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The influence of optode pressure on the quality of functional Near-infrared Spectroscopy signal

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Preface

The research presented in this thesis was conducted as a completion of the master's in Universal Design of ICT in the Department of Computer Science, Faculty of Technology, Art and Design of the Oslo Metropolitan University (OsloMet).

Working on this master thesis has provided me the opportunity to meet a lot of remarkable persons who taught me valuable knowledge about computer science and Brain-Computer Interfaces. I want to express my sincere gratitude towards my supervisors Anis Yazidi, Pedro Lind, and Peyman Mirtaheri for their guidance, valuable input, and support throughout my master's period.

I am grateful to my dearest family and friends, who have always been extremely supportive and believed in me.

Abstract

Near-infrared spectroscopy (NIRS) is a cutting-edge and optical Brain-Computer Interfaces (BCIs) that measures the concentration changes of oxygenated (Oxy-Hb) and deoxygenated hemoglobin (deoxy-Hb) in the cerebral blood flow.

The use of fNIRS as a neuroimaging technique has a rapid growth over the last 20 years due to the significant advantages, including non-invasively, portability, and safe procedure. However, fNIRS signals are influenced by multiple factors that create an ongoing challenge for the quality signal distinction among the studies. The effective factors on the fNIRS signal quality contain the number and placement of the optodes, motion artifacts, heartbeat, and respiration. Besides, the effect of applied optode pressure on the fNIRS signal quality by the preservation of user convenience remains largely unanswered.

The presented research contains two phases. The first phase of this master study aims to find some of the efficient metrics for the fNIRS signal quality through the reliable open-access database. Furthermore, the impact of optode pressure variation on the signal quality is distinguished through the user experiments in the second phase. Three pressure levels were applied to the fNIRS optode, and two pressure metrics of Partial Pressure of CO2 (pCO2), and Laser Doppler flowmeter (LDF) were used in the experiments. The user experiments contained four healthy subjects that were asked to do the mathematical calculation task for 120 seconds with 60 seconds of initial baseline.

The main conclusions, drawn from the quality metrics analyzed through the reliable datasets indicate four metrics, including Running Correlation (RC) between oxy-Hb and deoxy-Hb, visual checking of the time series, heartbeat extraction, and Moving Variance per channel. Among the founded metrics, RC has been chosen as a quality metric for the second phase due to the stability and

quantitative variable. The results indicate a negative correlation between RC and signal quality.

The results from the user experiments in the second phase represented that increasing the optode pressure impacts negatively on the signal quality at first and then improves the quality on the maximum pressure level. However, enhancement of the optode pressure to the maximum level creates inconvenience for the subjects and is not an efficient solution to increase the fNIRS signal quality.

The study advances future studies especially for investigations of the influential pressure metrics in the fNIRS experiments.

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Chapter 1: Introduction

How to provide a direct communication pathway between a human brain and an external device? This question has been a main motivation for researchers to investigate the brain structure to find out the relation between brain activities and human attributes. Brain imaging or neuroimaging refers to the process of using images to discover the structure and function of the nervous system. Neuroimaging divided into two categories of structural imaging and functional imaging. The structural imaging is concerned with diagnosing intracranial disease and brain injuries such as tumors and injury (Tool Module: Brain Imaging, n.d.). Computerized Tomography (CT) and Magnetic Resonance Imaging (MRI) are instances of structural imaging methods. On the other hand, functional imaging aims to measure the activity of the specific part of the brain and diagnose metabolic diseases such as epilepsy seizures and Alzheimer's disease (Filler, 2009). Examples of the functional imaging methods include Electroencephalography (EEG), Functional Magnetic Resonance Imaging (fMRI), Positron Emission Tomography (PET), and Functional Near-Infrared Spectroscopy (fNIRS) (Hirsch et al., 2015).

As the power of advanced technology grows over the last decades, researchers try to discover the communication between brain activities and computer devices. Brain-computer interfaces (BCIs) refer to the systems that enable the interaction between the brain signals and computer. BCIs analyze and translate brain signals to the commands, and the interpreted commands are sent to the output devices to perform the desired human action (Yanagisawa et al., 2012).

The main intention of BCIs is to recover or replace neuromuscular disabilities like cerebral palsy, motor impairment, or permanent maim. Further, BCIs effectively help the rehabilitation process after stroke and other physical disorders (Shih et al., 2012).

BCIs have become one of the most investigated research areas at the intersection between computer science and neuroscience. Although BCIs monitoring devices were expensive and required a controlled environment, they have become less costly and portable lately (Ekandem et al., 2012).

Currently, BCI has applications in broad aspects of human life, including medicine, rehabilitation, marketing, education, games & entertainment. One of the examples of BCIs is brain remote-controlling that refers to controlling a video game or a physical activity by thoughts. Brain-controlled activities promote independence among people with disabilities and improve the quality of their life significantly (Grabianowski, 2007).

fNIRS is a non-invasive, portable, and wearable functional imaging technique that tracks brain tissue changes of oxygenated hemoglobin (oxy-Hb) and deoxygenated hemoglobin (deoxy-Hb). The tissue hemoglobin changes are received through the optodes attached to the scalp. The use of fNIRS has increased during the last years due to multiple advantages of this technique amongst other BCIs. Specifically, fNIRS is harmless, portable, and usable for extensive age ranges (Pinti et al., 2018).

Although, fNIRS has several valuable features; the user comfortability and producing constant signal quality in the experiments are still ongoing studies. Multiple factors affect the quality of fNIRS signals, including motion artifacts, heartbeat, respiration, and unacceptable environmental conditions. The universal design of fNIRS elements considering the user comfort has been discussed widely among the researchers. In the first phase of this master thesis, numbers of the computable metrics are discussed to estimate the fNIRS signal quality. In the second phase, the fNIRS user experiments are conducted to investigate the impact of optode pressure and user comfortability on the signal quality. This master thesis proposes and evaluates several metrics to estimate the fNIRS signal quality. Furthermore, the impact of fNIRS optode pressure on the head is discussed to find out the optimal pressure considering the user comfort.

1.1 Problem statement

Information retrieval from the human brain is a challenging process in neuroscience research. This process is a crucial part of BCIs. BCI plays a significant role in fostering and advancement of medical sciences, and it is used to address some of the challenges in rehabilitation processes, brain disorders, and daily life experiences. There are several BCI technologies with different advantages and disadvantages. Nowadays, the correlation between new computer solutions and BCI technologies brings a significant opportunity to increase BCI efficiency. The fNIRS technology is a non-invasive BCI technique that has become an active research topic among neuroscience researchers. Although many studies have been carried about the usability of the fNIRS method, there are various unsolved issues related to increasing the quality of the fNIRS signal. The involved factors are interrelated and might lead to unreliable results. One of the existing challenges of fNIRS design concentrates on enhancing the user comfortably. The optode pressure and their location on the head have a significant impact on the quality of fNIRS signals. Indeed, ergonomics and quality of the signal are two contradictory objectives in fNIRS applications. To get a good signal, we need to exercise high pressure and increase the number of electrodes. The ergonomics of these sensors, as well as the signal quality, is a function of sensor type, number, placement, pressure amount, pigmented elements of the object (e.g. hair and skin), etc. Since human brain signals carry on various unnecessary information as noises, removing noises from the signals is a barrier in the fNIRS procedure.

To improve the quality of the fNIRS signals, a standard for collecting fNIRS data that takes into account different factors affecting the quality needs to be developed. In addition, a higher amount of optode pressure on the scalp during long experiments cause inconvenience for the users. Currently, limited studies are available to investigate the effect of optode pressure on the fNIRS experiment outcomes. Some of the elements affecting the quality of the fNIRS signal include:

- Environmental conditions and instrumentation
- Mechanical feature including the placement of the sensors on the scalp, pressure amount from the optodes, and laser heating time
- Demographic variation and psychological behaviors for instance age, gender, stress, and heartbeat
- Physiological features like head shape, pigmented components of hair and skin
- Interspersion algorithms and data analysis (Ekandem et al., 2012; Loup-Escande et al., 2017; Orihuela-Espina et al., 2010).

One of the existing challenges of the fNIRS technique is the impact of motion artifacts on the signal quality. Motion artifacts like head movement cause the relocation of optodes on the head and produce noises. One of the solutions to overcome the effect of head and facial movements is to increase the optode pressure and provide a stable experimental environment. On the other hand, increasing the optode pressure, increase the user's inconvenience during using the head cap. The purpose of this study is to determine some measurable fNIRS signal quality metrics and suggest the optimal optode pressure preserving signal quality and user convenience.

1.2 Research questions

At this juncture, the considered research question relied on the problem statements is explained:

- What are the main metrics to measure the fNIRS signal quality?
- What are the impacts of optode pressure on the fNIRS data quality?
- What is the optimal pressure of fNIRS optodes, considering user convenience and signal quality?

(Kopton & Kenning, 2014; Krampe et al., 2018; Soltanlou et al., 2018)

1.3 Toward universal design standard

Based on the sixth principle of universal design, “the design product or environment should be used efficiently and comfortably and with a minimum of fatigue. The product needs to have the following features:

6a. Allow users to maintain a neutral body position.

6b. Use reasonable operating forces.

6c. Minimize repetitive actions.

6d. Minimize sustained physical effort” (The 7 Principles | Centre for Excellence in Universal Design, n.d.)

The quality of obtained fNIRS signals depends on biological and environmental conditions. One of the influential factors on the fNIRS signal quality is the pressure of optodes on the scalp. However, the optode pressure may impose inconveniently on the user during the experimental process. The purpose of this master thesis is (I) finding the quality metrics to evaluate the fNIRS signal. The next phase (II) is to determine the correlation between optode pressure and the fNIRS signal quality. Indeed, the study aims to estimate the optimal optode pressure, considering users comfortably and acceptable signal quality.

1.4 Human brain anatomy

The placement of the fNIRS optodes on the scalp corresponding to the desired brain activity is one of the effective criteria to obtain the valuable results. Since BCIs focused on receiving signals from the activated brain area, it is essential to study the relation of the active region and the type of brain activities.

The human brain weighs about three pounds and involves 100 billion nerve cells. The brain is the main organ that is responsible for sending and receiving the neural signals from body sensors such as smell, hearing, taste, pain, and sight. Brain neurons control several processes as multiple procedures of speech, thoughts, emotions, decision making. The human nervous system includes the central nervous system (CNS) and peripheral nervous system (PNS) that connect the body organs to the brain. The brain involves three main organs called the cerebral cortex (cerebrum), cerebellum, and brain stem. The brain and spinal cord are the two main elements of CNS. BCI techniques detect the brain signals from the cerebral cortex (Bansal & Mahajan, 2019).

The cerebral cortex includes four lobes of frontal, temporal, occipital, and parietal—each element of the cerebral cortex involved with specific brain functions. The front part of the brain called the frontal cortex is responsible for emotions, cognitive functions, and decision making. The parietal lobe is located behind the frontal cortex and is associated with the sensation of pain, pressure, and touch. The occipital lobe is located on the backside of the brain and is responsible for visual detection and simulation. The occipital cortex lobe is divided into two primary and secondary visual areas. The primary area receives the signals from visual objects, and the secondary area decodes the detected signals to the information by comparing it with past knowledge. A severe injury to the primary visual area causes blindness or significant visual impairments. Besides, any damage to the secondary visual area may have an impact on relating the received visual signals with meaningful information. For instance, it causes complexity in reminding names and memory disorders like Alzheimer's. The temporal cortex lobe is located anterior to the occipital lobe and is responsible for language processing and speech production. Similar to the occipital lobe, the temporal lobe includes a primary and secondary auditory area that receives and analyzes the detected auditory signals (Bansal & Mahajan, 2019; Rao et al., 2012).

The cerebellum is a vital part of the brain and located underside of occipital and temporal lobes. The cerebellum transmits the information from the cerebral cortex to body muscles and is responsible for body balance and body motion control. Any damage to the cerebellum of the brain causes motion defects or motor impairments (Looney et al., 2014).

Although identifying the pattern of brain activities according to the activated region is a complex process that depends on multiple factors, recently developed computer technologies such as machine learning, data analysis, and imaging techniques provide facilitated solutions in human brain activity detection (Bansal & Mahajan, 2019).

Chapter 2: Background and literature review

In the following chapter the BCI components, comparison of different BCI techniques, and the chronological investigations on fNIRS are discussed.

2.1 BCIs components

BCI is a direct communication method between the human brain and external devices. The output devices of BCIs are robotic arms, wheelchairs, cursor controllers, or other types of exoskeletons. Figure 2-1 shows the basic components of BCIs (Ponce et al., 2014).

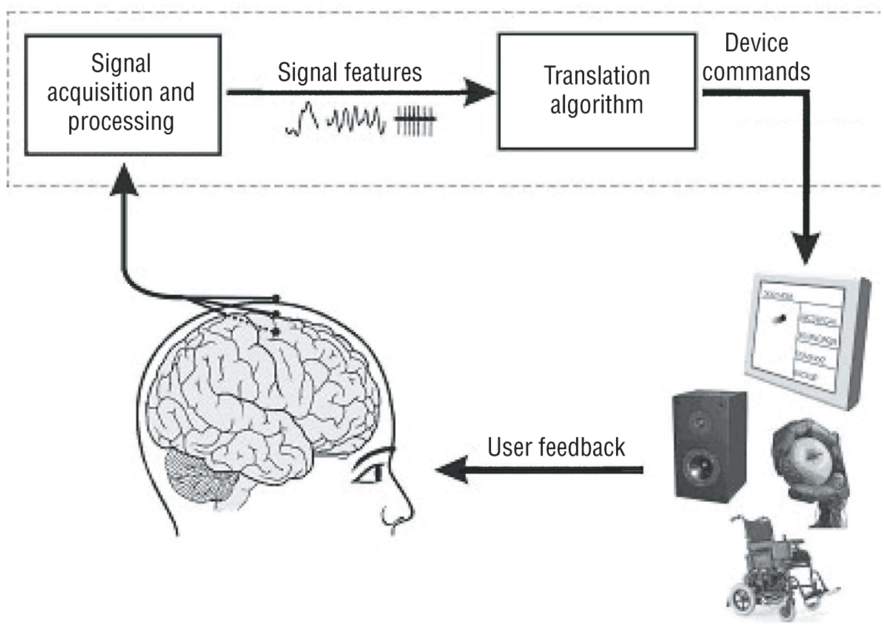

Figure 2-1. Basic components of the BCI data processing unit (McFarland & Wolpaw, 2008)

Similar to other communication systems, BCI components contain input, data processing unit, and output. BCI data processing unit is considered as a heart of the system that includes five phases of signal acquisition, signal preprocessing, feature extraction, classification, and translation algorithm (McFarland & Wolpaw, 2008).

