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Use of Brain Sensing for Operator Training and Interaction with a Control System

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Project description

Today's industrial processes tend to be larger and more complex as well as dynamic. As such, the requirements to the operators' competence and skills increase. In a control room setting, it is both of interest as well as feasible to understand the user as an integrated part of the system, in order to improve the operator's working conditions as well as improving the system in itself. This project aims to explore the potential of using brain sensing technology as an interaction device with a control system, by sensing deviations in the operator's mental state. Brain sensing is not intended to be used for controlling, but to explore the possibility for the system to adapt to the operator's mental state. Different states could represent the operator's ability to stay focused, current level of stress, level of drowsiness etc.

EEG (electroencephalography), is the recording of electrical activity along the scalp. It is commonly used in clinical contexts where the brain's spontaneous electrical activity is measured over time. It can be used for diagnostics, but is also a valuable tool for research purposes. Recently, off-the-shelf systems have become available on the market.

The main objectives will be to:

1. Develop a concept demonstrator based on a use case
2. Perform initial user tests to evaluate the potential of using brain sensing technology as an interaction device for a control system regime

Research question

The main research question to be answered in this project is:

> *Is it possible to use today's low cost brain sensing technology to identify deviations in the states of the mind, and to use this in interaction with a control system?*

Tasks

This project has a major focus on testing and evaluating brain sensing technologies in order to evaluate the potential of using such interaction technologies in a control room environment. The project includes the following tasks:

1. Perform a state-of-the art review of interaction devices with a focus on brain sensing technologies and the usages of these
2. Define a use case (simulator scenario)
3. Investigate how mental states can be found from EEG signals
4. Become familiar with the brain sensing technology
5. Develop a concept demonstrator based on the brain sensing technology to control simple functions in a control system environment. This should include:
   - Obtain raw data from the brain sensing system
   - Create algorithms for processing and evaluation of raw data
   - Calibrate initial measurements from test subjects
   - Real time feedback to a control room simulator to potentially enforce a new scenario
6. Perform user tests
7. Evaluate the potential of such technology based on the initial user tests
8. Write the M.Sc. thesis

The project will be performed in close collaboration with ABB Chemicals, Oil and Gas. The concept demonstrator is expected to be designed and tested in ABB's offices in Oslo under supervision of ABB specialists. The use case(s) should describe the setting such as tasks, total workload and phase of operation (normal, start-up, ...). The tests will be limited to evaluating simple interactions with the system. If time allows, more functionality will be tested.

Preface

This thesis was written after completing a master thesis in the fifth year of a M.Sc. program at the Institute of Engineering Cybernetics, NTNU in spring 2015. The project was conducted in cooperation with ABB, which came up with the idea of the project and provided a neuroheadset and a control room simulator. The thesis will give an introduction to all fields necessary for the understanding this thesis such as operators and contol room, digital signal processing, brain sensing technology and human factors. The overall purpose of the thesis is to develop a brain sensing application which could help improve an operator's working conditions, and then evaluate the potential of today's low cost neuroheadsets.

The thesis deviates from the project description in that instead of completing a concept demonstrator based on deviations in a mental state, a study on how to identify workload from EEG signals was conducted.

Trondheim, 01-06-2015

Lise Bjørkvoll

Acknowledgment

I would like to thank my supervisors Tor Onshus and Charlotte Skourup. Tor's monthly meetings have helped me in keeping the overall process of this project structured. He has helped me to see the progress in my work and provided constructive feedback. Charlotte has given me great insight into the field of control rooms and operators. She has provided me with exiting challenges that have been great fun to work with. In addition, she has provided me with inspiration, motivation and guidance trough the entire process.

I would also like to thank ABB for providing me with a neuroheadset and a control room simulator. A special thanks goes to Rikard Hansson and Elise Thorud for their support, help and enthusiasm, Rikard for his technical help and Elise for coming up with the idea to this project.

(L B)

Summary

The aim of this project has been to evaluate the possibility of identifying an operator's mental state from electroencephalography (EEG) signals in a control room setting using a low cost neuroheadset. This has been done through the development of a brain sensing application. To carry out the project, the neuroheadset Epoc from Emotive has been utilized. Epoc has 14 sensors, and the EEG signals measured by the neuroheadset are acquired via a wireless connection. A thorough study on brain sensing technology, in conjunction with extensive research in identifying mental states from EEG signals has been crucial. After designing a number of possible use cases, it was decided to focus on an overall goal of improving work conditions for operators. This can be achieved either through utilization of the application in operator training or in developing improved control room systems and better user interfaces. The brain sensing application was designed and implemented based on using raw EEG data and identifying mental states through a spectral analysis. The application provides the option of either processing a data set for analysis, or in real time for use in a concept demonstrator. The application has been tested and shown to work well through initial measurements from test subjects, as well as through a concept demonstrator based on the use cases that were developed, by integrating the application in a control room simulator.

A study within the field of neuroscience, neurophysiology and brain sensing technology showed that in the state of the art, researchers are currently working to identify mental states from EEG signals. So far, they lack a simple, accepted methodology for identifying any of the desired mental states for this project; workload, fatigue and mental stress. Seeing as no methodology was ready for implementation, it was decided to utilize the developed brain sensing application to investigate if prior research explaining how to identify workload from EEG signals was valid. A study with ten participants performing an IQ-test was conducted, and the participants EEG signals were analyzed. The NASA-TLX assessment form was used to obtain subjective workload for the study. The results of the study showed that power in the parietal lobe decreases significantly under increasing workload for signals within the alpha-, beta- and theta- frequency bands. According to previous research, all indications should mainly be seen in frontal lobe. Alpha

power should decrease under increasing working memory load, concentration and hard thinking, whereas theta power should increase. A recent paper points to alpha power as the main indication of variation in workload, but despite identifying a trend of decreasing alpha power, too few of the results are significant and the test group is too small to confirm any methodology.

The potential of low cost brain sensing technology for use in a control room setting has been evaluated in this project. A significant portion of the project has been a theoretical study as well as a technology review. This, in addition to obtained results, experiences working with the Epoc neuro-headset, and the development of a brain sensing application have provided the basis for such an evaluation.The evaluation has shown that the neuroheadset can be utilized for operator training, or development of user interfaces and control room systems. In an operative control room setting, the technology must be further developed before it can be used, as the unit is uncomfortable to wear over an extended period of time. The brain sensing application has been proven to work well through testing, and the project shows that it is feasible to integrate a brain sensing application in a control room setting, and thus interact with a control system. Research on identifying mental states from EEG signals is the constraining factor, and once research within this field has progressed, the developed brain sensing application can be updated, and a use case fully implemented. This will provide a concept demonstrator ready for further testing.

Sammendrag

Formålet med prosjektet har vært å utforske muligheten for å detektere endringer i en operatørs mentale tilstand via hans hjerneaktivitet og prøve å utnytte dette i en kontrollromsammenheng. I prosjektet er det designet og implementert en applikasjon for et billig headset (neuroheadset) som måler elektroencefalografi-signaler (EEG-signaler). Flere rimelige headsett ble vurdert og Epoc fra Emotiv ble funnet å være best egnet. Epoc har 14 sensorer og overfører data trådløst. Det er gjennomført en studie av hva slike neuroheadset kan benyttes til, og hvor langt utviklingen har kommet når det gjelder systemer som kan styres av hjernesignaler. Det er også gjennomført et studie for å kartlegge hvordan man kan identifisere mentale tilstander ved hjelp av EEG signaler.

Flere bruksområder av applikasjonen er forslått og det er utarbeidet et konsept som beskriver hvordan applikasjonen kan brukes både i forbindelse med trening av kontrollromoperatører og ved utvikling av kontrollromsystemer med tilhørende brukergrensesnitt. For demonstrasjon av konseptet ble applikasjonen integrert i en kontrollromssimulator. Applikasjon benytter rå EEG-data og detekterer mentale tilstander gjennom en spektralanalyse. Den kan brukes til å prosessere et helt datasett for analyse i etterkant eller til å prosessere data i sann tid. Applikasjonen er testet og er vist å fungere godt.

Et grundig studie innen nevrovitenskap, nevrofysiologisk måling og teknologi for måling av hjerneaktivitet har vist at per dags dato arbeides det med å gjenkjenne mentale tilstander fra EEG signaler. Så langt mangler man en akseptert metode for å gjenkjenne de mentale tilstandene som har vært aktuelle for dette prosjektet; arbeidsbelastning, tretthet og stress. En slik metode kunne dermed heller ikke implementeres i konseptet. Det ble derfor bestemt å gå videre med å teste applikasjonen, for å se om den kunne fungere til å avdekke indikasjoner på endringer i mentale tilstander i samsvar med funn i litteraturen.

Arbeidet ble avgrenset til å finne endringer i arbeidsbelastning og det ble gjennomført et forsøk der 10 personer utførte en IQ-test i to trinn hvor første halvdel av testen var lettere enn siste

halvdel. Arbeidsbelastningen i de to trinnene ble målt ved hjelp av verkøyet NASA TLX som gir et subjektiv mål på arbeidsbelastning. På basis av NASA-TLX ble det fastslått at arbeidsbelastningen økte gjennom testen. Dette gjaldt alle forsøkspersonene. Forsøkspersonenes EEG signaler ble målt med neuroheadset. Analysene av EEG- signalene viste at power i parietallappen (isselappen) minker signifikant ved økende arbeidsbelastning for både alfa-, beta-, og theta-frekvensbåndene. I følge tidligere studier vil man se tydeligst endringer i frontallappen. Power i alfa -frekvensbåndet bør i følge tidligere forskning minke ved økende arbeidsbelastning, konsentrasjon og hard tenking. Resultatet fra forsøket i alfa frekvensbåndet er dermed i tråd med tidligere forskning, mens power i theta-frekvensbåndet burde økt. En nyere publikasjon viser dog til at alfa power er den mest interessante indikator på endring i arbeidsbelastning. Selv om vi påviste redusert alpha power i forsøket, er det grunn til å peke på at få av resultatene er signifikante og testgruppen er for liten til å kunne konkludere med at vi har funnet rett metode for å identifisere økende arbeidsbelastning fra EEG-signaler.

På grunnlag av bredt teoristudie, resultater fra utført forsøk og erfaringer ved bruk av Emotiv's Epoc ble potensialet til neuroheadsettet evaluert for bruk i en kontrollrom-setting. Neuroheadsettet viste seg å være tilfredsstillende for bruk til utvikling av brukergrensesnitt og kontrollrom-systemer, samt for operatørtrening. Dessverre var det tidkrevende å plassere neuroheadsettet korrekt og ubehagelig å benytte det over lengre tid. Det ble dermed ikke vurdert som realistisk å kunne benytte det i et operativt kontrollrom i dag. Applikasjonen som er utviklet for å prosessere og analysere EEG data fungerte godt, og prosjektet har vist at det er mulig å integrere en slik type applikasjon i en kontrollromsammenheng for interaksjon med et kontrollsystem. Per i dag er dermed aksepterte metoder for gjenkjenning av mentale tilstander den begrensende faktoren for en slik anvendelse. Når forskningen kommer lengre kan applikasjonen raskt oppdateres, og et konsept for bruk i kontrollrom vil være klart for videre testing.

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Acronyms

API	-	Application programming interface
BCI	-	Brain-computer interface
EEG	-	Electroencephalography
ERP	-	Event related potential
HMI	-	Human machine interface
IQ	-	Intelligence quotient
MS	-	Multiple sclerosis
PSD	-	Power spectral density
SA	-	Situation awareness

Chapter 1: Introduction

1.1 Background

Measurement of electroencephalogram (EEG) signals provides a possibility to measure the brain's electrical activity along the scalp [48], and has been used for many years by neurophysiologists and neurologists to understand and diagnose certain diseases and disorders such as epilepsy and multiple sclerosis [22,41].

In recent years, a group of new EEG devices that go under the term *neuroheadsets* have become available on the market. The neuroheadsets were originally designed for gaming [1], and are cheaper than medical equipment designed to measure EEG signals. They are wireless, and have a smooth design. The neuroheadsets are capable of measuring EEG signals and transmit these as digital data, which can then be processed by a computer and utilized in a brain computer interface (BCI). BCIs open a communication link between a brain and a computer, and provide an opportunity of controlling a system with your mind. With this technological development, researchers and developers have grasped the technology.

It is expected to see a great development in the field within near future [26] and one can already see the field growing in terms of international attention; the Institute for Knowledge Discovery at Graz University of Technology, Austria, introduced one of the first EEG-based BCIs over 20 years ago, and has now held 6 huge international BCI conferences over the past 10 years [2]. Controlling

[1] http://www.madshrimps.be/articles/article/551/OCZ-Actuator-lets-you-control-video-games-with-your-brainaxzz3UXvsZyTi visited: 16.03.2015

[2] https://bci.tugraz.at/ visited: 08.01.2015

a system with brain signals has opened up the possibility of helping impaired individuals, and one can see that most BCI systems developed so far are based on this. BCI systems are based on the recognition of patterns in thoughts or facial movements. Because EEG signals are unique for all humans, it often requires months of training to get a BCI to work properly, with a varying degree of success. One of the biggest problems in developing a system based on thoughts is that it is hard to decide which thoughts are meant for controlling the system, and which thoughts occur uncontrolled [35].

Another way of utilizing EEG signals is to identify mental states by doing a frequency analysis of the signals. Historically, this approach has mainly been used for neurofeedback, a technique aiming to recover people by teaching them to control their own brain signals [3]. Recently, one can see that a lot of research is being done to try to understand mental states from this approach.

Several new areas of BCI application are frequently emerging, and it is interesting to investigate the possibility of utilizing the technology in the industry. One of the strongest industries in Norway is the oil and gas industry. Within this field, control rooms are an area where a high level of human performance is essential, and with the ongoing development of BCI systems we see today, it is possible to imagine this as an up and coming area off application for BCI systems.

Since 1950-1960, centralized control rooms have been an important part of the Norwegian process industry [4, 25]. Since then, engineers have aimed at developing better and more logical control rooms, either in the sense of design of the room itself, or the control systems displayed on the monitors. The user interfaces have improved over the years, but research points to the fact that many of the systems still are quite complicated and alarms are hard to spot. Another challenging factor is that unexpected situations seldom occur; it could take months or years between each unexpected situation. To maintain skills and competence, many operators go through a routine training procedure each year.

[3] http://www.ntr.no/html/hva_er_neurofeedback-.htm visited: 24.01.2015

1.2 Objective

Many researchers and developers focus on developing BCIs where we can actively control a system with our minds. What if we could be able to obtain a passive measure of our brain signals, and let the system adapt to our mind states? One could imagine a BCI being able to sense which out of two choices a person prefers, or having a laptop telling you to go to sleep, because you are too tired. These are toy examples, but a lot of possibilities will open up if brain-sensing technology can identify mental states.

Applying this idea to the industry, one could imagine it being a great asset to get passive measurements of an operator's brain signals and utilize these measurements either to enforce a new scenario in a system, or to get additional and valuable information on an operator's mental state. If the answer to this is yes, how could this be utilized in a good manner? This leads us to the research question of this project

Is it possible to use today's low cost brain sensing technology to identify deviations in the states of the mind, and to use this in interaction with a control system?

To answer this question, one main focus will be on developing a brain sensing application that can improve the working conditions for control room operators. To do this, it is necessary to analyze EEG data to identify one or more mental states, and utilize the analyzing algorithms in a BCI. To develop such an application it is essential for the application to work in real time, and be able to connect to an independent system, either a control room system or a control room simulator, and alter the scenario depending on changes in mental states. If this can be achieved, it will provide a possibility to create a new link between human and computer, which can help us understand an operator's ability to perform correct actions by exploring new technology.

1.3 Limitations

The project assignment has been quite open, which requires constraining the project assignment due to limited time. It has been necessary to start with a broad overview of relevant technology and to understand which options are available, before concentrating on a smaller area and investigating a given mental state. With a background in cybernetics, it has been necessary to see the assignment from a computer science point of view, and the neurological insight to this subject is therefore somewhat limited.

The assignment specifies utilization of a low cost neuroheadset. Cheaper equipment often introduces more uncertainties and noise, which might lead to somewhat uncertain results. The results should therefore be seen in the light of this.

Due to the scope of this project and limited time, implementation has been limited to using soft real time requirements, meaning that it was not prioritized to set any hard requirements to how fast data processing should be done.

1.4 Approach

In order to investigate if brain sensing technology can give additional information about an operator at work, it is important to start with a technology review of brain sensing, focusing on both cheap headsets and more expensive solutions. Such a review provides information on what brain sensing is used for today and how far researchers and developers have come. This provides a good starting point for which information one can expect to find and what it can be used for. Another aspect is to identify cognitive processes that are important for an operator, and investigate if mental states can be detected. Throughout this process, it is of importance to understand brain signals from a neuroscientific perspective.

Next, it is essential to understand the user in this context; the control room operator. How does a control room operator work, what kind of problems can occur for an operator at work, what is done to prevent such problems, and how can brain sensing potentially help in these situations? These are just some of many questions that need to be answered. Understanding a human working in a loop with machines also requires some insight into cognition.

Evaluating today's low cost brain sensing technology requires access to a low cost brain sensing headset. It was necessary to choose and buy a low cost headset and become familiar with this technology. From this point in time, a brain sensing application based on the technology review and the objectives could be designed, implemented, tested and evaluated.

1.5 Structure of the report

All background theory that is needed for a thorough understanding of the work carried out in this project is described in chapter 2. This include theory on the four areas

- Operators and control room
- Human factors explained by cognition and neuroscience
- Brain sensing technology
- Digital signal processing
- Statistics

In chapter 3, two use cases are discussed and defined. Chapter 4 describes the choise of which EEG sensor system that is to be utilized for this project, and the given software and interface for this particular system is described. Lastly, this chapter includes design and implementation of a brain sensing application. Chapter 5 includes a test program. It was deemed necessary to conduct initial testing of the brain sensing application and the neuroheadset. This is described in the first section of the chapter. The next section of the chapter shows how a real time application can work together with an ABB control room simulator whereas the last section supports and describes a test conducted for identifying workload from EEG signals. A detailed description of how this test was carried out is also included. Chapter 6 consists of the test results on all parts of chapter 5. Chapter 7 discusses these results as well as puts the results in a bigger perspective and evaluates the possibility of utilizing brain sensing in an control room setting using today's brain sensing technology and the newest research in the area. The project is summed up with a conclusion together with proposals for further work.

Chapter 2: Theory

2.1 Operators and control room

In a control room, the operators perform tasks such as to monitor, evaluate, plan and take actions for optimal operation of the process. The operator supervises the process state through a control system. The process is displayed through process monitors. Control rooms can have different ways in presenting measured values and information on the monitors. It can be seen as e.g. numbers, trends, bars and levels, and indicators for alert and alarms [25].

In the process industry, you will usually find large screens displaying the overall system state and smaller monitors on the operators' working stations, which display details of the process. The operators usually work in teams and either observe automatically controlled processes, or control a process manually by e.g. changing setpoints. The operators are responsible for detecting incorrect values and performing correcting actions for these. They coordinate tasks with maintenance personnel, have responsibility for planned changes in production and report process states and possible errors [4].

The human machine interaction (HMI) in a process control room setting is illustrated in figure 2.1, where the operators are in a closed loop with the system.

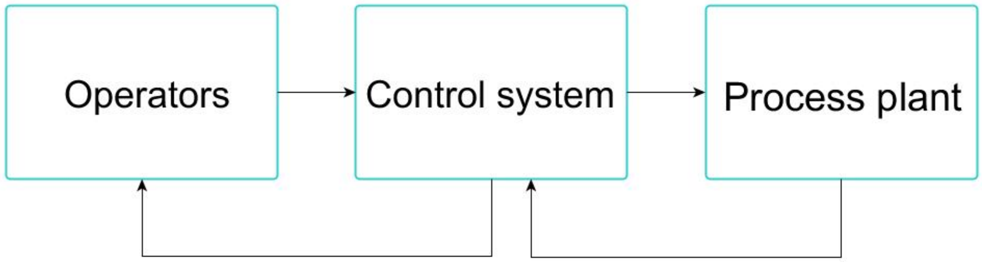


Figure 2.1: HMI in a process control room setting

2.1.1 Development of process control rooms and HMI systems in Norway

Towards the end of the 1960s, centralized control rooms became common in the Norwegian process industry. The rooms were often huge, and the operators had to walk quite a long distance to keep the whole process plant up and running. A development from pneumatic to electric instruments led to smaller control rooms, and digital computers and monitors were utilized from the mid-1970s [4, 25]. During the last 40 years, one can see a strong technological development in the industry in general, towards more automatization.

Today, most information on the process plant can be displayed on monitors, and the development of user interfaces have been important. A lot of research and user surveys have therefore been conducted to develop better user interfaces. Introducing more automation does not mean less focus on operators or separation of operators from the process. Developers seem to put emphasis on the human as a part of the system. This can be seen both through reports and specific models for good HMI development such as “Operator centered system working model”, which puts the focus directly on the operator and his needs through the entire developing process [9].

The development of control rooms is an ongoing process, and developers urge to find solutions that can create better overview and control of the process and improve both the physical and mental working environment. Humans are in general quite adaptive to new settings and solutions, but good working conditions will result in improved productivity, improved health and safety and overall better employee satisfaction [16].

2.1.2 Erroneous actions and operator training

A part of understanding the operator is to investigate what an erroneous action involves, and the reasons to why this occurs. Only then, we are able to point at the real problems and weaknesses of the HMI, and will know how to improve it.

In addition to not taking an action, erroneous actions by operators can be understood by the following [4]:

- A necessary action is performed wrong
- A necessary action is performed in a wrong order
- A necessary action is performed at a wrong time
- An unnecessary action is performed

These actions can be performed either with a fully operational system, or in an already erroneous system. A well designed control system should, on the other hand, incorporate robustness. It is a requirement that error handling is implemented, to avoid an erroneous action. Also, design faults or unpredicted situations can be detected and compensated for [4].

