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“Headband for Reading and Processing Brain Signals”

A Dissertation for Master of Science in Electrical and Computer Engineering

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A Dissertation
for Graduate Study in MSc Program
Master of Science in Electrical and Computer Engineering

"Headband for Reading and Processing Brain Signals"

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INSTITUTO DE SISTEMAS E ROBÓTICA
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I would like to dedicate this thesis to my family. My loving parents and brother, whose support and help through this stage of my life has been essential and without it I wouldn't be able to conclude this part of my student career.
Family is always going to be there. The material things, they come and go.

Acronyms and symbols

Abbreviation	Meaning
ADC	Analog to Digital Converter
ANN	Artificial Neural Network
BCI	Brain Computer Interface
BLE	Bluetooth Low-Energy
BMI	Brain-Machine Interface
CM	Confusion Matrix
EEG	Electroencephalography
IOT	Internet Of Things
ISR	Institute of Systems and Robotics
LDA	Linear Discriminant Analysis
LSL	Lab Streaming Layer
MMI	Mind-Machine Interface
MRI	Magnetic Resonance Imaging
NN	Neural Networks
PSD	Power Specctral Density
SR	Sampling Rate
SDK	Software Development Kit
SVM	Support Vector Machine
UC	University of Coimbra

Thanks

One looks back with appreciation to the brilliant teachers, but with gratitude to those who touched our human feelings. The curriculum is so much necessary raw material, but warmth is the vital element for the growing plant and for the soul of the child.
(Carl Jung)

I would like to thank my advisors Paulo Coimbra and Mateus Mendes, and all my friends and colleges at the lab for guiding and supporting me through this entire process.

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Your ideas, feedback and help have been absolutely invaluable to me and I shall never forget all the moments we shared, thank you for everything.

Abstract

Start by doing what's necessary, then do what's possible, and suddenly you are doing the impossible.
(Francis of Assisi)

Brain-wave measurement sensors, EEG based, have been popularized lately, becoming ever more precise and cheap. Nowadays, anyone is able to measure brain waves and patterns of someone outside of medical laboratories. Besides analyzing brain signals, applications can even be implemented as a way of controlling electronic devices, know as a brain-computer interface. Brain-computer interface along with the "Internet of Things", are becoming evermore popular as people have accepted wearables and smart devices as a part of our everyday life. In this thesis, I will attempt to explore EEG to investigate EEG signals, and build a proof of concept application able to detect if the user has eyes open or closed using machine learning algorithms, with good detection accuracy. The end goal is an interface between a driver using a BCI headband and a smart device, where brain signals are being constantly collected and processed, in the event that the driver becomes sleepy, the smart device will promptly send an auditory signal warning the driver of danger.

Keywords: BCI - Brain Computer Interface, IOT - Internet of Things, EEG - Electroencephalography, Brain Signals, EEG signals, Machine Learning

Resumo

Our lives begin to end the day we become silent about things that matter.
(Martin Luther King, Jr.)

Sensores de leitura de ondas cerebrais, baseados em EEG, tornaram-se populares ultimamente, tornando-se cada vez mais precisos e baratos. Nos dias de hoje, qualquer pessoa é capaz de medir ondas cerebrais e padrões de qualquer indivíduo fora dos laboratórios médicos. Para além de analizar os sinais cerebrais, as aplicações podem até implementar um método de controlar dispositivos electrónicos, conhecido como Brain Computer Interface. Brain-computer interface e "Internet of Things," estão a tornar-se cada vez mais populares já que as pessoas têm aceitado bem dispositivos electrónicos e dispositivos electrónicos inteligentes como parte do seu quotidiano. Nesta tese, proponho-me a explorar dispositivos EEG e investigar sinais EEG, e desenvolver uma aplicação prova de conceito capaz de detectar se o utilizador têm os olhos abertos ou fechados utilizando algoritmos de inteligência artificial, com boa precisão de deteção. O obejectivo principal será o desenvolvimento de um interface entre um condutor utilizando uma BCI headband e um dispositivo electrónico inteligente, onde os sinais cerebrais estão a ser constantemente colectados e analizados, e numa eventual ocorrencia onde o condutor apresenta sonolência, o dispositivo electrónico inteligente deverá prontamente emitir um sinal sonoro avisando o utilizador do perigo.

Keywords: BCI - Brain Computer Interface, IOT - Internet of Things, EEG - Electroencephalography, Brain Signals, EEG signals, Machine Learning

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Chapter 1

Introduction

An investment in knowledge pays the best interest.
(Benjamin Franklin)

1.1 Motivation

The task of driving is a distinct and complex task requiring perceptual, cognitive, and decision-making skills. Falling asleep behind the wheel is extremely dangerous, driving while fatigued impairs the ability to drive safely. Response time, attention, and decision-making capabilities all suffer when sleep-deprived. A certain level of alertness is essential to guarantee the safekeeping of the driver and other road users. Reducing the extent of sleep-deprived driving is critical to improve the safety of roads.

According to the World Health Organization (WHO) over 1.35 million people die each year on road accidents, it is also now the leading cause of death for children and yound adoults aged to 29 years old, and the 8th leading cause of death for people of all ages [1]. In a recent report [2], between 20 to 30% of road accidents are caused by tiredness.

Available techniques for detecting drowsiness and sleepiness in drivers can be generally divided into the following categories: sensing of driver operation, sensing of vehicle response, monitoring the response of driver, ranging from lane detection mechanisms, traffic analysis vision systems, sensing of physiological characteristics and tiredness estimation systems [3]. Available physical detection methods could involve changes in heart rate, the open and closure of the eyes and electroencephalographic (EEG) the later being known to have a positive correlation with sleep patterns [4].

The existence of a real time system that supervises driver drowsiness and warns him of potential threats can be very useful, potentially avoiding accidents. However, this system should not interfere with the driving ability, to ensure the safety of the driver and those around him.

1.2 Objectives

This thesis proposes to use a low-cost EEG device, along with supporting portable hardware and software, to design and validate a system to detect if a drirver has his eyes open or closed, and emit a sound alert, in real-time. Such a system could be used by truck drivers, aircraft pilots or a regular driver to detect and warn drivers of their drowsiness and inattention with a very quick response time. This system would not need to monitor driving patterns nor would it affect the field of view and could be paired, although not required, with traditional computer vision detection systems for peak accuracy, such as feature based detection using on-board cameras [5]. This system will record multiple EEG signals via the available dry sensors and apply filters to split the signal into frequencies. Time-frequency analysis will be implemented to monitor changes in these frequencies over time. When the EEG transitions resemble sleep, the device will produce an audible alarm.

