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Investigation of "Begena" Sound Emotional effect on a Depressed Subject based on Frequency-Domain EEG Signal Analysis

A Thesis submitted to School of Graduate Studies of Jimma Institute of Technology, Jimma University, in Partial Fulfillment for the Degree of Master of Science in Bioinstrumentation

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DECLARATION

I declare this research with the title of **Investigation of "Begena" Sound Emotional Effect on a Depressed Subject Based on Frequency Domain EEG Signal Analysis** is my original work except for cited summaries denoted by quotation marks and I assure it with my signature.

Name: Anteneh Mekuria Signature ……………………. Date ……………….

On behalf of the School of Biomedical Engineering at Jimma Institute of Technology, we the advisors of this research entitled **Investigation of "Begena" Sound Emotional Effect on a Depressed Subject Based on Frequency Domain EEG Signal Analysis** and we, the evaluators, confirm that this research is approved as an MSc. thesis for the student.

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ABSTRACT

Depression is a common mental disorder that causes disabilities and loss of life. Methods including EEG have been used to diagnose depression, as it relates to a decrease in the Alpha mean power across depression-sensitive brain regions. Although psychotherapy and medication are the two common treatment options, the associated gaps such as; high treatment cost, medication side effects, and treatment failure due to psychotherapist turnover are some of the current challenges. Alternatively, music therapy found to be a natural option to relieve depression. A potential healing capability exhibited in the Begena sound is a motivation for this study.

Hence, the objective of this study was to investigate the emotional effect of the Begena's sound on a depressed subject based on EEG signal analysis. Six subjects of age 22±3 were screened based on their PHQ-9 score to confirm depression. A 16-channel EEG signal was acquired from the subject for two minutes in each condition (before and after exposure to the Begena sound). EEGLAB software used for pre-processing and the Welch's method was applied to extract the Alpha mean power at the depression-sensitive parts of the brain; particularly at temporal (T3&T4), Parietal (P3 & P4), Occipital (O3 & O4), and prefrontal cortex (Fp1& Fp2). Then a paired sample T-test was done at a 0.05 confidence level (P) to determine any significant change in the Alpha mean power.

The results showed an increased Alpha mean power nearly to all depression-sensitive areas of the brain after Begena sound intervention compared to a silent resting state, and their brain performance more closely resembled a healthy subject's waveforms as reported in literature. A statistically significant change ($p<0.05$) was observed in all subjects. Although the study was conducted with a limited sample size, the results warrant further study of the therapeutic benefit of the Begena's sound.

Key-word: Begena sound, EEG, Alpha mean power, depression

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ACRONYMS

BSS……………………………………………Blind Source Separation

DASS………………………………… …...Depression Anxiety and Stress Scales

DFT……………………………………………Discrete Fourier Transform

ECG ………………………………………. Electrocardiography

EEG…………………………………………...Electroencephalography

EMG………………………………………. Electromyography

FFT……………………………………………Fast Fourier Transform

FIR……………………………………………Finite Impulse Response

FT……………………………………………. Fourier Transform

ICA……………………………………………Independent Component Analysis

ICs………………………………………… Independent Components

JUMC……………………………………...Jimma University Medical Centre

IIR……………………………………………Infinite Impulse Response

JU-SC……………………………………..…Jimma University Student Clinic

MT…………………………………………...Music Therapy

PHQ-9………………………………… …. Patient Health Questionnaire

PSD…………………………………………...Power Spectral Density

SPSS………………………………………. Statistical Package for the Social Science

STFT………………………………………Short Time Fourier Transform

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PREFACE

This thesis contains six chapters. In chapter one, overall background information related to depression such as current impact, causes, diagnosis, treatment options, and related work are presented, along with the base problem, scope, objective and significance of the research. Chapter two briefly discusses the human brain anatomy and overview of music therapy. Chapter three continues to discuss in detail about the electroencephalography (EEG) processing techniques and different human brain waves. Chapter four explains the methodology and material used in EEG signal analysis. Chapter five provides analysis, results, and discussion followed by Chapter six to explain the conclusion and gives insight into future work

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Depression is a common mental health disorder that affects people's emotional, cognitive, physical, and social wellbeing regardless of the state of their immune system, leading to underemployment and reduced productivity [1].

According to the World Health Organization (WHO) current report, 332 million people, about 4.4% of the world population of all age types, are suffering from depression [2]. Figure 1 shows the prevalence of depression in WHO regions.

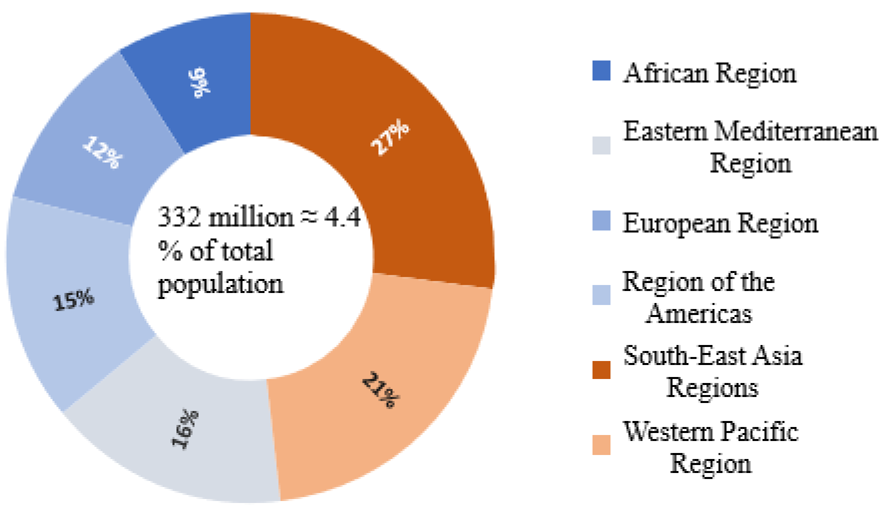


Figure 1. Prevalence of depressive disorders in WHO Region.

"It accounts for 6.5 % of the burden of diseases in Ethiopia"[3]. A study was conducted on 354 staff members of Jimma University and showed that 22.9% of the total participants were in the depressed states [1]. Figure 2 shows a 2019 study result that participate 760 Jimma university students and it indicates that 58.4% of the sampled students have been affected and 83.8% of students with this problem required treatment help [4].

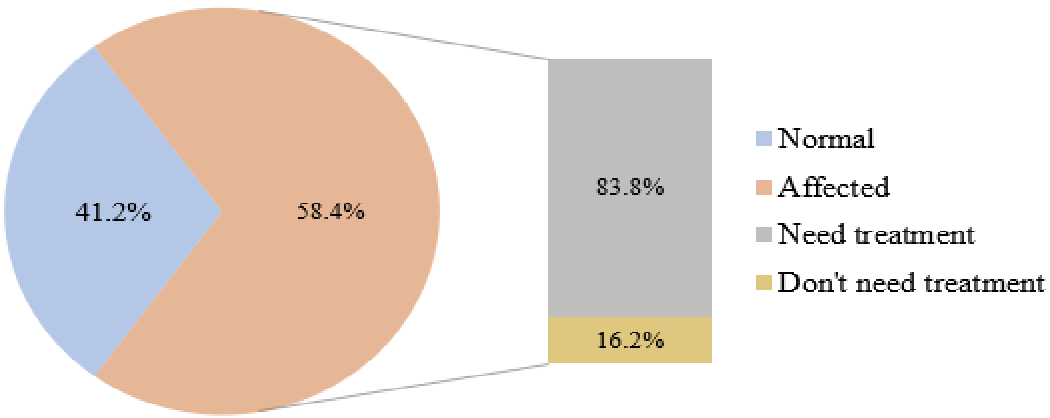


Figure 2. Depression prevalence among 760 Jimma university students in 2019.

Even though the root cause of depression is not clearly understood, experts believe that change in hormone levels, including serotonin, is the best indicator of disease [5]. The level of this hormone inside the brain becomes unbalanced due to physical, social and emotional factors, including: Loss of loved ones, drug or substance use, previous history of mental illness, and academic load in the university study [1, 2, 5].

In most Ethiopian healthcare institutions, the standard patient health questionnaire (PHQ-9) test is used as a first-line diagnostic tool to know the severity level of depression, e.g. scores 5, 10, 15, and 20 represented mild, moderate, moderately severe, and severe depression level, respectively [6]. Further studies include the use of an electroencephalogram (EEG) machine to diagnose depression [7, 8].

Electroencephalography is a non-invasive and safe medical diagnostic device [9],used to monitor the brainwaves of a subject by correlating voltage fluctuations of 0.5 to ±100 μV to different mental states [7]. Alpha brain waves (8-13Hz) were determined to be the key frequency range indicative of depression, where its μv^2 value decreases with respect to depressed mental state [8, 10].

The common current treatments options are either anti-depressant medication or psychotherapy. Medications reduce psychological pain by regulating brain hormone levels whereas psychotherapy aims to shift negative thought into a positive attitude [11]. Alternatively, music therapy has emerged as one of the upcoming promising natural treatment options, gaining attention from many researchers across the world since it's freely available everywhere with minimal cost and side effects. Current studies indicate that music therapy have positive stress and depression relief effect [12, 13].

Begena Instrument

In Ethiopia, there are many traditional musical instruments used in different cultural events and public ceremonies. Among them, the Begena instrument is characterized by a very specific buzzing sound. It is a chordophone instrument with ten strings, belonging to the lyre family of instruments.

In 1000B.C years ago the healing mechanism of the Begena (Harp of David) sound was mentioned in the Holy Bible 1 Samuel16 - 14-23 which states that the evil spirit from King Saul departed and relief came when King David played it [14].

Practically, it is common to see this effect within a subject who plays with or listen to it. It produces a low bass heart-warming vibrational sound and can attract people's attention, putting them into a new emotional mood. Due to this reason, it's one of the lovely traditional instruments in Ethiopia and common to see people spending time to practice and learn how to play it [14, 15]. Hence, this research focused on the effect of the Begena instrumental sound and was designed with different melody contents so as synchronize with a subject's emotion.

Tuning the Begena Instrument

As shown in Figure 3, the Begena's sound is modified by adjusting tuners (መቃኛዎች) road shaped stick found on the upper part of it. Begena is typically played in the Anchyhoye kegnet (key of C) using string numbers 2, 5, 7, and 9 as the resting string. In this case string number 4 is tuned to the first scale and assigned to 'C', String number 6 is tuned to the second scale and assigned to 'C#', String number 1 is tuned to the 3rd scale and assigned to 'F', String number 10 is tuned to the 4th scale and assigned to 'F#', String number 8 is tuned to the 5th scale and assigned to 'A', and string number 3 is the last tuning scale below octave string number 8.

Figure 3:Begena instrument playing and recording

The goal of this research is to investigate the emotional effects of Begena sound on a depressed subject brain activity at a specific region such us temporal (T3&T4), Parietal (P3 & P4), Occipital (O3 & O4), and prefrontal cortex (Fp1& Fp2) areas based on frequency domain EEG signal analysis study. The Alpha mean power at these regions was selected as the key feature to analyze the EEG signal in pre- and post-exposure to the Begena sound. The Alpha frequency band was selected as researchers found that it produces key emotional sensitive frequency components at the specified sections of the brain [16]. Also, it is routinely used as an indicator of depression [8], and it serves as a baseline for investigating the effect of music on human brain activities [13, 17, 18, 19, 21].

1.2 Related Work

Different studies carried out have proven the beneficial use of MT sound effects on mental depression and related illness [16, 18, 19, 21, 24, 26, 24]. Table 1 summarizes a review of original research work that uses an EEG-derived Alpha power, i.e. power spectral density (PSD) feature, to analyze and investigate the effects of instrumental or group sound therapy on participants with depression and related mental disorders. Those studies demonstrated that the increase in Alpha power was associated with a therapeutic benefit of the MT.

Table 1:Summary of related work on MT that utilizes EEG-PSD analysis

No	Study Year	Objective	Method used	Finding/result	Limitation
1	2012[23]	The effect of Violin sound on the human brain	Stimuli: Violin instrumental Method: EEG (PSD) mean Alpha power analysis using FFT with and without violin sound	Result: Balanced Mean Alpha power in the left and right brain part	*On single sample size *short term
2	2018[20]	Investigating the emotional effect of MT on the human brain	Stimuli: alpha binaural beat vs other sound Method: Alpha PSD analysis using FFT	Tools: ANOVA statistical method Result: Alpha binaural beat shows a soothing effect with $p<0.05$	*Few subject number (5) *short term experiment *effect on depression is not addressed
3	2018[17]	Investigating the MT effect on mental stress relief	Stimuli: classical vs personal preferred Method: FAA analysis based on DWT with 2- sec	Tools: ANOVA statistical method Result: classical MT has a significant effect	*short term experiment *Limited to Fp1and Fp2 (EEG-channel)

			epoch	with p<0.05 at the frontal pole	
4	2016[24]	Investigating the MT emotional effect on the human brain	Stimuli: classical symphonic, Rock, pop, and roll Method: visual PSD spectrum analysis	Result: change in the spectrum of EEG is noted after classical symphonic therapy	* lack of q-EEG analysis
5	2018[21]	Investigating the emotional effect, the Mozart music on EEG	Stimuli: Mozart &Beethoven Method: Pre.M & Post.M Relative PSD analysis based on FFT in Alpha-Band	Tools: ANOVA-statistical method Result: A significant change in adult and elderly subject after MT with p<0.05	*small sample size *lack of q-EEG analysis
6	2013[22]	To investigate the MT effect on Fronto-Temporal brain part of a depressed patient	Stimuli: group music Method: FAA analysis based on FFT with 2- sec epoch	*Tools: Z-test statistical method *Result: shows an increased alpha power in Fronto Temporal with MT P<0.03	*Limited sample size *focused on a few no. of EEG electrode
7	2010[19]	Investigating the emotional effect of MT on the depressed patient	Stimuli: soft music Method: FAA analysis based on FFT using 2sec time window	*Tools: T-test statistical method *Result: FAA at electrode F7-F8 shows a significant effect after MT with p<0.05	*limited only to frontal EEG electrode analysis *analysis was only based on specific brain lobe

1.3 Gap Analysis

The emotional effect analysis of Begena's sound on a depressed subject based on EEG signals has not been addressed in any of the research conducted previously. Other forms of MT serve as preliminary evidence for the further full-scale study to determine its long-term effect on the clinical setup and to provide on-field use in the healthcare center after getting approval and licenses from the responsible governing institution.

1.4 Statement of the Problem

Depression is a current global burden, affecting over 300 million people, about 4.4% of the world population [2]. It is also a national problem of Ethiopia that accounts for a 6.5% burden of the disease [3]. Current studies in JU showed, 22.9% of 354 participated staff members Jimma University suffer under the pain of depression [1]. Another study indicates that 58.4% of 760 participants of Jimma University students were affected with depression [4]. According to Dr. Eliyas, head school of Physiatry in JUSH and Mr. Sisaye, a senior psychologist at JU student clinic, the only treatment options are psychotherapy and medication and these have the following gaps:

- High treatment cost (e.g., physician, medication, travel) for six to twelve months
- Treatment requires skillful medical specialist (e.g. needs neurologist or psychotherapist)
- The adverse side effect of medication and its effect on day-to-day tasks (e.g., schooling, Driving)
- The medication's addictive nature: if stopped, the symptom come back

Studies found music that therapy (MT) was a third alternative to improve gaps related to medication and psychotherapy. MT has been found to have a positive effect on patients with depression. Although the sound of the Begena exhibits potential healing capabilities, there is less awareness and no scientific investigation to demonstrate any clinical benefit in this area.

1.5 Hypothesis

The subject's EEG-Alpha Mean Power ($\mu V^{2)}$ at depression sensitive brain region will increase significantly after receiving Begena sound stimuli intervention.

1.6 The Scope of the Study

This study investigates the emotional effect of Begena sound on the brain activity at a depressed mental state based on frequency domain EEG signal analysis approach. It uses Alpha mean power with the condition that the patient has their eyes closed as the key feature to compare any significant changes before and after Begena sound intervention.

The study duration was from April 2019 – March 2020 G.C at JUMC and the participants were screened out from a total population of 80 Jimma University undergraduate medical students using the PHQ-9 depression analysis questionnaire. Though 25 students among the total suffered from depression, only six subjects successfully met the inclusion criteria and underwent the experimental protocol.

Participants with hearing disability, those who took medication (PHQ-9 score greater than 14), and those who didn't offer to participate were excluded from the study. The study conducted in the short term and not implemented in the clinical therapy unit, and lacks a control group due to a shortage of necessary materials and limited budget.

1.7 Significance of the Study

Begena sound therapy provides short term beneficial effects for a subject with depression. This preliminary finding can be a reference for further, in-depth study that could prove as an alternative therapy option to help and alleviate the pain of depression. It can be one of the natural alternative therapy options in health facilities that would avoid the adverse side effects of the medication. It will be a natural option that can found everywhere with very low cost and require less specialist expertise.

1.8 Motivation

- To make Begena’s instrumental sound as a part of music therapy.
- To understand the causal relationship between Begena’s sound therapy and factors related to depression.

1.9 Research Question

- What is the emotional effect of Begena’s sound on depressed subject regional brain activity?
- What features of an EEG signal can be used to investigate the relationship between Begena sound and regional brain activity?
- What is the best method to extract the feature of EEG signals in the frequency domain?
- How does the emotional effect of Begena sound relate to regional alpha mean power?
- How do we measure the significant effects of the Begena sound on a depressed subject’s regional brain activity?

1.10 Objectives of the Study

1.10.1 General Objective

The general objective of this study is to investigate the emotional effect of Begena instrumental sound on a depressed subject.

1.10.2 Specific Objectives

The specific objectives of this research study are:

- To determine the emotional effect of Begena sound at a specific brain part of a depressed subject.
- To identify the method for extracting and determining the features of the EEG signal in the frequency domain.
- To investigate the relationship between Begena sound stimuli and Alpha mean power.
- To determine the significance of the effect of the experiment based on a statistical analysis

CHAPTER TWO

Overview of the Human Brain Anatomy and Music Therapy

2.1 Human Brain Anatomy

To explore human brain activities in responses to different external stimuli and to conduct an EEG-based analysis study, it is required to understand the basic parts of the human brain and their function.

The Human brain is analogues to computer central processing unit (CPU) and Its weight is approximately 3-pounds and contains 100 billion neurons (nerve cells) which allow for interpretation and information processing from different sensory organs and to perform corresponding actions, e.g. body movement, controlling emotions, intelligence, and response to external stimuli [28].

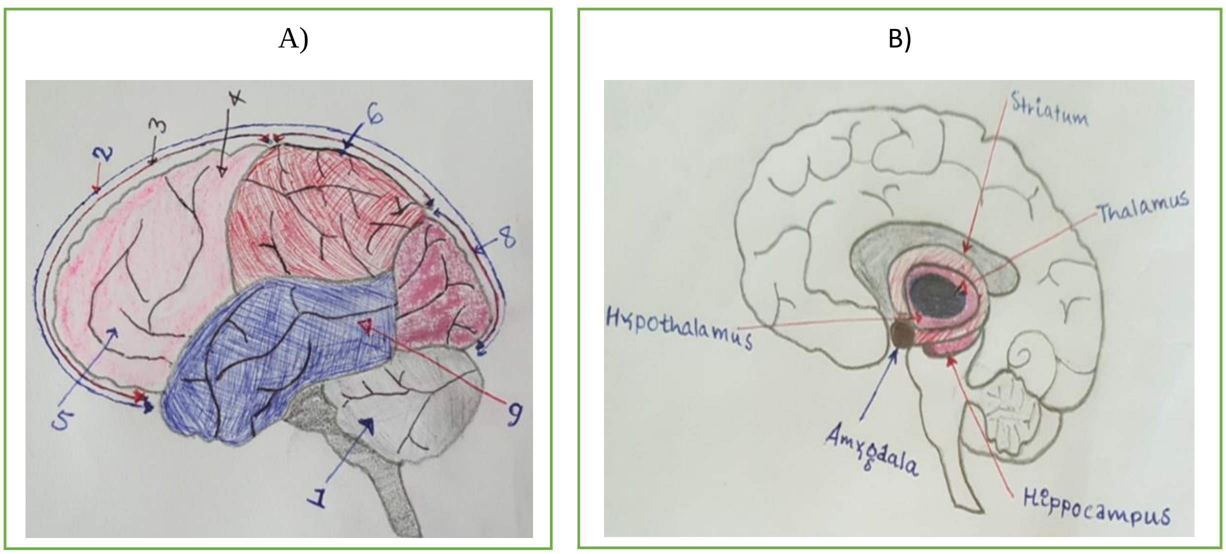


Figure 4: The human brain anatomy .

The human brain includes three main parts: the Cerebrum, Cerebellum, and brain stem. As indicated in Figure **4**A, the Cerebrum (2) and Cerebellum (1) are located just above the brainstem. The cerebrum is the largest brain part that is divided into the left and right region with each part controlling the opposite side of our bodies, and is responsible for interpreting messages coming from our sensory organs such as touch, vision, hearing, speech, reasoning, emotions, learning, and fine control of movement.

As shown in Table 4, Cerebrum contains four lobes such as frontal lobe (3), Temporal lobe (9), parietal lobe (6), and occipital lobe (8) each separated with distinct fissures [28]. Each brain lobe has a very specific function as mentioned in Table 2.

Table 2: Brain lobes and their functions[28].

Lobe	Actions
Frontal lobe	Conscious thought, emotion, decision making, problem-solving, speaking, writing, intelligence, concentration, and self-awareness.
Temporal lobe	Language recognition, audio (hearing) process
Parietal lobe	Motor control, sensory processing (touch, pain, temperature, spatial)
Occipital lobe	Visual processing

2.2 The emotional response of a human brain

Figure 4B shows human brain parts that are responsible for emotional response and these are called the Hippocampus, Amygdala, Hypothalamus, and Thalamus. Those are the areas having a high probability to be implicated with depression [22]. Hippocampus has a role in processing long term memories and recollection, especially trauma, e.g. if you had bitten by a dog in someplace, then you may not forget that place and dog after a long-time period [28].

Very close to the hippocampus, there is a brain part called Amygdala that found in the frontal portion of the temporal lobe whose role associated with emotions such as anger, pleasure, sorrow, and fear [22]. The Hypothalamus, on the other hand, receives and directs sensory information to the appropriate part of the cerebral cortex to respond to necessary action and the Thalamus is the other part near the Hypothalamus that carries information to and from the spinal cord and the cerebrum [28].

2.3 Overview of Music Therapy

This section includes the definition of MT, its benefit, pathways as well as an effect on the human brain activity.

2.3.1 Definition of Music Therapy

Music therapy is the application of music to relieve stress, improve moods, treat depression and physical disorders with or without the help of a therapist [25]. Music therapy can be instrumental, vocal, or both, and can be delivered to the patient through singing while playing instruments or listening to recorded musical sounds [26]. Its therapeutic use has been recorded since ancient times. For example, David has played the Begena (Harp of King David) to soothe King Saul's suffering due to demon-possession and was able to heal his insomnia [14]. Ancient Egyptians, Aboriginals, and Babylonians were also using tools such as didgeridoo and low frequency drumming to have better mood and relaxation [29].

2.3.2 The Key Attributes of Therapeutic Music Sound

MT can create either positive or negative emotional feeling depending on the nature of its attributes [30]. These are;

- Rhythm: It is a pattern of repeated sounds and silences captures an individual's attention, influences motor control and function based on its recurring patterns, skeletal muscle synchronization, and dynamic physical movement.
- Melody: is the arrangement of length and intensity or a sequencing of musical pitch and intervals between musical notes, causing feelings of happiness and calm, or sadness and anger. The distance between each note is the integral component of the melody, giving it its character and emotional response.
- Pitch refers to the number of cycles that a particular sound vibrates per second.
- Harmony; is the collection pitch to a combined sound.

2.3.3 Sound Pathway and its Effect on the Brain

The sound waves first reach the pinna, the visible part of the ear, and moves into the auditory canal, a path to hit the tympanic membrane (eardrum), causing a vibration that allows further transmission into the middle ear where the three bones called the hammer, incus, and the stapes are located, transmitting the sound through the oval window that direct the sound waves to the cochlea (in the inner ear) which then stimulate the hair cells in the organ of Corti (within the cochlea) which in turn stimulates the cochlear branch of the vestibulocochlear nerve that causes a transmission of electrical impulses to the auditory region of the brain in the temporal lobe [25].