Although not all erroneous actions lead to hazardous consequences for the overall process, a good developed HMI will result in less risk and better working conditions for the operators. Even though good user interfaces have been widely studied and the development process is continuous, some operators may still claim that their interests are not preserved when user interfaces for control room systems are developed. Problems mentioned include:

- Too many alarms
- Alarms are hard to spot
- Some alarms are unnecessary

They point to a main problem, namely that operators have to process a lot of data in a short time, and it becomes hard to maintain the process overview. Stress can be an important factor that influences our cognitive processes [3]. To avoid operators being overwhelmed by stress, it is normal practice to arrange stress reduction courses.

Operators does also have to go through a lot of training to be better prepared in given situations. With the increasing automation that we have seen in the process industry over the past decades, simulators have been developed, mainly to help in the following situations [16]:

- Training and education of new operators
- Training and education of operators in relation to a plant change
- Rehearsal in order to maintain old knowledge
- Rehearsal of situations that only occur in rare occasions

In many companies, training to maintain competence and rehearsal of situations that only occur in rare occasions, is carried out at least twice a year.

2.2 Human factors explained by cognition and neurosience

In a human-machine-interaction approach, we can look at the human as a part of a system. All humans are different; we have for example different knowledge, experience and perceptions. This makes us unpredictable elements. According to a well referred theory by the Danish engineer J. Rasmussen [44] humans process information and behave according to his skills, knowledge and interpreted rules when conducting a complex, cognitive task. Such competence is built up and depends on educational background, training, motivation, goal and experience. These elements can be seen as limiting factors, and we can therefore suggest that a person might lack some type of skills, knowledge or interpreted rules if a task is not completed correctly. To develop good human-machine interactions, it is important to understand the human. This may not be fully possible, but psychology and neurosience can take us part of the way [9].

2.2.1 Cognition

A person's mental activity is a combination of acquisition, storage, transformation and use of knowledge. In psychology, this term is known as **cognition** [34].

Human information processing and memory

Two of the main fields within cognition is **human information processing** and **memory**. A theory on how human process information evolved in the late 1940s by Shannon and Weaver [31]. This theory was influenced by how computers worked; information is perceived sequentially, taking in one bit at a time. According to a model by Atkinson and Shiffin (1968) [34], all information we get from our senses will be received by a storage system called "the sensory memory". The sensory memory has high capacity, but will only store information for about two seconds. Most of the information is then lost, while the rest of it is saved to short-term memory (or working memory). In this working memory, we find all information that we are currently using. Rehearsed information is stored in the long time memory, and include all memories and knowledge [14,34].

Skill learning

When learning a new skill, a person often begins by drawing on what he or she already know. During the next stage of skill learning, practice will involve that one less frequently have to recall memories on how to perform a given action. Eventually, a skill becomes rapid and effortless [18].

Situation awareness, attention and workload

Situation awareness (SA) could easily be described as "knowing what is going on", and is essential when making decisions and performing tasks. Two important and limiting factors for situation awareness is workload and attention. Attention is defined as concentration on a task or to be prepared to receive information [34]. Workload is an abstraction of several terms that when combined represents the cost of carrying out a task and is often defined different in literature and amongst people. According to a thorough study carried out by NASA, workload can be seen as a combination of the degree of mental demand, physical demand, temporal demand, performance, effort and frustration [20].

High situation awareness does not necessarily mean that a task is easy, or a situation is under control. In [14], Endsley define the following four combinations of situation awareness and workload that is of relevance when a person is performing a task

- low SA - low workload
- low SA - high workload
- high SA - low workload
- high SA - high workload

With low situation awareness and low workload, a person cannot see the complexity of a task. Low situation awareness and high workload might imply that a person has not understood the triviality of a task, or that a task is obscure. Having high situation awareness and low workload would imply that a person is focused but is in control of the situation, and a high situation awareness with a high workload could indicate that a person is working hard on a problem he or she is well aware of.

2.2.2 Cognitive neuroscience

Cognitive neuroscience as a field has its focus on how cognitive processes can be explained by the brain, and the mapping of these. A brain has four sections that makes up the cerebral cortex; the frontal, paritetal-, temporal- and occipital lobe. The four lobes can be seen in figure 2.2.

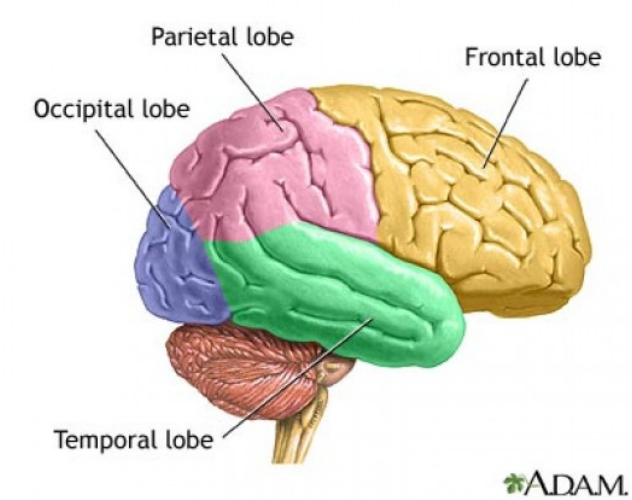


Figure 2.2: The four lobes of the brain (Courtesy of A.D.A.M http://www.nlm.nih.gov/medlineplus/ency/imagepages/9549.htm visited: 13.05.2015)

The paritetal-, temporal- and occipital lobe make up the sensory cortex. Pain and taste are perceived by the paritetal lobe, hearing and memory by the temporal, and vision-related tasks are processed in the occipital lobe. Information is then passed further to a number of other areas [34]. The frontal lobe is associated with emotions, problem solving, speech and movement, so a part of it makes up the primary motor cortex. The primary motor cortex controls e.g. facial movements such as movement of lips, eyes, jaw and tongue [11, 26].

Cognitive neuroscience expanded as an area of research in the 1980s, when brain-image techniques became available. Examples of localized areas include brain areas important for attention and learning a new skill. Attention has been pinned to the back of the parietal lobe, and the front of the frontal lobe [34]. When learning a new skill, researchers have found that in addition to the cerebral cortex, several other brain regions contribute such as the Basal ganglia and the cerebellum. Mental processes are however intricate, and research has shown that it is hard to determine the origin of a task's execution [34]. The cerebral cortex is closely related to skill learning and performance, but it is hard to know exactly how everything is connected [18].

Additional means of measurement: The NASA-TLX

Doing research on the human brain could also be challenging due to the fact that it is hard to obtain an objective measure on how a person really feel about something. Because of this, other means than brain sensing has been utilized to obtain a correct measurement of a cognitive process. One of these is measurement of heart rate, which will vary as a function of mental load [51]. It is also known that a person tends to blink more when being stressed. Studies have shown that the eye blink rate decreases under cognitive load [7] and increases when a person is tired [1]. Another mean that has been developed as a compensator for this exact problem is subjective assessment tools, such as the The NASA Task Load Index (NASA-TLX). The NASA-TLX is a subjective *workload* assessment tool. It was developed by the Human Performance Group at NASA Ames Research Center over 20 years ago for operators working with human machine systems [2], and has since then been widely used [20].

In order to obtain an individual estimate of workload in a test, a form is filled out for every participating person. Six subscales are defined which each represent different parts of what one can define as workload as a concept; mental demand, physical demand, temporal demand, performance, effort and frustration. All six sub-scales are paired up, giving a total of 15 pairs. The user is told to pick the member of each pair that he consider most important for increasing workload. This gives each of the six sub-scales a weighted score.

After finishing a test, every person weigh the six subscales in an interval from 0 to 20 ranging from very low to very high, to evaluate how they found the test. This scale score is presented as a value from 0 to 100.

The weighted score calculated prior to the test is then multiplied with the scale score from after the test is completed. All the products are then added, and the result is divided by 15, the num-

[1] http://www.nbcnews.com/id/3076704/t/why-do-we-blink/.VVNKTpNKWDc visited: 13.05.2015
[2] http://humansystems.arc.nasa.gov/groups/tlx/ visited: 27.05.2015

ber of weighted scores, giving a mean workload score of the overall task between 0 and 100 [21].

The NASA TLX form can be found in appendix A.

2.3 EEG signals and brain sensing technology

2.3.1 EEG measurement and interpretation

EEG signals

Electroencephalographic (EEG) signals are electric potentials that can be detected along the scalp. The electrical signals have their origin from neurons, or nerve cells, that utilize the signals for transferring and processing information. When measuring EEG, one will find the summation of this activity. The EEG-signals are measured in microvolts due to their small amplitudes, which usually range between 10-100 μV, and most of the signals power can be found at frequencies bellow 30 Hz [26, 48]. Frequencies are divided into the following bands:

Table 2.1: Frequency bands

Name	**Frequency**
Delta	<4 Hz
Theta	4-8 Hz
Alpha	8-13 Hz
Beta	13-31 Hz
Gamma	32+ Hz

EEG signals have high temporal resolution, but low spatial resolution. The signals are continuous, nonlinear and nonstationary [26].

Event-related potentials and neural networks

An event-related potential (ERP) is a tiny fluctuation in the brain. The response comes to a spesific sensory, cognitive or motoric event. It can often be seen after external stimuli, but is also associated with spontaneous mental activity [35]. An examle is attention, which can be seen as an ERP lasting only milliseconds [34]. Event-related potentials are recognizable in EEG signals through pattern recognizing algorithms (neural networks). This is usually done by averaging the EEG response from several trials [26]. ERP's can therefore be different amongst different people.

10-20 system and the cerebral cortex

The 10-20 system is an internationally recognized location system for the placement of electrodes on the scalp when recording EEG signals. The system was developed so that one could easily compare different EEG studies. The system has it's name from the placement of the electrodes relative to the Nasion, Inion and the ears, see figure 2.3.

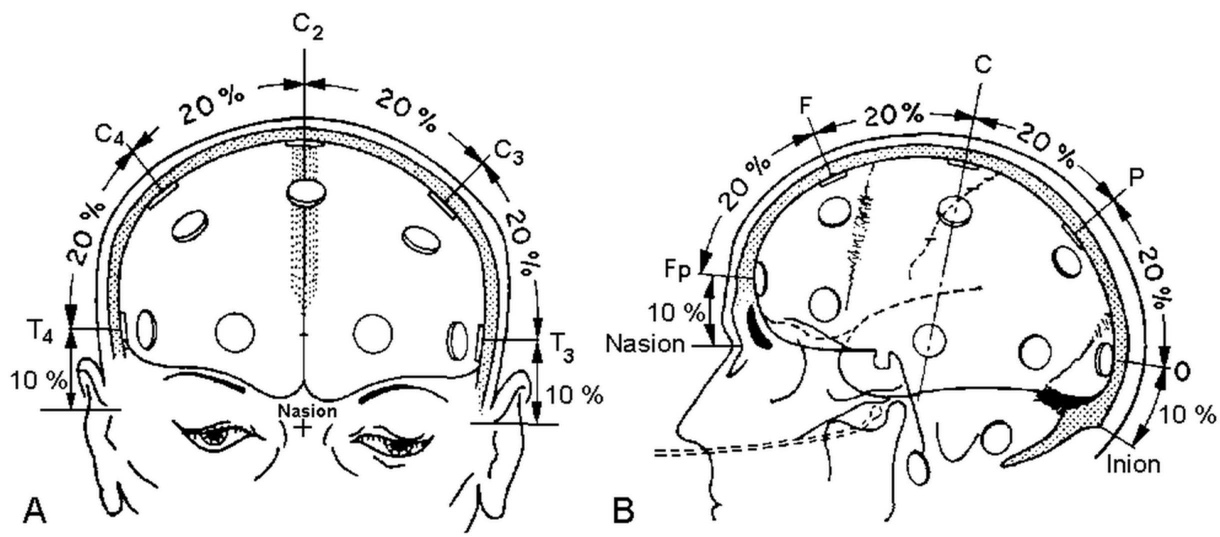


Figure 2.3: Original figure of the 10-20 system (jasper, 1958), note that the electrodes are placed inside the scull, on the cortex

The electrode placement in the 10-20 system is organized with a capital letter and a number. and an overview with names and position of the electrode placement in the 10-20 system can be seen in figure 2.4.

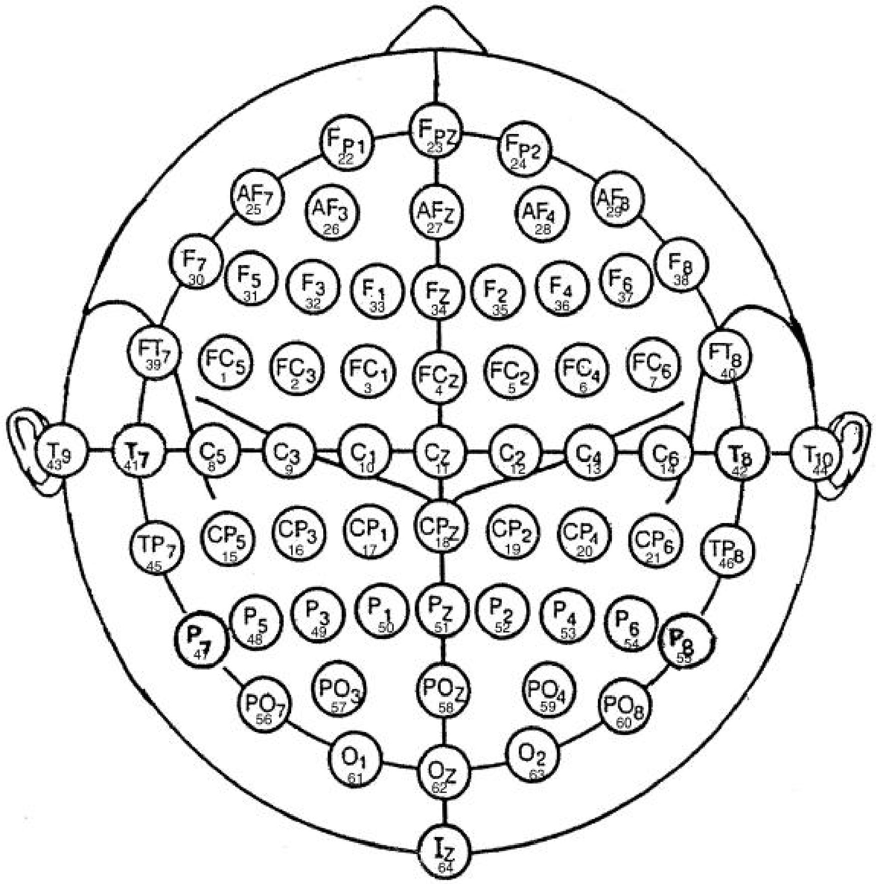


Figure 2.4: Electrode placement in the 10-20 system from (Sharbrough, 1991)

The capital letters in the 10-20 system is given after which of the brains four lobes it is placed over

F - Frontal

T - Temporal

C - Central [3]

P - Paritetal

O - Occopital

[3]Central is for reference purposes, a central lobe does not exist

Identifying mental states from EEG signals

EEG signals are very complex signals that are hard to analyze. They are highly susceptible to noise and can vary severely from one person to another. This does not provide much hope when seeking to discover our brain's secrets. Researchers and psychologists have been working for years to identify mental states from EEG signals. Many questions stand unanswered, but still, there are some findings that seem robust after years of research and testing:

Frequency bands:

- The power of **alpha waves** will increase if a person is relaxed or has closed eyes, and decrease under excitement or if the eyes are open [38]. They are also found decreasing under concentration and hard thinking [39]. Alpha waves are the easiest to detect, and can be seen mainly in the occipital area (see figure 2.2).
- The power of **beta waves** increases with muscle activity or anxiousness, and decreases with active concentration and thinking [6] [26].
- **Delta waves** are mostly seen in infants and during given stages of sleep. The waves tend to have high amplitudes [19].
- Most of the brains activity during sleep is **Theta waves** [45].
- **Gamma waves** have been associated with consciousness, attention, perception and cognition [43].

The following examples of mental states; general emotions, workload, stress and fatigue, are included because they are of relevance for a working control room operator:

General emotions

Emotions are not easy to recognize through EEG signals, because emotions are highly personal and therefore vary widely from person to person. Research has proven that to some extent, it is possible to recognize given patterns in EEG signals using pattern recognizing algorithms or neural networks when people look at pictures that give them a feeling of different emotions e.g. happiness, sadness and fear [2, 37]. One particular study using this method is able to differentiate between five different emotions, although with the varying results of detecting 30-40 % of vague emotions and 70-80 % of extreme emotions [23]. Often, physiological signals such as heartbeat and skin conductivity is used over EEG signals when investigating human emotions [28].

Workload

There is no accepted methodology that states how one can find the overall *level* of workload from EEG signals. Results from previous studies reports that power in the alpha frequency band decreases with increased working memory load due to increasing task difficulty [10, 17, 29], whereas theta activity, especially in the frontal lobe, is found to increase together with higher workload for adults [24, 29, 40]. Another frequency band investigated in context with identifying workload is the beta frequency band, although few results are reported in the literature on how beta waves are affected [10]. In a recent review (2012) it is suggested that focus should be on alpha band activity [30]. It is argued that the classical view about alpha band response is challenged as under certain task demands increased power can be observed. Besides, alpha band oscillations are the dominant oscillations of the brain and the alpha band is the only frequency domain that responds to a task demand either with a decrease or increase in power. Thus, the alpha band is therefore assumed to be of particular interest, also compared to the other bands.

One of these studies is conducted with operators in AIR traffic control and claims that one cannot know for sure that higher workload results in more errors [10]. The study provides results showing that most errors occur under medium workload. The concept of workload has also been used to investigate diverging levels of performance for experienced and less experienced operators [5]. The study found large difference between experienced and newly hired operators.

Fatigue

EEG signals are often used to determine quality of sleep, and use the correlating factor between quality of sleep and fatigue as a measure of fatigue [1]. Increasing fatigue is also reported to be associated with increased activity in the theta frequency band [17, 46] and increasing alpha power [50], both at frontal sites.

Mental stress

Researchers have tried to map stress through investigating EEG signals. Several research groups find increasing or decreasing activity in some part of the brain being correlated to increasing level of mental stress. One interesting example is a research group providing results of increasing level of stress leading to higher activity in frontal cortex and amygdala [3]. Still, there does not seem to be any accepted theory that explains how to deduce the level of mental stress from EEG signals.

All results on how to identify mental states from EEG signals are based on statistical tests – and thus reported valid for groups of test subjects. However, the findings are not unambiguous. In fact, it is also reported that effects show a high variability or even reverse effects across experimental settings and also across subjects [30, 50]. In a number of studies the alpha band is split and reported results are related to specific sub-bands [17, 29]. Several EEG indices have also been proposed [27, 46], such as ratio of theta power to alpha power, and also for such indices results are reported to vary [27].

2.3.2 Utilization of brain sensing technology in today's industry

EEG is a electrobiological measurement method, such as electrocardiography (ECG, heart) and electrogastrography (EGG, stomach) [47]. The signals EEG are recorded by metal electrodes on a cap or on a headset, and good connection to the scalp is ensured by a conductive media [39]. Since the electrodes are placed on the scalp, EEG recording is non-invasive. This means that it can be used with very little risk.

Another mean of detecting active brain areas is imaging techniques, where the two most used are PET scan and fMRI. PET scan is conducted by injecting a test subject with a radioactive chemical, before measuring the blood flow. In fMRI, one measure the amount of oxygen in the blood in various areas of the brain, and sees areas where the blood is rich of oxygen, as active areas [34]. Because brain imaging techniques are slow to provide any precise information about timing of the brain activity, EEG is often preferred over brain imaging techniques because of its high temporal resolution.

Clinical use

Since the first human electroencephalograms was recorded in 1924 [8], the most beneficial use of EEG has been clinical, by assessment of functional disturbances in the brain [4]. A clinical EEG recording can correctly diagnose 90 % of people with epilepsy [22]. EEG recordings are used to evaluate people in coma for diagnosing brain death [5], under intensive care and to diagnose demyelinating diseases such as multiple sclerosis (MS) [41]. The EEG recordings are interpreted by a specialist, such as a clinical neurophysiologist or a neurologist. Today's research within the medical industry using EEG signals involve e.g. trying to diagnose schizophrenia and placing cognitive centers [6].

Neurofeedback

A different branch of EEG utilization is neurofeedback, offered by clinics that claim to provide treatment for a multiple of conditions e.g. ADHD, anxiety, depression and migraine [7] based on EEG feedback. The theory behind this treatment method is that people are able to manipulate their own brainwaves by being presented to the wave's frequency via sounds or images. Depending on which condition you have, it is desirable to raise the amplitudes of some waves relative to others.

A search for research papers that proves the efficiency of neurofeedback gives several results [8] [9] [10]. Other papers point to the fact that it is hard to know if the change is due to placebo or

[4] http://tidsskriftet.no/article/2953219visited:08.01.2015

[5] http://tidsskriftet.no/article/2949306 visited: 08.01.2015

[6] http://www.news-medical.net/news/20111212/New-method-for-detailed-analyses-of-electrical-activity-in aspx visited: 09.01.2015

[7] http://www.ntr.no/ visited: 15.01.15

[8] http://www.innsikt.org/index.asp?id=28464 visited: 16.01.15

[9] http://www.sciencedaily.com/releases/2010/03/100310114936.htm visited: 16.01.15

[10] http://www.sas.upenn.edu/psych/history/orne/paskewitzorne1973science360363.html visited: 16.01.15

if it actually works [11]. Although critics seem to define Neurofeedback as expensive alternative medicine, where you have to pay around $ 165 for a single session, a lot of research is still being conducted to prove the theories behind Neurofeedback.

BCI and technology development

An area for utilizing EEG that seems to be growing rapidly over the past few years is research and development of brain computer interface (BCI) systems. A BCI is an interaction between a brain and a computer, which allows processing of EEG data in real time. Brain computer interface systems allows the brain to communicate with- or control an external device, where a program changes only based on the users brain signals [47]. BCI systems are often developed by researchers and developers with an engineering background. Such systems require a high level of efficiency and performance. One of the main reasons the field is growing is due to the fact that since 2007 [12], a multiple of low cost neuroheadsets has become available on the market. As the brain sensing technology becomes cheaper, it becomes easier for researchers and developers to embrace the technology and find new areas of application. Within this low cost technology branch, one can see a development that lean towards helping disabled and developing control systems for gaming.

