VYSOKÉ UČENÍ TECHNICKÉ V BRNĚ
BRNO UNIVERSITY OF TECHNOLOGY

FAKULTA ELEKTROTECHNIKY A KOMUNIKAČNÍCH TECHNOLOGIÍ
ÚSTAV BIOMEDICÍNSKÉHO INŽENÝRSTVÍ

FACULTY OF ELECTRICAL ENGINEERING AND COMMUNICATION
DEPARTMENT OF BIOMEDICAL ENGINEERING

WHEELCHAIR CONTROL USING EEG SIGNAL CLASSIFICATION

DIPLOMOVÁ PRÁCE
MASTER'S THESIS

AUTOR PRÁCE Bc. LUKÁŠ MALÝ
AUTHOR

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OVLÁDÁNÍ INVALIDNÍHO VOZÍKU POMOCÍ KLASIFIKACE EEG SIGNÁLU

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SUPERVISOR

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VYSOKÉ UČENÍ TECHNICKÉ V BRNĚ

Fakulta elektrotechniky a komunikačních technologií

Ústav biomedicínského inženýrství

Diplomová práce

magisterský navazující studijní obor
Biomedicínské inženýrství a bioinformatika

Student:	Bc. Lukáš Malý	***ID:***	133973
Ročník:	2	***Akademický rok:***	2014/2015

NÁZEV TÉMATU:

Ovládání invalidního vozíku pomocí klasifikace EEG signálu

POKYNY PRO VYPRACOVÁNÍ:

1) Prostudujte základy elektroencefalografie (EEG), způsob měření EEG signálů, jejich zpracování a hodnocení. 2) Seznamte se s možnostmi využití EEG signálů pro řízení invalidního vozíku. 3) Seznamte se s řídící jednotkou invalidního vozíku na UAMT a navrhněte způsob ovládání pomocí parametrů získaných z EEG signálu. 4) Naměřte dostatečný počet EEG signálů a proveďte výpočet vhodných parametrů. 5) Realizujte proces řízení a vyzkoušejte jeho funčnost na testovacím zařízení. 6) Dosažené výsledky vhodně prezentujte.

DOPORUČENÁ LITERATURA:

[1] SORNMO, L., LAGUNA, P. Bioelectrical Signal Processing in Cardiac and Neurological Applications. Elsevier Academic Press, 2005.
[2] JAN, J. Číslicová filtrace, analýza a restaurace signálů (438 str.) 1. vydání. Brno: VUTIUM Press Brno, 1997. 437 s. ISBN: 80-214-0816- 2.

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Vedoucí práce: doc. Ing. Luděk Žalud, Ph.D.
Konzultanti diplomové práce:

prof. Ing. Ivo Provazník, Ph.D.
Předseda oborové rady

ABSTRACT
This diploma thesis presents the concept of mind-controlled electric wheelchair designed for people who are not able to use other interfaces such as hand joystick. Four main components of concept are described: electroencephalography, brain-computer interface, shared control and the electric wheelchair. In the text used methodology is described and results of conducted experiments are presented. In conclusion suggestions for future development are outlined.

KEYWORDS
BCI-controlled wheelchair, Brain-computer interface, BCI, Electric wheelchair, Electroencephalography, EEG, Sensorimotor rhythms, SMR, Shared control, Robotics, Robot, EEGbot, VirtualEEGbot

ABSTRAKT
Tato diplomová práce představuje koncept elektrického invalidního vozíku ovládaného lidskou myslí. Tento koncept je určen pro osoby, které elektrický invalidní vozík nemohou ovládat klasickými způsoby, jakým je například joystick. V práci jsou popsány čtyři hlavní komponenty konceptu: elektroencefalograf, brain-computer interface (rozhraní mozek-počítač), systém sdílené kontroly a samotný elektrický invalidní vozík. V textu je představena použitá metodologie a výsledky provedených experimentů. V závěru jsou nastíněna doporučení pro budoucí vývoj.

KLÍČOVÁ SLOVA
Brain-computer interface, BCI, rozhraní mozek-počítač, elektrický invalidní vozík, elektroencefalografie, EEG, senzomotorický rytmus, SMR, sdílená kontrola, robotika, robot, EEGbot, VirtualEEGbot

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DECLARATION

I declare that I have written my master's thesis on the theme of "Control of the electric wheelchair using EEG classification" independently, under the guidance of the master's thesis supervisor and using the technical literature and other sources of information which are all quoted in the thesis and detailed in the list of literature at the end of the thesis.

As the author of the master's thesis I furthermore declare that, as regards the creation of this master's thesis, I have not infringed any copyright. In particular, I have not unlawfully encroached on anyone's personal and/or ownership rights and I am fully aware of the consequences in the case of breaking Regulation § 11 and the following of the Copyright Act No 121/2000 Sb., and of the rights related to intellectual property right and changes in some Acts (Intellectual Property Act) and formulated in later regulations, inclusive of the possible consequences resulting from the provisions of Criminal Act No 40/2009 Sb., Section 2, Head VI, Part 4.

Brno . . . .

(author's signature)

ACKNOWLEDGEMENT

I would like to thank associate professor Luděk Žalud for coming up with an idea of using brain-computer interface to control specifically electric wheelchair. And I would like to express my appreciation to associate professor Jana Kolářová for getting me in touch with him and for letting me work on my own idea of diploma thesis.

Brno ....

(author's signature)

CONTENTS

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INTRODUCTION

Electric wheelchairs are some of the most important devices to assist physically handicapped persons. This diploma thesis presents the concept and applications for brain controlled electric wheelchair designed for people who are not able to use other interfaces such as a hand joystick, and in particular for patients suffering from amyotrophic lateral sclerosis (ALS). The objective was to investigate the possibility to control the direction of an electric wheelchair using noninvasive scalp electroencephalogram (EEG). Basics of EEG signal acquisition and analysis are described in chapter 1.

Amyotrophic lateral sclerosis is a degenerative disease of the motor neuron which, in the latest stage, leads to complete paralysis of every single muscle in the body. Patients suffering from ALS have often been identified as a population who may benefit from the use of a BCI. The components of a satisfactory system were identified in a recent ALS patient survey [11] as highly accurate command generation, a high speed of control, and low incidence of unintentional system suspension, i.e. continuity of control. While these needs were reported from a patient population with ALS, similar if not identical needs are likely identifiable in a wide variety of other neurodegenerative disorders.

Paralysis following spinal cord injury, brain stem stroke, amyotrophic lateral sclerosis and other disorders can disconnect the brain from the body, eliminating the ability to perform volitional movements. The development of brain-computer interfaces (BCI) is aimed at providing users with the ability to communicate with the external world via a computer through the modulation of thought, as it is described in chapter 2. Especially in the case when the patient is completely paralyzed, this technology may provide the only possible way for him/her to gain control over basic aspects of his/her daily life. BCI technology shows great potential to help patients perform everyday tasks, such as feeding and grooming themselves or using a computer and entertainment devices, by recording their brain activity to extract signals about their motor intentions.

Many assistive devices targeted at the integration of disabled individuals into society have been developed in the past. The probably most important one, as far as people with physical disabilities who are unable to walk are concerned, is a wheelchair. The wheelchair allows them to build up and maintain mobility and thereby have a social life despite of their disability. Especially the electric wheelchair offers the possibility to travel even longer distances without exhaustion. More about electric wheelchairs is written in chapter 3.

BCI-controlled wheelchair as a system is described in chapter 4. In this chapter chosen methods for EEG signal classification are introduced and layout of an architecture between human brain and control unit of the electric wheelchair is described. One of the crucial element of concept of using the EEG classification to control robot is shared control system. This system continuously evaluates the data from EEG classification and from sensors of obstacle avoiding system to safely guide the wheelchair because user's safety was the important part of this concept.

Methods, devices and algorithms that were used or developed are described in chapter 5. The pipelines of two software for BCI that were used are described. Developed program EEGbot covers all the communication and control between EEG classification and final control of the robot. This program also implements previously mentioned shared control.

Part of this diploma were two experiments. The first was conducted before development of the system for acquiring the signal, it's classification and control of device. The aim of this experiment was to proof that chosen method of control using EEG signal could be used. Aim of second experiment was to evaluate quality of result from methods and algorithms that were used for the classification of EEG signal and thus ability to control movement of wheelchair or any other robot. Experiments are described in chapter 6.

The aim of this diploma thesis was to come up with the solution of BCI-controlled wheelchair. Achieved results are evaluated in last chapter. During work on this project many observation were made. The most important are discussed in this chapter. Also based on these observation the recommendations for possible future development are given.

1 ELECTROENCEPHALOGRAPHY (EEG)

Electroencephalograms are recordings of the electrical potentials produced by the brain. In electroencephalography (EEG) a set of electrodes is applied on the scalp and wired to an amplifying-filtering-digitalizing device, which transfers the signal to a computer for further analysis specific to the paradigm and application. The EEG is widely used for diagnostic evaluation of various brain disorders such as determining the type and location of the activity observed during an epileptic seizure or for studying sleep disorders. Compared with other biomedical signals, the EEG is difficult for an untrained observer to understand, partially as a consequence of the spatial mapping of functions onto different regions of the brain and electrode placement. Sample of EEG recording acquired during experiment described in chapter 6 can be seen in figure 1.1.

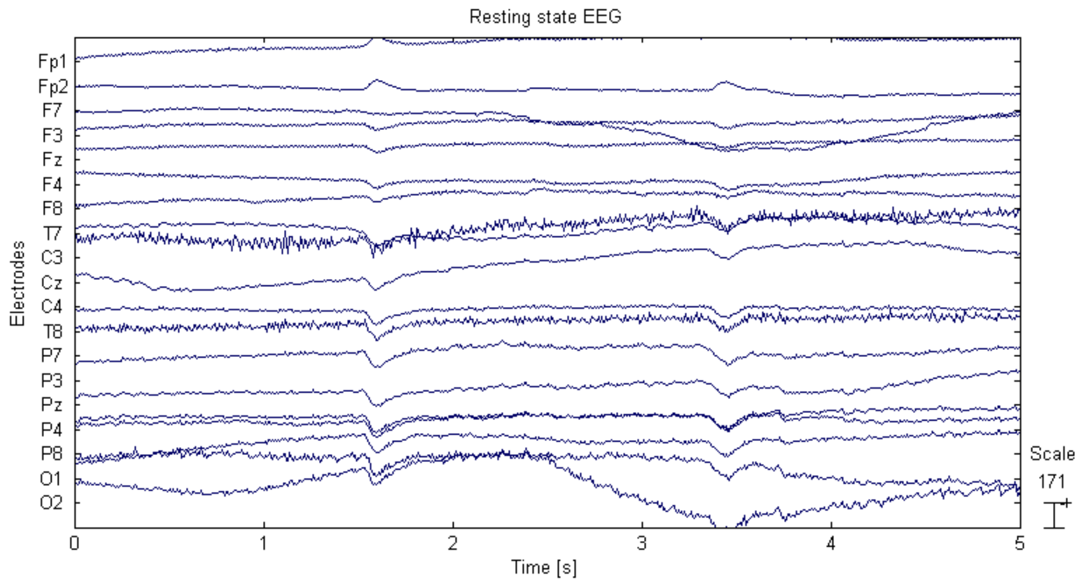


Fig. 1.1: Sample of EEG recording

On the other hand total cost associated with recording instrumentations is very low which makes EEG perfect for use as a brain-computer interface (BCI). The technical demands on equipment for recording EEGs are relatively modest and are, for a basic recording setup, restricted to a set of electrodes, a signal amplifier, and a system for signal analysis.

1.1 Source of EEG signal

EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. The neuron is the basic functional unit of the nervous system. The neuron consist of a cell body, the *soma*, from which two types of structure extend: the *dendrites* and the *axon*, see figure 1.2.

