, expect the Oxford BCI, have been tested with people with different disabilities (for example spinal cord injuries and ALS). Perhaps the BCI most used by disabled people is the TTD, which have been used by 12 patients with severe or total paralysis. The Wadsworth BCI has also been used by several patients with disabilities. [31].

3.3.5 Mental tasks and imagery

The six BCIs can be divided into two groups concerning the kinds of mental tasks or imagery they require. Four of the BCIs (Alberta, Oxford, ABI and Graz BCI) are based on pattern recognition approach and use mental tasks. Two other BCIs (the TTD and the Wadsworth BCI) are based on the operant conditioning approach and require the self-regulation of the EEG response. There are no predefined mental tasks.

Although the Alberta BCI was based on the pattern recognition approach, it had no predefined mental tasks. The subjects could choose what tasks they wanted to use in controlling the cursor movements. This was possible, because in the pattern recognition approach the BCI system can be trained to classify the EEG patterns related to the tasks the subject has chosen. However, in other BCIs based on the pattern recognition approach, the subject is provided with predefined mental tasks.

In the Graz and Oxford BCI experiments, the mental tasks were the same for all of the subjects (motor imagery and math task in the Oxford BCI and left-hand movement, right-hand movement, foot movement, subtraction and tongue movement in the Graz BCI). In the ABI there are six predefined mental task (relax, subtraction, cube rotation, right and left hand movement and word association), but the subject is able to choose which three of those he or she wants to use. These three BCIs (ABI, Graz and Oxford) have two mental tasks in common, namely the imagination of the movement of the left or the right hand and the math (subtraction) task. Although the mental tasks are defined in these three BCIs, the definitions are not very strict and subjects can use different mental strategies while performing them.

With the TTD subjects are not instructed which kind of mental strategies they should use in order to change their SCP amplitude. Therefore, the subjects can use different mental strategies in order to acquire control of their SCP amplitude. Examples of these strategies can be found in [31] (see also the section 2.3.2). However, it is possible that the user loses the control of his or her SCP amplitude. One of the subjects in the study reported in [7] achieved a 65% control of his SCP amplitude, but lost it after several months of training when he changed his cognitive strategy. He never regained it despite of several days of a new training.

With the Wadsworth BCI new users are advised that various kinds of motor imagery are usually helpful in beginning to acquire control. The control of the Wadsworth BCI may become almost automatic [65]: “As training continues, users often report that they use imagery less and less."

3.3.6 Applications

Use of different kinds of applications have been reported with all six BCIs expect the Oxford BCI. The TTD has been used by ALS-patients as a communication tool with the language support program. More recent applications include the environment control unit and the Internet browser "Descartes" [22]. The Graz BCI has been used to control a prosthetic arm [53]. The Alberta BCI has been used as the environmental control device [28]. The Wadsworth BCI has been used to answer simple YES and NO questions [41]. The ABI has the Virtual keyboard and Pacman applications [13].

3.3.7 Biofeedback

Some kind of biofeedback is provided for the user in all the six BCIs, expect in the Graz BCI. However, during the years, different kinds of feedback has been used in the Graz BCI (see the section 2.6.3). The most popular form of biofeedback has been the cursor control. In a typical experiment user tries to move the cursor to the goal, which is located on one side of the screen by using two commands (i.e., up&down or left&right). Cursor control was used in Alberta, Oxford, TTD and Wadsworth BCIs. In the ABI colored balls are used as feedback (see Figure 3.6. TTD's feedback display can be seen in Figure 2.8. Positive reinforcement is provided by a smiley face after the cursor successfully hits the target. In the Wadsworth BCI the target flashes for 1.5 s as a reward.

3.3.8 Performance

It is difficult to compare the performances of the BCI systems, because the researches present the results in different ways. However, in this section the comparison is made in accuracy, application specific performance and selection speed. In addition, asynchronous use is discussed.

Accuracy

As described in the section 2.8 there are basically three ways to report accuracy of a BCI: Hit rate, correct classification rate and confusion matrix. In addition to that, some of the results reported with the TTD and the Wadsworth BCI are *application specific* and are not in any way comparable with the results of other BCIs.

The hit rate is reported with three of the six BCIs (Alberta, Wadsworth and TTD). In the Alberta BCI it was reported that the subjects achieved hit rate close to 100 % with two classes and 70-85 % with four classes [32]. 32 cursor steps were used. Four subjects achieved hit rates of 78-93 % with the Wadsworth BCI [41]. 3 patients achieved approximately hit rates of 70 % with the TTD [7]. The hit rate does not tell much about the classification accuracy and it is dependent on the number of the cursor steps. Better way to report the results is the correct classification rate or accuracy.

The correct classification rate was reported with the Oxford BCI. Overall mean classification rates (fraction correct) were 0.8648 (hard rejection), 0.7595 (soft rejection) and 0.5318 (baseline) [58]. However, the correct classification rate does not tell how the errors are distributed between the classes. Therefore, the results should be presented using confusion matrices. That was done with the ABI and the Graz BCI. The channel capacities can then be calculated from the confusion matrices. In the ABI the maximum channel capacities with three subjects were 1.20, 1.19 and 0.64 [16], while in the Graz BCI they were 0.42, 0.81, and 0.56 [48]. Furthermore, the results from the Graz BCI were offline results, while in the ABI they were online results.

Application specific performance

Kűbler et al. [31] compared BCIs on the basis of text input speed. That is not a good way to compare the performances of the BCIs, because

a) Not every BCI has a writing application.

b) Even if a BCI has a writing application, the text input speed is affected by the application used.

Of course, this kind of comparison can give some indication of the performances of the BCIs, but only the ABI and the TTD have the writing applications. In the TTD it took subjects about 2 minutes to write one letter whereas in the ABI the same can be done in about 20 seconds. Other BCIs have had other applications. In the environment control application used with the Alberta BCI [28], it took 6.8, 7.6 or 8.3 seconds for three subjects, respectively, to select one button. In the Wadsworth BCI's question-answer protocol, subjects were able to answer questions at a rate of 4.0 to 4.6 question per minute (13-15 seconds for one question).

Selection speed

When considering using a BCI as a communication or a control tool, it is important to know how long does it take to make one *selection*. Although the classification can be made in short time intervals (for example, in 63 ms in the TTD, see Table 3.3) it does not mean that one selection can be made in that same time. For example, in the TTD, the actual time for one selection in the language support program (see the section 3.1.4) was much longer, 4-6 seconds. That time is the *trial length*, including the initial baseline period (2 seconds) and the time when the subject tries to move the cursor to the target (2-4 seconds). In the Graz BCI the trial length was fixed at 8 seconds. It included the initial 2 second reference interval at the beginning of each trial. These two BCIs (the TTD and the Graz BCI) require the initial baseline or the reference interval. This means that they must be operated in a predefined time window. In other words, they are operated in externally paced, *synchronous* mode (see the section 2.9)

Wadsworth, Alberta and Oxford BCIs had trials in which the subject tried to move the cursor to the target. The length of one trial was dependent on the subject's performance as well as on the speed of the cursor (i.e., step in Table 3.3). In addition, the number of the steps required to hit the target affects the length of one trial. No baseline or reference interval were needed in the trials of these BCIs. The ABI differs from all of the five other BCIs in the fact, that no trials were used. Therefore, the subject could theoretically make one selection in the same time as one classification is made (i.e., in half a second). The ABI has 60 seconds baseline period before each recording session.

Asynchronous use

The four BCIs (Wadsworth, Alberta, Oxford BCIs and ABI) could theoretically be used continuously, i.e., no predefined time window is needed. However, this does not automatically mean that these BCIs could be used in asynchronous mode. At least the Wadsworth

BCI	Approach	Classes	Training duration	Biofeedback	Electrodes
Alberta	PR	2 or 4	not reported	cursor	4
Oxford	PR	2	not reported	cursor	2
Wadsworth	OC	2	weeks or months	cursor	2
TTD	OC	1	months	cursor	1
Graz	PR	5	No training	No FB	29
ABI	PR (offline)	3	> 1h	Balls	8

Table 3.4: Summary of the six BCIs. PR=pattern recognition and OC=operant conditioning

BCI cannot detect when the EEG control is intended or not, because the EEG sample is always classified to either of the two classes. In addition, the application (the question-answer protocol, see the section 3.1.3) of the Wadsworth BCI used the same kind of trials as the training period. The Alberta BCI, although based on the pattern recognition approach, did not have a reject option. However, in the environmental control unit application [28], a kind of asynchronous mode was tried to be initiated through software. The user of the application could “lock” the system. In the lock-mode, the control of the system was blocked until a certain sequence of four buttons was selected. However, the lock-mode did not work perfectly, because the subject who could not see the screen, accidentally unlocked and then re-locked the system in about five minutes. Also in the TTD the use of lock-mode has been studied in [27].

The ABI and the Oxford BCI are both based on the pattern recognition approach and use the rejection of uncertain classifications. Therefore, they could theoretically detect when the subject is not concentrating on the mental tasks by rejecting them, i.e., work in true asynchronous mode. However, it remains unclear how efficiently the rejection works when the subject is not performing any of the mental tasks.

3.3.9 Summary and discussion

Table 3.4 displays the summary of all six BCIs described in this chapter.