The signal-acquisition phase refers to amplifying and measuring the brain signals that carry out the user’s intent. The preprocessing phase removes the noisy components of the signals that are called motion artifacts. The brain's signals might contain motion artifact noises mainly due to low contact of electrodes to the scalp, head movement, heartbeat, and respiration. Three powerful de-noising techniques are Principal Component Analysis, Independent Component Analysis, and Wavelet de-noising. In the feature extraction part, the preprocessed signals are converted to the set of vectors where each vector is related to a specific group of features. The feature extraction phase aims to minimize losing useful information in order to precise the translation of the human activity to the data commands. Examples of feature extraction approaches are variance, mean, maximum & minimum of the signal, median, and standard deviation. In the classification phase, the signal features are classified into the categories during the data mining process. The purpose of the data classification is to specify the label of each class and connect the statistical signal features to the corresponding classes. Some of the classification techniques include Probabilistic Neural Network, Linear Discriminant Analysis, and Fuzzy inference system. The last phase, named translation interpreted the classified data to the device commands through the translation algorithm (McFarland & Wolpaw, 2008).

2.2 BCIs recording techniques

According to the placement of the electrodes on the scalp or inside the skull, BCI techniques fall into three main categories namely invasive, semi-invasive, and non-invasive. The following figure illustrates the human brain layers (Leuthardt et al., 2009).

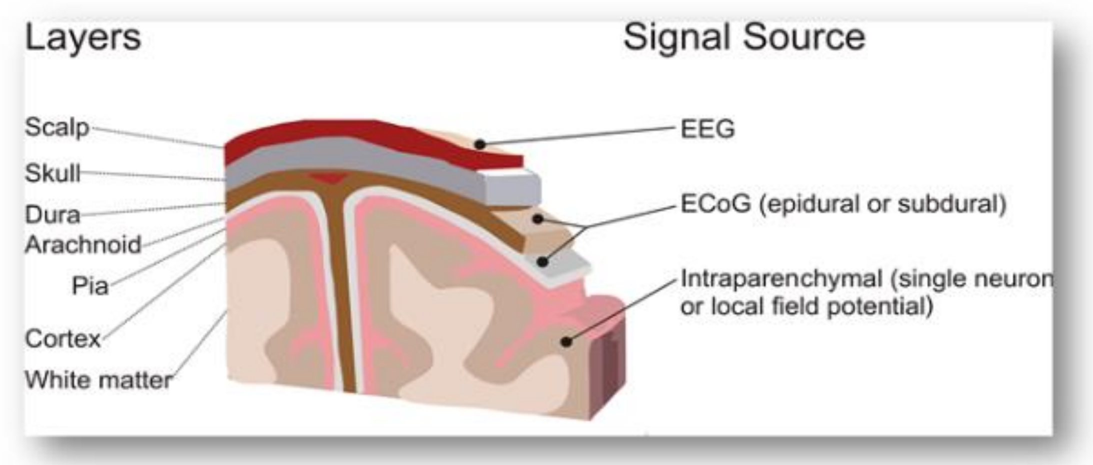

Figure 2-2 Different layers of human (Leuthardt et al., 2009)

Invasive BCI is a high-risk technique that requires neurosurgery to imbed the electrodes directly inside the cortex layer of the brain (Waldert, 2016). Although the received signals have high quality while the invasive technique is used, several serious barriers limit the implementation of this method widely. Detection of the signals from the small area of the brain is one of the disadvantages of this technique. Besides, the neurosurgery might cause serious health risks due to the body reaction to the electrodes in the skull. The scars around the electrodes might reduce the received signal quality over time. Due to the mentioned reasons, the invasive BCI technique involves significant barriers in the long term applications. In consequence, invasive applications are limited to rare cases of blind people or patients with profound disabilities (Panoulas et al., 2010).

In the semi-invasive technique, part of the electrodes is imbedded above the cortex in the dura or arachnoid layer, and the rest of them are located outside of the brain. In this technique, the implementation of the electrodes requires neurosurgery and might cause health issues due to cutting the brain membranes during the surgery. Although the semi-invasive signals have lower quality than invasive techniques, obtain better results compared to the non-invasive methods. Furthermore, the risk of creating the scar tissue in the dura or arachnoid layer is less than the corresponding risk in the cortex layer associated with the invasive method (Panoulas et al., 2010). Electrocorticography (ECoG) is an example of a semi-invasive technique.

The non-invasive technique includes the simply attached electrodes on the scalp. Generally, the electrodes are embarked inside a head cap or headband. Although this method is non-intrusive and safe, the signals have lower quality and carry more noises compared to previous techniques (Babiloni et al., 2009). Currently, the non-invasive BCIs have been used successfully in several types of research and medical purposes such as BCI gaming, control wheelchairs, and rehabilitation process. fNIRS and EEG are instances of the non-invasive BCI technique. Figure 2-3 shows the implementation of the BCI electrode in three BCI recording techniques.

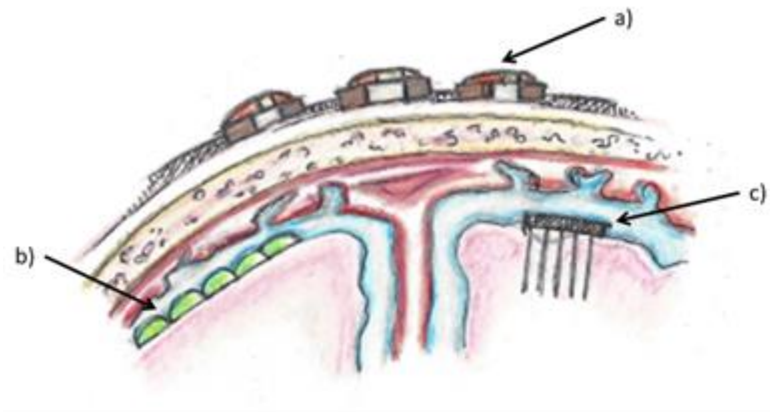

Figure 2-3 Exemplification of BCI electrode implementation. (a) Non-invasive BCI (EEG or fNIRS), (b) semi-invasive BCI (ECoG), (c) invasive (Single-neuron recording) (Ponce et al., 2014)

2.2.1 Functional near-infrared spectroscopy (fNIRS)

The fNIRS is one of the non-invasive BCIs that has considerable advantages compared to other techniques including portability, low price, user convenience, and higher special resolution. In the fNIRS technique, changes in blood hemoglobin are detected by radiation of near-infrared light to the skull through the optodes attached to the head. The measurements result in the estimation of oxygenated hemoglobin (oxy-Hb) and deoxygenated hemoglobin (deoxy-Hb) in the brain region of interest (Di et al., 2015).

During brain activities, the amount of oxy-Hb increase and deoxy-Hb decrease. Figure 2-4 shows the negative correlation of Oxy-Hb and deoxy-Hb while the brain is active by a task (Gagnon et al., 2011). The hemodynamic response function of deoxy-Hb is less than Oxy-Hb and has a bit of a delay (Lee et al., 2018).

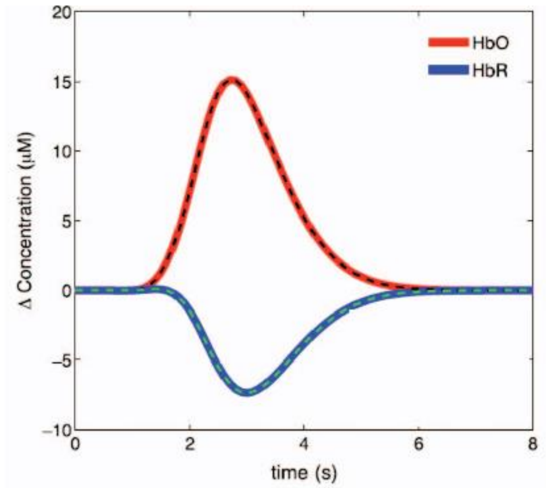

Figure 2-4 The hemodynamic response functions of Oxy-Hb and deoxy-Hb (Gagnon et al., 2011)

In the fNIRS technique, the infrared light with the wavelength from 650nm to 950nm passes from the source electrodes through the brain. Then the scattered light is received by detectors. The reflected light depends on the amount of available oxygen in the blood hemoglobin. Since the absorption and diffusion of light from Oxy-Hb and deoxy-Hb are different, brain activity is recognizable (Chaddad et al., 2013).

Each pair of fNIRS sources and detectors creates a channel. The maximum distance between source and detector is 30-40 mm for adults and 20-25 mm among infants due to their thinner skull. The mentioned distance allows the light to penetrate up to 35 mm through the skull. Although reduction of the source-detector distance leads to deeper light penetration through the brain, it causes more noises in the signal. In other words, the detected signals from optodes with higher distance have less Signal to

Noise Ratio (SNR) whereby it decreases the signal quality (Tessari et al., 2015). Figure 2-5 represents a pair of source-detector.

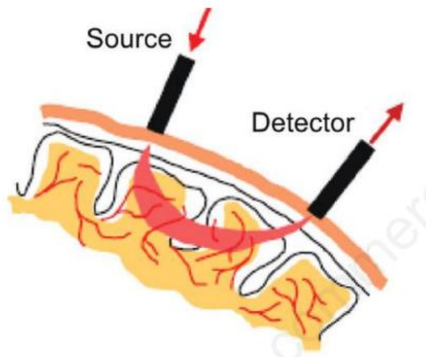

Figure 2-5 A pair of fNIRS source-detector (Tessari et al., 2015)

fNIRS head caps are headsets with the holes on specific areas that are used to implement the fNIRS optodes on the head. Figure 2-6 shows one of the fNIRS head caps.

Figure 2-6 fNIRS head cap with attached optodes (Tessari et al. 2015)

However, the ergonomic design of fNIRS head caps that provide more convenience for subjects is an ongoing challenge. As previously mentioned, biological features affect the quality of fNIRS signals including respiration, heartbeat, and motion artifacts. In addition to biological conditions, users' physical attributes such as head shape, hair intensity, and hair color may change the obtained fNIRS data.

2.2.2 Electrocorticographic (ECoG)

ECoG is a semi-invasive BCIs technique that detects the brain signals from the electrodes into the skull. ECoG signals received directly from the cortex thus carry fewer noises compared to non-invasive techniques. In addition, ECoG signals are characterized by better spatial resolution compared to non-invasive signals (Chong et al., 2010). The ECoG technique has been tried on humans for the first time in 2004 at Washington University (Panoulas et al., 2010).

The successful applications have been implemented by ECoG to perform motor activities over the last two decades. Leuthardt et al. proposed a procedure to control the mouse cursor by ECoG signals (Leuthardt et al., 2009). In semi-invasive methods, the electrodes do not interpenetrate the brain, and therefore, the neurons are kept intact. However, the lifetime of this technique is still not explicit, as there is no study to investigate how the signals degrade over the years (Panoulas et al., 2010).

2.2.3 Functional magnetic resonance imaging or functional MRI (fMRI)

The fMRI technique measures brain activities based on the variation of the brain blood flow. During the brain activity, the brain cells consume more oxygen that causes the enhancement of the blood flow (Babiloni et al., 2009). The fMRI identifies the associated active brain by color mapping. The most common use of fMRI is among the clinical processes such as psychiatric disorders, neurologic disorders, and substance abuse.

Since the 1990s, fMRI has become one of the brain mapping techniques as it does not either need any neurosurgery or impose any harmful ionizing radiation on the user. Currently, the standard technique is Blood Oxygenation Level-Dependent (BOLD) of fMRI signals, which measures the changes in the vascular system correlated by neural activity. The fMRI is more sensitive to noises compared to other technologies, because of the random variation of BOLD signals. A combination of fMRI with other modalities, such as EEG, is considered a valuable technique in medical brain neuroimaging (Babiloni et al., 2009).

2.2.4 Magnetoencephalography (MEG)

MEG is a functional neuroimaging technique that simulates magnetic brain activity from arrays of sensors positioning over the skull. MEG produces a direct and real-time measurement of neural activities (Stam, 2010). Although MEG is not a new technique and was introduced in the 1960s, the full potential of MEG was implemented in the early 1990s with 200 detecting sensors over the whole head. The use of MEG in medical neuroimaging has grown up over the last two decades. In order to determine the great attraction of MEG Hansen et al. discussed an example of human reaction while facing an unexpected event. They presented that during the car driving, if you notice that the car in an opposite line is swerving to your line, the procedure of decision making, motor events, and unconscious reactions happen in a time window of 750 ms or less.

Interestingly, MEG tracks at least 750 brain snapshots from the implemented sensors and creates real-time three-dimensional plots of the current brain activities. While the brain measurement in fMRI is based on the local variation of the oxygenated blood cells, it detects non-real-time brain signals that make it a low inefficient BCI solution for fast decision making reactions (Stam, 2010; Hansen et al., 2010).

2.2.5 Electroencephalogram (EEG)

EEG refers to recording the electrical activity of the brain from attached electrodes on the scalp. The human brain generates impulse signals during the activity period. The recorded waveforms are weak and measured in microvolts (µV). Each brain activity produces specific EEG that is used to distinguish the type of activities. For instance, the brain, electrical waveforms are more stable in sleeping times. Therefore EEG is mostly used to detect unusual brain activities such as epilepsy, seizure, or brain death (Nageshwar V. et al., 2015).

The EEG signal processing is real-time, which includes amplifying and noise reduction and decoding signals to the corresponding brain activities (Barros et al., 2015). EEG signals have low spatial resolution and are sensitive to electrical noises (Yanagisawa et al., 2012).

Multiple factors affect the quality of EEG signals. Nageshwar V. et al. enumerated that signal conversion algorithms, data filtering, and environmental conditions are useful elements of the EEG signal quality (Nageshwar V. et al., 2015).

Usakli studied techniques to overcome the electrical noises on the EEG signal and investigated the effect of numbers and placement of the electrodes on the EEG signal quality (Usakli, 2010).

In addition to the detection of brain disorders such as epilepsy, EEG has been used in various medical processes such as rehabilitation for motor impairment patients and human emotion detection.