Improve 2.3.4 Music Sound Therapy Benefits to Relief Depression and Stress

Music therapy has a strong power to evoke various emotional reactions. It helps to improve brain memory and used in physiotherapy treatment to achieve enhanced motor function [25]. According to recent studies, music therapy used to alleviate depression symptoms [5, 18, 19, 21, 25, 26, 29, 31, 34], to relieve stress and improve moods [13, 17, 25, 26], for healing pain, lower blood pressure, and improve sleep quality [17, 26].

2.4 Effect of Music Sound on the Human Brain

According to recent studies, the reason for depression is some negative factor that evokes a painful emotion registry part of the brain called Amygdala and Hippocampus (see Figure 4) to generate stress hormone. As a result of this, we feel depressed. Conversely, music sound has a major role in deactivating stress hormone production and assists for happy hormone release that helps to gain a gradual positive feeling [25, 33].

Listening to music can also help to increase a happy hormone called dopamine, "a neurotransmitter that controls the brain reward circuit." [34]. Since the parts of the brain are connected with each other, this feeling propagates through and stimulates different parts of our brain, especially in the parietal lobe which controls the auditory, motor, and limbic systems [28]. Another study also shows that MT can activate the prefrontal cortex and occipital region of the brain and improve its function [35]. Since music stimulates the mind and the mind influences the body, it alters emotional levels and in this way, music therapy used to heal depressed people [28].

CHAPTER THREE

Electroencephalography and Human Brain Waves

3.1 Overview of Human Brain Waves and Electroencephalography

Electroencephalography is noninvasive and safe brain mapping techniques to record and study the electrical activity of a brain in a real-time situation [36]. It is a process of recording an electrical impulse that generated as a result of neuron firing at each electrode site of the brain. This impulse is then detected using a sensor called an EEG electrode that usually made of either from silver or gold [37]. Although the EEG signal is non-stationary in nature, it assumed stationary within a short interval time, which are sometimes called quasi-stationary [38]. According to the study, the EEG signal in a time window less than 12 seconds can be taken as stationary [39].

the electroencephalogram device is used to study brain function and to monitor the brain wave of the subject by relating to amplitude and frequency variation with respect to mental state change. now a day's it becomes a key biomarker to diagnose depression by analyzing the change in EEG parameters such as amplitude, frequency, and power spectrum by focusing on a specific frequency bandwidth [8 , 40].

3.2 EEG Signal Acquisition

Electroencephalograph is a machine that used to acquire an EEG signal using a sensor called EEG electrodes by properly putting them on the subject scalp with following standard placement rule. The international 10-20 standard EEG electrode placement rule is one of the fundamental ways to correctly place the EEG electrode on the subject's scalp[41]. Based on this standard, each electrode labelled with a letter followed by a number to indicate the specific brain region and location on the subject scalp. As shown in

Figure **5**, each labelling contains a letter and number to indicate specific brain part and orientation from the reference point.

F = Frontal
T = Temporal
Fp = frontal Polar
Cz = midline central
P = Parietal
O = Occipital
Fz = midline frontal
Pz = midline parietal,
Oz = midline occipital
Even No = right side
Odd No= left side

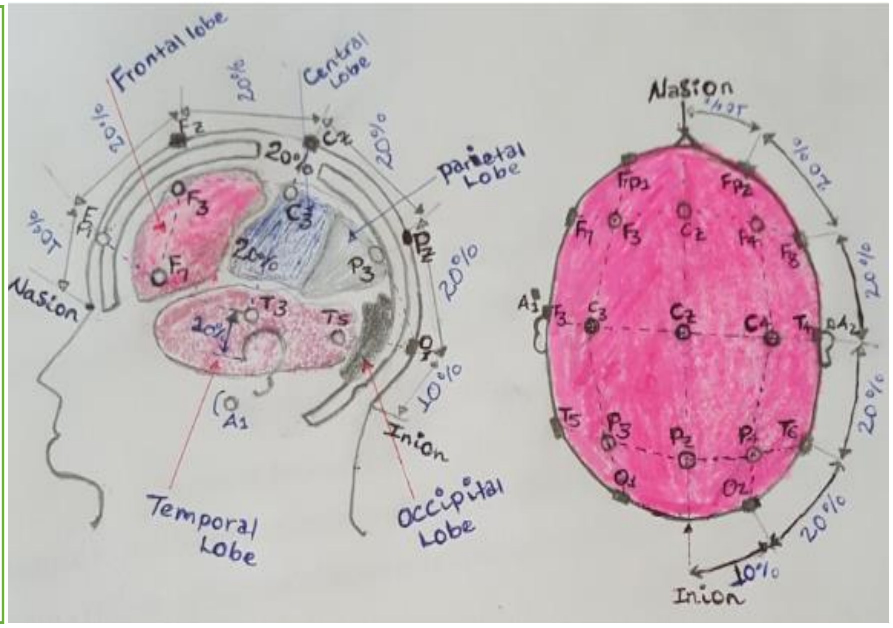


Figure 5: 10-20 EEG electrode placement.

A pair of electrodes form one channel and the signal coming via this channel feed to EEG machine to be amplified and displayed in the EEG-computer interface screen as a continuous waveform for further analysis and interpretation [9]. These waves are called brainwave patterns and can be classified into five types (gamma, beta, alpha, theta, and delta wave) based on the current mental state of the subject.

3.3 Brain Waves Classification

Even though five types of brainwaves have been investigated by researchers, four of them shown in Table 3.

Table 3: Brainwave types and range of frequency bands in different mind states [38].

Brain wave type	Delta	Theta	Alpha	Beta
Frequency band	0.5-4 Hz	4-8 Hz	8-12Hz	12-30Hz
Amplitude	20 to ± 100µV	20-100 µV	20-60 µV	0.5-20 µV
Mental state	In deep sleep	state of drowsiness	Relaxed and Eye closed	Active brain state (engaged in work)

As shown in Figure 6, these brainwaves exhibit a pure sinusoidal in eye closed and relaxed condition and usually have an amplitude range from (0.5 to ±100μV) [43] and a frequency range up to 100Hz [39].

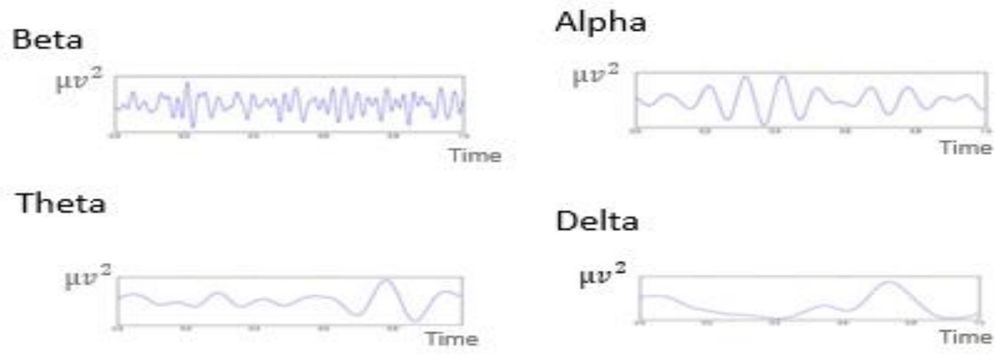


Figure 6: Common brain waves.

Alpha wave is quite stable in healthy subjects and shows a frequency and amplitude value variation around the set point in response to "neurophysiological" and "pathological process" change[43]. Due to these properties, different researchers have been selected this region in their study for example; to investigate the depth of anesthesia [43]. Alzheimer's disease [45]. Addiction [46]. Sleep marker [47]. Insomnia [48]. It is also a key biomarker to diagnose depression [8, 10]. Alpha wave has a frequency range of 8-13 Hz [8]. Alpha wave frequency range is sometimes divided into alpha 1 (8-10Hz) and alpha 2 (11-13Hz) [33].

Alpha wave is generated by a brain part called Thalamus [43]. It dominantly appears in a relaxed and eye closed state[16]. Generally, each channel EEG signal has a probability to include different types of brainwaves and can be expressed in a mathematical model for further analysis and quantification purposes [49].

3.4 Mathematical Representation of EEG Signal

Each channel EEG signal is the sum of different brain wave type and represented in mathematical expression as follows:

$$\mathbf{X(t)} = [\boldsymbol{X_1}\,(\mathbf{t}), \boldsymbol{X_2}\,(\mathbf{t}), \ldots \ldots .. \boldsymbol{X_m}(\mathbf{t})]^{\boldsymbol{T}} \ldots\ldots\ldots\ldots 3.1$$

In this case, X(t) is rows of matrices and represent a recorded EEG signal at m channel, T stands for transposition and m is the number of channels in such a case any variation with respect to time of a row signal is noted in the column of the matrix. In order to truly represent the EEG signal shown in equation 3. 2 the following action is necessary;

3.5 Conversion of analog to digital

Analog EEG signal represents the actual signal inside the brain and mathematically it can be expressed in time and amplitude value and can vary from -∞ to +∞. Inside the EEG machine the it converted to a digital value using default digital to analog converter (ADC), which has multiplexers which sample potential value at each sampling time interval (Δt) measured in a millisecond. So with this method, the continuous signal amplitude is converted into a series of discrete value and represent in mathematical form as amplitude, V(n) where n=0 1 2, which represent discreet value with a sampling frequency of 1/ Δt[49].

3.6 Filtering of Raw EEG Signal

To remove lower, higher, or between the two-frequency component of EEG signal, low pass (stomping high-frequency band), high pass filter (allowing higher frequency band to pass), or bandpass filter (allowing only interest region of frequency component) done by using different filter types such as finite impulse response (FIR) and infinite impulse response (IIR) such as (Butterworth, Chebyshev, and Elliptic)[50].

In this research work, a zero-phase basic FIR bandpass [0.5 30Hz] filtering done to retain common brain wave components before removing power line interference and followed by a zero-phase basic FIR bandpass (8-13Hz) filter to get alpha frequency band as a region of interest for this study.

3.7 Identifying and Removing Artifact from EEG Signal

In practice, the EEG signal is not purely existing and probably contaminated by other non-brain sourced signal, which is known as EEG artifact. EEG artifact may arise either from the physiological (intrinsic) or extrinsic (environmental) sources.

3.7.1 Intrinsic Artifact Source

- Electrooculogram (EOG) which produced and distributed into an EEG signal when the subject moves his/her eyeball and blink. This signal has an amplitude of 0.01- 0.1mVand frequency 10Hz
- Electromyography (EMG) is produced while muscle of the subject contracts and relaxes or simply by the movement of a muscle. This signal has an amplitude of 1-10 mV, and frequency 0 to more than 200 Hz
- Electrocardiogram (ECG) signal produced as heart muscle activity and propagated into EEG electrode placed closed to blood vessel. This signal has an amplitude of 1-5 mV, and a frequency of about 1.2 Hz. Figure 7, shows this common intrinsic artifact.

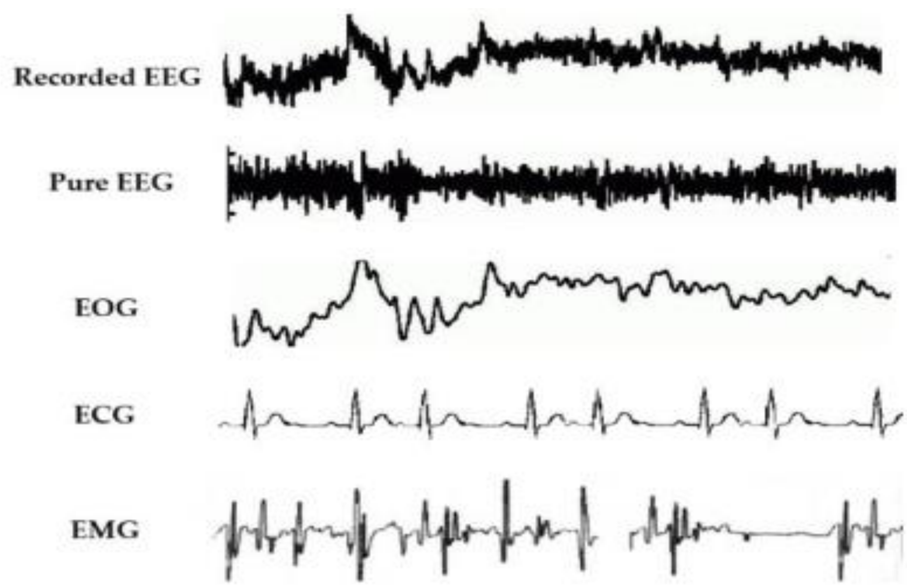


Figure 7: Physiological EEG artifact [51].

3.7.2 Extrinsic Artifact Source

Besides the physiological artifact, an EEG signal can be contaminated due to EEG cable movement and displacement of the electrode during the experiment. Electromagnetic interference that comes from nearby medical equipment and powerline noise that originated from an electrical socket (outlet) can also contaminate the EEG signal [51].

3.8 EEG Signal Artifact Removal Technique

As noted in section 3.7, an EEG signal has a relatively weak amplitude than EEG artifact. Hence, it can be contaminated either by intrinsic or extrinsic artifact then causes difficulties in reading and analyzing EEG data as well as leads to abnormal analysis results. For this reason, researchers have developed a different technique to remove and separate this artifact from EEG data and some of them are summarized in Table 4, below with detail information available on [52, 53].

Table 4: EEG Artifact Removal Technique [51].

No	Technique /method	Do require additional reference	Can it work automatically	Can it work Online	Can we apply to a single channel
1	Adaptive filter	Y	Y	Y	Y
2	Winner filter	N	Y	N	Y
3	Wavelet blind source separation	N	N	N	Y
4	Empirical mode decomposition BSS	N	N	N	Y
5	Blind source separation -support vector machine (BSS-SVM)	N	Y	Y	N
6	Regression	Y	Y	N	N
7	Wavelet	N	Y	N	Y
8	Independent component analysis (ICA)	N	N	Y	N
9	Canonical correlation analysis (CCA)	N	N	Y	N

As indicated in Table 4, some of the methods don't require an additional reference for subtracting artifact from EEG instead they utilize the principle of blind source separation technique. The information about the source is blind and the system don't have reference signal (known output signal) hence, these methods use unmixing matrix to separate independent source.

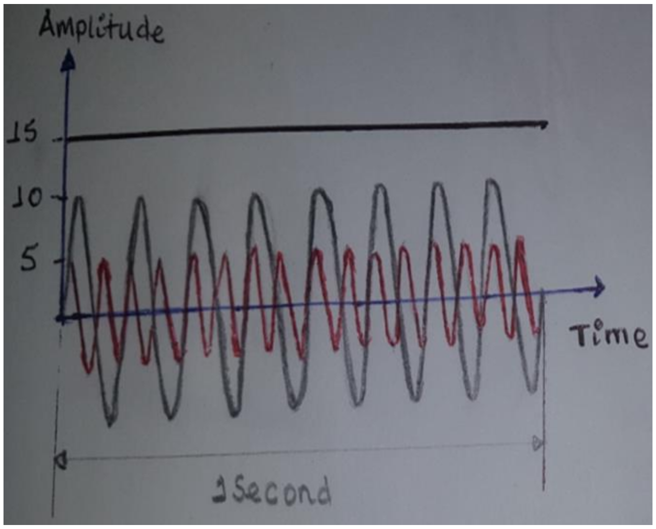
Others method used reference the output of the initial signal will be the reference for next operation and the procedure is based on the principle of feedback system. Hence, the residual artifact is the difference between the desired signal X(n) and update signal y(n).

Some method works automatically to remove the artifact from online within each channel while others not. These shows that the method has its own advantage and disadvantage which mean that there is no perfect choice to remove artifact and it depends on the user's requirement.

3.9 Frequency Domain EEG Signal Analysis Technique

EEG signal exhibits a sinusoidal wave [43]. Any sinusoidal wave can be "defined by its frequency, amplitude, and phase" which can be expressed either in time or frequency domain. The time-domain indicates a change in amplitude (voltage) with time, whereas frequency domain shows a change in amplitude with frequency (amplitude vs frequency) [54].

A



B

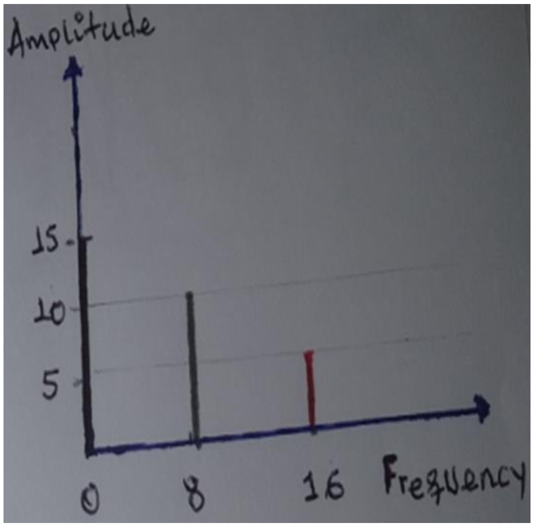


Figure 8: Time and frequency domain representation of the sinusoidal wave.

Figure **8**-A shows sine wave in the time domain at 0, 8, 16 Hz and

Figure 8-B shows sine wave in the frequency domain at 0, 8, 16 Hz. The frequency domain is more compact and useful when more than one sine wave expressed, as an example figure 8 shows three sines wave each with different amplitude and frequency. In frequency domain, all components are represented by three spikes. In EEG signal analysis the relationship between amplitude and frequency of a signal is very essential to study the characteristic of a brainwave at each frequency bandwidth, hence the signal in the time domain has to be converted into a frequency domain. To do this several techniques have been introduced in different literatures and some of them are discussed in this paper.

3.9.1 Fourier Analysis Technique

Fourier transform is the most fundamental technique to convert time domain EEG signal into a frequency component signal and thereby possible to analyses the activity of brain wave in different frequency bandwidth (beta, alpha, theta, and delta) [55]. “According to Fourier analysis, any composite signal (periodic and non-periodic) is a combination of simple sine waves with different frequency, amplitude, and phase can be decomposed into a series of simple sine waves” [54].

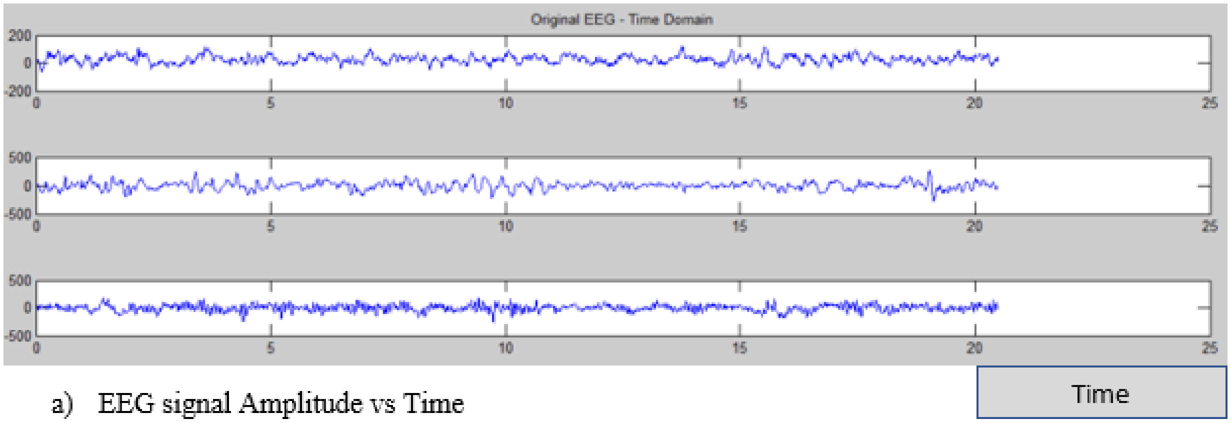
A signal X(t), where t varies from -∞ to + -∞ can be converted into frequency domain X(ω) and vice versa with the help of Fourier transform (FT) [56]. This can be expressed in the mathematical equation as follows:

$X(\omega) = \int_{-\infty}^{+\infty} x(t)e^{-j\omega t}dt$ Forward transform ……………………………………...3.2

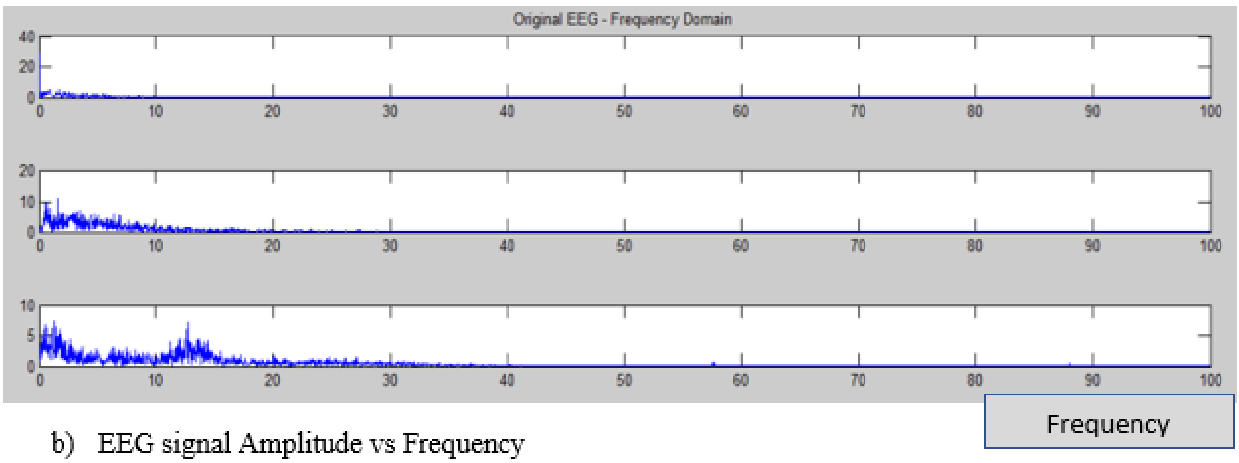
$x(t) = \frac{1}{2\pi}\int_{-\infty}^{+\infty} X(\omega)e^{j\omega t}d\omega$ Inverse transform ………. ……………………………3.3

Where $X(\omega)$ is a frequency-domain continuous function, x(t) is a time-domain continuous function, ω is the angular frequency is time, and $e^{j\omega t}$=cos $\omega t + jsin\omega t$.

Due to it’s less complexity operation, its preferred for monitoring real-time EEG signal monitoring and analysis of different physiological signals [55]. As shown in Figure 9, the Fourier transform can help us to easily separate an EEG signal into a frequency component (frequency spectrum) that allows us to visualize the sate of the brain [55].



a) EEG signal Amplitude vs Time



b) EEG signal Amplitude vs Frequency

Figure 9: Raw EEG signal in time vs frequency domain[57].

Figure 9 shows the time and frequency domain EEG signal representation of a single channel. As shown in figure 9.a, each channel has 23.6, second time duration and as indicated in figure 9.b, each duration divided into 100 intervals to reduce signal to noise ratio while representing into equivalent frequency component.

Although Fourier transform gives information about frequency component present in time domain signal, it can't provide localized information of a signal for example in the frequency domain the value at 13 Hz might be maximum, but there is no clue to when (at which time interval does it occurs [55].

3.9.2 Short-Time Fourier Transform Analysis

This is also one of the techniques in the frequency domain analysis which can provide localized information and improve the gap seen in Fourier transform. It is also called windowed Fourier transform where Fourier transform is applied to a segmented part of a continuous time-series EEG signal [55]. Short-time Fourier transforms work by assuming that a small portion of the non-stationary signal is stationery and to do this it utilizes a shifting window length such as hanning, hamming, or rectangular window which can segment the continuous EEG signal into a small-time component as shown in Figure 10.

