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Efficient Classification of Electroencephalogram
for Brain Machine Interface with a Knitted Headset

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**Efficient Classification of
Electroencephalogram for Brain Machine
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Thesis Abstract

One of the major causes of physical disability is a motor impairment, it includes muscle weakness and fatigue. Any impaired motor function control can have a detrimental effect on a person's capacity to enjoy life. It is shown in several research works, that motor imagery activates signals in motor cortex of the brain. This is the underlying process for Brain Machine Interfaces, that can help people to rehabilitate their muscular activity or replace it with machinery ones. It is important to notice that motor imagery control is a skill, that must be practiced in order patient to achieve a good performance.

To perform motor imagery practices, patients need to go to the laboratory and have assistance for EEG measurement device montage, that takes 30-70 minutes to setup. The time of setup decreases number of patients that can practice, it also gives a time limit for one training and as a result the development of motor imagery skill is slower, while other people that need the training do not have opportunity to do one.

To overcome this limitation a comfortable wearable easy to set up knitted electroencephalograph device was designed. Candle type micro-needle electrodes, that penetrate through hair and do not require any special preparation were used. Cotton yarn showed the best properties for the device design needs: it reduces sweating, no damage to electrodes needles, gives comfortable skin touch, small elongation for control of electrode placement. Special knitting technique was used to create a tube shape and make space for discrete electrode placement. The device set up takes 1-2 minutes, no assistance is needed, fits any size of the head. Electrode placement freedom is given as well as different headband placement mode can be used for different brain area study purposes. Device performance and user experience showed that the device can measure EEG signals with acceptable quality with given comfort for more than one hour and does not cause stress or feeling of embarrassment.

This work gives deep analysis of number and location of electrode needed for classification of left hand, right hand, feet, and tongue imagery movements. The results show that it is possible to classify motor imagery task with only three electrodes and the best classification accuracy for electrodes located at CP3, CPz, CP4 reached 75%.

This study additionally makes a proposal of a robotic system, using NAO6 Robot, for motor imagery practice assistance, as a future prospect of this work.

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Table of Contents

Thesis Abstract.....	i
Acknowledgements	ii
Chapter 1 Introduction	1
1.1. Brain Machine Interface	1
1.1.1. What is Brain Machine Interface?	1
1.1.2. How BMIs work?.....	3
1.1.3. Motor Imagery	4
1.2. The Human Brain	4
1.2.1. Brain structure.....	5
1.2.2. Parts of the brain and their functions	5
1.2.3. Lobes and their functions.....	5
1.2.3.1. The Occipital Lobes	6
1.2.3.2. The Temporal Lobes	6
1.2.3.3. The Parietal Lobes.....	6
1.2.3.4. The Frontal Lobes	7
1.2.4. Structure of Neuron	7
1.2.5. Methods to Measure Brain Activity	7
1.2.5.1. Functional Magnetic Resonance Imaging (fMRI)	8
1.2.5.2. Magnetoencephalography (MEG).....	8
1.2.5.3. Electroencephalography (EEG).....	8
1.3. EEG.....	9
1.3.1. Advantages of EEG for BCI application.....	9
1.3.2. EEG derivation method	10
1.3.2.1. Bipolar montage	10
1.3.2.2. Unipolar montage	11
1.3.3. Location of brain activity measurement.....	12
1.3.4. Noses mixed with EEG signals.....	13
1.3.5. Skin to electrode impedance	16

1.3.6. Useful information derivation from EEG signals.....	17
1.3.6.1. Event-related potentials	18
1.3.6.2. Spontaneous potentials	19
1.4. EEG measurement systems.....	20
1.4.1. Dry and wet electrodes	21
1.4.1.1. Wet electrodes	21
1.4.1.2. Dry electrodes	22
1.4.2. Passive and active electrodes	23
1.4.2.1. Passive electrodes.....	23
1.4.2.2. Active electrodes	24
1.4.3. Review of wearable EEG devices	25
1.5. Research on EEG measurement system in our laboratory.....	28
1.5.1. Candle-type micro-needle electrode	28
1.5.2. Wearable headphone electroencephalograph	31
1.6. Objective of the present study	33
1.7. Overview of the thesis.....	34
Chapter 2 Design, Fabrication and Evaluation of the Wearable Knitted Electroencephalograph	35
2.1. Design and Fabrication	35
2.1.1. Electrodes.....	35
2.1.1.1. Fabrication of microneedle dry electrodes	36
2.1.2. Knitted headband	38
2.1.2.1. Selected yarn analysis	38
2.1.2.2. Yarn and Fiber Properties	40
2.1.2.3. Size of a knitted headband	43
2.1.2.4. Fabrication process.....	43
2.1.3. Electrodes placement	45
2.2. Experimental results and discussion	47
2.2.1. Performance of the device.....	47
2.2.1.1. Experimental conditions.....	47
2.2.1.2. Experimental results and discussion	48
2.2.2. Usability of the device	49

2.2.2.1. Experimental conditions.....	49
2.2.2.2. Experimental results and discussion	50
2.2.3. User experience of the device	50
2.2.3.1. Experimental conditions.....	50
2.2.3.2. Experimental results and discussion	51
2.2.4. Results.....	52
Chapter 3 Electroencephalogram Classification for BMI application	62
3.1. Imaginary movements classification	54
3.1.1. Dataset for imaginary movements classification	54
3.1.1.1. MOABB	54
3.1.1.2. BNCI 2014-001 Motor Imagery dataset	55
3.1.2. Tools for EEG processing and classification	56
3.1.2.1. MNE-Python	57
3.1.2.2. Braindecode.....	57
3.1.2.3. Shallow and Deep ConvNet.....	57
3.1.3. Classification with limited number of electrodes	58
3.1.3.1. Pre-processing	58
3.1.3.2. Processing.....	58
3.1.3.3. Classification model.....	59
3.1.3.4. Classification results	60
3.2. Motor imagery classification using knitted EEG headband	66
3.2.1. Data Acquisition Preparation.....	66
3.2.2. Data Acquisition	67
3.2.3. Data Processing.....	67
3.2.4. Classification.....	68
3.2.5. Discussion	69
3.3. BMI application after classification.....	69
3.3.1. NAO6 Robot	70
3.3.2. NAO Robot programming tools.....	72
3.3.3. Motor imaginary practice with NAO6.....	73
Chapter 4 Conclusion	83

4.1. Summary	75
4.1.1. Design and evaluation of a wearable knitted encephalograph	75
4.1.2. Motor Imagery Classification Analysis	76
4.1.3. BMI application proposal for motor imagery practice	77
4.2. Future prospects	78
References	79

Chapter 1

Introduction

1.1. Brain Machine Interface

1.1.1. What is Brain Machine Interface?

Brain Machine Interface (BMIs) or Brain Computer Interface (BCIs) has become a very promising area of study and application in the twenty-first century, it has an enormous potential to improve human lifestyle. The fantasy to control objects using only your imagination, your brain was in movies, science-fiction novels as well as fantasized by people around the world and throughout the history. BMIs allows doing exactly that! BMIs allows to convert humans' thoughts into actions by certain devices, machines, robots, computers without the necessity of muscular activity. This relatively new user interface technology not only provides a new way for those with severe neuromotor disabilities to interact with their surroundings, but it can also provide effective and engaging rehabilitation to restore motor or cognitive functions that have been impaired due to disease or trauma [1], [2]. With proper study and implementation of breakthroughs, BCI can contribute to a wide range of fields like robotics, mass communication, healthcare, military applications, vehicles, gaming, entertainment, and so on. Several experiments have been conducted over the last three decades to investigate the idea that brain signals captured from the scalp or from within the brain could form into a new technology that does not require muscle control [3]–[6]. Current study is intended to contribute to BMI development as possibility to provide users comfortable conditions for a longer BMI use and allow to use BMI on daily basis, outside laboratories and without specialized assistance.

How is the movement control happening? Any natural communication or control necessitates the use of peripheral nerves and muscles. The procedure starts with the user's intent. It initiates a complex process in which certain brain areas are activated, resulting in signals being delivered via the peripheral nervous system (namely, the motor pathways) to the associated muscles, which then perform the movement required for the communication or control task. This action is commonly referred to as motor output or efferent output. Efferent means transmitting impulses from the central neural system to the peripheral nervous system and then to an effector (muscle). Afferent communication, on the other hand, refers to transmission from sensory receptors to the central nervous system. The motor (efferent) route is required for motion control. The sensory (afferent) pathway is critical for learning motor skills and dexterity tasks like typing or playing an instrument. Rather than relying on peripheral nerves and muscles, a BMI directly measures brain activity related with the user's intent and converts the recorded brain activity into control signals for BMI applications. This translation requires signal processing and pattern identification, which are commonly performed by computers. The system is known as a Brain-Machine Interface because the measured activity originates directly from the brain rather than through peripheral systems or muscles and processed, recognized and applied with computers or machines. It is important to add that BMIs are not devices that passively monitor changes in brain activity that occur without purpose, such as EEG activity related with workload, arousal, or sleep [7]. To create such a system, we will need to have a deeper understanding of how BMIs work.

1.1.2. How BMIs work?

A BMI system is, in general, composed of the following components: signal acquisition, preprocessing, feature extraction, classification (detection), and application interface. The procedure for translating brain activity into external system control is following[8]:

- 1) EEG recording to capture the signal
- 2) Signal processing step to remove noise and artefacts from the EEG signal,
- 3) Feature extraction to identify and extract EEG features relevant to the context of application
- 4) Classification, which includes training a classifier using Machine Learning algorithms with extracted features and using the trained classifier to classify the data. This part gives an analysis of the unprocessed EEG waves and results into predicting desired action
- 5) Activation or control of the needed application
- 6) User feedback, which helps to approve the process, reinforce it

It is important to mention that the ability to properly manage specific electrophysiological signals rather than perfect muscle control is a new skill that the user must learn and retain to operate a BCI successfully. The BCI must also convert this control into output that serves the user's intended purpose [6]. The user needs to be trained to execute a certain mental technique to concentrate on the proper stimuli (such as a particular body part or one of several flickering lights, flashing objects, or text on the screen) to produce a particular EEG signal pattern. It is an important point to remember, as the tests of the system that will be conducted in current research more likely to be performed by an unexperienced BMI user. BMI that will be used in current study will be based on motor imagery.

1.1.3. Motor Imagery

Every muscle contraction or a limb movement alters cortical brain activity. Moreover, the so-called sensorimotor rhythms are also altered by movement preparation or movement imagination. Motor imagery has been proven to alter sensorimotor rhythms [9]. Motor imagery based BMI systems decode the user's imagination of moving his own limbs (hands, feet), for example, picturing right/left hand movement following right/left instructions or even imagining tongue movement to operate, for example, a wheelchair or a mouse cursor [10].

To understand how imagery-based BMI systems decode the brain signals we will have a closer look at what is the human brain, how it works and what can be measured. The following chapters will help to understand how and where in the brain it is possible to recognize the imagination of movements.

1.2. The Human Brain

Understanding the human brain functioning is important before one can comprehend BCI structure. Brain is the most crucial component of the nervous system, which is made up of billions of neurons. This recent study suggests that the human brain probably contains 86 billion neurons [11]. It is a unique and very complex organ that gives us the ability to move, feel, see, hear, taste, smell, and simply every process that regulates our body. Human brain controls our body, as well receives, processes, and stores information.

In this part the brain structure will be discussed together with functions in the human body that these parts are responsible for. Following by the structure of the anatomy of neurons - cells that carry the information and that provide electrical field that can be measured. At last, some commonly used methods to measure brain activity will be described.

1.2.1. Brain structure

There are two distinct parts of the central nervous system: gray matter and white matter. Gray matter in the brain refers to the darker, outer layer, and white matter to the lighter, inner layer beneath. Gray matter is primarily composed of neuron somas (the round central cell bodies), and white matter is mostly made of axons (the long stems that connects neurons together) wrapped in myelin (a protective coating). White matter transports information to other regions of the nervous system while gray matter is principally in charge of processing and interpreting it [12].

1.2.2. Parts of the brain and their functions

At a high level, the brain can be divided into the cerebrum, brainstem and cerebellum.

The Brainstem (“reptilian brain”) comprising the midbrain, pons and medulla. Controls autonomic body processes (heartbeat, breathing, bladder function).

The Limbic System (“emotional brain”) buried deep within the brain includes the thalamus, hypothalamus and amygdala. Plays a central role in arousing fight-or-flight situations.

The Cerebellum (“little brain”) integrates inputs from spinal cord and other brain areas to regulation and control of fine movements, posture, balance.

The Cerebrum (or cortex) divided into four lobes two hemispheres connected through a mass of nerve cells (corpus callosum). Carries higher brain functions: conscious thought, sensory processing [13].

1.2.3. Lobes and their functions

Each brain hemisphere (parts of the cerebrum) has four sections, called lobes: frontal, parietal, temporal, and occipital [14]. Each lobe controls specific functions [15] and their locations are demonstrated in Figure 1-1.

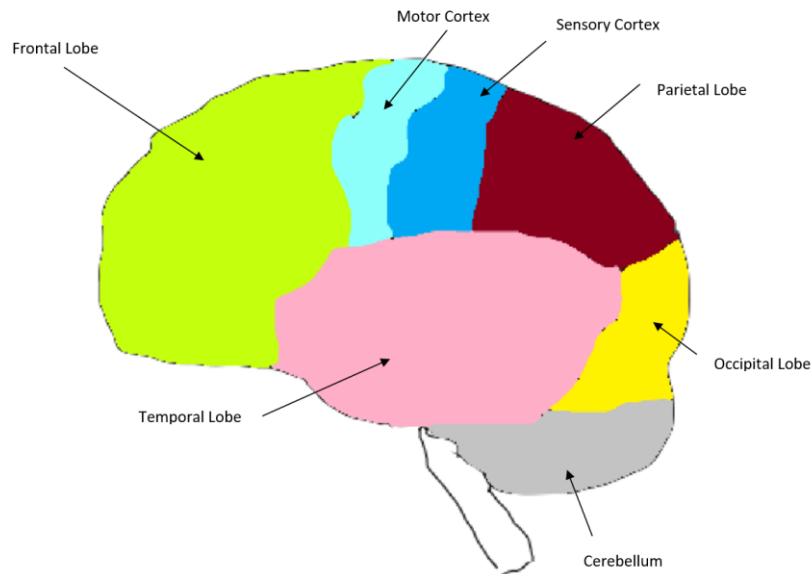


Figure 1-1 Lobes of the brain

1.2.3.1. The Occipital Lobes

Humans can receive and analyze visual information thanks to the lobes at the back of the brain. They affect how people perceive color and shape. While the left occipital lobe performs the same task for the right visual space, the right occipital lobe processes visual information from the left visual area.

1.2.3.2. The Temporal Lobes

These lobes, which can be separated into two sections, are located at roughly ear level on each side of the brain. Each hemisphere has two parts: one is on the bottom (ventral) and the other is on the side (lateral). Visual memory is controlled by a region on the right side, which aids in object and face recognition. The left side of the brain has a region that is engaged in verbal memory and aids in language understanding and recollection.

1.2.3.3. The Parietal Lobes

Integrating information stemming from external sources and merging it into a coherent representation of how our body relates to the environment, and how all things in the environment spatially relate to us.

1.2.3.4. The Frontal Lobes

The frontal lobes are the largest of the four lobes responsible for many different functions. These include linguistic, cognitive, behavioral, and motor skills like voluntary movement. The primary motor cortex, also known as the precentral gyrus, contains the regions that cause movement in various body parts. This part will make a major interest in the current research, as this part of the brain is directly responsible for movements and therefore is useful for motor imagery. Memory, intelligence, focus, temperament, and personality are all significantly influenced by the prefrontal cortex. Area next to the primary motor cortex is called the premotor cortex. It directs a person's sense of orientation as well as eye and head motions. The frontal lobe's Broca's region, which is crucial for language creation, is often on the left.

1.2.4. Structure of Neuron

Cells that carry out the most of communication in the brain – neurons. Neurons consist of a cell body and one or more axons which all end at synapses. Synapses act as gateways of inhibitory or excitatory activity between neurons. Synaptic activity often generates a subtle electrical field, which is also called a postsynaptic potential.

Not all brain electrical fields are strong enough to spread all the way towards the scalp surface. Pyramidal cells (can be found in all cortical areas) have unique orientation that generates an electrical field with a very stable orientation. Their synchronized activity (in synchrony for hundreds of thousands of similarly oriented neurons) can be measured from the scalp.

1.2.5. Methods to Measure Brain Activity

The brain activity consists of several types of signals such as magnetic and electrical signals. Both invasive and noninvasive procedures can be used to find this activity. The invasive approaches need brain implants via surgery, which is

excessively risky and increases a number of surgical complications and adverse effects, making them unsuitable for real-world use. Signals are detected using electrodes or bands on the surface of the scalp in noninvasive methods, which do not require any kind of implantation and hence pose no danger of physical harm. These techniques include electroencephalography (EEG), magnetoencephalography (MEG), and functional magnetic resonance imaging (fMRI), which are currently mostly employed for medical purposes.

