COMENIUS UNIVERSITY IN BRATISLAVA
Faculty of Mathematics, Physics and Informatics

Introduction to brain–computer interface

Bachelor's thesis

2012
Dominik Zajíček

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Study programme:	Computer Science
Field of study:	2805 Informatics
Supervisor:	doc. Ing. Igor Farkaš, PhD.

2012
Dominik Zajíček

87656252

Univerzita Komenského v Bratislave
Fakulta matematiky, fyziky a informatiky

ZADANIE ZÁVEREČNEJ PRÁCE

Meno a priezvisko študenta: Dominik Zajíček
Študijný program: informatika (Jednoodborové štúdium, bakalársky I. st., denná forma)
Študijný odbor: 9.2.1. informatika
Typ záverečnej práce: bakalárska
Jazyk záverečnej práce: anglický
Sekundárny jazyk: slovenský

Názov: Úvod do rozhrania mozog-počítač

Cieľ: 1. Naštudujte si literatúru z oblasti (BCI) systémov s rozhraním mozog-počítač, a zamerajte sa na metódy merania signálu EEG, algoritmy na extrakciu príznakov a klasifikáciu signálu.
2. Urobte prehľad vybraných existujúcich systémov a typov BCI aplikácií.

Anotácia: Systémy s rozhraním mozog-počítač predstavujú v súčasnosti veľkú výzvu, nakoľko ovládanie počítača mozgovou aktivitou ponúka široké uplatnenie, od medicínskych aplikácií až po počítačové hry. Bakalárska práca má za cieľ ponúknuť úvod do tejto dynamicky sa vyvíjajúcej oblasti výskumu a predstaviť niektoré známe BCI systémy, ktoré sa vo svete vyvíjajú.

Poznámka: Požiadavky: dobrá znalosť angličtiny, zvládnutie problematiky spracovania číslicového signálu, ochota pracovať priebežne.

Vedúci: doc. Ing. Igor Farkaš, PhD.
Katedra: FMFI.KAI - Katedra aplikovanej informatiky

Dátum zadania: 25.10.2011

Dátum schválenia: 25.10.2011

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vedúci práce

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Comenius University in Bratislava
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THESIS ASSIGNMENT

Name and Surname:	Dominik Zajíček
Study programme:	Computer Science (Single degree study, bachelor I. deg., full time form)
Field of Study:	9.2.1. Computer Science, Informatics
Type of Thesis:	Bachelor´s thesis
Language of Thesis:	English
Secondary language:	Slovak

Title: Introduction to brain-computer interface

Aim: 1. Study the literature related to brain-computer interface (BCI) systems, with focus on methods of measuring the EEG signal, algorithms for feature extraction and feature translation.
2. Write an overview of selected existing systems and the types of BCI applications.

Annotation: BCI systems represent a big challenge for the current research, since the computer control, based on user's brain activity offers a vast range of applications ranging from medicine to computer games. The bachelor thesis aims to provide an introduction to this dynamically progressing research area and to present several well-known BCI systems, being developed in the world.

Comment: Requirements: good knowledge of English, mastering the theory of digital signal processing, the will to work systematically.

Supervisor: doc. Ing. Igor Farkaš, PhD.
Department: FMFI.KAI - Department of Applied Informatics
Assigned: 25.10.2011

Approved: 25.10.2011

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Abstrakt

V poslendom desaťročí sa výrazne posunul výskum v oblasti rozhraní mozog–počítač (BCI), ktoré majú potenciál zabezpečiť lepšiu kvalitu komunikácie medzi ľuďmi a strojmi. Cieľom tejto práce je byť vstupnou bránou do tejto oblasti. Prezentujeme poznatky o mozgových vlnách a ich meraní vo forme EEG. Takisto sa zameriavame na vybrané metódy, konkrétne extrakciu príznakov a preklad/klasifikáciu príznakov, ktoré sa používajú na generovanie riadiacich príkazov pre počítač. Práca poskytuje aj zbežný prehľad vybraných fungujúcich BCI systémov a ich môžných zlepšení.

Kľúčové slová: rozhranie mozog–počítač, electroencefalografia, mozgové vlny, spracovanie signálu

Abstract

In the last decade, there has been a significant advance in research concerning the brain–computer interfaces, that have the potential to provide a new quality to human–machine interaction. This thesis aims to be a good starting reference into the field of BCI. We present basic knowledge about brain waves, and their measurement in the form of EEG. Then we focus on selected methods, namely feature extraction and feature translation/classification, that are used to generate control commands for the computer. The thesis also provides a brief overview of selected working BCI systems and their possible improvements.

Keywords: brain–computer interface, electroencefalography, brain waves, signal processing

Declaration of authorship

I hereby declare and confirm that this thesis is entirely the result of my own work except where otherwise indicated.

Bratislava, 31. May 2012

Dominik Zajíček

Acknowledgement

I would like to thank my supervisor doc. Ing. Igor Farkaš, PhD. for his guidance, support, and advices throughout writing this thesis.

Contents

Introduction

The topic of controlling things by just thinking stays in minds as futuristic and fictional. We decided to have a closer look at the current situation in this field aiming to describe what are the newest gains, attitudes and possibilities. Thus to bring a compilation of basic methods and principles.

Having a look at how it all started might explain the enthusiasm of some scientists working in this field.

The first known measurement of brain electromagnetic waves took place in 1912 and was performed by Vladimir Pravdich-Neminsky who measured the electrical activity in the brains of dogs. He called it “electrocerebrogram”. Ten years later, the first recording of EEG waves in human was performed by Hans Berger who also gave the process its current name - electroencefalography [Szafir, 2010].