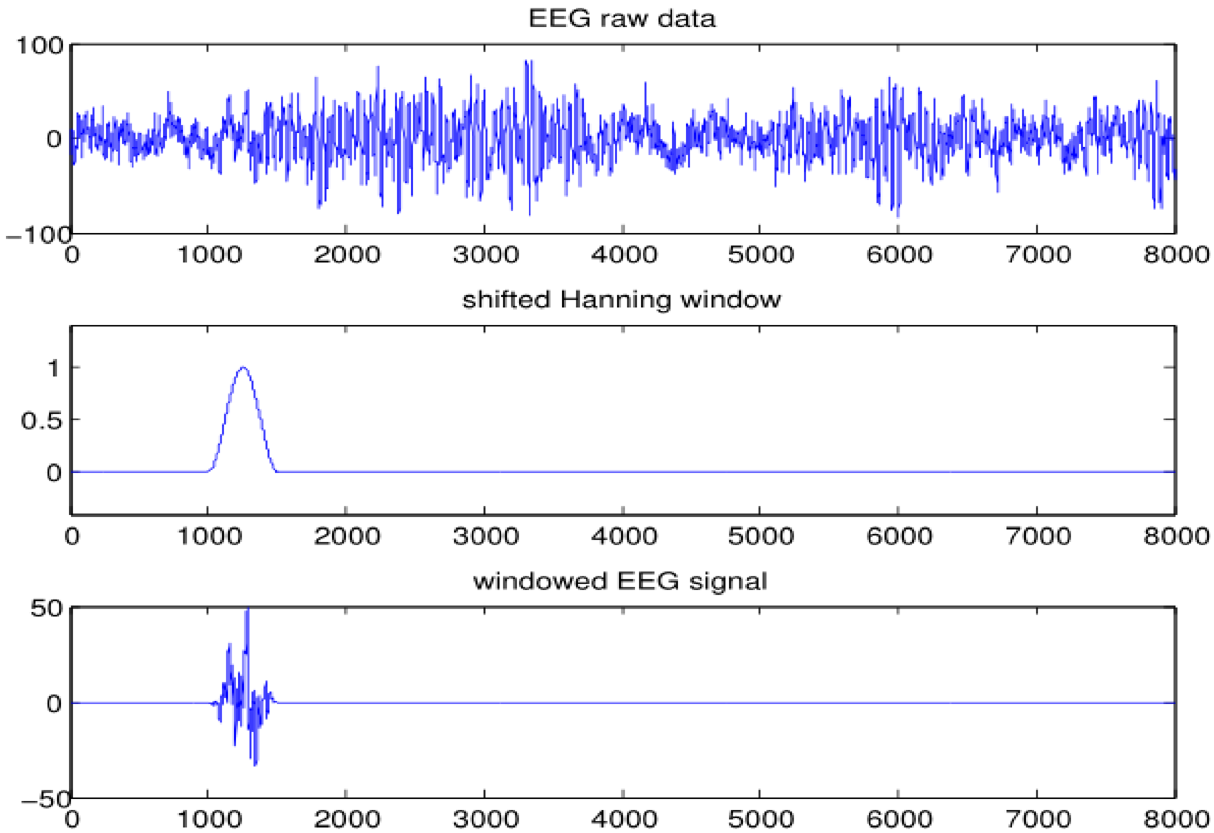


Figure 10: short-time Fourier transform (STFT) of a continuous signal [55].

3.9.3 Discrete Fourier Transform(DFT)

To conduct the Fourier transform on a discrete set of the sample signal X(t), discrete Fourier transform (DFT) is used with a slight modification of a continuous Fourier transform algorithm that has been discussed earlier

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j\frac{2\pi}{N}kn} \qquad k = 0,1,2\ldots..N\text{-}1\ldots\ldots\ldots..3.4$$

$$x(n) = \frac{1}{N}\sum_{n=0}^{N-1} X(k) e^{j\frac{2\pi}{N}kn} \qquad n = 0,1,2\ldots.N\text{-}1\ldots\ldots\ldots...3.5$$

Where, X(n) = sample in time, X(k) = sample in frequency, n = time index, k = frequency index $\omega o = 2\pi / N$, while N = number of samples

DFT is widely used in digital processing [56]. In EEG signall processing, this technique used to compute an amplitude value of the signal within each frequency sample point of the given time interval signal X(n).

A) B)

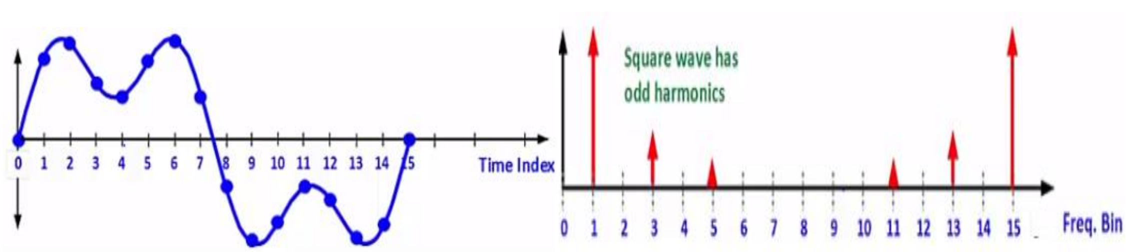


Figure 11: Discrete Fourier transform [56].

Figure 11-A shows time-domain sampled signal, and figure 11-B shows frequency domain DFT value at a particular sample point. DFT it is also used in digital processing to convert analog signal to digital signal. However, this method is relatively slower as the number of sample increases than the FFT (fast Fourier transform) [58].

3.9.4 Fast Fourier Transform (FFT)

One of the most widely used mathematical tools to represent a time series signal into a frequency component is the FFT spectrum [59]. Figure 12, shows how FFT can represent a one second time series of EEG signal at different frequency into FFT-spectrum.

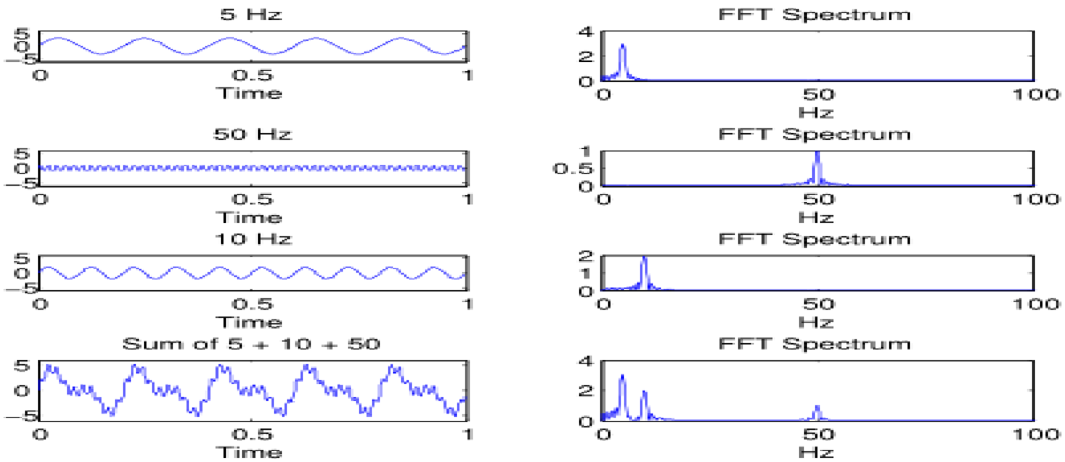


Figure 12: Representing time series raw EEG signal into FFT spectrum [59].

FFT can also compute the frequency component value of the corresponding time-domain sample X(n) using similar mathematical equation divided in DFT:

$$X(k) = \sum_{n=0}^{N-1} X(n) e^{-j\frac{2\pi}{N}kn} \qquad k = 0,1,2\ldots..N-1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.6$$

FFT has the advantage of reducing computation time and computational complexity compared to DFT. For example, if we had a given number of sample N, the number of computations in DFT multiplication is N^2 whereas in FFT becomes $\frac{N}{2} * \log2(N)$ Hence, FFT is the fastest way to compute a discrete Fourier transform (DFT) [56].

As shown in **Error! Reference source not found.**, FFT can also compute average amplitude alue at a particular frequency in a given time interval of the signal and create a curve of amplitude (microvolt) on the 'Y' axis and frequency on 'X' axis [60].

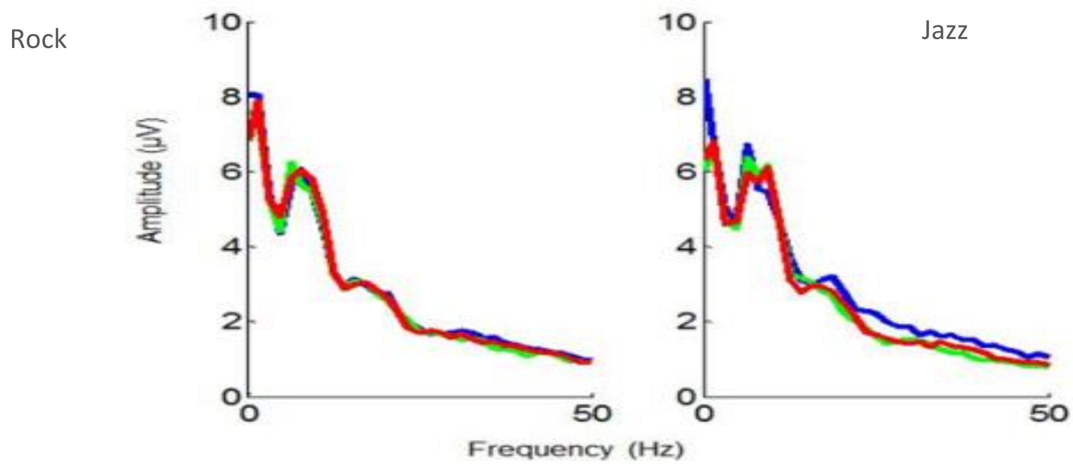


Figure 13. Average FFT output in 1-30 Hz frequency bandwidth [60]. Figure13 shows the FFT output of single subject and single-channel corresponding to each blue (fast), green (medium), red (slow) music stimuli of rock and Jazz rhythm.

FFT algorithm is utilized for signal spectral analysis and commonly used in EEGLAB and Matlab software under the Welch method to compute power spectral density (PSD) [61].

3.10 Feature of EEG Signal

In the time domain, features are amplitude related to time such as power, mean, and variability, and, regularity and all of these features provide only spatial information and don't provide temporal information [55]. To investigate the effect Begena sound at a specific frequency band of the brain wave, a quantifiable feature in the frequency domain required. Hence this study focused on a frequency domain EEG signal feature. The most commonly used feature in the frequency domain is an absolute power of a specific frequency band also called PSD [55, 62]. Fast Fourier transform (FFT) use to compute PSD value of epoched and cleaned time-series EEG data and one of the methods that use FFT to compute the PSD is Welch's method [62].

3.11 Power Spectral Density (PSD) Analysis

Power spectral density (PSD) is the power at a given frequency and mathematically it can be expressed as $\mathrm{PSD} = \frac{\mathrm{P(f)}}{\mathrm{df}}$ where p(f) is a power at 'f' divided by the frequency interval df. To further illustrate, let's assume we have a complex waveform X(t) in time domain then to compute PSD, first, we need to convert it into frequency domain using FFT to X(f) with amplitude X(f) as a function of frequency then PSD becomes $\frac{\mathrm{X(f)}^2}{\mathrm{df}}$which mean the power contained in frequency interval. Science the amplitude square $\mathrm{X(f)}^2$represents $\mu\mathrm{V}^2$ the unit of PSD is energy per frequency and sometimes has a unit of dB (decibel) or Power per frequency [63].

3.11.1 The Technique to Compute Average Power Spectral Density

One of the methods used to compute Average PSD using FFT values is called "Welch's method". In this method, first appropriate time windowing length is selected to cut the infinite length time-domain EEG signal into smaller (finite duration) epoch length which usually takes 1, 2 or 4 second duration [64, 26]. And the selection of each epoch length (T) is compromised between gaining either good frequency resolution (1/T) or good PSD in such a case good PSD estimation is gained by increasing epoch number and in opposite less frequency resolution [61]. Hence, for the reason of getting good PSD estimation 2-second epoch length with 0.5 Δf (frequency resolution), and 30 epoch is selected in this experiment to analyze 60 second raw EEG data.

Then during the analysis of EEG data in the frequency-domain, the whole epoched EEG data is multiplied with the Hanning window. Hanning window is used in the frequency response of the signal with the main lobe about 4Δf, where Δf =(f_s/N) and can remove discontinuities that associated with rectangular windowing as well as reduce data leakage[65]. It can be expressed in a mathematical formula [66].

The Hanning window, $w(n)$ is defined as:

$w(n) = \frac{1}{2}\left[1 - \cos(2\pi.\frac{n}{N})\right]$ where n = 0, 1,…N-1…………………………………………3.7

For a given signal X(n) a zero-padded windowed frame($X_m(n)$ from signal X(n) is given by :

$X_m(n) \approx X(n + mD), n = 0,1,2, \dots, M - 1 \; Were \; m = 0,1,2, \dots, K - 1$............................3.8

Where D = (stepping size) = 1/window length, K= No of available frame(segment), m=ith window, n=sample ,point in time domain signal, M=max sample point, and $\boldsymbol{\omega}_k$(angular frequency) =2π/T= $2\pi f$ then PSD at m block is given by:

$P_{xm,M}(\boldsymbol{\omega}_k) = 1/M|FFT_{N,K}\left(X_m(n)\right)|^2 \approx \frac{1}{M}\sum_{n=0}^{N-1} X_m(n)\, e^{-j2\pi nk/N}|$^2……………………3.9

And the average PSD across the number of available frames (K) is called welch's PSD estimate and given by:

$P_x^W(\boldsymbol{\omega}_k) = \frac{1}{K}\sum_{n=0}^{N-1} P_{xm,M}(\boldsymbol{\omega}_k)$…………………………………………………………..3.10

In this study, each input EEG signal X(n) has 60-sec length, each window(m) has 2sec with D=1/2sec=0.5, K = 60sec/2sec =30, $\boldsymbol{\omega}_k$ =$2\pi f$, and $w(n)$ is computed by substituting values

3.12 EEG Power Spectral Density in the Case of Depression and Music Therapy

PSD can be computed for each epoch sequentially or using the whole recorded interval length [61]. Then the computed PSD is used for the analysis of the EEG signal that can allow us to have a better visualization across different brain parts of the subject who are different mental conditions [1].

According to current studies, when the subjects are in depressed mental condition mean PSD in an Alpha frequency band (8-13Hz) also called Alpha mean power shows a significant reduction [67, 8]. More specifically across specific parts of the brain such as temporal (T3&T4), parietal (P3 & P4), occipital (O3 & O4), and prefrontal cortex (Fp1& Fp2) region [8]. Other studies indicate that the subject with depression has less alpha power in the left prefrontal cortex (Fp1) than the right side (Fp2) [40].

Alpha mean power found as a powerful tool to visualize the effect of music sound on brain activity [33]. In contrast to depression, the Alpha mean power increase across the temporal and posterior side of the brain while the subject stimulated with a music sound [33, 63]. The emotion (depression) controlling part of the brain which is called Amygdala is stimulated as a result of increased alpha power in the auditory cortex during music sound stimuli [33].

CHAPTER FOUR

Methodology and Material

4.1 EEG Data Collection Process

4.1.1 Subject

In this study, six participants (age 22±3) were recruited from the school of medicine and public health at Jimma University. A direct interview and clinical screening have been done based on the standard patient health questionnaire (PHQ-9) assessment tools to select participants. In this study, all the participants are undergraduate (UG) students of Jimma university school of public health and medicine. Depression screening has been done by our clinical advisor's Dr. Eliyas, Head school of psychiatry, Ms. Omega psychiatry nurse (MSc), and Ms. Menen lecturer at, school of psychiatry.

4.1.2 Inclusion Criteria

Those students whose PHQ-9 score are from 5 to 14, (mild to moderate level of depression), who were not start taking any drug during the day of the experiment, as well as those who were clearly informed about the aim of this research and showed willingness to give their informed consent, was participated

4.1.3 Exclusion Criteria

In this study, subjects with hearing disabilities and subjects who were in severe level depression cases (PHQ-9 score > 14) haven't participated since they were taking medication that affects the central nervous system, which may also affect the result of this study.

4.1.4 Ethical Issue

Each participant was informed about the aim and purpose of the research and received their informed consent from each participant enrolled in this volunteer-based research study. Also, the experimental procedure and setup were designed after clearly understand and considering the underlined issue raised by the national research ethic review guideline which prepared by the FEDRE ministry of science and technology [68]. Each data is securely maintained during after research project, so that only authorized person may access and used for only education purpose.

4.1.5 Subject Demographics and PHQ-9 Score Result

Table 6, shows the subject demographics-based information such as age, gender, and table 7 showed pre-experimental PHQ-9 score test result as well as the standard reference to distinguish depression severity level of the subject.

Table 5: Subject demographics

Subject ID	Age	Gender
01	25	M
02	18	F
03	25	M
04	22	M
05	21	M
06	25	M

Table 6: Pre-experimental PHQ-9 score test

Subject ID	Pre-PHQ-9 Score	Depression severity	The Standard reference value of PHQ-9	
			PHQ-9 score	Depression severity
01	11	Moderate	1-4	Minimal
02	7	Mild	4-9	Mild
03	11	Moderate	10-14	Moderate
04	6	Mild	15-19	Moderately sever
05	10	Moderate	20-27	Sever
06	14	Moderate		

4.1.6 Begena Sound Preparation

Begena sound that composed of four different melodies recorded at Jimma University Music department studio with a frequency range of 232Hz -344Hz using Cubase software which is a digital studio work station developed by Steinberg. This sound reparation made in collaboration with Mr. Jenenus, head school of the Music department at JU.

As shown in Figure 14, the Begena sound played by Mr.Henok who is a traditional instrument lecturer in Jimma town and this sound recorded in a noise-free room that sealed with thick spongy and other material to protect incoming external noise sound that might disturb the quality of sound output. In such a way 15-minutes sound clips that included four major traditional scales (“Tezeta”, “Bati”, “Ambassel”, “Anchihoye”) was recorded by Mr. Natnael, studio technical person at Jimma university school of music. Figure 14-A shows while Mr. Henok, was playing Begena in the acting room and Figure 14-B shows while Mr. Natnael, was recording Begena sound in the recording room.

A) B)

Figure 14: Begena sound preparation at JU Music school studio

4.1.7 Features of Begena Stimuli

The following features of Begena sound was designed to avoid biased analysis results across all subjects. So Begena sound contains the following features.

- Total sound duration: 15 minutes
- Sound type: Begena Instrumental sound
- Frequency range: 232Hz -344Hz
- Ear stimulation: both left and right ear
- Loudness (based on a recent study sound within the amplitude range of 60 -70 dB is categorized as a soft base and has a better result in music therapy compared to loud (80-90 dB) and medium (70-80dB) [69]. Hence, the loudness of the speaker is was selected to 65 dB
- Sound delivery device: speaker with the loudness of 65 dB placed at 50 cm away from the subject.

4.2 EEG Data Acquisition Process

EEG signal was recorded with and without begena sound stimuli intervention from 6 volunteer subjects based on the flow chart shown in Figure 15, all the EEG data has been recorded in Eye closed condition to reduce the effect of visual disturbance and artifact during the experiment. This experiment was undertaken in a silent room to minimize external sound disturbance. EEG data recording started after insuring the subject comfort seat and correct EEG electrode placement.

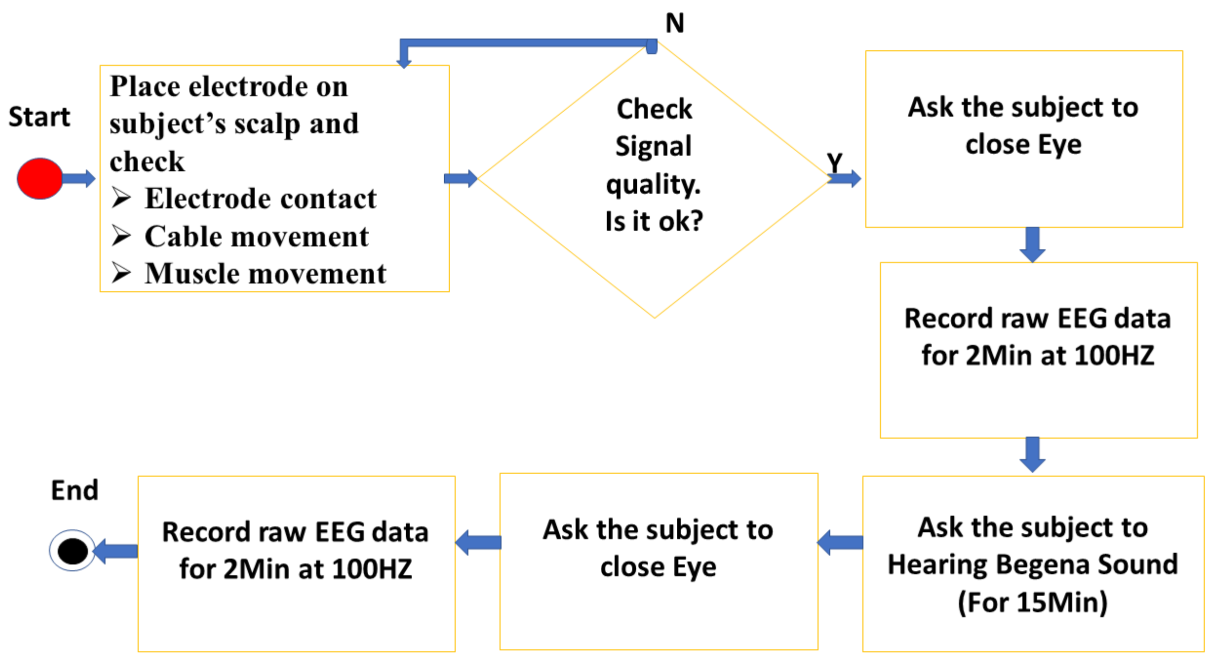


Figure 15: EEG signal acquisition flow chart

Using EEG machine (KT88, 16 channel) that has the following key component such as

(a) Electrodes with conductive media

(b) Amplifiers with filters

(c) A/D converter

(d) Recording device.

EEG data in Bio semi data format (BDF) has been acquired directly from the primary source (our screened subject) at 100Hz as shown in Figure 16.

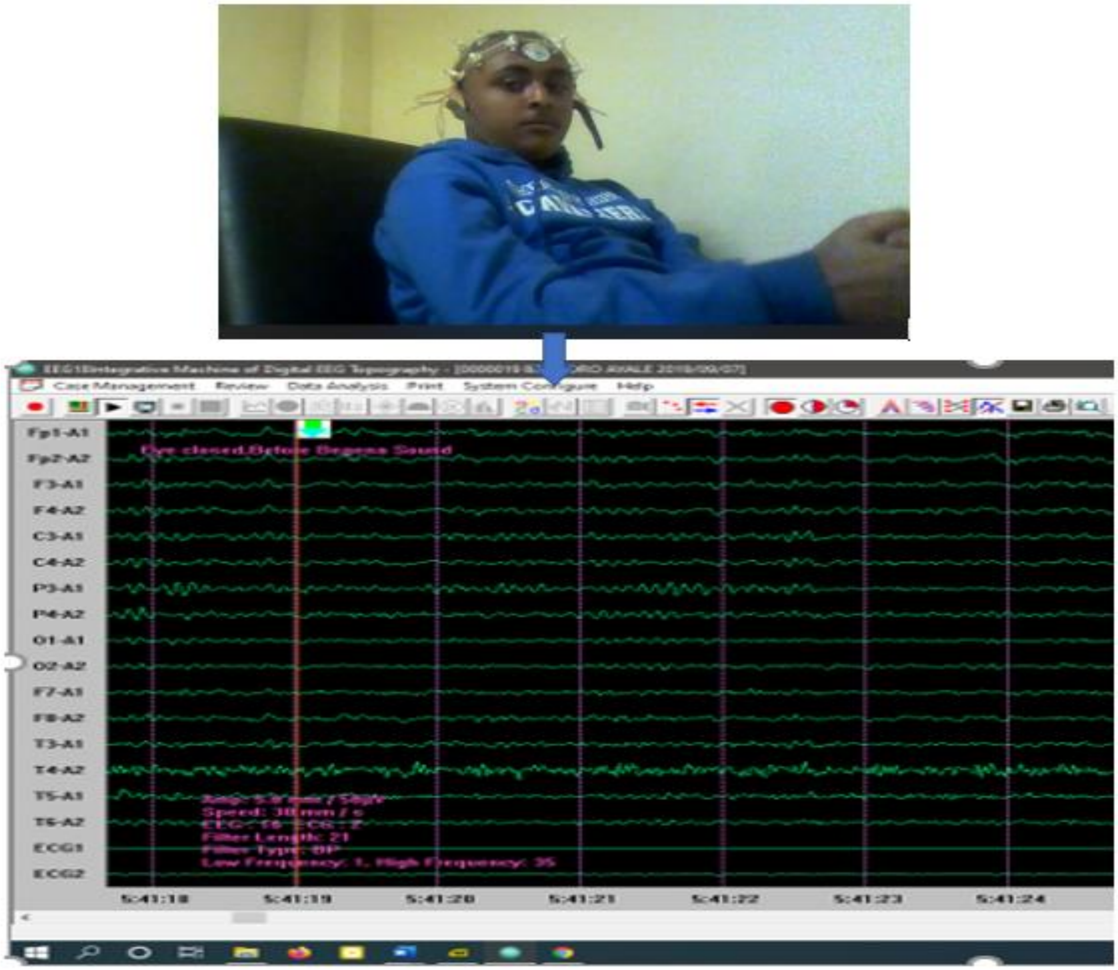


Figure 16: EEG signal acquisition

The EEG signal was band passed to (0.5 -35Hz) during the acquisition by default filter present in the EEG device. EEG signal was acquired from the subject using 20 AgCl electrode (EEG-sensors) and the impedance level of this electrode was kept below 10 KΩ to provide impedance matching with a subject and to keep the current in the circuit in the milli-Ampere range for electric safety. These electrodes are labelled and placed on the subject scalp based on the 10-20 international placement rule [41]. Figure 17-a shows total used electrode while acquiring EEG data and Figure 17-b is the study interest region.

