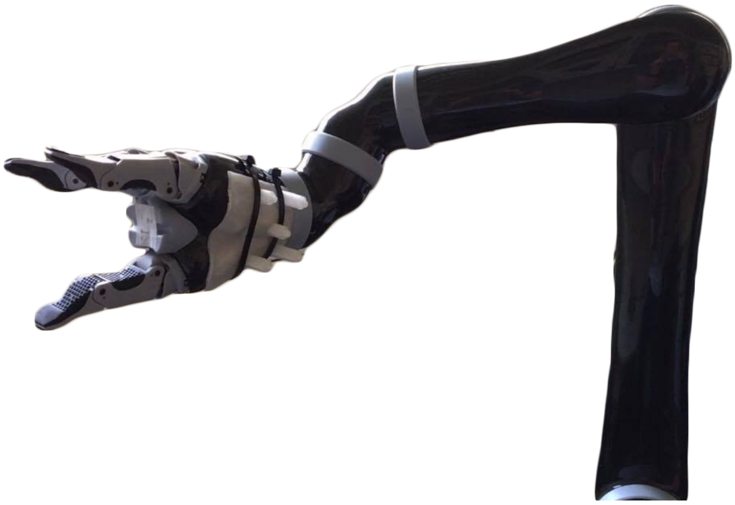
Brain Wave Control

Assistive Robot - Sensing the Surroundings



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STUDENT REPORT

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Abstract:

This project investigates how a robotic solution can be controlled with the use of EEG brain wave signals. The sensor used was a Emotive Epoc headset which is able to detect and record brain activities, and as for the robotic solution a 6 DOF Kinova JACO^2 was used. In this project the target group was tetraplegia patients, who are paralyzed below the neck level due to their condition.
This project explores the viability of two different approaches, brain activities and facial gestures, concluding that the use of artifacts from facial gestures was more manageable and simple to implement for this concrete case.
In order to create a classification system, seven subjects were instructed to do a certain sequence of facial movements in a specific order. The results from the recordings were used to write a program for determining which facial movement was produced and thereby what command to execute in order to control the robot. Hereafter the final system was tested and its results were evaluated based on the set requirements.
The resulting solution showed that the offline control of a robot with artifacts was possible. However, it was restricted to the person the program was designed for, showing more unreliable results for the other test subjects.

Preface

Aalborg University, June 6, 2017

This report is written by seven, 4th semester Robotics students from Aalborg University, Denmark.

The report was written over a period of 118 days, with the purpose of designing a robotic solution for tetraplegic patients using EEG with the help of the resources provided by AAU. The project includes testing a prototype of the solution with a JACO^2 robotic arm and a Emotiv Epoc.

Throughout the paper the authors have used the IEEE method for referencing e.g.: (1), (2).

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Abbreviations

Acronyms	Description
AAU	Aalborg University
BCI	Brain Computer Interface
CSAIL	Computer Science and Artificial Intelligence Laboratory
DOF	Degrees of freedom
EEG	Electroencefalography
EMG	Electromyography
EP	Evoked Potential
ERP	Event Related Potential
MEG	Magnetoencephalography
MEP	Motor Evoked Potential
SDK	Software Development Kit
SEP	Sensory Evoked Potential
TCP	Tool Center Point of the robot
VEP	Visual Evoked Potential

Contents

Part I

Prologue

Chapter | 1

Introduction

Despite being complex and sophisticated, the human nervous system is still fragile. Therefore, certain kinds of damage involving either the brain or the spinal cord can lead to a state of paralysis in which a person is hardly able to interact with the world.

In order for the brain to interact with the surroundings, it communicates with peripheral nerves through the spinal cord. Whenever change happens in someone's surroundings, it is received as a stimuli, which can be visual, tactile or other sensory input on the body. Then, this stimuli is integrated and after the information is processed, a motor output, which is a body movement, can occur as a response to the initial stimuli.

However, when a person suffers from damage in the spinal cord, this path is altered. Since some of the parts of the nervous system are damaged, there are certain stimuli which can no longer be either received or integrated, and therefore the body will not be able to produce a response. On the other hand, those stimuli which occur at a point where the nervous system is not damaged still can be received.

In the case of tetraplegia, all four limbs and torso are completely paralyzed and the nervous system remains undamaged only from the neck and above. Meaning that the person is able to receive all sorts of visual, auditory or other sensory input which is located above the injury level and process it, but the person can only physically respond with motion within neck and above. Even when the motor output can not be generated since it involves parts of the body below the injury level, the command on how to respond to the stimuli is still produced. Therefore, due to improvements in science and technology, it is possible to analyze the brain activity which is happening in the brain and aid tetraplegics to form a response accordingly based on the commands originated in their brains. This process is done by recording the brain activity triggered by neurotransmitters causing an electrical polarity change. Thus, by using sensors the electrical impulses can be measured and recorded with help from electroencephalography (EEG), which allows to process the brain waves and control a robotic solution that improves the quality of life of tetraplegic patients. (1).

Part II

Analysis

Chapter | 2

Spinal Cord

The following chapter is an overview of the spinal cord and the different injuries involving it, as well as the consequences they imply. The purpose of this chapter is to provide basic information about the challenges people with spinal cord injuries are facing.

To get a better understanding of the spinal cord anatomy a detailed description of the system will be given. This is a system of nerves in-closed by Myelin and butterfly-shaped vertebrae. This is divided into distinct regions which can be seen in figure 2.1. A more detailed description of the figure can be seen in the list below.

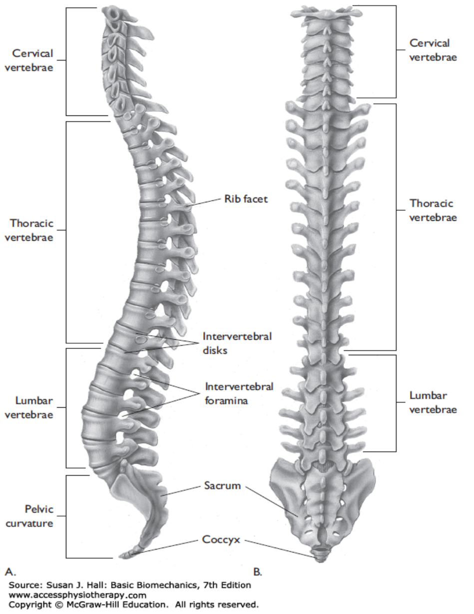

Figure 2.1: Representation of the segments and functions of the spinal cord (2)

1: The cervical spinal cord, is where the spinal cord, neck, and back are connected, known as C1-C8.

2: The thoracic spinal cord, is the middle part of the back, with twelve vertebrae numbered T1-T12.

3: The lumbar spinal cord, lower middle on the back, with five lumbar vertebrae, numbered L1-L5.

4: The sacral spine, this is the lowest part of the back of the tail bone, where the nerve roots exit the spine.

5: The coccygeal region, where the tail bone is, with a vertebra at the base of the spinal cord (3).

2.1 Types of Spinal Cord Injuries

There are two types of spinal cord injuries (SCI): complete SCI and incomplete SCI. In the case of complete SCI, any motor and sensory function below the level of injury is lost. Whereas incomplete SCI patients are still able to move to some extent below the injury, but with reduced mobility and sensibility.

There exist different types of incomplete SCI depending on the location of the injury, some of them are Anterior Cord Syndrome, Central Cord Syndrome, and Brown-Sequard Syndrome. Anterior Cord Syndrome hits the motor and sensory pathways in the spinal cord. This type of injury will leave the patient with some sensation but struggle with movement. Central cord syndrome is damage to the nerves that carries signals through the spinal cord. This will leave the patient with loss of fine motor skills, paralysis of the arms or partial impairment. The damage from Brown-Sequard syndrome, can vary depending on the patient, the effect of this could be a loss of control of either the left or right side of the body, leaving that side paralyzed.

Complete SCI includes Tetraplegia, which is a type of spinal cord injury that leads to paralysis of all four limbs. It is defined as damage in cervical vertebrae (C1-C7), as described in Figure 2.1. When SCI occurs, the connection of the nervous system between the brain and below the neck is broken. Therefore, motor commands from the brain and sensory signals from the nerves below the neck are not able to flow smoothly (4) (5).

This chapter gives an insight into the different types of injury. However, this project is mainly designed for patients who have limited or no mobility such as tetraplegics, meaning that it is assumed that patients are only able to move their neck or make facial expressions.

Chapter | 3

EEG, Signal Processing and Classification

This chapter describes necessary background knowledge and concepts used in this project. This will consist information about EEG, what kinds of signal that can be found in recordings from EEG, basic theories and concepts of Fourier transform and various filters and how a classification system works.

3.1 EEG

Electroencephalography (EEG) is a method to detect and read the electrical activity that occurs in the brain and it is used in various medical applications, such as psychology and neuroscience (6). In robotics, EEG can be used for Brain Computer Interface (BCI), which is a communication system that enables the brain to control computers or other external devices (7).

An EEG signal consists of different brainwaves that reflects the brain electrical activity, depending on from which brain region it is extracted. Its amplitude ranges from 0.5 to 100μV (8), and it's divided into 5 categories based on frequency bands: delta (1 to 4Hz), theta (4 to 7Hz), alpha (7 to 13Hz), beta (13 to 30Hz), and gamma (above 30Hz) (9).

There are mainly two methods to record EEG signals: an invasive and non-invasive method (10). The invasive method is measured by using fine needles, which measure the EEG signal by implanting them directly into the brain. This provides a good quality signal since it gets a signal directly from the cortex. The non-invasive method measures EEG signal using either dry or gelled electrodes, which is placed on the scalp. This, however, also measures other signals, such as those from facial muscle activities, which means that this method requires more processing to get a clear and useful signal. However, the non-invasive method is preferred since it does not require any medical supervision or certification (10).

There are other ways of obtaining signals from the scalp or the brain, such as Electromyography (EMG) and Magnetoencephalography(MEG). Electromyography(EMG) is a method used to record muscle activities, whereas Magnetoencephalography (MEG) is the process of measuring electrical currents in the brain by using magnetic fields, showing which part of it is activated. But since MEG requires a machine and a shielded chamber to avoid magnetic fields from the outside (11), and EMG is just limited to the muscle activities, it can be concluded that EEG is more suitable compared to the other methods for this project.

3.2 Evoked potential

After a stimuli is received, the brain will generate a response including a change in the electric potential which is denominated as evoked potential. However, compared to other signals in the same recording, the evoked potentials present low amplitudes and therefore can be unnoticed. In order to make the evoked potentials more recognizable, certain processing tools can be used, such as filters. Although filters can help extract the signal, there is still the risk of losing important information it might carry.

There are two major types of evoked potential: sensory evoked potentials (SEP) and motor evoked potentials (MEP). SEP is recorded from the central nervous system after some stimulus to any of the senses, such as visual or auditory. MEP is recorded from muscles after some stimulus in the motor cortex, see Figure 3.1.

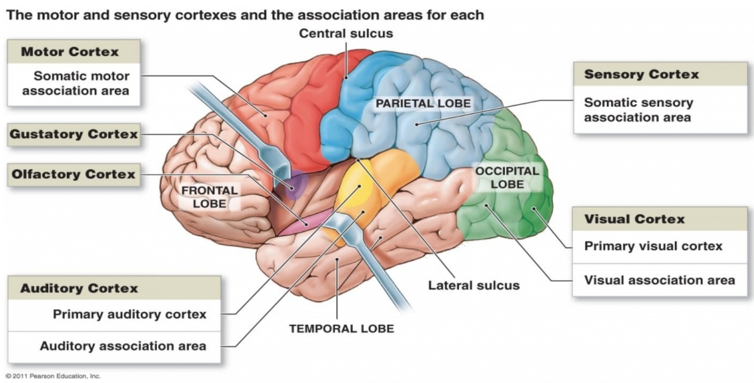

Figure 3.1: Graphical representation of the brain showing its different sections (12)

For tetraplegics, certain types of SEP and MEP are viable. However, visual evoked potential (VEP) which is part of the SEP and facial MEP can be useful. VEP is measured from the occipital cortex, see Figure 3.1, by e.g. flashing a light. It is hard to detect within the raw EEG signal without processing. The way it is processed is by extracting it from the EEG signal by using repetitive stimulation and time-locked signal filters (13). The positive aspect of VEP is that even people who suffer from conditions or diseases that do not allow the use of the facial muscles can still use this system.

3.3 Artifacts

The original purpose of EEG is to record the brain activity, but other electrical activities that are not originated from the brain are also recorded. These are called artifacts, and they are categorized into physiologic and extraphysiologic artifacts. Physiologic artifacts are generated from the user, such as muscle activities, tongue and eye movements. Where as, extraphysiologic artifacts are generated from outside the body, such as electrodes (14).