A discovery, that brain emits electromagnetic waves led some thinkers to designing better electrodes and sensors able to capture the brainwave. After a certain time a vast research focused on relationship between brain state and electromagnetic waves arose. Sleep phases, for example, were explored from the electromagnetic point of view, too. On the one hand, there is an everlasting desire to understand, which forces people to explore brain and make use of brainwaves, but on the other hand, brain–computer interfacing became a useful tool for enabling severly disabled people to communicate. Questions arise from both of these aspects.

Although there are many interesting topics to be discussed, we only focus on brain–computer interfacing - the BCI.

Chapter 1

What exactly is the BCI?

To gain a basic conception about BCI, a slight knowledge about brain functions and states is needed. In this chapter we will focus on different brain observation methods, their basic differences and advantages.

1.1 Brain observations

Electro-magnetic pulse is a “side product” of neuron’s work. That makes observing of brain’s funcionality possible. Having some properties of brain signal captured, we can determine whether the person is asleep or not. That is useless unless it teaches us something about different brain states. We observed, that different sleep phases produce different electro-magnetic outputs. Furthermore, while thinking of signicantly different things like emotions, movements or relaxing signals change somehow too. BCI is based on these differences, which makes computer control possible.

When the subject experiences a strong feeling or performs a brain–area–specific activity, a certain parts of brain become more active. We know, that oxygen is necessary for thinking and the more active the brain part, the more oxygent supply is needed. That is why there is a high bloodlflow level. Thus bloodflow is a good indicator of brain activity in the area. Luckily, there is a non-invasive way of brain bloodflow measurement, which uses laser light. The laser comes through skull to the brain causing some light reflections. The level of reflected light indicates current bloodflow level in target area. Although bloodflow level measurement is a valuable source of information, it is not frequently used, because lasers are much more expensive, and possibly also more difficult to set up than electrodes.

Here are the most interesting methods. **Electrocorticography** (ECoG) a method where sensors are placed on cerebral cortex (exposed surface of the brain), **magnetoencefalography** (MEG) a non-invasive method of recording magnetic waves naturally created by brain and **electroencefalography** (EEG) a non-invasive method where there are sensors placed on scalp are all possible input sources for BCI. None of them requires movement and each is suitable for a certain field of observation. So far, there were many researches dealing with comparison of these approaches. A study [Schalk and Leuthardt, 2011] presents, that ECoG is capable of recording wider range of frequencies, than EEG. The loss of information when using EEG is caused by physiological barriers. There is probably no way how to record frequencies higher than 40Hz with EEG scalp electrodes.

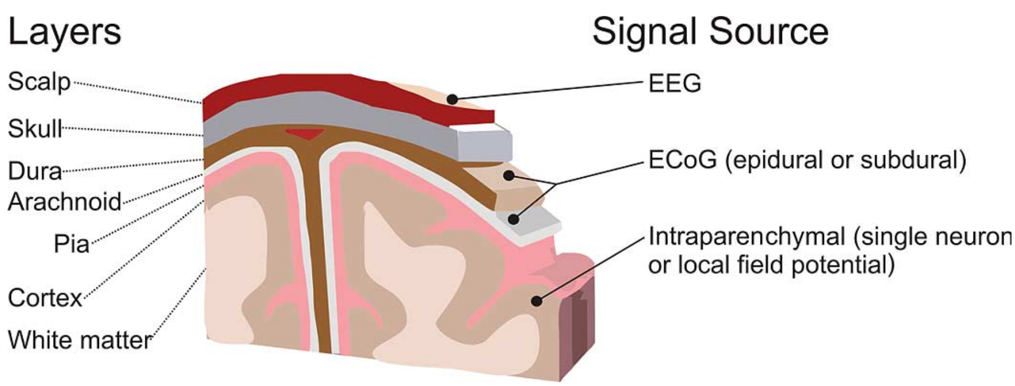

Figure 1.1: Recording domains. EEG as a non-invasive approach and other deeper and more precise approaches - ECoG and single neuron electrodes. From [Schalk and Leuthardt, 2011]

On the other hand, there are some more brain outputs. One of these is a method of connecting a peripheral device directly to nerves. For example a robotic arm prostheses can be connected to nerves that originally worked as arm controller. The purpose remains the same. This method, however, is not used in BCIs and as will be explained in following chapter, the information for BCI must come directly from the brain.

1.2 Definition

BCI stands for **brain–computer interface**. It is a direct communication pathway between the brain and an external device. It allows us to transfer and use information from distinct brain states for communicating with a machine.

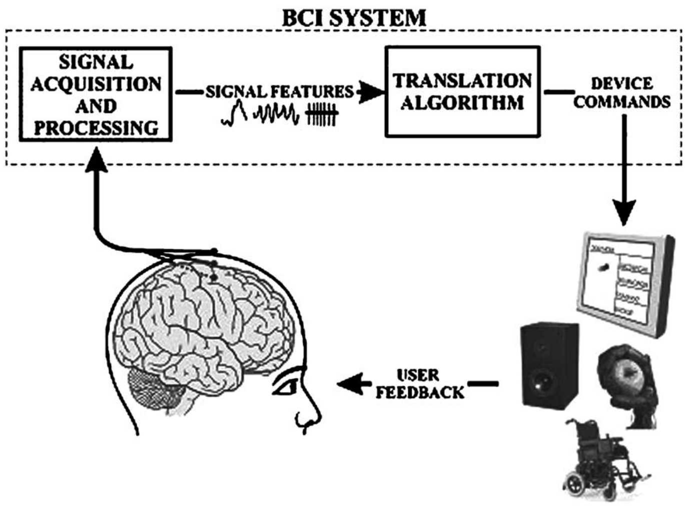

Figure 1.2: A BCI system diagram showing closed-loop paradigm. From [McFarland et al., 2006]

BCIs must fulfill these conditions:

- Input comes directly from the brain.
- Signals are processed realtime.
- Subject witnesses reaction on his/her action.
- Commands that are executed must be completely intentional.

