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EEG BASED ASSESSMENT OF EMOTIONAL WELLBEING IN SMART ENVIRONMENT

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ABSTRACT

Smart technologies are frequently united and automated in our everyday settings and commonplace task by linking computers and other devices. While there has been a necessity to build smart environments for an easy and comfortable life, research on measuring wellbeing in this environment becomes increasingly intensive. Emotion is one of the decisive aspects of wellbeing that encourages us to work effectively, manage, and cope with stress, and affect our physical health. This work evaluates the EEG signal to measure individuals the different emotional states in a smart space by creating a computer gaming scenario. EEG, a physiological signal which provides details on mental, physiological, and emotional states, EEG frequency bands are strongly correlated with positive and negative emotional responses. Since brain left frontal cortical area is responsible for positive emotion and the right frontal region associate, therefore, we choose two pairs of EEG electrodes F3-F4, and F7-F8 to assess the game player emotional states during the gaming situations. We measure the EEG frontal alpha asymmetry (FAA) by comparing variations in the alpha band power levels in the left and right frontal cortex, corresponding to positive and negative emotions. Our experiment outcome reveals considerable support with the emotional variance of the test participants. We note that multiple interruptions during the gaming situation create irritation to the test subjects. These findings also confirm that F3 and F4 EEG channels are the most sensitive to human emotional responses compared to F7 and F8 channels.

Keywords: Wellbeing, emotions, EEG, frontal alpha asymmetry, digital game

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FOREWORD

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LIST OF ABBREVIATIONS AND SYMBOLS

GUI	Graphical User Interface
EMG	Electromyography
EEG	Electroencephalogram
USB	Universal Serial Bus
AgCl	Silver Chloride
ADHD	Attention Deficit Hyperactivity Disorder
LMS	Least Mean Squares
RLMS	Recursive Least Mean Squares
PSD	Power Spectral Densities
ICA	Independent Component Analysis
PCA	Principal Component Analysis
PCs	Principal Components
SVD	Single Value Decomposition
CICA	Convolutive Independent Component Analysis
BSS	Blind Source Separations
DWT	Discreted Wavelet Transform
SC	Skin Conductivity
EDA	Electrodermal Activity
GSR	Galvanic Skin Response
HR	Heart Rate
PANAS	Positive And Negative Affect Schedule
SAM	Self-Assessment Manikin
SSAQ	Simple Self Assessment Questionnaire
FAA	Frontal Alpha Asymmetry
RF	Random Forest
HMM	Hidden Markov Model
LPP	Late Positive Potential

1. INTRODUCTION

A smart environment refers to space or an environment where all kinds of information technology are continually operating to make people's lives more convenient [1]. A smart environment can build up using embedded sensors, actuators, displays, and computational elements connected with a continuous network [2, 3],for example smart office, smart campus, smart building. Propelled by breakthroughs in technology, wellbeing in the smart environment is becoming crucial in our daily lives. According to Lovén et al. [4], wellbeing can be measured in various aspects of human life, including mental, emotional, physical, social, material, and professional dimensions, in a smart context it can be defined by flow (state of mind), low levels of stress, and a balance between negative and positive affect [4].

Emotional wellbeing is an integrated part of our overall wellbeing, which encourages us to work productively, decide and cope with the stressful condition, and affect our physical wellness [5]. Smart spaces can help improve the wellbeing of the person if the person's emotional status is known. Halkola et al. [6], Set up an experimental framework for assessing wellbeing in a smart space by building a proxy environment utilizing a video gameplay setting. Some researches revealed that computer game involvement might change the user's stress, flow, and other emotional states [7, 8]. Although emotional states can be recognized using some nonphysiological signals like speech signal, facial expression, and body gesture [9, 10]. However, those attributes can influence individuals' social and cultural background [11, 12]. On the other hand, physiological signals are more robust and offer a direct method for emotional recognition. Since the brain signal responds strongly to any emotional stimulation, much more than other biological signals, EEG is the most prevalent emotion recognition technique [13].

EEG is a brain monitoring technique that records brain electrical activity from the scalp and provides information on mental activities and emotional states [13]. Moreover, it has been proven that EEG frequency bands correlate with emotional stimulation [14]. Therefore EEG frequency bands are one of the features which can be used for emotion recognition. Since the EEG alpha frequency considered to signify activation of cortical function and contralateral inhibitory interactions between the left and right hemispheres [15], frontal alpha asymmetry (FAA) has been using as an index for assessing both positive and negative emotions [16]. FAA usually measures by taking the band power difference of alpha frequency(8–13 Hz) over the frontal cortical regions between the left and right hemispheres [17].

In 1992, Davidson proposed a approach/withdrawal theory of emotion, he stated that both left and right hemispheres triggered according to the motivational orientation of emotional states [18]. The left frontal hemispheric activity is correlated with the approach, while the right frontal hemispheric activity is associated with withdrawal [18]. Here approach indicates the emotions related to a positive feeling and withdrawal refer to the emotions correlated with a negative feeling [13]. In addition to approach/withdrawal theory, Silberman and Weingartner, given the concept of valence theory of emotion. This hypothesis indicates that positive emotional states are related to the left frontal cortical activities , and negative emotions are related to the right frontal cortical activities [19]. The cortical brain activation negatively correlated to the Alpha activities [17]. A decrease of alpha-band power in the left frontal hemisphere reflects positive emotional information, and a decrease of alpha-band power in the right frontal hemisphere reflects negative emotional information [17].

This research aims to identify different emotional states in a smart sense built by digital gameplays' environment. We focused on analyzing the variation of the flow, stress, and the negative effects in gaming situations. The negative affects were introduced by interrupting the gameplay with Skype call ringing, and external Mouse interruptions while the users were fully immersed in the gaming situations, and stress elicited by setting game difficulties. Moreover, the flow was introduced by setting easy games and allowing users to play freely. We used the recorded EEG data and analyzed frontal alpha asymmetry(FAA). We experimented on three mid-level EEG frequency bands(theta, alpha, and beta) to compare the test subjects different states of emotions in contrast to before and after the event in each experimental phase. We observed that the EEG Alpha frequency band is more responsive than the other to characterized both positive and negative emotions. Thus, this thesis concentrated only on the EEG alpha-band power analysis for emotion recognition to measure wellbeing in a smart environment built up with the computer gaming scenario.

We selected two pairs of frontal EEG electrodes, such as F3-F4 & F7-F8. F3 & F7 are located on the left cortex, and F4 & F4 are on the right cortex. Then, alpha band powers are measured for each selective EEG channels using the Welch periodograms and estimated FAA by comparing the relative alpha frequency power levels on the left and right brain frontal regions. A higher value of FAA demonstrated the power decreases in the right hemispheres compared to the left due to negative emotions and lower FAA indicates power decreases in the left hemisphere for positive emotional responses. Our experimental result reported a significant agreement with the test subjects emotional variation, mostly negative affects during the gaming situation. We find that different interruptions during the gaming situation create irritation to the test subjects. Nevertheless, we did not observe any indication of game difficulty correlation with either positive and negative emotional responses that was supposed to happen in phase 3 to 5 according to experimental design, potential reasons for the lack of proof in assessing the stress and flow addressed in the discussion section. Furthermore, these results also unveil that F3 and F4 EEG channels are the most devoted to individual emotional responses compare to F7 and F8 channels.

The thesis outline as follows,the first chapter presented a brief introduction to the study-related analysis, issue, and motivation. Chapter 2 Emotional well-being, dissect definitions, some theories related to emotion, and addresses some researches related to different states of emotion recognition that comprise the emphasis of the analysis and the techniques used in the experiment. Chapter 3 discusses some techniques for emotion recognition. Chapter 4 EEG signal processing, provide details of the EEG signal, measurement method, artifact removal technique. Chapter 5 presents a detail of the experimental protocol and data collection procedures. Chapter 6 explains the approach taken for signal processing, feature extraction, and statistical analysis method. Chapter 7, Result, addresses the experimental and statistical results. Chapter 8, Discussion, offers an interpretation of the results and exposes the study's main limitations and possible solutions. Chapter 9, Conclusion.

2. EMOTIONAL WELLBEING

2.1. Definition of Wellbeing

Although there is no clear concept of wellbeing made yet, wellbeing usually refers to feeling positive feelings, life satisfaction at a high level, happiness, and the ability to regulate negative emotions [20, 21]. Lovén et al. [4] mentioned that wellbeing could be described by measuring six-dimensional factors including mental, emotional, physical, social, material, professional, and characterized by a balance between negative and positive affect, low levels of stress, and flow. In this work, we mainly focused on emotional wellbeing in a smart space. So emotional wellbeing briefly described in this section. Figure 1 shows six dimensions of wellbeing.

Figure 1. Wellbeing dimension according to Lovén et al [4].

2.1.1. Emotional Wellbeing

Both negative and positive feelings are related to emotional wellbeing. Usually, emotional wellbeing considered to experiencing positive feelings and the ability to cope with negative feelings successfully [20]. Emotional wellbeing is one of the critical aspects of overall wellbeing, its effects on our personal, professional relationship and makes our life happier and helps to pursue our goals more effectively [20].

Benefits of emotional wellbeing

It is as essential to focus on our emotional wellbeing as physical and mental wellbeing. Some benefits of emotional wellbeing described below.

1. **Resilience**: The ability to manage stress helps susceptibility to physical illness by impacting the immune system [22].
2. **Communication**: Emotionally healthy people usually have excellent communication skills and respond to others positively and productively [23].
3. **Self-regulation**: People with good emotional health able to handle challenging situations and continue working even under pressure [24].
4. **Motivation**: Emotionally good people are always optimistic and motivated by a sense of determination to excel in any situation [24].

2.2. What Is Emotion

Emotion is an affective state of mind in which happiness, sadness, anxiety, hate, or the like are experienced, as distinguished from the cognitive and volitional state of mind [25]. Don Hockenbury and Sandra E. Hockenbury described in the book "Discovering Psychology," an emotion is a complex psychological state combination with three components, including subjective experience, physiological response, and behavioral or verbal response [26].

Subjective experiences

Basic universal emotion such as happiness, sadness, fear, and anger are expressed by all individuals irrespective of culture or origin that experiencing emotion can be subjective [27].

physiological response

Emotions are accompanied by the physiological state of the autonomic nervous system that lead to physical symptom such as increase heart rate,respiration and sweating [28].

Behavioural response

Behavioural response is often called the outward expression of the emotion. Facial expression, body gestures, posture are the example of the behavioural responses of the emotion [28].

2.2.1. Theories of Emotion

Many theories have been proposed to define emotion. In this section, we mention some of them.

The James-Lange theory of emotion

Two famous physiologists, William James & Carl Lange, proposed a theory of emotion known as the James-Lange theory of emotion. They stated in their theory that people experience emotions due to physiological responses to external events [29].

The Cannon-Bard Theory of Emotion

The Cannon-Bard Theory of Emotion proposed by two other physiologists Philip Bard & Cannon, this theory indicated that individuals might undergo emotionally induced physiological responses without necessarily experiencing certain types of emotions. For instance, one might feel a big heart race due to exercising, and heart-racing is not only an indication of fear [30].

Valence Theory of Emotion

Emotional Valence theory first proposed by Silberman and Weingartner [19].That theory states that the pattern of emotional valence relies heavily on hemisphere dominance activation [19]. The left hemisphere predominates in experiencing positive emotions while the right hemisphere for the experience of negative emotions [19]. According to the valence theory of emotion, fear, disgust, and anxiety are the example of negative emotions, whereas joy, happiness, and excitement are considered positive emotions [19].

The Approach-Withdrawal Theory of Emotion

This theory explains the emotional model's evolutionary principles, implying that emotions are correlated to an individual's actions in its surroundings [18]. The approach method encourages appetite behavior and stimulates approach-related positive affects, such as a feeling that arises when a person gets closer to the desired goal [18]. The approach method encourages appetite behavior and stimulates approach-related positive affects, such as a feeling that arises when a person gets closer to the desired goal. The withdrawal method promotes an individual's removal from sources of aversive stimuli [18].

Both Valence and approach/withdrawal theory agree with positive and negative feelings except anger. In the approach/withdrawal paradigm, anger is classified as an approach emotion because it influences the person to defend with sources of stimulation and thus identified the same attribute as happiness [18].

Circumplex Model of Emotion

Russell, J. A [31] proposed a circumplex model of emotion in a 2D space of valence and arousal. In this 2D space, all emotional states can be defined as a linear combination of valence and arousal. For instance, stress is expressed with a state of high arousal and negative valence; on the contrary, relaxation often characterized by a positive valence with low arousal. In particular, this emotional model provides a theoretical and experimental framework for analyzing the neuronal basis of affects, also expect to support information into the neurophysiology of affective disorders. Generally, the circumplex model is used to evaluate triggers of emotional words, facial expressions, and cognitive responses [32]. Figure 2 shows the circumplex model of emotion, X-axis represents the valence states and Y-axis defines the arousal, and the centre of the model describes a neutral valence and a medium level of arousal.

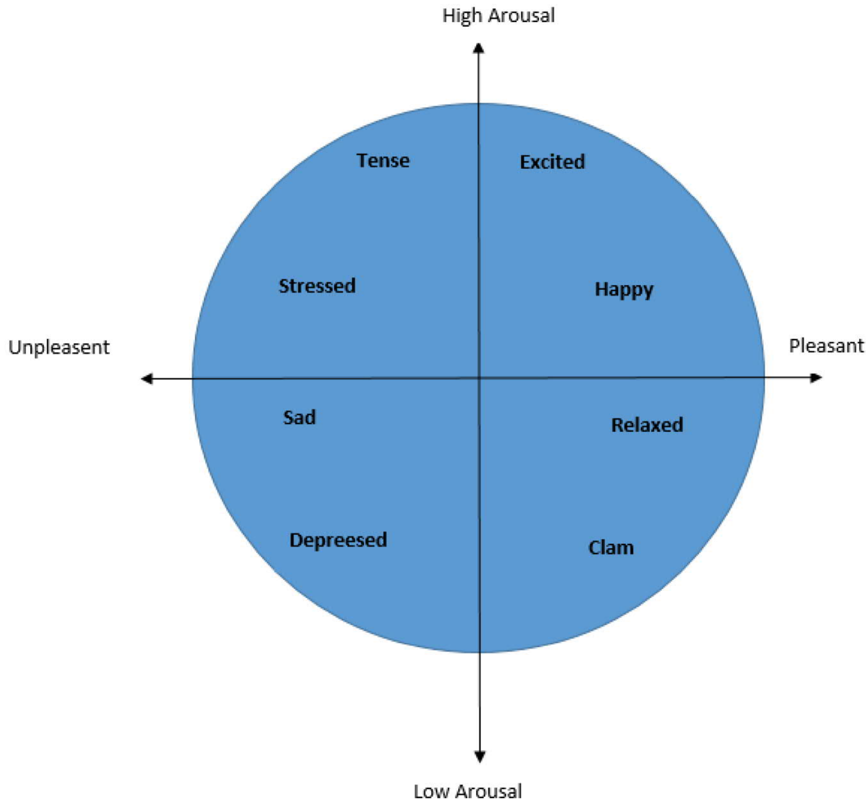

Figure 2. Russell's circumplex model of emotion.

2.3. Brain Frontal Cortex for Emotion Regulation

The human brain's prefrontal cortical area is responsible for regulating the influence of cognitive functions at a high degree which associated with controlling different aspects of the emotional states [33]. Davidson stated that the brain prefrontal cortex is accountable for an emotion-based decision-making system [34]. The left hemisphere's anterior region is related to approach behaviours or positive affects, while the right hemisphere's anterior area is correlated with withdrawal behaviour or negative emotions [33]. The two other neuro-imaging experiments suggested by Jones and Fox [35] , and O' Doherty et al. [36] have also shown this evidence. The brain prefrontal cortex is the part of the frontal cortex situated at the very front of the brain. The prefrontal cortex accounts for more than 10% of the brain volume and is thus engaged in processing different tasks [37]. Controlling short-sighted, reflexive behaviours like planning, decision-making, problem-solving, self-control, and acting with long-term goals in mind are executed in the brain prefrontal cortex [37]. The human brain anatomy is shown in figure 3, and the yellow shaded area denotes the brain prefrontal cortex used in emotion detection.

Figure 3. Brain pre-frontal cortex (yellow shaded area).

3. EMOTION RECOGNITION

3.1. Emotion Recognition

The technique by which human emotion is detected is called emotion recognition [38]. Emotion can be identified in our everyday lives by conventional approaches such as facial, voice, body gesture and text [38]. Generally, five distinct dimensions evaluate human emotional responses: Behavioral tendencies, physiological reactions, motor expressions, cognitive appraisals, and subjective feelings. The first four dimensions can be assessed automatically by measuring different body parameters or electric impulses [31]. Subjective feelings can be measured using the self-assessment method by rating the multiple questionnaires [39]. EEG, ECG, EMG, EDA, skin resistance measurements, blood pressure, and motion analysis are the most popular in the automatic emotion detection method. In this section, the most acceptable and widely used emotion recognition system is discussed.

3.1.1. EEG

EEG is the brain monitoring technique used to record the electrical from the scalp. By recording the EEG signal, brain electrical activities that respond to various stimuli typically assessed and evaluated the human emotion recognition technique. In most case, the EEG signal collected using 8,16 or 32 pairs of metal electrodes placing on the different part of the human scalp according to the international 10/20 system. Figure 4 showed the sensor position of a 32 channels EEG device, which follow the International 10-20 System. EEG sensors labelled with the letters to name after the underlying area of the brain. For example, pre-frontal (Fp), frontal (F), central (C), temporal (T), parietal (P), and occipital (O). Furthermore, the number including with this letter indicates the lateralized location of the brain, and odd numbers indicate the left hemisphere and even numbers are for the right hemisphere. In contrast, electrodes over the midline (zero lines) are labelled with the letter “z”.

Brain responses to different emotional stimuli are typically assessed and evaluate by extracting EEG frequency band, namely: delta, theta, alpha, beta and gamma. Hence EEG frequency bands relate to different emotional states, so the frequency domain indexes are widely used for emotion detection and classification methods. Focusing on the area of interest,a number of different approaches are introduced to interpret and analyze EEG signals. The statistical analysis [17], machine learning [40], deep learning methods [41] can be applied to recognize specific emotional states by utilizing various EEG features.