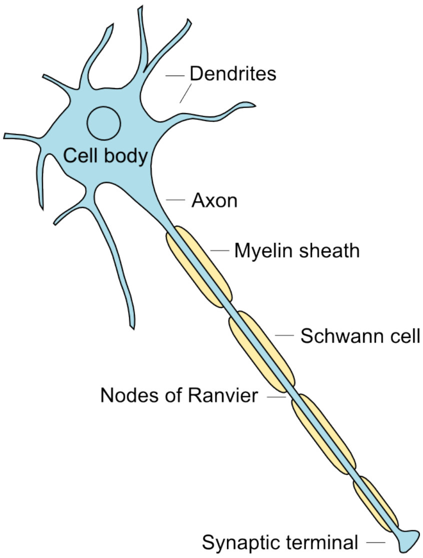


Fig. 1.2: Neuron

Dendrites can consist of thousands of branches, with each branch receiving a signal from another neuron. The axon is a single branch which transmits the output signal of the neuron to other neurons. The transmission of information from one neuron to another takes places at the *synapse*, a junction where the terminal part of the axon is in contact with another neuron. The signal, initiated in the soma, propagates through the axon encoded as a short, pulse-shaped waveform, the action potential. Initially electrical signal is converted in the presynaptic membrane to a chemical signal (neurotransmitter) which diffuses across the synaptic gap and is then reconverted to an electric signal in the postsynaptic membrane of another neuron, see figure 1.3. [24]

The electric potential generated by a single neuron is far too small to be measured by EEG. So EEG measures electrical field as the summation of the synchronous activity of millions of neurons that have similar spatial orientation. The electrical field is mainly generated by currents that flow during synaptic excitation of the dendrites, the excitatory postsynaptic potentials. [21]

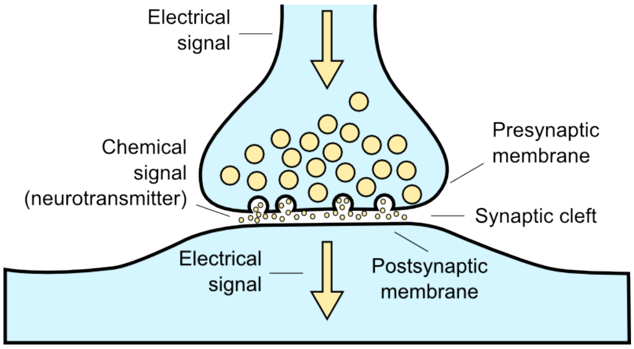


Fig. 1.3: Synapse

1.2 Electrodes

EEG is commonly recorded using International 10-20 system, which is a standardized system for electrode placement. [7] This recording system uses 21 electrodes attached to the surface of the scalp. The numbers 10 and 20 refer to percentages of relative distances between different electrode locations on the skull. Layout of the 10-20 system can be seen in figure 1.4.

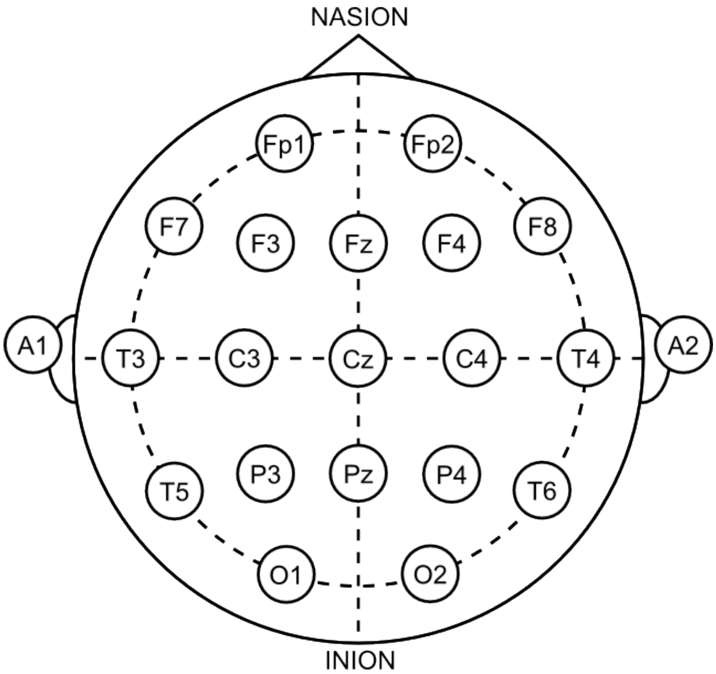


Fig. 1.4: Electrode locations of International 10-20 system

Commonly used scalp electrodes are small metal discs usually made of Ag-AgCl with flexible leads plugged into an amplifier. Using the silver-silver chloride electrodes require proper electrode application (i.e. skin preparation, application of conductive gel, and correct positioning of electrodes, etc). This could be a challenge to caregivers and might cause discomfort to longterm users of brain-computer interface. The development of more user-friendly dry electrodes offers a more convenient way for recording brain signals and may enhance the usability of the BCI system, as long as signal quality is comparable with that of standard EEG wet electrodes. [12]

1.2.1 Electrode-skin interface

The fields generated by activity in excitable tissues (nerves or muscles) in the body can spread through the aqueous environment inside the body to appear at the skin surface. Electrodes placed on the skin can detect these potentials. Electrodes are coupled to the skin via an electrolyte – either sweat or an electrolyte solution (gel) applied between the electrode and skin. Electrode-skin interface is depicted at figure 1.5.

The gel used in electrodes has multiple objectives: a) to provide a fluid material that will surround and enclose hairs, therefore providing contact with the skin when the electrode is applied to a hair covered surface, b) to provide an interface that allows minor movements without loss of contact, and c) to keep the skin wet and conductive.

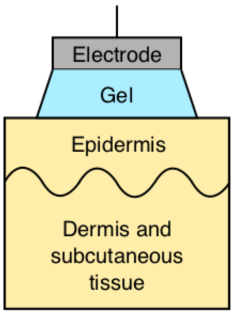


Fig. 1.5: Electrode-skin interface

The skin comprises three main layers – the subcutaneous fat (the deepest layer), the dermis and the epidermis (at the surface). The deeper layers of the skin contain blood vessels, nerves, sweat glands and hair follicles. The uppermost layer, the epidermis, is comprised of three sub-layers: the stratum germinativum, stratum granulosum and stratum corneum. The stratum corneum is a layer of dead cells on the surface which protects the underlying layers. New cells are continuously generated in the stratum germinativum and migrate to the stratum corneum, which replace old cells that have been worn off or shed. Because the stratum corneum is composed of dead cells, it has a high impedance. As well, the tissues under the stratum corneum contain dissolved ions. When an electrode is coupled to the skin via an electrolyte the stratum corneum can be considered a semi-permeable membrane, so a potential difference exists across the skin. The model for an electrode attached to the skin surface is at figure 1.6.

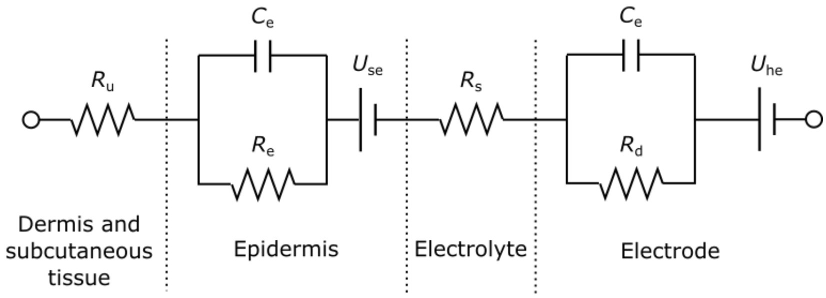


Fig. 1.6: Model of electrode-skin interface

U_{hc} – electrode half cell potential, C_d and R_d – electrode double layer capacitance and resistance, R_s – electrolyte resistance, $U_(se)$ – potential due to ionic differences between electrolyte and stratum corneum, C_e and U_e – capacitance and resistance of stratum corneum, R_u – dermis and subcutaneous tissue resistance.

The properties of the electrode-skin interface result in two issues with regard to recording biological signals: high skin impedance can result in poor signal detection and relative movement between the electrode and the skin produces motion artifact.

1.3 EEG artifacts

In EEG recordings, a wide variety of artifacts can occur. These artifacts can be divided based on their origin into physiological and technical. The influence of artifacts of technical origin can be reduced mainly by paying an attention to the proper attachment of electrodes to the scalp surface. It is not possible to avoid the influence of artifacts of physiological origin but there is a majority of algorithms developed for reduction of such artifacts.

The scope of artifact processing ranges from artifact rejection, in which a simple marker is created to identify the artifact, to complete cancellation of the artifact from the EEG signal. The demands on artifact cancellation depend on the context in which the algorithm is to be used.

Physiological artifacts

Common artifact is caused by eye movement and blinking. Eye movement produces electrical activity - the electrooculogram (EOG) - which is strong enough to influence EEG. The EOG reflects the potential difference between the cornea and the retina which changes during eye movement. The strength of the interference with EEG depends mainly on the distance of the electrode to the eye. The blinking artifacts is usually more suddenly changing waveform than eye movement and it contains more high-frequency components. Another common artifact is caused by electrical activity of muscles which is measured on the body surface by the electromyography (EMG). This type of artifact occurs during swallowing, grimacing, frowning, chewing, etc. The influence of the EMG signal depends on the degree of muscle contraction. Also electrical activity of the heart can interfere with EEG. Although the amplitude of the cardiac activity is usually low on the scalp ($1-2$ μV) compared to amplitude of the EEG ($20-100$ μV). The repetitive, regularly occurring waveform pattern which characterizes the normal heartbeats helps to reveal the presence of this artifact. [21]

Technical artifacts

Sudden movement of electrodes causes changes in the DC contact potential at the electrode-skin interface produces an artifact known as “electrode-pop”. This artifact is usually manifested as an abrupt change in the baseline level, followed by a slow, gradual return to the original baseline level. The electrode wire which connects the electrode to the acquisition equipment is another possible source of artifact. Insufficient shielding of the electrode wire makes it susceptible to electromagnetic fields caused by currents flowing in nearby powerlines or electrical devices. As a result, 50 Hz interference is picked up by the electrodes and contaminates the EEG signal. Technical related artifacts also include those produced by internal amplifier noise and amplitude clipping caused by an analog-to-digital converter with narrow a dynamic range. [21]

1.4 EEG rhythms and waveforms

Signals recorded from the scalp have, in general, amplitudes ranging from 20 to 100 μV and a frequency content ranging from 0.5 to 30-40 Hz. Electroencephalographic rhythms are conventionally classified into five different frequency bands.

Delta rhythm, $<$4 Hz

The delta rhythm is typically encountered during deep sleep and has a large amplitude. It is usually not observed in the awake, normal adult, but is indicative of, e.g., cerebral damage or brain disease (encephalopathy).

Theta rhythm, 4-7 Hz

The theta rhythm occurs during drowsiness and in certain stages of sleep. Theta rhytms are observed in infancy and childhood. In the awake adult, high theta activity is considered abnormal and it is related with different brain disorders.

Alpha rhythm, 8-13 Hz

This rhythm is most prominent in normal subjects who are relaxed and awake with eyes closed; the activity is suppressed when the eyes are open. The amplitude of the alpha rhythm is largest in the occipital regions.

Beta rhythm, 14-30 Hz

This is a fast rhythm with low amplitude, associated with an activated cortex and which can be observed, e.g., during certain sleep stages. The beta rhythm is mainly observed in the frontal and central regions of the scalp.

Gamma rhythm, $>$30 Hz

The gamma rhythm is related to a state of active information processing of the cortex.

1.5 EEG analysis

Signal processing methods can be divided into two general categories: methods developed for the analysis of spontaneous brain activity and brain potentials which are evoked by various sensory and cognitive stimuli (evoked potentials).

Initial efforts did bring in the use of frequency analysis to the study of brain wave activity. The Fourier transform decomposes the EEG time series into a voltage by frequency spectral graph commonly called the "power spectrum", with power being the square of the EEG magnitude, and magnitude being the integral average of the amplitude of the EEG signal across the time sampled, or epoch. The epoch length determines the frequency resolution of the Fourier transform.

Although power spectral analysis provides a quantitative measure of the frequency distribution of the EEG at the expense of other details in the EEG such as the amplitude distribution and information relating to the presence of particular EEG patterns. Hence time–frequency signal-processing algorithms such as discrete wavelet transform (DWT) analysis are necessary to address different behavior of the EEG in order to describe it in the time and frequency domain. It should also be emphasized that the DWT is suitable for analysis of non-stationary signals, and this represents a major advantage over spectral analysis.

Known locations of electrodes allows brain mapping. Mapping constitutes a spatial analysis technique in which the EEG activity is represented as a topographic map projected onto the scalp. Example of use such maps is in section 6.1.1 where are results of the conducted experiment discussed.

1.5.1 Event related potentials (ERP)

EEG activity is present in a spontaneous way or can be generated as a response to an external stimulation (e.g. tone or light ash) or internal stimulation (e.g. omission of an expected stimulus). The alteration of the ongoing EEG due to these stimuli is called event related potential (ERP), in the case of external stimulation also called evoked potential (EP).

There are mainly three modalities of stimulation: auditory stimuli are single tones of a determined frequency, or clicks with a broadband frequency distribution. Visual stimuli are produced by a single light or by the reversal of a pattern as for example a checkerboard. Somatosensory stimuli are elicited by electrical stimulation of peripheral nerves.