The goal is to use other than typical brain output channels to get information without need for any muscular action. (Disabled people might not be able to control devices by mechanical commands.) BCIs don't even use nerve connections to read from which is common when connecting robotic prostheses.

A typical BCI system (as the one in figure 1.3) consists of a sensor, usually also signal amplifier, a processing unit (a computer) and a feedback device (a monitor or a robotic arm). In the figure, there is a demonstration of equipment, but it is not a good example of

Figure 1.3: For a simple EEG session we need an electrode cap, a signal amplifier, a processing unit (the computer) and a feedback device (in this case a computer screen).

a real BCI test run. The subject should sit straight, breathe calmly and should not smile, bacause every facial movement is recorded via EEG electrodes. Even a wink can be seen on a EEG plot as a peak. Thus every movement is a sort of distortion to the electromagnetic signal and can be considered being a noise in the recorded signal.

BCI is not a mind reading device and electro–magnetic impulses or any other outputs used in BCI only work one way. What that means is, that neither mind reading, nor thought implantation is possible with BCI. All it does (if it works) is noticing specific properties of the signal (brainstate) and executing appropriate command or action.

The whole system works on a basis of gradual learning. Watching, hearing or otherwise sensing the right response creates a sense of using successful methods instead of those unsuccessful. And after some time, the subject learns how to control the response through self control (mind state control). Some BCIs also implement machine learning, so that machine tries to match the subject too. That way the time needed to learn a certain task might be decreased significantly. The idea is similar to two people trying to agree on something. If both of them compromise, no one has to adapt completely.

1.3 Problems

There are some difficulties in **distinguishing intentional commands**. We know, that thinking about moving ones hand is not necessarily connected with an intention of moving. Niels Birbaumer, an ECoG BCI specialist from Austria, says, that intentions create slow (8-12 Hz) electromagnetic brainwaves which are not difficult to capture. The problem is, that intentions overlap. There are just few situations where there is only one significant and strong intention. Mostly, when performing a simple task, for example standing up from a chair, the intention to stand up is short, but followed and overlapped by many other intentions. For example, having a cup of water, thinking about going out with a dog, etc. Because of that complication, there is a number of different approaches trying to detect intentional commands.

Choosing the right **method of getting signal** is subject to the objective of actual BCI. Non-invasive methods are certainly more suitable for education and entertainment usage, while invasive for high precision measurements, maybe also for everyday use by severly injured or disabled people.

The aquired signal has to be processed realtime. Sometimes, we have to choose a specific point of view, because the computer in unable to process everything. When analysing waves of certain wavelength there might be no spare processor time to analyse the whole recorded spectrum. An attentive reader might ask: "Why do we need the signal processing to be that fast?". The reason is, that BCI works in a closed loop. If we want to make use of human ability to learn, we have to generate immediate response to a brainstate change. Otherwise, slow responses would lead to confusion of subject. Thus, to overall inapplicability of such BCI system.

From the beginning on we somehow supposed, that the brainwave recordings have relatively similar characteristics throughout the population. Unluckilly there is an unpleasant problem of "**BCI defficiency**" - a fact, that there is approximately 15-30% of population unable to control BCI applications. This number is non-negligible and therefore the defficiency becomes a major obstacle for general broad BCI deployment [Blankertz et al., 2010]. The reason for such distinction remains unknown until the investigation in this field brings new dependencies or at least common features of these people.

Chapter 2

Getting the signal

In this chapter we will mention the brainwave activity induced by thinking, relaxing or activating different brain centres. Continuing by what are all possible BCI inputs and finishing with a simple conclusion about which inputs are suitable for various BCI applications.

2.1 Closer look at brainwaves

Electromagnetic emission is subject to a variety of conditions such as stress, relax, alert, hypnosis and sleep as well as specific thoughts and mental activities. These states can be determined by observing brainwave powers in specific frequency ranges (bands).

Band	Frequency (Hz)
Delta	0.1-4
Theta	4-7
Alpha	8-12
Beta	13-30
Gamma	30+

Figure 2.1: This table shows characteristic frequencies of the standard bands. This distribution is not uniform and might be described differently in various documents.

2.1.1 Alpha and theta rhythm

It has been shown [Aris et al., 2010], that alpha and theta waves respond inversely during mentally difficult task and relaxation with closed eyes. Alpha waves are strongly bound to relaxation, while theta waves to concentration. The higher the concentration, the higher the theta waves power and inversely with alpha. Participants in this study were 23 or 24 years old students. Their performance was labeled with one of 7 IQ indexes according to *Wechsler scale* based on results from the IQ test which was the mentally difficult part of the measurement. The most significant difference between alpha and theta was found among students in the index 6 (Superior IQ) group. This discovery suggests, that people who can concentrate well have higher power of their theta waves when concentrating and also conversely, the high power of theta waves might indicate high level of concentration.

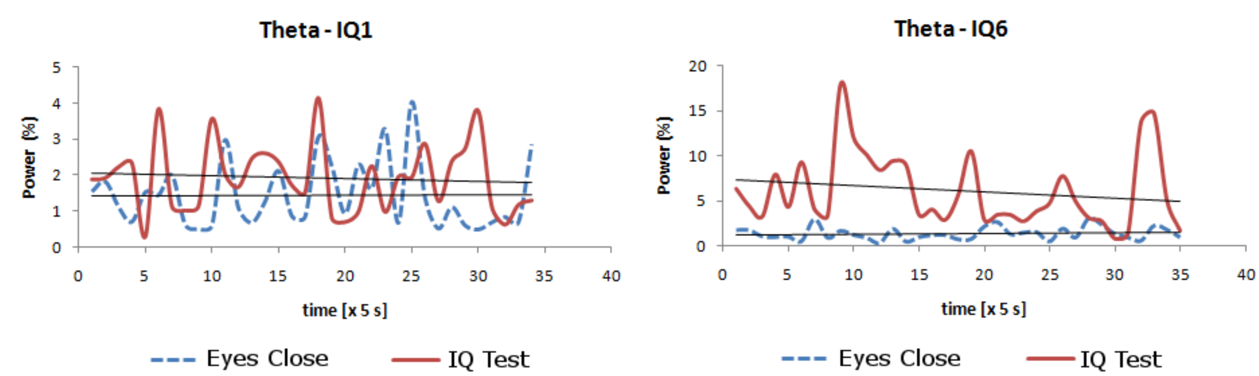

Figure 2.2: Comparison of a IQ1 and IQ6 group theta band power during relaxation and IQ test. From [Aris et al., 2010]