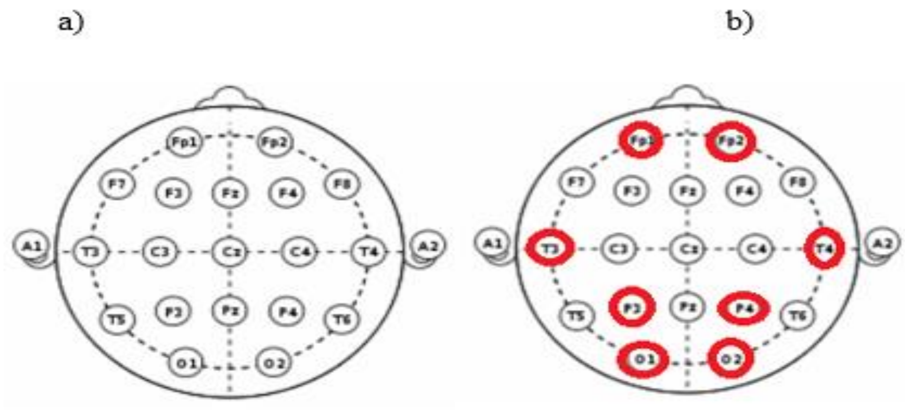


Figure 17: Standard 10-20 EEG electrode placement [55].

Each labelling is assigned using integer number (odd and even) followed by a letter to indicate the left and right portion of the specific brain part. This research was focused on the activity of a brain in the region of the prefrontal cortex (Fp1, Fp2), temporal (T3, T4), parietal (P4, P5) and Occipital (O1, O2) by using left and right mastoid (earlobe) reference at A1 for odd electrode and A2 even electrode.

4.4 Software Used

EEG18V5.04,2012 digital brain mapping software used to collect Primary EEG data directly from the subject. For processing and analyzing of the EEG data Matlab2015Ra and a Matlab integrated open-source toolbox called EEGLAB version14.1.2b used.

4.5 Material Used

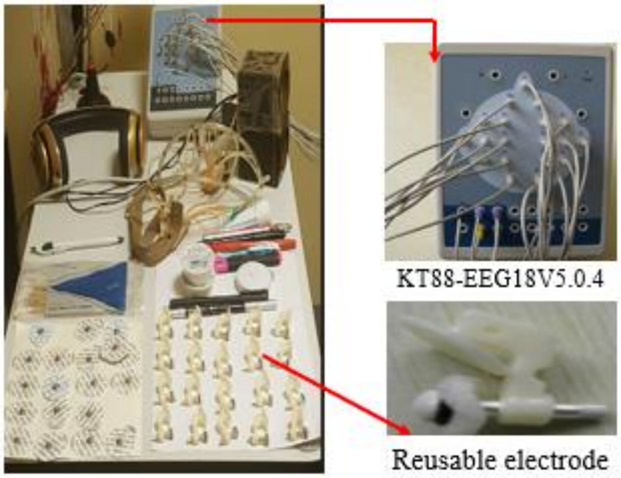


Figure 18. Material used

As indicated in Figure 18, this study utilizes the following materials:

- KT88 digital brain electrical activity mapping 16 channel, 100Hz EEG machine
- 10-20 EEG-paste
- Gel
- Dry AgCl electrode
- Applicator stick
- Disposable electrode
- Speaker
- Laptop
- Plastic meter
- Marker (body compatible)
- Plastic EEG cape
- Tools: Matlab 2015a,
- and EEGLAB version 13.4.5

4.6 General Methodology for EEG Signal Processing

Figure 19 shows a complete block diagram for processing the EEG signal. Here the step in each action is adopted from the method developed by EEGLAB guideline [70].

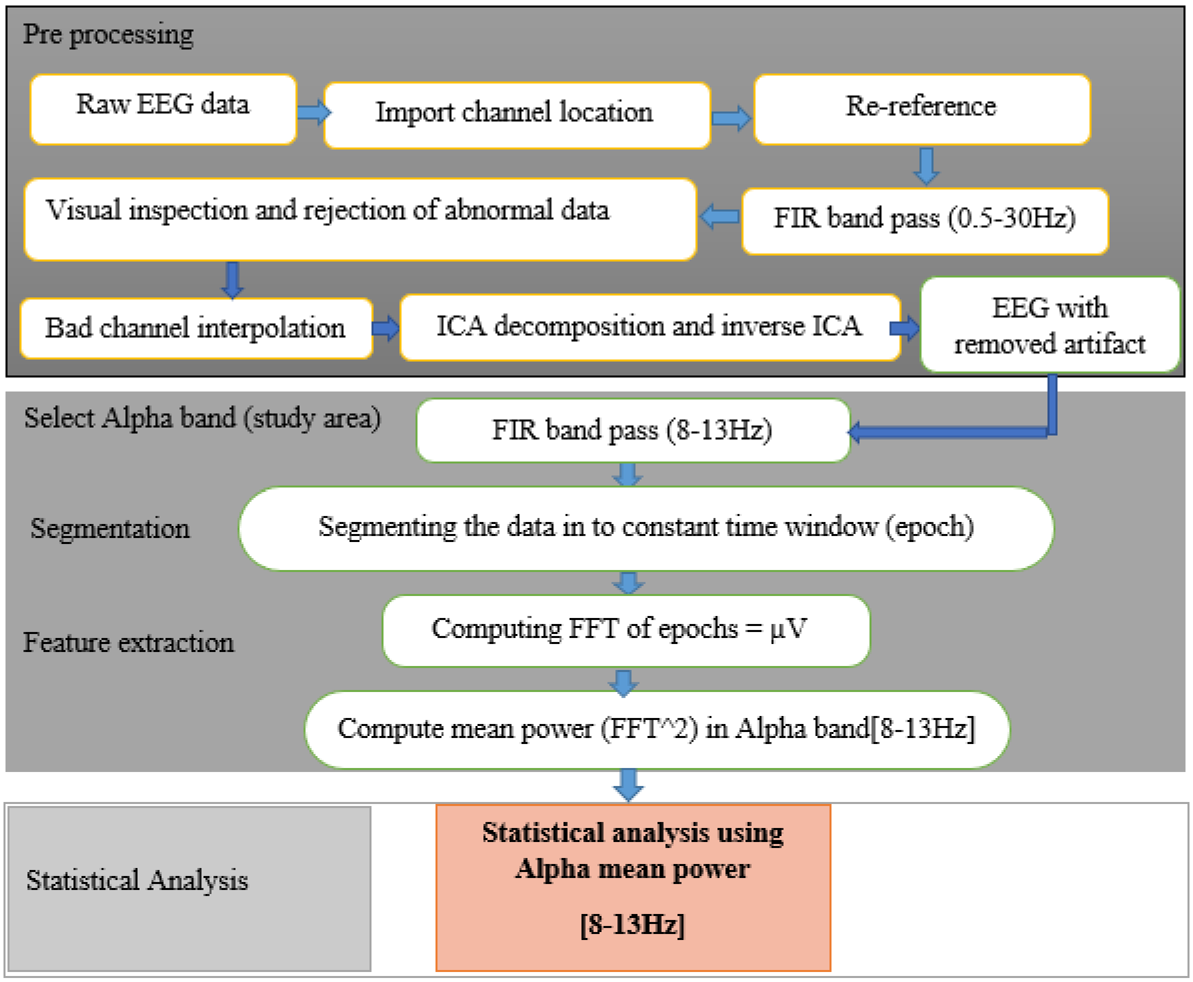


Figure 19: flow chart for the complete data processing cycle

4.6.1 Pre-Processing of EEG Data

As shown in Figure 19, the pre-processing steps include dawn sampling, import channel location, re-referencing, filtering (blocking frequency range out of this study interest), rejecting bad-continuous data and channel, removing line noise (50Hz) using clean- line application of EEGLAB, and running ICA to remove other biological signals such as EOG, EMG, and ECG if they are present in raw EEG signal. The pre-processing steps were designed based on the guideline developed by Delorme & Makeig[63].

4.6.2 Raw EEG Data

EEG data has been acquired based on the procedure mentioned in section (4.2). In this study, a bio semi data format (BDF) of 16 channels at 100Hz sampling frequency used. Each EEG data obtained from the subject before and after Begena sound intervention at Eye closed state. For each condition, two minute EEG data were acquired and feed to EEGLAB V14.1.2b, open and standard software for EEG signal processing [70]. Figure 20 and Figure 21 shows a 16-channel raw EEG signal and selected 8-channel EEG signal respectively.

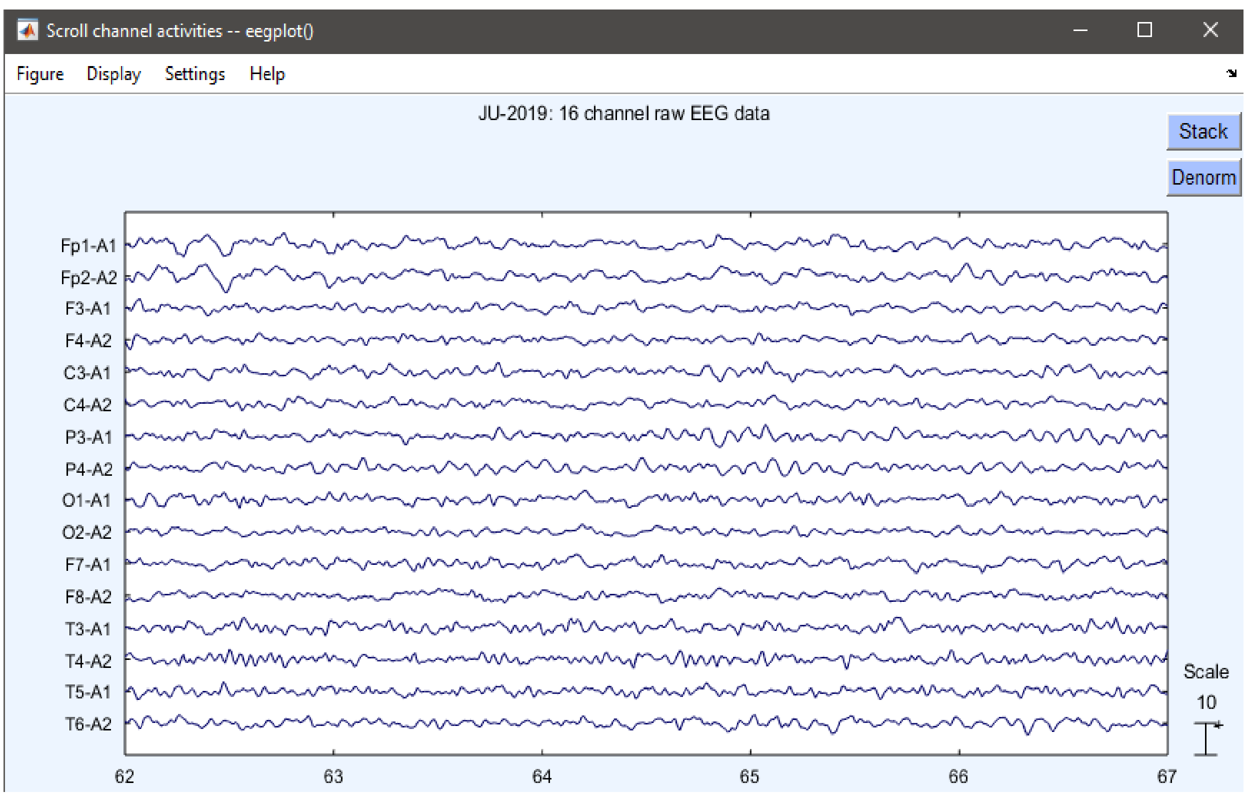


Figure 20: Sample 16-channel raw EEG data

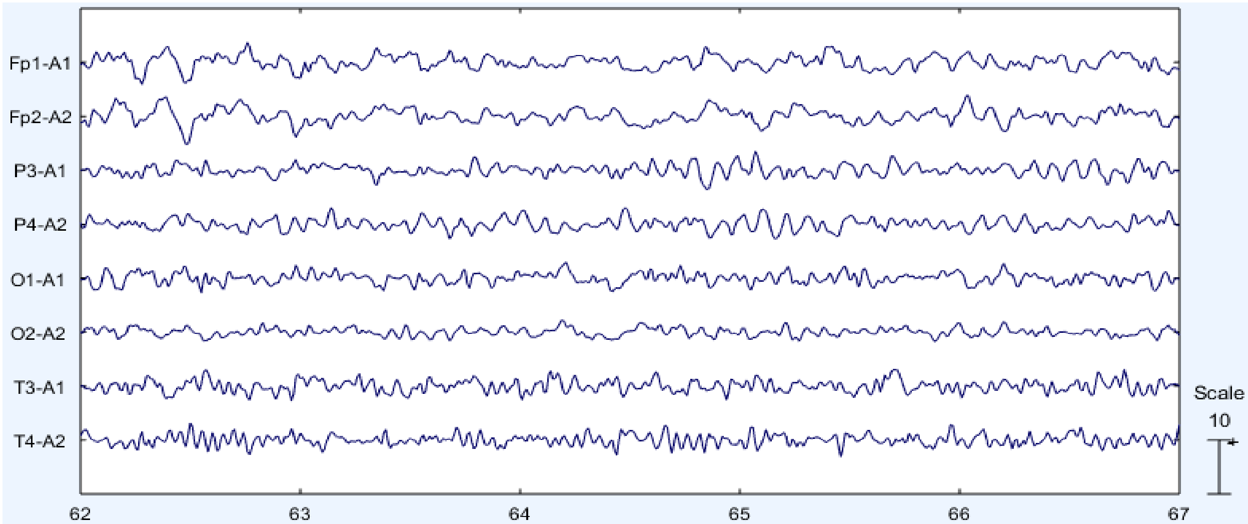


Figure 21: Selected-channel from raw 16 channel EEG data

4.6.3 Importing Channel Location

Channel location was prepared manually by referring the standard 10-20 electrode placement rule that allowed for .locs file format (supported file format for EEGLAB channel location) in such a way each coordinate, direction and magnitude for every electrode described as show in Table **7**. The two-dimensional electrode position is shown in Figure 22-A for 16-channel and Figure 22-B for selected channel.

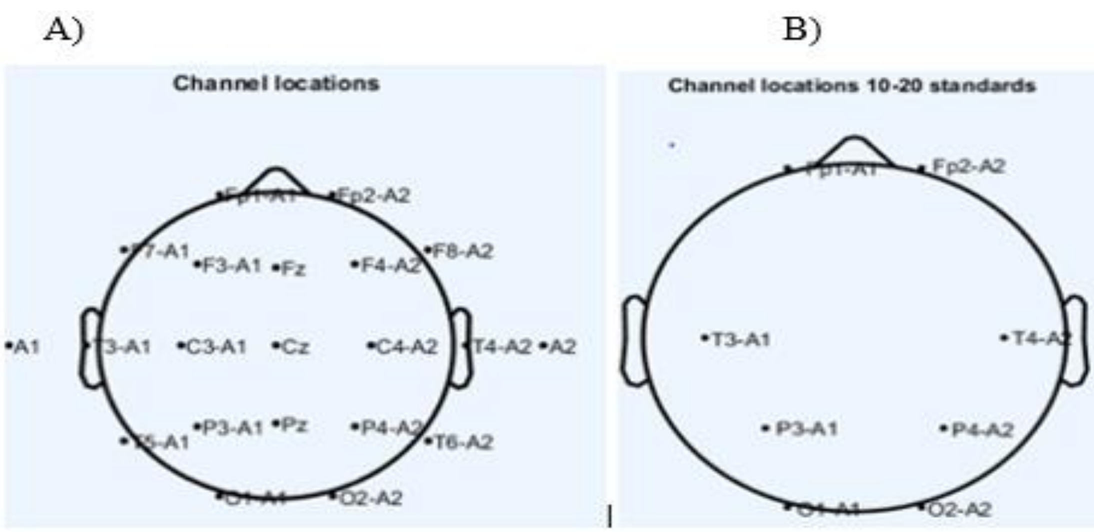


Figure 22: 2D-EEG-electrode position on the scalp

Table 7: 10-20 16- channel EEG-Electrode position on the scalp

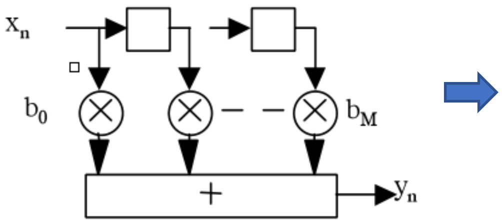
N0	Polar angle	Radius	Label
1	-18	0.51111	Fp1-A1
2	18	0.51111	Fp2-A2
3	-39	0.33333	F3-A1
4	39	0.33333	F4-A2
5	-90	0.25556	C3-A1
6	90	0.25556	C4-A2
7	-141	0.33333	P3-A1
8	141	0.33333	P4-A2
9	-162	0.51111	O1-A1
10	162	0.51111	O2-A2
11	-54	0.51111	F7-A1
12	54	0.51111	F8-A2
13	-90	0.352	T3-A1
14	90	0.352	T4-A2
15	-126	0.51111	T5-A1
16	126	0.51111	T6-A2
17	-90	0.639	A1 (reference for odd number electrode
18	90	0.639	A2 (reference for even number electrode)

4.6.4 Re-Referencing to Average Channel

Initially, the raw EEG data were acquired from the subject using mastoid (earlobe) reference, A1 (for odd number electrodes) and A2 (for even number electrodes). However, the current study indicates the signal of earlobes interfere and cause distortion as well as cause imbalance by adding redundant values to brain signal [71]. Another study suggests that “average reference (AR) is one of the most widely adopted references which is now implemented by offline re-referencing instead of the original online recording setup” and in AR principle, the average potential of the overall electrode tends to be zero [72]. Hence re-referencing EEG data to the average reference used during pre-processing steps.

4.6.5 Filtering the EEG Data

As discussed in section 3.6, digital filters can be either finite impulse response (FIR) or infinite impulse response filter (IIR) such as Butterworth, Chebyshev, and Elliptic which are commonly used in signal processing to remove lower frequency component (high pass), and to remove higher frequency component (low pass filter), and to retain specific frequency component as bandpass filter [52, 53]. FIR filter is inherently stable, easy and convenient to use, and designed to have linear phase [73]. As a result, this filter has been selected in the pre-processing steps. For a given FIR length M and order N=M-1 FIR filter output is defined mathematically as follows



$$y(n) = \sum_{k=0}^{M-1} b_k x(n-k)$$

$$H(z) = \sum_{k=0}^{m} bkZ^{-k}$$

Where impulse response is given by $h(k) = \begin{cases} b_k, & o < k < m \\ 0, & otherwise \end{cases}$ ………………4.1

EEGLAB allows users to do filtering based on the default setup called basic FIR filter. In this study, FIR band pass (0.5-30Hz) filtering has been done initially to retain the basic brain wave rhythm (delta, theta, alpha, and beta) and the second band-pass filter used on artifact-free EEG signal to retain the alpha wave (8-13Hz), the signal of interest for this statistical analysis study. Figure 23, and Figure 24 shows the output of both filters respectively.

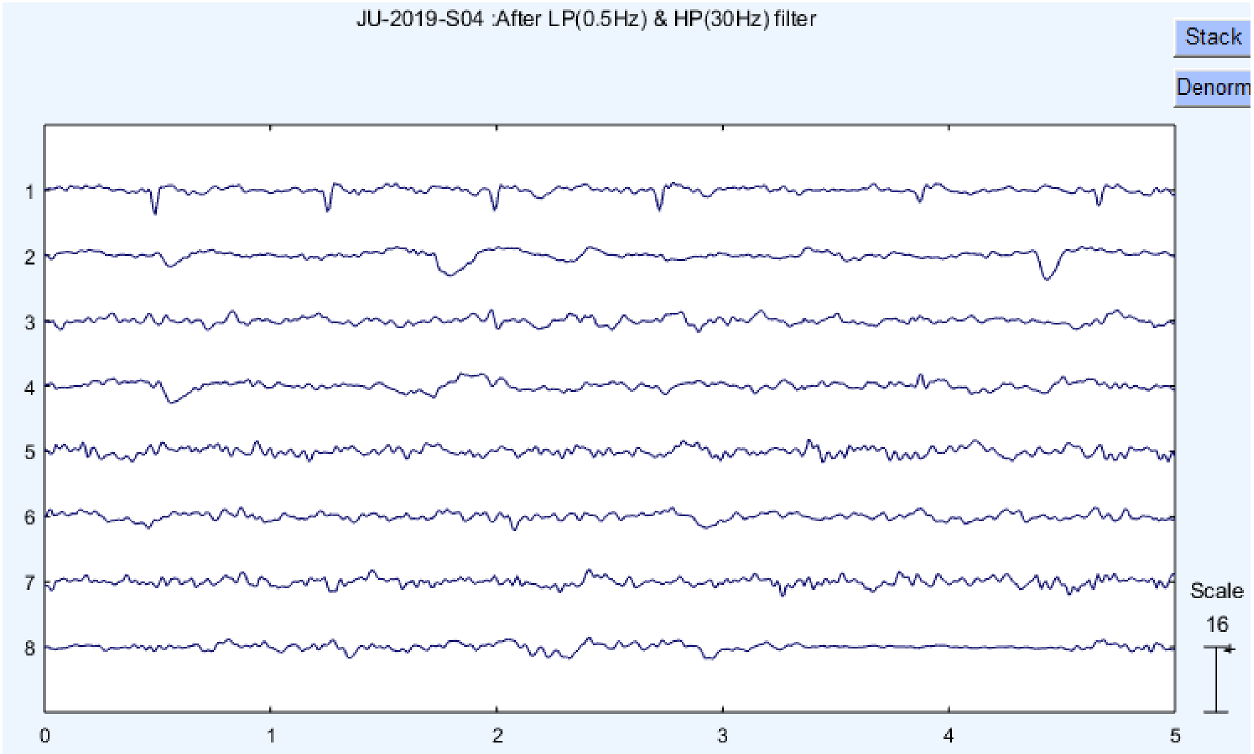


Figure 23: FIR high pass (0.5Hz) and low pass (30Hz) filter output

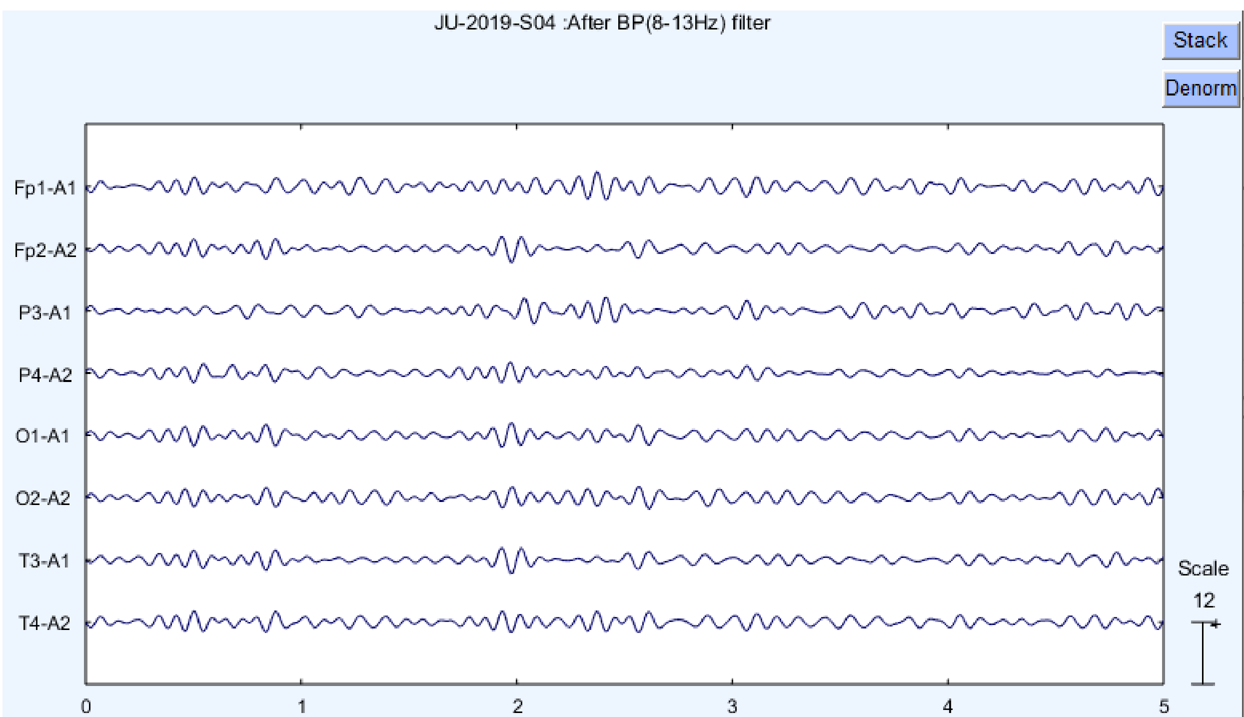


Figure 24. FIR bandpass 8-13Hz filter output

4.6.6 Visual Inspection and Rejection of Abnormal EEG-Signal

In some cases, an artifact that can't be predicted by the usual EEG signal processing algorithm may appear in the raw EEG data. In this case, visual inspection and manual rejection is important and can be done using EEGLAB tools. This component should be removed before computing ICA because ICA assumes this artifact as an independent source and causes an increased number of the weight matrix. In this study, motion artifacts such as cable movement were taken as a good example. Cable motions change the magnitude of a pre-amplified impulse voltage and generate voltage fluctuations with a peak amplitude of 100µV in AgCl [74]. Figure 25, shows a motion artifact that has been produced due to cable movement.