This is why many researchers who want to observe EEG signals try to filter out and minimize artifacts using various signal processing techniques. However, there are still some difficulties: for example, the gamma frequency band of EEG signals overlaps with the frequency band of muscle activities (apx. 20-300Hz) (15).

On the other hand, it is possible to make use of artifacts, without going through the complicated process of removing them. For instance, one can detect various facial movements from artifacts.

3.4 Fourier Transform

Fourier transform is used to analyze frequency components of signals so that filters can be applied to extract desired frequency bands. In this section, it will be described the general concept of Fourier transform and the filter used in this project.

Fourier transform is basically an extension of Fourier series(16), which expresses any periodic signal into a sum of harmonically related sines and cosines. It can also be expressed in complex exponentials using Euler's formula:

$$e^{ix} = cosx + isinx \tag{3.1}$$

The original periodic signal x(t) can be expressed by Fourier series as

$$x(t) = \sum_{k=-\infty}^{\infty} a_k e^{ik\omega_0 t} \tag{3.2}$$

where ω_0 is the fundamental frequency of the signal. The coefficients a_k are

$$a_k = \frac{1}{T_0} \int_{T_0} x(t) e^{-ik\omega_0 t} dt \tag{3.3}$$

where T_0 is the fundamental period, $T_0 = \frac{2\pi}{\omega_0}$. Any periodic signal can be represented as a Fourier series if it satisfies certain convergence conditions, but they are mostly satisfied in real world applications.

Fourier transform extends Fourier series to aperiodic signals by $T_0 \to \infty$ and $\omega = k\omega_0$, therefore ω becomes continuous. Equation 3.4 and 3.5 show the definition of the inverse Fourier transform and the Fourier transform, respectively (17).

$$x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\omega) e^{i\omega t} d\omega \tag{3.4}$$

$$X(\omega) = \int_{-\infty}^{\infty} x(t) e^{-i\omega t} dt \tag{3.5}$$

Fourier transform shows the distribution of frequency components of the original signal in time domain by placing the signal in frequency domain. After transforming the signal, various frequency filters can be applied to extract desired frequency bands.

3.5 Filters

Raw EEG signals contain a lot of information, but before being processed, that information is hardly usable. Therefore filters are applied to make the signals more manageable.

Frequency-selective filters are applied to extract wanted frequency band from the signal being processed, by multiplying them to the signal represented in frequency domain. Therefore, these filters should be applied after Fourier transform. There exit various kinds of filters: low pass filter passes the frequency range lower than cutoff frequency, high pass filter does the opposite, passing higher than cutoff frequency, and band pass filter passes only the selected frequency band. Plus, band stop filter passes all frequency range except the selected part.

Ideal frequency-selective filter completely passes desired frequency range and rejects the rest. It works by multiplying one to the wanted frequency band and zero to the rest, see Figure 3.2 (17).

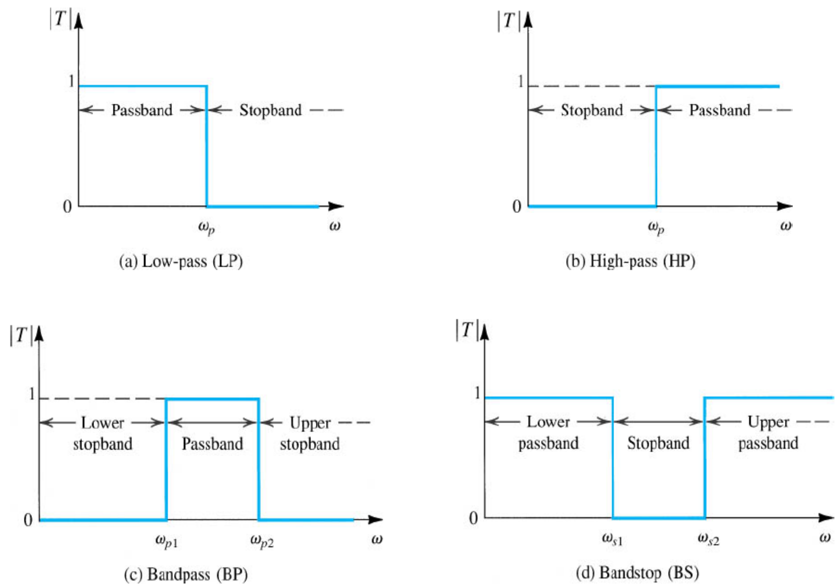

Figure 3.2: Frequency response of ideal frequency-selective filters (18)

With the help of filters, noise can be removed from the signal, such as ambient noise. Ambient noise is generated from electromagnetic radiation sources like radio transmission devices, fluorescent lights, and electrical wires. The frequency range of this noise is 50 to 60Hz, so a band stop filter can be applied to remove it (10).

3.6 Classification

The recorded signals should be classified into certain commands that will be transmitted to a robotic device. Therefore, a classification system is necessary. It gets some unclassified data as an input, extracts some features from the input, matches those features with the reference patterns, and classifies it. The reference patterns are obtained from features of training data. The features are chosen by analyzing the trends in the training data, focusing on the differences between different classes. A general block diagram of a classification system is shown in Figure 3.3.

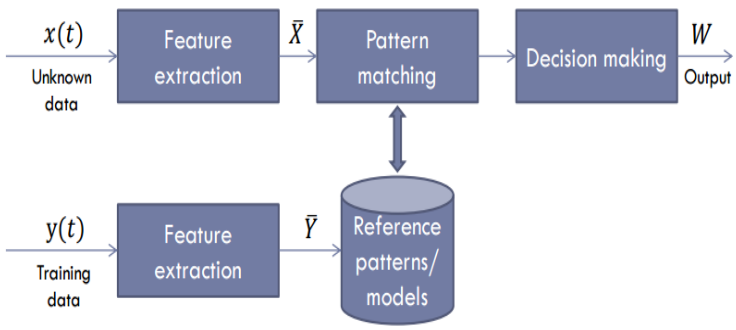

Figure 3.3: Block diagram of a classification system (19)

For example, a classification system can be used for deciding whether a picture of a fish is of a salmon or a sea bass. Length and lightness can be chosen as features for this system, since salmon is shorter and darker than sea bass. Then those two features are extracted from training data, providing information for reference patterns. It is important to have enough amount of training data. See Figure 3.4.

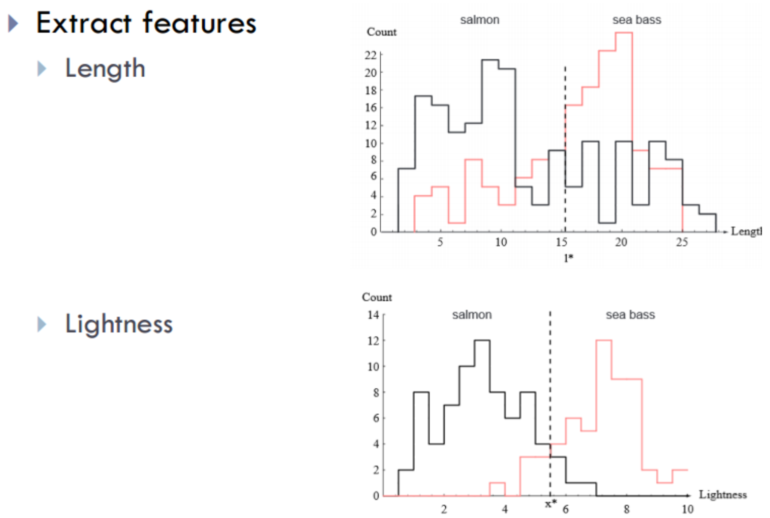

Figure 3.4: Distribution of features extracted from training data in the salmon and sea bass example (19)

Since there are usually more than one features to consider, a feature vector is formed. As for the salmon and sea example, length = X_1 and lightness = X_2, therefore the feature vector is $X = [X_1, X_2]$. There are several methods to determine the class of input data. A decision boundary can be created like Figure 3.5. Other methods like nearest neighbor classifier and Bayes classifier exist (19).

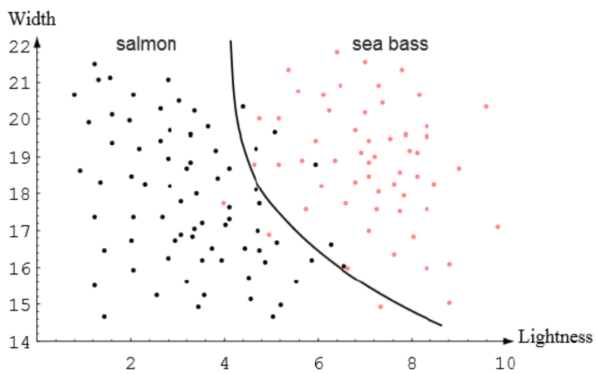

Figure 3.5: 2D feature plot with a decision boundary in the salmon and sea bass example (19)

From this chapter, it is concluded that EEG is a useful method to observe brain activities and facial movements of tetraplegics, which they can control. In order to make raw EEG recordings into usable form for controlling a robotic device, the signal processing methods and the classification system introduced in this chapter can be applied.

Chapter | 4

The Task

In the case that the user is affected by any spinal cord injury, EEG signals as described in chapter 3, can be used in a control system to read the EEG of the user. The problem lies in the recording, extraction, sampling and processing of the signal to extract the features needed to control a robotic device. The goal for this project, is to acquire signals from sensors, process them and make a classification system. This will make it possible to control a robotic arm, which in theory will enable the users to manipulate their surroundings with their brain and/or facial movements.

Chapter | 5

Current Solutions

This chapter will describe several solutions that currently exist or are being researched, to enable paralyzed patients to interact with their surroundings.

EEG has gained more popularity as a research topic during the last 20 years, and in 2015 a total of 5979 papers on the topic were published (20). Because of the increased popularity, a lot of progress is being done in EEG control of robots. Such as using wearable robotics devices that can restore control of paralyzed muscles, as they can aid in moving the patient arm or leg. Because patients with SCI usually have normal brain function, they are able to send a signal from the brain to a computer-assisted device which will allow the patient to manipulate their surroundings. This could be in the form of an Exoskeleton which helps a patient walk or perform different tasks.

An example of a real life application that uses EEG to control a mobile robot showed that they had a performance ratio of 74%. This was achieved through a combination of asynchronous EEG analysis, machine learning techniques, and advanced robotics. This example also used a statistical classifier that would classify EEG samples into three different classes or as an unknown class. The techniques used here show that noninvasive electrodes can get useful information which can be used control a mobile robot. Practical usage of this, could be to control wheelchairs for people who are paralyzed (21).

A method developed by MIT's Computer Science and Artificial Intelligence Laboratory (CSAIL) lets people correct robot mistakes. This is done is by looking for error-related potentials which occurs when the brain notices a mistake. The robot seen in Figure 5.1 places an item in one of two baskets. If it is about to place it in the wrong basket, it will trigger an error-related potential in the observer and the robot will correct itself. At the moment this method uses simple binary choice activity but researchers expect that in the future they will be able to control robots more intuitively using EEG (22).

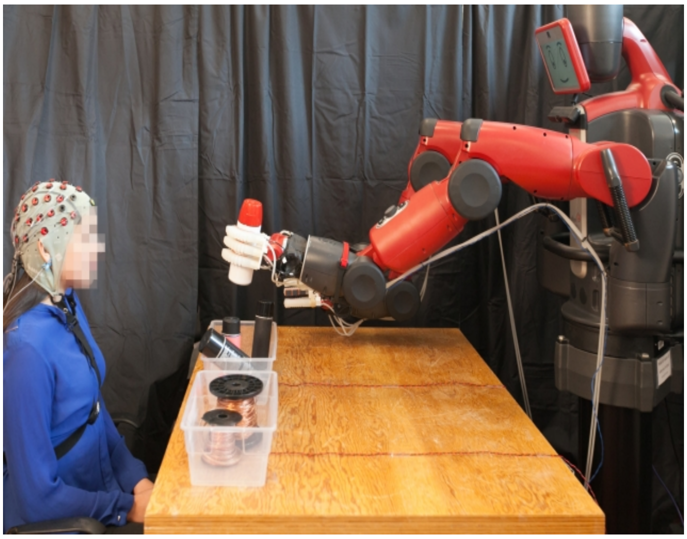

Figure 5.1: Robot developed by MIT's CSAIL. Credit for the photo goes to Jason Dorfman at MIT CSAIL.

In this chapter some of the current robotic solutions that exist or are still under research, were described. This is an overview of the advances in technology to guide this project as it develops.

Available Resources

This chapter is an overview of the available resources provided for the project. It showcases both the hardware and software and how they work together.