1.3 Work Developed

During development, an algorithm for EEG channel analysis, for the headband was developed, where the bluetooth data packages are gathered and shown on the screen in real-time, another algorithm was developed for recording user EEG data. A NN classifier algorithm was created that takes this data and give a prediction if the user is with eyes closed or open, and sends an auditory signal to warn the user, if the eyes closed state is predicted. A database was produced and can be used in future similar projects, containing user data of closed and open eyes, of 20 seconds continuous periods, for each of 3 subjects, obtained in a lab environment. Since the muse headband team does not provide programming software to work with, any packages and projects with this particular headband is rather scarce, the developed algorithms can improve this research field with this particular headband.

1.4 Dissertation Structure

Chapter 1, "Introduction", introduces Brain Computer interface and its components. Also, this chapter explores different techniques of the brain measuring activities. Finally, this chapter discusses the research questions of this thesis. Chapter 2, "Background and Related Works", shows the biomedical and system background, and discusses the related works. In this chapter, brain anatomy and brain lobes activity will be discussed. Also, it explains EEG signals in more details and discusses EEG signal processing, EEG sleep patterns, driver fatigue as well as discuss similar work and contributions. Chapter 3, "Development", this chapter compares different EEG headsets and why this thesis chooses Muse Headband, discusses classification methods, introduces neural networks and discusses how the work was developed and the database produced.

Chapter 4, "Conclusion", concludes the thesis, and discusses its limitations. Also, in this chapter, results are discussed and compared to other related research, alternatives are given on how to obtain better results and what other methods available could be used.

Chapter 2

Background and Related Works

Happiness lies in the joy of achievement and the thrill of creative effort.
(Franklin D. Roosevelt)

2.1 Brain Computer Intrerface

Brain-computer interfaces (BCI) acquire brain signals, analyze them, and translate them into commands that are relayed to output devices that carry out desired actions. The neural activity can be measured using invasive or noninvasive techniques. BCI applications that have been implemented vary in use, such as applications for disabled people to interact with computational devices, in gaming to play games with their thoughts, social applications to capture feelings and emotions, and application for human brain activities [6].

A BCI system, Figure - 2.1, consists of three sequential components: signal acquisition, making sence of the extracted signals through feature extraction and feature translation, using these idicators to preform a task . These are controlled by an application that defines the onset and timing of operation, the details of signal processing, the nature of the device commands, and the oversight of performance. An effective operating protocol allows a BCI system to be flexible and to serve the specific needs of each user.

- **Signal acquisition**, the measurement of brain signals using a particular sensor modal-

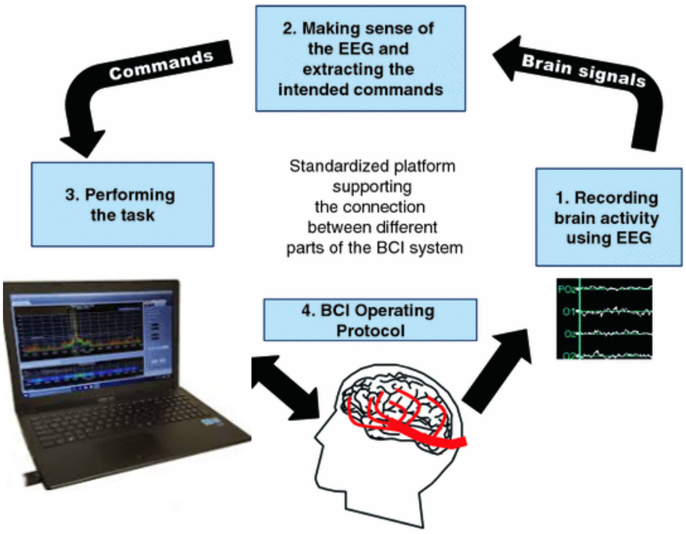


Figure 2.1: BCI System

ity (eg, scalp or intracranial electrodes for electrophysiologic activity, fMRI for metabolic activity). The signals are amplified to levels suitable for electronic processing (and they may also be subjected to filtering to remove electrical noise or other undesirable signal characteristics). The signals are then digitized and transmitted to a computer.

- **Feature extraction**, the process of analyzing the digital signals to distinguish pertinent signal characteristics (ie, signal features related to the person's intent).

- **Feature Translation**, the resulting signal features are then passed to the feature translation algorithm, which converts the features into the appropriate commands for the output device (ie, commands that accomplish the user's intent). The translation algorithm should be dynamic to accommodate and adapt to spontaneous or learned changes in the signal features and to ensure that the user's possible range of feature values covers the full range of device control.

- **Device Output**, the commands from the feature translation algorithm operate the external device, providing functions such as letter selection, cursor control, robotic arm operation, and so forth. The device operation provides feedback to the user, thus closing the control loop.

In short BCI, refers to a system that translates data from the brain to an external device. To undestand this type of communication, it is primarily necessary to measure the brain neural activity.

2.1.1 Measuring brain activity

Magnetic Resonance Imaging

Magnetic resonance imaging (MRI) of the brain is a safe and painless test that uses a magnetic field and radio waves to produce detailed images of the brain and the brain stem. It does not use radiation.

This technique requires an MRI bed to scan a subject, which limits space movement and due to the magnet effects, metallic items are not allowed during the scan which limit its applications. It takes several seconds, the data collection is slowed down.

Functional Magnetic Resonance Imaging

An FMRI-BCI system is a special MRI technology that measures brain activity by detecting changes associated with blood flow. Spatially localized brain activity is measured by fMRI using the BOLD effect which is the neurovascular response to electric brain activity. Usually, Echo Planar Imaging (EPI) sequences are applied to acquire functional images when the subject is performing a mental task or imagery. Images are reconstructed, distortion corrected, and averaged by the signal acquisition component. The signal analysis component retrieves the data, and performs data preprocessing, such as including 3D motion correction, and statistical analysis. The signal time series of interactively selectable regions of interest are then exported to the custom-made visualization software (signal feedback component) which provides feedback to the subject using video projection. FMRI scans have poor temporal resolution. Temporal resolution refers to the accuracy of the scanner in relation of time: or how quickly the scanner can detect changes in brain activity. However, the temporal resolution, temporal resolution refers to the accuracy of the scanner in relation of time (how quickly the scanner can detect changes in brain activity), is limited by a blurred intrinsic hemodynamic response and a finite signal-to-noise ratio.