As in for the case of MEG, EEG detects real-time information from the neural activities of the brain. However, EEG signals are more influenced by electrical changes between the brain, skull, and scalp that cause more noises in the signals. Both MEG and EEG estimate activities from the center of the detected active area. In other words, the shape of information is not recognizable from the signals and needs related analysis processing methods (Stam, 2010; Hansen et al., 2010).

2.2.6 Single-photon emission computed tomography (SPECT)

SPECT is a nuclear imaging technique that uses gamma rays and provides three-dimensional images. It requires gamma-emitting, generally by injection into the patients' bloodstream. During the SPECT procedure, the gamma-ray camera rotates 180 or 360 degrees around the patient and takes several two-dimensional images. Afterward, the algorithms are used to analyze the data and provide three-dimensional images. The spatial resolution of SPECT is about 1 cm. During the gamma-ray injection, the system can detect the cerebral blood flow that is corresponded to brain activities (Babiloni et al., 2009; Castermans et al., 2013)

2.2.7 Positron emission tomography (PET)

PET is a nuclear function imaging technique that uses gamma rays to detect the patient's disorders. PET requires an injection of radioactive materials (radiotracers) in the blood and produces three-dimensional images from the injected part of the body (Maisey, 2005).

PET is a costly procedure compared to SPECT that counts as a downside of the PET technique (Neil R. Carlson, 2013).

Fornell stated that in addition to the high costs, PET tracers have only 75 seconds half-live while it is about six hours for SPECT. Therefore, SPECT provides longer available time to take neuro-images (Fornell, 2008)

2.3 fNIRS optode Pressure

Few studies have critically investigated the impact of extra pressure of cerebral tissue on the blood flow signals. Vrena et al, (2016) implemented the pressure simulation experiments on the lower back of 12 chronic lower back pain patients and 20 healthy subjects by using fNIRS. Their study aimed to find out whether the pressure simulation makes any changes of Oxy-HB in the supplementary motor area (SMA) and the primary somatosensory cortex (S1). They performed the experiments through three levels of pressure force, including a painful level (based on the individual pressure-pain-threshold), non-painful level, and mean level by using a tactile brushing stimulus. Their investigated results showed changes of Oxy-Hb in right S1 among patients, while Oxy-Hb has a significant response in the healthy group in both SMA and S1. On the other hand, the group comparison of the experiment did not show significant hemodynamic changes between patients and healthy subjects. The substantial achieved result from this study indicates the importance of health feature similarity such as clinically relevant measurements among the subjects (Vrana et al., 2016).

Chapter 3: Methodology

The research methodology that has been used in this study falls in quantitative and qualitative research. The aspect of the phenomenon has been considered through classification features and statistical analysis. The correlation analysis has been used during this study, which is a statistical method to find the relationship between quantitative variables. If the variables have a strong relationship, they are highly correlated, while a weak correlation means that they are not so connected to each other (Franzese & Iuliano, 2019). The correlation between variables can be positive and presents that the variation of the variables is unidirectional. On the other hand, the negative correlation describes the inverse relationship between variables.

The procedure of this master thesis contains two phases, including fNIRS signal quality metrics and the impact of optode pressure on the quality of the signals.

The purpose of the first phase of this study is to find out the measurable fNIRS signal quality metrics. In order to reach to the reliable result, data obtained from an accurate open-access database that is provided by the Technical University of Berlin.

Forasmuch as the open-access database did not contain the data from the different levels of optode pressure, the user experiments have been conducted in the second phase. The goal of this step is to discover the impact of optode pressure on signal quality through the adequate quality metric obtained in the first phase. The users' comfort feedback on the applied pressure level were collected during the experiment as a qualitative variable. As specifying the optimal amount of optode pressure requires quantitative analysis, two calculated metrics for measuring the pressure level were used in the second phase of the study. The pressure level metrics include partial pressure of carbon dioxide (pCO_2) and Laser Doppler flowmetry (LDF). PCO_2 is the measurement of carbon dioxide (CO_2) in the bloodstream that obtained by skin sensors attached to the skin (Nassar and Schmidt 2017). LDF offers the detection of tissue blood flow changes through the prob that is placed close to the intended fNIRS optode (NaderPouratian, 2002).

3.1 Hypotheses

The hypotheses of this study are stated in the following content.

Hypothesis 1: If the users' feedback and pressure level metrics are correlated, accordingly pressure level metrics substitute the users' feedback. In this case, the relation between pressure level metrics and signal quality metric will be evaluated and if they are correlated, then the optimal amount of the optode pressure will be estimated.

Hypothesis 2: If the users' feedback and pressure level metrics are not correlated, the results are provided from a qualitative methodology. Therefore the relationship between users' feedback and signal quality metrics will be measured and if they are correlated, then the effect of optode pressure level on the signal quality will be discussed.

Hypothesis 3: Although the Users' feedback and pressure level metrics are related, there is no correlation between signal quality and pressure level metrics.

Null hypothesis: There is no relationship between users' feedback and pressure level metrics. In addition, if increasing the optode pressure does not affect the quality of the fNIRS signal, there is no relationship between fNIRS signal quality and optode pressure based on this research.

The following flow chart illustrates the methodology procedure in this study.

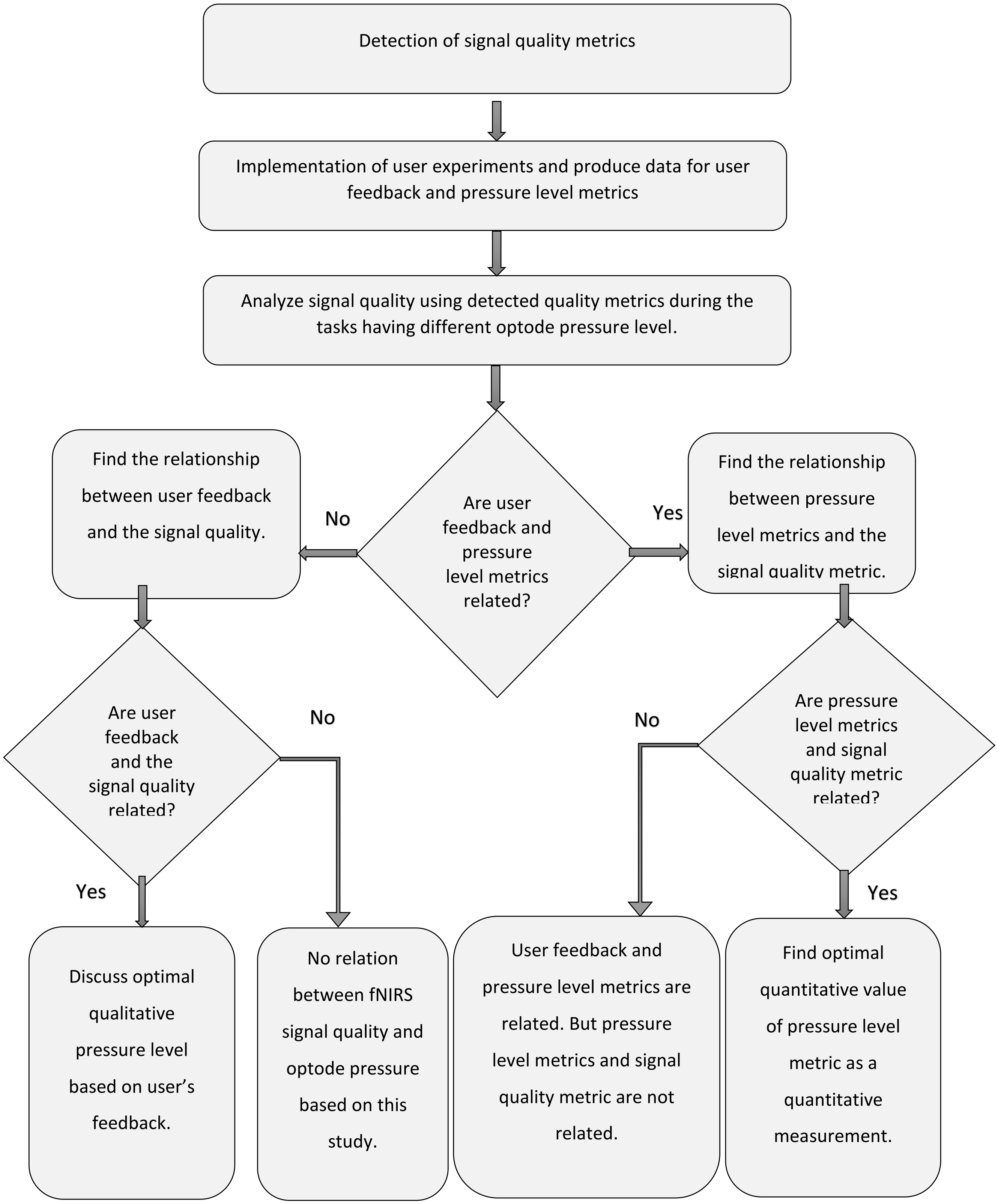

Figure 3-1 Flow chart of methodology process

3.2 Ethical consideration

No personal information, including name, address, personnel number, and email was collected in the applied database and user experiments. The subjects were identified by the subject numbers. All the participants were aware of the experimental procedure and they consent the form before the test. The volunteers did not experience any physical harm or discomfort and participation was voluntary.

3.3 Phase 1: Signal quality metrics

3.3.1 Data Acquisition

In this phase, the data are obtained from an open-access dataset for simultaneous EEG and NIRS BCI (Shin et al., 2017). The aforementioned database is published by J. Shin et al, members of the Computer Science Department in the Institute of Technology in Berlin, Germany in October 2017. Over the last years, BCI technology has been used in various medical and commercial applications. Furthermore, BCI experimental data collection needs a multitude of reproducibility investigations. Since the measured datasets during the studies are not often published, J. Shin et al have published an open-access experimental BCI database to be used for validation purposes through future studies. Furthermore, achieving reliable BCI data sets is a time-consuming process. Therefore the open-access database has been used in this study to statistically analyze data concentrated on valid data and achieve reliable results. The database collection was conducted according to the declaration of Helsinki and was approved by the Ethics Committee of the Institute of Psychology and

Ergonomics, Technical University of Berlin (approval number: SH_01_20150330) (Shin et al., 2017).

In this phase of the master thesis, Matlab R2019r has been used to conduct statistical data analysis.

3.3.2 Subjects

In the abovementioned open-access database, 29 subjects (14 males and 15 females) with an average age of 28.5, participated in the experiments. All subjects were healthy, and none of them declared any physical or brain impairments. The participation was voluntary, and the experimental tests were conducted in a comfortable condition (Shin et al., 2017).

The research sampling during the study is random sampling which the entire target population has an equal and independent chance of being selected to meet the assumptions of many statistical procedures.

3.3.3 Experimental procedure

NIRS data were collected by NIRScout (NIRx GmbH, Berlin, Germany) at a 12.5 Hz sampling rate. In this experiment, fourteen sources and sixteen detectors have been used that created 36 NIRS channels. Nine channels were placed at the frontal head, twelve channels in the right and left (total 24 channels), which are related to motor activities, and three channels were located in the backside of the head that represent visual activities. The optode distance was 30 mm (Shin et al., 2017). Figure 3-2 represents the structure of the optodes in the fNIRS head cap.

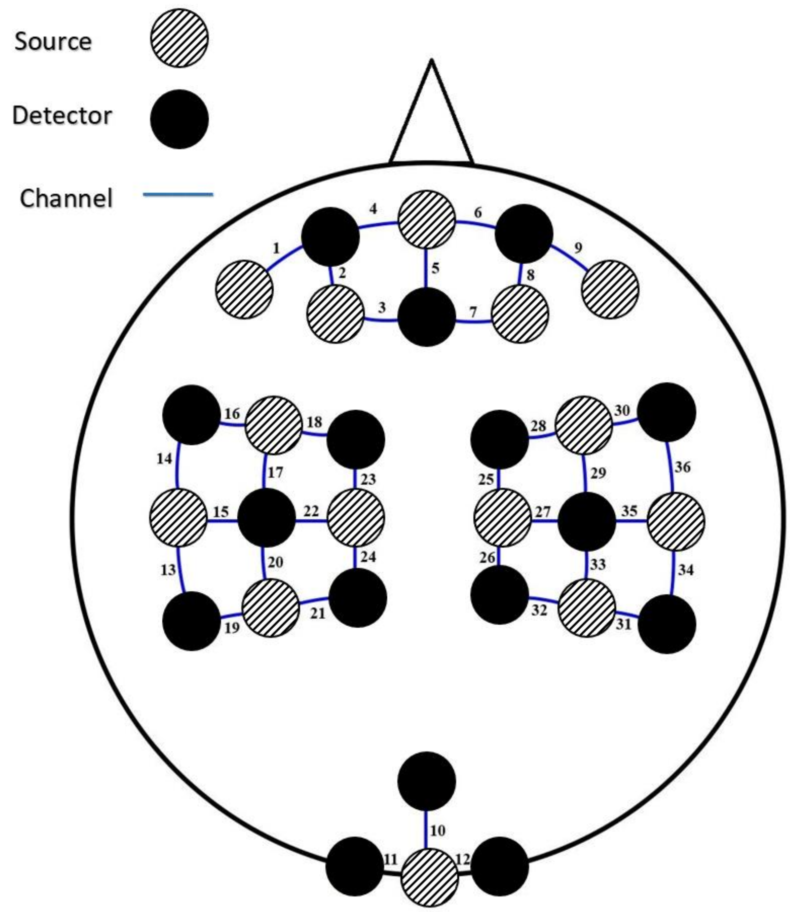

Figure 3-2 Structure of fNIRS optodes in phase 1: sources are presented by Stripes circles, detectors by filled circles, and channels by lines.

The subjects had a comfortable condition during the experiment. They sat in front of a 50-inch screen at a distance of 1.6 m. They were asked not to move any part of their body during the test conduction. The mentioned database contains mental functions, including motor imagery (i.e. imagining of opening and closing hand while holding a ball) and mental arithmetic (mathematical process on digit numbers). In addition to mental tasks, five motion artifacts are recorded independently in the database. The motion artifacts datasets, including blinking eyes, moving eyes, moving head, clenching teeth, and opening mouth. In this thesis, the opening mouth datasets have been used. During the test process, the objects heard a beep sound then opened their mouth for 2 seconds. After each trial, they had rest time. This sets repeated ten times at 5 seconds intervals (Shin et al., 2017).