6.1 Emotiv Epoc

Emotiv epoc is a pre-assembled tool, that via bluetooth, is able to transmit a reading of a person's brain activity and thereby provide an overview of what brain parts react to different situations. The headset does this by utilizing the EEG signals that is conducted from the brains electrical activities. See 3. The headset has 16 channels, including two that are references sensors. If the two references sensors are not connected properly, no signal will be received from any of the electrodes. The equipment follows the 10-20 electrode placement. See the leftmost Figure 6.1

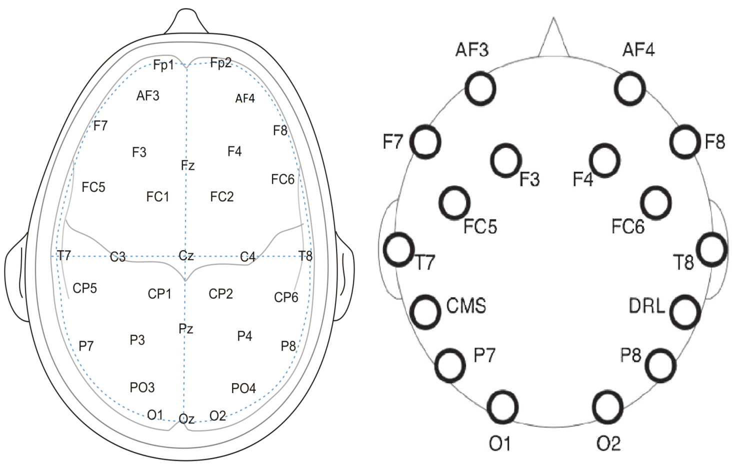

Figure 6.1: A figure of 10-20 electrode placement and the Emotive Epoc sensor placement accordingly to the 10-20 system (23)

The headset is designed so that it fits as many different head sizes and shapes as possible, thereby attempting to make it available for everyone. It has sensors strategically placed covering the frontal lobe, parietal lobe, occipital lobe and the temporal lobe of the cortex. See Figure 3.1 to see placement of lobes. The reason why these lobes were selected is due to what each individual lobe control and sense. The Frontal lobe (AF3,F7, F3, FC5, FC6, F4, F8, AF4) houses the primary motor cortex and is for controlling voluntary movement, like walking. Parietal lobe (P7, P8) houses the primary sensory cortex, and is for processing sensory information from different parts of the body. Temporal lobe (T7, T8), is for processing sensory input into either visual memory, language comprehension, and emotion association. Occipital lobe (O1, O2), houses the visual cortex which is used for visual representation of the world. The CMS and DRL is the placement of the reference sensors. See electrode placement in the rightmost Figure 6.1.

Signal resolution

The headset uses a sequential sampling method, which means that it will keep taking new observations and test them until the null is rejected. The headset has an internal sample rate of 2048 Hz and have a transmission rate of 128 Hz or 256 Hz.

6.2 Kinova JACO^2

General description
The Kinova JACO^2 robotic arm is a RRR-robot with 6 DOF that allows the robot to reach any point and orientation in space. The JACO^2 consists of 6 joint axes with actuators made of aluminum and the links of carbon fiber that gives the robot a total weight of 4,4 Kg. The reach of the JACO^2 is 900 mm which can be seen in figure 6.2 with a payload of 2,6 kg and a maximum linear arm speed of 20 cm/s.

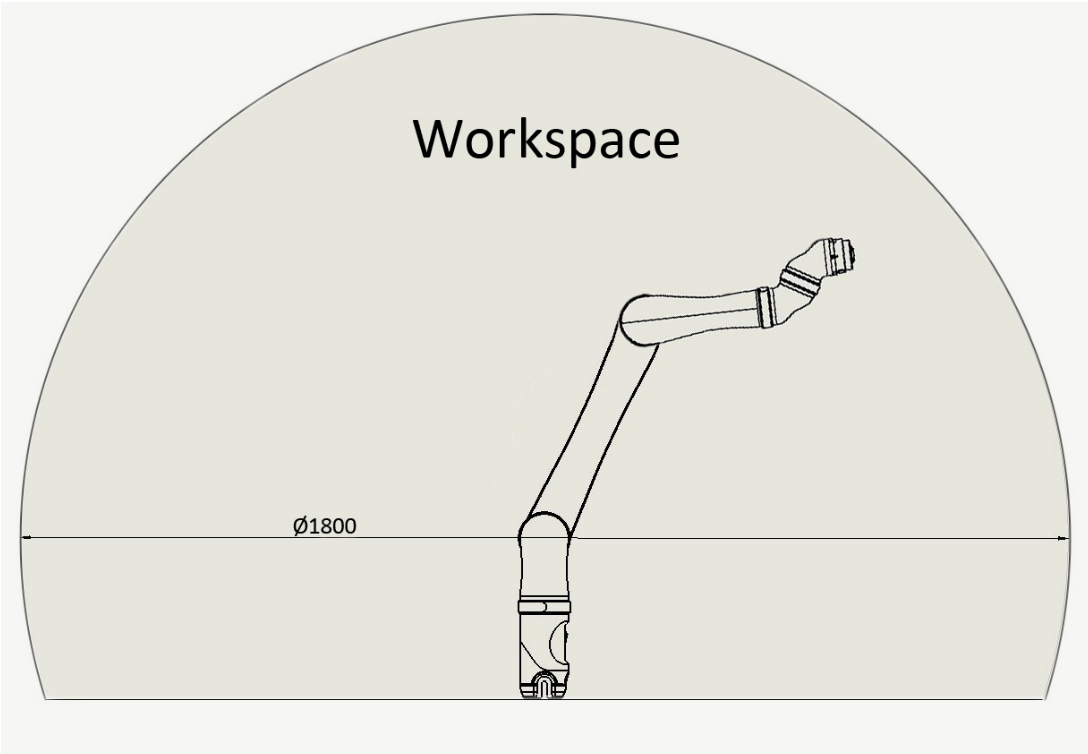

Figure 6.2: Sideview of the reachable workspace of the JACO^2 robot.

The robot can be controlled by a joystick, but can also be connected through the USB 2.0 port (24). Together with the JACO^2 comes the software "Kinova SDK", the software has a virtual joystick that makes it possible to control the robot from the computer. It also has trajectory planning and monitoring to keep track of forces, angles and position of the robot. See Figure 6.3

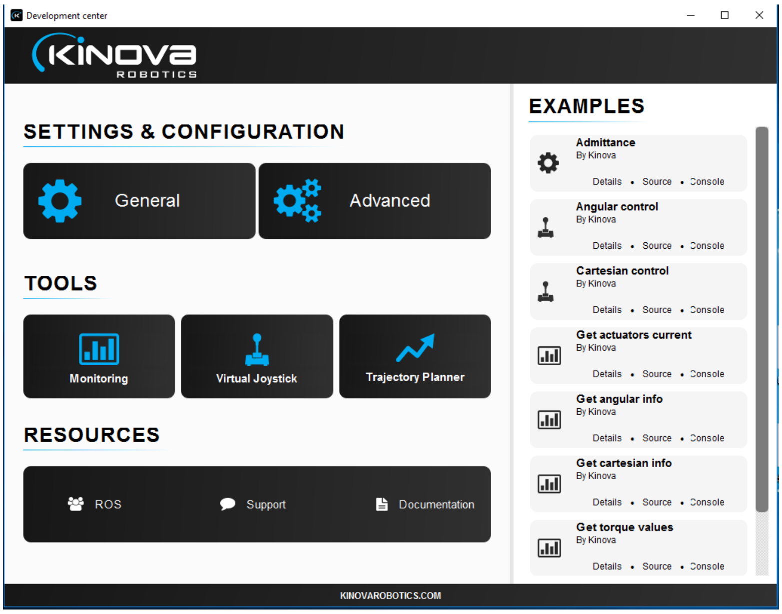

Figure 6.3: The Kinova SDK software

3D models

With a 3D model of the JACO^2 seen in figure 6.4, its possible to know specifications of the robot that otherwise could be difficult to measure or calculate. The 3D model is created by Kinovo Robotics with the measurements equal to the real world (25).

Figure 6.4: A rendered picture of the JACO^2 6-DOF 3D model

With the information provided about the sensor placement and what part of the brain they record from. This gives an idea on what sensor to use for the different recording of the user. With the use of different recording, the robot can then be control through the software provided.

Chapter | 7

Problem formulation

The problem formulation is derived from the introduction and problem analysis. The following chapters are based on the problem formulation.

- *How can sampled signals from a Emotiv Epoc be processed to control a Kinova JACO^2 robot?*

Chapter | 8

Delimitations

As the problem formulation suggests, the solution involves Emotiv Epoc and Kinova JACO^2 robot, which should fulfill certain safety regulations, as well as a number of requirements and be able to perform correctly.

This project presents data processing concepts of signals from the Emotiv Epoc to the Kinova JACO^2 robot. It also demonstrates the solution with it. The designing of the system contains: acquiring data from the Emotiv Epoc, data processing, programming, and performing tests with the robot and the Emotiv Epoc.

As the Kinova JACO^2 and the Emotiv Epoc are the only resources available, the solution is therefore limited. The finished prototype will fulfill the basic principles. However, it will not be an ideal solution to the problem presented. Subjects who suffer from tetraplegia are also not available to test the solution, therefore the authors wear the Emotiv Epoc during demonstrations and tests.

Chapter | 9

Requirement Specifications

This chapter aims to illustrate the objectives and constraints of the solution. It is an analysis of both the software and the hardware and how they work together along with a success criteria and safety requirements to ensure that the final prototype meets its needs and expectations.

Project Overview:

The solution features a system which records either EEG or artifacts, process the signal and converts that information into commands, which is used to control a robotic manipulator.

Purpose and scope:

The purpose of this project is to increase the quality of life of people who suffers from tetraplegia. This is done by analyzing either EEG or artifacts recorded from the scalp of tetraplegic patients and using that information to recognize patterns. This software classifies and sends commands based on the data, thus controlling a robotic arm accordingly.

9.1 Requirements

In Scope:
EEG or artifacts recording
EEG or artifacts sampling
EEG or artifacts processing
Data conversion into commands
Robot controlling
Testing is done with non-tetraplegic students.

Out of Scope:
Online robot control
Tetraplegic patients

Product context:
The final solution is a combination of three different products, the Emotiv Epoc, the

designed software which converts the EEG or the artifacts into usable commands, and the robotic device which performs the motor output.

User characteristics:
The final solution is aimed towards people who are paralyzed and still have a functional brain.

Assumptions:
Emotive Epoc is able to record EEG signals from the scalp.
The tetraplegic patients are able to generate movement above the neck, therefore being capable to create artifacts with facial movement.

Constraints:

System resources - Emotiv Epoc is not the most suitable device to record EEG or artifacts, but was the equipment available.

User - when recording EEG, the signal of imaginary movement of the arm and the one from actually moving it are different.

9.2 Success Criteria

Success Criteria		
Requirement	*Criteria*	*How to test*
EEG signal recording	The Emotiv Epoc must be able to record the brain activity and electrical muscles movements from the scalp	A user will wear the headset and a computer will receive the signal
Feature extraction	The EEG signal must be filtered in order to obtain useful information	By applying filters and summing several samples which show with precision a certain event happening at the same time over all the samples, the desired feature will be represented clearly and the noise will cancel out.
Pattern recognition	The software must be able to differentiate and recognize specific features.	By making a number of test and achieve a 78%(26) or higher success rate, independently of the user.
Data conversion	The software must be able to convert the extracted features into distinguishable commands	By using filters and classification it is possible to recognize and distinguish commands.

9.3 Safety regulatory framework for medical devices by European Commission

An assistive robot such as the Kinova JACO^2 falls in the category of medical devices which are regulated by Council directive 93/42/EEC first issued on the 14th of June 1993 receiving its latest amendment on the 5th of September 2007 (27). As the European Commision puts it: The aim of these Directives is to ensure a high level of protection for human health and safety. This directive is implemented into the Danish Act on Medical Devices (28).

The following section will give a summary of the segments relevant to this project.

1. The devices must be designed in a fashion that, they will not compromise the safety of the patients or other persons under its intended use. Any risk which

may occur during the associated intended use, shall be weighed against the benefits to the patient.

2. The risk of use error shall be reduced as far as possible. This includes the ergonomic features, prior technical knowledge and experience, medical and physical condition of the user.

3. Devices equipped with programmable electronics must ensure the reliability, repeatability and performance for the intended use.

4. The risks connected with resistance, stability and moving parts must be minimized.

5. The device shall have the lowest possible vibration and noise levels.

All of the above mentioned requirements are important in order for the robot to be considered functional and safe. It is therefore important that the final version of the prototype is able to fulfill all these requirements.

Part III

Development

Solution Proposals

This chapter describes the possible solutions for this project, as well as the advantages and disadvantages of them, together with the test and a discussion. Lastly, the choice of solution to work with, is made.

There are two different approaches to solve the task stated in chapter 4. One utilizes EEG signals and another uses artifacts. Each approach has its advantages and disadvantages.