1.2.5.1. Functional Magnetic Resonance Imaging (fMRI)

A functional neuroimaging method called functional MRI (fMRI) is used to visualize neural activity using MRI, which assesses brain activity by monitoring for changes in blood flow. fMRI has been widely utilized to study a variety of brain processes, including cognition, language, movement, and vision [16].

1.2.5.2. Magnetoencephalography (MEG)

The idea of the magnetoencephalography technique is to map the magnetic fields created by brain electrical currents to the activity of the brain. MEG is employed in fundamental studies of perceptual and cognitive brain functions, in figuring out how distinct areas of the brain work, and in neurofeedback [17].

1.2.5.3. Electroencephalography (EEG)

Electroencephalography technique measures the electrical activity generated by the sum of the synaptic potentials generated by thousands of neurons in the brain. EEG is detected using electrodes placed on the scalp [15]. This technique is mainly chosen for BMI applications. To understand the reasons, as well as to start working with this method of measuring brain activity the following part will consist in detailed information on EEG.

1.3. EEG

In the past, EEG has been widely used in clinical practice for diagnosis of epilepsy and determination of brain death [18], [19]. Currently, EEG is being used to elucidate the mental states and cognitive functions of subjects, and its application in non-clinical settings is increasing [20], [21]. On the other hand, there has been a lot of research in the field of applying EEG to medicine, business, and education by focusing on the human "mind" and elucidating the mechanism of mental activity [22].

Currently, only EEG provide the prospect of a new non-muscular communication and control channel, a workable BCI. The advantages of EEG and BCI, which has been attracting attention in recent years, are described in the first part of this chapter. Next the EEG derivation method describing how EEG works in detail will be explained. This will be followed by discussion on standardized international 10-20 system for measuring electrode placement, difficulties that can occur during the measurements and reasons of untrusted data, methods to retrieve useful information from obtained EEG data will be described.

1.3.1. Advantages of EEG for BCI application

The first advantage is ease of use and the ease of installation. The price of an electroencephalograph varies, but once purchased, there are basically few maintenance costs. The functional magnetic resonance imaging (fMRI) and magnetoencephalography (MEG) are ten times more expensive than EEG [23]. The second advantage is the high experimental flexibility. In recent years, wearable electroencephalographs have been developed, making it possible to measure brain activity outside of the laboratory [24]. In other words, the device can be used to measure cognitive activities in daily life. In contrasts with fMRI, which is a huge device, and makes constrains on daily use. There are other brain activity measurement

methods such as near-infra-red spectroscopy (NIRS), which reads transient blood flow changes associated with brain activity, but EEG has superior temporal resolution compared to NIRS, making it suitable for real-time applications. As a conclusion EEG has relatively short time constants, can operate in most situations, and require relatively simple and inexpensive equipment.

1.3.2. EEG derivation method

EEGs taken at the scalp's surface show combined electrical activity produced by a huge number of neurons. The difference in electrical potentials between two locations on the cerebral cortex that are closest to the recording electrode are shown by the scalp EEG. Electrical potentials are obtained from the scalp surface indirectly during routine use, and they include waveform analyses of frequency, voltage, morphology, and topography. Most of the human cortex, which represents a two-dimensional projection of a three-dimensional source and is buried deeply beneath the scalp surface, presents a challenge for scalp EEG generator localization [25]. The process of EEG recording is the following: place EEG electrodes, record the electrical data, digitize the data, amplify the data, receive time series of voltage values, transmit to the recording computer.

EEGs produce a comprehensive collection of data covering the whole scalp from the individual brain signals picked up by electrodes. This is accomplished by joining all the electrodes together in a structure known as a montage. There are two main montage categories: bipolar and referential.

1.3.2.1. Bipolar montage

In a bipolar montage, a chain of electrodes is created by linking and comparing the voltages of each electrode to those of its neighbors. There are several different kinds, but the double banana bipolar montage is the most popular one. In this

arrangement, each electrode is connected to and contrasted with the one behind it, such that Fp2 is contrasted with F8, F8 is contrasted with T4, and so on all the way back. The double banana, from which it gets its name, has two chains per side: an interior parasagittal chain made up Fp2→F4→C4→P4→O2, and an outer temporal chain made up Fp2→F8→T4→T6→O2. A short center chain is formed by the "z" electrodes Fz, Cz, and Pz (Figure 1-2) [26]. Because the potential difference between the active electrodes is observed, when an abnormal EEG occurs, a phase inversion is observed around the location of the abnormal EEG. This property makes it easy to detect localized abnormalities. However, the waveform is easily distorted because of the potential difference between the heads, and errors occur if the distance between the electrodes is not accurate. Because EEG signals are weak, differential amplifiers are generally used to amplify the signals. An electrode is attached to the earlobe or mastoid process as a potential reference for the differential amplifier and connected to the GND of the amplifier. This is called a neutral electrode.

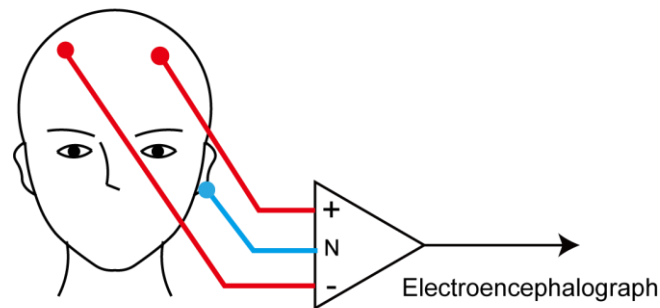


Figure 1-2 Bipolar montage

1.3.2.2. Unipolar montage

The unipolar derivation method records the potential difference between two electrodes by placing one electrode as a reference electrode on a potentially inactive area where brain activity has little effect, and the other electrode as an active electrode on the electrically active scalp (Figure 1-3). The reference electrode is generally placed on the inactive earlobe or mastoid process (a small bone behind the ear),

making it easy to detect left-right differences and hemispheric abnormalities [26]. In addition, because absolute EEG values can be recorded, waveform distortion is minimized. However, large amplitude EEG occurs in the temporal region, and the potential may spill over to the earlobe or mastoid process. This phenomenon is called activation and is a source of noise. Because it is easy to detect global EEG changes, it is often used in non-medical EEG measurements such as BCI and social interaction studies.

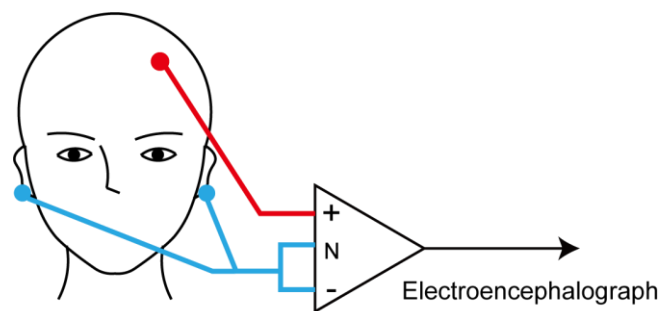


Figure 1-3 Unipolar montage

1.3.3. Location of brain activity measurement

A standardized international 10-20 system that uses anatomical landmarks on the skull has standardized electrode placement, that keeps the electrodes consistently overlying their appropriate regions of the brain despite varying head shapes and sizes. To determine the location of an electrode, these sites are then divided into sections at intervals of 10% to 20%. Although digital EEG now has the capacity for more, a minimum of 21 electrodes are advised for clinical studies. Depending on age and head size, fewer electrodes are used during infant EEG recordings. A more recent modified combinatorial electrode system employs electrode placement with 10-10 electrodes that are more closely spaced apart. The designations: Fp (frontopolar), F (frontal), T (temporal), O (occipital), C (central), and P (parietal) are utilized in the 10–20 system. Subsequently, numbers combined following the letters for location reflect either the left (odd numbers) or right (even numbers) hemisphere of electrode placement. The

“z” designation reflects midline placement (i.e., Cz = central midline). Electrode placements systems use either a 10-20 system or modified combinatorial system with 10-10 electrode placement. In the 10–10 system, lower numbers in their positions reflect locations closer to the midline, and T3/T4 become T7/T8, while T5/T6 become P7/P8 [27]. Both system’s electrodes locations are shown on Figure 1-4.

Figure 1-4 Electrode placements:
10-20 system (black circles)
10-10 electrode placement (black circles + grey circles)

1.3.4. Noses mixed with EEG signals

represent only brain activity of the subject, otherwise the conclusions from the results can be completely opposite from what they should be. There are several reasons why the quality of EEG signal can happen to be low: electrode metals corrode, Ag/AgCl electrodes deteriorate over time (lose ions), high impedance (case of dead skin cells, oily skin secretions, sweat), too much gel on wet electrodes can create gel bridges between neighboring electrodes, hair pins might cause connections between neighboring electrodes, picking up electrical activity from other sources (artefacts).

Physiological and non-physiological artifacts are the two primary types of unwanted non-brain signals. Electrical and magnetic fields produced by the heart, muscles, especially those of the face and eyes, and the retina are examples of physiological artifacts. These artifacts often have a distinctive topography and may be deleted using spatial artifact rejection techniques, even though they can be many orders of magnitude bigger than the EEG signals of interest. For instance, EEG sensors placed above the anterolateral scalp exhibit the effects of eye blinks and eye movements. The eye has a strong electromagnetic field that is established by the millions of neurons in the retina.

To reduce the artifacts subjects can focus on the center and blink at the end of the trial, although realistic experimental designs might not allow this. Electro-oculographic (EOG) measures make it simple to keep a watch on blinks and eye movements. However, if blinks and eye movements are time-locked to the transmission of stimuli or to behavioral reactions, they may become troublesome. Yet, electrocardiographic (ECG) activity appears to be more pronounced in EEG recordings when sensors reach down over the left side of the neck and tends to be biggest on posterior and inferior EEG/MEG sensors. This activity needs to be removed using artifact rejection techniques during data pre-processing because it cannot be stopped at the time of data gathering. It is advised to apply ECG electrodes

to the chest and include their output with the data for the best cardiographic rejection. Conversely, by maintaining a cool, pleasant temperature in the lab, sweat gland activity can be reduced. The EEG will show extremely slow, big amplitude excursions that are caused by sweat gland potentials [28]. Additionally, sweating can change the impedance of the EEG electrodes and the skin, resulting in large changes in EEG baseline [29]. Muscle activity generates electric currents that are picked up by electrodes. The closer the muscles are to the electrodes, the stronger their impact on the recording. head swinging or banging changes the water distribution, which affects the electrical properties and fields generated by the brain.

Power line noise at 50 or 60 Hz (depending on the country) produced by any close electric equipment is an example of a non-physiological artifact. Electrostatic induction, electromagnetic induction, and leakage current are the main sources of noise. Generally, the degree of noise contamination in a single environment is considered to be constant. Fortunately, the cognitive frequencies of the brain are often below the 50 or 60 Hz range, allowing you to filter data accordingly. Movement of an electrode or headset movements is another source of severe artifacts that are visible in the affected channel or in all channels.

Following things is what we can do to get the cleaner data:

- Run more experiments
- Use the right combination of electrode metal and conductive paste
- Always check electrode quality before a session: if the electrode looks dull, you can record
- After a recording always make sure to properly clean electrodes
- Disinfect electrodes with alcohol (70% isopropanol) prior the recording
- Make sure that the electrodes are placed in the expected location
- Place electrodes evenly across the scalp

- Introduce a reference electrode R to avoid electrical noise.
- Respondents should have washed and dried hair and to not wear any hair pins or clips
- Apply electrode gel/conductive paste, but not too much
- Clean all electrode sites with alcohol
- Instruct respondents to avoid chewing or tensing their jaw
- Monitor heart rate
- Record eye movements using eye trackers or by placing additional EEG electrodes surrounding the eyes
- Exclude the trials with blinking or use statistical procedures to remove artefacts
- Make sure that the headset sits snug on the head, and that all electrodes are securely attached to the skin
- Instruct respondents to not turn their head too fast or look up or down abruptly

No matter how careful one is in conducting experiments, it is impossible to eliminate all noise. To extract valid EEG components with a small number of electrodes, it is important to process noise as much as possible and narrow down the EEG components to be measured.

1.3.5. Skin to electrode impedance

The skin-electrode contact impedance is an important parameter in EEG measurements and its magnitude and stability have a great influence on the quality of EEG signals [30] Figure 1-5 shows the equivalent circuit between the electrodes and the bioelectromotive force [31]. The impedance composed of the internal tissues of a living body and the impedance of the electrode itself is small and negligible (less than 100 Ω). The body EMF e_s , the input voltage to the amplifier e_i , the contact impedance

between the skin and the electrode Z_s , the input resistance R_i . The resistance and skin-electrode contact impedance play a significant role in the reproducibility of the biological signal. The electroencephalogram (EEG) is defined as the biosignal reproducibility.

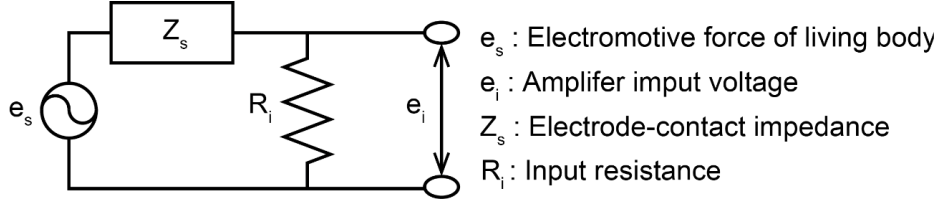


Figure 1-5 Equivalent circuit of electrode and biological signal

If R_i is the resistance, Figure 1-5 shows that the reproducibility r after signal amplification can be expressed as following:

$$r = \left| \frac{e_i}{e_s} \right| = \frac{R_i}{|R_i + Z_s|}$$

where, if $r = 1$, the bioelectromotive force e_s and the input voltage to the amplifier e_i will be equal and therefore we can correctly measure the electroencephalogram. Equation shows that the higher the skin-electrode contact impedance Z_s the smaller the repeatability. In addition, a high skin-electrode contact impedance makes the EEG susceptible to noise, which leads to distortion of the EEG. Therefore, it is important to lower the skin-electrode impedance appropriately when measuring EEG. Common methods to reduce the impedance include hair brushing, hair washing, and the application of conductive gel.

1.3.6. Useful information derivation from EEG signals

EEG analysis and feature extraction can be overwhelming by the extensive pre-processing procedures you must do to go from raw signals to results. In fact, when it comes to signal processing, artifact identification, attenuation, or feature extraction, it unquestionably calls for a certain level of competence and experience. Any of these

procedures necessitates making well-informed choices on how to highlight the relevant EEG processes or metrics of interest. EEG signals are broadly classified into spontaneous potentials and event-related potentials (ERPs).

1.3.6.1. Event-related potentials

The idea is that there is always ongoing EEG activity as well as random noise completely unrelated to the onset of a stimulus continually occurring. This is “default activity“. When stimulus is preset, stimulus-related EEG activity is triggered. The goal of event-related EEG paradigms is to collect those brain processes which are triggered by external stimuli. Event-related EEG paradigms present stimuli repeatedly – 100 times or more, for example. At the same time, stimuli are shown just very briefly for 200 to 1000 ms [15]. The process is following:

1. Collecting data - stimulus is shown very briefly for 200 to 1000 ms several times - 50 times or more
2. At the end there are 50 or more trials, which are data portions of EEG activity + stimulus-related EEG activity in a range from about 200 ms prior to stimulus onset to 1000 ms after stimulus onset
3. Segmentation (or epoching) – the selection of data portions from the continuous EEG recording
4. The exclusion of epochs containing artifacts (or the correction of data due to blinking, for example)
5. The remaining epochs are averaged into EEG waveform that is the event-related potential, which reflects the average stimulus-related EEG activity

Numerous properties, including appearance and form, quantity, latency, amplitudes of the "wiggles," ERP components (positive and negative peaks), and topography, can be used to define ERPs (which is the voltage distribution at peak

times across all electrodes). Some of the ERP components that have been studied and understood the most in academic study are the N400, P300, and N170 [32].

1.3.6.2. Spontaneous potentials

ERP models are restricted to a certain subset of brain activity brought on by sensory stimuli. The brain, however, is a constant oscillator and produces rhythmic activity even when there are no external inputs, such as while you are sleeping. A different analytical technique that is based on the examination of frequencies is necessary to tap into the brain activity that controls our behavior, ideas, motives, and emotions.

Brain generates primarily low frequencies between 1 and 80 Hz. These can be classified into specific frequency bands (delta, theta, alpha, beta and gamma) and associated with brain processes in specific regions underlying attention, cognition and emotion.