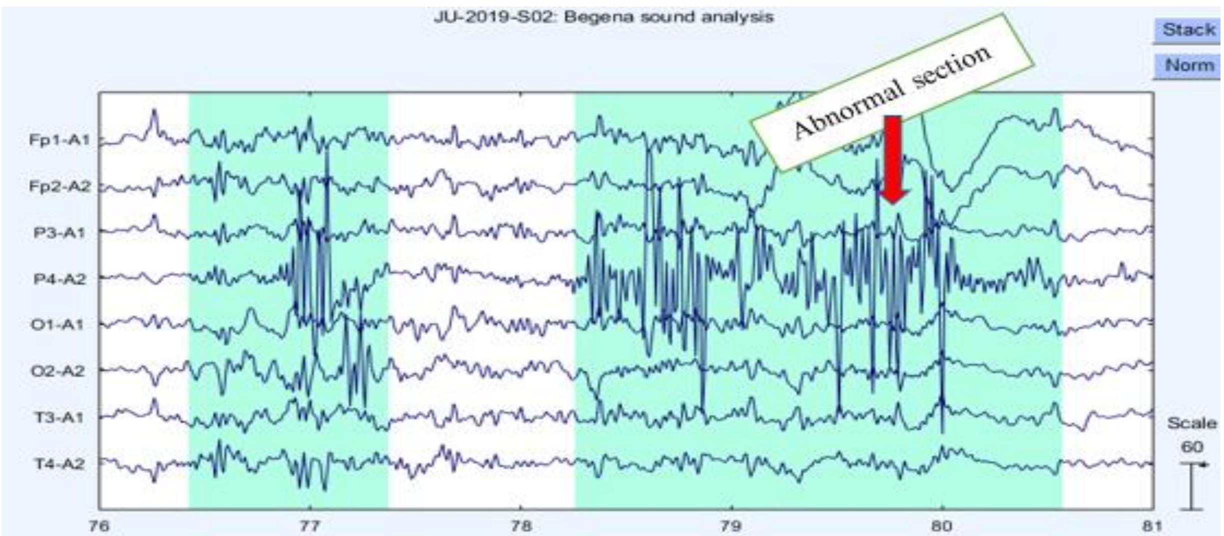


Figure 25: Visual inspection of motion artifact in EEG signal

4.6.7 Bad Channel Rejection and Interpolation

EEGLAB software has the capability to scan and remove bad channels that are below or above the Kurtosis value. Kurtosis is a 4th order moment statistic that measures the data amplitude (sharpness) of the EEG channel signal and given by the mathematical equation 4.2. For marking bad channel EEGLAB uses the Z score threshold value = 5 and if the absolute Z value of the channel is greater than the threshold value = 5, the channel is marked as bad and will be interpolated using the closest- channel by default spherical interpolation method of EEGLAB.

$$\boldsymbol{Kurt} = \sum(\boldsymbol{X} - \overline{\boldsymbol{X}})^4 \,/\boldsymbol{S}^4 \ldots\ldots 4.2$$

Where X = n sample $\bar{X}$ = mean of sample S =standard deviation

As shown in Figure 26, of the pre-processing steps, Fp1-A1 channel of subject S04 measures amplitude above the reference Kurt value =5 and was marked in red to mean bad channel and has been interpolated with the closest channel Fp2-A2 using default spherical interpolation method of EEGLAB.

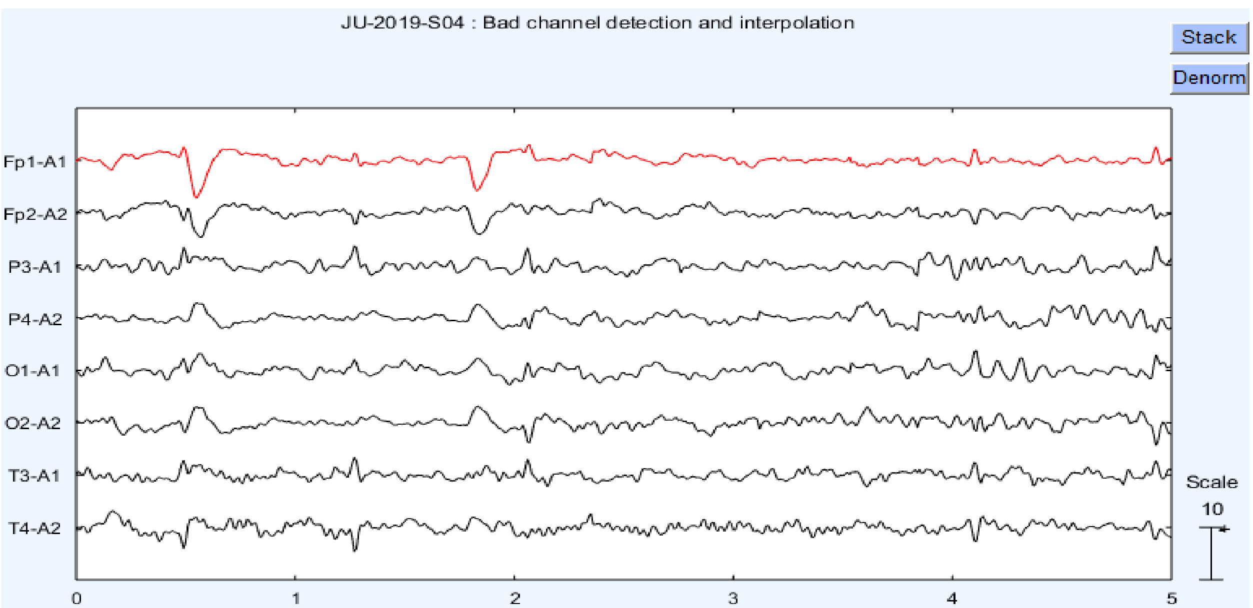


Figure 26: Marking bad channel for interpolation

4.6.8 Independent Component Analysis

In the signal processing technique, independent component analysis (ICA) is the most common method to separate statistically independent and unknown source signals from the observed signal [42]. ICA works based on blind source separation technique.

4.6.9 Blind Source Separation

It is a well-known method in signal processing that is used to separate the underlined source signal from a linear mixture of mixed-signal without any prior information about mixed-signal [53]. It was primarily used in the cocktail party problem, where the receptor attempts to detect one voice from a mixed source of signal in the crowded room [61].

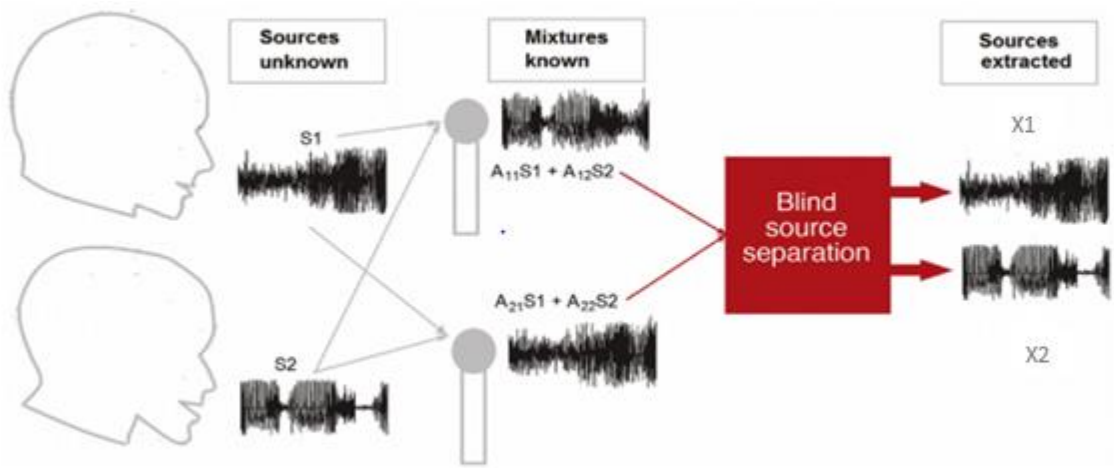


Figure 27: Cocktail party problem [61].

As shown in Figure 27, if two unknown speaking source of signal S1, S2, and two microphones with in the same room then the relationship of source signal (S) and the output signal (X) can be expressed as:

$$X_1(t) = A_{11}S_1(t) + A_{12}S_2(t) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.3$$

$$X_2(t) = A_{21}S_1(t) + A_{22}S_2(t) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.4$$

This equation (1) can be represented as a matrix form as:

$$X = AS \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.5$$

Computing for S from the equation by:

$$S = XA^{-1} = WX \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4.6$$

Where mixing condition and matrix A is unknown. Therefore, ICA tries to compute the unmixing matrix W (A^{-1}) to separate the mixed signal into independent components. EEG signal processing during ICA computation work in the similar principle of this cocktail party problem by considering the multi-channel EEG signal observed in LCD monitor as a mixture of different sources such as cerebral (EEG) signal, eye blinking (EOG), muscle signal (EMG), and the other sourced artifact.

4.6.10 ICA Decomposition

ICA technique provides capabilities to decompose the multichannel EEG signal into a principal component (PC) so as to further study the mental state of the subject under different stimuli [70].

Based on the idea of ICA the weighted sum of all electrode activity produces some independent source each component has a one-time course and N number of electrodes. If the sample data are taken from an 'N' electrode then each component has 16 weights in such a case "ICA can be seen as an alternative linear decomposition to principal component analysis (PCA)" [70].

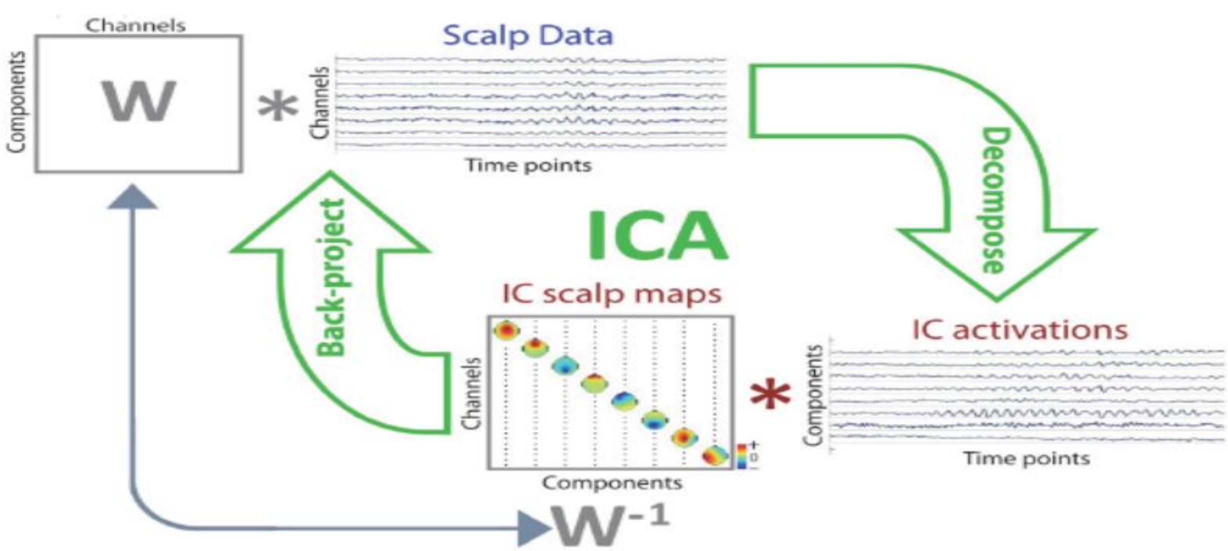
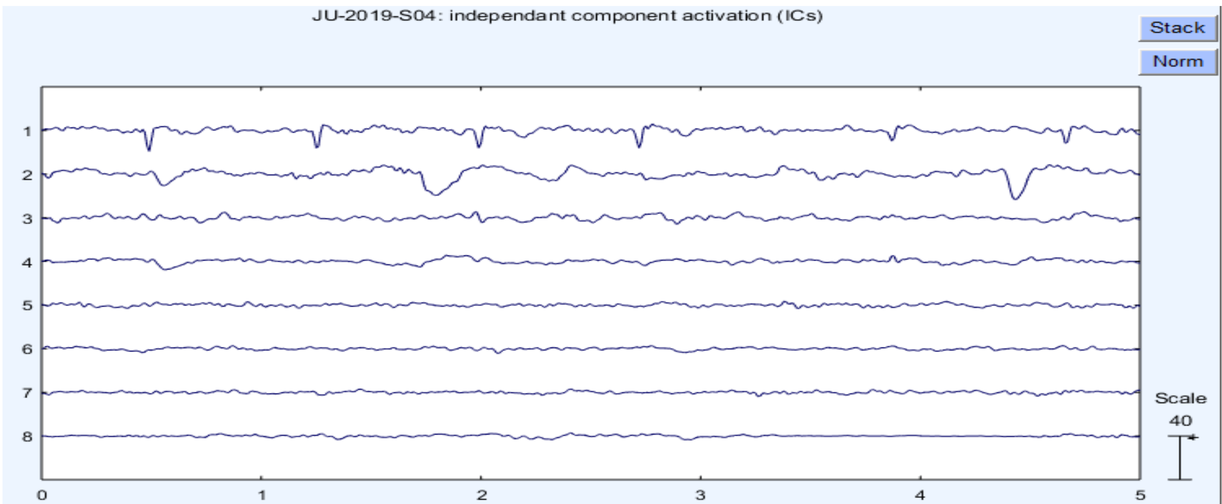


Figure 28 ICA analysis [44].

As indicated in Figure 28, ICA compute the unmix matrix with weight 'W' then multiplied with raw scalp EEG data (channel * time point). This gives IC activation with the process called ICA decomposition. This process can reversible and give back the original scalp data when IC activation multiplied with ICs scalp map. Figure 29-A and B shows IC component activation and ICs scalp map respectively. Each single time course independent component (ICs) has 8 electrodes and 8 weights. The ICA decomposition helps to visualize and analyze each component and to apply inverse ICA if the components are contaminated by artifact.

A.



B.

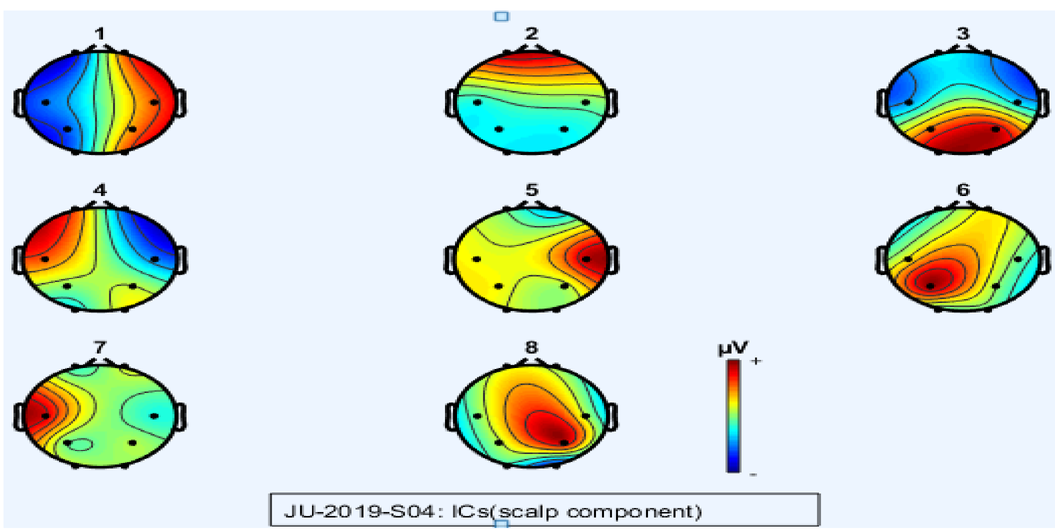


Figure 29 : ICA Decomposition

4.6.11 Artifact Removal using ICA Back Projection

In EEG signal analysis ICA is mostly used to detect and remove an intrinsic (physiological) artifact such as eye blink (EOG), muscle movement (EMG), electrocardiogram (ECG) which propagate via the electrode and mixed with our EEG data [61]. ICA uses the step shown below to remove the artifact.

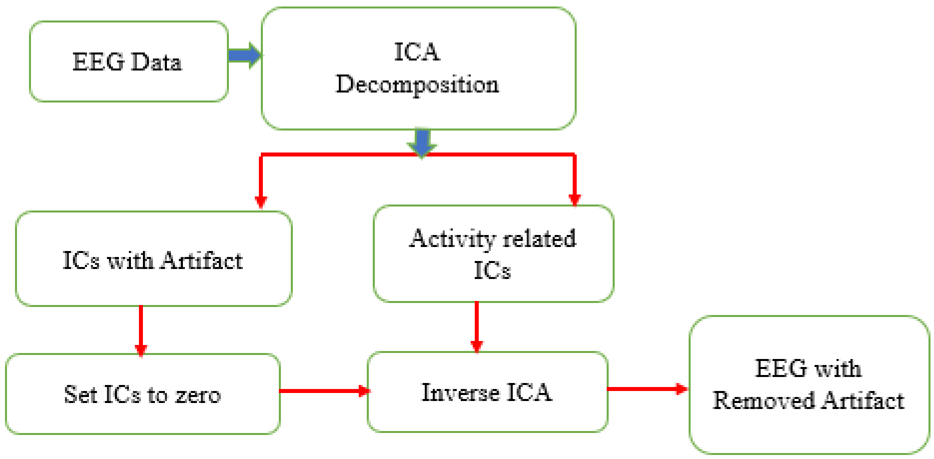


Figure 30: Artifact removal step in ICA

As indicated Figure 32, raw EEG data with artifact has been decomposed in ICs with an artifact and ICs with brain activity those ICs related to brain activities have been retained and ICs with artifact has been removed (set to zero) within a process called Inverse ICA (back projection) to have clean EEG data.

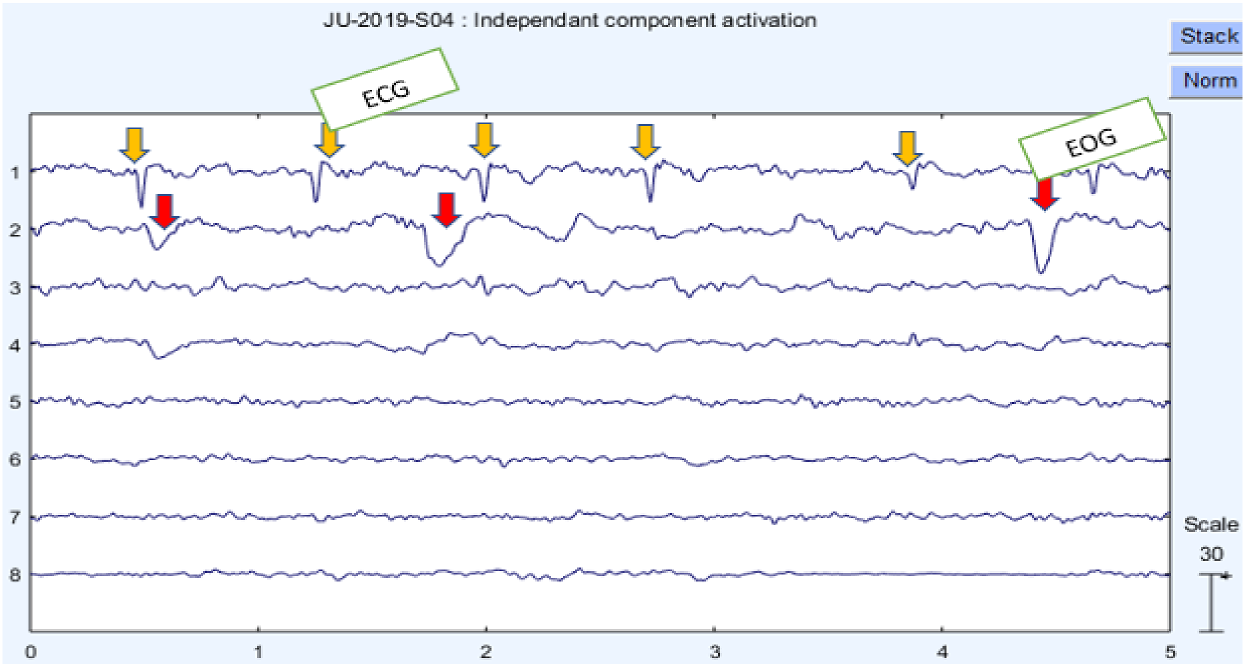
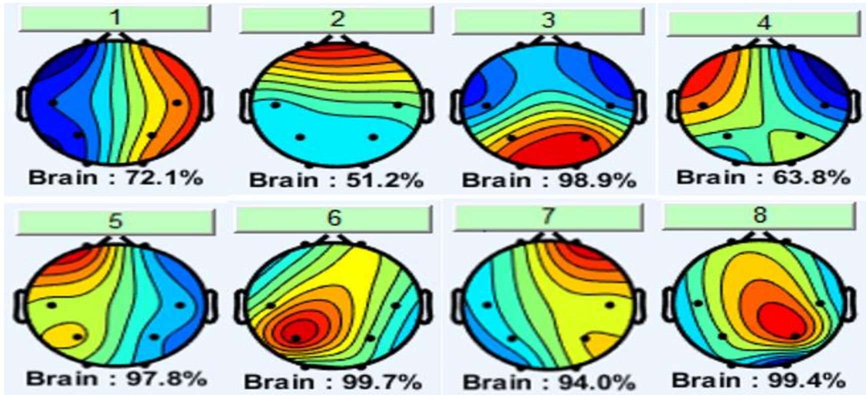


Figure 31: Raw data with blink artifact on channel Fp1-A1 and Fp2-A2

Figure 31 shows, two of the most common EEG noises appeared in subject 04. The first was due to Eye-blink, EOG and the other was due to heart muscle contraction and relaxation, ECG. This artifact in each EEG channel has been identified based on manual observation by comparing the feature observed in the recording signal to the feature that has been described in the research work that explained in section 3.6.1. EEGLAB also allows, visualizing and automatically labelling of each independent component as shown in appendix four and Figure 32-A. Figure 32-B showed Identified artifact within ICs.