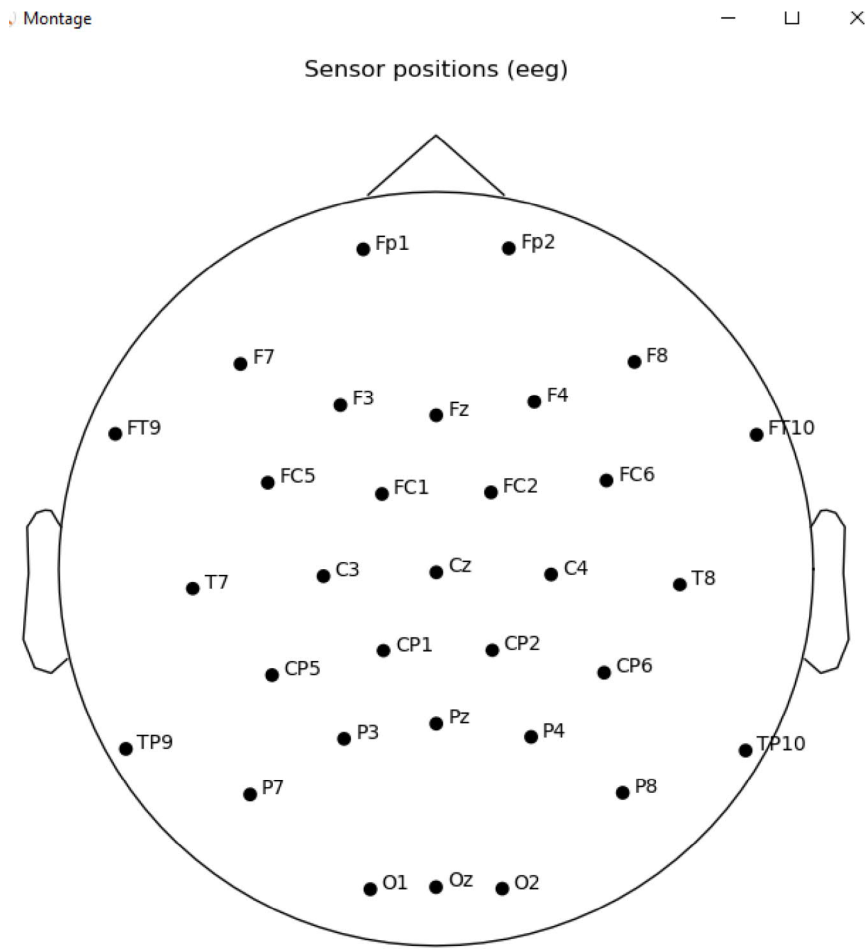

Figure 4. Sensor position of 32 channel EEG recording device.

3.1.2. ECG

ECG stands electrocardiography, a physiological signal used for the non-invasive real-time analysis of the heart's electrical activity. Since heart activity is intimately connected to the human nervous system, ECG is not only crucial to measure the functioning of the heart but also used as a technique for emotion detection [42]. QRS Complex (shown in figure 5) of the ECG is used as a feature to identify emotions. The QRS complex determines heart activity related to the human emotional state and is a useful predictor for identifying key emotions [42]. An automated emotion recognition technique, ECG signal, requires advanced and robust signal processing techniques that allow detection and extraction of the useful features from the raw signal. There is a body of literature available that focuses on individual emotion recognition utilizing various forms of feature extraction methods like rate variability (HRV) and with-in beat analysis (WIB) [42].

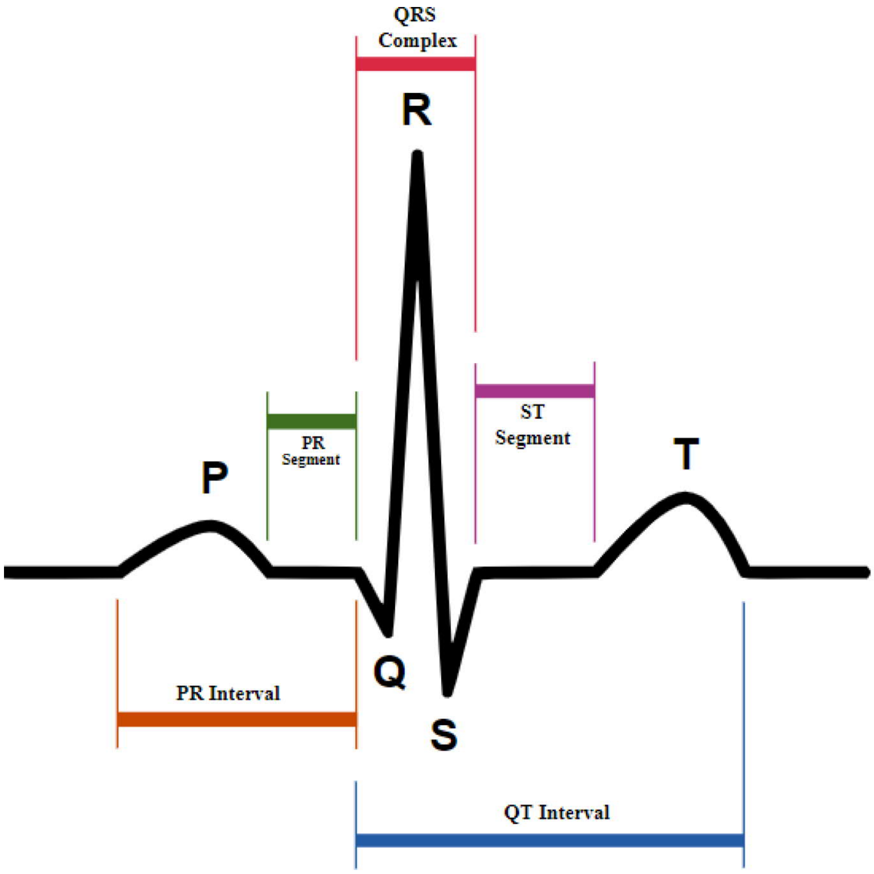

Figure 5. QRS complex shown in ECG signal [43].

3.1.3. EDA

EDA refers to an electrodermal activity that measures the skin's electrical conductance in response to sweat secretion. The skin's electrical conductance is recorded using one or two electrodes made of Ag / AgCl (silver-chloride) by placing on the skin surface. Although EDA is correlated with controlling our internal temperatures [44], it has also demonstrated an influential association with emotional arousal [45]. Generally, emotional changes trigger sweat reactions, often visible on the fingers' surface and the soles of the hands. The EDA signal is not only strongly associated with the level of arousal, but it also has a strong association with stress, excitement, engagement, frustration, and anger. Therefore the EDA signal is used as a good indicator of emotional state and its intensity.

3.1.4. Facial Expression, Speech, and Body Gesture

Research into emotion detection methods based on the study of facial expressions, voice, body posture, and gestures has gone up very significantly [9, 10]. In emotion recognition, a computer vision system and algorithm usually test and analyses facial expression, voice, and body gestures. These are very reliable technique nowadays as it facilitates non-contact measurements and provides very accurate results.

3.2. Related Work

Research related to emotion is still very prominent in many industries, including measuring wellbeing in smart space, gaming, psychology, and computer science. Since emotion is one of the critical elements of overall wellbeing, much research is still ongoing. Due to its high accuracy and objective assessment in contrast to other external expressions such as facial, speech, body gesture, methods focused on electroencephalogram (EEG) signals are more accurate among emotion recognition approaches. Various types of EEG indexes are utilizing in emotion recognition and classification method. EEG features are characterized by time-domain, frequency-domain, and time and frequency domain, the frequency -domain attributes are most accessible to the researchers.

Shon et al. [46], extracted a set of EEG features, including statistical, band power, Hjorth parameters, and frontal alpha asymmetry for emotional stress detection. This paper used a public EEG data set *Database for Emotion Analysis using Physiological Signals* (DEAP) data, the dataset was recorded using 32 channels EEG device and emotion stimulated by showing music video clip to the volunteers. Statistical, band power, Hjorth parameters are computed from all EEG channels and frontal alpha asymmetry estimated using Fp1-Fp2 by taking signal power difference between left and the right cortex. Then PCA and genetic algorithm (GA)-based feature selection method applied to select a subset of features that are suitable for stress detection and taught the selected indexes to the k-NN classifier. The result of this research suggested that the GA-based method better than PCA and well-chosen features method for emotion detection.

Other researchers also used EEG signal to classify two basic emotions-happiness and sadness elicited by showing pictures of a smile and cry facial expression [47]. In this study, they applied common spatial patterns (CSP) and linear-SVM to choose an optimal EEG frequency band and found that the ERD/ERS activities in gamma band are significant to classify happiness and sadness with high time resolution. Pane and her colleagues [40] apply Random Forest(RF) on DEAP dataset to classify happy, sad, angry and relaxed states during gaming situation of test subjects. In this research, they used six pair of asymmetry EEG electrodes which have a strong correlation with audio, visual (T7–T8, O1–O2) emotional stimuli (F7–F8, C3–C4, Cp5–Cp6, P7–P8). The Cp5–Cp6 and P7–P8 channels were used for the ERP study for emotion recognition using LPP (Late Positive Potential). For emotion recognition, solely beta frequency is operated by extracting hybrid features that consist of time, frequency (PSD) and time-frequency (wavelet)-domain. The finding of this study suggested that left hemisphere is correlated to classify happy and relaxed states and the right hemisphere is much concerned with sad and angry emotion, and also indicates RF outperform over the SVM and LDA while using three pair of asymmetry channels namely, T7–T8, C3–C4 and O1–O2 to identify those emotional states.

Zheng et al. [41] introduced an advanced deep learning model to classify both positive and negative emotions. They used 62 channels EEG device to record experimental data by showing some emotional movie clips to elicit both positive and negative emotions. The differential entropy feature calculated in five frequency bands for all EEG channels then trained and tested estimated features employing five classifiers, KNN, SVM, Graph regularized Extreme Learning Machine (GELM), Deep Belief Network (DBN), DBN-HMM (Hidden Markov Model). The experimental results show that high-frequency band (beta and gamma) features are more related to both positive and negative emotion and the DBN and DBN-HMM methods obtained higher accuracy than the other four classifiers. Teager-Kaiser Energy Operator (TKEO) is one of the useful features for EEG based emotion recognition technique. Prashant Lahane & Mythili Thirugnanam researched for detecting stress using TKEO with a k-nearest neighbour (KNN), neural network(NN) and Classification Tree (CT) classifiers based on EEG [48]. This research carried out using the DEAP data set, a bandpass filtering technique applied on EEG signal to separate alpha and beta band from FC1 and FC2 channels. KTE logistic coefficients and signal logistic coefficients calculated to generate a feature vector from FC1 and FC2. Then this feature vector is taught into KNN and NN to classify the happy and stress by comparing the TKEO feature with Relative Energy Ratio (RER), and Kernel Density Estimation (KDE) techniques regarding accuracy. The study findings revealed that the extraction of the index using the Teaser-Kaiser energy operator works well for all classifiers. FC1 channel provides the highest accuracy for the alpha band and FC2 for the beta band in stress detection.

Besides, other studies also analyze the human brain waves for emotion recognition when the persons are playing video games. In this work, they use Fp1 and Fp2 EEG channels and obtained the PSD of the alpha and beta frequency band [49]. The study compares brain wave activities before and after playing the video game. The result indicates that the PSD of alpha-band for all samples decreased after playing the game and difference of the alpha PSD slightly small in Fp2 compared to Fp1 channel, and the result is same for beta-band also. Their findings conclude that the person experiences the stress while they are playing the video game. Moreover, EEG frontal asymmetry is a more acceptable alternative for emotion recognition. EEG frontal asymmetry examined for two positive emotions (amusement and tenderness) and two negative emotions (anger and fear) using power in three bands (theta, alpha and beta) analysis [50]. Thirty-three EEG data recorded by showing some Chinese emotional movie clips and then mean band power of the theta, alpha and beta bands calculated from frontal (FP1-FP2 and F3-F4), and the midline to parietal lobe (FZ, FCZ, CZ, CPZ and PZ). The asymmetry of EEG frequency calculated by taking the band power difference from the right to the left hemisphere using the selected EEG recording channels.The study result confirms that frontal theta and alpha asymmetry on Fp1-Fp2, F3-F4 significant for positive and negative emotions, also showed that theta power at midline channels significantly identified negative emotions. In contrast, alpha and beta power at midline useful for positive emotions recognition. In short, this experiment settles that frontal EEG asymmetry and midline power can use to recognize discrete emotions described in the valence-arousal theory. Geoffrey and Schwartz [17] also confirm that that differential lateralization in frontal brain areas related to positive and negative emotion recognition, relative left-hemispheric activation is measured by decreases in alpha abundance for positive emotions and relative right-hemispheric activation for negative emotions.

4. EEG SIGNAL PROCESSING

4.1. What Is EEG

EEG stands for electroencephalogram, a physiological method for recording the brain's electrical activity from the scalp. It is the most common and fastest brain monitoring technique for evaluating several brain disorders, and this technique can be used to identify normal and abnormal brain electrical activity within a fraction of second for clinical and research purposes [51, 52]. EEG signals are typically recorded by small metal disks called electrodes placed in different locations to the scalp [51]. The electrodes receive the brain signal sent to the amplifier in an EEG machine to amplify the signals and then printed on the computer screen in a wave pattern [52]. Figure 6 shown a time course raw EEG signal recorded with EEG devices.

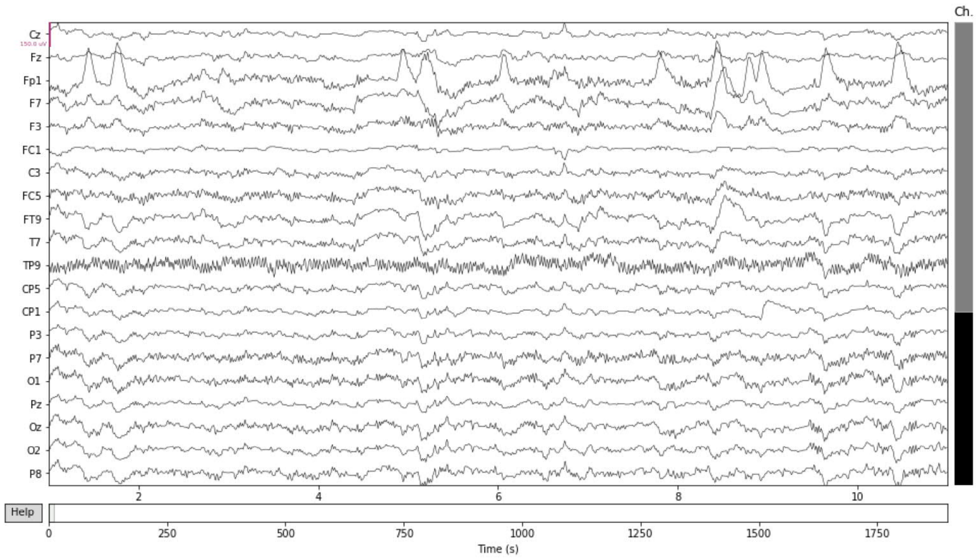

Figure 6. Example of Raw EEG signal. The vertical axis represents the EEG channels and horizontal axis indicates the time (ms).

4.1.1. How Does EEG Signal Generates

The Human brain consists of hundreds of thousands of communicative cells called neurons, which are interconnected via thousands of synapses [52]. Synapses are responsible for the inhibitory or excitatory activity of the human brain. Excitatory involves transferring information between neurons, and inhibitory refers to preventing the transfer of information from one neuron to the next neuron. [52]. Whenever a smaller group of neurons is triggered, they generate an electrical field. This electrical field strength is strong enough to spread the signal through tissue, bone, and skull, and it can be capture on the surface of the skull using small disks, which are called electrodes [52].

Generally, the human brain consists of two halves of hemispheres, namely the left and right hemispheres. Four different lobes separate each of these hemispheres, and they are Frontal, Temporal, Parietal, and Occipital cortex. Every lobe of both hemispheres in the human brain is responsible for processing information in EEG signal [53]. Among the four lobes, the Frontal lobe is the largest part of the hemisphere, located just behind the forehead. This frontal lobe involves the response of a person's emotions, behavior, Judgment, planning, problem-solving, personality, memory, Body movement (motor strip), language, intelligence, concentration, and self-awareness [54]. The parietal lobe is situated behind the frontal lobe and engaging in processing different sensory information, like Sense of touch, pain, temperature (sensory strip), interprets signals from vision, hearing, motor, sensory and memory, spatial and visual perception [54]. Occipital is worked to process visual information, and Temporal is related to sound, speech, and various aspects of memory [53].

4.1.2. EEG Signals Characteristic

Many more variables depend on categorized EEG signals such as frequency, amplitude, continuity (rhythmic, intermittent or continuous), synchrony, and electrodes position [55]. Among these, the most familiar and frequently used method is the frequency-based category. According to this EEG, the waveform can be classified into five distinct types:-

Delta:

Delta rhythm lies in the frequency range between 0.5 Hz to 4 Hz. It is the slowest wave with the highest amplitude. Delta waves customarily appear when a person is in most profound meditation and dreamless sleep and also involved in unconscious bodily function [53].

Theta:

The theta brain wave oscillates between 4Hz and 8 Hz (cycles per second), which is associated with creativity, emotional connection, intuition, and relaxation. Having too low theta may lead us to experience anxiety, poor emotional awareness, and stress, and too high frequency indicates attention deficit hyperactivity disorder (ADHD), depression, hyperactivity, impulsivity, inattentiveness [53].

Alpha:

This brain wave is commonly seen in adult persons when they are awake but relaxed with closed eyes, and it is disappeared with an opening eye. The alpha waves lie in the frequency range between 8 to 13 Hz [53].

Beta:

It is known as a high-frequency brain wave with a low amplitude, which oscillates between 13 Hz and 30 Hz. Beta waves are commonly involved in conscious thought, logical thinking, and stimulating affect [53].

Gamma:

This frequency band is invented after the development of digital EEG device, since the frequency of this brain wave is more than 25Hz, so it was not possible to record and measured with analog EEG devices. Among the other brain waves, the gamma is the fastest brain waves with small amplitudes [53].

4.1.3. EEG Use Case

Since the EEG considered a safe and comfortable brain monitoring method, which is why it has many uses in the various fields of application. In this section, some of its use cases have been discussed.

Wellness Technology

Nowadays, EEG gained popularity among athletes, biohackers to track their brain activity. They use this technology to measure their cognitive functions—such as attention and distraction, the stress in daily life events. By getting feedback from EEG data they can design scientifically informed strategies to reduce stress, improve focus or enhance meditation [56].

Healthcare

EEG has been playing a significant role in the healthcare sectors to diagnosing brain disorders such as brain dysfunction, head trauma, sleep disorders, memory problems, brain tumors, stroke, dementia, seizure disorders [56].