Delta band (1 - 4 Hz)

Slow wave sleep (SWS) - the stronger the delta rhythm, the deeper the sleep. Stronger in the right brain hemisphere, and the sources of delta are typically localized in the thalamus

Theta band (4 - 8 Hz)

Associated with brain processes underlying mental workload or working memory, become more prominent with increasing task difficult. Can be recorded from all over cortex

Alpha band (8 - 12 Hz)

Correlates reflecting sensory, motor and memory functions. Levels increase during mental and physical relaxation with eyes closed. Alpha power is suppressed during mental or bodily activity with eyes open (indicates that brain is getting ready to

pick up information from various senses)

Beta band (12- 25 Hz)

Increase in active, busy or anxious thinking and active concentration, planning or executing movements, particularly when reaching or grasping requires fine finger movements and focused attention. Interestingly, this increase in beta power is also noticeable as we observe others' bodily movements.

Gamma (>30 Hz, typically 40 Hz)

Gamma-Some researchers argue that gamma reflects attentive focusing and serves as carrier frequency to facilitate data exchange between brain regions. Others associate gamma with rapid eye movements, so-called micro-saccades, which are considered integral parts for sensory processing and information uptake [33].

Frequency analyses have a closer connection to physiological processes and brain structures than ERPs do. Therefore, it's often much easier focus on the analysis of frequencies and frequency bands. Frequency analyses also have the advantage of using far less data to get to the results. However, in contrast to ERP that allow insights into millisecond changes of voltages, frequency-based EEG measures have much less time precision.

1.4. EEG measurement systems

To measure EEG signals EEG measurement systems are used. In the current study EEG measurement knitted head band was developed for purpose of comfortable and daily practice of BMI. To design a new wearable EEG measuring device it is necessary to inspect existing systems. In this part different type of electrodes that are used in measuring systems nowadays will be described. Then an overview and analysis of comparison studies of wearable EEG measuring devices available on the market.

1.4.1. Dry and wet electrodes

Electrodes that receive EEG signals are an important element of an EEG measurement system. Electrodes are broadly classified into wet and dry electrodes based on differences in attachment methods and characteristics.

1.4.1.1. Wet electrodes

The electrodes used in conventional EEG measurements are wet electrodes (Figure 1-6) [34]. Electrodes are applied to the scalp, but because the stratum corneum on the top surface of the scalp has high electrical resistance, prior grinding is required. Generally, after washing hair thoroughly, oil and dirt are removed from the scalp with alcohol, the stratum corneum is thinned by grinding it with an abrasive gel, and electrodes coated with electrolyte paste are applied. These pretreatments significantly reduce the contact impedance between the skin and electrodes, enabling highly accurate EEG measurements. However, these pretreatments are time-consuming and burdensome for the person taking the measurements and causes discomfort to the subject. It is difficult for a patient to install these electrodes without assistance. Another problem is that the electrolyte paste dries out over time during long-term EEG measurements, causing the impedance to rise.

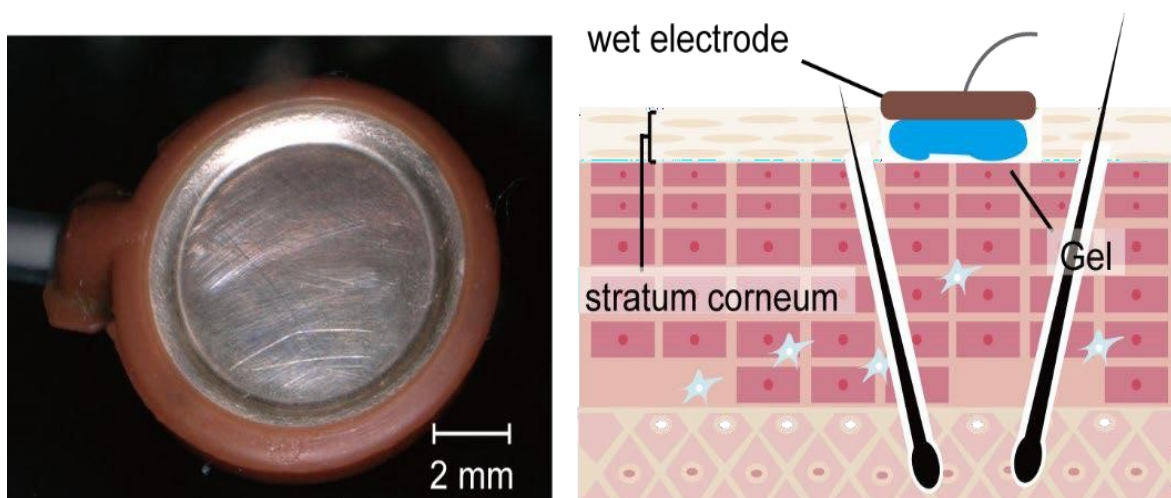


Figure 1-6 Wet electrode

1.4.1.2. Dry electrodes

To solve the problems of wet electrodes, dry electrodes that do not require pretreatment have been developed. The dry electrode is classified into contact and non-contact electrodes (Figure 1-7) [35]–[41]. Contact electrodes can be divided into two types according to shape. The electrodes with needle-shaped arrays and the electrodes with cylinder-shaped arrays [35]–[40]. Needle-shaped electrodes measure electroencephalograms by inserting needles into the scalp. The microscale needle penetrates the stratum corneum and reaches deep into the epidermis, where electrical resistance is low, thus reducing contact impedance.

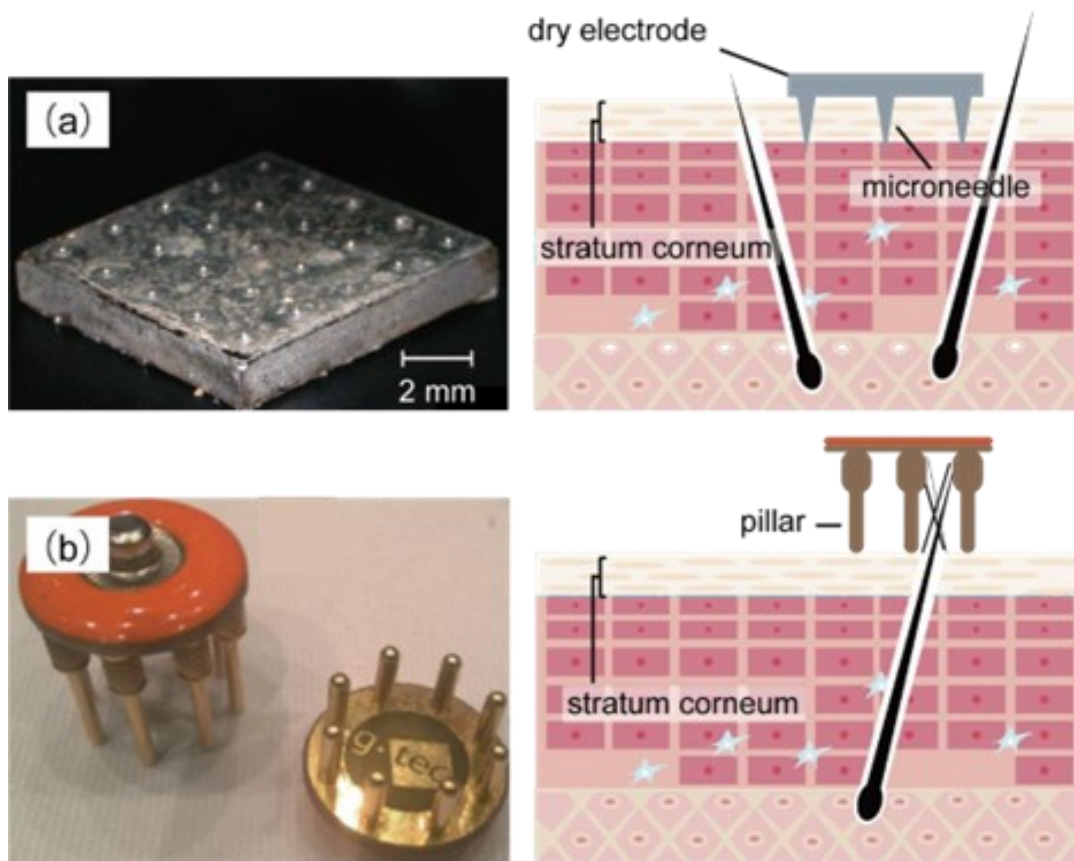


Figure 1-7 Dry electrode
(a) Needle type dry electrode (b) Cylinder type dry electrode [37]

The needle is designed to penetrate the stratum corneum but not the dermis, where nerves are located, so the subject does not feel pain. However, the hairs obstruct the needle in the hairy area, making it impossible to fully penetrate the needle. On the

other hand, cylindrical electrodes can avoid hairs and reach the scalp like a brush by designing the cylindrical structure on the millimeter or centimeter scale. However, since the stratum corneum is not processed, the contact impedance between skin and electrode tends to be higher than that of a wet electrode. In recent years, dry electrodes have realized highly accurate EEG measurement even at high impedance by applying active electrodes as described below. Non-contact electrodes measure electroencephalogram (EEG) by capacitively coupling with the scalp [41]. Because there is no direct contact with the scalp, EEG measurement is possible in the hairy area. However, because the measured signal is small, an amplifier with a very high impedance is required for the electrode itself, resulting in a decrease in signal quality [35]. In addition, since the electrode does not contact the scalp, it is difficult to fix the electrode, and noise is likely to be generated by vibration and movement. For this reason, contact-type dry electrodes are often used in commercially available wearable electroencephalographs intended for everyday use.

1.4.2. Passive and active electrodes

In the past, signal amplification was performed by the electroencephalograph itself, but active electrodes with amplifiers attached to the electrodes themselves have been developed to enable EEG measurement under high impedance conditions, such as when dry electrodes are used.

1.4.2.1. Passive electrodes

Conventional EEG measurement uses passive electrodes that send the received EEG signals directly to the electroencephalograph. The signal is amplified by a differential amplifier in the main body of the electroencephalograph. Since the signal is amplified by the differential amplifier in the main body of the electroencephalograph, a weak EEG signal is transmitted in the lead wires connecting

the electrodes and the electroencephalograph. Therefore, even the slightest movement of the lead wires can introduce noise into the EEG signal, requiring the subject to be in a strictly stationary state. The differential amplifier amplifies the potential difference between the signal obtained at the active electrode on the scalp and the signal obtained at an inactive electrode (reference electrode) such as the earlobe. In this process, if the skin-to-electrode contact impedance of the active and reference electrodes is matched, noise introduced at both electrodes is subtracted and reduced to zero. Since the skin-to-electrode impedance of the reference electrode site, such as the earlobe, is lower than that of the scalp, the noise can be reduced by lowering the impedance of the active electrode and moving it closer to the reference electrode. However, as mentioned above, a time-consuming pretreatment is required to significantly lower the impedance.

1.4.2.2. Active electrodes

Active electrodes have an amplifier built into the electrode itself [30]. After amplifying the EEG signal the amplifier can flow to the lead wire, thus reducing the effect of noise caused by lead wire movement. The high input impedance of the amplifier in the electrode reduces noise due to the impedance difference between the active electrode and the reference electrode. Therefore, even at relatively high skin-electrode contact impedance, the signal can be obtained with the same accuracy as that of a wet electrode. In the past, the size of the electrode increased due to the built-in amplifier, but recent advances in semiconductors have made the size of the electrode almost the same as that of a passive electrode. Therefore, active electrodes have advantages such as simplified measurement preparation, noise immunity during data recording, and reduced restraint of the subject, and are effective for EEG measurement in daily life.

1.4.3. Review of wearable EEG devices

The development of EEG technology has led to active social implementation of EEG, and many wearable electroencephalographs have been developed and marketed, which are designed to enable appropriate electrode fixation [42]–[52]. Table 1.1 shows an overview of existing wearable EEG devices and their characteristics.

Table 1.1 Examples of some existing wearable EEG devices

Type	Product Name (Company)	Number of electrodes	Electrodes type	Applications
Net	R-Net (Brain Products)	Up to 160	Saline based	Clinical
	antiCAP (Brain Products)	Up to 256	Dry	Virtual Reality
Cap	eego sports (ANT Neuro)	Up to 128	Gel or dry	Neurofeedback
	Quick Cap (Compumedics Neuroscan)	32	Gel	Functional Brain Imaging
	g.LADYbird (g.tec GmbH,)	16	Gel	Research and medical use
	g.SAHARA (g.tec GmbH,)	16	Dry	Research and medical use
	ActiveTwo (BioSemi)	Up to 128	Wet	Stationary scientific
	Smarting (mBrainTrain)	24	Wet	Hyperscanning
	Enobio 20 (Neuroelectronics)	20	Wet	Clinical
	Ultracortex Mark IV (Open BCI)	32	Dry	BCI

	32 Trilobite (Mindo)	32	3 foam- based, 29 spring- loaded pins	Virtual Reality Games
	Quick-30 (CGX)	30	Dry	Mental Health
	B-Alert X24 (Advanced Brain Monitoring)	20	Wet	Driving Assistance
	Wet and Dry System (Cognionics)	64	Wet or dry	Mobile Scientific
	EPOC+ (Emotiv)	14	Saline based	Mass market
	BR8+ (BRI)	8	2 foam- based, 6 spring- loaded pins	BCI research
	MyndBand (MyndPlay)	3	Dry	Meditations
Headband	Muse (Interaxon)	4	Dry	Meditation
	MindWave Mobile2 (NeuroSky)	1	Dry	Education

There were several research conducted to compare wearable EEG devices in comfort wearing aspect as well as functionality. In the first research [43] the Emotiv's EPOC and NeuroSky's MindWave were compared in comfort and wearing duration aspect. 13 subjects (2 of them excluded) participated in the experiment. Wearing experience was 15 minutes. The conclusion was that EPOC more comfortable it is possible to wear it at least for 20 min.

Another study [44] conducted compared the following EEG devices: g.tec's g.SAHARA, Emotiv's EPOC, Cognionics' Dry System, ANT Neuro's asalab, Brain Products' actiCAP, BioSemi's ActiveTwo, and Cognionics' Wet System. They were compared according to comfort, cap fit, mood, and movement restriction. There were

4 subjects (2-3 hours); 9 subjects (1-2 hours) in this experiment. The results have shown that asalab and actiCAP induced general discomfort although participants did not report unpleasant feeling under cap nor high pressure of electrodes. ActiveTwo and systems without adjustment possibilities received negative ratings regarding cap fit. EPOC, g.SAHARA, and asalab yielded a more negative mood at the end of the session. The wired systems asalab and actiCAP were rated as more movement restricting.

Another recent research [42] used 7 mobile EEG devices: MindCap (NeuroSky), EPOC (Emotiv), Jellyfish (Mindo), Trilobite (Mindo), BR8+ (BRI Inc), g.SAHARA (g.tec GmbH), g.LADYbird (g.tec GmbH), and compared them for their wearing comfort, type of electrodes, visual appearance, and subjects' preference for daily use. 24 subjects participated in this study the devices were worn for 60-min duration.

As the result the EPOC device had the best user experience results, but it also had a high percentage of artifacts. For the traditional gel-based but portable g.LADYbird device, exceptional results were obtained in terms of maximum wearing time and signal quality. For neuroscience research that requires prolonged, accurate measurements without sacrificing comfort, this device can be advised. Self-application and wearing devices in public, however, are not advised. Good user experience outcomes and satisfying signal quality were reported for the MindCap device. Users must consider that the availability of just one electrode may not give enough of information. Particularly due to comfort issues, the BR8+ and Trilobite devices failed to meet requirement for user experience. Additionally, the signal quality was poor.

It is important to notice that the primary determinant of a device's daily use was the wearing comfort. Undoubtedly, the device's appearance was an important consideration. However, it only became influential when comfort was provided. Users

did not want to sacrifice comfort for a more visually appealing headset design. Only when the product's behavioral level was satisfactory did the reflective level of emotional design become significant.

1.5. Research on EEG measurement system in our laboratory

There have been several research conducted in our laboratory intended to create a wearable electroencephalograph, that can be used on daily basis, outside of the laboratory with an easy montage. The main issue that should be overcome is electrodes that could measure brain activity at hairy areas of the head without special preparations. This was achieved with candle-type micro-needle electrodes being designed and analyzed. They will be described on the first part of this section. Following part will describe the headphone wearable electroencephalograph that was designed in the laboratory for electrode implementation.

1.5.1. Candle-type micro-needle electrode

The laboratory has developed candle-shaped microneedle electrodes (Figure 1-8) that enable EEG measurements at all measurement points, including especially hairy area of the scalp, without special skin preparation or conductive gel [53].

These electrodes consist of 144 pillars measuring 1mm in length and 0.4mm in diameter ending in 0.2mm micro-needles spaced at 0.43mm intervals on a 10mm square substrate. The shape and spacing of the pillars and micro-needles were determined by factors such as human scalp structure and hair density and diameter (Table 1.2) [54]. The electrode uses SU-8 (SU-8 3005, MICROCHEM, Westborough, USA) epoxy resin as the substrate, silver is vacuum-deposited to provide conductivity, and a parylene deposition is applied to protect against silver exfoliation. The electrode was designed with the intention that the pillar structure avoids hair follicles, and the micro-needles penetrate the stratum corneum to lower the contact impedance between

the skin and the electrode without pre-treatment of hairy areas.