All the six BCI systems described in this chapter have much room for improvements. Some problems are specific for the pattern recognition approach and some for the operant conditioning approach. However, all the six BCIs have several problems in common:

1) Accuracy Accuracy is maybe the most important aspect in any BCI. As described in the section 2.8, the accuracy affects greatly the channel capacity, and thus, the performance of a BCI. If a BCI is used for communication, the false classifications hinder the communication by slowing it up or by producing errors. This can make the user frustated and further hinder the performance. If a BCI is to be used in the control applications (environmental control, hand prosthesis, wheel-chair, etc.), the accuracy is crucial. Imagine the wheel-chair going to the wrong directions at the junction of the street.

Today's BCIs have not achieved 100 % accuracies even with only two classes. Hit rates of close to 100 % have been reported in [32, 41]. However, what the actual sample-by-sample accuracy has been is not known. In addition, the differences between the performances of the individual users are great. The number of the false classification can be reduced by rejecting uncertain classifications. The rejection of uncertain classifications decreases the number of the false classifications and, thus, increases the performance. However, the rejection was used only with the ABI and the Oxford BCI.

2) Speed Beside accuracy, speed is also very important when considering using a BCI for communication. As described 3.3.8, the speed of a particular BCI is affected by the trial length, i.e., the time needed for one selection. Typically, one trial lasts many seconds. This time should be shortened in order to make a BCI effective in communication. In the ABI, no trials are used and the time for one selection is theoretically 0.5 s. However, in the practical applications it is longer (see the section 3.2.5.

3) Usability The preparation for the use of a BCI takes time, because of the EEG measurement. Ideally, the user, even a disabled one, could use a BCI independently after the EEG cap or electrodes have been put on. However, an operator is normally needed and one cannot use a BCI independently (see also asynchronous use).

4) Feedback The most common type of feedback has been the cursor control. However, compared to those feedback methods (different kind of games) used in the EEG biofeedback (see the section 2.6.2), they seem unimaginative and boring. The goal of many BCI researches may be a mouse-like interface, but this goal is still far away (see "BCIs as cursor control device" later this section).

5) Asynchronous use At least four of the six BCIs (Alberta, Graz, Wadsworth and TTD) cannot currently be used in asynchronous mode. In addition, further experiments are needed to find out if the rejection methods used in the ABI and the Oxford BCI can prevent unintended commands. However, if true asynchronous use is not possible, a lock-mode or on-off switch can be implemented through software. This has been tried with the Alberta BCI and the TTD.

6) Training duration This problem is more specific to BCIs based on the operant conditioning approach (the Wadsworth BCI and the TTD), which may require months of training. It means that the user must have patience and motivation to take part in such a long training.

7) Changing EEG patterns This problem is more specific to BCIs based on the pattern recognition approach. The EEG patterns related to the mental tasks can change between the days or even during the use of a BCI [31]. The changed patterns mean that for the optimal use of a BCI, the re-training of the classifier is needed from time to time.

Pattern recognition vs. operant conditioning approaches

Which one of the two approaches is better? There is no definite answer. It is clear that the training period is much longer in BCIs based on the operant conditioning approach. It means that the user must have patience and motivation. However, the long training duration might pay for itself, if in the end the performance is better than in BCIs using the pattern recognition approach. In todays BCIs this does not seem to be the case. However, as discussed in the sections 3.3.1 and 3.3.8, the experiments have been too short and inadequately reported with many BCIs, that no definite conclusions can be made.

The pattern recognition approach has its problems too. The EEG patterns related to the mental task change in time. This means that the classifier should be re-trained after some time. In addition, at least some of the mental tasks (for example, math tasks) are not at all related to the task user tries to accomplish (moving the cursor or selecting menus or letter). Could then the operant conditioning approach offer more *stable* and *natural* interface?

To end this section, the use of BCI for controlling cursor is considered.

Using a BCI for controlling cursor

Considering that many BCIs have used the cursor control as feedback, those interfaces are still far a way from an ordinary mouse. A mouse ables us to do several things which seem not possible with today's BCI technology. First, using the ordinary mouse, one can move the cursor to *any* direction in 2-dimensional space. Today's BCIs can provide only 2 directions with reasonable accuracy. Experiments with 4 directions have been made (see [32, 67]), but the hit rates were around 65 %. Second, one can easily change the direction of the cursor with the mouse. Is this possible with the BCI control? In all the experiments reported today the goal has been to hit the target located on one side of the screen. Therefore, it is not clear how well the subjects would have been able to change the direction of the cursor in the course of the trial. Third, a mouse ables us to use a *graded* control, i.e., we can move the cursor faster or slower. Today's BCIs cannot provide this kind of control. Fourth, we can stop the cursor easily by stopping the mouse and do other things such as watch the screen for any length of time before moving the mouse again. With the current BCIs this kind of *asynchronous* control does not work. Finally, the mouse has one to three buttons. To implement this in a BCI would require even more classes.

Chapter 4

Experiments with ABI

The experiments with a new ABI system were performed with three subjects in the Laboratory of Computational Engineering in February 2002. In the beginning of this chapter the hardware and software of the new ABI system are reviewed. The experimental methods and the online results are then presented along with the discussion. In addition, the subject reports about the mental task strategies and the feedback experiences are also presented in this chapter.

4.1 The ABI system

The ABI system consists of the hardware, which is used to measure the EEG and four Microsoft Windows based programs: EEP H11 Server, ABI Learning and online programs and ABI Visualization.

4.1.1 Hardware

The hardware used in these experiments was different from the hardware previously used with the ABI (see the section 3.2). The EEG system here was Electro Encephalo Processor model H11 (EEP H11) manufactured by Fase Sistemi, one of the partners of the ABI project. The whole system consists of EEG device, battery, battery charger and electrode cap. The EEG device is small, its dimensions are only $160 \times 110 \times 55$ mm and it weights 700 g.

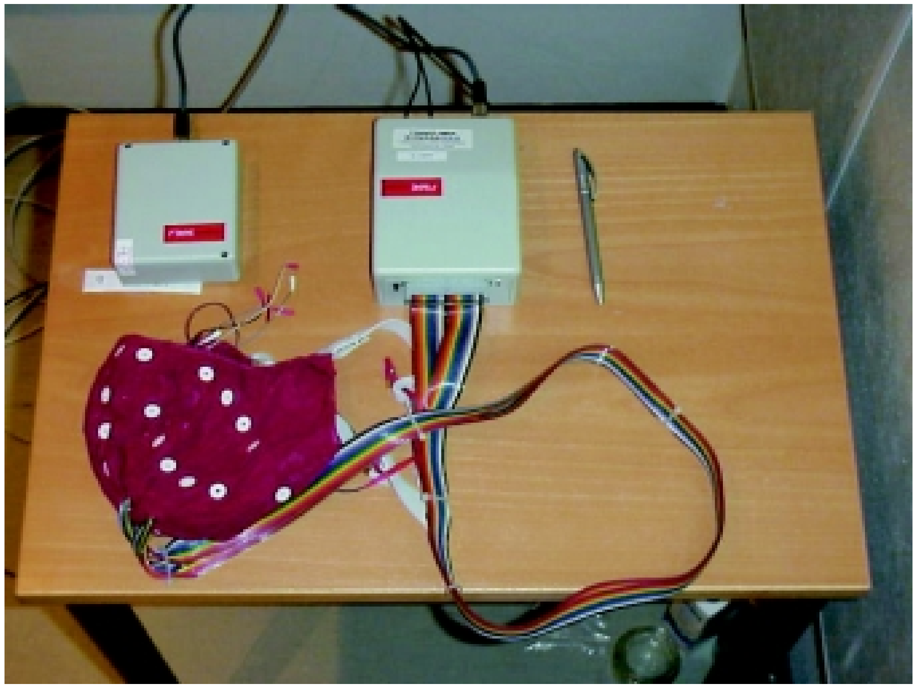

Figure 4.1: EEP H11 EEG device, its battery and the electrode cap used in the experiments. The pen is in the picture to give a reference in size.

The system has 38 analogical single ended channels and 2 electrical references. The analogical signal from each electrode is converted to digital signal with 16 bit resolution and sampling rate of 6800 Hz. The EEG device is battery powered. The data is transmitted to the computer via fiber-optic cable. This makes the EEG device isolated from the surrounding electrical fields. The electrode cap of medium size (54-58 cm) is ECI Electro-Cap Electrode System manufactured by Electro-Cap International, Inc. The cap has 32 electrodes for scalp EEG and 6 additional electrodes, which can be used as reference electrodes and measuring the EOG. Cap, EEG device and battery can be seen in Figure 4.1.

4.1.2 Software

Three Microsoft Windows based programs are needed in order to operate the ABI system: EEP H11 Server, ABI Learning program, and ABI online program. The EEG signal can be visually inspected with the ABI Visualization program.

EEP H11 Server and ABI Visualization

This program acts as a server (application programming interface (API)) for the ABI applications. In other words, it sends the EEG signal coming from the EEP H11 system to the ABI online and the ABI Visualization programs. The electrodes used with the ABI are selected with this program. The EEG signals can be seen in the main program window. It is possible to filter the EEG signals, for example, if they contain the 50-Hz component (see the section 2.4.4).