Sleep Monitoring

EEG can be used to measure a person's polysomnography. The term polysomnography used to diagnose sleep disorders. The polysomnography is usually done to monitor overnight sleep patterns, heart rate, breathing, and oxygen saturation levels [56].

Academic Research

Researchers are extensively using EEG technology to study mental disabilities, cognitive psychology, neuroscience, etc. Recent advances in computer hardware and processor technologies have created an opportunity to extend current understanding of the human brain functioning and to explore the basic neuronal processes involved in behaviour, perception, or emotional regulation that remain previously unexplained [52].

4.2. EEG Signal Recording.

EEG signal recording method comes with following:

4.2.1. EEG Electrodes

The EEG electrodes are one of the most crucial components to collect brain electrical activity. These are typically metal disks or pellets made of stainless steel, tin, gold, or silver place on the skull using conductive gel, paste, or saline. There are two types of EEG recording electrodes commercially available, wet and dry electrodes.The most common wet electrode is Ag/AgCl, which made of silver (Ag), and silver chloride (AgCl) layer. On the other hand, dry electrodes can be used for the same purpose directly on the skull without requiring electrode gel [57].

4.2.2. Electrode Placement

The 10/20 system is the most common standardization for the electrode placement system. In 1958, the International Federation in Electroencephalography and Clinical Neurophysiology had proposed this standardization based on an electrode location and the underlying area of the cerebral cortex [58]. The numbers 10 and 20 indicate the distance between the electrodes from skull landmarks (nasion, preauricular points, inion). According to this system, the inter-electrode distance would be either 10% or 20% of the total front-back or left-right [58]. Electrodes labeled according to the brain region or lobe: F (frontal), C (central), T (temporal), P (posterior), and O (occipital) along with the number. The odd number indicates the left hemisphere, and even number indicates the right hemisphere, and "Z" stands for zero refers to electrodes position over the midline central brain regions [57].

4.2.3. Number of Electrodes for Recording

There is no fixed optimal number of electrodes for EEG recording. It depends on the actual results and findings. The number of electrodes for the experiment can be 3 to more than 128 channels.

4.2.4. Electrode Impedance

Dead skin and scalp sweating, oily skin secretions (sebum), can obstruct brain electrical activity propagation.The obstacle of this electrical activity technically expresses as impedance, which is measured in units of Ohm (Ω).Therefore, to collect good quality EEG data, it is essential to keep electrodes impedance as low as possible. Impedance can be minimized by adequately cleaning all electrode sites with alcohol and applying an appropriate amount of electrode gel or saline [57].

4.2.5. Signal Digitization, Amplification and Forwarding

Within an active brain, there are continuous fluctuations and changes in the voltages produced by an ionic current within the neurons [57]. The generated voltage collected by the electrodes and passes to the amplifiers to amplified and digitized. After that, this amplified and digitized signal is transmitted to the recording computer through a wired connection (e.g.via USB) or wirelessly (e.g., via Bluetooth) [57].

4.3. EEG Artifacts

The recorded EEG signals that are come from other sources rather than cerebral is termed as EEG artifact. Mainly there are two types of EEG artifacts, the physiologic artifacts and extra physiologic artifacts. The physiologic artifacts generated from the different parts of the subject body while extra physiologic artifacts arise outside of the subject body.

4.3.1. Physiologic Artifacts

As the physiological artifacts come from the patient body itself, it can be categorized as intrinsic artifacts [59]. Here, we also include a short overview of some significant physiologic artifacts.

Muscle artifacts

Muscle activity is a very common artifact of the EEG signal. This kind of activity, also known as an EMG signal (Electromyogram). Notably, the EMG signals (shown in figure 7) generated due to facial muscles' movements like forehead, cheek, mouth, neck muscles, and jaw musculature. Usually, the duration of muscle activity is shorter

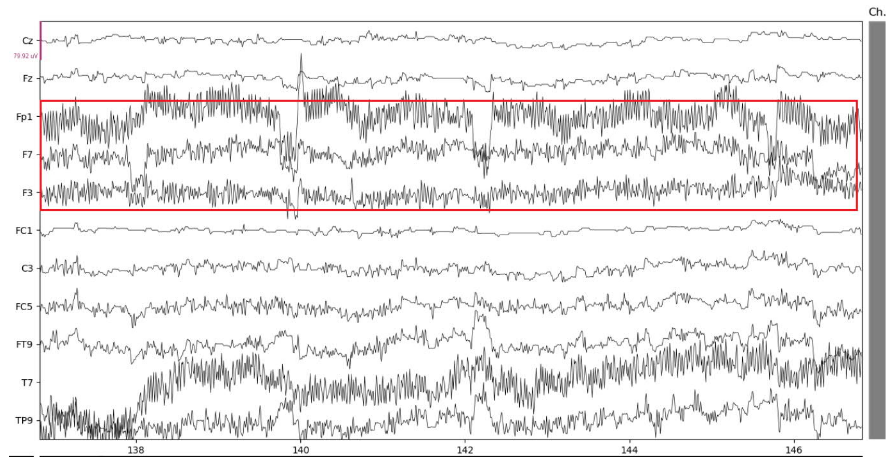

Figure 7. EMG artifact (identified in the red rectangular box) mixed with the raw EEG signal.

than the brain activities so, it can be identified quickly based on duration, morphology, and frequency [60].

Eye movements

Eye movement is a very common artifact seen in the recorded EEG signal. The human eye generated a strong electromagnetic field by firing the millions of neurons in the retina [57]. This electromagnetic field also generated an electrical activity that is distinct from the brain's electrical activity. Eye movement artifacts can be two types, horizontal and vertical. The vertical eye movements look like a sinusoidal wave, while horizontal eye movements appear box-shaped (figure 8).

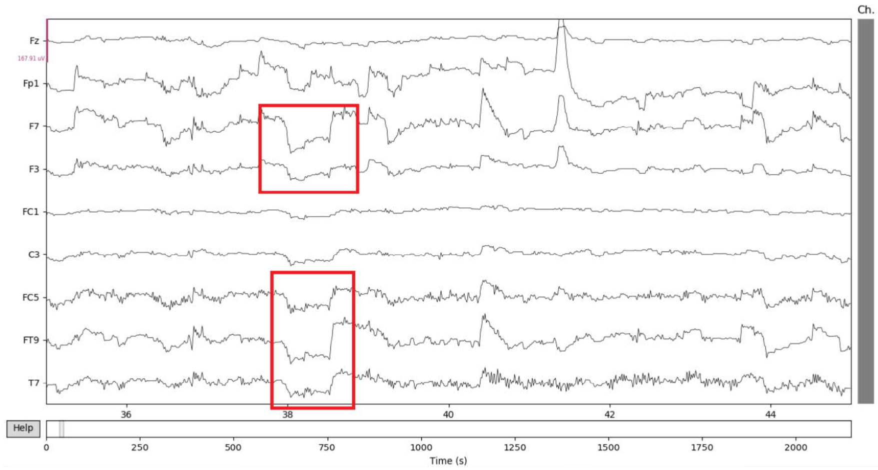

Figure 8. Eye movement artifacts usually seen in frontal electrodes.

Eye Blinks

The eye blinking and eye movement artifacts are also known as an electrooculogram (EOG) that can be propagated on the head scalp and recorded by the EEG electrodes. The reason behind generating eye blink artifacts is ocular conductance, created by the alterations of corneal interaction with eyelid [59]. Generally, the amplitude of EOG is higher than the EEG signal, but its frequency is same as EEG [59]. The eye blinking artifacts displayed in the figure 9.

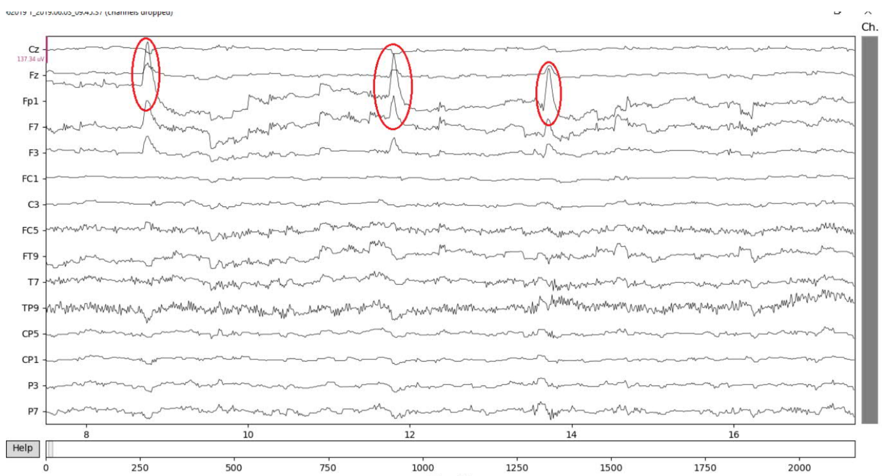

Figure 9. Eye blink artifacts.

4.3.2. Extra Physiologic Artifacts

The extra physiologic artifacts come from external sources like environment and experimental error. For this reason, these artifacts are classified as extrinsic artifacts [59].

Instrumental artifacts

The electrodes and headsets movement can cause this type of extrinsic artifacts visible in the affected channel or all channels. Appropriate procedures and planning can eliminate these artifacts. Before starting to record EEG activity, it is imperative to make sure that the headset sits snug on the scalp, and all electrodes are securely contacted with the skin. An example of the instrumental artifacts shown in the figure 10.

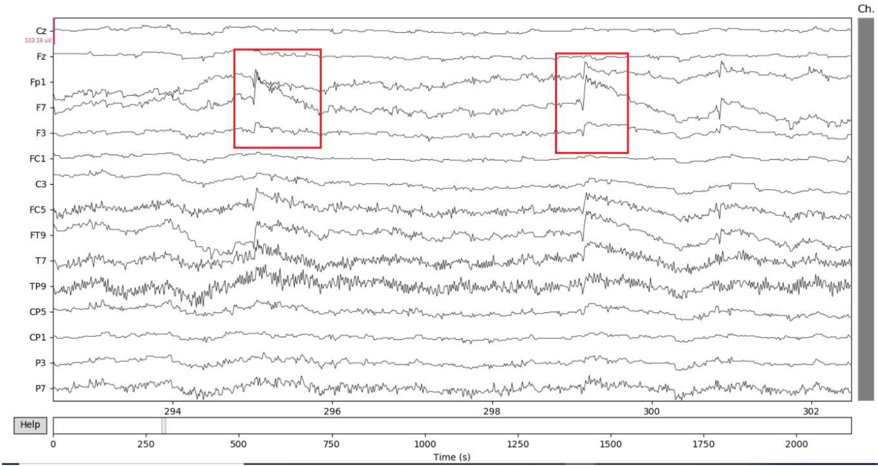

Figure 10. Instrumental Artifacts.

Power Line Artifacts

The frequency of the power line artifact is 50Hz in the EU and 60 Hz in the US. It is potent and quite apparent artifacts (figure 11) in the raw EEG signal. This artifact arises when electrodes' impedance is reduced, and line noise became stronger and generated artifacts [57], and this kind of artifact very frequent in the EEG signal. Since the brain's cognitive frequencies are often below the power line frequencies, and it is straightforward to get rid of this noise from raw EEG data. The lowpass filter with a cutoff below the line frequency (50 or 60 Hz) and notch filters are a common technique to remove this artifact.

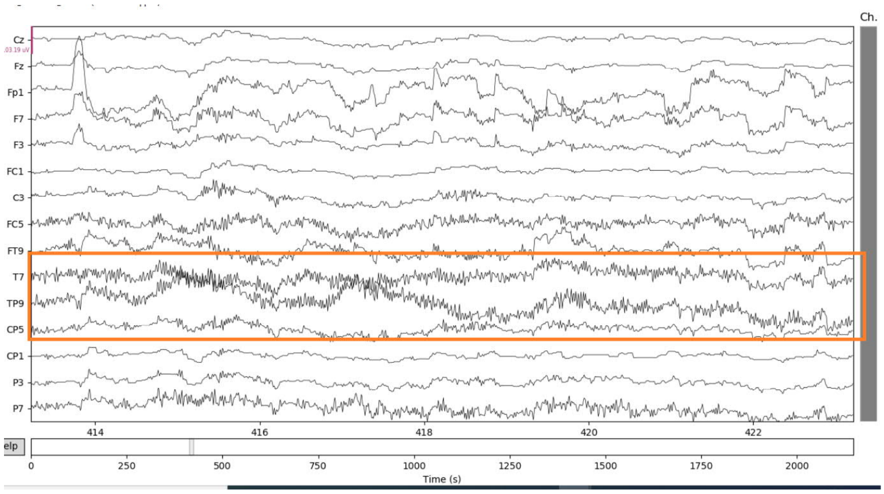

Figure 11. Power-line Artifacts shown in the yellow rectangle box.

Head Swinging

The head swinging and swaying can create a powerful artifact on the recording EEG signal. It is recommended not to turn the patient or subject head too fast or look up or down abruptly during recording. Since this artifact can shifts in the data so it will be too hard to take care of during processing [57]. In figure 12, head swinging artifacts in the EEG is shown.

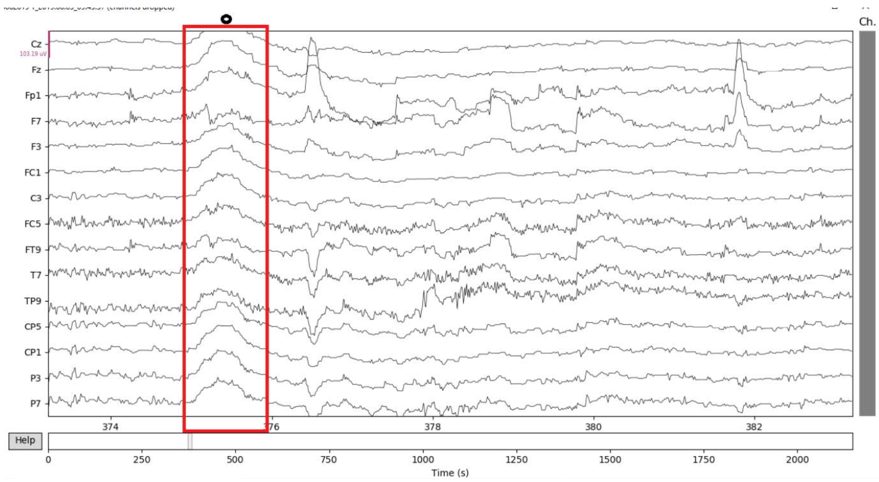

Figure 12. Head Swinging Artifact.

4.4. Artifacts Removal Techniques

A lot of general techniques have been used to remove or separate EEG artifacts from raw EEG data. Generally, we can use classical filtering techniques -such as low, high, bandpass filter, Etc. However, this method is usually done whenever the artifact's frequency bands and the desired signal do not overlap. When the EEG spectral is overlap with the artifact, this technique will not be sufficient,in this situation alternative techniques must be adopted [61].

4.4.1. Regression Methods

Regression Methods is one of the oldest EEG artifact removal methods. Hillyard and Gallambos have first proposed the time domain regression method; later on, Whitton et al. proposed another regression method based on the frequency domain, and these two methods were combined with EEG detection software [59] to clean up the signal. The regression algorithm is applied based on the assumption that each channel is the cumulative sum of pure EEG data and a proportion of artifact, which can be defined as the amplitude relationship between the reference channel and EEG channel [59]. In mathematics, this algorithm can express as:

$$EEG_{\text{corr}} = EEG_{\text{raw}} - \gamma F(HEOG) - \delta F(VEOG) \quad (1)$$

Where (γ) and (δ) are the transmission factors of EOG and EEG respectively. EEG_{corr} represents the clean EEG data and EEG_{raw} define the raw EEG data. HEOG and VEOG indicate horizontal and vertical EOG signals. Although, blind source separation-based methods are gained popularity to the researchers but still regression-based algorithms used as a gold standard to assess the performance of the new approach [59].

4.4.2. General Filtering Techniques.

Filter

The filter refers to a circuit designed in a way to separates one frequency or range of frequencies out of a combination of various frequencies in a circuit.

Low Pass Filter

A low-pass filter is a digital filter that allows passing frequencies that are lower than the cutoff frequency (edge of frequency) and attenuates the frequencies that are higher than the cutoff frequency [62].

High Pass filter

It is just the opposite of low pass filter, i.e., .which allows to pass frequencies higher than the cutoff frequency (edge of frequency) and attenuates the frequencies that are lower than the cutoff frequency [62].

Band Pass Filter

The bandpass filter works in between highpass and lowpass filters. It means it passes frequencies within a specific range and attenuates the frequencies outside in that range [63].

Notch Filter

A notch filter is a bandstop filter used to attenuate a narrow range of frequencies [63].

4.4.3. Advance Filtering Methods

Several filtering methods can be used in artifact removal techniques from the raw EEG, for instance, adaptive filtering, Wiener filtering, and Bayes filtering. Here two most common filtering methods are briefly illustrated:

Adaptive Filtering

It is a digital filtering method based on the assumption that the desired signal s(n) and the artifact v(n) are uncorrelated [61]. In this filtering technique, an artifact reference is used as one of the inputs originated from undesired electrophysiological signals, for example, EOG, EMG. By iteratively adjusting the weights factor of the filter generates a signal $\hat{v}(n)$, which is associated with the original artifact signal v(n) from a reference signal u(n) [61]. Then the artifact that is estimated from the system is then subtracted from the recorded signal x(n), and the residual $\hat{s}(n)$ is an estimate of the original signal s(n) [61]. In this system, some optimization algorithm is used to update its

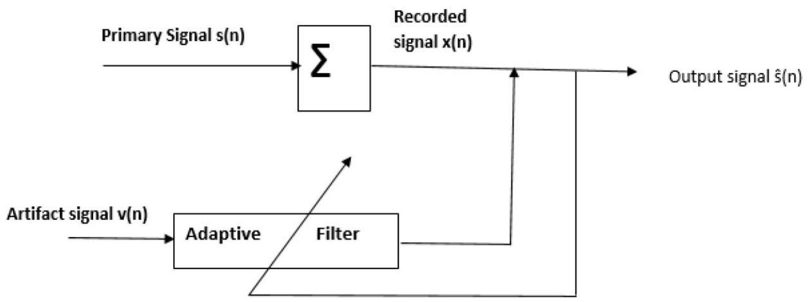

Figure 13. Functional diagram of an adaptive filter.

weight parameter like least mean squares (LMS) or recursive least squares algorithm (RLMS). RLMS is much faster than LMS but requires a high calculation cost [59]. Although the implementation of adaptive filtering is easy, it can operate in-line and without prepossessing or calibration [61], but this system has disadvantages because the system needs to provide additional sensors for reference inputs. Functional diagram of the adaptive filtering technique is shown in figure 13.

