

Computer Game Control through Relaxation-Induced EEG Changes

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Lausanne, 4.2.2002

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A human-computer interaction device that is built on the principle “think and make it happen without any physical effort” is called a Brain-Computer Interface (BCI). Our research team has developed a simple computer game that is based on this principle. The game enables the user to control a simple object on the screen through his degree of relaxation. The goal in this project is to improve the degree of control the user has over the object on the screen. To achieve this, the following tasks have to be carried out:

- Familiarization with the state of the art in BCI and the above mentioned game system
- Design and implementation of an effective training protocol
- Testing and modification of the training protocol with different subjects
- Implementation of a new game control and analysis of results
- Evaluation of the performance and possible avenues for further improvements

Prerequisites: MATLAB, Signal Processing Basics

Conditions in the attached document on directives for student projects apply in performing this work.



Prof. T. Ebrahimi

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Abstract

An essential characteristic of human being is communication, communication with other humans, communication with a machine. To reach another level of communication a more sophisticated method has been found: Brain Computer Interface. Electrical potential, which are correlated to activity in a human brain can be used to operate a machine. The electrical activity is measured by electrodes that are placed on the scalp i.e. by an Electroencephalogram (EEG).

An algorithm has to be worked out to analyse the measured activity. A machine does not recognize different mental tasks. It measures a value and an algorithm has to be found to associate a meaning to this measured value.

The computer has to be trained to learn which electrical activity means either relaxation or excitation. The hypothesis is to operate a computer by a relaxed or excited state of the brain.

The algorithm implies a training program to teach the computer how to associate the values to the corresponding state of the brain. The measured data from the EEG has to be handled. Filtering in different frequency ranges is a possible method because brain activity is classified in different rhythms. The further step is to extract the important information out of the filtered data and classify this information. Fisher Discriminants are used as classification method.

After the training period the subject operates the computer by the two different states of his brain. A graphical interface allows the subject to see if the machine recognized his brain activity correctly.

The algorithm which is discussed in this report allows the computer to recognize the right state of the brain activity with an efficiency of over 80%. The results are presented in chapter 6. Therefore the method is useful to operate a machine by relaxing or exciting the activity of the brain.

Some improvement is useful to increase the efficiency. Measurement can be made in a more effective way by placing more electrodes on the scalp and let increasing the spatial resolution. More sophisticated discrimination methods can reduce the classification error. A large investigation exists to improve the communication with the help of brain activity.

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Chapter 1

Introduction

It has already been proved that the control of a machine only by thoughts is possible. Which technology has to be used to measure brain activity and how do these signals recorded from the brain have to be analyzed and classified? Which method can be implemented to find and extract information out of the brain activity?

These two questions or problems introduce this work. To find a way to relax and excite people such that their brain activity changes is one main aim. The method has to train the machine to recognize the different states of the brain activity.

1.1. Human communication

Communication is one of the main characteristics of humans; it distinguishes a man from an animal. People talk together, express emotions and experiences one to another, people communicate to machines and machines to people. In the history of mankind, we have been successful in finding multiple ways of expression [1].

Even if the way to communicate has become more sophisticated and efficient, the central role, transmission of information, maintains. In the early days of cave men told stories around a fire and now a person in Lausanne is talking by mobile phone to his brother who lives in New York.

The quality of communication between man and machine improves continuously but the interface does not change. The computer can stimulate our hearing, our vision, our sense of touch, our olfaction etc. but how do we tell the computer what it has to do?

We still use rather primitive interfaces. A kind of device such as a keyboard is used to give a command to a machine. To write a text people use the computers keyboard, to switch on the radio people press the on button.

An evolution of human-machine interface is the speech recognition. A computer is able to distinguish between different speakers and recognize different words. This technology still has to be improved. Research and development in other areas indicate some hope that human-machine interaction improves. Visual sensors mimic the human eye in machines to allow them to see or at least to interpret visual cues emanating from a user. Haptic devices allow machines to feel and measure pressure for machines to react in a more natural way to commands and actions.

What will be the next revolution in communication? Which new interface increases the ability to communicate to a machine? Why we do not use the source of our emotion and thinking, our brain?

1.2. Brain activity

The electrical Brain 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.

Brain activity is generated by billions of nerve cells, called neurons. Each neuron is connected to thousands of other neurons. The signals that are sent from one neuron to another are electrical impulses. The sum of all the impulses of the neuronal network can be measured in an invasive or non-invasive way. Invasive means that electrodes are implanted to the brain. Recent progress in technology also allows to probe and measure brain activity in an efficient non-invasive way. Such methods are Magneto Encephalography (MEG) [4], Positron Emission Tomography (PET), Single Photon Emission Computer Tomography (SPECT) [5], optical brain imaging and electroencephalography (EEG) [6]. MEG and EEG give continuous and instantaneous recordings of the brain activity. MEG is not practical to be used because measurements are made using a large device inside a magnetic shielded room. The measuring to detect the brain activity in this work is based on the EEG.

The EEG detects electrical potential differences which are measured in voltage. The order of these electrical impulses is of 5 – 100 μ V. Much of the time, the brain waves are irregular and no general pattern can be observed.

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. These rhythms are affected by different actions and thoughts, for example the planning of a movement can block or attenuate a particular rhythm.

The brain rhythmic activity can be separated in different frequency ranges. Some different brain rhythms have been proposed in literature. The following list of frequency ranges is according to NiederMayer[6].

Wave name	Frequency [Hz]
Delta	0.5 – 3.5
Theta	4 – 7.5
Alpha	8– 12
Beta	13 – 30
Gamma	30 – 40

Delta waves: Infants (around the age of 2 months) show irregular delta activity of 2-3.5 Hz in the waking state. Adult's delta waves are only seen in deep sleep.

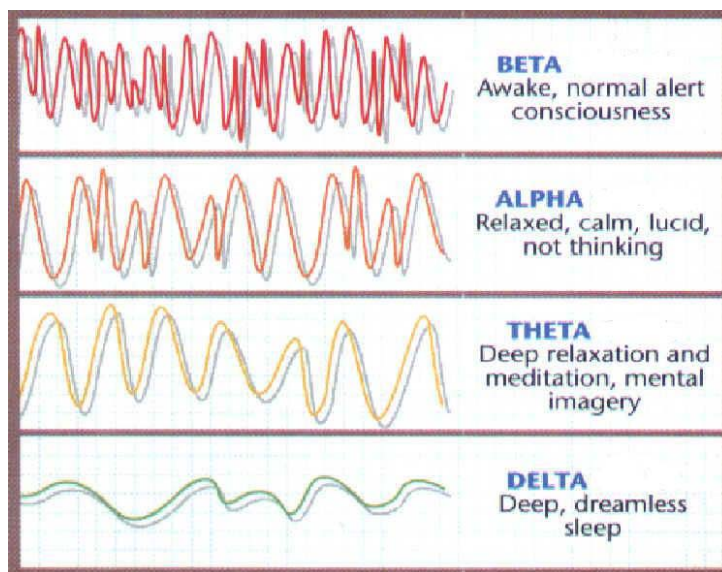
Theta waves: Theta rhythm plays an important role in infancy and childhood. Normal adult's theta waves are seen mostly in states of sleep. During waking hours the EEG contains only a small amount of theta activity and no organized theta rhythm.

Alpha waves: The International Federation of Societies for Electroencephalography and Clinical Neurophysiology proposed the following definition of alpha waves: *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 wave 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 a typical mean adult alpha frequency.

Beta waves: Beta rhythm can mainly be found over the frontal and central region and the amplitudes of this rhythm are seldom larger than 30 μV .

Gamma waves: Gamma rhythm has the highest frequency. Does a higher mental effort affect this rhythm? Investigation figured out, that this frequency was measured primarily in the hippocampus [6].



different brain rhythms and the associated states of the brain

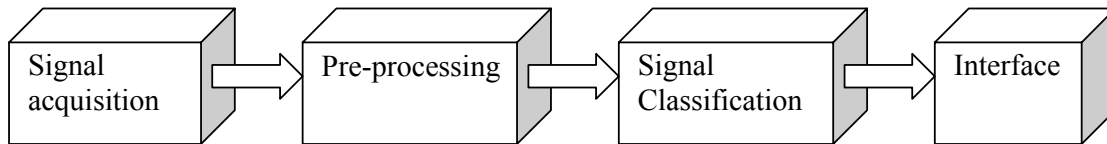
1.3. Brain Computer Interface (BCI) and its use

In the first international meeting devoted to BCI research held in June 1999 at the Rensselaerville Institute near Albany, New York, Brain Computer Interfaces were defined as follows: “A brain computer interface is a communication system that does not depend on the brain's normal output pathways of peripheral nerves and muscles” [7]

According to Allison [8] there are at least five components necessary for an 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.