3.4 Phase 2: Impact of optode pressure on signal quality

The fNIRS signal quality is affected by the pressure of optodes on the scalp. Optode pressure may create inconvenience for the users, especially for long experiments. The enhancement of optode pressure impacts on cerebral blood flow and cause changes in the amount of Carbon Dioxide (CO_2) and tissue blood flow (Kiaer et al. 1990).

The second phase of this study is to perform the fNIRS experiment with different levels of optode pressure and investigate the user's comfort levels.

3.4.1 Experimental design

The experimental design aimed to find out the relation between fNIRS signal quality and user comfortability is sketched in figure 3-3. In order to distinguish the optimal optode pressure, two quantitative measurements were considered for posterior comparison including pCO_2 and LDF. The aforementioned indexes were measured by Sentec monitor and MoorVMS-LDF laser Doppler in Motion Analysis Lab. A higher optode pressure is associated with lower comfort, a relation that is investigated in the analysis of the data collected during the experiment. The subject’s feedbacks concerning the comfort level were collected upon the Visual Analog Pain Scale (VAS), which was applied through a brief questionnaire after mounting the fNIRS sensors. VAS is a validated pain scale based on the self-reported measures the rate from a 10 cm line between no pain and worst pain (Delgado et al., 2018).

Both the optode pressure and the VAS will be compared with each other, and each one with the quality index, which quantifies the quality of the fNIRS data extracted during one specific trial.

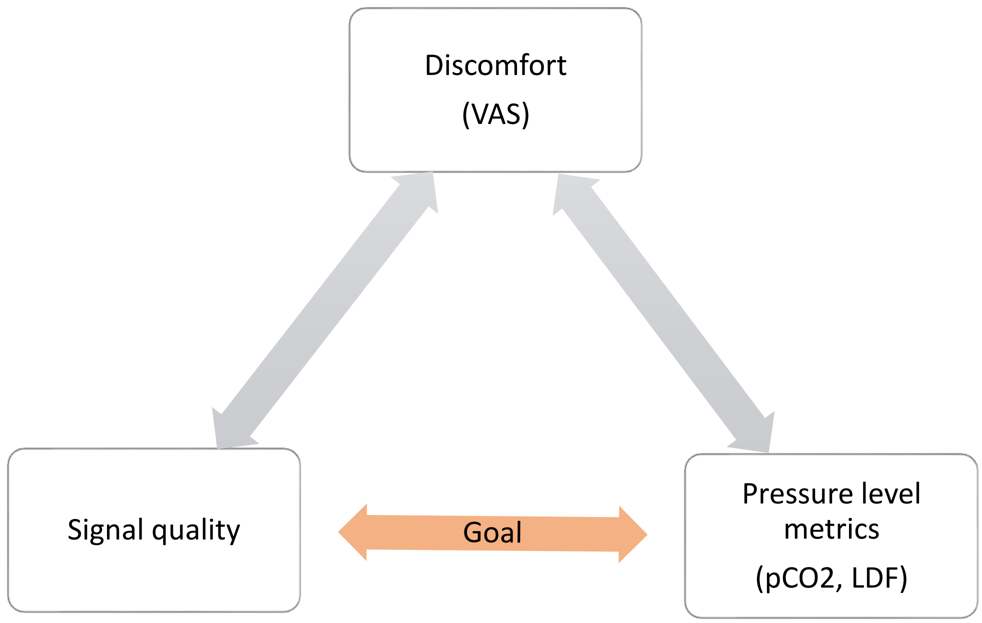

Figure 3-3 The Goal of experimental design

3.4.2 Data Acquisition

The user experiments have been conducted at the Motion Analysis Lab at Oslo Metropolitan University to collect the data that includes multiple optode pressures.

The following context describes the necessary equipment that has been used during the fNIRS experiment and data analysis:

- The NIRScout is a precise fNIRS neuroimaging system that measures hemodynamic responses to neuro activities by oxygenated, deoxy oxygenated, and total hemoglobin changes in the cerebral cortex (NIRScout fNIRS Neuroimaging, n.d.).

Figure 3-4 The NIRScout system (NIRScout fNIRS Neuroimaging, n.d.)

- NIRS cap contains optodes location and is implemented on the subject's head during the experiment (NIRS Caps & Probes, n.d.).

Figure 3-5 fNIRS cap with the implemented optodes (NIRS Caps & Probes, n.d.)

• Dual tip NIRS optodes are the fiber optic laser sources and detectors. Dual tip optodes are a preferred choice for sensitive subjects because of the spread of the optode pressure into two points (NIRS Caps & Probes, n.d.).

Figure 3-6 Dual tip NIRS optode (NIRS Caps & Probes, n.d.)

• A spring-loaded grommet was used to improve the fNIRS signal quality, as the spring inside the grommet tops gently pushes the optodes through the hair, allowing for better contact with the scalp. Besides, the grommet with the screw was used to implement the multiple pressures on the optode (NIRS Caps & Probes, n.d.)

•	The SenTec Digital Monitoring System to measure the Partial Pressure of CO2 (pCO2) produced by the skin tissue under the fNIRS optodes (SenTec Digital Monitor - SenTec, n.d.).

Figure 3-7 SenTec Digital Monitoring System (SDMS) for PCO2 measurement (SenTec Digital Monitor - SenTec, n.d.)

•	The moorVMS-LDF laser Doppler monitor to measure the subcutaneous tissue blood flow (MoorVMS-LDF Laser Doppler Monitor for Blood Flow, n.d.).

Figure 3-8 MoorVMS-LDF laser Doppler (MoorVMS-LDF Laser Doppler Monitor for Blood Flow, n.d.)

•	NIRStar software is a multiplatform instrument controlling environment that is designed to control, interact, and real-time display of fNIRS data.

• NirsLAB is a comprehensive Data Visualization that is developed for analyzing the collected data and visualizing the time series.

• Visual Analog Pain Scale (VAS)

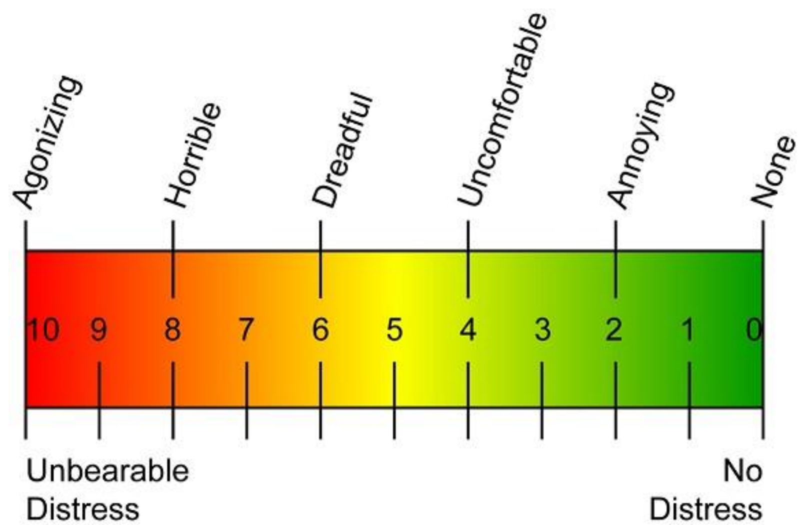

Figure 3-9 Visual Analog Pain Scale (Al–Saffar et al., 2013)

3.4.3 Subjects

The fNIRS user experiments include 4 participants with the age range of 25-35. All the subjects were healthy and without intracranial or metabolic brain disease. The subjects were chosen among the male gender to avoid the gender-related differences in the signal quality and focus on the outcome of the multiple optode pressures.

3.4.4 Experimental procedure

The experiments were conducted in a quiet and adequate lighting condition. The subject was seated in front of a laptop on a comfortable chair. Fifteen fNIRS optodes (eight sources and seven detectors) were placed on the prefrontal area. The optodes provide 20 channels, shown in figure 3-10. Detector 4 was implemented by a screw in the spring-loaded grommets to apply the multiple optode pressures shown by a plaid red circle. Detector 4 was surrounded by four source optodes and provided four channels under the influence of pressure that numbered with channels 7, 9, 12, and 14. PCO2 and LDF sensors were placed close to D4 to measure the Partial Pressure of carbon dioxide, and tissue blood flow in the skin.

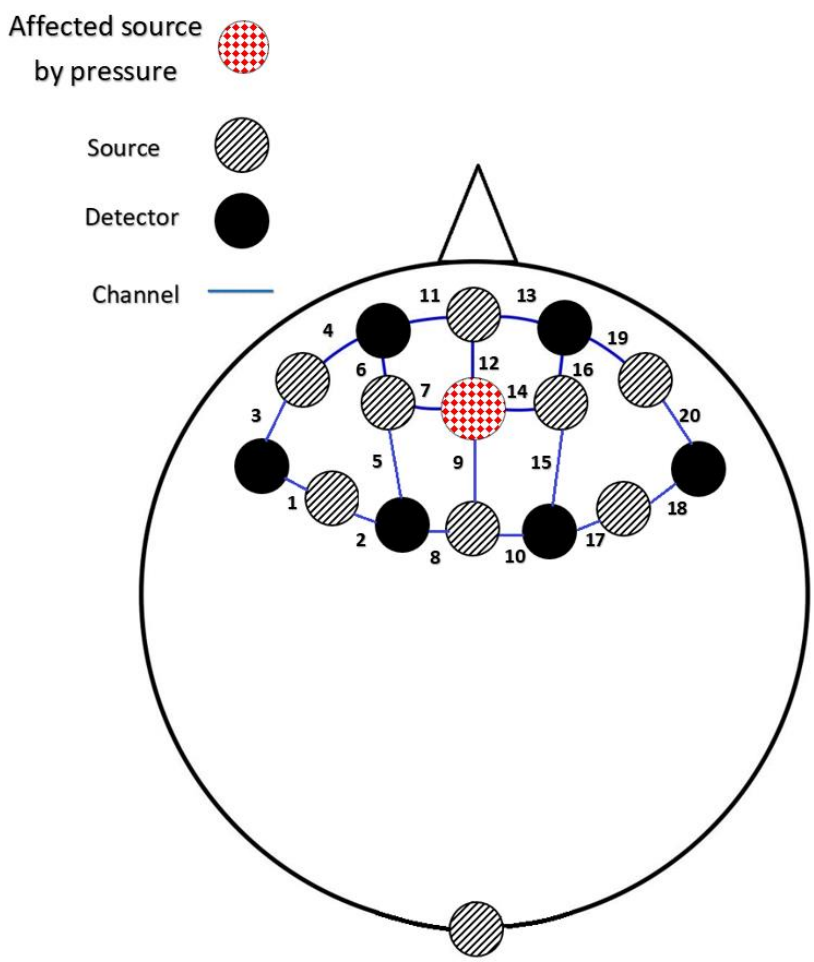

Figure 3-10 fNIRS sources and detectors structure for the user experiments in phase 2. Sources are presented by Stripes circles, detectors by filled circles, and channels by lines. Detector 4 shows by a plaid red circle.

Figure 3-11 Detector 4 with the Spring-loaded grommet and a screw

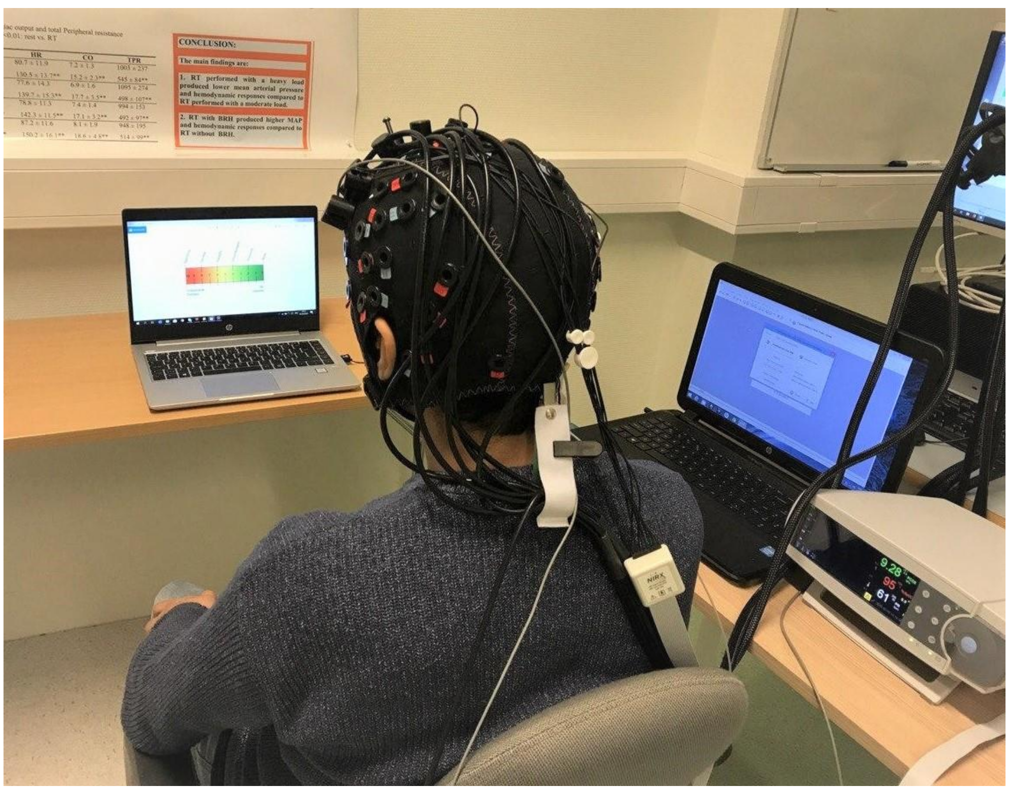

Figure 3-12 fNIRS experimental setup and subject position in front of the laptop

The experimental task contained 20 seconds of mathematical calculation task and 20 seconds of rest afterward. The task was repeated three times, and the optode pressure of D4 increased for each task. The first task was conducted by the least pressure, the second task had medium, and the third task was carried out by the high level of optode pressure. The subjects were asked to subtract from 100 minus 7 in the first task, minus 5 for the second task, and minus 3 in the last task. The subjects expressed their feedback on the felt comfort level upon the Visual Analog Pain Scale (VAS). The initial baseline was 60 seconds and the task took 120 seconds. Overall, the experiments took 180 seconds

Chapter 4: Results

4.1 Phase 1: Signal quality metrics

In the following content, four fNIRS metrics are discussed to investigate the quality of the fNIRS signals through the open-access database.