Wiener Filtering

Wiener filter is also an optimal filtering technique that operates based on a linear statistical filtering approach to remove unwanted artifacts[59]. In this filtering technique, it is assumed that the desired signal and the artifacts are uncorrelated with each other, and it also assumed that the original signal and the artifact are stationary linear stochastic processes with known spectral characteristics [61]. This filter generates a linear time-invariant filter to minimize the mean square error between the actual desired signal and the estimated signal by estimating power spectral densities (PSDs) of the signal and the artifact [61] since there is no prior knowledge on the PSD so it must be estimated from measurements [61].

4.4.4. Wavelet Transform

Wavelet transform is widely utilized in digital signal analyzing and processing mechanisms. It transforms a time-domain signal into time and frequency domain signal. From this time-frequency signal, a set of wavelet coefficients are encapsulated for non-stationary signal analysis [59]. The time-frequency transformation is accomplished by selecting the subsets of the scales (t) and the time shift (k) of the mother wavelet ($\Psi(t)$). Mathematically it can be written as:

$$\Psi_{\text{j,k}} = 2^{(\frac{j}{2})}\Psi(2^{j}t - k) \tag{2}$$

where *j* and *k* are integers. Then the wavelet transform can be expressed by:

$$\Psi_{\text{j,k}}W = \langle f, \Psi_{\text{j,k}} \rangle \tag{3}$$

The above equation indicates the inner product of the time-domain signal and wavelet function. The DWT (discrete wavelet transform) derived from continuous wavelet can be applied when the input signal and the decomposition can be expressed as:

$$X_{\text{a,L}}(n) = \sum_{k=1}^{N} X_{\text{a-1,L}}(2n - k)g(k) \tag{4}$$

$$X_{\text{a,H}}(n) = \sum_{k=1}^{N} X_{\text{a-1,L}}(2n - k)h(k) \tag{5}$$

Here *g(k)* and *h(k)* are refer to a low pass and a high pass filter respectively.Moreover, these filters generate a low-frequency high-frequency component. Then thresholding is applied to this decomposition signal to remove the artifacts signal and to get the reconstructed clean EEG signal [59].

4.5. Blind Source Separation (BSS)

Blind Source Separation is a class of unsupervised learning algorithms developed and applied to digital signal processing to separate the original signal from a mixture of signals [61]. This algorithm is beneficial when both the sources and the mixing methodology are unknown; only mixture signals are available without prior information [61]. This methodology can be expressed as follows:

$$X = AS \tag{6}$$

Where *"X"* is the original signals obtained from scalp electrodes,and *"S"* is the combined source and artifact signal.*"A"* refers to the unknown matrix of source signal *"S"*. The BSS can be written as:

$$U = WX \tag{7}$$

Where *U* is the estimation of the original sources, and *W* is the unmixing matrix. When the original sources' estimations are known, then the corresponding sources of the artifact signals can be removed [61]. In this section, some BSS algorithm has been described that is usually adopted in EEG signal processing.

4.5.1. Independent Component Analysis (ICA)

Raw EEG signals are often contaminated with some other undesired signals like eye movements, blinks, muscle, heart, and line noise, which cause a severe problem to EEG interpretation and analysis. There are several algorithms have been proposed to remove eye movement and blink artifacts from raw EEG. ICA-based artifact removal method is an acceptable method to the researchers that helps to separate and remove a wide range of variety of artifacts from the raw EEG data [64]. This technique works based on the assumption below:

1. The cerebral and artifactual sources are statistically independent of each other and instantaneously mixed [59].

2. The dimension of the original signal will be greater than or equal to the source signal [59].

3. The signal source will be non-Gaussian. Alternatively, only one source can be Gaussian [59].

As we know, the acquisition of biomedical signals is non-linear instantaneous; therefore, a Convolutive ICA (CICA) was proposed to approach considering weighted and delayed contributions of signals [65]. On the contrary, for ICA implementation, the source of estimate original signals must be non-Gaussian; it is not always possible to know that the signal sources are Gaussian or non-Gaussian [59]. Figure 14 and 15 presenting the raw EEG with eye blinking artifacts and filtered EEG signal in where artifacts were removed using ICA respectively.

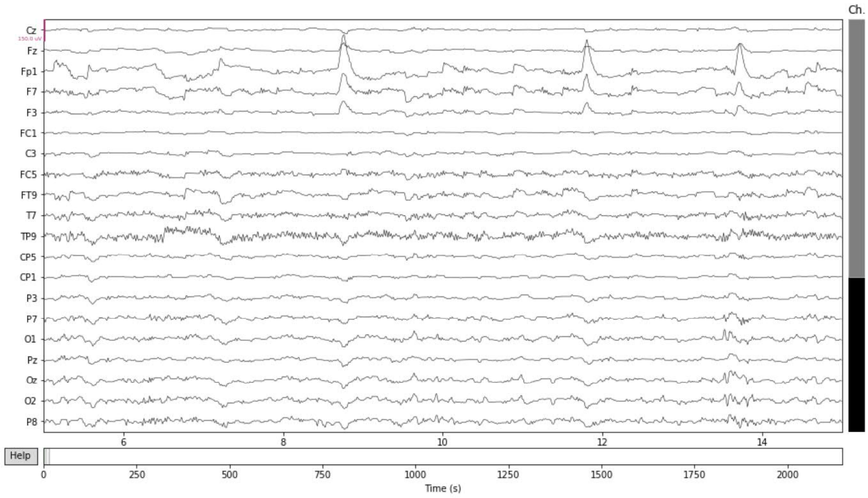

Figure 14. Raw EEG signal including eye blink artifacts.

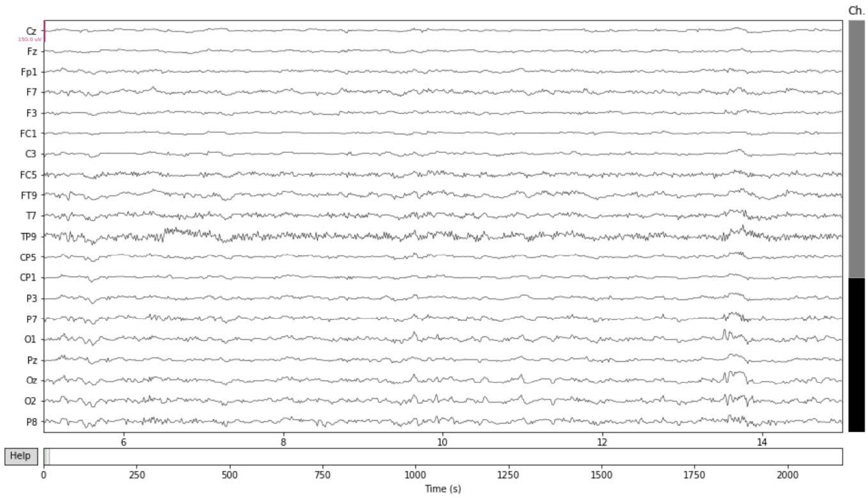

Figure 15. EEG artifacts removed by ICA using *Infomax* algorithm.

4.5.2. Algorithm for Independent Component Analysis (ICA)

Some accessible and widely acceptable algorithms have been developed depending on running time, allocated memory of the system, accuracy, and scalability of implementation [66]. Here two widely used algorithms have been introduced:

Hyvarinen's fixed-point algorithm (FastICA)

FastICA is one of the classical ICA algorithms often used in 'real time' applications and can solve a maximum likelihood estimation problem [67]. FastICA converges quickly and uses kurtosis for the estimation of the independent components [67]. This algorithm applied after performing the whitening on the data set [67]. Algorithm of FastICA is as follows:

1. Initialize w_{i} in a random.

2. w_i^+ =E(∅ $(w_i^T X)w_i$ -E(x∅$(w_i^T X)$) .
3. w_i = $\frac{w_i^+}{w_i^+}$
4. for i = 1,go to step 7, ELSE continue with step 5,
5. w_i^+ =$w_i - \sum_{j=1}^{i-1} w_i^T w_i w_j$
6. Repeat step 3.
7. If not converged, go back to step 2. Else go back to step 1 with i = i + 1 until all components are extracted

Infomax

It is a widely used algorithm in neuroscience-based on the maximization of entropy, which presents a natural gradient for the computation of the independent components.The mathematical formula for the neural learning method can express as:

$$W(t+1) = W(T) + \eta(t)(I - f(s)s^T)W(t) \tag{8}$$

Here $\eta(t)$ is a learning-rate function, and f(s) is a function that depends on the nature of distribution, such as super-Gaussian or sub-Gaussian. Here, W defines as a random matrix [66].

4.5.3. Statistics Used for ICA Analysis

Skewness, Kurtosis, and variance are very used statistics to compute ICA for EEG data.

Kurtosis

Kurtosis is one of the classical statistics to measure the non- gaussianity of data to use ICA implementation. It is a fourth-order cumulant and can be defined as:

$$kurt(y) = E\{y^4\} - 3(E\{y^2\}^2) \tag{9}$$

Here, *y* considered as a random variable that has zero-mean and variance equal to one and also assumed that *y* is the unit variance, so the right-hand side of the equation 9,can simplify to $E\{y^4\} - 3$. That means that Kurtosis is merely a simplified variant of the fourth Ey^4. For a gaussian y, the equation becomes $kurt(y) = 3(E\{y^2\}^2)$. Therefore Kurtosis is zero for a gaussian random variable and non zero for nongaussian random variables [68]. On the contrary, Kurtosis can be positive or negative. The negative Kurtosis is called subgaussian, which typically has a flat probability density function. Moreover, the positive Kurtosis is called super gaussian, in which the probability density function is spiky [68]. The absolute value of Kurtosis is used as a measure of non-gaussianity in ICA. In computational and theoretical aspects, Kurtosis can be estimated simply by using the fourth moment of the sample data.

Skewness

Skewness is the other statistic used in ICA, which measures are the degree of distortion from the symmetrical bell curve in a probability distribution. Unlike Kurtosis,Skewness can be positive or negative. When the degree of skewness greater than zero, it is called the distribution is positively skewed. Conversely, when the degree of skewness less than zero, then distribution is called negatively skewed. Negatively skewed distribution means that the left tail is long relative to the right tail, and positively skewed distribution indicates the right tail is long relative to the left tail.

Variance

Variance is a statistic that measures how far a set of random variables are spread out from their average value. It is equivalent to a second-order cumulant of a probability distribution and mathematically define as:

$$var(x) = E[(x-\mu)^2] \tag{10}$$

where x is a random variable and μ is the mean of variable x.

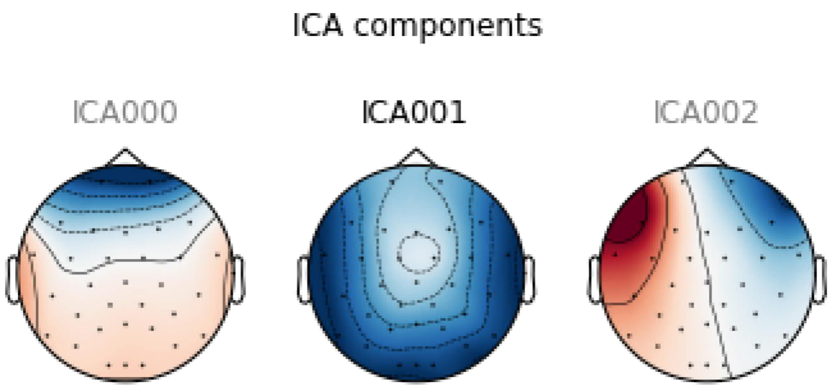

Figure 16. Artifact components detected by using skewness, Kurtosis and variance (left to right) in ICA analysis. Sensor positions of the artifact signal in where the artifact is generated.The dark blue represent heart signal and dark red identified the EOG signal.

4.5.4. Principal Component Analysis

Principal Component Analysis(PCA) is first proposed by Berg and Scherg to separate the EOG signal from raw the EEG signal [59]. PCA is one of the most straightforward and computationally efficient BSS techniques, which algorithm developed based on the covariance matrix's Eigenvalues. In PCA, the algorithm first converts correlated variables into uncorrelated variables using orthogonal transformation, called principal components (PCs). The PCs of EEG signals is implemented using Single Value Decomposition (SVD). Then the artifact is rejected by the related components through an inverse operation [59].

5. DATA DESCRIPTION

5.1. Game Selection

The study aims to analyze the individual emotional wellbeing in smart space, especially stress and flows and affect. As a part of our experimental procedure, we selected one of the most familiar and comfortable games called the *Bubble Shooter*[1] (figure 17) to elicit the subjective emotional state. We have chosen this game so that a player quickly adopts in the digital gaming system and adjusts to induce variation in the players' stress, flow, and affect by modifying the speed, difficulty, and the strategy settings of the game. In this game, the player has given the challenge to clear all bubbles. To clean up all the bubbles, the player needs to make a group of 3 or more bubbles of the same color and hit these with other same color bubbles. Once the player would have enough bubbles underneath the group, he/she can remove the top bubbles, and the entire row of bubbles will have vanished. When a row of bubbles is clean, a new row will be formed on the top and moves the whole bubble field 1 row down. This task can be done very fast. Otherwise, if the bubbles touch the bottom of the screen, the game will over.

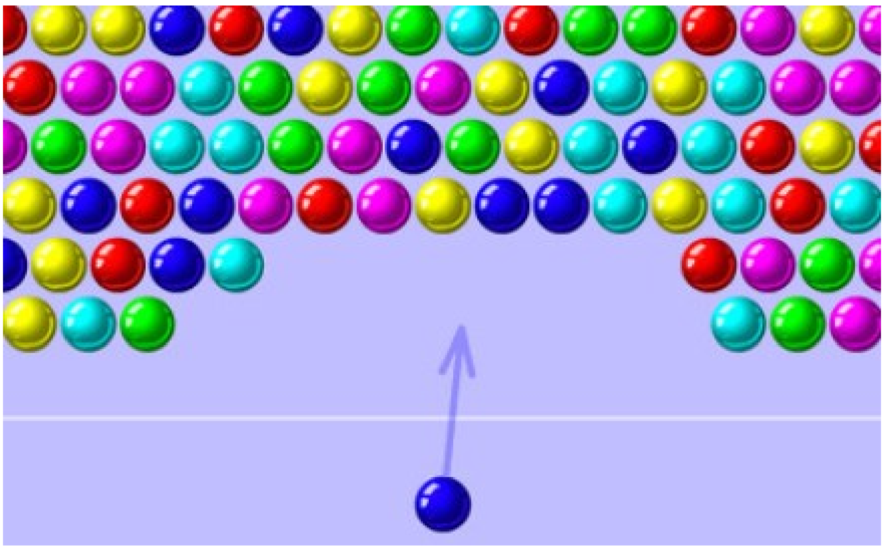

Figure 17. Screenshot of Bubble shooter game.

5.2. Subjects

We selected eighteen healthy volunteer subjects, both male and female, for the data collection procedure. Most of the volunteers were researchers from the University of Oulu, Finland, but they come from different nationalities. All subjects were right-handed between the age of 20 and 45 years with no history of mental illness, brain injury, and psychiatric disorders. Before this experiment, we explained the volunteers all about our experimental producers and purpose of this experiment and given a

[1] https://www.bubbleshooter.net/original-bubble-shooter/

questionnaire from where they were asked about their age, gender, whether they had any head, brain injury, neuralgic or chronic diseases, and taken the written consent.

5.3. Experimental Devices

Emotiv EPOC Flex kit (shown in figure 18) was used for acquiring the EEG data in this experiment. This Flex kit comes with an EEG head cap, including 32 channels EEG recording electrodes (plus CMS/DRL references). The electrodes' placement was located on the scalp according to the international 10-20 system, as shown in the figure 19. To record the EEG signal, Emotive EPOC Flex uses the sequential sampling method with a single ADC at a resolution of 14 bits and a sampling rate of 128 Hz[2]. Emotiv EPOC Flex is convenient to use as it has wireless connectivity, relatively cheap, long-life battery support, and can be visualized a real-time EEG signal using EmotivePRO software.

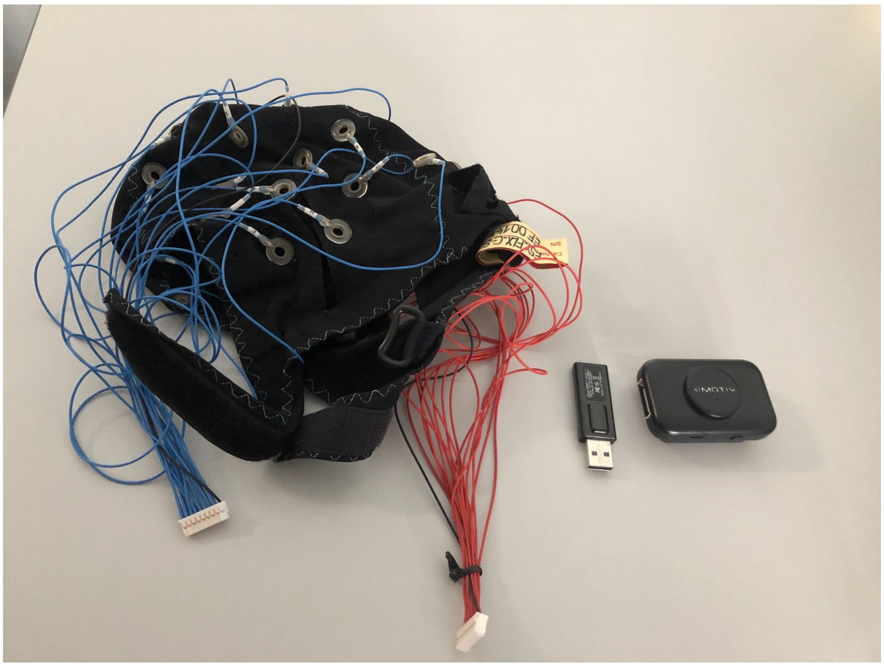

Figure 18. 32 channels Emotiv EPOC Flax Cap.