2 BRAIN-COMPUTER INTERFACE (BCI)

Brain–computer interfaces (BCI) are systems that aim to restore or enhance a user's ability to interact with the environment via a computer and through the use of only thought. Such a task is achieved through a closed loop of sensing, processing and actuation. Bioelectric signals are sensed and digitized before being passed to a computer system. The computer then interprets fluctuations in the signals through an understanding of the underlying neurophysiology, in order to discern user intent from the changing signal. The final step is the actuation of this intent, in which it is translated into specific commands for a computer or robotic system to execute. The user can then receive feedback in order to adjust his or her thoughts, and then generates new and adapted signals for the BCI system to interpret. General scheme of the BCI is in figure 2.1. [11]

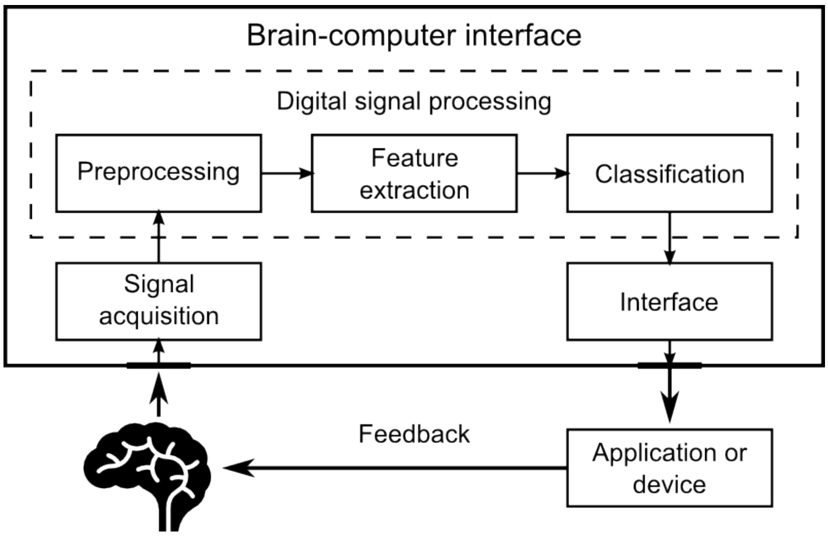


Fig. 2.1: Scheme of brain-computer interface

Setting the threshold has a direct influence on the accuracy and latency of the system: with low threshold the system is fast but may commit classification errors, which might be a desirable setting for a speller. On the other hand, if the threshold is high, the system will make very few errors but the response time will be long. The ideal BCI system should allow subjects to control effectors without extensive training by simply thinking about what they want the effector to do. In human subjects, such mental efforts activate neural circuits normally involved in overt motor control. For instance, cerebral cortical motor areas become active when paralyzed humans are asked to try to move body parts or to imagine that they are moving an effector [3]. The neural activity evoked during those covert volitional motor efforts has several properties in common with that recorded in able-bodied subjects during overt arm movements. [5]

The activity used for calibration is usually recorded while they perform overt arm movements to control an effector in a learned motor task (arm-control mode). However, paralyzed patients cannot move. Instead, activity to calibrate the decoder is evoked by asking the patients to think about moving their arm or to watch an effector as it moves under computer control and to imagine they were moving it in the same way.

Irrespective of how it is generated, the activity recorded during calibration is used to parameterize algorithms that describe how each neuron's discharge varies with selected motor parameters such as spatial position, direction and speed. Ideally, the decoder once calibrated should be able to combine the movement-related information extracted from neural activity to generate an output signal about how the subject wants the effector to move. [5]

No BCI user to date has consistently achieved the level of precision, speed, and flexibility of effector control seen during overt arm movements. The reduced nature of the BCI neural control circuitry, neural sampling biases, non-optimal decoder algorithms, frequent decoder recalibration and other factors could all impose limits on the level of skill that can be acquired and retained with current BCI technology.

2.1 Methods

Various signals can be extracted from the EEG to develop BCIs. There are various BCI systems based on evoked potentials, event-related potentials, motor imagery, slow cortical potential μ and β rhythms, etc.

2.1.1 P300 evoked potentials

The P300 evoked potential is a well-studied, stable brain signal. This natural, involuntary response of the brain to infrequent stimuli can provide a BCI with an oddball paradigm. In this paradigm, a random sequence of stimuli is presented, only one of which interests the subject. Around 300 milliseconds after the target flashes, there is a positive potential peak in the EEG signal. When the system detects a P300 signal (P for positive, 300 for the 300-millisecond delay), it determines that the target stimulus occurred 300 ms earlier. [17]

2.1.2 Sensorimotor rhythms (SMR)

Brain computer interfaces based on modulation of sensorimotor rhythms classify differences in EEG patterns during different types of movement imagination (MI) tasks such as hand or foot MI. For example in a typical two-class hand vs. foot MI paradigm these differences enable a BCI user to control an object in a two-dimensional movement environment, for example a computer cursor on a screen. In this case, imagination of hand movement would head the cursor upward; foot MI would head it downward. Hence controlling the cursor would be a balance of two imaginations. SMR-based BCIs is supported by research indicating that the ability to generate SMRs remains present in users with other neurodegenerative disorders such as muscular dystrophy and spinal muscular atrophy [3]. Voluntary movement is primarily controlled by the area of the frontal lobe just anterior to the central sulcus - the motor cortex.

2.1.3 Slow cortical potentials (SCPs)

Slow cortical potentials, i.e. the voluntary production of negative and positive potential shifts generated on the cerebral cortex, are signals with a duration varying between 0.5 and 10 seconds. Healthy subjects as well as severely paralyzed patients can learn to selfcontrol their SCPs when they are provided with visual or auditory feedback of their brain potentials and when potential changes in the desired direction are positively reinforced. [10]

2.2 Applications for BCI

BCIs offer their users new communication and control channels without any intervention of peripheral nerves and muscles. Many researchers focus on building BCI applications, in the hope that this technology could be helpful for those with severe motor disabilities. Various BCI applications have very recently been developed thanks to significant advances in the field of EEG-based BCI. EEG signals are used by most BCI applications, because they offer an acceptable signal quality that combines low cost and easy-to-use equipment.

Communication

BCI applications for communication deal with severe communication disabilities resulting from neurological diseases. This kind of application probably represents the most pressing research in the field of BCI, because communication activity is essential for humans.

There was a speller BCI system developed to type words by making the user select letters and words from a display. The system flashes letters randomly on a 6 by 6 matrix on the screen while the user thinks about the next letter he/she wants to type. It uses the P300 signal obtained from several electrodes on the scalp to control the BCI system. [4, 8]

Locomotion

BCI applications that allow disabled people to control a means of transportation represent an important field in their use. Thanks to these applications, people suffering from paraplegia or with other physical impairments can autonomously drive a wheelchair, making them more autonomous and improving their life quality. [25, 16, 13]

Motor imagery-based BCI was used even to control quadcopter in three-dimensional space. [11]

Neural Prosthetics

Spinal cord injury or other neurological diseases with associated loss of sensory and motor functions dramatically decrease the patient's quality of life and create life-long dependency on home care services. Motor restoration may alleviate their psychological and social suffering. Restoring movement, such as grasping, is feasible in quadriplegic patients through neuroprostheses guided by functional electrical stimulation (FES).

Application was developed where a tetraplegic patient, suffering from a traumatic spinal cord injury, was able to control paralyzed hands to grasp a cylinder. In that application, the patient generated beta oscillations in the EEG by foot movement imagery. Then, the BCI analyzed and classified the beta burst and the output signal was used to control the FES device that activated the extremity. [14]

2.3 Information transfer rate (ITR)

Information transfer rate is a standard method to evaluate an online BCI's performance. Method for ITR calculation in BCI research was defined by Wolpaw et al in 1998 [28], which is a simplified computational model based on Shannon channel theory under several assumptions:

$$B = \log_2 N + P \log_2 P + (1 - P) \log_2[(1 - P)/(N - 1)] \tag{2.1}$$

where B is the ITR in bit rate (bits/choice), N is the number of possible choices and P is the probability that the desired choice will be selected, also called classifier accuracy.

Generally, B_t in bits/min is used to indicate the ITR ITR

$$B = B * (60/T) \tag{2.2}$$

where T (seconds/choice) is the time needed to convey each symbol.

2.4 BCI software

Software platforms specifically targeted towards the development of BCIs frequently offer blocks such as data acquisition, feature extraction, classification, and feedback presentation modules. Two major software platforms are BCI2000 and OpenVIBE. Both are released under open source licenses.

BCI2000

BCI2000 is a general-purpose software platform for BCI research. It can also be used for a wide variety of data acquisition, stimulus presentation, and brain monitoring applications. BCI2000 has been in development since 2000 in a project led by the Brain-Computer Interface R&D Program at the Wadsworth Center of the New York State Department of Health in Albany, New York, USA, with substantial contributions by the Institute of Medical Psychology and Behavioral Neurobiology at the University of Tubingen, Germany. BCI2000 can be downloaded at `http://www.schalklab.org/research/bci2000`. [19]

OpenViBE

OpenViBE is a free and open-source software platform for designing, testing, and using brain-computer interfaces. The platform consists of a set of software modules that can be easily and efficiently integrated to develop fully functional BCIs. OpenViBE features an easy-to-use graphical user interface for non-programmers and it has many capabilities such as signal processing algorithms, machine learning functions and scripting support. OpenViBE is released every three months by the French National Institute for Research in Computer Science and Control (INRIA). OpenViBE homepage is `http://openvibe.inria.fr/`. [18]

3 ELECTRIC WHEELCHAIR

Electric wheelchair is a wheelchair that is propelled by electric motor rather than manual power. It is the principal means of mobility of large percentage of the physically handicapped population. The first successfully working electric-powered wheelchairs were developed in the 1950s. The invention is usually attributed to Canadian inventor George J. Klein. [2] Although wheelchairs with different characteristics have been designed, the most common type is that shown in figure 3.2.

The propulsion system for the common electric wheelchair consists of two direct current (DC) motors. Steering and propulsion are accomplished with the drive motors by independently varying the velocity of each motor. Straight-line movement of the chair is achieved by running both drive motors at the same velocity. Steering is performed by increasing or decreasing the velocity of one motor relative to the other. During normal operation, the wheelchair user will apply command inputs, using a joystick, based upon his/her perception of the wheelchair's speed and direction. An electronic controller will then adjust the voltage or current to the DC motors to achieve the desired velocity of each motor. Method of controlling a robot (in this case the wheelchair) with only two motorized wheels is called differential drive.

3.1 Alternative methods for wheelchair control

The standard way of steering an electrical wheelchair involves the use of one hand to operate two dimensional joystick. Usage of electroencephalography to control wheelchair will be described in next chapter.

3.1.1 Chin-operated control

Modifications of the joystick have resulted in the development of an inconspicuous chin-operated control which enables quadriplegics with high-level spinal cord injuries to operate electric wheelchairs. Through the use of the chin-operated control such quadriplegics can manipulate any of these devices or systems without the help of an attendant and without interfering with the use of a mouthstick. [20]

3.1.2 Voice control

One problem with voice control is that the voice's limited bandwidth renders it impossible to make frequent small adjustments to the wheelchair's velocity. One possible solution is to utilize voice control in combination with the navigation assistance provided by smart wheelchairs, which use sensors to identify and avoid obstacles in the wheelchair's path. The uses vocabulary (e.g., "*forward*," "*slower*," "*right*") and a feedback control system to maintain the chair speed and direction. [22]

3.1.3 Electrooculographic potential (EOG)

The EOG ranges from 0.05 to 3.5 mV in humans and is linearly proportional to eye displacement. The human eye is an electrical dipole with a negative pole at the fundus and a positive pole at the cornea. The derivation of the EOG is achieved by placing two electrodes on the outer side of the eyes to detect horizontal movement and another pair above and below the eye to detect vertical movement. A reference electrode is placed on the forehead. The aim of this control system is to guide an electric wheelchair using the positioning of the eye in its orbit. [1]

3.1.4 Electromyogram (EMG)

Head movement is a natural form of gesture and can be used to indicate a certain direction. Since the users can move their head even if they are the serious disabled people, electromyogram (EMG) may be utilizable for recognizing head movement. EMG is the electric manifestation of neuromuscular activation contracting a muscle and can be measured from near neck muscle according to the head movement. In addition, the speed of wheelchair can be controlled by EMG signals since the amplitude of EMG has static relationship with force information [6]. We can also easily detect the emergency situation based on EMG signals [6]

3.2 Mathematical model of electric wheelchair

As depicted in figure 3.1 the robot velocity is determined by the linear velocity $v(t)$ and angular velocity $\omega(t)$, which are functions of the linear and angular velocity of each wheel $\omega_i(t)$ and the distance L between the two wheels, $v_1(t)$, $\omega_1(t)$ are the linear and angular velocity of the left wheel, $v_2(t)$, $\omega_2(t)$ are the linear and angular velocity of the right wheel, ϕ is the orientation of the robot and r_1 and r_2 ale left and right wheel radius. [15]

The linear speed of each wheel is determined by the relationship between angular speed and radius of the wheel as

$$v_1(t) = \omega_1(t)r_1, v_2(t) = \omega_2(t)r_2. \tag{3.1}$$

The robot velocities are composed of the center of mass's linear velocity and angular velocity generated by the difference between the two wheels.

$$v_1(t) = v(t) - (\frac{L}{2})\omega(t), v_2(t) = v(t) + (\frac{L}{2})\omega(t) \tag{3.2}$$

The robot velocities equations are expressed by

$$v(t) = \frac{v_1(t) + v_2(t)}{2}, \omega(t) = \frac{v_1(t) - v_2(t)}{L}. \tag{3.3}$$

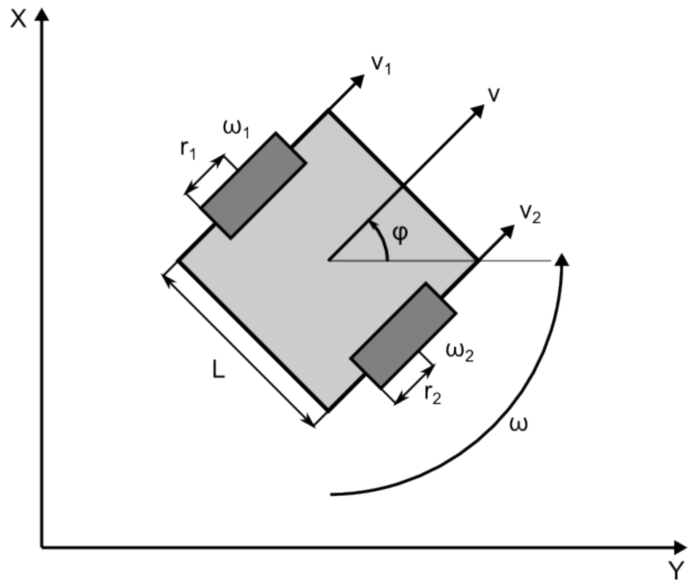


Fig. 3.1: Two-wheeled differential robot

3.3 Wheelchair description

Wheelchair which is located at the Department of Control and Instrumentation is model SPACE 1 by Italian company Vassilli (`http://www.vassilli.it`) (figure 3.2).