The paper "Combining Brain–Computer Interfaces and Assistive Technologies: State-of-the-Art and Challenges" [36] from 2010 states:

We identify four application areas where BCI assistive technology can have a real, measurable impact for people with motor disabilities; namely "Communication and Control", "Motor Substitution", "Entertainment", and "Motor Recovery".

These four areas provides a good representation of areas where brain sensing devises are utilized. The following list shows a few examples of what has been done using low cost brain sens-

[11] http://www.psychologytoday.com/blog/brain-myths/201302/read-paying-100s-neurofeedback-therapy-0 visited: 16.01.15

[12] http://www.digi.no/372232/skal-la-deg-styre-spill-med-hjerne-folere visited: 10.01.2015

ing equipment:

- In the 1980's, L.A. Farwell and E. Donchin [15] developed a BCI helping people not capable to talk, to type. This BCI, referred to as "P300 BCI system", has been implemented toghether with the low cost brain sensing system Epoch. [13]

- Motor wehicles reacting to facial expressions or thoughts can help people with motor disabilities. A group of researchers has been able to steer a wheelchair trough ERPs [14], while the autonomos lab at Freie universität Berlin are using ERP's to steer a car [15].

Every year since 2010, the Annual BCI Research Award has been given to a project that provides outstanding and innovative research in the field of Brain Computer Interfaces. The award committee receives around 70 contributions every year, with research projects from leading universities and some of the most prestigious research institutions [16]. Taking a look at nominated and winning projects gives a good indication of where the technology is today, and what one can expect to be developed in the near future. Examples of nominated and winning projects include:

- Rehabilitation of stroke patients (winner 2010 and 2014)
- Predictive Spelling with a P300-based BCI
- Neurofeedback training by motor imagery
- Eye Tracking to control a robot arm

Taking a look at the bigger picture, the development utilizing higher cost EEG equipment also seem to lean towards a desire to help people with disabilities.

The contributors reasons for development initiatives

What drives the brain sensing technology forward has it background in where the interest lies and where the money is found. The medical industry and the gaming industry seems to be big initiators, whereas the low cost technology opens up for more creativity.

[13] http://www.biomedical-engineering-online.com/content/12/1/56 visited: 10.01.2015
[14] https://ece.uwaterloo.ca/~schoudhu/projects/fydp/ visited: 08.01.2015
[15] http://autonomos-labs.com/ visited: 10.01.2015
[16] http://www.gtec.at/ visited: 08.01.2015

Low cost brain sensing technology

As mentioned in the previous section, one can see an evident development towards cheaper brain sensing devices over the last decade. A company called OCZ Technology launched the "Neural Impulse Actuator" at the end of 2007, as one of the first low cost BCI devices that utilized EEG.

Figure 2.5: OCZ Technology's Neural Impulse Actuator (Courtesy of amazon http://www.amazon.com/OCZ-OCZMSNIA-NIA-Impulse-Actuator/dp/B00168VU4U visited: 08.01.2015)

OCZ wanted to bring the brain sensing technology to the consumer market, making the technology available to a lot more people. Selling more and cheaper devices opened up a possibility of a very low market prize for the "Neural Impulse Actuator", which had a prize around $100 as opposed to $2000 for advanced equipment from the medical sector at that time [17].
After 2007, several actors has entered the market. Emotiv's neuroheadset "Epoc" was launched in 2009 to a prize of $300. This headset was primarily designed for use in the gaming industry. NeuroSky launched a neuroheadset called "MindWave" in 2011 for $80. In 2014, Muse launched a neuroheadband for $300, while Emotiv launched the upgraded Epoc+ for $499 . Emotiv is planning to launch the neuroheadset "Insight" in summer 2015, as an easier and more comfortable option to Epoc. See table 2.2 for comparison of the neuroheadsets currently on the market.

[17] http://www.madshrimps.be/articles/article/551/OCZ-Actuator-lets-you-control-video-games-with-your-brainaxzz3UXvsZyTi visited: 16.03.2015

Table 2.2: Specifications of neuroheadsets currently on the market

	Muse	**Emotiv Epoc**	**Emotiv Epoc+**	**NeuroSky MindWave**
EEG sensors	7	14	14	1
Sampling rate	220 Hz	128 Hz	256 Hz	512 Hz
Axis sensors	3x accelerometer	2x gyroscope	3x gyroscope 3x accelerometer 3x magnetometer	-
Connection	bluetooth	wireless	bluethooth and wireless	wireless
Battery capacity	>5 hrs	>12 hrs	>6 hrs bluetooth >12hrs wireless	>8 hrs
Compatibility	Windows, Mac, iOS, Linux, Android, Ubuntu	Windows, Mac, Android, Linux	Windows, iOS, Mac, Android, Linux	Windows, Mac
Prize	$ 300	$ 300	$ 499	$ 80
Access to raw data	No	If purchased	If purchased	Yes

Figure 2.6: Muse (Courtesy of Muse http://muse.totemapp.com visited: 08.01.2015)

Figure 2.7: Emotiv Epoc (Courtesy of Emotiv http://emotiv.com visited: 08.01.2015)

Figure 2.8: NeuroSky MindWave (Courtesy of NeuroSky http://press.neurosky.com/ visited: 08.01.2015)

2.4 Digital signal processing

2.4.1 Sampling of analog signals

Sampling of an analog signal is done as follows:

$$x[n] = x_a(nT), \quad -\infty < n < \infty \tag{2.1}$$

Where $x(n)$ is the digital sampling of the analog signal $x_a(t)$ taken every T seconds [42]. T is the sampling period, and the sampling rate is given as

$$F_s = \frac{1}{T} \tag{2.2}$$

2.4.2 Nyquist-Shannon sampling theorem

When sampling an analog signal, one need a sampling rate that is greater than twice the highest frequency that appears in the analog signal

$$F_s > 2F_{max} \tag{2.3}$$

The sampling rate F_s is then twice the bandwidth, and is called the **Nyquist rate**. When the sampling rate is higher than the Nyquist rate, the spectrum of the analog signal can be fully recovered from the spectrum of the discrete-time signal. This means that no spectral information is lost, we avoid aliasing [42].

2.4.3 Highpass filter

EEG signals are highly susceptible to noise, and have a DC-offset due to hardware [26]. Although the degree of noise will depend on the quality of the sensors, the EEG signals still needs to be filtered. A highpass filter can be used for this purpose. A highpass filter is a digital frequency-selective filter. It has the following frequency response characteristics

$$H(\omega) = \begin{cases} 1, & \omega_c < \omega \leq \pi \\ 0, & |\omega| \leq \omega_c \end{cases}$$

The highpass filter will pass signals with a frequency higher than the cutoff frequency ω_c (passband), and suppress signals with a frequency lower than the cutoff frequency ω_c (stopband). Ideal filters are not physically realizable, and an transition band between a passband edge frequency ω_p and a stopband edge frequency ω_s is seen for for real-time signal applications [42].

2.4.4 Discrete Fourier Transform

Frequency analysis of discrete-time signals can be performed by applying the Discrete Fourier Transform to a time-domain sequence. The time-domain sequence will then be converted to an equivalent frequency-domain representation [42].

We have the following syntesis equation for a discrete-time signal $x[n]$ with a sample size N [42]

$$x(n) = \sum_{n=0}^{N-1} c_k e^{j2\pi kn/N}, \quad 0 \leq k \leq N-1 \tag{2.4}$$

And the following analysis equation

$$c_k = \frac{1}{N}\sum_{n=0}^{N-1} x(n)e^{-j2\pi kn/N}, \qquad 0 \le k \le N-1 \tag{2.5}$$

Where c_k is the fourier coefficients. The fourier coefficients represents the amplitude and phase associated with the frequency component $e^{-j2\pi kn/N}$.

There exist several algorithms for computing Discrete Fourier Transforms. Fast Fourier Transform (FFT) algorithms can be used for efficient computation if N is a power of 2 or a power of 4 [42]. FFT is a standard processing algorithm for EEG-signals, and since FFT is a linear method, one assume stationarity in EEG signals. The most used FFT algorithm is called the Radix-2 FFT algorithm.

2.4.5 Power spectral density

The power spectral density (PSD) is found when it is of interest to find the power of a signal over all present frequencies. A periodic signal has infinite energy and finite average power, and we have the following relation for average power

$$P_x = \frac{1}{N}\sum_{n=0}^{N-1} |\, x(n)\,|^2 \tag{2.6}$$

Following the deduction in [42], the power of the discrete-time periodic signal in terms of the Fourier coefficient c_k can be derived

$$P_x = \tfrac{1}{N}\textstyle\sum_{n=0}^{N-1} x(n)^* x(n)$$

By equation 2.4 we obtain

$$P_x = \tfrac{1}{N}\textstyle\sum_{n=0}^{N-1} x(n)\left(c_k^* e^{-j2\pi kn/N}\right)$$

And by equation 2.5 we get

$$Px = \textstyle\sum_{n=0}^{N-1} c_k^* \left[x(n)e^{-j2\pi kn/N}\right]$$

Which gives the power of the frequency components in a signal

$$P_x = \sum_{k=-\infty}^{\infty} \mid c_k \mid^2 \tag{2.7}$$

Where c_k is the fourier coefficients, and equation 2.7 is called *Parseval's relation* for power signals.

2.4.6 Mean frequency and mean power

A mean frequency can be calculated from the fourier transform by taking the weighted sum of spectral estimates in a frequency band and divide it by the power in the same band [29]

$$\frac{\sum_{f_1}^{f_2}(a(f) \times f)}{\sum_{f_1}^{f_2} a(f)} \tag{2.8}$$

In equation 2.8, $a(f)$ is the power of a signal from the power spectral density at frequency f, and in a frequency band, f_1 is the lowest frequency and f_2 is the highest frequency.

A mean power can be calculated from the fourier transform by adding the spectral estimates in a frequency band and divide it by the number of spectral estimates added

$$\frac{\sum_{f_1}^{f_2} a(f)}{n} \tag{2.9}$$

In equation 2.9, $a(f)$ is the power of the signal at frequency f, and in a frequency band, f_1 is the lowest frequency and f_2 is the highest frequency. The number of powers added between f_1 and f_2 is denoted n.

Chapter 3: Use Case

The idea behind this project is to explore the possibility of sensing deviations in a control room operator's mental state, and find a way to exploit this aspect in order to improve an operator's ability to take correct actions. The approach investigates the possibility of quantitatively characterizing an operator's mental state and help us understand the human in the human-computer interaction even better.

The concept is that the measured mental state will impact a system passively trough a feedback loop, see figure 3.1. This principle allows the system to adapt to the operator's mental state.

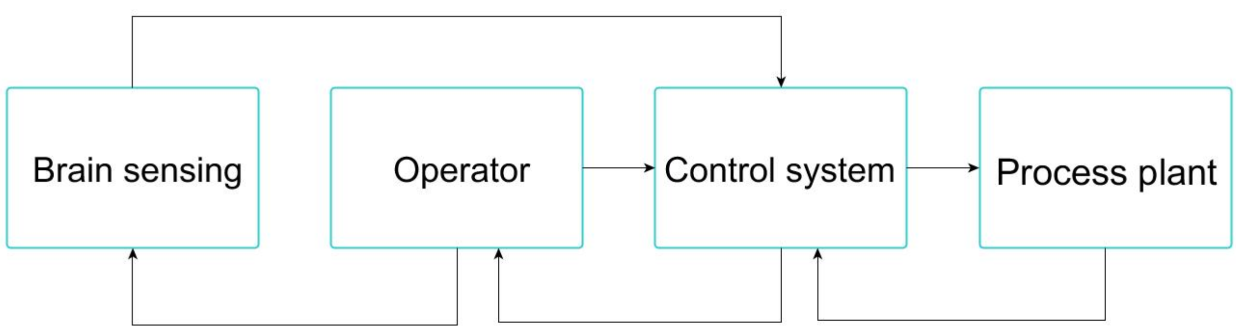


Figure 3.1: Overview of active sensors

Current neuroheadsets are unfortunately rather uncomfortable to wear. Seeing as it often takes days or weeks between challenging situations for the operator, the use such a headset on a daily basis in a will most likely not be desirable. Additionally, the development of a concept demonstrator requires a significant amount of testing. In light of these facts, one can conclude that with current technology, the use of a neuroheadset during normal operation in a control room is currently not a viable option. However, if the technology discussed in this project can be fully developed and the design of neuroheadsets improve, several areas of application will emerge:

- A led light can indicate the operator's mental state. E.g. red can indicate that the person is busy working on something, and green can indicate a relaxed situation. This will tell co-workers when to interrupt and when to stay away.
- Tasks can be scheduled between operators based on their mind state
- An alarm can trigger if a person is too tired
- Words and symbols can be enlarged and sounds can be higher if a person is tired
- If for example the mental state indicate that workload imposed on the operator is "very high" or the operator is too tired or too stressed, the control system may shift into a "safe mode", more easily controlled by the operator. Here, the control room system can be set to use automatic routines or alarms can be filtered differently. Normal mode can be resumed as an indicator based on EEG signal is reduced to a "low" level.

Based on the brain sensing technology today, two use cases are established to pursue the idea of this project:

1. Brain sensing technology for improving **operator training**
2. Brain sensing technology for improving **user interfaces and control room systems**

These two use cases are designed so that they are suitable for use in a concept demonstrator and will allow repeated testing within a shorter period of time.

Operator training

If it is possible to measure the level of stress, fatigue or workload under operator training, the brain sensing technology could be beneficial both during a stress reduction course and for regular operator training. In this use-case the operator could practice a given scenario until the assignment is mastered sufficiently and the scenario is under control. When this is achieved, the operator is given a new assignment. To indicate performance, it is a possibility is to give an overall score after a scenario is over. Another possibility is to trigger an alarm if a mental state exceeds a given limit during the assignment. To implement brain sensing in operator training, one can then develop a control room simulator including a BCI, and having the system adapt according to the operator's mental state following figure 3.1.

Letting the operator be in control of the system will probably create a more confident environment for the operator, and avoid the possibility of having the operator feeling supervised. However, this question is not addressed further in this project and the operator's perception of the situation in such a setting appears to be an interesting issue itself.

Improving user interface and control room systems

As mentioned, a lot of research is done to investigate what types of user interface fit best in a control room setting. It is interesting to look at the possibility of designing these interfaces based on measurement of how operators react unconsciously, to reveal which alternative the operator prefers.

Using brain sensing technology under development of control systems opens a possibility to investigate several additional aspects. One could for example find out what happens when an error occurs or detect changes in the mind under stressful or increasing workload, assuming that the brain signals change when an operator detects an alarm. This would increase our insight to how an operator reacts to different control room systems.It will in general improve our understanding of the human being a part of the system, and it might even be possible to determine, which of two systems an operator not only prefers, but objectively operates best.

Developing an application for use cases

All concepts in the two use cases can be tested as a single concept by developing a brain sensing application that incorporates and processes EEG signals, and sends the level of a mental state as a controlling signal.

The brain sensing application can be used for initial testing of a neuroheadset as well as to provide an opportunity to find out if it is possible to have a control room system that adapts due to deviations in an operator's mental state. Once such an application is developed, it can easily be adjusted to a given use case. This will help answering the research question stated in the project assignment.

Chapter 4: Developing a brain sensing application with Emotiv's Epoc

4.1 Choosing a neuroheadset

One of the challenges in this master project was choosing an appropriate neuroheadset. All neuroheadsets available on the commercial market provide discretization of continuous EEG signals, but to be able to investigate mental states, raw data access was needed. Based on the specifications in table 2.2, this requirement excluded the Muse headset. It was decided that the NeuroSky's MindWave would not be sufficient, because it only includes one EEG sensor. The headset will therefore not provide enough information about more areas of the brain.

The Emotiv's Epoc seemed like a good choice; raw data access is available and the sampling rate of 128 Hz is sufficient to investigate frequencies up to 64 Hz according to the Nyquist-Shannon sampling theorem (equation 2.3). This is sufficient to investigate all frequency bands in chapter 2.3.1. As seen from table 2.2, Epoc includes 16 sensors of which 14 sensors measure the voltage potential in mV to the remaining 2 reference sensors. Having more sensors within one area makes it easier to detect voltage spikes, which can be deviating or erroneous measurements. The sensors cover a large area of the brain, which provides an opportunity of a more extensive analysis than any of the other headsets. The Emotive's Epoc has been on the market for several years, giving it time to be thoroughly tested by researchers and developers. Epoc has received good reviews and provides a wiki/blog and a forum where one can find a lot of information, such as solutions to potential problems and tips on how to get the system up and running. Based on all these positive specifications, it was decided to order an Epoc.

4.2 User guidance to Epoc

To ensure good and correct usage of the Emotiv's Epoc, it is important to follow the user guidance. All of the Epoc's 14 sensors have a felt pad that needs to be hydrated to achieve sufficient contact with the scalp. The saline used is a contact lens saline solution. The two reference sensors can easily be identified since they have rubber instead of felt. When placing the headset, it is important to follow figure 4.1, where the reference sensors are placed on the bone behind the ears.

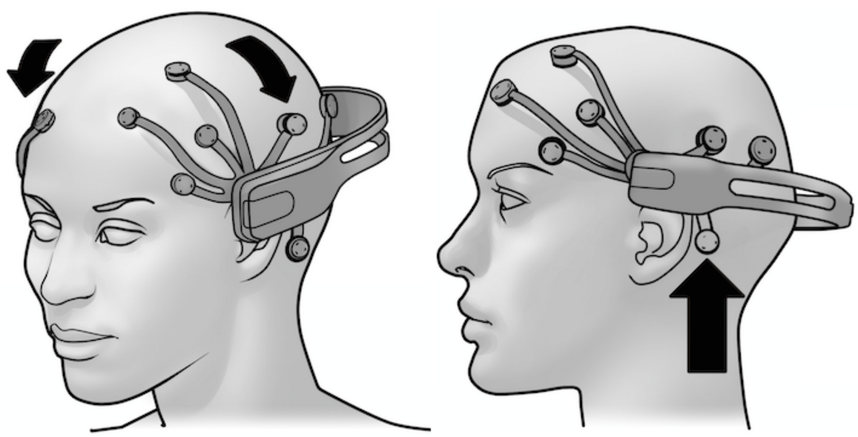


Figure 4.1: Correct placement of the Epoc neuroheadset (courtesy of Emotiv)

When the headset is placed correctly, the sensors will be positioned according to the 10-20 system:

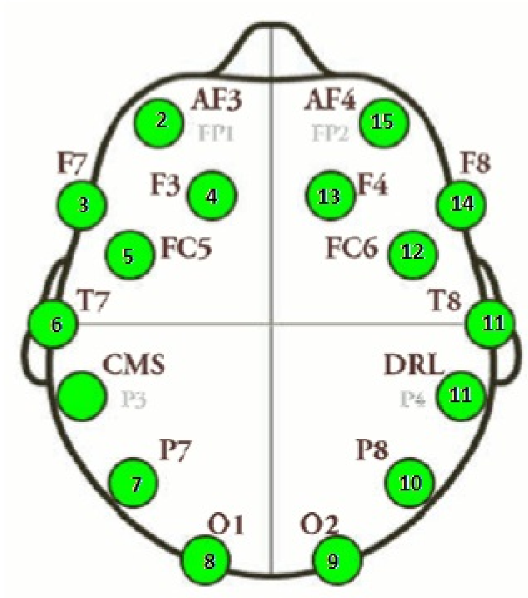


Figure 4.2: EEG Sensors

The Emotive Epoc's wireless connection is established by inserting a USB stick to a computer before turning on the headset for pairing.

4.3 Included software

When purchasing the Emotiv's Epoc you will get access to an application called **Control Panel**, see figure 4.3. The control panel has a graphical user interface and provides valuable information of engine status. It detects if a new headset has been paired and displays such as system status, system up time, wireless signal, battery power and how well each of the 14 sensors are connected to the scalp. The contact quality is represented by a colour code:

Table 4.1: Indicators of connection quality

Black	-	No signal
Red	-	Very poor signal
Orange	-	Poor signal
Yellow	-	Fair signal
Green	-	Good signal

This existing software is of great value as it allows one to verify that the headset is well connected, and identify sensors with a poor connection. These sensors can then be omitted in further processing and investigation.