A)



B)

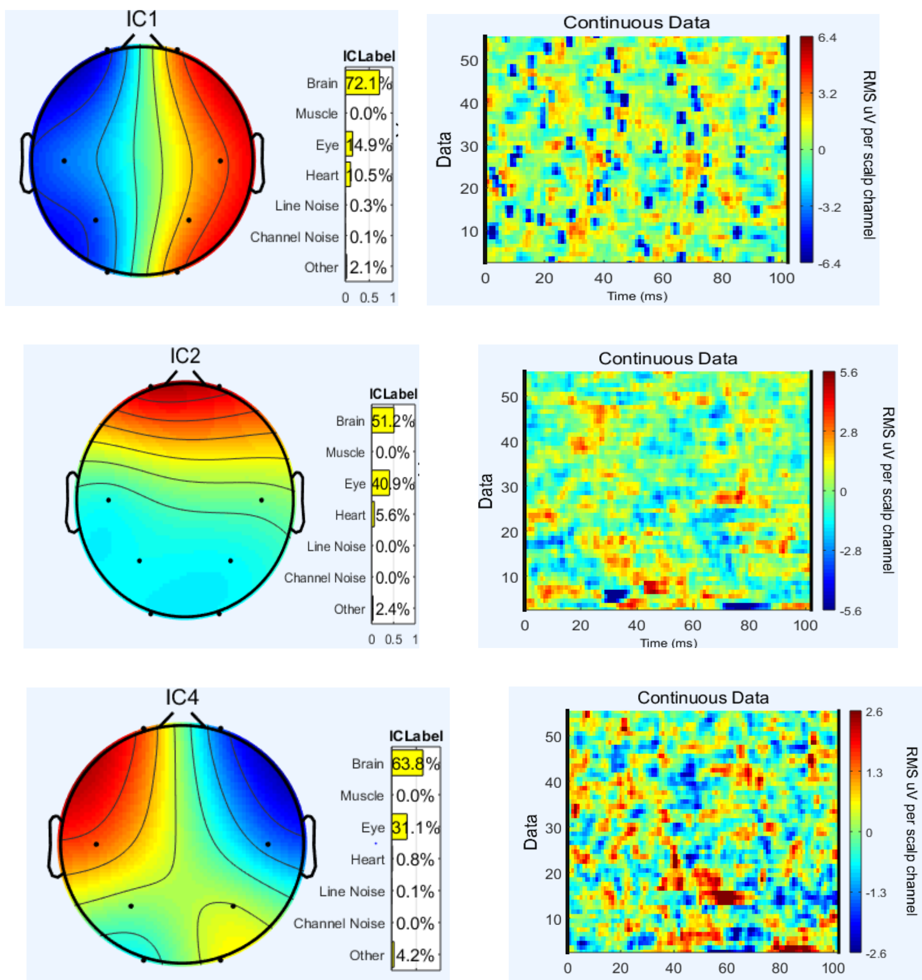


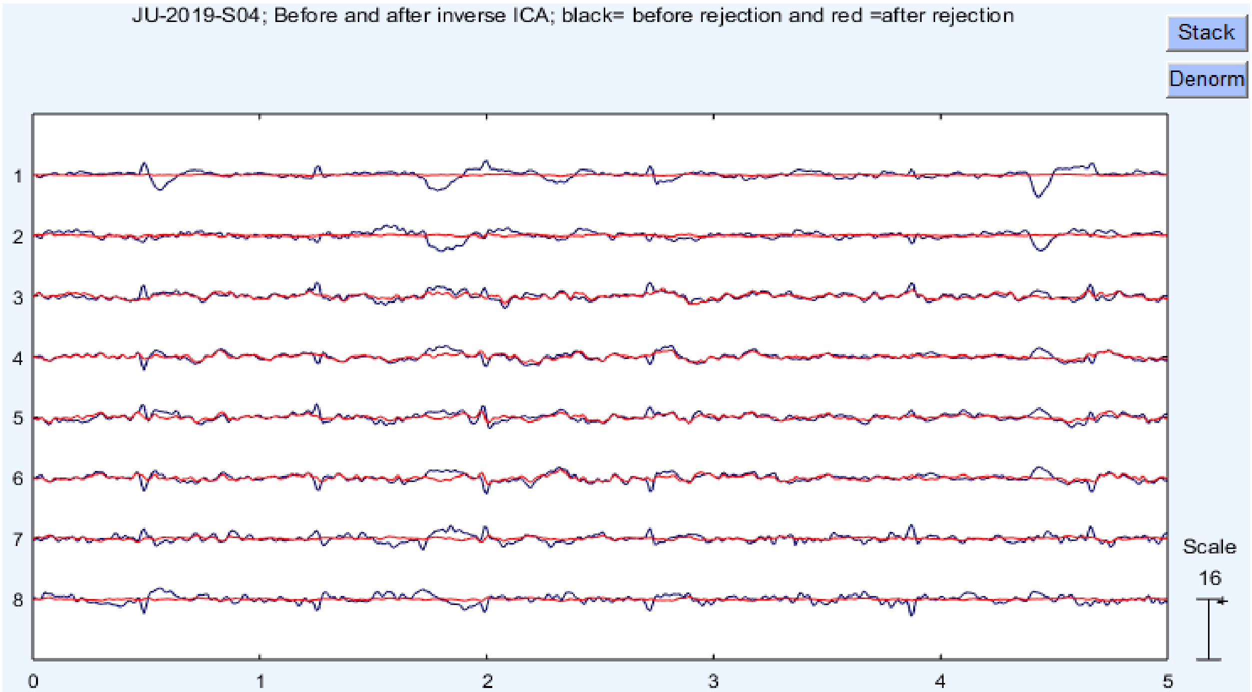
Figure 32: Identifying ICs with brain sourced and artifact component

4.6.12 Removing Artifact Using Inverse ICA

ICA decomposes multi-channel EEG data into independent components (ICs) using their weighting matrix and differentiates into ICs that contain noise and brain signal based on Kurtosis estimation. This operation is achieved by extracting a single noise variance and by making a comparison to a normal Gaussian distribution that has exactly Kurt values=3. Mathematically, Kurtosis is defined by 4th order moment as described in equation 4.2.

Therefore, depending on the contents of noise in EEG data, the signal peak-amplitude and distribution nature defer from the normal Gaussian reference [64]. Using this assumption ICs one, two, and four shown in Figure 32-B contain a significant amount of noise and they were set to zero during inverse ICA to- have clean EEG data. Figure 34-a and 34-b show the EEG signal before and after inverse-ICA operation.

a)



b)

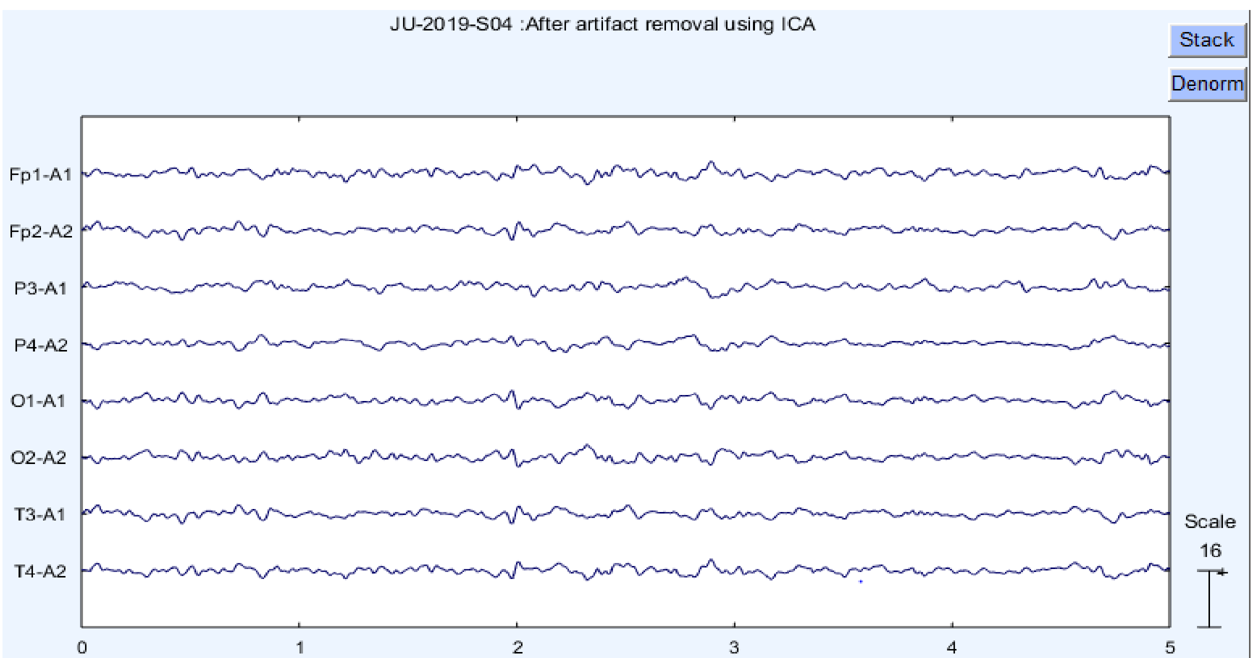


Figure 33 : Removing artifact using inverse ICA. Figure 33-a shows both signals before inverse ICA (black) and after inverse ICA (red). Figure 33-b shows corrected EEG data after inverse ICA.

4.7 Frequency Domain EEG Signal Processing and Statistical Analysis

This step continued next to pre-processing steps after the noise removed. It includes key tasks such as selecting study frequency bandwidth, data segmentation, and feature extraction.

4.7.1 Selecting Signal of Interest for Statistical Analysis Study

This study focused on the brain wave that extends within 8-13Hz frequency ranges called Alpha wave because it has relatively stable amplitude value in normal adult and shows variation corresponding to the subject mental state and physiological changes [64]. It is also an important frequency component for diagnosing depression [8]. And to analyze the effect of music on the human brain [64]. Hence this study focused on change in the spectral content of alpha wave (8-13Hz). EEGLAB allows filtering of this frequency range from raw EEG data using FIR basic bandpass filter and the output is shown in Figure 34.

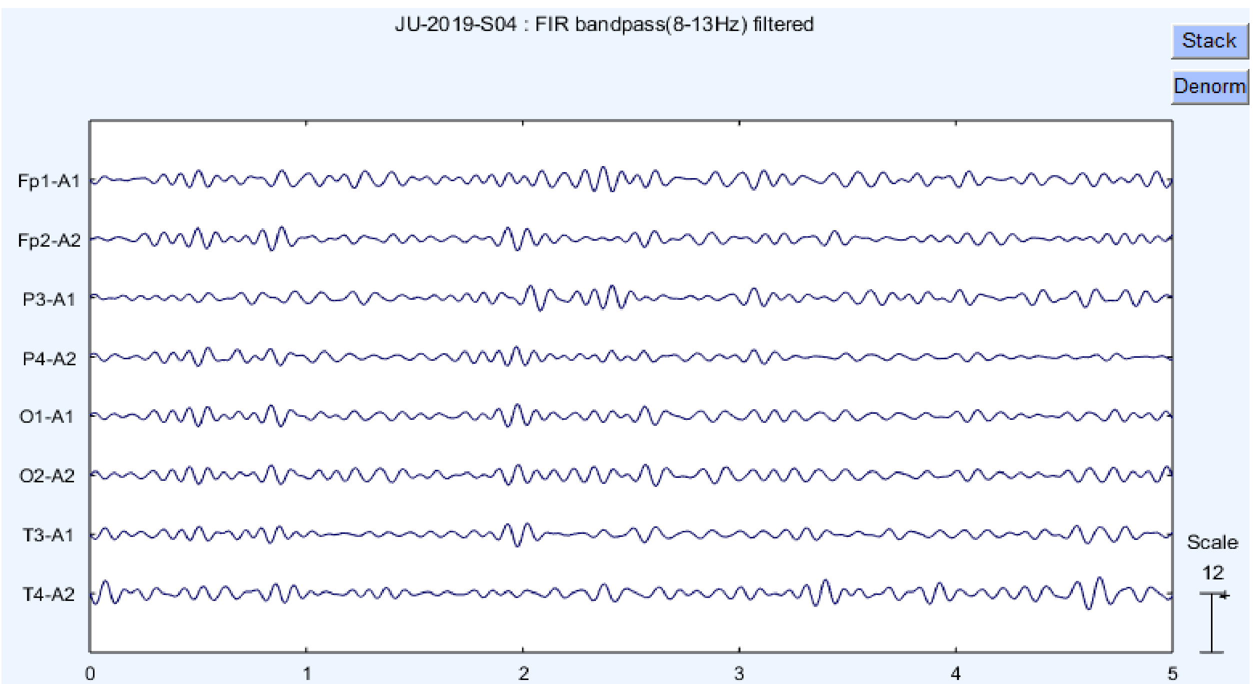


Figure 34: FIR band-pass filter (8-13Hz) output

4.7.2 Segmentation of EEG Signal into Equal Epoch

As a part of processing steps, segmentation of EEG Signal into equal epoch done for the following reason. First is to improve the signal to noise ratio [75], second to improve the power spectrum estimation [64, 26], third to estimate frequency resolution and contents [64] and lastly to create uniform frequency and time distribution[76]. It is also a pre-request step to extract frequency domain EEG features by Welch's method[62]. For this reason, each channel of a continuous-time series EEG signal segmented into equal small time length (epoch) before applying FFT and the length of each epoch is a compromise between either getting good frequency resolution or good PSD estimation [61]. The most commonly used epoch length is 1, 2, or 4 seconds [64, 26]. A time-domain EEG signal can be segmented by using a constant moving rectangular time window, w(t) [31]. And expressed mathematically using the following equation 4.8.

$$f(t) = F(t) * w(t) \qquad t = 0.5, 1, 1.5, 2, 2.5, 3 \ldots \ldots \ldots \ldots\ldots\ldots 4.8$$

$$w(x) = \begin{cases} 1 & t - 0.5 < t < t + 0.5 \\ 0 & else \end{cases}$$

Where F(t) is a time-domain EEG signal, w(t) rectangular time window function, and f(t) epoched data. In our study, each channel time-series clean EEG signal has been filtered by FIR bandpass (8-13Hz) filter and segmented into a two-second epoch length using eeg_regepoch function and the result is shown in Figure 35.

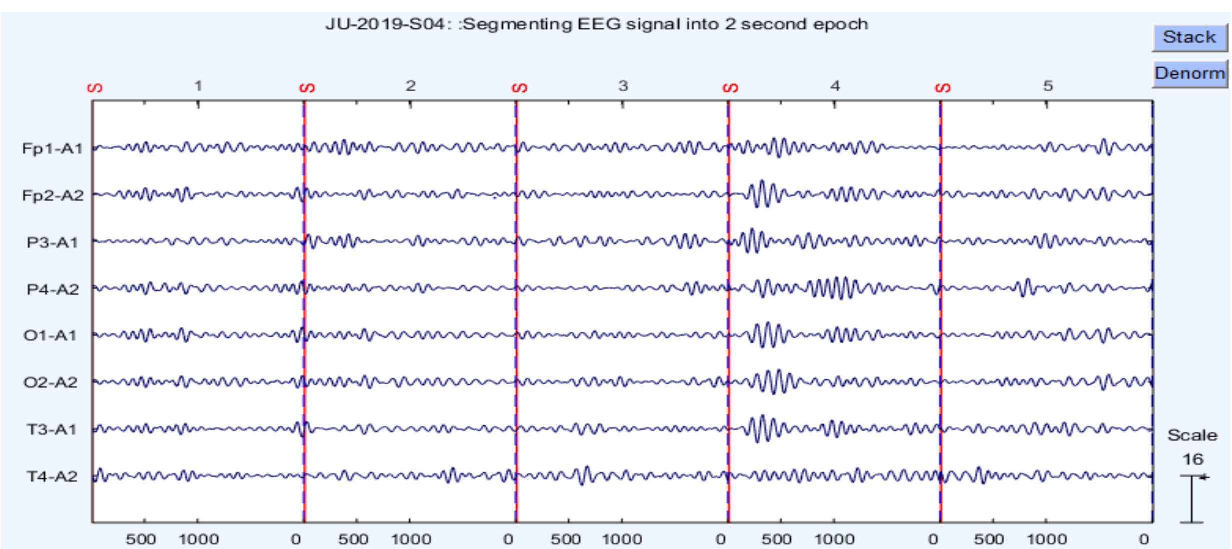


Figure 35: Data segmentation, a 2-second epoched EEG signal

4.7.3 Creating EEG Data Set

For each subject, a 60-sec pre-Begena sound and a 60- sec post-Begena sound EEG data set used for processing. Each EEG data set was cleaned to remove artifacts by applying a uniform pre-processing step. Then filtered to a frequency band of the study, Alpha wave (8-13Hz) using the FIR bandpass filter option of EEGLAB followed by segmentation into equal time window. Figure 36 shows the total created data set under the EEGLAB GUI. It comprises a total of 6 subjects data set and the total length of the data analyzed was 6 subject*60 second *2 condition which is 720 seconds.

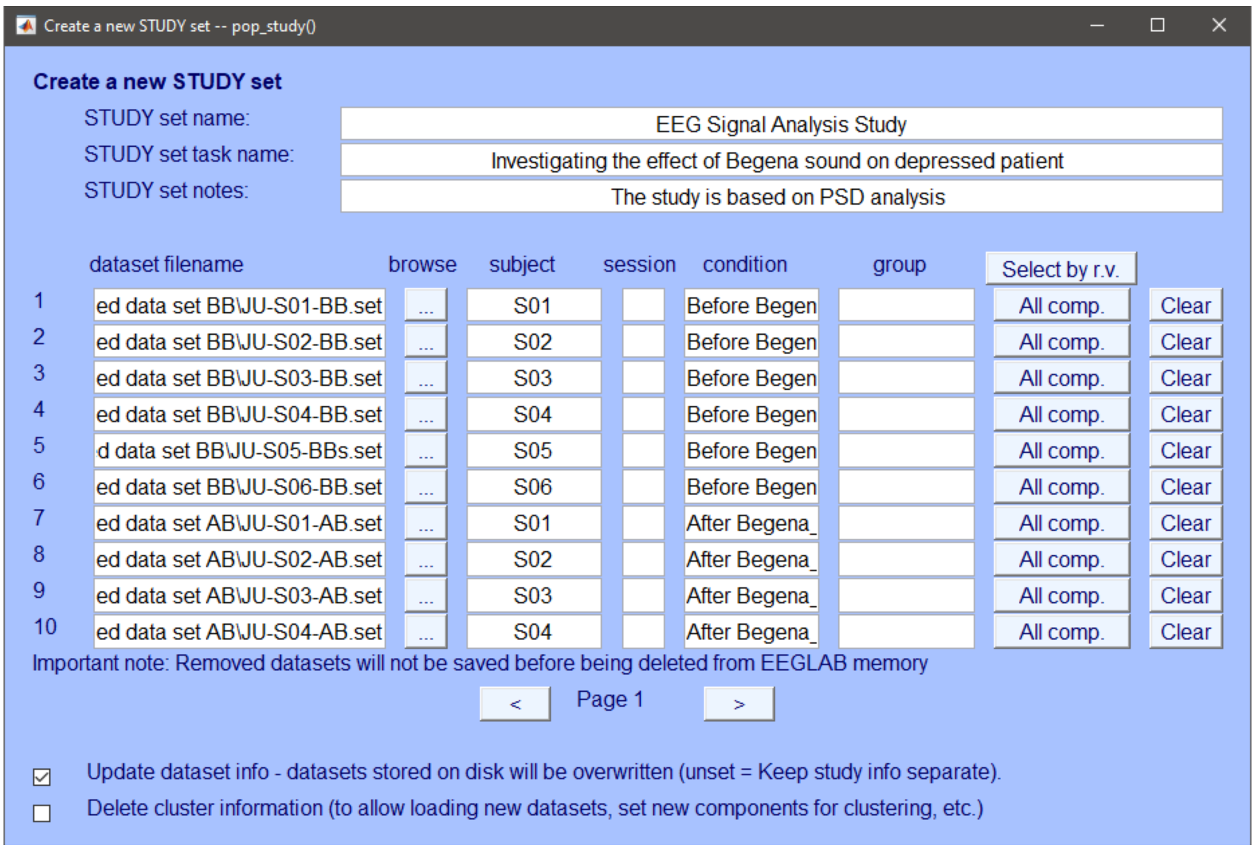


Figure 36: Figure EEG data set creating process in EEGLAB GUI

4.7.4 Feature Extraction

After processing all created EEG dataset in the frequency domain, the following quantifiable features extracted.

A) Alpha Mean Power

B) Statistical features such as mean, standard deviation, and P-value.

4.8 Method for Frequency Domain EEG Signal Analysis

The method used for EEG signal analysis is a fast Fourier transform (FFT). Thus represents a time series EEG signal by its frequency component and allows us to estimate all related features found in the frequency domain by a process called frequency domain analysis [55]. As discussed earlier, FFT is the fastest algorithm to convert time domain EEG signal into its frequency component (amplitude vs frequency). Here amplitude is equal to µV (FFT value) as a function of frequency and the square of this value (fft^2) gives spectral power (PSD) where all specified features are related to this value. Since the power resides in the Alpha frequency band were found as a key diagnostic tool for depression [6] and as a key parameter to investigate the effect of music sound on the human brain by different studies [33, 63]. All extracted features in this study are in the Alpha frequency (8-13Hz) range.

4.8.1 Analysis of EEG Signal Using Alpha Mean Power

The most commonly used feature in the frequency domain analysis is an Alpha mean power of a specific frequency band also called power spectral density (PSD) [55, 62]. In this study, the mean Alpha power at specific brain regions used as a key feature for investigating the effect of Begena sound stimuli on the human brain at depressed state.

As shown in appendix 3 discrete Alpha power (PSD) at each frequency sample point (8, 9, 10, 11, 12, 13Hz) was computed for all selected EEG channels of the created data set and an average of them was used for analysis. To do this, the specific method based on the FFT algorithm called Welch’s method was used.

4.8.1.1 Steps Followed to Compute Mean Alpha Power in Welch's Method

Welch's method, also known as the 'periodogram' method which is used to estimate the PSD value within a given frequency band of the interest based on the FFT value of the input signal [77].

Welch's method followed the algorithm to compute PSD over none-overlapped segment

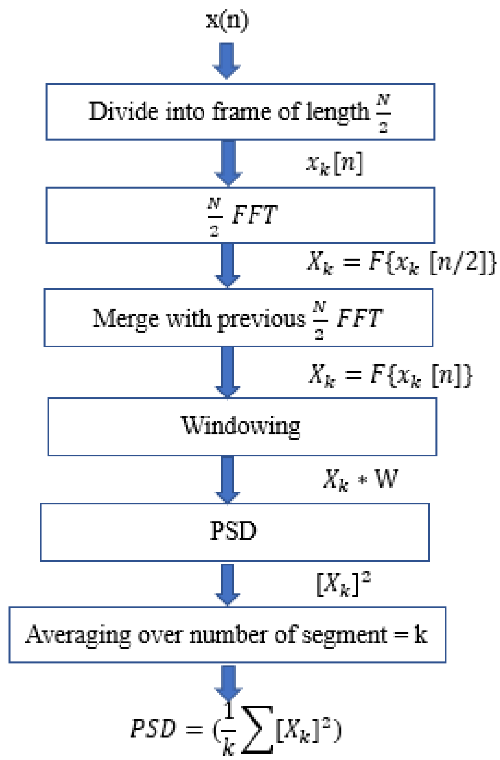


Figure 37: Welch's algorithm to compute PSD.

The steps described in the PSD algorithm, shown in Figure 37 are more elaborated as follows

a) Splitting the input signal x(n) into the L+1 non-overlapping segment

where L is No of segments (in this study each 60 second / 2 sec = 30 segments)

b) Apply FFT to N/2- points, where N is window length (in our case N=2sec)

c) combining the two N/2 point FFT gives N point FFT is computed to (reduce computational complexity)

d) Apply frequency domain window (commonly Hanning window) which was defined by $w(n) = \frac{1}{2}\left[1 - \cos(2\pi.\frac{n}{N})\right]$where n = 0,1,…N-1……………………………………4.9

e) Compute a modified PPSD for windowed data

f) Taking the average of this modified PSD over number of segment (k)

Welch's method used the mathematical equation described in section 3.11.1 to compute mean PSD value of a subject at each depression sensitive region.

