# AUTOMATIC DETECTION OF ALERTNESS LEVEL FROM ELECTROENCEPHALOGRAM SIGNALS AND CORTICAL AUDITORY EVOKED POTENTIAL RESPONSES

**by**

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# Certificate

I, Alaleh Rabie, hereby declare that this thesis titled, automatic detection of alertness level from EEG signals and its application to the assessment of hearing using the CAEP response, and the work presented is the product of my own work. I certify that:

- This work was done wholly or mainly while in candidature for master degree by research at this university.
- Where any part of this thesis has been previously submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

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Date:

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# Dedication

I would like to dedicate this thesis to all broken heart parents who have children with hearing loss. God bless you all for your patience.

# ABSTRACT

This research aims to identify the degree of alertness of subjects that undergo the Cortical Auditory Evoked Potential (CAEP) based hearing test. One of the important factors that influence this is the alertness state of subjects. Research has shown that for this test to be useful, subjects need to stay at a constant state of engagement. Accordingly, this thesis focuses on developing a system that will be able to classify each portion of the recorded signal into one of four states; engaged, calm, drowsy and asleep. In order to achieve this, we studied the relationship between CAEP responses and the alertness states, and we validated the existence of this relationship. We have also developed a method to search for the best channel/rhythm combination for each alertness state.

In the first study, two sets of features were considered to represent the recorded data. The first set was based on the wavelet transform of the background EEG, while the second set was obtained from the peaks of the CAEP responses. Obtained results suggest that the CAEP-based features were very comparable, in terms of classification accuracy, to the well-established wavelet-based features of EEG signals (79% compared to 80%). In the second study, the EEG rhythms of subjects were analysed. Investigation of the importance of the different EEG rhythms in terms of their capabilities in differentiating between the different alertness states was conducted. This is followed by considering subsets that contain 2, 3, 4 as well as all 5 EEG rhythms. Finally, a feature subset selection method based on differential evolution (DE) that has been proposed particularly to deal with multi-channel signals is used to search for the best subset of EEG rhythms for the various channels. It was shown that higher frequency EEG rhythms (γ, β) are better classifiers for the subject's alertness state than α, θ, and δ (lower frequency EEG rhythms). Optimal combinations of different EEG rhythms have been described. The proposed differential evolution feature selection

algorithm is shown to produce better results than the ranking and sequential forward selection approaches. Obtained results suggest that the best subsets are formed using combinations of channels and features that are influenced by high frequency rhythms.

# ABBREVIATIONS

ABR: Auditory Brainstem Response

ANN: A Nearest Neighbour

ANOVA: Analysis of Variance

AP: Action Potential

AR: Autoregressive

BERA: Brainstem Evoked Response Audiometry

BSS: Blind Source Separation

CAEP: Cortical Auditory Evoked Potential

CAP: Compound Action Potentials

CM: Cochlear Microphonic

CN: Cochlear Nucleus

CNS: Central Nervous System

CWT: Continuous Wavelet Transform

DE: Differential Evolution

DEFS: Differential Evolution Feature Selection

DWT: Discrete Wavelet Transform

EEG: Electroencephalogram

EP: Evoked Potential

FFT: Fast Fourier Transform

GA: Genetic Algorithm

ICA: Independent Component Analysis

KNN: K-nearest Neighbour

KSOM: Kohonen's Self-organizing Map

LDA: Linear Discriminant Analysis

LSD: Least Significant Difference

MLR: Middle Latency Response

MP: Matching Pursuit

OAE: Otoacoustic Emissions

PCA: Principal Component Analysis

PNS: Peripheral Nervous System

PP: Projection Pursuit

PS: Physiological Signals

PSA: Particle Swarm Optimisation

REM: Rapid Eye Movement

SEP: Sound Evoked Potentials

SFS: Sequential Forward Search

SP: Summating Potential

SPL: Sound Pressure Level

SVM: Support Vector Machine

SWS: Slow Wave Sleep

TEC: Total Error of Classification

TM: Tympanic Membrane

TRN: Thalamic Reticular Nucleus

uLDA: uncorrelated Linear Discriminant Analysis

VEO: Vertical Electro-Oculogram

VCN: Ventral Cochlear Nucleus

WT: Wavelet Transform

WPT: Wavelet Packet Transform

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# Chapter 1

## 1. INTRODUCTION

EEG analysis can provide a variety of applications to detect problems, diseases and abnormalities in biological activities. However, EEG signal cannot be interpreted directly at the time of monitoring. Appropriate intelligent techniques are applied to extract and process the desired signals. As a consequence biomedical signal processing plays an important role in diagnosing any defects that can indicate a disability in a person as a first step followed by a proper therapy to help to improve of the life of the person who is suffering from the disability.

This research aimed to investigate the extraction and classification of brain activities at different states of alertness by hearing stimulus during the CAEP test that is used to detect hearing loss.

The background and problem statement and research objectives are going to be described in detail in this chapter.

### 1.1 Background and Problem Statement

According to a recent study in the Australian Communication Exchange (ACE) organization, 1 in 6 Australians are suffering from hearing loss. Detection of hearing loss following by an appropriate intervention program is very critical in helping patients to overcome their disability in speech and sound recognition, social communication and interaction. In fact, research has shown that children with certain hearing loss may develop normal speaking capabilities if they are provided with hearing aids in their early stages of life as well as special therapies [1].

It is important to mention that spoken language development can prevent children with hearing loss from perceived sense of loneliness. In the study that designed to monitor the social interaction of those children with hearing problem, researchers demonstrated that the ability of speech has a definite effect on how successful the child is in being integrated in the classroom with others especially in group work [2].

Objective hearing tests, which do not require feedback from participants about their own hearing level, are found to be suitable for infants and elderly people with dementia [3].

Brainstem evoked response audiometry (BERA or ABR) is a type of "Objective" test. The literature review [13] suggests that BERA shows noticeable limitations and disadvantages, i.e. ABR clicks used as hearing stimulus have the most power in the 2 kHz region which will cause problems when testing at lower frequencies. In addition, low frequency nerve fibres are indeed less synchronised with the click sound ("phase locking"). In some cases, such as with a low frequency tone, nerve fibres would not stimulate enough hair cells at the end of the cochlea to get consistent responses. Another important disadvantage is that each movement which can be known as electrical activity creates more noise which makes it hard to distinguish and extract the desired responses [14]. Consequently, it always requires general anaesthesia or at least sedation in the subject under the test to enable clinical practitioners to obtain the precise measurements.

CAEP has a number of advantages over BERA, which include [13, 15]

- Better threshold accuracy.
- More frequency specific.
- Response morphology does not degrade at low stimulus frequencies.
- Potentially quicker than the BERA (with appropriate software).
- Tests more of the neural pathway.
- No patient relaxation needed.
- ABR testing was found to be impractical while assessing the efficiency of hearing aids on people with hearing loss in comparison

CAEPs can be evoked by much longer stimuli and other types of stimuli so in combination with hearing aids, it presents better real-life conditions.

The above mentioned problems have led researchers to become more interested in another type of “Objective” hearing measurement that utilises the Cortical Auditory Evoked Potentials (CAEP).

The hearing system is the only remote sense system which is open during sleep. An example would be a baby’s cry at night that awakens its parents. The activity of this sensory system is changed during different levels of alertness and concentration and different sleep phases. The literature has shown that a loss of the sensory input typically caused by disruption of the peripheral sensory fibres (deafferentation) will happen during drowsiness levels, ignore condition as well as sleep states. In fact sleep is like a blockage of the auditory inflow, thus the sleeping brain imposes rules on information processing [6].

As mentioned above since the auditory evoked potential activities change waveforms and amplitudes as a result of variation in the subject condition such as different alertness stages, it is necessary for CAEP subjects to stay at a constant state of arousal. Subsequently, subjects need to be kept alert, as alertness affects the magnitude of the measured CAEP. It is essential to note that this problem has not been thoroughly investigated before, and hence this thesis aims at studying the detection of alertness states and their effect on CAEP responses from a pattern classification perspective.

## 1.2 Research Objective

The research objective is to identify the degree of alertness of subjects during the Cortical Auditory Evoked Potential (CAEP) based hearing test. One of the important aspects that affect the test results is the alertness state of subjects. Research has shown that for this test to be useful, subjects need to stay at a constant state of engagement. This thesis focuses on developing a

system that will be able to classify each portion of the recorded signal into one of four states; namely engaged, calm, drowsy and asleep. By separating the different levels of alertness during the CAEP measurement, the tester will be able to evaluate the recording condition of the test and whether he/she needs to take certain measures to improve it.

## 1.3 Research Methodology

To achieve the above stated objectives, the following steps were implemented:

- **Data Type**

EEG data in the presence of an auditory stimulus from ten adult subjects with normal hearing were used. Data collection took place at the National Acoustic Laboratories using the NEUROSCAN system.
Both background EEG and CAEP signals were used for detection of alertness state.

- **Feature extraction**

Different feature extraction methods from both time and frequency domains were implemented. These included power spectrum, wavelet parameters, as well as amplitude and latency of CAEP peaks. To the best of our knowledge, no one before has extracted features from the CAEP responses to classify the alertness state.

- **Dimensionality reduction**

Due to the multi-channel nature of EEG, the number of extracted features can be quite high. Hence, a dimensionality reduction step is needed to reduce the size of the feature set, which is an important factor for real time classification applications. A number of feature selection methods are investigated.

- **Classification**

Accurate classification of alertness level is quite challenging due to the non-stationary nature of the signal. The non-stationary nature of EEG makes most EEG-based classification tasks quite challenging. In order to reduce the effect of that, we considered using wavelet (explained in section2.7.1), which is a time-scale feature extraction method that has proved to work reasonably well with EEG data. The wavelet features are used as a benchmark that we compared the results of our proposed method with (section 4.3).Support Vector Machine (SVM) classifier has been chosen to verify the accuracy of the desired feature sets as literature shows promising results when using this classifier with EEG signals. An investigation of the EEG rhythm/channel combination with respect to the problem of alertness state classification is presented.

## 1.4 Thesis Significant Contribution

The approach we proposed to detect alertness states using CAEP features is novel (chapter 4). We have presented a comprehensive study about the best channel/EEG rhythm combination to detect alertness states of subjects undergo CAEP hearing test (chapter 5).

## 1.5 Thesis Arrangement

This thesis is organised as follows:

Chapter One: This chapter includes an introduction describing the importance of the problem under consideration and the adopted research approach.

Chapter Two: This chapter provides detailed information on; how the human brain system works, recording of brain activities through the electroencephalogram (EEG), a description of the auditory system, responses to auditory stimuli and a detailed explanation about CAEP

signals and the factors affecting CAEP responses. In addition the literature review provides detailed information about existing EEG classification methods as well as a description of existing alertness detection methods.

Chapter Three: This chapter describes the EEG recording method.

Chapter Four: This chapter provides a statistical analysis of CAEP peaks as well as identifying the subject alertness level using CAEP peaks and wavelet transform of background EEG features using both subject wise and subject independent methods.

Chapter Five: This chapter includes analysis of the EEG rhythms of the subjects undergoing CAEP test and investigation of their capability in differentiating between the different alertness states by considering 64 channels EEG montage. EEG feature subset selection method based on differential evolution has been also conducted to search for the best subsets for each channel.

Chapter Six: This chapter provides a conclusion and summary of the research followed and suggests future directions that could lead to a more optimal approach in order to achieve better results.

## 1.6 Publications

1. Rabie, A. Al-Ani, B. VanDun and H. Dillon. Detection of Alertness States using Electroencephalogram and Cortical Auditory Evoked Potential Responses. The 6th International IEEE EMBS Conference on Neural Engineering. (Submitted).
2. A. Al-Ani, B. VanDun, H. Dillon and A. Rabie. Analysis of Alertness Status of Subjects Undergoing the Cortical Auditory Evoked Potential Hearing Test. 19th International Conference, ICONIP 2012, Part I, LNCS 7663, pages 92-99, 2012.

# Chapter 2

## 2. LITERATURE REVIEW

This chapter focuses on describing EEG signals, brain structure, how the brain process a stimulus, functionality of the auditory system as well as literature survey on the pre-processing of EEG data, feature extraction and classification.

### 2.1 Introduction

Electro-Encephalogram (EEG) is a collection of potentials from widely different processes recorded from the human skull that can be used to detect different kind of disorders and abnormalities in patients.

Cortical auditory evoked potential (CAEP) is a brain response to an auditory stimulus originating from the auditory cortex. It has a morphology as depicted in Figure 2.1, and can be recorded using electrodes placed on the subject's scalp [16].

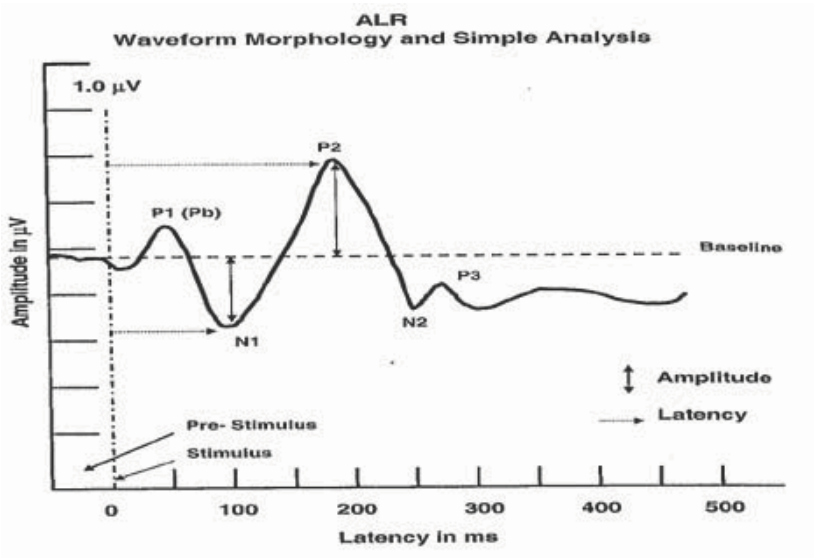



**Figure 2.1: Typical components of a CAEP collected from a young adult with normal hearing. It generally starts from 50 milliseconds after stimulus presentation.**

Several factors determine the morphology, i.e. amplitude and latency, of the CAEP responses, including subject age, stimulus type and the state of alertness of the subject. CAEPs are used by clinical practitioners to determine hearing thresholds and possible abnormalities of the auditory pathway. They have been the focus of renewed research since auditory brainstem response (ABR) testing was found to be impractical while assessing the efficiency of hearing aids on children with hearing loss [17].

Clinically, ABRs are evoked by click sounds or tone bursts. Therefore they might get filtered away or at least significantly modified by a hearing aid's signal processing when passing through the device [15].

This is not the case for the longer stimuli that are used for CAEP testing.

Other advantages of CAEP over ABR include better threshold accuracy in some hearing disorders, better frequency-specificity, response morphology does not degrade at low stimulus frequencies, a larger part of the neural pathway is tested as it originates from the auditory cortex instead of the brainstem, fewer constraints on patient relaxation, smaller number of stimulus repetitions required (as the CAEP has a larger amplitude), lower susceptibility to exogenous noise sources, and speech sound stimuli can be presented [11]. However, the main limitation of the CAEP test, in contrast with the ABR test, is that the subject should stay alert or in a constant alertness state, as it has been found that the subject's alertness state during the test can significantly affect the nature of the CAEP responses [18]. Hence, when the subject shifts from one state into another, CAEP morphology changes and the averaged waveform might be annihilated. As a result it is important to keep track of the subject's state of alertness, which is not so straightforward when testing children, infants, or incapacitated adults. It is important to mention that the effect of the different alertness states on CAEP responses has not been fully investigated, as the literature contains a limited number of papers that deal with this issue.

The automatic detection of alertness states have started to receive increased attention from researchers, which include studies that focus on identifying the drowsiness level in drivers [19]. In [20], power spectrum of EEG data, independent component analysis (ICA) and a fuzzy neural network model were utilized in the estimation of the alertness state. A combination of power spectrum estimation, principal component analysis (PCA) and artificial neural network was considered in [21,23].Campbell and Muller-Gassin showed that CAEPs changed significantly when presenting stimuli close to threshold during different states of alertness (awake and the sleep stages) in adults [24]. This chapter will introduce the various concepts above.

In addition, for better understanding of EEG signals it is valuable to know how they are originated and how they are categorized into different types of rhythms in terms of amplitudes and frequencies.

## 2.2 Brain and Nervous System

This chapter describes different parts of the brain and the nervous system function.

### 2.2.1 Brain Structure

The human nervous system consists of two major parts namely; central nervous system (CNS) and peripheral nervous system (PNS). Brain and spinal cord form the CNS. PNS consists of cranial and spinal nerves; each of them contains of motor fibres and sensory fibres. Motor fibres divided into two parts called; somatic and autonomic systems as shown in Figure 2.2. Different parts of the brain are described below;

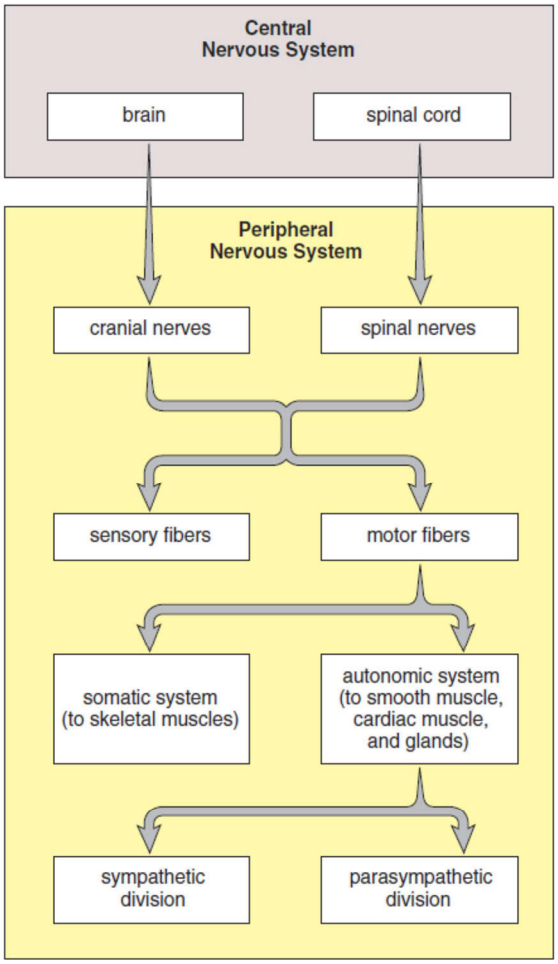



**Figure 2.2: The human nervous system organization [12].**

As shown in Figure 2.3, the brain consists of three main parts called Cerebrum, Cerebellum and Brain stem. Among them, the most important and advanced unit is the cerebrum that handles conscious thought and voluntary movements. A specific region that the information from sense organs like ears be processed is sensory cortex. Sub-cortical white matter is a region under the cerebral cortex which is responsible to carry information. The thalamus works as a final transmission to carry information to cerebral cortex. The data received from different senses are combined and packed to proper regions along the cortex. Under the thalamus is hypothalamus that controls some needs such as sleep, thirst, hunger and so on. The cerebellum which is like a small cerebrum plays an important role for balance and harmonization. As it is shown in Figure2.3, brain stem continues to spinal cord and it consists of three regions called Midbrain, Pons and Medulla Oblongata. They are responsible for controlling functions, such as: digestion, breathing and even the beating of the heart. Also it is like a route to connect the cerebral cortex with spinal cord and peripheral nerves[2, 3].

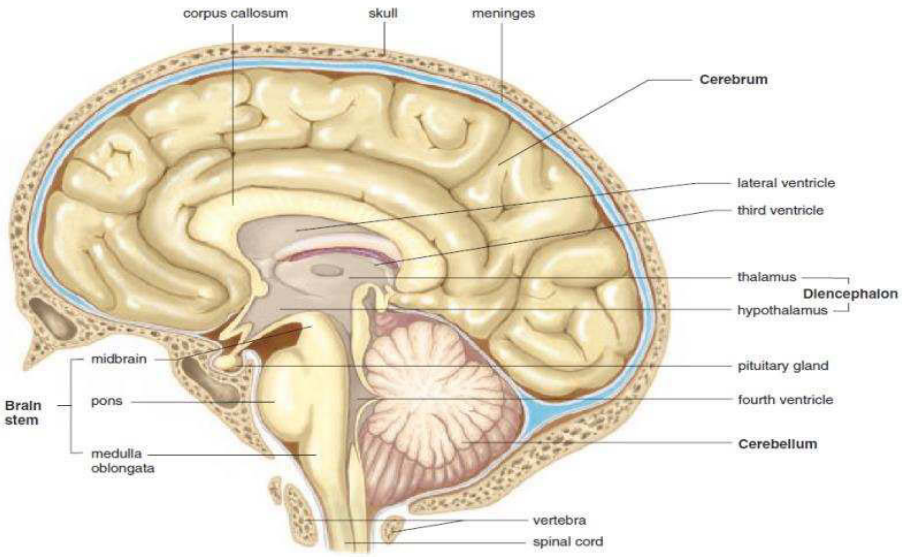



**Figure 2.3:The human Brain[12].**

The information related to auditory system for hearing any internal or external sound as a part of sense organ is to be processed by sensory system which is responsible for processing sensory information and it consists of three parts; sensory receptors, neural pathways and some parts

of the brain related to sensory perception. The information passes thalamus and then goes to specific region through the cerebral cortex.

A rapid multiplication of cells through the front end of the neural tube develop the brain and as a result 250,000 neurons are created every minute and the three units of the brain will be formed namely; Forebrain, Midbrain and Hindbrain. This is just a start for representation of the three major parts of the brain stated above. In 7 weeks human foetus forebrain becomes larger than the midbrain and hindbrain, by passing the time forebrain change to two cerebral hemispheres then thalamus and hypothalamus will be appeared followed by formation of cerebellum. The brain stem appears also by combination of hindbrain and midbrain. With this continuous development the cerebral hemispheres seems like a smooth ping pong balls at five month foetus. The huge amount of neurons forces the cerebrum to be formed to fit itself in the small area known as skull, Figure 2.4. As cerebral cortex develops ventricular zone and sub-ventricular are revealed. They include glial cells named radial glia. The thickness of the cerebral cortex depends on these cells. The radial glia which looks like a rope ladder leads the neurons to migrate to their right destinations. While neurons travelling to their destination, they get off the radial glia to give way to more neurons to reach their destinations, as a result we have six different layers of the cerebral cortex, Figure 2.4. Finally, neurons get their exclusive responsibility to play their roles in the most complicated mechanism in the world called brain [11]. Nervous system is described in the next section

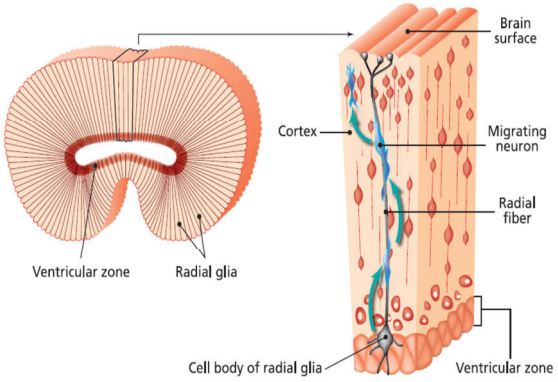



**Figure 2.4: Cerebral cortex components[11]**

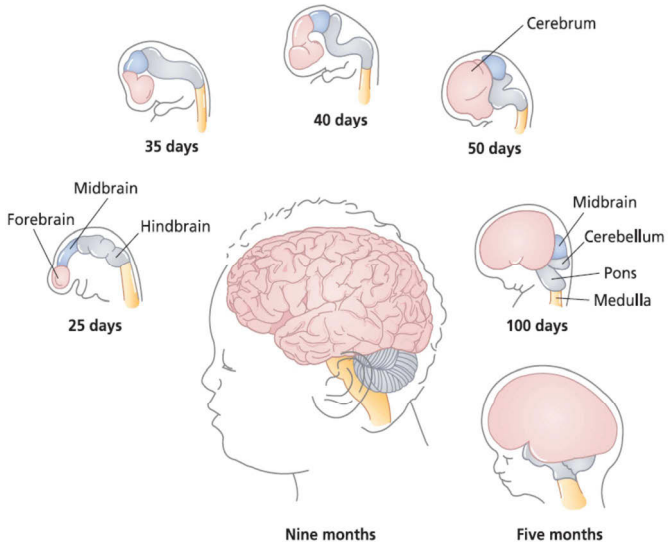



**Figure 2.5: Development of the human brain[11]**

### 2.2.2 Nervous System

Our nervous system consists of neurons which are known as message transmitters. Each neuron divided into different parts with dissimilar functions called, cell body, dendrite and axon, Figure 2.6. Dendrites receive and transfer the data to the cell body for processing; transferring of the information happens along the axon, myelin acts as an insulator to prevent the possible leakage of action potentials while travelling through the axon's length. Action potentials are short process of electrical discharges event that play an important role in communication between cells to cell, that will be explained in details in the next section.

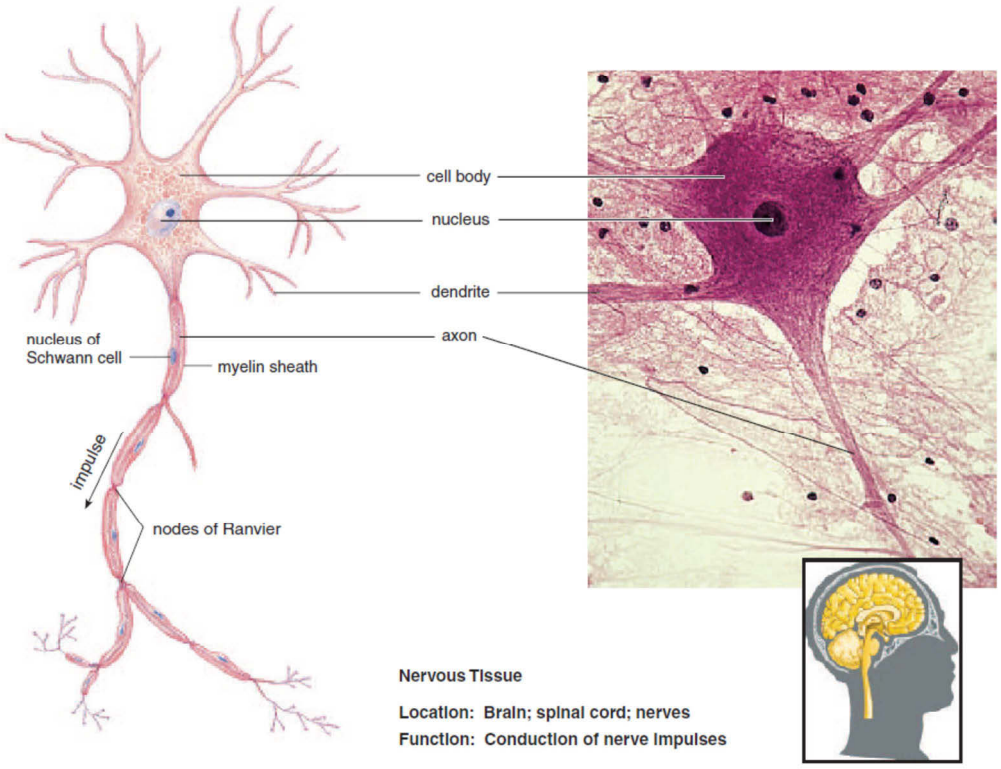



**Figure 2.6:A nervous tissue [12].**

A junction that allows a neuron to transmit electrical or chemical signals to another cell is called synapse, Figure2.7.