Beside the EEP H11 Server program, the EEG signals can be visually inspected with the ABI Visualization program, which displays the signals coming from the electrodes used in the ABI system (F3, F4, C3, Cz, C4, P3, Pz and P4).

ABI Learning

This program is used to train a set of prototypes from the recorded data. Each prototype corresponds to one particular mental task as described in the section 3.2.1. The classifier will then use these prototypes in the online classification of the EEG signals. In order to train a new set of prototypes, the processed data of one recording is loaded up into the program. Usually, the data without transitions is used. The data does not contain the initial resting period. The mental tasks are labeled in the data. The data is then divided into training and validation sets in such a way that three consecutive samples go to the training set and every fourth one goes to the validation set.

A new set of prototypes can be trained using the training and validation sets. It is also possible to load old prototypes or use a clustering method, the Self-Organizing Map (SOM), to create a set of prototypes from the training set. The old prototypes or those created by the SOM can then be used as a starting point for training of new prototypes.

The learning window (see Figure 4.2) can then be opened to train the new prototypes or to evaluate the prototypes already present. If no initial prototypes are present, the program will compute 1 prototype, averaging the samples of that class. Before starting the training, the number of iterations can be adjusted, i.e., how many times a new set of prototypes is trained. *probability* and *distance* thresholds can also be adjusted.

The thresholds affect on how easily the samples are classified to belonging to one of the mental tasks and how easily they are rejected. The classifier computes probability values for a sample belonging to each of the mental task included in the dataset. Then the highest probability value is chosen and this value is compared to the probability threshold. If the value exceeds the threshold, the sample is classified to the corresponding task, otherwise it is rejected. A sample is classified to a class based on the Mahalanobis distance [9]. If the distance is relatively long, the probability that the sample belongs to a class becomes uncertain. If the Mahalanobis distance exceeds the value defined by the distance threshold, then the sample is rejected.

After the number of the iterations and the thresholds are adjusted, the training of the new prototypes can be started. During the training, a new set of prototypes are trained in every iteration. After the training has finished, the confusion matrices corresponding to each iteration can be reviewed. The operator can then choose the best iteration (best prototypes) either manually or automatically. In automatic selection the operator can put all emphasis on validation set. The best prototypes can be then saved to be used later in the ABI online program.

ABI online program

The ABI online program was used to gather data for the Learning program and to give the feedback for the subject. A part of the main program window can be seen in Figure 4.3. This program acts as a client for the EEP H11 Server, i.e., the program gets the EEG data from the server. This data can be be saved in two formats: Raw data and processed data. The raw data is the data coming from the EEP H11 Server. The processed data goes through the feature extraction methods explained in the section 3.2.1 expect that in these experiments a spline Laplacian method [4] was used instead of the surface Laplacian. The classifier uses the processed data. The raw data is saved for later evaluation.

The program can also be used to give feedback for the subject. In order to do this, the prototypes trained in the Learning program must be loaded for each of the mental tasks. The probability and the distance thresholds of the classifier can be adjusted. It is also possible to choose either *positive* or *total* feedback. Positive feedback means that only the correct classifications are shown for the subject. If total feedback is used, all the classifications are shown for the subject.

The actual acquisition starts with the resting period in which the baselining is made (see the section 3.2.1). After the resting period, the classifying period starts. The mental tasks are labeled by the operator, who pronounces the name of the task and at the same time

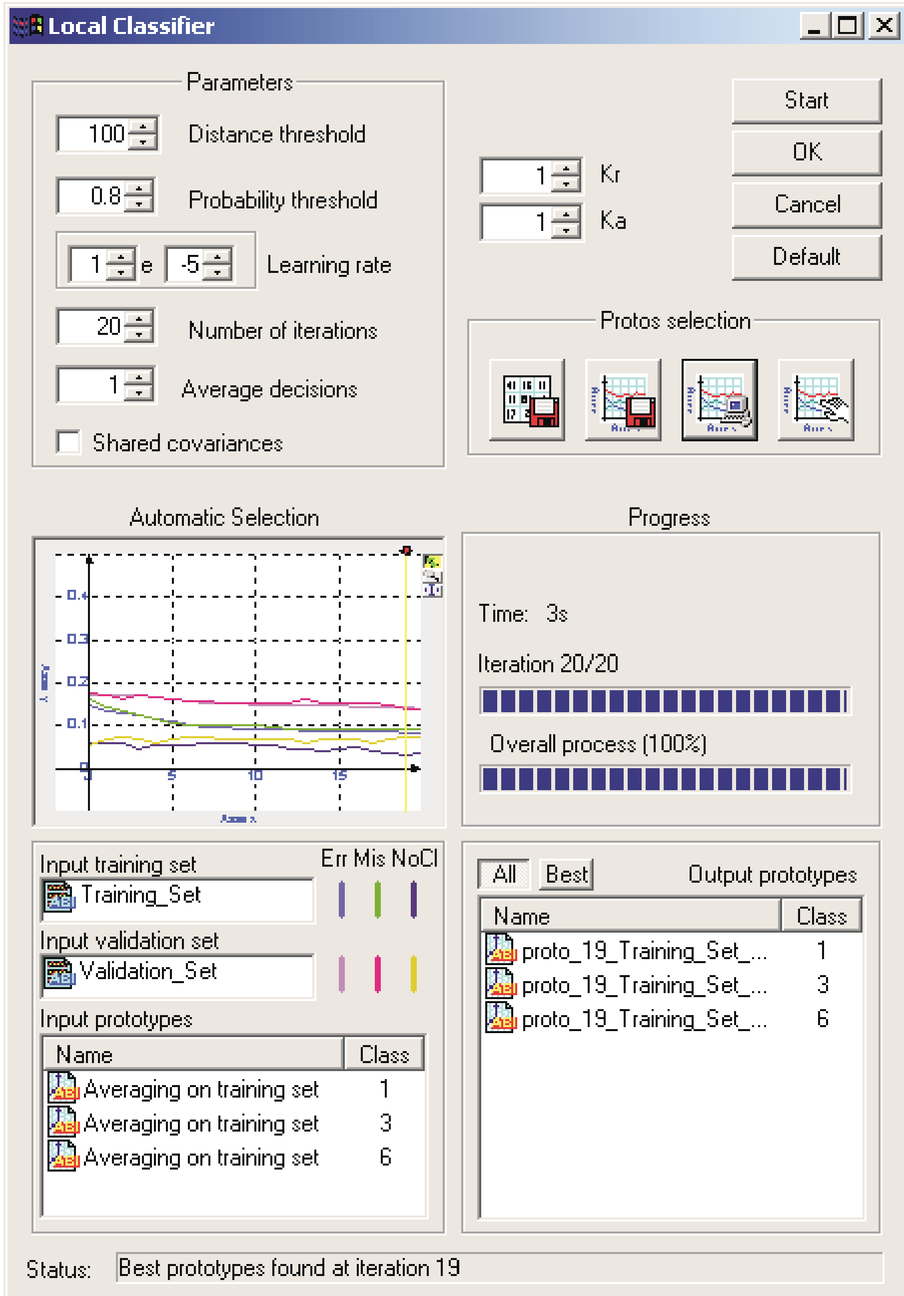

Figure 4.2: ABI Learning program.

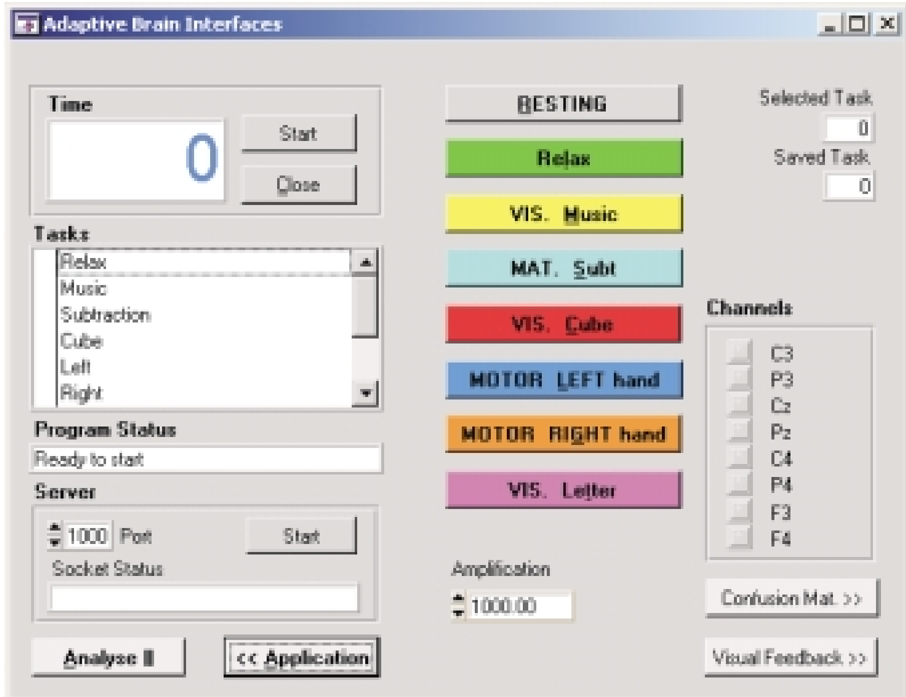

Figure 4.3: ABI online program.

presses the corresponding button in the program. These labels are saved in the raw and processed data.