2.1.2 μ rhythm

Mu rhythm is as well as alpha rhythm astonishing brainwave phenomenon. The remarkable synchronisation of motor cortex neurons somewhere in alpha (8-12Hz) band can be likened to a sea-flower movement in the sea. But as soon as the person performs a motor specific task, a strong desynchronisation occurs. We could say, that motor neurons synchronise for fun, when there is nothing to do. Or maybe that it is the activity necessary for remembering and learning new skills.

At rest, sensorimotor neurons fire in synchrony , leading to large amplitude EEG oscillations in mu frequency band. When subjects perform an action, these neurons fire asynchronously, decreasing the power of the mu-band oscillations. Mu power recorded from electrodes at scalp locations over sensorimotor cortex is reduced in normal adults by self-initiated movement, imagined movement, and observed movement.

Mu rhythms are found with scalp EEG in most, if not all, healthy adults. Mu rhythm appears to occur in the absence of processing sensory information or motor output. This oscillation is attenuated by voluntary movement, but is minimally affected by visual stimulation. Studies show that humans can learn to volitionally control the mu thythm. It is not clear whether the control reflects direct access to the neural mechanisms. Because mu-rhythm frequencies overlap those of the occipital or classical alpha rhythm, it is sometimes difficult to separate them.

Different levels of suppression or enhancement (i.e. different levels of mu amplitude or power) can then be mapped to a variety of computer-controlled functions [Pineda, 2005]

In a research [Šilar et al., 2011] on motor resonance based mu-rhythm desynchronisation, 4 healthy subjects participated in an experiment. The subjects were comfortably seated at a table, going through a number of experimental conditions involving relaxed state and a kind of motor movement (self-executed, observed or imagined). The recoded EEG signal was processed offline and analysis focused on power spectral density in alpha band. In 3 out of 4 subjects there was a decrease of 8-12Hz power in every condition compared to relaxed state with opened eyes. Executing, observing or imagining moslty leads to power decrease in the specified range and can be used well in BCI because of naturally easy controllability of motor imagery.

Motor brainwaves play an important role in many BCI applications. A description of motor imagery (mu-rhythm) based BCI can be found in section 4.3 concerning research in Wadsworth Center.

2.1.3 P300 wave

P300 wave is a very interesting brainwave. Its occurence is tightly bound to sensual witnessing of an expected or extraordinary event. The most famous P300 application is probably a “P300 speller", which is depicted in figure 2.3. Every time, the letter the subject is looking at flashes brain emits a P300 wave approximately 300ms after the flash. This allows the BCI system in P300 Speller to calculate which letter is the desired one.

The speller paradigm is as follows. Rows and columns on the screen blink periodically. Every letter is highlighted twice the period, so every time the flash occurs, signal is being checked for P300. After getting two P300 signals during the period we can compute the coordinates of the desired letter.

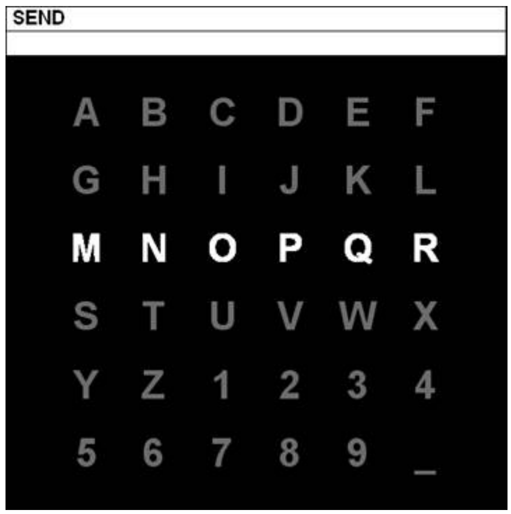

Figure 2.3: The famous P3OO Speller. Letters organized to a grid. Rows and columns blinking rapidly.

Other instructive example of P300 application is a BCI controlled 2D cursor.[Kanoh et al., 2011] The idea in this case is very simple. User gazes at a point around the cursor in the desired direction (see fig. 2.4). As soon as a P300 is recorded, a quick analysis takes place. The point which blinked approximately 300ms before the P300 is chosen and the cursor moves in an appropriate direction.

There are many other interesting P300 applications. A different BCI 2D cursor controller description and results can be found in [Li et al., 2008]. It is a creative combination of mu rhythm and P300.

All these signals are fascinating and offer a rich "armament" which is ready to be used and improved. Now, we will focus on methods of signal acquisition. In the first section we will

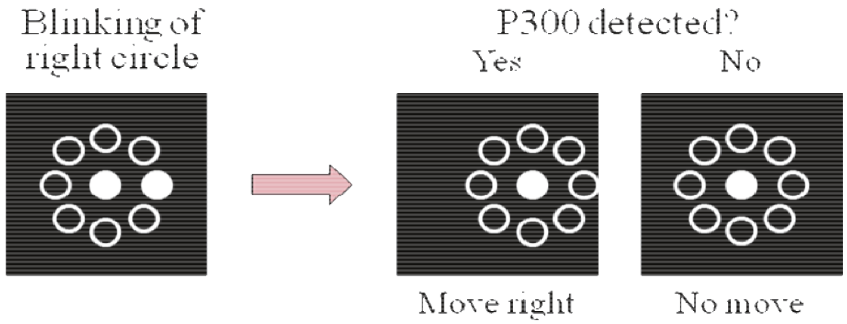

Figure 2.4: A cursor surrounded by 8 direction points which blink randomly. From [Kanoh et al., 2011]

mention mainly electrocorticography (ECoG) as a representant of invasive BCI methods and in the second section electroencefalography (EEG) for non-invasive.