Fig. 3.2: Electric wheelchair Vassilli SPACE 1

The wheelchair is equipped with previously described differential drive. It has two motors SRG 01 by MT Schmid GmbH & Co (`http://www.amt-schmid.com`). The system is powered by two 12 V lead–acid batteries in serial connection. Current architecture of the wheelchair is at figure 3.3.

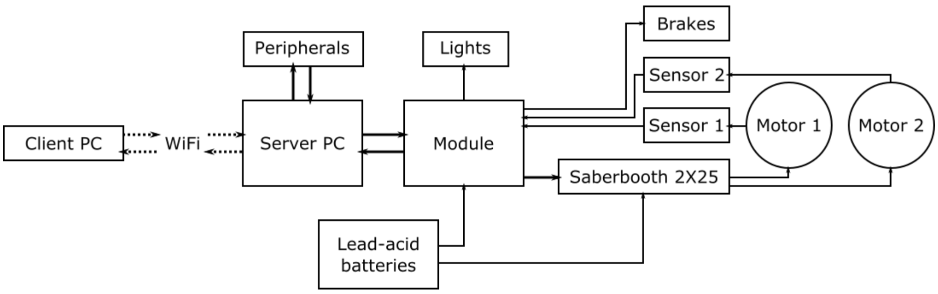


Fig. 3.3: Architecture of the wheelchair at the DCI

The communication over Wi-Fi between remote client PC and server PC mounted on wheelchair was already developed by Ondřej Vožda as a part of his bachelor's thesis [27]. He has also installed four ultrasonic sensors SRF08 which are located in each corner of the wheelchair. This makes possible usage of shared control which is described at section 4.2.1. There is also a camera on the wheelchair. Functions for sending and receiving data were developed using C#. The data are transferred through the UDP protocol described later in section 5.4.3.

4 BCI-CONTROLLED WHEELCHAIR

There are several projects presenting use of EEG BCI to control an electric wheelchair. But the methodology of EEG classification and usage of each component is very various. Older projects are using mostly the P300 evoked potentials (described in section 2.1.1) and as the computational power grows newer project are based on use of sensorimotor rhythms (section 2.1.2) as there is a need of use of basic methods of a machine learning. Some project does not implement method the shared control which could possibly lead to dangerous situation for the user.

One of the fundamental aim of this project is to use the most up to date EEG classification technology to achieve best results.

In comparison with the classical analog joystick the BCI input generally has a limited resolution and higher uncertainty. As with other BCIs, EEG yields a low information transfer rate: either the waiting time between consecutive commands is long, typically several seconds, or uncertainty about the command is high. The difficulty is figuring out how to use such a poor signal to control a wheelchair that requires real-time specification of its position within the 3D space of planar motion. One solution is to give the system some autonomy, such that the user must provide the wheelchair with directives only from time to time.

4.1 Sensory motor rhythms classification

For purposes of controlling electric wheelchair the sensorimotor rhythm (SMR)-based BCIs has been chosen as it provides high speed of control and low incidence of unintentional commands. Methodology of training and control is inspired by team from University of Minnesota which used it to control quadcopter [11].

Subject will be trained in 1D and 2D cursor movement task using motor imagery. EEG data will be acquired and processed using aforesaid development platform BCI2000 [19]. This software will allow to identify the specific electrodes and frequencies that will be most differentially active during the actuation of a given imagination pair. The spectrogram of the R^2 value, a statistical measure of degree of correlation of temporal components of the EEG signal with different imagination state pairings, will be calculated so electrode and frequency bin (3 Hz width) with the highest correlation value to a given imagination state could be used. By evaluation of this spectrogram, the subject specific electrode-frequency configuration will be identified as a control signal for BCI to classify intended movement. [11]

There are three different commands proceeded to the shared control system: imagination of squeezing both hands will result in command *forward* or *stop* (depending on whether the robot is already moving), imagination of squeezing left hand will result in command to turn *left*, and imagination of squeezing right hand will result in command to turn *right*. Command for going back is not necessary because wheelchair can turn around its own axis.

4.2 Architecture of the system

The control signal decoded from the scalp EEG is sent regularly to shared control system together with signal from proximity sensors on wheelchair. Shared control system using predefined method determinates speed of each motor which is sent via into control unit of robot.

4.2.1 Shared control

In the past years, a fair number of research groups have ventured into the search for shared control techniques in order to provide assistance to patients as they experience problems when driving an electrical wheelchair. Because of the many different types of maneuverer that may induce driving problems, for example, driving through a door, obstacle avoidance, driving in a small corridor, docking at a table and others, different algorithms have been developed to cope with these specific situations. [26]

The nature of BCI-classified mental commands, generated by the subject to indicate some desired movement is quite different from those generated by a continuous joystick. First and foremost, there is an important reduction in resolution due to the limited amount of different mental commands that a BCI classifier can reliably discern. As a consequence, a command-to-movement scheme must be adopted which ensures that smooth motion will result from these discrete input signals. The EEG classifier system used in this work is able to distinguish three discrete commands that may express the need for movement into a certain direction. The steering signals that the classifier outputs consist of a probability distribution over these three discrete steering commands: *forward*, *left*, and *right*. [26]

Forward or *stop* means that translational speed v should be increased to predefined constant value when chair is not moving or to stop the wheelchair when it is in move. A *left* or *right* signal means that the user intends to rotate the wheelchair in the respective direction, thus increasing or decreasing the rotational velocity ω. Both velocities are superimposed, so that a command to turn when the wheelchair is already moving forward will result in a smoothly curved path.

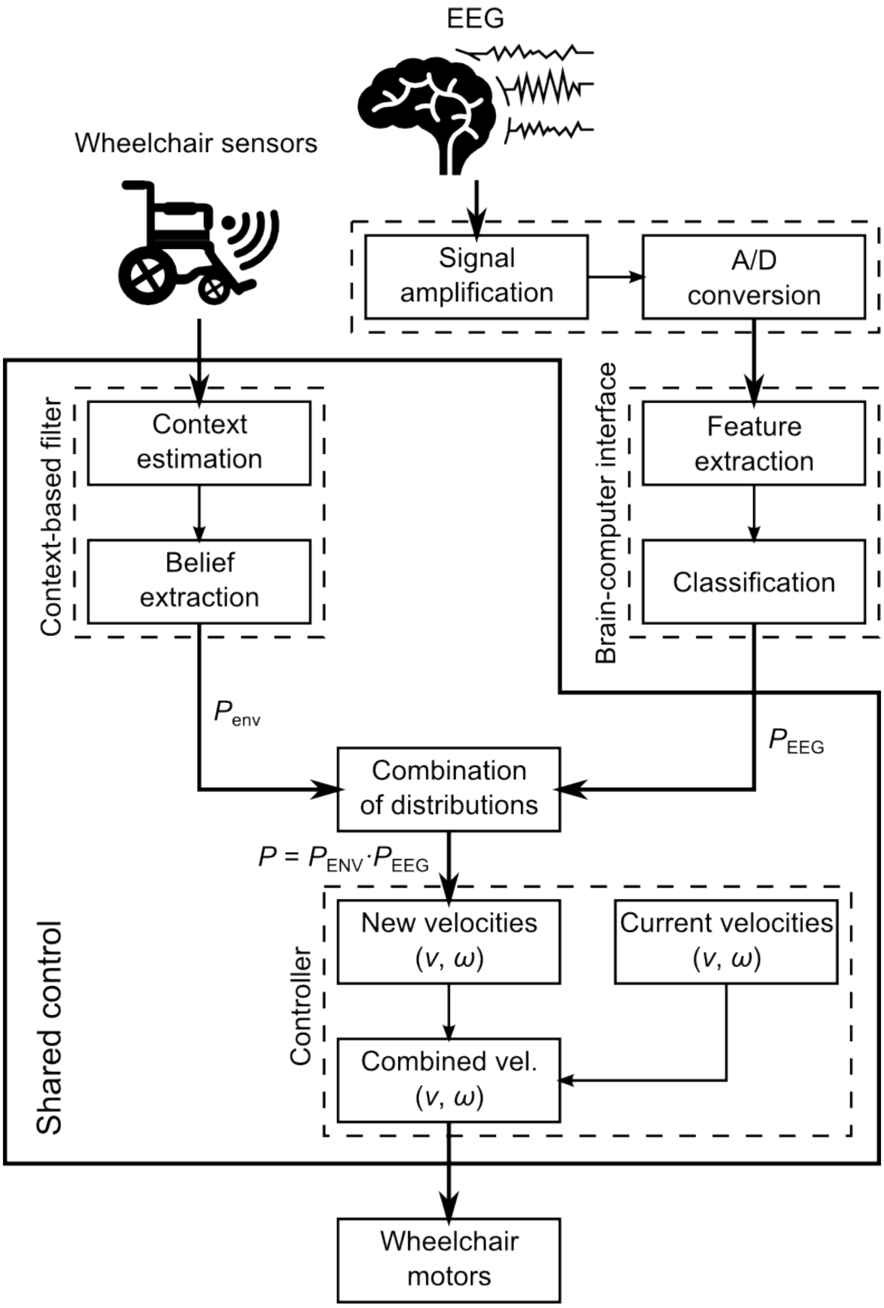


Fig. 4.1: Architecture of the BCI-controlled wheelchair

4.2.2 Obstacle avoiding system

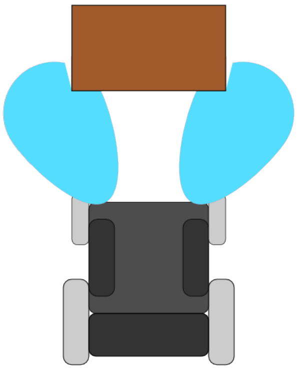
A conventional approach to autonomy is to equip the vehicle with sensors to perform obstacle detection and localization. There are two possible approaches: ultrasonic proximity sensors or a laser.

Ultrasonic proximity sensors

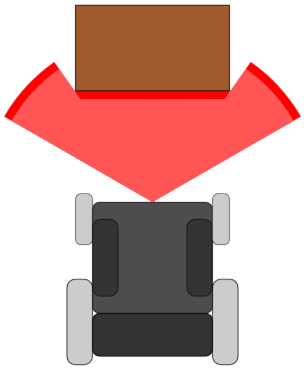
Ultrasonic proximity sensors are used in many automated production processes. They send an ultrasonic sound to the target point. This sound is reflected at the target and an echo thrown back to the sensor. The duration of this process is measured and converted into a corresponding distance. Their advantage is their simplicity and they are inexpensive. On the other hand results can be affected by the wind or fluctuating temperatures.

Laser proximity sensors

The laser sensor emits a laser pulse to the target point. The pulse is reflected by a photocell in the unit. The time interval between transmission and reception of the laser pulse calculates the distance. They have excellent accuracy but measuring on highly reflective or transparent surfaces is not possible.



(a) Ultrasonic sensor



(b) Laser sensor

Fig. 4.2: Proximity sensors

4.3 Model of the electric wheelchair

By agreement with the supervisor of the diploma thesis, interface was tested between classification system and control unit of model wheelchair instead of using actual electric wheelchair. The resulting quality of classification was not sufficient to control actual wheelchair.

For testing purposes model of electric wheelchair was made using kit to creating customizable, programmable robots LEGO® MINDSTORMS® NXT. This model allows to simulate some system of BCI-controlled wheelchair, i.e. shared control, proximity sensor or speed of each wheel. Mainly interface between classification system and control unit of electric wheelchair was simulated. And also very simple usage of obstacle avoiding system was tested. This model will be also used in experiments before participant will proceed to control of real electric wheelchair.