4.1.1 Running Correlation between oxy-Hb and deoxy-Hb

According to NIRS functionality, during brain activities, while the amount of oxy-Hb increased, the deoxy-Hb decreased. In other words, the change ratio of oxy-Hb and deoxy-Hb has an inverse pattern; thus, they are supposed to have a negative correlation. If the correlation between oxy-Hb and deoxy-Hb is positive, the signal presumably carries noise (Cui et al., 2010). In this study, the Running Correlation (RC) is used to explore the relation between two variables that vary in time. RC is a useful method to extract “the global information” of the signal by sliding windows. Indeed, the correlation is calculated in a window of the first observations, then the window is moved by one position, and the correlation is recalculated for the whole data series. RC helps to distinguish the signal noises in the scope of subjects.

The following figures compared the RC of all channels between two subjects with the same task. Each column is one channel and each row represents a data point. The color bar on the right side shows Pearson Correlation values from 1 (red color) to −1 (blue color). Figure 4-1 presents the first subject and the RC of oxy-Hb and deoxy-Hb are strongly negative shown in blue color. Whereas, the RC of the second subject in figure 4-2 is mainly positive among the channels that are presented in red color. Thus it is assumable that the brain signals of the second subject carry noises. The noises may be caused by motion artifacts like head or facial movements.

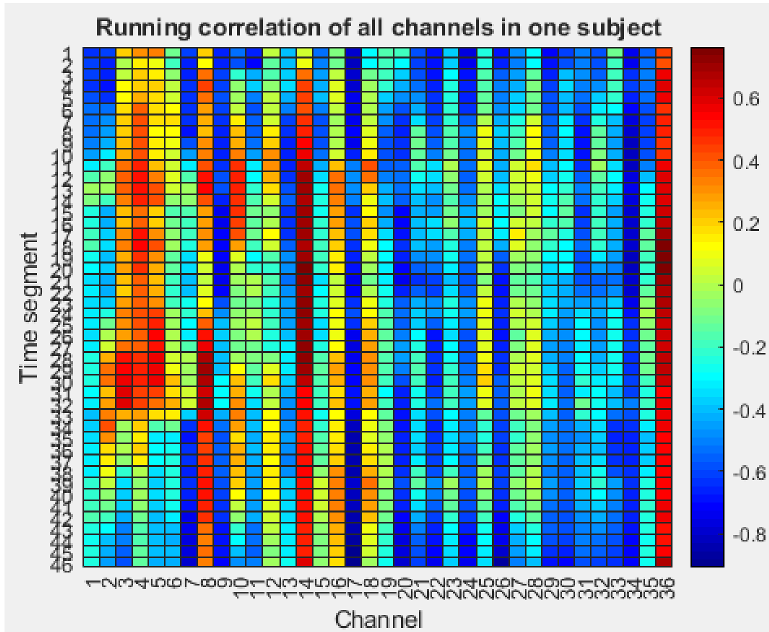

Figure 4-1 Running correlation of all channels during a task-Subject1. RC in most of the channels are negative, shown in blue color, which represented fewer noises during the experiment

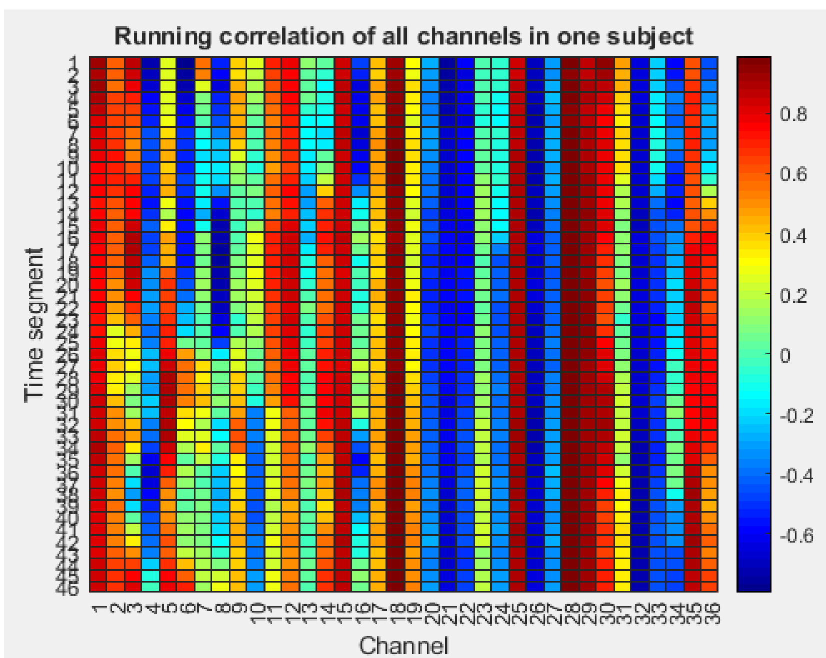

Figure 4-2 Running correlation of all channels during a task- subject2. Positive RC is shown in red color. The signals carried some noises during the experiment.

4.1.2 Visual check of the time series

A visual overview of the oxy-Hb variations of the fNIRS signals gives important information about the signal quality. The noisy channels are specified by the considerable differences in the oxy-Hb time series compared to other channels. The following figure presents the oxy-Hb changes in all channels in one subject. As can be seen, the oxy-Hb variations in the three channels of 14, 22, and 23 are differentiable. Therefore those channels could contain noise.

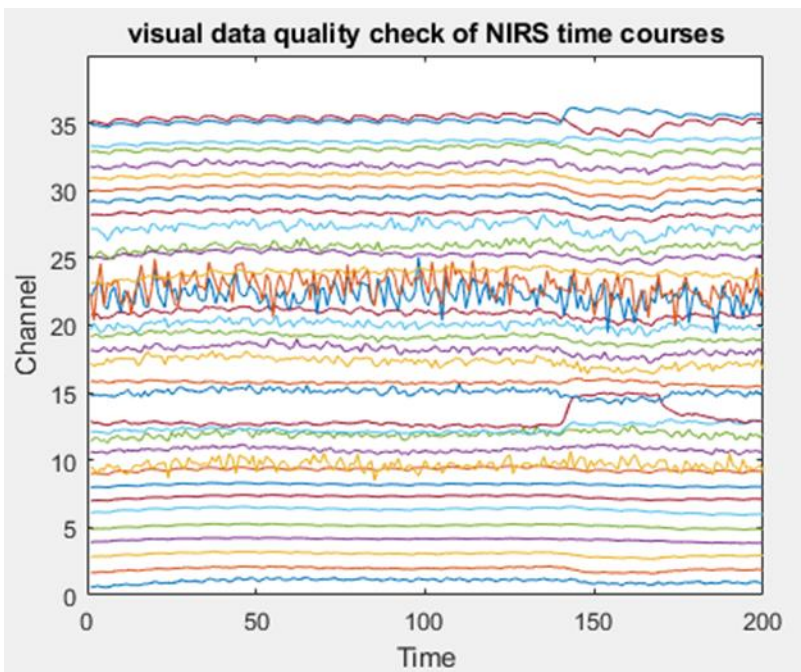

Figure 4-3 fNIRS oxy-Hb variations of all channels in one subject

Additionally to the signal visual checking, the variance of the oxy-Hb time series verifies the obtained noisy channels. Figure 4-4 shows the comparison between the variance of the oxy-Hb among thirty-six channels in one subject. The spikes in three channels of 14, 22, and 23 represent high noisy channels. Comparing the variance of channels leads us to specify noises in the scope of channels (Cui et al., 2010).

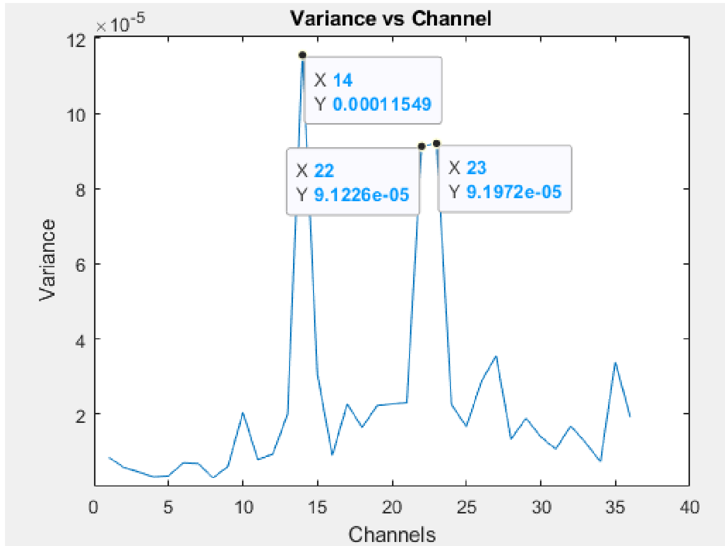

Figure 4-4 Comparison of the variance of channels in one subject

4.1.3 Extract heartbeat among signals

The heartbeat has an effect on the obtained fNIRS brain signals. The wavelength of the heartbeat is approximately stable of ~1 Hz. Thus the heartbeat in the accurate signal is differentiable and can be extracted from fNIRS signals. The wavelet transform toolbox is a method to extract the heartbeat from the fNIRS signal. In this method, the heartbeat is recognizable by the light band in the Wavelet transformation plot (Nozawa et al., 2016). Wavelet transform coherence (WTC) is a method for analyzing the coherence and phase lag of series as a function of both time and frequency domain (Chang & Glover, 2010).

The following plot shows the heartbeat recognition between two channels in the same subject. The bright band of the heartbeat in yellow color is differentiable in figure 4-5 that presents the channel with less noise. Figure

4-6 shows the noisy channel that the heartbeat band is unclear. However, an indistinctive heartbeat band does not mean that the signal is trash and therefore the estimation of the signal quality requires more cautions.

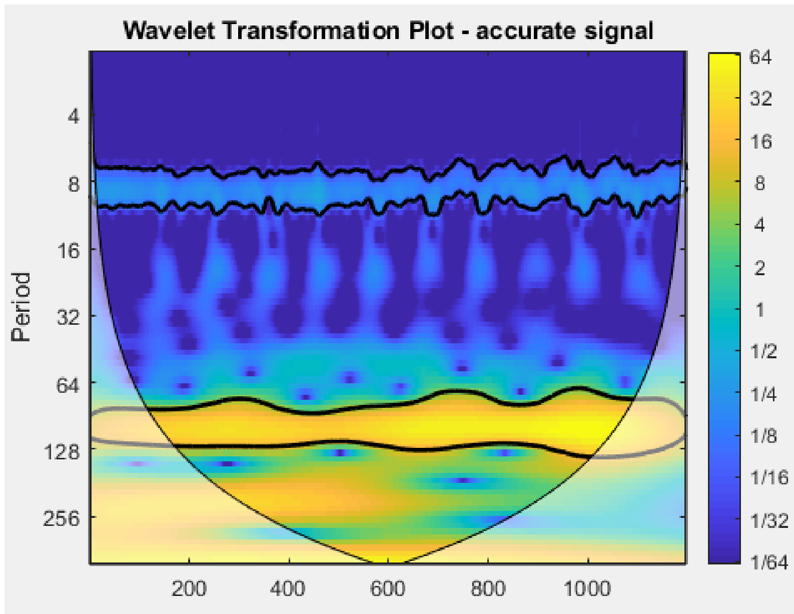

Figure 4-5 Wavelet transform of oxy-Hb in one channel of the fNIRS signal. The bright yellow band clarifies the heartbeat

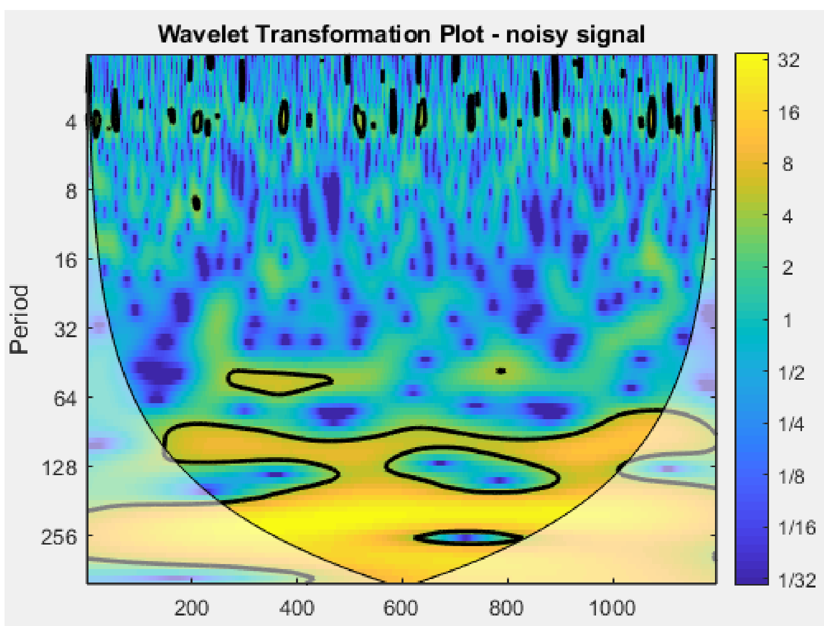

Figure 4-6 Wavelet transform of oxy-Hb in one channel of the fNIRS signal. The heartbeat is not recognizable in the signal.

4.1.4 Moving variance per channel

Variance, which is the standard deviation squared, measures the separation of the variables from the average value (Salonen, 2014). The Moving Variance, computes the variance over the sliding window. In the sliding window method, a window with a specific length moves block by block over the data. Oxy-Hb Moving Variance per channel is one of the suggested metrics to distinguish the noisy blocks in one fNIRS channel. In other words, Moving variance specifies the time occurrence of noise in a channel.

Figure 4-7 shows oxy-Hb Moving Variance in one channel by time window length of 200 frames. The high spikes in the graph present the occurrence periods of noises.