Magnetoencephalography

MEG is the primary process through which central nervous system (CNS) neuronal activity can be detected, cataloged, and analyzed. MEG identifies the very small magnetic fields that are created by infinitesimal electric currents flowing throughout CNS neurons during different mental activities. MEG essentially works because neuromagnetic signals penetrate the skull and scalp without being distorted. A magnetic source image (MSI) is created when MEG information is superimposed on a magnetic resonance image. The ability of the MEG process to identify mental activity with pinpoint accuracy is accomplished with the use of SQUIDS (superconducting quantum interference devices). This technique allows capturing MEG of the head efficiently and rapidly. Also, this technique is non-invasive and can be used as complement for other techniques such as EEG and fMRI. Due to the fact that MEG uses magnetic fields, this technique makes less distortion than the electric fields. However, the same restriction applied on fMRI and MRI can be applied to MEG due the to its sensitivity metallic objects.

Electroencephalogram

EEG is the most commonly used technique to measure this activity: electrodes are placed on the scalp and can be used in pairs to measure the electrical differential. The EEG technique is one of the most studied non-invasive interfaces as it has a fine temporal resolution. The main advantages of EEG lie in the relatively low setup price, possibility of portability and relative ease of use. Among the main drawbacks of EEG is the quality of spatial resolution that tends to be poor. Only certain types of activity in the superficial layers of the brain can be measured and the amplitude of the electrical activity is in the microvolts. EEG is a weak signal and needs to be amplified in order to be displayed or stored on a computer. In a digital acquisition system the analog signal is digitized and typically sampled at a rate of 256 to 512 Hz. Two approaches to recording the EEG signal are invasive and non-invasive. In the invasive approach, Electrocorticography (ECoG), the electrode is implanted inside the human brain, which requires surgery. In a non-invasive approach, electrodes are placed on the surface of the skull, which have benefits such as risk free, easy setting, and repeating measurement. In addition, it is more favorable in developing and designing application for normal people. The focus of this thesis will be based on this non-invasive EEG technique.

2.1.2 Signal acquisition

Brain signals vary greatly between people and everyday in a person. This is due to the low spatial resolution of scalp EEG and to the fact that the measurement of EEG is indirect. This means that averaging is required to obtain reliable measurements, which in turn slows down the speed at which EEG can be processed and used to detect phenomena and results in a low bitrate. The bitrate represents the amount of information transmitted by the BCI per minute. The person, who wants to use a BCI-based system should be trained to produce the stable brain patterns the more training the user undergoes or the more training trials are captured, the faster the detection can be made [7]. This training can require hours and days of repetitive practice. We can split the BCI architecture into synchronous and asynchronous systems.

In synchronous (or system-paced) BCIs the commands are imposed by the system, which is restricted to a predefined time frame, this is a cue based BCI. These systems include two stages. First stage requires the subject to perform mental tasks (e.g. imagination of tongue movement), in order for the system to collect a sufficient amount of supervised data. At this stage no feedback is provided to the user. The acquired data is processed offline, and allows defining features, classifiers and their parameters. Once the classification accuracy is sufficient from the offline learning, a second, supervised stage is proposed: the user is asked on the tasks to perform and now receives feedback on the result of the classification.

In contrast, in asynchronous (self-paced) BCIs the commands are issued at any time whenever the user decides, this is a self paced system which operates independently of a cue stimulus.

Still, the synchronous setting remains common, as the performance of such BCIs can easily be evaluated, table 2.1, thus making this setting desirable for experiments and for comparing system in an in the lab setting. Moreover, a continuous classification (required for asynchronous systems) greatly increases the computational requirements towards achieving a real-time BCI system.

Training a BCI is a slow and tedious process, it may take from 10 minutes to several hours, varying from system to system.

2.2 Electrodes Placement

There are different system placements of electrodes on the scalp. There is the 10/20 system

Table 2.1: Synchronous vs Asynchronous BCI

	Advantages	Disadvantages
Synchronous BCI	Easier control for user artifacts: allotted time to move or blink eyes. System knows ahead off time when the command from the user will be received	Commands are imposed by the system, user cannot choose when to perform an action
Asynchronous BCI	Can be operated on free will of the user	More prone to noise by the user: involuntary movement of eyes and blinks. Computationally more demanding as it provides continuous classification in real-time

which has 21 electrodes, the system 10/10 system which has 81 electrodes, and the 10/5 system which has 300 electrodes. We will use the 10/20 system. The numbers 10 and 20 in the 10/20 system refer to the distance between adjacent electrodes, which is 10% or 20% of the total front back or right-left distance of the skull. The positioning of the EEG electrodes on the scalp, that we will focus on are: in the forehead, correspondant to Fp1 and Fp2, and the back of the ears, A1 and A2, see figure 2.2.

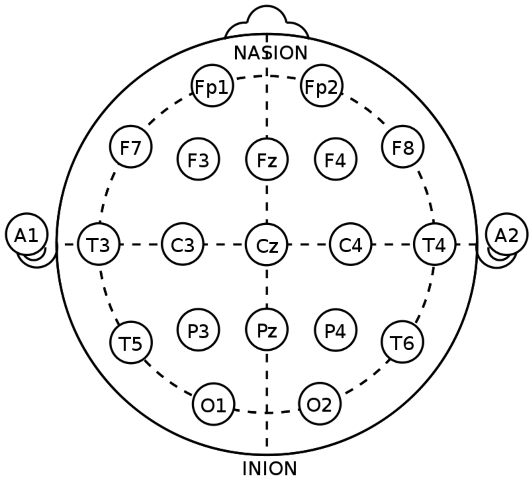


Figure 2.2: Eletrode placement 10-20 system. [1]

2.3 EEG Signals

In 1924 a German physiologist and psychiatrist, Hans Berger, recorded EEG signals for the first time on human beings and introduced alpha and beta waves. Hangs Berger also introduced the term "electroencephalogram". In the mid- 1930s, Alfred Loomis showed that in humans EEG patterns dramatically changed during a night's sleep. In most of EEG studies, usually, alpha, beta, theta and delta waves are used for sleep studies. Alpha and beta waves can be used to represent conscious states, while theta and delta waves are mostly used to represent unconscious states. Alpha waves significantly increase during closed eyes and eyes blinking in relax and active states [8]. While, drowsy, under stress or heavy mental work load the alpha wave power decreases and the theta band power increases [9]. Hence, alpha, beta, theta and delta band can be used to measure the drowsiness.

[1]https://en.wikipedia.org/wiki/10%E2%80%9320_system_(EEG)

Different electrical frequencies can be linked to actions and different stages of consciouses. This has been done by observing subjects performing different tasks, while recording their EEG.

- Gamma waves are in the frequency range of 31Hz and up. It is thought that it reflects the mechanism of consciousness. Beta and gamma waves together have been associated with attention, perception, and cognition [9].

- Beta waves are in the frequency range of 12 and 30 Hz, but are often divided into 1 and 2 to get a more specific range. Small waves associated with focused concentration and best defined in central and frontal areas. When resisting or suppressing movement, or solving a math task, there is an increase of beta activity [9].