The definition of a BCI structure is based on the statement of Allison [8]:

- **Signal acquisition:** The EEG measures the brain neurons potential continuously by electrodes and sends it through an amplifier to the recording computer that samples and saves the data. The aim is to look for brain activity and the relevant physiological signal is the neurons electrical potential.
- **Pre-processing:** From the saved data the useful information has to be extracted. Filtering according to the frequency ranges defined in paragraph 1.2. This can be a solution to get the necessary information about brain activity.
- **Signal classification:** After extracting the required information from the data a classification is needed to associate a mental task to the corresponding data. This task completes the training part of the BCI.
- **Interface:** After training a visual interface is developed for the operating period. During the operating period recorded data is compared to the trained data and the result of the comparison is visualized through the interface.



block diagram of general BCI structure

What are the thoughts of a BCI user? An ideal BCI could detect the user's wishes and commands directly. However, this is not possible with today's technology. Therefore, BCI researchers have used the knowledge they have had of the human brain and the EEG in order to design a BCI.

Technology allows a maximum information transfer rate up to 10-25 bits/min. This limited capacity only allows the execution of a few tasks. A classification between four, five targets maximum is supported by the BCI system.

What will an investigation in the domain of BCI bring to the mankind? In clinical work an EEG is aimed to detect epilepsy. The brain communicates with neuromuscular channels through the whole body. The control of these channels can be disrupted by different disorders. Numerous diseases like amyotrophic lateral sclerosis, brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, multiple sclerosis, impair the neural pathway that control the muscles and affect a voluntary muscle control. A new pathway to communicate to the muscles has to be found and BCI is a possibility to communicate to the muscles. More sophisticated devices are developed to assist disabled people, suffering diseases [2].

Neuroscience research based on EEG and BCI can help to understand brain neural signals and brain functions. Mental diseases can be understood and treated.

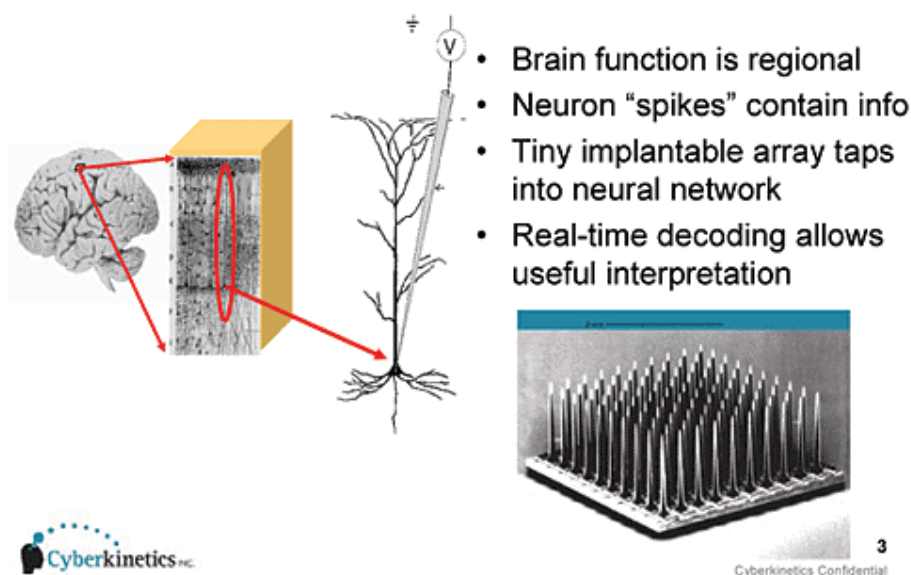
BCI brings new possibilities to communicate to a machine. Imagine a person lying on his bed selecting music only by his thoughts, and by his mood.

1.4. Overview of BCI-research

Cyberkinetics

Five quadriplegic patients might be months away from testing a brain-computer interface created by Cyberkinetics, a privately held company in Foxboro, Massachusetts. The company's system, called BrainGate, could help patients with no mobility to control a computer, a robot or eventually their own rewired muscles, using only their thoughts. If the trials go well, a product could be on the market by 2007. Microelectrodes are implemented in the brain nervous system to measure the neuronal signal direct from the source. Cyberkinetics already has trained monkeys to move a cursor using only thought, the next step is to implement the microelectrodes to human.

Core Concept



microelectrodes that are implanted to the neural system

Wadsworth Center

Jonathan Wolpaw and his colleagues have done BCI research at the Wadsworth Center, 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 a study made in 1998, 64 EEG channels were recorded from the surface of the scalp. Each channel was referenced to the electrode in the right ear.

The training was done in a 30 min session. After the initial training the targets were replaced with words YES and NO and the subjects were asked simple questions like "is $2+2=4$ ". The subjects answered to the questions by moving a 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.

64% - 87% of the answers were confirmed with the RV procedure. 93% to 99% of these answers were correct. [7]

The Thought Translation Device (TTD)

During the 1990's Niels Birbaumer and his colleagues developed a BCI called the Thought Translation Device at the University of Tübingen in Germany. They studied five patients using the TTD.

The EEG was recorded from the electrode Cz (location of the international 10 – 20 system) referred to mastoids at a sampling rate of 256Hz. The EEG signal was filtered and corrected for the eye movement artefacts. Slow cortical potential 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.

The patients started working 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 slow cortical potential (SCP) shift. 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 speed of writing was slow. Subjects needed an average about two minutes for the selection of one letter.

Birbaumer and his colleagues have now taken part in a project called "BCI2000".

BCI2000 tries to combine the slow cortical capacity of the TTD with the μ and β rhythm capacity of the Wadsworth BCI. [9]

Graz Brain-Computer Interface

Pfurtscheller and his group at the Graz University of Technology, in Austria, started the "Graz Brain-Computer Interface" project in 1991. In a study made in 2001, their research was based on the classification of the EEG patterns during five different mental tasks. One aim was to study how the number of mental tasks affected the channel capacity. A symbol representing one of the five different types of mental tasks was shown on the screen between 3 s and 4.25 s. The 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 the trial (8s). Each mental task was performed 40 times in one training session.

The EEG was recorded with 29 electrodes. 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. A hidden Markov model was used as a classification method. [10]

Chapter 2

Algorithm and BCI structure

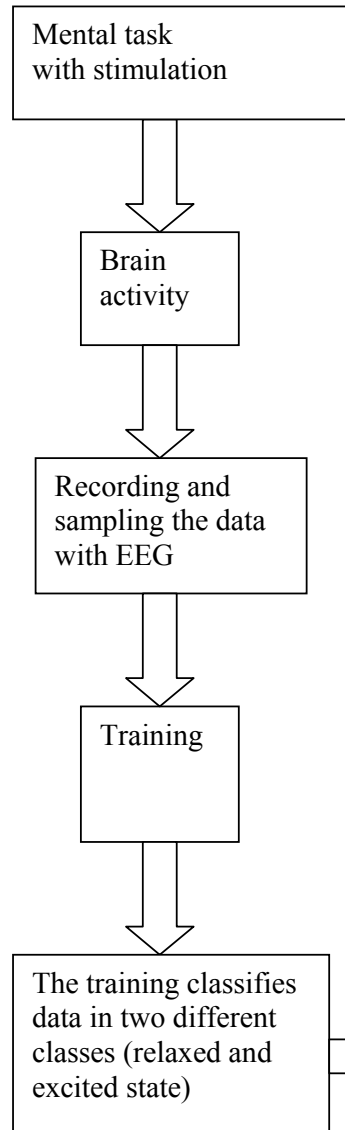
2.1. Algorithm

With the help of the EEG a computer records and visualizes brain activity. It is possible to measure the different potential of the brain impulses but the computer does not know from the start which potential means the relaxed state of the brain and which potential means that the person is excited. It is essential to train the computer and to explain if the recorded data correspond to calm activity or nervous activity with a lot of thinking. After training the computer is able to distinguish between excited brain waves and relaxed brain waves.

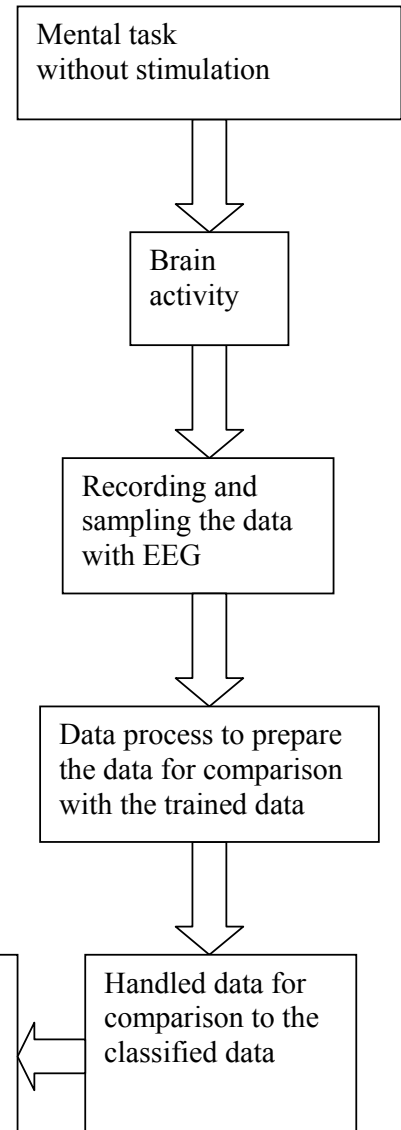
During the control period the subject executes the two different mental tasks (relaxing and thinking, calculating). The computer associates the now measured pre-processed and feature extracted data to the right mental task. A feedback to the user shows him the detected state of his brain.