[2]https://emotiv.gitbook.io/epoc-flex-user-manual/epoc-flex/technical-spec

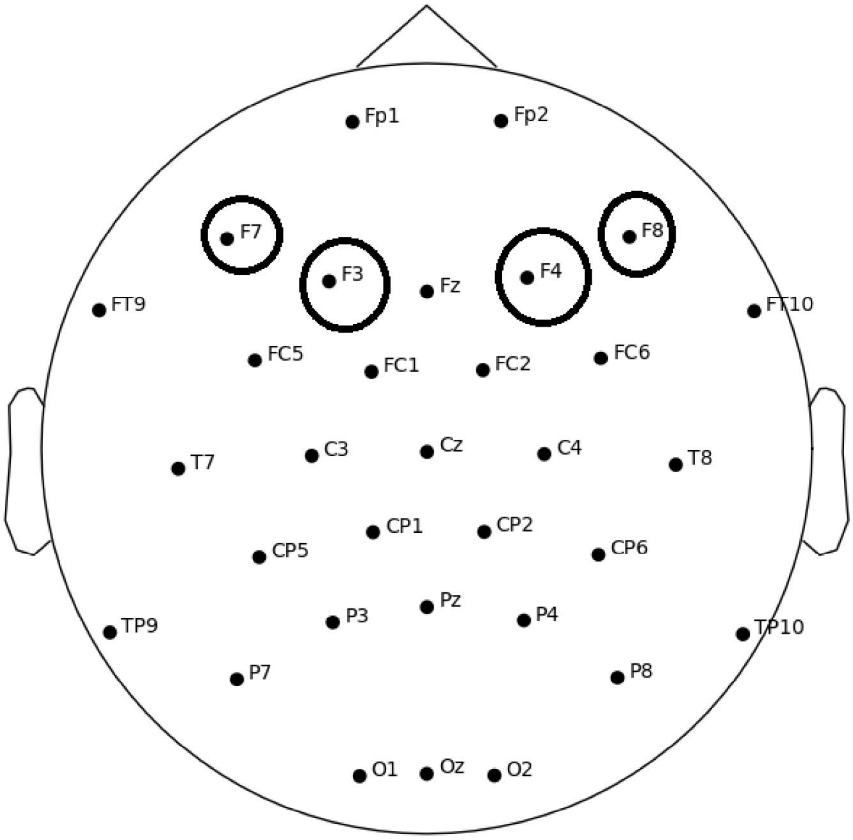

Figure 19. The channel location used in the Emotive EPOC Flex cap. And four selected EEG frontal electrodes used for feature extraction method.

5.4. Environment Setting

This experiment was done in a room that was equipped with a large LED screen with mouse control, and two laptop one is used for operating EmotivPro software and the other one used for controlling the video game by a researcher. Two cameras were used, one is placed infront of the subject, and the second camera is positioned right behind the researchers. Two researchers were in this room and situated behind the subject. One researcher was involved in instructing the test subject, monitoring the sensors, and adjusting the game settings while the other researcher collects user feedback with queries. Game playing scenario and data collection procedure are presented in figure 20.

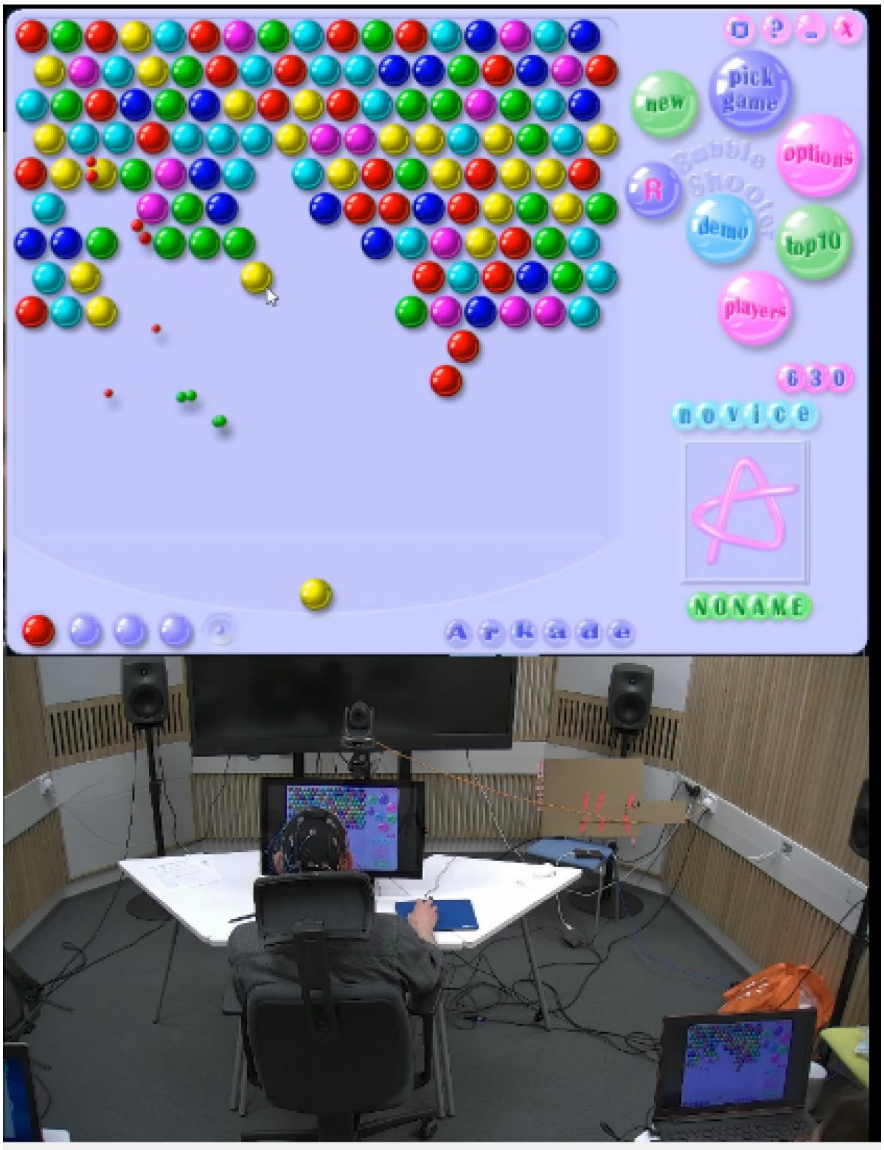

Figure 20. Experimental setup for data collection.

5.5. Course of Measurement

The experiment consisted of six main phases from 0 to 5:

- Phase 0, the player was allowed to play freely to get familiar with the game. Target is in the immersion of a player into the game, as well as flow inducing.
- In phase 1, the gameplay was interrupted with a Skype call ringing to reduce the game player's flow.
- Phases (2 and 3), the game was further interrupted by external control over the mouse to create difficulties for playing; the target was to increase stress and induce the negative affect.

- Phase 4, the player had given the challenge to win the game. In this phase, the game was set in a way that the player will certainly lose. The aim of this phase to increase player stress levels.

- Phase 5, an easy game which allows the subject to cool off.

Table 1. Experimental protocol proposed by Halkola et al. [6].)

Phase	Time (min)	Comments
0	3-5	easy game, warm-up
1	8-10	easy game, Skype call while playing
2	8-10	easy game, external control of mouse
3	5-10	difficult game, losing
4	3-8	difficult game, losing
5	5-10	easy game, winning, cool-off

5.6. Self-Report Measurements

A set of questionnaire was filled by the test subject after each phase of this experiment to measure their current emotional state(stress, flow, and affect). For knowing the positive, negative emotional affect we used PANAS [69] and for arousal, valence we followed Self-Assessment Manikin (SAM) queries [70]. We also designed a simple self-assessment questionnaire(SSAQ) scale to measure overall happiness, stress, flow, negative affect and attention, and flow-related questions.

5.7. Synchronization.

The software was used for both Mood Metric ring and heart rate readings in a smartphone because they share that very same reference time. Moreover, the same smartphone was used for EEG data time synchronization. When an event was started, the smartphone was tilted on specific EEG measurement electrodes, which created a marker in the EEG signal and other wearable sensors. The same job was done when the event was finished. Moreover, when the smartphone was tilted, it consecutively generated a number shown on the phone screen (figure 21). It recorded the time of the experimental event, and also video recording helps in time synchronization. In addition to this, we also created markers in the raw EEG data with EmotivPRO software's help. A graphical user interface(GUI), MNELAB[3] used to visualize the raw EEG signal that also helped in time synchronization (figure 22). From the video recording data, we found out the specific EEG electrode is where the mobile phone was tilted. Then we exported the time of the experimental event from the mobile phone. We carefully look up the raw EEG data on the MNELAB GUI and EmotivPRO software to figure out the tilted artifacts and mark them as the starting or ending point of the experimental events.

[3]https://pypi.org/project/mnelab/

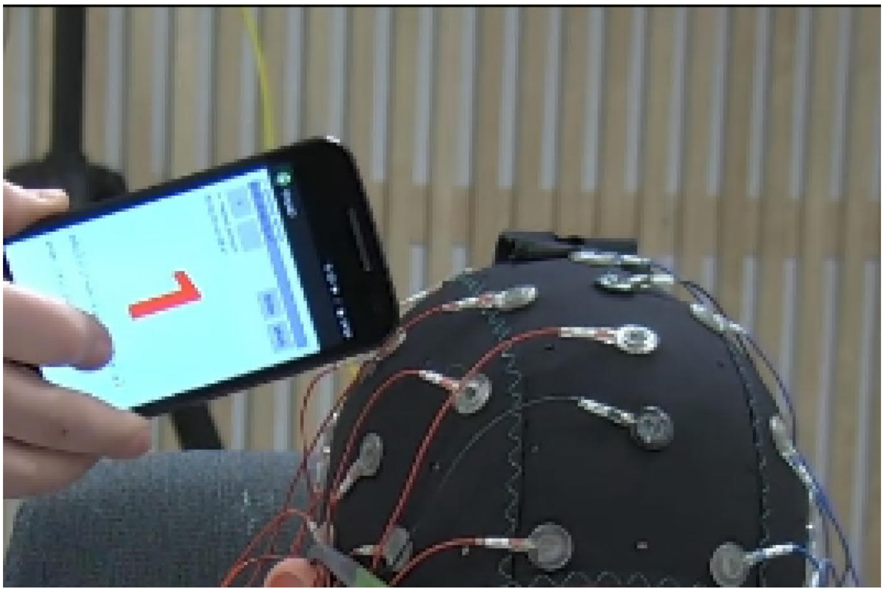

Figure 21. EEG electrode and tilt number is shown on the mobile phone screen during the data collection procedure.

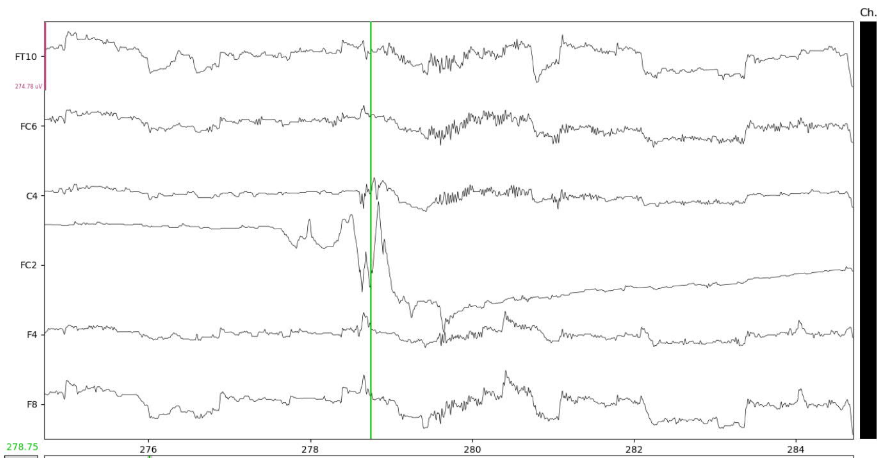

Figure 22. Tilt artifact identified in MNELAB GUI, the green line indicates the exact time point of the event.

6. SIGNAL PROCESSING

6.1. Preprocessing

EEG signals are feeble and usually contain different kinds of artifacts in it. It is imperative to prepossess the raw EEG signal before the analysis. The term prepossess means removing the artifacts from the EEG signal and to preparation for feature extraction algorithms. Power line interference, environmental noises, and drifts can remove by applying a 0.5-50Hz bandpass filter [71, 72]. Signal preprocessing and analysing steps are described in diagram 23.

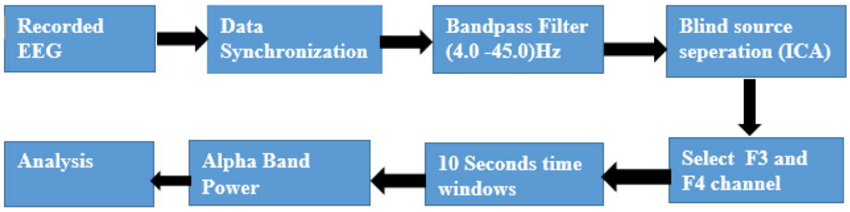

Figure 23. Schematic representation of EEG data preprossessing method.

6.1.1. Digital Filtering

Generally, the digital filtering method can be applied to remove artifacts that the frequency bands do not overlap with the desired signal frequency. To remove the extra physiological artifacts such as slow drifts, powerline noise, and instrumental artifacts, we used the bandpass filter with a lower cutoff frequency of 1 Hz and a higher cutoff frequency 50 Hz. We implemented an FIR filter technique to design it. Figure 24 shown the raw EEG signal before applying the bandpass filter and observed some artifacts in it. After implementing the FIR filter, it removed slow drift and other extra physiological artifacts from the original EEG signal (figure 25). Power spectrum density (PSD) of the EEG signal before and after the utilising bandpass filtering technique shown in figure 26 & 27 respectively.

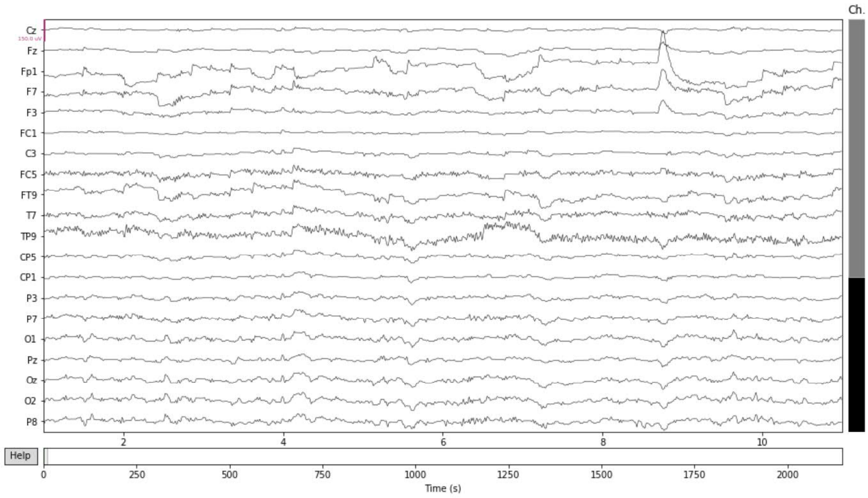

Figure 24. Raw EEG data before applying bandpass filter.

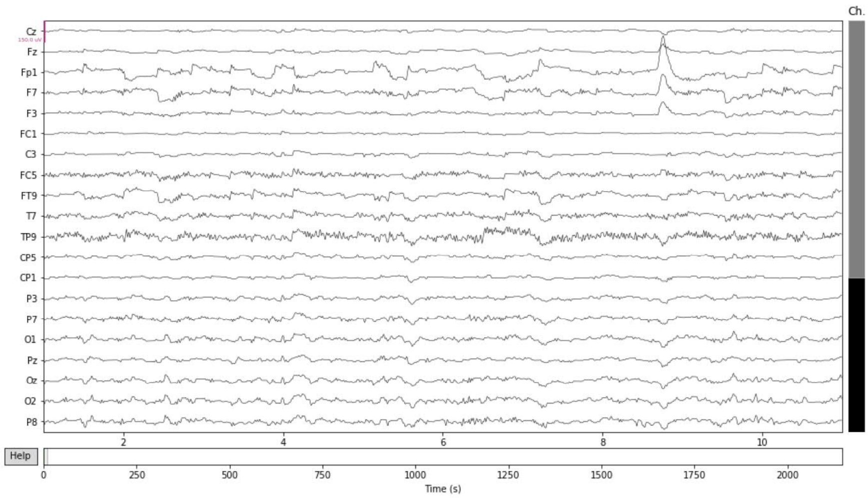

Figure 25. Raw EEG data after applying bandpass filter.

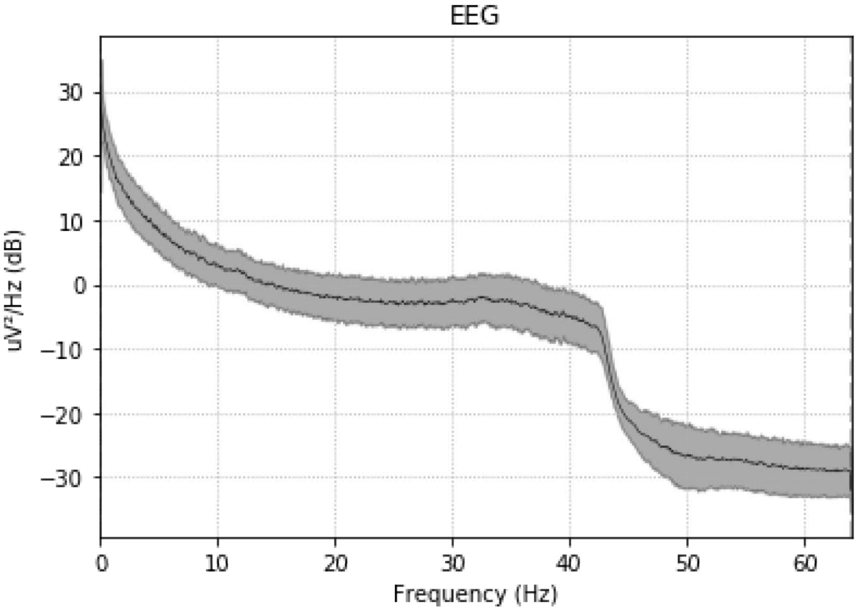

Figure 26. PSD for unfiltered EEG signal.