- Alpha waves, ranging from 7.5 to 12 Hz, are slower and associated with relaxation and disengagement. Thinking of something peaceful with eyes closed should give an increase of alpha activity. Most profound in the back of the head and in the frontal lobe [9].

- Theta waves, ranging from 3.5 to 7.5 Hz, are linked to inefficiency, daydreaming, and the very lowest waves of theta represent the fine line between being awake or in a sleep state. Theta arises from emotional stress, especially frustration or disappointment [9].

- Delta waves, ranging from 0.5 to 3.5 Hz, are the slowest waves and occurs when sleeping. If these waves occur in the awake state, it thought to indicate physical defects in the brain. Movement can make artificial delta waves, but with an instant analysis (just observing raw EEG records) [9].

2.4 EEG headset device comparison

Selecting the correct EEG device can be a difficult process. Many aspects must be considered, and the relevance of each one depend on the approach. Moreover each manufacturer, may or may not show the information perceptively clear. There are many EEG headsets available on the market with different characteristics, the most widely used devices considered are:

- Muse Headset: an EEG device developed mainly as a meditation tool. Possessing 4 channels, 1 reference and two ground electrodes. It is one of the easier bands to get started with, as it requires no head preparation, has a 256 Hz Sampling Rate, 12 bits ADC(Analog to Digital Converter). There are research tools available for Windows, Mac and Linux, although compatibility with the 2016 version is not possible, an interface must be manually implemented, price is around 150 euros, Figure - 2.3.

Figure 2.3: Muse headband.[2]

- OpenBCI: open source EEG and can have up to a maximum of 16 channels, 256 Hz Sampling Rate, 24 bits ADC, open source software and hardware, prices vary from 400 euros for 8 channels and 800 euros for 16 channels, Figure - 2.4.

Figure 2.4: OpenBCI.[3]

- Emotiv Epoc: one of the first consumer EEG devices released on the market, easy to wear, comes with 14 EEG channels with static form factor. Less economic than other commercial headsets and has an additional cost for accessing the data that the headset collects. 2048 Hz Sampling Rate, 14 bits ADC, costs around 650 euros, Figure - 2.5.

[2]https://choosemuse.com/

[3]http://www.mdtmag.com/sites/mdtmag.com/files/imecneuropro.jpg

[4]https://www.emotiv.com/wp-content/uploads/2016/06/emotiv_epoc_square-w.jpg

Figure 2.5: Emotiv Epoc.[4]

- Emotiv Insight: second product which Emotiv brought the market, considered a more economic option to the Epoc headset. Comes with 5 channels, Sampling rate varies from 126 Hz and 256 Hz, 15 bits ADC, around 250 euros, Figure - 2.6.

Figure 2.6: Emotiv Insight.[5]

- Neurosky Mindwave: Simple design having only 1 channel for use, 512 Hz Sampling Rate, 12 bits, Available SDK, around 80 euros, Figure - 2.7.

The number and placement of electrodes is an important factor to consider, depending

[5]https://www.emotiv.com/wp-content/uploads/2016/04/emotiv-insight-square-w.jpg

[6] https://www.robotshop.com/media/catalog/product/cache/1/image/900x900/9df78eab33525d08d6e5fb8d27136e95/n/e/ne
mindwave-mobile-eeg-sensor.png

Figure 2.7: Neurosky Mindwave. [6]

Table 2.2: - Voltage 2- Bit Digital Representation.

Voltage	2- Bit Digital Representation
0-2.5	00
2.5-5.0	01
5.0-7.5	10
7.5-10.0	11

on the type of brain response needed to be measured, a minimum number of electrodes may be required. Measuring Relaxation levels is simple with 1 or 2 electrodes. Sampling Rate of an EEG translates the number of samples in a second received to the device. Most of the devices have a minimum of 256 samples a second, but there are some with higher sampling rate. Depending on the frequency we are trying to measure, the sampling rate must be at least 2.5 times greater. The Analog to Digital Converter (ADC) Bits represents the resolution of the signal. The number of bits is an important measurement unit to be able to accurately estimate the voltage, however more bits does not necessarily mean better quality data. For example if we have 4 ADC bits and we are attempting to measure a signal between 0 and 10 Volts. The data must be represented as depicted in table 2.2.

Table 2.3 compares some of the characteristics that need to be considered when choosing an EEG headset.

To further the research using this device, the Muse headband was selected, the price, battery and comfortability are the most important aspects for a consumer product, moreover the existence of LSL support adds an additional layer of customization, by allowing the programmer to access

Table 2.3: - EEG Headset comparison

Device	Channels	ADC Bits	Motion sensors	LSL Support	Battery	Cost
Muse 2016	4+1 ref	12	3 axis	Yes	5 hours	Medium
Epoc	14+2 ref	16	9 axis	Possible	6 hours	High
Insight	5+2 ref	15	9 axis	Possible	4 hours	Medium
OpenBCI	up to 16 channels	24	3 axis	Yes	26 hours	High
N.M.	1+1 ref	12	N/A	N/A	8 hours	Low

Figure 2.8: Muse Headband Electrode Placement

the sensors data using his own code.

2.5 Related Work

Although popularity as been rising lately on BCI systems, it is a relatively recent field of study. Researchers have given attention to video and image processing, they have used driver's eye and face videos for drowsiness detection. In 1998, [10] described a new approach for driver's drowsiness detection based on analysis of their eyelid movement. Time series of interhemispheric and intrahemispheric cross spectral densities of full spectrum EEG is another study in 2001 by [11] they used three types of artificial neural networks: the linear network, the non-linear artificial neural network (ANN), and the Learning Vector Quantization (LVQ) neural network. [12] in 2006 used the Relative Band Ratio (RBR) of the EEG frequency bands, then statistical tests were used for drowsiness detection. [13] used wavelet transform for decomposition of EEG signal to its sub bands . Twenty human subjects underwent driving simulations with EEG monitoring, Alert EEG was marked by dominant beta activity, while drowsy EEG was marked by alpha dropouts. The duration of eye blinks corresponded well with alertness levels associated with fast and slow eye blinks. Samples of EEG data from both states were used, for increasing the accuracy of diagnosing the transition from wakefulness to sleep, they applied EEG sub bands and also left and right EOG and chine EMG to artificial neural network. In 2009, [14] showed that support vector machines are the best classifier for wake to sleep transition diagnosis.