2.2. BCI Structure

Training period



Operating period



Comparison between the trained and classified data and the handled data of the operating period

Execution of an operation
Graphical interface

BCI structure diagram

According to the algorithm the different phases of the BCI structure mentioned by Allison [8] are:

- **Data acquisition:** All measuring is based on an EEG. The electrodes measure the electrical potential. After amplifying the data is sampled and saved in Matlab. Recording and sampling is done as well in the training part as the operating part.
- **Training:** The training is used to associate a meaning to the measured values. Data handling takes part of the training. Filtering in the five different brain rhythm frequency ranges. Calculating the mean value of the energy is a part of the data processing before use this handled signal as input for the classification method.
- **Pre-processing:** Filtering and calculating the mean value of the energy is also the pre-process executed during the operating period. The data is then prepared to compare it to the output of the training.
- **Comparison:** The handled data of the operating period is compared to the output of the training and associated to a brain activity state. According to the associated state a different operation can be executed.
- **Interface:** The graphic interface allows receiving a feedback from the computer and to supervise the executed task.

Chapter 3

Training and Measuring

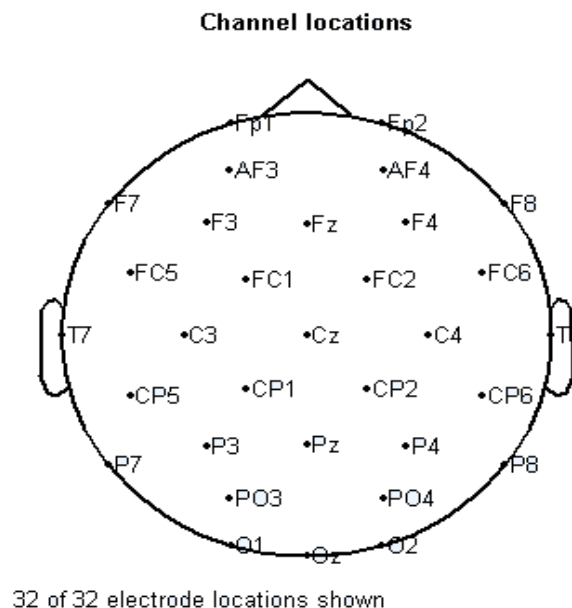
Measuring is done with an Electroencephalogram (EEG).

3.1. EEG

Even if Hans Berger's discover in 1930, that the EEG shows structured patterns of the brain impulses, the EEG was used mainly to evaluate neurological disorders in the clinic and to investigate brain function in the laboratory. EEG-based communication attracted little serious scientific attention until recently. The possibility to recognize a single message from such a complex and variant signal, as brain impulses are, appeared to be remote. The measuring of brain activity requires to analyze the EEG in real-time, the required technology did not exist until recently

The ongoing EEG is characterized by amplitude and frequency. The amplitude of the EEG signals typically varies between 10 and 100 μV (in adults more commonly between 10 and 50 μV) [6].

The temporal resolution of EEG is very good: milliseconds or even better. However, the spatial resolution is poor. It depends on the number of electrodes, but the maximum resolution is in centimetre range. 32 electrodes are placed all over the head to measure electrical activity of the cerebral cortex.

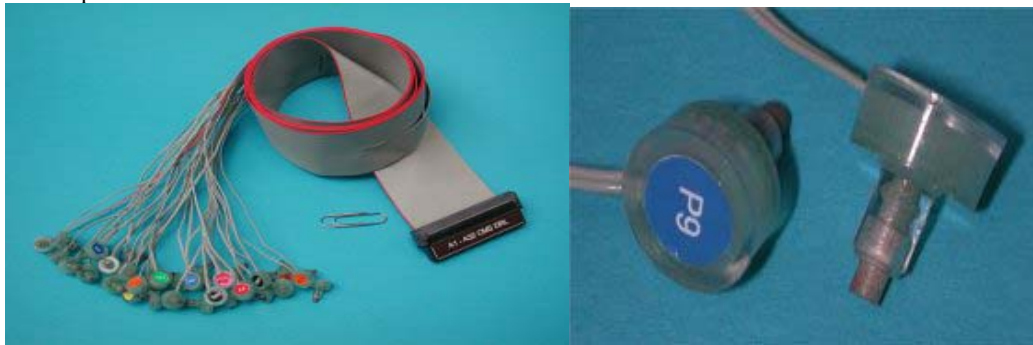


electrodes position based on the international 10-20 system

The locations of the electrodes are based on the international 10-20 system [11]. The potential difference can only be measured between two points so reference electrodes are needed. Unfortunately the layers of bone, skin and cerebrospinal fluid introduce attenuation and volume conduction to the signals captured by the electrodes.



head cap where the electrodes are fixed.



electrodes used to measure electrical potential

Allison [8] 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. Various properties in EEG exist, which can be used as a basis for a BCI:

1. Rhythmic brain activity as mentioned in chapter 1. 3.
2. Event-related potentials (ERPs) [6]
3. Event-related desynchronization (ERD) and event-related synchronization (ERS) [6]

ERP: The potential changes in the EEG that occur in response to a particular event or a stimulus.

ERD is an amplitude attenuation of a certain EEG rhythm.

ERS is an amplitude enhancement of a certain EEG rhythm.

3.2. Training protocol

Music can relax and excite people. Calm music helps people relaxing and loud, noisy music brings people to an excited state. A nice, calm picture supports the effect of the music. To get to an active state of the brain the subject is supposed to solve equations. Loud, noisy music interrupts the subject so that he is more stressed and more brain activity is forced.

It is important, that the subject keeps the eyes open. The fact to close the eyes changes brain activity. The nerves of the eyes excite the backside of the brain. The electrodes placed on the backside of the cerebral cortex record more intensity when the eyes are closed. It is undesirable to measure the activity when a person closes her eyes.

This work doesn't examine the affect of closing the eyes. The aim is to prove that there exist a difference in brain activity between the calm state and a state when a person is stressed and thinking when people are realising and seeing what's happening around them.

Entire duration of the training session is 7.8 minutes (468 seconds). The recorded time is six minutes. Some instructions are showed to explain the process of the training. During the instructions no data is recorded. The two parts, relaxation and excitation, last 30 seconds without instructions. They are alternated eleven times. Entire time for the relaxation part is 42 seconds, for the excitation part is 36 seconds.

relax = relaxation

ex = excitation



Relaxation:

Music: sea roaring during 42 seconds

Instructions:

- Let your eyes open
- Breathe deeply
- Listen to the roar of the sea
- Focus on your breath

Each instruction is showed during three seconds. Entire time of the instructions is twelve seconds, while music is sounding.

Show picture of a beach with waves streaming to the beach for 30 seconds



During this time data is recorded (30 seconds)

Excitation:

Music: loud, stressing Hardcore; “refuse resist of Sepultura” during 30 seconds

Instructions:

- Do you like maths ?!?
- Lets go !!!
- Fill the right operations in the brackets

Each instruction is showed during two seconds to show that it goes faster than relaxation. Entire time of the instructions is six seconds, without music. The subject shouldn't prepare for music. The music has to stress him from the beginning.

Show a math equation without solution for 30 seconds

$$8 [] 3 [] 3 [] 7 [] 2 = 4$$

During this time data is recording (30 seconds)

It is important that the user is able to reach the same excited state of his brain during the control period. While the user is training the computer he is stimulated by music and math equations but while he tries to control the machine with his brain activity a stimulation does not exist. It is important that the stimulation during the training period is efficient but not too exaggerated. To visualize a lot of different pictures and animated riddles can make the subject freak out. In this way, the user is unable to reach the same brain activity during the control period.

3.3. Measuring problems

While the EEG is measured, not all of the signals come from the electrical activity of the brain. Many potential changes seen in the EEG may be from other sources. These changes are called artefacts and their sources may be the equipment or the subject.

Technical artefacts:

A constant contact between the electrodes and the scalp is crucial. An electrode without contact can perturb the whole system. The measured electrical potential is weak ($5 - 100 \mu$). Without contact the electrode measures a higher voltage because of interruptions. A classification of a disturbed channel is impossible.

The surrounding electrical equipment may induce different components to the signal. The power supply system works at 50 Hz. The monitor of the used computer works at 70 – 75 Hz.

Physiological artefacts:

All movement of the subject must be avoided. Touching and shaking the cable that connects the electrodes to the amplifier cause enormous amplitude of the measured signals because of their weakness.

Eye movement, like blinking causes artefacts.