4.2 Experimental methods

This section describes the methods used in the experiments. The experiments were done in the Laboratory of Computational Engineering, in the Helsinki University of Technology, during five consecutive days starting from 4th of February and ending 8th of February 2002. The experiments were made in 2×4 meters room (see Figure 4.4).

4.2.1 Subjects

Two healthy male subjects (subjects TN and JL) and one healthy female subject (subject LL) in their mid-twenties were the test subjects. Both male subjects were familiar with the ABI system (subjects TN and JL). They had used it a couple of times before these tests, but no actual training were done with them. The ABI was new to subject LL.

Figure 4.4: Test environment

4.2.2 Mental tasks

For the subject unfamiliar with the ABI (subject LL), the first step was to introduce the system to her. She was able to try the mental tasks (form the list presented in the section 3.2.2) by herself and decide which three were the most suitable for her. Before the actual first measurement a test run was made with these tasks in order to introduce the whole procedure to the subject.

Two of the subjects (TN and JL) used the mental tasks they were familiar with. Subject JL used relax, subtraction and right hand. Subject TN used relax, cube and left hand. The third subject, LL used three different combination: Relax, subtraction and right (days 1 and 2), relax, left and right (days 2 and 3) and relax, right and words (days 3, 4, and 5). Three different combinations were used because the first two did not work.

4.2.3 Data acquisition

The same electrodes were used in these tests as with the ABI before (F3, F4, C3, Cz, C4, P3, Pz and P4). The signals were referenced to the right ear. The ground electrode was in the left ear. The signals were checked with the ABI Visualization program and if they were noisy, a bandstop filter of order 24 and the frequency band from 45 Hz to 55 Hz was selected in the EEP H11 Server. Instead of the local surface Laplacian method used previously with the ABI, the spline Laplacian method [4] was applied to the raw data. In addition, before each recording the EEG signals were visually checked with the ABI Visualization program to ensure that all electrodes were giving good signals.

Each recording lasted about 300 seconds, including the initial resting period (60 s). After the resting period, the operator instructed the subject which mental task to perform first. The operator then changed the mental tasks so that each mental task lasted between 10-25 seconds. The order and length of the mental tasks were random. Three to five recordings were done in one session (day). There was about 5-10 minutes break between each recording.

4.2.4 Feedback

The feedback was provided the same way as described in the section 3.2.1. In addition, to the lighting up of the ball, the color or the "darkness" of the ball displayed the classification probability. Auditory feedback in the form of "beeps" was provided with the relax task (remember that relax task is performed eyes closed). Matrox G550 Dualhead display adapter was used in order to display the feedback on the separate screen. The operator sat about two meters away from the subject. The operator's display was situated sideways from the subject, so the subject couldn't see the operator's display (see Figure 4.4)

Subject LL received no feedback during the first session (day). This session consisted of four recordings, which included two combinations of mental tasks. The other combination was relax, left and right (first and third recording) and the other relax, subtraction and right (second and fourth recording). Feedback was not given in the first day, because the idea was to find out which mental tasks suited best for subject LL by trying these two combinations offline. It is better not to train a set of prototypes from the very first recordings and give feedback according to them. The mental tasks and the whole situation are so new for a subject unfamiliar with the ABI, that he or she improves in performing the mental taks very rapidly during the first recordings. Therefore, prototypes would become outdated between two recordings. Contrary to subject LL, only the first recordings were done without feedback with subjects TN and JL. This was because they were already familiar with the ABI system and the mental tasks used.

Positive feedback was given to all three subjects. Total feedback was given only for subject JL in some recordings (for complete list, see Appendix A.1) because he was the only one who achieved such a good level of performance at the first day that total feedback was thought to be more suitable than positive feedback.

4.2.5 Training

A new set of prototypes were trained after each recording using the data from the previous recording or the combined data from 2 or 3 recordings. Sometimes prototypes used in the previous recording were used as the initial prototypes. After the training, the confusion matrix of the new prototypes was compared to the confusion matrix of the old prototypes. If the new confusion matrix was better than the old one, the new prototypes were used in the next recording. The idea behind this approach was to find the best set of prototypes for each recording. If a good set of prototypes was found, then it was used in several recordings. This was the case with the prototypes created from the recording 3, day 1 for subject JL. He used them in all the recordings of day 2 and in the first recording of day 3. However, the results got considerably worse in days 2 and 3. Therefore, new prototypes were trained and used in days 3, 4, and 5. However, in the first recordings of days 4 and 5 the prototypes from day 1 were still tried, but with no success.

In the approach used previously with the ABI (see the section 3.2.3), same prototypes were used in every recording of one day. We adopted a different approach, because we felt that the prototypes should be more “up to date”, keeping up with the changes in the EEG between the days and even recordings during one day. However, changing the prototypes almost after every recording means that the subject does not have a chance to adapt to the particular set of prototypes. However, it was thought that it is first necessary to find prototypes which perform reasonable good (for example, giving correct classification rates over 50 % and false positive rates below 10 %) before the subject can really adapt to them.

4.3 Online results

In this section the online results of the experiments are presented. The results are from the real online situation, i.e., the subject has received feedback according to the results presented in this section. The only difference is that two seconds before and after each transition are removed. This removes the communication between the operator and the subject and avoids mislabeling of the mental tasks.

The results are presented in two different formats. In the other, the correct and false classifications of three mental tasks are presented for every recording. In the other, the channel capacities (in bits/trial) for all recordings are presented. Finally, the best and mean online results for each subject are presented. Notice that the probability and the distance tresholds varied between the recordings (see Appendix A).

4.3.1 Correct and false classifications

Correct and false classifications of each mental task for each subject are presented in the Figures 4.5, 4.7 and 4.6. Solid lines represent the percentage of the classifications (including the rejections) classified to the corresponding task. Dashed lines show the percentage of the classifications (including the rejections) classified to the wrong class. In the graphs, each of the mental tasks is color coded. Green is for relax, cyan for subtraction, red for cube, blue for left hand, black for right hand and magenta for words.

4.3.2 Channel capacities

The channel capacities for each three subjects of all online recordings are presented in Figure 4.8. The channel capacities were calculated using the Arimoto-Blahut algorithm [10].

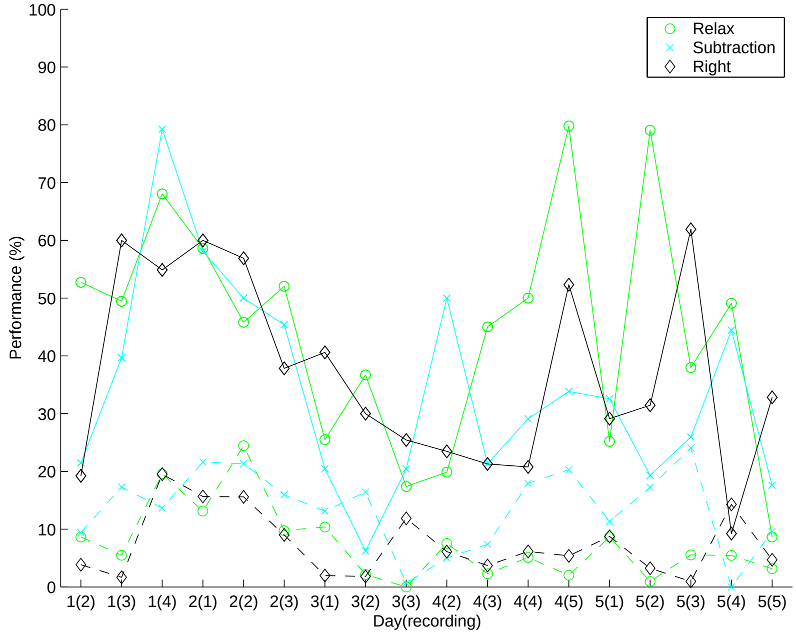

Figure 4.5: The online performance for subject JL over five consecutive days of all online recordings. For thresholds and feedback used, see Apendix A.1.

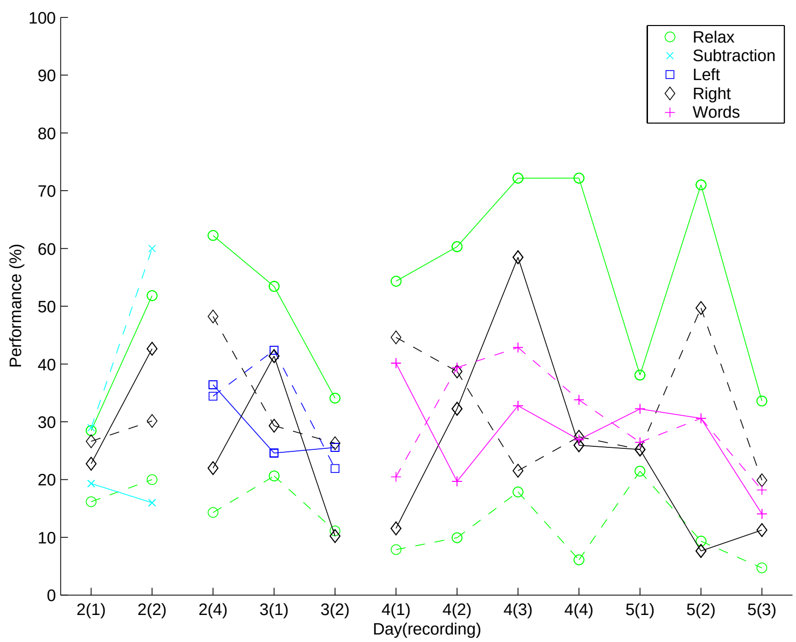

Figure 4.6: The online performance off all recordings for subject LL over four consecutive days. Notice that the combination of the three mental tasks changed three times during the training. For thresholds used, see Apendix A.2.