Chapter 3

State of the Art

3.1 The Brain During Sleep

The task of sleep can be broken down to four sleep stages proceeded by Rapid Eye Movement (REM) sleep. Stage 1 sleep is the transition from wakefulness to sleep. At this stage, a person can be woken easily, and may not be aware that they were sleeping. During stage 1 sleep, EEG signals are low amplitude and low frequency. During stage 2 sleep, body temperature decreases and the heart rate slows. In stage 2 sleep, alpha waves are periodically interrupted by alpha spindles or sleep spindles. Alpha spindles are 12-14 Hz bursts of brain activity that last at least half a second [15]. These periods of alpha spindle activity are sometimes called alpha spindle epochs. Stages 3 and 4 are deeper sleep, with stage 4 being deeper than stage 3. REM sleep follows stage 4 sleep. REM sleep is most readily identified by rapid eye movement. During REM sleep, dreaming occurs and brain activity increases. Each of these stages continue to cycle from stage 1 through REM sleep throughout the sleeping period. The majority of brain activity during the transition from wakefulness to sleep occurs in the frontal and occipital lobes. High occipital lobe activity is associated with relaxed wakefulness. During stages 2-4, delta activity in the frontal lobe increases and theta activity in the occipital lobe increases [16]. Methods for sleep detection can be created by observing these features in the brain during the transition from wakefulness to sleep.

[0] http://psychmuseum.uwgb.org/wp-content/uploads/2016/10/what-are-the-four-lobes-of-the-brain_1-300x232.jpg

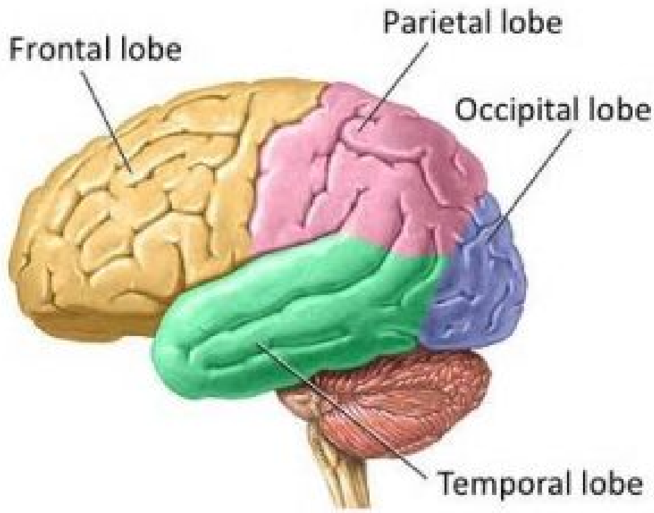


Figure 3.1: Lobes of the Center Cortex

3.2 Driver Fatigue Detection

The existent commercial systems able to detect driving patterns of fatigued drivers, such as the Ford Driver Alert, the Mercedes Attention Assist, the Volkswagen Driver Alert System, or Volvo Driver Alert Control and Lane Departure Warning. Each of these systems monitor changes in driving displayed by drowsy drivers like jerky steering movements or drifting out of lanes. When this occurs, an audible and visual warning is produced. Ford's Driver Alert system even includes scenarios in which if the warning is ignored for too long, it can only be discontinued by stopping and exiting the car [17]. The Danish "Anti Sleep Pilot" not only monitors driving patterns, but it requires that the driver push a button on the device as quickly as possible when indicated to verify that the driver's response time is adequate. Other systems like the Fraunhofer's Eyetracker or the Toyota Driver Monitoring System monitor the driver's eyes to confirm that they are watching the road. The driver can be warned if they are not watching the road when an obstacle is ahead. The driver is also warned if their eyes close for a period of time. Systems that monitor driving patterns can monitor all forms of erratic driving, which includes distracted driving. Their disadvantage is a slow response time, it may be too late to stop an accident from occurring. Driver monitoring systems have the potential to detect driver drowsiness before an accident occurs, but they rely on being able to monitor a driver's eyes to determine if they are open. An EEG based device may be able to detect the onset of sleep and improve on these existing systems, and it has the added benefit of not requiring an unhindered view of the driver's eyes.

3.3 Data Classification

This is the step after feature extraction of EEG signals. These are the algorithms considered to obtain the classification:

- **Support Vector Machine**, given a points set, subset of a larger set (space), in which each of them belong to one of two possible categories, SVM algorithm builds a model that predicts whether a new point (whose category is unknown) belongs to one category or the other.
- **Neural Networks**, independent processing units are assembled and connected with each other. Moreover, these generate a function of their total inputs.
- **Linear Discriminant Analysis**, the data is divided into hyper planes to represent different classes. Due to linear nature of EEG data, is not recommended to use LDA.
- **Bayes Rule**, posterior probability of a feature vector is computed to belong to a particular class. In addition, feature vector is located into a class where it belongs to the highest probability .

3.4 Artificial Neural Network classifier

Inspired by the human nervous system and more specific the human brain, which is capable not only to learn and to generalize rules, but also to perform parallel tasks, the artificial neural network (ANN) also consists of elements called neurons. Figure - 3.2 shows the architecture of an ANN with three main layers: input layer, hidden layer and output layer. Since all connections are in one direction and there are also no feed-back loops between neurons, this architecture is called a feed-forward network. This network is memoryless, because the output to a specific input does not depend on the previous state of the network. The number of features and the number of classes determine the number of inputs and outputs, respectively. Therefore, only the number of neurons and hidden layers are free parameters to be selected. Considering too many neurons or hidden layers leads to the overfitting of the network and consequently lack of generalization.

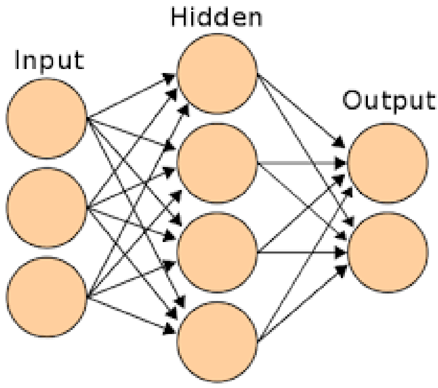


Figure 3.2: Artificial Neural Network

On the contrary, too small numbers of them prevent the network from learning rules adequately. The impact of the number of neurons on the classification performance is discussed in the next sections.

3.4.1 Network architecture

As shown in 3.3, the input layer sends the input values x_i to the hidden layer without processing them. The hidden layer neurons calculate the weighted sum of the inputs called net activation (net). These calculated values are then fed to a non-linear activation function f() whose outputs y_j are the inputs to the next layer. Mathematically, we have the equation:

$$y_j = f(net_j) = f\left(\sum_{i=1}^{D} w_{ij}^{(1)} x_i + w_{0j}^{(1)}\right)$$

where index j refers to the j-th hidden neuron and $w_i j^(1)$ corresponds to the input-to-hidden neuron weights (Fig. 3.2 and 3.3).