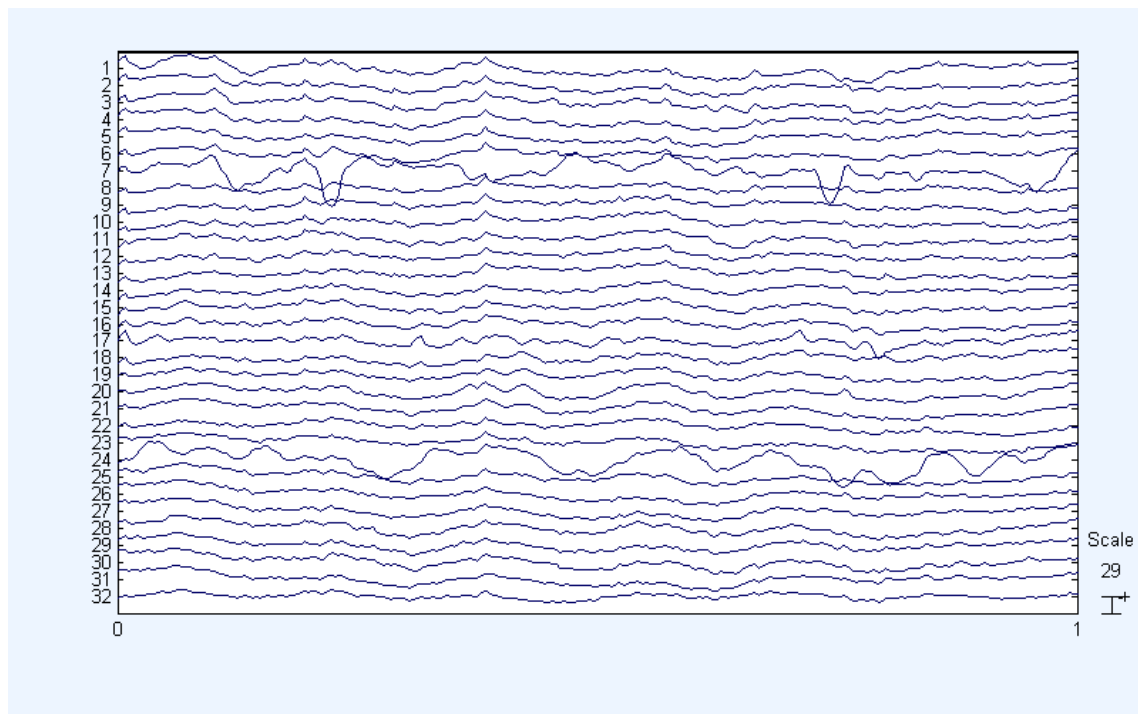
All movement of scalp may shift the electrodes and causes artefacts.

Chapter 4

Data Handling

4.1. Recording and Sampling

The EEG samples the measured electrical potential with a sample rate of 2048 Hz. The signal passes through an amplifier because of the low voltage of the measured potential. After amplification it is transmitted by fibre optic cable to the Computer. The data is saved as a matrix in MATLAB. Each row represents a different electrode.



measured brain activity incoming from the EEG, x-axis: time (1 minute), y-axis: amplitude of each electrode

4.2. Signal pre-processing

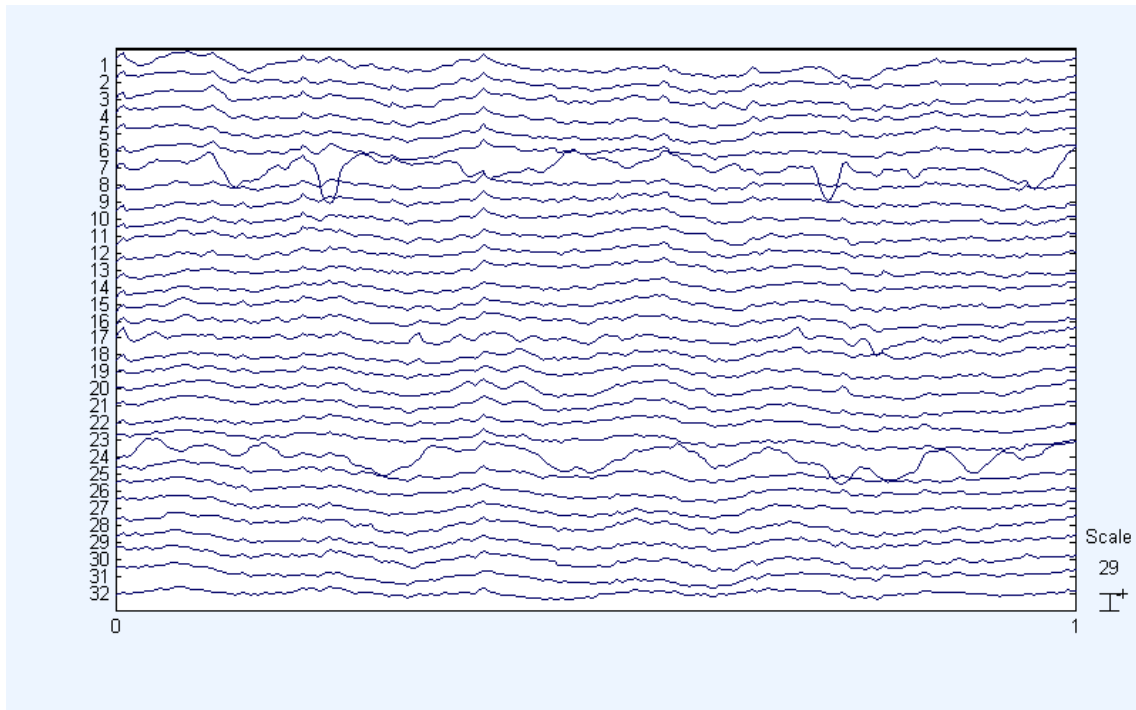
All data acquisition is done and the signal is saved in MATLAB. As in the BCI structure mentioned the pre-processing consists of down sampling, filtering, data cleaning from artefacts and feature extraction to prepare the data for my classification.

4.2.1. Down sampling

The amplifier samples the signal at a rate of 2048 Hertz. The highest frequency that contains important and desirable information is 40Hz. The theorem of Nyquist explains that the sample rate has to be the double of the highest frequency of the desirable signal to reconstruct it. The lowest possible sample rate is 80Hz. Therefore the sample rate is decimated eight times to 256Hz.

Down sampling reduces the size of the incoming data without losing information in the lower frequencies. The higher frequencies without useful information are removed. Data reducing is advantageous for real-time suitability because the size of the data defines the processing-time. Before down sampling a filtering is necessary to avoid interferences from higher frequencies. A low pass Tchebbycheff filter type 1 is used to eliminate higher frequencies.

$$\text{Cut off frequency: } f_c = 0.8 * \frac{\text{samplerate}}{16} = 0.8 * \frac{2048\text{Hz}}{16} = 102.4 \text{ Hz}$$



down sampled data of the incoming signal, x-axis: time (1 minute), y-axis: amplitude of each electrode

4.2.2. Filtering

The down sampled data has to be filtered to eliminate the undesirable artefacts. As mentioned in paragraph 3.3. the frequency of these artefacts is 50 Hz or higher. The highest frequency range of EEG brain activity is the gamma rhythm; from 30 to 40 Hz. Interference from the electrical equipment frequency therefore doesn't exist.

Brain activity is classified in five frequency ranges. It is necessary to filter the data of the brain in these five bandwidths to extract the important information. All five bandwidths contain information to use for the classification to distinguish between the relaxed and excited

state of the brain. With the help of the filtering in different bandwidths it is possible to figure out what frequency range is the most important for the recognition of relaxed or excited state.

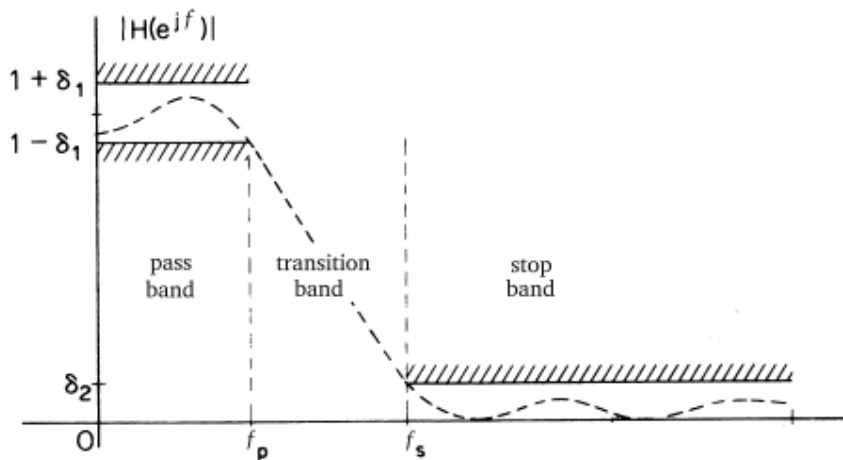
The filtering is based on a frequency selective band pass elliptic filter. It is an IIR (Infinite Impulse Response) filter approximated by the elliptic method (see appendix A), which means that the filter coefficients are calculated by the elliptic method.