Model has powered front wheels. In figure 4.3 is visible ultrasonic proximity sensor in the front part of wheelchair. It has a 32-bit ARM7TDMI-core Atmel AT91SAM7S256 microcontroller with 256KB of FLASH memory and 64KB of RAM, plus an 8-bit Atmel AVR ATmega48 microcontroller. Computer communicates with control unit and sensors of the robot via Bluetooth.

Fig. 4.3: Model of the electric wheelchair made of LEGO® MINDSTORMS® NXT

Model was primarily used to test obstacle avoiding system of shared control. Thanks to its ultrasonic sensors it was able to tune its parameters and interaction.

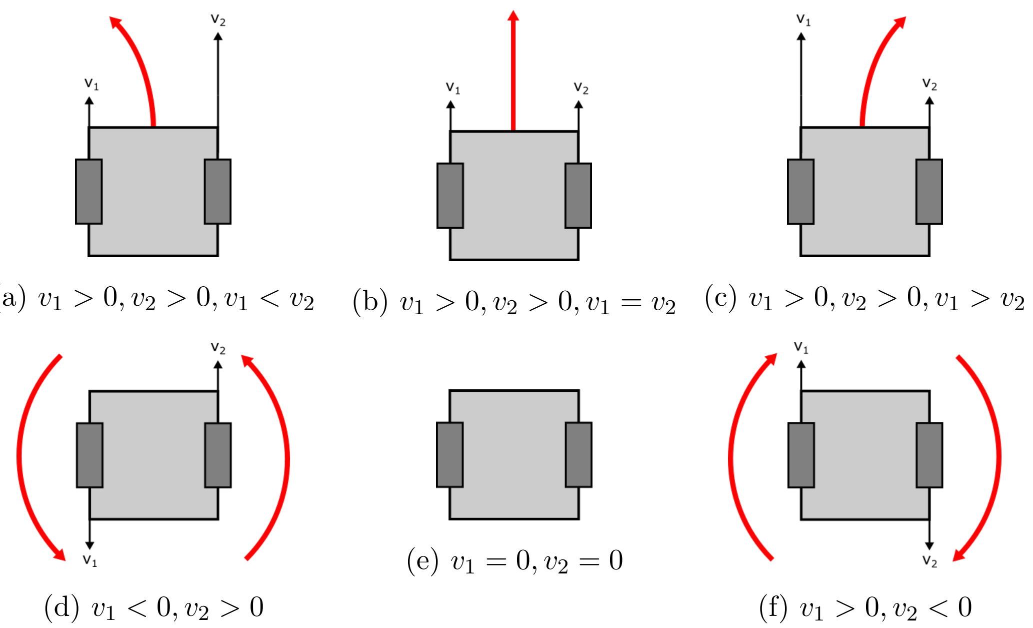
Using robot as a testing device for control with classified EEG signal turned out to be unsuitable. The first disadvantage was that person controlling such robot haven't had first person view from the seat as it would had on actual wheelchair. Due to insufficient quality of the classification the robot sometimes did moved into not intended direction. This lead to loosing user's focus which is highly important to maintain for proper classification. There was developed virtual environment simulating control of the wheelchair named VirtualEEGbot as a replacement.

4.4 Robot's movement states

Robot's movement can be in six different states.

The first state is while robot is stopped (figure 4.4e). Its left and right wheel are not moving. Second state is when robot is moving forward and both wheels are rotating with same speed. The robot can turn on spot while both wheels have same speed of rotation but different direction (4.4d, 4.4f). Same direction of wheel rotation but different speed results in robot's turning which leads to states 4.4a and 4.4c.

The robot can't go reverse as there was intentionally not implemented mind command for such state because this would highly probably make whole classification more unstable as there would need to be fourth class.



(a) $v_1 > 0, v_2 > 0, v_1 < v_2$ (b) $v_1 > 0, v_2 > 0, v_1 = v_2$ (c) $v_1 > 0, v_2 > 0, v_1 > v_2$

(d) $v_1 < 0, v_2 > 0$ (e) $v_1 = 0, v_2 = 0$ (f) $v_1 > 0, v_2 < 0$

Fig. 4.4: Robot's movement states

5 METHODS

There were applied three different methods of EEG signal classification. All of them are being used in experiments with motor tasks by researchers from BCI community. Also two different software for BCI were used to find most suitable classification algorithm.

During development of the system for robot's control using EEG classification multiple programs have been integrated and developed. All of them are described in this section.

5.1 EEG system

EEG system located at Department of Biomedical Engineering does not natively provide the possibility of on-line signal processing. It has only capability of storing acquired data into files. So by the nature of brain-computer interface it was not suitable for intended use.

Fig. 5.1: g.tec g.MOBIlab+

5.1.1 g.tec g.MOBIlab+

The system used to acquire EEG data was g.MOBIlab+ (figure 5.1) by the Austrian company g.tec (`http://www.gtec.at`). g.MOBIlab+ is portable biosignal acquisition system for recording multimodal biosignal data. The device is capable of acquiring EEG, ECG, EOG, EMG and other signals. g.MOBIlab+ is equipped with low-noise biosignal amplifiers and a 16-bit A/D converter with sampling frequency 256 Hz. It transmits biosignal data wirelessly via Bluetooth 2.0 to a PC or notebook or it can log data directly on an MiniSD card. System is powered with four AA batteries. The biggest advantage of this device is that it is recommended to use with BCI2000 and OpenViBE.

Used model was delivered in 2007 and the driver was in version 2007.03.05. The included 8-pin EEG electrode connector box (at figure 5.2) consists of eight inputs while one of them is for reference electrode and second is for ground electrode. Remaining six electrodes are used to acquire EEG signal. Used EEG cap had perforated holes for electrodes according to standard 10-20 system so it was easy to configure electrodes placement for use with motor tasks.

Fig. 5.2: g.MOBIlab+'s electrode connector box

5.1.2 Electrodes placement

Electrodes were placed according to standard 10-20 reference system to locations FC_3, FC_4, C_3, C_4, CP_3, CP_4 (at figure 5.3 filled with red color) to cover motor cortex area as a source of EEG signal for classification of motor tasks. The reference electrode was placed on location F_{pz} (at figure 5.3 filled yellow) and ground electrode on C_z (filled brown at 5.3) according to same placement on EEG caps by Alien technik s.r.o. (`http://www.alien.cz`) which are being used at the Department of Biomedical Engineering.

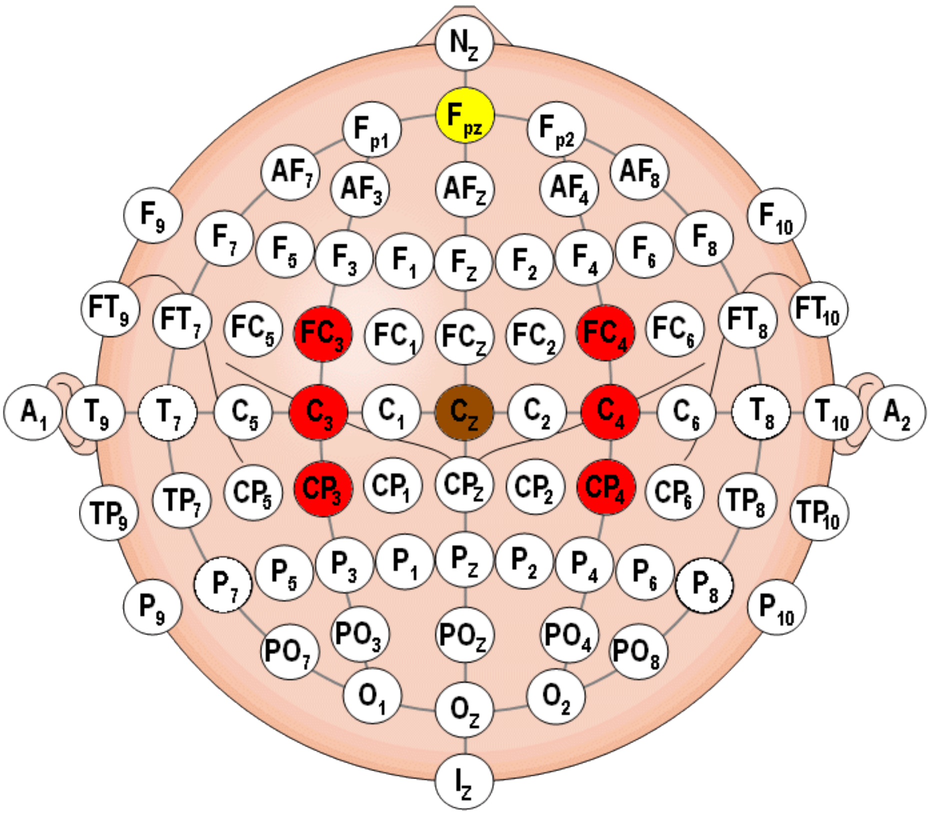


Fig. 5.3: Placement of electrodes

5.2 Classification software

As there are several platforms for classification already developed which are widely used and tested by researches in the brain-computer interface, there was no need to develop the new one. For purposes of motor tasks two major platforms were used: BCI2000 and OpenViBE. Both of them were briefly described in section 2.4. There should be mentioned that these two sets of tools are not directly ready to use for classification of EEG signal. They are more like development environments where the user can set up his or her own chain of signal processing. BCI2000 uses modules called from operational window. OpenViBE uses graphical representation of signal processing chain where different modules are connected using lines. This approach is called graphical programming.

Both classification softwares have already implemented driver for communication with g.Tec's g.MOBIlab+. As it was already mentioned before this is why was this system used.

5.2.1 BCI2000

Any BCI2000 configuration consists of different filters in the Data Acquisition, Signal Processing, and Application module. These filters determine what device BCI2000 acquires data from, what data format it uses for data storage, which feature extraction and translation algorithms it uses to translate brain signals into device commands, and which kind of user feedback is provided.

Each of the three BCI2000 core modules contains a chain of filters, i.e. a sequence of filters forming a pipe where, basically, brain signal data enter on one side, and a processed version of these data leaves on the other side.

The notion of a pipe implies that, for each portion of data entering on the input side, there will be exactly one portion of output data on the output side. The flowchart at figure 5.4 shows modules and filters of BCI2000.

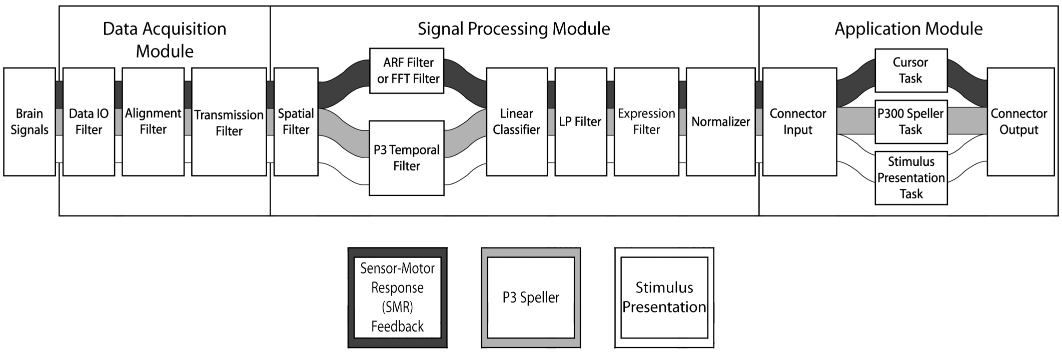


Fig. 5.4: Flowchart of the BCI2000's Filter Pipeline

In the Data Acquisition Module, the data filter manages data acquisition and storage in a general manner. Actual acquisition of data is provided by ADC filters, actual writing into data files is done by file writer filters representing various data formats. In addition to managing the operation of ADC and file writer filters, the data filter handles signal calibration into physical units (typically μV), and visualization of the source signal.

In the Signal Processing Module, brain signals are filtered spatially and temporally, resulting in a set of extracted features. In the Classifier, these features are used to differentiate amongst a small number of mental states (classes). Finally, the Normalizer adjusts the Classifier's output to zero mean and unit variance.

The Application Module contains a single filter that handles trial sequencing and brain signal feedback. In this standard configuration, these filters allow for exchanging data with external software over a UDP based socket protocol.

5.2.2 OpenViBE

OpenViBE Designer is an tool dedicated to creating and executing OpenViBE scenarios. As developers are pointing out it is targeted at a broad range of users, including students and researchers of the BCI community. It relies on a graphical user interface to provide signal processing tools in an intuitive way, and doesn't require almost any programming skills. Each of these tools comes as a plugin, which communicates with the application via a generic interface hiding implementation details. As a result, it is easy to extend the range of tools provided with the platform. An ever growing number of these signal processing boxes, or 'box algorithms' in OpenViBE terminology, are exposed by the Designer. Users may arrange any number of these boxes in a very flexible fashion, considering there is virtually no limit as to the number of boxes that may be included in a given scenario. Boxes arrangement is also made less error prone by typecasting box inputs/outputs.