2.2 Invasive BCI

For now, invasive BCI experiments and measurements only occur with patients who already have part of their skull removed for other, say serious reason. For example those who suffer epilepsy and undergo a treatment or ECoG measurement. Between examinations, brain activity testings and other activities patients are proposed to take part in BCI experiment. Willingness and good physical and mental condition are very important factors here. Not everyone is interested in spending more than half an hour by several exausting metal tasks. Therefore the personnel have to be ready to start the test immediatly when there is a good will from the other side. The preparation for such experiment is besides getting to brain cortex quite straightforward. Usually a 10 times 10 macrogrid consisting of so-called microgrid arrays is placed on brain cortex. As soon as the macrogrid is in place, the experiment is ready to begin. Few introduction words about what subject is supposed to do and data capture starts.

ECoG seems to have much better results than EEG in many aspects. Directly from capture it is obvious, that ECoG can capture much wider range of frequiencies than EEG. This easy access to amplitudes in higher frequencies appears to be important, as signals at higher

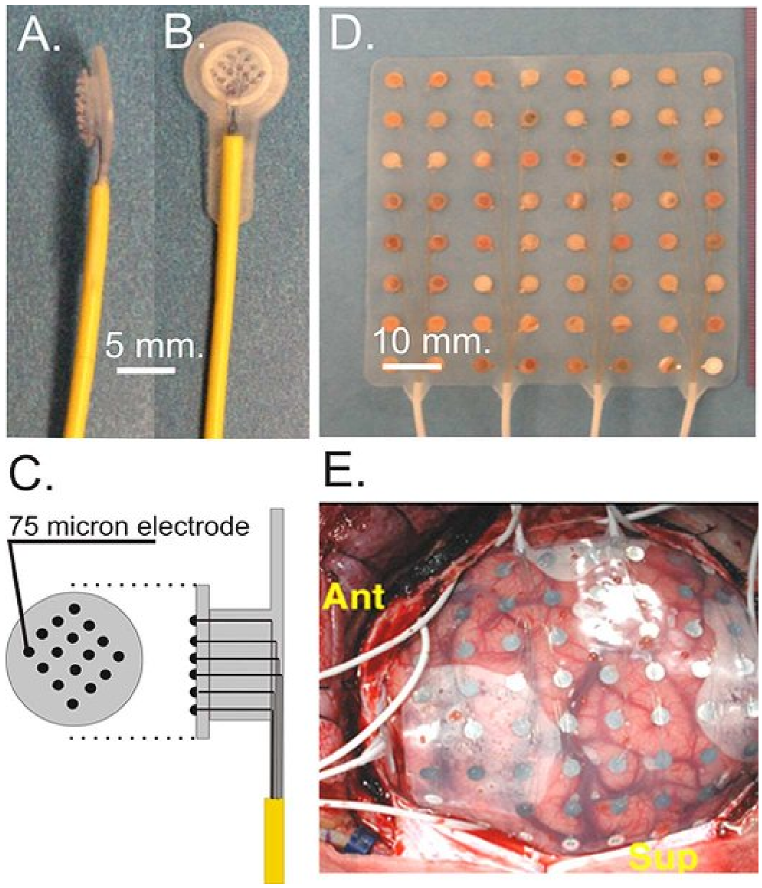

Figure 2.5: ECoG Electrodes: Microgrid arrays (A, B, C) are organized 1cm apart each other to form a macrogrid, which is then placed on a cerebral cortex (E). From [Schalk and Leuthardt, 2011]

frequencies have been shown to carry substantial information about cognitive, motor, and language tasks, and thus may provide critical information for BCI control that is not readily accessible with EEG. [Schalk and Leuthardt, 2011]

2.3 Non-invasive BCI

Although there are multiple non-invasive brain signal acquisition methods as mentioned in introductory section, we will focus on EEG scalp electrodes in this section. The main downside of EEG electrodes is a corruption of EEG data by artifacts, signals collected by EEG electrodes that are not originating from cortical neurons. The most common cause of artifacts is eye movement and blinking, however also neck muscle activity or bad electrode contact can cause signal disruption.

Many EEG systems attempt to reduce artifacts and general noise by utilizing reference electrodes placed in locations, where there is little cortical activity and attempting to filter out correlated patterns. Non-invasive methods are limited in that they are often susceptible to noise, have worse signal resolution due to distance from the brain, and have difficulty recording the inner workings of the brain. However more sophisticated systems are constantly emerging to combat these difficulties and non-invasive techniques have the advantage of lower cost, greater portability, and the fact that they do not require any special surgery. [Szafir, 2010]

The advantages of EEG are for example higher flexibility. A setup time of a EEG cap can range from 5 to 20 minutes depending on number of elecrodes used, because most of EEG electrodes require inductive get to be applied between the electrode and the scalp. Non-invasive approach can be used with BCI2000 and is also used in the Berlin BCI(BBCI).

2.4 Single neuron electrode

These electrodes are used to get specific neuron's firing information. These electrodes were used within an experiment with monkeys performed on University of Pittsburgh. To be precise, single neuron electrodes were not the only source of information in this experiment. Most of the signal was taken from ECoG - invasive electrodes. Single neuron measurement added some additional relevant information so that the signal could be classified more easily.