This filter is chosen because of its good frequency selection and the reduced order of the filter. The order is the number of filter coefficients that are calculated. A reduced order means less calculating time and better real-time suitability.

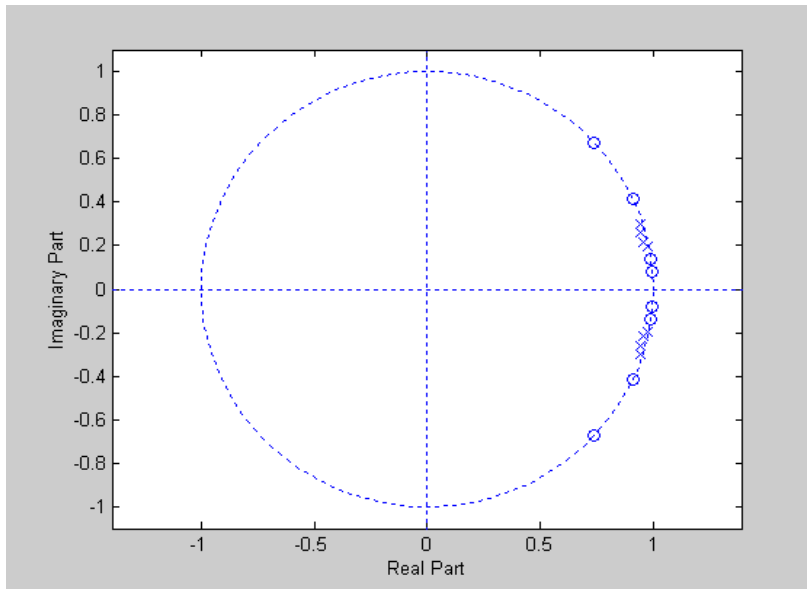
The important characteristics of the IIR filter:

- High selection in frequency. The frequency ranges are short compared to the down sampled incoming signal. It is essential to have a strict cut off frequency. The different bandwidth of the brain rhythms must not interfere one to another. That implies a short transition band for the filter.

For all five bandwidth $\Delta f = 0.5$ Hz is chosen as transition band.



- The filter is causal. A system is causal if the output $y[n_0]$ only depends on the sequence of input for $n \leq n_0$. The filter response $h(n)$ has to satisfy the condition:
 $h(n) = 0$ for all $n < 0$



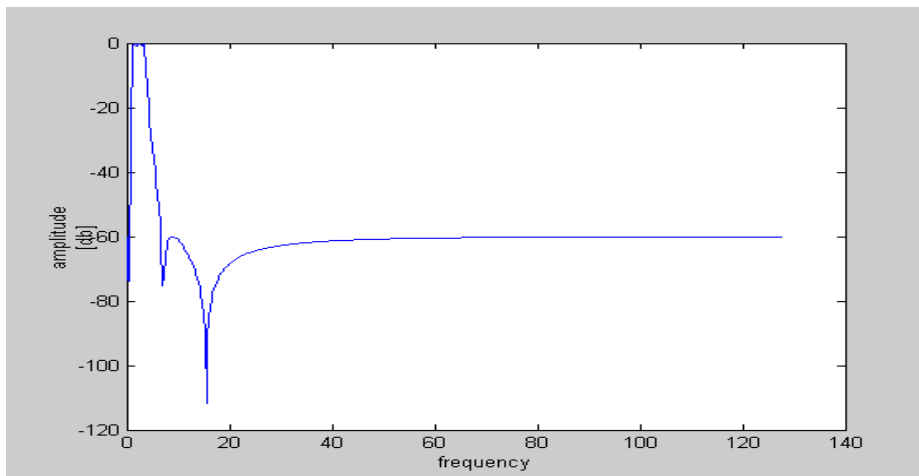
zeros and poles of the elliptic filter that filters in the alpha rhythm.frequency.

- The filter is stable. A system is stable if for a bounded-input a bounded-output (BIBO) comes out. The filter response $h(n)$ has to satisfy the condition:

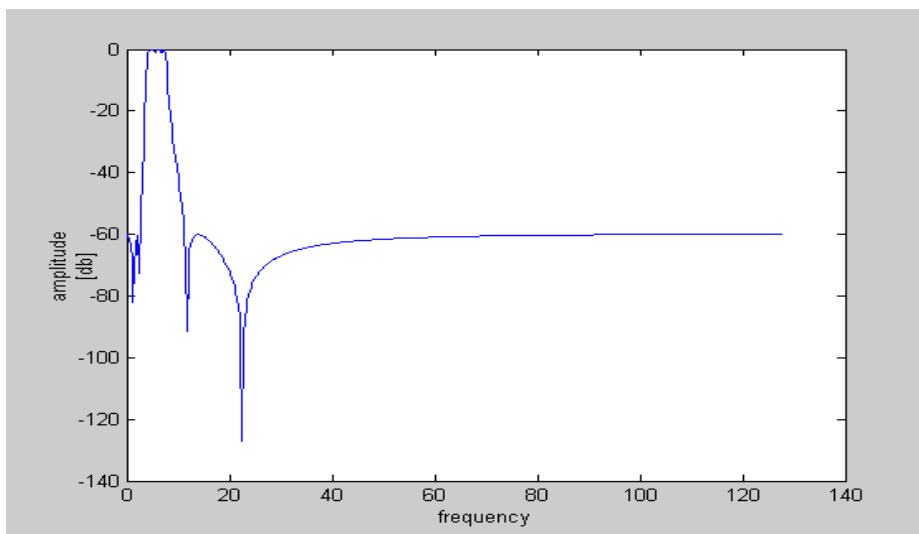
$$\sum_{n=0}^{+\infty} |h(n)| < \infty$$

This implies that all the poles of the Z-transformation of the filter function $H(z)$ are inside the unity circle.

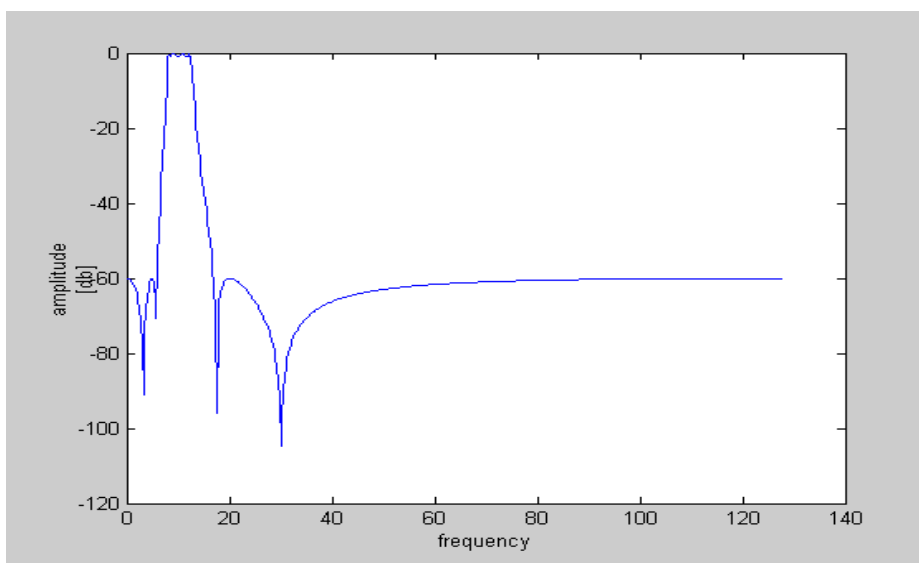
- The amplitude of the filter has to be equal in all the five pass bands. The pass band filtered signal of all the five frequency ranges of brain activity has to be amplified by the same gain. The five filtered bandwidth have to be comparable after filtering. The attenuation in the stop band has to be clear-cut to avoid interference with the wanted signal. The attenuation is set to at 60 db, the stop band is attenuated 1000 times. The frequency response of the elliptic filter is equirippled in the pass band and in the stop band. The ripple does not disturb the signal because is negligible to the attenuation of 60 db.