5.3 Classification algorithms

5.3.1 Autoregression (AR)

Autoregression is a spectral estimation algorithm which is together with fast Fourier transform based algorithm implemented in BCI2000's Spectral Estimator. The Spectral Estimator computes a continually updated estimate of the spectrum of its input data, i.e. the distribution of amplitude or energy over frequencies. Spectral estimation is done separately for each of the filter's input channels. The autoregression algorithm computes an autoregressive model of its input data using the maximum entropy method based on Burg algorithm. The Burg algorithm is a popular method for estimating the coefficients of an AR model because, unlike most other methods, it is guaranteed to produce a stable model. The algorithm recursively estimates the reflection coefficients of an AR lattice filter by minimizing the mean of the forward and backward least squares linear prediction errors. Its output may be raw AR coefficients, or an estimated power spectrum collected into bins. AR coefficients are actually the coefficients of an all-pole linear filter that is fitted to reproduce the data's spectrum when applied to white noise. The resulting model can be used to estimate the power spectrum as follows [9]:

$$\widehat{P}\left(e^{j\omega}\right) = \frac{1}{\left|1 - \sum_{k=1}^{p} a_p\left(k\right) e^{-jk\omega}\right|^2} \tag{5.1}$$

where $a_p\left(k\right)$ are the estimated filter coefficients and p is the AR model order.

Thus, the estimated power spectrum directly corresponds to that filter's transfer function, divided by the signal's total power.

AR modeling is well suited for EEG for several reasons. First, EEG is highly non-stationary and must be evaluated using short time segments over which the data are presumed to be stationary. The spectral resolution of an AR model is not explicitly limited by the length of the input process and therefore is capable of providing superior resolution for short data segments.

5.3.2 Linear discriminant analysis (LDA)

Linear discriminant analysis is used to find a linear combination of features that can better separate two or more classes. The LDA finds such direction a that provide maximum linear separation of classes. The aim of LDA is to create a new variable that is a combination of the original predictors. This is accomplished by maximizing the differences between the predefined groups, with respect to the new variable. The goal is to combine the predictor scores in such a way that, a single new composite variable, the discriminant score, is formed. This can be viewed as an excessive data dimension reduction technique that compresses the p-dimensional predictors into a one-dimensional line. At the end of the process it is hoped that each class will have a normal distribution of discriminant scores but with the largest possible difference in mean scores for the classes. In reality, the degree of overlap between the discriminant score distributions can be used as a measure of the success of the technique. Discriminant scores are calculated by a discriminant function which has the form [23]:

$$D = w_1 Z_1 + w_2 Z_2 + w_3 Z_3 + ... + w_p Z_p \tag{5.2}$$

As a result a discriminant score is a weighted linear combination of the predictors. The weights are estimated to maximize the differences between class mean discriminant scores. Generally, those predictors which have large dissimilarities between class means will have larger weights, at the same time weights will be small when class means are similar [23].

5.3.3 Support vector machine (SVM)

Previous classifier separate classes using hyperplanes that split the classes, using a flat plane, within the predictor space. SVMs broaden the concept of hyperplane separation to data that cannot be separated linearly, by mapping the predictors onto a new, higher-dimensional space in which they can be separated linearly.

The method's name derives from the support vectors, which are lists of the predictor values taken from cases that lie closest to the decision boundary separating the classes. It is practical to assume that these cases have the greatest impact on the location of the decision boundary. In fact, if they were removed they could have large effects on its location.

The basic support vector classifier is very similar to the perceptron. Both are linear classifiers, assuming separable data. In perceptron learning, the iterative procedure is stopped when all samples in the training set are classified correctly. For linearly separable data, this means that the found perceptron is one solution arbitrarily selected from an (in principle) infinite set of solutions. In contrast, the support vector classifier chooses one particular solution: the classifier which separates the classes with maximal margin [23].

5.4 EEGbot

EEGbot is name of developed set of functions for working with EEG controlled robot. It wraps up multiple parts that are necessary to control robot or virtual environments with data from EEG classification.

First it is communication part which receives data from EEG classification tools. This is implemented as user datagram protocol (UDP) client in case of using classification from BCI2000 or as function from Virtual Reality Peripheral Network (VRPN) in case of using BCI2000. There are functions for communication with robot or virtual environment included. Then EEGbot implements shared control and lastly it includes set of supporting functions as for example is function for reading XML with configurations. Configurational XML is described in appendix A.1.

5.4.1 Implemented shared control

Shared control operates with three values of distance and maximal allowed speed of robot. Alert distance d_{alert} and stop distance d_{stop} are obtained from configuration file. Current distance d is obtained from the distance sensors on the robot. When current distance is higher than alert distance no intervention into robot's speed are being made. If current distance decreases under alert distance shared control starts to handle speed of robot to avoid obstacle in its way. The speed is then linearly dependent on values of alert distance d_{alert} and stop distance d_{stop} based on equation:

$$v = v_{max} * \frac{d - d_{stop}}{d_{alert} - d_{stop}} \tag{5.3}$$

This means that when current distance is equal to alert distance robot is moving at the maximal allowed speed and when current distance equals to stop distance robot is stopped.

Implemented in the code:

```
if (sensorData.distance < paramData.alertDistance)
{
    float speedCoef = (sensorData.distance - paramData.stopDistance) /
        (float)(paramData.alertDistance - paramData.stopDistance);
    if (speedCoef < 0)
        speedCoef = 0;
    bot.ctrlData.speed = bot.paramData.maxSpeed * speedCoef;
}
```

While setting values of alert distance and stop distance current environment should be taken in account.

5.4.2 Graphical user interface (GUI)

For easier understanding of robot's control and current state of whole system, graphical user interface was developed. GUI was developed using OpenGL with use of supporting functions from FreeGLUT library (`http://freeglut.sourceforge.net`).

All elements are visualized using basic OpenGL primitives. The sample of screen from GUI is at figure 5.5.

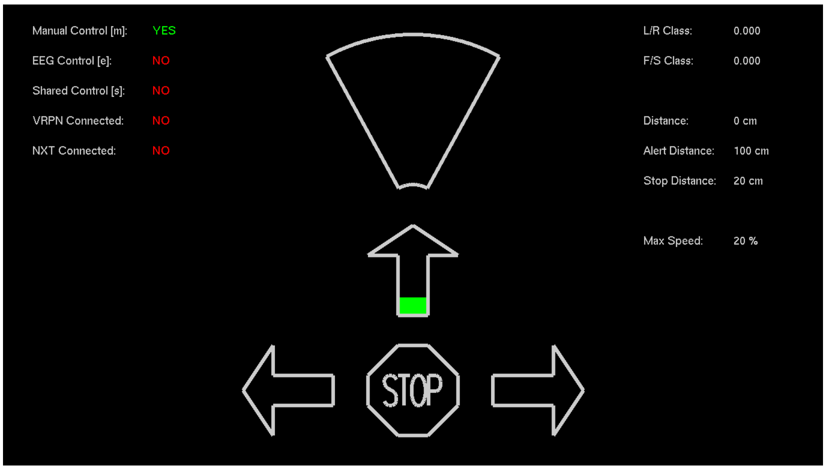
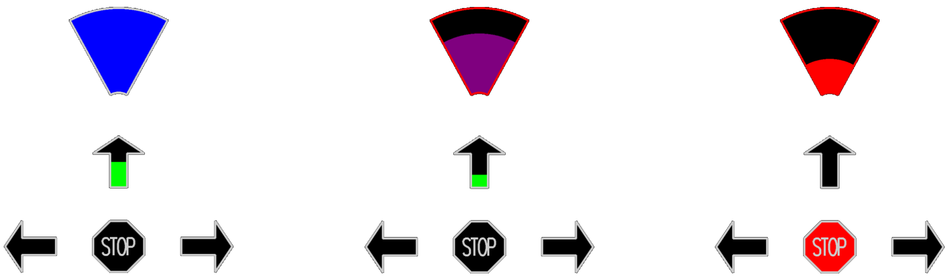


Fig. 5.5: Graphical user interface of EEGbot

Screen is divided into three parts. In the top left corner is displayed current state of each module. User can turn on or off each module by pressing assigned key on keyboard. These parameters can be also set using configurational XML (appendix A.1).

In the top right corner are showed raw data from classification for setting of parameters and debugging.

In the middle is depicted control of robot as three arrows (pointing up, left and right) and stop sign. Arrows are filled with green color based on current speed in depicted direction while fully filled arrow represents maximum speed in given direction.



(a) Safe distance (b) Alert distance (c) Stop distance

Fig. 5.6: Imagination of hands movement

On top of arrow pointing up is graphical representation of obstacle avoiding system. If current distance to obstacle is lower than alerting distance, border of the shape becomes red as signalization of possible threat. This is visible on figure 5.6 where alerting distance was set to 100 cm and stop distance to 50 cm. When the distance to obstacle is higher than 100 cm, symbolic is depicted as on figure 5.6a. If the distance is bellow alerting distance 5.6b, the symbolics starts to show relative distance to the obstacle. Also it should be noticed that the speed had change according to green fill of upward point arrow compared to green fill in previous situation. In the moment when distance is equal or less than stop distance (in this case 50 cm) the wheelchair is stopped as it can be seen at figure 5.6c.

5.4.3 Communication between programs

User Datagram Protocol (UDP)

User Datagram Protocol UDP is a communications protocol that offers a limited amount of service when messages are exchanged between computers in a network that uses the Internet Protocol (IP). UDP is an alternative to the Transmission Control Protocol (TCP). Like the TCP, UDP uses the IP to actually get a data unit (called a datagram) from one computer to another. Unlike TCP, however, UDP does not provide the service of dividing a message into packets (datagrams) and reassembling it at the other end. UDP uses IP network without prior communications to set up special transmission channels or data paths. UDP is suitable for purposes where error checking and correction is either not necessary or is performed in the application, avoiding the overhead of such processing at the network interface level.

This makes UDP ideal for purpose of sending values from classification software BCI2000 although it is used only on computer as *localhost*.

Virtual-Reality Peripheral Network (VRPN)

The Virtual-Reality Peripheral Network (`http://www.cs.unc.edu/Research/vrpn/`) is used to obtain data from OpenViBE. This approach was used because OpenViBE has already implemented VRPN server.

VRPN is a set of classes within a library and a set of servers that are designed to implement a network-transparent interface between application programs.

5.4.4 Communication with robot

NXT++

NXT++ is library used control model of electric wheelchair. It is an interface written in C++ that allows control of LEGO MINDSTORMS NXT robots directly through a USB or Bluetooth connection. NXT++ allows to easily initiate Bluetooth connection with model. It is also able to control each motor separately. Functions for obtaining distance to obstacle from NXT's ultrasonic sensor is also implemented so it was beneficial for testing algorithms of shared control.

Observed latency between classification of EEG signal and execution of classified command by robot was about one second.

5.5 VirtualEEGbot

For purposes of testing and training virtual environment was created. The virtual environment was developed using Unreal Development Kit (UDK) by Epic Games (`https://www.unrealengine.com/previous-versions`. It is 3D game engine and toolset used in video game development, architectural visualization and 3D rendering.

In UDK was built environment which simulates narrow rooms with multiple turns to test and train control of robot with bran-computer interface. Map of built environments is at figure 5.7.

User starts at point highlighted with blue. He or she can try control of wheelchair in wider room at the beginning. Then user can drive through one of the green point and get to the other green point while crossing yellow point. Time that took user to drive between two green points is then highlighted on the screen. This virtual environment can be used for training purposes before controlling the actual wheelchair.

UDK natively supports only control of movement using keyboard and mouse or gamepad. So there had to be implemented workaround which is parsing control commands from EEGbot into virtual gamepad. This is described in appendix D.