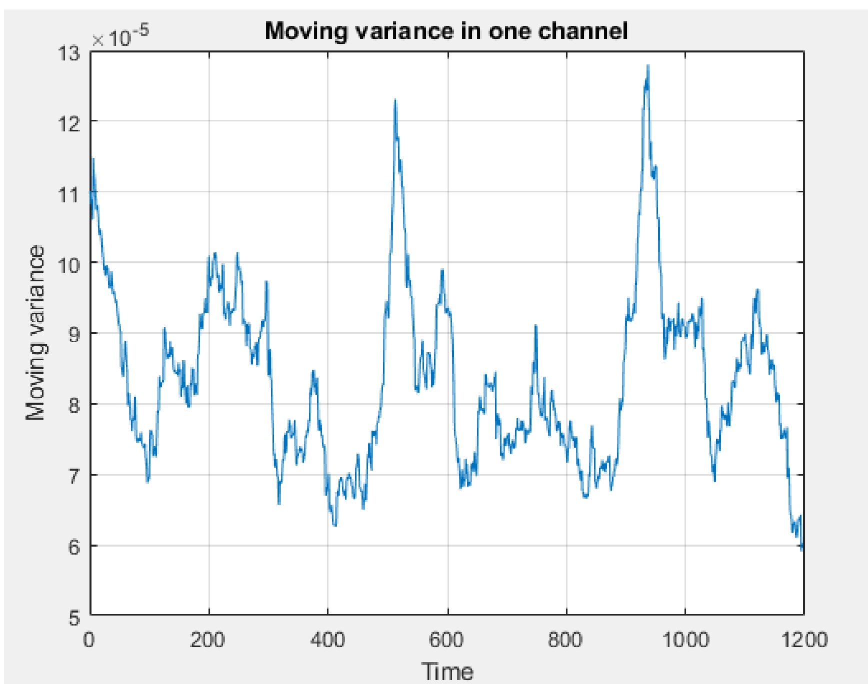

Figure 4-7 Oxy-Hb moving variance in one channel by the time window length of 200. Spikes of Moving Variance between 400-600 and 800-1000 presents the time occurrence of noises.

Phase 2: Impact of optode pressure

According to the definition of the Human-Centered Design (HCD), focusing on the users and their requirements enhances the efficiency and usability of the system. Besides the significant advantages of fNIRS as the new portable BCI technique, the user experiment processes are inconvenienced. The pressure of the fNIRS optodes during the ongoing experiments causes discomfort and reduces user satisfaction.

The second phase of this master thesis aims to clarify the effect of fNIRS optode pressure on the quality of the signal. Despite the quantitative pressure metrics (pCO2, and LDF), the user feedback is a qualitative metric that is affected by the user's attributes, including gender, age, stress, and pain tolerance. Therefore, the goal is to specify the correlation of pressure metrics with the user feedbacks and replace the quantitative metrics with the user's feedback.

4.1.5 Estimation of signal quality in consideration of pressure indexes

At this junk, the obtained result from the fNIRS user experiment is discussed.

Table 4-1 shows the mean of the pCO2 variation with different optode pressures. The pCO2 ratio slightly growth in two subjects remained steady in one subject and decreased in the last subject of the user experiment.

Table 4-1 PCO2 (kPa)* affected by different optode pressure levels

Pressure Level	Subject1	Subject2	Subject3	Subject4
1 (Minimum)	9.59 (kPa)	8.18 (kPa)	7.41 (kPa)	13.17 (kPa)
2 (Medium)	9.67 (kPa)	8.42 (kPa)	7.59 (kPa)	13.06 (kPa)
3 (Maximum)	9.47 (kPa)	8.42 (kPa)	7.82 (kPa)	12.16 (kPa)

*kPa: kilopascal

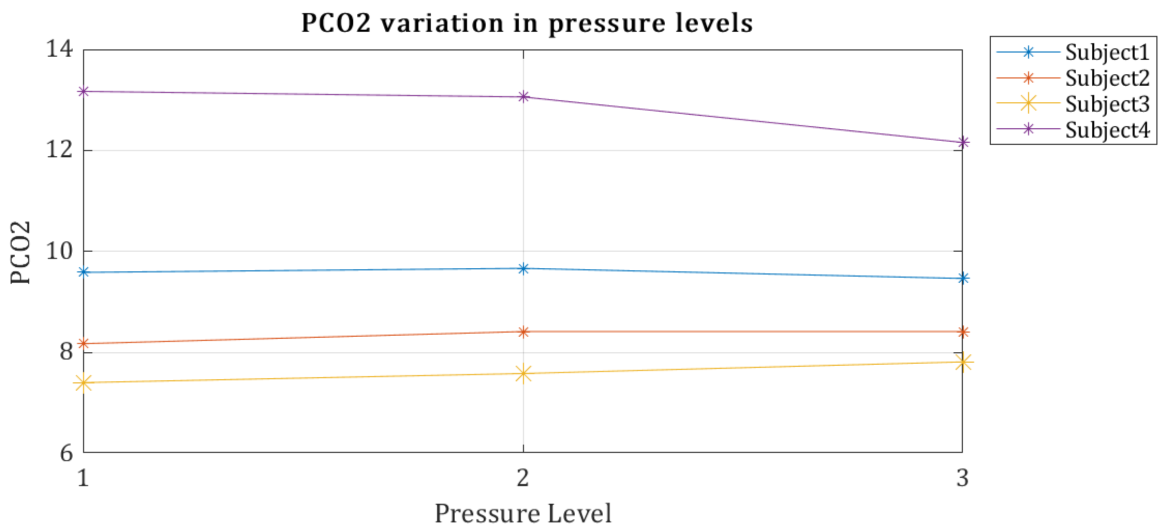

Figure 4-8 PCO2 variation affected different optode pressures

Table 4-2 presents the change of LDF by the enhancement of the optode pressure during the user experiment. LDF ratio slightly changed in subject 1, dropped dramatically in subjects 2 and 4, and went up in subject 3. It is considerable that the changes from pressure levels 2 and 3 did not change significantly.

Table 4-2 LDF (PU) variation affected different optode pressures*

Pressure level	Subject1	Subject2	Subject3	Subject4
1 (Minumum)	25.005 (PU)	273.09 (PU)	35.77 (PU)	130.97 (PU)
2 (Medium)	40.72 (PU)	129.48 (PU)	122.3637 (PU)	128.21 (PU)
3 (Maximum)	32.09 (PU)	125.19 (PU)	116.7844	97.63 (PU)

*PU: Perfusion Unit

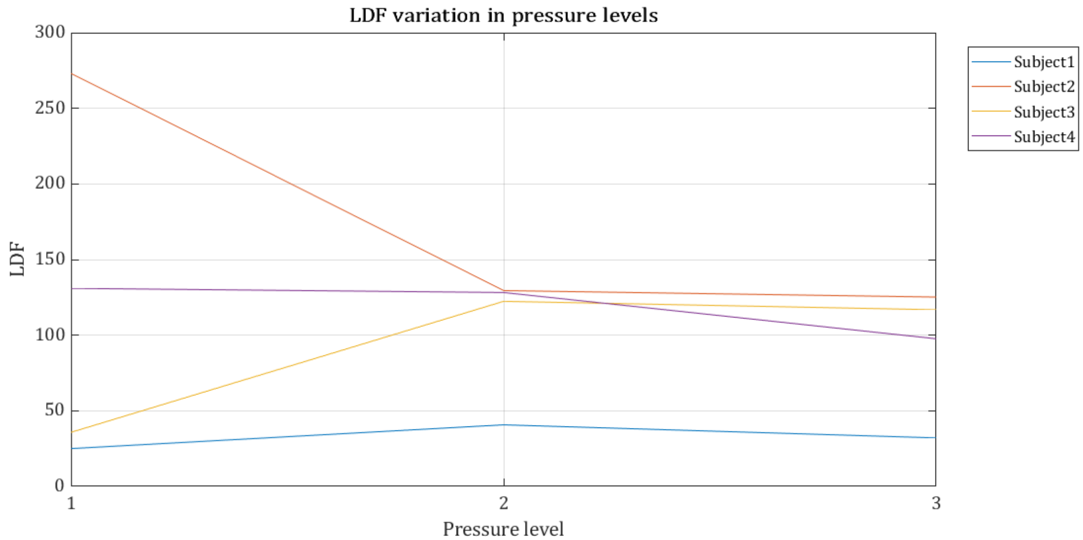

Figure 4-9 LDF variation affected different optode pressures

Overall, the analysis of the pCO2 and LDF variation changes slightly by applying different optode pressure levels.

The experiment data obtained from NIRScout was interpreted to fNIRS signals by NIRStar software. Then the signals filtered and analyzed by NirsLAB software. The signals are filtered by the bandpass filtering to comprise physiological noise such as heartbeat.

Among the discussed metrics in phase 1, the Running Correlation between oxy-Hb and deoxy-Hb was considered as a quality criterion. The variation of

RC between oxy-Hb and deoxy-Hb investigates the accuracy of the brain activity during the task in one subject. Accordingly, the negative RC indicates the reverse changes of oxy-Hb and deoxy-Hb that represent the higher signal quality.

In consideration of distinct attributes and health conditions, the signal quality was investigated independently for each subject.

The following graphs show the mean RC changes focused on four affected channels by the pressed optode. Pressure level 1 indicates minimum and 3 is the highest applied pressure. The corresponded tables explicit the obtained data in detail.

Table 4-3 Mean of RC change in four affected channels in Subject 1

Pressure Level	Channel7	Channel9	Channel12	Channel14
1 (Minimum)	-0.5818	-0.506	-0.5201	-0.6144
2 (Medium)	0.2918	-0.5126	0.5335	0.4032
3 (Maximum)	-0.5221	-0.3152	-0.3878	-0.5422

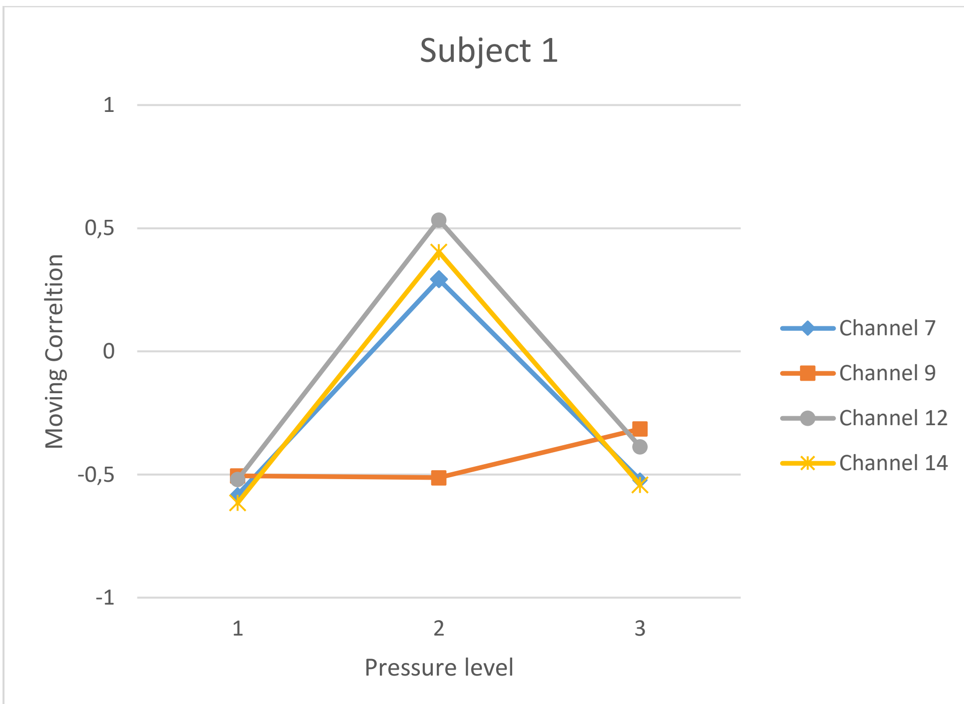

Figure 4-10 Comparison of Mean of RC over the Task period for four affected channels by the pressed optode in Subject 1

Table 4-4 Mean of RC change in four affected channels in Subject 2

Pressure Level	Channel7	Channel9	Channel12	Channel14
1 (Minimum)	-0.9942	-0.9876	-0.875	-0.9159
2 (Medium)	-0.9924	-0.974	-0.8867	-0.9047
3 (Maximum)	-0.9896	-0.9502	-0.881	-0.8602

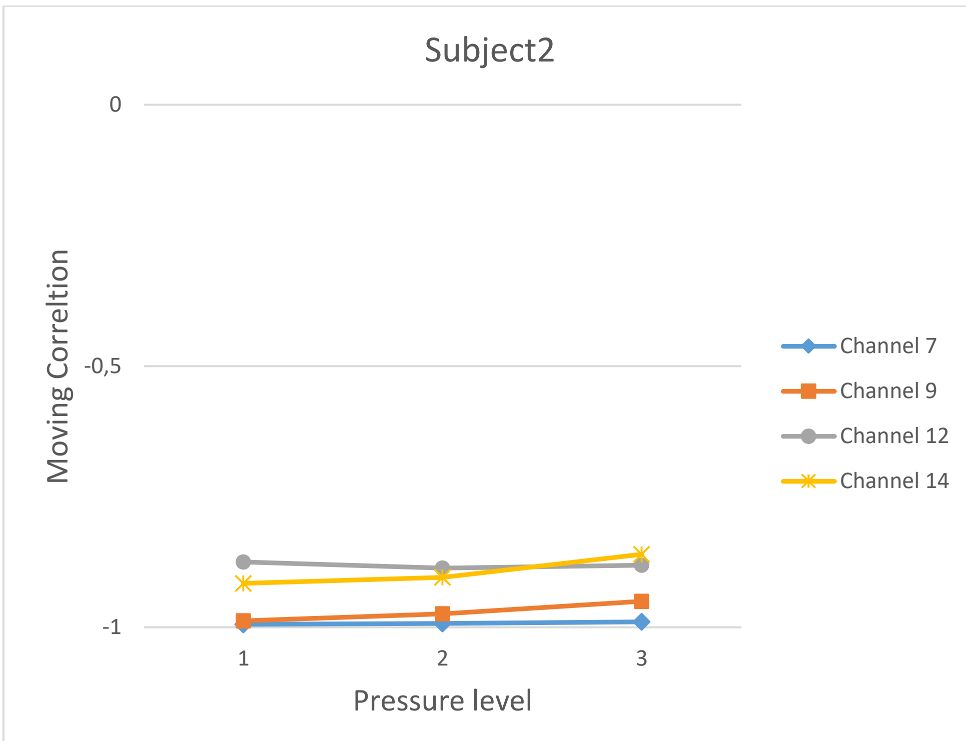

Figure 4-11 Comparison of Mean of RC over the Task period for four affected channels by the pressed optode in Subject 2