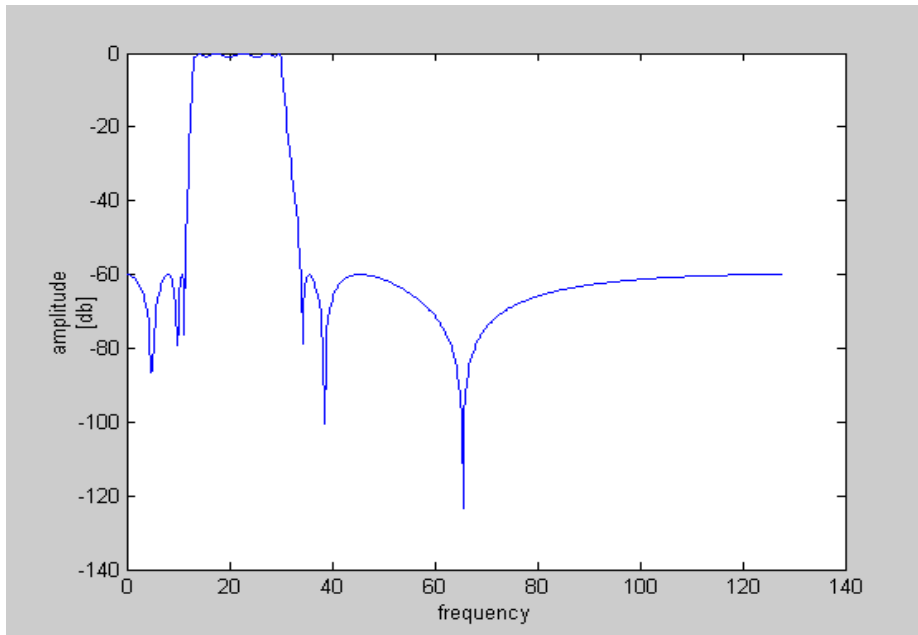
frequency response of the elliptic filter, delta band pass



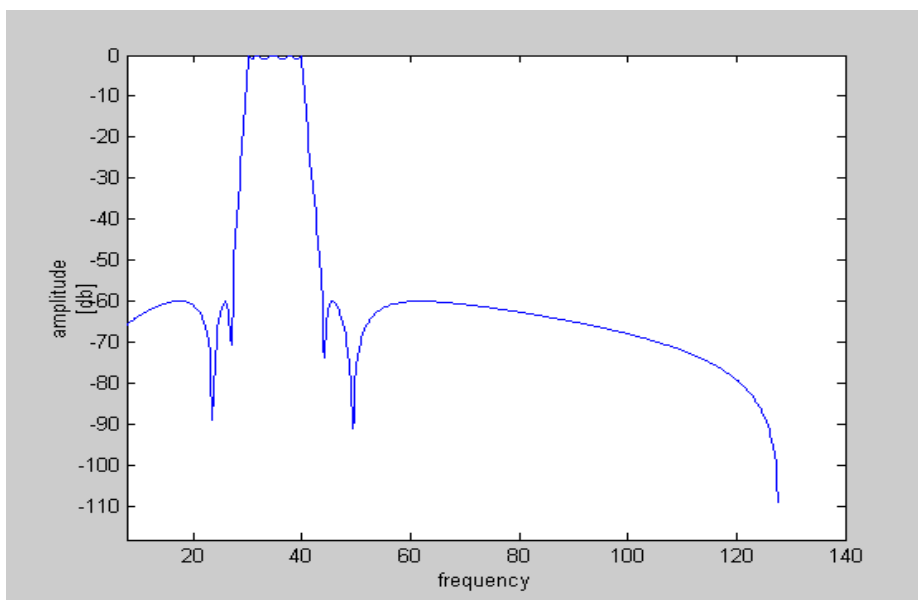
frequency response of the elliptic filter, theta band pass



frequency response of the elliptic filter, alpha band pass



frequency response of the elliptic filter, beta band pass



frequency response of the elliptic filter, gamma band pass

- The phase of the elliptic filter is not linear. That means that it distorts the phase of the filtered signal. The algorithm is based on the amplitude of the electrical potential of brain activity. Therefore no interesting information is extracted out of the phase of the signal. The non-linear phase of the filter does not disturb the signal for the application.

Filter characteristics for each brain rhythm:

Brain rhythm	Order	cut off frequencies	transition bands
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Delta waves	4	1Hz – 3.5Hz	0.5Hz – 1Hz and 3.5Hz – 4Hz
Theta waves	4	4Hz – 7.5Hz	3.5Hz – 4Hz and 7.5Hz – 8Hz
Alpha waves	4	8Hz – 12Hz	7.5Hz – 8Hz and 12Hz – 12.5Hz
Beta waves	6	13Hz – 30Hz	12.5Hz – 13Hz and 30Hz – 30.5Hz
Gamma waves	5	30Hz – 40Hz	29.5Hz – 30Hz and 40Hz – 40.5Hz

Design technique for digital IIR filters

Elliptic filter

The elliptic filter is equirippled in the pass band and in the stop band. The approach to calculate the frequency response of the elliptic filter is:

$$|H_c(j\Omega)|^2 = \frac{1}{1 + \varepsilon^2 U_N^2(\Omega)}$$

where $U_N(\Omega)$ is the elliptic Jacobin function. To get an equirippled constant error in the pass band and stop band the filter has to have poles and zeros. The zeros are in the $j\Omega$ axis. [12]

Imperfection of filtering

It is impossible to design a perfect filter without transition band. A perfect filter with a rectangular window does not exist. The transition band introduces a negligible part of the frequencies out of the range of the different brain frequencies.

The stop band does not eliminate the undesirable signal completely. This signal is attenuated by a factor of 1000 (60 db). It is enough attenuated to consider it as eliminated.

The oscillations in the pass band are negligible as well and do not disturb the main information out of the signal. These oscillations are in all the five bandwidth equal and act in the same way to all the five frequency ranges.

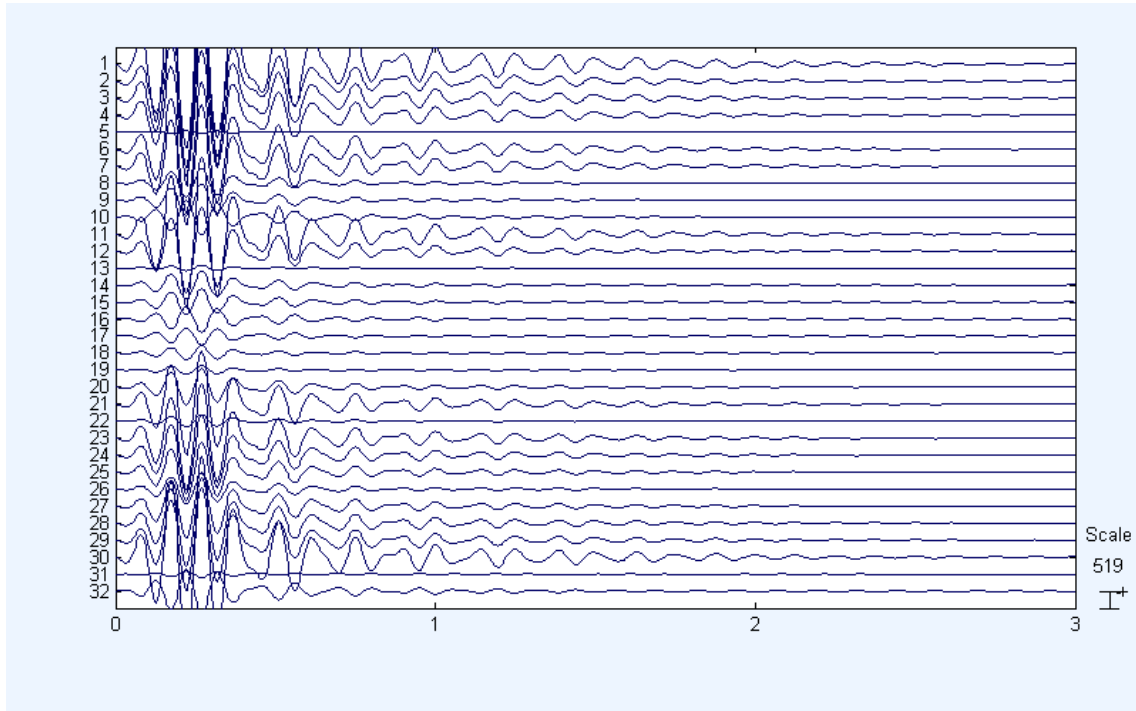
Filtering is a convolution between the input data and the filter impulse response. This convolution introduces an improper signal at the beginning because initial conditions do not exist.

The filter impulse response for such a narrow bandwidth swings out at the beginning and contains high positive and negative amplitudes. The multiplication and summation of the convolution between the filter response and the first samples of the signal cause high values and therefore distortion to the first samples of the filtered signal. When the signal covers the entire important part of filter impulse response, multiplication and summation of the convolution is done between the signal and the entire part of the filter with important amplitudes and the convolution becomes balanced.

The choice of initial conditions could avoid the distortion.

Another possibility to avoid this undesirable distortion the first three seconds (768 samples) of each relaxed and excited part are deleted. The training protocol provides six relaxed and six excited parts. The total deleted time is:

$$12 * 9 \text{ seconds} = 108 \text{ seconds}$$



filtered data of the incoming signal, x-axis: time (3 minute), y-axis: amplitude of each electrode
filter distortion in the first three second is visible.

4.3. Feature extraction and classification

It is necessary to prepare the filtered data for the classification. The first step is already done because the distortion introduced by the elliptic band pass filters is deleted.

The next step is to extract the important information and prepare the data for the classification method. The preparation is to compact the data in a useful information for the Fisher discrimination.