4.8.2 The Paired Sample T-test Statistical Analysis Based on Statistical Features

In this study, the paired sample T-test is also called dependent T-test used to compare the mean value between paired observation (e.g. pre and post Begena sound stimuli) and this allows to look whether there is significant test deference in the experiment of the paired sample. To do this we initially select 'α' or sometimes called P-value, which is a probability value for rejecting the null hypothesis when it is true [78]. It can take the value between 0-1 where the selection of this value is decided by the researchers and the most commonly used 'α' value is 0.05 [79, 80]. The following series of steps used to perform a paired sample T-test statistical analysis [78].

- Define the statistical hypothesis
- State Alpha value
- Calculate the degree of freedom
- State decision rule
- Calculate test statistics
- Sate result and conclusion

i. Define the statistical hypothesis

A) Null Hypothesis (Ho):

When everything treated in the same and equal ways then this hypothesis assumes there is no difference in their mean and variance value between the two paired sample [80]. (e.g. mean power before Begena sound = mean power after Begena sound) which means there is no a significant difference in alpha mean power of EEG before and after Begena sound stimuli intervention.

B) Alternative Hypothesis (Ha):

Even if, we treat everything in the same and equal ways, a significant difference in their mean and variance value between the two paired samples is noted [80]. (e.g. mean power before Begena sound ≠ mean power after Begena sound) which means there is a significant difference in alpha mean power of EEG before and after Begena sound stimuli intervention.

ii. **State Alpha Value**

The most commonly used 'α' value in different studies is 0.05 [79]. And "there is nothing sacred about using the 95% confidence interval level" to make a decision on a sample mean of an experimental test [80]. Hence Alpha (P) value of 0.05 selected in this study also.

iii. **Calculate the Degree of Freedom**

The degree of freedom of a sample (N) is given by N-1. In this study, eight samples selected for analysis. So, the maximum degree of freedom becomes seven.

iv. **State Decision Rule**

Since the direction of the relationship between each sample is not specified, a two-tail used in this experiment. Hence, α/2 = 0.025 has been set in each direction of the tail. If we look at the T-critical value $(-\overline{X}*)$ and $(\overline{X}*)$ for two tail α =0.05 at 7 degrees of freedom from the T-distribution table shown in appendix 1 we obtain the value T-critical = 2.365.

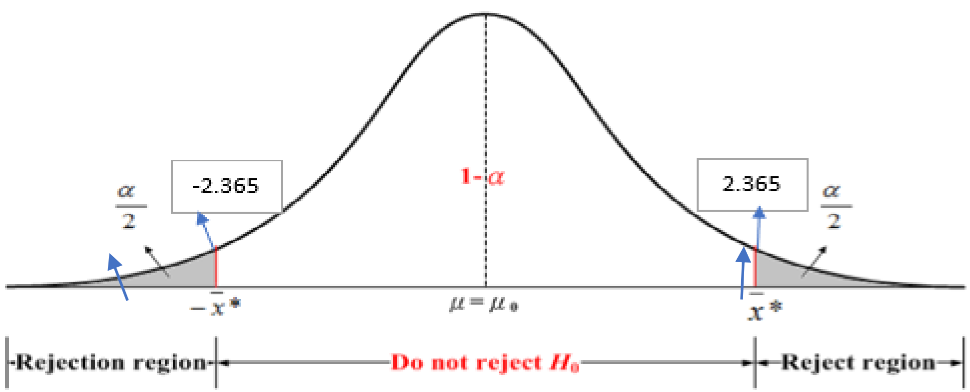


Figure 38: Two-tail hypothesis test curve.

Figure 38 shows, the two-tail hypothesis test curve the shaded region indicates the area of rejecting the null hypothesis (Ho) and T-critical point $(-\overline{X}*)$ and$(\overline{X}*)$. According to the decision rule stated in current studies [78 – 80], if T-computed rest in the Ho rejection region or if P (T-test) is less or equal to α is true, then the null hypothesis (Ho) should be rejected and if the opposite the null hypothesis (Ho) should be accepted.

v. **Calculating A T-Statistics, Paired Two-Tail T-Test and P(T-Test) Value**

T-test value can be computed manually using the mathematical equation found in[78].

$$\frac{\bar{x}_D - \mu}{\frac{S_D}{\sqrt{n}}} \ldots \ldots \ldots \ldots \ldots \ldots \ldots . .4.10$$

since μ is expected to null (0) and rewriting the equation

$$\frac{\bar{x}_D}{\frac{S_D}{\sqrt{n}}} \ldots \ldots \ldots \ldots \ldots \ldots \ldots . .4.11$$

Here**,** $\boldsymbol{x} = BB - AB \bar{X} = \frac{BB-AB}{n}$ and $S_D = \frac{\sqrt{\sum \boldsymbol{x}^2 - (\sum \boldsymbol{x})^\wedge 2/\, \boldsymbol{n}}}{\boldsymbol{n-1}}$

Where x is sample difference, in this case before Begena sound stimuli (BB) vs after Begena sound stimuli (AB) $\bar{X}$ is mean sample difference and S is our variance (the square of the standard deviation), n is our sample number, S_D = standard deviation (the square root of variance), n = sample number, and n-1 is degree of freedom. Therefore, by substituting all values in equation 4.11, all T-test values for each subject can be computed manually. For comparison and speedy work, a statistics package for social science (SPSS) used in this research.

CHAPTER FIVE

EEG-Signal Analysis Result and Discussion

5.1 Introduction

In this study, all subjects undergo within a repeated measure experimental design to investigate the emotional effect observed on a depressing subject as a result of listening to the recorded Begena sound stimuli that composed of four major Ethiopian traditional music scale (“Tezeta”, “Bati”, “Ambassel”, and “Anchihoye”).The study mainly focused on cause and effect analysis by repeating a similar experimental setup for all subjects enrolled in the study.

In this chapter, both pre and post Begena sound stimuli intervention with EEG analysis result is presented and the interpretation of the result has been discussed.

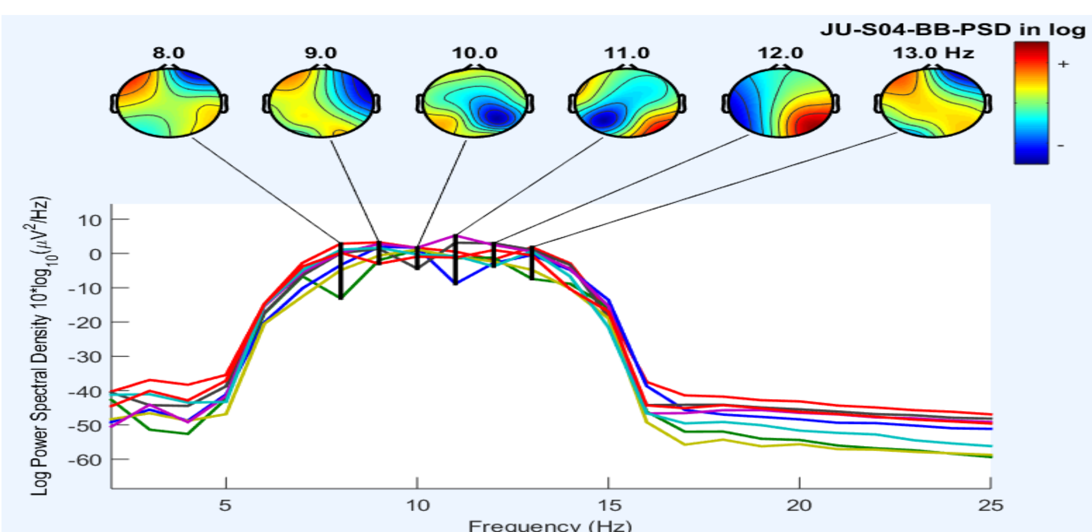
5.2 Result

In this study, the total size of 10.5 MB and length of 720 seconds duration (6 subject*60 seconds *2 conditions) EEG-data was gathered from selected scalp EEG-channel of six subjects (age 22 ± 3) was analyzed based on designed methodology and the following result has been obtained:

5.2.1 The Analysis Result Using Mean Alpha Power

I. Result Using EEGLAB GUI based Analysis

EEGLAB allows users to analyses channel spectrum by representing power concentration in each brain part with color. Figure 39 shows the spectral power density in each channel and at each discrete frequency point (8, 9, 10, 11, 12, 13Hz). Each colored line represents a single channel activity spectrum. However, in this result, it is difficult to tell how much power is available in each channel and frequency point. For this reason, Welch’s method which discussed in section 4.8.1.1 was applied. Figure 39 -A shows channel-spectrum before Begena (BB) stimuli, and Figure 39 -B show the spectrum after Begena (AB) stimuli.



A)

B)

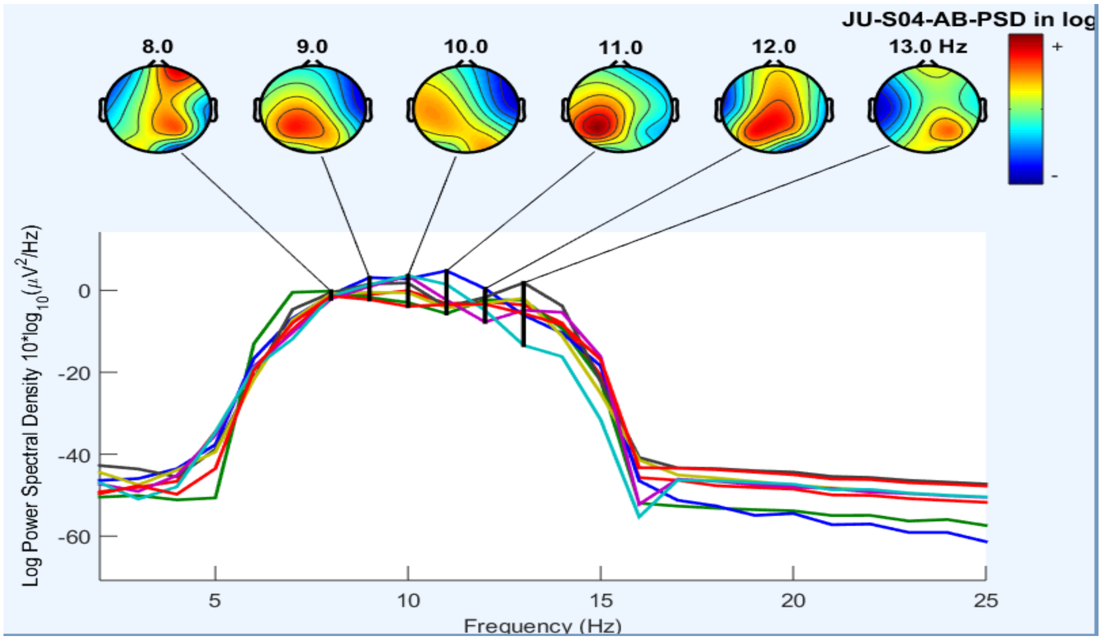


Figure 39 : Channel spectral power at discrete frequency point

II. Analysis Result using Mean Alpha Power Result Based on Welch's Method

This was computed for each discrete frequency point (8, 9, 10, 11, 12, 13Hz) as shown in appendix three. Then it was averaged by a number of sample points to compute Alpha mean power at each scalp channel using Welch's algorithm that was discussed in section 4.8.1.1. As it is shown in Table 8 Each channel Alpha mean power result of each subject before and after Begena sound stimuli is presented. The result showed a significant increase in Alpha mean power at each study EEG-channels of a subject was achieved after Begena sound stimuli compared to the initial state (without Begena sound stimuli) and support the study hypothesis that stated in section 1.4.

Table 8: Alpha Mean Power Result at Each Study Channel of the corresponding Subject

Channel	Subject 1		Subject 2		Subject 3		Subject 4		Subject 5		Subject 6	
	BB	AB	BB	AB	BB	AB	BB	AB	BB	AB	BB	AB
Fp1-A1	0.268	0.805	0.179	0.497	0.184	0.450	0.575	0.975	0.003	0.112	0.011	0.395
Fp2-A2	0.302	0.808	0.211	0.586	0.249	0.596	0.593	1.035	0.011	0.139	0.046	0.490
P3-A1	0.416	2.109	0.337	1.216	0.312	0.519	0.226	0.455	0.003	0.290	0.060	0.841
P4-A2	0.276	1.032	0.227	0.915	0.598	0.364	0.877	1.436	0.049	0.222	0.146	0.630
T3-A1	0.180	0.349	0.146	0.509	0.121	0.479	0.432	1.003	0.003	0.152	0.172	0.413
T4-A2	0.171	0.442	0.157	0.518	0.239	0.637	0.504	1.025	0.003	0.152	0.088	0.440
O1-A1	0.129	0.192	0.074	0.152	0.139	0.360	0.220	0.280	0.003	0.035	0.106	0.168
O2-A2	0.303	0.552	0.211	0.452	0.159	0.278	1.252	1.297	0.007	0.150	0.171	0.624

BB = before Begena, AB = after Begena, Fp1-A1 = frontal pole(left), Fp2-A2 frontal pole(right), P3-A1 = parietal(left), P4-A2 = parietal(right), T3-A1 = temporal (left), T4-A2= temporal (right), O1-A1 = occipital (left), O2-A2 = occipital (right).

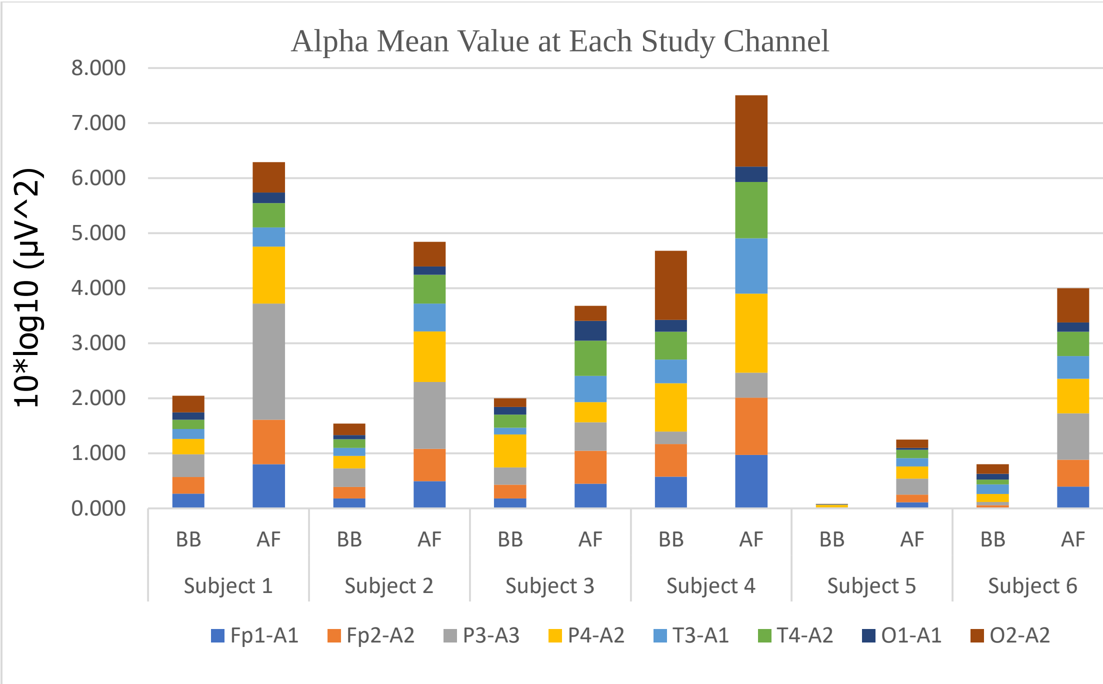


Figure 40: Mean Alpha Power Analysis Result.

Figure 40, shows Alpha mean power at each study channel in the log scale with respect to each condition (BB and AB). Each colure indicates the corresponding channel.

As indicated in Table 8 and Figure 40 Alpha mean power was significantly increased at each brain region of a subject. In particular, a peak quantitative change around the parietal region (P3-A1) was noted. According to studies report, such increases around this site is associated increased memory task [67], effortful cognition, where it tries to maximize neural network activation by maintaining optimal excitation and focusing attention towards external stimuli [79].

5.2.2 T-Test Statistic Analysis Result for Two-Tail Paired Sample

This section provides a quantitative two-tail T-test statistical analysis result that compares the Alpha mean power value of paired observations (pre and post begena sound stimuli) for each subject. Table 9, showed this result at a 95% Confidence Interval of the Difference ($\alpha_{2-tail} = 0.05$).

Table 9: The paired sample T-test Statistic analysis result

			Two tail T-test value for paired sample Paired Differences		
			95% Confidence Interval of the Difference ($\alpha_{Two-tail} = 0.05$)		
Subjects	Mean	Std. Deviation	Paired T-test(2-tail)	df	P(2-tailed)
Sub1, BB vs AB	-0.531	0.521	-2.881	7	0.023617
Sub2, BB vs AB	-0.413	0.254	-4.604	7	0.002471
Sub3, BB vs AB	-0.210	0.202	-2.949	7	0.021445
Sub4, BB vs AB	-0.353	0.215	-4.643	7	0.002362
Sub5, BB vs AB	-0.146	0.071	-5.823	7	0.000648
Sub6, BB vs AB	-0.400	0.207	-5.475	7	0.000930

- $\alpha_{Two-tail} = 0.05$
- $P_{subject\ 1} = 0.023617$ $P_{subject\ 4} = 0.002362$
- $P_{subject\ 2} = 0.002471$ $P_{subject\ 5} = 0.000648$
- $P_{subject\ 3} = 0.021445$ $P_{subject\ 6} = 0.000930$

All significant level (P value) that obtained from two-tail paired sample statistical analysis are less than the set α value and thus shows the presence of a significant effect caused by Begena sound stimuli in each subject.

5.3 Discussion

The main objective of this study was to investigate the emotional effect evoked by Begena's instrumental sound stimuli on brain activity of a depressed subject. This investigation was done by computing the Alpha mean power on depression sensitive brain regions before and after Begena sound intervention. Then a statistical comparison test is done to detect any change between the two conditions. To compute Alpha mean power at each selected channel first power at each discrete frequency bean was computed then average over the number of sample point for each EEG-channel of each subject was done.

$$\text{Alpha mean power} = \text{Alpha power at } \frac{8+9+10+11+12+13\text{Hz}}{6}$$

In this study, Alpha mean power was computed at left and right side of; temporal (T3&T4), Parietal (P3 & P4), Occipital (O3 & O4), and prefrontal cortex (Fp1& Fp2) brain region. All value was computed at eye-closed state to avoid visual effect on the result.

Table 10. Result comparison with other study on healthy subjects at resting and eye closed state [16].

Brain Part	Alpha mean power value over 6 Subjects Before Begena sound	Alpha mean power value over 6 Subjects After Begena sound	Normal Adult Value figured out by other study over 40 subjects
Fp1	0.203	0.539	1.34
Fp2	0.235	0.609	1.38
P3	0.226	0.905	1.10
P4	0.362	0.766	1.04
T3	0.176	0.484	0.79
T4	0.194	0.536	0.84
O1	0.112	0.198	1.31
O2	0.351	0.559	1.30

As shown in Table 10 a better close to a healthy value figured out by other study was achieved after Begena sound than the silent state. This Implies, with long term study on large sample size a more similar value can be resulted.

Once the discrete regional Alpha mean power before and after Begena sound of eye-closed sate obtained, a paired sample T-test statistical analysis done to investigate the significant effect change caused by Begena sound stimuli.

The paired sample T-test result at Ptwo-tail =0.05 shown in Table 9 indicates a significant level (P) $\leq$ 0.05 achieved for all subject. Based on the definition of a paired sample T-test discussed in section 4.8.2 this means, there was significant change after Begena sound intervention.

According to recent studies, an increase in Alpha mean-power is associated with positive emotional effect and show the therapeutic nature of the stimuli sound that was used during the experiment [18, 22, 24, 60, 63, 67]. Therefore, the analysis result found in this research conformed that Begena sound has a strong therapeutic benefit for a depressed subject. This result indicates all subject enrolled in this study were able to get a short term relief effect. Hence, this is a sound result found for the first time. So, can be used as a preliminary evidence and initiation for further development.

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CHAPTER SIX

Conclusion and Future Work

6.1 Conclusion

Depression affects more than 300 million peoples in the world and caused 800,000 death annually due to self-suicide attack. Although, medication and psychotherapy are commonly used as a treatment option the associated medication related side effects, antidepressant effect on daily task activity, and frequent psychotherapist turnover becomes a challenge. As a solution music therapy emerges as a current alternative, but still it remains unfamiliar and under usage in most developing country including Ethiopia. In history, Begena sound is known for its strong and natural buzzing sound that mediately attract people's attention and make them to stay in a calm state. But its clinical effect on the depressed subject is not addressed and unknown

Hence the objective of this study was to investigate the emotional effect of Begena sound on a depressed subject. This was done using statistical analysis on EEG signal in the frequency domain. The statistical analysis result showed, significant increases in Alpha mean power nearly to all depression sensitive brain region. Based on the literature, this was interpreted as relaxing and calming down emotional benefit gained as a result of this sound. Thus, support the study hypothesis stated in section 1.4.

From a paired sample T-test result a significant level (P) ≤ 0.05 was achieved for all subjects and by definition, this means there was a significant change after Begena sound intervention.

This study lacks a control group due to a few working materials availabilities and a limited budget. Also done with a small sample size and short-term period. But a preliminary work the result found indicates the strong emotional effect of the Begena sound and it reflects the power of Begena sound to relief depression. Thus, suggest after long term study, Begena sound can be used as a therapeutic alternative in the clinical setup.

6.2 The Future Work

The future work will be a full-scale clinical study to investigate the long term emotional effect Begena's instrumental sound on a depressed subject and on control group.

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Appendix

Appendix one

t Table

cum. prob	$t_{.50}$	$t_{.75}$	$t_{.80}$	$t_{.85}$	$t_{.90}$	$t_{.95}$	$t_{.975}$	$t_{.99}$	$t_{.995}$	$t_{.999}$	$t_{.9995}$
one-tail	**0.50**	**0.25**	**0.20**	**0.15**	**0.10**	**0.05**	**0.025**	**0.01**	**0.005**	**0.001**	**0.0005**
two-tails	**1.00**	**0.50**	**0.40**	**0.30**	**0.20**	**0.10**	**0.05**	**0.02**	**0.01**	**0.002**	**0.001**
df											
1	0.000	1.000	1.376	1.963	3.078	6.314	12.71	31.82	63.66	318.31	636.62
2	0.000	0.816	1.061	1.386	1.886	2.920	4.303	6.965	9.925	22.327	31.599
3	0.000	0.765	0.978	1.250	1.638	2.353	3.182	4.541	5.841	10.215	12.924
4	0.000	0.741	0.941	1.190	1.533	2.132	2.776	3.747	4.604	7.173	8.610
5	0.000	0.727	0.920	1.156	1.476	2.015	2.571	3.365	4.032	5.893	6.869
6	0.000	0.718	0.906	1.134	1.440	1.943	2.447	3.143	3.707	5.208	5.959
7	0.000	0.711	0.896	1.119	1.415	1.895	2.365	2.998	3.499	4.785	5.408
8	0.000	0.706	0.889	1.108	1.397	1.860	2.306	2.896	3.355	4.501	5.041
9	0.000	0.703	0.883	1.100	1.383	1.833	2.262	2.821	3.250	4.297	4.781
10	0.000	0.700	0.879	1.093	1.372	1.812	2.228	2.764	3.169	4.144	4.587
11	0.000	0.697	0.876	1.088	1.363	1.796	2.201	2.718	3.106	4.025	4.437
12	0.000	0.695	0.873	1.083	1.356	1.782	2.179	2.681	3.055	3.930	4.318
13	0.000	0.694	0.870	1.079	1.350	1.771	2.160	2.650	3.012	3.852	4.221
14	0.000	0.692	0.868	1.076	1.345	1.761	2.145	2.624	2.977	3.787	4.140
15	0.000	0.691	0.866	1.074	1.341	1.753	2.131	2.602	2.947	3.733	4.073
16	0.000	0.690	0.865	1.071	1.337	1.746	2.120	2.583	2.921	3.686	4.015
17	0.000	0.689	0.863	1.069	1.333	1.740	2.110	2.567	2.898	3.646	3.965
18	0.000	0.688	0.862	1.067	1.330	1.734	2.101	2.552	2.878	3.610	3.922
19	0.000	0.688	0.861	1.066	1.328	1.729	2.093	2.539	2.861	3.579	3.883
20	0.000	0.687	0.860	1.064	1.325	1.725	2.086	2.528	2.845	3.552	3.850
21	0.000	0.686	0.859	1.063	1.323	1.721	2.080	2.518	2.831	3.527	3.819
22	0.000	0.686	0.858	1.061	1.321	1.717	2.074	2.508	2.819	3.505	3.792
23	0.000	0.685	0.858	1.060	1.319	1.714	2.069	2.500	2.807	3.485	3.768
24	0.000	0.685	0.857	1.059	1.318	1.711	2.064	2.492	2.797	3.467	3.745
25	0.000	0.684	0.856	1.058	1.316	1.708	2.060	2.485	2.787	3.450	3.725
26	0.000	0.684	0.856	1.058	1.315	1.706	2.056	2.479	2.779	3.435	3.707
27	0.000	0.684	0.855	1.057	1.314	1.703	2.052	2.473	2.771	3.421	3.690
28	0.000	0.683	0.855	1.056	1.313	1.701	2.048	2.467	2.763	3.408	3.674
29	0.000	0.683	0.854	1.055	1.311	1.699	2.045	2.462	2.756	3.396	3.659
30	0.000	0.683	0.854	1.055	1.310	1.697	2.042	2.457	2.750	3.385	3.646
40	0.000	0.681	0.851	1.050	1.303	1.684	2.021	2.423	2.704	3.307	3.551
60	0.000	0.679	0.848	1.045	1.296	1.671	2.000	2.390	2.660	3.232	3.460
80	0.000	0.678	0.846	1.043	1.292	1.664	1.990	2.374	2.639	3.195	3.416
100	0.000	0.677	0.845	1.042	1.290	1.660	1.984	2.364	2.626	3.174	3.390
1000	0.000	0.675	0.842	1.037	1.282	1.646	1.962	2.330	2.581	3.098	3.300
z	0.000	0.674	0.842	1.036	1.282	1.645	1.960	2.326	2.576	3.090	3.291
	0%	50%	60%	70%	80%	90%	95%	98%	99%	99.8%	99.9%
					Confidence Level						

Appendix two

Patient Health Questionnaire [81].