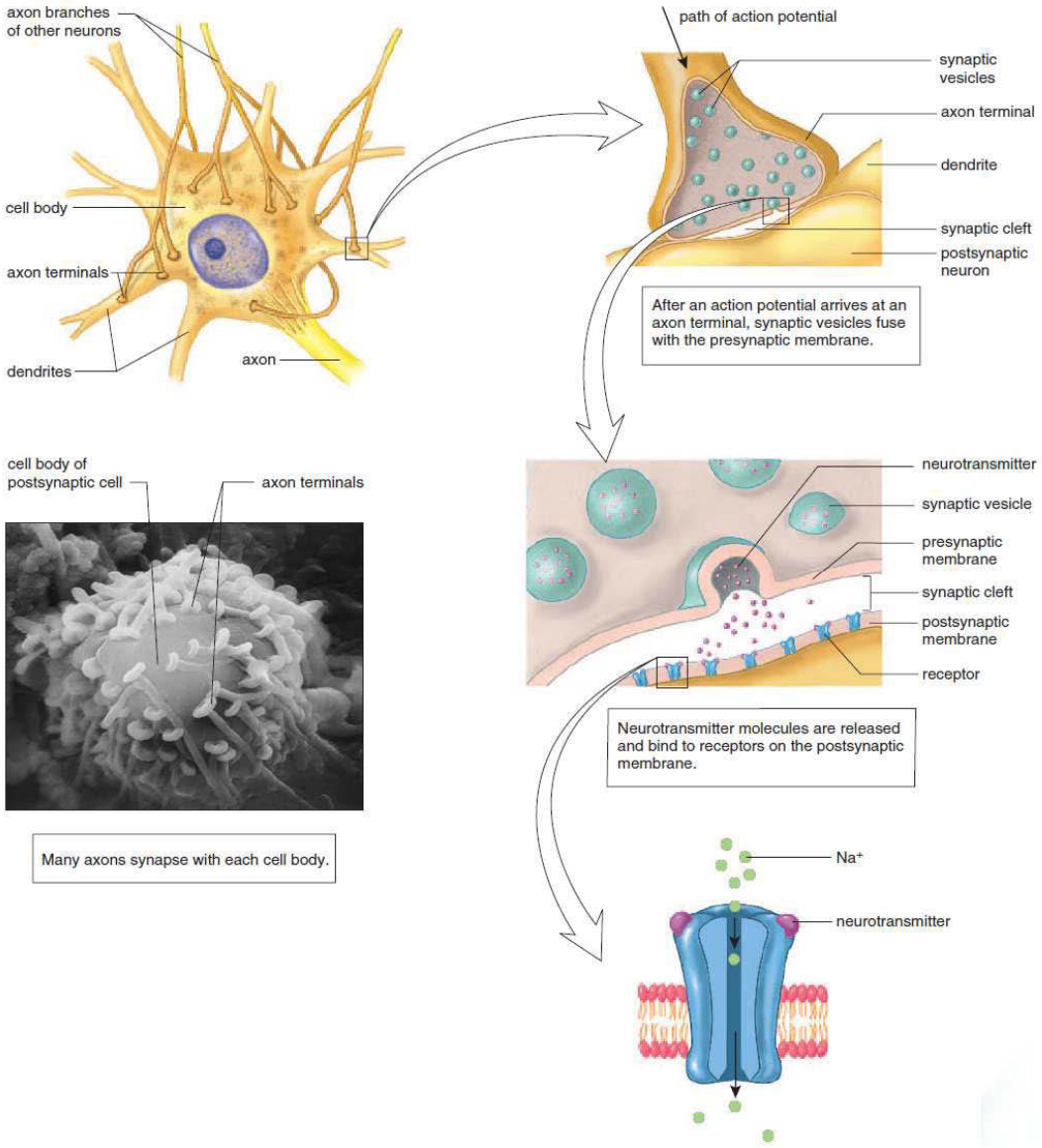



**Figure 2.7: A Synapse structure and transmission of the information through neurons [12]**

While an axon terminal receives a nerve impulse a special chemicals released into the synapse, called neurotransmitters. They help messages to be transmitted across the synapse from cell to cell. Those chemical signals during a process called electrochemical process are converted to electrical signals and vice versa[12].

### 2.2.3 The Action Potential

An action potential (AP) is a short-lasting explosion of an electrical activity occurs when a stimulus reaches a neuron. As it is shown in Figure 2.8, as soon as the data is received by a neuron the resting potential move from -70mV toward +30mV, when this depolarisation become about -55mv where the neuron's threshold is, the action potential will be fired. According to a principle called all or none principle, the size of the action potential for all neurons is the same. The ions change through the neuron membrane and cause the action potential. As soon as a stimulus arrives, sodium(Na+) channels will be opened, as a result the outside of the cell get more sodium ions than the inside therefore sodium ions go forward inside the neuron via the membrane which is negative, so the neuron become more positive. This action called depolarisation. During the inverse of depolarisation, called repolarisation action potential return to -70 mv, during this process potassium (K+) leave the cell and sodium channels start to close[9].

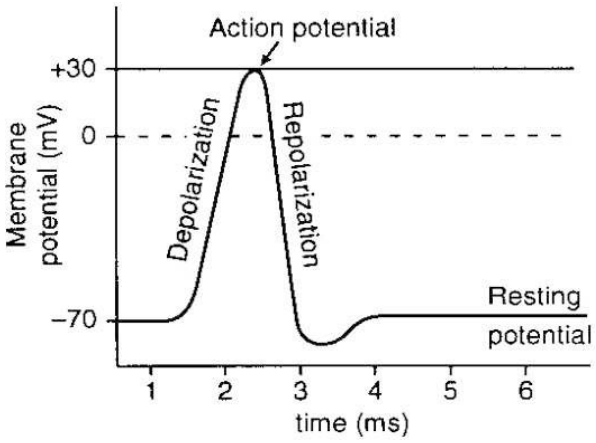



**Figure 2.8: An action potential[9].**

## 2.3 The Electroencephalogram [EEG]

Electrical activity of the brain recorded from the scalp and produced by the firing of the neurons within the brain is called an Electroencephalogram (EEG) This electrical activity happens spontaneously during all applications of the human actions such as eye movement, hearing a sound, hand movements and so on for both voluntary and impulsive controls. Hans Berger is known as the first person who published work on how to record the EEG signal in 1924 by using a primordial galvanometer with a surface electrode using human subjects. Berger discovered the rhythmic Alpha brain waves [25].

### 2.3.1 EEG Rhythms

EEG rhythms can be classified according to their different specifications these are known as amplitude, frequency, shape and the site on the scalp where the electrodes are located. These particular features are affected by some factors discussed earlier in this chapter such as state of alertness and age of the patient and also they show distinguishable differences from person to person under the same conditions. For example, the frequency recorded in an adult who is awake is 7.5 Hz and higher; accordingly waves with 7 Hz or fewer frequency are often classified as an abnormality in an adult who is awake but is completely normal to be seen in children or adults who fall asleep[9].

EEG rhythms are categorized into the following waveforms with the frequency range between 0.5-500 Hz.

Examples of waveforms are presented in Figure below:

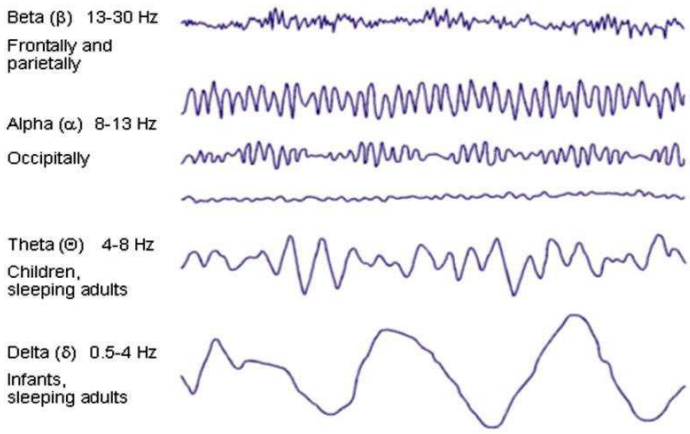



**Figure 2.9: EEG Waveforms[9].**

- **Alpha waves**

The frequency spectrum of alpha waves is between 8 and 13 Hz and happen normally during wakeful and relaxation status in adults with closed eyes. They start to become visible after three years of age and they will disappear during concentration, awareness or attention conditions.

As an example alpha waves occur in an individual who is under stress. Although they can appear on both sides of the head, slightly higher amplitudes of these waves can be seen on the non-dominant side. This result is revealed more in right-handed persons than left-handed ones [28].

- **Beta waves**

The frequency band of the beta activity which is considered as fast activity is between 13 and 30 Hz. This frequency band can be detected from the parietal lobe and frontal lobes. Beta waves exist for all ages from a new born baby to an adult. They are known as a normal rhythm with small amplitude which happens in open eyes status or the state of being alert or anxious [28].

- **Theta waves**

Theta waves are known as slow activity and have the frequency range between 4 and 8 Hz. They are observed in children up to 13 years of age as well as sleeping adults. They occur when the person is engaged in active motor behaviour and in the rapid eye movement (REM) stage of sleep [28].

- **Delta waves**

Delta activity with the frequency range between 1 to 4 Hz is known as the slowest wave with the highest amplitude which appears during slow-wave sleep or deep sleep and it also occurs in infants up to one year old [28].

- **Gamma waves**

Gamma activity with the frequency range between 30 and 90 Hz appears in the state of wakefulness and attention. The waveform will be attenuated during sleep and will be removed completely in the unconsciousness condition[28].

### 2.3.2 Changes in EEG Rhythms

EEG rhythm oscillations are from 1 Hz and 200 Hz that can be classified into three types known as slow, fast and ultra-fast frequencies. There are four kinds of synchronized oscillations that occur in the wakefulness states as well as rapid eye movement (REM) sleep. Alpha rhythm is amplified by visual stimulus and spread out in the cerebral cortex. In contrast the spindle oscillations can be seen during slow wave sleep and are associated with the thalamic reticular nucleus (TRN). The frequency range of spindle oscillation is from 7 to 14 Hz.

The literature [7] shows that by any stimulation of the brain, high-frequency rhythms around 35 to 45 Hz will occur in two parts of the brain, one in the motor cortex and the other in the parietal association cortex. Theta waves are associated with some behaviours such as running, walking, and head movements but not with spontaneous reflexes and/or behaviour, for example: chewing, licking or teeth-brushing. Fast waves are called Beta/Gamma and ultra-fast rhythms are called Ripple. They are observed at the occipital cortex when the subject is engaged. Non-REM sleep characterizes spindles with 7 to 15 Hz, delta waves with 1 to 4 Hz and slow oscillations with 0.5 to 1 Hz frequency bands.

Figure 2.10 shows the EEG signals in a cat by stimulation of the cerebellothalamicus axons at different states of alertness [7].

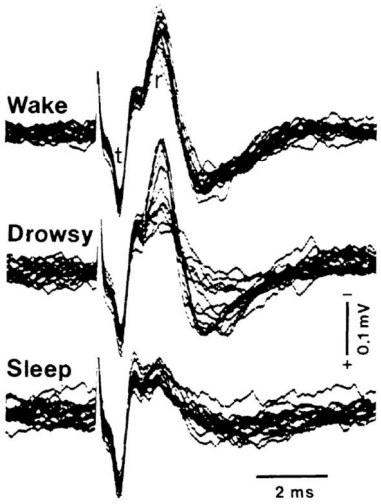



**Figure 2.10: Different states of alertness in cat by stimulating the cerebellothalamicus axons [7].**

## 2.4 The Auditory System

The human auditory system consists of three parts. Locations of different parts are shown in Figure 2.11:

● Outer ear that consists of two parts (pinna or auricle and ear canal). The length of the ear canal is approximately 2.5 cm and its diameter is approximately 0.6 cm. This "S" shaped organ is covered by hairs and wax without any sweat glands.

● Middle ear that consists of the tympanic membrane, three small bones called malleus, incus and stapes, two small muscles called tensor tympani and stapedius.

● Inner ear that consists of the vestibular apparatus for balance and the cochlea that is a sensory snail shaped organ for hearing. The length of the cochlea is around 3.1 to 3.3 cm, and it has a height of 0.5 cm when uncoiled. The cochlea and vestibular are surrounded by one of the hardest bones in the body called the temporal bone. It has three canals filled with fluid; the scalavestibuli, the scala tympani and the scala media.

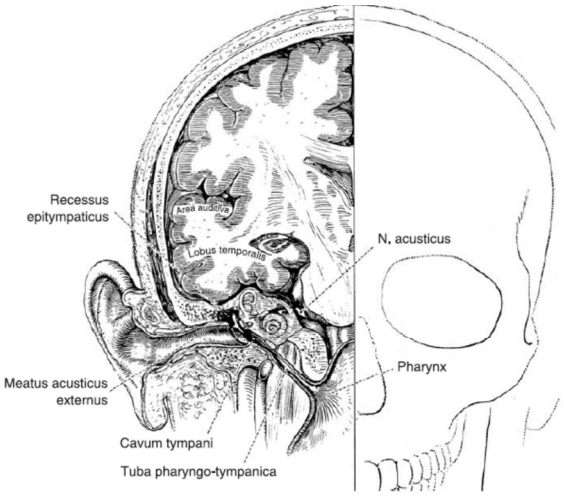



**Figure 2.11: Location of different parts of the hearing system in human head.**

The spiral organ or the organ of Corti that is located in the inner ear consists of hair cells or auditory sensory cells. The hair cells are organised in rows through the basilar membrane. They have also bundles of stereocilia on the top. Two main types of hair cell are outer hair cells and inner hair cells. The human auditory organ consist of approximately 12000 outer hair cells with 3 to 5 rows and with 50 to 150 W shaped stereocilia organized in 3 to 4 rows

and 3500 inner hair cells in a single row with compressed U shaped stereocilia. Sounds pass through the outer ear and middle ear, then go to the cochlea where they are separated according to their frequency levels. Hair cells act as transducer and they convert the sounds to a neural code in auditory nerve fibres.

Sound pressure level (SPL) is affected by different factors before the sound reaches the tympanic membrane. For example the outer ear, head and ear canal act as a barrier to the sound waves; for the sound wave, the head direction in relation to the sound source also changes the amount of this pressure level. The sound pressure reaching the right ear is different compared with that reaching the left ear; this difference is distinguished at the central auditory nervous system so we can recognize the direction of the sound source. The ear canal resonates the sound and transfers it to the tympanic membrane where the sound pressure increases by approximately 10dB in comparison with the sound at the entrance of the ear canal [8] as shown in Figure 2.12.

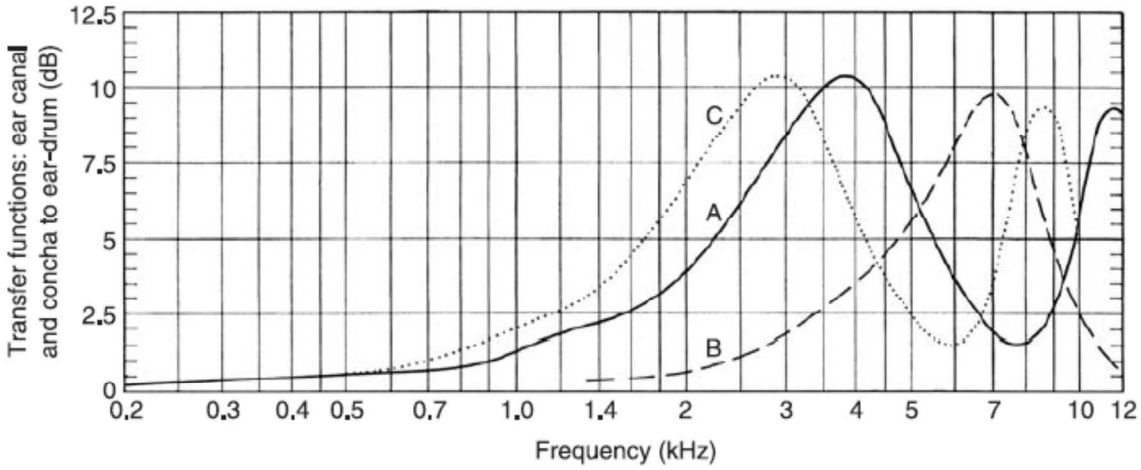



**Figure 2.12: The ratio between the sounds pressure level at the entrance of the ear canal and the tympanic membrane (frequency transfer function): (A) average ratio of the sound pressure between the ear canal and the tympanic membrane, (B) the sound pressure ratio between a point in ear canal (1.25 cm from the tympanic membrane) and the tympanic membrane, (C) theoretical estimation of the sound pressure ratio between the tympanic membrane and a geometric centre of the concha[8].**

Two factors have an effect on transferring the sound to the cochlear fluid. First, the large difference in impedance between air and fluid causes a problem in converting a fluid into a motion. Second problem is that during the conversion of the fluid into vibration just 0.1% of the energy will be converted and the rest which is 99.9% will be reflected at the air-fluid interface. Surprisingly those problems are solved by the presence of the middle ear. The middle ear as an impedance transformer plays a role in matching the low impedance of air to the high impedance of fluid; this is the only part in the human auditory system which distinguishes it from an animal's auditory system. The outer hair cells known as "motors" play an important role in compensating for the energy losses in the cochlea especially for those sounds with low intensities. The outer hair cells have an ability to change spontaneously and vigorously, so they can spread and expand. Demonstration of this motility function can be divided into two types: fast change in the hair length that is normally up to 5% and slow change that can be expanded even more than this. The first one helps the cochlear to distinguish different frequencies. Slow change effect on the ear sensitivity, occurs by generating receptor currents at the hair cells after motion caused by sound stimulation; this is the reason that the outer hair cells are called "motors". Indeed they act as a vibration amplifier in the basilar membrane. This is one of the reasons that the human auditory system is known as the most complex human sensory system that performs the best spectral analysis by discriminating even small changes in the frequency[8]. As a brief explanation for step by step analysis of the auditory system; sound pressure makes motion at the tympanic membrane, this movement is transferred to the auditory ossicles in the middle ear, these ossicles then move the vestibular or oval window membrane, this movement make motion at the cochlear fluid and the basilar membrane, as a result of this motion the inner hair cells will be bend, this change stimulates the hair cells and in the end the action potentials are produced at the nerve fibres.

## 2.5 Brain Responses to Auditory Stimuli

Energy of the sound moves the air molecules and the ear organs act as a transducer to convert this energy to electrical signals in the brain.

Electrical impulses sent from the ear to the brain travel through the auditory nerve and go to the ventral cochlear nucleus (VCN). From the VCN signals project to superior olivary complex that is one of the components of the brainstem to determine the location of the sound then a message is sent to the inferior colliculus which is located in the midbrain.

At this stage all the information received from both ears and transferred through the thalamus reach the temporal lobe positioned at the cerebral cortex for more complex processing of the sound.

Characteristics of the sound can be described by the loudness, pitch and timbre. The loudness is identified by the amplitude of the sound, the pitch is recognized by different frequencies and the timbre demonstrates the complexity of the sound. Moderate and high frequency sounds are recognized and processed in the brain by the intensity of the basilar membrane movement.

The hearing process is different for the low frequency sounds. The liquid in the cochlea moves along with some certain cells at the end of basilar membrane then from the oscillations and movements the sound is transduced into an electrical message for the brain to process [8].

### 2.5.1 Sound Evoked Potentials (SEPs)

Sound evoked potentials (SEP) can be divided into three different types; cochlear microphonic (CM), summating potential (SP) and action potential (AP). Cochlear hair cells create CM and SP while auditory nerve generates

APs. By using an appropriate auditory stimulus all three SEPs can be recorded from an electrode placed at the cochlea[8].

The following paragraphs explain in detail the three stated above SEPs:

- Cochlear Microphonic

The CM was recorded in the 1930s for the first time using an electrode attached to the cochlea window in an animal. A person's speech sound was used in this test and it was observed that after the sound passed the amplified CM could be heard by an observer. Such that the amplifier is connected to a microphone and the name cochlear microphonic is coming from this observation[29, 30].This method came into attention for the assessment of cochlea functionality.

- Summating Potential

The SPs are the summation of SEPs. The stimulus used is a tone burst and it is generated at the basilar membrane. SP has been used to diagnose problems related to the inner ear. The best measurements can be achieved by placing the electrode onto the cochlear capsule where the amplitude and the polarity of the SPs are not affected by different factors such as pressure in the scala media and/or functionality of the cochlea.

- Action potential

AP can be recorded from different locations; cochlea window, inside the cochlear capsule and from the surface of the cochlear capsule. Two negative peaks were observed when recording from a small animal; N1 and N2. The waveform shape is similar in different electrode positions but the amplitude is larger when the electrode is placed inside the cochlea. The waveform latency and amplitude are also affected by the types of stimulus [31].

### 2.5.2 Near- and Far-Field Potentials

- Near-Field potentials

The near-field potentials are recorded directly from the auditory organs and they usually have high amplitude. Compound action potential (CAP) is one of the well-known near-field potentials that are produced by a click sound that is recorded from the eighth cranial nerve. The waveforms are the N1N2 similar to observed signals from APs explained above. Figure 2.13 below shows the CAP waveforms recorded from a monkey:

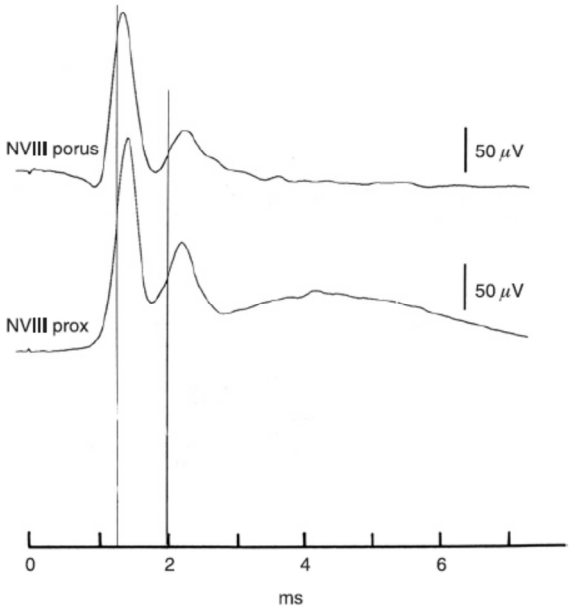



**Figure 2.13: CAP waveforms recorded from auditory nerves. The stimulus was click sound at 107 dB peak equivalent SPL. Electrodes were placed into two positions; near the brainstem and near the porus acousticus[8].**

The cochlear nucleus (CN) measurements using various types of sound stimuli are also known as near-field potentials have been recorded in humans [32, 33]. The observed positive-negative waveforms namely; P1N1-P2N2 is shown in the Figure below:

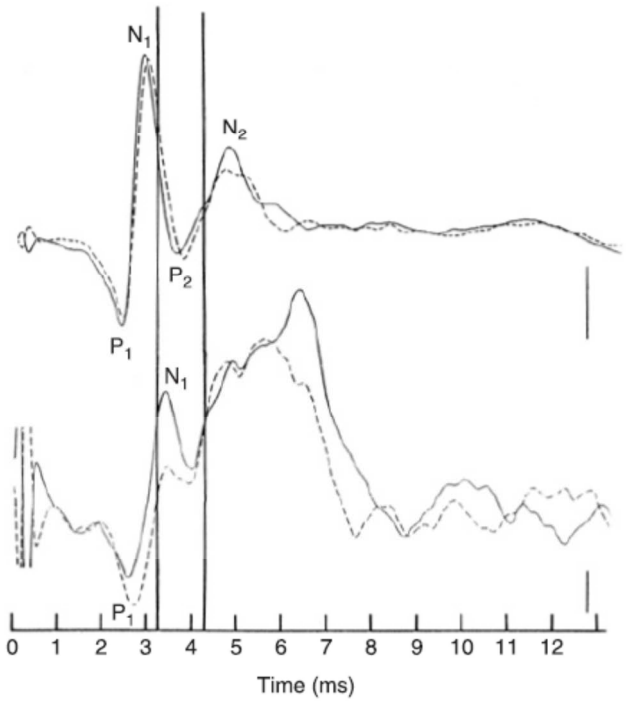



**Figure 2.14: CAEP components recorded from auditory nerve and cochlear nucleus. Solid lines are associated with the "rarefaction clicks" stimuli and dashed lines are associated with "condensation clicks" stimuli[8].**

- Far-Field potentials

As suggested by the name, far-field auditory evoked potentials are the responses to auditory stimulus recorded from electrodes that are placed far from the source and as a result they have much smaller amplitudes in comparison with near-field potentials. These potentials are more complex; the electrode can be affected by different sources of the nervous system because of the distance between the location of the electrode and the main source where the auditory response happens. Auditory brainstem response

(ABR), middle latency responses (MLR) and cortical auditory evoked potentials are known as far-field potentials.