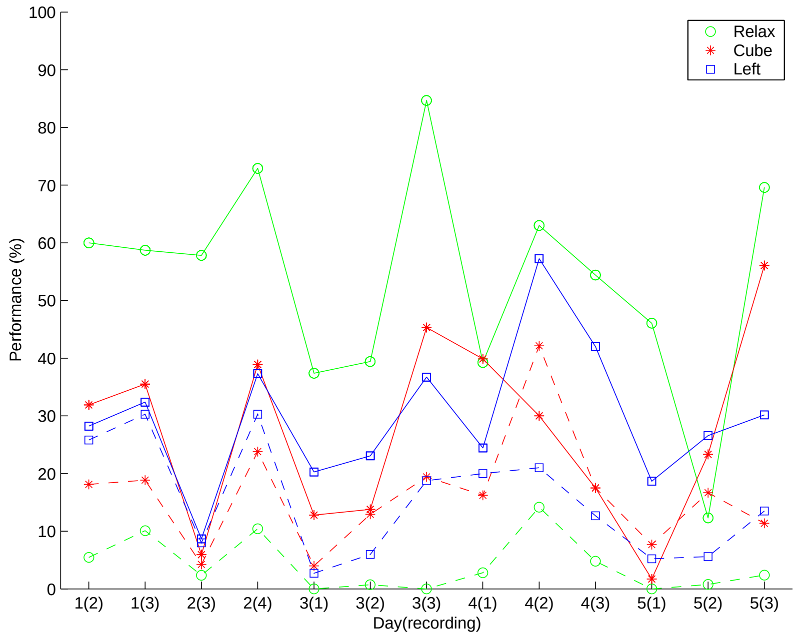

Figure 4.7: The online performance for subject TN over five consecutive days of all online recordings. For thresholds used, see Apendix A.3.

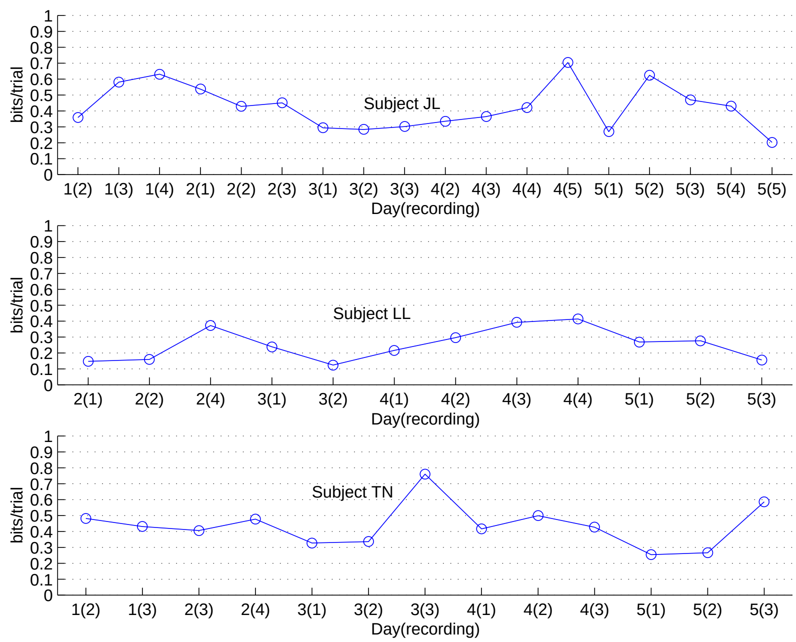

Figure 4.8: Channel capacities for all subjects of all online recordings. Subject LL was unfamiliar with the ABI at the start of the training were as subjects JL and TN had some experience.

4.3.3 The best and mean results

Here the best and mean (according to highest channel capacity) online results for each subject are presented. All online results can be seen in Appendix A. The best online results are presented in Tables 4.1, 4.2, and 4.3. The results are presented in two tables. The left table presents the confusion matrix of the online results. The right table displays three values: TP, FP and CC. TP displays the percentage of all the samples (including classified and rejected samples), which were correctly classified. FP displays the percentage of all samples, which were falsely classified. CC is the channel capacity in bits/trial. The mean results and standard deviations are presented in Table 4.4.

CM (%)	Relax	Subtr.	Right	Reject
Relax	79.8	1.0	1.0	18.2
Subtraction	2.3	33.8	18.0	45.9
Right	0.8	4.6	52.3	42.3

TP (%)	FP (%)	CC (bits/trial)
51.4	9.8	0.70

Table 4.1: The best online results for subject JL. Obtained at day 4, recording 5. Probability threshold was set at 0.9 and distance threshold at 100. Prototypes used were from day 4, recording 5.

CM (%)	Relax	Right	Words	Reject
Relax	72.2	2.6	3.5	21.7
Right	12.6	25.9	14.8	46.7
Words	6.2	27.6	26.9	39.3

TP (%)	FP (%)	CC (bits/trial)
36.7	24.7	0.41

Table 4.2: The best online results for subject LL. Obtained at day 4, recording 4. Probability threshold was set at 0.8 and distance threshold at 110. Prototypes used were from day 4, recording 2.

CM (%)	Relax	Cube	Left	Reject
Relax	84.7	0.0	0.0	15.3
Cube	1.4	45.3	18.0	35.3
Left	0.8	18.0	36.7	44.5

TP (%)	FP (%)	CC (bits/trial)
50.9	13.8	0.76

Table 4.3: The best online results for subject TN. Obtained at day 3, recording 3. The probability threshold was set at 0.8 and distance threshold at 100. Prototypes used were from day 3, recording 1.

Subject	JL	LL	TN
Recordings	18	12	13
Mean CC	0.43	0.26	0.44
std	0.14	0.10	0.14

Table 4.4: The number of recordings, mean channel capacities, and standard deviations (in bits/trial) over all recordings for each three subjects

4.4 Subject reports

What do the subjects think when performing the different mental tasks? Although some instructions are given for performing each of the mental task in the ABI, the subjects can use different and individual *strategies*. There can be many strategies with each of the mental tasks and they can change during the training. The only way to find out what these strategies are, is to ask it from the subjects. The subjects were presented with the question form displayed in Appendix B. In addition to the mental task strategies, the feedback experiences were questioned. The mental strategies and feedback experiences are presented in this section based on the answers of subjects JL, TN and LL.

4.4.1 Mental task strategies

Every subject had *relax* as one of the mental tasks. Everyone found it easy and did not use any specific strategy.

Every subject used the hand movement task, either the *right hand movement* (subject JL and LL) or the *left hand movement* (subject TN). Subject JL used mainly two strategies with the right hand movement. In the first he tried to imagine his thumb touching other fingers. In the other strategy, he imagined tapping his fingers against a chair arm-rest. Subject LL imagined moving her fingers up and down with about one movement occurring every second. In other strategy, she left the finger up and tried to some circles in the air, but it did not seem to work well. At the beginning of training subject TN imagined running his fingers along guitar strings as he was playing a solo. At the end of the training he just felt that his left hand was “active”.

Subject JL used the *subtraction* task for the whole training week. He reported that it took first a little time, second or two, to pick up the two numbers. He usually first picked the “base” number (to subtract from) between 80-250 and the fixed number (to subtract with) between 5-9. He found out that it was more difficult to concentrate on subtraction in the experimental situation than normally. He made calculation errors quite a lot, especially if he hesitated (which he usually did). He mentally pronounced the numbers when calculating.

Subject TN used the *cube* task. He used three different strategies. In the first, he imagined a yellow framed cube which started to rotate at slowly accelerating speed around one of its axis. In the second strategy, he imagined a rotating box moving at the inner edge of a thin ring. In the third strategy, he imagined a rotating cube going through a square and drawing a number eight. He found out that it was efficient to switch between the strategies during the time the mental task was performed (approximately 15 seconds).

Subject LL used the *word association* task from the day 3 to the end of the training (day 5). She found it difficult at first. She decided beforehand what word she started with. She, for example, took a name of a friend or, alternatively, a word of some thing see could see in the room. At the beginning she used a lot of Finnish words and especially names. Towards the end of the week, she started using more English and Swedish words. She found out that Swedish words worked well, because they end with so many different letters (the problem with Finnish words when used with the word association task is that most of the Finnish words end in vowels like ’a’ and ’o’). Subject LL is bilingual (she can speak Finnish and Swedish).