Single neuron electrode is the truly invasive method, because it not only requires skull to be removed, but also reaches into the brain matter, while for example ECoG electrodes are only placed on brain surface. That, on the other hand, could be called a "partially invasive" method.

As we can see, there are many potential data recording approaches and a variety of references. The next goal is to learn how to transform the signal into a more readable form than a raw signal time sequence. As we will see, there are methods to look at various signal properties. Frequences, amplitudes and decomposition.

Chapter 3

Signal processing

Signal processing consist of two essential parts. Feature extraction and translation. The former is preprocessing of signal by transforming it into a set of features, the latter translates them into desired commands for computer.

Feature extraction is an important intermediate step to be taken if we want to compare two signals. The method that will be described transforms the time series of signal into a feature vector, then into a number and numbers can be compared. It is possible to distinguish signals that have more suitable properties form signals which do not.

Important question is *How do we calculate frequency from signal, that is currently being recorded?* We know, that there can be multiple frequencies in a signal. For example when listening to music. In a certain moment, there are many sounds being played simultaneously i.e. there are multiple frequencies present in the signal. Analogously to music, electromagnetic signal consists of many. Fourier transform might be the tool, which could allow us to find the necessary information.

3.1 Feature extraction

In this part, we will discus various approaches to feature extraction, which is basically an effort to reduce dimensions of measured data (or data stream when processing on-line which is exactly the case of BCI) so that comparing and classifying is simplified enough to be done realtime. Another important role of feature extraction is reducing the noise, so that most of information in the signal can be controlled by user.

3.1.1 Fourier transform

Let us start with *Fourier series.* Fouries series is the most widely known and historically first method used for decompositing signal into a (possibly infinite) sum of *sin* and *cos* functions with specific frequention and phase. Fourier series, however works only for periodic functions (signals). If the signal is finite, no problem - we can make it periodic by simply putting the same signal over and over and get the Fourier series for such modification. The vector of so called Fourier coefficients (coefficients before *sin* and *cos* functions) can be a good representation of currently analyzed signal.

"Every signal is just a sum of simple sinusoids of different frequencies."

Building upon Fourier series we can get *Fourier transform.* This method allows us to transform signal into its "Fourier transform" which is a function depending on frequencies. We can then simply ask by putting the frequency as an argument, how much power of the signal is bound in a specific frequency. This function or it's values in specific frequencies can be a good representation of currently analyzed signal.

In practical uses, the BCI signal we process has a form of discrete time series. There is an algorithm called "Discrete Fourier Transform" - the **DFT**, which transforms a particular discrete time series into a function of frequencies. The computation of DFT for a sample has the computational complexity of $O(N^2)$ (where N is a number of data points in a sample) which is not a good news. Luckilly, there is a "Fast Fourier Transform" - the **FFT** that does pretty much the same as DFT, but it has a computational complexity of $O(N.logN)$. The only disadvantage of FFT is, that we need $N = 2^k$ for some k - the number of data points in sample to be a power of 2. That is, on the other hand, not that difficult to achieve. [FFT]

3.1.2 Wavelet transform

Besides Fourier transform, also *Wavelet transform* is used. This approach translates a given function to a vector of wavelets instead of simple periodic functions. Wavelets are nonperiodic functions, which tend to zero when variable goes to plus and minus infinity. A graph of a wavelet resembles a heartbeat graph, or a wave on a water surface. It is a kind of "brief oscillation".

Transient signal characteristics mean good wavelet feature extraction, while smooth, periodic signals are better extracted by other methods. According to [Zhao, 2009] when using Visual Evoked Potential (VEP) based BCI, choosing Wavelet transform instead of Fourier resulted in avoiding spectrum leakage and improvement of information transmission rate.

Now, having a non-redundant representation of analysed signal we have "extracted its features". In this state, we can compute a feature vector that specifies received signal well enough, but not too precisely. From FFT we know how much power is in specific frequency - the feature vector can be constructed as a vector of powers in 5, 8, 10, 12, 20 and 30Hz. Such feature vector carries information that might be enought for a simple mu- or alpha-rhythm detection. The next step needed to succesfully implement a BCI system is classifying the signal.

3.2 Feature translation

Having the goal of feature translation on mind, we are now trying to "translate" the feature vector of a certain sample to a useful command. The first method for feature translation we will mention is LDA.

3.2.1 LDA

LDA stands for *Linear Discriminant Analysis*. Its functionality can be simply imagined as a hyperplane in a space of features, that separates features of class A from class B by simply looking at the new feature vector and computing whether it is "over" or "under" the hyperplane.

Applied to electromagnetic signal feature translation e.g. when recognising a 2D cursor movement commands. Determined by previous calibration, subject might supply samples of brain activity when thinking about specific things. These samples are labeled by activity number, which gives us sample classes later used to classify the feature using LDA. The following definition was taken from [Teknomo].

Discriminant function for to-be-classified feature vector $\boldsymbol{F}$ is

$$f_i = \boldsymbol{\mu}_i \boldsymbol{C}^{-1} \boldsymbol{F}_k^T - \frac{1}{2} \boldsymbol{\mu}_i \boldsymbol{C}^{-1} \boldsymbol{\mu}_i^T + ln(p_i)$$

where there is

g	a number of classes
N	a number of samples
n_i	a number of samples in group i
$\boldsymbol{x}_i$	a class i sample data matrix. Each row contains a feature vector of a sample.
$\boldsymbol{\mu}_i$	a mean of class i. Usually an average value.
$\boldsymbol{\mu}$	a global mean value.
$\boldsymbol{x}_i^o$	a mean corrected data matrix. I. e. matrix row is a feature vector minus $\boldsymbol{\mu}$
$\boldsymbol{c}_i$	$= \frac{\left(\boldsymbol{x}_i^o\right)^T \boldsymbol{x}_i^o}{n_i}$ a covariance matrix of class i
$\boldsymbol{C}$	$= \frac{1}{N} \sum_{i=1}^{g} n_i . \boldsymbol{c}_i$ a pooled covariance matrix
p_i	a probability of occurence of class i feature vector.