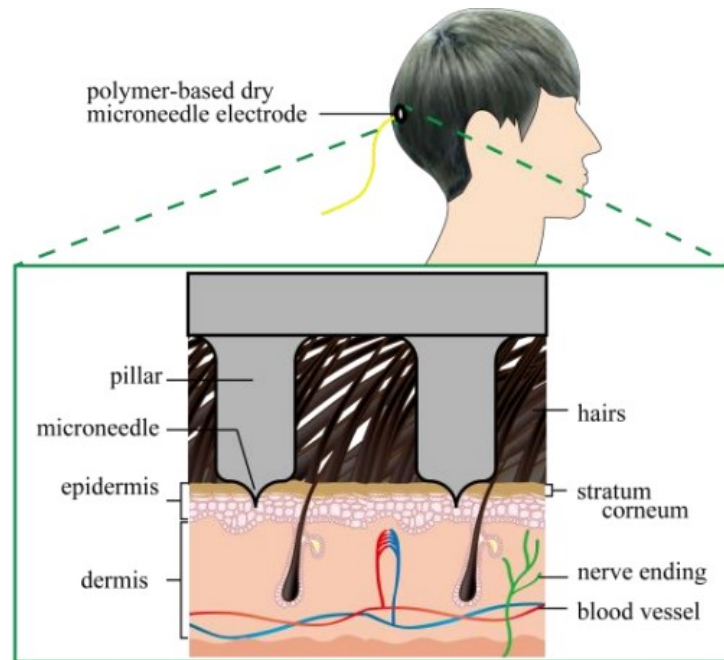


Figure 1-81 Conceptual diagram of the candle-like microneedle electrode [53].

The micro-needles are designed to be short enough to not cross the pain threshold so the patient may wear the electrodes without feeling discomfort. The electrode allows for simple and low-load EEG measurement in follicle-dense areas and considered useful for applied research in various fields. In certain cases, however, this pillar structure could not completely avoid hair in areas that are especially dense, and the microneedles may not reach the scalp.

Table 1.2 Comparisons of hair density [54]

Location	Hair density (<i>hair/cm²</i>)			
	Asian	Caucasian	African (race)	Hispanic
Frontal	154	230	160	174
Vertex	163	226	149	178
Occipital	160	214	148	169

A microneedle electrode with a larger contact space was then fabricated by changing the pillar length and pillar spacing with the intention to facilitate reduced impedance. Avoiding hair becomes integral to good EEG measurements, therefore an

electrode with a larger space was fabricated to avoid hair. This said spacing is defined as S below:

$$S = (l_p - l_n) \times w$$

For the expression above, w is the pillar spacing, l_p is the pillar length, l_n is the needle length. The electrode is required to maintain the concept and performance of a micro-needle electrode while expanding the space to avoid hair follicles. The conventional electrodes are designed to penetrate the stratum corneum, the substrate large enough that the adjacent electrodes do not come in contact, and the pillar diameter is designed to be folded to prevent fibers from being caught between the pillar tip and the scalp.

The intention was to keep the design of the electrode as minimalistic as possible to avoid affecting the hair. The microneedle electrode space was enlarged; the length and number of pillars was changed. The pillar length and diameter of the pillars was increased. Because the diameter was increased, the number of pillars on the substrate shrank. The pillar length was set to 3mm. The number of pillars were determined to be 36, 49, 64, 81, and 100. More pillars are desirable because as the number of pillars shrank, the subject felt more pressure and discomfort. In this study the performance of these new electrodes was evaluated based on contact impedance between the skin and electrodes on the parietal area of the head in response to the electrode pressing force. Hair density and comfort of the electrode were evaluated at the same time. EEG signal quality was evaluated with wet electrodes as a baseline. The electrode with 64 candle type microneedles performed the best according to this study therefore it was preferred to the other types of electrodes and chosen to be in the present study. The description of fabrication process as well as performance result of the electrodes will be discussed in Chapter 2.

1.5.2. Wearable headphone electroencephalograph

The electrodes were made with a purpose of comfortable and easy montage EEG measurement, therefore a device with these electrodes is needed to be designed. Comfort and design of the electroencephalograph are important for the daily use of the measurement device. Therefore, headphone type, wearable electroencephalograph was designed in our laboratory based on the following two ideas (Figure 1-9)

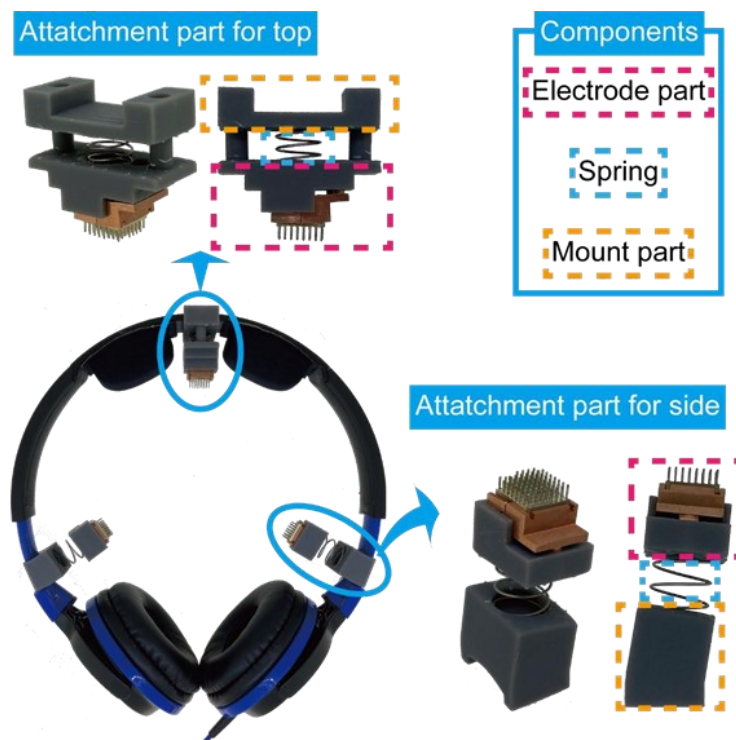


Figure 1-92 Wearable headphone electroencephalograph

1. Headphones are typically used for long hours daily because they are easy to wear and comfortable. In addition, the tactile stimulation of the earpieces reduces the discomfort of the electrodes.
2. Since the electrodes are not fixed to the skin, they can be easily removed and reattached if the subject feels discomfort.

However, due to the specificity of the headphone type electroencephalograph the ear canals are always blocked and implies types of use with sounds included or where the surrounding sounds are not important, as well as it can lead to uncomfortable

feeling on the ears, that one can feel after long time headphone usage. Another issue is that the attachment parts for electrodes need to come in very different sizes to fit people's head unique features, sizes, and shapes to maintain good contact and go through hair level.

Considering previously described points the new device should be developed that can maintain the ear canal open for more flexible device usage and can manage the problem of different head sizes without need of extra parts production.

1.6. Objective of the present study

Motor impairment is a partial or total body part disfunction, that has negative impact on person's life. Motor imagery alters brain activity, that can be detected with EEG and used for BMI to rehabilitate muscular activity or replace it with a machinery one. Motor imagery is a skill, that must be practiced in order to achieve good results at BMI control, rehabilitation. For one motor imagery practice current EEG device setup take 30 to 70 minutes and patients cannot montage the devices without assistance. As a result less practice time per patient and low rehabilitation centers capacity lead to slow learning process for the people of need.

Objective of the present study is to Increase motor imagery practice time per patient through decreasing EEG set mounting time, allowing patients to setup EEG without assistance, finding solution for a training without supervision.

Many wearable electroencephalographs have been developed to measure EEG in daily life. However, due to the issues such as functionality and appearance, electroencephalographs have not yet been developed to be widely used in society.

Therefore, this study will be focused on developing a headband-type knitted wearable electroencephalograph (EEG) and limitation of number of electrodes for efficient EEG signals classification. The electroencephalograph designed should the following aspects: it can be used in daily life without discomfort, it can be easily montaged by the patient, reattached, and measured over a long period of time, it can fit all type of head sizes with minimal adjustments, it allows flexibility in usage.

Based on the above, this study aims to develop an efficient classification of motor imagery for BMI application and to design and develop a knitted headset that can measure EEG at the scalp hairy areas with high accuracy. Use Robot for motor imagery practice assistance will be discussed as one of the ways to allow patients to perform motor imagery training with no specialist supervision and even at home.

1.7. Overview of the thesis

This thesis presents the work of designing an EEG measuring wearable knitted head band for efficient BMI application. The efficiency of the device as well as its limitations are discussed.

In Chapter 1 BMI introduction and its applications are given. Information on human brain, its structure, functionality of brain zones, brain activity measurement methods was given. Full overview of EEG measuring technique, existing EEG measurement systems, previous studies in our laboratory, and the purpose of this study are described.

Chapter 2 deals with the determination of the design, the fabrication process and performance analysis of knitted EEG measurement headband.

Chapter 3 presents the practical implementation of knitted EEG headband for motor imagery BMI application. Existing motor imagery dataset, toolboxes for EEG signal processing and classification, NAO6 Robot are presented. Analysis for efficient motor imagery classification and experimental results are given.

The discussion points arisen from the fabrication and experimental results are summed up in Chapter 4, as well as the future points of study to be treated.

Chapter 2

Design, Fabrication and Evaluation of the Wearable Knitted Electroencephalograph

2.1.Design and Fabrication

Chapter 2 is dedicated to design, fabrication, and performance evaluation of wearable knitted electroencephalograph. This section includes description and fabrication of the most important part of any EEG measuring device - the electrodes, followed by headband material analysis and choice, headband optimal size analysis, fabrication process.

2.1.1. Electrodes

The most important part of any electroencephalograph is electrodes. The goal of this work is to design wearable, comfortable electroencephalograph for daily use that does not imply time consuming device montage. The electrodes that do not need any skin preparation or conductive gel should be used. The electrodes that were developed in our laboratory (Figure 2-1), which purpose is comfortable wear with efficient hair avoidance giving the impedance sufficient for EEG data analysis [53], will be used. The latest study in our laboratory showed that an electrode with a pillar length of 3 mm and 64 needles has the lowest skin-electrode contact impedance under the same experimental conditions. The impedances and corresponding forces are shown on Table 2-1, and that indicating that pressing with 1 N or more force is sufficient for EEG measurement. In general, the impedance required for high-precision EEG measurement, such as for clinical use, is 10 k Ω or lower. However, it is known that

even about 100 k Ω can maintain sufficient accuracy of EEG measurement [30]. During the measurement of skin-electrode contact impedance, a comfort questionnaire was administered to the subjects.

Table 2-1 Comparisons of hair density [54]

Force, N	1	2	3	4	5
Impedance, k Ω	126	92	71	58	57

The results showed that 100% of the subjects could measure the electroencephalogram without feeling pain when the electrode force was less than 1 N and 75% when the electrode force was less than 3 N when the pillar length was 3 mm and 64 needles were used, respectively.

Based on the above results, it can be said that the micro-needle dry electrodes we fabricated can measure EEG with sufficient accuracy in the hairy area.

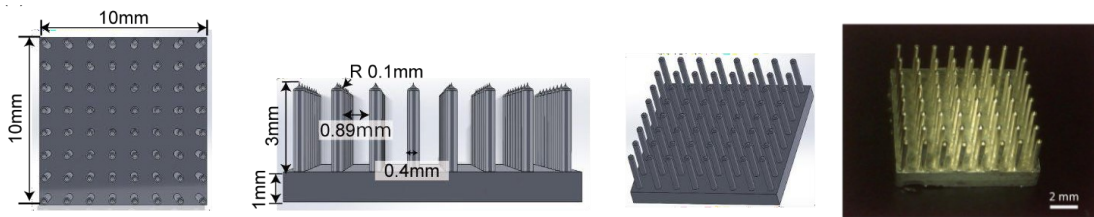


Figure 2-1 Structure of the fabricated micro-needle electrode

2.1.1.1. Fabrication of microneedle dry electrodes

The fabrication of the candle type microneedle electrodes (Figure 2-2) begins with a brass prototype. The brass prototype was designed using 3D CAD software (SolidWorks, Dassault Systems) and fabricated using a 5-axis, high-precision vertical machining center (NMV 1500 DCG, DMG Mori Seiki). A mold was made of PDMS (Sylgard 184, Toray Dow Corning). The mold was placed in a petri dish with the PDMS mixed with the main agent and hardener at a volume ratio of 10:1. The mold was then defoamed under reduced pressure in a dessicator for 30 minutes and subsequently heated on a hot plate at 60°C for 4 hours to harden the mold. The mold

was then used to manufacture the substrate of the electrode. The substrate material, SU-8 (SU-8 3005, MICROCHEM), was poured into the mold. After setting, the electrode is defoamed under reduced pressure in a desiccator for 10 minutes and the foam is cleaned using a brass brush. This process is repeated three times to completely fill the mold with material. The mold was then heated to 100°C for 14 hours and then exposed for 120 seconds. After exposure, the SU-8 substrate is heated again for 1 hour at 100°C to complete the curing. The PDMS and electrode were peeled off leaving the electrode and its pillars. A 0.1 μm silver coat is applied to the pillars using an electron beam vacuum evaporation system (SVC-700EB, Sanyu Electronics) to ameliorate the conductivity of the electrode. The thickness of the silver layer is controlled by a quartz crystal meter inside the chamber.

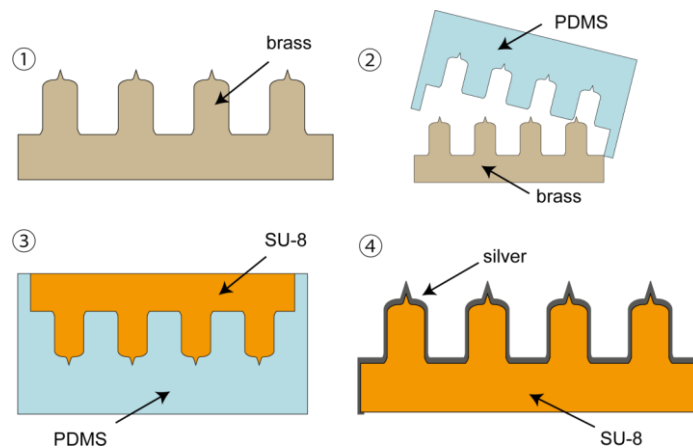


Figure 2-2 Electrodes fabrication process

For the use the electrodes should be mounted on a copper electrode holder (Figure 2-3) developed in our laboratory which size is 16x13x5mm and should be connected to a wireless biometric device Polymate Mini AP108(Miyuki Giken, Tokyo, Japan), that connects to computer by Bluetooth, using an electrode cord AP-C132-015 of 1.5m (Miyuki Giken, Tokyo, Japan). The neutral Kendal electrode should be placed on the right mastoid bone and the reference Kendal electrode on the left mastoid bone.



Figure 2-3 Connected electrode

2.1.2. Knitted headband

Comfort is an important quality criterion in case of wearable EEG device. If it is comfortable for a person, then there's a big chance the experiment can be conducted longer time as well as the stress of discomfort would not influence the data obtained. Yarn that should be used in the EEG headband design is a second key component after the electrodes. It should not only be comfortable for a human touch, but it should also be able to stretch well to fit different head sizes, as well as put enough pressure to keep electrodes on place. Another important quality is to be breathable and prevent a person from sweating, absorb the sweat and cool down the areas of the measurement. That is why at first, we discuss the yarn analysis, compare them, and chose the best one for our needs. Second the fabrication process will be explained. The last part will compare different headbands and the optimal model will be chosen.

2.1.2.1. Selected yarn analysis

Textiles are specific types of materials characterized by a unique combination of properties including strength, flexibility, elasticity, softness, durability, heat insulation, low weight, water absorbency/repellence, dyeability and resistance to chemicals [55].

Yarns were chosen as follows: Y1–100% cotton; Y2–100% wool; Y3–100% PAN (polyacrylic or acrylic), and Y4–100% PA (polyamide or nylon) – materials that are available in market that are most frequently used to make knit sportswear and casual outerwear [56], [57].

Cotton

One of the most significant natural textile fibers of plant origin is cotton, which makes up about one-third of the world's total production of textile fibers. Cotton is a natural 90-95% cellulose fiber. It is a soft, breathable, and absorbent fabric which is commonly used in summer clothing. Cotton material transmits moisture away from the body, it is absorbent and removes sweat from the skin, like a towel. It is a big advantage as the material that will be used for headband should prevent sweating to reduce artifacts as well as to not have changes in impedance value. This material has other useful characteristics like comfortable, soft to skin, washable in machine, good strength.