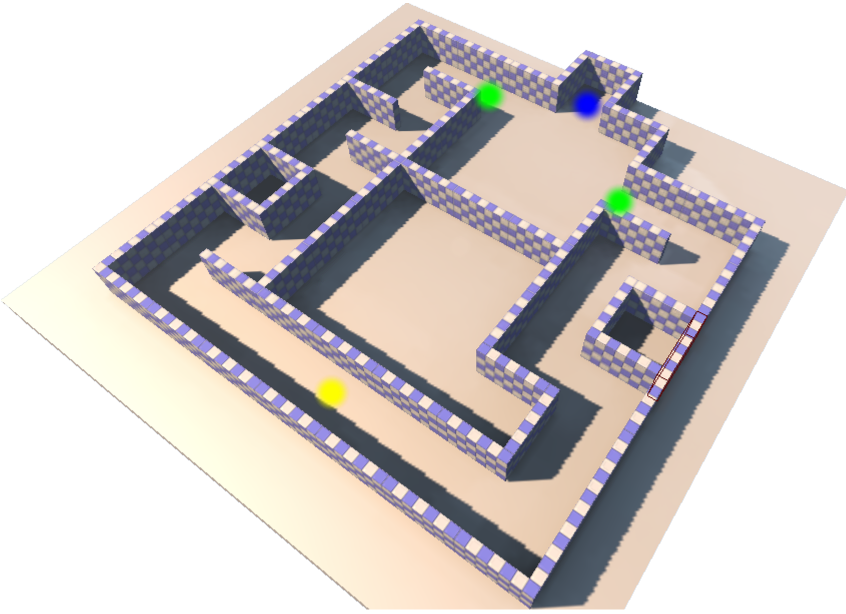


Fig. 5.7: Map of developed arena in VirtualEEGbot

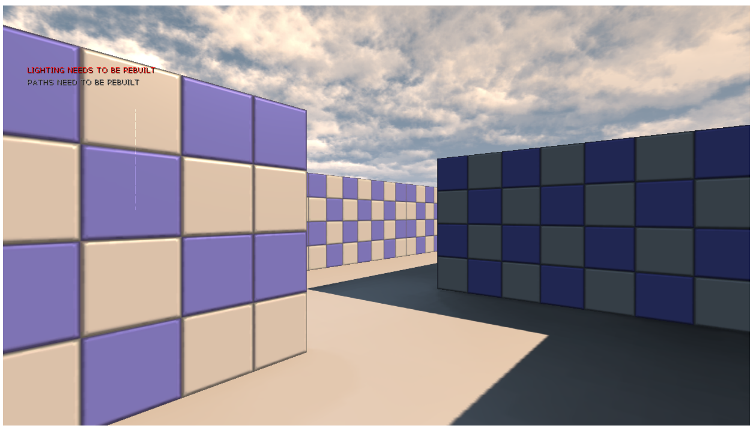


Fig. 5.8: First person view in VirtualEEGbot

6 EXPERIMENTS

6.1 Preliminary experiment

An experiment was conducted to acquire EEG data for testing purposes and to verify prerequisites of using EEG to control electric wheelchair. Data were acquired using EEG system TruScan 32 delivered by Alien technik s.r.o. (`http://www.alien.cz`) in the Laboratory of functional diagnostics at the Department of Biomedical Engineering.

EEG signals were acquired with sampling frequency $F_s = 128$ Hz and using cap with 10-20 system electrode placement. Subject, healthy 22 years old man, sat in a comfortable chair and was instructed to perform different tasks.

Data acquisition was divided into three parts. In the first part 90 seconds of resting state data was gathered. Such signal is result of spontaneous brain activity. In the second EEG signal as a result of evoked potentials was acquired: subject was squeezing his left hand then right hand and in the end both of them. Each subphase took 30 seconds. In the last phase subject was imaging movement from previous phase. Also 30 seconds of EEG data of each phase were acquired.

6.1.1 Results of preliminary experiment

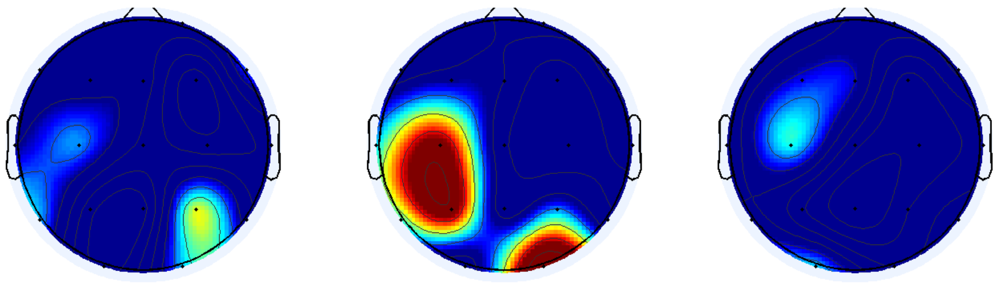
From phase of real hand movement and phase of imagination of movement topographic maps have been created. These maps represent distribution of frequency $F = 12$ Hz in all electrodes. Each map is a result of subtraction of resting state topographic map from topographic map of given subphase.

In the figure 6.1 are clearly visible differences between representation of each phase. In figure 6.1a frequency of $F = 12$ Hz is mainly represented in electrode P4 (see figure 1.4). In figure 6.1c is visible that this frequency is mostly represented in electrode C3. These results correlate with knowledge that activated motor areas are located contralateral to the moving hand. Squeezing both hands results in much bigger difference in both areas compared to resting state.

In figure 6.2 are visualized topographic maps obtained by same method but with maps of EEG acquired during imagination of squeezing each hand or both of them. Results correlate with previous maps but the difference in imagination of left and right hand movement is slightly smaller. On the other side, imagination of both hand squeezing resulted into massive difference in many electrodes compared to data obtained during resting state.

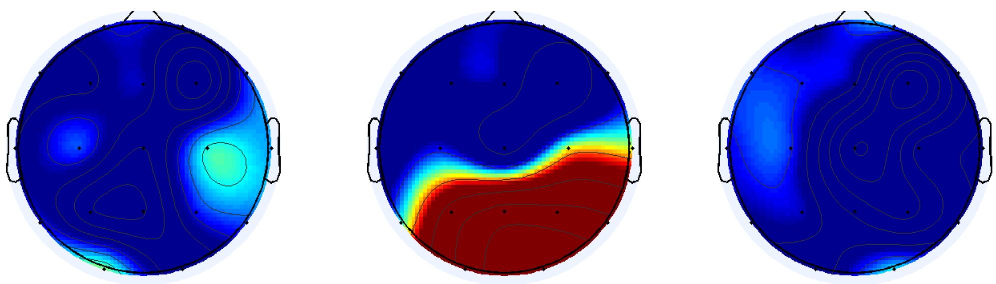
Results of this experiment proved assumptions that there are detectable and after processing clearly visible differences of amplitudes of frequency $F = 12$ Hz between resting state and imagined or real hand squeezing. Also these results confirm that frequency distribution of imagined hand squeezing does not much differ from the real hand squeezing.

Finally these result prove that concept of using sensorimotor rhythms to control the electric wheelchair is feasible.



(a) Left hand (b) Both hands (c) Right hand

Fig. 6.1: Real hands movement



(a) Left hand (b) Both hands (c) Right hand

Fig. 6.2: Imagination of hands movement

6.2 Final experiments

The aim of set of final experiments was to evaluate achieved quality of EEG signal classification. Achieved results did not fulfill expected results as it is described in the end of this chapter.

6.2.1 Experiment setup

The experiment was conducted using g.tec's g.MOBIlab+ described in section 5.1.1. Medium sized EEG cap with 10-20 reference system was made by Electro-Cap International, Inc. (`http://www.electro-cap.com`). As electrolyte between electrodes and scalp was used Synapse Conductive Electrode Cream by Kustomer Kinetics (`http://www.kustomerkinetics.com`). Sapling frequency was 256 Hz and data were acquired from 6 electrodes. The computer which was processing the data had Intel®Core i5 processor and 4 GB of memory.

The participants were instructed about basics of EEG recording. To avoid artifacts one shouldn't blink his or her eyes or clench jaws.

The experiment was divided into two main parts which differed in whether user was actually moving with the wrist or imaging such a movement. The content of experiment was same.

The aim of first part was to gather EEG data for learning phase of classification. Users were presented with arrow pointing in four different directions (*left*, *right*, *up* and*down*). *Left* and *right* meant that participant should move (or imagine moving) with corresponding hand. That meant that user should squeeze or curl his or her hand. *Up* pointing arrow meant that participant should do (or imagine) such movements with both hands. While the arrow was pointing *down* users shouldn't do or imagine any movement. According to LaFleur et al [11] user should focus on a nonmuscular part of the body and relax. Subjects were instructed to perform movement according to displayed arrow for whole time when green cross was depicted in case of conducting experiment in OpenViBE or whole time of arrow being showed in case of BCI2000.

Subjects were demonstrated with each arrow 20 times (80 times altogether). While each of four phases took about 20 minutes there were recorded around 400 minutes of EEG data in each part of experiments (real and imagined hand moving).

During the experiment signal was observed on separate screen. When there was noticeable deterioration of EEG signal quality on one of the electrodes, the

(a) Stimuli in BCI2000

(b) Stimuli in OpenViBE

Fig. 6.3: Presented stimuli

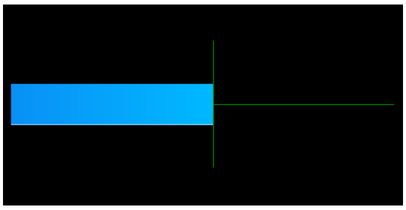


Fig. 6.4: Result of classification in OpenViBE

experiment was interrupted and affected electrode was filled with gel and fixed to head.

Subjects who would demonstrate the ability to correctly select 70% or more of valid targets in each of four consecutive 2D cursor trials would be deemed proficiently skilled in BCI control for participation in the control of virtual wheelchair.

6.2.2 Participants

Altogether five human subjects, aged 24–63 (two female and three male), were participating in experiment. None of the participants has had prior experience with brain-computer interface or even with recording of EEG. There was prior intention to cover wider spectra of human population in the matter of age.

During data acquisition it was noticeable that recording EEG signal of user with bald head versus the users with hairs had no influence of signal quality. Only difference was that electrodes were not so prone to loose contact with skin.

6.2.3 Results of final experiment

The results as percentage of success rate are presented in next two tables (6.1 and 6.2). These values were gather by this approach: if there was observable right classification lasting at least one second in three seconds after stimuli presentation, the classification was declared as right. In BCI2000 it was observed from values of outgoing data. In OpenViBE it was observed graphically as a blue bar pointing in one direction as it is depicted at figure 6.4. As it is obvious achieved results are not sufficient for controlling any device. The best result were achieved when using LDA algorithm. There could be doubt about correctness of recorded EEG signal, but all descriptors (application of Fourier transform to see frequency spectra, artifacts from eye-blinking or alpha waves during closed eyes) were pointing to correctness of these data.

Method	**AR**		**LDA**		**SVM**	
Class	**L/R**	**F/S**	**L/R**	**F/S**	**L/R**	**F/S**
1	55,0 %	60,0 %	52,5 %	80,0 %	50,0 %	50,0 %
2	52,5 %	65,0 %	52,5 %	65,0 %	50,0 %	50,0 %
3	52,5 %	55,0 %	47,5 %	67,5 %	50,0 %	50,0 %
4	47,5 %	60,0 %	45,0 %	67,5 %	50,0 %	50,0 %
5	52,5 %	65,0 %	55,0 %	65,0 %	50,0 %	50,0 %
Average	52,0 %	61,0 %	50,8 %	70,8 %	50,0 %	50,0 %

Tab. 6.1: Results of trials with real hands movement

Method	**AR**		**LDA**		**SVM**	
Class	**L/R**	**F/S**	**L/R**	**F/S**	**L/R**	**F/S**
1	52,5 %	55,0 %	47,5 %	60,0 %	50,0 %	50,0 %
2	50,0 %	52,5 %	50,0 %	65,0 %	50,0 %	50,0 %
3	47,5 %	47,5 %	50,0 %	55,0 %	50,0 %	50,0 %
4	55,0 %	60,0 %	47,5 %	57,5 %	50,0 %	50,0 %
5	55,0 %	55,0 %	45,0 %	55,0 %	50,0 %	50,0 %
Average	52,0 %	55,0 %	48,0 %	58,5 %	50,0 %	50,0 %

Tab. 6.2: Results of trials with imagined hands movement

There was not conducted controlling of wheelchair in virtual environment because of insufficient quality of classification.

7 CONCLUSION

In this diploma thesis the method for control of the electric wheelchair using brain-computer interface (BCI) was introduced. This method is based on classification of sensorimotor rhythm (SMR) from scalp EEG. There are four commands implemented (*left*, *right* and *forward/stop*), induced by three motor tasks: imagination of squeezing or curling left hand, right hand or both of them.

Description of four main components and basic prerequisites to having a functional prototype were outlined. Those main components are: *EEG*, *brain-computer interface*, *shared control* and *electric wheelchair*.

The achieved results basically did not fulfill expected outputs. None of chosen methods is applicable to control actual electric wheelchair. So there was developed virtual environment for future testing of EEG classification methods and other components of this system. Control of wheelchair described at section 3.3 was not integrated because of its temporal unavailability and insufficient quality of EEG classification which was discussed in 6.2.3. If this project should continue it is crucial to improve quality of EEG signal classification.

7.1 Suggestions for improvement

During research, development and testing some points for future improvement were observed. Those with highest potential of impact on whole system's usability are described in next paragraphs.

7.1.1 Use of different BCI task

As the classification is part which has highest impact on applicability other methods should be tested. Whole system was developed on basis of motor task. Main benefit of this approach is much higher independency of such robot control. The system is not dependent on any knowledge base (e.g., arrangement of the room or layout of the building) except learned classification. If this knowledge base would be available the system of brain-computer interface could be done simpler.

P300

Wheelchair which relies on a P300 (described in section 2.1.1) needs automated navigation. When in operation, the user faces a screen displaying either a real-time virtual reconstruction of the building's scenario or names of rooms. The user concentrates on the location of the space to reach. A visual stimulation process elicits the neurological phenomenon P300, and the EEG signal processing detects the target location. This location is transferred to the autonomous navigation system that drives the wheelchair to the desired location while avoiding collisions with obstacles in the environment detected by the shared control. This method was presented by [?].