Table 4-5 Mean of RC change in four affected channels in Subject 3

Pressure Level	Channel7	Channel9	Channel12	Channel14
1 (Minimum)	-0.4826	-0.2427	-0.2457	-0.4191
2 (Medium)	0.8644	-0.0365	0.5101	0.9603
3 (Maximum)	0.2231	-0.1836	0.381	0.0415

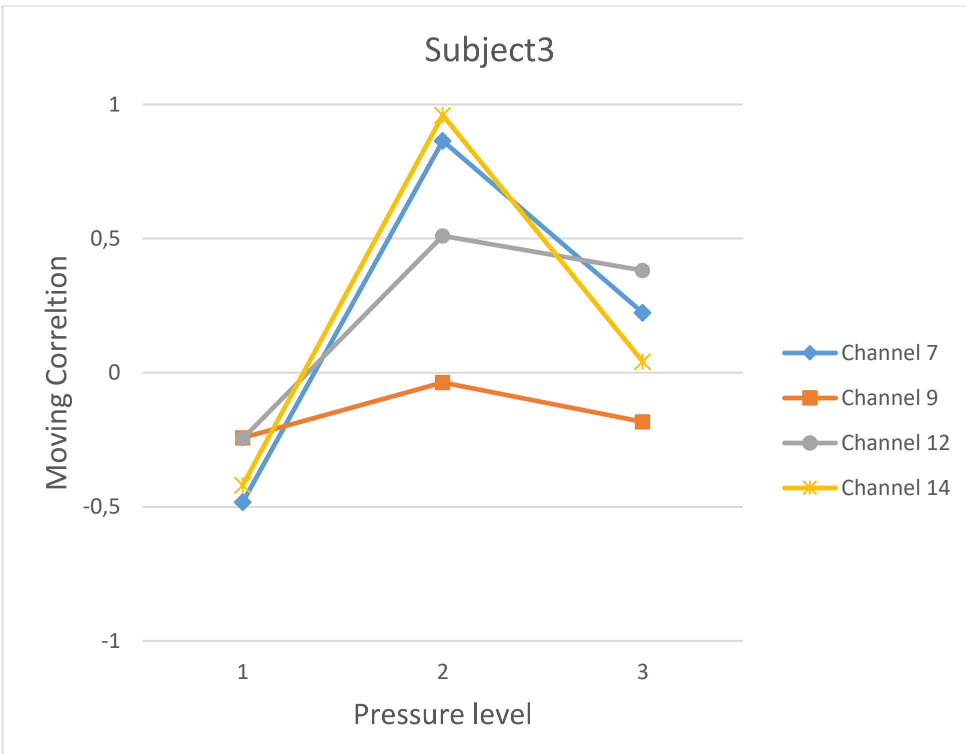

Figure 4-12 Comparison of Mean of RC over the Task period for four affected channels by the pressed optode in Subject 3

Table 4-6 Mean of RC change in four affected channels in Subject 4

Pressure Level	Channel7	Channel9	Channel12	Channel14
1 (Minimum)	-0.7688	-0.8135	-0.714	-0.52
2 (Medium)	-0.5124	-0.6567	-0.4526	-0.3196
3 (Maximum)	-0.8312	-0.8008	-0.8147	-0.8044

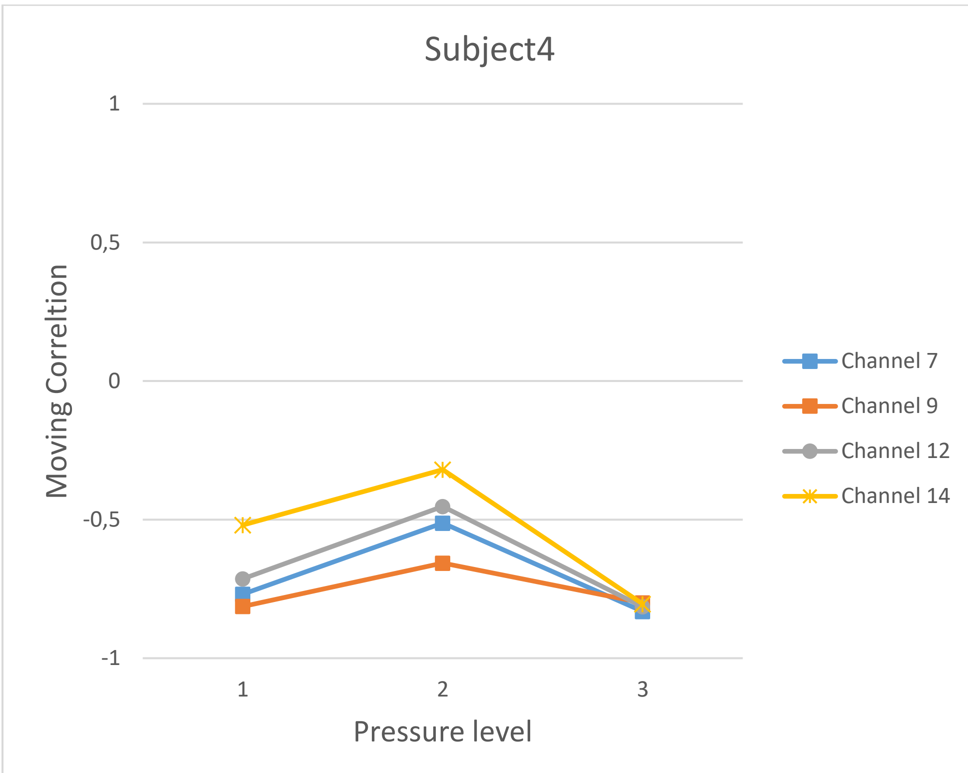

Figure 4-13 Comparison of Mean of RC over the Task period for four affected channels by the pressed optode in Subject 4

According to the investigated experiment data, the RC increased in the majority of the subjects. Then it dropped sharply by applying more pressure up to level 3. However, enhancing the optode pressure to level 3 cannot be applied for the longer experimental period and cause user inconvenience and skin damage.

4.1.6 Corresponding user feedback to the pressure level

The subjects were asked to express their comfort status based on the Visual Analog Pain Scale (VAS) by enhancing the optode pressure during the task. Table 4-3 presents the corresponding scale to each subject by variation of the pressure.

Table 4-7 Corresponding subjects' feedback to the optode pressure levels (VAS)

Pressure Level	Subject1	Subject2	Subject3	Subject4
1 (Minimum)	3	2	2	3
2 (Medium)	5	4	5	5
3 (Maximum)	8	6	8	7

As a result of subjects' feedback to the applied pressure level during the task, Subjects 1 and 3 reported more pressure on their skin. The Comparison of RC changes and subjects' feedback led us to conclude that producing significant changes in RC, requires applying major optode pressure on the skin. Although enhancement of the optode pressure can increase the signal quality, is not an efficient solution to longer tasks du to user inconvenience.

Chapter 5: Discussion

5.1 Summary of key findings

Estimation of fNIRS signal quality is one of the main precision factors of the experiment's validity. As the biometric features vary, the quality of fNIRS signals differs among the subjects.

The purpose of this study is to detect an efficient quantitative signal quality metric in the first phase and use the metric for further analysis considering optode pressure in the second phase. To find the signal quality metrics, we discussed qualitative and qualitative measurements and analyzed them by the precise open-access database. Our findings noted that the running correlation between oxy-Hb and deoxy-Hb gives us the whole comparison of fNIRS signal quality changes among users. The extraction of the heartbeat band is another discussed metric that is influenced by the physical and mental conditions of the subject. Therefore detection of heartbeat is not considered as a quantitative factor in the second phase of this study. Moving variance per channel distinguishes the high or low-quality channels in one subject during the task period. Since the second purpose of the current study is to compare the data of different pressure variables that conducted in different time scope, moving variance per channel is not used in the second phase.

The second phase of the study aims to find out the influence of different levels of optode pressure on the fNIRS signal quality. Since the subject's feedback is a qualitative response and is affected by body condition, quantitative variables are considered as substitute metrics. We used two pressure level metrics including PCO2 and LDF, to measure the different levels of fNIRS optode pressure. The results indicate that PCO2 and LDF cannot be used as a substitute measurement for the pressure level and they do not have a direct correlation with the applied pressure.

5.2 Interpretation of findings

The results support the claim of Ortiz-Prado et al. about the Partial pressure of oxygen in the brain. Ortiz-Prado et al. declared that changes in tissue brain partial pressure of oxygen and dioxygen depend on various factors, including cerebral blood flow (CBF), hypoxia, exercise, stress, and physiological conditions (Ortiz-Prado et al., 2019). Accordingly, PCO2 and LDF were influenced by the abovementioned factors during the fNIRS experiment. Contrary to the hypothesized one association to estimate the optimal optode pressure by considering the user comfort and fNIRS signal quality, the expected correlation between quantitative metrics did not obtain from the data. Therefore the optimal measurable amount of optode pressure cannot be evaluated.

Interpretation of the users' feedback indicates a relation between the level of pressure and signal quality metric (RC) during the tasks. The results from users' feedback explicit that creating a significant influence on the signal quality requires a significant enhancement of the optode pressure on the scalp. In other words, small growth in the optode pressure creates negligible changes in the signal quality.

5.3 Discussion of implication

The experiment provides new insight into the relationship between the signal quality and applied fNIRS optode pressure during the experiment based on subjects' feedback.

As the user inconvenience is one of the existing obstacles of the use of fNIRS in the long period tasks, the obtained results are valued in the enhancement of user comfort during the fNIRS experiments. The study claims that a major amount of optode pressure is required to achieve a significant improvement in signal quality. Therefore it is not efficient to ignore the user comfort and obtain the qualified signals during the experiments.

5.4 Limitation of the research

The generalizability of the results is limited by the male gender with the age range of 25-35. The limited selection was due to physical and pain tolerance variety between male and female subjects.

It is beyond the scope of this study to estimate and suggest an efficient measurable amount for the optode pressure in the fNIRS experiments because of the uncorrelated quantitative variables obtained from the results.

Chapter 6: Conclusion

As interest for fNIRS as a novel brain-computer interface increases in the computer interaction community, the mater of signal quality has been discussed in several studies. Due to ease of use, portability, and fast set up time, fNIRS becomes an efficacious BCI technique recently. However unacceptable environmental conditions and unique features of human physiology have caused a challenging process in the detection of the fNIRS signal quality.

In addition, the mater of user physical comfort in the fNIRS experiments opens up the new study focusing on the human convenience during the implementation procedure.

This research aimed to identify the efficient measurable metrics of fNIRS signal quality. Furthermore, the effect of optode pressure on signal quality was discussed. Through this thesis, I tried to distinguish that how increasing the fNIRS optode pressure affects the signal quality and the user comfort. The ultimate goal of my study was to estimate the optimal optode pressure while the user is not undergoing inconvenience.

Based on the collected metrics, the moving variance between oxy-HB and deoxy-Hb was chosen to distinguish the signal quality rate while applying unequal optode pressure levels. In the second phase, the user experiment was conducted to obtain the fNIRS data that affected unequal optode pressure. The experiments contained 3 tasks with different pressure levels including minimum (task 1), medium (task 2), and maximum (task 3). In order to reach an optimal optode pressure, the relation between two quantitative pressure metrics (PCO2 and LDF) and user's feedback was studied. The results contradict the first hypothesis that indicates that pressure metrics and user feedback do not have a steady correlation. Therefore, quantitative metrics could not replace user feedback. Following the second hypothesis that focused on qualitative data analyzing, the results show the relationship between user's feedback and signal quality. Based on the conducted data from the user experiments, the signal quality did not increase by pressure enhancement to medium level. The expected enhancement of the signal quality happened on the third task with the maximum pressure level. Accordingly, by applying major optode pressure on the scalp, the quality of the signal increases. However, the applied pressure in task 3 does not seem an efficient solution for longer tasks and may cause inconvenience for the users.

6.1 Future research

Further research is required to establish whether any quantitative pressure metrics can apply following the analyses of this study.

Future studies should take into account gender and age variety. The reason for the limitation of subjects during this study is to deduct the variety of effective variables and increase the validation of the study. It is worth mentioning that subgrouping in the chosen subjects is an essential process in the fNIRS experiments, because the analysis of the data and achieved results highly depend on the individual attributes and cannot compare the groups with a variety of conditions. Despite new efforts to improve the fNIRS performance, more research is needed to improve the usability and user comfort in the fNIRS experiments.