10.1 EEG proposal

The EEG approach is based on either VEP, as described in 3.2, or imaginary movements. The VEP method can be implemented by flashing a light in different patterns and speed in front of the subject. This would then be registered in the occipital lobe 6.1, which induces a recordable signal. See Figure 3.1. The imaginary movement method, works by imagining a specific movement such as moving the left arm. This would create a reaction in the brain, which is reflected in the EEG signal. Both signals resulting from the two approaches can be processed into commands, to control a robotic device.

10.2 Artifacts proposal

The other approach is to use the artifacts. Whereas the imaginary movements create a change in the EEG recording due to brain activity. The artifact proposal is focused on creating distinguishable features, due to the displacement of the sensors on the scalp, when the subject makes a facial gesture.

10.3 Proposal discussion

In order to see the difference between the the proposals, three tests were setup. The first test was used as a baseline where the subject was told to sit still and clear his or hers mind. This test was used to see the difference between a test with and without provoked artifacts or EEG. The second test the subject was told to make two hard blinks. Hard blink is defined as a controlled forced blink from the user with a lot of force. In the third test a light source of 20 Hz was flashing in front of the subject.

When the tests were made different filters was applied to get a EEG signal working within its amplitude 0.5-64Hz. To do this a high pass and a band-stop filter was used. The high-pass removed signals below 0.5Hz and the band-stop removed signals from 48-53 Hz.

The result from the tests can be seen in Figure 10.1, 10.2 and 10.3

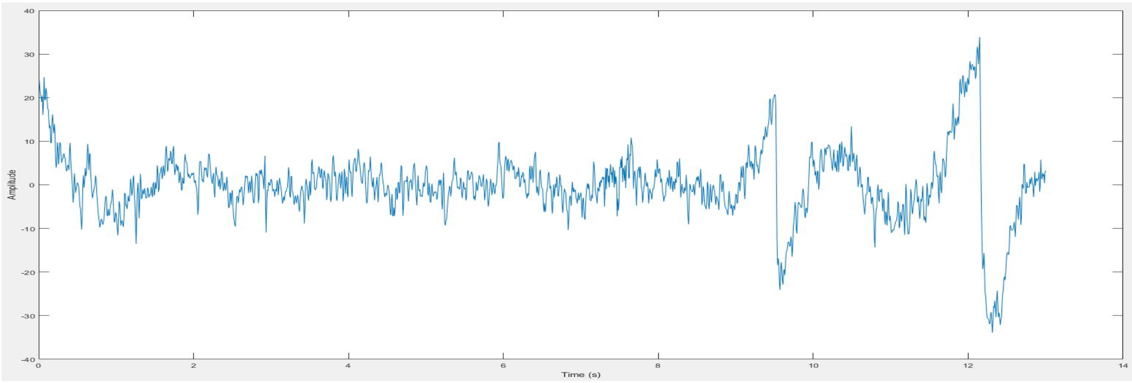

Figure 10.1: This picture shows the EEG recording of doing nothing

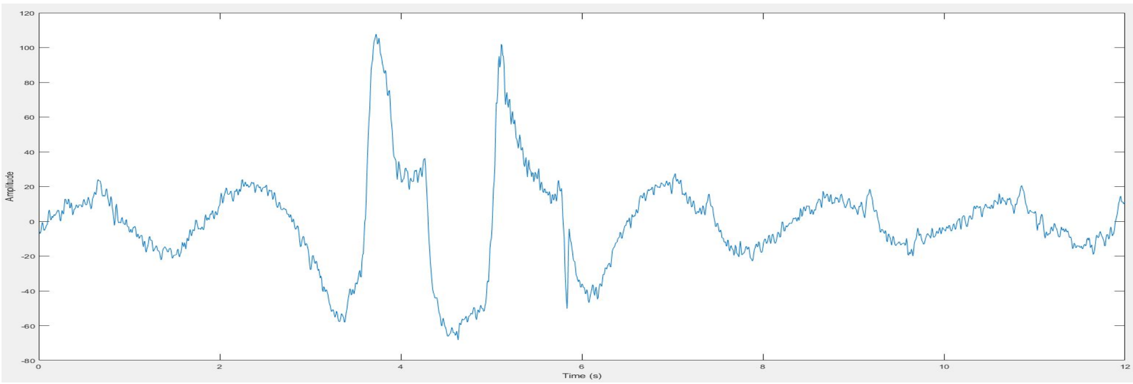

Figure 10.2: This picture shows the result of two hard blinks

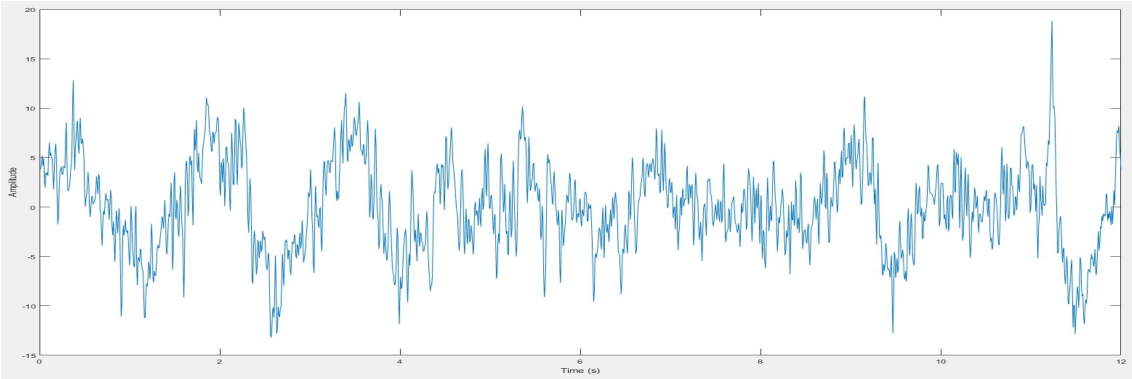

Figure 10.3: This picture shows the result of a 20Hz light source

Looking at the Figure 10.1, the result is more or less steady with no massive change in shape, going from -10 to 10 μV. This was also the expected outcome since the subject was doing nothing. Though the two sudden changes occurring around 9 and 12 seconds could be due to recording errors, resulting from a lost connection between the electrodes and the skin.

By comparing the Figure 10.1 and Figure 10.2. It can be seen that large changes happens to the shape of the signal, resulting from the forced artifacts. By comparing Figure 10.1 and Figure 10.3. There is a difference but not as detectable as in Figure 10.2.

The disadvantages of EEG signals is that the muscle activity frequency bandwidth overlaps the high-frequency brain activity. This happens due to the fact that the muscle activity frequency varies from 20 to 300 Hz, while the EEG gamma-frequency band covers from 30 to 80 Hz. Therefore, it is likely that all of the recordings are a combination of both signals, making it rather complicated to target and isolate one of them (15).

Secondly, another issue about using the EEG method, is that in order to get a proper signal, it must be properly synchronized. Due to their small amplitude, these signals are vulnerable to noise and artifacts, which makes them unreliable. Therefore, in order to solve this problem, several samples of the same of the same stimulus happening at the same time will solve the issue. When time-locking the signal and then averaging all the samples, only the features which are consistent over time in all the samples will remain, while those which differ from one another, will be cancelled out. Thus creating a event-related potential (ERP) (29).

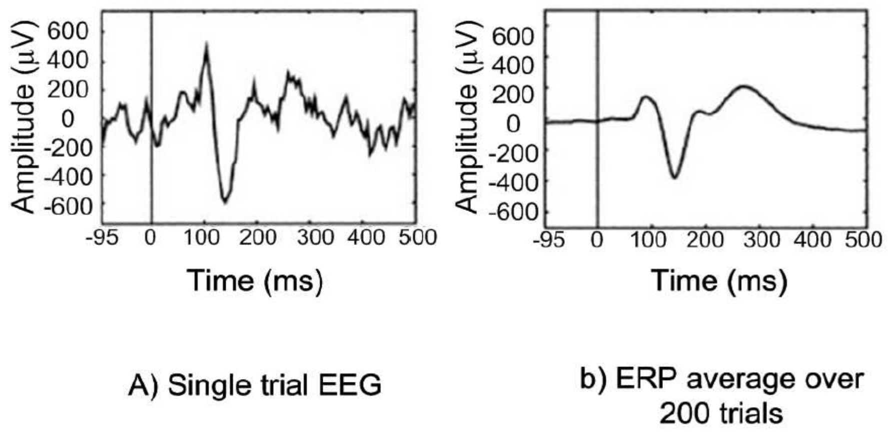

Figure 10.4: This picture shows the result from averaging 200 EEG samples to create a ERP (29)

Whereas when using artifacts, these are easier to recognize and provide more consistency as seen in Figure 10.2, they are not as influenced by noise as the EEG signals. Therefore, for this project artifacts was chosen as the solution, with the advantage of making the classification clearer, due to the shape from a forced artifacts.

After exploring and testing both proposals, the advantages of using the artifacts out weights those from the EEG brain activity, therefore, from this chapter on, the main focus of the project is to achieve control of a robot with the use of artifacts.

Chapter | 11

The Control System

This section aims to illustrate how the components of the system function together as a solution and which methods they use in order to communicate with each other.

This chapter will go through the whole system for this project, from the Emotiv Epoc to the Kinova JACO^2. The system consists of three components: The Emotiv Epoc which is the sensor for recording signals, the Computer processing where the signals are processed, and the Kinova JACO^2 which is the robotic device controlled. See Figure 11.1.

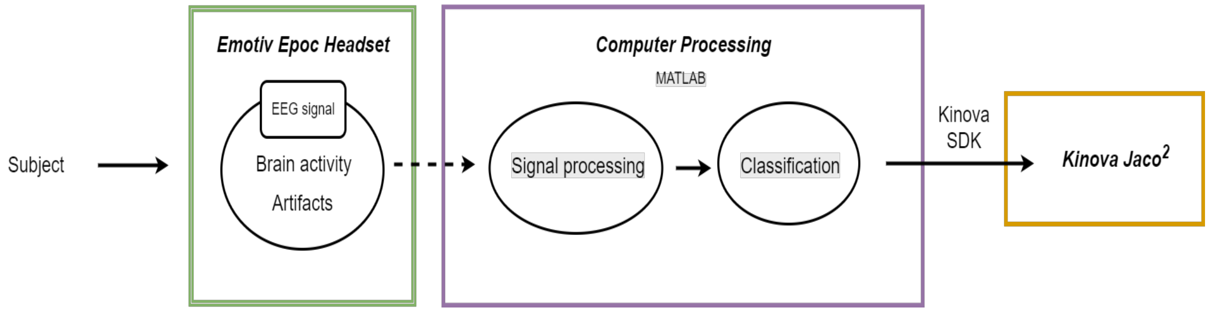

Figure 11.1: Block diagram of the system

Emotiv Epoc

This component reads the raw EEG signal directly from the scalp of the user. This data is recorded and saved as a file in the computer by the Emotiv Epoc software.

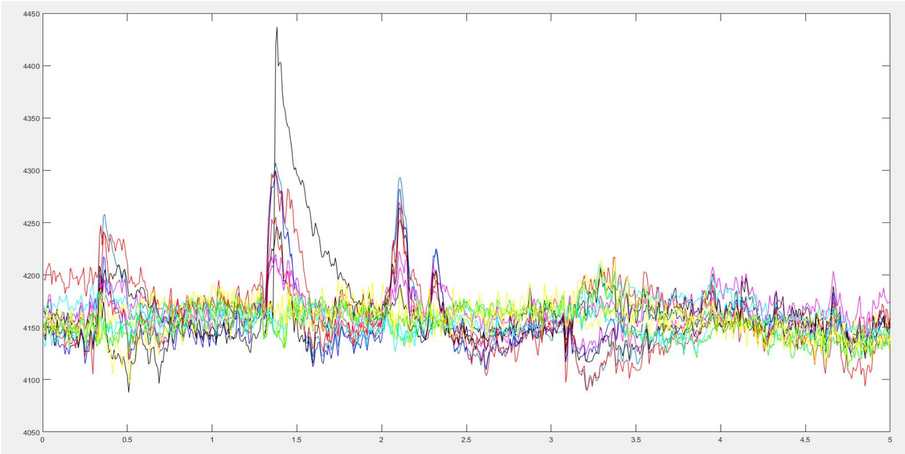

Figure 11.2: A raw EEG signal from all 14 channels. On the Y axis the amplitude in μV and on the X axis the time in seconds.

Computer Processing

In the computer, the prerecorded signal is processed through MATLAB, using Fourier Transform and filters. This is not done at the same time as recording, which means that this system is offline, expressed as a disconnected arrow in Figure 11.1. After the signal processing, the classification comes. In order to implement this, certain facial movements were selected to generate commands to the robot. Artifacts from those facial movements had certain features that can distinguish each other, which allowed to design the classification system. Therefore, the processed signal is classified and a command is generated accordingly. This is also written in MATLAB code.