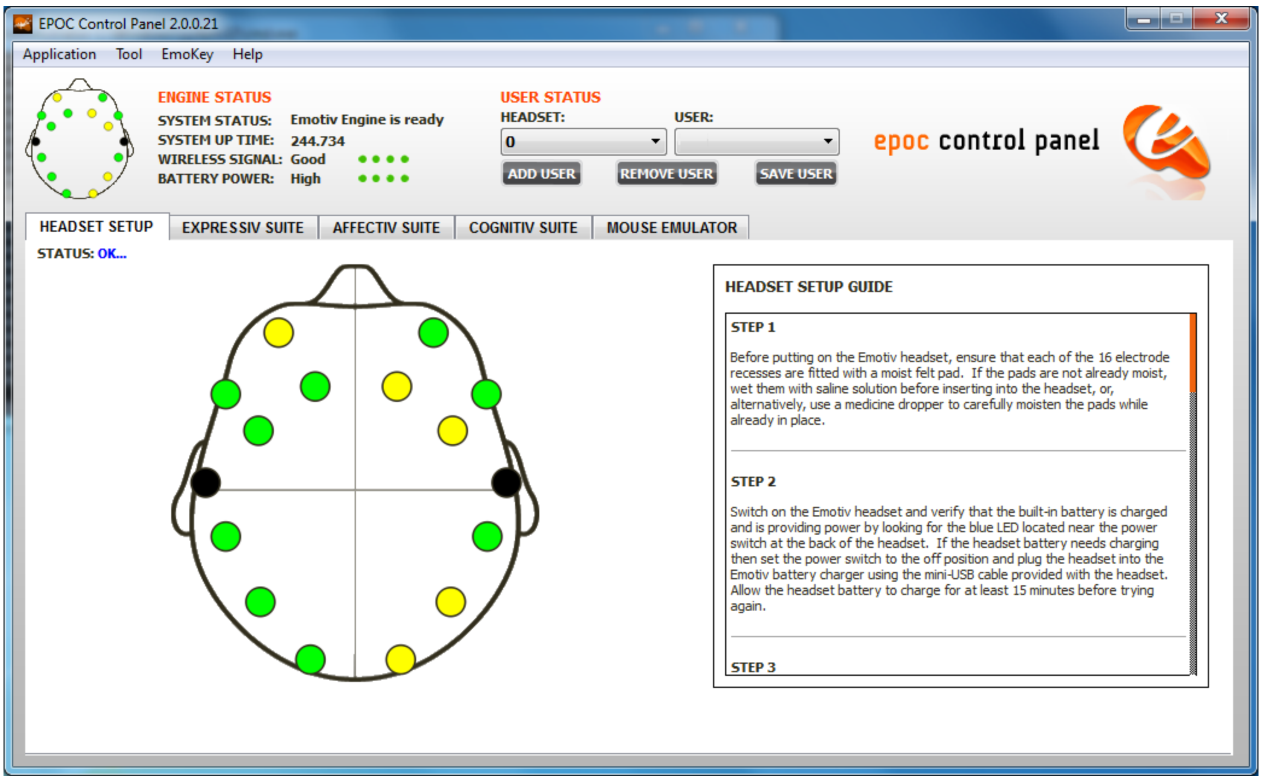


Figure 4.3: EPOC control panel

The control panel can be used for initial testing of the Emotiv Epoc, allowing a user to create a profile and train thoughts in a cognitiv suite, display facial movements in an expressiv suite or show mental states in an affectiv suite. The different actions in the expressiv suite are blink, right wink, left wink, look right, look left, raise brow, furrow brow, smile, clench, right smirk, left smirk and laugh. The different mental states in the affectiv suite are excitement/calm, engagement/disinterest and meditiation.

4.4 Interface

Epoc's application programming interface (API) is an ANSI C interface declared in three header files (edk.h, EmoStateDLL.h, edkErrorCode.h) and implemented in two Windows DLLs (edk.dll, edk _ utils.dll). The communication between API and the Epoc that is provided in edk.dll, is called Emotiv EmoEngine^{TM}. This logical abstraction is exposed by the Emotiv API, through commands like $EE\_EngineConnect()$, that will open the connection between API and Epoc.

An example code provided by Emotiv extracts raw data from the headset and saves such data to a .txt file. The example code is written in C++, which makes it possible to run the .exe file from cmd and concurrently choose in which .txt file you want to save the raw EEG data. The raw data in the .txt file is saved as comma separated values with a new row for each new measurement, as be seen in table 4.2.

Table 4.2: Example of a .txt file with EEG raw data

COUNTER,AF3,F7,F3, FC5, T7, P7, O1, O2,P8, T8, FC6, F4,F8, AF4,GYROX, GYROY, TIMESTAMP,
45,4271.28,4627.69,4096.41,4277.44,4347.18,4263.08,4200,3928.72,4568.21,3924.1,4276.41,4367.18,3942.05,4432.82,2259,1736,6.027,
46,4286.67,4630.77,4089.74,4277.95,4343.08,4256.41,4184.1,3937.44,4573.33,3924.1,4282.56,4356.92,3947.69,4430.77,2259,1734,6.027,
47,4271.79,4626.67,4088.72,4276.92,4339.49,4248.21,4169.74,3952.82,4585.13,3924.62,4280.51,4359.49,3936.92,4412.82,2260,1733,6.029,
48,4261.54,4623.08,4093.85,4274.36,4336.41,4248.21,4169.23,3969.74,4589.74,3922.56,4277.44,4370.26,3933.85,4402.56,2260,1733,6.037,
49,4281.03,4621.54,4090.26,4265.13,4335.38,4246.15,4163.08,3971.28,4584.62,3923.08,4282.05,4369.74,3943.08,4402.05,2261,1733,6.045,

The Emotiv API also provides available open source code for automatic detection of preprogrammed ERPs, such as detecting facial movements (expressiv) or mental commands (cognitive). It also provides an opportunity to get the level of the mental states in the affectiv suite as a performance matrix. After initial testing, this was not used further in this project.

4.5 Design and implementation of a brain sensing application

4.5.1 Design

Working with EEG signals requires extensive data analysis, and it was decided to use Matlab for this purpose. Matlab offers a lot of tools that can process and plot data fast and easily. From **Mental states** chapter 2.3.1, we know that investigating signals power and frequency in various frequency bands will be the right approach to detect mental states from EEG signals. A brain sensing application for processing and evaluation of raw EEG data was therefore needed for this purpose. This application was designed to consist of two parts; one for processing and evaluating a whole data set, and one for processing and evaluation of raw data in real time. The option of analysing a whole data set is good for initial testing and to get familiar with the technology, whereas a real time application can be used for feedback to a control room simulator.

The brain sensing application's main tasks will be to take in the given .txt file after the Emo-Engine is connected, process the data and calculate mean power and mean frequency of various frequency bands. Part one will do this once for a whole data set, whereas part two will do this during time as new data are saved to the .txt file. For a full flowchart of the brain sensing application see figure 4.4.

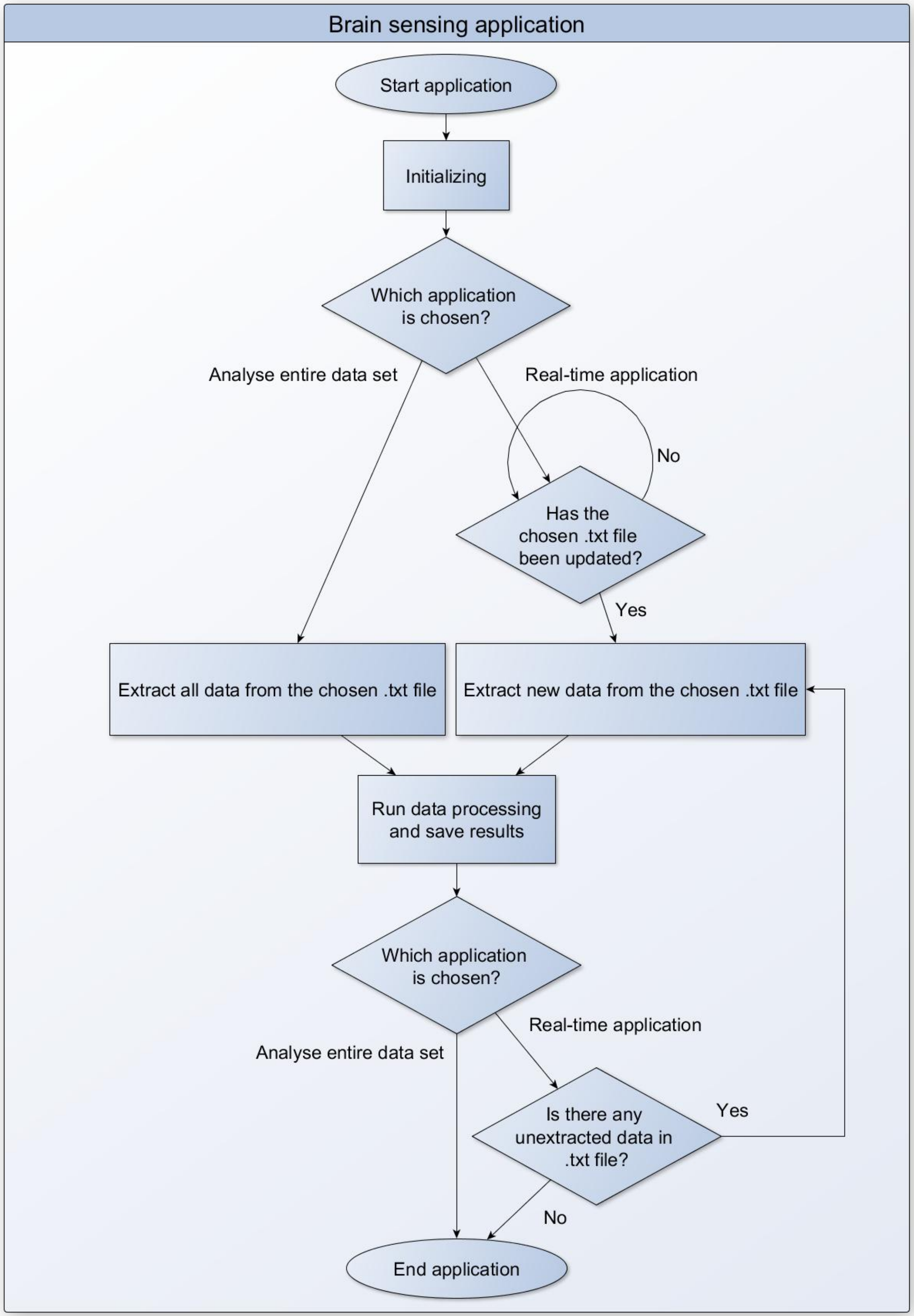


Figure 4.4: Structure of brain sensing application

4.5.2 Details on implementation

Extracting data from the .txt file

The brain sensing application has to run before connecting the EmoEngine. When the application is set running, a "date- and time stamp" is saved, containing information about when the .txt file was last modified. This time stamp is then evaluated relative to a new date and time stamp, which is concurrently updated. These will diverge when EmoEngine is connected and raw data is saved to the .txt file. Part one will take in the entire file and run a data processing script once. If the real time application is chosen, new data from the .txt file will be extracted and saved every 0.5 second, providing a constant stream of new data available for processing during run time. Keeping track of which line is read in the .txt file ensures no loss of data. Always processing data after extraction will ensure that data is not pulled faster than it is saved.

Initialization and data processing

When the brain sensing application is started, the user will get a number of choices. These choices are gathered in an initialization procedure. Data processing is also done through a procedure. Both these scripts are run from the brain sensing application, see figure 4.5.

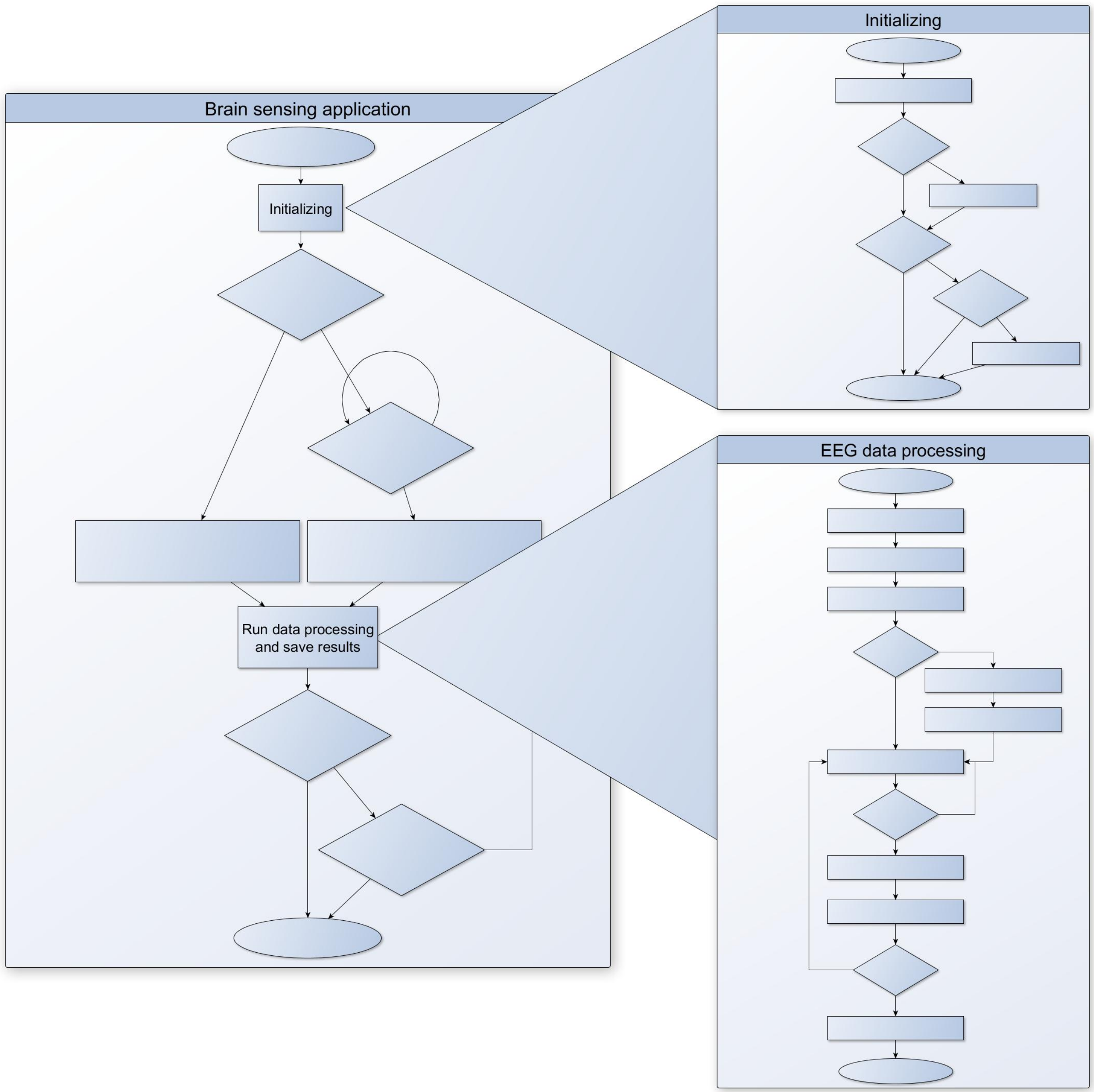


Figure 4.5: Overview of brain sensing application with subsystems

The initialization procedure is included to specify choices prior to running the brain sensing application. It provides an opportunity to choose, which .txt file to be analyzed, which sensors to extract data for analysis and whether it is of interest to run a real time application or to analyze either a data set or parts of one. Figure 4.6 illustrates this.

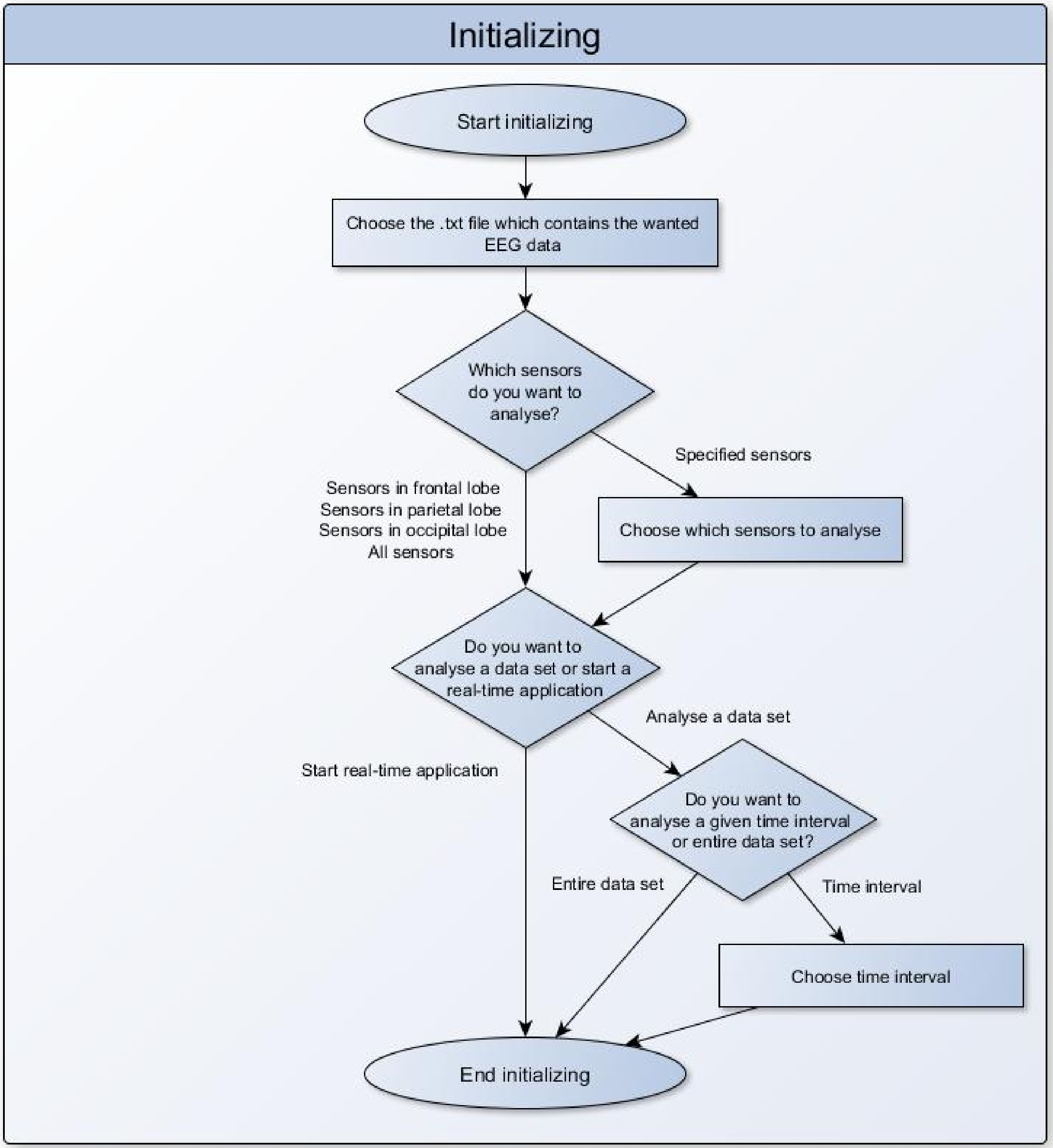


Figure 4.6: Structure of initializing process

After the raw EEG data is extracted from the .txt file, it needs to be processed. The following routine for data processing is implemented:

- A high pass filter is enforced to remove DC noise, by setting the stopband frequency to 2 Hz and the passband frequency to 4 Hz. This is OK since we are only interested in the power of frequencies higher than 4 Hz.

- To find the power spectral density (PSD) of the EEG signals, a fast fourier transform algorithm is employed. Equation 2.8 and refeq:meanPow are then used to calculate the mean power and mean frequency for the three frequency bands theta (4-8 Hz), alpha (8-13 Hz) and beta (13-31).

- Since the fast fourier transform finds power and frequency of *periodic* signals, it needs to be applied to a time interval. This interval has to be long enough to provide sufficient information, but cannot be too long since we want to see how the mean frequency and mean power of different frequency bands develop over time. To calculate developing trends it is chosen to find the fast fourier transform (FFT) from the previous 5 seconds of data. This implies that the FFT is found from 640 samples of data, since we have a sampling rate of 128 Hz. Employing the fourier transform on the previous 5 seconds of data excludes the need of a windowing function. If a real time application is chosen, the first FFT is found after 5 seconds, and then updated every 0.5 second, to have the updated mean power and mean frequency values available. If it is chosen to analyze an entire data set, developing trends will be calculated in the same way, but instead of being updated every 0.5 second, they are calculated for the entire data set. In addition to calculating developing trends, it is provided a possibillity to calculate the mean frequency and mean power of an enitre data set. The fourier transform is then employed to the entire data set.

- A routine to avoid loosing data when using the brain sensing application in real time is implemented. This is done by choosing chunks of 0.5 second data and add this to the previous 4.5 seconds prior to processing. If there is less than 0.5 seconds of unprocessed data available, the application will end the processing routine temporarily to extract more data from the .txt file. The remaining, less than 0.5 second of data is then still left unprocessed. In order not to loose these data, they are always saved prior to ending the processing routine, before being added to the beginning of the new extracted and unprocessed data.

The whole "EEG data processing"-routine can be seen in 4.7. Note that all calculated values are saved to .txt files.

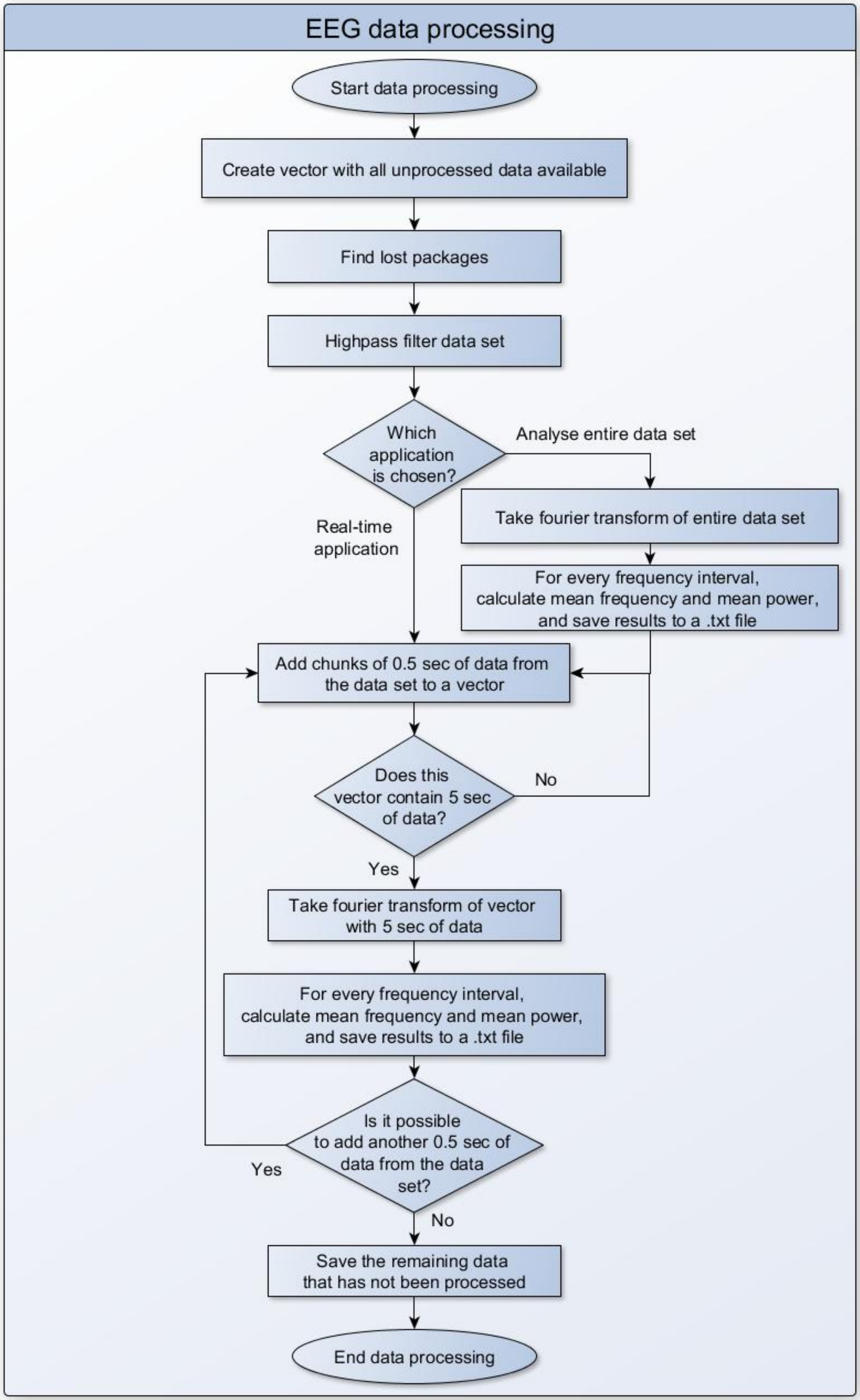


Figure 4.7: Structure of EEG data processing

Several functions that for example identifies correct intervals, plot developing trends and save results to .txt files are used in the brain sensing application. These functions are not described in detail in this thesis, as they are not needed for understanding how the brain sensing application function.