7.1.2 Development of own EEG classification

The classification is basically based on frequency of EEG signal and location of electrode where this frequency is observed. There could be used some of other method of machine learning than those which were described in section 5.3. For example artificial neural networks.

7.1.3 Use of other EEG systems

As g.MobiLab+ was only available EEG device that is supported by both used BCI systems (BCI2000 and OpenViBE) it was chosen for use. The disadvantage was that it has only 6 input channels so the whole scalp could not be covered. EEG cap used in experiments allowed to choose own placement of electrodes. So two most important positions C3 and C4 for use in motor tasks were covered.

There should be an intention to use compact EEG system. Such approach would be more comfortable for the user compared to regular clinical EEG cap and it could bring new knowledge and experiences into current research of BCI-controlled robots. But there is an issue that most of the compact systems does not contain C3 and C4 electrodes which are important for EEG classification while using (SMR)-based BCI.

Usage of dry electrodes

Before every use the electrodes have to be filled with conductive EEG gel to decrease the impedance on interafce between skin and electrode. The gel is drying by the time which leads to increasing of impedance. Also electrodes can completely loose their contact with the skin which results in high noise on the electrode. This could lead into no or wrong classification and then into bad control over wheelchair. Some

EEG systems provide ability to meassure impedance on each electrode. Increase of impedance above some threshold should lead into

7.1.4 Using laser scanner

Current setup of wheelchair consists only of ultrasonic sensors. Such sensors are good for detection of obstacles above ground level but poor in detection of holes and drops such as steps.

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LIST OF ABBREVIATIONS

ALS Amyotrophic lateral sclerosis

AR Autoregression

BCI Brain-computer interfaces

BCI2000 Software platform for BCI research [19]

DC Direct current

DWT Discrete wavelet transform

EEG Electroencephalography, electroencephalogram

EMG Electromyography, electromyogram

EOG Electrooculography, electrooculogram

EP Evoked potentials

ERP Event-related potentials

FES Functional electrical stimulation

ICA Independent component analysis

IP Internet Protocol

ITR Information transfer rate

LDA Linear discriminant analysis

MI Motor or movement imagination

PCA Principal component analysis

SCP Slow cortical potentials

SMR Sensorimotor rhythms

SVM Support vector machine

TCP Transmission Control Protocol

UDP User Datagram Protocol

Wi-Fi Wireless local area network

LIST OF APPENDICES

A RUNNING EEGBOT

Folder EEGbot consist's of multiple folders and solution file EEGbot.sln. EEGbot was developed in Microsoft Visual Studio 2013 using C++ language.

Copy folder `EEGbot` from included DVD to your computer.

Run `EEGbot.sln` from `EEGbot` and build it. Copy DLL's from folder `DLLs` into Debug or Release folder according to your chosen configuration. Also copy `EEGbot.xml` from `Configs` directory on DVD to same folder.

Configure your EEGbot's setup using `EEGbot.xml` which is described in next section.

Run EEGbot either from Visual Studio or folder where it was built using `EEGbot.exe`.

A.1 Configurational XML

The user can easily setup multiple parameters of robot's control by editing configuration XML file. The file can be edited during execution of programs which allows easy debugging and customization. XML is well commented so it should be easy to set its parameters.

This is snippet from from configuration XML `EEGbot.xml` located in `Configs` directory on DVD:

```
<?xml version="1.0" encoding="UTF-8"?>
<EEGbot>
    <config>
        <data>
            <input>openvibe</input>
            <!-- source of data (bci2000, openvibe, dummy) -->
            <output>virtual</output>
            <!-- controlled device (nxt, virtual, wheelchair, dummy) -->
        </data>
        <modes>
            <manualCtrl>1</manualCtrl>
            <!-- turn on/off manual control from keyboard (0, 1) -->
            <eegCtrl>0</eegCtrl>
            <!-- turn on/off EEG control (0, 1) -->
```

```
            <sharedCtrl>0</sharedCtrl>
            <!-- turn on/off shared control (0, 1) -->
        </modes>
...
    </config>
    <debug>
    <!-- this makes possible to override incoming and outgoing values
    with value in argument by changing its "override" parameter to "1" -->
        <classLR override="0">0</classLR>
        <!-- incoming value for left/right class from classifier -->
        <classFS override="0">0</classFS>
        <!-- incoming value for forward/stop class from classifier -->
...
    </debug>
</EEGbot>
```

B RUNNING OPENVIBE

Install OpenViBE using installer `openvibe-gmobilab-0.18.0-setup.exe` in directory `Installs` on included DVD.

Copy folder `openvibe-eegbot` from directory `Configs` on included DVD to your computer.

Run `openvibe acquisition server` from `OpenViBE` directory in `Programs` folder in Start menu.

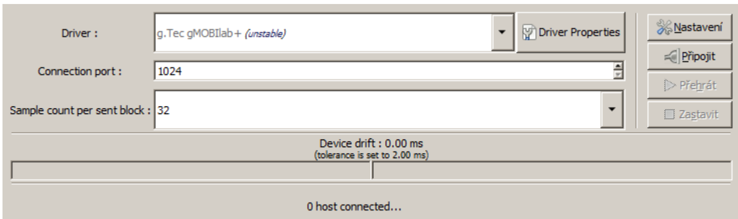

Fig. B.1: OpenViBE Acquisition server

Set parameters **Port name** and **Channel names** in **Driver Properties** according to your setup.

Click on **Connect** and the **Play** button to send data to **Acquisition client**.

Run `openvibe designer` from `OpenViBE` directory in `Programs` folder in Start menu.

In **OpenViBE designer** open files `eegbot-0-signal-monitoring.xml`, `eegbot-1-acquisition.xml`, `eegbot-2-train-CSP.xml`, `eegbot-3-classifier-trainer.xml` and `eegbot-4-online.xml` from previously copied folder `openvibe-eegbot`.

Use `eegbot-0-signal-monitoring.xml` to check the quality of the signals before starting an experiment. Ensure that eye blinks and jaw clenching are visible.

Use `eegbot-1-acquisition.xml` to acquire training data. You will be presented with left / right / up / down arrows to let you imagine left / right / both / no movement. There will be 20 arrows on each side. To start the scenario press **Play** symbol in menu.

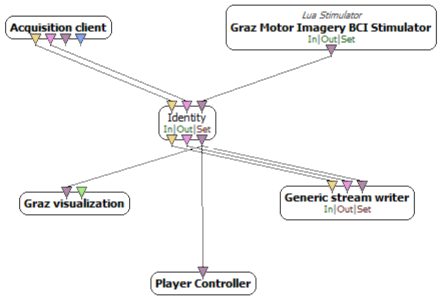

Fig. B.2: Acquisition of the data

Use `eegbot-2-train-CSP.xml` to train common spatial pattern filter that will be used in further steps. To start the scenario press **Fast forward** symbol in menu.

Use `eegbot-3-classifier-trainer.xml` to train the LDA classifier used to detect left / right and both / no hands movement.

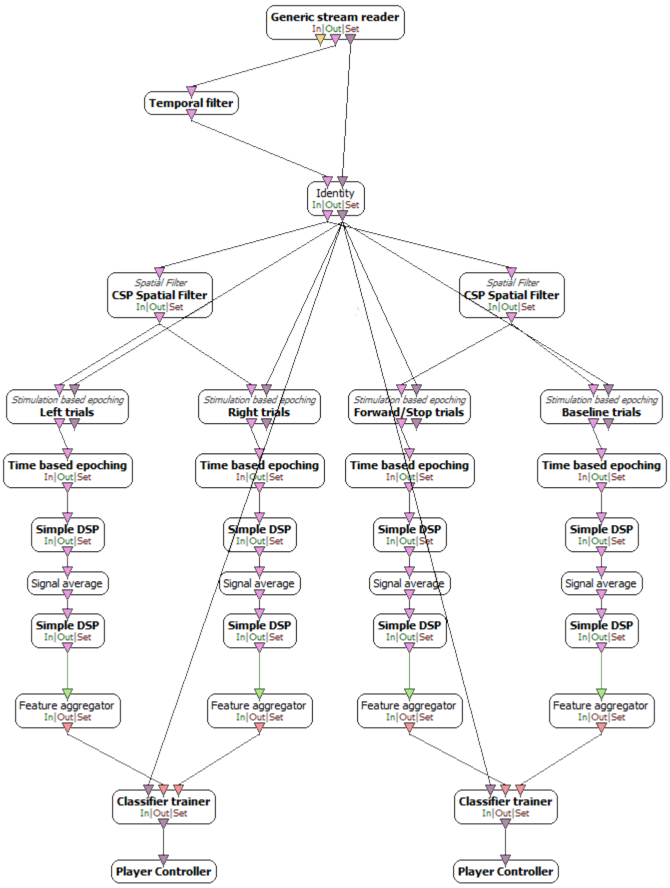

Fig. B.3: Training of the LDA classifier

Use `eegbot-4-online.xml` for online classification based on learned parameters and sending its values to EEGbot via VRPN.

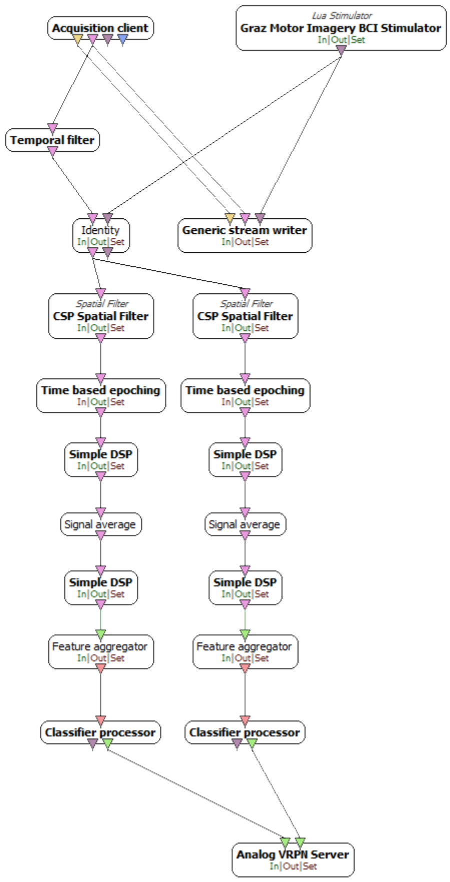

Fig. B.4: Online classification of EEG data

C RUNNING BCI2000

Install BCI2000 using installer `BCI2000Setup.exe` in directory `Installs` on included DVD.

Run `Operator.exe` from `prog` folder in directory with installed BCI2000.

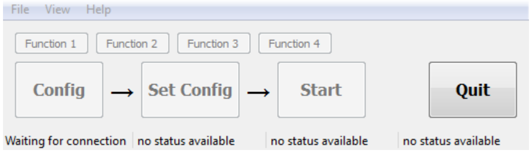

Fig. C.1: Operator module of the BCI2000

Then run `gMOBIlabPlus.exe` (or other Data Acquisition Module in case of using different EEG device), `ARSignalProcessing.exe` as Signal Processing Module and `DummyApplication.exe` as Application Module.

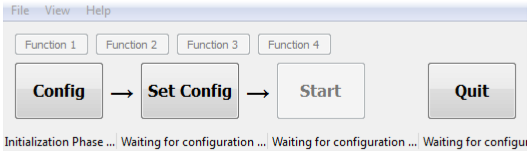

Fig. C.2: Operator module after loading submodules

Click on **Config** button and then on **Load Parameters...**. Choose `EEGbot.prm` from `Configs` directory on DVD. This is file with preset parameters. In case of using gMOBIlab+ set **COMport** on **Source** tab to Bluetooth COM port to which is device connected.

Then click on **Set Config**. If everything was set correctly **Start** button should be enabled.

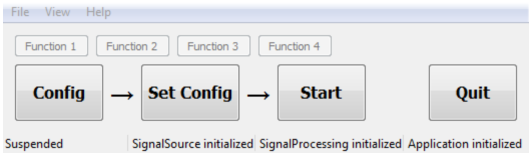

Fig. C.3: Module is ready to start operating

After clicking on **Start** data from classification are being send to EEGbot via UDP. Tune parameters of classification to achieve acceptable results.

D RUNNING VIRTUALEEGBOT

Install **VirtualEEGbot** using installer `UDKInstall-VirtualEEGbot.exe` in directory `Installs` on included DVD.

Install **vJoy** using installer `vJoy_205_200315.exe` in directory `Installs` on included DVD.

Copy content of folder `x360ce` in directory `Configs` on included DVD to folder `Binaries/Win32` in install directory of **VirtualEEGbot**.

Run **EEGbot** and previously copied **x360ce**.

You should be able to control virtual wheelchair from within **EEGbot**.

E CONTENT OF INCLUDED DVD

`Configs/` – folder with configuration files containing input parameters for applications

`EEGbot/` – folder with source files of developed system for controlling devices

`Installs/` – folder with installations of external applications necessary to run all configurations

`LukasMaly-DP.pdf` – this diploma thesis