Kinova JACO^2

The last component of the system is the robot, which receives commands from MATLAB through the Kinova SDK which is described in 6.2. A menu system was implemented to control the robot. This has several menus, each of them defining a certain type of movements of the robot such as right and left, or up and down. Each menu is binary, so only two types of commands are necessary to control within a menu. There is an additional third command, which is assigned for navigating through the menus. By implementing this menu system, types of facial movements required are minimized while the degrees of freedom of the robot are maximized, making the entire system simple both for the authors and the users.

This chapter gave an overview of the system for this project, the solution will then focus on is the Emotiv Epoc and the Computer Processing.

Chapter | 12

Implementation

In this chapter a go through of the implemented software will be presented and how the artifacts used to control it was selected.

12.1 Artifacts

EEG signals were recorded from the Emotiv Epoc when subjects were doing these certain movements: lifting eyebrows(12.1, lower right), blinking both eyes(12.1, lower left), blinking only the left(12.1, upper left) or the right eye(12.1, upper right). These movements are rather easy to practice and not as confusing with daily movements such as chewing or frowning. Those kinds of eye blinking used here is 'hard blinking', forced blinking with more strength than usual unintentional blinking. This experiment only focused on channel AF3/AF4 and F7/F8 which are closely located to the eyes and eyebrows. See Figure 6.1.

However, EEG recordings from AF3 and AF4 were more noisy than those from F7 and F8. See (12.1, lower right). Also, it was difficult to distinguish between eyebrows lifting and blinking by observing the shapes of the signals from F7/F8. See Figure 12.1, lower right and (12.1, lower left). However, as for blinking, three kinds of movements are available as shown in Figure (12.1, upper left and right, lower left) and there were obvious differences between EEG signals from those three artifacts. Therefore, only EEG signals from channel F7/F8 by blinking are implemented for classifying commands, discarding eyebrows lifting.

Figure 12.1: The facial movements used for testing. The two top pictures show the left and right eye hard blink. The lower left picture shows hard blink with both eyes and the lower right shows lifting eyebrows.

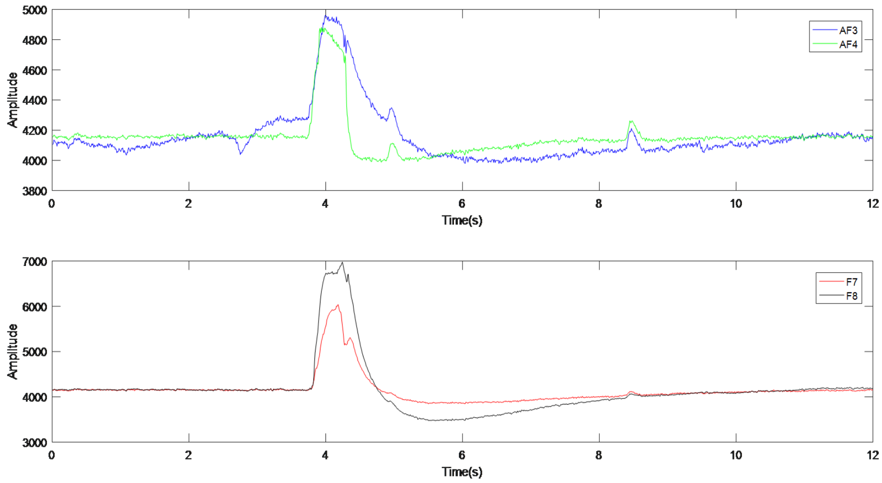

Figure 12.2: Blinking both eyes by a right dominant eyed person: channel AF3/AF4, F7/F8

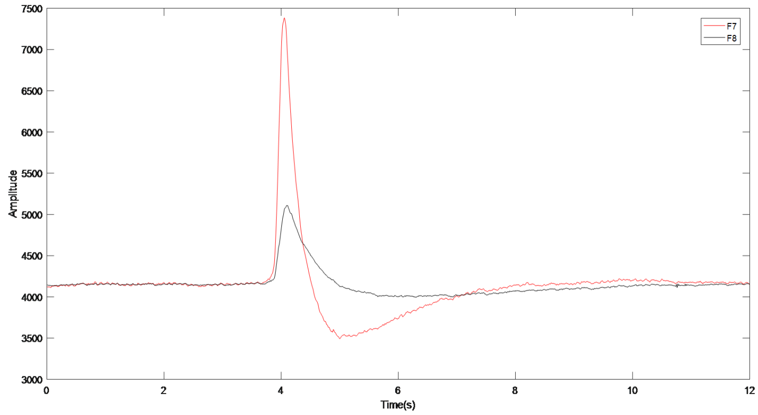

Figure 12.3: Blinking both eyes by a left dominant eyed person: channel F7/F8

For blinking with both eyes, both F7 (left) and F8 (right) had one high spike, but it seems like there was an interesting difference between dominant left- and dominant right eyed people. For dominant left eyed people, F7 had a higher spike than F8, where dominant right eyed people had a higher spike in F8 than F7. See the difference between right and left eyed subjects in Figure 12.2 and Figure 12.3.

When the subjects blinked their left eye, F7 had one high spike, and the opposite happened when they blinked their right eye. These are illustrated in Figure 12.4 and Figure 12.5. Therefore, 3 types of actions -blinking both eyes, the left eye, and the right eye- are detected and classified by sensing spikes in EEG signals from channel F7 and F8.

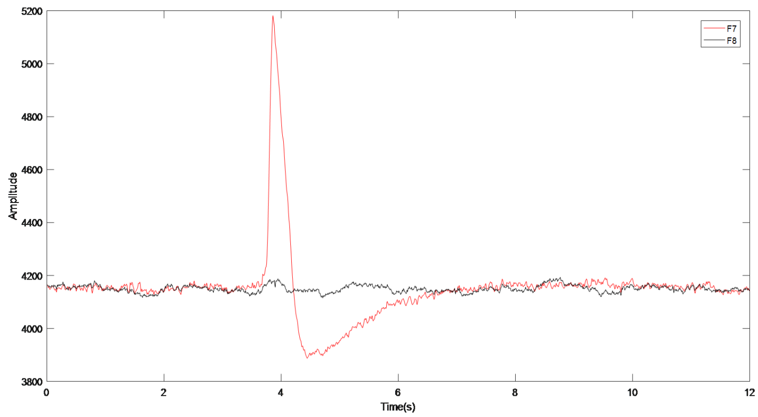

Figure 12.4: Blinking left eye: channel F7/F8

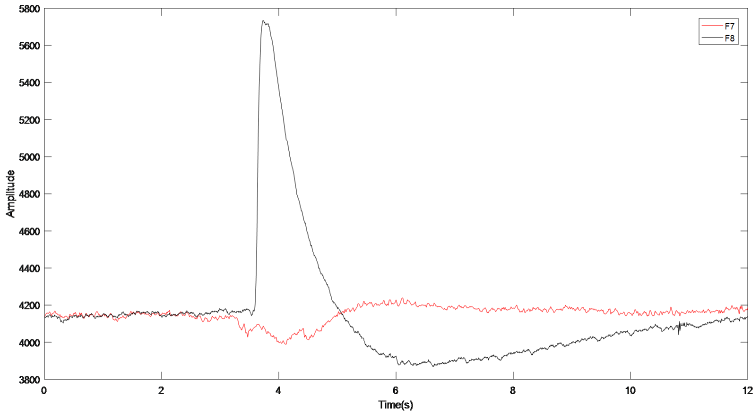

Figure 12.5: Blinking right eye: channel F7/F8

12.2 Signal Processing

First, raw EEG recordings were Fourier transformed to show their frequency distributions. Then, an ideal low pass filter was applied to remove high frequency components above 5Hz and a band-stop filter to remove the ambient noise, which makes the analyzing easier. Figure 12.6, 12.7, 12.8 and 12.9 show the procedure of Fourier transform and filtering of the signals from channel F7 and F8.

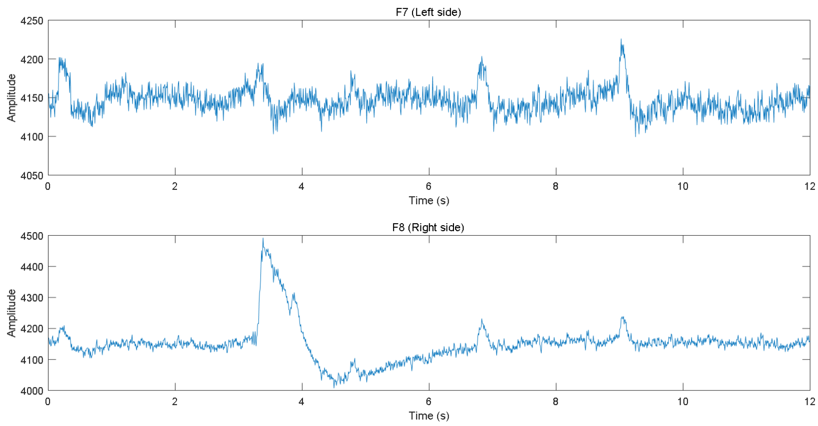

Figure 12.6: Original signals

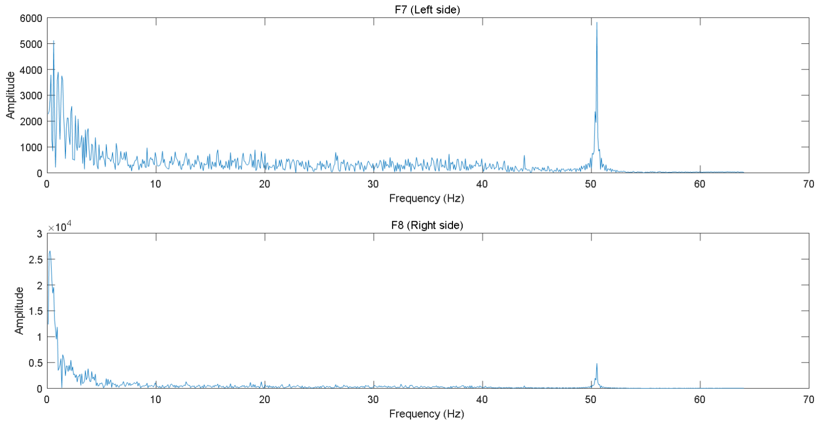

Figure 12.7: Fourier transformed signals

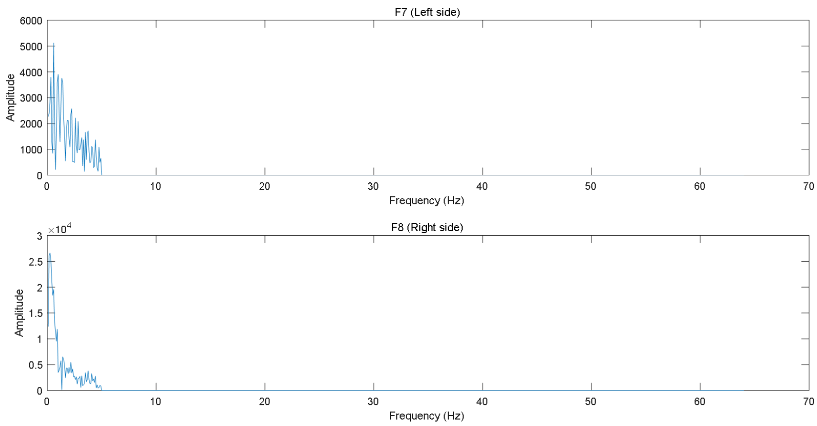

Figure 12.8: Fourier transformed signals after applying the low pass and band stop filter

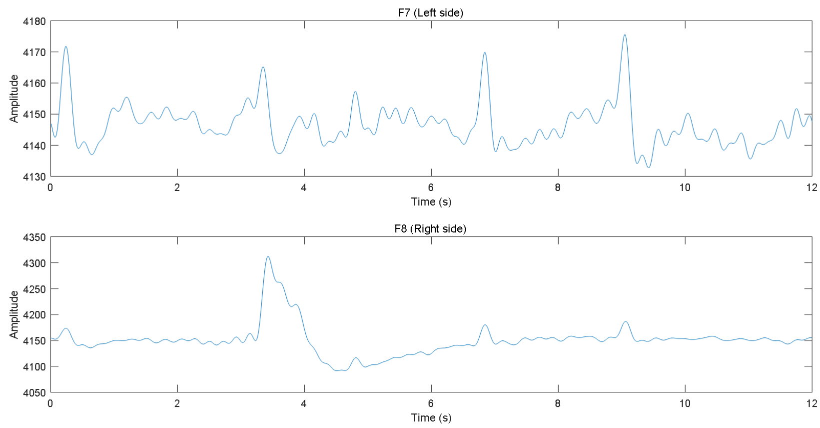

Figure 12.9: Inversed Fourier transformed signal after filtering

12.3 Implemented Code

The initial plan of this project was to make the communication between the Emotiv Epoc and MATLAB online. This however turned not possible in the time frame given for this project. The communication is therefore done offline where the user first records data from the headset by doing necessary actions. See Figure 12.1. This data is saved as a file from the Emotiv Epoc. Then the MATLAB program opens the file and generates key-commands for the Kinova SDK.