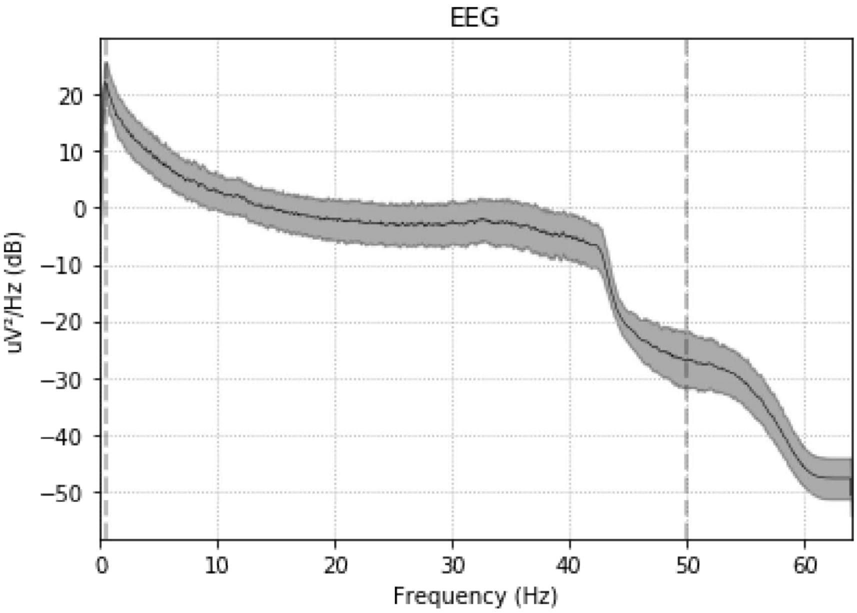

Figure 27. PSD for filtered EEG signal.

6.2. Independent Component Analysis

Artifacts remain still in our filtered EEG signal (seen in figure 25). The digital filter technique could not remove altogether the artifacts that come from other physiological sources like eye blinking, muscle signal, and heart signal. ICA is a popular technique that widely used EEG signal preprocessing to separate desired brain signal mixed with some other physiological signals. We choose this method as it does not require any reference signal. We applied a newer ICA algorithm **Picard** [73]. It converges faster than FastICA and Infomax and is more robust than the other algorithms when the sources are not entirely independent. Using a Principal Component Analysis (PCA), the raw EEG signal is whitened (de-correlated and scaled to unit variance) before fitting and implementing the ICA. Then We passed the n_components =3 (number of principal components) to the ICA algorithm and identified artifact components by visual in plotting inspection (figure 29). Then the captured artifacts were removed, and the EEG signal was reconstructed. In the schematic below (figure 28) is outlined the fitting and reconstruction techniques which govern dimensionality at different stages.

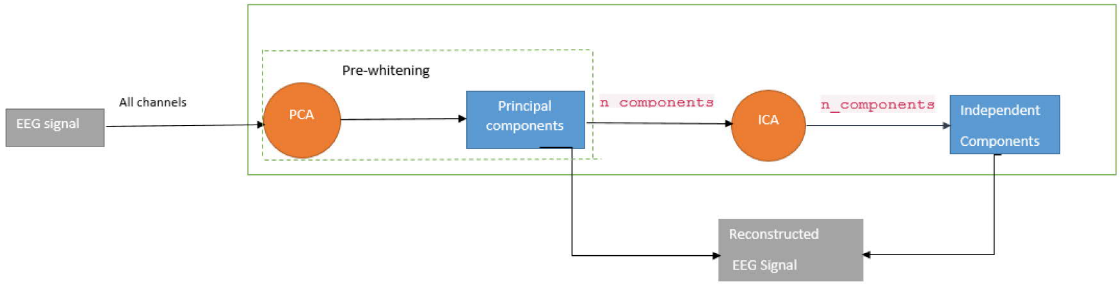

Figure 28. The schematic diagram of ICA implementation.

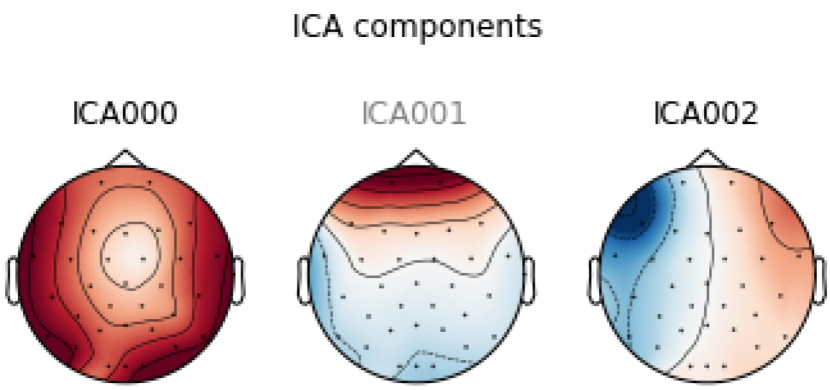

Figure 29. Figure shown that the **ICA001** detected as a artifact component.

The scalp projection is shown in figure 29 ; the component ICA001 identified as an eye artifact because the scalp map shows a robust far-frontal prediction. Besides this, the power spectral density of component ICA001 is typically for EOG artifacts because the EEG alpha peak is missing in it. The component-time course plot (figure 31) and ERP (figure 30) also confirm this assumption. The raw EEG and artifacts free pure EEG signal are shown in figure 32 & 33 respectively, also shown PSD of the clean EEG in the figure 34.

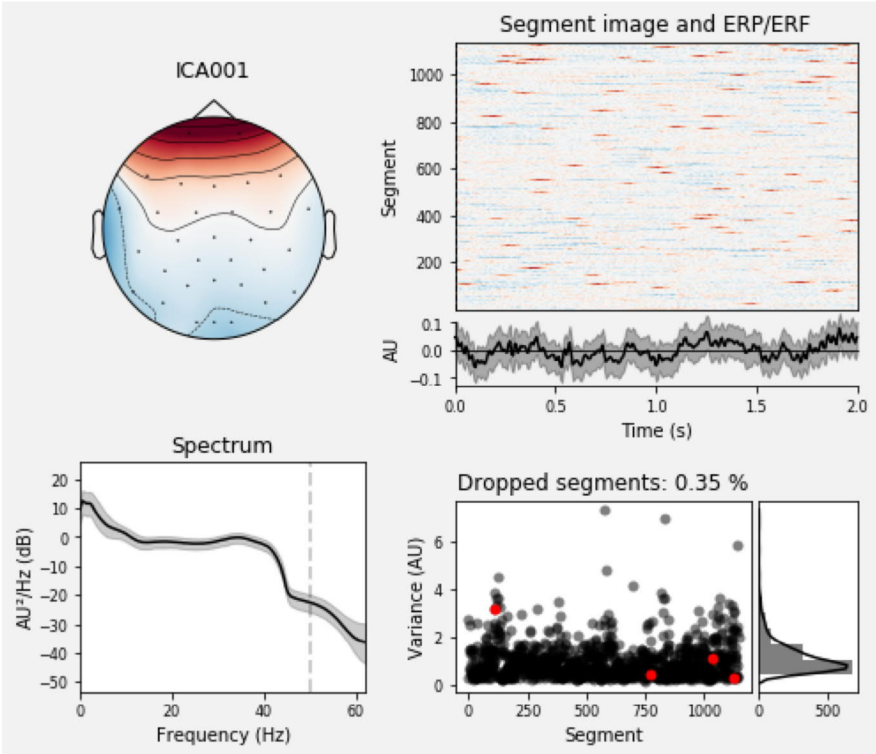

Figure 30. Scalp topographies for artifacts components.

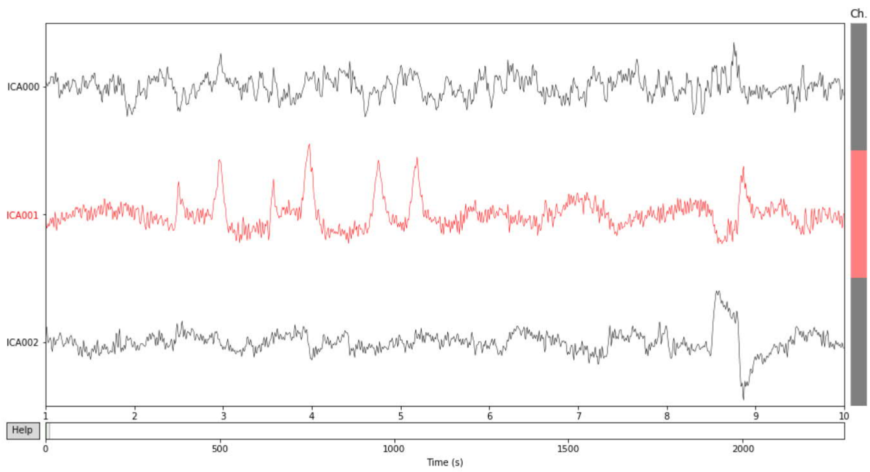

Figure 31. Time course plot showing the artifact component.

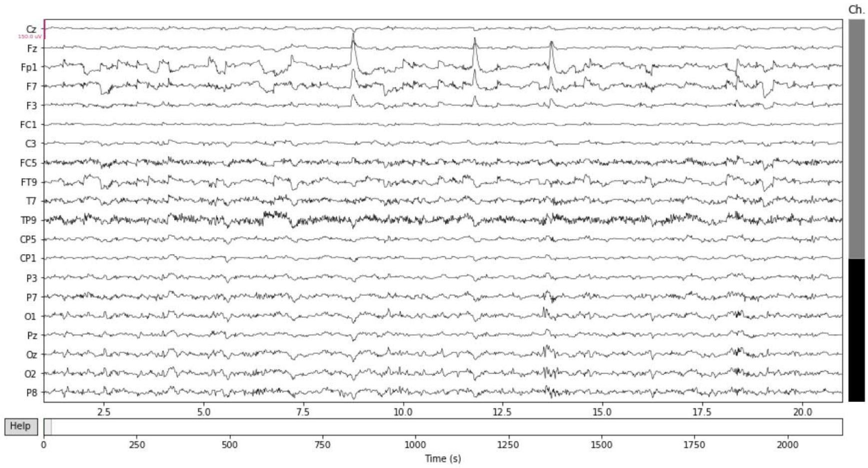

Figure 32. Raw EEG signal which shown the eye blinking artifacts .

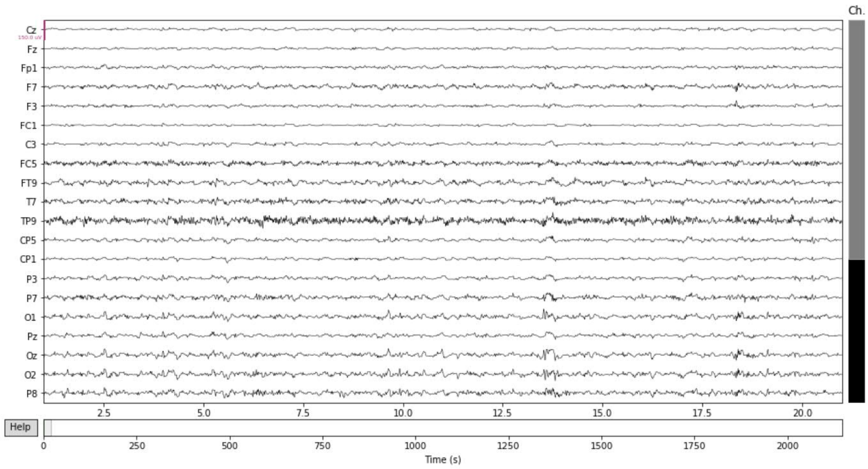

Figure 33. Reconstructed EEG signal after implementing ICA.

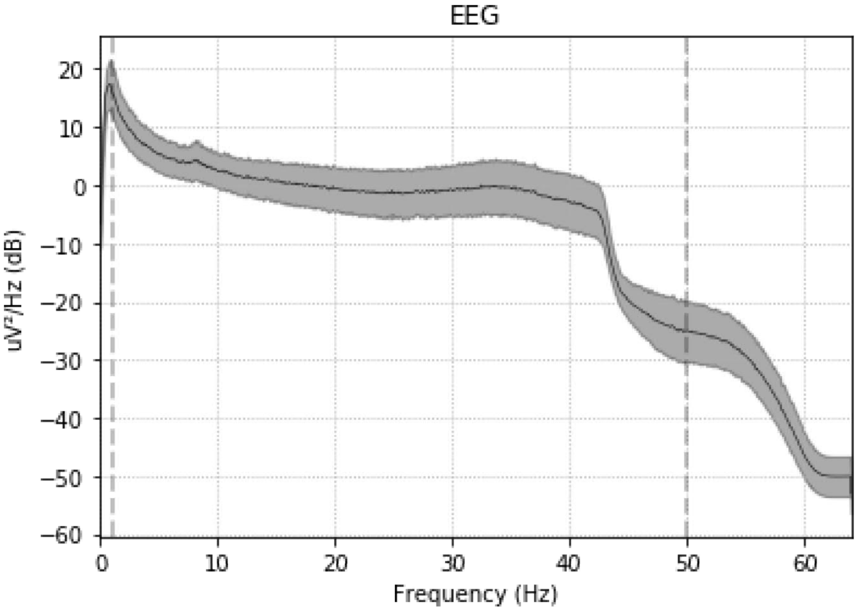

Figure 34. PSD of the EEG signal after implementing ICA.

6.3. Feature Extraction

Features are the distinguishing properties of the signal. EEG feature extraction meant obtaining useful information from the brain signal to characterize different emotional states. In this thesis, we have selected four frontal EEG electrode F3 & F4 and F7 & F8, and extracted important features for analysis. Before started analysis, we segmented the clean EEG signal into 10 seconds time windows right before each interruption or right after each experimental phase has started and right after interruptions or end of the testing phases. We then computed EEG alpha band (8-13Hz) power ($\mu V^2/Hz$), using Welch periodograms [74] on the F3, F7 (located in the left hemisphere) and F4, F8 (located in the left hemisphere) EEG recording channels. To evaluate the variation of the user's emotions, we compared EEG band power changes after and before contrast in each experimental phase. We compare this variation by calculating band power differences and ratio in each selected EEG sensors using the following equations:

The band power difference d_i:

$$[H]\ d_i = alpha_i^a - alpha_i^b \tag{11}$$

The band power ratio r_i :

$$[H]\ r_i = alpha_i^a / alpha_i^b \tag{12}$$

Here superscript ***a*** and ***b*** indicate **after** and **before** each interruptions and gaming phases.

Table 2. *Before* and *after* time windows used to extract alpha band power.

Phase	Before	After
ph0	10s in the beginning of phase 0	10s before end of phase 0
skp	10s in the right before Skype call interrupt	10s right after Skype call interrupt
m1	10s in the right before 1st Mouse interrupt	10s right after 1st Mouse interrupt
m2	10s in the right before 2nd Mouse interrupt	10s right after 2nd Mouse interrupt
ph3	10s in the beginning of phase 3	10s before end of phase 3
ph4	10s in the beginning of phase 4	10s before end of phase 4
ph5	10s in the beginning of phase 0	10s before end of phase 0

We then estimate FAA by computing the lateralized alpha band power ratio between the left and right hemispheres. Finally, We compare the lateralized power ratio to measure relative changes in the alpha band power between 10 seconds time windows of recorded EEG at the beginning of the gaming phase 0 and right after interruptions or right before the end of the game phase. We consider a 10 seconds time interval at the beginning of the game phase0 as our baseline for analysis.

Table 3. *Before* and *after* time windows used to assess emotional variation during the gaming event. [75]

Phase	Before	After
1	10s in the beginning of phase 0	10s after interrupt
2	10s in the beginning of phase 0	10s after interrupt
3	10s in the beginning of phase 0	10s before end of Phase 3
4	10s in the beginning of phase 0	10s before end of Phase 4
5	10s in the beginning of phase 0	10s before end of Phase 5

The lateralized power ratios P for alpha band are determined as follows:

$$FAA = \frac{L - R}{L + R}, \tag{13}$$

where L and R refer to alpha band power for left and right hemisphere respectively.Therefore, a higher FAA values of equation (13) imply band power decreases in the right hemisphere, which indicates the negative emotion. On the contrary, a lower FAA value (13) imply band power decrease in the left hemisphere resulting from positive emotion.

6.4. Statistical Analysis

The pseudo-medians [76] are calculated from the resulting FAA value obtain from equation the (13) and evaluated with a non-parametric 95% confidence interval [76]. To tests the statistical significance of the after and before contrasts in our experiment, the robust paired Wilcoxon signed-rank exact test [77] performed, as it does not require normality in the data. Significant tests is performed according to Chowdhury et al. [75]

$$C_i = P_{i_a} - P_{i_b}, \tag{14}$$

Here, $i \in \{1, 2, 3, 4, 5\}$ indicates the experimental phases, and *b* and *a* denote for the *before* and *after* timing windows mentioned in Table 3.

7. RESULT

7.1. Power Level Comparison In Testing Phases

According to table 2, we calculated band power difference and ratios in each testing phases to visualize the power level variation after and before contrast. We presented this result for all selected EEG channels in this section.

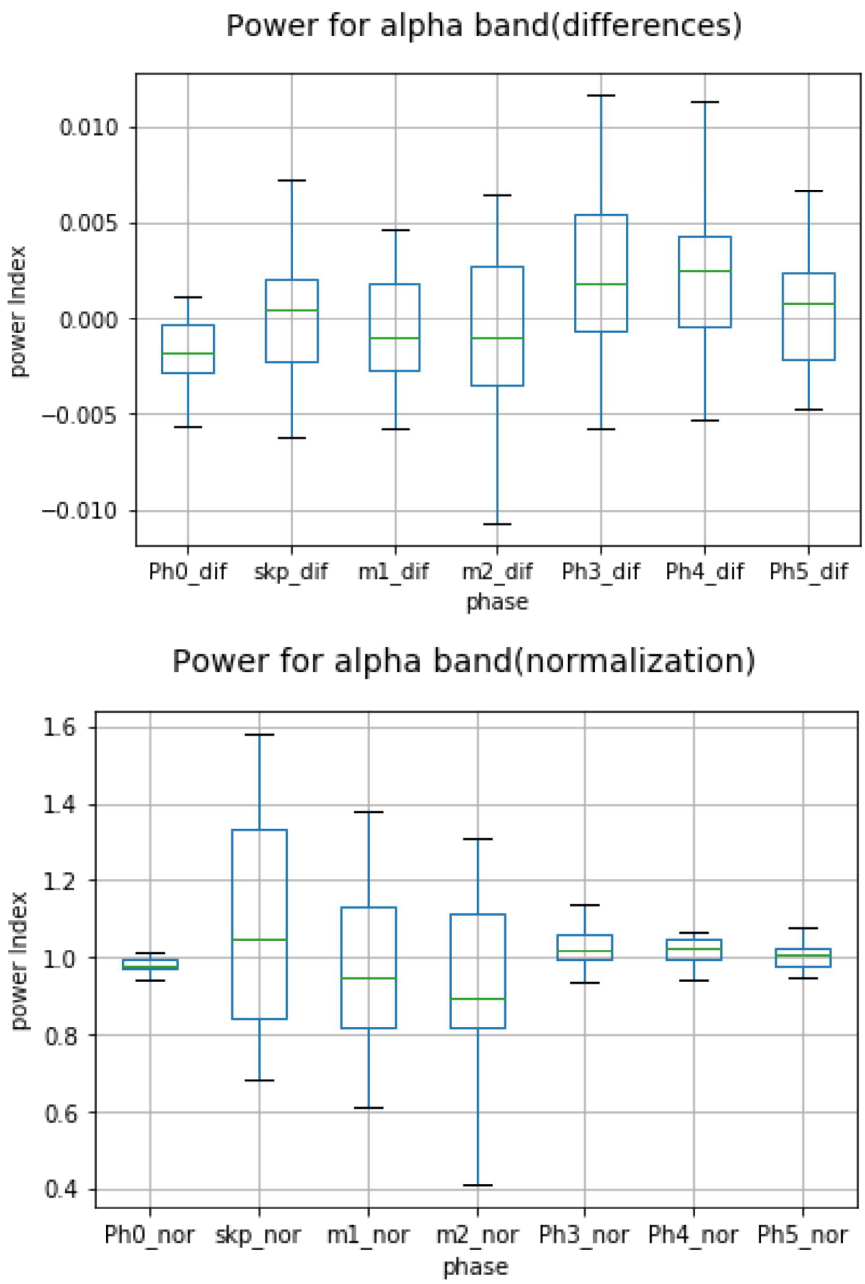

Figure 35. Band power variation after and before contrast in each gaming phase for F3 channel.