All scripts for the brain sensing application in addition to files needed to acquire EEG data from Epoc, can be found by reading appendix F.

Chapter 5: Test program

A test program was developed for the brain sensing application, with the following purpose:

- Get familiar with the Epoc neuroheadset
- Check that the brain sensing application worked as expected
- Integrate the brain sensing application with a control room simulator to see if it was possible to have an adaptive control room system that changes due to deviations in an operator's mental state
- Try to identify workload from EEG signals

The program was divided into three parts:

1. Initial testing
2. Testing the brain sensing application in real time with a control room simulator
3. Developing and conducting a test program for identifying workload

5.1 Initial testing

It was seen necessary to conduct initial testing of the included software for Emotiv's Epoc in order to get familiar with the neuroheadset and to test the brain sensing application by checking that all algorithms were correctly implemented and provided the expected results.

5.1.1 Algorithms

The first part of the initial testing included to check that the following algorithms worked as expected:

- Algorithms for data processing
- Algorithms for finding **mean** of frequency and power in different frequency bands
- Algorithms for finding **development** of frequency and power in different frequency bands

This was done for testing purposes only, by changing the frequency of a sinousoidal function from 10 Hz to 15 Hz after 10 seconds, see equation 5.1.

$$f(t) = \begin{cases} 10sin(20\pi t), & 0 < t \leq 10 \\ 10sin(28\pi t), & 10 < t \leq 20 \end{cases} \tag{5.1}$$

5.1.2 Using Epoc and observing events

The second part of the initial testing was conducted to get the Epoc system up and running, to try out the included software and to see how easy it would be to recognize motoric movements. The neuroheadset was placed on a test subject. Initially, it was checked to see if it was possible to detect the three facial movements; blinking, nodding and looking up and down. These are some of the facial movements that are most relevant for an operator at work. A test subject was therefore asked to repeatedly perform each of the three facial movements for about 30 seconds. Out of these three, eye blinking was investigated further. The PSD, mean frequency and mean power for the three frequency bands alpha, beta and theta were found, in addition to the developing power and frequency. The purpose of this was to get an indication of how much facial movements will affect the results.

5.2 Connecting to a control room simulator

It is significant to investigate if the brain sensing application is able to send updated values to a control room system. To explore this, it was decided to integrate the brain sensing application with a control room simulator. If this can be conducted smoothly, we have established a foundation that can be utilized to test various future use cases.

5.2.1 ABB Simulator

The simulator used is developed by ABB and simulates an inlet separator at an oil platform. The separator separates water, gas, sand and other particles from the oil. In the interface display, gas can be seen as yellow pipelines, whereas water is green and both oil and the stream from the wells are brown. The bars and graphs display trends of oil, gas and water to get a good overview of the situation by only glancing at the display, see figure 5.1.

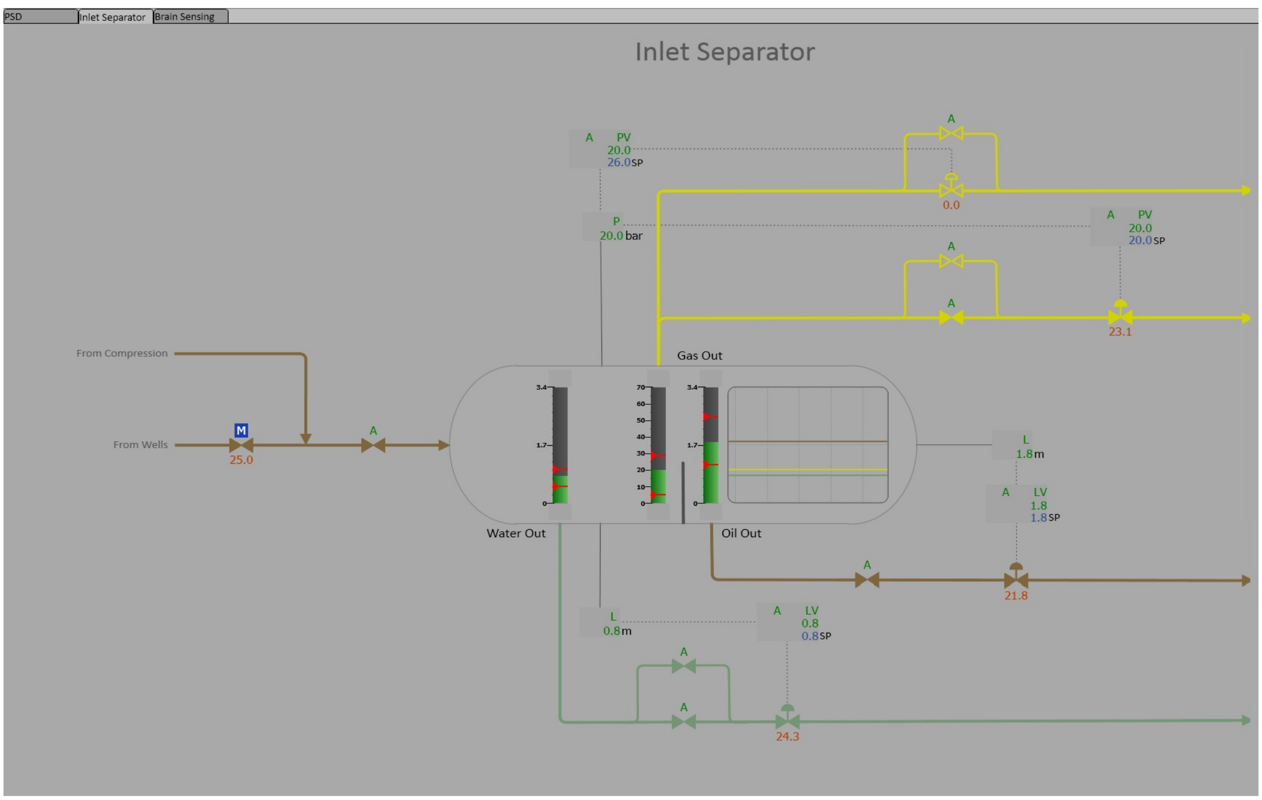


Figure 5.1: ABB simulator

5.2.2 Adaptive control room simulator

One of the ideas from the use case was to develop an adaptive control room system where the simulator adopts changes according to an operator's mental state, see figure 5.2.

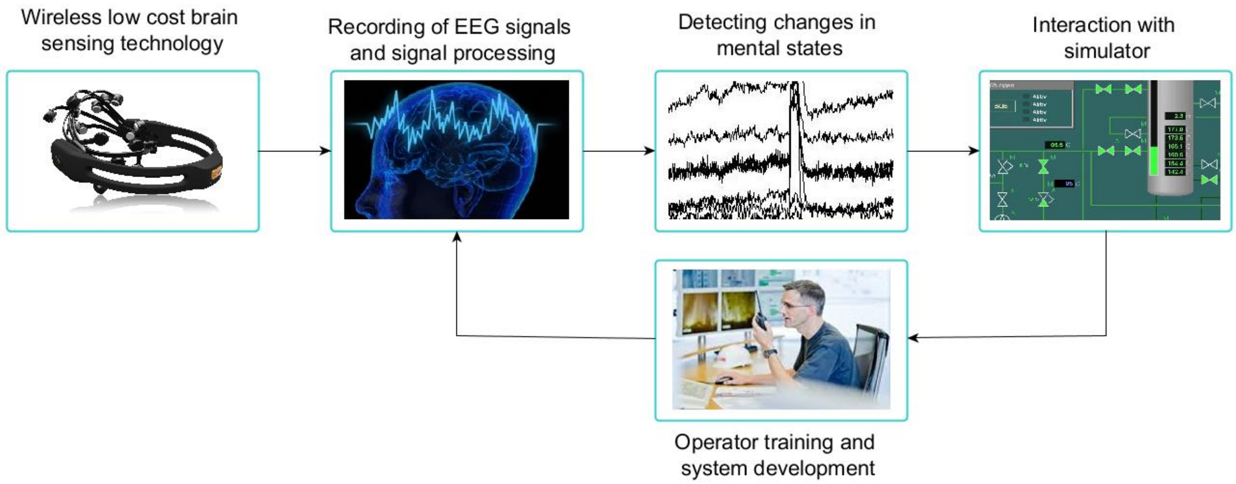


Figure 5.2: System flow

For a proof of concept, it was decided to calculate and send updated values of the mean power in alpha and beta frequency bands from one sensor to the ABB simulator, in addition to raw data from the Epoc. Based on initial testing and calibration from a test subject, threshold values were set for alpha- and beta power to trigger alarms if the power became too high. The simulator interfaces to OPC. Through a provided C++ script that connects to a OPC client, the .txt file with updated EEG data were sent at 10 Hz, and the updated alpha and beta values was sent at 2 Hz. The EEG data is then displayed in the simulator, together with two bars showing "alpha level" and a bar to show "beta level" for the given chosen sensor.

5.3 Identifying workload

5.3.1 Objective

Through the use case, it was decided to focus on using brain sensing for operator training and/or development of control room systems. Several areas of application were suggested and in order to implement a use case, it was critical to go further with a given mental state and to develop a concept demonstrator. As we could see in chapter 2.3.1, none of the mental states investigated provided a good and straightforward theory ready for implementation. The lack of such a theory explaining how to find mental states from EEG signals is hard to work around, when searching for a good utilization of a brain sensing device in a control room setting. It was therefore decided to investigate if it is possible to detect a chosen mental state from the brain signals acquired by the chosen neuroheadset. Three of the mental states were judged to be relevant in this setting:

- Fatigue
- Stress
- Workload

Fatigue will have a huge impact on a persons ability to perform a task. It is easy to imagine that one becomes less efficient and makes more mistakes when fatigued. Of the three mental states mentioned, fatigue is the mental state that specialists have investigated mostly, through analyzing sleeping patterns (see chapter 2.3.1). This provides a high probability of finding good techniques for analyzing EEG signals, but can not be used in this project as we wish to investigate the mental state of a *working* operator. Intricate techniques will also be problem from a non-medical perspective, as EEG signals ideally should only be interpreted by a specialist. This can however be solved by conducting a simple and non-parametric test, in order to make the test result easy to interpret. A methodology based on previous research is also provided in chapter 2.3.1, but it is hard to come up with a fast and simple test to investigate increasing fatigue.

The level of **stress** could be utilized as an indicator on how well an operator performs with a new control room system, or a high stress level could trigger an external alarm. On the other hand, finding a simple way to mitigate a stressful situation in a safe setting, with the goal of identifying stress from EEG signals might be challenging. One could, for example, poke a test subject with a needle, but this would neither create a realistic setting for an operator at work or perhaps be ethically accepted. However, there exists a lot of other biophysical stress indicators that could be measured in a thoroughly stress study, such as sweat and increased heart rate, as mentioned in chapter 2.2.2.

A well-designed and well-conducted study focusing on the mind might be able to show what happens in a person's mind under increasing **workload**. Despite various findings among papers

in chapter 2.3.1, we know from chapter 2.2.1 that the workload level must be seen together with the level of situation awareness. Being able to identify workload will provide a measure, not only on the complexity of an operator's task and his ability to perform the task, but also indicate, for instance, how concentrated, awake or stressed the operator is. This would provide a good base for understanding an operator's mental state and can be useful for several of the concepts discussed in chapter 3, Use case.
Customizing two of the concepts in use case to workload, will provide a possibility of developing the following two use cases

- For operator training: an operator have to practice a routine until his workload level is at an acceptable level
- For development of control room systems: An operator should not experience "overflow" in workload when using a new system, and the average workload level for a routine should be lower in the newest version of the control room system

Identifying workload can also help to get a better understanding of human factors; to help us to understand if the level of workload is correlated with erroneous decisions in a high-pressure situation.

As we could see in chapter 2.2.2, the well established NASA-TLX tool was available for subjective workload assessment. In addition, robust results providing a possible methodology on how to identify increasing workload from EEG signals was provided in chapter 2.3.1. This made it possible to define a hypothesis which could be tested, and it was therefore chosen to go further with workload.

5.3.2 Intelligence quotient (IQ) test

An intelligence quotient (IQ) test was used to examine EEG signals under increasing workload to identify workload in EEG signals. An IQ-test is a good tool for testing increasing workload.

For this purpose, Mensa[1] Norway's online IQ test [2], was chosen. The online IQ test is a figure reasoning test with 35 tasks with increasing difficulty. The test person gets 25 minutes to solve it. The online IQ test is not a scientifically designed test, but will provide a good indication of the IQ. Since the test includes tasks with increasing difficulty, it suits perfectly for the purpose in this project.

The 35 tasks in the online IQ test was divided into two groups; one with the first 20 tasks to create an easier tasks, and a second with the 15 last harder tasks. Although some tasks may be easier to solve for some people, both groups of tasks will have an overall increasing difficulty. This provides an opportunity to detect a difference in workload between the two parts of the test.

Prior to the test, all test subjects had to fill out a safety and information form. This form is found in appendix B. It provides detailed information about the experiment, so that test subjects understand what to do and the purpose of the experiment. It also explains that the test subjects will be handled anonymously.

5.3.3 NASA Task Load Index

The NASA Task Load Index was used to obtain a subjective workload estimate of each of the two parts of the IQ test. The NASA Task Load Index is found in appendix A.

[1]Mensa is a high IQ society with members from 100 different countries. All members have proven their IQ to be among the top 2 % in the population through an approved IQ test http://www.mensa.org/ visited 23.04.2015

[2]Developed by Olav Hoel Dørum in 2007-2008 http://www.mensa.no/iq/hjemmetest/ visited: 15.04.2015

5.3.4 Methodology and statistical tests

From chapter 2.3.1 we know that increasing task difficulty might be seen by decreased activity in the alpha frequency band and increased activity in the theta frequency band, mainly in the frontal lobe. In addition, the beta frequency band might be of interest. The program described in chapter 4.5 is able to find mean frequency, mean power and developing trends for these frequency bands, and was therefore used to analyze data after conducting the IQ-tests. Calculating mean frequency and mean power for both the first and the second part of the IQ test allows us to see if the values goes up or down.

The significance of the results was examined by a **binomial test** and a **Wilcoxon signed-rank test**, calculated in Excel. For details on all statistical tests see appendix E. Because it is of interest to see if any of the measurement values goes up OR down, both directions of deviation from the null hypothesis are interesting, and so it was necessary to find a two-tailed probability. The **Kolmogorov–Smirnov test** was used to check if the measurement variables came from a normally distributed data set, by the Matlab command

$$h = kstest(x)$$

The test returns 1 if H_0 is rejected, and 0 if H_0 holds.

The **statistical null hypothesis** was given as following

The probability of the frequency or power of a frequency band to go up under increasing workload is equal to the probability of the frequency or power of a frequency band to go down

With the **nominal variables**

- First part of IQ test
- Second part of IQ test

And the following **measurement variables** for both the entire brain, the frontal lobe, the pareterial lobe and the occipital lobe

- Power and frequency of alpha frequency band
- Power and frequency of beta frequency band
- Power and frequency of theta frequency band

This gives 48 measurement variables, where 24 are for the first part of the IQ test and 24 for the second part.

5.3.5 Executing the IQ-test

All test subjects were given 5 minutes to get used to wearing the headset, by playing around in the control panel. The purpose of this was to reduce additional stress and discomfort caused by wearing the headset, to avoid impact on the testresults. After starting to capture EEG data, the test subjects were given an additional 30 seconds to relax before starting the test.

The individual time of the first part and the second part of the IQ test was measured with a stop-watch. This was considered to be sufficient because of the length of the test (25 minutes), and a few milliseconds margin of error would not have a huge impact in this non-parametric test.

The test was stopped either when the test subject ran out of time, or when the test subject had completed all questions. After the data capturing was ended, the connection of the sensors was checked and saved. Only sensors with a fairly good connection indicator or better, see table 4.1, was included as a source for the further data processing.

Chapter 6: Simulation and results

6.1 Initial testing

6.1.1 Algorithms

In equation 5.1, FFT identified the two frequency components of the sinusoidal function correctly, as can be seen in figure 6.1. The average alpha frequency of the whole data set was found to be 11.8830 Hz, whereas the development of mean frequency can be seen in figure 6.2.

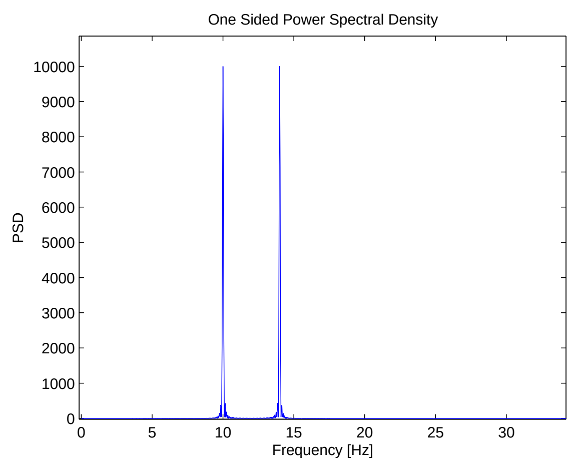


Figure 6.1: PSD after FFT

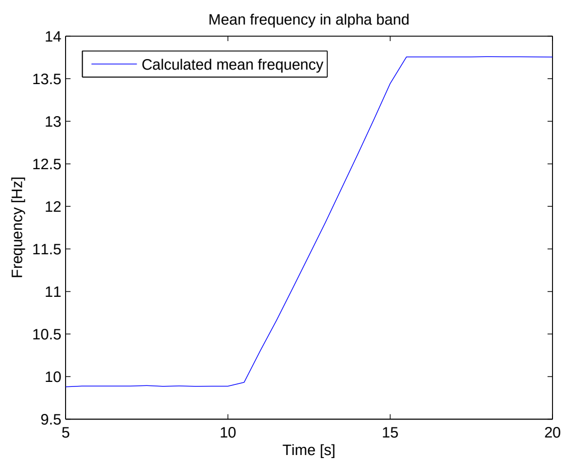


Figure 6.2: Development of mean frequency

6.1.2 Using Epoc and observing events

To obtain good contact with the scalp, a lot of contact lens solution had to be applied to each felt pad. Figure 6.3 shows that it was possible to obtain good and fair signals from all sensors. Note that sensors T7 and T8 are the two reference sensors.

The included software "Control panel" worked well, except for the affective suite; two of the mental states went up and down without any obvious correlation to the user, while the last was constantly disconnected. Connecting the EmoEngine and extracting EEG data worked as expected, with less than 3 lost packages per 30 seconds.

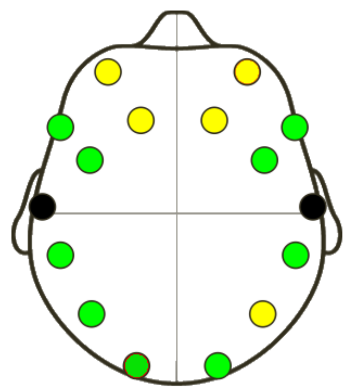


Figure 6.3: Overview of active sensors

Having a "good" connection to almost all sensors, the test subject was asked to perform the predefined facial movements for about 30 seconds. On average, it took 4.05 seconds from the EmoEngine was connected to the beginning of data logging. Figure 6.4, 6.5 and 6.6 show that several types of motoric movement will have an impact on the raw data to be analysed, and that the effect of facial movements is largest for the sensors in the frontal lobe, AF3, F7, F3, FC5, FC6, F4, F8 and AF4.