Patient Health Questionnaire (PHQ-9)

Patient Name: ______________________ **Date:** ____________

	Not at all	Several days	More than half the days	Nearly every day
1. Over the *last 2 weeks*, how often have you been bothered by any of the following problems?				
a. Little interest or pleasure in doing things	☐	☐	☐	☐
b. Feeling down, depressed, or hopeless	☐	☐	☐	☐
c. Trouble falling/staying asleep, sleeping too much	☐	☐	☐	☐
d. Feeling tired or having little energy	☐	☐	☐	☐
e. Poor appetite or overeating	☐	☐	☐	☐
f. Feeling bad about yourself or that you are a failure or have let yourself or your family down	☐	☐	☐	☐
g. Trouble concentrating on things, such as reading the newspaper or watching television.	☐	☐	☐	☐
h. Moving or speaking so slowly that other people could have noticed. Or the opposite; being so fidgety or restless that you have been moving around a lot more than usual.	☐	☐	☐	☐
i. Thoughts that you would be better off dead or of hurting yourself in some way.	☐	☐	☐	☐
2. If you checked off any problem on this questionnaire so far, how difficult have these problems made it for you to do your work, take care of things at home, or get along with other people?	Not difficult at all ☐	Somewhat difficult ☐	Very difficult ☐	Extremely difficult ☐

PHQ-9* Questionnaire for Depression Scoring and Interpretation Guide

For physician use only

Scoring:
Count the number (#) of boxes checked in a column. Multiply that number by the value indicated below, then add the subtotal to produce a total score. The possible range is 0-27. Use the table below to interpret the PHQ-9 score.

Not at all	(#) _____	x 0 =	_____
Several days	(#) _____	x 1 =	_____
More than half the days	(#) _____	x 2 =	_____
Nearly every day	(#) _____	x 3 =	_____

Total score: _____

Interpreting PHQ-9 Scores		**Actions Based on PH9 Score**	
		Score	**Action**
Minimal depression	0-4	< 4	The score suggests the patient may not need depression treatment
Mild depression	5-9		
Moderate depression	10-14	> 5 - 14	Physician uses clinical judgment about treatment, based on patient's duration of symptoms and functional impairment
Moderately severe depression	15-19		
Severe depression	20-27		
		> 15	Warrants treatment for depression, using antidepressant, psychotherapy and/or a combination of treatment.

* PHQ-9 is described in more detail at the McArthur Institute on Depression & Primary Care website www.depression-primarycare.org/clinicians/toolkits/materials/forms/phq9/

Appendix Three

Result of Discrete Alpha Power at each frequency point and mean over the number of sample point

JU-S01-BB: Average and instant Power in 8-13Hz (without Begena sound)								
chn No.	P at 8Hz	P at 9Hz	P at 10Hz	P at 11Hz	P at 12Hz	P at 13Hz	sub total P	mean Pow
Fp1	0.038	0.182	0.858	0.290	0.124	0.116	1.608	0.268
Fp2	0.151	0.211	0.880	0.302	0.119	0.147	1.811	0.302
P3	0.201	0.186	1.144	0.528	0.373	0.065	2.497	0.416
P4	0.140	0.176	0.781	0.279	0.090	0.193	1.659	0.276
T3	0.074	0.196	0.524	0.066	0.104	0.119	1.083	0.180
T4	0.033	0.113	0.577	0.134	0.047	0.121	1.024	0.171
O1	0.172	0.143	0.273	0.090	0.062	0.036	0.777	0.129
O2	0.283	0.422	0.513	0.124	0.224	0.254	1.820	0.303
Grand Total							12.279	
Grand average							1.535	

JU-S01-AB: Average and instant Power in 8-13Hz (with Begena sound)								
chn No.	P at 8Hz	P at 9Hz	P at 10Hz	P at 11Hz	P at 12Hz	P at 13Hz	sub total P	mean Power
Fp1	1.292	0.263	2.055	0.724	0.326	0.170	4.830	0.805
Fp2	0.345	0.496	2.606	0.707	0.495	0.200	4.850	0.808
P3	0.283	0.884	4.137	6.000	0.654	0.695	12.653	2.109
P4	0.300	1.170	2.366	1.894	0.263	0.201	6.194	1.032
T3	0.126	0.132	1.169	0.309	0.289	0.067	2.092	0.349
T4	0.113	0.273	1.145	0.407	0.584	0.132	2.654	0.442
O1	0.420	0.153	0.198	0.229	0.111	0.042	1.153	0.192
O2	0.385	0.663	0.650	0.916	0.067	0.634	3.314	0.552
Grand Total							37.741	
Grand average							4.718	

JU-S02-BB: Average and instant Power in 8-13Hz (without Begena sound)								
chn No.	P at 8Hz	P at 9Hz	P at 10Hz	P at 11Hz	P at 12Hz	P at 13Hz	sub total P	mean Pow
Fp1	0.229	0.041	0.369	0.325	0.072	0.036	1.073	0.179
Fp2	0.360	0.120	0.356	0.260	0.099	0.070	1.264	0.211
P3	0.265	0.120	0.617	0.561	0.254	0.208	2.025	0.337
P4	0.090	0.109	0.583	0.391	0.073	0.116	1.362	0.227
T3	0.207	0.016	0.288	0.244	0.078	0.041	0.874	0.146
T4	0.223	0.084	0.277	0.254	0.056	0.047	0.940	0.157
O1	0.073	0.068	0.157	0.055	0.060	0.034	0.447	0.074
O2	0.273	0.127	0.193	0.254	0.186	0.235	1.268	0.211
Grand Total							9.253	

JU-S02-AB: Average and instant Power in 8-13Hz (with Begena sound)								
chn No.	P at 8Hz	P at 9Hz	P at 10Hz	P at 11Hz	P at 12Hz	P at 13Hz	sub total P	mean Power
Fp1	0.564	0.550	0.608	0.724	0.391	0.146	2.983	0.497
Fp2	0.518	0.663	0.887	0.938	0.360	0.148	3.514	0.586
P3	0.447	0.883	2.045	2.558	1.100	0.265	7.298	1.216
P4	0.378	0.689	1.493	2.118	0.641	0.169	5.489	0.915
T3	0.300	0.494	0.813	0.816	0.400	0.233	3.056	0.509
T4	0.357	0.537	0.858	0.857	0.296	0.203	3.107	0.518
O1	0.147	0.143	0.189	0.208	0.140	0.085	0.911	0.152
O2	0.551	0.513	0.497	0.523	0.356	0.269	2.709	0.452
Grand Total							33.912	

JU-S03-BB: Average and instant Power in 8-13Hz (without Begena sound)								
chn No.	P at 8Hz	P at 9Hz	P at 10Hz	P at 11Hz	P at 12Hz	P at 13Hz	sub total P	mean Pow
Fp1	0.207	0.246	0.195	0.218	0.130	0.108	1.104	0.184
Fp2	0.288	0.260	0.316	0.320	0.170	0.140	1.493	0.249
P3	0.299	0.445	0.285	0.345	0.294	0.203	1.872	0.312
P4	0.617	0.904	0.738	0.493	0.446	0.390	3.589	0.598
T3	0.222	0.160	0.116	0.081	0.082	0.067	0.727	0.121
T4	0.237	0.226	0.399	0.218	0.157	0.200	1.436	0.239
O1	0.246	0.205	0.105	0.102	0.093	0.080	0.831	0.139
O2	0.184	0.166	0.187	0.136	0.136	0.142	0.952	0.159
Grand Total							12.005	
Grand average							1.501	

JU-S03-AB: Average and instant Power in 8-13Hz (with Begena sound)								
chn No.	P at 8Hz	P at 9Hz	P at 10Hz	P at 11Hz	P at 12Hz	P at 13Hz	sub total P	mean Power
Fp1	0.591	0.752	0.440	0.441	0.301	0.174	2.699	0.450
Fp2	0.550	1.249	0.610	0.536	0.339	0.292	3.575	0.596
P3	0.541	0.781	0.612	0.609	0.308	0.263	3.113	0.519
P4	0.303	0.774	0.462	0.268	0.153	0.221	2.181	0.364
T3	0.474	0.936	0.629	0.331	0.254	0.253	2.877	0.479
T4	0.553	1.589	0.689	0.407	0.303	0.280	3.820	0.637
O1	0.373	0.639	0.396	0.265	0.220	0.270	2.163	0.360
O2	0.303	0.346	0.394	0.249	0.154	0.220	1.666	0.278
Grand Total							22.095	
Grand average							2.762	

JU-S04-BB: Average and instant Power in 8-13Hz (without Begena sound)								
chn No.	P at 8Hz	P at 9Hz	P at 10Hz	P at 11Hz	P at 12Hz	P at 13Hz	sub total P	mean Pow
Fp1	0.449	0.549	1.305	0.569	0.298	0.279	3.449	0.575
Fp2	0.572	0.458	1.402	0.623	0.309	0.192	3.555	0.593
P3	0.147	0.131	0.604	0.307	0.108	0.061	1.358	0.226
P4	0.476	0.505	2.488	1.283	0.323	0.188	5.262	0.877
T3	0.304	0.273	0.900	0.690	0.274	0.147	2.589	0.432
T4	0.391	0.410	0.984	0.851	0.176	0.214	3.027	0.504
O1	0.303	0.189	0.304	0.272	0.126	0.123	1.317	0.220
O2	0.970	1.350	1.009	1.893	1.064	1.226	7.512	1.252
Grand Total							28.071	

JU-S04-BB: Average and instant Power in 8-13Hz (with Begena sound)								
chn No.	P at 8Hz	P at 9Hz	P at 10Hz	P at 11Hz	P at 12Hz	P at 13Hz	sub total P	mean Power
Fp1	0.609	0.875	2.533	1.320	0.321	0.191	5.848	0.975
Fp2	0.613	0.777	2.967	1.336	0.321	0.194	6.207	1.035
P3	0.148	0.237	1.601	0.521	0.133	0.090	2.731	0.455
P4	0.407	0.682	5.634	1.327	0.368	0.198	8.616	1.436
T3	0.362	0.533	3.197	1.367	0.313	0.248	6.020	1.003
T4	0.438	0.527	3.380	1.304	0.311	0.192	6.153	1.025
O1	0.204	0.220	0.615	0.350	0.164	0.126	1.678	0.280
O2	1.075	1.034	1.950	1.217	1.247	1.258	7.782	1.297
Grand Total							45.034	

JU-S05-BB: Average and instant Power in 8-13Hz (without Begena sound)								
chn No.	P at 8Hz	P at 9Hz	P at 10Hz	P at 11Hz	P at 12Hz	P at 13Hz	sub total P	mean Pow
Fp1	0.003	0.006	0.003	0.002	0.002	0.002	0.018	0.003
Fp2	0.012	0.023	0.013	0.010	0.006	0.004	0.069	0.011
P3	0.003	0.006	0.003	0.002	0.002	0.002	0.019	0.003
P4	0.062	0.143	0.035	0.030	0.015	0.012	0.297	0.049
T3	0.003	0.006	0.003	0.002	0.002	0.002	0.018	0.003
T4	0.002	0.004	0.003	0.003	0.003	0.002	0.017	0.003
O1	0.003	0.006	0.003	0.002	0.002	0.002	0.018	0.003
O2	0.009	0.012	0.008	0.004	0.006	0.005	0.044	0.007
Grand Total							0.501	
Grand average							0.063	

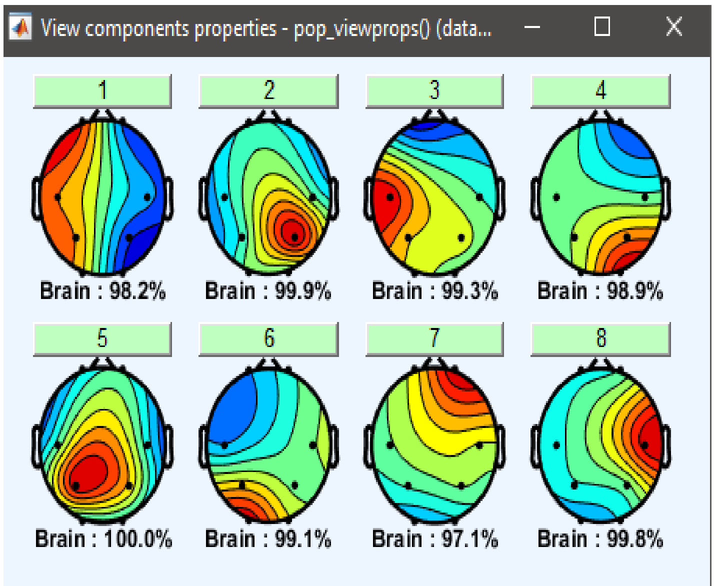
JU-S05-AB: Average and instant Power in 8-13Hz (with Begena sound)								
chn No.	P at 8Hz	P at 9Hz	P at 10Hz	P at 11Hz	P at 12Hz	P at 13Hz	sub total P	mean Power
Fp1	0.064	0.106	0.168	0.209	0.075	0.048	0.670	0.112
Fp2	0.064	0.121	0.231	0.315	0.068	0.036	0.836	0.139
P3	0.148	0.232	0.537	0.535	0.183	0.105	1.740	0.290
P4	0.094	0.190	0.330	0.470	0.183	0.062	1.330	0.222
T3	0.101	0.159	0.228	0.204	0.109	0.113	0.914	0.152
T4	0.120	0.195	0.235	0.192	0.098	0.073	0.912	0.152
O1	0.019	0.027	0.073	0.052	0.027	0.012	0.210	0.035
O2	0.182	0.167	0.197	0.154	0.105	0.093	0.899	0.150
Grand Total							7.511	
Grand average							0.939	

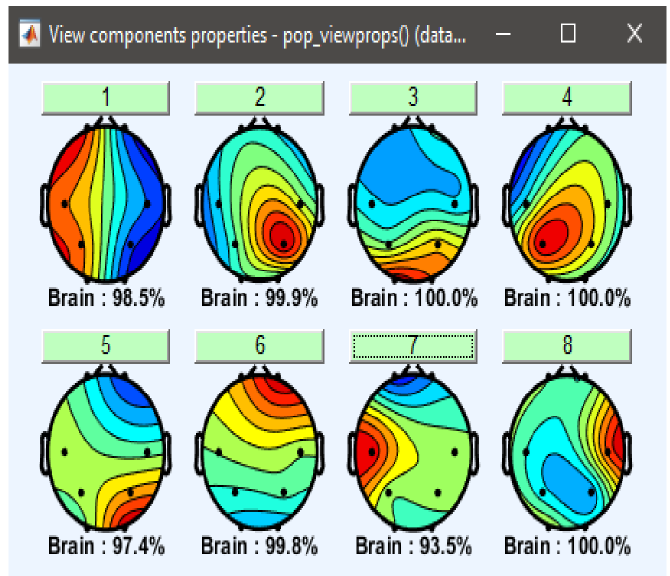
JU-S06-BB: Average and instant Power in 8-13Hz (without Begena sound)								
chn No.	P at 8Hz	P at 9Hz	P at 10Hz	P at 11Hz	P at 12Hz	P at 13Hz	sub total P	mean Pow
Fp1	0.015	0.014	0.008	0.009	0.009	0.010	0.064	0.011
Fp2	0.055	0.048	0.043	0.039	0.061	0.031	0.277	0.046
P3	0.062	0.061	0.064	0.064	0.073	0.038	0.363	0.060
P4	0.201	0.195	0.118	0.116	0.151	0.098	0.878	0.146
T3	0.164	0.220	0.185	0.146	0.156	0.164	1.034	0.172
T4	0.089	0.111	0.098	0.073	0.112	0.047	0.529	0.088
O1	0.147	0.124	0.081	0.098	0.105	0.082	0.636	0.106
O2	0.248	0.206	0.116	0.134	0.208	0.113	1.025	0.171
Grand Total							4.808	

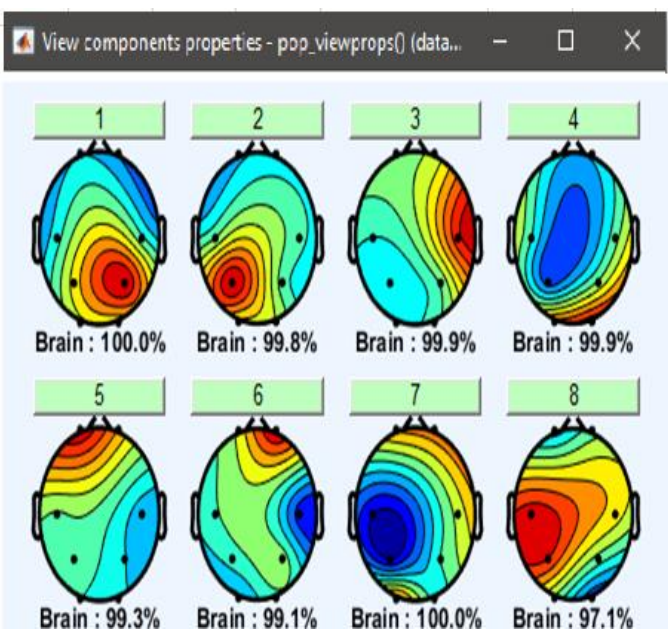
JU-S06-AB: Average and instant Power in 8-13Hz (with Begena sound)								
chn No.	P at 8Hz	P at 9Hz	P at 10Hz	P at 11Hz	P at 12Hz	P at 13Hz	sub total P	mean Power
Fp1	0.438	0.374	0.489	0.755	0.221	0.092	2.369	0.395
Fp2	0.458	0.321	0.693	1.071	0.221	0.179	2.942	0.490
P3	0.316	0.690	1.388	1.829	0.505	0.319	5.047	0.841
P4	0.237	0.253	1.185	1.614	0.390	0.101	3.781	0.630
T3	0.225	0.281	0.596	0.829	0.305	0.241	2.477	0.413
T4	0.309	0.241	0.717	1.009	0.211	0.150	2.637	0.440
O1	0.193	0.170	0.204	0.173	0.175	0.093	1.007	0.168
O2	0.917	0.540	0.614	0.616	0.478	0.580	3.745	0.624
Grand Total							24.007	

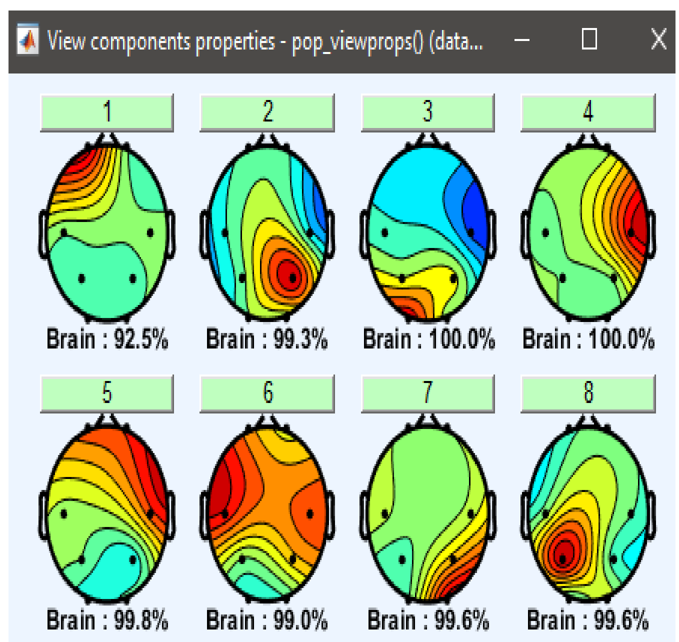
Appendix Four

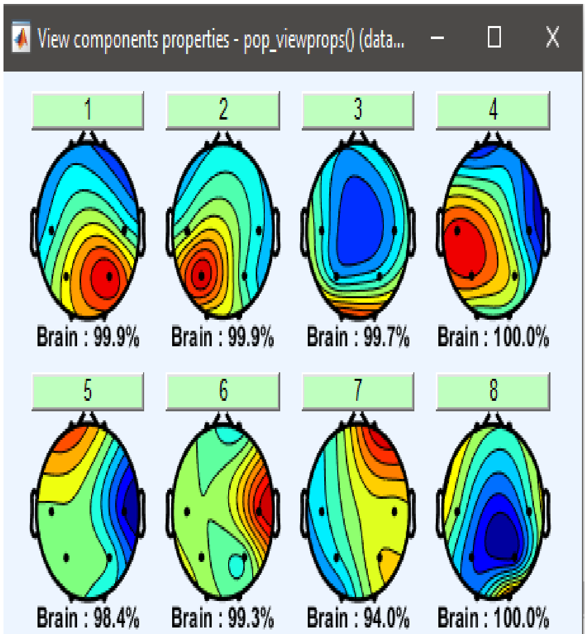
Independent components (ICs) of all subject's vs Brain signal quality







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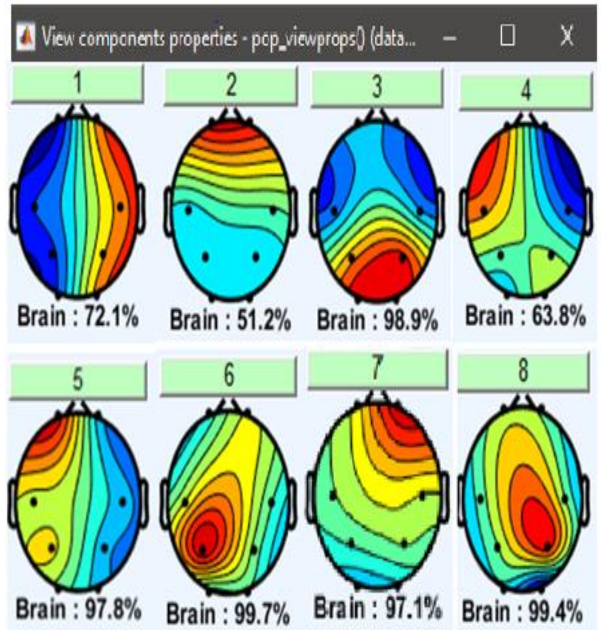
1
2
3
4
Brain : 99.9%
Brain : 99.9%
Brain : 99.7%
Brain : 100.0%
5
6
7
8
Brain : 98.4%
Brain : 99.3%
Brain : 94.0%
Brain : 100.0%

View components properties - pop_viewprops() (data...
1
2
3
4
Brain : 72.1%
Brain : 51.2%
Brain : 98.9%
Brain : 63.8%
5
6
7
8
Brain : 97.8%
Brain : 99.7%
Brain : 97.1%
Brain : 99.4%