In the beginning, the program will read the recording and start processing the signal from channel F7 and F8 with Fourier Transform and a low-pass filter. The low-pass filter is added to reduce the high frequency spikes which will make the signal smooth and easier for the program to read. Then the program classifies the signal among three facial movements with the help of threshold values.

The threshold values, set from the observations in 12.1, detect high spikes by looking at the amplitude of the signal. The classification system works by observing which channel that high spikes are generated from, since they appear in both channels when the user is blinking both eyes, only in F7 when blinking only the left eye, and only in F8 when blinking only the right eye. After the classification, the program generates commands accordingly and sends them to the Kinova SDK. This communication is done online.

The user is able to control the robot by either blinking left or right eye. These actions controls the robot's TCP which can be:

- Open and Close gripper
- Right and left

- Up and down
- Forwards and backwards
- Yaw +/-
- Pitch +/-
- Roll +/-

Each pair of these actions are called a "Menu", and by blinking with both eyes at the same time, the user swaps between these Menus.

Chapter | 13

Data collection and Test

After the implementation of the signal processing and classification in MATLAB code, tests were executed to ensure that the system worked.

13.1 Subjects

To test the system, recordings from seven adults, both male and female, between 19-30 were sampled. Each subject was told to do a sequence of facial movements. The participants did not have any history of neurological or psychiatric illness nor did any of them use any chronic medication. All participants gave informed consent before the testing.

13.2 Data Collection

A procedure for generating artifacts was created, and the sequence consisted of 17 artifacts in the following order: 3, 1, 1, 3, 2, 3, 1, 1, 1, 3, 2, 2, 3, 2, 3, 1, 1. Where 3 represents blinking both eyes at the same time, 1 showcases blinking just the left eye and 2 is for blinking the right eye. This gave participants instructions on which movement to do during each repetition. Every subject repeated the sequence 10 times. This was done with the subject looking straight into a white wall in a quiet room to get the least amount of noise or alterations in the brain activity. Each sequence was on average 30 seconds long. This sequence of data is recorded and saved. After that, it will be uploaded to the program which communicates with the robot and extracts commands to move it accordingly.

When a wrong movement occurred during the test, the data was made invalid and that specific sequence was redone to ensure consistency. Other kinds of facial movements were tried before this testing to observe their feature, but they were too inconclusive and therefore discarded. There were some sources of error in the data collecting, such as long or thick hair. This made the data gathered from the subjects having either or both unreliable because the sensors couldn't make a proper connection. Therefore, at the end of the testing, only five of the seven original subjects were able to provide observable samples.

13.3 Test

Once the artifacts are uploaded to MATLAB, the test started evaluating two different aspects:

In the first part of the testing, the focus is placed on the movement of the robot from a point A, the starting location, to an area B. The reason why the second location is an area instead of a point is to give the robot a margin of error. If the robot reached the B area within the sequence performed, the test would be considered as a success, otherwise, it would be a fail. The test was performed a total of 50 times, with ten samples by five different subjects. For the test, the robot had an starting position in meters as showed in vector

$$\overrightarrow{A} = \begin{pmatrix} 0.2123 \\ -0.2572 \\ 0.5097 \end{pmatrix} \tag{13.1}$$

In order to calculate the area B, the tests where the robot performed accordingly, the artifacts were taken as a reference, and an arithmetic mean with some margins was calculated to find the area B. The resulting area B is described by the following vector:

$$\overrightarrow{B} = \begin{pmatrix} 0.2812 \pm 0.0350 \\ -0.2290 \pm 0.0100 \\ 0.5558 \pm 0.0450 \end{pmatrix} \tag{13.2}$$

The results are illustrated in the following tables, where all the units correspond to meters and are measured in relation to the base of the robot.

Person 1				
Number of test	***A to B***	***X Coordinate***	***Y Coordinate***	***Z Coordinate***
1	YES	0.2884	-0.2207	0.5791
2	YES	0.3067	-0.2356	0.5125
3	NO	0.2465	-0.2714	0.5267
4	NO	0.2467	-0.2465	0.5670
5	NO	0.2685	-0.1903	0.5910
6	NO	0.2163	-0.3007	0.4649
7	NO	0.2329	-0.2456	0.5274
8	YES	0.2487	-0.2308	0.5757
9	NO	0.1930	-0.2754	0.4775
10	NO	0.2727	-0.1876	0.5682

Person 2				
Number of test	***A to B***	***X Coordinate***	***Y Coordinate***	***Z Coordinate***
1	NO	0.1694	-0.2615	0.4894
2	NO	0.1840	-0.2418	0.4798
3	NO	0.2256	-0.1737	0.5072
4	NO	0.0748	-0.2770	0.4818
5	NO	0.2063	-0.2579	0.5058
6	NO	0.1970	-0.2100	0.5070
7	NO	0.2177	-0.2013	0.4462
8	NO	0.1785	-0.2688	0.4778
9	NO	0.1461	-0.2538	0.4560
10	NO	0.1718	-0.2729	0.4704

Person 3				
Number of test	***A to B***	***X Coordinate***	***Y Coordinate***	***Z Coordinate***
1	NO	0.2740	-0.3048	0.5315
2	NO	0.2824	-0.1294	0.5005
3	NO	0.2750	-0.2900	0.5012
4	NO	0.3253	-0.2787	0.4992
5	NO	0.3265	-0.2480	0.4907
6	NO	0.2499	-0.2934	0.5037
7	NO	0.2346	-0.3452	0.4782
8	NO	0.2365	-0.3592	0.4928
9	NO	0.3342	-0.2626	0.5209
10	NO	0.2155	-0.3370	0.5141

Person 4				
Number of test	***A to B***	***X Coordinate***	***Y Coordinate***	***Z Coordinate***
1	NO	0.1884	-0.2490	0.5173
2	NO	0.2055	-0.2488	0.5531
3	NO	0.2127	-0.2548	0.5006
4	NO	0.2012	-0.2490	0.5262
5	NO	0.2202	-0.2521	0.5127
6	NO	0.2148	-0.2625	0.5055
7	NO	0.2119	-0.2526	0-4828
8	NO	0.2254	-0.2647	0.5137
9	NO	0.2268	-0.2615	0.5031
10	NO	0.2190	-0.2900	0.5105

Person 5				
Number of test	***A to B***	***X Coordinate***	***Y Coordinate***	***Z Coordinate***
1	NO	0.2017	-0.2593	0.4888
2	NO	0.1684	-0.2871	0.4841
3	NO	0.1402	-0.2875	0.4995
4	NO	0.0013	-0.2938	0.4864
5	NO	0.1795	-0.2741	0.4541
6	NO	0.1114	-0.2719	0.5067
7	NO	0.1974	-0.2505	0.5057
8	NO	0.1500	-0.2488	0.4616
9	NO	0.0749	-0.3586	0.4708
10	NO	0.2385	-0.1808	0.4614

The second part of the testing, does not focus on the performance of the robot, but rather on the accuracy of the program to recognize and classify the recorded artifacts. In order to do that, every artifact is performed and checked whether or not the command is recognized accordingly. The results are illustrated in the following tables. The dots describe a correctly detected artifact, the cross a misread one and the lines tells when no artifact was detected. The 'Extras' is the amount of more artifacts identified than expected.

This chapter contains the specification of the test-subjects and explains the procedure which was used to test the accuracy of the robot and the program. It also showcases the results obtained from these tests.

Artifacts of person 1																		
Test	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***	***12***	***13***	***14***	***15***	***16***	***17***	***Extras***
1	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	—
2	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	—
3	•	•	•	•	•	X	•	•	•	•	•	•	•	•	•	•	X	—
4	•	•	•	•	•	•	•	•	•	•	•	•	•	X	•	•	•	—
5	•	•	•	•	•	•	•	X	•	•	•	•	•	•	•	•	•	—
6	•	•	X	•	•	•	•	X	X	•	•	•	•	•	•	•	•	—
7	•	X	•	•	•	•	•	X	X	•	•	X	•	•	•	•	X	—
8	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	—
9	X	X	X	•	X	X	X	X	•	•	X	•	•	X	X	X	•	+2
10	•	•	•	•	•	•	X	X	•	•	X	•	•	•	•	•	X	—

Artifacts of person 2																		
Test	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***	***12***	***13***	***14***	***15***	***16***	***17***	***Extras***
1	•	•	X	X	X	X	X	X	X	X	—	—	—	—	—	—	—	-7
2	•	X	X	X	•	•	X	X	X	—	—	—	—	—	—	—	—	-8
3	•	X	X	X	•	X	X	X	X	X	—	—	—	—	—	—	—	-7
4	X	X	X	X	•	X	X	X	X	•	•	—	—	—	—	—	—	-6
5	X	X	X	X	•	X	X	X	X	•	—	—	—	—	—	—	—	-7
6	X	X	X	•	•	X	X	X	X	•	•	—	—	—	—	—	—	-6
7	•	X	X	X	•	X	X	X	X	•	•	X	X	—	—	—	—	-4
8	•	X	X	•	X	X	X	X	X	•	•	X	X	—	—	—	—	-4
9	•	X	X	•	•	X	X	X	X	•	•	—	—	—	—	—	—	-6
10	•	X	X	X	X	X	X	X	X	X	•	•	•	•	—	—	—	-3

Artifacts of person 3																		
Test	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***	***12***	***13***	***14***	***15***	***16***	***17***	***Extras***
1	•	•	X	X	X	•	X	X	•	•	X	X	•	X	X	X	X	+1
2	•	•	X	•	X	•	X	•	•	•	•	•	•	X	•	•	•	—
3	•	•	X	•	X	•	X	X	•	•	X	X	•	X	X	X	•	+2
4	•	•	X	•	X	•	X	X	•	•	X	X	•	X	•	•	•	—
5	•	•	•	•	X	X	X	X	•	X	X	X	•	X	•	X	X	+1
6	•	X	X	•	X	•	X	X	•	X	X	X	•	X	•	X	X	+1
7	•	X	•	•	X	•	X	•	•	•	X	X	•	X	X	X	•	+1
8	•	X	•	•	X	•	X	•	X	•	X	X	•	X	•	•	•	—
9	•	•	•	•	X	•	X	•	•	•	X	X	•	X	•	•	—	-1
10	•	X	X	•	X	•	X	•	•	•	X	X	•	X	•	X	•	—

Artifacts of person 4																		
Test	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***	***12***	***13***	***14***	***15***	***16***	***17***	***Extras***
1	•	X	X	X	X	•	X	X	X	•	X	•	X	—	—	—	—	-4
2	•	X	•	•	X	X	X	X	X	X	•	X	•	—	—	—	—	-4
3	•	•	X	X	X	X	•	•	X	X	X	X	•	X	•	X	—	-1
4	•	X	X	•	X	X	X	X	X	X	X	X	•	X	—	—	—	-3
5	•	•	X	•	X	•	•	X	•	X	X	X	•	•	•	—	—	-2
6	•	•	X	X	X	X	X	•	X	X	X	X	•	—	—	—	—	-4
7	•	X	X	•	X	•	X	X	X	•	•	X	•	X	X	•	—	-1
8	•	•	X	X	X	X	•	•	X	X	X	X	•	X	X	X	—	-1
9	•	•	X	•	X	•	•	•	X	•	X	X	•	X	•	•	X	—
10	•	•	•	•	X	•	•	X	•	•	X	X	•	•	X	X	X	—

Artifacts of person 5																		
Test	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***	***12***	***13***	***14***	***15***	***16***	***17***	***Extras***
1	•	X	•	•	•	X	X	X	•	•	•	X	X	—	—	—	—	-4
2	X	•	X	X	•	•	X	X	X	X	•	X	X	X	—	—	—	-3
3	•	X	X	•	X	•	•	X	X	X	•	X	•	X	X	X	—	-1
4	X	•	X	X	•	X	X	X	X	X	X	X	X	•	—	—	—	-3
5	•	X	X	X	X	X	X	X	X	X	X	•	X	—	—	—	—	-4
6	•	X	X	X	•	X	X	X	X	X	X	X	—	—	—	—	—	-5
7	•	X	X	X	X	X	X	X	X	•	X	—	—	—	—	—	—	-6
8	•	X	X	•	X	X	X	X	X	X	X	X	•	•	—	—	—	-3
9	•	•	X	X	•	X	X	X	X	X	•	•	•	•	•	•	X	+1
10	X	X	X	X	•	X	X	X	X	X	X	•	•	•	—	—	—	-3

Statistics of test

The aim of this chapter is to mathematically analyze the viability of the solution. In order to do so, a statistical analysis was performed based on the testing.