From the above figure 35, it is observed that the band power differences are apparent in phase 0, phase 3 & 4 and also slight variation seen in the power ratio at testing phases skp_nor (Skype call interruption), m1_nor (1st Mouse interruption), and m2_nor (2nd Mouse interruption) in channel F3.

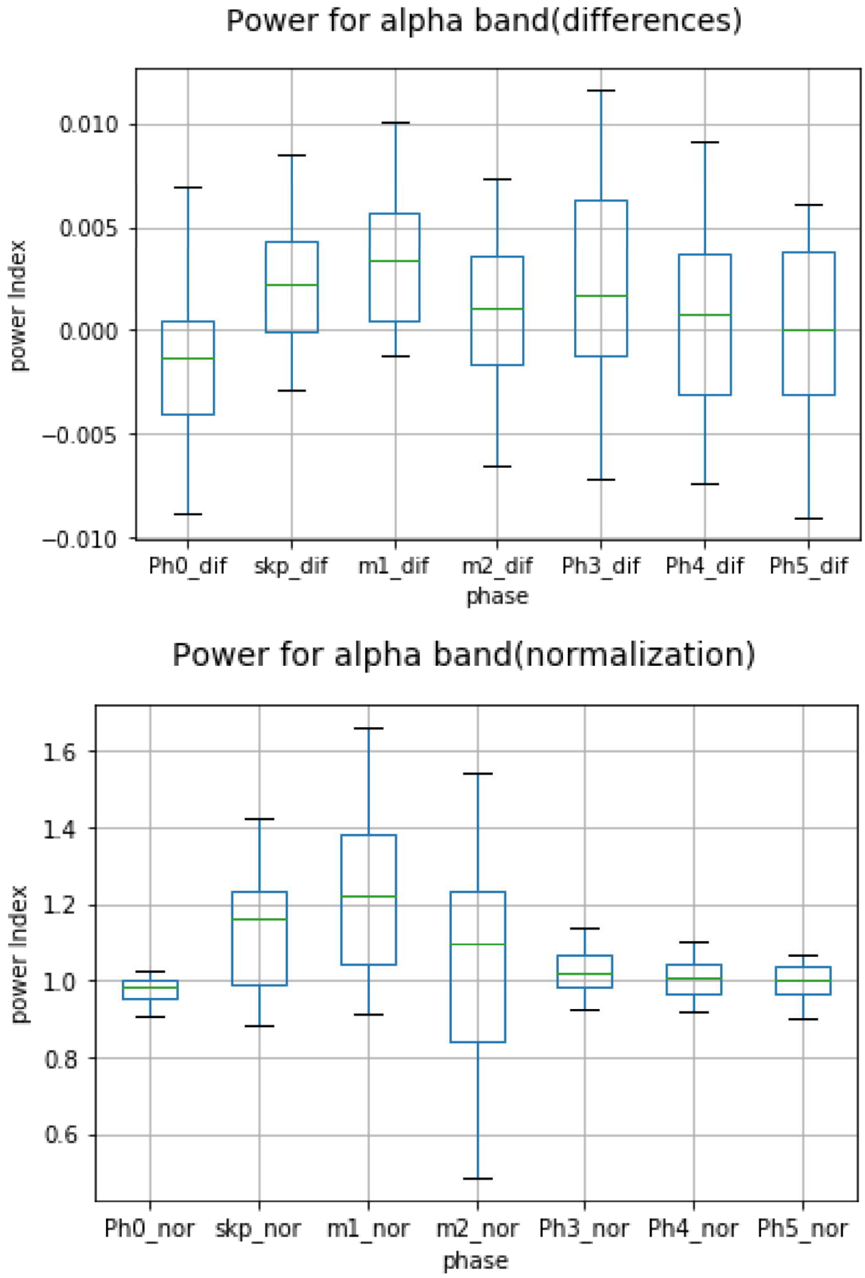

Figure 36. Band power variation after and before contrast in each gaming phase for F4 channel.

For the F4 channel (figure 36), higher band power differences are perceived in Ph0_dif, skp_dif (Skype call interruption), m1_dif (1st Mouse interruption). Also, the power ratios are higher in skp_nor (Skype call interruption), m1_nor (1st Mouse interruption), m2_nor (2nd Mouse interruptions).

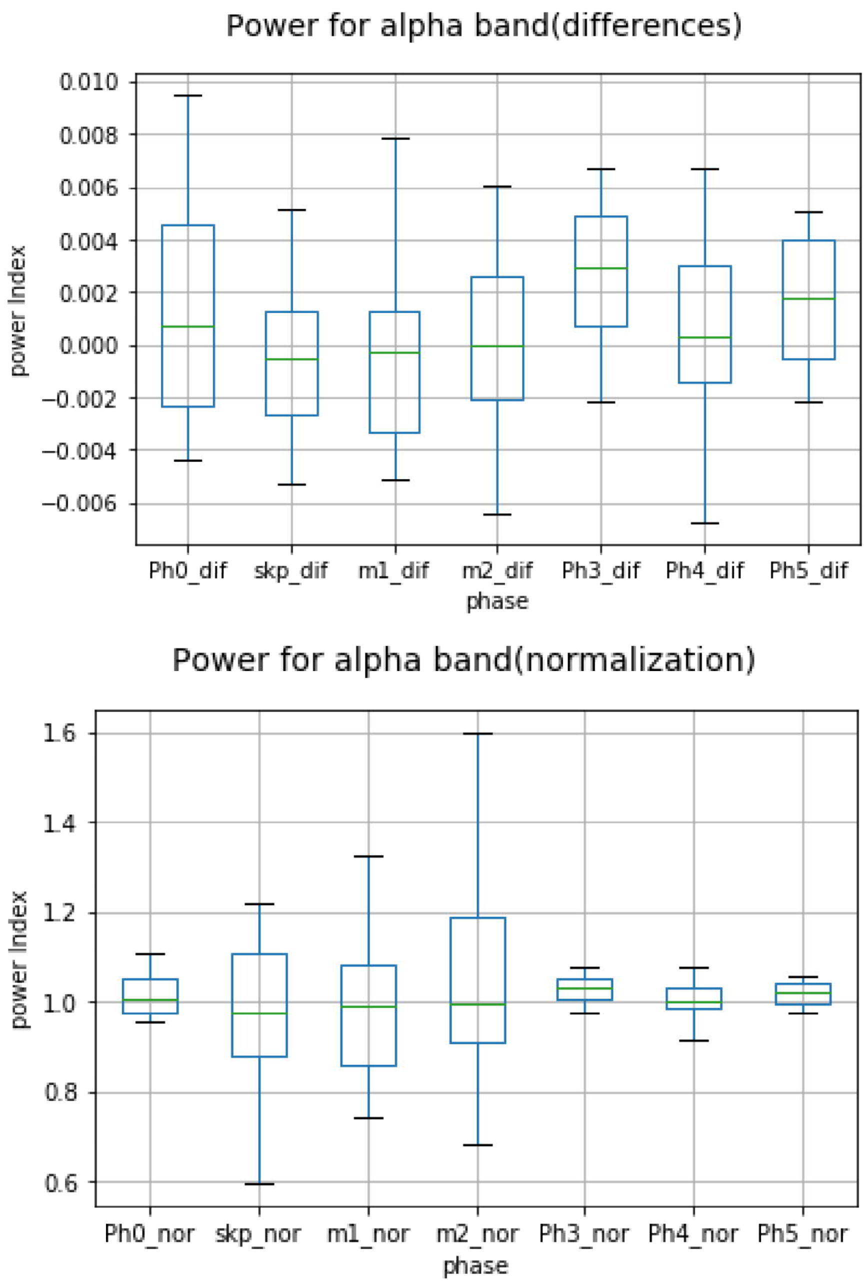

Figure 37. Band power variation after and before contrast in each gaming phase for F7 channel.

In figure 37, only a small difference is seen in Ph3_dif (phase 3) & Ph5_dif (phase 5). Other than no detectable changes observed in power ratios for all cases in figure 37.

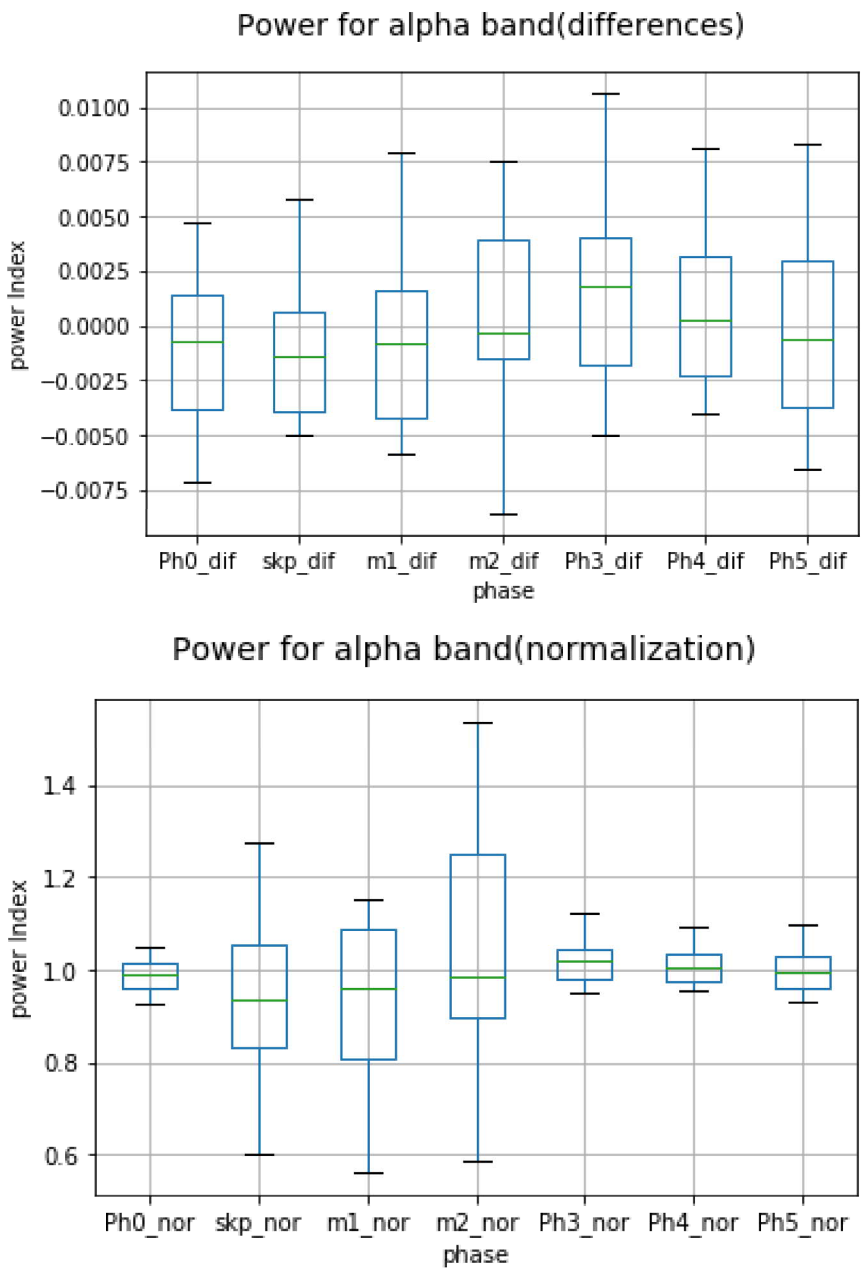

Figure 38. Band power variation after and before contrast in each gaming phase for F8 channel. Band power level changes is very low in skp_dif, Ph3_dif (phase 3) and skp_nor, Ph3_nor (phase 3) as well.

Overall, presenting results indicate that band power level changes after and before contrast are much higher in the F3- F4 than F7-F8. The power variations are notable in F4 channels for both differences and ratios in each gaming interruption. Only a little variation has been observed in phase 3 (in differences) in channels F8, unless no changes have been seen associated with power level in channels F7 and F8.

7.2. Frontal Alpha Asymmetry Analysis

We estimated Frontal Alpha Asymmetry Analysis (FAA) by computing the lateralized band power ratios between left and right frontal EEG electrodes for each gaming phase. In this stage, we compare relative changes in the alpha band power between 10 seconds time windows of recorded EEG at the beginning of the gaming phase 0 and right after interruptions or right before the end of each game phase. This experiment does not have any baseline data. For this reason, we decided to compare band power changes after each event with 10 seconds beginning of phase 0.

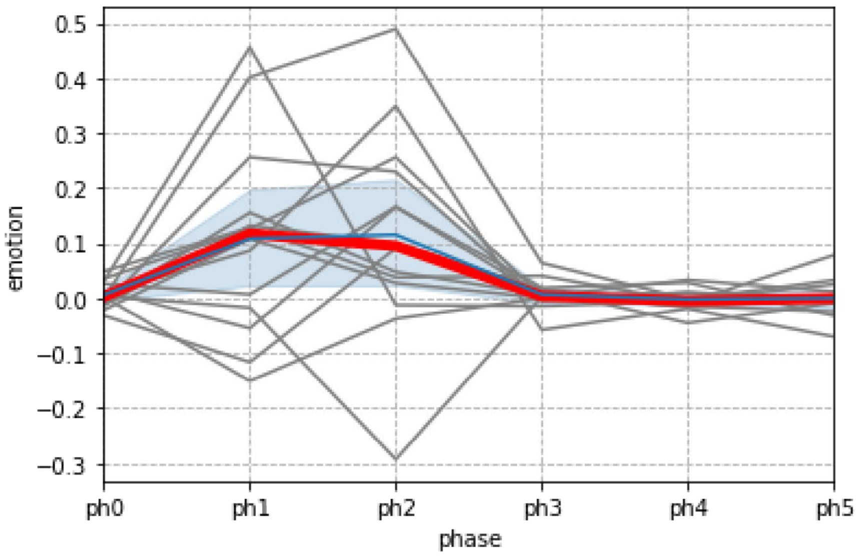

Figure 39. The Frontal Alpha Asymmetry (FAA) was measured between F3 and F4 channels. The gray lines represent individual band power ratio from the left to the right cortex, the blue line indicating the FAA's pseudo median, and the red shaded area indicating the 95% confidence interval.

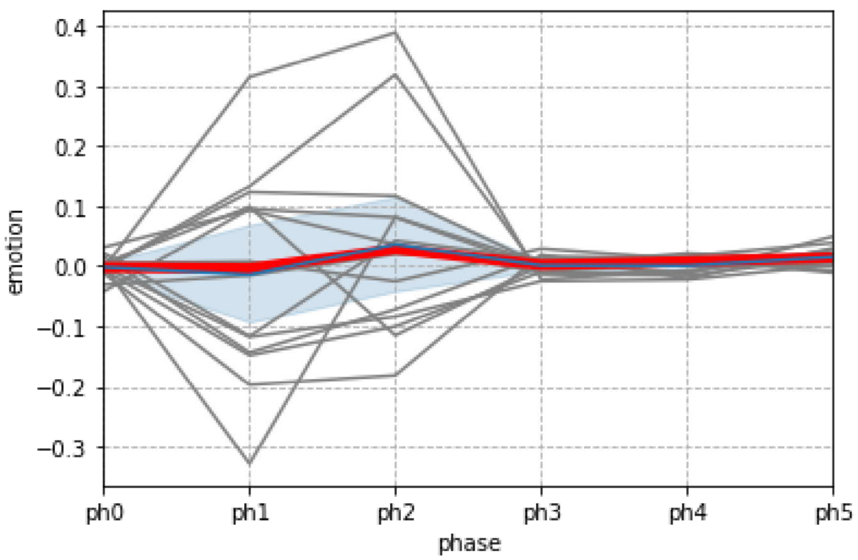

Figure 40. The Frontal Alpha Asymmetry (FAA) was measured between F7 and F8 channels. The gray lines represent individual band power ratio from the left to the right cortex, the blue line indicating the FAA's pseudo median, and the red shaded area indicating the 95% confidence interval.

Figure 39 presenting the result of lateralized band power ratios between F3 and F4 frontal EEG electrodes. In this result, we found that high volatility in phases 1 to 2, low volatility in phases 0 and 3 to 5. It also indicates that the lateralized band power ratio's pseudo median increased from phase 0 to 1, then leveled off from phase 1 to 2, and dropped from phase 2 to 3, no changes from 3 to 5. Moreover, a much variation seen in the individual band power ratio from phase 0 to phases 1 and phase 2. This may be the cause of varying individual emotional responses during the interruptions. Figure 40 displaying the result of lateralized band power ratios between F7 and F8 frontal EEG electrodes. This result reports that the lateralized band power ratio's pseudo median slightly increased from phase 2 to 3, otherwise no remarkable changes in the entire test phases. In comparing results from the figure (39 & 40), we conclude that individual emotional responses are mostly associated with F3 and F4 channels. Furthermore, our results confirm a high emotional response elicited (mostly negative) in phases 1 and 2, indicating that the interruptions during game-play cause emotions in test subjects, mostly irritation. Besides, we have not found any evidence of game difficulty correlation with an emotional response in phases 3 to 5.