ABR was recorded for the first time by Kiang [34]. ABR waveforms can be observed the first 10ms after stimulus. The stimulus types can be click sound, chirp or tone burst. The amplitude of ABRs is less than 0.5µV and this amplitude decreases when the stimulus intensity decreases. Two electrodes are used for this measurement placed at the vertex and mastoid along with the reference electrode placed on the forehead close to the hairline. The roman numerals are used to label the waveforms [35]. Figure below shows the ABR waveforms:

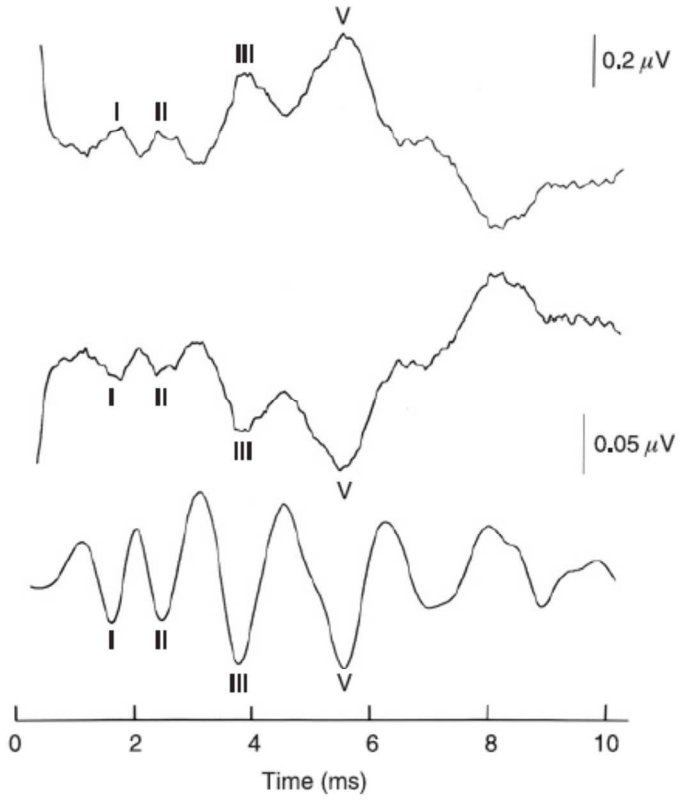



**Figure 2.15: A typical ABR recorded from a person with normal hearing[8].**

The MLR happens after 10 to 100ms after stimulus and the recording scheme is very similar to ABR, the only difference is that MLR has the component of auditory cortex. The MLR was investigated for the first time by Geisler et al [36]. The components are labelled as Na, Pa, Nb, Pb, Nc, Pc, and Nd where P stands for Positive and N stands for negative waveforms[37]. An MLR is shown in Figure 2.16.

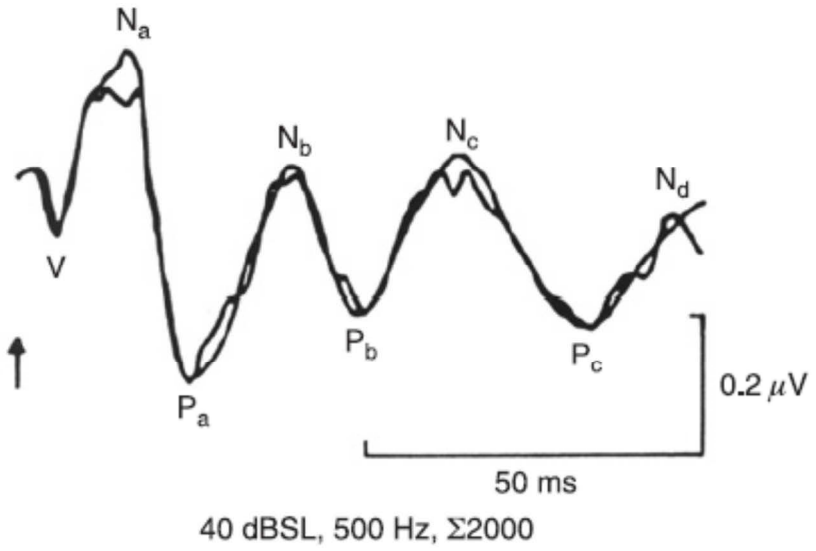



**Figure 2.16: A typical middle latency response. The stimulus was click sound with 10 pulses per second (PPS) [8].**

As mentioned earlier CAEP is another far-field potential that is explained in detail in the next section and is the selected stimulus type used in this study.

### 2.5.3 Cortical Auditory Evoked Potential Response

Cortical auditory evoked potential (CAEP) response has attracted considerable attention from neurologists, physiologists, scientists and researchers. They can be used to detect hearing loss as an objective approach with considerable advantages over ABRs.

The ABR disadvantages are listed below[15, 17, 38]:

- ABRs were found to be impractical while assessing the efficiency of hearing aids on children with hearing loss.

- ABRs are evoked by click sounds or tone bursts, se they might be filtered away or at least significantly modified by a hearing aid's signal processing when passing through the device.

In comparison, the CAEPs advantages are[15, 17, 38]:

- CAEPs have better threshold accuracy in some hearing disorders.

- CAEPs have better frequency-specificity.

- In CAEPs response morphology does not degrade at low stimulus frequencies.

- With CAEP a larger part of the neural pathway is tested as it originates from the auditory cortex instead of the brainstem.

- When recording CAEP fewer constraints on patient relaxation are needed.

- In CAEPs a smaller number of stimulus repetitions are required (as the CAEP has a larger amplitude), they have lower susceptibility to exogenous noise sources, and speech sound stimuli can be presented.

The CAEP response is referred to as the P1-N1-P2 complex and they occur together in an adult, as in Figure 2.17. The latencies and amplitudes differ from subject to subject and they depend on the type and intensity of the stimulus as well. The first major component of the CAEP is P1 that appears 50ms after stimulus. In an adult the amplitude of P1 is less than 2µV however in young children this amplitude will increase.

The CAEP negative waveform (N1) appears 100ms after stimulus. It has an amplitude between 2-5µV in adults. It is followed by another positive wave called P2 that can be observed 150ms after stimulus and occur with the same amplitude as N1[4].

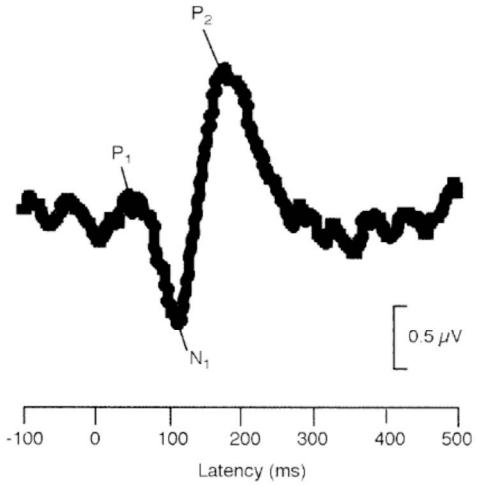



**Figure 2.17: The P1-N1-P2 complex[4].**

## Factors Affecting CAEP;

When processing CAEP signals the physiologist should take into consideration some important factors that have major effects on recorded CAEPs these are stimulus factors, subject factors and recording factors[4]. A brief explanation of the factors is described as follows:

- Stimulus factors that effect CAEP are intensity, frequency, rate, stimulus duration, ears and number of stimuli:

  - Intensity: The CAEP amplitude increases when stimulus intensity increases.
  - Frequency: The CAEP amplitude decreases by an increase in stimulus frequency.

- Rate: The CAEP amplitude increases by decreasing in the rate of stimulus presentation, up to an inter-stimulus interval of 10 seconds.
- Stimulus duration: The CAEP amplitude increases when the stimulus duration increases up to 30-50ms but it decreases when the duration exceeds 50ms.
- Number of stimuli: The CAEP amplitude decreases when the number of stimuli increases. However this effect is specific to each stimulus which means that if another sound occurs the amplitude of N1 will increase by a number that is proportional to the stimulus change magnitude.

- Subject factors than effect CAEP are age, gender and state of alertness:

  - Age: The N1 waveform begins to appear after the age of 2 and the latency of the complex is larger in young children in comparison with adults.
  - Gender: Some experiments show that N1 latency is shorter and the amplitude is larger in women and the amplitude-intensity function is sharper in women than men.
  - State of alertness: CAEP is affected by the state of alertness of the subjects as the drowsiness and sleep as well as ignore condition reduced the amplitude of the P1-N1-P2 waveforms.

- Recording factors: Measurement and recording parameters such as signal to noise ratio effect the P1-N1-P2 complex therefore a proper approach for threshold estimation seems necessary[4].

Experiments[39-41] demonstrate clear changes by the side of dissimilar physiological circumstances such as; different states of alertness level

known as wakefulness, sleep stages I and II, slow wave sleep (SWS), stages III, IV and paradoxical sleep (PS) that can be with or without rapid eye movement (REM) at the compound action potentials (CAP), cochlear microphonic (CM) as well as CAEP.

Although it is believed that physiological functions attenuate during sleep, in the study of electrophysiology, the evoked potentials related to visual and auditory information in some certain cases are bigger during SWS in comparison with wakefulness[7].

As shown in Figure 2.18, the human EEG waveform related to auditory evoked potentials is not removed but is attenuated during sleep.


**Figure 2.18: (A) the human auditory evoked potentials during sleep, (B) the human auditory evoked potentials during wakefulness [7].**

Another study shows that the auditory evoked potentials waveforms are both significantly increased with the attention to the sound stimulus in comparison with the "ignore condition" but there is no substantial change in the peak latency between those states. The N1 component had a latency of 82±9ms during the attend condition and 83±8ms during the ignore condition. The P2 component measurements were 163±19 and 158±19ms respectively", there is a significant shift in the latency at the condition of asleep compared with the awaking state[39-41].

Figure 2.19 shows the differences between the data processing pathway in the waking brain and sleeping brain.

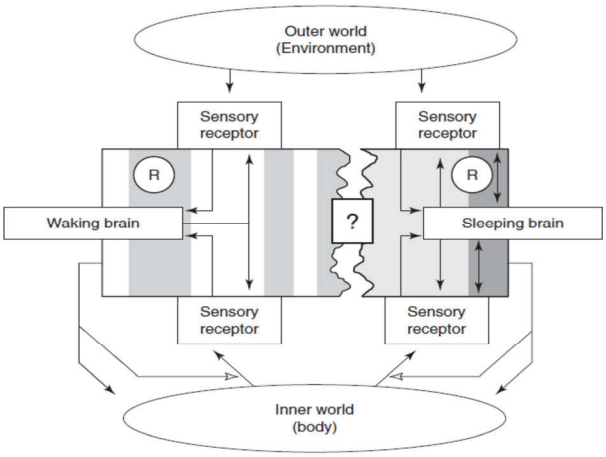



**Figure 2.19: Difference between data processing pathway in waking brain and sleeping brain[6].**

The only difference in information processing during wakefulness and sleep is that in the waking brain data received from the inner world (body) by sensory receptors can be transferred to the sensory receptors relating to outer world (environment) or vice versa, while there is no straight forward connection between them during sleep[6].

## 2.6 Objective Ways to Record Auditory Capabilities

Hearing assessment is classified into two main methods; behavioural testing and objective testing. A behavioural hearing test that relies on participant demonstration of a change with hearing stimulus can be used for adults and children. Pure tone audiometry, play audiometry, visual reinforcement orientation audiometry (VROA), behavioural observation audiometry (BOA) and speech discrimination testing are subjective (behavioural) hearing tests that require the participant to make a judgement about the auditory capability[42]. As this research focuses on CAEP measurements assessment it seems unnecessary to investigate the subjective testing here.

The objective hearing test is used for infants, children and incapacitated adults who are not capable of giving a reliable feedback during behavioural testing. There are several methods known as objective hearing tests; CAEPs and ABRs that have been discussed in detail in Sections 2.4.1.2 and 2.4.1.3 of this thesis, as well as tympanometry and otoacoustic emissions (OAEs).

### 2.6.1 Tympanometry

Tympanometry is used to determine the functionality of the middle ear and eardrum or tympanic membrane (TM). This test is not to evaluate hearing level and it has to be followed by pure tone audiometry but it measures the energy transmitted into the middle ear by using a soft probe that is placed in the ear canal. The stimulus is a low-frequency tone of 226 Hz [43].

### 2.6.2 Otoacoustic Emissions (OAEs)

OAEs are sounds that are created in the ear canal. This test is used to evaluate the functionality of the cochlea, middle ear and inner ear. OAEs cannot be produced if there is an abnormality in the cochlea or middle ear and if there is a blockage in the ear canal [44].

The stimulus in this test is either a clicking sound or tones that are produced from a very small loud speaker placed with a special foam or rubber tip inside the ear canal. The subject under test has to stay quiet for a few minutes during the test. Researchers found that OAEs can be observed in all people with normal hearing who also have normal functioning of their TM and middle ear [42].

## 2.7 Feature Extraction and Classification of EEG signals

One of the important aspects in signals and systems analysis in biomedical engineering is that all physiological signals (PSs) are joined to some extent and this interconnection caused complication in all stages of signal processing from extraction to classification. Some of the main properties of PSs are listed below:

- They are nonlinear.
- They have multiple inputs and outputs.
- They often have transfer delay connecting their nodes.
- They usually are extremely parallel systems.

To represent the PSs in a way that they can be processed easier and faster a sampling method can be used so the data will be recorded at some certain points and converted to digital signals. Bioelectric signals recorded from the skin surface produce an electroencephalogram (EEG) that has been mentioned in Section 2.3 as an example of PSs. To form the periodic and stochastic EEG signals as discrete measurements periodical sampling is used from the analogue signal $x(t)$,and changing each sample to a digital number, $x\,(k\mathrm{t})$, where $k$ is the number of samples.

This concept can be mathematically represented as:

$$x\,(k\mathrm{t}) = \sum_{k=0}^{\infty} x(t)\delta(t - kT)$$

Using delta functions and sampling period (T)[45].
Three steps of pattern recognition are feature extraction, dimensionality reduction and classification that will be discussed below in details.

### 2.7.1 Feature Extraction

The first and the most important step in data analysis is feature extraction as they provide input data for the two remaining steps and directly affect

the classification accuracy; in fact the extracted features must be as relevant as possible to the desired data in order to achieve promising classification results [46]. According to current knowledge in this area of research, brain electrical activity has dynamic variation in time, frequency and space which means that EEG signals are non-stationary.

In the feature extraction process the signal converts to a set of specific time windows called feature and variable components. This extracted feature vector should be much smaller than the original signal size [47]. Logically, are more relevant extracted feature should result in better classification accuracy; however some experimental analysis reject this theory [48, 49]. Some feature extraction methods will fail as a result of real time restrictions because they assume that EEG signals are stationary such as; Fourier transform (FT) coefficients, autoregressive coefficients and zero-crossing rate, although these linear operators represent computational simplicity. As an example in the comparison of wavelet transform (WT) and the linear time frequency representation of the signal called Fast Fourier Transform (FFT) for the spectral analysis of the EEG signals, it has been shown that WT is to a great extent more efficient than the FFT[50]. Stephen Mallet in 1989 [38] brought about a revolutionary change in physiological signal processing by introducing the wavelet transform method[51]. Thakor et al in 1993 applied this new method of signal representation to analyse the evoked potentials for the first time, in regard to its capability to distinguish signals with the same frequencies with different temporary locations[52]. This method has two limitations and drawbacks; the bandwidth of the signal has inverse proportion with the time-scale which can have an effect on the resolution, and the other one is that the representation of the signal is sensitive with the time-shift at the pre-analysed window. Those concerns were solved by using the matching pursuit (MP) method[53].

The main factors to be considered when dealing with multi-channel EEG signals in order to achieve better performance and quality features [46,54, 55] are:

- The number of extracted features should be as low as possible when analysing a huge number of EEG recorded signals for a considerable amount of time using multi-channel EEG cap.
- Features which are correlated do not add any value to the proposed algorithm.
- The computational method to achieve the desired signals should be as simple as possible to reduce computing time close to a reasonable real-time application.
- Feature shall be selected in a way to have maximum separability without any overlap in each class.
- Feature interaction shall be considered, as an irrelevant feature by itself may carry valuable information when combined with another feature to provide better separability between classes [56].

**The Wavelet Transform;**

The wavelet transform represents the signal in a certain time-frequency domain with coefficients that define the power spectral density of the signal. The wavelet function decomposes the signal to an orthogonal multi-resolution $L^2(R)$ subspace, approximation of the original signal $x$ at scale $2^j$ is $A_2^j x$, clearly there is a loss of information between two; $2^j$ and $2^{j+1}$ scales. To solve this problem detailed signals $(D_2^j x)$ were introduced. $V_2^j$ and $O_2^j$ are two operators and their inner summation is $V_2^{j+1}$. Wavelet function $\Psi$ stands for detail signal and $\Phi$ which is scaling function is related to approximations of the signal. Assume that $\Psi_2^j(t) = 2^j\Psi(2^j t)$ therefore, $[\sqrt{2^{-j}}\Phi_2^j(t-2^{-j}n)]_{n\in Z}$ and $[\sqrt{2^{-j}}\Psi_2^j(t-2^{-j}n)]_{n\in Z}$ construct orthonormal foundations of $V_2^j$ and $O_2^j$ correspondingly, as a result the wavelet; $[\sqrt{2^{-j}}\Psi_2^j(t-2^{-j}n)]_{n\in Z^2}$ is an orthonormal basis of $L^2(R)$. Finally the original signal $x(t)$ is decomposed to the wavelet coefficients according to the equation below:

$$D_{2_j}^n(x) = \{x(t), \Psi_2^j(t-2_2^{-j})\}$$

If we assume that the Nyquist frequency is $fN$ then at the scale zero the frequencies from $fN/2$ to $fN$ will be covered, scale 1 will cover up the frequencies in the range of $fN/4$ to $fN/2$ and so forth [51].

In the other word a modified signal called a mother wavelet is used in the wavelet decomposition. The average value of the mother wavelet is zero and must satisfy the below condition:

$$\int_{-\infty}^{+\infty} \Psi(u)du = 0$$

$$\int_{-\infty}^{+\infty} \Psi(u)^2 du < 1$$

The signal will be reconstructed after decomposition from its wavelet features so the mother wavelet properties are playing an important role in this re-establishment [57].

There are several mother wavelets such as Daubechies, Haar (db1), Biorthogonal and Coiflets. Scale and position of the signal is used in the wavelet approach rather than the signal's amplitude and phase, as per the equation below:

$$C(\text{scale}, \text{position}) = \int_{-\infty}^{+\infty} x(t)\Psi(scale, \quad position)dt$$

Where $x(t)$, is the original signal to be decomposed and $\Psi$ is the mother wavelet[10].

Figure below is a Daubechies mother wavelet.

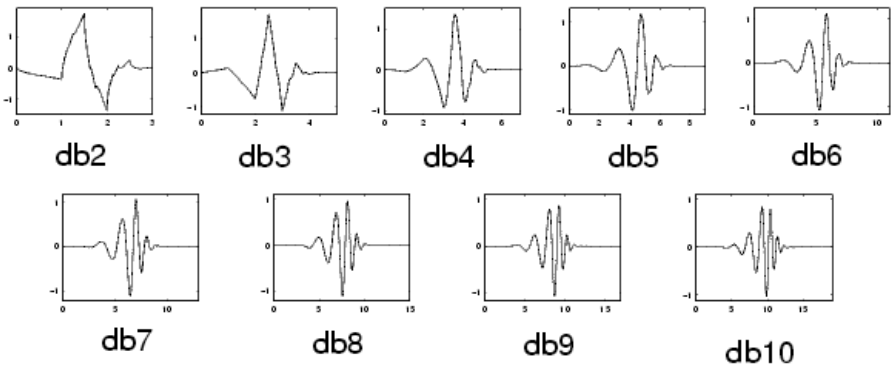



**Figure 2.20: Daubechies wavelet [10].**

The wavelet has two forms; continuous and discrete. Continuous wavelet transform CWT (Figure 2.21) is described by the equation below:

$$WT\{x(t): a, b\} = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t) \Phi^{*}_{a,b}\left(\frac{t-b}{a}\right) dt$$

Where $x(t)$ is the finite energy signal and this becomes the mother wavelet when $b = 0$ and $a = 1$.

The waveform stretches along the time axes when $a > 1$ and squeezes when $0 < b < 1$.

$a$ is a scaling parameter and $b$ is a position parameter.

Where $a, b \in \Re, a \neq 0$

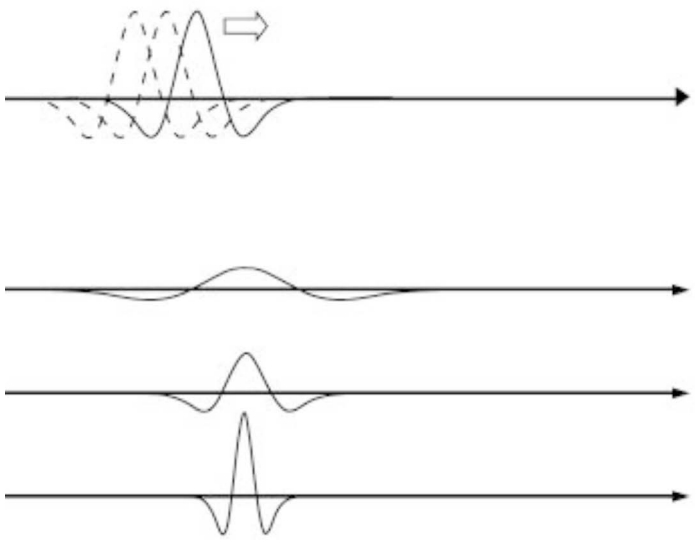


**Figure 2.21: Continuous wavelet transform[5].**

The Discrete Wavelet Transform (DWT) is used where searching for a more computationally efficient method that works with a lower number of coefficients and as a result less memory storage is required [58]. DWT decomposes the signal into a digitized discrete signal. It applies a series of high and low pass filters to analyse the signal [47, 59]. DWT decomposes the signal into scaling and wavelet coefficients. Scaling coefficients are high-scale, low frequency components while the wavelet coefficients are low-scale, high frequency components.

Scaling coefficients and wavelet coefficients are called approximations and details respectively [60, 61]. Wavelet models shall be chosen to suit each application followed by an appropriate number of decomposition levels; these two factors play an important role in signal analysis while using the DWT approach [62].

Figure 2.22 represents a signal x(t) decomposition sampled at a certain frequency level by using high-pass ( g[n] ) and low-pass ( h[n] ) filters [59].

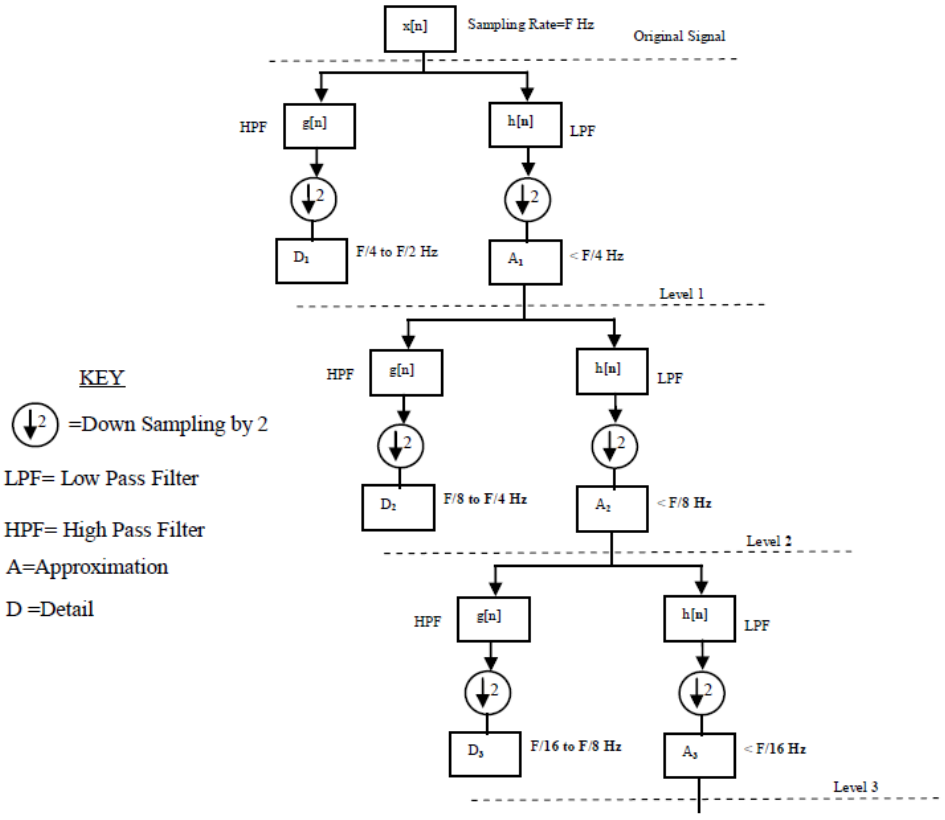



**Figure 2.22: Three level decomposition by wavelet transform [59].**

Another method which is a generalized version of DWT is called wavelet packet transform (WPT) where time-frequency resolution is adjustable [51]. WPT decomposes both details and approximations as shown in Figure 2.23:

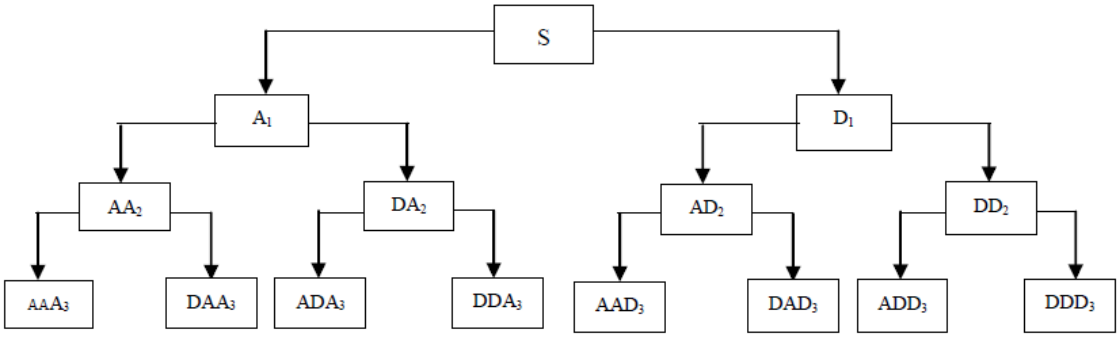



**Figure 2.23: Three level decomposition using WPT[60].**

There are several methods of time-frequency signal analysis, such as, Wigner distribution, Gabor transform and Choi-Williams distribution [63]. However wavelet features for EEG-based applications are commonly used by researchers and have shown promising results. For instance, Subasi in 2005 used DWT for extraction of $\alpha, \beta, \theta$ and $\gamma$ bands to classify alertness levels to three pre-defined stages called alert, drowsy and sleep. He used neural network classifier and the classification accuracies reached $92\% \pm 5$ and $95\% \mp 3$ [64]. In [65-69]wavelet transform was used to analyse EEG-based signals for different applications.