Similarly, the output layer also calculates the net activation and the final result corresponds to the classifier output. Therefore, we have equation:

$$z_k = f(net_k) = f\left(\sum_{j=1}^{N_h} w_{jk}^{(2)} y_j + w_{0k}^{(2)}\right)$$

In the above equation, index k denotes the k-th output unit 3.3. N_h denotes the number of neurons in the hidden layer. In the case of a multi-class classification problem with m classes,

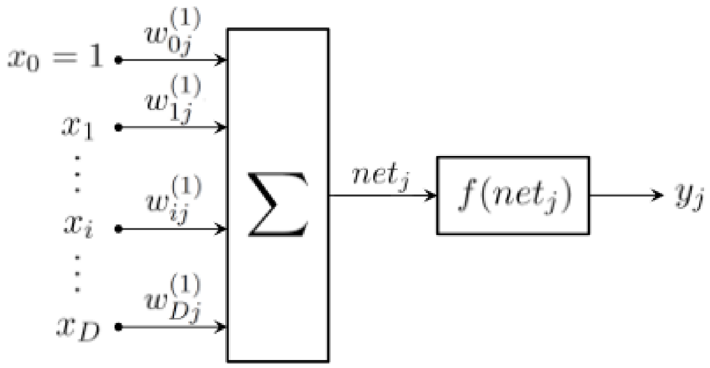


Figure 3.3: Mathematical representation of the input to hidden layer of a network

the class with the maximum value of z_k will be selected as the final classification result by the ANN classifier as follows:

$$\hat{c} = \underset{k=1,\cdots,m}{\arg\max}\ z_k$$

The overall output of the introduced three-layer network in 3.2 can be represented as:

$$z_k = f\left(\sum_{j=0}^{N_h} w_{jk}^{(2)} f\left(\sum_{i=0}^{D} w_{ij}^{(1)} x_i\right)\right)$$

where z_k is given as the function of the input x_i by replacing 3.4.1 in 3.4.1 for y_j and $x_0 = y_0 = 1$. The generalization of 3.4.1 also allows considering other activation functions at the output layer in comparison to the hidden layers. The non-linear activation function can be either a hard threshold function such as the sign function or a soft thresholding one such as the sigmoid function. The sigmoid function is popular for having the following properties as shown in 3.4 for the tangent sigmoid $f(net) = \frac{2}{1+e^{-2net-1}}$

- It is non-linear.
- It saturates which bounds the possible output values.
- It is continuous and differentiable.

It will be shown later that non-differentiable activation functions are, in general, not of interest. Since f() is a non-linear function, ANN is also a non-linear classifier and consequently can handle complex rules between features and classes.

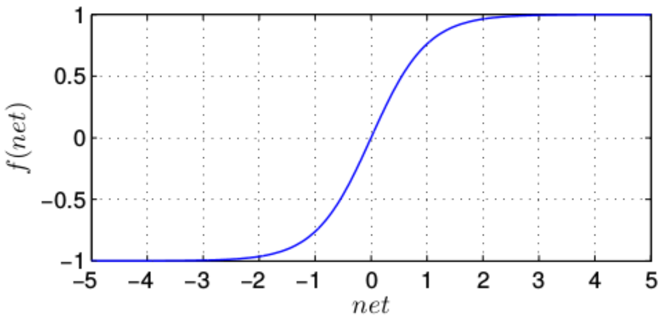


Figure 3.4: Sigmoid activation function

3.5 Support Vector Machine

SVM is a classifiation algorithm of binary output. SVM builds a hyper plane or set of hyper planes in a dimensional space very high and it can use this to classification and regression of signals. This hyper plane is created perpendicularly to points and it has to separate a set of points optimally. An algorithm based in SVM takes a set input data (in SVM a data point is viewed as a dimensional vector) and builds a model which can classify that set of points, which they have been given, in one category or another. SVM is also known as maximum margin classifiers because it is looked for the hyper plane which is further away of points which are nearer than that hyper plane.

3.6 Power Spectral Density

The power spectrum of a time series describes the distribution of power into frequency components composing that signal. According to Fourier analysis, any physical signal can be decomposed into a number of discrete frequencies, or a spectrum of frequencies over a continuous range. The statistical average of a certain signal as analyzed in terms of its frequency content, is called its spectrum.

When the energy of the signal is concentrated around a finite time interval, especially if its total energy is finite, one may compute the energy spectral density. More commonly used is the power spectral density , which applies to signals existing over all time, or over a time period large enough that it could as well have been over an infinite time interval. The power spectral density (PSD) then refers to the spectral energy distribution that would be found per unit time, since the total energy of such a signal over all time would generally be infinite. Summation or integration of the spectral components yields the total power or variance.

Chapter 4

Development

No man should escape our universities without knowing how little he knows.
(J. Robert Oppenheimer)

4.1 Communication from headband to computer

4.1.1 BLE technology

The muse headband uses Bluetooth Low Energy to broadcast its recordings. BLE is the intelligent, power-friendly version of Bluetooth wireless technology. It is already being widely used and is playing a significant role in transforming smarter gadgets by making them more compact, affordable, and less complex, its initial focus was to provide a radio standard with the lowest possible power consumption, specifically optimized for low cost, low bandwidth, low power, and low complexity.

4.1.2 LSL Layer

The Lab Streaming Layer is a python library for the unified collection of measurement time series in research experiments that handles both the networking, time-synchronization, real-time access as well as optionally the centralized collection, viewing and disk recording of the data.

The LSL distribution consists of: The core transport library (liblsl) and its language interfaces, we specifically only use python for this.

This layer will allow us mediate communication between the headband and the computer used to store and process the data received.

4.1.3 Keras

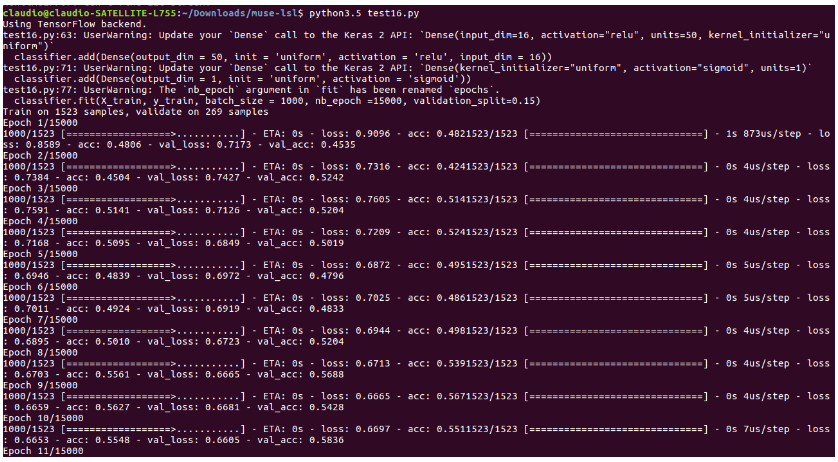
Keras is an open-source neural-network library written in Python, with a high-level API to build and train neural network models.