Based on the data, two different kinds of statistical approaches were used. The first one is descriptive statistics which summarizes the data obtained in the sampling. The second one, inferential statistics, draws conclusions from data which is subject to random variation, such as EEG.

In order to withdraw conclusions, the solution was tested in two different ways. The first method analyzes how capable is the solution to identify each artifact correctly. The second analysis, instead of focusing on the individual artifacts, evaluates on the final outcome. It does so by testing if the robot is able to move from point A to area B in a defined number of performed artifacts, disregarding weather or not all of the artifacts are correctly identified.

The following Venn diagram 14.1, shows the results from the testing.

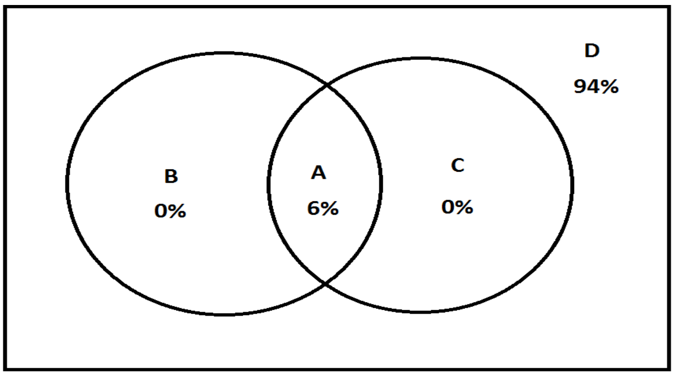

Figure 14.1: Representation of the test. Not at scale.

The square where the image is contained represents the sample space, where a total of 50 tests were performed. The section A represents the percentage of the tests where the robot was able to move from one point to another and correctly identify every single artifact. The section B showcases the tests where the robot accomplished the displacement, but at least one of the artifacts was misread. The section C is a representation of the tests where the robot did not move from a specified location to another even though all of the artifacts were properly interpreted. Finally, the area outside of the circles, which is represented as D, showcases the tests where the robot did not accomplish the desired movement and at least one of the artifacts was misread. From this, it can be assumed that the robot will only achieve the desired end position, if all of the artifacts are correctly identified. It also showcases a small success rate when analyzing both tested aspects together. The reason why B and C is 0%, is because it never reach B or C, instead all results is either A or D, since according to the test the robot preform accordingly.

When analyzing how well the program interpreters the artifacts, a frequency table was drawn.

Number of misread artifacts	*Number of tests*
0	3
1	2
2	1
3	1
4	1
5	3
6	5
7	5
8	9
9	8
10	8
11	5

The column to the left is a numerical representation of how many artifacts, that were unsuccessfully read in the tests. The column in the right, shows the number of tests which presented this outcome. The column is ranging from 0-11, due to no misreadings above 12.

From all of the tests, it was obtained that out of the 850 artifacts performed, 376 of them (44%) were correctly recognized, 363 (43%) were mistaken and 111 (13%) were not able to be recognized. Additionally, 9 artifacts (1%) were recognized when they were not supposed to. The individual analysis of the five subjects showed that the first person achieved a 84% success rate, followed by the third person, with 52%, then the fourth with 39%. The fifth person got a 25% success rate and finally the second person achieved 20%.

The following Figures 14.2, 14.3, 14.4, 14.5, 14.6 showcase the position in space of the end-effector in all of the tests. The three black x represent the successful tests.

The blue dots correspond to the first person, the red to the second and the green to third. Likewise, the fourth person is represented by the yellow dots and the fifth by the pink ones.

All figures shows the same set of points but from different perspectives, showing the different sides of the sampling space.

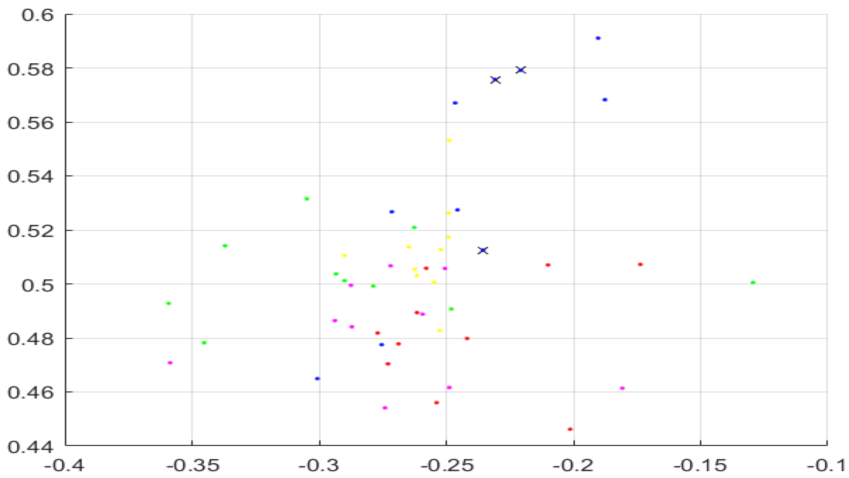

Figure 14.2: Coordinate representation from the front

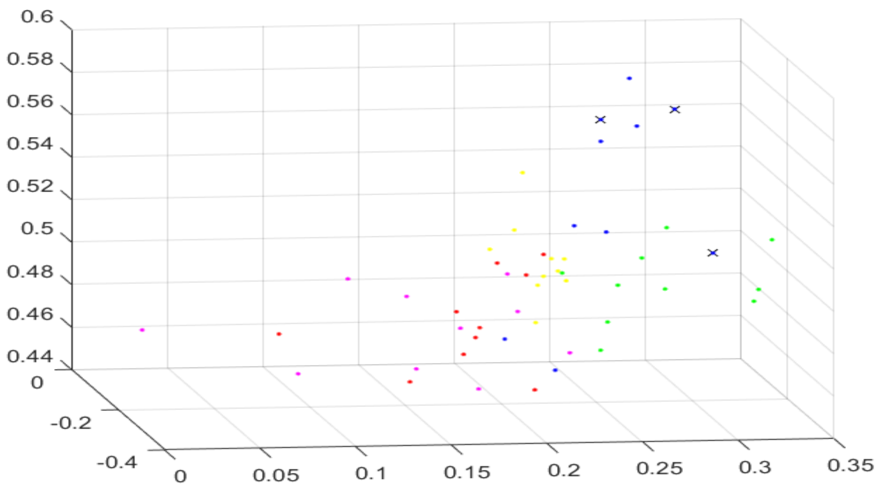

Figure 14.3: Coordinate representation lateral view

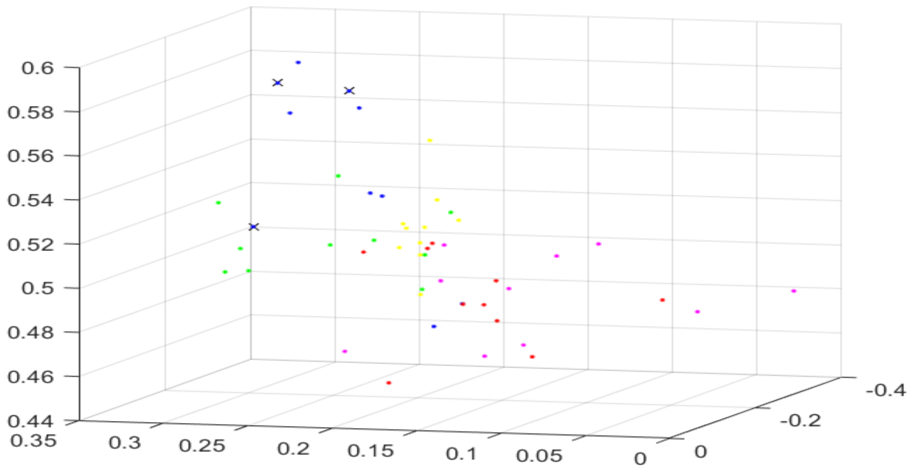

Figure 14.4: Coordinate representation from opposite lateral views

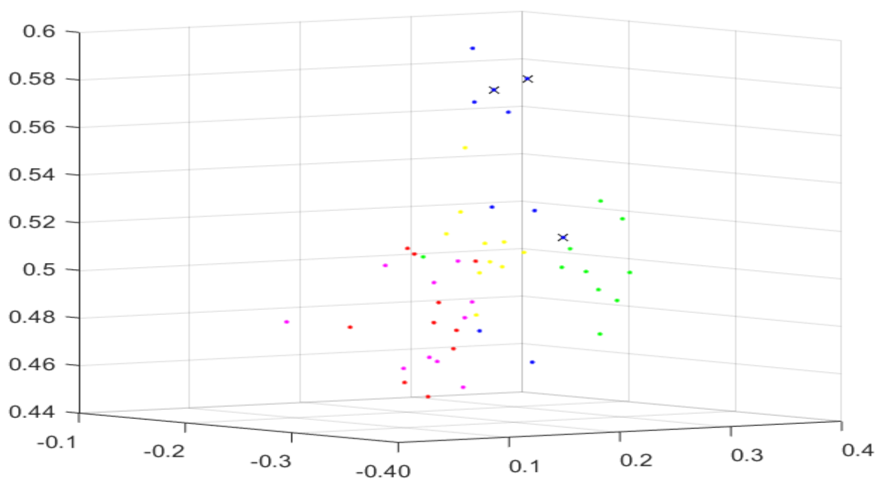

Figure 14.5: Coordinate representation with depth perception

Figure 14.6 is a 2D representation of the samples from above.

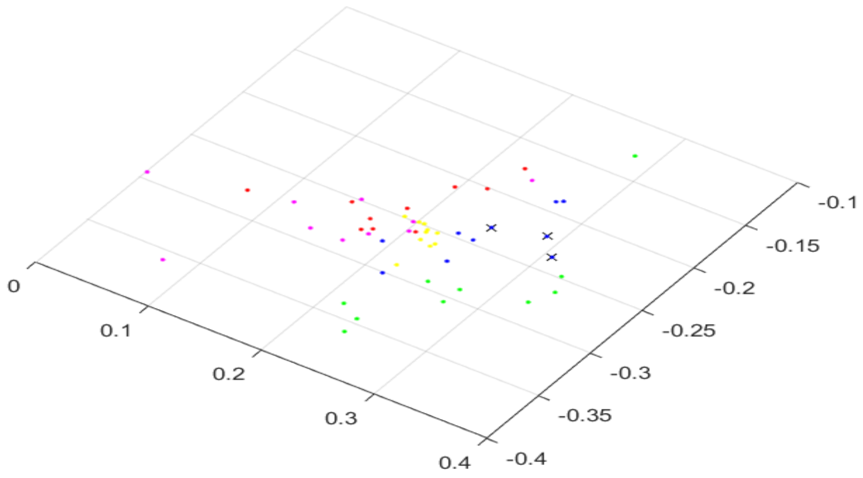

Figure 14.6: Coordinate representation from above

Finally, the following graph 14.7 is a histogram of the variation in the position taken by the end-effector through the different axis.

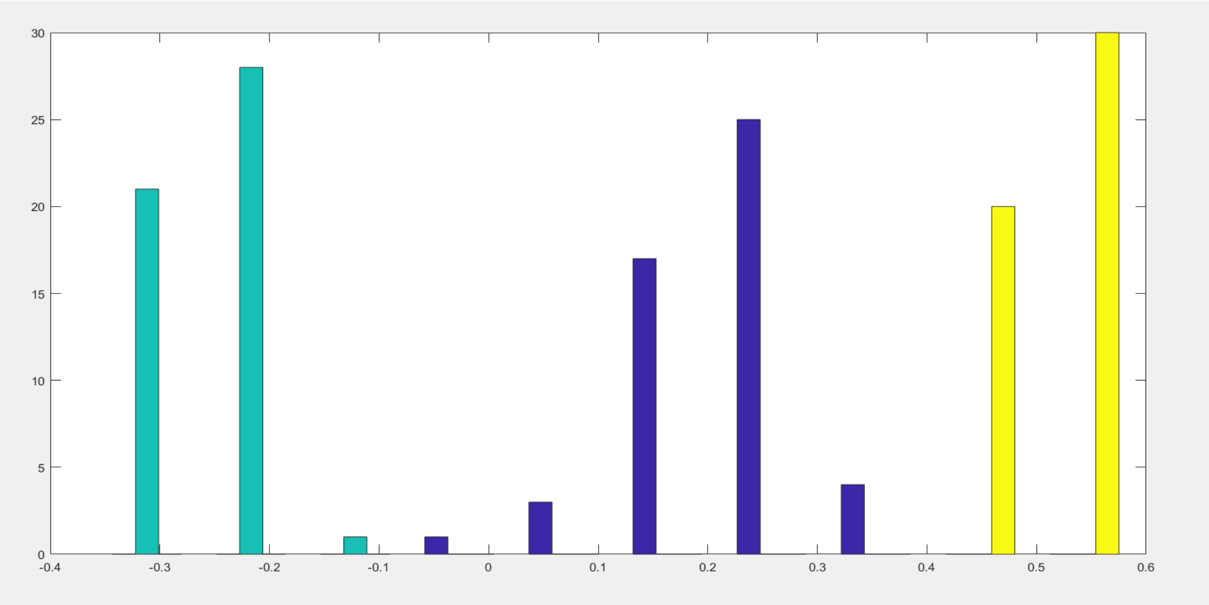

Figure 14.7: Histogram of the 3D location of the end-effector

The green bars represent the Y coordinates. The blue ones the X coordinates and the yellow ones correspond to the Z axis.