### 2.7.2 Dimensionality Reduction

Dimensionality reduction is a process of transferring the information from high dimensional feature space to the less inherent dimensions. The number of variables that are measured on each observation represent the dimension of the data [53]. It is useful in machine learning to reduce the number of variables for better classification, presentation, regression, visualization and understanding of the data correlation in a data set. Several dimensionality reduction methods have been introduced in the literature. Those methods can be divided into feature selection and feature projection approaches.

#### 2.7.2.1 Feature Selection Methods

The "curse" of dimensionality refers to intractability of analysing data throughout a high-dimensional space. This term was introduced by Richard Bellman in 1961[70]. Feature selection strategies aim to deal with this problem by reducing variable dimensions. They search through all subsets of variables and select the ones that perform the best with chosen classifiers. All feature selection methods contain the following elements [71-73]:

- Starting criteria: Empty, full or randomly selected feature set can represent the starting point. Other feature sets will then evolve based on the adopted search strategy.

- Search development: various search procedure methods have been proposed in the literatures that vary in their complexity and optimality. These methods range from a sequential-based approach to stochastic approaches.

- Evaluation functions: there are three methods of evaluation techniques, filters, wrappers and embedded. Features subset scoring varies between those three approaches.

- Stopping point: An appropriate stopping criterion has to be chosen for each application such as; running time, stopping on a certain point.

It is important to mention that the selected data subset be relevant to the desired data and classification problem, with as little cardinality as possible. Some of the well-known feature selection methods are developed using Kohonen's self-organizing maps(KSOM) [74], density networks [75], neural networks [76] and genetic algorithms [77].

#### 2.7.2.2 Feature Projection Methods

Feature projection technique is a way of dimensionality reduction that can be linear and non-linear depending on its objective function [78, 79]. In projection methods the data is mapped from the input with $d$-dimensional space to a new space with $k$ dimension where $k < d$. This transformation must occur with minimum loss of information. The projection function is as follows where $x$ is the input data and $W(z)$ is the direction:

$$z = W_x X \in R^d, z \in R^k$$

The literature demonstrates several methods of feature projection approaches. Independent component analysis (ICA), principle component analysis (PCA)[80, 81], linear discriminant analysis (LDA),factor analysis (FA) [53] and uncorrelated LDA (uLDA) are examples of linear methods.

Another useful approach is known as blind signal separation or blind source separation (BSS). Such method attempts to separate a set of basis signals from a set of mixed signals while the basis signals are not defined, i.e. there is no information about the basis signal [46].

Considering EEG signals that are recorded from different parts of the brain with different electrodes placed on the scalp, there are many different messages coming to the attached electrodes at the same time of recording. Some of them are associated with the desired signals therefore it is necessary to apply a method to separate those signals without knowing much information about the source. This is how researchers found the EEG signal processing as a clear example of BSS application.

This effective approach separates the source signals by getting the means of each decomposed multi-channel EEG and setting them up as subsets of neural sources as well as removing the artifactual features [82].

For some datasets that do not match the Gaussian distributions, it is suitable to use higher-order dimension reduction techniques that do not use the covariance matrix, such as projection pursuit (PP) [83] and ICA [84]. In the non-linear techniques the objective functions that verify the output as an optimal weight are non-linear. Some of the popular feature projection methods of this type are non-linear principle component analysis [85], non-linear independent component analysis [86] and principle curves [87].

### 2.7.3 Classification Problem

Classification problem must be considered as one of the main parts in data analysis because classification tools evaluate the predictive power of desired signals and as a result assess the predicted information they carry[88].

Classifiers can be categorized into two different approaches; supervised and unsupervised and they are commonly based on learning and testing phases. In the supervised method training feature sets are classified with class labels subsequently the output data is defined so they can predict the future dataset, while the unsupervised approach classifies the data without knowing what the output is.

In the supervised approach at the first step the discriminant function is matched to a segment of the data known as the training data set, and then these trained data are employed to distinguish between the classes through the new data sets[89].

Figure 2.24 below shows the process of supervised classifiers:

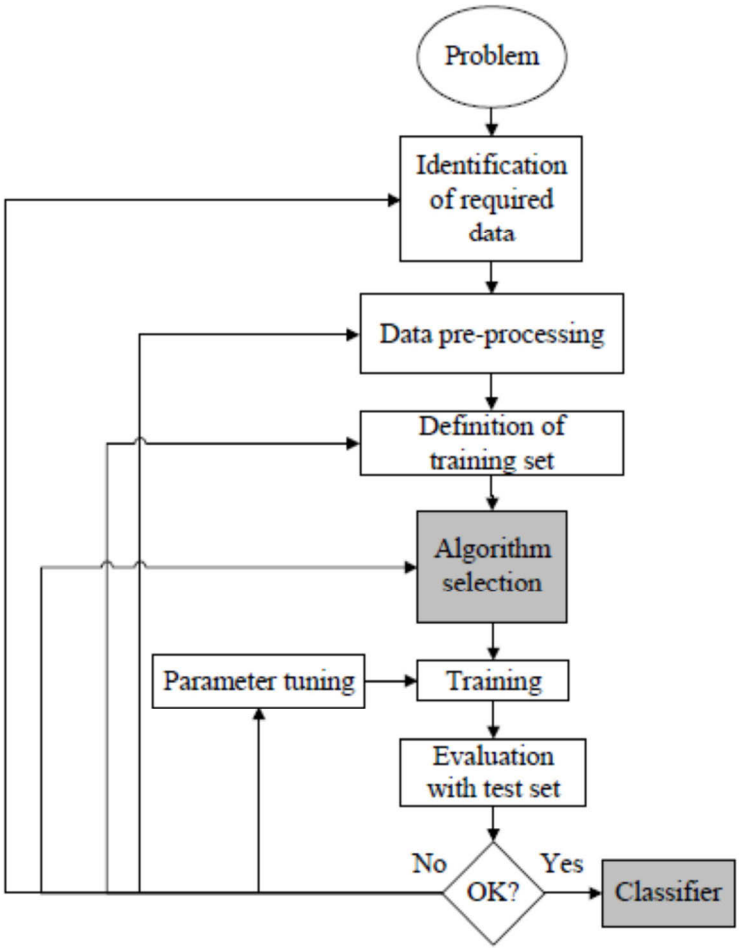



**Figure 2.24: Supervised classification process[89].**

Some well-known supervised classifiers are discussed below:

#### 2.7.3.1 K-nearest Neighbour

K-nearest neighbour (KNN) classifier relies on the closest features to define a label for each of them on the training set to predict the class labels of the testing sets. The Euclidean distance is calculated to determine the mean of the distances in each set of data. This approach can be summarized as below:

For a given training dataset $(X_i, Y_i)$;

Where:

- $X_i$is input feature vector of pattern $i$
- $X_i$is the class label to be achieved

First, the distance between training and testing dataset is to be calculated: Assume that the two points are; $X(x_1, \dots, x_n)$and$Y(y_1, \dots, y_n)$

$$Distance\ (D) = \sqrt{\sum_i^n (X_i, Y_i\ )}$$

The next step is to find nearest neighbours $(k)$ in the training sets and label them accordingly. Then the class labels of testing sets are then defined by applying a principle to search for its $k$ nearest neighbours [90].

#### 2.7.3.2 Linear Discriminant Analysis (LDA)

Linear discriminant analysis (LDA) is a method employed in different fields such as pattern recognition and machine learning to identify a linear combination of the chosen features that differentiate the classes of each samples or events to minimize total error of classification (TEC). The method is based on a linear fitness function applied to the original data; the numerical representation of this explanation can be defined as below:

For a given dataset $x$:

$$f(x) = wx + b$$

$b$ is known as bias while $w$ is the common vector to the decision boundary where$f(x) = 0$.

In general the classification rules assign an object to a group through the highest conditional probability called Bayes Rule as well as minimize the TEC.

Methodology:

- Assume there are C classes.
- $\mu_i$ is the mean vector of class *i* and *i* = 1, 2… C.
- $M_i$ is supposed to be the number of samples within class *i*, *i* = 1, 2… C.
- M = $\sum_{i=0}^{C} M_i$is the total number of samples.

Therefore within-class scatter matrix is:

$$S_w = \sum_{i=1}^{c} \sum_{j=1}^{c} (y_j - \mu_i)(y_j - \mu_i)^T$$

And between-class scatter matrix is:

$$S_b = \sum_{i=1}^{c} (\mu_i - \mu)(\mu_i - \mu)^T$$

Where μ is the mean of whole data:

$$\mu = \frac{1}{c} \sum_{i=0}^{c} \mu_i$$

By implementation of LDA the between-class scatter matrix will be maximised at the same time as minimising the within- class scatter matrix: Maximize$\frac{\det(S_w)}{\det(S_b)}$. As a result data sets are maintained more separate.

#### 2.7.3.3 Support Vector Machine (SVM)

Support vector machine (SVM) classifier was introduced by Vapnik in 1979 for the first time[91]. SVM classifier is a robust implementation for classification purposes. In contrast with LDA that build a probabilistic representation by using all data points in each class, as mentioned above SVM focuses on minimizing the separation error by employing neighbouring points which can be both linear and non-linear. Data are labelled differently according to their location from the margins and the points that are far from the separation space will be discarded in the testing phase. Figure 2.25

shows the difference between those classifiers in real time application[88]. The linear SVM will be describing below as a comparison with LDA:

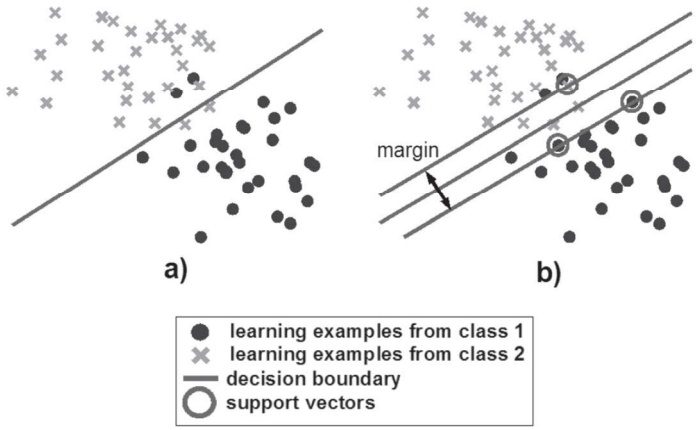



**Figure 2.25: figure a, shows the decision boundaries using LDA classifier, figure b, shows the decision boundary using SVM classifier.**

The linear discriminant function of SVM is the same as LDA therefore we have:

$$f(x) = wx + b$$

Assume that $x_i$ is the $i - th$ data point in the training data sets and fits in to the vector $x$ and the class label is $yi$ while $y_i = +1$ shows the data point belongs to class 1 as $y_i = -1$ belongs to class 2. The margin defined at the area of the decision boundary represented by the equations $f(x) = +1$ and $f(x) = -1$. The margin width maximizes by SVM while the majority of the data points stand at the outside of the defined boundaries. The equation below demonstrates this function:

$$(w^*, b^*) = argmin_{w,b} C \sum \varepsilon_i + \frac{\|w\|^2}{2}$$

Where $y_i(< w, x_i > +b) \geq 1 - \varepsilon_i, \forall_I$ and $\varepsilon_i \geq 0, \forall_i$

$\sum \varepsilon_i$ is the "separation error term", $\frac{\|w\|^2}{2}$ is the "regularization term" and C is a "user-defined regularization term parameter". This algorithm gets some point at the boundary surface known as support vectors [88, 91].

Some references that maybe useful for a better understanding of different classification methods are listed in the reference section [64, 92-96].

# Chapter 3

## 3. EEG RECORDING METHOD

### 3.1 Recording Scheme

Data recording took place at the National Acoustic Laboratories (NAL), using a Compumedics Neuroscan Synamp 2(Refer to appendix A).A multi-channel EEG Quikcap with 66 electrodes that included 64 EEG and 2 EOG channels were used to collect the data from different parts of the scalp. Each test took one hour and each stage was broken into six blocks of ten minutes with 1000 Hz sampling rate.

Subjects were asked to press the response buttons to indicate their level of alertness each half a minute and they were asked to try to go to sleep in a darken room during the test. Those three indicators were engaged, calm but alert and drowsy as shown in Figure 3.1.

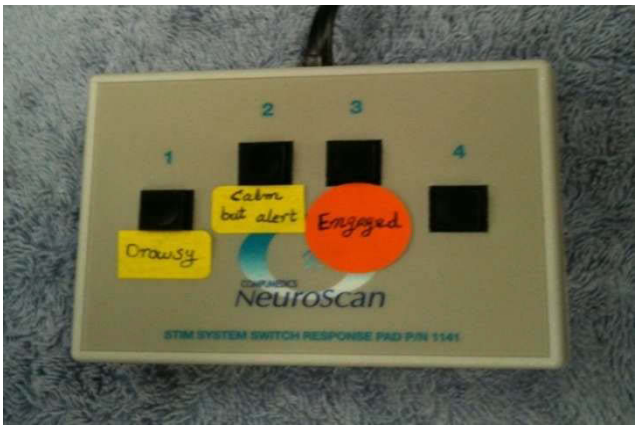



**Figure 3.1: Subjects alertness level indicators**

## 3.2 Stimulus

Stimuli were presented using with an inter-stimulus interval (ISI) of 1125ms using a loudspeaker at 55 dB SPL. The stimulus was a 21 millisecond speech sound /g/, as shown in Figure 3.2. The /g/ sound's primary energy has been measured in the range between 800 to 1600 Hz, and has been used in other studies of NAL[97].

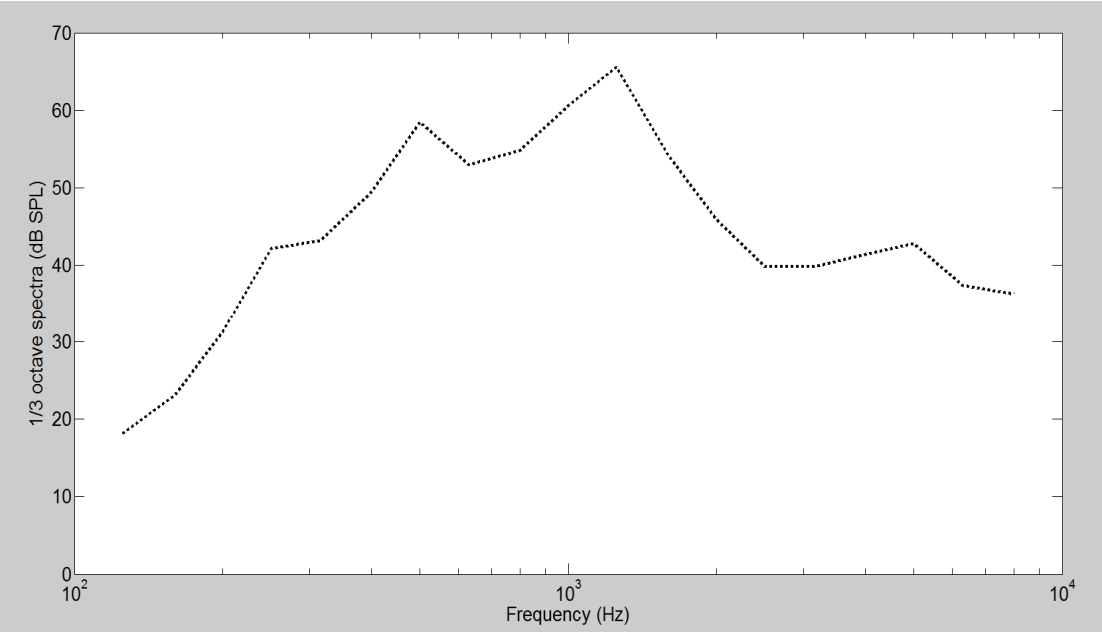



**Figure 3.2: Spectrum of the 21ms speech stimulus /g/**

## 3.3 Participants

CAEPs were recorded from 10 adult subjects, 4 females and 6 males with normal hearing and ages that range between 24 to 53 years (the mean age is 33 years and 5 month with the standard deviation of 8 years and 5 months). We provided the test information followed by a consent form to all participants to read and sign prior testing (refer to appendix C).

Pure tone audiometry test were applied for all subjects to make sure about the normality of their auditory system in four audiometric frequency levels; 500, 1000, 2000 and 4000 HZ. Figure 3.3 shows the audiometry test results on one of the subjects:

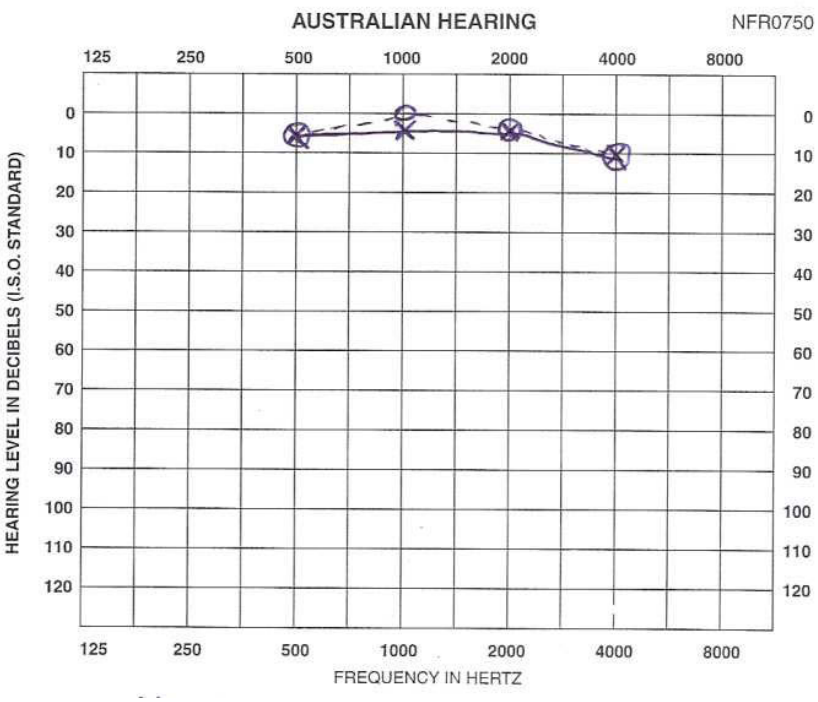



**Figure 3.3: Pure tone audiometry test result. The cross is related to the left ear and the circle is related to the right ear.**

All subjects had hearing levels equal to 20 dB HL or lower.

It is important to mention that we have found a noticeable variation between the recorded labels of the different subjects, as shown in Figure 3.4.

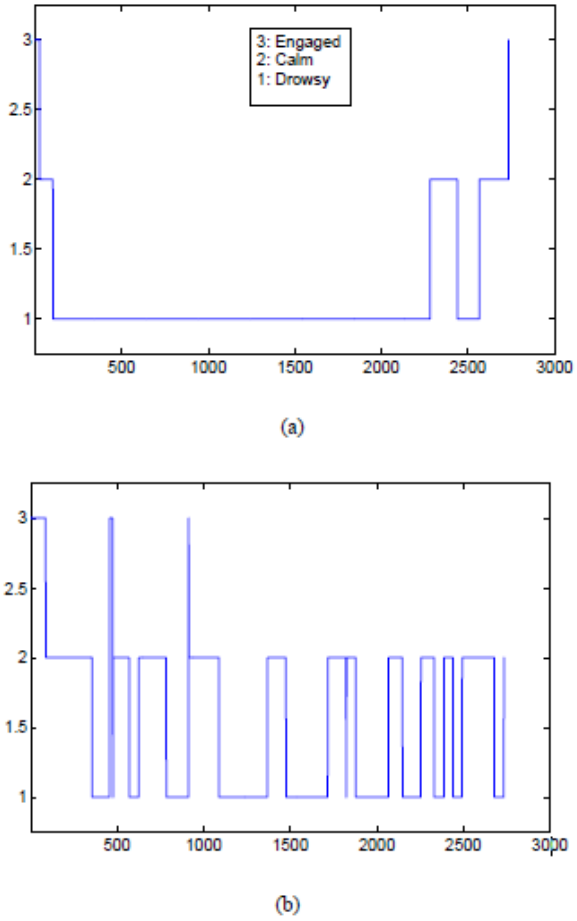



**Figure 3.4: Recorded labels of two subjects with different fluctuation levels. Horizontal axis: time in seconds. Vertical axis: three states of alertness as indicated in the legend.**

If the subject did not press any button in any of the 10 minute blocks of the 1 hour recording, then a label of 0 (sleeping status) is inserted for that block. The percentage of the four classes ("engaged", "calm", "drowsy" and "sleeping") from 10 subjects are: 15.19%, 34.29%, 46.20% and 4.32% respectively.

As mentioned in section 2.5.3, there are several factors that can affect CAEP recording; stimulus, recording scheme and subject factors.

In this study in addition to the above aspects affecting CAEP recording, we encountered other problems that must be considered when dealing with different subjects as they have significant effect on data processing. Subject indication of alertness states might not be correct as this judgment varies

from person to person. Subject movements during data recording which gave us a very noisy data in some cases.

## 3.4 EEG Cap Channels Location

Electrode placement is defined by a particular standard for example 10-20 International system. 10 and 20 refer to the distance between each adjacent electrode that is either 10% or 20% [98, 99]. The number of electrodes can vary in each specific application. As EEG signal has a very small voltage, it is important to choose the electrode to be used in data processing as far as possible from reference electrode. In our case reference electrode is located on the central lobe close to CZ. According to current direction which starts from the ear and goes toward the central lobe the best channel is a channel with installed electrode far from the reference electrode, this voltage differentiation gives the most clear and bigger waveform in term of amplitude. Therefore in the analysis that has been conducted in this research we used channels T7, M1, P7, T8, M2 and P8 that are located on a region immediately behind the ear called mastoid (M1, M2) and two other surrounding channels (T7, T8, P7, P8).Figure 3.5 demonstrates different locations of the electrodes on scalp.

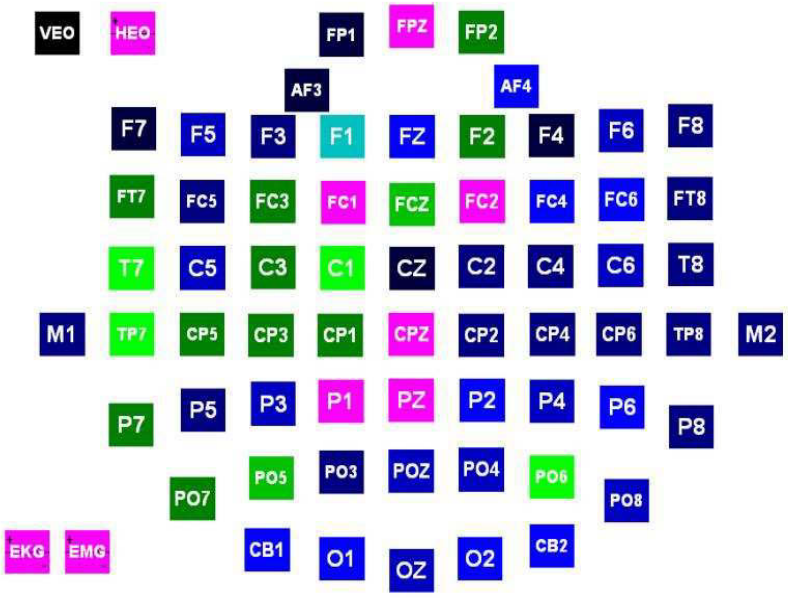



**Figure 3.5: EEG cap channels location (different colours indicate different impedances on the corresponding electrodes with blue low impedance and pink high impedance).**

# Chapter 4

## 4. CAEP ANALYSIS AND CLASSIFICATION vs. BACKGROUND EEG

### 4.1 Introduction

This chapter presents analysis of CAEP responses and their applicability to the classification of alertness states.

Collected EEG data was processed to extract the CAEP components. This is implemented both manually and using an algorithm that was developed to identify the amplitudes and latencies of the CAEP peaks in order to validate the capability of CAEP in detecting alertness states, a comparison is presented with features extracted from discrete wavelet transform of the EEG data.

### 4.2 Analysis of CAEP Responses

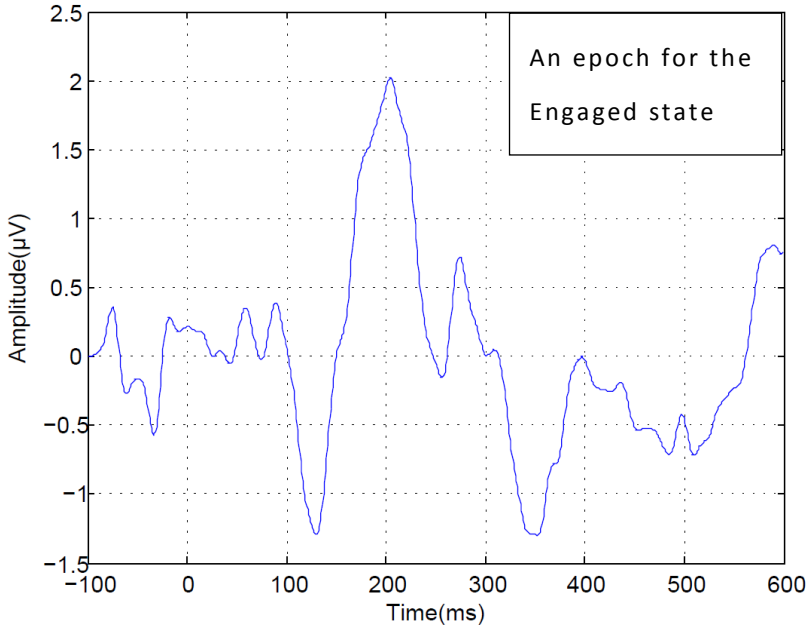
The collected data from Neuroscan system was imported into MATLAB using EEGLab (refer to appendix B). Manual and algorithm based approaches are used to identify the N1, P1, N2, P2 peaks in order to statistically analyse the obtained results. Analysis of Variance (ANOVA) [100],[101]was utilized.
The ANOVA analysis gave a post-hoc "pair-wise comparison" between alertness conditions with fisher's least significant difference (LSD) test for multiple comparisons to find relationship between stages of alertness and subjects [102].Each extracted epoch starts from about 100ms before hearing stimulus onset and runs till 600ms after the stimulus onset.

A stimulus is presented in each 1120ms. Hence, based on the sampling frequency and ISI mentioned in Section 3.2, each block of 10 minutes (600 seconds) contains approximately 535 stimulus events.

### 4.2.1 CAEP Components Peak Extraction – Manual Approach

The epochs that have absolute average amplitude above 150µv were rejected. Vertical electrooculogram (VEO) that is recorded to show the status of vertical eye movements was employed for this purpose. To remove any DC bias, i.e. to reduce the effect of baseline shift, the mean from whole epochs were calculated and eliminated from the data by using the first 100ms before stimulus.

**A) Without averaging and filtration:** We have first attempted to identify the peaks without applying any filter and with no averaging of epochs. We wanted here to investigate the possibility of identifying the CAEP peaks from the "row" EEG data. Figure 4.1 shows an epoch for each of the three alertness states of "engaged", "Calm" and "drowsy". The epochs appear a bit noisy with multiple peaks.



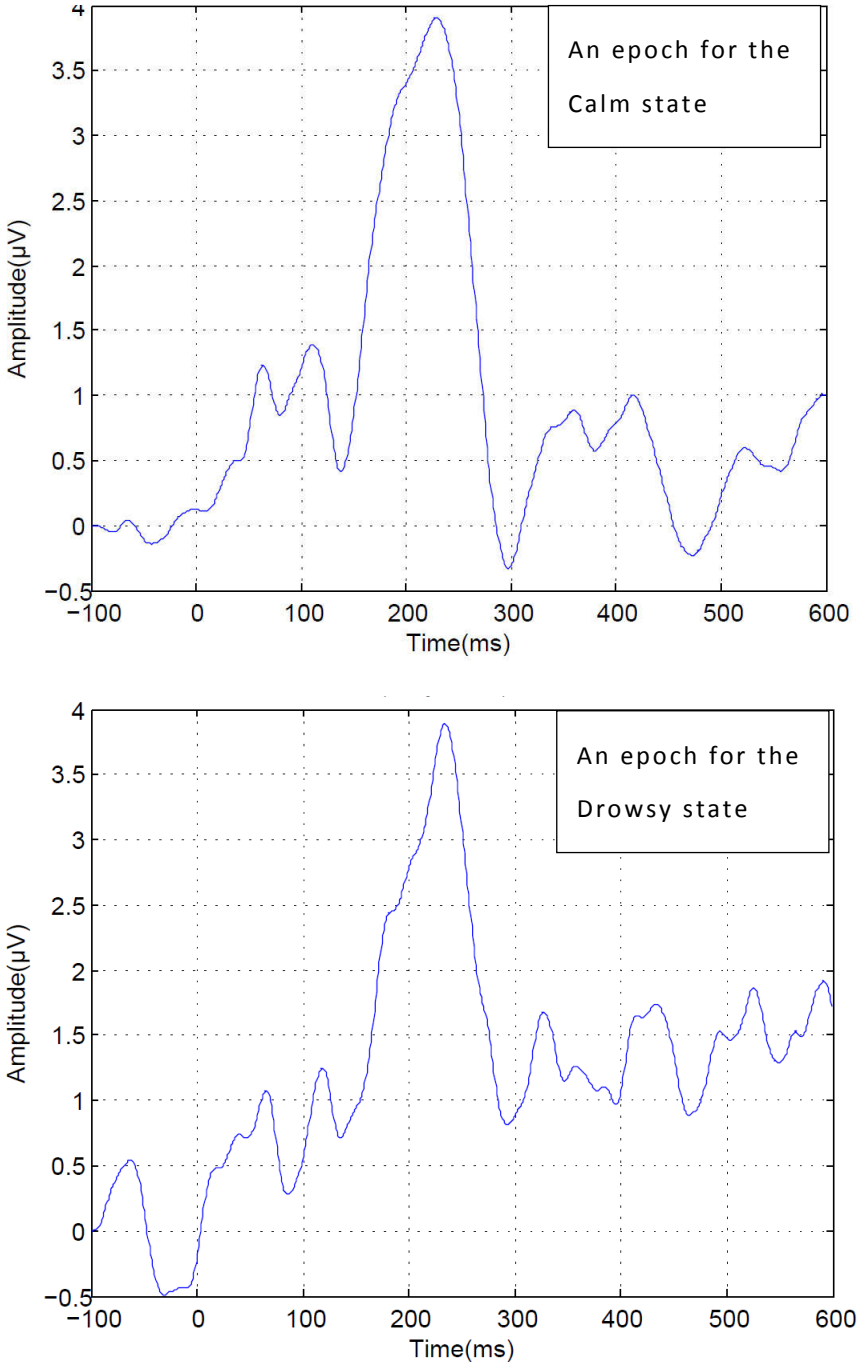
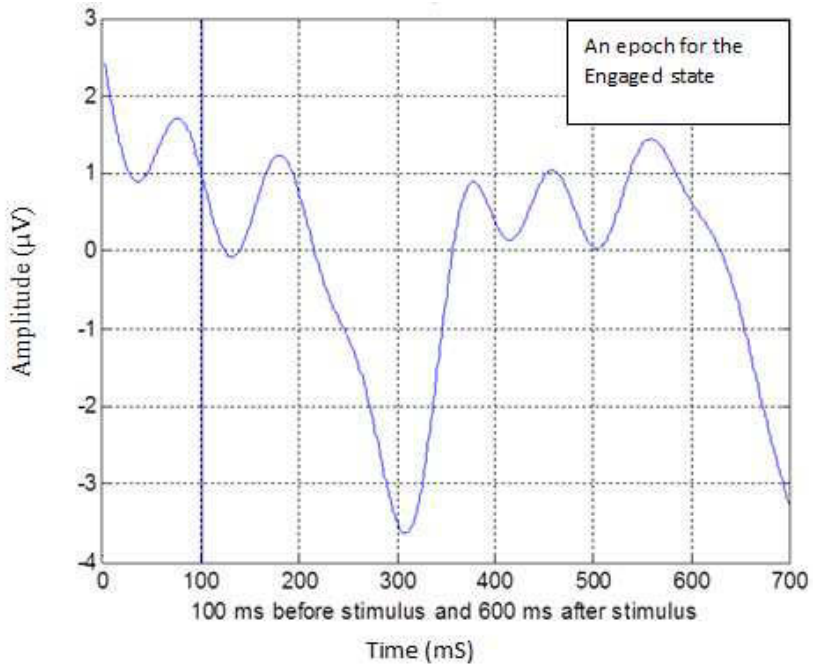
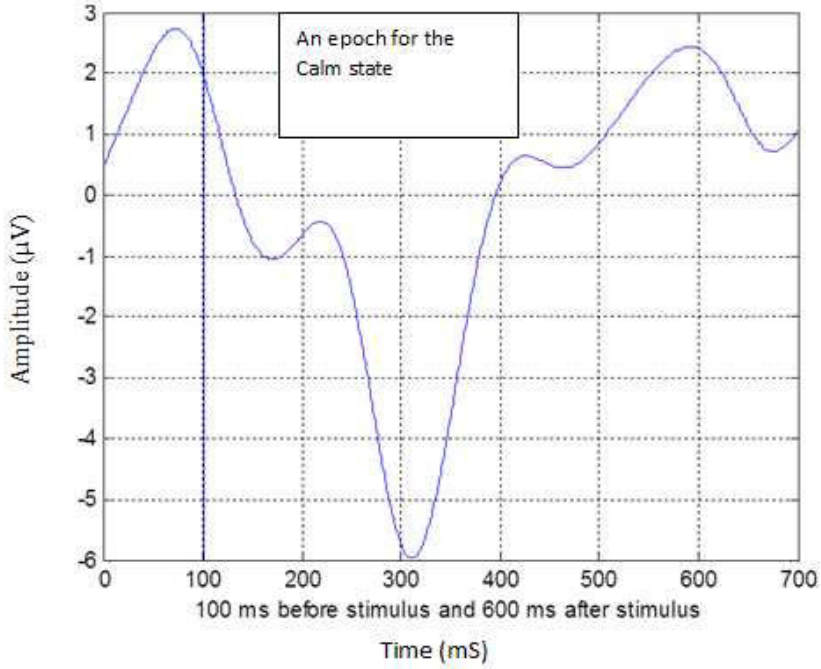



**Figure 4.1: CAEP response extracted from subject 1 in different states of alertness, "engaged, calm but alert and drowsy" respectively.**

**B) With averaging and filtration:** A band-pass filter was applied with cut-off frequencies of 1 and 20Hz. 100 sweeps were averaged by increment of one sweep to suppress the background EEG and emphasize the CAEP responses, as the morphology of CAEP responses may not be clearly identifiable when considering a single epoch. It is clear that the waveforms are smoother with

less noise when compared with the waveforms shown Section A and as a result the CAEP peaks are easier to identify.



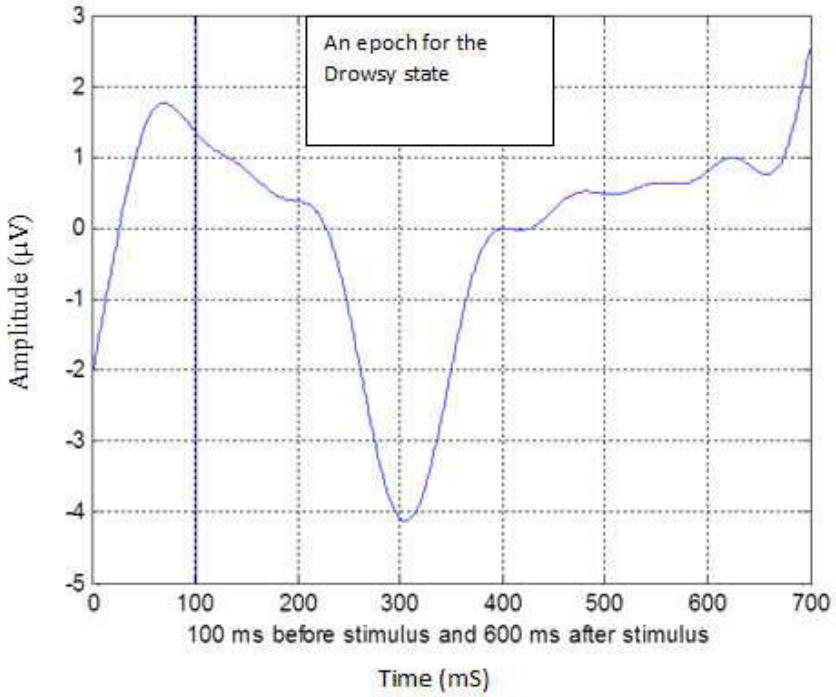
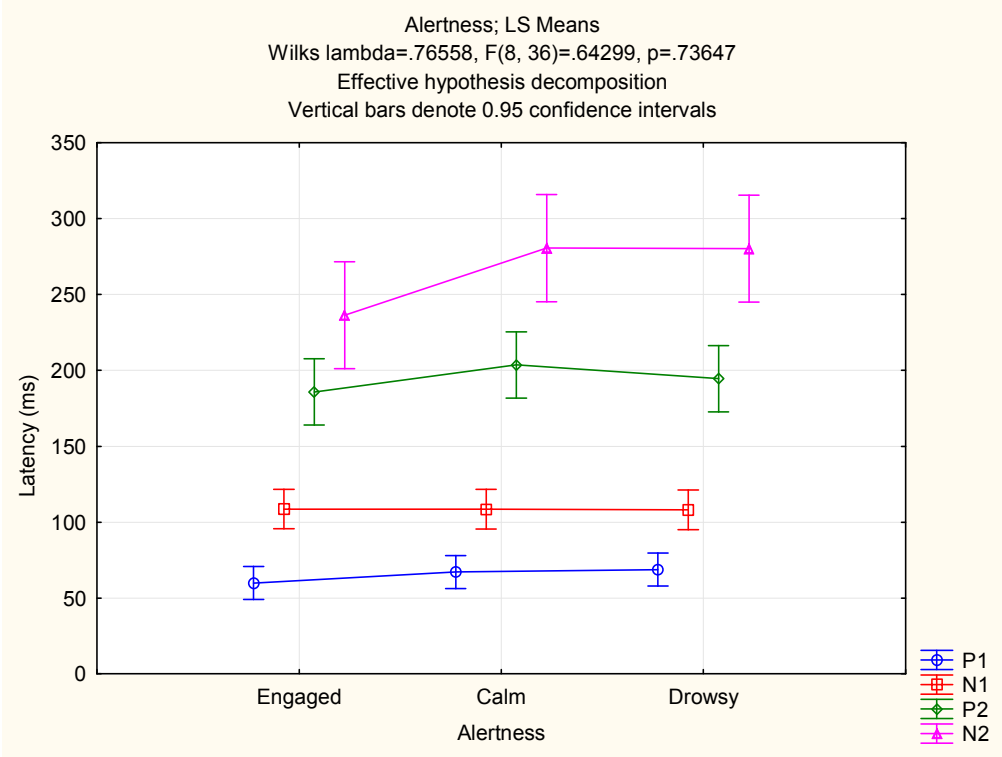



**Figure 4.2: CAEP response extracted from subject 1 in different states of alertness, "engaged, calm but alert and drowsy" respectively.**

N1, P1, N2, P2 peaks were manually observed from channel 33 and recorded for ANOVA analysis. Figures 4.3 and 4.4 demonstrate statistical investigation on both amplitude and latency of CAEP responses observed from Sections A and B. One can notice that Figure 4.3 has on average a higher variance when compared to Figure 4.4, The multiple peaks that exist in A (without averaging) make it hard to identify the true ones especially with the later peaks of N2 and P2, as they span on a longer duration of time. Moreover, the average amplitude and latency for the three alertness states differ slightly between Figures 4.3 and 4.4.



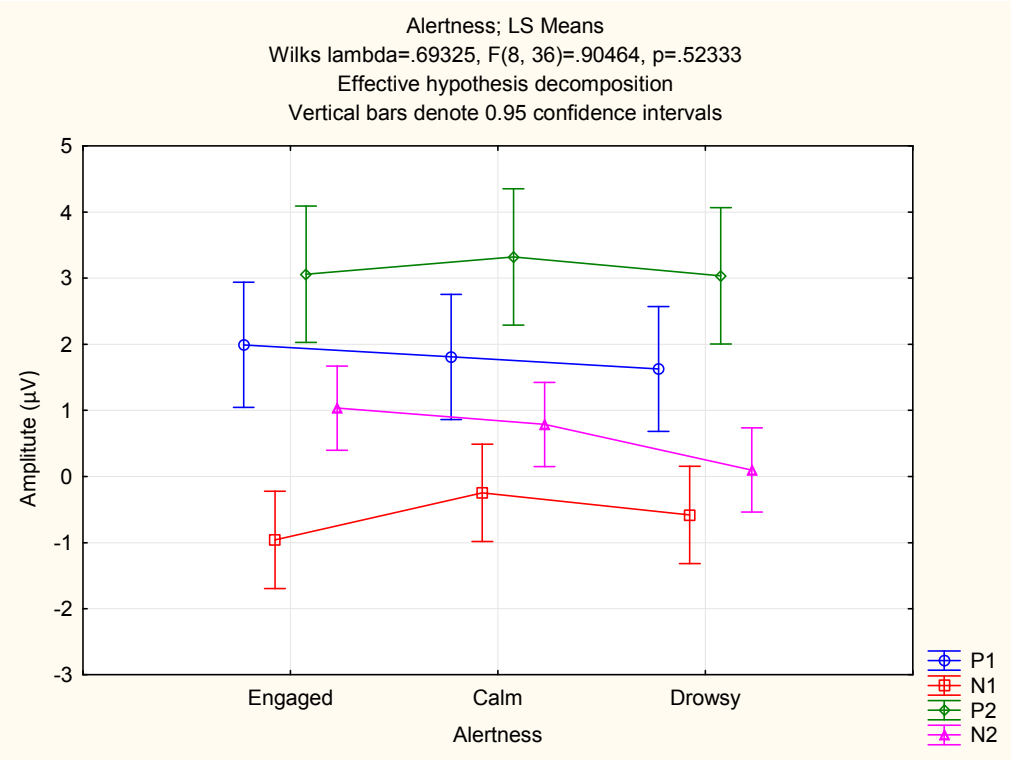




**Figure 4.3: P1N1P2N2 peak amplitude and latency variation among subjects using data of section A.**

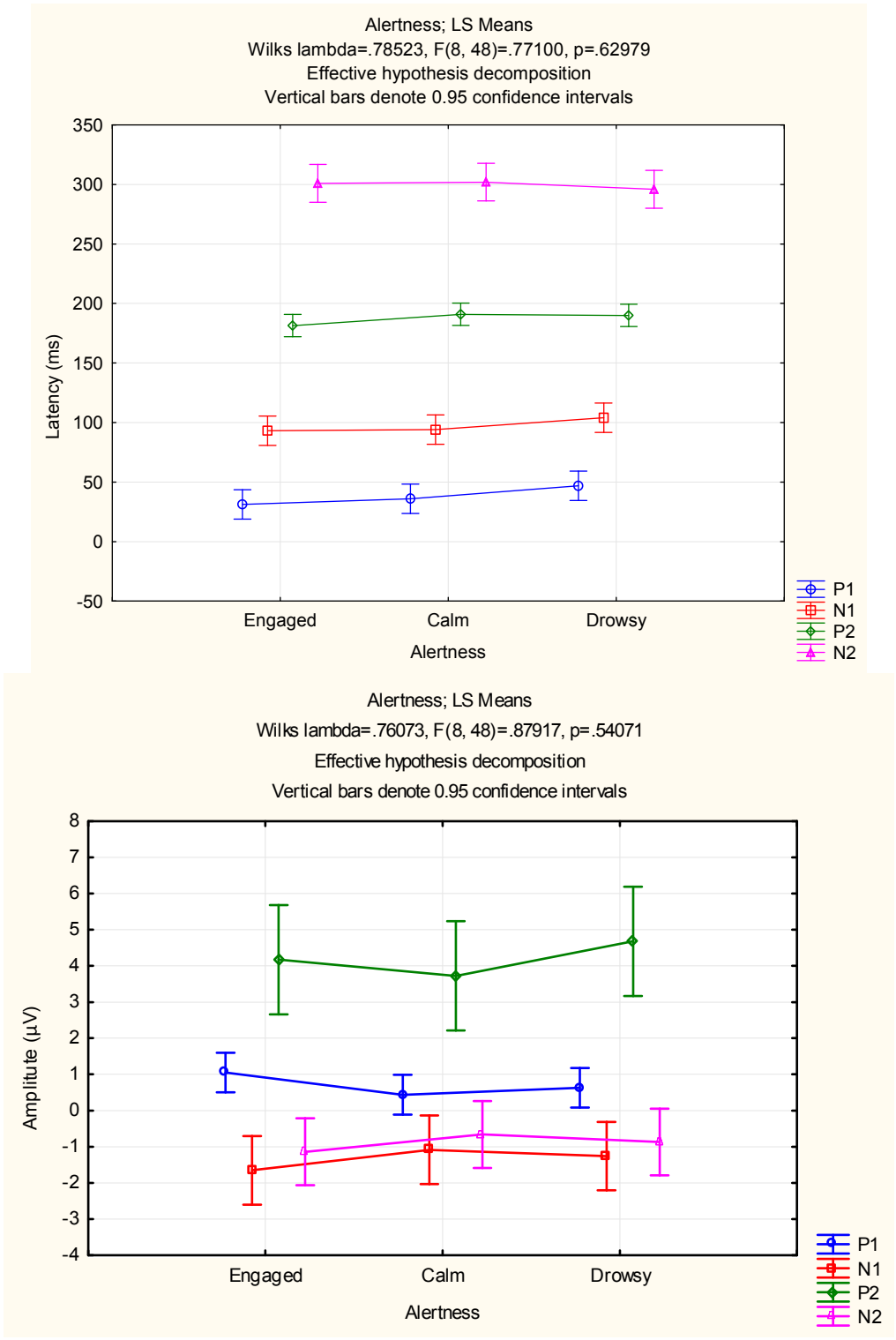


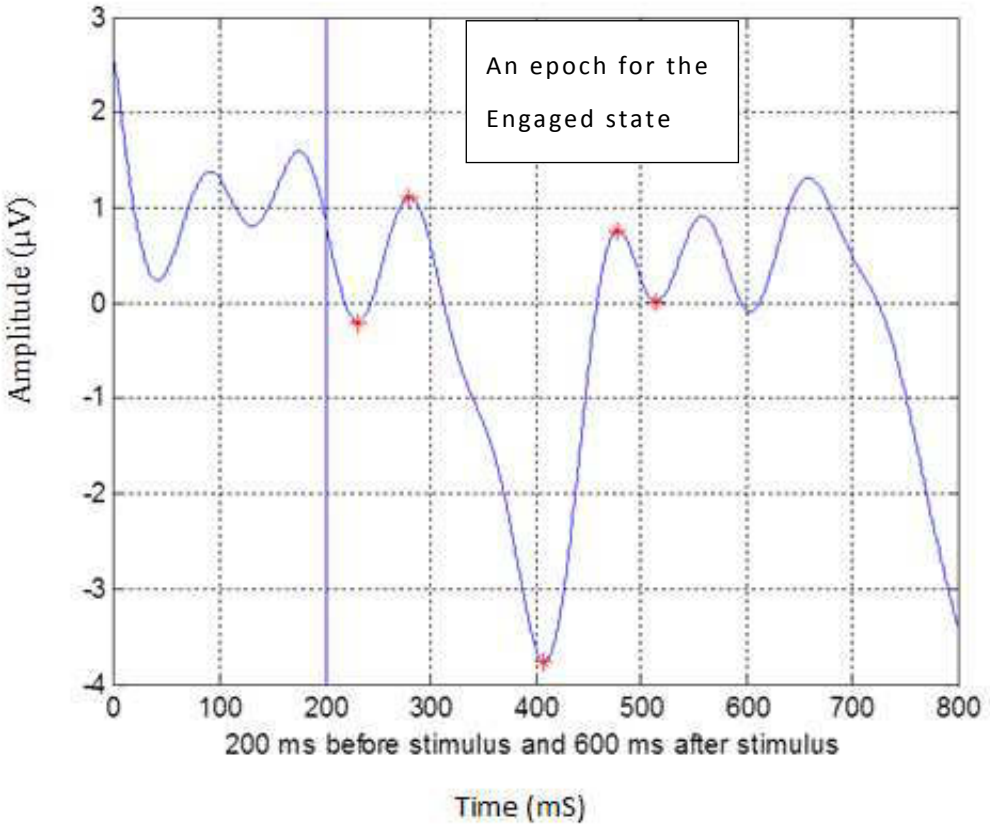

**Figure 4.4: P1N1P2N2 peak amplitude and latency variation among subjects using data of section B.**

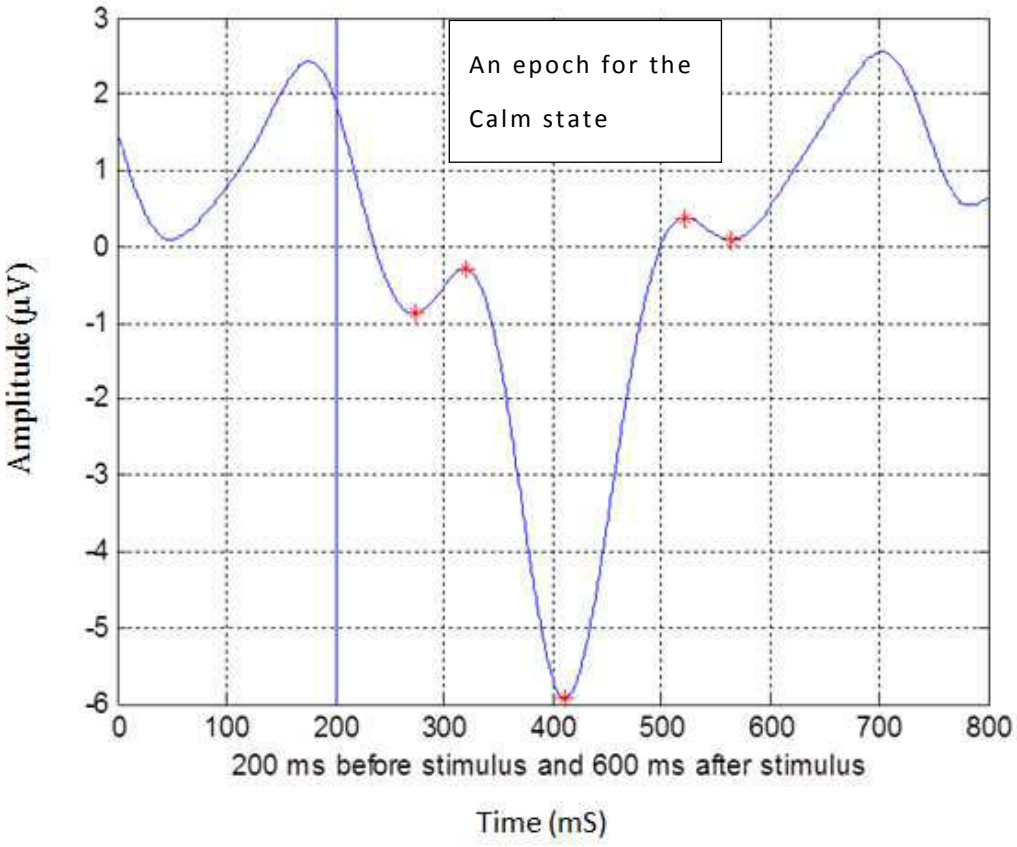
As discussed in Section 3.3 CAEP is affected by some factors as well as the fact that subjects may misjudge their alertness states. The existence of overlap between the alertness states makes it hard to identify distinct attributes for each of them.

### 4.2.2 CAEP Components Peak Extraction – Algorithm-based Approach

This experiment has been done to compare the results against manual approach described in Section 4.2.1 (Section B). In this approach the stimulus onset was used as a reference, were an epoch was formed using the EEG data of a given channel 200ms before the stimulus onset and 600ms after it. Similar to the previous section, the following pre-processing steps were considered: i) a band-pass filter was applied with cut-off frequencies of 1 and 20Hz,ii) the mean of each epoch was subtracted from its samples to reduce the baseline shift, and iii)100sweeps where averaged by increment of one sweep.

An algorithm was developed to identify the P1, N1, P2, N2 and P3 peaks, where the search for each peak was restricted in the following time ranges from the stimulus onset: $P_1 < 90\,ms$, $50\,ms < N_1 < 160\,ms$, $150\,ms < P_2 < 250\,ms$, $180\,ms < N_2 < 300\,ms$, and $230\,ms < P_3 < 400\,ms$. When no peak is found in a given region then the latency was identified based on the minimum of the first derivative of the curve in that region. Each peak was represented using two values; namely amplitude and latency. Channel 33 was used in this trial to be consistent with the manual based approach described in Section 4.2.1. Some of the waveforms extracted from the EEG data of the first subject are shown in Figure 4.5.


An epoch for the
Engaged state
Amplitude (μV)
3
2
1
0
-1
-2
-3
-4
0
100
200
300
400
500
600
700
800
200 ms before stimulus and 600 ms after stimulus
Time (mS)


An epoch for the
Calm state
Amplitude (μV)
3
2
1
0
-1
-2
-3
-4
-5
-6
0
100
200
300
400
500
600
700
800
200 ms before stimulus and 600 ms after stimulus
Time (mS)

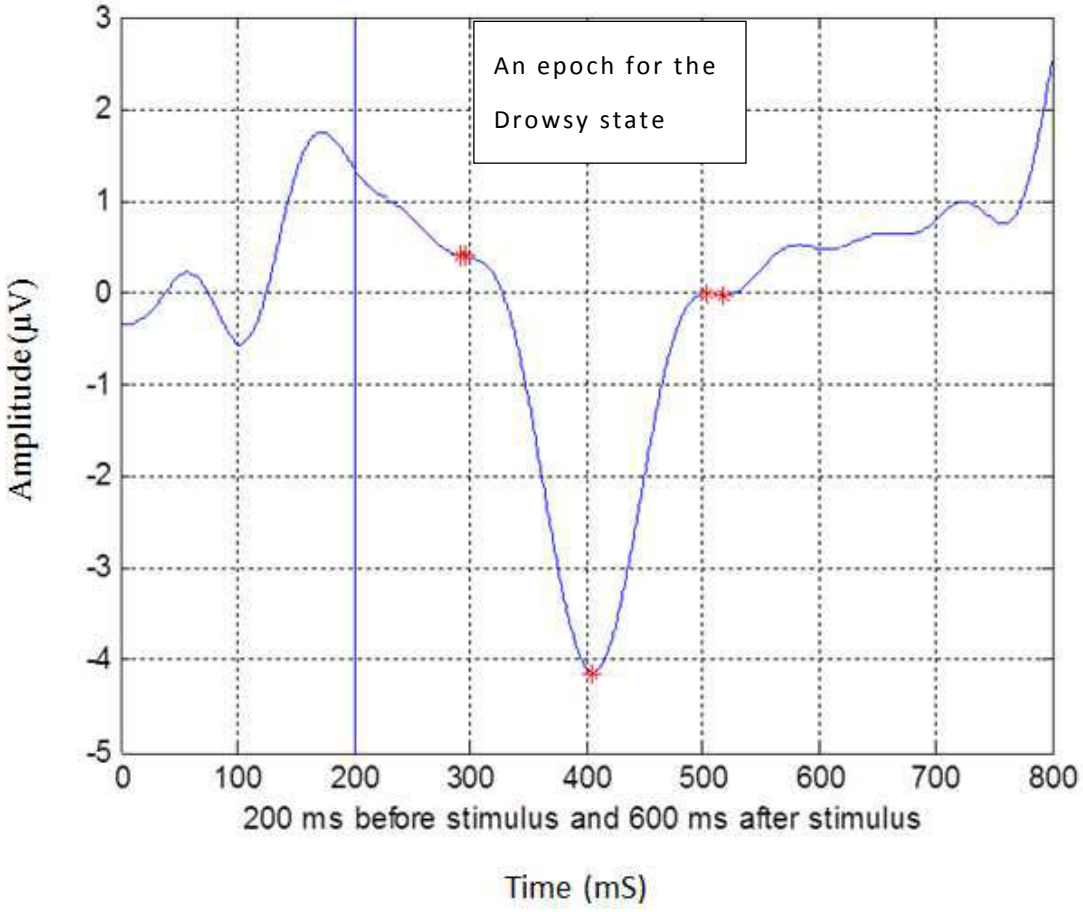



**Figure 4.5: CAEP response extracted from subject 1 in different states of alertness, "engaged, calm but alert and drowsy" respectively. The red asterisks are the CAEP components peak.**

ANOVA analysis was applied to the peaks obtained from the algorithm approach; results are shown in Figure 4.6.

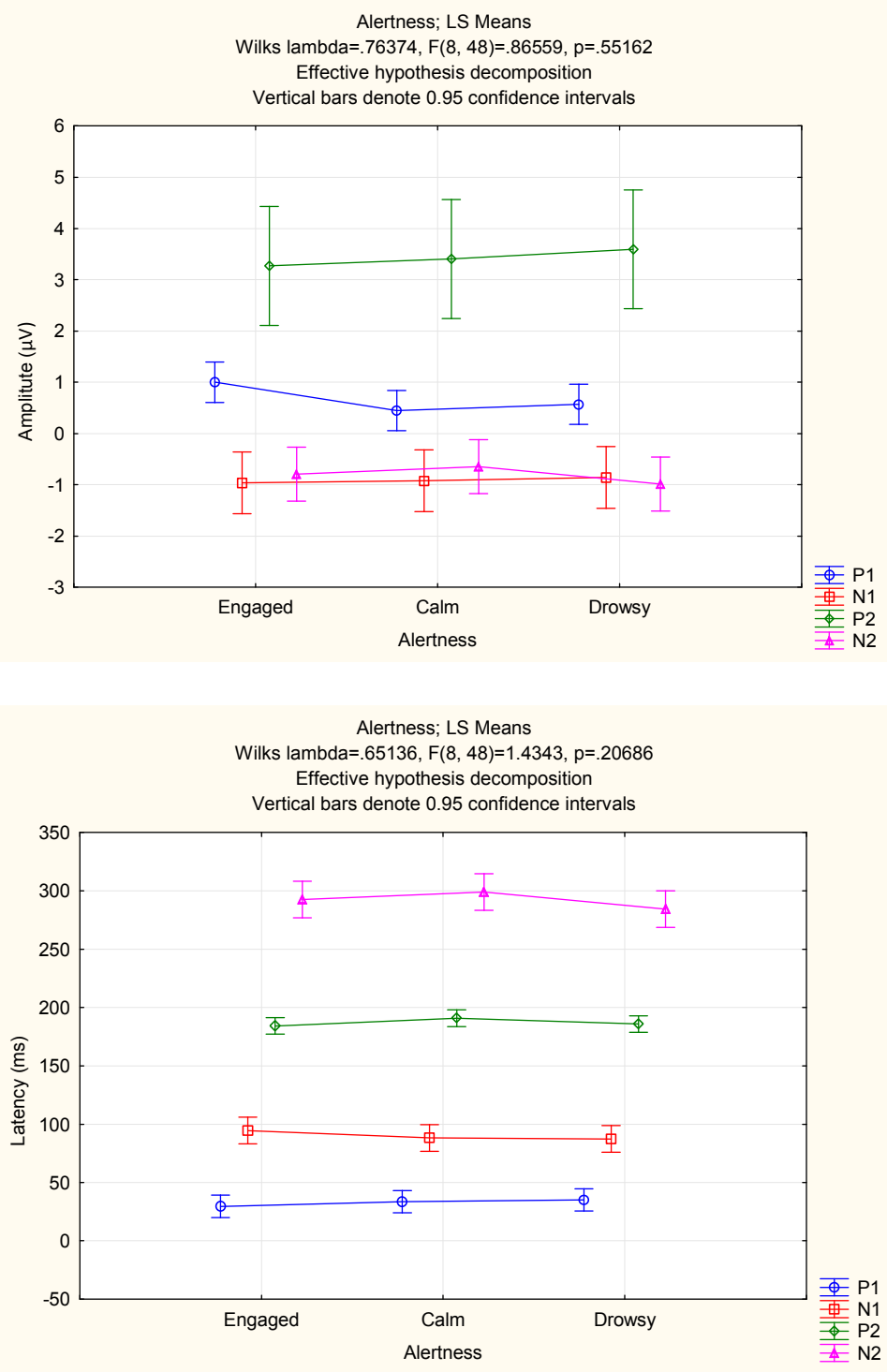



**Figure 4.6: P1N1P2N2 peak amplitude and latency variation among subjects at different states of alertness.**

The results show that there is no big difference between the peaks achieved from manual-based and algorithm-based approaches, for example the average amplitude of P1, N1, P2 and N2 from three defined states in manual approach are 45, 100, and 180 and 300ms respectively which is very close to

the results obtained from algorithm-based approach. To prove this statistical significant testing has been performed and the p-values were less than 0.05 which shows there is no significant difference between amplitude and latency achieved from manual and algorithm-based approach. Therefore, we decided to use algorithm-based approach for the rest of data analysis because it was easier to generalize.

## 4.3 Alertness Classification Using CAEP and Wavelet Features

In this experiment a supervised classification approach was adopted to classify the alertness state. Two sets of features were considered here to represent the recorded data. The first is based on the wavelet transform of the background EEG, while the second is obtained from the peaks of the CAEP responses. The rationale behind using the second feature set is to evaluate the relationship between CAEP responses and alertness levels. To the best of our knowledge, such study has not been conducted before. As explained in section 3.3 “If the subject did not press any button in any of the 10-minute blocks of the 1 hour recording, then a label of 0 (sleeping) are inserted for that block. The percentages of the four classes (“engaged”, “calm”, “drowsy” and “sleeping”) from all 10 subjects are: 15.19%, 34.29%, 46.20% and 4.32% respectively”.

### 4.3.1 Wavelet-Based EEG Feature Extraction

In this study 6 channels were used namely: T7, M1 and P7 and the corresponding channels on the opposite side; T8, M2 and P8. We considered those channels as they produced the maximum peaks with respect to the reference electrode that was placed on the central lobe close to Cz as discussed in Section 3.4.

A smaller number of channels can be considered; however we wanted to reduce the effect of noisy channels, as it is not unusual to receive noisy data from some of the channels.

The background EEG signal of each of the six channels was divided into windows of 5 seconds with an overlap of 3 seconds; in this way window size will contain enough information about the classification task under consideration. Overlapping is a very common approach that is used to avoid losing any information especially if smoothing window is applied such as the hann window. The time-scale representation of each window was used to obtain 9 features that represent the energy of the dyadic wavelet transform, where an order 2 Daubechies mother wavelet was used. Thus, based on the sampling frequency, the 9 frequency bands are: 0-2, 2-4, 4-8, 8-16, 16-32, 32-64, 64-128, 128-256, 256-512 Hz. In order to form the wavelet feature vector, the extracted features from each of the six channels were concatenated, and hence a total of 54 features were used to represent each window.

### 4.3.2 CAEP-Based Feature Extraction

Same channels described in Section 4.3.1 were employed for this experiment. The peaks extracted and described in algorithm-based approach Section 4.1.2 were employed in this experiment.

In order to obtain the same feature vector size as that of the wavelet-based EEG feature (Section 4.3.1), latencies of the five peaks and amplitude values of the first four (P1, N1, P2 and N2) were used. Accordingly, for the six channels, each epoch was represented using 54 features.

### 4.3.3 Classification Approach and Analysis of the Results

The obtained windows/epochs of each method were divided into segments of 30 seconds each, such that each of these segments is either used for training or testing. In other words, each segment consists of multiple windows/epochs. 75% of the segments of each subject were used for training while the remaining 25% for testing. A multi-class support vector

machine (SVM) was employed to individually classify and estimate the accuracy of the labelled data for each of the ten subjects.

Confusion matrices for both methods achieved by averaging the results of the ten subjects are shown in Tables 4.1 and 4.2. It can be noticed from the two tables that the wavelet features perform better with the engaged and sleeping classes, while the CAEP features achieved better results for the calm class, likely because CAEPs are most clearly visible in this class. The engaged class introduces more noise to the CAEPs, i.e., drop in identification capability, and the sleep stage gives more rise to variable CAEPs and an increased noise level in the low frequencies. Both methods achieved comparable results for the drowsy class. One important aspect that can be obtained for the two tables is that both methods tend to achieve lower misclassification rates with the increase of distance from the true class. For example, when the true class is engaged (column 2 of Tables 4.1 and 4.2), none of the two methods predicted sleeping, and a slightly higher misclassification with the drowsy class, while the highest misclassification was achieved with calm, which is the closest class to engaged.

**Table 4.1: Confusion matrix of the CAEP features (T: true, P: Predicted)**

| | Engaged (T) | Calm (T) | Drowsy (T) | Sleeping (T) |
|---|---|---|---|---|
| Engaged (P) | 0.57 | 0.07 | 0.02 | 0.04 |
| Clam (P) | 0.28 | 0.80 | 0.18 | 0.03 |
| Drowsy (P) | 0.15 | 0.13 | 0.79 | 0.24 |
| Sleeping (P) | 0 | 0 | 0.01 | 0.69 |

**Table 4.2: Confusion matrix of wavelet features (T: true, P: Predicted)**

| | Engaged (T) | Calm (T) | Drowsy (T) | Sleeping (T) |
|---|---|---|---|---|
| Engaged (P) | 0.63 | 0.09 | 0.03 | 0 |
| Clam (P) | 0.30 | 0.72 | 0.15 | 0.02 |
| Drowsy (P) | 0.07 | 0.18 | 0.81 | 0.03 |
| Sleeping (P) | 0 | 0.01 | 0.01 | 0.95 |

The overall classification accuracy shown in Table 4.3 indicates that both methods achieved comparable performance with the wavelet features

achieving a slightly better performance than their CAEP counterparts. It is important to mention that the developed algorithm may have not been optimal in terms of correctly identifying every peak. Incorrect values of amplitude and latency could have been corrected by considering the temporal (before and after) as well as spatial (other channels) information. The obtained results represent a proof-of-concept on the applicability of CAEP feature on the estimation of the alertness states.

**Table 4.3: Overall classification accuracy**

| | Accuracy | STD |
|---|---|---|
| CAEP features | 78.81% | 8.43 |
| Wavelet Features | 79.78% | 8.96 |

# Chapter 5

## 5. CLASSIFICATION OF ALERTNESS STATES USING EEG RHYTHMS

### 5.1 Introduction

In this chapter we conduct the analysis of the EEG rhythms. Investigation of the importance of the different EEG rhythms in terms of their capability in differentiating between the different alertness states when considering 64 channel EEG montage will be shown. We also present comparison between subsets that contain 2, 3, 4 as well as all 5 EEG rhythms namely; namely delta (up to 4 Hz), theta (4 - 8 Hz), alpha (8 - 13 Hz), beta(13 - 30 Hz), and gamma (30 - 100 Hz).Finally, a feature subset selection method based on differential evolution (DE) that particularly proposes to deal with multi-channel signals, will be used to search for the best subset of EEG rhythms for the various channels.

### 5.2 Differential Evolution

Differential evolution (DE) is an optimization method that is capable of analysing nonlinear, non-differential and multi modal objective functions. This method is simple and has the fast implementation properties[103, 104]. DE utilized two operators; namely differential combination and uniform crossover. Assume that we have $N_p$ members in the population; the DE optimization starts by creating a D–dimensional real value parameter vector for every member. Therefore the matrix size will be $N_p$ x D[105].

For the deferential combination each member of the population will be evolved based on the weighted difference between two other population members that are randomly identified in each iteration. More precisely

each element jof vector$\mathbf{x}_i$, where i is the population member index that ranges from 1 to$N_p$is shaped by adding the weighted difference between the element j of two randomly chosen members m and n, $x_{j,m}$ and $x_{j,n}$to the value of a third randomly selected member $x_{j,p}$ in order to obtain the new element $v_{j,i}$:

$$v_{j,i} = x_{j,p} + F * (x_{j,m} - x_{j,n})$$

Where;

$F \in (0,1)$ is a scaling factor

It is important to mention that DE also uses uniform crossover. Therefore a new $x_{j,i}^{new}$ is created by changing the dimension of selected $v_{j,i}$ by the corresponding dimension of $x_{j,i}$ with probability of$CO \in [0,1]$, the formula below describes this function:

$$x_{j,i}^{new} = \begin{cases} v_{j,i} & if\ rand(0,1) \leq CO \\ x_{j,i} & otherwise \end{cases}$$

If the new vector $\mathbf{x}_i^{new}$ shows better fitness in the population then it will replace the previously selected vector $\mathbf{x}_i$ .[106].

Over the years, there have been some modifications to the original DE algorithm. These include:

$$v_{j,i} = x_{j,l} + F * (x_{j,m} - x_{j,n})$$

$$v_{j,i} = x_{j,i} + F * (x_{j,l} - x_{j,i}) + F * (x_{j,m} - x_{j,n})$$

$$v_{j,i} = x_{j,l} + F * (x_{j,p} - x_{j,q}) + F * (x_{j,m} - x_{j,n})$$

Where $l$ is member of the population with the lowest objective function called the "elite" and $m, n, p$ and $q$ are randomly selected members.

The difference between the original method and the modified ones is in the way of selecting the best member of the population. The DE parameters can be randomly selected, although with a modified algorithm the selection would produce an improved convergence velocity. DE has been already used in many applications including project scheduling [107], process imaging [108]and others [109, 110].

DE has been chosen in this study because Al-Ani et al. in [111] and Khushaba et al. in[112] have shown that DE-based feature selection approach achieves better classification accuracy in comparison to two of the well-known optimization methods, which are genetic algorithm (GA) and particle swarm optimization (PSO). In this work we opted to adopt the differential evolution feature subset selection method described in [110]. In addition, we are going to use the algorithm used in this reference and the scale is 0.5 for choosing the parameters such as F, CO etc. The method utilized a wheel structure to reduce the search complexity as described below.

## 5.3 Wheel-based Search Strategy

Wheel-based search strategy approach introduced by Al-Ani, et al. [111] to search for optimal feature subsets. Assume that the total number of features is $N_F$, the algorithm searches for the best $DN_F$ features (desired number of features) where $DN_F \leq N_F/2.DN_F$ wheels will be formed and the features will be shuffled and placed equally in each wheel (Figure 5.1a).

One feature from each wheel is chosen to construct a feature subset. This prevents duplication in each feature subset and it will reduce the search space. For example if $N_F$ is equal to 62 and the desired subset size, $DN_F$ is equal to four then we will have four wheels, two of them with 16 features and the other two with 15 features. If $N_{Fw}$ denotes the number of features in each wheel then $N_{Fw} = \{16, 16, 15, 15\}$.

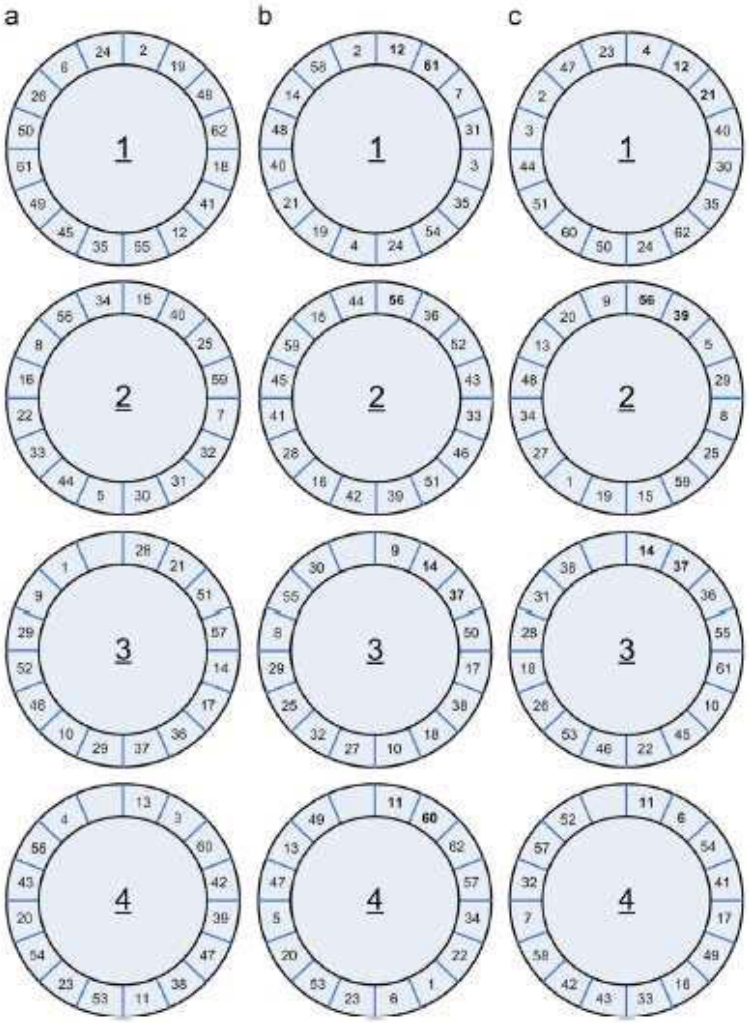



**Figure 5.1: Constructed wheels for subset selection of size 4 from 62 features.**

Now it's time to construct the subsets i.e. $S = \{f1, f2, f3, f4\}$, one feature from each wheel is selected, for example; $f1$ is chosen from wheel 1. The search will then evolve over a certain number of iterations with the current feature distribution. Wheels will then be re-shuffled (as shown in Figure 5.1b) apart from features that form the elite subsets (the ones in bold font), and the search will start again. This process will be repeated for a few times till the stopping criterion is met (Figure 5.1c), which represent the selected subset of features.

## 5.4 Multi-Channel Feature Subset Selection

The objective of multi-channel EEG feature selection in this study is to search for the optimal feature representation (using the five EEG rhythms) for each channel. Thus, we aim at maximizing the classification accuracy of the selected feature subsets (formed by concatenating the features of all channels) for the alertness state classification problem. We proposed here to encode all possible feature subset combinations using grey code. Hence, for the 5 rhythms, 5 binary bits are used in the following order: 00000, 00001, 00011, 00010, 00110, . . ., 10001, 10000, where for each of the five rhythms '1' represents the inclusion of the feature, while '0' represents absence of the feature. For instance, if for channel *j*the binary code chosen by the algorithm is 10101, this means that channel *j* is represented by the δ, α and γ rhythms. The particular code 00000 indicates that channel *j* is not used. A circular representation of the code is adopted, i.e., 00000 comes after 10000.

The differential evolution based feature selection algorithm is implemented as follows:

1- For each of the $N_p$ members of the population, randomly generate a real value vector, $\mathbf{x}_i$ of length N*Ch*, where N*Ch* is the number of channels. The values of the vector have to be in the range [0.5, $N_{Fc}$ + 0.5), where $N_{Fc}$ represents the number of feature combinations in each channel (32 for the 5 EEG rhythms). Thus, when the numbers are rounded they are bounded by the list boundaries, i.e., 1 and 32.

2- Produce the corresponding subset for each member of the population from the rounded numbers then evaluate the subset
3- Find the k best subsets (the elite subsets)
4- For each member of the population *i*;

- For each channel,j determine whether to perform uniform crossover or differential combination by evaluating the following formula: $\text{rand}\,(0,1) \leq \text{CO}$, where CO is crossover probability as defined previously

- To implement differential combination, choose two members of the population, other than $i$. The first member is randomly chosen from the k best members, while the other is randomly chosen from the rest of the population. Let's refer to those two members as $m$ and $n$. Calculate a new value for this vector element according to the equation;

$$\mathrm{x}_{j,i}^{new} = \mathrm{x}_{j,i} + F * (\mathrm{x}_{j,m} - \mathrm{x}_{j,n})$$

- Otherwise, to perform uniform crossover, assign $\mathrm{x}_{j,i}^{new} = \mathrm{x}_{j,l}$where,$l$ is a randomly chosen member of the best $k$ subsets identified in step 3 (selected using a roulette wheel approach).
- check the boundaries as follows:

$$\mathrm{x}_{j,i}^{new} = \begin{cases} \mathrm{x}_{j,i}^{new} - N_{Fc} & if\ \mathrm{x}_{j,i}^{new} > N_{Fc} + 0.5 \\ \mathrm{x}_{j,i}^{new} + N_{Fc} & if\ \mathrm{x}_{j,i}^{new} < 0.5 \end{cases}$$

- Identify the features of the newly generated subset, and then evaluate the subset.
- If the newly generated subset achieved a lower fitness than the old one, then assign $\mathrm{x}_i = \mathrm{x}_i^{new}$ otherwise keep $\mathrm{x}_i$ unchanged.

5- Go to step 3 until the stopping criterion is met.

The rationale behind using of a grey-scale binary representation is to only allow the inclusion or removal of one rhythm between any two successive binary values, and hence makes the transition smoother than using the normal binary representation. Figure5.2 shows the grey code representation of four bits.

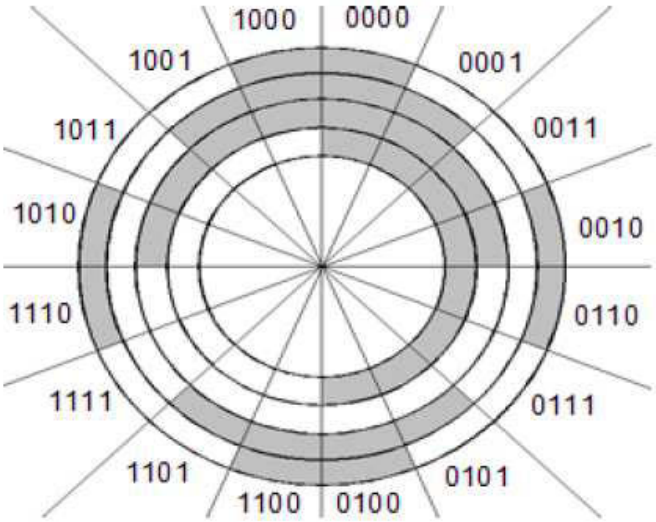



**Figure 5.2 - Gray code representation of four bit**

### 5.4.1 Classification Approach and Analysis of the Results

The recorded signal has been divided into windows of 5 seconds with overlap of 3 seconds. Each window is represented by the energy value of each of the5 EEG rhythms i.e. five features/window. A linear support vector machine (SVM) classifier has been used to evaluate the performance of features, where windows have been split into two groups, namely training and validation given that each alertness state is well represented in each group.