4.4.2 Feedback experiences

Subject JL felt that feedback helped him to concentrate on the current task, because he had to try his best in order to get a lot of feedback. On the other hand, he felt that feedback interfered a bit the concentration on the mental tasks. He did not usually look straight to the feedback balls. He noticed that feedback seemed to be related to breathing with the relax task. Especially, during start of inhaling he noticed that feedback stopped and started again soon after that. The right hand seemed to give feedback best when he got in good “rhythm”, i.e., could imagine tapping his fingers rapidly. With the subtraction he did not notice any particular point when feedback was given or not given.

Subject JL was the only one of the subjects who used both positive and total feedback. In the first day of the training he was getting positive feedback. The last two recordings of day 1 and the first recording of day 2 went so well, that feedback was switched to total.

With total feedback he noticed that feedback worked in both ways. Especially, if during the subtraction feedback for right hand was given, he began sometimes to think his right hand even if he was supposed to think the subtraction. It was then little difficult for him to get back to the subtraction.

Subject LL reported that the auditory feedback (the “beeps”) used in the relax task were annoying at the beginning. However, she found out soon that the beeps helped her to concentrate on the relax task as they took away her thoughts. The more she heard the beeps the more she got relaxed. With other tasks, she found it difficult at first to keep eyes on the screen and at the same time concentrate on the current mental task. With the hand movement tasks she felt that the feedback worked best. She felt that the feedback ball blinked when she imagined moving her finger up and sometimes when she imagined moving them down. The feedback made her to speed up the movements and not to spend so much time either up or down position. With the words task, she noticed that she got feedback at the moment when she ended with a difficult letter and was really trying to find a new word. Subject LL also highlighted one important thing: Beside the feedback balls, the operator also gives feedback to the subject. Subject LL reported that during the recording small, unconscious sneers from the operator gave a lot of negative feedback. The little body movements and the hand movements when operator was using the mouse also disturbed subject LL.

Subject TN felt that he benefited from feedback, but only in the cube and the left tasks. Especially in the cube task, he saw clear differences in feedback when he rotated the cube at different speeds or switched between the different strategies.

All subjects reported the color changes in the feedback balls (due to classification probability, see section 4.2.4) did not help them. Subject TN reported that it distracted him, because there was no constancy in the color changes.

4.5 Discussion

4.5.1 On the results

The results show up several things. They are discussed in this section.

There were great individual differences between the subjects

As can be seen from the online results, the results were significantly worse for subject LL than for subjects JL and TN. Only in one recording (day 5, recording 1), the correct classifications exceed the false classifications in every three classes. The fact that subject LL had no previous experience with the ABI while subjects JL and TN had, may partly explain the differences. In addition, the subjects used different combinations of mental tasks and different kinds of mental task strategies (see the section 4.4.1). It also seems that people have individual differences on which mental tasks (or rather which combination of three mental tasks) suit them best. It would require more time to find out the best combination of the tasks for each of the subjects.

The original idea with subject LL was to find out the best combination in the first day of the training and then use it for the next four remaining days. However, the first combination (relax, subtraction, right) did not seem to work (there were more false classifications than the correct ones with one or two classes). In addition, the subject wanted to change subtraction to left hand. This combination was then used in three online recordings, but the results did not improve, rather the opposite. Therefore, the third combination (relax, right and words) was tried out. This combination gave then the best results of the week, but still not very good.

There was high variability between the recordings with each of the subjects

This can be a result of the variability in the EEG (as discussed in [31] and the section 3.3.9). The prototypes are trained with the data obtained from the previous recording. The idea of training and updating the prototypes frequently did not seem to help. One can see that almost without exception there was performance drop between the days (see Figure 4.8). The exceptions were days 3 and 4 with subject JL. However, as can be seen from the figure, the recording 1 is not displayed for the day 4. This recording was done online, but the operator made an error and the results are not comparable with other results.

There was no performance development during the training with any of the subjects

This may also be related to variability in the EEG between the days. During one day some development can be seen with each of the subjects (days 1 and 4 with subject JL, day 4 with subject LL and days 3 and 5 with subject TN). The idea in the ABI is the mutual learning process. The BCI learns the subject specific patterns of each mental task and the subject learns to produce this tasks so that the ABI detects them better. This requires that first the BCI (classifier) adapts to the user sufficiently and good prototypes can be trained from the recorded data. Then these prototypes could be used in several recordings in which the subject tries to learn from the feedback. However, we were not able to really use this approach, because we were not able to train sufficiently good prototypes for any of the subjects. The most promising looking prototypes were those trained for subject JL on day 1, recording 3 and they were used in several recordings. However, the results declined.

The results were generally worse than with the previous ABI version

This can be due the fact that different EEG equipment was used than with the previous version of the ABI. The EEG equipment (EEP H11) used in these experiments seemed to work well and give good EEG signals. Sometimes the signal contained clear 50 Hz component, but that was filtered out. However, an in-depth study of the EEP H11 equipment should be carried out to find out if it works as it should. In addition, only an electrode on the right ear was used as reference in these experiments were as linked-ear reference was previously used with the ABI. The linked-ear reference may give better signal and could improve the detection of the left-right difference (especially important when using the left and right hand movement tasks).

The results presented in this chapter are the real online performance. It was found out, that the previous results (see the section 3.2.4) were obtained from the ABI Learning program using the online data as a training data. This procedure does not give the actual online performance of the system, which we is the most important performance meter.

The relax task was classified best with all subjects

This is quite reasonable. The power level of the alpha rhythm (8-13 Hz) during the relax task is the most distinct from all other tasks. This makes the relax task the easiest task to classify.

4.5.2 On the mental tasks

The relax task is different from all other tasks, because it does not need any cognitive effort. It can be argued if it is a proper mental task to be used in a BCI. The closing and opening of eyes produces a large change in the EEG signal. During the training period, they are removed from the EEG data, because the transitions between mental tasks are removed. However, in the applications the situation is different. In addition, the closing of eyes means that it is not very practical in applications like the Virtual keyboard. It also can be questioned how well people suffering from the locked-in syndrome can use it, because they cannot freely close their eyes.

Other tasks have their downsides too. The subtraction requires first that the user picks up the two numbers. This takes time, at least about one second. It does not matter so much in training period, but the use of an application can suffer. The same criticism goes to word association task too, in which the subject has to make up a word to start with. The cube rotation task can be difficult or even impossible for some people. In addition, it is not very good task in applications, which require constant visual attention.

The most "natural" mental tasks are the left and the right hand movement. They also are most closely related to what happens in the applications than the other tasks. For example, if one wants to select something from the right, it is more natural to think moving the right hand than, for example, visually rotating a cube or mentally subtracting numbers from each other.

4.5.3 On the feedback

It may be that total feedback sessions should be used only to train a subject, not a classifier. At least in the beginning, total feedback itself affects the subject's concentration on the mental tasks. The only subject who received total feedback was subject JL. In his case, the total feedback sessions were used to train new prototypes. However, he reported that total feedback affected his concentration (see the section 4.4.2). The more successful strategy might have been to use the positive feedback sessions to re-train the classifier and the total feedback session to train the subject. The subject could freely try different mental tasks strategies during positive feedback sessions without the fear that it affects the future prototypes.

The feedback used with the ABI tells in which class the classifier thinks the EEG sample belongs. In addition, the color of the ball tells the classification probability. However, the color changes did not provide any additional feedback to the subjects (see the section 4.4.2. Maybe size of the ball would be more concrete and better way to show the classification probability.

Chapter 5

Conclusions

In this work six EEG-based brain computer interface systems were reviewed and compared. Experiments lasting five days with three subjects were done with the new Adaptive Brain Interface system.

The comparison of the BCI systems, especially their training duration and performance, proved to be difficult. This was because the results were reported inadequately and differently in most of the papers. Reporting the experiments and results should be standardized. The results from each recording or training day should be presented in order to see the evolution of the performance. Instead of hit rates and correct classification rates, the results should be presented using confusion matrices and channel capacities. This would make the comparison of the performances possible.

In this work the BCI systems were divided into the pattern recognition and the operant conditioning approaches. From the two approaches, the pattern recognition approach seems more plausible. Compared to the operant conditioning approach, the training duration is much shorter. However, the high variability in the EEG between the days and and changing EEG patterns during the actual use cause problems with this approach. This means that the classifier needs to re-trained often. In the future, *online learning* could be used, in which the classifier is updated after every recorded EEG sample.

Accuracy, speed, usability and feedback methods should be improved in the current BCI systems. Accuracy is the most important and affects greatly on the performance of the BCI. Many of the BCI systems are operated in a synchronous way, using trials lasting many seconds each. This means that time required for making one selection is long. This time should be kept short (below one second). Feedback methods could be improved, maybe using games like in the EEG biofeedback. Some of the mental tasks used in the ABI and the experiments in this work are not good. The relax task is the easiest to classify, but it includes eye opening and closing, which is not permitted in a BCI by the definition presented in the beginning of the second chapter. It can be argued if people suffering from locked-in-syndrome can use the relax task. In addition, it is not good in applications, because eyes are closed. Subtraction, word association and cube rotation tasks are not very natural and practical in applications. The left and the right hand movement are the most natural of the current tasks.