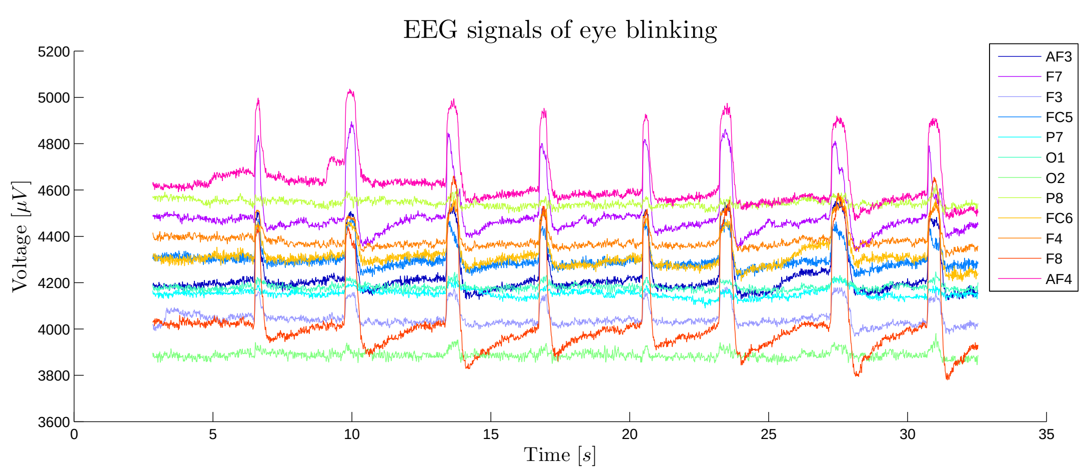


Figure 6.4: Measured EEG signals of eye blinking

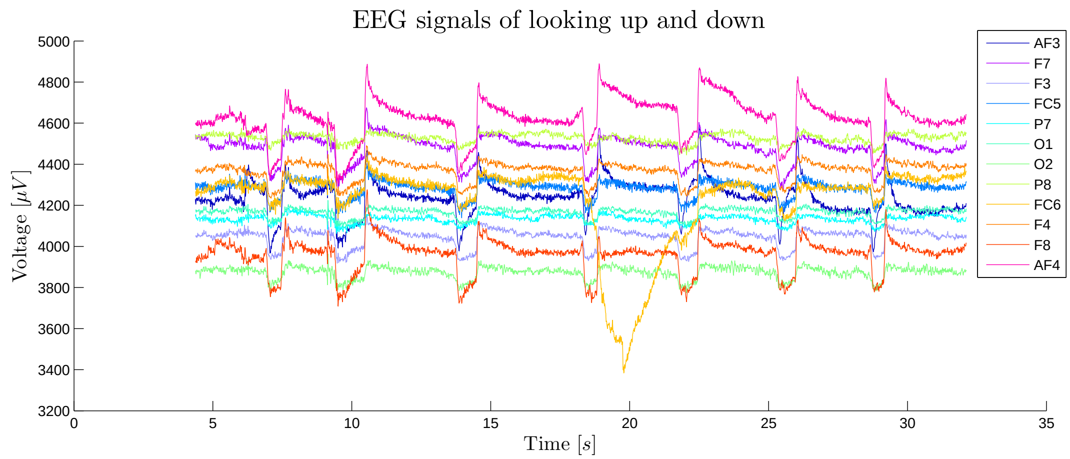


Figure 6.5: Measured EEG signals of looking up and down

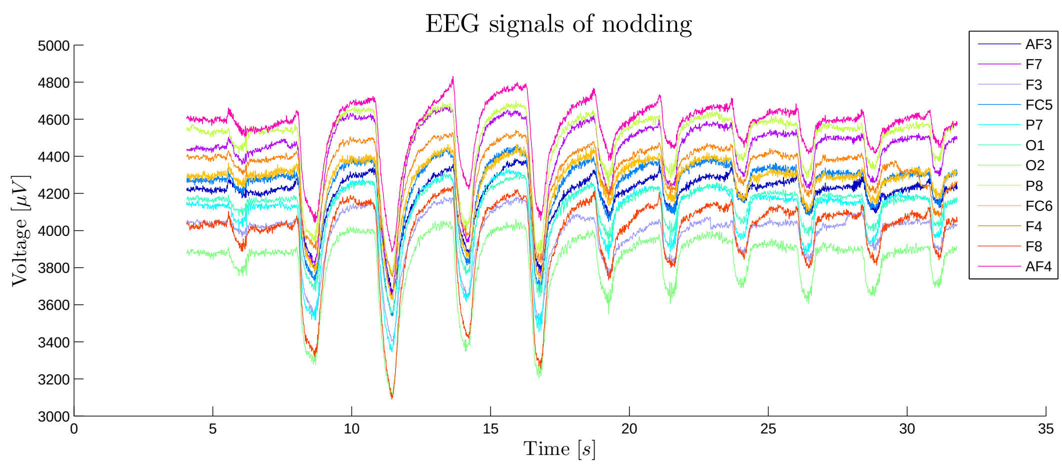


Figure 6.6: Measured EEG signals of nodding

It was decided to further investigate the impact of facial movements further. The fourier transform should be taken from at least two ERPs, and accuracy of the result increases when the fourier transform is calculated over a longer time interval. Data were therefore captured for one minute, where the test subject was instructed to relax for the first 30 seconds, see figure 6.7 , and then relax while blinking his eyes rapidly during the next 30 seconds, see figure 6.8.

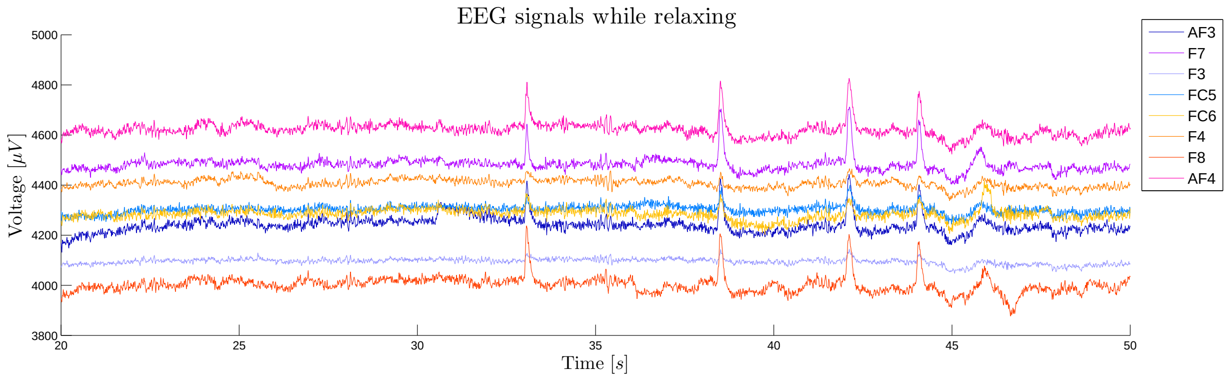


Figure 6.7: Thirty seconds of EEG data from frontal lobe when relaxing

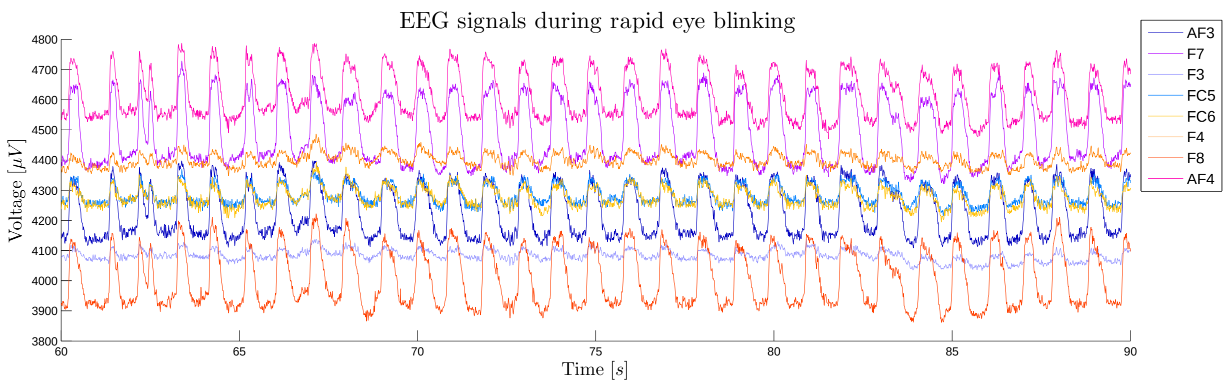


Figure 6.8: Thirty seconds of EEG data from frontal lobe under rapid eye blinking

Facial movements are mainly detected in the frontal lobe. Therefore, it was decided to use the sensors covering this lobe when analyzing data to investigate the impact of eye blinking. These sensors are marked with a red square in figure 6.9.

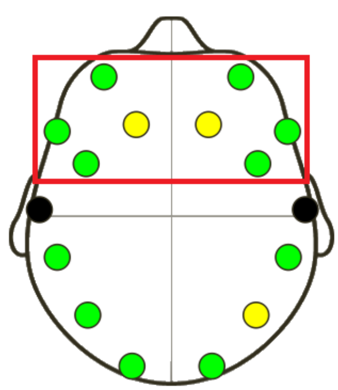


Figure 6.9: Contact quality of sensors to scalp during eye blink investigation

For both intervals in figure 6.7 and 6.8, data were processed and the PSD was found. The PSD of sensor F7 is included in 6.10 for figurative reasons. This sensor was chosen because it had good contact with the scalp under data capturing, as clearly seen in figure 6.9.

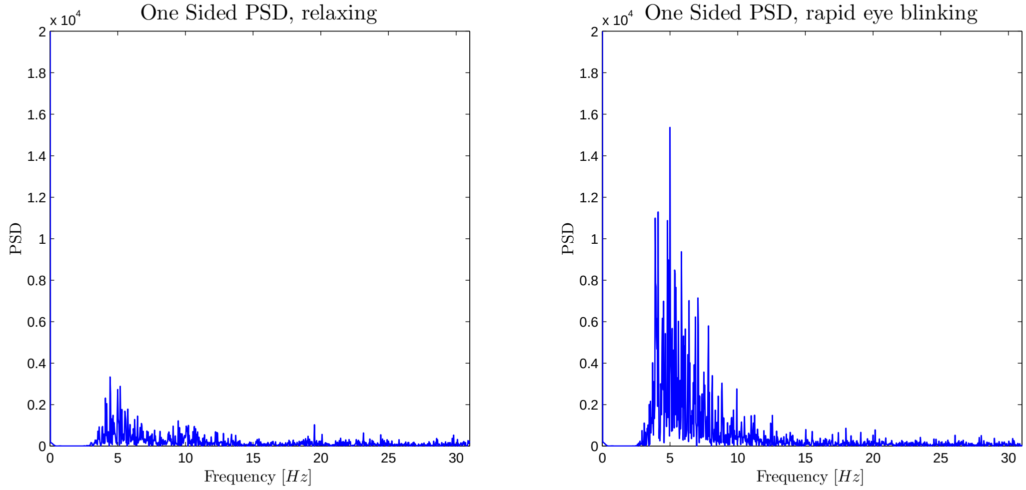


Figure 6.10: PSD of F7 when relaxing and blinking rapidly

Table 6.1 illustrates the values for sensors in the frontal lobe obtained from the data set when the test subject was first relaxing (left) and then blinking rapidly(right).

Table 6.1: Mean values in different frequency bands when relaxing or blinking rapidly

	Alpha freq	**Beta freq**	**Theta freq**	**Alpha pow**	**Beta pow**	**Theta pow**
Relaxing	10.27 Hz	21.78 Hz	5.81 Hz	282.56 $\frac{\mu V^2}{Hz}$	113.84 $\frac{\mu V^2}{Hz}$	368.48 $\frac{\mu V^2}{Hz}$
Blinking	10.28 Hz	20.44 Hz	5.78 Hz	383.95 $\frac{\mu V^2}{Hz}$	100.28 $\frac{\mu V^2}{Hz}$	1235.3 $\frac{\mu V^2}{Hz}$

Plotting the development of mean power and frequency over the last 5 seconds gave the results in figure 6.11 and 6.12. In figure 6.11 one can see that power in the theta band increases with 70.2 % when the test subject is blinking rapidly, whereas nothing significant can be seen in the power in alpha- and beta frequency bands. Note that frequencies bellow the theta frequency band is filtered out. In figure 6.12 the frequency in the beta band drops when the test subject is blinking rapidly, whereas nothing significant can be seen in the frequency for alpha- and theta frequency bands.The calculated mean values in table 6.1 appeared to correlate well with the developing trends in figure 6.11 and 6.12.

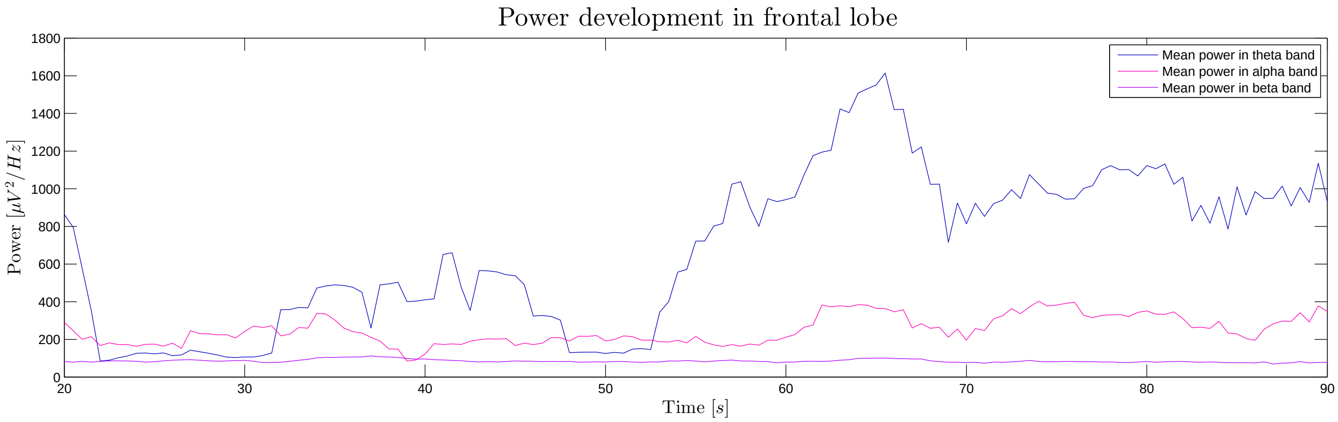


Figure 6.11: Development of power in theta-, alpha- and beta frequency bands

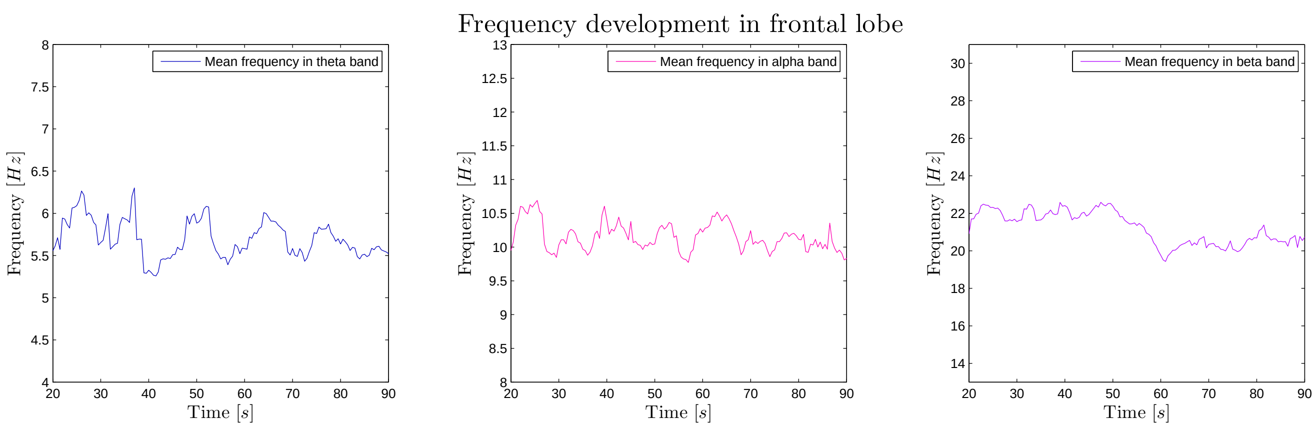


Figure 6.12: Development of frequency in theta-, alpha- and beta frequency bands

6.2 Connecting to a control room simulator

It was critical to test thoroughly in order to set threshold values for the simulator. The maximum and minimum values that occurred during initial testing for power in the alpha- and beta frequency bands are found in table 6.2, in addition to the average value when relaxing and the threshold for alarm triggering.

Table 6.2: Simulator threshold values for alpha- and beta power

	Max	Min	Relax	Threshold alarm
Alpha	1050 $\frac{\mu V^2}{Hz}$	25 $\frac{\mu V^2}{Hz}$	500-600 $\frac{\mu V^2}{Hz}$	700 $\frac{\mu V^2}{Hz}$
Beta	600 $\frac{\mu V^2}{Hz}$	11 $\frac{\mu V^2}{Hz}$	50-60 $\frac{\mu V^2}{Hz}$	100 $\frac{\mu V^2}{Hz}$

Table 6.2 shows that there were clearly distinct differences between the different threshold values for power in alpha- and beta frequency band.

Figure 6.13 shows the original simulator for an inlet separator, now with the developing trends of alpha- and beta power for one sensor (F7) in the left corner. Figure 6.14 illustrates that a high value in beta power has triggered an alarm.

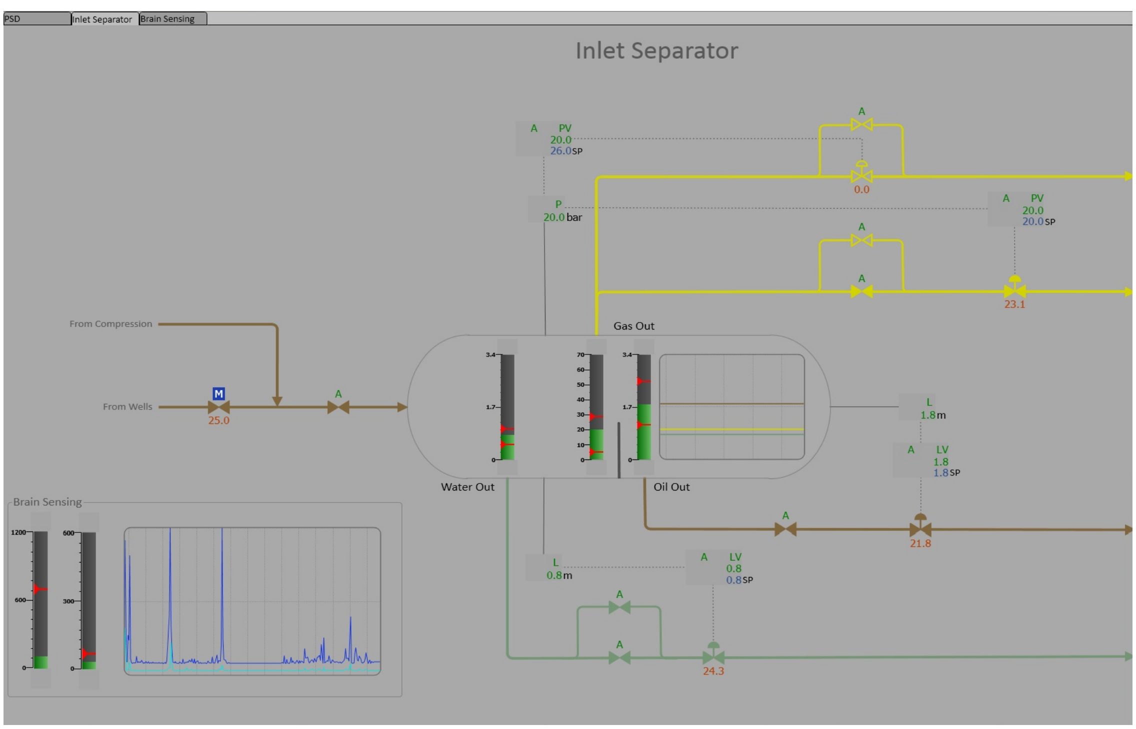


Figure 6.13: Integrated brain sensing in control room simulator

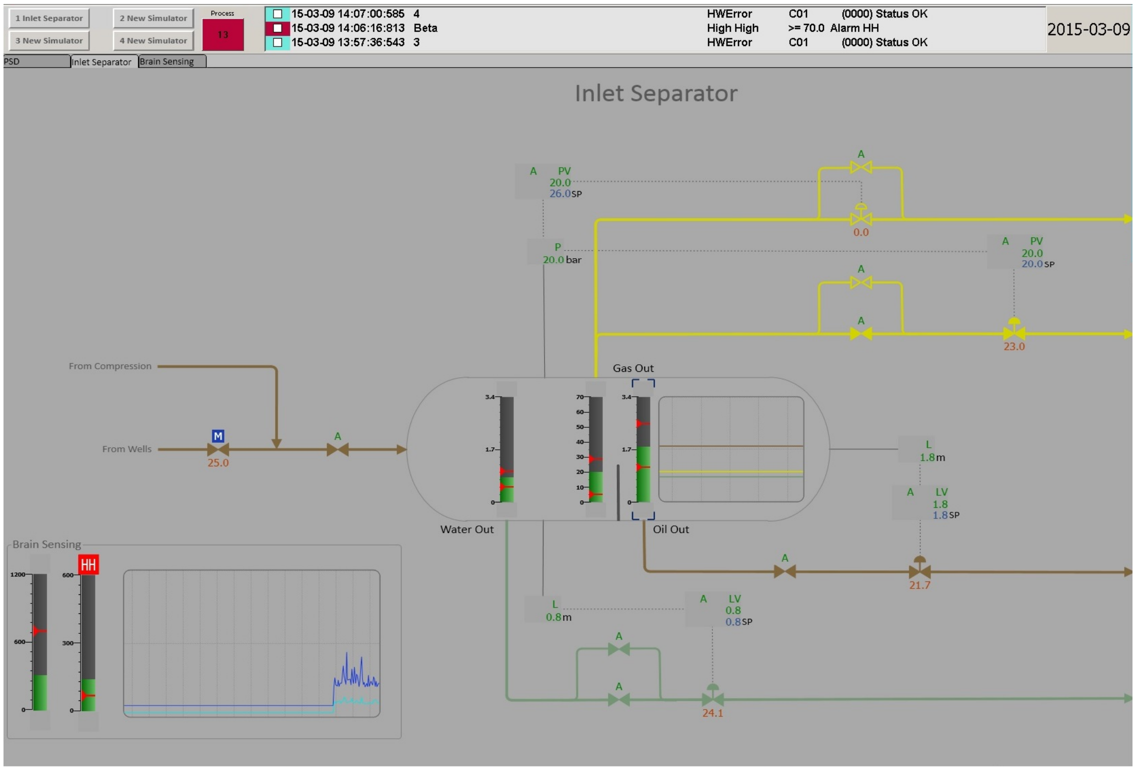


Figure 6.14: Alarm triggered by brain signals in control room simulator

Figure 6.15 shows a new tab in the simulator, which shows the the brain sensing demo. The upper graph shows developing power in alpha- and beta frequency bands for one sensor (F7). The bottom graph, shows raw EEG data. To the left, one can see bars indicating power level.