Wool

Wool fiber is the natural hair grown on sheep and is composed of protein substance called keratin. The fineness and the structure and properties of the wool will depend on the variety of sheep from which it was derived. One of the most breathable materials is wool. Wool fibers have a significant capacity to absorb moisture to evaporate it into the atmosphere. Wool yarn is comparatively expensive on the current market, especially merino wool, that comparing to regular wool that can be scratchy, does not irritate the skin.

Polyacrylic (PAN)

Polyacrylic fibres are produced from acrylonitrile [58]. First it is polymerized and then it is spun into a fibre, either in a wet or dry procedure. Polyacrylic fibres have a similar feel to wool and are resistant to chemicals and light. Acrylic fibers have a

variety of advantageous qualities, including longevity and wear resistance, strong resistance to sunlight, resistance to all biological and many chemical agents. Acrylic fibers are more flammable than wool, but less flammable than cotton. The fiber is moderately stiff and has excellent resiliency and recovery from bending deformation.

Polyamide (PA)

Originally, polyamide (commonly called nylon) was created as a substitute for silk when the latter material became difficult to obtain. Nylon is strong, slightly stretchy, and generally cheaper than natural fiber yarns.

2.1.2.2. Yarn and Fiber Properties

The following properties has been chosen to describe and compare fibers of chosen yarn for the future headband [55], [56], [59]:

Breaking elongation (dry) is a measurement that shows how much a material can be stretched — as a percentage of its original dimensions — before it breaks.

Elastic recovery is the ability of the material to recover after deformation $ER = \frac{\text{recovered strain}}{\text{imparted strain}}$ Elastic recovery of a fabric also depends on the fabric construction. Knit fabrics have good stretch and recovery. Moisture affects the ability to recover from deformations

Strain or elongation – deformation of fiber. When a fiber of original length l is stressed along its axis and extends an amount Δl then the strain is $\Delta l/l$

Tenacity is the term used to measure the strength of fiber/yarn. It is usually defined as the ultimate or breaking force of the fiber (in gram-force units) divided by the linear density (denier). Stress at failure is called strength.

Specific gravity also called relative density, ratio of the density of a substance to that of a standard substance. In case of fiber, it is defined as the ratio of material's density to the density of water at 23°C

Moisture Regain the amount of water that a material can absorb after being dried. The

weight/weight percentage (w/w%) of water in a material compared to its dry weight is how moisture regain is expressed.

Table 2-2 shows all these fiber properties for wool, cotton, PAN and PA fibers. After analyzing this table one can tell that the best elastic recovery is observed for PA fiber, while it has comparatively low density, that might be good for air permeability and therefore preventing sweating better.

Table 2-2 Fiber Properties Comparison [56], [57]

Property	Wool	Cotton	PAN	PA
Breaking elongation (dry)	35%	10%	25%	60%
Elastic Recovery (5% strain)	69%	52%	50%	89%
Elastic Recovery (1% strain)	99%	91%	92%	90%
Tenacity (g/d)	1.6	4.0	2 - 4	5.5
Specific gravity	1.31	1.52	1.16-1.18	1.14
Moisture Regain	14%-18%	7.5%	1.0%-2.5%	4.1%

According to this study [60] all knitted samples produced from PA filament displayed the lowest air permeability, lowest heat resistance, and lowest water vapour resistance, is extremely elastic and has a high toughness. It follows that sportswear constructed of PA filament performs best in warm indoor or outdoor settings. The knitted samples were made using Shima Seiki SES 122 RT knitting machine, so it was possible to use the PA filament, while the current study involves a hand-crafted knitted patterns and only spun yarn can be accepted. Important information that was retained from this study is that according to the correlation analysis, yarn's linear

density, yarn short fibers hairiness, and mass per unit area have the most effects on heat resistance and the factors that affect air permeability the most include yarn linear density, yarn hairiness of the longer projecting fibers, and knit fabric thickness. Table 2-3 shows characteristics of the chosen yarn.

Table 2-3 Yarn Characteristics Comparison

Characteristics	Alpaca Wool	Cotton	PAN	PA
Yarn Hairiness	Excessive	Little	Moderate	Little
Weight, gr	50	30	60	100
Length, m	100	55	108	155
Linear Density, gr/m	0.50	0.55	0.56	0.64
Thread diameter, mm	1.25	1.25	2	1.5

After knitting first samples and comparing fiber properties (Table 2) and yarn characteristics (Table 3) the following conclusions have been made: the excessive and even moderate yarn hairiness can damage electrodes while installation as well as during exploitation, micro-needle can be tangled in the fabric hairs and can easily be broken. Cotton and nylon yarns have little hairiness, and both could be chosen as a material for headband.

The main difference between nylon and cotton is that nylon has a very high elasticity. Elasticity is indeed needed as the fabric should stretch to make a pressure and fit different head sizes, but it will be additionally achieved with knitted textile structure. But excessive elasticity can cause problems such as uncontrollable and unpredictable electrode location, if user will stretch the band too strong.

As a result, the cotton yarn was chosen for headband fabrication. Additionally,

cotton has a pleasant skin contact sensations, does not irritate the skin and is breathable.

2.1.2.3. Size of a knitted headband

After choosing the yarn material, size of the headband should be chosen. Once can see the maximum circumference size is 62.5cm for a man of 200cm height and minimum size is 50.5 for a woman of 140cm height [61].

Considering the elasticity property of the knitted fabric and a margin for the loop fastener the chosen length is 550mm. The width of an electrode together with the holder is 13mm, to make a good margin, the width of a headband is decided to be 25mm.

2.1.2.4. Fabrication process

After choosing the yarn material and size of a future headband the fabrication method should be chosen. Fabrication process includes knitting with knitting. Knitting is the process of weaving yarn into fabric by creating loops that interlock with the aid of needles. While knitting can be done with a machine, in this work knitting will be done by hand. The size and shape of the loops and knitted structure will be important for the electrode placement on the EEG band. The fixation of electrode will be done by placing electrode on one side of the material, while part of the copper holder body with the cylinder for cord end connection (3.5mm diameter, 4mm long) will be on another side of the material. During the fixation procedure the fabric will be clamped between the copper holder with an electrode and cord connector. Considering that this technique in use the size of knitted loops should be small enough to not let the electrode slide on the other side and big enough that after stretching the loop the part of the copper holder body can go through. Taking this into account 2.5mm knitting needles (20cm long) were used.

The simplest way to turn yarn into fabrics is by weft knitting. In the process of creating a fabric known as weft knitting, loops are formed horizontally from a single yarn and are intertwined crosswise into a circular or flat pattern. With this technique, each weft thread is supplied roughly perpendicular to the direction that cloth is constructed. A weft knit is constructed in courses, each of which builds upon the one before. [62]

To begin knitting, it is needed to create a foundation row of 12 stitches on needle by "casting on" [63]. Then the following row will be knitted using a knit stitch [64].

After knitting a first row without turning the work to the back side, but staying on the front side, slide all the loops to the other end of the needle and continue the work with knit stitch. As a result, on one side of the work will be a thread connecting left side of the knitting with the right side. This connection will create a tube and at the same time creating the space for electrodes “hugged” by fabric from both sides. Continue knitting using these instructions until the desired length is reached (55cm). Bind off to end the work [65].

The result of the knitted band will be a 55cm long, 3cm wide knitted tube with knitted pattern on one side (front side) and on a back side will be knitted pattern with rows of bridges (Figure 2-4). The back side will be with electrodes and will be pressed to a head. Inside of the formed loop the wires coming from electrodes will be hidden.



Figure 2-4 Knitted pattern on front side (a), and on back side (b) without electrodes

For the headband fixation hook and loop fastener tape was used on both sides.

With this type of fixation and stretching, the knitted headband can be placed on different head sizes without additional adjustments or extra parts.

2.1.3. Electrodes placement

To place electrodes, it will be needed apply deformation of the loop located on the desired electrode placement, on the middle of the row. The fabric formation pattern is shown on Figure 2-5 loop that will be stretched from to make a bigger hole is marked by dark gray color.

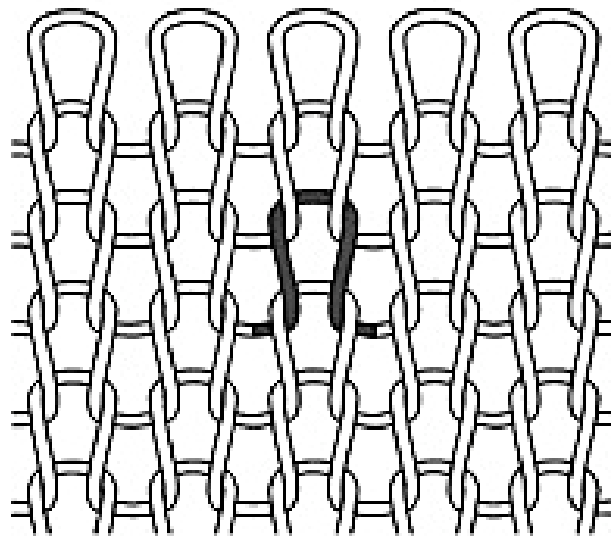


Figure 2-5 Weft knitted fabric

On the Figure 2-4 it is noticeable that the hole of a 5mm long loop is almost invisible, but after fabric deformation and stretching the loop, the maximum diameter reached was 20mm. This size is enough to put the copper holder body part and to put a wire connector through, which size is 7x5mm. The wire goes through the inside of a tube to one of the ends of the headband and from there connects to wireless biometric device Polimate Mini. After electrode placement the stretched loop is released, and the shape of a loop comes back to initial state. The fixated electrode is shown on Figure 2-6.



Figure 2-6 Electrode fixation on knitted EEG headband front side (a), and back side (b)

The final look of wearable knitted EEG headband is shown on Figure 2-7. The example of three placement modes of knitted headband for different electrode measurement locations are shown of Figure 2-8.

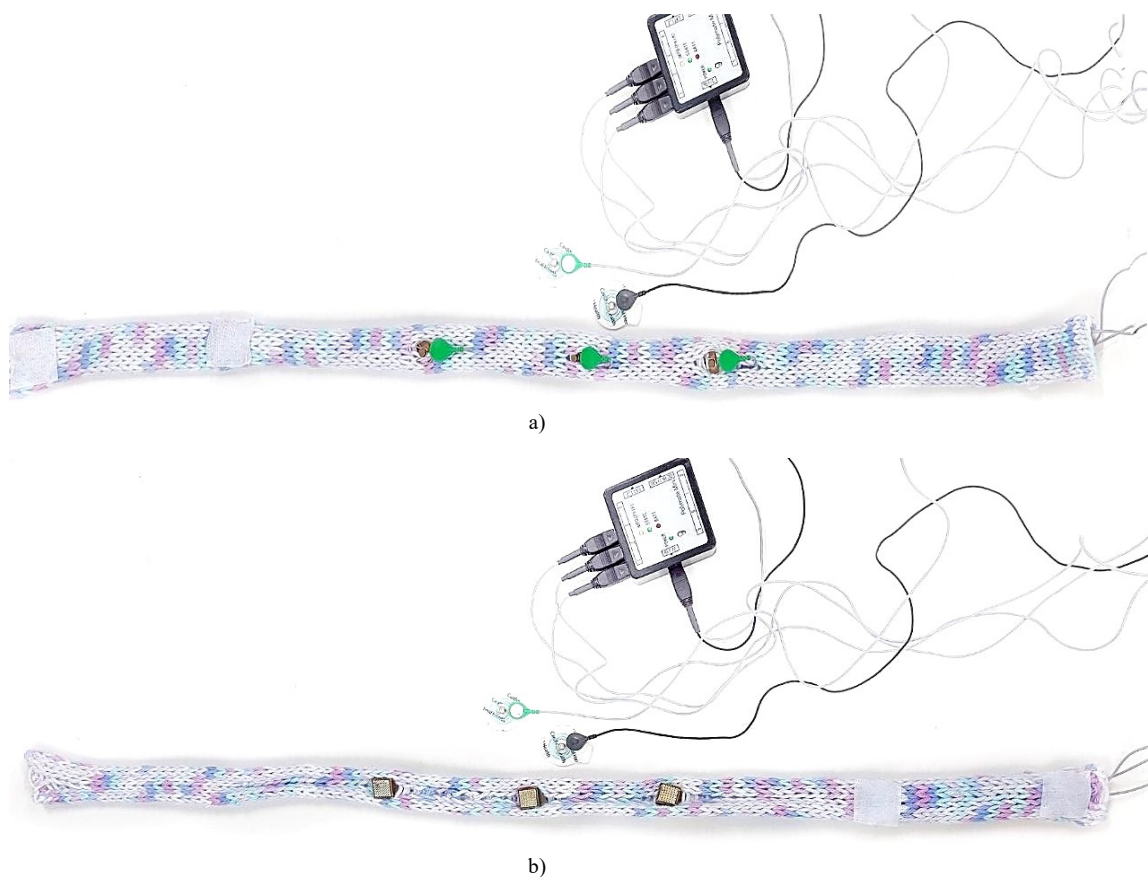


Figure 2-7 Knitted EEG headband front side (a), and back side (b)



Figure 2-8 Knitted EEG headband three placement modes

2.2.Experimental results and discussion

After the fabrication process next step is, the evaluation of knitted EEG headband. In this section three different tests were performed to evaluate the device: performance test, usability and user experience, conclusion summarizing the headband advantages and disadvantages are given at the end of this section.

2.2.1. Performance of the device

First is performance evaluation, check if the headband work, we can use it to measure EEG, if an electrode impedance is stable enough and how long can the headband be used without losing the performance.

2.2.1.1. Experimental conditions

A subject was sat comfortable in the chair. The timer has started to show how long will it take to montage the EEG measurement device. The steps for setting up the device were performed: right and left mastoids are cleaned; the neutral Kendal electrode is placed on the right mastoid and the reference Kendal electrode on the left mastoid and connected with Polimate Mini device with electrode cord. The headband

with electrodes is mounted around the head placing three electrodes on C3, Cz and C4 according to 10-20 electrode placement, this area is responsible for motor functions.

Initial value of impedance on the electrodes were 55 k Ω , 46 k Ω , 44 k Ω accordingly.

The subject was asked to relax and do any activities wanted while seated. Impedance of the electrodes was measured every 5 minutes and the experiment lasted 100min long. At the beginning and at the end of the experiment subject was asked to evaluate from 1 to 5, how strongly would they like to remove the object from the head, where 1 - do not care and 5 - very strongly.

2.2.1.2. Experimental results and discussion

At the beginning of the experiment the answer representing the willing to remove the headband from their head was recorded as 2. During the experiment subject was taking, eating, drinking, reading, using mobile phone, moving, but without touching the headband or changing the mounted system at any way. The graph showing the impedance change with the time is shown on Figure 2-9. We can see that two electrodes (C3, Cz) changed the impedance value by approximately 20 k Ω and C4 electrode by 10 k Ω . At the end of the experiment, after 100min of headband use the subject has showed higher desire to remove the headband, the answer to the question how strongly they would like to remove the object from the head has become 4.

This experiment has shown a good performance and was proved to be usable for a long time, by mean, at least 100min. While there is indeed the change in impedance value, the impedance at the end of the experiment can still be acceptable for EEG measurement. The construction itself include the possibility to adjust the electrode, it can easily being take on and off in a matter of seconds. The montage process at the very beginning, with Kendal electrode placement has taken 2.5min. This time is short enough, comparing to the EEG devices existing on the market [66].

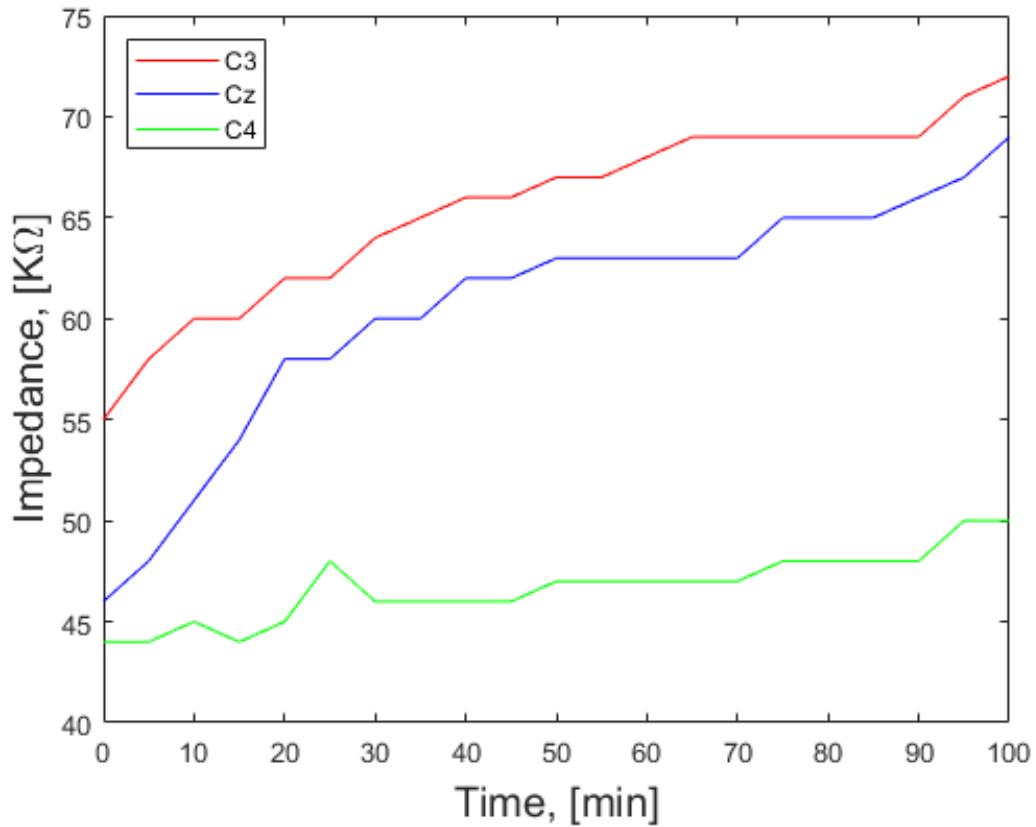


Figure 2-9 Impedance changes of C3, Cz, C4 electrodes with time

2.2.2. Usability of the device

Eye-opening and eye-closing trials in the occipital region were performed to evaluate the EEG signals obtained by the knitted EEG measuring device and prove that it can be usable for the applied tasks.