Part IV

Evaluation and Conclusion

Chapter | 15

Evaluation

This chapter focuses on evaluating whether the requirements were met by the prototype, as well as conclude on the project as a whole, whether the problem formulation question was answered or not.

15.1 General discussion

This study demonstrates that the control of a Kinova JACO^2 with the use of a Emotiv Epoc can be achieved by specific facial gestures. This chapter provides an overview of the results from the testing and statistics. It also showcases whether or not the requirements set earlier in this report have been met and how well the robotic solution fulfill it's task.

15.2 Test

The following section will discuss the testing, the results done in chapter 13 and how it possibly could be improved. When doing the tests the sample size of test-subjects was not particularly large, and due to certain problems with the headset not being able to be in direct contact with some of the subject's scalp, the sample size was reduced to just five. This was a problem only discovered late during the project and therefor made it hard to compensate for the lack of test subjects.

When looking at the results of the test, for all subjects it can be seen that 44% of the artifacts were read as true positives meaning that it registered the correct artifacts when it was supposed to. 43% was mistakenly registered as the wrong artifact, 13% was were false negatives and 1% were false positives. Taking a closer look at the individual subjects that were tested, it can be seen that the person with the highest success rate had 84% while the person with the lowest success rate had 20%. With a set success rate above 78% for the testing, as stated in section 9.2, the goal of doing the tests offline can be classified as a success, but only with person one, whose recordings the program was designed by.

During the test for section 13.3 is was also observed that the program often mistook right eye blink, and left eye blink with blink with both eyes. This is probably caused by the similarity of one eye blink and both eye blink. When blinking with one eye, subjects had a tendency to partly move the other eye as well.

The JACO^2 robot was more likely to give false negative, meaning it did not move at times where is was supposed to, than false positive. And by looking at figures 14.2, 14.3, 14.4, 14.5 and 14.6 it is clear to see that when the robot moves from start to finish, the subject with high success rate often had the end-effector near the same position. Improvements to get the spread even closer, would require the data collecting to be more specific. So a hard blink lasting 0.3-0.5 seconds would make the robot travel a longer distance, however, without any feedback this approach is a bit controversial when doing everything offline.

15.3 Requirements

This section examines which requirements have been met using the solution proposed in this report. The requirements for this report are described in chapter 9.

Sucess Criteria
This paragraph goes through the Success Criteria seen in section 9.2.

EEG signal recording, as stated on 13.2 the Emotiv Epoc was able to properly record the brain activity and electrical muscles movements, as long as the electrodes were in a position where they could make direct contact with the surface of the scalp.

Feature extraction, using certain filters it was possible to distinguish specific facial gestures from the background and extract them individually.

Pattern recognition, this requirement was only fulfilled partially. Resulting in one subject achieving 84% success rate, while the other four did not accomplish the 78% set baseline.

Data conversion, as shown in section 13.3, during the testing the robot was able to convert specific features into commands and move accordingly.

Safety regulations
Generally the requirements in section 9.3 are fulfilled by the solution from this report. However:

Despite the fact that the solution does not compromise the safety of the patients by itself, it could be potentially dangerous if the user decided to manipulate any hazardous objects or tools. Since this is out of the scope where the authors can directly intervene, designed wise the first safety requirement is met.

In regards of error reduction, this aspect is also fulfilled. As stated in the section 15.2 the solution is more likely to present a false negative, which results in minimizing the risk of error and potential danger.

For requirements three, four and five the solution and robot is made to move in a slow motion and with stability. Furthermore the robot does not make any sudden nor unexpected movements, making it a rather reliable and repeatable solution.

15.4 Further Development

Because of the limited time and resources to work with the project proposal, some features were left out. Therefore, if the project were to continue, certain aspects would be modified. This further development is applicable to both, software and hardware, and the aim of all the adjustments is to achieve the best possible system.

- **EEG** - In the current solution, artifacts are used to control the robot. However, an improved method would be to use EEG signals. This will ensure that those who are not able to perform the different artifacts can still use the solution. Furthermore, the use of brain waves activity also has the advantage of being able to avoid accidental movements. At the moment, in order for the system to recognize the artifact as a desired facial gesture, it has to be very emphasized, but there still is the possibility of unintentionally moving the robot when blinking.
- **System learning** - The method used to set the threshold for a specific person, was by trial and error. This has proven to be a rather time consuming and not very successful approach. Therefore, a future continuation of the project would suggest to implement a way which automatically sets the threshold based on the data it receives. This new feature would make the solution more flexible and easier to implement to new users, making the learning curve gradual and easy to overcome.

- **Make the solution work live** - At the moment, the solution works offline, meaning that the artifacts must be recorded beforehand and without any kind of feedback from the robot. Which makes the signal processing and robot controlling based on the users anticipation of how the robot should move, without any chance of correction while performing the movement. Therefore this prototype would not be able to be used in the real world unless some development was done to make it work live.
- **Hardware** - The last modification of the solution involves the Emotive Epoc. This headset has proven not to be the most suitable piece of equipment. One of the weaknesses found throughout the project is its inability to receive signals if a subject's hair is too long or thick. The solution is also made to detect spikes in the signal when doing artifacts and because the headset is not made to look for artifacts, spikes in the signal can also be made by other actions e.g. hitting the head or the headset. By changing the equipment it would then ensure that the solution accommodates a larger population and might work better with less errors.

Chapter | 16

Conclusion

This chapter provides an overview of the process of the solution development and concluding on whether the problem statement formulated in chapter 7 has been answered correctly throughout the chapters of this report.

The intention of this project was to make a robotic solution that could be controlled with EEG, this was to help tetraplegic patients regain some control over their daily life. A prototype, as a solution to this problem, was made with the help of a Kinova JACO^2 robotic arm and an Emotiv Epoc headset. In order to do so, the authors first had to analyze the problem and look into existing solutions, followed up by making a new solution to solve the problem and fulfill the requirements.

The flexibility of the choice of solution allowed for the discussion of two possible approaches. One of them involving electrical brain activity and the second one based on muscle electrical activity. Both solutions could have been successfully implemented, each of them with arguable advantages and disadvantages. However, due to the available resources, one of the solution was more viable. The chosen solution was to proceed using the artifacts because they are easier to detect when they occur, making the classification system simple enough to be detected with bare eyes after the processing of the signals. Once the solution was chosen, a control system was designed to showcase how the three different components of the prototype function and cooperate to make a solution. This lead to the implementation. The implementation was the process of defining how the control system should be built ensuring that it was operational and effectively integrated. This process focused on two main aspects, the implementation of the artifacts, and the implementation of the code. Thus allowing the system work as a whole, with the drawback of being offline.

Lastly the project ended with a test with the solution. The test was done by recording signals from seven test-subjects which later was played back on the program controlling the robot. Results was noted about the recognition of the artifacts and the position of the robot. With the result from the test, calculations were done and discussed in the evaluation. Since the solution is fulfilling all the requirements and success criteria to a certain extent, it is concluded that the solution is viable.

Problem formulation answer The task the authors set to do, as defined in the problem formulation, is answered through the contents of this paper. It details how to design such a system, therefore the problem, as formulated, is solved.

Part V

Appendix

Bibliography

[1] P. S. P. Michael-Titus, Adina Revest, *The nervous system*. Edinburgh : Churchill Livingstone, 2007.

[2] "The spinalcord." http://accessphysiotherapy.mhmedical.com/ content.aspx?bookid=1586sectionid=99982627. 29-05-2017.

[3] http://www.spinalcord.com/types-of-spinal-cord injuries, "Types of spinal cord injuries," vol. 1, p. 1, 27/03-2017. 27/03-2017.

[4] A. A. of Neurological Surgeons, "Spinal cord injury." http://www.aans.org/Patient20-03-2017.

[5] S. I. Network, "Spinal-injury.net : Tetraplegic spinal cord injuries." http://www.spinal-injury.net/tetraplegia.htm. 20-03-2017.

[6] S. A. A. K. C. M. S. I. Noor Kamal Al-Qazzaz, Sawal Hamid Bin MD. Ali and J. Escudero, "Role of eeg as biomarker in the early detection and classification of dementia, review article." https://www.hindawi.com/journals/tswj/2014/906038/, 30 June 2014. 23-05-2017.

[7] W. Jia, D. Huang, X. Luo, H. Pu, X. Chen, and O. Bai, "Electroencephalography(eeg)-based instinctive brain-control of a quadruped locomotion robot," *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, vol. 5, 2012. 10.03.2017.

[8] M. Teplan, "Fundamentals of eeg measurement," *Measurement Science Review*, vol. 11, pp. 2, 10, 2002. 26.05.2017.

[9] M.-M. Moazzami, "Eeg signal processing in brain-computer interface," *Computer Science, Michigan State University*, vol. 68, p. 11, 2012. 26.05.2017.

[10] B. Z. Jamal, *Computational Intelligence in Electromyography Analysis*. Intech, 2012. 2016.12.15.

[11] U. of Washington, "What is magnetoencephalography (meg)?." http://ilabs.washington.edu/what-magnetoencephalography-meg. 10-03-2017.

[12] P. E. inc., "The brain." http://humananatomylibrary.com/anatomy-and-functional-areas-of-the-brain/anatomy-and-functional-areas-of-the-brain-brain-and-the-cranial-nerves/, 2011. 29-05-2017.

[13] A. A. of Ophtalmology, "Visual evoked potential." https://www.aao.org/bcscsnippetdetail.aspx?id=45cef5ac-2f4e-4b67-81ff-85f3fd02878c. 18-04-2017.

[14] S. R. Benbadis, "Eeg artifacts." http://emedicine.medscape.com/article/1140247-overview, 2017. 26.05.2017.

[15] S. D. Muthukumaraswamy, "High-frequency brain activity and muscle artifacts in meg/eeg: a review and recommendations." https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3625857/, 2013. 28.05.2017.

[16] H. C. Taneja, *Advanced Engineering Mathematics:, Volume 2*. I. K. International Pvt Ltd, 2008.

[17] A. V. Oppenheim, *Signals and Systems*. Prentice Hall, 1997.

[18] A. S. Sedra, *Microelectronic Circuits*. Oxford University Press, 5 ed., 2004.

[19] R. Gade, "Lecture 6: Classification systems." https://www.moodle.aau.dk/course/view.php?id=20025, 2017. 29-05-2017.

[20] T. Thiagarajan, "Eeg and fmri papers by the numbers." http://sapienlabs.co/500000-human-neuroscience-papers/, November 1 2016. 27-04-2017.

[21] J. del R. Millán, F. Renkens, J. Mouriño, and W. Gerstner, "Noninvasive brain-actuated control of a mobile robot by human eeg," *IEEE Transactions on Biomedical Engineering*, vol. 8, 2004. 27.04.2017.

[22] A. Conner-Simons, "Brain-controlled robots." http://news.mit.edu/2017/brain-controlled-robots-0306, March 6 2017. 15-12-2016.

[23] M. Åberg, "Picture source." http://physiol.gu.se/maberg/images.html, 2006. 23-05-2017.

[24] K. Robotics, "Jaco2 specifications." http://kinovarobotics.com/wp-content/uploads/2015/02/JACOC2B2$_6DOF_Technical - specifications - v1.0.pdf.08 - 03 - 2017$.

[25] K. Robotics, "Jaco2 cad model." http://kinovarobotics.com/wp-content/uploads/2015/02/PJ-0090-0006-JACO 09-03-2017.

[26] J. Sauro, "What is a good task-completion rate?." https://measuringu.com/task-completion/, 2011. 21-03-2011.

[27] "Council directive 93/42/eec," pp. 25–30, 2007.

[28] D. M. Agency, "Legislation and guidance on medical devices," 2016.

[29] M.-M. Moazzami, "Eeg signal processing in brain-computer interface," *Michigan State University*, 2012. 10.04.2017.

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