Chapter 7: Reference list

Al–Saffar, M. T., AL-Sandook, T. A., & Y-Taha, M. (2013). A Possible New Concept in the Mechanism of Action of Local Anesthesia. *American Journal of Medical and Biological Research*, *1*(4), 134–137. https://doi.org/10.12691/ajmbr-1-4-5

Babiloni, C., Pizzella, V., Gratta, C. D., Ferretti, A., & Romani, G. L. (2009). Chapter 5 Fundamentals of Electroencefalography, Magnetoencefalography, and Functional Magnetic Resonance Imaging. In *International Review of Neurobiology* (Vol. 86, pp. 67–80). Academic Press. https://doi.org/10.1016/S0074-7742(09)86005-4

Bansal, D., & Mahajan, R. (2019). Chapter 1—Introduction. In D. Bansal & R. Mahajan (Eds.), *EEG-Based Brain-Computer Interfaces* (pp. 1–19). Academic Press. https://doi.org/10.1016/B978-0-12-814687-3.00001-6

Barros, R. Q., Santos, G., Ribeiro, C., Torres, R., Barros, M. Q., & Soares, M. M. (2015). A Usability Study of a Brain-Computer Interface Apparatus: An Ergonomic Approach. In A. Marcus (Ed.), *Design, User Experience, and Usability: Design Discourse* (pp. 224–236). Springer International Publishing. https://doi.org/10.1007/978-3-319-20886-2_22

Castermans, T., Duvinage, M., Cheron, G., & Dutoit, T. (2013). Towards Effective Non-Invasive Brain-Computer Interfaces Dedicated to Gait Rehabilitation Systems. *Brain Sciences*, *4*(1), 1–48. https://doi.org/10.3390/brainsci4010001

Chaddad, A., Kamrani, E., Le Lan, J., & Sawan, M. (2013). Denoising fNIRS Signals to Enhance Brain Imaging Diagnosis. *2013 29th Southern Biomedical Engineering Conference*, 33–34. https://doi.org/10.1109/SBEC.2013.25

Chang, C., & Glover, G. H. (2010). Time–frequency dynamics of resting-state brain connectivity measured with fMRI. *NeuroImage*, *50*(1), 81–98. https://doi.org/10.1016/j.neuroimage.2009.12.011

Chong, L., Hai-bin, Z., Chun-sheng, L., & Hong, W. (2010). Classification of ECoG signals for motor imagery tasks. *2010 2nd International Conference on Signal Processing Systems*, *3*, V3-185-V3-188. https://doi.org/10.1109/ICSPS.2010.5555442

Cui, X., Bray, S., & Reiss, A. L. (2010). Functional near infrared spectroscopy (NIRS) signal improvement based on negative correlation between oxygenated and deoxygenated hemoglobin dynamics. *NeuroImage*, *49*(4), 3039–3046. https://doi.org/10.1016/j.neuroimage.2009.11.050

Delgado, D. A., Lambert, B. S., Boutris, N., McCulloch, P. C., Robbins, A. B., Moreno, M. R., & Harris, J. D. (2018). Validation of Digital Visual Analog Scale Pain Scoring With a Traditional Paper-based Visual Analog Scale in Adults. *Journal of the American Academy of Orthopaedic Surgeons. Global Research & Reviews*, *2*(3). https://doi.org/10.5435/JAAOSGlobal-D-17-00088

Di Domenico, S. I., Rodrigo, A. H., Ayaz, H., Fournier, M. A., & Ruocco, A. C. (2015). Decision-making conflict and the neural efficiency hypothesis of intelligence: A functional near-infrared spectroscopy investigation. *NeuroImage*, *109*, 307–317. https://doi.org/10.1016/j.neuroimage.2015.01.039

Ekandem, J. I., Davis, T. A., Alvarez, I., James, M. T., & Gilbert, J. E. (2012). Evaluating the ergonomics of BCI devices for research and experimentation. *Ergonomics*, *55*(5), 592–598. https://doi.org/10.1080/00140139.2012.662527

Filler, A. (2009). The History, Development and Impact of Computed Imaging in Neurological Diagnosis and Neurosurgery: CT, MRI, and DTI. *Nature Precedings*, 1–1. https://doi.org/10.1038/npre.2009.3267.4

Fornell, D. (2008). *SPECT Scanner vs. PET, Which is Best?* DAIC. https://www.dicardiology.com/article/spect-scanner-vs-pet-which-best

Franzese, M., & Iuliano, A. (2019). Correlation Analysis. In S. Ranganathan, M. Gribskov, K. Nakai, & C. Schönbach (Eds.), *Encyclopedia of Bioinformatics and Computational Biology* (pp. 706–721). Academic Press. https://doi.org/10.1016/B978-0-12-809633-8.20358-0

Gagnon, L., Perdue, K., Greve, D. N., Goldenholz, D., Kaskhedikar, G., & Boas, D. A. (2011). Improved recovery of the hemodynamic response in diffuse optical imaging using short optode separations and state-space modeling. *NeuroImage*, *56*(3), 1362–1371. https://doi.org/10.1016/j.neuroimage.2011.03.001

Grabianowski, E. (2007, November 2). *How Brain-computer Interfaces Work*. HowStuffWorks. https://computer.howstuffworks.com/brain-computer-interface.htm

Hansen, P. C., Kringelbach, M. L., & Salmelin, R. (Eds.). (2010). *MEG: An introduction to methods*. Oxford University Press.

Hirsch, G. V., Bauer, C. M., & Merabet, L. B. (2015). Using structural and functional brain imaging to uncover how the brain adapts to blindness. *Annals of Neuroscience and Psychology*, *2*. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6168211/

Kopton, I. M., & Kenning, P. (2014). Near-infrared spectroscopy (NIRS) as a new tool for neuroeconomic research. *Frontiers in Human Neuroscience*, *8*. https://doi.org/10.3389/fnhum.2014.00549

Krampe, C., Gier, N. R., & Kenning, P. (2018). The Application of Mobile fNIRS in Marketing Research—Detecting the “First-Choice-Brand” Effect. *Frontiers in Human Neuroscience*, *12*. https://doi.org/10.3389/fnhum.2018.00433

Lee, G., Jin, S. H., Yang, S. T., An, J., & Abibulaev, B. (2018). Cross-correlation between HbO and HbR as an effective feature of motion artifact in fNIRS signal. *2018 6th International Conference on Brain-Computer Interface (BCI)*, 1–3. https://doi.org/10.1109/IWW-BCI.2018.8311513

Leuthardt, E. C., Schalk, G., Roland, J., Rouse, A., & Moran, D. W. (2009). Evolution of brain-computer interfaces: Going beyond classic motor physiology. *Neurosurgical Focus*, *27*(1), E4. https://doi.org/10.3171/2009.4.FOCUS0979

Looney, D., Kidmose, P., & Mandic, D. P. (2014). Ear-EEG: User-Centered and Wearable BCI. In C. Guger, B. Allison, & E. C. Leuthardt (Eds.), *Brain-Computer Interface Research: A State-of-the-Art Summary -2* (pp. 41–50). Springer.

https://doi.org/10.1007/978-3-642-547072_5

Loup-Escande, E., Lotte, F., Loup, G., & Lécuyer, A. (2017). User-Centered BCI Videogame Design. In R. Nakatsu, M. Rauterberg, & P. Ciancarini (Eds.), *Handbook of Digital Games and Entertainment Technologies* (pp. 225–250). Springer.

https://doi.org/10.1007/978-981-4560-50-4_3

Maisey, M. N. (2005). Positron Emission Tomography in Clinical Medicine. In D. L. Bailey, D. W. Townsend, P. E. Valk, & M. N. Maisey (Eds.), *Positron Emission Tomography: Basic Sciences* (pp. 1–12). Springer. https://doi.org/10.1007/1-84628-007-9_1

McFarland, D. J., & Wolpaw, J. R. (2008). Brain-Computer Interface Operation of Robotic and Prosthetic Devices. *Computer*, *41*(10), 52–56. https://doi.org/10.1109/MC.2008.409

MoorVMS-LDF laser Doppler monitor for blood flow. (n.d.). Moor Instruments. https://www.moor.co.uk/products/monitoring/laser-doppler-monitor/

NaderPouratian, A. W. T. (2002). *Optical Imaging Based on Intrinsic Signals*. https://doi.org/10.1016/B978-012693019-1/50007-1

Nageshwar V., Sai, Y. P., Rao, K. S., & Anoop. (2015). Spike detection in Electroencephalogram (EEG) using Arduino UNO. *2015 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT)*, 629–631. https://doi.org/10.1109/ICCICCT.2015.7475354

Neil R. Carlson. (2013). *Physiology of Behavior: Pearson New International Edition*. https://www.pearson.ch/HigherEducation/Pearson/EAN/9781292023205/Physiology-of-Behavior-Pearson-New-International-Edition

NIRS Caps & Probes. (n.d.). NIRx Medical Technologies. https://nirx.net/nirscaps

NIRScout fNIRS Neuroimaging. (n.d.). NIRx Medical Technologies. https://nirx.net/nirscout

Nozawa, T., Sasaki, Y., Sakaki, K., Yokoyama, R., & Kawashima, R. (2016). Interpersonal frontopolar neural synchronization in group communication: An exploration toward fNIRS hyperscanning of natural interactions. *NeuroImage*, *133*, 484–497. https://doi.org/10.1016/j.neuroimage.2016.03.059

Orihuela-Espina, F., Leff, D. R., James, D. R. C., Darzi, A. W., & Yang, G. Z. (2010). Quality control and assurance in functional near infrared spectroscopy (fNIRS) experimentation. *Physics in Medicine and Biology*, *55*(13), 3701–3724. https://doi.org/10.1088/0031-9155/55/13/009

Ortiz-Prado, E., Dunn, J. F., Vasconez, J., Castillo, D., & Viscor, G. (2019). Partial pressure of oxygen in the human body: A general review. *American Journal of Blood Research*, *9*(1), 1–14.

Panoulas, K. J., Hadjileontiadis, L. J., & Panas, S. M. (2010). Brain-Computer Interface (BCI): Types, Processing Perspectives and Applications. In G. A. Tsihrintzis & L. C. Jain (Eds.), *Multimedia Services in Intelligent Environments: Integrated Systems* (pp. 299–321). Springer. https://doi.org/10.1007/978-3-642-13396-1_14

Ponce, P., Molina, A., Balderas, D. C., & Grammatikou, D. (2014). Brain Computer Interfaces for Cerebral Palsy. *Cerebral Palsy - Challenges for the Future*. https://doi.org/10.5772/57084

Rao, T. K., Rajyalakshmi, M., & Prasad, D. T. V. (2012). An Exploration on Brain Computer Interface and Its Recent Trends. *International Journal of Advanced Research in Artificial Intelligence (IJARAI)*, *1*(8), Article 8. https://doi.org/10.14569/IJARAI.2012.010804

Salonen, J. (2014). *Efficient and accurate rolling standard deviation – The Mindful Programmer*. https://jonisalonen.com/2014/efficient-and-accurate-rolling-standard-deviation/

SenTec Digital Monitor—SenTec. (n.d.). https://www.sentec.com/products/sentectranscutaneous-monitoring-system/sentec-digital-monitor/

Shih, J. J., Krusienski, D. J., & Wolpaw, J. R. (2012). Brain-Computer Interfaces in Medicine. *Mayo Clinic Proceedings*, *87*(3), 268–279. https://doi.org/10.1016/j.mayocp.2011.12.008

Shin, J., von Lühmann, A., Blankertz, B., Kim, D.-W., Jeong, J., Hwang, H.-J., & Müller, K.-R. (2017). Open Access Dataset for EEG+NIRS Single-Trial Classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *25*(10), 1735–1745. https://doi.org/10.1109/TNSRE.2016.2628057

Soltanlou, M., Sitnikova, M. A., Nuerk, H.-C., & Dresler, T. (2018). Applications of Functional Near-Infrared Spectroscopy (fNIRS) in Studying Cognitive Development: The Case of Mathematics and Language. *Frontiers in Psychology*, *9*. https://doi.org/10.3389/fpsyg.2018.00277

Stam, C. J. (2010). Use of magnetoencephalography (MEG) to study functional brain networks in neurodegenerative disorders. *Journal of the Neurological Sciences*, *289*(1), 128–134. https://doi.org/10.1016/j.jns.2009.08.028

Tessari, M., Malagoni, A. M., Vannini, M. E., & Zamboni, P. (2015). A novel device for non-invasive cerebral perfusion assessment. *Veins and Lymphatics*, *4*(1), Article 1. https://doi.org/10.4081/vl.2015.4650

The 7 Principles | Centre for Excellence in Universal Design. (n.d.). Centre for Excellence in Universal Design. http://universaldesign.ie/What-is-Universal-Design/The-7-Principles/

Tool Module: Brain Imaging. (n.d.). Retrieved September 9, 2020, from https://thebrain.mcgill.ca/flash/capsules/outil_bleu13.html

Usakli, A. B. (2010). Improvement of EEG Signal Acquisition: An Electrical Aspect for State of the Art of Front End. *Computational Intelligence and Neuroscience*, *2010*, 1–7. https://doi.org/10.1155/2010/630649

Vrana, A., Meier, M. L., Hotz-Boendermaker, S., Humphreys, B. K., & Scholkmann, F. (2016). Cortical Sensorimotor Processing of Painful Pressure in Patients with Chronic Lower Back Pain—An Optical Neuroimaging Study using fNIRS. *Frontiers in Human Neuroscience*, *10*. https://doi.org/10.3389/fnhum.2016.00578

Waldert, S. (2016). Invasive vs. Non-Invasive Neuronal Signals for Brain-Machine Interfaces: Will One Prevail? *Frontiers in Neuroscience*, *10*. https://doi.org/10.3389/fnins.2016.00295

Yanagisawa, K., Tsunashima, H., & Sakatani, K. (2012). Brain-Computer Interface Using Near-Infrared Spectroscopy for Rehabilitation. *Infrared Spectroscopy - Life and Biomedical Sciences*. https://doi.org/10.5772/35641

Chapter 8: Appendices

Information statement

For the Master Thesis Project in Universal Design ICT

"**The relationship between optode pressure and quality of fNIRS signal**"

By Shokooh Alinaghizadeh Khezri

Supervisors: Anis Yazidi, Pedro Lind, and Peyman Mirtaheri

You are being invited to participate in a research study about the fNIRS, conducted by Shokooh Alinaghizadeh Khezri, under the supervision of Anis Yazidi, Pedro Lind, and Peyman Mirtaheri at the Motion Analysis Lab of Oslo Metropolitan University.

The objective of this research project is to access the relation between the user's comfortability and the quality of the fNIRS signals. After the non-invasive implementation of the fNIRS equipment on the head, you asked to report the comfort level that you feel during the experiment for 3 times. The task contains 2 minutes of number calculation.

Your participation in this study is voluntary. In case you accept to participate in this research study, there are no risks for you of any kind. The collected information may not benefit you directly, but it will provide general benefits to researchers and future studies. All data that identifies you will be kept confidential.

If you have any concerns about your rights in this study, please contact us with email Shokooha@oslomet.no.

Consent Form

For the Master Thesis Project in Universal Design ICT

"The relationship between optode pressure and quality of fNIRS signal"

by Shokooh Alinaghizadeh Khezri

Supervisors: Anis Yazidi, Pedro Lind, and Peyman Mirtaheri

February 2020

I agree to participate in the research project titled *"The relationship between optode pressure and quality of fNIRS signal",* conducted by Shokooh Alinaghizadeh Khezri who has discussed the research project with me.

I have received, read, and kept a copy of the Information Statement. I have had the opportunity to ask questions about this research and I have received satisfactory answers. I understand the general purposes and methods of this research.

I consent to participate in the research project and the following has been explained to me:

- The research may not be of direct benefit to me
- My participation is completely voluntary
- My right to withdraw from the study at any time without any implications to me
- The steps that have been taken to minimize any possible risks
- What I am expected and required to do
- Security and confidentiality of my personal information.

In addition, I consent to:

- Publication of results from this study under the condition that my identity will neither be revealed nor recovered from the published data.

Participant name:

Signature:

Date: