ABSTRACT

ELECTRICAL MONITOR OF PHYSICAL ACTIVITY USING BIOELECTRICAL SENSORS

by Alexandre Patrick Tessier

One of the most significant problems facing individuals in the modern workplace is injuries due to physical exertion. The purpose of this study is to demonstrate a correlation with elevations of Electroencephalography (EEG) biological signals alongside Electrocardiography (ECG or EKG) and oxygen levels to determine the thresholds of exertion for individuals. Demonstrating such a correlation between these measurements would provide a basis for future investigations into developing technologies to monitor individuals in physically intense work areas and recovery through physical therapy.

This goal was achieved in this thesis using a nonintrusive EEG headset sensor with a compatible ECG lead. This study also introduces the use of various signal processing and data comparison techniques to demonstrate correlations between the various biological signals. A secondary portion of this research utilizes a newer signal processing technique adopted from a previous work.

ELECTRICAL MONITOR OF PHYSICAL ACTIVITY USING BIOELECTRICAL SENSORS

A Thesis

Submitted to the

Faculty of Miami University

in partial fulfillment of

the requirements for the degree of

Master of Science

by

Alexandre Patrick Tessier

Miami University

Oxford, Ohio

2019

Advisors: AKM Jahangir Alam Majumder

Advisors: Qihou Zhou

Reader: Donald Ucci

Reader: Miao Wang

This thesis titled

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by

Alexandre Patrick Tessier

has been approved for publication by

The School of Engineering and Applied Science

and

Department of Electrical Engineering

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AKM Jahangir Alam Majumder

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Qihou Zhou

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Donald Ucci

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Miao Wang

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Dedication

I dedicate this thesis to my family for all the support and encouragement they have given me in pursing my degree in this two-year program. I am very grateful to my mother for her constant support and motivation as well as her aid through her own experiences to aid in my decisions. To my father for his financial support and his own experiences through acquiring a Masters and for acting as a role model. Finally, to my sisters and brother for dragging me around and reminding me that though a degree is important, there is more to life than just that.

Acknowledgments

I would like to thank Dr. AKM Majumder for having accepted me as one of his graduate students. His time and effort with aiding me in my first year in the graduate program is something I will always be thankful for. I also greatly appreciate his dedication in pushing me to participate in a research competition and thus experiencing opportunities I would never had experienced otherwise.

A special thanks to Dr. Zhou for becoming my co-advisor during my second year of research. His knowledge in the area of biological signals were instrumental in allowing me to complete my research. His determination to have me demonstrate my potential to the best of my abilities will always be appreciated and utilized in my future endeavors.

Many thanks to Dr. Ucci for taking the time out of his own busy schedule to aid me in writing my thesis and participating as one of my committee members. His constructive criticism and suggestions to improving my thesis has greatly influential in increasing the quality of my research.

I would also like to thank Dr. Wang for accepting my request to be part of my committee for my research. Her questions and recommendations have helped improve the overall quality of my research and writing my thesis.

Finally, I would like to thank all of my friends and colleagues in the Electrical and Computer Engineering Department at Miami University. Brenton Bischof, Isaiah Qualls, Austin Lowder and Santhiya Sampath in particular have been instrumental in aiding me throughout my research. Be it by informing me of important documents that need to be submitted to ensure graduating on time to simply making my time at Miami even more memorable. I will always treasure the times we have had together and will use our experiences in the future.

Chapter 1: Introduction

In any given society, one of the most crucial aspects is the ability to provide for the health of all citizens and for the efficient treatment of all injuries. To this end, there has always been a desire in the development of new technologies and methods to help improve the welfare of individuals. Thus, development of wireless devices and sensors that provide the patients with live feeds of information on their health and the improvement of the accuracies and clarity of the data acquired have been achieve this. Such developments allow the patient to be able to monitor their own health more efficiently and be able to provide crucial information to their physicians quickly.

Background

Advancements in sensory technology in a variety of medical practices have improved the variety of available information provided to physicians and the usability by patients. Some crucial developments have arisen in the medical field are the uses of Brain Computer Interfacing (BCI) sensory devices. The introduction of such devices has enabled the medical fields to correlate more variables and factors that were previously unknown to conditions and methods of detecting such situations. This has been further improved using such devices and their gradual removal of permanent fixation in laboratories to more mobile and accessible models. Due to these improvements, there has been a significant increase in the utilization of BCI devices. With this increase, the number of peer review studies that utilize BIC device has exponentially increased through the years and will most likely continue to do so as technology continues to advance [1].

BCI technology has been utilized in the medical field for a wide variety of conditions and treatments. In the utilization of EEG, there has been cases that were utilized for seizure disorders, encephalitis, sleep disorders and used for patients under anesthesia. Monitoring Depth of Anesthesia (DOA) has proven to be a significant challenge to anesthetists, particularly with regards to examining vital signs. Using a liner discriminate analyzer along with EEG and ECG hear rate and arterial pressure data showed an 89.4% DOA [2].

ECG and EKG have a variety of uses that include analyzing heart rhythm, diagnoses for poor blood flow and recognizing heart attacks. A particular use that has been implemented which is relevant to this research is the examination of changes in ECG waves during physical activity. Such test has concluded that there were noticeable changes between the spatial maximum of the P wave and the onset of the QRS complex as well as P magnitude increases during exercise as oppose to nonphysical activity [3]. Fig. 1 demonstrates the parts of an ECG wave used to compare against patterns of various conditions based on the previously described discoveries.

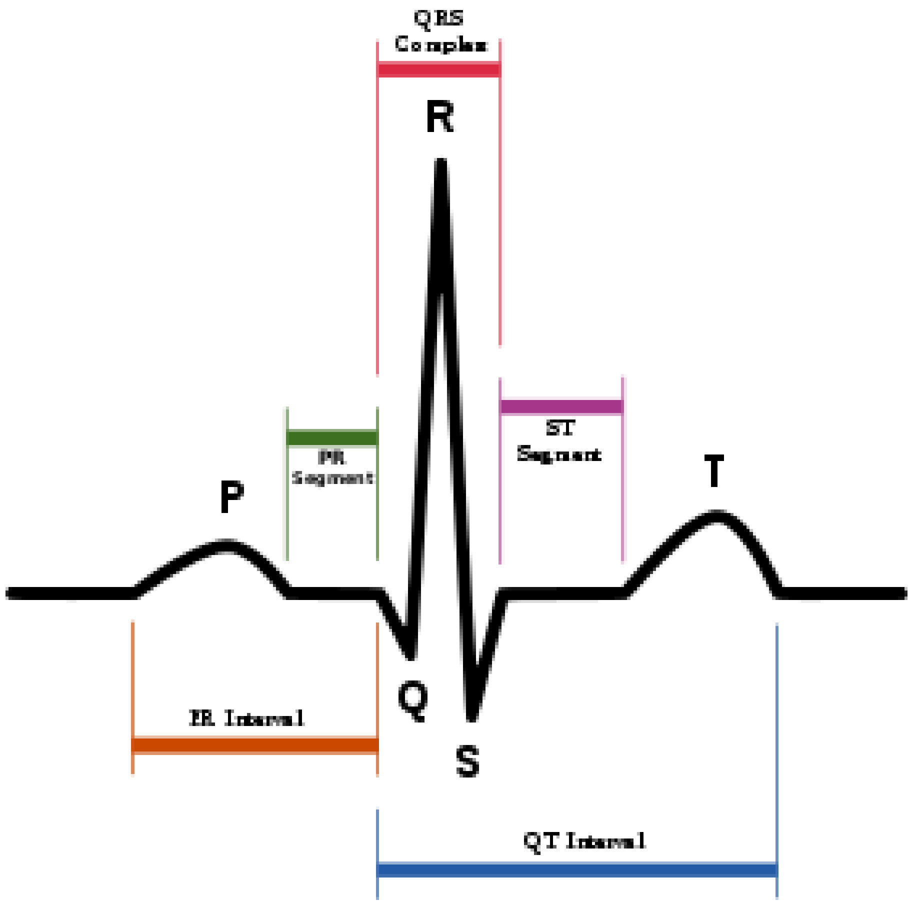

Figure 1: Electrocardiography wave

This thesis focuses on the uses of EEG and their probability of being utilized in the basis of physical activity, an area that is not yet studied or utilized as much as mental analysis and stress of patients. This specific utilization of EEG will also incorporate the implementation of ECG and EMG to aid in determining physical overexertion. Having multiple variables alongside the EEG to compare will help detect noticeable correlating data. EEG, along with all BCI technology has improved greatly in technological advancements. Such advancements include the introduction of wet or dry sensor pads and wireless communications.

The internationally 10 vs 20 setup recognized method to describe the locations of the scalp electrodes. This system was developed based on the relation between the location of the node and the underlying area of the cerebral cortex. Found in Fig. 2 demonstrates the labeling of the 10 vs 20 setup.

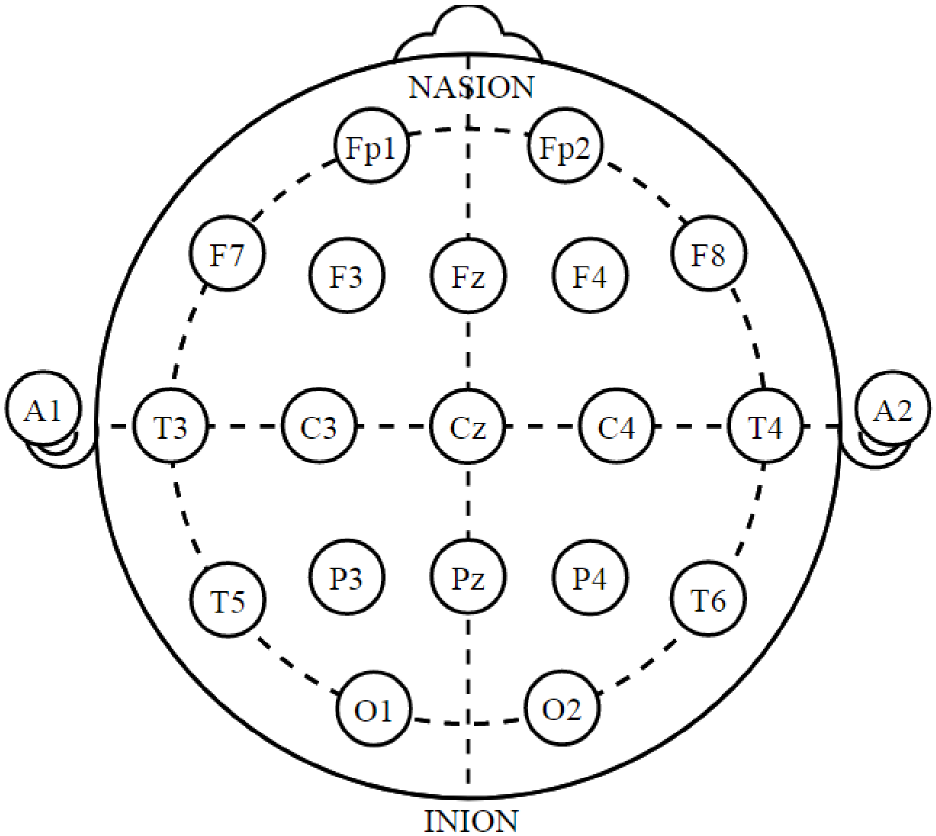

Figure 2: EEG 10/20 labeling setup

The reference to numbers 10 and 20 is due to the distance between adjacent electrodes to either be 10 or 20 percent of the total front-back or right-left distance of the skull. Each site has a letter to designate which lobe the node is on and are numbered to identify which area of the lobe the node is placed. There is also the utilization of the letter z in replacement of numbers for nodes found in the midline of the skull [4]. Table 1 identifies the electrode letter designation with the corresponding lobe.

Electrode	**Lobe**
F	Frontal
T	Temporal
C	Central
P	Parietal
O	Occipital

Table 1: Electrode Letter Identification (Note no central lobe exists, C is used for designation purposes only)

Due to the focus of the research being regulated to physical activity, it was determined that a 10 setup would prove to be more efficient than a 20 setup. With this decision, there is the necessity to account for potential overlap of data over several nodes of the brain compared to utilizing a 20 setup, but it was determined that this should not be significantly problematic [5]. However, even with the increase in variations and advancements, there is still a significant factor in interference due to nearby wireless devices and unnecessary head and eye movement.

Problem Description

The improvement of the efficiency, affordability, accuracy, and mobility of BCI sensors has increased the possible implementations that can be designed for such devices. One of the fields this increase has been found is in reaction times by subjects. In the study, BCI technology was used with the subject reacting to a computer-generated image of a ball and the use of a bar to simulate being the goalkeeper. The main objective was to collect data with relation to quick decision making and the effect on brain wave activity [6]. While there has been significant improvement to the technology surrounding BCI sensors, there has yet to be a serious effort of expansion in the utilization of such technology into the areas of physical activity. Due to this lack of increased variety of possible implementation, this project will be focused on utilizing the variety of available BCI sensors to aid in reliably detecting increased levels of brain wave activity relative to increased physical activity.

The overall premise for this project is the desire to demonstrate the proof of concept of a utilizing EEG biological signals, in conjunction with other signals to model levels of an individual's physical activity. Finding additional means of locating biological signal patterns to determine levels of physical exertion, this would allow more in-depth studies to be performed in this area. This would also demonstrate more conclusively that certain patterns and levels of the signals can indeed be associated with certain activities. This thesis will also be examining the various ways to filter and use signal processing techniques that prove to be the most beneficial in providing accurate results from the collected EEG data.

Research Challenges

The objective of this work is twofold: first, produce an adaptive system that will be able to collect reliable EEG biological signals and second, to provide filtered and analyzed data that can be compared to other listed biological signals, thus providing correlations with levels of EEG signals with physical exertion. In the process of performing this task, there were several challenges that have arisen from the project:

1. Noise errors caused to the EEG sensor due to sensitivity known with all nonintrusive EEG techniques.
2. Developing an accurate and adaptive signal processing methodology.
3. Acquiring a significantly sized data pool that considers major factors of age, gender and physicality for developing average thresholds in exertion

Our Approach

The overall purpose of this thesis is to determine paths of biological signal acquisition to newer efficient and mobile means of measuring physical exertion. Due to the lack of notable examinations into this field of study that can be found utilizing EEGs, this goal would allow for an ability to demonstrate the utility of developing a system to aid patients with physical difficulties. Focusing on developing another means of variables that will determine the levels of an individual's physical activity would aid individuals as well as medical professionals or coaches in monitoring activity levels. Additionally, due to the amount of time it takes to have individuals recover from physical therapy, such developments would aid in reducing that allotted time. The development of such techniques would allow them to increase their recovery rate by helping determine if it is a physical difficulty or a mental perception keeping the individual at his or her current level of activity.

This process begins with the use and implementation of implement a portable neurosensory device that will record the brain signals of the patient in question. One of the main focuses in this portion of the approach is to ensure that reduction in interference and accuracy can be achieved. This will ensure that the data being collected will prove to be reliable and can be compared to the base threshold settings and other biological signals. Part of ensuring these results is in determining the types of activity in which the individual that would generate some errors.

Following this portion of the procedure is the need to utilize a communication device to submit the information being provided from the sensors. The desire to utilize a low powered means of wireless communication is twofold. The first reason is to reduce the power consumption of the device recording the data acquired by the sensor and, if not, it could be set into a standby mode to reduce even further power consumption. The second reason is due to the use of wireless communication; using this mode of communication will avoid the use of wires that would both need to be tied and managed to allow the user to perform activities without interference. It would also counter the need to examine cable interference as, without the use of cables, the effect of interference caused by wire swaying would be avoided and not have to be filtered [7].

Once the data has been collected from the sensors, the data is processed through a filter in order to remove levels of interference and noise generated during data gathering. The type of filter currently being utilized is a Fourier transform, as well as the utilization of another short time Fourier program to allow comparison of different analysis for the data collected. The data of interest will be from the frontal lobe section of the system, as the temporal lobe house the main motor control signals in the brain [8].

Upon acquiring the signals after having been filtered for any unwanted disturbances, the data collected would be compared to already register average threshold levels. The database will be constructed to use three levels of exertion for comparison: low, medium, and high. This comparison data would be based on the collected data of various individuals in accordance to gender, age and physical health to allow the ability to adjust the thresholds to the specific users and select a range of anticipated error for individual deviation from the general average.

Motivation

The following section will discuss the real-world problems that have promoted the creation of this research and possible implementations of the development. The discussion will explain the situation and statistics regarding monitoring physical exertion and some of the scenarios that the research obtained from this paper could be implemented in.

Physical Exertion

The main premise of this paper is to determine a method of utilizing recordable biological signals generated in the form of EEG and ECG in relation to physical activity. With this collection of data, it would be determined that another set of variables and signals can be used with other current systems in unison would be able to be utilized in a fashion that could alert a user to the current level of physical exertion and the time the individual is in such a state. This system would allow for the continued study into prevention of injuries due to such circumstance and improvement of previous injuries.

The problems generated by these sorts of injuries have accounted for nearly one third the overall work injuries each caused by cases of overexertion. It has been concluded that in a 2015 study performed by the United States Department of Labor that physical overexertion had accounted for 33.9% of all workforce injuries in the single year [9]. By finding a method that could either out rightly prevent or curtail this trend of the number of injuries received would most certainly prove beneficial to society in respect to the economy and to individual families who rely on a single bread winner.

Statistics indicate that, due to physical overexertion injuries significant amount of money lost due to these injuries. In a study that was performed by Liberty Mutual Insurance Company, it was determined that in 2016, in the United States also the associated costs due to such injuries resulted in over 15.8 trillion dollars [10]. This included the amount of money that was needed to be allocated for medical expenses, insurance, compensation, and loss of product revenue due to the loss of an employee for a certain amount of time. It was decided that, if efforts could be made and active prevention methods could be implemented, the money gained from the reduction of such situations could be used in more beneficial means.

Scenarios

In this section, we consider two scenarios indicated the importance of solving the problem at hand.

Scenario 1

The first scenario that was considered would the eventual implementation for the system regarding sports or military training. Utilized in the military for example, this would allow the sergeants to monitor the recruits to ensure that they are in fact giving the exercise high levels of exertion and not lowering their efforts. This is particularly important as at the moment the military is currently having trouble recruiting new solders, primarily due to physical requirements and loss due to the job market for new employees [11, 12].More importantly, this system would alert the sergeants that the individual is already performing towards his or her maximum of physical exertion and thus could react appropriately to maintain the recruit at that level for effective training. This would potentially reduce the amount of injuries to potential recruits that would otherwise have been accepted into the file and rank and ensure better performance overall.

Scenario 2

The second scenario that was considered is the utilization of the system in the hospital for physical therapy due to injury. In consideration of physical recovery cases, an individual in the hospital would most likely would want to recover as soon as possible to allow lower overall medical costs and the ability to return to a normal life. A significant problem for physical therapist comes from an ethical standpoint. At what point do they need to press their patients to ensure progress yet avoid unintended problems [13]. With the given system, it would prove most beneficial that the patient be aware that they are either at a threshold that is not benefiting the amount of exertion needed to allow a fast recovery or that they are pushing themselves too far and thus would result in reinjuring the area that is recovering.

Chapter 2: Related Work

When originally formulating this problem and possible solutions, we examined the recent research that has currently been done in the filed regarding biological signal analysis. Upon completing the examination, it was concluded that there has been significant research performed in the fields of study regarding the utilization of ECG for medical prevention and alert systems. It was also determined however that there was no indicated research performed regarding utilizing EEG in monitoring the levels that are associated with physical exertion. As such, this thesis will examine the relation between EEG and physical exertion levels, resulting in a focus on two factors related to EEG to perform this research. The first factor being examined was work done to identify the biomarkers related to EEG and related activity corresponding to it. The second factor that examined was the change in detectable EEG waves over the course of various exercises.

EEG BIOMARKERS

When considering the use of EEG for the purposes of physical exertion and activity, it was determined necessary to decide which of the different waves that are generated inside the EEG signal spectrum would be of most importance to record. In the studies that have been performed regarding these waves, it has been determined that any given brain wave can contain any combination of five different waves, the more prominent based on the activity having been performed during the data collection process. The five waves are listed as follows: delta, theta, alpha, beta, and gamma waves. One such study included the examination of physical signals and movement for patients who have had a stroke. After examination it was found through their own biomarker application, the predictive values and sensitivity of the markers was 81.3% and 90.9% [14]. Thus, the utilization of biomarkers has been shown to be useful and relatively accurate.

Based on the studies done, each wave is found to be prevalent in certain areas of activity or bodily functions. To perform these studies, it was determined that the waves are marked based on the frequency range they are most concentrated. Delta waves, which are the lowest detectable brain wave, is found at 4 Hz and often found during dreamless sleep. Theta waves are primarily found in ranges of 4 to 8 Hz and mainly associated with dream recall and emotional conduct of an individual. Next are the Alpha waves, which are found in ranges of 8 to 15 Hz and are commonly prominent in activities related to general everyday activity. Beta waves are in the ranges of 15 to 30 Hz, are the dominant wave for cognitive tasks and alert state. They have three bands which range from musing states to complex thought and activity. Finally, the last brain wave to be examined are Gamma waves, which are found in ranges of 30 to 150 Hz, and are the fastest brain waves, which can be related to the fact that they a most prominent in the processing of information to different brain areas. Thus, due to these identification and studies, Alpha and Beta waves are considered for this thesis to be the most important element [15]. The established biomarker hierarchy can be seen in Fig. 3.

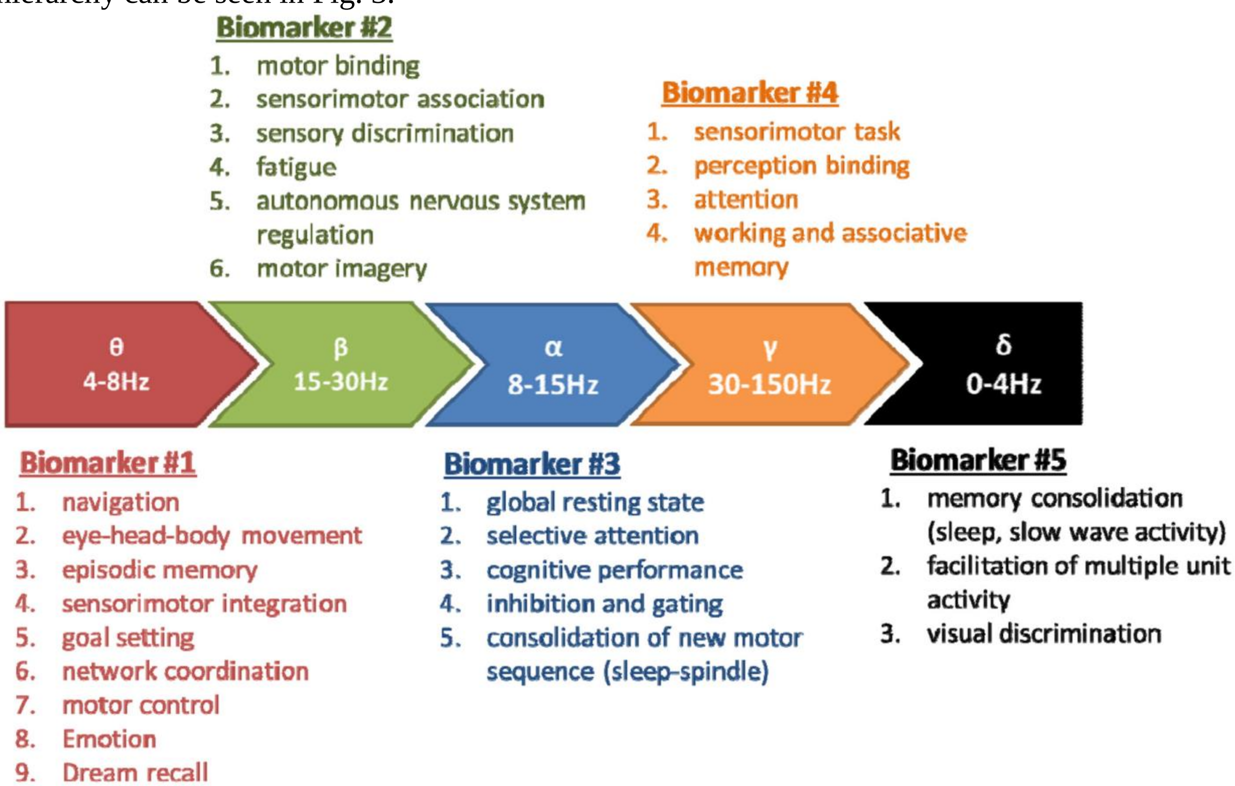

Figure 3: EEG Biomarker Hierarchy based on function [15]

A further study that was performed regarding physical activity in relation to EEG signal levels inquired into which specific nodes of the brain contained the highest levels of activity during exertion. In the research, the individuals were tasked with performing cognitive thinking exercise alongside jump rope activities. As the study progressed, it was found that, after the jump rope activity was performed, the areas of the brain that were the primary centers for cognition showed increased activity and allowed the individuals on average to perform better than before [16]. Thus, this demonstrated that the biomarkers utilized in the previous study can be correlated as certain frequencies and certain lobes of the brain correspond to varying activities.

Fluctuations in Biological Signals

Next we examined the peaks of the waves of the biological signals that are generated from physical activity. One of the concerns when starting this thesis was the uncertainty the way the EEG would change with the effect of physical activity. One study examined researched the effect of the mean individual alpha peak frequency (iAPF) neurophysiological marker of brain wave activity in relation to intense verses steady exercise. This was done by testing the subjects before a four-week training session and after the session. The tests composed of steady state exercise (SSE) and an exhaustive exercise (EE) on separate days. It was found that in the conclusion of intense physical exercise the effect was an increase in the subject's attention whereas the effect from steady exercise was unchanged [17]. The resulting data graphs can be found in Fig. 4.

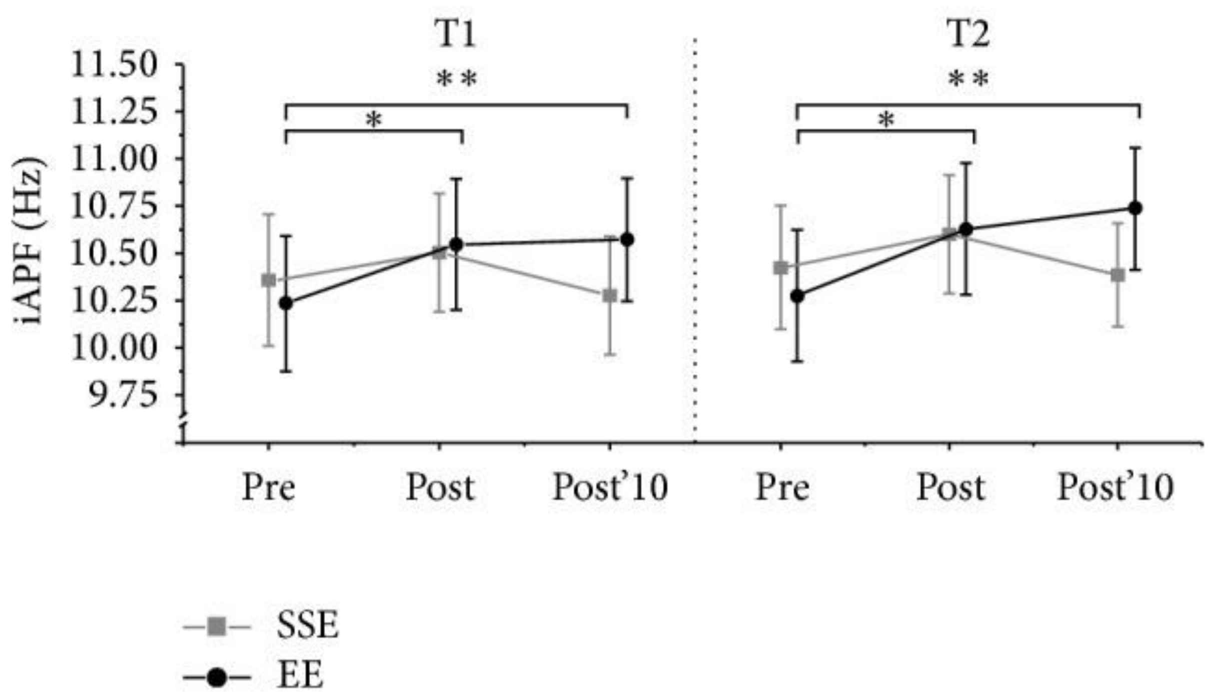

Figure 4: iAPF before exercise (pre), immediately after exercise (post) and after 10 minutes of rest. T1 before training and T2 after training.

The second study examined was examined that focused on the examination of EEG signal strength and fluctuation before, during, and after physical activity on a cycle. While this study had investigated the overall changes in the brain during such physical activity, it was also noted that the most prominent areas that needed to be examined in correlation with physical activity were those found primarily in the temporal region of the brain [18].

The resulting study had run several graphs over the different brain waves that are detected by EEG and have concluded that three of the waves showed the most prominently when regarding physical activity. More specifically, just as we had determined in this study, it was revealed that alpha and beta waves were most prominent alongside theta waves when measuring a difference in intensity of the waves during the exercises. More to the point, it was determined that the change of detectability of the waves from a normal rested state increased the more detectable power was generated. There also was a demonstration that while the wave activity would rapidly decrease after the conclusion of an exercise, it did take some time to for the levels to return to normal as seen in Fig. 5. It could be feasible to record the activity right after exercise to avoid noise and minimize interference within the acquisition of data.

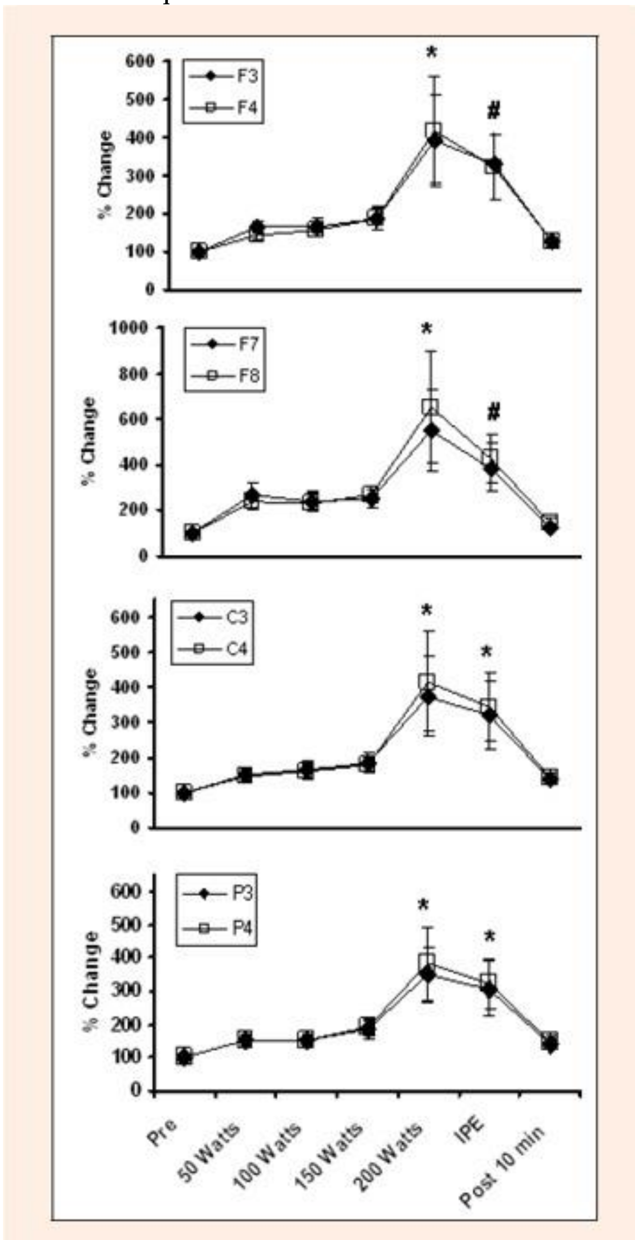

Figure 5: Detectable changes in the Beta wave activity [18]

Chapter 3: System Architecture

Architecture Overview

The hardware and software setup of this thesis will rely on the output of all three biological signal sensors that have been listed in the previous sections of this thesis. One of the main concerns when determining the setup of this system will be to determine the best way to position the various sensors on the individual in question. There also were the considerations for what sort of activities and experiments that could be performed that would result in useful determinations of normal vs abnormal levels of EEG and ECG with regards to physical exertion.

The considerations for what constitute for abnormal signals from the sensors need to be based on a control value that shows the signal patterns and level for normal levels in all three signal types. In EEG specifically, this would also constitute the examination of the normal levels of Theta, Beta and Alpha waves as well as a heavy focus on levels found in the frontal lobe region of the brain as this is the main area related to physical activity [19]. Quantitative analysis of the results would allow the detection of correlations in line with the prediction of physical overexertion, such as a combination of elevated EEG signals and irregular are abnormal ECG signals. This would allow the fabrication of a prediction model based on the contributing factors and could be relayed into an alert for the individual.

As seen depicted in Fig. 6, the overall structure of the architecture is as discussed in the above sections. The beginning portion is the sensors being utilized and collecting the data. Following this, through a Bluetooth wireless means of communication, the data is then sent into software designed to separate the data collected into its useful components. This data will then be analyzed and compared to the designated thresholds and finally be submitted via a designated means of presentation to the user.

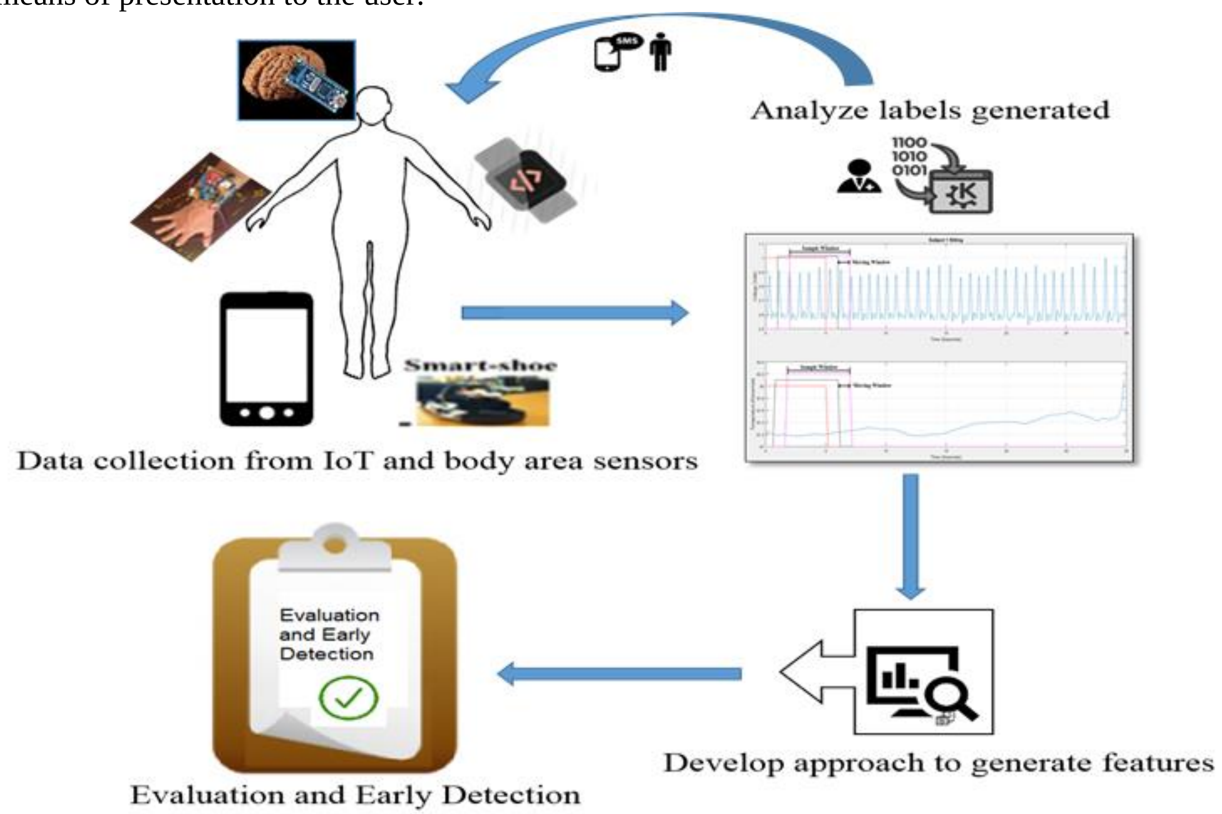

Figure 6: System Architecture

Hardware

There will be two components of hardware that will be utilized in the research, which is the B Alert x10 system for measuring the EEG and the Pulse oximeter device. For the ECG component of the research, the ECG data will be collected by the ECG leads of the B Alert x10 headset. The images of the hardware listed can be found in Fig. 7 found below. The X 10 B Alert System has built in wireless low power Bluetooth built into the device as well as a node adapter that allows the measurement of ECG signals alongside the acquisition of EEG data.

Figure 7: B-Alert x10 Hardware

The hardware that will be utilized for EEG data in this research will be the B Alert x10 sensor. For this headset, the positions of the 3, 4 and Z of the Frontal, Central and Parietal lobe nodes as determined by the 10/20 setup of EEG placement are used. The image of the node placement on the brain can be found in Fig. 8, with the red dots designating the actual nodes of the system compared to a complete EEG node headset. This device collects data from the wearer at a rate pf 256 samples per second and within a voltage limit range of $^{+}/_{-}$ 1000 uV. Included within this device is the use of Bluetooth communications to submit information to the computer utilizing the Stat software and the ECG adapter. Due to these additional capacities from the device, acquiring data from both EEG and ECG during activity at the same time will be facilitated and easier to compare for analysis.

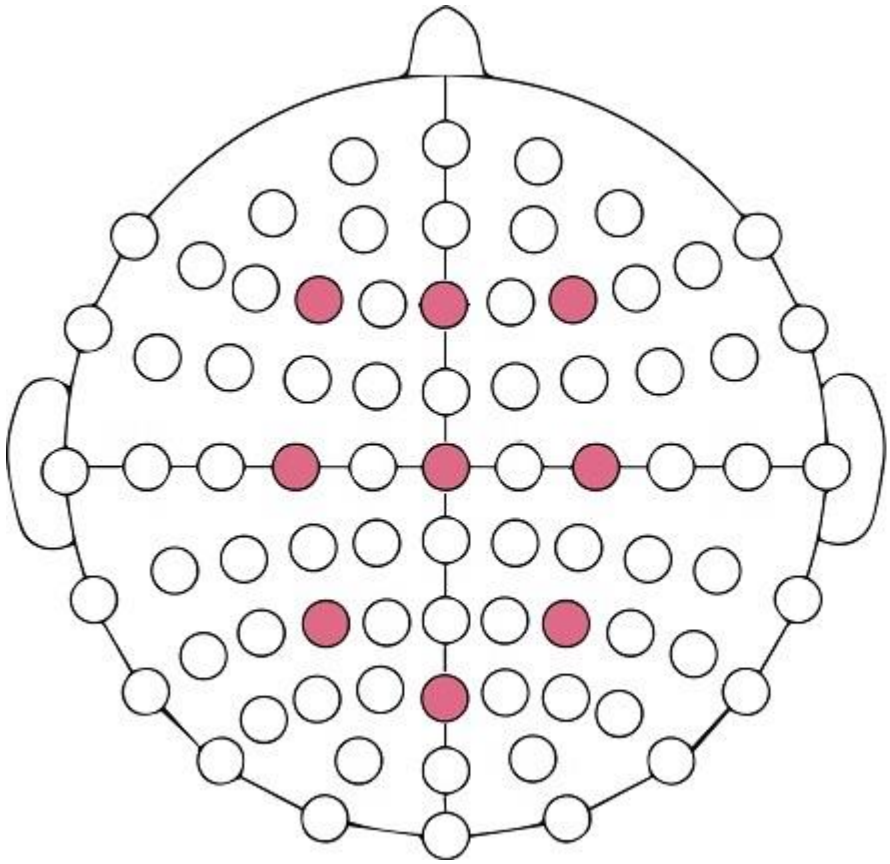

Figure 8: EEG placement of B-Alert x-10 nodes (red)

The other sensor being utilized in this study is the pulse oximeter. Pulse oximetry is utilized as a noninvasive and painless test to measure oxygen saturation levels in the blood of the subject [20]. The device was attached to the subject's finger before and after each trial to assess the change in heartbeats and to determine if there was a notable drop in oxygen levels due to the activity being done. This was done to account for potential variables that may originate from a decreased blood saturation level.

Software

Upon acquiring the data from the headset for the EEG and ECG, the data is stored in an edf file from the STAT software. This software includes parameters to test and provide the impedance of the resulting values from the nodes to demonstrate effectiveness of placement and whether the data to be collected will be accurate within accepted tolerance. After this test is completed and the operator is satisfied with the values of impedance, the acquisition can commence and be maintained as desired by the operator for various tests. During the process, there is a real time data acquisition and graphing shown on the interface which includes all the nodes for collecting data as well as the ECG values and the head position detected by the headset in the X, Y, and Z axis. Upon ending the acquisition phase, the data can be examined and seen on an overall scale through the entire phase of data collection.

MATLAB will be utilized in this research for the purposes of analysis and comparisons to the data collected from the various sensors. In order to utilize the information from the STAT software edf files in MATLAB, the EdfRead program for MATLAB Central will be implemented [21]. Regarding the data analysis, a Short-Term Fourier Transform following the standard method of analyzing EEG data will be used. Based on the sampling rate of the device, the parameters regarding this will be accounted for when graphing the EEG data. The ECG data will be used for comparison against the EEG data and used in demonstrating the time correlation between peaks in EEG activity with increased heart rate.

Chapter 4: Data Collection

The process of collecting data from the subject is in two parts. The first part of this process is the collection of data by the various sensor systems and the means of saving the collected data for future analysis. The second portion of this process is the designation of what type of trial the subject is currently participating and meaningful identifiers of the subject in the data. The need for this sort of process and manner of which the data is collected is to ensure the best accuracy and consistency with the data being collected.

Sensor Data Acquisition

Due to the different sensors that will be utilized at the same time to acquire data from the subject, sample rates of the various sensor will need to be considered in the analysis. In order to utilize the various information gathered from each sensor and to allow for relative comparison accounting for the sample rates of the devices allows for easier comparison based on the timing of significant portions of the data.

Subject Data and Trials

With the setup of the various sensors decided on, the next portion of collecting data is to determine what groups of interest should be considered when examining physical overexertion and the manner of acquiring said data. Since physical overexertion can happen to any group of individuals of various age ranges, gender and physical fitness, the selection of subjects was done from a range of 18 to 55 years of age, with four women and three men being selected. The range of individuals who are stated to be regularly physically active versus not being physically active varies from a few times a month to every day, with an average of one to two times a week. Being considered physically active was stated as either performing a regular job that utilizes a significant amount of activity such as landscaping or going to the gym. The activities selected for finding thresholds as a basis for comparison for EEG activity are of a set of three. For acquiring data for a low threshold of physical exertion, the subject was set to be relaxed and sitting or lying down. In order to acquire the medium level threshold data, the subject was instructed to move around the area for the duration to provide a basis of normal physical activity, such as writing on a white board. Finally, for the threshold of high physical exertion, the subjects were instructed to do as many sit-ups, squats or pushups as they can within the collection cycle, a focus on subjects maintaining the high level of exertion on their muscles for the data. Found in Table 1 are a more visual examination of subject parameters.

Subject Parameters	
Total Number of Subjects	**7**
Parameter Categories	**Number of Subjects in Category**
Gender	
Female	4
Male	3
Age	
18-20 years old	1
20-25 years old	3
25-30 years old	1
30+ years old	2
Physical Activity	
A Few Times a Month	1
Once a Week	3
Three times a Week	2
Everyday	1

Table 2: Subject Parameters

Chapter 5: Data Analysis Technique

The objective for the data analysis of this report is to demonstrate a correlation between the changes in EEG levels in relation to increasing levels of physical activity. For the following research the main program of analysis was done with MATLAB. This program is a multi-paradigm numerical computing environment and proprietary programming language that allows publicly created functions to be developed. In order to discuss the methods chosen to analyze the data provided, it will first be necessary to discuss the purposes of signals.

One of the main concerns for researchers when dealing with signal analysis is the effect of noise that accompanies a signal. Noise, regarding signal processing, is unwanted signaling that will degrade collection, storage, processing, or transmission. The EEG can be found to have instances of noise from movement of the head and shifting of the placement of the nodes in the headset. Due to the headset also utilizing Bluetooth connection for submitting the data to the STAT software to be written into an edf file, another section of noise error will need to be considered in analysis. This also can be found in the ECG signals that were taken during the testing. This was noted during the more active trials, needing to examine ways to reduce and filter noise. A work that was noted dealt with the development of an adaptive recurrent filter structure to deal with this situation that was examined for filtering ECG data [22].

Short Term Fourier Transform

When analyzing the data that has resulted from the trials being performed, it was determined to utilize a Short-Term Fourier Transform (STFT) over the signal given. More specifically, in MATLAB this is done utilizing the function *spectrogram ()* to generate such a graph. Due to the sampling rate of the device being the standard EEG device setting, 256 samples per second, this was the number utilized for setting the frequency in the function, as well as the segment window. For the no overlap window, it was determined that a 0.7 sec window or 70% of the sampling rate produced the best results for the EEG signals [23]. There was also a limiting of maximum frequency of 60 Hz as that is the maximum value of brainwave activity.

There is also the utilization of another MATLAB Program utilized for the analysis of EEG. The program in question utilizes and adaptive period gram technique (APT). The technique used determines the signal's coherent length, achieving optimal resolution in both time and frequency domains [24]. This program will be implemented to provide a secondary analysis for comparison against the standard STFT done by MATLAB's *spectrogram()* built in function.

ECG Low pass Filtering

Once the analysis of EEG was completed, the next set of analysis that was done was focused on the collected ECG data during the trials. As can be seen in Fig. 8, the first graph shown demonstrates that while readable ECG data was able to be collected, there was significant high frequency noise generated during the tests. To resolve this, a two part filtering process was decided. To begin filtering, the wave collected was processed through a low pass filter utilizing the *lowpass()* function found in the MATLAB library. As seen in the second graph of the figure, the filter reduced the exceptionally high peaks found in the graph.

The second process in the filtering that was taken into account was smoothing the data. Due to the movements of the individuals, there is a noticeable baseline wander. This is the wave like characteristic of the overall base of the ECG wave that is not reminiscent of the standard flat base of the ECG wave as seen in Fig. 1. In order to account for this, the *smoothdata()* function from MATLAB's library was utilized to show the low frequency component remaining that needed to be removed from the signal. This can be seen in the third graph found in Fig. 9. Finally, by passing the signal through the low pass filter and subtracting the smoothed signal of the low pass filter of the signal, the final graph is given and produces a more usable ECG signal for future portions of the analysis.

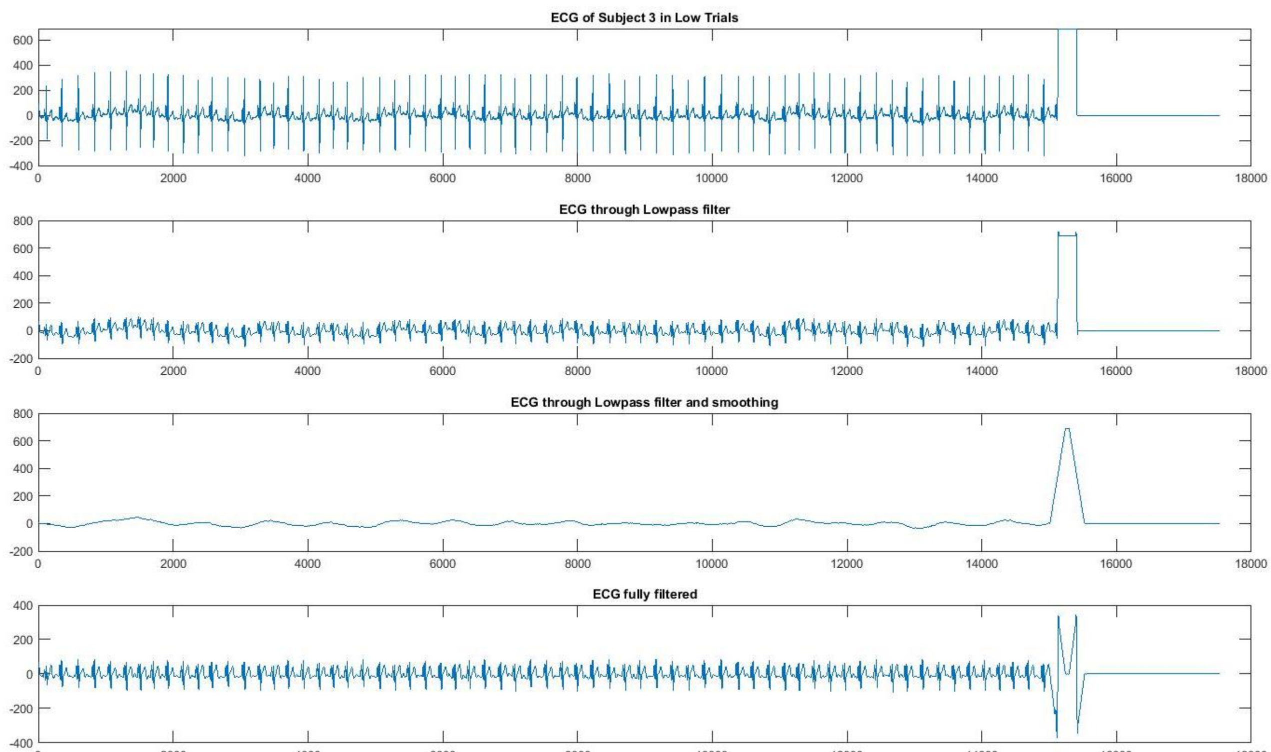

Figure 9: ECG filtering process

Chapter 6: Results and Evaluation

The objective of the thesis is to examine and determine if there is a notable range of frequency that changes for EEG data that can be directly correlated with physical exertion. This consideration would be based on noticing a continuing trend through multiple runs of the same subjects over the different trials compounded with ECG and pulse oximeter measurements.

Pulse Oximeter Analysis

The first set of data examined was obtained from the results found from the pulse oximeter. After having tested the subjects throughout the various trials, it was found that the overall oxygen saturation levels remained around 97% to 99% SPO_2, regardless of the type of trials that were being conducted. The heartbeats of the individuals all increased from each level of activity as would be expected, thus it can be concluded that the oxygen levels of saturation with regards to the pool of individuals that were used will not be a variable needed for analysis.

Short-Time Fourier Transform

Upon completing the STFT analysis utilizing the *spectrogram()* function in the MATLAB library, there was a possible trend in the increase of overall electrical brain wave activity with the increase in physical exertion. When examining the low-level exertion trials, the average trend of the peak levels appeared below a frequency of 15 Hz. Medium level exertion trials generated a range generally around 25 Hz for most of the noticeable peaks. Finally, the peak ranges for the high exertion level trials all concentrate at 35 Hz or above. These peaks can be noted in Figs. 10 through 18, of which all subjects were female and were of the age ranges of 18-30.

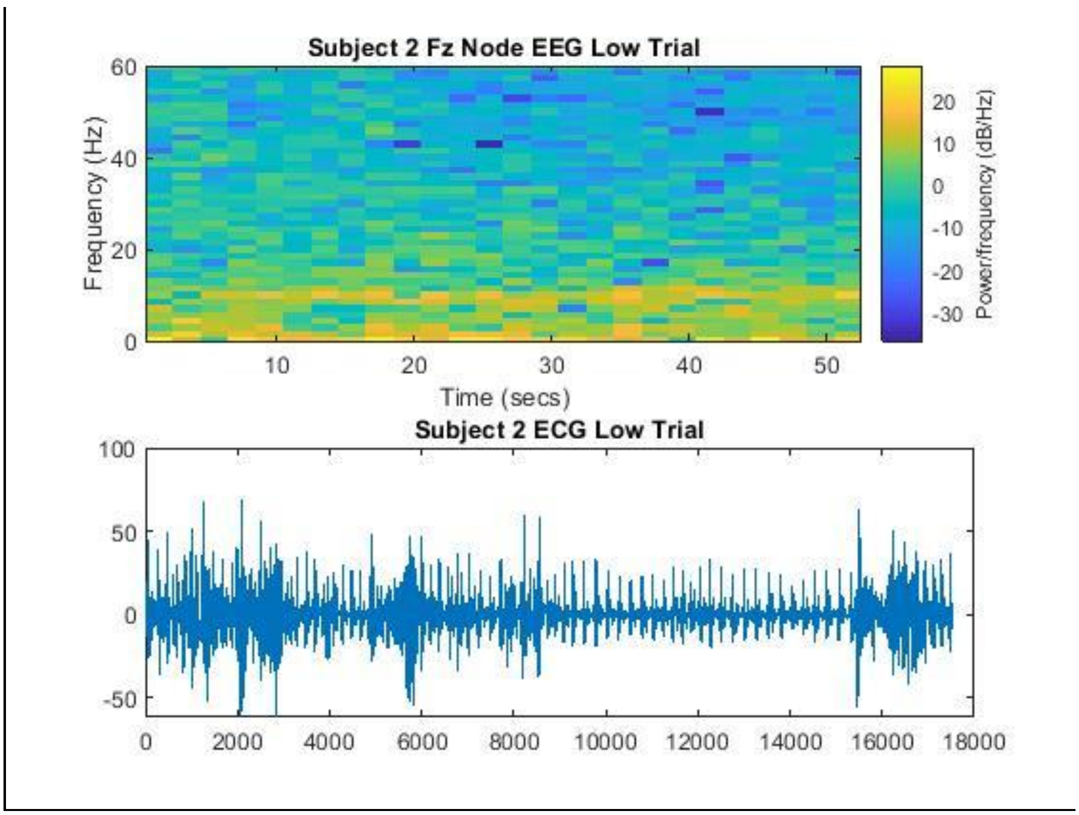

Figure 10: Subject 2 Fz Node EEG STFT and ECG Low Trial Data

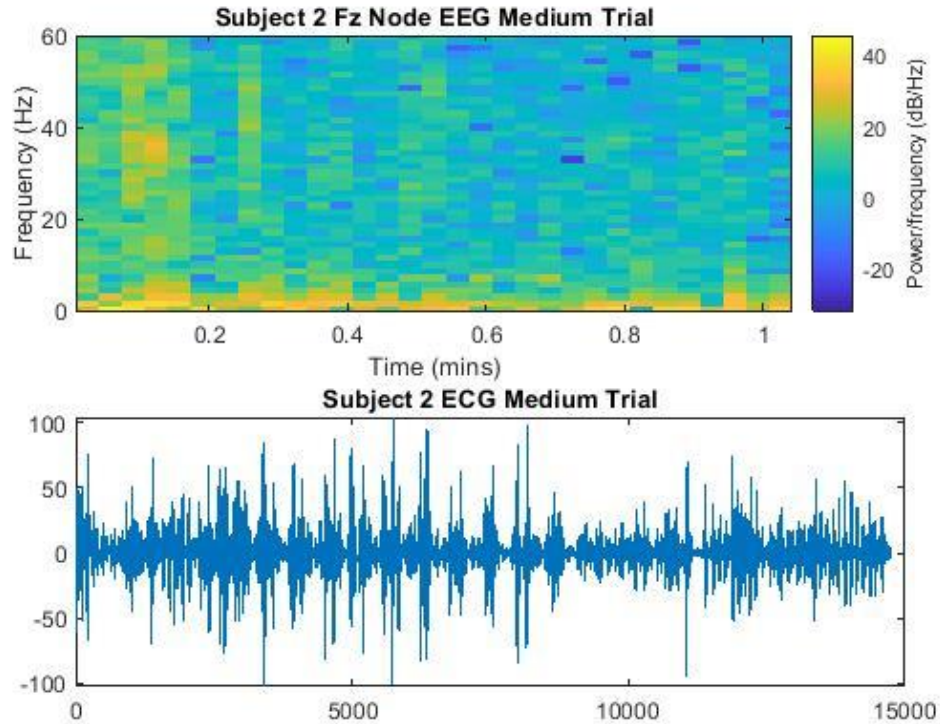

Figure 11: Subject 2 Fz Node EEG STFT and ECG Medium Trial Data

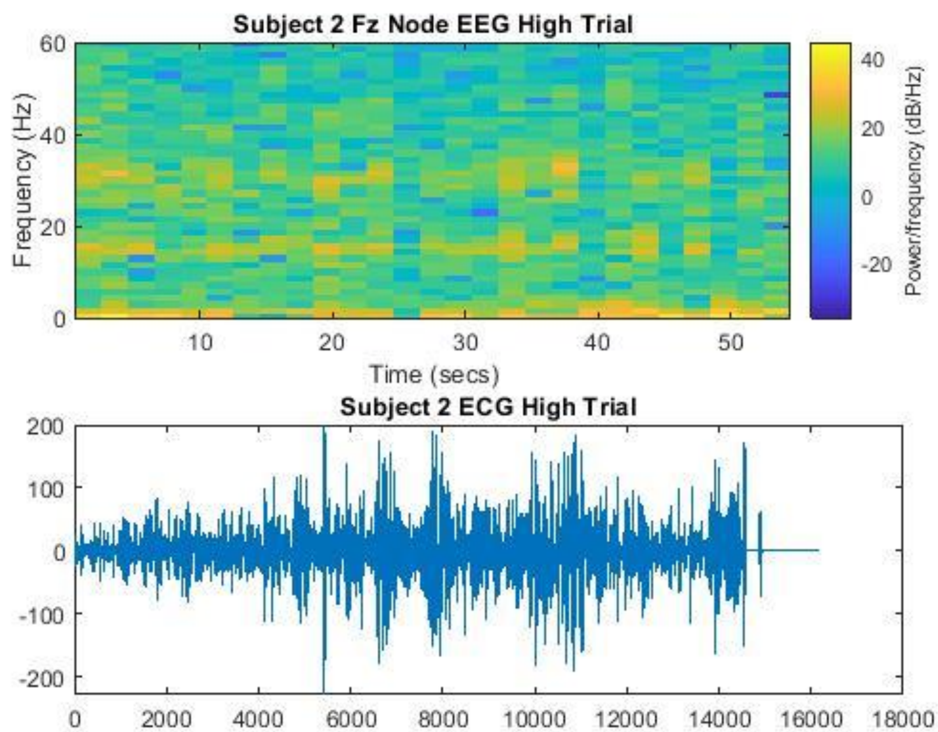

Figure 12: Subject 2 Fz Node EEG STFT and ECG High Trial Data

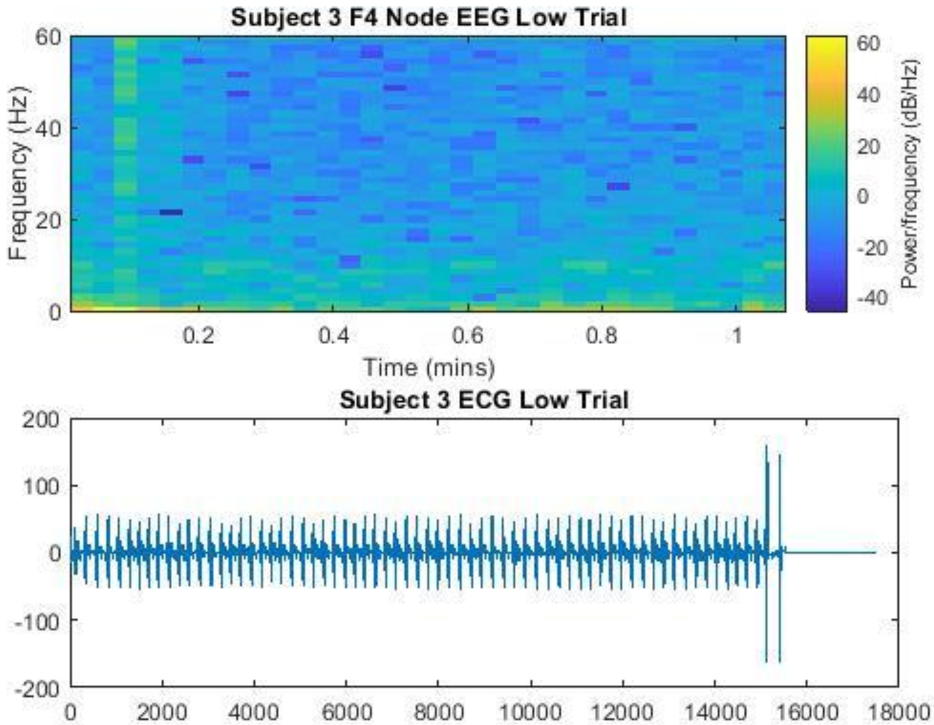

Figure 13: Subject 3 F4 Node EEG STFT and ECG Low Trial Data

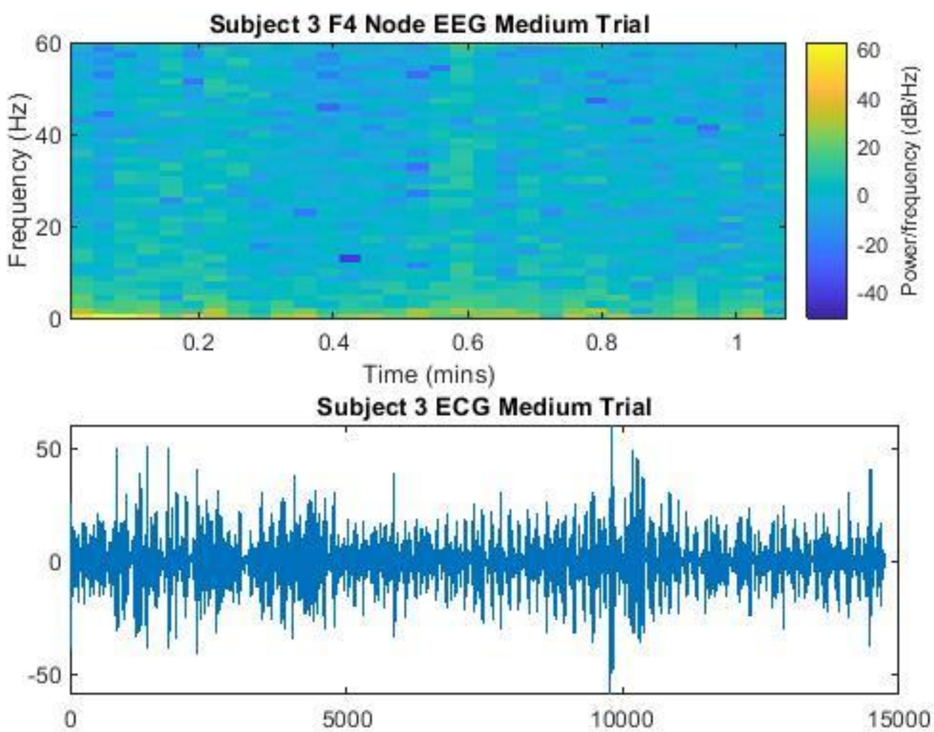

Figure 14: Subject 3 F4 Node EEG STFT and ECG Medium Trial Data

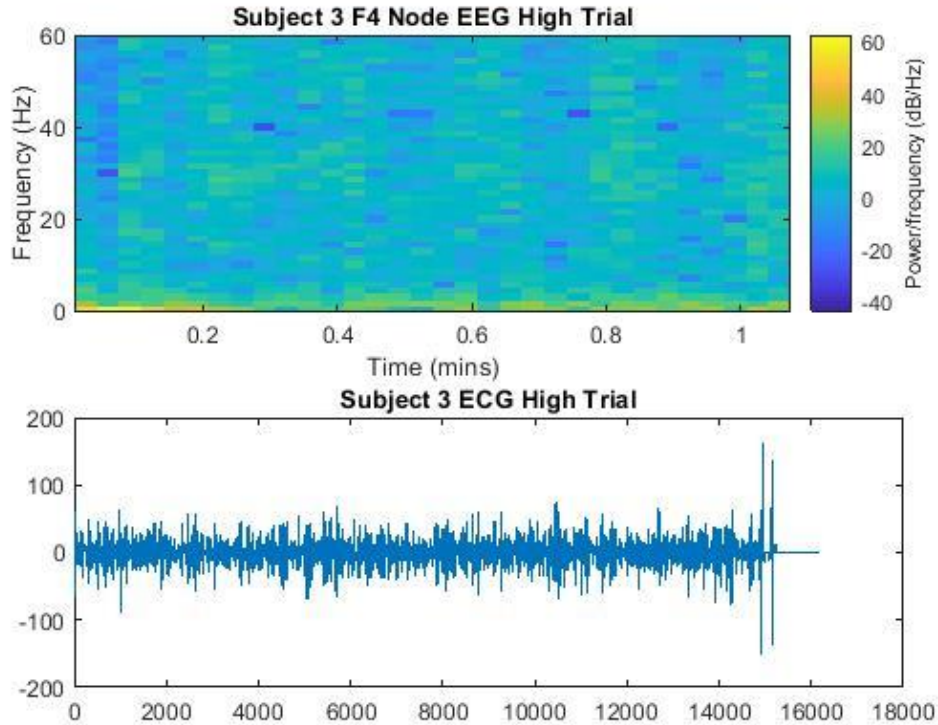

Figure 15: Subject 3 F4 Node EEG STFT and ECG High Trial Data

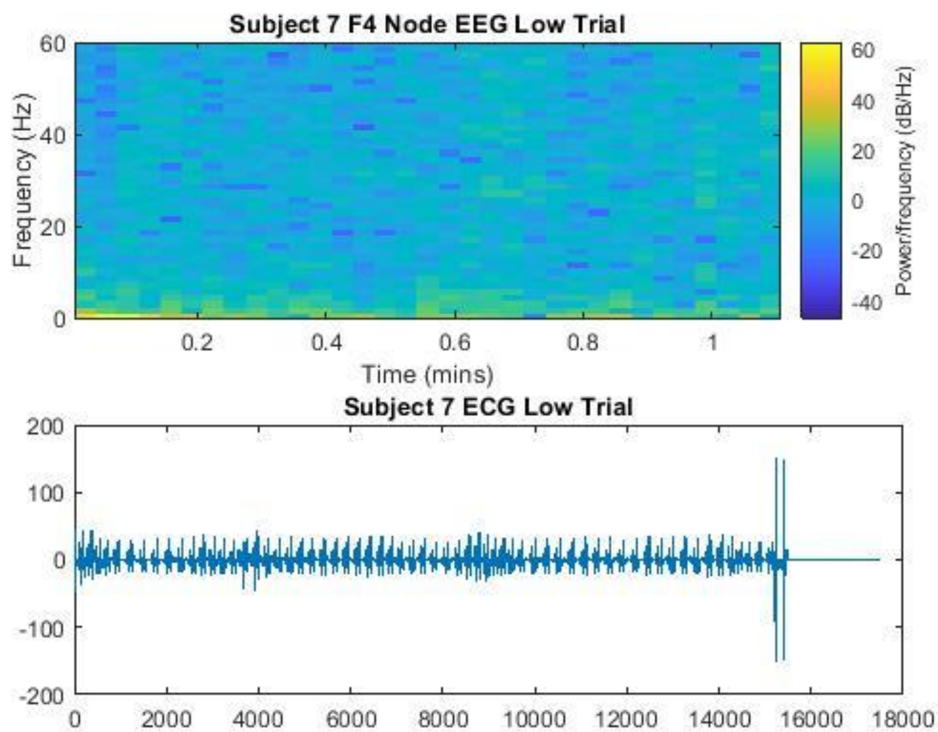

Figure 16: Subject 7 F4 Node EEG STFT and ECG Low Trial Data

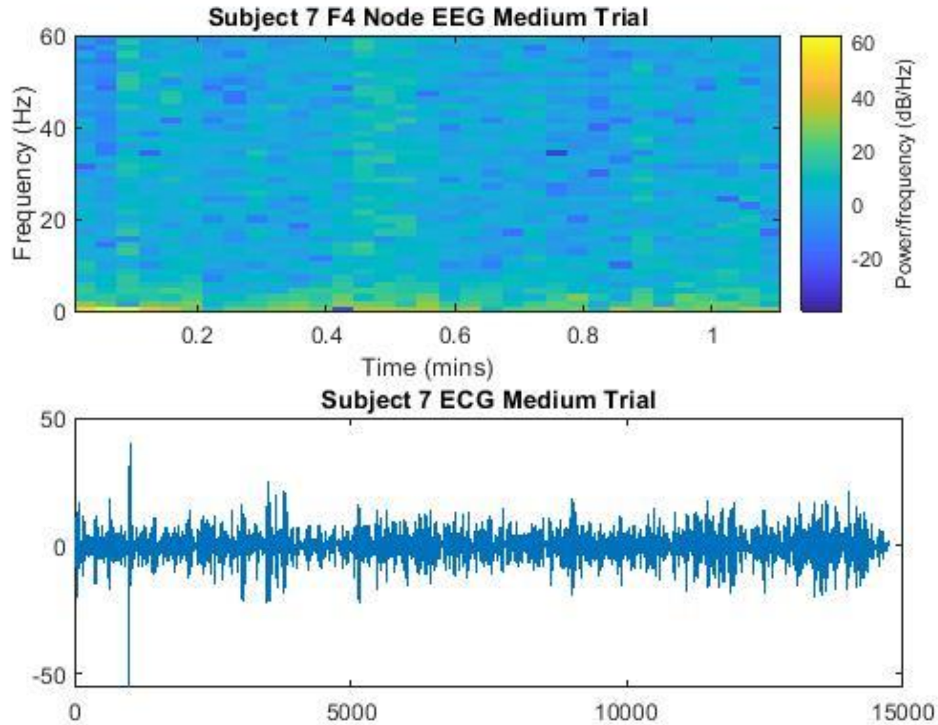

Figure 17: Subject 7 F4 Node EEG STFT and ECG Medium Trial Data

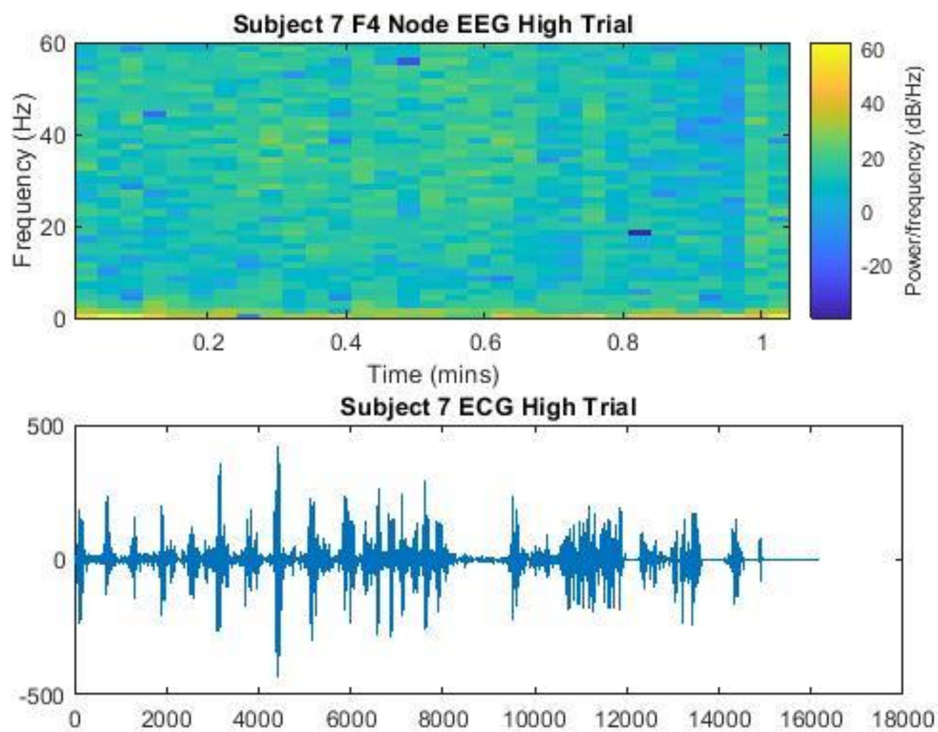

Figure 18: Subject 7 F4 Node EEG STFT and ECG High Trial Data

ECG Analysis

This trend in EEG frequencies in relation to physical activity seems to also be seen with regards to the male subjects, as can be seen in Figs. 18 through 23. For the ECG analysis, it is found that while there is a notable standard ECG pattern in the low trial of the tests, there is a loss of integrity in the medium and high exertion trials. Such loss of integrity is found even after having performed a lowpass filter and a smoothing filter on the acquired data. This can most likely be accounted for by limitations in the ECG adapter used for the B-Alert x10 device with regards to handling movement. Based on the data presented, the ECG in the low exertion trials did not correlates with any specific peaks and the data found in the other trials also do not have a correlation with the noted peaks in EEG signals. While ECG is utilized to aid in determining the level of exertion based on the change in beats per minute of the heart would aid in determining the level of physical activity, it would not be useful as a variable to determine levels of peaks in frequency in the EEG waves.

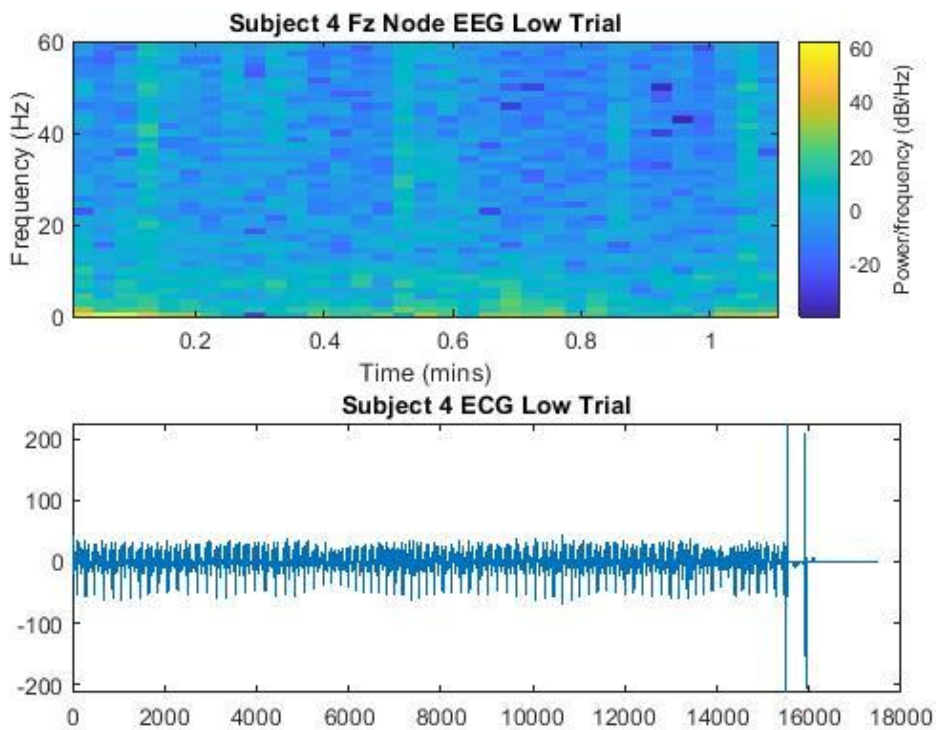

Figure 19: Subject 4 Fz Node EEG STFT and ECG Low Trial Data

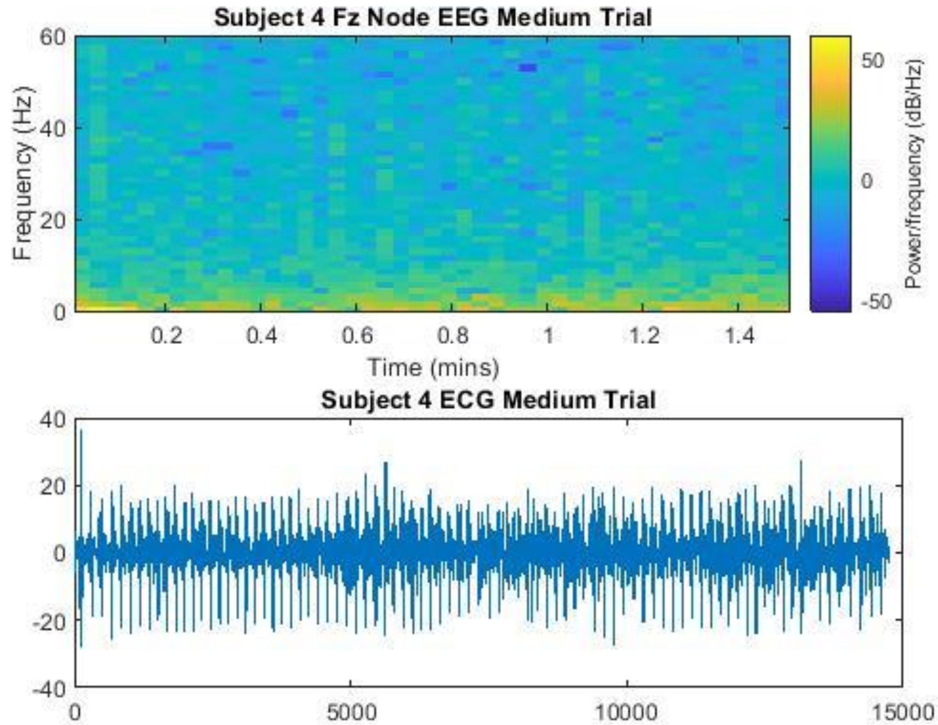

Figure 20: Subject 4 Fz Node EEG STFT and ECG Medium Trial Data

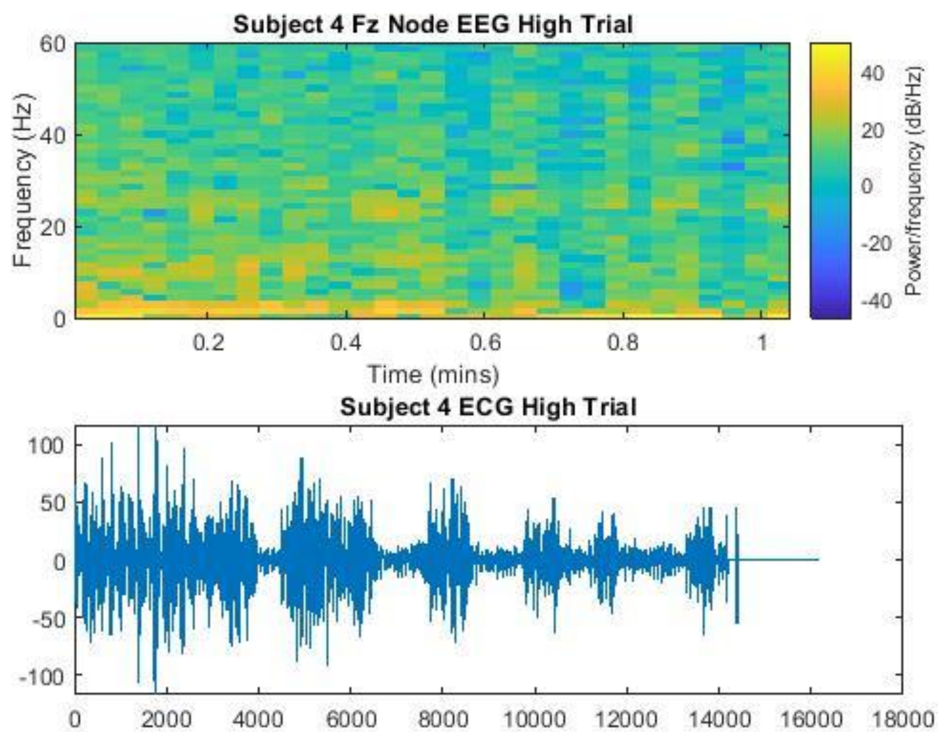

Figure 21: Subject 4 Fz Node EEG STFT and ECG High Trial Data

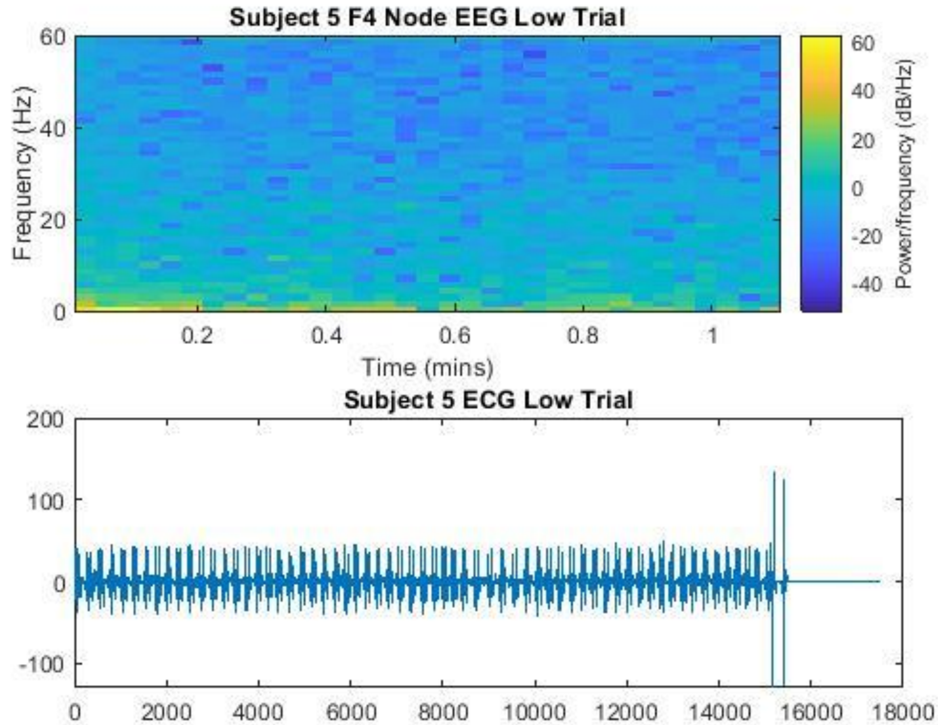

Figure 22: Subject 5 F4 Node EEG STFT and ECG Low Trial Data

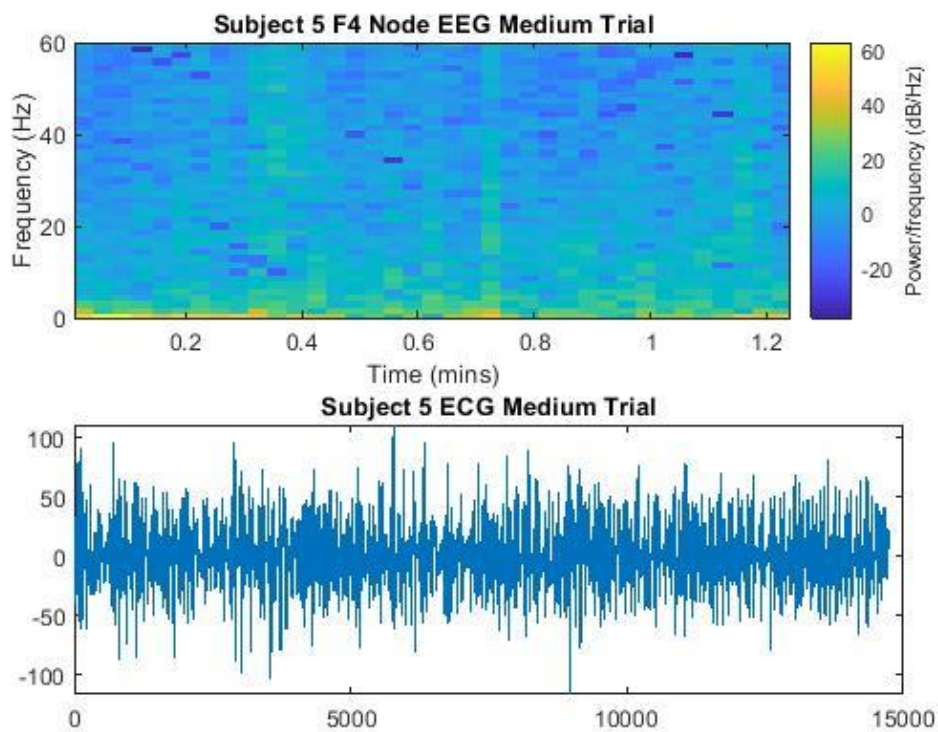

Figure 23: Subject 5 F4 Node EEG STFT and ECG Medium Trial Data

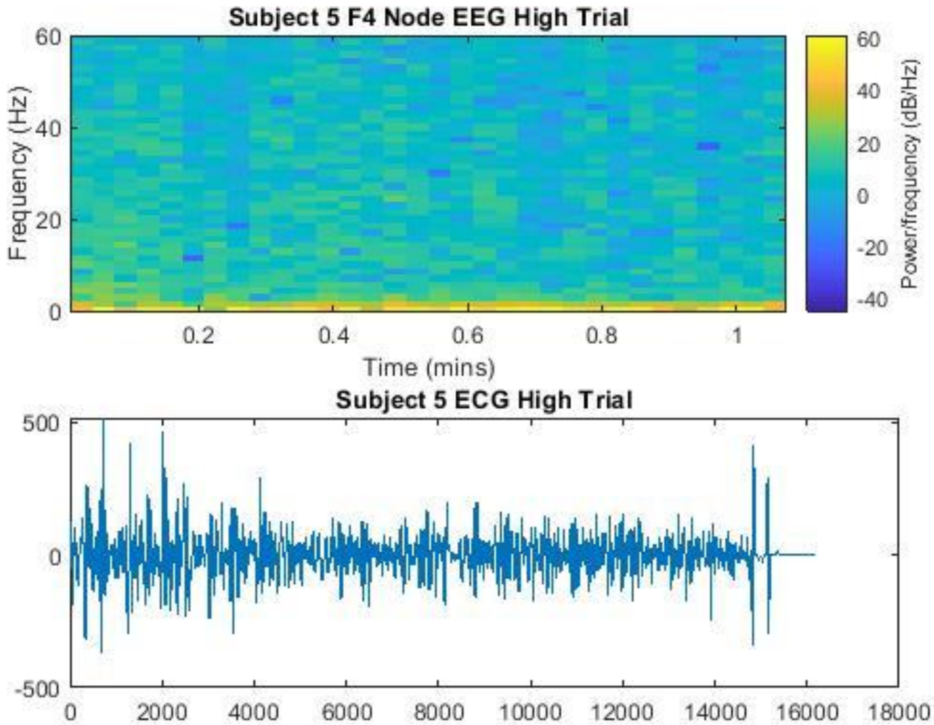

Figure 24: Subject 5 F4 Node EEG STFT and ECG High Trial Data

APT Program Analysis

When performing the analysis with the APT analysis program, similar situations seemed to occur as well. As a case of study, the APT analysis of Subject 4 was examined to demonstrate analysis result. For this thesis, the main graph of focus will be the Frequency graph with time of *log(Px2d.*wL2d)*. In the low exertion trial, there is a detectable amount of low frequency at significant sections throughout time. In the medium exertion trials this low frequency is still noticeable but greatly reduced from the low trials before. Finally, the high exertion trials appeared to have the lowest amount of remaining levels of low frequency. However, these graphs are done with normalized frequency, resulting in more difficult comparison with the two programs utilized. The results mentioned can be seen in Figs. 24 through 26.

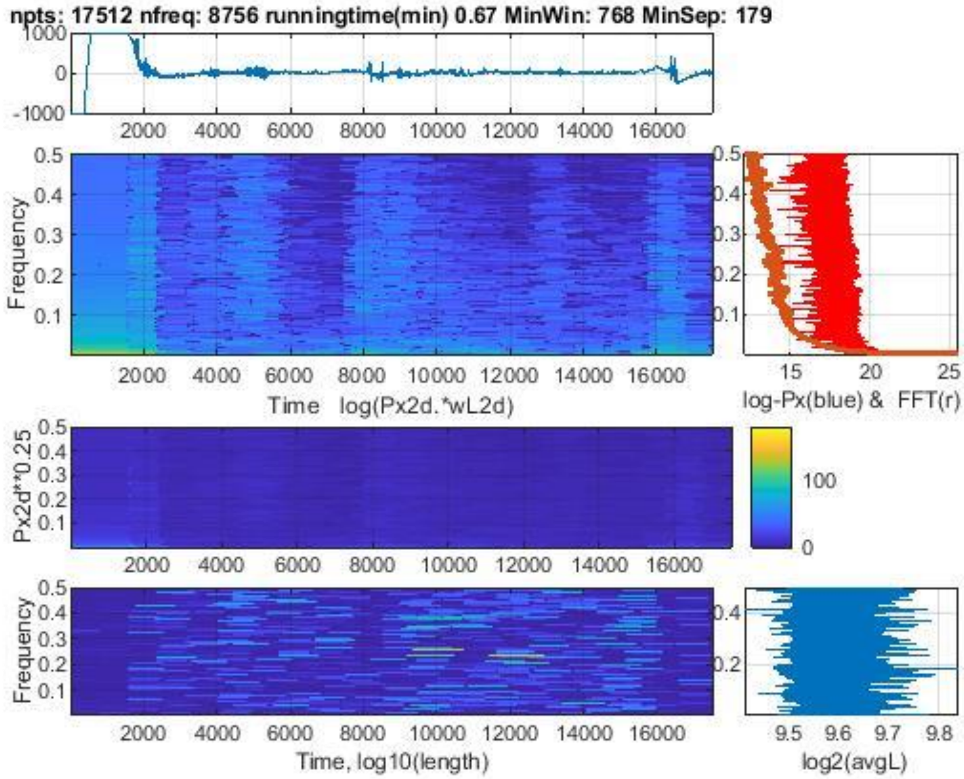

Figure 25: Subject 4 F4 Node Low Exertion Trial APT Data

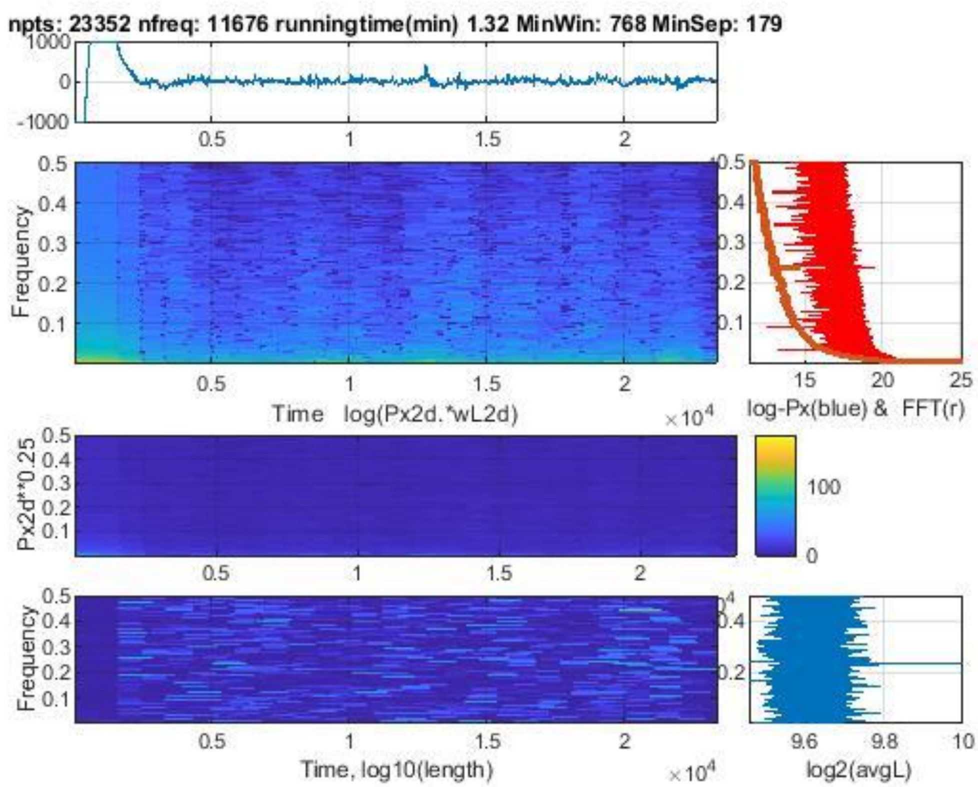

Figure 26: Subject 4 F4 Node Medium Exertion Trial APT Data

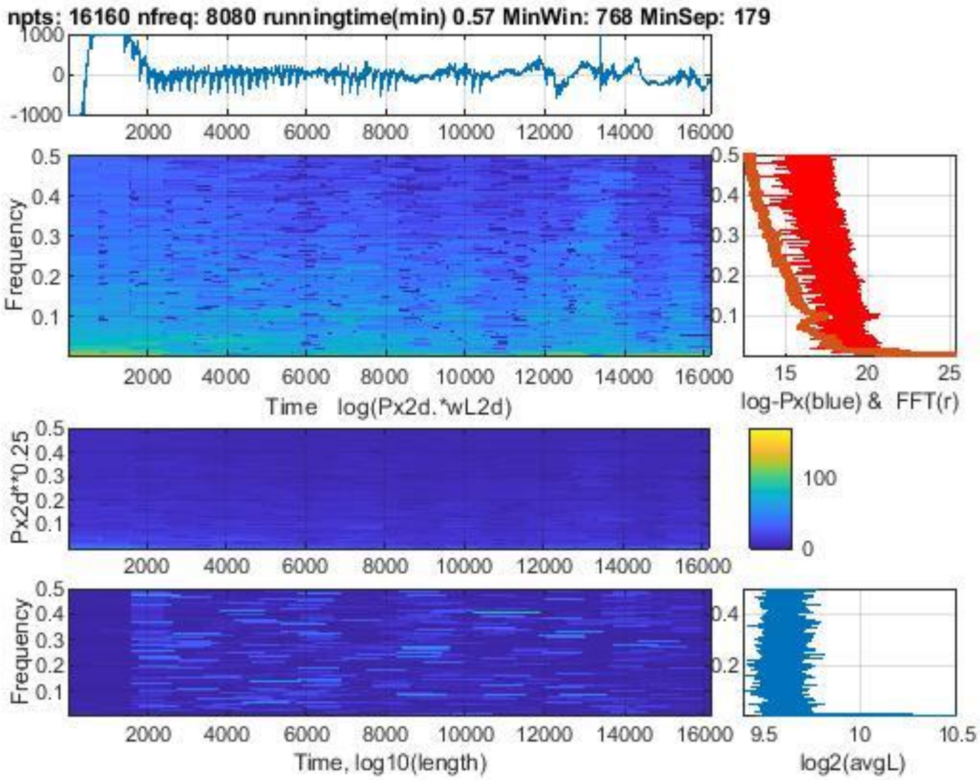

Figure 27: Subject 4 F4 Node High Exertion Trial APT Data

Simplified Trial Analysis Comparison

With the completed analysis of the trials done with the subjects, it became necessary to examine a control situation to verify accuracy. Regarding this, Subject 4 was required to move their head around in various directions for a minute to ensure that movement interference would be picked up during the tests. This process was done with the subject remaining seated in order to ensure that the only significant potential variable for noise and interference was due to the movement of the head. The resulting data and spectrogram analysis generated the image found in Fig. 28. By examining the image, it can be found that there is a high possibility that the number of peaks found exceeding 10 to 15 Hz of frequency is most likely generated by the head movement.

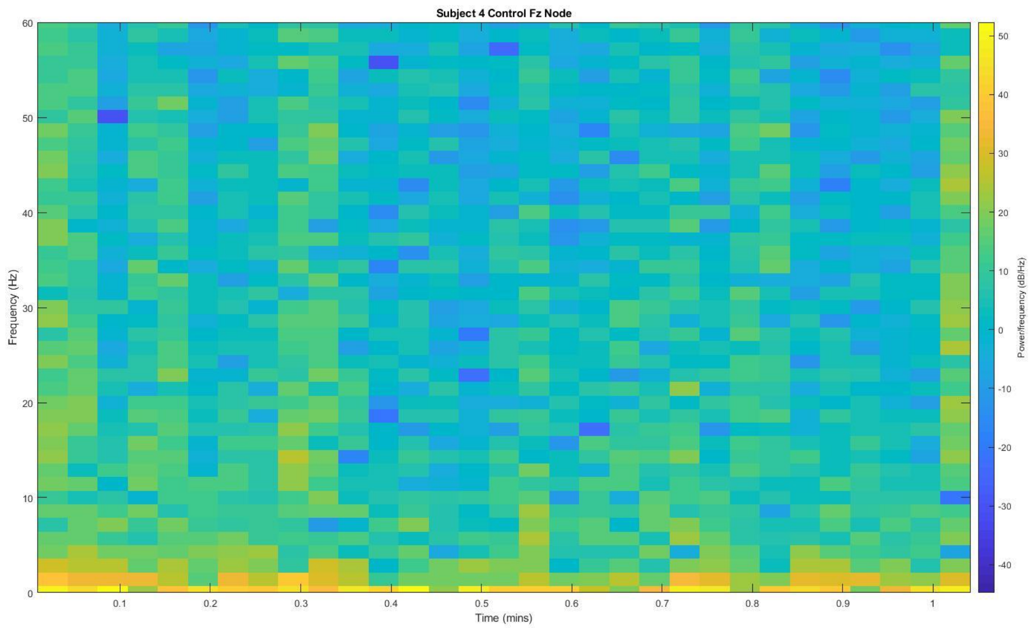

Figure 28: Subject 4 Control test

Alongside the considerations for interference caused by head movement, there was also a necessity to determine the statistical reliability and consistency of the trials performed. To determine the viability of the data, all five trials performed by Subject 4 were utilized to determine what sort of trends could be expected. The process included doing the low, medium and high trials five times each. It was determined the best approach was to do all five trials of low exertion first, then all the medium trials before performing the five high trials. This was to ensure the least amount of interference and change in the results due to influence of the subject having done the high trial tests right beforehand. Based on the results found by calculating the mean of the spectrogram results through MATLAB, as can be seen in Fig. 29. There appears to be a pattern with the frequencies found to be more concentrated in the low trials, with an increase in frequency ranges as the subject progressed through the medium and then the high trials. This trend also appears to be the case when comparing the mean results of all 7 subjects, as seen in Figs. 30 through 32.

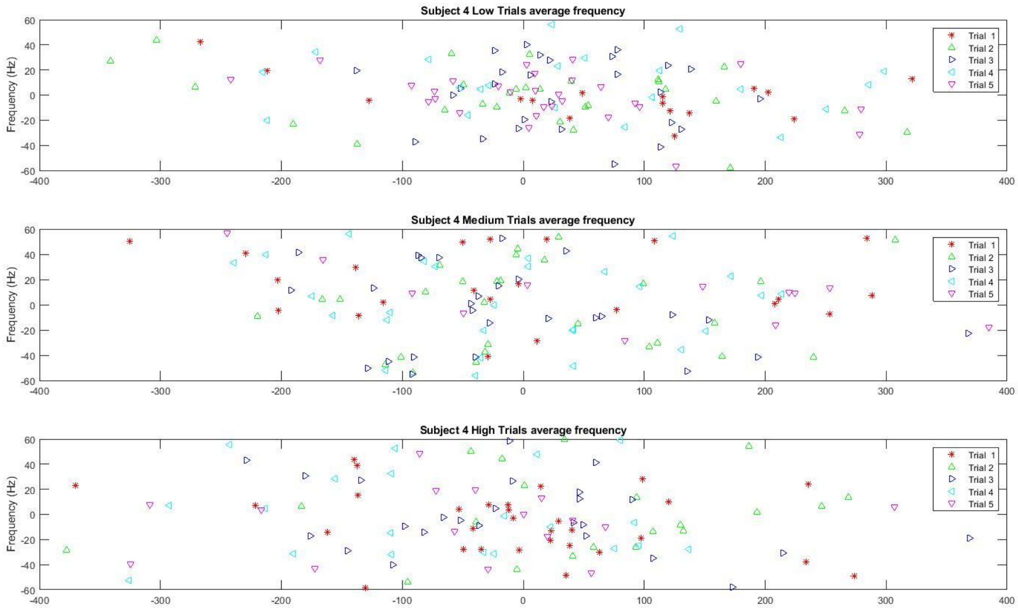

Figure 29: Subject 4 Trial Comparisons

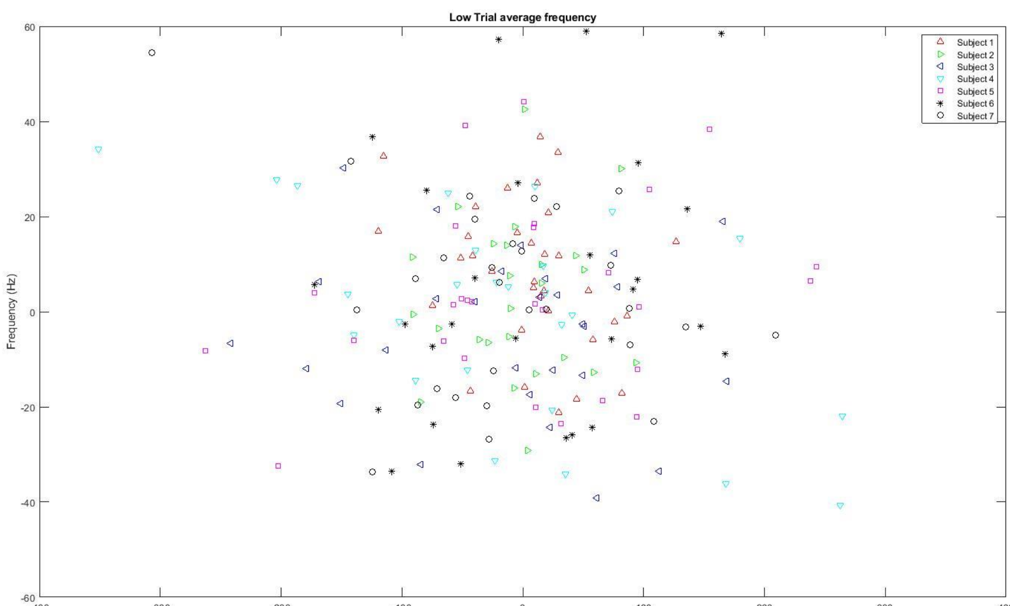

Figure 30: Comparison of all Low Exertion Trial Subjects

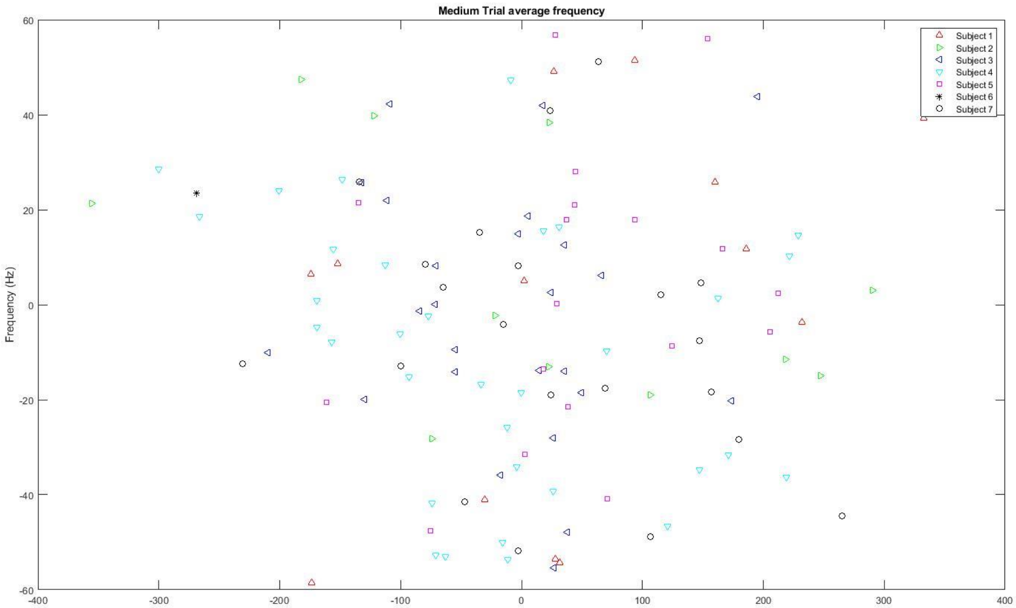

Figure 31: Comparisons of all Medium Exertion Trials

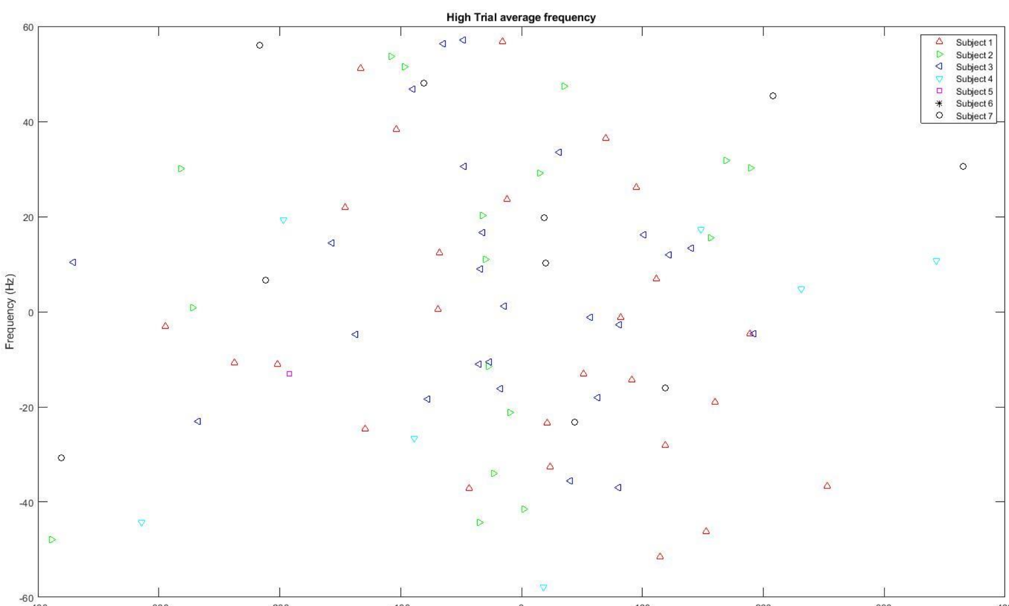

Figure 32: Comparisons of all High Exertion Trials

To further examine this potential pattern, an analysis was done to examine the average values of the frequency found in the data collected. The data was the average values found throughout all seven subjects and then graphed in correspondence to the level of exertion that was performed. These results can be found in Fig. 33. As can be seen, all but two of the subject are averaging in values that far exceed the anticipated frequency, most likely due to a large amount of noise and other interference for the overall values. This is further compounded by the results found in Fig. 34, which contains the average value of all the trials done by the subjects and illustrating the average values of the frequency based on exertion level. While once again the average frequency value far exceeds the levels of frequency anticipated to be found in brain waves, it does have a trend of increased value.

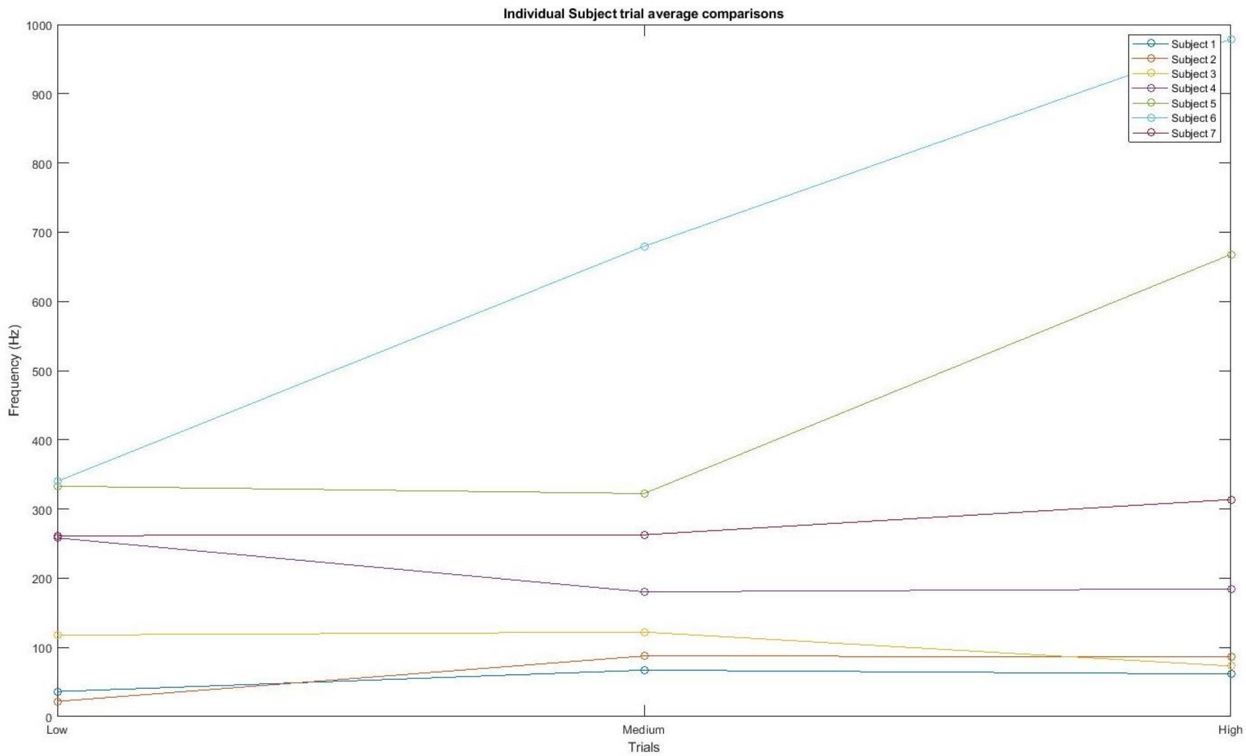

Figure 33: Individual Subject trial average comparisons

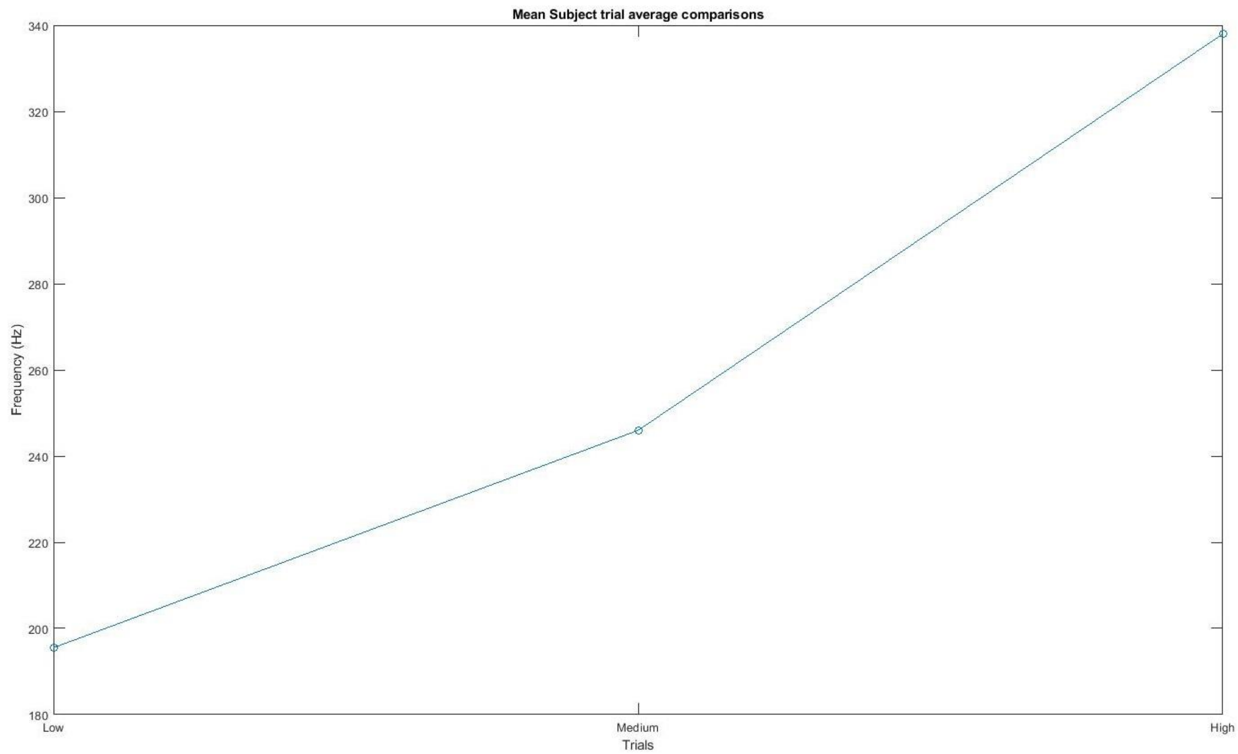

Figure 34: Mean Subject trial average comparisons

Finally, the multiple trials of Subject 4 can be found in Fig. 35. While the low exertion trials generated an average frequency far below the medium and high trials, there is a near equal average for the two higher trial frequency values. This result would further demonstrate that due to the case dependent nature of these experiments of EEG, there will need to be a heavy focus on examining ways to account for far more variables to potentially bring a more substantial conclusion.

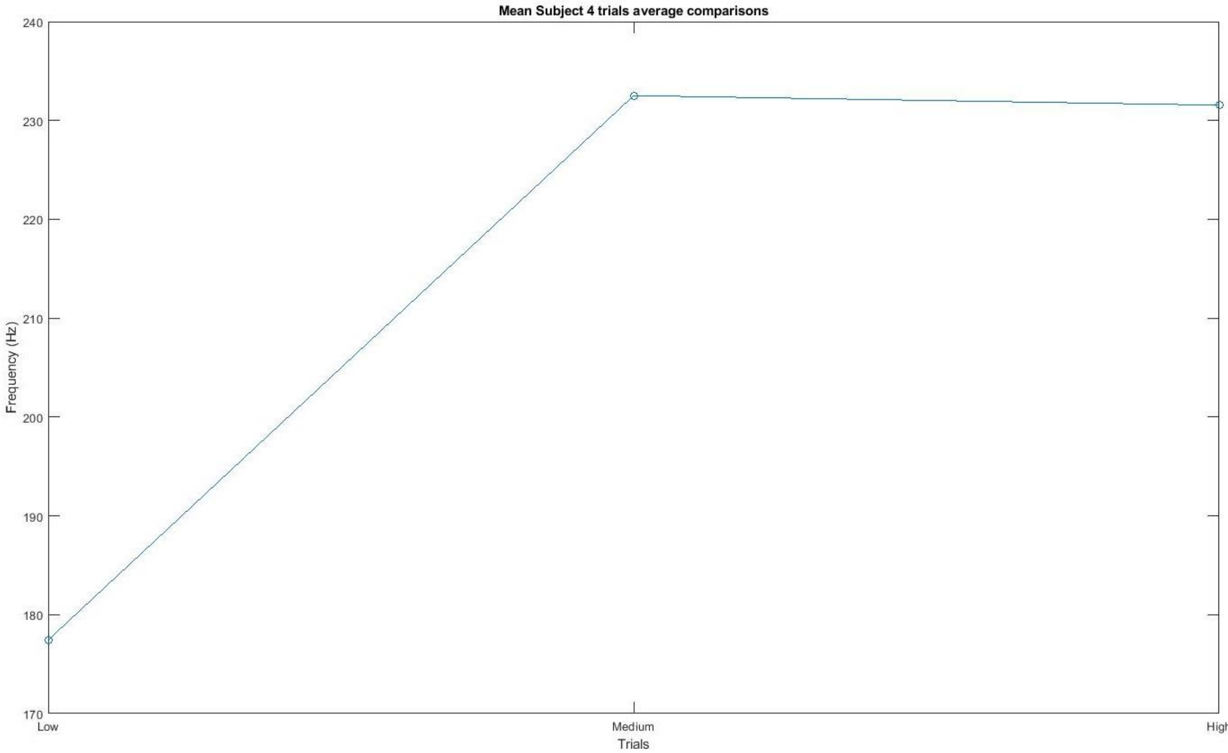

Figure 35: Mean Subject 4 trials average comparisons

Chapter 8: Conclusion and Future Work

As seen from the results of the trials that have been done with analysis, there may be indications that there is a readable and reliable change of levels of EEG levels to warrant further investigations. However, due to the amount of noise found in all levels of activity and the inability to differentiate thinking processes alongside physical movement activation, it would be prudent that a lot more studies be conducted. The use of a pulse oximeter has shown that there is no significant change of the oxygen saturation, determining that there is no need to consider such a variable in general analysis. The ECG value use was limited by the limitations of the ECG adaptor device employed. However, based on low exertion trial results, the ECG did not seem to be able to be correlated to spikes of EEG frequency values. The ECG utilization alongside an EEG would still be advantageous as the detectable increased heart rate would help correlate with EEG as to what range of exertion the patient is experiencing. It should be noted that values are susceptible to device limitations, user and analysis error, and a limited pool of subjects. Future experimentation with other methods would be advised.

Future suggested research that could be conducted may consider utilizing wavelet transform analysis. Given that standard STFT techniques are done with an examination of the overall wave, such a technique could be used to view sections of the waves and potentially be able to better detect the waves in question [25, 26]. There could also be a considerable effort to include other types of biological signals, such as EMG to focus on more specific instances. Utilization of other EEG and ECG biological signal devices would also be warranted to compare against the B-Alert x10 system. Finally, a far greater pool of subjects to allow comprehensive comparison would most certainly be needed to provide far greater emphasis in this sort of study.

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