We will use this library in the design of our neural network, inputs such as layers, objectives and activation functions, optimizers, to make working with the data easier.

4.2 Work Developed

4.2.1 Dataset and algorithm development

Three subjects data was used, each was instructed to gaze directly forward parallel to the ground, with as minimum as possible movement of the head and eyes, if too much involuntary movement was present, data was scrapped and the task restarted. Therefore, twenty seconds data is recorded with eyes open and another twenty seconds with eyes closed, for 3 different subjects. At the first step features are extracted from the signals in such a way that represent the signal very well. We extracted Fourier transform (FT) and power spectrum density (PSD) features and their harmonics in the Fourier domain. These features should contain all important information about the signal. The next step is the classifier, a specific pattern is allocated to a class based on the characteristic features selected for it. In order to evaluate the proposed system in real-time applications, three temporal intervals of 1 second . Each twenty second data is divided into non-overlapping segments with the length equal to each interval. Muse has a



```
claudio@claudio-SATELLITE-L755:~/Downloads/muse-lsl$ python3.5 test16.py
Using TensorFlow backend.
test16.py:63: UserWarning: Update your `Dense` call to the Keras 2 API: `Dense(input_dim=16, activation="relu", units=50, kernel_initializer="u
niform")`
  classifier.add(Dense(output_dim = 50, init = 'uniform', activation = 'relu', input_dim = 16))
test16.py:71: UserWarning: Update your `Dense` call to the Keras 2 API: `Dense(kernel_initializer="uniform", activation="sigmoid", units=1)`
  classifier.add(Dense(output_dim = 1, init = 'uniform', activation = 'sigmoid'))
test16.py:77: UserWarning: The `nb_epoch` argument in `fit` has been renamed `epochs`.
  classifier.fit(X_train, y_train, batch_size = 1000, nb_epoch =15000, validation_split=0.15)
Train on 1523 samples, validate on 269 samples
Epoch 1/15000
1000/1523 [=================>..........] - ETA: 0s - loss: 0.9096 - acc: 0.4821523/1523 [==============================] - 1s 873us/step - lo
ss: 0.8589 - acc: 0.4806 - val_loss: 0.7173 - val_acc: 0.4535
Epoch 2/15000
1000/1523 [=================>..........] - ETA: 0s - loss: 0.7316 - acc: 0.4241523/1523 [==============================] - 0s 4us/step - loss
: 0.7384 - acc: 0.4504 - val_loss: 0.7427 - val_acc: 0.5242
Epoch 3/15000
1000/1523 [=================>..........] - ETA: 0s - loss: 0.7605 - acc: 0.5141523/1523 [==============================] - 0s 4us/step - loss
: 0.7591 - acc: 0.5141 - val_loss: 0.7126 - val_acc: 0.5204
Epoch 4/15000
1000/1523 [=================>..........] - ETA: 0s - loss: 0.7209 - acc: 0.5241523/1523 [==============================] - 0s 4us/step - loss
: 0.7168 - acc: 0.5095 - val_loss: 0.6849 - val_acc: 0.5019
Epoch 5/15000
1000/1523 [=================>..........] - ETA: 0s - loss: 0.6872 - acc: 0.4951523/1523 [==============================] - 0s 5us/step - loss
: 0.6946 - acc: 0.4839 - val_loss: 0.6972 - val_acc: 0.4796
Epoch 6/15000
1000/1523 [=================>..........] - ETA: 0s - loss: 0.7025 - acc: 0.4861523/1523 [==============================] - 0s 5us/step - loss
: 0.7011 - acc: 0.4924 - val_loss: 0.6919 - val_acc: 0.4833
Epoch 7/15000
1000/1523 [=================>..........] - ETA: 0s - loss: 0.6944 - acc: 0.4981523/1523 [==============================] - 0s 4us/step - loss
: 0.6895 - acc: 0.5010 - val_loss: 0.6723 - val_acc: 0.5204
Epoch 8/15000
1000/1523 [=================>..........] - ETA: 0s - loss: 0.6713 - acc: 0.5391523/1523 [==============================] - 0s 4us/step - loss
: 0.6703 - acc: 0.5561 - val_loss: 0.6665 - val_acc: 0.5688
Epoch 9/15000
1000/1523 [=================>..........] - ETA: 0s - loss: 0.6665 - acc: 0.5671523/1523 [==============================] - 0s 4us/step - loss
: 0.6659 - acc: 0.5627 - val_loss: 0.6681 - val_acc: 0.5428
Epoch 10/15000
1000/1523 [=================>..........] - ETA: 0s - loss: 0.6697 - acc: 0.5511523/1523 [==============================] - 0s 7us/step - loss
: 0.6653 - acc: 0.5548 - val_loss: 0.6605 - val_acc: 0.5836
Epoch 11/15000
```

Figure 4.1: Training The Neural Network

sampling rate of 256 Hz and four channels, each second we have 256 samples, so in 20 seconds we have 5120 samples, each containing 4 channel values, in total for each state we have 20480 samples (electrode values), this will be the input for the neural network. The output of the network is binary, so two states must be defined, we have established closed eyes state equals zero, and open eyes state equals one and train the network based on this arquitecture.

4.2.2 Tests and Results

In order to test the neural network accuracy in predicting if the user has their eyes open or closed, we developed two different neural network architectures, one where we give it an input array size of sixteen, which are correspondent to the electrode values of four samples, for each of the four channels, and the second NN we gave as input 256 samples, per channel, increasing input size in the hopes of improving the network robustness, both have an hidden layer of 50 neurons, trained under batch size of 1000, 15000 epochs, 30% of training input was used as test data, and 15% used as validation, this static values were found to be optimal on accuracy tests. For each of these architectures we use each recorded subject data, and test for both eyes closed and open.

The prediction average, is a metric that consists on the sum of all prediction values divided by the number of samples. This means the closer the prediction average is of one or zero, one represents eyes open and zero eyes closed state, the more confident the network is on the given prediction, and in reverse the closer it is of the middle value of 0.5 the more uncertain the

Table 4.1: - 16 input ANN results

Eyes State	Subject 1	Subject 2	Subject 3
Open	0.6795	0.7186	0.7608
Closed	0.3658	0.1516	0.3171

Table 4.2: - 256 input ANN results

Eyes State	Subject 1	Subject 2	Subject 3
Open	0.9178	0.9821	0.5532
Closed	0.4648	0.0178	0.4505

prediction is.