The filtered data is cut in pieces of 3 seconds. The calculation of the mean values of the energy of the three seconds pieces is the feature extraction and therefore the input for the Fisher discrimination.

Total time recorded: 360 seconds \rightarrow 92160 samples (sample rate = 256 Hz)

Time deleted because of filter distortion: 108 seconds \rightarrow 27648 samples

Time left: 252 seconds \rightarrow 64512 samples

Energy mean values of 3 seconds: $252 \text{ seconds} / 3 \text{ seconds} = 84$ input vectors for classification designed as feature vectors. Each feature vector is associated to a brain activity

state, the label of each vector. Seven vectors of relaxed state followed by seven vectors of excited state of the brain. After six repetition of this alternating cycle the input data contains 84 feature vectors.

Fisher's Discriminant is a learning technique to solve optimization problems. The aim of a discriminant analysis is to find a function returning scalar values that allow discriminating different input data. These discriminants are used to train the classifier to recognize the two classes of input data that exist (relaxed or excited input data) [3].

Fisher Discriminants

Linear Discriminants

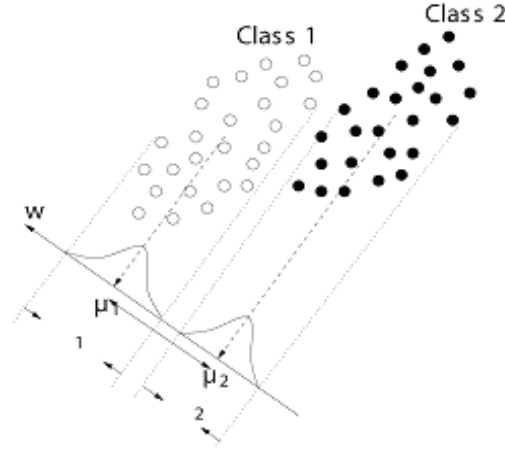
The aim is to find a function $f : \chi \rightarrow \mathbb{R}^D$, such that $f(x)$ and $f(z)$ are similar whenever x and z are. Similarity is measured by Euclidean distance. The linear discriminant is looking for a linear function, a set of projections

$$f(x) = W^T x + b, \quad W^T \in \mathbb{R}^{N \times D},$$

where the matrix W is chosen such that some characteristics are satisfied. For the solution of the existing problem a one-dimensional discriminant function of the form $f = (w^T x + b)$ $w^T \in \mathbb{R}^{N \times D}$, is sufficient.

Fisher's Discriminant

Probably the most well known example of a linear discriminant is Fisher's discriminant. Fisher's idea was to look for a direction w that separates the class means while achieving a small variance around these means. The hope is that it is easy to decide either of two classes. This discrimination works therefore for two classes.



mean projections μ_1 and μ_2 with the corresponding variance.

The quantity measuring the difference between the means is called between class variance and the quantity measuring the variance around these class means is called within class variance. The aim is to find a direction w to maximize the between class variance and to minimize the within class variance at the same time.

The mathematical description defines χ as the space of observations $\chi \subseteq \mathbb{R}^N$ and ψ (for my example $\psi = \{1,2\}$) as the set of labels associated to χ . $Z = \{(x_1, y_1) \dots (x_M, y_M)\} \subseteq \chi \times \psi$ denotes the training sample of the size M . Two labels are necessary to associate them to the relaxation and excitation part. $Z_1 = \{(x, y) \in Z \mid y = 1\}$ and $Z_2 = \{(x, y) \in Z \mid y = 2\}$.

$$m_i = \frac{1}{M_i} \sum_{x \in Z_i} x$$

It is further possible to calculate the means of the data projected onto some direction w in the same way.

$$\mu_i = \frac{1}{M_i} \sum_{x \in Z_i} w^T x = w^T m_i \quad (4.3.1.)$$

For the classification of the relaxed and excited state the fisher discrimination returns the corresponding mean projection μ_1 for the relaxed part and the mean projection μ_2 for the excited part of brain activity. The main goal is to find the projection vector w .

The corresponding variance is:

$$\sigma_i^2 = \frac{1}{M_i} \sum_{x \in Z_i} (w^T x - \mu_i)^2 \quad (4.3.2.)$$

To maximize the between class variance and to minimize the within class variance at the same time the equation has to be maximized:

$$G(w) = \frac{(\mu_1 - \mu_2)^2}{\sigma_1 + \sigma_2} \quad (4.3.3)$$

has to be maximized.

Substituting the expression 4.3.1 for the means and 4.3.2 for the variance into 4.3.3 yields

$$G(w) = \frac{w^T S_B w}{w^T S_W w} \quad (4.3.4)$$

where a between scatter matrix S_B and a within scatter matrix S_W are defined..

$$S_B = (m_2 - m_1)(m_2 - m_1)^T \quad S_W = \sum_{i=1,2} \sum_{x \in Z_i} (x - m_i)^2$$

One particularly property of Fisher's discriminants is that 4.3.4 has a global solution and that a such a globally optimal w maximizing 4.3.4 can be found.

$$w = S_W^{-1}(m_2 - m_1)$$

S_W is the sum of the covariance matrix of Z_1 and Z_2 .

$$w = S_W^{-1}(m_2 - m_1)$$

Regularization

The use of a covariance matrix poses some problems. To impose certain regularity, the simplest possible solution is to add a multiple of the identity matrix to the covariance matrix. To impose regularity makes the scatter matrix numerically more stable as it becomes more positive definite.

The new scatter matrix is:

$$w = (S_W^{-1} + \alpha I)(m_2 - m_1)$$

where I is the identity matrix and α a multiple coefficient.

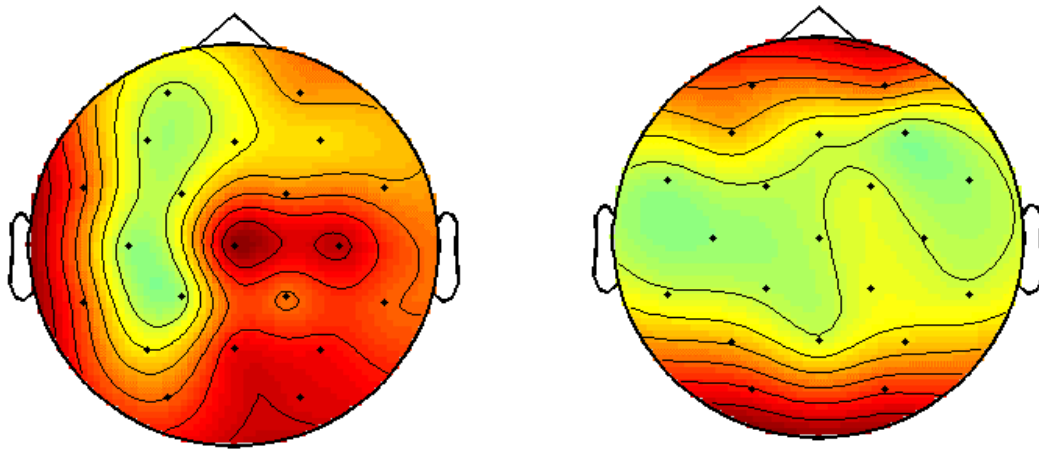
Increasing the multiple coefficient of the added Identity matrix decreases the variance and the estimation of the projection vector w becomes less sensitive to the covariance structure.

With a little multiple the projection vector w depends more of the covariance matrix calculated out of Z_1 and Z_2 .

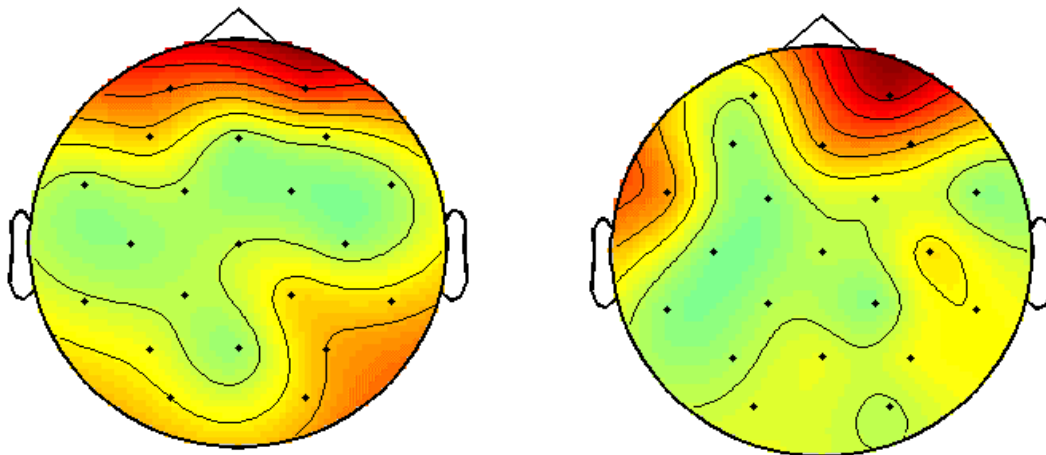
Chapter 5

Weight of different electrodes in the different brain rhythms

The projection vector w contains important information. The projection vector contains the weight of all the 32 electrodes placed over the scalp for the frequency ranges of the brain rhythms. A topographical plot the weights of all the electrodes for the most important rhythms is plotted.