In the future, an exhaustive research about the mental tasks should be done. A study of the left and right hand movements using high-resolution EEG and MEG is planned. Research topics would include the localization of the brain activity during the mental tasks and how the EEG changes in process of time. Other research areas would be feedback methods and online learning.

There are many challenges in the future of the BCI field. Currently none of the BCIs are capable of proper cursor control, which could be used to control ordinary computer applications. In the near future it is not possible and special applications must be developed for BCIs. Today, special writing applications or Internet browser can provide communication tools for severely disabled people. These applications could be improved. In the future, BCIs could be used to control a hand prosthesis. How well that can be achieved with EEG-based BCIs is not yet known. Non-invasive BCIs recording activity directly from the motor cortex may be used for this kind of purpose in the future.

Appendix A

Online results

A.1 Subject JL

Day 1

Recording 2

- Prototypes from day 1, recording 1
- Probability threshold: 0.8
- Distance threshold: 100
- Feedback: Positive

CM (%)	Relax	Subtraction	Right	Reject
Relax	52.8	6.3	2.4	38.6
Subtraction	1.3	21.5	8.1	69.1
Right	3.8	0.0	19.2	76.9

TP (%)	FP (%)	CC
27.3	8.6	0.36

Recording 3

- Prototypes from day 1, recording 2
- Probability threshold: 0.8
- Distance threshold: 120
- Feedback: Positive

CM (%)	Relax	Subtraction	Right	Reject
Relax	49.5	0.0	5.5	45.1
Subtraction	1.1	39.7	16.2	43.0
Right	0.0	1.7	60.0	38.3

TP (%)	FP (%)	CC
44.2	11.7	0.58

Recording 4

- Prototypes from day 1, recording 3
- Probability threshold: 0.8
- Distance threshold: 120
- Feedback: Positive

CM (%)	Relax	Subtraction	Right	Reject
Relax	68.0	17.5	2.1	12.4
Subtraction	1.9	79.2	11.7	7.1
Right	3.7	15.9	54.9	25.6

TP (%)	FP (%)	CC
66.1	17.9	0.63

Day 2

Recording 1

- Prototypes from day 1, recording 3
- Probability threshold: 0.8
- Distance threshold: 120
- Feedback: Positive

CM (%)	Relax	Subtraction	Right	Reject
Relax	58.6	6.1	7.1	28.3
Subtraction	0.7	58.1	20.9	20.3
Right	2.6	13.0	60.0	24.3

TP (%)	FP (%)	CC
56.6	18.8	0.54

Recording 2

- Prototypes from day 1, recording 3
- Probability threshold: 0.8
- Distance threshold: 110
- Feedback: Total

CM (%)	Relax	Subtraction	Right	Reject
Relax	45.8	18.3	6.1	29.8
Subtraction	0.0	50.0	21.3	28.7
Right	0.0	15.6	56.9	27.5

TP (%)	FP (%)	CC
49.9	21.3	0.43

Recording 3

- Prototypes from day 1, recording 3
- Probability threshold: 0.8
- Distance threshold: 100
- Feedback: Total

CM (%)	Relax	Subtraction	Right	Reject
Relax	52.0	7.3	2.4	38.2
Subtraction	0.8	45.4	15.1	38.7
Right	0.9	8.1	37.8	53.2

TP (%)	FP (%)	CC
42.0	10.6	0.45

Day 3

Recording 1

- Prototypes from day 1, recording 3
- Probability threshold: 0.9
- Distance threshold: 100
- Feedback: Total

CM (%)	Relax	Subtraction	Right	Reject
Relax	25.5	7.5	2.8	64.2
Subtraction	0.0	20.4	13.1	66.4
Right	0.0	2.0	40.6	57.4

TP (%)	FP (%)	CC
28.6	8.2	0.29

Recording 2

- Prototypes from day 1, recording 4
- Probability threshold: 0.9
- Distance threshold: 100
- Feedback: Total

CM (%)	Relax	Subtraction	Right	Reject
Relax	36.7	0.7	1.4	61.2
Subtraction	0.0	6.3	16.4	77.3
Right	1.8	0.0	30.0	68.2

TP (%)	FP (%)	CC
22.7	7.5	0.28

Recording 3

- Prototypes from day 3, recording 2
- Probability threshold: 0.9
- Distance threshold: 100
- Feedback: Total

CM (%)	Relax	Subtraction	Right	Reject
Relax	17.4	0.0	0.0	82.6
Subtraction	0.0	20.4	0.7	78.9
Right	0.0	11.9	25.4	62.7

TP (%)	FP (%)	CC
22.1	4.0	0.30

Day 4

Recording 2

- Prototypes from day 1, recording 3
- Probability threshold: 0.9
- Distance threshold: 100
- Feedback: Total

CM (%)	Relax	Subtraction	Right	Reject
Relax	19.9	6.8	0.7	72.6
Subtraction	0.0	50.0	5.0	45.0
Right	0.0	6.1	23.5	70.4

TP (%)	FP (%)	CC
27.7	7.1	0.34

Recording 3

- Prototypes from day 4, recording 2
- Probability threshold: 0.9
- Distance threshold: 100
- Feedback: Total

CM (%)	Relax	Subtraction	Right	Reject
Relax	45.0	2.3	0.0	52.7
Subtraction	2.5	21.3	4.9	71.3
Right	0.0	3.7	21.3	75.0

TP (%)	FP (%)	CC
25.7	5.4	0.36

Recording 4

- Prototypes from day 4, recording 2
- Probability threshold: 0.9
- Distance threshold: 100
- Feedback: Total

CM (%)	Relax	Subtraction	Right	Reject
Relax	50.0	5.1	0.0	44.9
Subtraction	0.0	29.1	17.9	53.0
Right	0.8	5.4	20.8	73.1

TP (%)	FP (%)	CC
28.8	11.9	0.42

Recording 5

- Prototypes from day 4, recording 3
- Probability threshold: 0.9
- Distance threshold: 100
- Feedback: Total

CM (%)	Relax	Subtraction	Right	Reject
Relax	79.8	1.0	1.0	18.2
Subtraction	2.3	33.8	18.0	45.9
Right	0.8	4.6	52.3	42.3

TP (%)	FP (%)	CC
51.4	9.8	0.70

Day 5

Recording 1

- Prototypes from day 1, recording 3
- Probability threshold: 0.9
- Distance threshold: 100
- Feedback: Positive

CM (%)	Relax	Subtraction	Right	Reject
Relax	25.2	7.1	1.6	66.1
Subtraction	0.0	32.6	11.4	56.1
Right	0.0	8.7	29.1	62.1

TP (%)	FP (%)	CC
28.2	10.6	0.27

Recording 2

- Prototypes from day 4, recording 3
- Probability threshold: 0.9
- Distance threshold: 100
- Feedback: Total

CM (%)	Relax	Subtraction	Right	Reject
Relax	79.0	1.0	0.0	20.0
Subtraction	2.1	19.3	15.2	63.4
Right	2.4	0.8	31.5	65.3

TP (%)	FP (%)	CC
39.4	8.5	0.62

Recording 3

- Prototypes from day 4, recording 3
- Probability threshold: 0.9
- Distance threshold: 100
- Feedback: Positive

CM (%)	Relax	Subtraction	Right	Reject
Relax	38.0	0.0	5.6	56.5
Subtraction	1.3	25.9	22.8	50.0
Right	0.0	1.0	61.9	37.1

TP (%)	FP (%)	CC
38.8	12.5	0.47

Recording 4

- Prototypes from day 5, recording 3
- Probability threshold: 0.9
- Distance threshold: 100
- Feedback: Total

CM (%)	Relax	Subtraction	Right	Reject
Relax	49.1	3.6	1.8	45.5
Subtraction	0.0	44.4	0.0	55.6
Right	0.0	14.3	9.2	76.5

TP (%)	FP (%)	CC
25.7	11.4	0.43

Recording 5

- Prototypes from day 1, recording 3
- Probability threshold: 0.9
- Distance threshold: 100
- Feedback: Total

CM (%)	Relax	Subtraction	Right	Reject
Relax	8.7	1.6	1.6	88.2
Subtraction	0.0	17.6	9.6	72.8
Right	0.0	4.7	32.8	62.5

TP (%)	FP (%)	CC
19.6	7.3	0.20

A.2 Subject LL

Day 2

Recording 1

- Prototypes from day 1, recording 4
- Probability threshold: 0.7
- Distance threshold: 120

CM (%)	Relax	Subtraction	Right	Reject
Relax	28.5	7.7	8.5	55.4
Subtraction	9.6	19.3	19.3	51.8
Right	2.6	24.0	22.7	50.6

TP (%)	FP (%)	CC
22.3	24.6	0.15

Recording 2

- Prototypes from day 2, recording 1
- Probability threshold: 0.7
- Distance threshold: 120

CM (%)	Relax	Subtraction	Right	Reject
Relax	51.8	8.2	11.8	28.2
Subtraction	15.2	16.0	44.8	24.0
Right	19.9	10.3	42.6	27.2

TP (%)	FP (%)	CC
33.8	39.7	0.16

Recording 4

- Prototypes from day 2, recording 3
- Probability threshold: 0.7
- Distance threshold: 120