2.2.2.1. Experimental conditions

The subject with mounted knitted EEG headband with electrodes placed on Occipital zone: O1, Oz, O2, was sat comfortable on a chair. EEG signals were sampled and recorded using the EEG recording software Mobile Acquisition Monitor. The subject was asked to sit with eyes being open and the data recording started. After one minute the subject was asked to close their eyes and sit with eyes closed for one minute, after the minute recording was stopped. The total recording length was 2 minutes – 1 minute with eyes open, 1 minute with eyes closed. The data was recorded

at 500 kHz, and bandwidth filters were used from 2 Hz to 30 Hz. The measured EEG time series data was a subject to spectral analysis in Jupiter Notebook. Fast Fourier transform was used to calculate frequency data from the time-series EEG data obtained, then one-sided power spectral density (PSD) from frequency data was calculated and signal-to-noise ratio (SNR) for alpha wave from PSD was performed.

2.2.2.2. Experimental results and discussion

Visual cortex is located at occipital area and alpha waves (8-13 Hz) are known to be amplified during resting eye closure [67]. If the headband measures EEG correctly, then when the eyes are closed during wakeful relaxation, an occipital alpha wave should be seen; when the eyes are open, it should be decreased. Figure 2-10 shows the power spectral density of the signals in each state, eye-opened and eye-closed. We can see that the figure demonstrates that the PSD of a subject with closed eyes had a peak in the frequency region of alpha wave. As a result, it can be claimed that the knitted EEG headband successfully measured the EEG without having any disruption by thick hair on the occipital area.

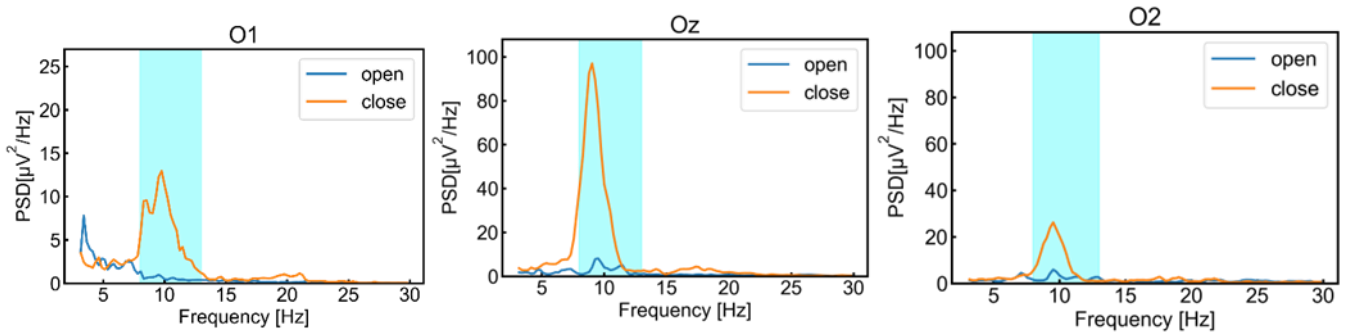


Figure 2-10 PSD of electrodes in the eye-closed eye-open test

2.2.3. User experience of the device

After it is proven that knitted EEG measuring device can be used for the experiments including EEG measurements, the user experience will be evaluated. The questions about wearing comfort and visual appearance were asked to 10 subjects.

2.2.3.1. Experimental conditions

In the experiment 10 male graduate students participated as subjects. A subject was sat comfortable in a chair and instructed about mounting system of the EEG headband. After knitted EEG headband is mounted the following questions were asked:

- 1) How easy the montage process was? Evaluate from 1 to 5, where 1 – “not easy, took a long time”, 5 – “very easy, fast”
- 2) Do you feel any major discomfort while wearing the band, how comfortable is it? Evaluate it from 1 to 5, where 1 – “not comfortable at all”, 5 – “very comfortable”
- 3) How strongly would you like to remove the object from the head? Evaluate it from 1 to 5, where 1 – “do not care, can stay like that”, 5 – “very strongly, want to remove right now”
- 4) Evaluate, how long could you stay like that wearing the headband?
- 5) Considering that the headband can come in different pattern and color, how strong was your feeling of being shy/embarrassed while having the object on the head in the presence of other people? Evaluate it from 1 to 5, where 1 – “no such feeling, could easily wear it”, 5 – “very strongly, wouldn’t like people to see me like that”

The responses were collected, recorded and averaged to see the whole picture of the user experience the subjects had.

2.2.3.2. Experimental results and discussion

Results of this experiment (Table 2-4) showed that subjects were satisfied with the process of montage and had reasonably low desire to remove the headband. The comfort was evaluated as 3.9/5 on average. Of course, the headband cannot stay unnoticeable, considering that it is still a measuring device, the result is satisfying.

Table 2-4 Questionary User Experience Results

Questions	Answers of 10 subjects	Average
1 - Montage	[3, 4, 5, 5, 4, 4, 4, 5, 4, 5]	4.3
2 - Comfort	[3, 4, 4, 5, 4, 4, 3, 3, 4, 5]	3.9
3 - Desire to remove	[2, 3, 3, 2, 1, 3, 2, 3, 3, 1]	2.3
4 - How long?	[1h+, 1h, 1h, 1h+, 1h, 30min, "all day", 1h, 30min, 1h+]	1h+
5 - Embarrassment	[3, 2, 3, 3, 2, 3, 3, 4, 1, 2]	2.6

The result shows that people in general ready to stay with the headband for longer than one hour, the results from performance test show, that headband can give impedance low enough to have continues measurement during this time. This time can be sufficient for majority of EEG tests, except sleeping tests. This knitted EEG band is intended to be merged with BMI system. The tasks for motor imagery are hard by themselves due to need of concentration, for this purpose 1 hour is reasonable amount of time and considering the speed and ease of headband montage, the experiments can be conducted with breaks without taking a long time and efforts for installation.

2.2.4. Results

The knitted EEG headband showed satisfying experimental results and it was shown that the headband can be comfortably worn for more than one hour, while keep the impedance for EEG measurements lower than 100k Ω . The main advantage is the easy (under 3 min) set up for different head sizes, as it can stretch and be adjusted with the locking system. Electrodes can be placed on any desirable position on the head circumference and on top of the head (in case of putting a locking system under the chin). People are used to knitted things so doesn't add stress that can add undesirable signals to measurements, the headband does not close the ears and as the

result can be used in all kinds of experiments: with surrounding sounds, person to person communication, as well as with earphones. The main disadvantage of the band is that it cannot fit more than 6 electrodes and the placement options are limited and the impedance value is higher than the one in medical need ($10\text{ k}\Omega$). The headband use is limited by these disadvantages, but in some EEG research such as BMI or social interactions/cooperation these disadvantages can be balanced by advantages this knitted EEG measuring headband has.

CHAPTER 3

Electroencephalogram Classification for BMI application

3.1. Imaginary movements classification

Our brain can represent perceptual information in our thoughts through mental imagery, a multimodal cognitive modeling process, without actual sensory work [68]. "Motor imagery" is a dynamic mental state in which the working memory representation of a specific motor activity is practiced without overt motor output. For motor imagery task the brain signals of the patient imagining the desired physical movement should be classified into the type of action the patient is imagining. For the classification the trained on big number of data classification model is needed. In this first section dataset used for classification model training will be described, analysis of classification results using the trained model will be given as well as tools that were used for the training will be outlined.

3.1.1. Dataset for imaginary movements classification

The classification of imaginary movements is a wide research topic [10], [24], [69]. The BCI research community have created public BCI datasets, including continuous usage, single sessions, and several sessions per subject. In the present study one of the existing datasets was accessed for further analysis, in this section the dataset will be described.

3.1.1.1. MOABB

The MOABB (Mother Of All BCI Benchmarks) [70] project is made of the

combination of numerous publicly accessible EEG datasets, transformed to a standard format, and a library of SOA (Service-oriented architecture) algorithms.

Dataset objects are functions which implement an interface for downloading and ordering recorded data, organizing it into a hierarchy of subjects, sessions, and discrete recordings per session. There are around 15 datasets that have already been included in the package. This benchmark was chosen in the current work as it includes the datasets that make an interest in the present study. BNCI 2014-001 Motor Imagery dataset Dataset IIa from BCI Competition 4 [69] was chosen and accessed with MOABB API.

3.1.1.2. BNCI 2014-001 Motor Imagery dataset

This continuous Multi-class Motor Imagery dataset consists of electroencephalographic data from nine subjects. The cue based BCI paradigm included four distinct motor imagery tasks: left hand (class 1), right hand (class 2), both feet (class 3), and tongue (class 4). For each subject, two sessions on different days were recorded. There are six runs in each session, separated by brief breaks. A session has a total of 288 trials, with one run consisting of 48 trials (12 for each of the four possible classes).

The EEG was recorded using twenty-two silver-silver chloride Ag/AgCl electrodes with an inter-electrode spacing of 3.5 cm, their location is on Figure 3-1 marked by pink color.

The procedure of the experiment was following. All of the participants were seated in plush chairs in front of computers. An initial fixation cross was seen on the pitch-black screen at the start of each trial ($t=0$ s). A brief acoustic warning tone was also played. A cue in the form of an arrow that might be pointed left, right, down, or up and denoted one of the four classes—left hand, right hand, foot, or tongue—appeared after 2 seconds ($t=2$ s) and remained visible for 1.25 seconds. The intended

motor imagery task was then carried out by the subjects as a result. No feedback was given. The motor imagery task was to be carried out by the subjects until the fixation cross vanished from the screen at $t=6$ s. There was a brief pause followed by a black screen.

Figure 3-1 Electrode montage corresponding to the international 10–20 system

3.1.2. Tools for EEG processing and classification

3.1.2.1. MNE-Python

MNE is open-source academic Python package, which objective is to create and supply a set of algorithms that enable users to put together full data analysis pipelines covering the majority of M/EEG data processing stages [71]. MNE-Python now provides a large

number of additional features, such as time–frequency analysis, non-parametric statistics, connectivity estimation, independent component analysis (ICA).

3.1.2.2. Braindecode

Braindecode is a deep learning toolbox to decode raw time-domain EEG. It is created for researchers to work with EEG data, analyze it and performs deep learning techniques, it is mainly focused on convolutional networks.

For raw time-domain EEG, Braindecode includes a few preconfigured convolutional neural network topologies. For the purpose of decoding and visualizing EEG, in this research the Shallow ConvNet and Deep ConvNet models will be used and compared. Braindecode object called EEGClassifier, that is in charge of managing neural networks training, will be used.

3.1.2.3. Shallow and Deep ConvNet

The following study [72] introduced ConvNets for EEG decoding. This study proposed generic architecture in order one could achieve competitive accuracies using generic ConvNet designed with only little expert knowledge, as well as they provided evidence in favor of the notion that standard ConvNets can be used as a general-purpose tool for brain-signal decoding tasks.

ConvNets, in general, integrate two concepts that are helpful for a variety of learning tasks on natural signals, such images and audio signals. Convolutions and nonlinearities allow ConvNets to learn local non-linear features, and they can represent higher-level information as composites of lower-level features.

Additionally, a lot of ConvNets employ pooling layers, which result in an intermediate feature representation that is coarser and can increase the ConvNet's translation invariance.

The final classifier output is produced by gradually transforming the EEG input (at the top) towards the class. Exponential linear units (ELUs) were used as activation function. More details on the architecture can be found in the paper [72].

3.1.3. Classification with limited number of electrodes

As was discussed in Chapter 2, the designed knitted EEG headband can fit maximum number of electrodes of 6, while the optimal number is 3. To be able to use knitted EEG headband for motor imagery classification we need to make sure that the classification can be done with a small number of electrodes. In section the open access BNCI 2014-001 Motor Imagery dataset will be analyzed using Deep ConvNet architecture for classification.

3.1.3.1. Pre-processing

For ConvNets is recommended to only minimally preprocess of the datasets to allow the ConvNets to learn any further transformations themselves. Pre-processing will be consisted in following: 4 Hz low cut frequency filtering, 38Hz high cut frequency filtering and convertation from volt to microvolt and exponential moving standardization [73] to highlight longer-term trends and smooth short-term peaks.

3.1.3.2. Processing

Processing step will create data that will be used as inputs for the deep networks during training. The ConvNet is trained using the trial signal as input and the associated trial label as target for each trial [72]. In the case of trial-wise decoding, the only thing that should be decided is if some part before and/or after the trial should be cut. In case of motor imagery is it often beneficial to cut out 500 ms before the trial

and after trial, because it takes time for a person during the experiment to start imagining the movement after a given signal to do so.

In this work more data-efficient cropped decoding was used. Trialwise decoding and cropped decoding are two acceptable options for training models in Braindecode. During the trialwise decoding the whole trial is used for the prediction, in case of cropped decoding several crops are taken from the trial, each crop is then classified, resulting in several predictions per trial, that are then averaged to get one prediction from the trial.

Trial-wise decoding.

A full trial is pushed to the network, a prediction is given by the network, to calculate the loss, the prediction is compared with the target (label) for that trial.

Cropped decoding

Crops are pushed to the network. Several nearby crops are simultaneously pushed through the network for computational efficiency, the neighboring crops are called compute windows. As a result, the network gives one per crop in the window predictions. Each crop predictions are averaged and then the loss function is computed.

Before we can divide the dataset into windows (crops), we must first create the model. This is due to the fact that determining the size of the window stride requires knowledge of the network's receptive field.

After cropping, dataset will be split into data for training and data for validation. In the case of present dataset one session was used for training and second session for validation.

3.1.3.3. Classification model

First, we select the size of the compute/input window that will be supplied to the network during training. This window size must be greater than the size of the

network's receptive field - a the size of the input region that generates the feature [74]. In this case - 1000 samples. Next, the model should be built. It will be needed to manually adjust the length of the final convolution layer to a length that makes the ConvNet's receptive field smaller than input window samples to make it effective for cropped decoding. Initial model with strides should be transformed to a model that outputs dense prediction, the properly predictions for all crops will be obtained. Now the receptive field can be found by calculating the shape of a model output for an irrelevant input. After all these step, finally the explicit window size and window stride (the distance the window moves at each step), can be used to create windows for the model input.

The Deep ConvNet model was trained using the following parameters:

learning rate (lr) = $1 * 0.01$ - a tuning parameter in an optimization algorithm that chooses the step size throughout each iteration while working toward a loss function minimum [75]; weight_decay = $0.5 * 0.001$ - weight decay adds a penalty term to the cost function; batch_size = 64 - number of samples that will be propagated through the network; n_epochs = 40 – number of times the entire training dataset will be passed forward and backward through the neural network.

For Shallow ConvNet the following parameters were chosen: lr = $0.0625 * 0.01$

weight_decay = 0, batch_size = 64, n_epochs = 40.

3.1.3.4. Classification results

First classification results by training classification model on the data from all subjects and all electrodes showed 63% classification accuracy using Shallow ConvNet and 68% using Deep ConvNet.

Motor imagery is a mental process when a person imagines or simulates a certain muscular action without performing actual muscular acidity. Motor imagery is a skill and requires a certain level of concentration and focus. Based on this fact was made a

proposal, that not every subject managed to perform the experiment well. At the same electrodes located at motor cortex area should be the one responsible for the classification accuracy the most.

This is a reason for the next step: Deep ConvNet training on three electrodes that are located at motor cortex area of the brain: C3-Cz-C4 for each subject. The results are shown on Figure 3-2. It is easy to notice that there is indeed a difference between different subjects' performances and a major drop at classification accuracy for subjects under number 2, 4, 5 and 6, while subject 3 and 9 performed the best and classification result reaches 71% and 69% accordingly on three electrodes. It can be already enough to show that the motor imagery tasks can be classified with the use of small number of electrodes.