Weight of the electrodes for the alpha brain rhythm. Topographical plot of subject 2 and 3.



Weight of the electrodes for the beta brain rhythm. Topographical plot of subject 2 and 3.

The red colour of topographical plot indicates that the classification bases on this region of the brain. Dark blue indicates low importance of the electrodes placed on this part of the brain for the classification.

As mentioned in chapter 1.2. alpha rhythm of the brain activity can be found in the posterior regions of the head. The topographical plot of the alpha band confirms this statement. The red part indicates that the electrodes in the posterior regions owe an important weight.

For the beta frequency range the frontal part of the head is important as shown in the second topographical plot.

Chapter 6

Efficiency test

The error that can appear is when the computer classifies a task by mistake, a relaxed state can be recognized as excited state and contrariwise.

Cross validation is used as method to specify the efficiency of the training algorithm. Only 90% of the feature vectors are used to train the computer and the other 10% are used to test the efficiency of the training program. The associated label of this 10% of the feature vector is known, therefore it is possible to detect if the computer recognizes the right state of brain. A random algorithm looks for 10% of the 84 feature vectors. A 10% loss of the training data is the consequence of the test.

Another method without separating the data provided for training exists. A non-stimulated brain activity data recording period is repeated after an entire training session but only for one minute. The subject passes 30 seconds of relaxed stimulation and 30 seconds of excited stimulation. This data is used to specify the efficiency of the training algorithm because the corresponding labels are known.

Application of the first method:

1. subject:

Student, male 23 years old. He studies Electrical Engineering and his hobbies are especially sports.

Efficiency test: mean value of 100 trials: 86 %

2. subject:

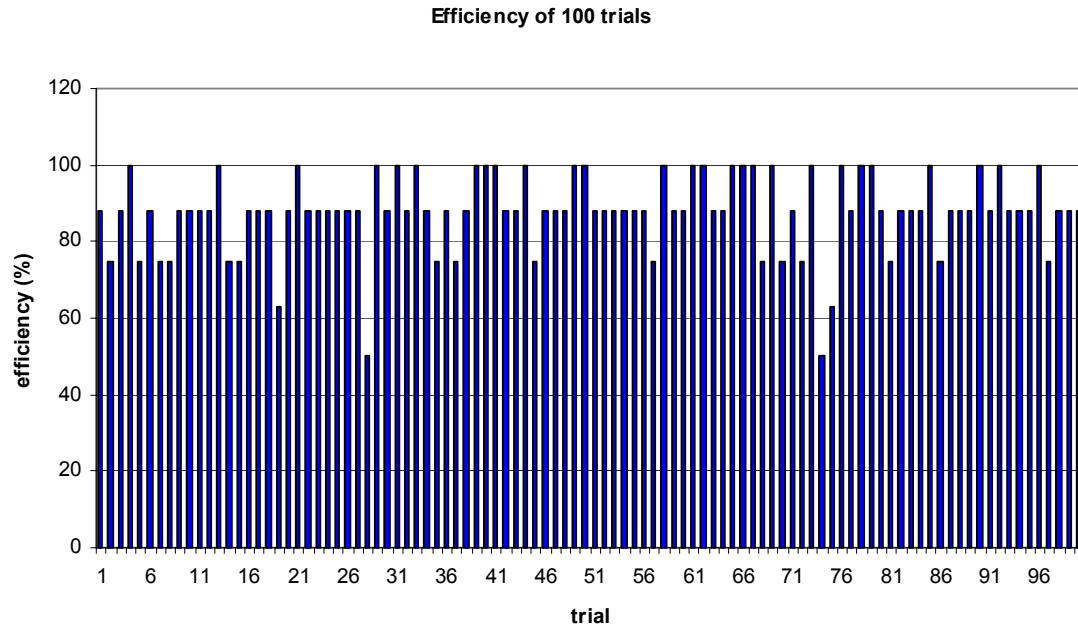
Student, male, 24 years old. He studies Electrical Engineering and his hobbies are snowboarding and music.

Efficiency test: mean value of 100 trials: 86 %

3. subject

Student, male, 22 years old. He studies Design and Art and his hobbies are snowboarding and painting.

Efficiency test: mean value of 100 trials: 88 %



efficiency test of 100 trials

Application of the second method:

Subject:

Student, female, 24 years old. She studies Electrical Engineering and her hobbies are skiing and shopping.

Efficiency test: mean value of 100 trials: 81 %

Different to the first method, the subject was not stimulated by music and pictures. She was asked to relax and focus on the breath during relaxation and asked to do maths operations during excitation. Without stimulation a high degree of efficiency has been achieved.

Chapter 7

Operating period

The training period is over. The Fisher classification issues the two mean projections μ_1 , μ_2 and the projection vector \mathbf{w} that is used to associate the weight of the 32 electrodes for the five frequency ranges.

During the next measuring period the EEG is recording brain activity continuously. Every three seconds the incoming data is handled by the same processes as in the training period. The recorded and sampled data is saved as a variable in MATLAB. The resulting feature vector after down sampling, filtering and feature extraction represents the mean value of the energy of three seconds (768 samples) as the feature vectors calculated during training period before classification. This vector is multiplied by the projection vector to associate the weight to each electrode in the five width bands. The feature vector is projected in direction of \mathbf{w} to approach the values to the mean projections. The out coming value is now compared to the mean projections μ_1 , μ_2 . If the out coming value is nearer to μ_1 the subject was in relaxation state during the three recorded seconds. If the out coming value is nearer to μ_2 the brain of the subject is excited.

Every three seconds the computer estimates the state of the subject's brain activity and every three seconds an outgoing variable can be used to operate the game.

A visual interface shows the subject what state the computer analyses. A smile face means that the subject is relaxed and an unhappy face means that the subject has a lot of brain activity. With the help of intermediate states the subject can pass from a smile face to an unhappy face by using only relaxed or excited state of his brain. The subject starts relaxing himself and the unhappy face becomes a smile after passing intermediate states. To pass directly from a smile to an unhappy face is not possible.



relaxation



intermediate state



excitation

Chapter 8

Conclusion

The implemented method trains the machine to recognize the two different states of the brain activity, relaxation and excitation. The error that the computer makes when he classifies the incoming data to the corresponding state of brain activity is between 10% and 20%. The algorithm and the associated training program are consequently effective to recognize relaxation and excitation of the human brain. Nevertheless some existing problems have to be considered.

The measurement depends on the subject. Every human has different head and brain characteristics. The EEG measures the electrical potential in a non-invasive way through the scalp and the skull that causes attenuation. For each subject the attenuation is different and more disturbing or not. The measurement also depends on the subject's brain activity itself. If the subject is not concentrated on the task he has to complete during the training period, if he is dreaming and thinking in whatever, the measured brain activity can not be classified.

To improve the efficiency of the algorithm some different approaches are possible. The measurement has to be ameliorated. Technical and physiological artefacts should not affect the measuring as much. An invasive way could be the solution. Invasive means that the electrodes are implemented in the human brain. The question is if the subject is prepared wearing electrodes in his head?

More sophisticated classification methods can be found that not refer to the Euclidean distance between a mean value and the further values. Non-linear discrimination can be a more sophisticated method to classify the incoming brain activity. The signal pre-processing and feature extraction can be done in a more efficient way. A more selective filtering with proper characteristics can be found.

However, a question that has to be asked is which limit should not be crossed? Data handling and classification are mathematical processes that are completely harmless. But more sophisticated measuring methods such as invasive methods intervene on the human brain and causes non reversible damages. The electrodes have to be fixed in the brain and a part of the nerves die, the skull has to be opened.

Should it not be the aim to approach communication through the usual outgoing pathway? Is it a need of humanity to communicate only by thoughts? The way how we express our self takes a part of our self and makes what we are. Should we lose the ability of expression and only communicate by thoughts?

All the research should be for humanity health, to assist disabled people. The transformation of the man to a machine should not be goal humanity is striving for. The knowledge and research of brain activity has to be used to understand human body and for clinical work.

Future perspectives of the project:

A more sophisticated classification method can be the next step to improve the project. Fisher's discrimination is a linear discrimination based on a projection mean value and a projection vector. A more sophisticated method would be the Kernel Fisher's discrimination as well as non linear methods.

With the help of a more complex discrimination it is maybe possible to classify more then to different mental task and increase the input variables for operating. The training classifies relaxation and excitation. It should be possible to classify three or four states of brain activity.

The graphical user interface can be improved. A sophisticated game can be worked out using the two variables relaxation and excitation. The graphical interface shows pictures and the depending on the picture the user sees what state of his brain the computer recognizes. A more complex interface could allow the user more choices.

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