CM (%)	Relax	Left	Right	Reject
Relax	62.2	7.1	7.1	23.5
Left	3.3	36.4	31.1	29.1
Right	9.2	39.0	22.0	29.8

TP (%)	FP (%)	CC
37.5	34.2	0.37

Day 3

Recording 1

- Prototypes from day 2, recording 4
- Probability threshold: 0.7
- Distance threshold: 120

CM (%)	Relax	Left	Right	Reject
Relax	53.4	6.1	14.5	26.0
Left	5.9	24.6	36.4	33.1
Right	8.3	21.1	41.4	29.3

TP (%)	FP (%)	CC
38.5	31.0	0.24

Recording 2

- Prototypes from day 3, recording 1
- Probability threshold: 0.8
- Distance threshold: 120

CM (%)	Relax	Left	Right	Reject
Relax	34.1	8.1	3.0	54.8
Left	8.0	25.5	13.9	52.6
Right	5.8	20.4	10.2	63.5

TP (%)	FP (%)	CC
22.5	19.8	0.12

Day 4

Recording 1

- Prototypes from day 3, recording 3
- Probability threshold: 0.7
- Distance threshold: 100

CM (%)	Relax	Right	Words	Reject
Relax	54.3	3.1	4.7	37.8
Right	11.5	11.5	33.1	43.8
Words	14.4	6.1	40.2	39.4

TP (%)	FP (%)	CC
32.8	24.8	0.22

Recording 2

- Prototypes from day 4, recording 1
- Probability threshold: 0.6
- Distance threshold: 120

CM (%)	Relax	Right	Words	Reject
Relax	60.3	3.8	6.1	29.8
Right	9.7	32.3	29.0	29.0
Words	13.4	26.0	19.7	40.9

TP (%)	FP (%)	CC
34.7	29.3	0.30

Recording 3

- Prototypes from day 4, recording 2
- Probability threshold: 0.7
- Distance threshold: 120

CM (%)	Relax	Right	Words	Reject
Relax	72.1	13.6	4.3	10.0
Right	6.2	58.5	15.4	20.0
Words	8.4	34.5	32.8	24.4

TP (%)	FP (%)	CC
53.0	28.8	0.39

Recording 4

- Prototypes from day 4, recording 2
- Probability threshold: 0.8
- Distance threshold: 110

CM (%)	Relax	Right	Words	Reject
Relax	72.2	2.6	3.5	21.7
Right	12.6	25.9	14.8	46.7
Words	6.2	27.6	26.9	39.3

TP (%)	FP (%)	CC
36.7	24.7	0.41

Day 5

Recording 1

- Prototypes from day 4, recording 4
- Probability threshold: 0.7
- Distance threshold: 110

CM (%)	Relax	Right	Words	Reject
Relax	38.1	5.6	15.9	40.5
Right	4.4	25.2	20.7	49.6
Words	0.0	26.4	32.2	41.3

TP (%)	FP (%)	CC
31.2	23.3	0.27

Recording 2

- Prototypes from day 5, recording 1
- Probability threshold: 0.8
- Distance threshold: 105

CM (%)	Relax	Right	Words	Reject
Relax	71.0	2.8	6.5	19.6
Right	13.4	7.6	36.3	42.7
Words	22.4	8.2	30.6	38.8

TP (%)	FP (%)	CC
32.6	32.2	0.28

Recording 3

- Prototypes from day 5, recording 2
- Probability threshold: 0.8
- Distance threshold: 100

CM (%)	Relax	Right	Words	Reject
Relax	33.6	0.8	3.9	61.7
Right	7.9	11.3	11.9	68.9
Words	5.0	13.2	14.0	67.8

TP (%)	FP (%)	CC
18.8	13.9	0.16

A.3 Subject TN

Day 1

Recording 2

- Prototypes from day 1, recording 1
- Probability threshold: 0.7
- Distance threshold: 120

CM (%)	Relax	Cube	Left	Reject
Relax	60.0	0.9	4.5	34.5
Cube	0.7	31.9	17.4	50.0
Left	0.0	25.8	28.2	46.0

TP (%)	FP (%)	CC
37.1	17.9	0.48

Recording 3

- Prototypes from day 1, recording 1
- Probability threshold: 0.8
- Distance threshold: 120

CM (%)	Relax	Cube	Left	Reject
Relax	58.7	7.3	2.8	31.2
Cube	1.4	35.5	17.4	45.7
Left	0.7	29.6	32.4	37.3

TP (%)	FP (%)	CC
39.9	20.9	0.43

Day 2

Recording 3

- Prototypes from day 2, recording 1
- Probability threshold: 0.8
- Distance threshold: 120

CM (%)	Relax	Cube	Left	Reject
Relax	57.8	0.0	2.3	39.8
Cube	1.7	5.9	2.5	89.8
Left	0.0	8.0	8.7	83.3

TP (%)	FP (%)	CC
25.9	6.3	0.41

Recording 4

- Prototypes from day 2, recording 3
- Probability threshold: 0.8
- Distance threshold: 120

CM (%)	Relax	Cube	Left	Reject
Relax	72.9	5.2	5.2	16.7
Cube	2.4	38.9	21.4	37.3
Left	4.2	26.1	37.3	32.4

TP (%)	FP (%)	CC
47.8	23.3	0.48

Day 3

Recording 1

- Prototypes from day 2, recording 4
- Probability threshold: 0.8
- Distance threshold: 100

CM (%)	Relax	Cube	Left	Reject
Relax	37.4	0.0	0.0	62.6
Cube	0.8	12.8	3.2	83.2
Left	0.0	2.7	20.3	77.0

TP (%)	FP (%)	CC
22.0	3.9	0.33

Recording 2

- Prototypes from day 2, recording 4
- Probability threshold: 0.8
- Distance threshold: 100

CM (%)	Relax	Cube	Left	Reject
Relax	39.4	0.0	0.7	59.9
Cube	0.0	13.8	12.9	73.3
Left	0.0	6.0	23.1	70.9

TP (%)	FP (%)	CC
24.7	8.4	0.34

Recording 3

- Prototypes from day 3, recording 1
- Probability threshold: 0.8
- Distance threshold: 100

CM (%)	Relax	Cube	Left	Reject
Relax	84.7	0.0	0.0	15.3
Cube	1.4	45.3	18.0	35.3
Left	0.8	18.0	36.7	44.5

TP (%)	FP (%)	CC
50.9	13.8	0.76

Day 4

Recording 1

- Prototypes from day 3, recording 3
- Probability threshold: 0.8
- Distance threshold: 100

CM (%)	Relax	Cube	Left	Reject
Relax	39.3	1.9	0.9	57.9
Cube	0.0	39.9	16.2	43.9
Left	0.0	20.0	24.4	55.6

TP (%)	FP (%)	CC
34.2	14.4	0.42

Recording 2

- Prototypes from day 3, recording 3
- Probability threshold: 0.8
- Distance threshold: 100

CM (%)	Relax	Cube	Left	Reject
Relax	63.0	4.7	9.4	22.8
Cube	0.0	30.0	42.1	27.9
Left	0.0	21.0	57.2	21.7

TP (%)	FP (%)	CC
49.2	27.0	0.50

Recording 3

- Prototypes from day 4, recording 2
- Probability threshold: 0.8
- Distance threshold: 100

CM (%)	Relax	Cube	Left	Reject
Relax	54.4	1.6	3.2	40.8
Cube	0.0	17.5	17.5	65.0
Left	1.3	11.3	42.0	45.3

TP (%)	FP (%)	CC
38.7	10.9	0.43

Day 5

Recording 1

- Prototypes from day 4, recording 4
- Probability threshold: 0.8
- Distance threshold: 100

CM (%)	Relax	Cube	Left	Reject
Relax	46.0	0.0	0.0	54.0
Cube	4.3	1.7	3.4	90.6
Left	5.2	0.0	18.7	76.1

TP (%)	FP (%)	CC
20.6	4.0	0.25

Recording 2

- Prototypes from day 5, recording 1
- Probability threshold: 0.8
- Distance threshold: 100

CM (%)	Relax	Cube	Left	Reject
Relax	12.3	0.0	0.8	86.9
Cube	0.0	23.3	16.7	60.0
Left	0.0	5.6	26.6	67.8

TP (%)	FP (%)	CC
18.9	7.5	0.27

Recording 3

- Prototypes from day 5, recording 2
- Probability threshold: 0.8
- Distance threshold: 100

CM (%)	Relax	Cube	Left	Reject
Relax	69.6	1.6	0.8	28.0
Cube	3.0	56.1	8.3	32.6
Left	6.3	7.1	30.2	56.3

TP (%)	FP (%)	CC
50.2	9.5	0.59

Appendix B

The question form

1. How did it feel?
2. What was easy, what was hard in each task?
3. Did you use different strategies in performing the mental tasks? What kind of?
4. Did you feel improving in performing the mental tasks during the week? How?
5. How did feedback feel?
6. Did feedback help or disturb concentration?
7. Did you notice when you got feedback, for example in certain "point" in mental task?
8. What is good and what is bad in the learning? Were there some things which disturbed or which could have done differently in your opinion?
9. How would you develop the learning?
10. Comment freely on subjects, which didn't come up above

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