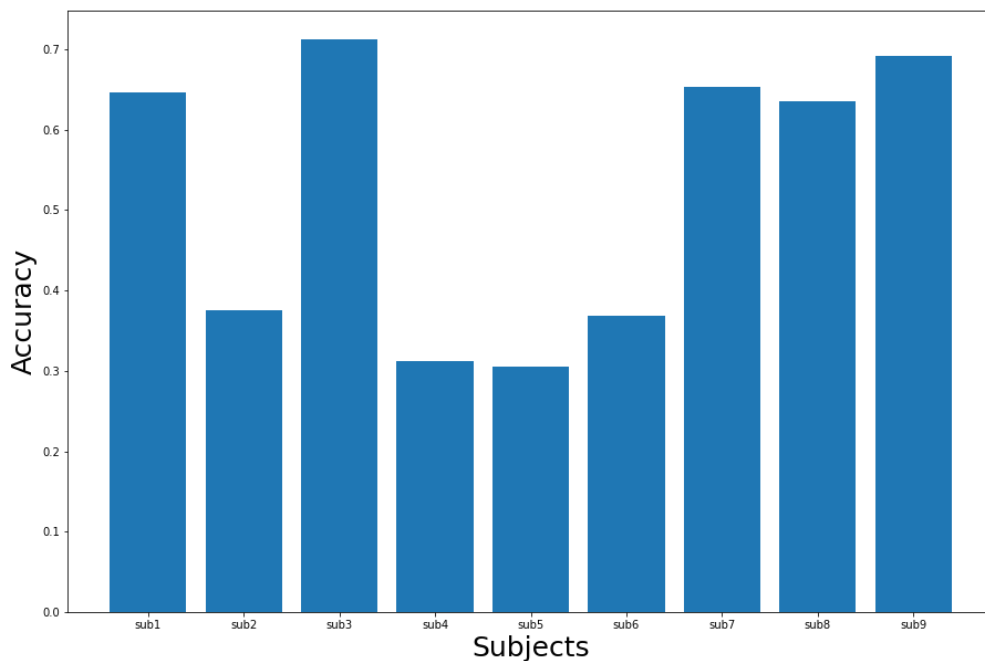


Figure 3-2 Classification Accuracy per subject

As subject number 3 has performed the best classification result, this subject will be used in the future analysis of the motor imagery dataset.

Analysis that was performed next was intended to compare performance of Deep and Shallow ConvNets, as well as check accuracy that can be obtained from

classification with other triplets of electrodes that are closely located to motor cortex. The results are shown on Figure 3-3. Deep ConvNet outperforms Shallow ConvNet and is chosen to be the only classification model for the future analysis. These results also show that CP3-CPz-CP4 triplet reaches the highest classification 74% accuracy. This location can be considered as an electrode placement for motor imagery tasks, but also the shown result gives a margin for electrodes placements, as the difference between C3-Cz-C4 and CP3-CPz-CP4 is omittable. So the electrode misplacement of 28 to 38 mm (given a head circumference of 58 cm) can be acceptable.

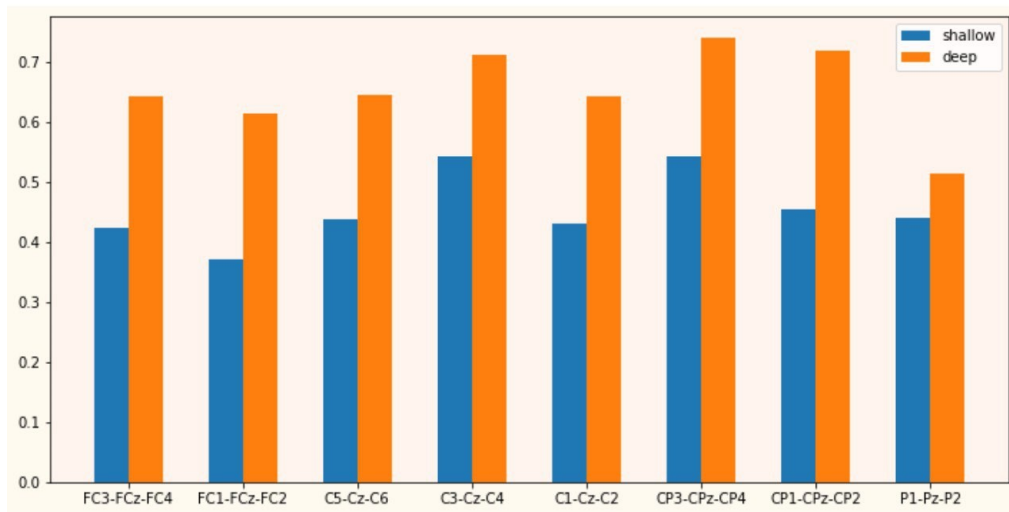


Figure 3-3 Shallow and Deep ConvNet classification results for subject 3

It was also interesting to evaluate how number of electrodes can influence the classification accuracy for one subject. In this analysis the electrodes were removed by how fare they are located from motor cortex. The order and which electrodes were removed from the training dataset at each run is shown in Table 3-1. The classification results are shown on Figure 3-4. The accuracy value does not change very much, but the highest accuracy was achieved for 'C3', 'Cz', 'C4', 'CP3', 'CP1', 'CPz', 'CP2', 'CP4' set of electrodes reaching 85% accuracy. While 8 electrodes is already too much for knitted EEG headband, the accuracy for only 6 electrodes: 'C3', 'Cz', 'C4', 'CP3', 'CPz', 'CP4' reached 80% and in this can be possible to implement,

but in this case the headband should be wider, being able to fit two rows of electrodes with 28 to 38 mm in between.

Table 3-1 Label interpretation

Label	Removed Electrodes	Electrodes used in classification
All	-	'Fz', 'FC3', 'FC1', 'FCz', 'FC2', 'FC4', 'C5', 'C3', 'C1', 'Cz', 'C2', 'C4', 'C6', 'CP3', 'CP1', 'CPz', 'CP2', 'CP4', 'P1', 'Pz', 'P2', 'POz'
All-2	-Fz-POz	'FC3', 'FC1', 'FCz', 'FC2', 'FC4', 'C5', 'C3', 'C1', 'Cz', 'C2', 'C4', 'C6', 'CP3', 'CP1', 'CPz', 'CP2', 'CP4', 'P1', 'Pz', 'P2'
All-4	-Fz-POz -FC3-FC4	'FC1', 'FCz', 'FC2', 'C5', 'C3', 'C1', 'Cz', 'C2', 'C4', 'C6', 'CP3', 'CP1', 'CPz', 'CP2', 'CP4', 'P1', 'Pz', 'P2'
All-4-1	-Fz-POz -FC1-FC2	'FC3', 'FCz', 'FC4', 'C5', 'C3', 'C1', 'Cz', 'C2', 'C4', 'C6', 'CP3', 'CP1', 'CPz', 'CP2', 'CP4', 'P1', 'Pz', 'P2'
All-4-2	-Fz-POz -P1-Pz-P2	'FC3', 'FC1', 'FCz', 'FC2', 'FC4', 'C5', 'C3', 'C1', 'Cz', 'C2', 'C4', 'C6', 'CP3', 'CP1', 'CPz', 'CP2', 'CP4'
All-6	-Fz-POz -FC3-FC4 - FC1-FC2-FCz	'C5', 'C3', 'C1', 'Cz', 'C2', 'C4', 'C6', 'CP3', 'CP1', 'CPz', 'CP2', 'CP4', 'P1', 'Pz', 'P2'
All-8	-Fz-POz -FC3-FC4 - FC1-FC2-FCz -C1-C2	'C5', 'C3', 'Cz', 'C4', 'C6', 'CP3', 'CP1', 'CPz', 'CP2', 'CP4', 'P1', 'Pz', 'P2'
All-8-1	-Fz-POz -FC3-FC4 - FC1-FC2-FCz -P1-PZ-P2	'C5', 'C3', 'C1', 'Cz', 'C2', 'C4', 'C6', 'CP3', 'CP1', 'CPz', 'CP2', 'CP4'
All-10	-Fz-POz -FC3-FC4 - FC1-FC2-FCz -C1-C2 -P1-PZ-P2	'C5', 'C3', 'Cz', 'C4', 'C6', 'CP3', 'CP1', 'CPz', 'CP2', 'CP4'
All-12	-Fz-POz -FC3-FC4 - FC1-FC2-FCz -C1-C2 -P1-PZ-P2 -C5-C6	'C3', 'Cz', 'C4', 'CP3', 'CP1', 'CPz', 'CP2', 'CP4'
All-14	-Fz-POz -FC3-FC4 - FC1-FC2-FCz -C1-C2	'C3', 'Cz', 'C4', 'CP3', 'CPz', 'CP4'

	-P1-PZ-P2 -C5-C6 - CP1-CP2	
All-14-1	-Fz-POz -FC3-FC4 - FC1-FC2-FCz -C1-C2 -P1-PZ-P2 -C5-C6	'CP3', 'CP1', 'CPz', 'CP2', 'CP4'
All-16	-Fz-POz -FC3-FC4 - FC1-FC2-FCz -C1-C2 -P1-PZ-P2 -C5-C6 - CP1-CP2 -CP3-CPz- CP4	'C3', 'Cz', 'C4'
All-16-1	-Fz-POz -FC3-FC4 - FC1-FC2-FCz -C1-C2 -P1-PZ-P2 -C5-C6 - CP1-CP2 -C3-Cz-C4	'CP3', 'CPz', 'CP4'

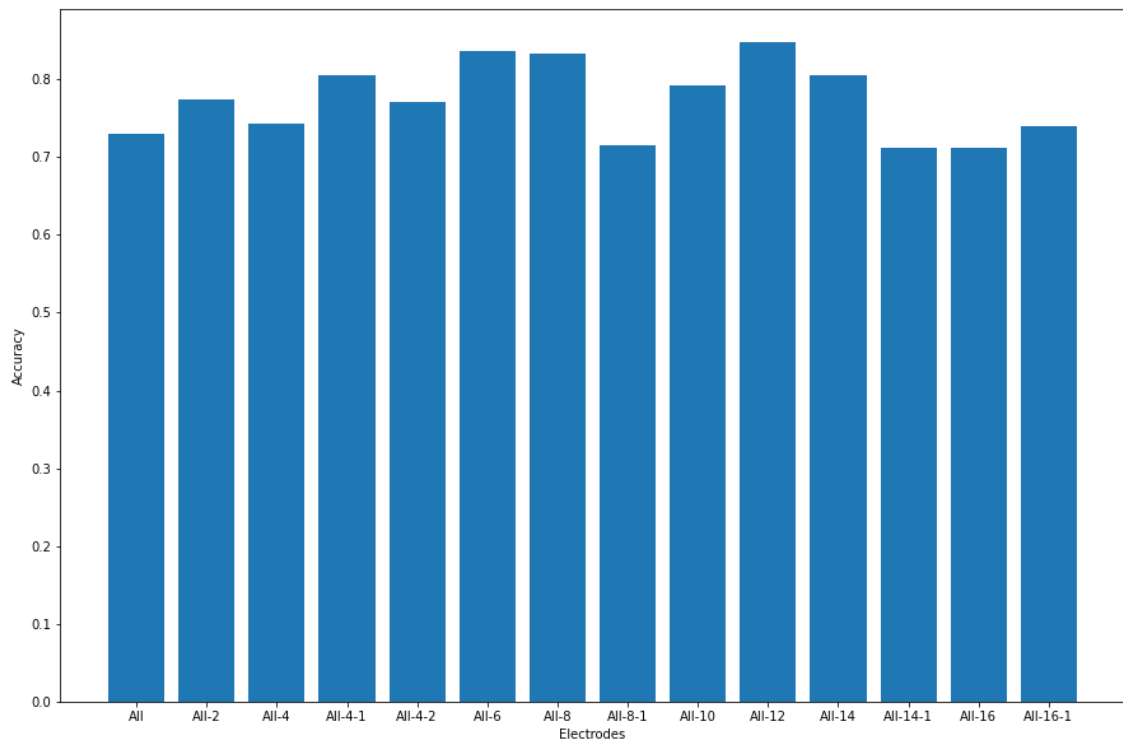


Figure 3-4 Classification results of reducing number of electrodes for subject 3

The confusion matrix for 6 electrodes 'C3', 'Cz', 'C4', 'CP3', 'CPz', 'CP4' classification was plotted for deeper analysis of the classification results and shown on the Figure 3-5.

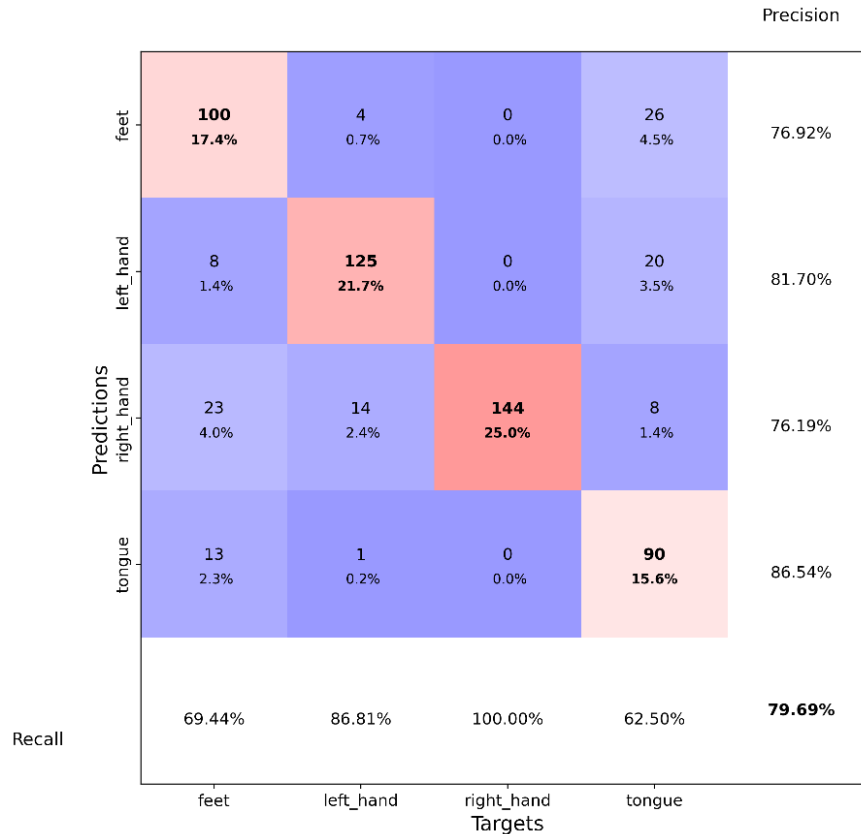


Figure 3-5 Confusion matrix for 'C3', 'Cz', 'C4', 'CP3', 'CPz', 'CP4', subject 3

Left and right hands are classified correctly more often than tongue or feet movements, the reason of it can be that right and left movements involve left and right hemisphere accordingly, so it is easier to differ the EEG signals and predict the correct class. But overall the recall and precision value are satisfying, they show that there is no strong disbalance in classification.

At last, analysis of classification accuracy of different triplets of electrodes around motor cortex was performed. Figure 3-6 shows classification results. The results show that there is no strong difference in accuracies, but the triplet CP3-CPz-CP4 gave the best accuracy of 75%. It is suggested that this also gives us the freedom for not very precise montage and the difference of 2cm in electrode placement will influence the results insignificantly. This freedom can be useful in case of montage without assistance. The accuracy is acceptable for most motor imagery practices. This result proves that it is possible to use only three electrodes for motor imagery classification

and with only three electrodes the processing time can be decreased.

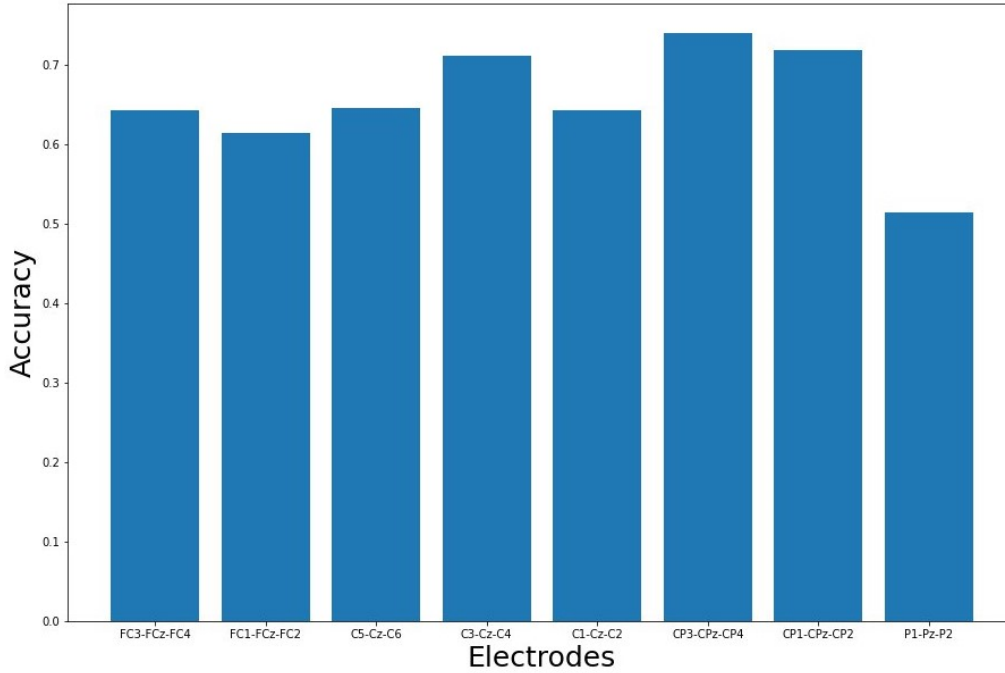


Figure 3-6 Classification results for triplets of electrodes for subject 3

3.2. Motor imagery classification using knitted EEG headband

After training the classification model on big amount of data accessed openly online, the next step would be to use designed knitted EEG headband for the feet, tongue, right and left hands movement classification.