Figure 6.15: Brain sensing demo in simulator

6.3 Identifying workload

6.3.1 Information on test subjects and execution of the test

The felt pads on the headset were wetted, and the headset was placed correctly for every test subject, so that all sensors had a good connection (green or yellow).

The test group contained three females and seven males, nine in the age of 23-26, one in the age 58-61. None of the participants had previous neurological diseases.

6.3.2 NASA TLX

The NASA-TLX test for validation of subjective workload can be seen in table 6.3.

Table 6.3: Workload levels for IQ test by NASA-TLX

Test subject #	**First part of IQ test**	**Second part of IQ test**
1	66,0	81,3
2	40,0	63,0
3	53,0	61,7
4	38,0	50,7
5	25,0	64,0
6	35,3	61,3
7	14,7	31,3
8	44,3	46,0
9	28,3	88,0
10	68,7	75,3

From table 6.3 we can see the following:

- All participants ended up with a higher workload score in part II than in part I
- The mean workload for part I was 41.3
- The mean workload for part II was 62.3

6.3.3 Results

Testing for statistically significance it is of interest to check individual responses. For all test subjects, the mean power and the mean frequency in equations 2.8 and 2.9 of the alpha-, beta- and theta frequency interval were found for both parts of the IQ test, for all sensors but also the sensors covering the paritetal lobe, the occopital lobe and the frontal lobe (temporal lobe is covered by reference sensors). Table 6.4 shows the nonparametric results for the parietal lobe; one can see if each measurment variable increases or decreases from the first part of the IQ test to the second.

Table 6.4: Nonparametric results of Parietal lobe from IQ test

Parietal	**Alpha frequency**	**Beta frequency**	**Theta frequency**	**Alpha power**	**Beta power**	**Theta power**
Test sub. 1	Up	Up	Down	Down	Up	Up
Test sub. 2	Up	Up	Up	Down	Down	Down
Test sub. 3	Down	Down	Up	Up	Up	Up
Test sub. 4	Up	Down	Down	Down	Down	Down
Test sub. 5	Down	Down	Down	Down	Down	Down
Test sub. 6	Down	Up	Up	Down	Down	Down
Test sub. 7	Up	Up	Up	Down	Down	Down
Test sub. 8	Up	Up	Up	Down	Down	Down
Test sub. 9	Up	Up	Up	Down	Down	Down
Test sub. 10	Up	Down	Down	Down	Down	Down

Table 6.4 shows that in the paritetal lobe, alpha power increases for only one subject. Beta- and theta power increases for only two subjects. Results on the frequencies are more mixed.

The nonparametric results from the entire brain, frontal lobe and occipital lobe can be seen together with all parametric results from the IQ test in appendix C.

Binomial probability

All four properties of a Bernoulli process (see appendix E section II) was fulfilled for the experiment, so a binomial distribution was used when testing the null hypothesis. With a significance level of 0.05, the null hypothesis was rejected for alpha power in the parietal lobe, because the probability of getting 1 or fewer out of 10 in a two-tailored test is P= 0.0215.This mean that it is significantly unlikely to obtain the results for alpha power in table 6.4 by pure chance.

Kolmogorov–Smirnov test

A paired t-test seem reasonable for investigating the significance of the results. However, the measurement variables appeared to vary noticeably. Accordingly, the Kolmogorov–Smirnov test was used to check normality.

The Kolmogorov–Smirnov test was conducted with a significance level of 0.05 %. Due to a small sample size, the residuals of the data sets were examined. The test showed that the null hypothesis on normality was rejected for 44 out of 48 measurement variables, see appendix D, table D.1 and D.2. It was therefore not possible to assume that the measurement variables came from a normally distributed dataset.

Wilcoxon signed-rank test

Due to the result on the Kolmogorov–Smirnov test, it was chosen to run a Wilcoxon signed-rank test, which do not assume that the data fit the normal distribution. The Wilcoxon singed-rank test with a significance level of 0.05 showed that only the median difference for alpha-, beta- and theta power in the parietal lobe was significantly less than zero, see table 6.5.

Table 6.5: P values in Wilcoxon signed-rank test

	P-value
Alpha power	0.0098
Beta power	0.0137
Theta power	0.0273

This means that based on the measurement value's parametric range between the first and second part of the IQ test, it is significant unlikely to obtain the results for alpha-, beta- and theta power in the parietal lobe on pure chance.

Chapter 7: Discussion and conclusion

7.1 Discussion

7.1.1 Decisions made

Epoc review

It turned out to be a good choice to use Emotiv's Epoc for the purpose of this project; to test low cost neuroheadsets and to develop a BCI system for a use case. Connecting Epoc to the USB pin was easy, the included software provided important, usable information and nearly all data were logged correctly. However, Emotiv's software is in general quite confusing due to a lot of software concepts. Emotiv keep changing names of neuroheadset editions, software and other terms. It is hard to find manuals and needed libraries, and it is confusing to understand what is accessible depending on which edition you have of the neuroheadset. The wiki and blog pages were of great support when starting up the project, and the fact that a C++ script example of data logging was available made the process of getting the system up and working much easier.

The headset is wireless and therefore very mobile. The headset has good design in the manner that it looks good and connects well with the scalp of different people. It is rather uncomfortable to wear for more than a few minutes, and it is time consuming to put it on and to get a good signal from all sensors. Imagine an operator wearing an uncomfortable device through a whole shift is not realistic. This factor is so critical for the Epoc that it is not satisfactory to use in a control room setting. A design like Muse or NeuroSky MindWave would be more beneficial seeing as these are simpler in their design (see figure 2.6 and 2.8) and more comfortable to wear.

Both are promoted for this, in addition to that they can be worn without the need of a contact lens solution to wet the felt pads for the sensors. Still, the downsides of using these simpler neuroheadsets are discussed in chapter 4.1. The main disadvantage is that they comprise fewer sensors. Utilizing a neuroheadset in a control room therefore requires further development of the technology.

Not utilizing included software from Epoc

As mentioned in chapter 4.4, it is possible to get a value representing the level of the mental states (excitement/calm, engagement/disinterest and meditation) through the Emotiv API. The control panel provides the user possibilities to test these mental states in the Affectiv suite (performance metrics), but these did not work satisfactory. Developers seems to know the problems:

> *Performance Metrics detections are the most heavily filtered and the most likely to be shut down temporarily by excess noise.* [1]

Using this in a brain sensing application for a control room setting would appear as a black box, without access to or control over the algorithms for identifying mental states. It was therefore decided to go further with extraction and processing of raw data, instead of building a BCI application based on automatic detection of mental states.

7.1.2 Initial testing

Initial testing was conducted to test the Epoc headset, to get the system up and running and to test the implemented processing algorithms for analyzing data sets. The processing algorithms were shown to work as intended through figure 6.1 and 6.2, and provided a good representation of the results. In figure 6.2, one can see that developing trends will be correctly updated every 0.5 second, and it takes 5 seconds to obtain the correct value.

[1] https://emotiv.zendesk.com/hc/en-us/articles/200782279-How-do-you-measure-emotions-in-the-first-place-so-you-can-compare-the-outputs-and-come-up-with-a-number-

Figure 6.3 shows that it was possible to get good and fair signals from all the sensors, although a lot of contact lens solution was needed to achieve this. Trying to detect events showed that the system was working properly, and that it was possible to get a significant indication on what affects EEG signals the most; motoric motion.

As mentioned in chapter 2.3.1, facial movements should mainly be seen in the frontal lobe. This can be confirmed by comparing the frontal response when blinking (figure 6.4), looking up and down (figure 6.5) and nodding (figure 6.6), to the response of the other sensors.It became clear that the facial motion cannot be detected to the same extent in other areas. This shows that the Epoc most likely is able to measure EEG signals for correct brain areas.

A single test on eye blinking was conducted in order to calculate how much eye blinking influences frequency and power in different frequency bands. Although this needs to be further tested to confirm results, it was found that the largest difference could be seen for low frequencies, where we could see a 70.2 % increase in mean power in the theta frequency band. The theory is strengthened by a study on eye blinking from EEG signals in [32], where it was found that the PSD of eye blinks is concentrated in the range 0.5 to 3 Hz.

A concern is the fact that eye blinking and other facial- or motoric movements may cause an impact on calculated power- and frequency values for the frequency bands. An eye blink clearly has an impact on the amplitude spectrum and might therefore result in erroneously results when searching for changes in the EEG signals due to changes in a mental state. A queston is whether these movements should be filtered out.

Removing motoric events would require the use of pattern recognizing algorithms to recognize events. These algorithms should be developed to recognize the average pattern amongst several people, and this would then have to be implemented and tested. There exist a wide range of different motoric events that potentially could be filtered out. Considering the scope of the work in this project in addition to the available time, it was decided to leave the EEG data unfiltered for motoric events. To support this decision is the fact that the tests designed for identifying workload were carried out on a computer (this working situation is to some extent transferable to an operator at work), and the test subjects were instructed to perform the tests without too much motoric movement. As described in chapter 6.1.2, eye blinks mainly appear in EEG signals as increasing activity in the theta frequency band in the frontal lobe and will therefore not influence all available data after an experiment. Rather the contrary, including eye blinks could provide additional information. As we saw in chapter 2.2.2, eye blinks are correlated with increasing stress, tiredness and cognitive load.

7.1.3 Identifying workload

Due to the fact that we are dealing with unconfirmed theories, it is significant to have a low significance level, to achieve a very clear result in order to reject the null hypothesis. Because the number of test subjects is n=10, it will only be possible to reject a null hypothesis with a significance level of 0.01 for a binominal probability test, if we see a decrease or increase for *all* subjects for a specific measurement value. This was not the case for any of the measurement values. However, the null hypothesis was rejected for alpha power, using a significance level of 0.05.

It is difficult to spot a concrete pattern that either confirms or rejects that under increasing workload one will see increasing activity in the theta frequency interval, and decreasing activity in the alpha frequency interval. Supporting the theory of identifying workload is the results from both the binominal probability test and the Wilcoxon signed-rank test on decreasing power in the alpha frequency band in the parietal lobe, whilst the power in the theta- frequency band in the parietal lobe is also found to be decreasing, something that conflicts with the methodology provided. In addition, it is not possible to draw any conclusions about the development of mean frequency in general or mean power in other brain lobes, but the Parietal lobe. There are several potential sources of error:

- Using the entire brain area for data collection might be too generalizing
- The IQ test might not be a good test for identifying workload
- The sensors are not able to collect correct data

- The methodology is inferior
- The test group is too small to say anything significant
- Results are affected because test subjects are not used to wear the neuroheadset
- The results would have been more evident if they had been compared to a relaxed situation

The mentioned potential sources of error are discussed below.

Using the entire brain area for data collection might be too generalizing

Due to the fact that we are not completely sure on how well the low-cost neuroheadset works compared to a more expensive, it was decided to investigate the average over the entire brain lobes. As we are testing a methodology without knowing exactly how we can expect to see changes under increasing workload, changes could potentially be seen in smaller areas than for the entire brain lobe.

The IQ test might not be a good test for identifying workload

A problem with the IQ test is that people conducting such a test will experience a cycle of concentration while trying to find an answer followed by a release when selecting the correct answer. This cycle will not result in a smooth increasing workload. In addition, if the second part of the IQ test is too hard for some people, participants might lose their concentration. One could generalize and say that due to the fact that all participants rated the workload of the second part higher, the test is actually good enough. What one has to keep in mind, is that people might have been influenced in their answers knowing that IQ tests often have an increase in difficulty throughout the test.

The IQ test is a good test, because it is equal for every person conducting the test which provides a good basis of comparison. An IQ test can also be conducted on a computer with minimal facial movement, where the subject only has to think and click with the mouse. This can easily be related to an operator at work. These two factors were strong enough to choose this specific test.

The sensors are not able to collect correct data

EEG signals are known to be noisy. They have high temporal resolution, but low spatial resolution. Noninvasive measurements also leave an uncertainty in signal quality. The question is how well a low cost neuroheadset really works compared to expensive equipment.

Few articles seem to have investigated how well the cheap brain sensing equipment performs compared to the more expensive. One of the most positive articles is found in [13]. This article concludes that the EEG signals from the Emotiv's Epoc are satisfactory compared to high cost technology, but it is hard to evaluate its objectiveness as the article mainly has citations from the Emotiv's web page. Another study comparing the Epoc headset to a medical device finds that the low cost headset is able to read EEG data far above chance level, but with a signal-to-noise level worse than for the medical device [12]. They encourage using Epoc in trivial and non-critical settings such as for communication and gaming, but question the reliability for use in medical settings such as for rehabilitation and prosthesis control.

The methodology is inferior

As mentioned previously, there is no accepted theory on how to easily identify workload or several other mental states from EEG signals. The methodology in this project could be inferior, and there might be other ways of identifying workload. The signals are complex. Hence, it might be that finding an easy solution to identifying workload from EEG signals also is non-existing.

The test group is too small to say any significant

A test group of ten people is good enough to spot a trend, but in order to confirm or reject any hypothesis the test group should have been larger.

Results are affected because test subjects are not used to wear the neuroheadset

Wearing a neuroheadset, perhaps for the first time, as well as taking an IQ test might result in additional stress for the test subjects. This could be a source of creating an unrealistic situation, which again can affect the participants' EEG signals. It would therefore be beneficial to let the test subjects wear the neuroheadset for a longer period of time, prior to conducting the test, or conduct several tests and see if the results are consistent.

The results would have been more evident if they had been compared to a relaxed situation
For comparing purposes, it could be of interest to let the test subjects relax while wearing the neuroheadset. As mentioned in the previous point, people might be affected by wearing a neuroheadset, and it is hard to know how good a person is at relaxing and not thinking or concentrating on something, particularly knowing that a neuroheadset is tracking your brain signals. As such, a baseline value corresponding to zero workload is difficult to determine. Once a test subject has started a test, their focus shifts to working on a problem in front of them. Comparing easy tasks with more difficult tasks gives a better basis for comparison od workload level and is the reason that a relaxing test was left out.

Although it is hard to spot a concrete pattern in the obtained results and there are several potential sources of errors, a recent paper [30] mentioned in chapter 2.3.1 reported that the focus should be on alpha band activity. If this holds, the conflicting result in the theta frequency band and the remaining unambiguous results for both beta- and theta frequency bands can be disregarded, and the obtained results on decreasing alpha power under increasing workload in the parietal lobe stands stronger.

7.1.4 Connecting to a control room simulator

During the second part of the test program, a real time application was developed to send updated values to a control room simulator. Figures 6.13, 6.14 and 6.15 show the resulting adaptive simulator. This adaptive simulator worked smoothly, and although it was implemented only as a concept demonstrator, it was possible to trigger an alarm through a lot of motoric motion. The concept demonstrator showed that it is possible to enforce a scenario in a control room simulator based on brain sensing.

The initial plan was to implement a use case with this adaptive simulator based on the results from chapter 6.3. Because no evident result could be extracted, it was not possible to implement the given use case. Therefore, no further features were included in the adaptive control room simulator. The adaptive control room simulator still shows that it is possible to integrate brain sensing in a control room simulator, which can easily be extended once an evident theory on identifying mental states is ready.

7.2 Further work

7.2.1 Ethics

Closing up on a working BCI system for a control room setting, it will be of importance to consider the ethics in order to ensure a person's privacy protection and well-being. It would probably not be beneficial to develop a BCI system where an employee feels that he is under surveillance, or that forces the employee to be fully concentrated until he is so tired that sleeping is the only solution for recovery.

This is however not a concern with respect to using brain sensing for developing better user interfaces and control room systems, seeing as the operator will in such a case have chosen to participate.The concern will be for utilizing brain sensing for operator training or in an operational control room.

It is advisable to have close communication with operators, so that a BCI which ensure all parts interests can be developed.

7.2.2 Other means of measurement for mental states

Identifying an operator's mental states could potentially be improved by obtaining additional information by combining several types of measurement methods, such as e.g. heart rate, fMRI or eye blinks, as mentioned in chapter 2.2.2 and 2.3.2.

7.2.3 Future testing

Much more work and testing needs to be conducted in order to obtain evident theories on how to identify mental states from EEG signals. Preferably the theories have to be simple enough to be implemented through algorithms so that they can be utilized in a BCI system.

To achieve this, it is advisable that the studies are conducted with a larger test group and that testing is performed by a multidisciplinary team of people representing such as; clinical neurophysiologists or neurologists, psychologists and engineers. It is also advisable to use more expensive equipment than the low cost neuroheadsets, seeing as these can affect results by not being able to detect correct EEG signals to the same extent as more expensive equipment. One should also urge to remove the potential sources of error mentioned in chapter 7.1.3.

Another thing that must be investigated trough more extensive studies is the uniqueness of each persons EEG signals. Because EEG signals are different amongst different people, initial calibration and training is very important for BCI systems that is based on recognizing events. Likewise, classification of mental states will probably also be unique for every person using the BCI. This must be investigated and atone for.

7.2.4 Motoric impact on EEG signals

It is advisable to investigate further the influence motoric movements have on EEG signals. The Control Panel can detect and distinguish 11 different facial actions, and this shows that there are a lot of recognizable actions that potentially could be filtered out. Emo Engine is capable of automatic detection of expressive actions, and it is an idea to utilize this property and get a notice if any facial movements have been recognized. If one performs a lot of testing, it might be possible to find out how much each of these events influences and improve filtering by compensate for these in a feedback loop.

7.2.5 Implementing a BCI real time application

Matlab was very useful for the scope of this project. The Emotive Epoc's interface is compatible with both Matlab and C/C++, but if a real time BCI control application is to be developed, it is advised to use C/C++ for implementation. This is because Emotiv provides more examples for C/C++ than Matlab, in addition to C/C++ being a far better language for real time programming. It will provide an opportunity of directly capture, process and send EEG data from a neuroheadset to a real time control room simulator.

As it looks today, we would most likely want to investigate how the power and frequency changes over time when identifying changes in a mental state. A change in power or frequency can easily be detected by comparing how the newest values are compared to previous values, or by evaluating the rates. Once an evident theory is ready, this needs to be implemented. It may be of interest to base an application on the idea from the simulator, and set constraints on high or low levels.

When developing a real time application, one should also keep in mind to find a good way of handling large data sets.

7.3 Final evaluation and conclusion

The purpose of this project was to investigate if detection of changes in an operator's mental state trough EEG signals can help improve user interfaces, control room systems or operator training. Through the project, we have seen that development of BCIs is an emerging field of study. A thorough technology review in chapter 2.3.2 showed that projects including brain sensing where engineers and developers are performing the projects, mostly utilizes pattern recognition in BCI systems, and is a good approach for engineers. In chapter 2.3.1 one could see this approach also can be used for mental states, because it is possible to detect a sudden given ERP as a response to a provoked external stimulus. For the purpose of this project, it was of interest to observe and analyse the state of the mind, and therefore, the focus of the project was identifying mental states through a frequency analysis. This has shown to be difficult as the research field is in an early phase of its development. Although we cannot conclude whether or not it is possible to identify workload based on the results from this project, we can spot a trend and conclude that more research and studies should be conducted. For this it is advised that a person with a neurological background performs interpretation of EEG signals.

This project has shown that once we have an evident hypothesis for identifying mental states, this can be implemented in the developed brain sensing application, which has proven to work well. The completed BCI can then be utilized for operator training or for development of control room systems, by any of the use cases developed. For use in a control room setting, one would preferably have to wait for a neuroheadset that provides all the features of Emotiv's Epoc, but is more comfortable and even easier to put on, to be developed.

In light of an increasingly technologically developing world, this project has identified the need for technology that can offer robustness to the human mind. The development of a low cost neuroheadset and the increasing utilization of these is a step in right direction to achieve this. Once a BCI that can identify mental states automatically is developed, one can only imagine the areas of application.