7.3. Statistical Test Result

Table 4 and 5 summarized the significant test statistics acquired from channels F3, F4, and F7, F8, respectively. It is seen from the results presented in Table 4, significant test statistics found for phase 1 (skype call) phase 2 (Mouse interruption) in channels F3 and F4. We have not encountered any significant value for all gaming phases except for step 5 in channels F7 and F8 .

Table 4. Tests statistics for comparing emotional affect in each experimental phase W, along with significance of the contrast to phase 0. $*$ marks indicate significance p-value. This results obtain using channels F3 & F4.

Phase	**W**	**p-value**
1	83.0	0.027 $*$
2	87.0	0.015 $*$
3	62.0	0.275
4	55.0	0.437
5	35.0	0.864

Table 5. Tests statistics for comparing emotional affect in each experimental phase W, along with significance of the contrast to phase 0. $*$ marks indicate significance p-value.This results obtain using channels F7 & F8.

Phase	**W**	**p-value**
1	44.0	0.296
2	60.0	0.318
3	57.0	0.388
4	58.0	0.364
5	86.0	0.017 $*$

8. DISCUSSION

Speedy technological advanced smart environments are expanding very fast. To secure a healthy and comfortable life of the consumer in a smart sense, it becomes imperative to measure wellbeing while engaging in this environment. This thesis mainly focused on measuring emotional wellbeing in the digital game playing scenario by EEG signal analysis. This work concentrated explicitly on evaluating the negative affects while the test subjects were wholly immersed in the gaming situation.

EEG activity has been using as an index or proxy for measuring physiological, mental, and emotional states. Many EEG features evaluate individuals' emotional states, such as time domain, frequency domain, and time-frequency domain, which are very common. Among them, EEG frequency band power is one of the famous indexes extensively using for emotion recognition. We have tested three EEG frequency bands, i.e., theta, alpha, and beta to assess the user's emotions by observing power level changes before and after in each gaming events and found that the EEG Alpha frequency rhythm is more sensitive to vigilance changes than the other frequency rhythms (results shown in the appendix). Henceforth, we focus only on the EEG alpha oscillation for final analysis. We have chosen two algorithms, the Teager-Kaiser Energy Operator (TKEO) and the EEG band power, to characterize the different emotional states. EEG band power is computed using the Welch periodogram, and for calculating TKEO, we decomposed the EEG signal utilizing discrete wavelet transform (DWT) to separate the desired frequency band and then applied the TKEO operator on the selected bands. We perform normality testing on Alpha band power and TKEO Alpha to select the appropriate features in this analysis. Our statistical result is indicating that TKEO does not follow the Gaussian distribution (Q-Q plot shown in appendices figure 11.45(a),11.45(b)). We decided to leave out TKEO alpha and concentrated on alpha power for assessing the user's emotional states.

Our analysis reveals that the band power variations are much higher in the F4 than F3 channels for both differences and ratios, and more notable in each gaming interruption. On the contrary, there is no distinguished changes have been noticed in channels F7 and F8 in both differences and ratios. Only a little variation has been observed in phase 3 in F7-F8 channels. This finding implies, F3 & F4 channels are more significant than F7 & F8 for evaluating the user's emotion recognition. Moreover, the pseudo median of FAA estimated using F3, and F4 also intimates a higher value in phase 1 and phase 2, the higher FAA shows that the alpha band power is lower in the right hemisphere than left due to irritation elicited by interruptions in gameplay. This result infers that human emotional responses are correlated more with channels F3 and F4, also confirm that the disruption during gameplay produced high negative emotions in test subjects. Furthermore, we did not encounter any sign of emotion (positive or negative) in phases 3 to 5 in changing the game level toughness. Lack of proof might be the cause of some reasons:

1. The small sample size might one of the reasons for . We had to discard some experimental data due to the high contamination of artifacts.

2. In each test phase, the subjects played the same game, and it might be another reason. The subject was familiar with this game, and the game difficulties did not change the game player's emotional states, either positive or negative.

3. The subject was continuously involved in doing the task, either playing or answering the game-related questions after each gaming phase. It might be the other reason. If the test subject gave a minimum one-minute rest and recorded EEG data, we can compare the gaming phase data with resting-state data. We might get the desired outcome for phase 3 to 5.

Overall we conclude that interruption during the game playing elicited negative affect, and the game player different states of emotion can be assessed by comparing relative the alpha band changes between the left and right frontal EEG channels.And emotions are more strongly reflects on F3 and F4 channels then F7 and F8.

9. CONCLUSION

For this research, the EEG signal studied to assess the emotional wellbeing of smart spaces. We used experimental data and measurement methods introduced by Halkola et al [6]. We measured the Frontal alpha asymmetry to determine for both positive and negative emotional responses of the test subjects. Alpha band power calculated from both left and right cortical areas using F3 - F4 and F7 - F8 EEG channels to compare the band power changes from the left to the right.

Our experimental result proved that the skype call ringing and mouse interruptions elicited negative emotions to the volunteers during the game playing situation.On the contrary, we did not get any evidence in our result for task difficulties that designed for eliciting stress or negative emotion.Our studies did not find any evidence for the flow that was supposed to happen in phase 5, according to Halkola et al. [6]. Although our measurement and analysis provided a significant result for measuring users' emotional states during gaming situations, it had some limitations. We can improve our test results by solving a few of them. We collected EEG data from eighteen healthy volunteers. Among them, we had to discard four test data due to contamination noise that was impossible to remove from the dataset. We recommend more data set to get good statistical significant tests. We also suggested recording baseline data for the test subject's EEG signal before starting each of the experimental phases. When we have baseline line data, we could relate to each experimental phase with the baseline, which will provide a more pronounced outcome. We can record baseline data for one minute before each phase, where the test subject closes her eyes in a relaxing mood and sits quietly. In further studies, this experiment and analysis method will expand for stress and flow monitoring in computer gaming situation to observe how a smart environment can influence wellbeing.

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11. APPENDICES

In this section, we included our preliminary analysis result that we have done for choosing the appropriate band power for emotion analysis. For this initial analysis initial, we include 10 seconds of time frames right before and right after interruptions. It also included 10 seconds time frame beginning of phase 4 and 10 seconds before the end of phase 4. We calculated power difference and ratio after and before variance in each selective experimental phase for comparing the different band power changes.

In the resulting graphs below, first three letters of boxes indicate the name of frequency bands,_dif & ***_nor*** indicates differences & ratio between after and before in the experimental events. Also 1,2,3, indicates 1st,2nd ,3rd interruptions,and 4 indicates phase 4. For example : ***thet_dif1*** defines the theta band power difference for interruption 1,and ***thet_nor1*** defines the theta band power ratio for interruption 1.

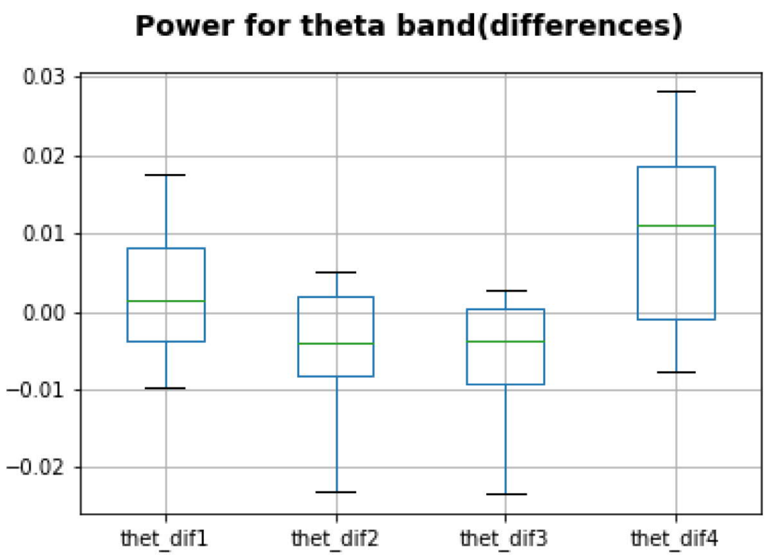


Figure 41. Theta power differences after and before contrast in F4 channel.

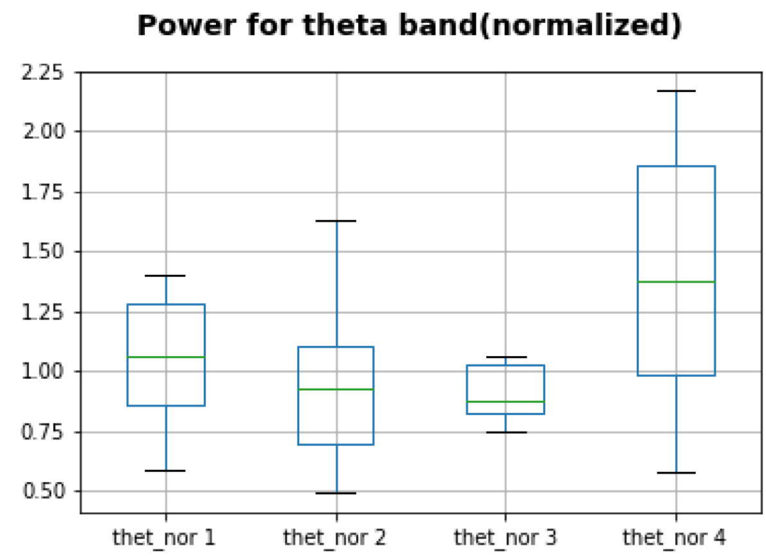
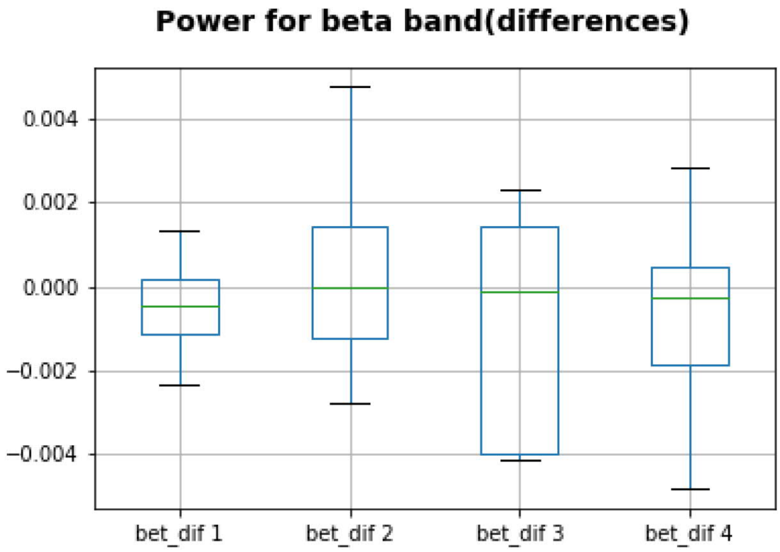
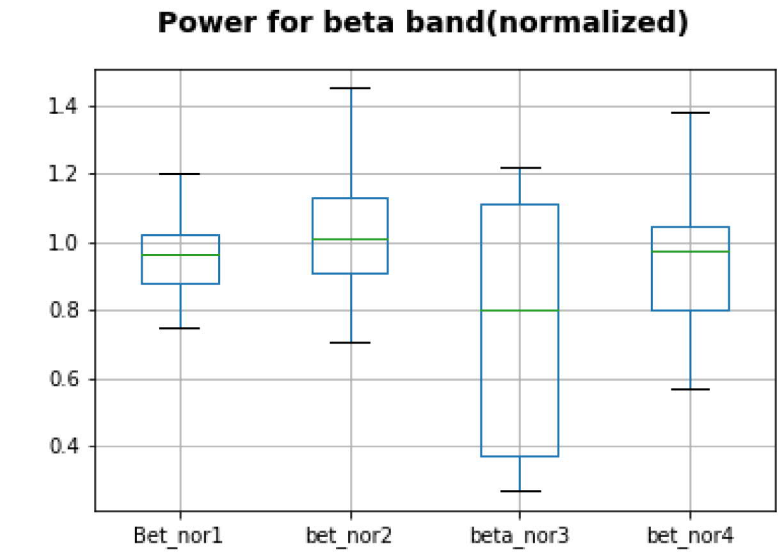


Figure 42. Theta power ratio after and before contrast in F4 channel.

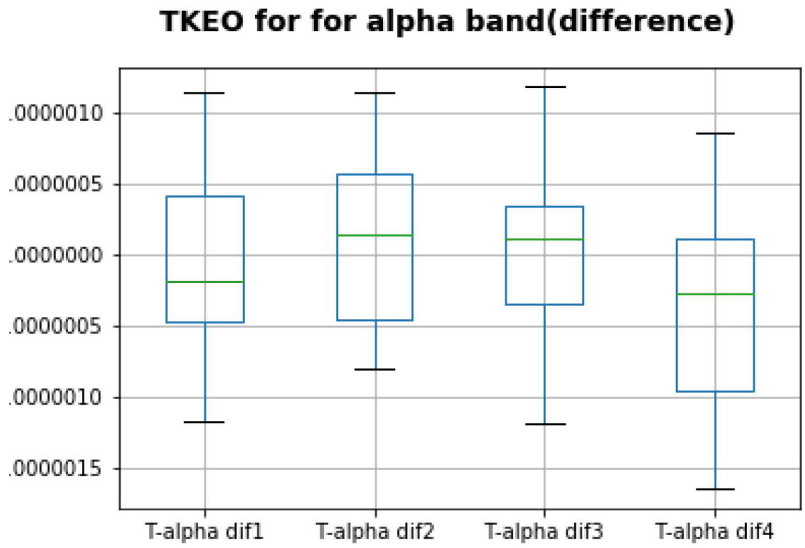


(a) Power differences after and before contrast in F4 channel.

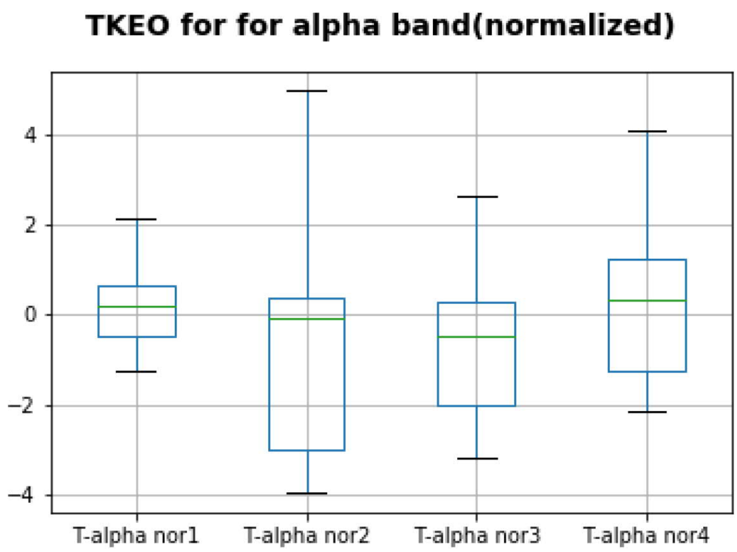


(b) Power ratio after and before contrast in F4 channel.

Figure 43. Results of beta band power changes in F4 channel.

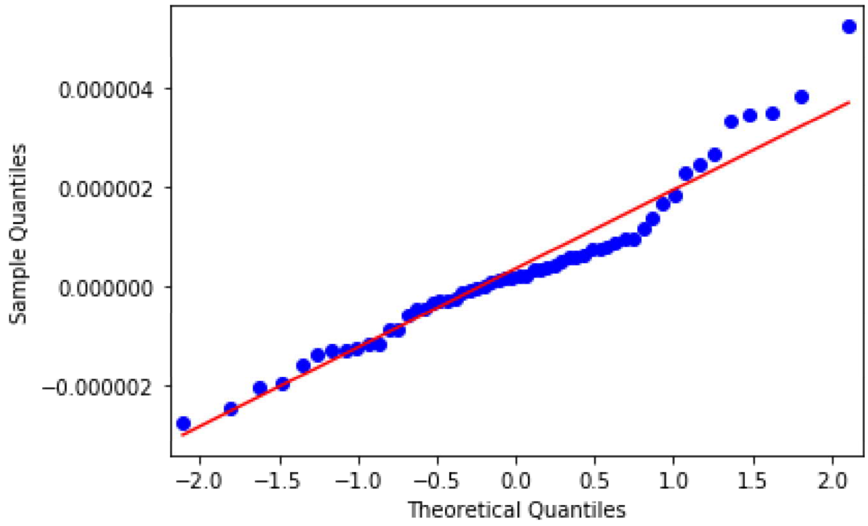


(a) TKEO differences after and before contrast in F4 channel.

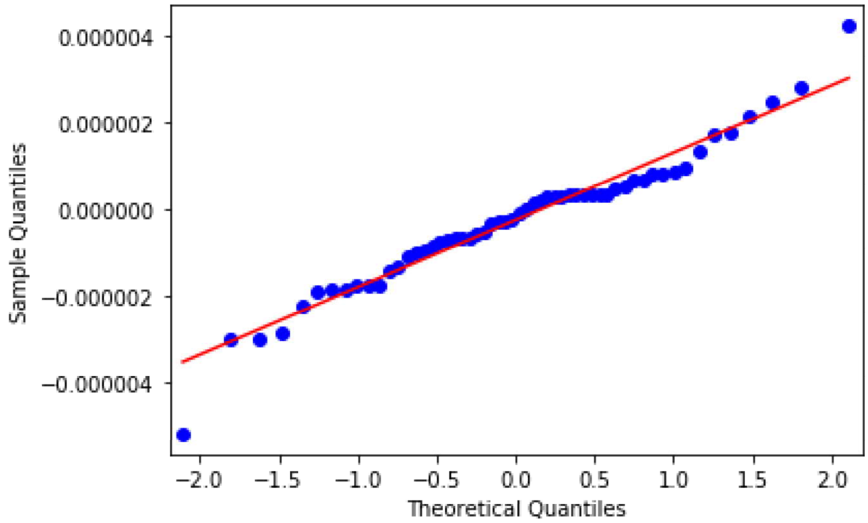


(b) TKEO ratio after and before contrast in F4 channel.

Figure 44. Results of TKEO alpha changes in F4 channel.



(a) Q-Q plot for TKEO alpha in F3 channel.



(b) Q-Q plot for TKEO alpha in F4 channel.

Figure 45. Q-Q plot for TKEO Alpha for normality testing.