First we perform a test to the prediction of both networks using samples of the same dataset, we should expect good accuracy on detection since we use samples of the same subject. Table 4.3 displays this metric, ratio of correct predictions in relation to the ground truth, this ranges from 0 to 1, using as input to the neural network, samples of the same subject to test both networks.

Table 4.4 displays the same metric using the same input but this time instead using the 256 input network.

Now instead of using the same subject samples, we train the network on a different dataset, since subject 2 appears to have had a better benchmark, we use this dataset to train the network and use the other dasetsets as input and analyze the prediction result.

Table 4.5 displays the prediction average using the 16 inputs network.

Table 4.6 displays the same metric using the same input but this time instead using the 256 input network.

We find an overall accuracy rate for this method ranging from 58% to 76% accurately diagnosed. The specific accuracy rates of interest are the true positive rate and the false negative rate. The true positive rate is the number of times the method accurately gave a drowsy diagnosis divided by the number of times the method gave a eyes closed state. In other words, this number represents the confidence that a subject may have that he or she is truly drowsy when given a

Table 4.3: - 16 input ANN results

Eyes State	Subject 1	Subject 2	Subject 3
Open	0.5678	0.5603	0.7058
Closed	0.4014	0.3088	0.2860

Table 4.4: - 256 input ANN results

Eyes State	Subject 1	Subject 2	Subject 3
Open	0.8385	0.5312	0.3500
Closed	0.3446	0.3500	0.2760

Table 4.5: - Subject 1 test accuracy

Subject	Channel	True	Positive True	Negative False	Positive False	Negative Percent
1	FP1	73%	30%	49%	47%	51%
1	FP2	96%	35%	39%	10%	67%

drowsy diagnosis. Again the results using this electrode placement and this sampling rate are highly variable ranging from 49% to 93% accuracy. The next accuracy measure of interest is the false negative rate. We define a positive signal as a drowsy diagnosis, and a negative signal as its opposite. Hence, the false negative rate is defined as the number of times the method reports that the user is alert when in fact she is drowsy divided by the number of times the method reports an alert diagnosis. Results vary from a high of 41% to a low of 14%.

The average accuracy rate across all the subjects comes to 71%. While this isn't necessarily an unsatisfactory result, the corresponding false negative rates do make this an unsatisfactory result. We would want to alert a driver who is drifting into drowsiness more than we'd like to accurately determine that he is alert.

Table 4.6: - Subject 2 test accuracy

Subject	Channel	True	Positive True	Negative False	Positive False	Negative Percent
2	FP1	63%	53%	43%	41%	58%
2	FP1	93%	50%	34%	14%	72%

Table 4.7: - Subject 3 test accuracy

Subject	Channel	True	Positive True	Negative False	Positive False	Negative Percent
3	FP1	53%	70%	36%	40%	62%
3	FP1	86%	68%	26%	18%	77%

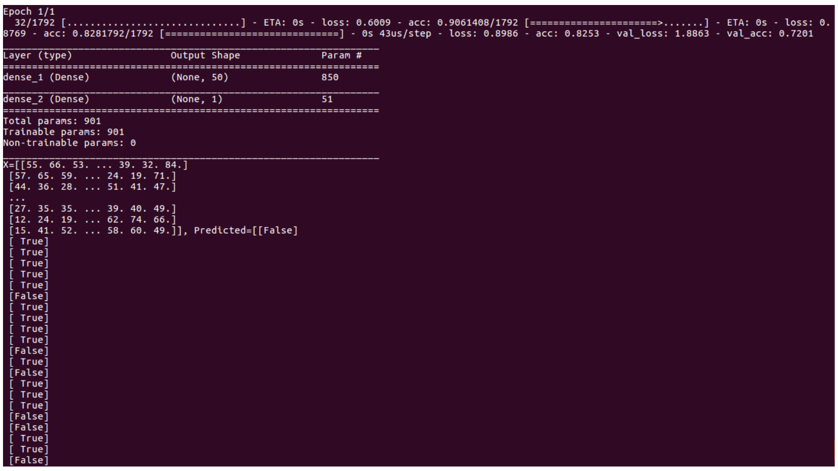


Figure 4.2: Prediction array for eyes open

Chapter 5

Conclusions

An expert is a man who has made all the mistakes which can be made in a very narrow field.
(Niels Bohr, Danish physicist)

The objective of this work was to advance our experience in producing a decision-making tool for sleep analysis based on Artificial Neural Networks using a wearable and wireless EEG device. Two configurations of the neural network were developed to compare the results each with different inputs. On the first attempt to evaluate the networks performance by using samples of the same dataset, the results are good for both networks, as it should be expected. The second test used different subject samples and datasets, on that experiment the only outlier is subject 3 on the 256 architecture having less that 0.5 as prediction, when the state should be eyes open.

All around results are correct although not as precise as equivalent works, using ANN and classification classes, these give results which vary between 61 and 80% [13]. Even if the results obtained are not as accurate does not always mean that the ANN is wrong. Another choice of parameters and/or the addition of other parameters resulting from another modeling techniques like the detection of the graphical-elements and the integration of the other physiological signals may be able to improve the results.

5.1 Future Work

This study could be used in future studies or researches. Also, this dataset can be analyzed with other methods and check different results. As mentioned in this thesis, there are many methods to analyze the datasets. As implemented one of them is Neural Network (NN). It can be used to extract pattern because this method has a high ability to understand the meaning from imprecise or complicated data. Besides, it has the ability of learning how to do task based on data. NN contains just one input layer where are input variables and the output layer where is the problem solution. This method has intermediate hidden processing layers to employ the problem. This is a structure of connected three-layer network. One the most important task in NN design is the determination of appropriate number of hidden layers.

Another one to perform the classification of EEG signals from this thesis in the future would be Bayes Rule, which is an easy mathematical function that uses for calculating conditional probabilities. Which computes a posterior probability of a feature vector to belong to a particular class. Bayes rule simplifies the calculation of conditional probabilities and clarifies significant features of subjectivist position. Later, results are compared and it can see with which method it gets the best result and the fastest one.

Other algorithm to perform the classification of EEG signals from this thesis in the future would be Linear Discriminant Analysis (LDA). It was more used in the past because it is able to produce an output which is continuous in time as well as in amplitude. To apply many different EEG parameters, LDA is a good algorithm, like common spatial patterns (CSP), as well as band power values (ERD) and Adaptive autoregressive (AAR) parameters. This algorithm assigns weights to the input data to carry out a best linear separation of such data. Another algorithm to perform the classification of EEG signals from this thesis in the future would be Case-Based Reasoning (CBR). This is the process of solving new problems based on solutions of previous problems wich scince this particular problem does benefit from stored data.

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