Let k be the number that satisfies $f_k = \max_{i=1}^{g}\{f_i\}$. The resulting class number will be k. The index of the group which discriminant function has highest result. LDA as a two class separator can be denoted simpler. See [Vidaurre et al.].

This method allows simple, quick and often satisfactory classification. However linear discrimination might not be enouth in many cases, so we mention few more classification and translation methods.

3.2.2 Perceptron

Contrary to LDA, perceptron as an adaptive linear discriminant gives us slighlty more opportunities. We know that perceptron is a primitive model of a brain neuron. Neurons work in a following manner. Every neuron has a number of inputs (dendrites), but only one output (axon). Firing of a neuron can be modeled as

$$f(\boldsymbol{x}) = \begin{cases} 1 & \boldsymbol{w}.\boldsymbol{x} + b > 0 \\ 0 & \text{otherwise} \end{cases}$$

where $\boldsymbol{w}.\boldsymbol{x}$ is a dot product of weight vector and input vector. Which actually computes a weighed sum. b is a fixed bias value. Weight vector adapts during the training and converges if the two classes are linearly separable. As we can see, perceptron - the model of neuron - turns an input (feature vector) into a binary value. This can be used as a classificator. After some training cases, the perceptron is ready to classify any incoming vector correctly. Description of the weight vector modification is beyond the range of this thesis, however, it can be found easily on the internet.

A perceptron basically classifies only two classes, nonetheless, more perceptrons can be combined to create a classifier of higher dimension. A two class separator itself could be barely used to control 2D cursor if it only translates features to two classes. If we call them “up” and “down” we can see, that it would result only in a 1D control.

Chapter 4

Current research in the world

4.1 Berlin

A BCI research group in Berlin is called "Berlin BCI" (BBCI). The main work of this research group concentrates on EEG based BCI. Trying to apply BCI research knowledge for non-medical purposes they discovered or verified many interesting hypotheses and phenomena.

The self-control of cortical potentials requires intensive training on the side of user. User training was still necessary because of somewhat fixed way of feature extraction which does not account for the high variability among subjects. That became a reason for usage of larger feature complexity, so it could be fitted beter to individual characteristics. There is often an initial calibration period, in which signals are acquired while the user generates control commands according to cues without receiving feedback. Machine learning is then applied to these labeled data to gain features that are optimized for subject's individual performace.

There is also an approach that skips callibration period. It is possible to set up a subject-independent classifier whis is then adapted to the individual. Two ways to achieve this are possible. Either supervised or unsupervised way of adaptation. Some research groups claim, that the unsupervised classifier adaptation is possible. However, most of research and trials use the supervised manner of adaptation. The term "supervised" means that the system needs to know the true intention of the subject, which is usually done by cueing the subject to generate certain control commands. Studies were made about effectivity of machine learning based approach. The result is, that such approach enables BCI novices perform well from the first session on.

Attention is crucial in many situations when workers or drivers are the least controllable factor of any system. Fatal errors of drivers are one of the leading causes of death in United States [Blankertz et al., 2010]. Parieto-occipital alpha waves are believed to be linked to idling of visual cortex. This idling is assumed the default mode when no visual information is being processed. Berlin BCI research group investigated use of EEG-derived driving assistance applications by relating band-power to driving performance in a realistic simulated scenario.

The investigation consisted of 3 stages - each subject was observed in three conditions. The first, looking at a steady cross cursor in the middle of the screen. The second, watching a video of a driving scene (passive driving) and the third, active driving with a steering wheel. The driving simulation was reduced to changing lanes upon presentation of corresponding signs. During all three conditions, randomized audio stimuli (high and low beep) was presented and had to be responded as quicky as possible as a secondary task by pressing buttons attached to thumbs. The 128 channels EEG signal underwent *post hoc* statistical analysis in the whole range of frequency bands and with respect to different topographic regions of interest. Theta, alpha, beta and gamma power was computed using FFT within 3500ms interval.

It has been shown, that alpha and gamma power decreased gradually from first to third condition, but most importantly alpha power was significantly higher for short, compared to long auditory reaction times. This means, that achieving fast reaction on auditory task is positively correlated to higher alpha power, which corresponds to lesser visual attention. Resulting in, that focusing on distractive events while driving results in higher alpha power.

Among many *BCI only* controlled games scientists from Berlin described their implementation of BCI tetris (Fig. 4.1), where left and right hand motor imagery moves the piece horizontally, mental rotation turns the piece 90° clockwise and foot motor imagery drops the piece. The four-class classifier trained on an offline calibration run was applied online every 40 ms. The results between tetris movement steps were accumulated and the most frequent command was then executed.

Another interesting piece of work from Berlin is Hexawrite application for writing involving motor imagery. A recording of Hexawrite being used can be found on `http://www.dcs.gla.ac.uk/~rod/Videos/hexawrite_Sonne.avi`

Figure 4.1: BBCI tetris game

4.2 Graz

This research group works in Austrian Graz. They have created a completely open-source signal-viewing program SigViewer. In their research they focus on BCIs, neuroprosthetics movement control and stroke rehabilitation.