We have started by evaluating the performance of the five EEG rhythms for each of the channels. Classification accuracies of the validation set averaged across the 10 subjects shown in Figure 5.3 indicate that none of the five rhythms was able to produce convincing results when relying on one channel only. Figure5.4 shows the ranking of the 64 channels for each of the five EEG rhythms. The channel with best performance is represented by dark blue, while that achieving the least classification accuracy is represented by dark red. The figure indicates that ranking of channels or association of brain

regions with each rhythm is not identical, especially when comparing the low frequency rhythms with the high frequency ones.

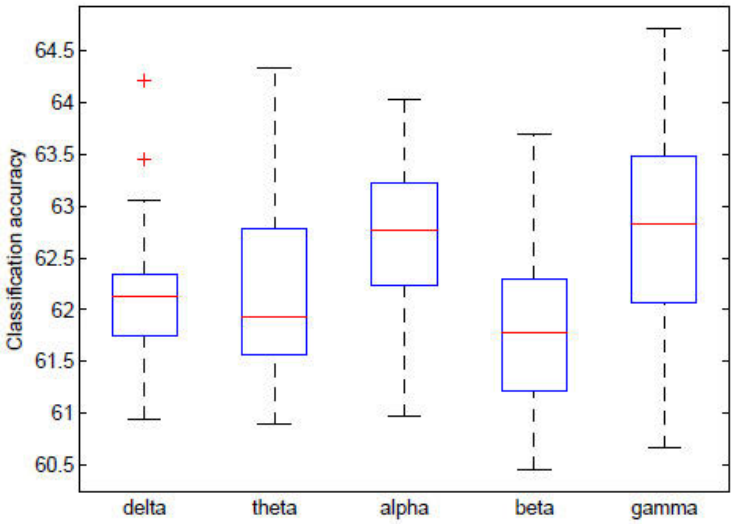



**Figure 5.3: Classification accuracy of the five EEG rhythms across the 64 channels**

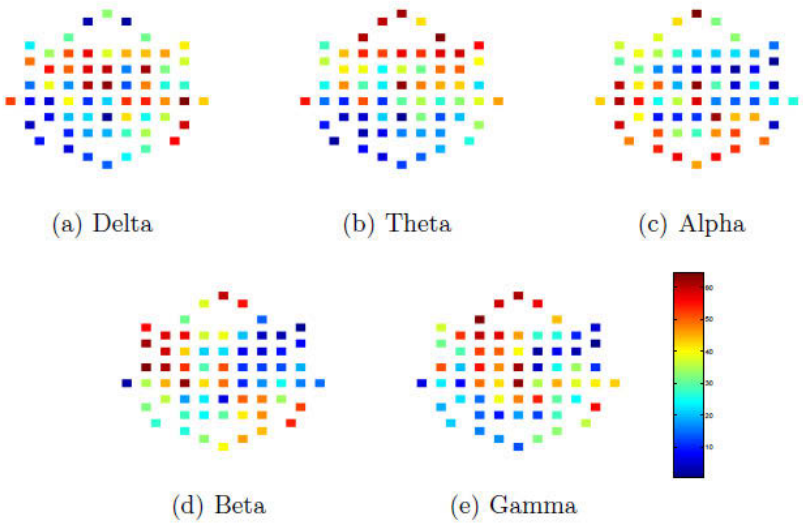



**Figure 5.4: Ranking of channels for each of the five EEG rhythms based on their classification accuracy.**

The performance of combined channels where then evaluated for each rhythm, where subsets of channels were formed by concatenating channels starting from the best one and ending with the channel that achieved the lowest accuracy to form subsets of sizes that range between 1 and 64. The obtained results are shown in Figure 5.5. The figure indicates that there is

noticeable difference in the performance of the five rhythms, with gamma achieving the best results followed by beta, alpha, theta and finally delta.

It is well-known that ranking of features (or channels) does not guarantee that the best k individual features would form the best subset of size k. This is quite logical as neighbouring channels are not expected to provide complementary information about the classification task. Accordingly, we implemented a sequential forward search (SFS) strategy that starts with the best channel then adds another channel to form a subset of two channels by examining all remaining63 channels with the already selected one. This process is repeated until all64 channels are selected.

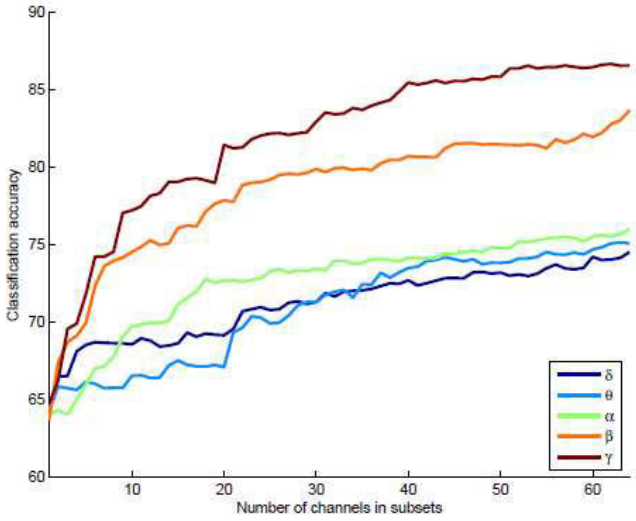



**Figure 5.5: Classification accuracy of the five EEG rhythms considering incremental subsets of the 64 channels.**

Figure 5.6 shows the 64 channels based on their selection stage for each of the five EEG rhythms.

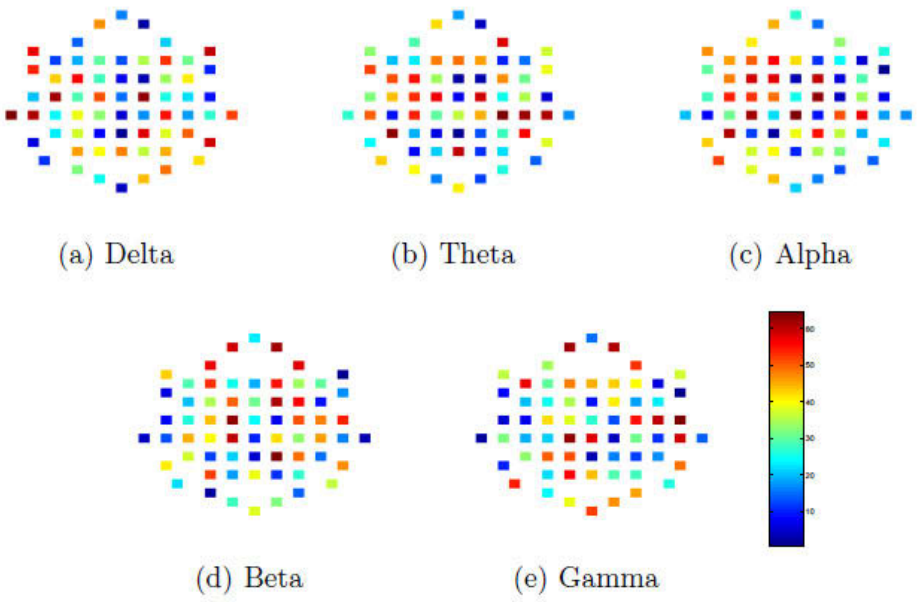



**Figure 5.6: Sequential forward selection of channels for each of the five EEG.**

One can notice that channel order is more scattered in Figure 5.6 in comparison to Figure 5.4, which indicates that complementary channels are not usually located next to each other and the performance of channel subsets formed using sequential forward search for the five rhythms, shown in Figure 5.7, indicates noticeably faster convergence than the ranking approach. In fact, for all rhythms near best solution was found using approximately half of the total number of channels.

Combined rhythms have then been examined, where each channel is represented by two rhythms. All possible ten combinations have been evaluated, and the two combinations that produced the best performance were: {θ, γ} and {α, γ}. The same procedure was followed to evaluation combinations of three rhythms and four rhythms. For the case of three rhythms, the best two combinations were: {δ, α, γ} and {δ, β, γ}, while {δ, α, β, γ} produced the best results when considering four rhythms. Figure 5.8 shows the performance when considering best subsets formed using 1, 2, 3, 4 and all 5 rhythms.

The figure indicates that differences in performance between combinations of 3, 4 and 5 rhythms are minimal with combination of 4 rhythms achieving slightly better performance than the rest of combinations.

The proposed feature selection algorithm described in section 5.4 has then been applied to search for best feature subsets in each channel. The population size was set to 30 and reaching a pre-defined maximum number of iterations, which was set to 350, was used as the stopping criterion. A crossover probability was fixed to CO = 0.5. We started by considering one feature per channel; however, channels were also allowed not to be represented by any feature, where in such case those channels will be discarded.

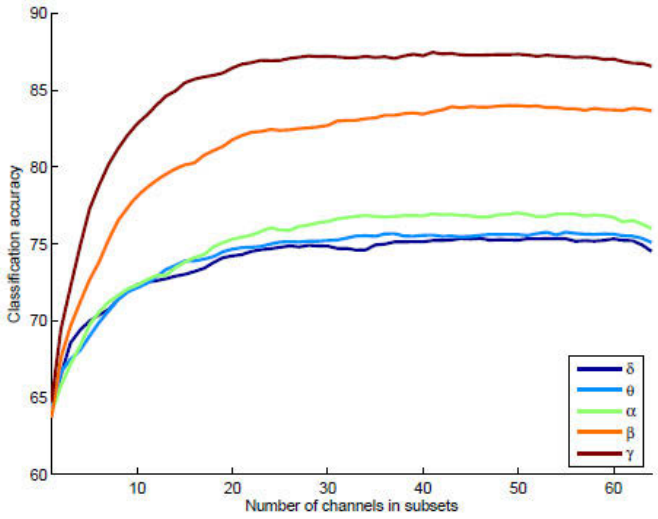



**Figure 5.7: Classification accuracy of the five EEG rhythms considering channel subsets formed using SFS.**

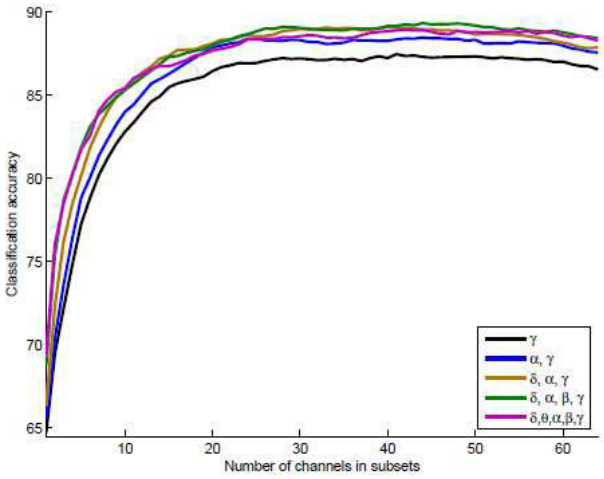



**Figure 5.8: Classification accuracy of different rhythm combinations considering channel subsets formed using SFS.**

Table 5.1 shows the best performance achieved by the three selection methods.

Unlike the ranking and sequential feature selection approaches, the proposed feature selection method is more flexible in representing channels, where not all channels have to be represented by the same rhythms. For example, with the selection of one feature per channel, the proposed method allows any of the five rhythms to be selected by a specific channel. It also allows that channel not to be represented by any of the five rhythms. Similarly, when considering two features per channel, the method allows each channel to be represented by any two rhythms, one rhythm only or none of the five rhythms. It is important to mention that the DEFS method is computationally more expensive than the ranking and SFS approaches, however, the objective here is to analyse the best subset of features for the classification problem at hand.

**Table 5.1: Best achieved testing accuracy of the three selection**

| METHOD | 1F | 2F | 3F | 4F | 5F |
|---|---|---|---|---|---|
| RANKING | 86.65 | 88.02 | 88.31 | 88.59 | 88.28 |
| SFS | 87.47 | 88.60 | 89.11 | 89.33 | 88.95 |
| DEFS | 89.42 | 90.61 | 91.23 | 91.31 | 91.31 |

The generalization capability of the classifier decays with the inclusion of more features than required this is the reason why classification accuracy decreases in the last column of table 5.1 for the ranking and SFS methods.

In addition, the result show that higher frequency EEG rhythms (γ, β) are better classifiers for the subject's alertness state than α, θ, and δ (lower frequency EEG rhythms). This can be explained physiologically, as higher frequency oscillations are associated more with active concentration and consciousness, which allows a clear discrimination between awake and drowsy states. Results also suggest that CAEP presence do not seem to influence EEG classification, however some additional effects need to be investigated further. Optimal combinations of different EEG rhythms have been described. The proposed differential evolution feature selection algorithm has shown to produce better results than the ranking and sequential forward selection approaches. Obtained results suggest that best subsets are formed using combinations of channels and features that are influenced by high frequency rhythms.

# Chapter 6

## 6. SUMMARYAND FUTURE RESEARCH

In this chapter, a summary of the objectives, results and main achievements are given followed by recommendations for future work that can be done to improve the findings.

### 6.1 Summary of the Thesis

In this work signal based alertness detection method was used by employing EEG signals. A detailed investigation was carried out on identifying the alertness states of subjects undergoing a cortical auditory evoked potential (CAEP) hearing test.

The results of an investigation on the usability of features obtained from the CAEP responses in the detection of alertness state of normal hearing subjects are presented. EEG data was collected from 10 subjects in the presence of an auditory stimulus. Data was then processed to obtain both CAEP features and wavelet features. The obtained classification results indicate that the CAEP features have the potential to achieve comparable results to that of the well-known wavelet transform (79% and 80% respectively).

The results obtained represent a proof of concept on the applicability of CAEP feature on the estimation of alertness levels.

The applicability of the five EEG rhythms on the classification of alertness states was investigated. It was shown that higher frequency EEG rhythms (γ, β) are better features to differentiate between the subject's alertness states than α, θ, and δ (lower frequency EEG rhythms). This can be explained physiologically, as higher frequency oscillations are associated more with active concentration and consciousness, which allows a clear discrimination between awake and drowsy state

Optimal combinations of different EEG rhythms have been described. The proposed differential evolution feature selection algorithm was shown to produce better results than the ranking and sequential forward selection approaches. Obtained results suggest that best subsets are formed using combinations of channels and features that are influenced by high frequency rhythms.

## 6.2 Future Research

The current research can be expanded as follows:

- Conducting a more in-depth analysis of the spatial domain by identifying the best region(s) of the brain that is (are) related to alertness identification.

- Identifying a set of "If then" rules that relate CAEP peaks to alertness states. Finding such rules, will be very beneficial in understanding relationships between CAEP responses and the different alertness states, and hence will add value to the utilization of CAEP in objective hearing assessment.

- The developed algorithm for finding the CAEP components peak may have not been optimal in terms of correctly identifying every peak. Incorrect values of amplitude and latency could have been corrected by considering the temporal (before and after) as well as spatial (other channels) information.

- Alertness level indications were labelled by subjects, where consistency was not guaranteed. This could have an effect on the obtained results. The recorded labels could be refined by a trained

technician who would monitor the video of recorded sessions. This would help in reducing differences between labels obtained from different subjects and would enable a subject-independent study to be conducted.

- Expanding the analysis using CAEP responses obtained from children of different ages.

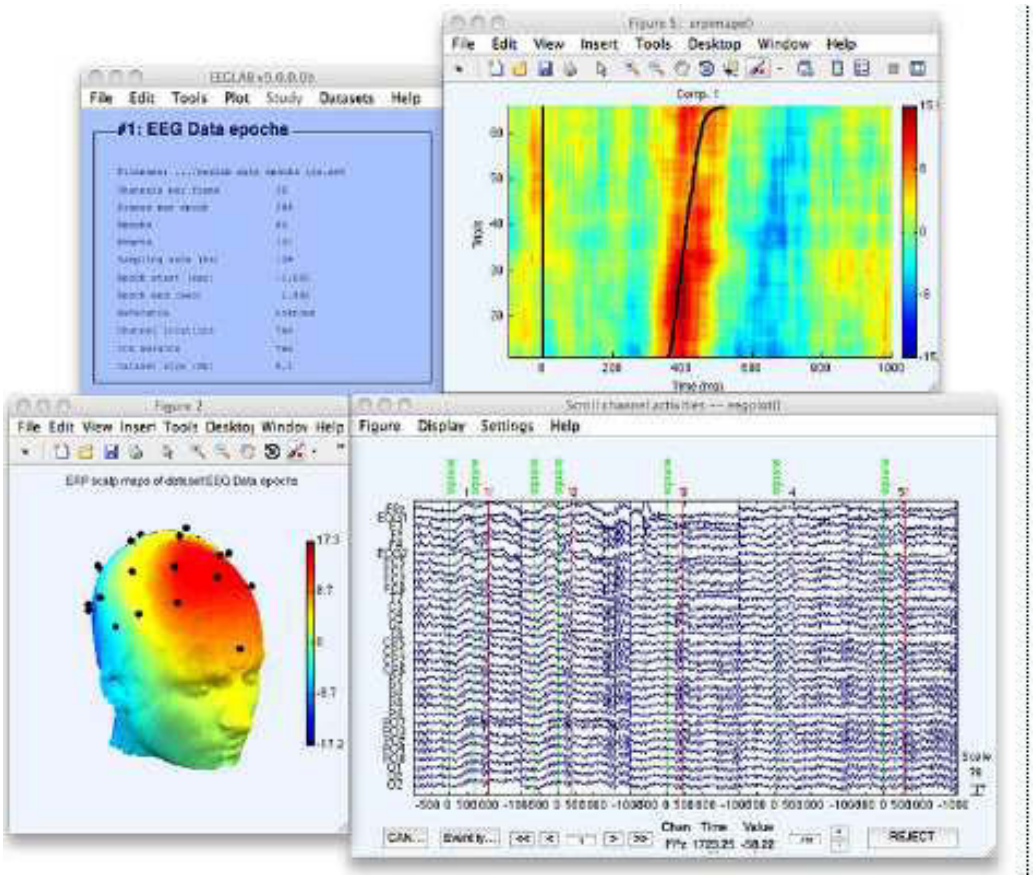
# Appendix A

## EEGLab

### 1. WHAT IS EEGLab?

EEGLab is an interactive MATLAB toolbox for processing continuous and event-related EEG, MEG and other electrophysiological data incorporating independent component analysis (ICA), time/frequency analysis, artefact rejection, event-related statistics, and several useful modes of visualization of the averaged and single-trial data.

First developed on MATLAB 5.3 under Linux, EEGLab runs on MATLAB v5 and higher under Linux, UNIX, Windows, and Mac OS X (MATLAB 7+ recommended).



## 2. WHY EEGLab?

EEGLab provides an interactive graphic user interface (GUI) allowing users to flexibly and interactively process their high-density EEG and other dynamic brain data using independent component analysis (ICA) and/or time/frequency analysis (TFA), as well as standard averaging methods.

EEGLab also incorporates extensive tutorial and help windows, plus a command history function that eases users' transition from GUI-based data exploration to building and running batch or custom data analysis scripts.

EEGLab offers a wealth of methods for visualizing and modelling event-related brain dynamics, both at the level of individual EEGLab 'datasets' and/or across a collection of datasets brought together in an EEGLab 'studyset.'

For experienced MATLAB users, EEGLab offers a structured programming environment for storing, accessing, measuring, manipulating and visualizing event-related EEG data.

For creative research programmers and methods developers, EEGLab offers an extensible, open-source platform through which they can share new methods with the world research community by publishing EEGLab 'plug-in' functions that appear automatically in the EEGLab menu of users who download them.

For example, novel EEGLab plug-ins might be built and released to 'pick peaks' in ERP or time/frequency results, or to perform specialized import/export, data visualization, or inverse source modelling of EEG, MEG, and/or ECOG data.

## 3. EEGLab RESOURCES REQUIRED

Core EEGLab runs on MATLAB 7 or later under any operating system (Linux/Unix, Windows, and Mac OSX). EEGLab may also run on MATLAB 6.5 or earlier, though a few functions might crash because of backward MATLAB incompatibility. MATLAB 5.3 is no longer supported.

However, the newest EEGLab toolboxes require the object-oriented programming capabilities of MATLAB 7.6 or later, which is thus recommended. Using 64-bit processors with large amounts of RAM may be essential for analysing large datasets -- 4-16 GB RAM per processor is recommended.

The MATLAB Signal Processing toolbox is also recommended; although EEGLab incorporates functions to replace functions it uses from this toolbox when necessary (e.g., for filtering and power spectra computation), they are not as efficient as the toolbox MATLAB functions.

Component clustering functions (introduced in EEGLab v5) also use the MATLAB Statistics toolbox.

Some EEGLab plug-in toolboxes use functions from other MATLAB toolboxes; see their documentation for details.

### 4. EEGLab CITACION REFERENCE

Delorme A. & Makeig S. (2004) EEGLab: an open source toolbox for analysis of single-trial EEG dynamics. *Journal of Neuroscience Methods* 134:9-21

### 5. EEGLab DEVELOPMENT - HISTORY

The chief EEGLab developers are Arnaud Delorme and Scott Makeig.

The predecessor to EEGLab, the ICA/EEG Toolbox (1997-2001), comprised functions written by Makeig with Tony Bell, Colin Humphries, Sigurd Enghoff, Tzyy-Ping Jung, Te-Won Lee, and others, was first released on the Web in 1997 by Scott Makeig at the Computational Neurobiology Laboratory of Terrence J. Sejnowski at The Salk Institute, La Jolla.

The first version of the integrated EEGLab toolbox was written there by Delorme and Makeig with subsequent contributions by many including Marissa Westerfield, Jörn Anemüller, Luca Finelli, Robert Oostenveld, Hilit Serby, Toby Fernsler, Nima Shamlo Bigdeley, Jason Palmer and many others. Dedicated beta testers include Andreas Romeyke and his team, who

developed a test suite for EEGLab, and other advanced users including Stefan Debener and Andreus Widmar.

EEGLab development is now centred at the Swartz Center for Computational Neuroscience (SCCN) of the Institute for Neural Computation at the University of California San Diego (UCSD).

Core EEGLab maintenance and development is supported by the US National Institute of Neurological Disorders and Stroke (NINDS).

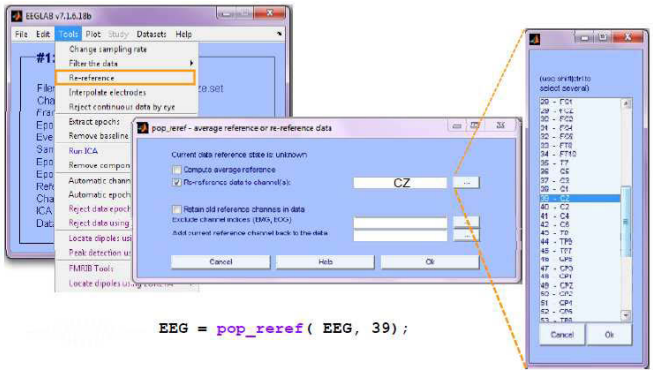
Recent additions to EEGLab from SCCN include several plug-in toolboxes including NFT (head modelling tools), SIFT (effective connectivity tools), MPT (source comparison tools), and BCILAB (BCI modelling tools).