Appendix A: NASA Task Load Index scale

NASA Task Load Index

Please pick the member of each pair that you feel is more important for workload

mental demand	-	physical demand
mental demand	-	temporal demand
mental demand	-	performance
mental demand	-	effort
mental demand	-	frustration
physical demand	-	temporal demand
physical demand	-	performance
physical demand	-	effort
physical demand	-	frustration
temporal demand	-	performance
temporal demand	-	effort
temporal demand	-	frustration
performance	-	effort
performance	-	frustration
effort	-	frustration

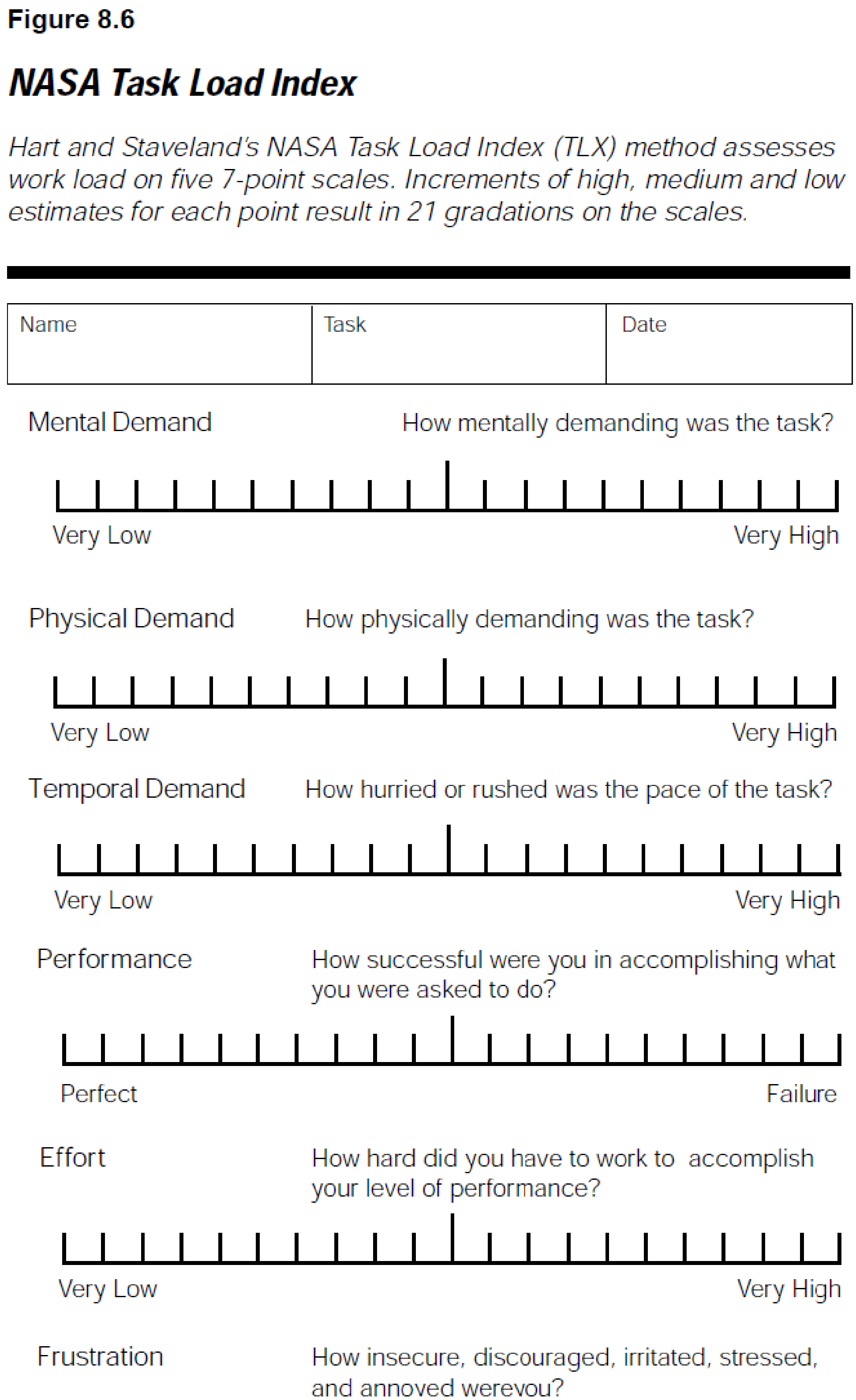


Figure 8.6

NASA Task Load Index

Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.

Name	Task	Date

Mental Demand — How mentally demanding was the task?

Very Low — Very High

Physical Demand — How physically demanding was the task?

Very Low — Very High

Temporal Demand — How hurried or rushed was the pace of the task?

Very Low — Very High

Performance — How successful were you in accomplishing what you were asked to do?

Perfect — Failure

Effort — How hard did you have to work to accomplish your level of performance?

Very Low — Very High

Frustration — How insecure, discouraged, irritated, stressed, and annoved werevou?

Figure A.1: NASA-TLX

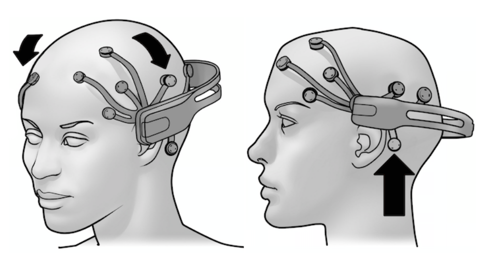
Appendix B: Instructions and information

Instructions and safety information on the experiment "Identifying workload through EEG-signals"

Information and safety: This consent form is written for test subjects being part of an experiment performed in conjunction with a master thesis at the Institute of cybernetics NTNU, spring 2015. The goal of the experiment is to recognize workload in EEG signals after the subject has conducted an online IQ test. All results from the experiment will be made anonymous, so that it will be impossible to trace resulting IQ or other experimental results back to the correct subject. The experiment is non-invasive and considered safe.

Instructions: To obtain an individual estimate of workload in the test, the form NASA-TLX needs to be filled out. The form has six subscales which each represent different parts of what one can define as workload as a concept; mental demand, physical demand, temporal demand, performance, effort and frustration. The form has two parts. Part one is to be filled out prior to the test. In this part, all the six sub-scales are paired up, giving a total of 15 pairs. Please pick the member of each pair that you feel is more important for workload.

After filling out part one of the NASA-TLX form, an EEG headset will be placed on you head. The felt pads are soaked in a contact lens saline solution. Place the headset on your head according to figure 1.



Figur 1: Correct placement of neuroheadset (courtesy of Emotiv)

The online IQ test used is Mensa Norway's online IQ test and is a figure reasoning test with 35 tasks. You will have 25 minutes to solve the tasks. After the time is up, your IQ will be calculated. The online IQ test is not a scientifically designed test, but will provide a good indication of your IQ.

Please follow the instructors lead to complete the test.

After the test is finished, you will be asked to fill out part two of the NASA-TLX form twice. In this part, you will be asked to weigth the six subscales in the form from 0 to 20 ranging from very low to very high, to choose how you found the test. You will need to do this twice. Once for the first 20 tasks of the IQ test and once for the last 15 tasks.

Please complete the following:

Place, date:

Name:

Age:

Gender:

Previous or current neurological conditions or disorders (yes/no):

I hereby confirm that I have read and understood the content in the form "Instructions and safety information on workload experiment", and I consent taking part in this experiment.

Signature: ________________________________

Appendix C: Results from IQ test

I Frequencies for test subjects

Table C.1: Mean frequencies in IQ test for test subjects

	1st Alpha frequency	2nd Alpha frequency	1st Beta frequency	2nd Beta frequency	1st Theta frequency	2nd Theta frequency
SUB 1						
Frontal	9.9827	10.0012	20.0174	19.9621	5.5383	5.4639
Parietal	10.1582	10.1852	20.9976	21.3440	5.6605	5.5748
Occipital	10.1635	10.1611	20.8545	20.3911	5.6797	5.6592
All	10.0539	10.0754	20.3809	20.3039	5.5894	5.5395
SUB 2						
Frontal	10.1371	10.1649	19.8582	20.6653	5.5591	5.6228
Parietal	10.1407	10.4356	19.9137	21.4700	5.5569	5.6221
Occipital	10.1329	10.2559	19.7963	20.7239	5.5594	5.6770
All	10.1370	10.2252	19.8571	20.8092	5.5588	5.6317
SUB 3						
Frontal	10.1037	10.0744	19.7182	20.0493	5.5044	5.5231
Parietal	10.3432	10.2826	20.6765	20.5967	5.8539	5.8667
Occipital	10.2745	10.2463	19.4455	19.7360	5.8341	5.8291
All	10.1721	10.1378	19.8325	20.0883	5.6176	5.6313

	1st Alpha frequency	**2nd Alpha frequency**	**1st Beta frequency**	**2nd Beta frequency**	**1st Theta frequency**	**2nd Theta frequency**
SUB 4						
Frontal	10.2369	10.3143	20.6056	20.6965	5.5916	5.5676
Parietal	10.5946	10.6708	22.3571	21.3258	5.7620	5.7182
Occipital	10.4300	10.5900	20.5759	20.6240	5.6595	5.7496
All	10.3287	10.4197	20.8926	20.7893	5.6313	5.6230
SUB 5						
Frontal	9.6641	9.6447	20.1233	19.2375	5.5813	5.5272
Parietal	10.0223	10.0000	20.4143	19.8060	5.4831	5.3900
Occipital	10.0217	9.8683	20.4769	19.5844	5.7036	5.6670
All	9.7834	9.7412	20.2307	19.3901	5.5853	5.5277
SUB 6						
Frontal	9.9779	9.9484	20.4904	20.3367	5.4000	5.3723
Parietal	10.5280	10.4705	22.1806	22.5145	5.7307	5.7667
Occipital	10.2840	10.3887	21.4849	21.8368	5.8124	5.8638
All	10.0836	10.0759	20.8249	20.8074	5.5053	5.4975
SUB 7						
Frontal	10.1002	10.4090	19.3831	20.8484	5.4911	5.6114
Parietal	10.0798	10.6089	19.3776	21.0762	5.5209	5.8996
Occipital	10.1130	10.6919	19.5090	20.9374	5.5006	5.9196
All	10.0989	10.4895	19.4031	20.9012	5.4976	5.7108

	1st Alpha frequency	**2nd Alpha frequency**	**1st Beta frequency**	**2nd Beta frequency**	**1st Theta frequency**	**2nd Theta frequency**
SUB 8						
Frontal	10.1613	10.6071	20.0781	21.3070	5.5560	5.5812
Parietal	10.1808	10.7419	20.0803	21.8057	5.5562	5.7644
Occipital	10.2571	10.8189	20.0889	21.0418	5.5658	5.8005
All	10.1805	10.6648	20.0803	21.3459	5.5576	5.6483
SUB 9						
Frontal	10.0991	10.0991	19.8728	21.3273	5.5270	5.5341
Parietal	10.1672	10.6045	20.0139	21.7189	5.5332	5.8097
Occipital	10.1915	10.7118	20.0458	21.6845	5.5397	5.7898
All	10.1258	10.2855	19.9252	21.4521	5.5302	5.6227
SUB 10						
Frontal	10.3429	10.3526	20.9358	20.5296	5.5877	5.6896
Parietal	10.6164	10.6345	21.5440	21.2727	5.8956	5.7861
Occipital	10.5277	10.4957	20.9955	20.4382	5.8327	5.6829
All	10.4193	10.4235	21.0471	20.6382	5.6799	5.7046

II Power for test subjects

Table C.2: Mean power in IQ test for test subjects

	1st Alpha power	**2nd Alpha power**	**1st Beta power**	**2nd Beta power**	**1st Theta power**	**2nd Theta power**
SUB 1						
Frontal	455.7816	848.6176	109.2893	210.2314	1.6248e+03	2.7401e+03
Parietal	39.6043	36.9039	13.9873	16.4902	104.0253	107.8603
Occipital	57.4339	120.3938	16.5278	35.3015	126.6032	306.6142
All	292.8766	482.4195	71.6766	124.1025	1.0210e+03	1.7269e+03
SUB 2						
Frontal	1.3215e+03	214.6392	385.4500	75.3960	4.1285e+03	436.6598
Parietal	1.2863e+03	161.2113	382.7460	70.7609	3.9562e+03	183.8434
Occipital	1.1002e+03	126.5404	316.8782	37.1395	3.4372e+03	149.2648
All	1.2788e+03	191.0514	373.5707	68.2474	3.9846e+03	346.6246
SUB 3						
Frontal	271.6456	250.7380	75.5473	75.6474	1.1188e+03	1.1354e+03
Parietal	66.1309	97.8567	30.1067	41.4682	66.1918	94.9911
Occipital	105.3023	148.1378	39.4973	50.6443	138.6230	174.9532
All	209.6693	208.1578	61.9655	65.7837	780.0172	801.9325
SUB 4						
Frontal	157.9497	130.8607	66.9256	54.7110	495.2946	464.9628
Parietal	130.6111	84.3005	127.7713	45.8095	119.7894	91.8820
Occipital	132.8424	101.8050	44.7101	36.5676	150.1207	123.6014
All	149.2087	118.2580	73.3640	50.2035	375.1814	345.8891

	1st Alpha frequency	**2nd Alpha frequency**	**1st Beta frequency**	**2nd Beta frequency**	**1st Theta frequency**	**2nd Theta frequency**
SUB 5						
Frontal	860.7902	2.6962e+03	137.4273	417.5232	2.5124e+03	9.8545e+03
Parietal	381.5216	317.9030	80.6963	53.1694	938.7107	693.9316
Occipital	404.9379	439.3079	90.7096	71.1257	765.5045	697.7680
All	704.9368	1.9237e+03	120.1859	299.0646	1.9589e+03	6.8016e+03
SUB 6						
Frontal	211.0563	250.9255	36.6337	42.3225	1.4563e+03	1.7443e+03
Parietal	39.9300	39.8092	43.5497	38.4221	55.8318	54.7918
Occipital	86.0932	96.5572	47.0772	55.6609	104.9371	93.9739
All	172.7788	203.6662	39.1613	44.3931	1.0833e+03	1.2906e+03
SUB 7						
Frontal	735.8808	256.7954	157.0870	76.0240	2.6602e+03	602.4659
Parietal	773.8226	165.9413	171.2605	69.4855	2.6745e+03	120.7615
Occipital	627.8710	182.3342	145.2285	76.5539	2.1283e+03	132.4777
All	724.2028	229.2428	157.4728	75.0225	2.5739e+03	443.8505
SUB 8						
Frontal	731.2034	137.1614	216.1254	70.1986	2.2326e+03	232.8261
Parietal	665.0929	121.8233	203.6933	94.6831	1.9612e+03	100.1821
Occipital	658.5128	194.6592	198.8441	87.7730	1.7336e+03	134.1131
All	708.0699	144.1880	211.1732	77.2084	2.1042e+03	194.2666
SUB 9						
Frontal	885.4818	250.8257	226.1367	80.3258	2.8928e+03	822.8859
Parietal	791.2142	171.8301	216.6186	80.7372	2.3337e+03	107.9760
Occipital	683.0134	165.6179	186.6502	69.8593	2.0059e+03	113.9344
All	836.0258	223.4585	217.9692	78.6500	2.6518e+03	585.5757

	1st Alpha frequency	**2nd Alpha frequency**	**1st Beta frequency**	**2nd Beta frequency**	**1st Theta frequency**	**2nd Theta frequency**
SUB 10						
Frontal	244.4063	157.2926	102.7785	57.0787	1.0035e+03	256.4259
Parietal	222.9764	127.9808	243.4773	108.3414	158.4019	116.4273
Occipital	215.7769	174.6672	117.8212	73.2946	225.4589	233.6818
All	236.0631	155.3031	128.7354	68.3251	733.0065	229.3021

III nonparametric results

Table C.3: Nonparametric results of Frontal lobe

Frontal	**Alpha frequency**	**Beta frequency**	**Theta frequency**	**Alpha power**	**Beta power**	**Theta power**
Test sub. 1	Up	Down	Down	Up	Up	Up
Test sub. 2	Up	Up	Up	Down	Down	Down
Test sub. 3	Down	Up	Up	Down	Up	Up
Test sub. 4	Up	Up	Down	Down	Down	Down
Test sub. 5	Down	Down	Down	Up	Up	Up
Test sub. 6	Down	Down	Down	Up	Up	Up
Test sub. 7	Up	Up	Up	Down	Down	Down
Test sub. 8	Up	Up	Up	Down	Down	Down
Test sub. 9	Eq	Up	Up	Down	Down	Down
Test sub. 10	Up	Down	Up	Down	Down	Down

Table C.4: Nonparametric results of Occipital lobe

Occipital	**Alpha frequency**	**Beta frequency**	**Theta frequency**	**Alpha power**	**Beta power**	**Theta power**
Test sub. 1	Down	Down	Down	Up	Up	Up
Test sub. 2	Up	Up	Up	Down	Down	Down
Test sub. 3	Down	Up	Down	Up	Up	Up
Test sub. 4	Up	Up	Up	Down	Down	Down
Test sub. 5	Down	Down	Down	Up	Down	Down
Test sub. 6	Up	Up	Up	Up	Up	Down
Test sub. 7	Up	Up	Up	Down	Down	Down
Test sub. 8	Up	Up	Up	Down	Down	Down
Test sub. 9	Up	Up	Up	Down	Down	Down
Test sub. 10	Down	Down	Down	Down	Down	Up

Table C.5: Nonparametric results of entire brain

All	**Alpha frequency**	**Beta frequency**	**Theta frequency**	**Alpha power**	**Beta power**	**Theta power**
Test sub. 1	Up	Down	Down	Up	Up	Up
Test sub. 2	Up	Up	Up	Down	Down	Down
Test sub. 3	Down	Up	Up	Down	Up	Up
Test sub. 4	Up	Down	Down	Down	Down	down
Test sub. 5	Down	Down	Down	Up	Up	Up
Test sub. 6	Down	Down	Down	Up	Up	Up
Test sub. 7	Up	Up	Up	Down	Down	Down
Test sub. 8	Up	Up	Up	Down	Down	Down
Test sub. 9	Up	Up	Up	Down	Down	Down
Test sub. 10	Up	Down	Up	Down	Down	Down

Appendix D: Kolmogorov–Smirnov test

I First part of IQ-test

Table D.1: Results on Kolmogorov–Smirnov test for first part of IQ-test

First part	**Alpha frequency**	**Beta frequency**	**Theta frequency**	**Alpha power**	**Beta power**	**Theta power**
Frontal	0	1	1	1	1	1
Parietal	1	1	1	1	1	1
Occipital	0	1	1	1	1	1
All	1	1	1	1	1	1

II Second part of IQ-test

Table D.2: Results on Kolmogorov–Smirnov test for second part of IQ-test

Second part	**Alpha frequency**	**Beta frequency**	**Theta frequency**	**Alpha power**	**Beta power**	**Theta power**
Frontal	0	1	1	1	1	1
Parietal	1	1	1	1	1	1
Occipital	0	1	1	1	1	1
All	1	1	1	1	1	1

Appendix E: Statistics

I Hypothesis testing

I.I Null hypothesis and alternative hypothesis

A null hypothesis, denoted H_0, is an assumption that one would want to test in order to find out if it holds or if it should be rejected. The null hypothesis is often formulated to be "no change is expected to occur". The alternative to the null hypothesis is the alternative hypothesis, denoted H_1.

I.II One- and two-tailed test

When testing a null hypothesis, a one-tailed test is a test where the pair of null hypothesis and alternative hypothesis is given by

$$H_0 : \theta = \theta_0$$

$$H_1 : \theta > \theta_0$$

or by

$$H_0 : \theta = \theta_0$$

$$H_1 : \theta < \theta_0$$

A two-tailed test is a test where the pair of null hypothesis and alternative hypothesis is given by

$$H_0 : \theta = \theta_0$$

$$H_1 : \theta \neq \theta_0$$

The null hypothesis will therefore be rejected in the two-tailed test either if $\theta > \theta_0$ or $\theta < \theta_0$ [49].

I.III Significance level

When investigating if we should accept or reject a given null hypothesis, we want to evaluate the probability of getting a given result or a more extreme result. This is done by predefining a significance level α. If the resulting probability from a test is bellow the significance level, we can say that we have found a significant result that is strong enough to reject the null hypothesis. Significance levels are often found to be in the interval $[0.01,\ 0.1]$, depending on how evident the result needs to be in order to reject the null hypothesis.

II Binomial distribution

When doing an experiment, one often label an outcome with success or failure. In this context, a **Bernoulli process** is defined as a process where the following four properties are fulfilled [49]

- The experiment consist of repeated trials
- Each trial result in an outcome that may be classified as a success or failure
- The probability of success, denoted by p, remains constant from trial to trial
- The repeated trials are independent

The probability distribution of getting X successes in a Bernoulli process is called a **binomial distribution**, denoted $b(x; n, p)$. When a trial in a Bernoulli process has n independent trials, a probability for success p, and the probability of failure is *q=p-1*, the binomial distribution is given by [49]

$$b(x;n,p) = \binom{n}{x} \cdot p^x q^{n-x}, \quad x = 0,1,2,...,n \tag{E.1}$$

If it is of interest to find the probability of the number of successes X being r or less, P(X<r), binomial sums are used

$$B(r;n,p) = \sum_{x=0}^{r} b(x;n,p) \tag{E.2}$$

This can be used in hypothesis testing to find the probability of a given, or a more extreme result.

III Kolmogorov–Smirnov test

A Kolmogorov–Smirnov test is based on goodness of fit, and can be used to test a data set for normality, with the following null hypothesis

$$H_0: \text{ The data sampled are from a normal distribution}$$

One will then expect the data set of N random samples to be fairly close to a normal distribution, and comparing is done by finding the largest difference between $F_n(x)$, the empirical cummulative distribution, and $F(x)$, is the hypothetical cummulative distribution

$$D_n = \sup_x |F_n(x) - F(x)| \tag{E.3}$$

A decision rule is used to test H_0:

$$\delta = \begin{cases} H_0: & D_n \leq c \\ H_1: & D_n > c \end{cases} \tag{E.4}$$

Where c depends on the significance level α, which can be found in a standard table for a Kolmogorov–Smirnov test, e.g. table 1 in [33].

IV Wilcoxon signed-rank test

The Wilcoxon signed-rank test is a nonparametric test with a null hypothesis saying that the median difference between the pair of two datasets are zero, $H_0 : \tilde{\mu}_1 = \tilde{\mu}_2$. The two data sets are nominal variables, n_1 and n_2, and the test is conducted by taking the absolute value of the measurement variables in these two datasets, sorting them in ascending order, and give each a rank of 1,2,..., $n_1 + n_2$. If two values are equal, both receives the mean of the two ranks they would be assigned if they were not equal. The sum of ranks for all measurement values in n_1 is denoted w_1 and The sum of ranks for all measurement values in n_2 is denoted w_2. As both w_1 and w_2 will vary, we can look upon them as random variables W_1 and W_2.

The null hypothesis will be rejected if W_1 is large and W_2 is small, because then $\tilde{\mu}_1 > \tilde{\mu}_2$. The same logic follows if W_2 is large and W_1 is small, because then $\tilde{\mu}_1 < \tilde{\mu}_2$ which also leads to a rejection of the null hypothesis [49].

In practice, the two values

$$u_1 = w_1 - \frac{n_1(n_1+1)}{2} \quad \text{or} \quad u_2 = w_2 - \frac{n_2(n_2+1)}{2}$$

are used to decide if the null hypothesis H_0 should be rejected or not, by checking if they are less or equal to a standard Wilcoxon signed-rank test table of critical values found in e.g. table A17 in [49].

Appendix F: Navigating the appended .zip folder

I Contents

The folder "*brainSensingApplication.zip*", is appended to this thesis. The .zip folder includes all Matlab files for the brain sensing application developed in this project.

Files needed to acquire raw EEG data from Epoc is not open source and therefore not available in the .zip folder. These files include example code, .dll files and libraries and are available for download from Emotiv's web page: www.emotiv.com.

II Brain sensing application

To use the brain sensing application run "*brainSensingApplication.m*" from Matlab. An example .txt file with EEG data acquired from Epoc is provided and can be used for testing the brain sensing application.

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