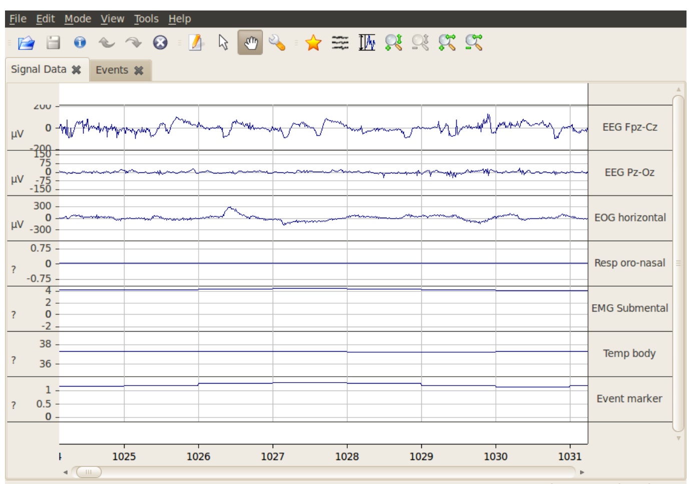

Figure 4.2: SigViewer screenshot

Another useful product of Laboratory of brain–computer interfaces of Graz University of Technology is library `tools4bci`. TiA (a part of tools4bci project) is a proposal for a standardized interface to transmit raw biosignals. It offers solution for multirate transfer, TCP / UDP transfer, block oriented transfer, multiple clients and exchange of meta-information between client and server. This library is licensed under LGPL, which does not force other researchers to make their sources and solutions opensource. This way, also private research groups and centres can benefit from this library and improve it. TiA library is also used by SignalServer program (also a part of tools4bci project), that acquires data from biosignal amplifiers and distributes the data via network connection. SignalServer is licensed under GPL [Breitwieser].

4.3 The Wadsworth Center

The BCI section of Wadsworth Center (which is a part of New York State Department of Health) aims its research at severly disabled people and improvement of their ability to communicate with others. Scientists from Wadsworth BCI have developed a BCI system which enables such people to write (e.g. an e-mail). The content of the first e-mail ever sent using this program can be found on their website `http://www.wadsworth.org/bci/`.

Their BCI system described in [McFarland et al., 2006] is based on mu and beta sensorimotor rhythms. Users learn the ability of controlling one- and two-dimensional cursor over a series of training sessions.

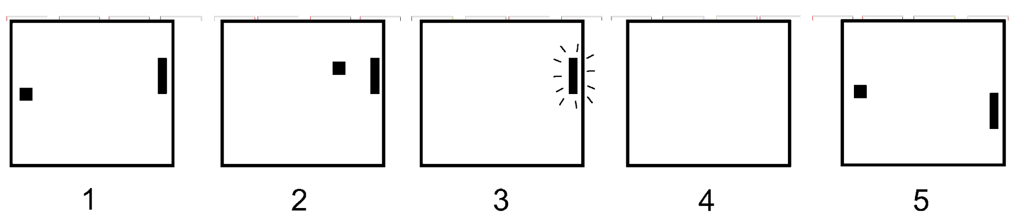

Figure 4.3: The cursor (square) moves at a steady rate from left to right. The rectangle on the right side is the target. Height of the cursor is controlled via BCI.

To control the height of the cursor they used either mu-rhythm activity (8-12Hz) over sensorimotor cortex, or the amplitude of higher frequency (approx. 18-25Hz) beta-rhythm activity, also over sensorimotor cortex. Further in the report they discuss advantages of regression to classification with respect to feature translation.

4.4 BCI2000

BCI2000 is an open-source solution for researchers in BCI field. Being open-source gives this system a remarkable ability to adapt to new situations. For example a lot of hardware equipment works out-of-the-box with BCI, because there has already been a research group, which worked with this particular hardware to record brain activity. No matter what the paradigm is, you are very likely to find the basic setup already done for you. BCI2000 supports real-time integration with Matlab for better overview and analysis.

We have found that the BCI2000 system strikes a great balance between a plug-and-play system that is ready to use with zero programming knowledge, and yet can be completely customizable to any researcher's needs for any system. The "stock" BCI2000 software contains many standard signal processing algorithms (FFT, AR spectral estimation, ERP/averaging, among others), and applications (2D cursor control, P300 speller) used currently in BCI research. [Garell, Felton, Wilson, and Williams]

Many research groups benefit from BCI2000 sophisticated architecture. Creating a custom real-time output channel is as easy as adding a new filter to signal processing chain which sends the data in a specific form to whatever device you are currently using. The data can be sent in any way you can succesfully program in C++ (it is the signal processing filter). Then the receiving side can be a client written in any language - or a hardware device that can read the data and execute the disired command.

More about BCI2000 on `http://www.bci2000.org/`

Conclusion

Many problems stated in the beginning now have solutions. They might not be mentioned in this thesis, but as the research continues, day by day, new solutions challenge the old ones. Choosing the right method of getting signal is now quite obvious. EEG electrodes are suitable for healthy users, while ECoG, for now, is applicable only when the subject has another reason for removing skull. The problem concerning realtime processing was actually a problem of what are the best regions to observe and what frequency bands contain the right information (because of limited computational power). A practical solution to this problem can be found by reading a few studies, that investigate impact of specific tasks on frequency powers.

Buying EEG electrodes, the amplifier and installing BCI2000 allows you to immediately start your own research. There is also other affordable or opensource software doing what you need and that is the main reason, why there are already so many applications of BCI, that are useful indeed.

The focus of BCI research also slowly moves towards applications for healthy users - to the commercial domain. Wealthy customers might soon sponsor more and more research aimed at appliances control, driver's attention watcher or simply augmentation of computer control to thoughts etc.

In Europe, there is a collaborative DECODER project `http://www.decoderproject.eu` which aims at the detection of consciousness in non-responsive patients using BCI. It diagnoses the state of mind by a variety of auditory, visual, tactile and mental stimulation paradigms.

Practical results of BCI research are still not very popular. People mostly hear about similar measurements only in connection with epilepsy or brain reaction examinations. Results in the field, however, suggest that BCIs have a broad application capability. As soon as certain tasks require only specific modules of amplifiers and software that is written specifically for that task the BCIs will become smaller in size, more reliable and affordable. Possibly also an everyday tool.

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