## 6. EEGLab software case analysis procedure

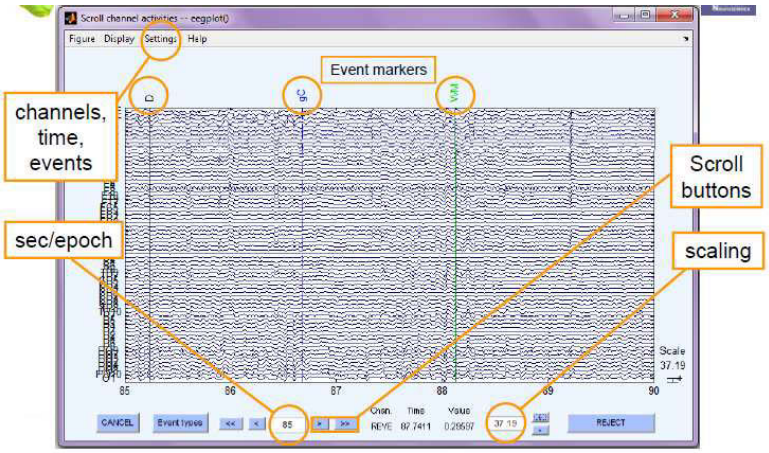
### a) Data import

#### i) Import raw data

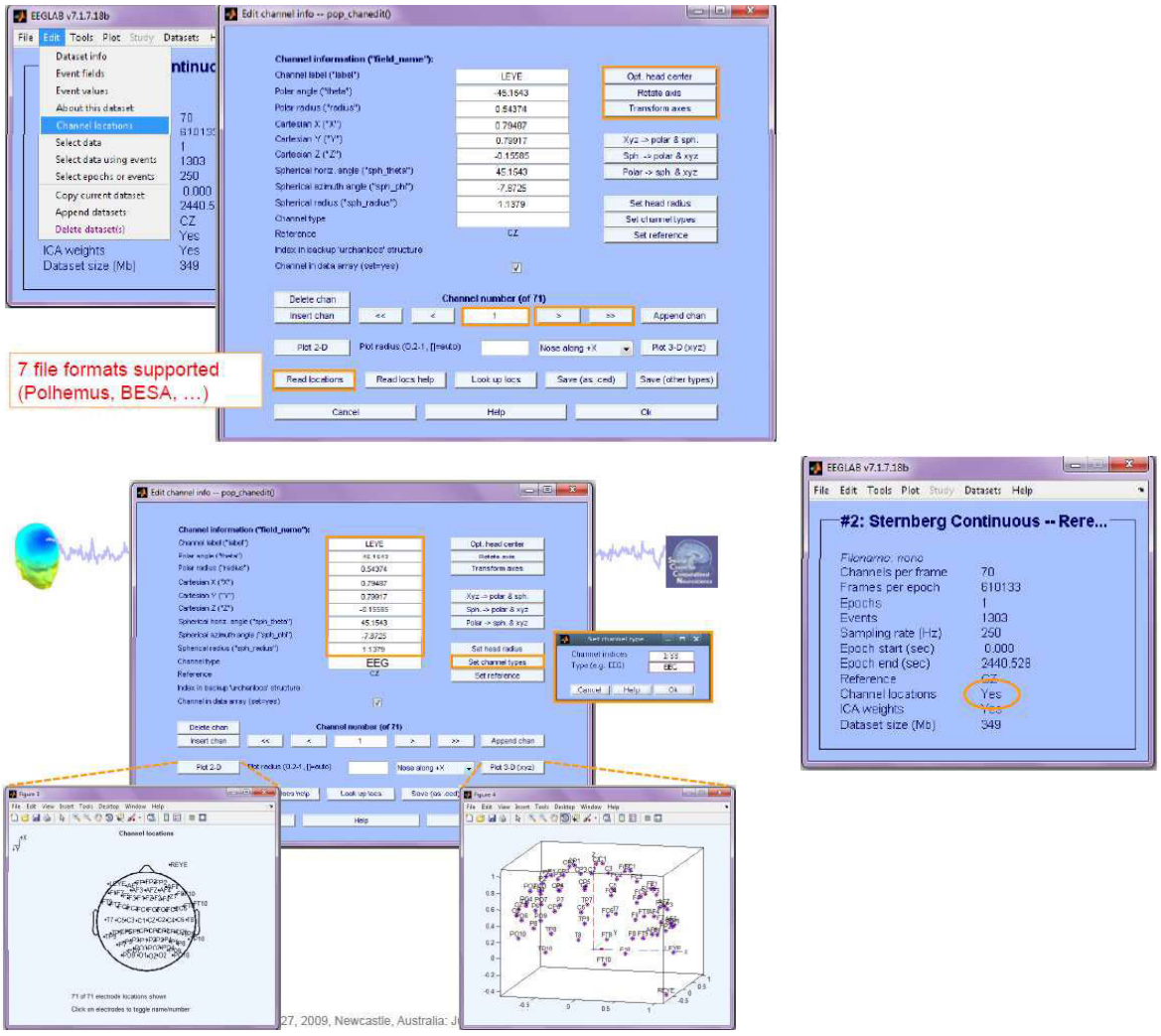

#### ii) reference data and scroll channel data



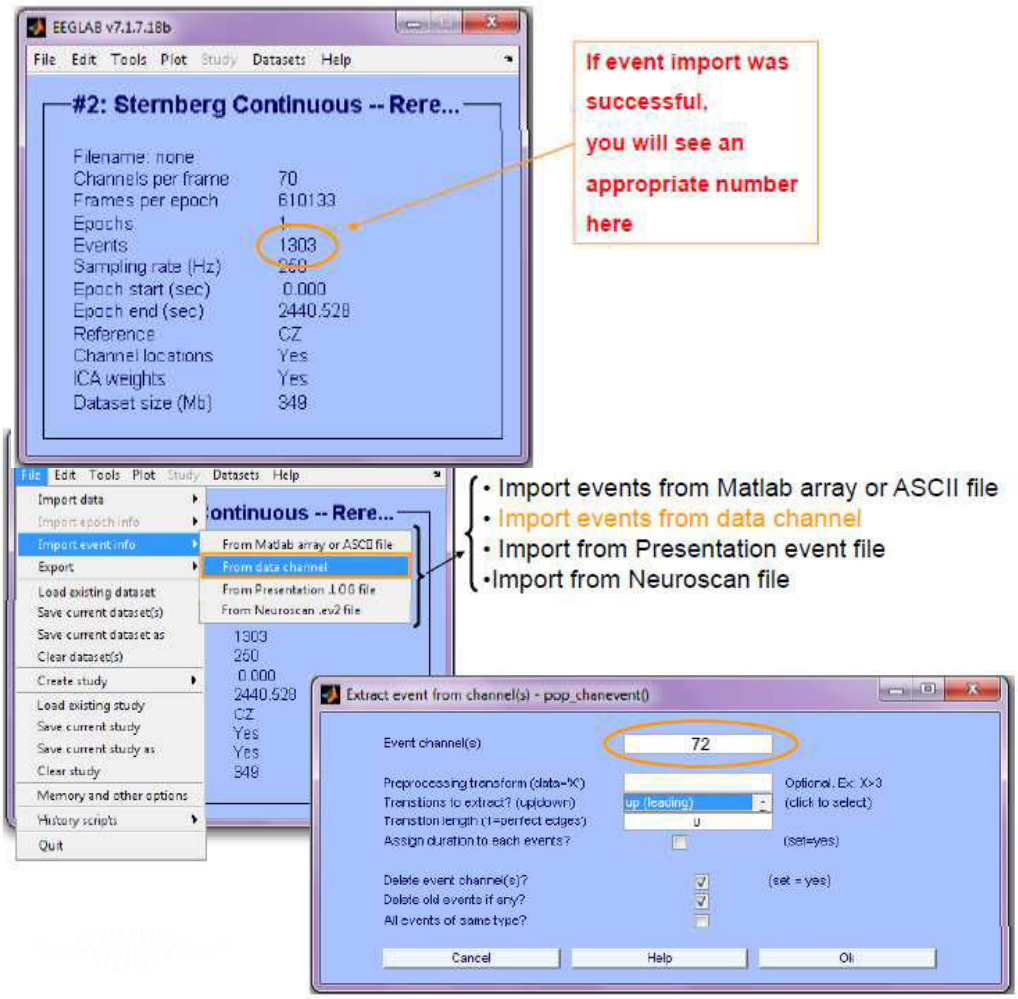
### iii) scroll channel data



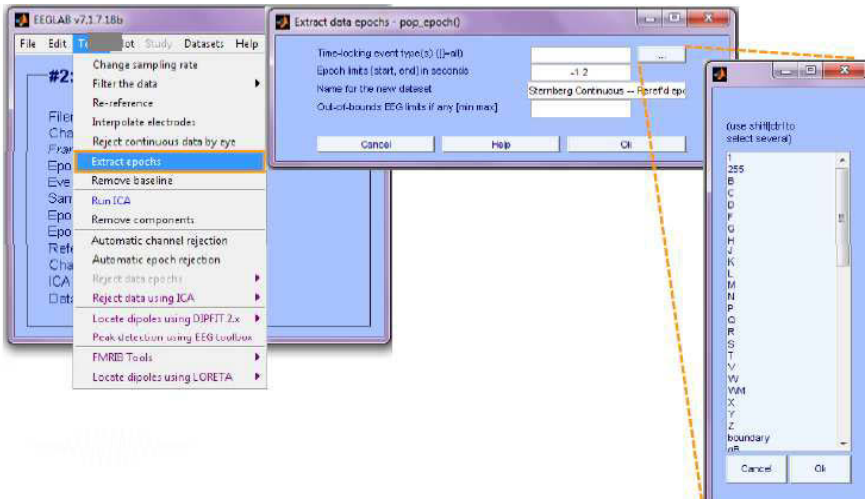

### iv) Import channel location file

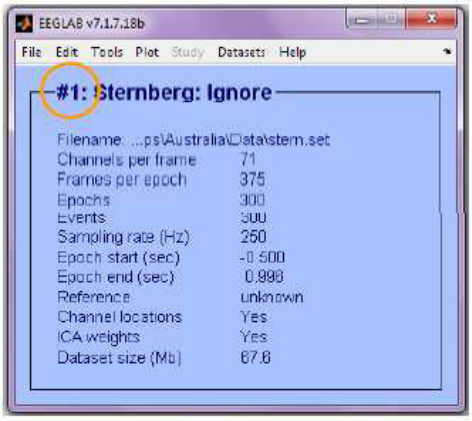


### v) Import data events

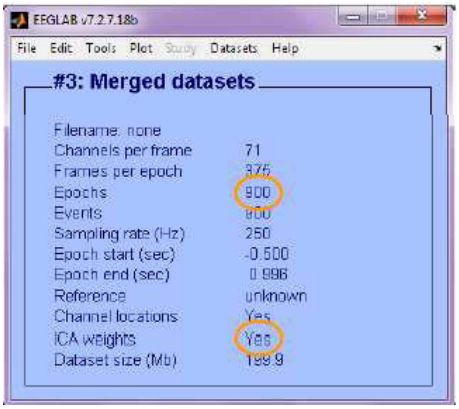


## vi) Extract data epochs

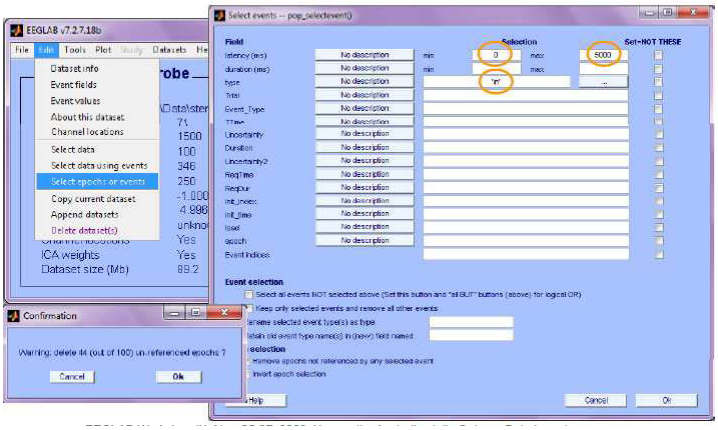


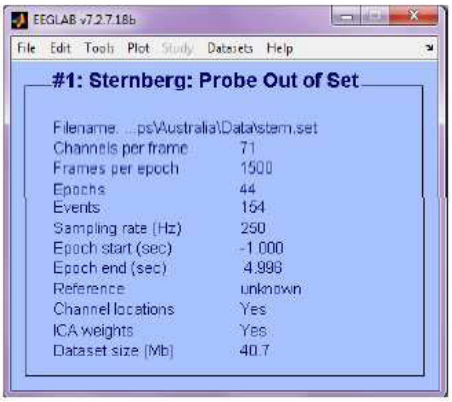



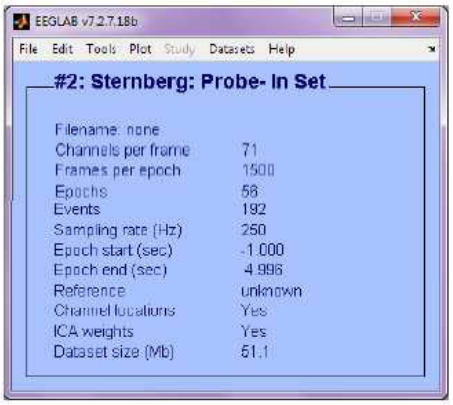




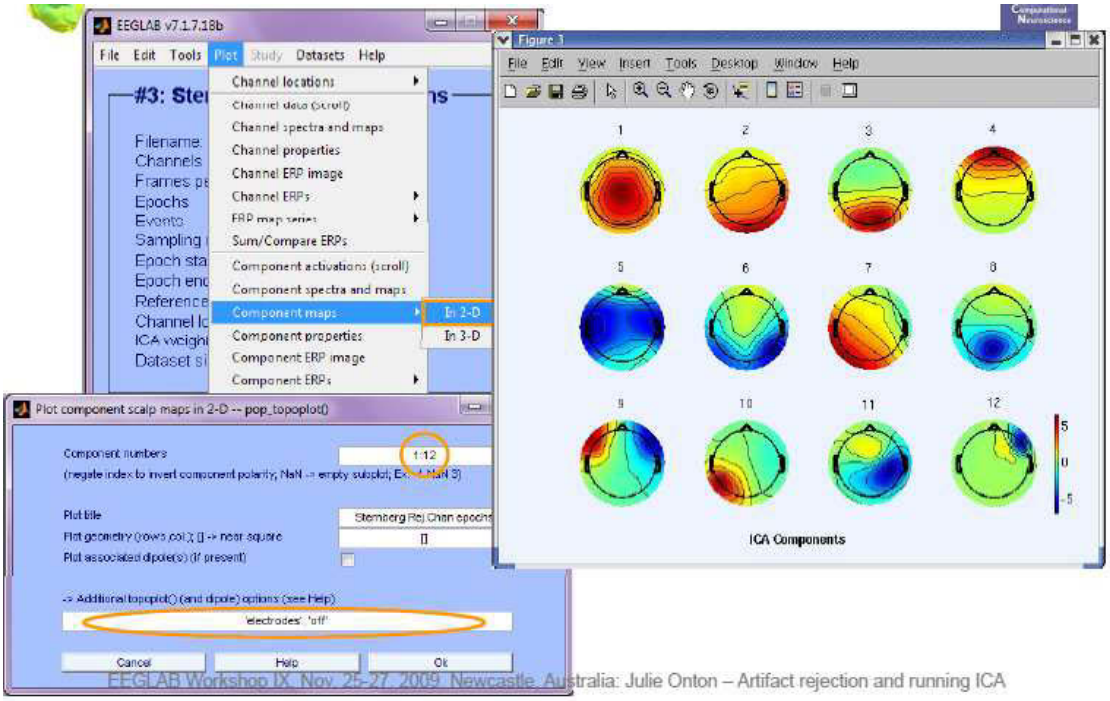
## vii) Select epochs / events



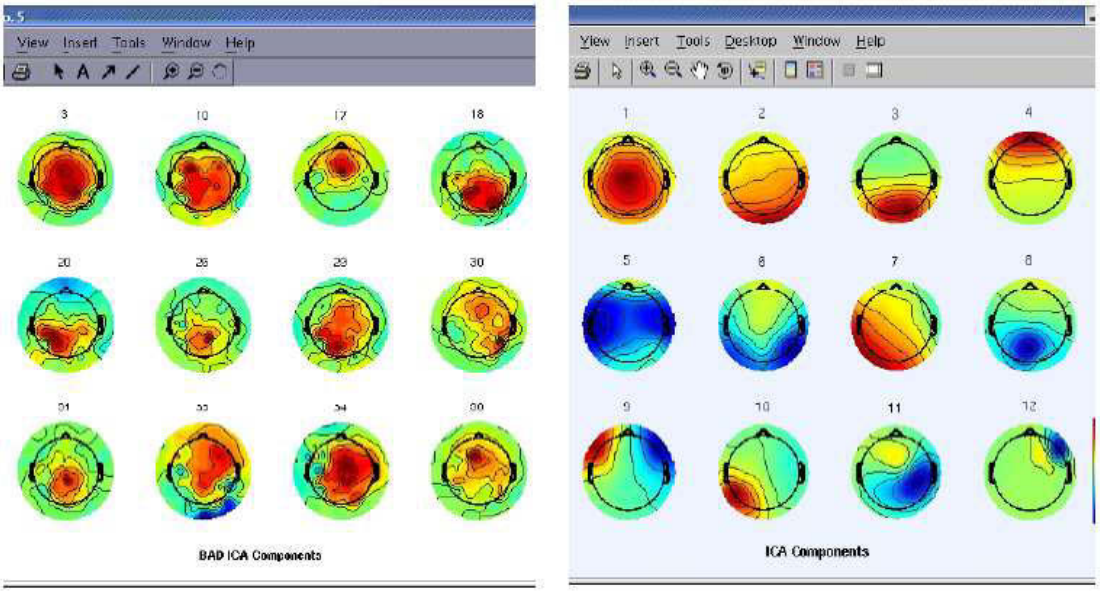



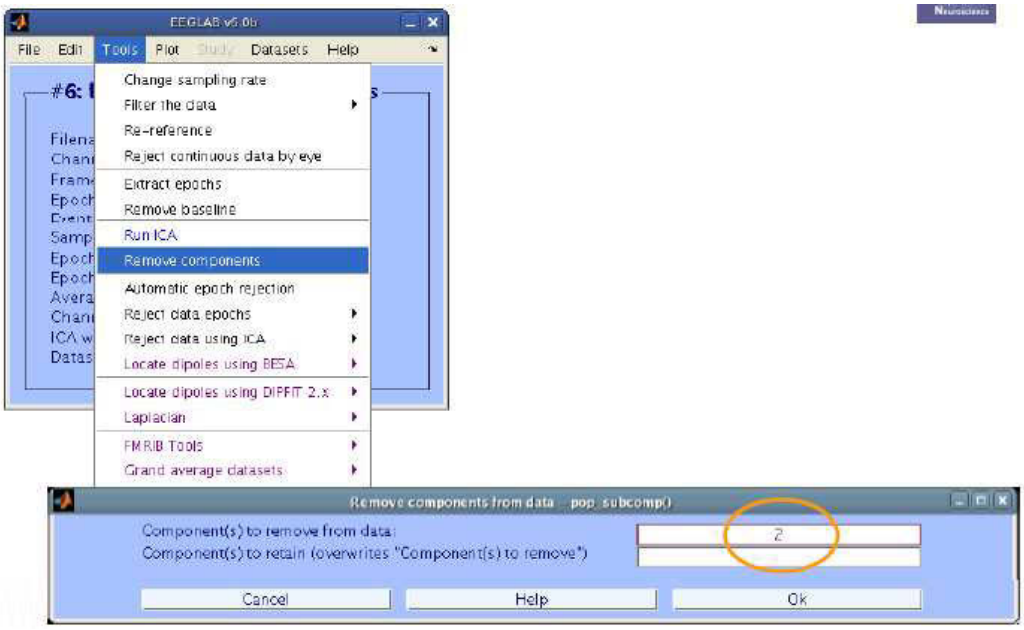
### viii) Plot components

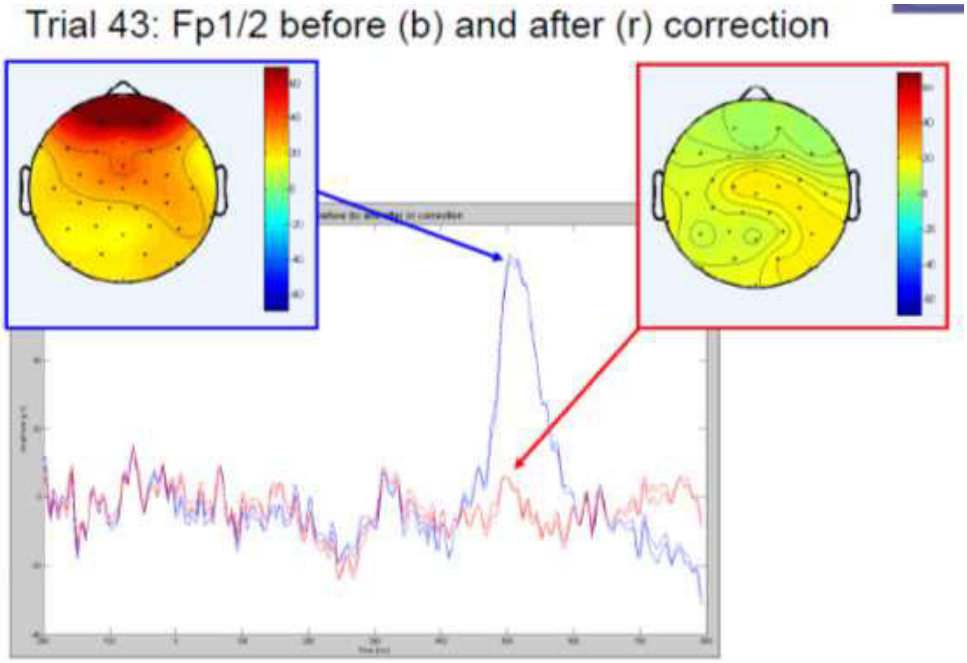



EEGLAB Workshop IX Nov 25-27, 2009 Newcastle, Australia: Julie Onton – Artifact rejection and running ICA



### ix) Remove components



# Appendix B

## Ethical Approvals

Ethical approvals were required for this research both from university of technology Sydney (UTS) and national acoustic laboratories (NAL).

1- EEG Pattern Recognition – clearance number is; UTS HREC REF NO. 2008-141A.

2- At NAL consent form were filled by all subjects attended in the experiment, information for participants were also included in the consent form and it is as follow:

126 Greville Street
Chatswood NSW 2067
Australia
T (02) 9412 6800
F (02) 9411 8273

National Acoustic Laboratories
A division of Australian Hearing

Dear Sir or Madam,

The National Acoustic Laboratories and the University of Technology in Sydney are investigating ways to monitor a person's state of arousal. These techniques could be valuable while monitoring a person's awakeness during surgery, when driving a vehicle, or during experiments that require participants to stay awake and alert. Additionally, responses from the auditory cortex (cortical auditory evoked potentials, or CAEPs) are monitored to analyse the effect of state of arousal on these CAEPs, which could influence the way we interpret specific parts of the brain. As part of this process we need to collect more information about the brain at different states of awakeness.

If you decide to participate, by signing and returning the consent form attached, you will be evaluated once at the National Acoustic Laboratories (NAL) in Chatswood. The appointment will take not more than 2 hours. The attached 'Information for Participants' describes what is involved for you at the evaluation. Participation is voluntary.

If you would like to discuss any aspect of the evaluation and/or participation, please feel free to contact Bram Van Dun Ph: 9412 6967; Fax: 9411 8273; Email: Bram.VanDun@nal.gov.au or Alaleh Rabie Ph: [redacted]; Email: ARabie@eng.uts.edu.au.

Yours sincerely,

Dr. Bram Van Dun
Research Electrophysiologist
National Acoustic Laboratories

Alaleh Rabie
Masters Degree Candidate
Faculty of Engineering & Information Technology
University of Technology, Sydney

126 Greville Street
Chatswood NSW 2067
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National Acoustic Laboratories
A division of Australian Hearing

**Information for Participants**

Date: 17 April 2013

Project Title: Automatic Detection of Alertness Level from EEG signals and its Application to the Assessment of Hearing using the Cortical Auditory Evoked Potential (CAEP).

*Background information*

The National Acoustic Laboratories (NAL) and the University of Technology in Sydney are conducting research to identify the degree of alertness of subjects that undergo a Cortical Auditory Evoked Potential (CAEP) based hearing test. CAEPs are tiny electrical signals that are produced by the hearing pathways of the brain when a sound is heard. These signals can be recorded using sensors attached to the surface of the head. When using a large number of sensors, an electroencephalogram (EEG) can be obtained from multiple locations on the scalp, thus providing a detailed map of the processes in the brain.

Hearing is the only remote sense which is open during sleep period. An example would be a baby's cry during the night that awakens its parents. The activity of this sensory system is attenuated during sleep however, causing CAEP waveforms to change. As a result, it is necessary for CAEP subjects to stay awake and alert, as alertness affects the accuracy of the measured CAEP. By separating the different levels of vigilance during the CAEP measurement, the tester will be able to evaluate the effectiveness of the test and whether he/she needs to take certain measures to improve it. Apart from this application, identifying the drowsiness level in drivers can also be considered related, and the monitoring of a patient's sedation during surgery.

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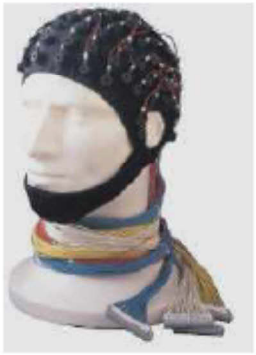
A division of Australian Hearing

*What is involved*

If you agree to participate, you will undergo a conventional hearing test, listening to tones through headphones. To participate as a subject you must have hearing within the normal range. If the testing shows that you have a hearing loss, then you will not be able to undergo the full study. Support will be offered and if desired you will be referred to a local audiologist for further investigation.

For the recording of CAEPs, a cap with 70 sensors (sometimes called 'electrodes') will be attached to the surface of your head, similar to the picture below. The sensors contain a small amount of water soluble gel. These sensors do not cause discomfort, but it is necessary to clean the skin while placing the sensors and this may cause some slight reddening of the skin. If reddening does occur this is temporary and usually disappears within 24 hours. The application of this cap takes about 45 minutes. Meanwhile, you are allowed to watch a DVD to pass the time.



During testing, you will sit in a comfortable chair while a recorded speech stimulus is presented through a loudspeaker at a comfortable presentation level. The sensors record the brain's response to the sounds. You will be facing an analog clock and asked to push a specific button every minute, depending on how awake and alert you feel. You are allowed to asleep during testing. The total test time is 2 hours.

*Privacy of information and Research outcomes*

Privacy of information will be strictly observed. Personal information and data collected will be treated in a confidential manner. Data may be used in research publications, however no individual information will be directly identifiable in any reports of results.

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Australia
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National Acoustic Laboratories
A division of Australian Hearing

*Your rights*

Participation is entirely voluntary. Although we value your participation, you are free to decide whether you wish to participate, and to withdraw yourself from the research at any time. Withdrawal of participation from this experiment will not affect your eligibility for services from Australian Hearing.

*Who to contact for complaints*

The ethical aspects of the research were approved by the Australian Hearing Human Research Ethics Committee. If you have any complaints or reservations about any ethical aspect of your participation, you may contact the Committee through the Secretary Dale Treglown on (02) 9412 6862 or email Dale.Treglown@nal.gov.au. All complaints will be treated in confidence and investigated, and you will be informed of the outcome.

dr. Bram Van Dun
Research Electrophysiologist
National Acoustic Laboratories

Alaleh Rabie
Masters Degree Candidate
Faculty of Engineering & Information Technology
University of Technology, Sydney

*The National Acoustic Laboratories (NAL) is the research arm of Australian Hearing, a statutory government authority. NAL is funded from the government, from sponsors, grants and from commercialization of its research. The results of this research will generally be reported on in NAL Research and Development Reports which can be accessed from www.nal.gov.au.*

126 Greville Street
Chatswood NSW 2067
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T (02) 9412 6800
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National Acoustic Laboratories
A division of Australian Hearing

*Consent Form*

Project Title: Automatic Detection of Alertness Level from EEG signals and its Application to the Assessment of Hearing using the Cortical Auditory Evoked Potential (CAEP).

I, _____ (your name)
of _____ (address)
_____ (phone no.) have read and understood the Information for Participants and the Consent Form.

I freely choose to participate in this research, and I understand that I can withdraw from participation at any time.

I also give permission for the exchange of information regarding myself and between researchers of this project.

Participant _____ Researcher _____

Signed _____ Signed _____

Date _____ Date _____

126 Greville Street
Chatswood NSW 2067
Australia
T (02) 9412 6800
F (02) 9411 8273

National Acoustic Laboratories
A division of Australian Hearing

**Please complete and return as soon as possible**
(stamped reply envelope enclosed)

**Re: Automatic detection of alertness level & cortical responses**

**Name:** _____

**Postal address:** _____

_____

_____

_____

**Email address:** _____

**Phone number:** _____

**Fax number:** _____

**Mobile number:** _____

How would you prefer to be contacted? _____

**Please tick one of the following:**

- ☐ Yes, I am able to participate in this research study
- ☐ I would like more information
- ☐ I would rather not participate this time, however may be available for future research studies
- ☐ I do not wish to be contacted in the future regarding research

If you have any queries, please contact Bram Van Dun on 9412 6967 or Alaleh Rabie on (
2 .

Thank you for your assistance.

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