3.2.1. Data Acquisition Preparation

To use the recorded data for classification on the Deep ConvNet trained model, the experiment data should be similar to the one the classification model was trained on. For this, the experiment steps should be repeated after experiment for Motor Imagery dataset Dataset IIa from BCI Competition 4. For the experiment with knitted headband a video was created following the timeline and description given by Motor Imagery dataset Dataset IIa creators: “At the beginning of a trial ($t = 0$ s), a fixation cross appeared on the black screen. In addition, a short acoustic warning tone was presented. After 2 s ($t = 2$ s), a cue in the form of an arrow pointing either to the left,

right, down, or up (corresponding to one of the four classes left hand, right hand, foot, or tongue) appeared and stayed on the screen for 1.25 s. This prompted the subjects to perform the desired motor imagery task. No feedback was provided. The subjects were instructed to carry out the motor imagery task until the fixation cross disappeared from the screen at $t = 6$ s. A short break with a black screen followed” [69]. The length of one trial for one motor imagery task is 7.5sec, the whole video created is 6min long – 48 trials, 12 trials for each motor imagery task

3.2.2. Data Acquisition

The experiment for data acquisition of a one run was conducted as following:

1. Subject was sitting in comfortable chair in front of the screen
2. The knitted EEG headband was mounted with three electrodes located at C3,Cz,C4 10-20 according to electrode placement system and connected to computer via Bluetooth
3. Th recording started using Mobile Acquisition Monitor
4. 10 seconds after the beginning of recording the video with motor imagery instruction was played.
5. Performance of motor imagery movements: to reduce artifacts during the motor imagery task, blinking, eye movements and swallowing was made only during the seconds of a break.
6. After the end of the video the recording was stopped

The steps were repeated 4 times with a short break, as a result 4 runs were recorded for future classification.

3.2.3. Data Processing

The recorded data was saved in CSV format. To use the data as an input for to the trained model and receive a classification result, the data should be transformed into acceptable format. First the data should be read and transformed into MBLDataSet

format, where start time and date, sampling frequency, events, channels names and location, dataset size will be saved together with EEG data. Before data transformation, the EEG signal 40Hz high cut frequency filtered and converted from volt to microvolt. The EEG signal obtained is shown on Figure 3-7.

Then the event generation was performed based on timeline of the experiment: initial delay is 10 seconds, 7.5 seconds period, delay after event start time is 3 seconds, the length of the event is 3 seconds. Next step is creating a windows dataset, this will be an input into the trained classification model.

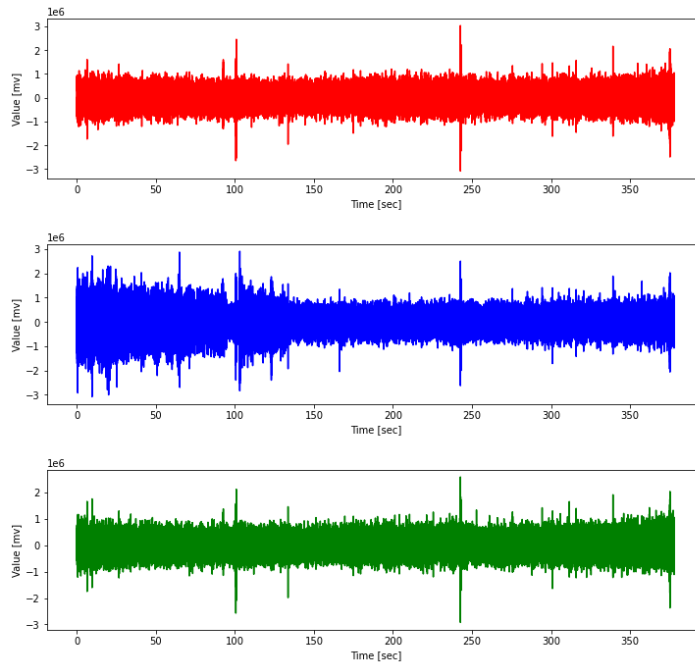


Figure 3-7 EEG signal from knitted EEG headset: C3 – red, Cz – blue, C4 - green

3.2.4. Classification

Recorded, processed and windowed data was pushed into the trained Deep ConvNet on C3-Cz-C4 EEG processed and windowed data of a subject 3 from Motor Imagery dataset Dataset IIa from BCI Competition 4. The results were not achieved. Classification model classified the whole test data recorded from knitted EEG headband as right-hand movement class. After facing this problem, the experimental data was inspected using EEGLAB (Matlab toolbox for EEG analysis [76]). Data

included several artefacts, the data was manually cleaned as well as with the use of CleanLine function of EEGLAB. After cleaning the data was not corresponding to event related windows and classification could not be performed further.

3.2.5. Discussion

The classification results of the data obtained from knitted EEG band was not satisfying. The reasons for it can be incorrect data acquisition that can include too noisy environment of the laboratory room, defective electrodes, too strong swallowing and breathing artifacts, that could move location and contact with the scalp as the knitted EEG band locking system is located under the chin and this area is moving during the swallowing or even breathing, not skilled performance of motor imagery tasks by a subject, as well as faulty code for data processing and event generation. Further improvement of the system could include repeating the experiments in quiet environment, checking the coding part thoroughly, designing a different locking system or composition of the headband for higher quality measurements of motor cortex zone, trying different type of dry electrodes that are available on the market. If, after the suggested improvements and tests, the classification with at least 50% accuracy could be achieved in the future using the designed knitted EEG headband, it could be used for BMI application in comfortable environment, outside of the laboratory and with this a life quality of people with motor impairment could be improved.

3.3. BMI application after classification

"Motor imagery practice" (sometimes known as "mental practice"), a mental simulation procedure that involves the systematic use of imagery to rehearse an action without performing it, is a well-known and extensively researched application of motor imagery [77]. Motor imagery practice improves skillful performance [78] and

in addition to enhancing motor learning, it also promotes "neural plasticity," or the brain's ability to change the physical makeup of neurons in response to repeated experiences [79].

In order to perform motor imagery practice, one needs a correctly set BMI system, assistance and scripted sequence of instructions should be given to help them visualize and experience the target skill in their minds [80]. This study proposes a way to perform a motor imaginary practice without guiding assistance of a human coach, but with a Humanoid Robot coaching assistance. Together with an easy set up knitted EEG band mental training could be done by a person at home and will allow the practice to be conducted more often, so results of the training could be improved for each person.

3.3.1. NAO6 Robot

To help people and improve their social lives, social robots have been employed in studies. In a variety of application sectors, including education, healthcare, industry, entertainment, and public service, these social robots have been imagined interacting with humans. For the purpose of guiding motor imaginary practice assistance, a NAO6 robot was chosen.

NAO6 is the sixth generation of the interactive humanoid robot NAO (Figure 3-8), developed by SoftBank Robotics, it is autonomous and programmable. This robot is aimed for the use by professionals and academics. As a result of its low cost and extensive capabilities, NAO has been one of the most often employed social robots in research on human-robot interaction. NAO is an autonomous and programmable humanoid robot that was created by the French company Aldebaran Robotics in 2008 and bought by the Japanese business Softbank Robotics in 2015.

NAO has been successfully used in research and development applications for children, adults, and the elderly. In more than 70 nations throughout the world, more

than 13,000 NAO robots are in use. In order to enable NAO to play the role of a tutor, therapist, or peer learner, a number of recent large-scale interdisciplinary projects, including ALIZ-E1, DREAM2, CoWriter3, SQUIRREL4, and L2Tor5, have examined child-centered research [81].



Figure 3-8 Nao6 robot

It can be connected to a wired or wireless (Wi-fi) network, enabling remote control and autonomous operation. This is crucial, especially when the robot is used in a real-world environment. It can move around and carry out actions thanks to its 25 degrees of freedom, of which 12 are for its legs, 5 are for its arms, and 2 are for its head. In addition, it contains two cameras, four directional microphones and speakers for object identification, face detection, recognition, and tracking, as well as built-in text-to-speech and speech recognition for 20 languages. Table 3-2 contains some basic specification of Nao6 Robot.

Table 3-2 NAO6 Specifications [82]

Dimensions	574x 311x 275 mm
Weight	5.48 Kg
Autonomy	60 minutes in active use and 90 minutes in normal use
Degrees of freedom	25
Processor	Intel Atom E3845
Built-in OS	Linux (Gentoo)
Compatible OS	Windows, Mac OS, Linux
Embedded programming languages:	C++, Python
Remote programming languages:	Java
Vision	2 OV5640 2592x1944 cameras
Connectivity	Ethernet, Wi-Fi

3.3.2. NAO Robot programming tools

The robot may be programmed and given the NAO behaviors thanks to the specialized NAOqi framework, the user-friendly graphical programming tool Choregraphe (for complicated applications and motion control), and Monitor (for robot feedback and sensor or joint verification).

The most essential software to use when working with NAO is “Choregraphe”. With this application one can develop programs, write dialogs, or control NAO's behavior. However, Choregraphe also gives other options, for instance, it shows what the camera sees, language and loudness settings, make a preview of created program, or change the source code for boxes.

NAOqi framework incorporates components that are typically necessary for robotic systems, such as parallel processing, resource management, synchronization, and event processing systems. NAO is an autonomous robot that was created to using a wireless internet platform, operate remotely, and without a human user's involvement. Like research [83] created a robotic system for retailing that can continuously update and learn new information about its user base, significantly improving the aid with shopping, the current research is intended to create a system for motor imagery practice.

3.3.3. Motor imaginary practice with NAO6

The robotic system for motor imagery practice should include EEG measuring device, motor imagery classification for a certain motor imagery type of practice, couch instructions for mental training program, NAO6 robot program for mental training guidance. Robot's behavior gives visual and acoustic neurofeedback as well as instructions. The interaction process between Robot and trainee is described in Table 3.3

Table 3-3 Trainee and NAO interaction process [82]

Trainee's behavior	Robot's behavior
Turns on the Robot	Greetings, shows positive emotions
Runs the training session algorithm	Encouraging to start the practice, share some improvement data from previous session
Set up the EEG band	Shows positive emotions, small reminders about the way to set an EEG band. Questions type "Are you ready?"
Says command "Ready" or "Start session"	Response: "Session is started", connection to the EEG headband signals.
Listens	Gives introductory instructions
Listens	Instruct the trainee to perform motor imagery action (according to a training program given

	by a trainee's couch), shows the needed action, at the end of instruction sends a signal to a program for motor imagery EEG classification of a motor imagery beginning
Performs the action following the instructions given by a robot	<p>Listens to classification result. Depending on the result informs the trainee:</p> <p>Classification failure: encourage, instruction to repeat</p> <p>Classification success: reproduces the motor imagery action (as a positive reinforcement technique, instructions of the task instruction.</p>
Stops the session	Positive emotions, gratitude, encouraging, shares statistics on time training.

While the training could be done with visual and audio feedback and instructions given from simple computer, the interaction between robot, physically present and moving according to the motor imagery task could improve the trainee performance. Another advantage for using the robot could be motor imagery training for children. It can be hard for a child to find enough attention to work with the program on computer, while with robot it can attract more attention, together with robot encouraging, suggesting taking a break after several training steps, and tell the child a story or even play a little game. The purpose of using humanoid robot during training is to make the experience enjoyable, interactive, and as following more efficient.

Chapter 4

Conclusion

4.1. Summary

In this study, the wearable knitted encephalograph was designed, material study, fabrication process and performance were evaluated. Analysis of minimal number of electrodes for efficient motor imagery classification was conducted. The designed and fabricated device was used for motor imaginary movements classification. At the end, brain machine interface algorithm with the use of NAO6 robot was suggested with intention to make motor imaginary practices available for at comfortable setting. In this part, we state the conclusions we arrived at and the possible future prospects they arise.

4.1.1. Design and evaluation of a wearable knitted encephalograph

In present study the knitted wearable EEG measuring device was developed. The main points to achieve was easy and short time set up, comfortable wear, long term measurement with acceptable impedance under 100k Ω . The candle-type microneedle dry electrodes that were developed in our laboratory were used. These electrodes can measure EEG signals in hairy area of the scalp without any necessary preparation, simply by pressing electrode to the head, without causing pain.

After material analysis cotton yarn was chosen due to fiber little hairiness, absent of excessive stretching, that would not cause the uncontrollable electrodes displacement. Cotton fabric is pleasant for a skin contact and breathable, that could prevent casing increase of impedance sweating. The fabrication process was chosen to

be by using basic knit stitch with a special knitting technique that forms the tube shape. This tube is essential for electrode mounting, that was carefully described at the present work.

The analysis of the headband performance showed that impedance value of the electrodes stays at acceptable level, under 100 k Ω during at least 100min use. The usability experiment, that involved open-closed eyes experiment showed prominent alpha wave with closed eyes, comparing to open eyes state, demonstrating that reasonable results representing EEG brain signals can be retrieved. User experience showed that it is indeed easy and fast to mount and take 1-2 minutes to setup. Comfort evaluation showed that subjects are willing to wear the headset for up to 1 hour and more without feasible discomfort.

4.1.2. Motor Imagery Classification Analysis

First, the dataset for training the classification model was chosen - Motor Imagery dataset Dataset IIa from BCI Competition 4, that includes four distinct motor imagery tasks: left hand (class 1), right hand (class 2), both feet (class 3), and tongue (class 4). This dataset was processed used for Convolutional Neural Network model that were designed for efficient EEG signals classification: Deep ConvNet and Shallow ConvNet. Cropping windowing technique was used to increase classification accuracy. The accuracy of classification was shown for different number and location of electrodes, as well as for each subject. The results have shown that Deep ConvNet performed better, that the classification accuracy depends a lot on the subject, showing the importance of motor imaginary practice. The best classification accuracy achieved is 85% with 8 electrodes. For 6 electrodes the accuracy was 80%. And the best triplet of electrodes with 75% accuracy was achieved by using data from CP3-CPz-CP4 electrodes.

Next the EEG data was obtained using designed knitted EEG headband. The experimental procedure was repeated after Motor Imagery dataset Dataset IIa data acquisition process. The data from C3-Cz-C4 electrodes placement was used, then data then was processed and classified using the Deep ConvNet trained on C3-Cz-C4 electrodes from Motor Imagery dataset Dataset IIa subject 3. Classification results of EEG data from knitted headband was not achieved. There are several reasons why it could happen: faulty code, defective electrodes, noisy experiment environment, lack of motor imagery skill, lack of data cleaning and pre-processing.

4.1.3. BMI application proposal for motor imagery practice

The idea of motor imagery practice at comfortable condition, at home environment, without special assistance lies at the basis of this study. Motor impairment for elder and for children can be improved by using motor imagery brain machine interfaces. To use these interfaces patients, need to develop motor imagery skill to control machines correctly. For this purpose, motor imagery practices exist. These practices need special setting and couch assistance.

In this work the algorithm for robot-trainee communication was proposed. NAO6 robot, a humanoid social robot can communicate, encourage, entertain, show needed movements, and assist through whole motor imagery practice. Together with designed knitted EEG headband, that can be set up quickly and easily, without additional assistance or special laboratory equipment, can make motor imagery practices accessible for wide category of people on daily basis and as a result improve the motor imagery skills quicker.

4.2. Future prospects

The present study focused on designing the wearable knitted EEG measuring device for daily use at home environment. This headband could be used for daily motor imagery practice outside of the laboratory with self-montage. And even though the created design achieved the goals of being comfortable, easily set, wearable and fitting all head sizes, the performance of the headband needs to be increased. It was shown in the present work, that the classification of motor imagery movements can be performed from only three electrodes, but the data measured with the headset must be of a higher quality. This can be achieved by different electrodes testing, changing experiment environments and better data pre-processing. Next future prospect of this work would be real time motor imagery classification, connected with NAO6 robot, realization of proposed algorithm for motor imagery practice without need of human supervision.

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