

CALIFORNIA STATE UNIVERSITY, NORTHRIDGE

Human Computing: Feature Extraction and Storage
Considerations for Multi-Channel Biometric Data

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ABSTRACT

Human Computing: Feature Extraction and Storage Considerations for Multi-Channel Biometric Data

By

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Master of Science in Computer Science

The purpose of this thesis is to examine the relationship of electroencephalogram (EEG) data using insight meditation techniques versus effects demonstrated using alternate nostril breathing techniques. The alternate nostril breathing technique consists of inhaling through one side of the nostril and exhaling through the other side of the nostril, utilizing your fingers to close the side of nostril not in use. Muse headband, 2016 version, is used to observe the effects on EEG utilizing these meditation techniques. This research will help determine if similar EEG patterns can be generated using breathworks in less time and whether EDA (exploratory data analysis) can yield insights regarding the specific brainwave changes produced by said breathing exercise.

Based on our experimental results, we were able to observe decreased beta during meditation and breathwork, as well as increased delta during meditation and breathwork with the most pronounced increase during alternate nostril breathing.

CHAPTER 1: INTRODUCTION

Stress and anxiety are something we experience more and more frequently in the fast-paced world we live in today and are one of the dominating causes of both mental and physical health problems. While many people understand the negative effects on mental health from stress and anxiety, few recognize the physical side effects that can stem from stress and anxiety. Not only can anxiety cause significant effect on the body, long-term anxiety increases risks of developing chronic physical conditions. (Leonard, 2018) The brain sends fight-or-flight signals to the body when a person becomes anxious, stressed, or scared and in return, the body responds by releasing chemicals such as adrenaline. While this response is valuable in confrontational or dangerous situations, it is less useful in day-to-day circumstances such as public speaking or meeting a new person; and when this response is persistent in a person, it becomes unhealthy and can have undesirable effects. Stress and anxiety can cause short-term effects such as hyperventilation, cardiovascular system response, impaired immune system, and change in digestive functions. Long-term negative effects range from difficulties with social settings, digestive issues, insomnia, to depression, substance abuse disorders, and even suicidal thoughts. (Leonard, 2018)

Although anxiety and stress can be treated with medications like common physical illnesses, doctors generally recommend a combination of medication, therapy and lifestyle changes such as physical activity and meditation so we do not become reliant on medications. Meditation has existed since the prehistoric era and has been practiced extensively throughout time for its positive effects on spiritual, emotions, and mind. With the increase in mental health awareness and its effects on physical health, meditation has been studied and shown to operate as a buffer of daily stress. (Schönfeld, Brailovskaia, Bieda, Zhang, & Margraf, 2016)

This thesis examines the relationship of electroencephalogram (EEG) data using insight meditation techniques versus effects demonstrated using alternate nostril breathing techniques using Muse headband. The Muse headband, a Bluetooth EEG device, consists of 4 (+1 for ground) finely calibrated EEG brain sensors on the Muse – 2 on the forehead, 2 behind the ears – to detect and measure the brain activity. The Muse headband works in tandem with Muse Monitor app on the mobile device and provides real-time feedback on the subject’s brain activity. The streamed data is collected into a database and analyzed for effects of these meditation techniques on brainwave.

In this study, participants are asked to put on the Muse headband, sit quietly, eyes closed, for the first part of the experiment with “busy thinking” to establish baselines. This part of the experiment is intended to characterize beta, non-meditative, high-frequency signals. Subjects are then asked to meditate for the second part of the experiment using the alternate nostril breathing techniques and then switch to breath awareness meditation for the last part of the experiment. The Muse headband transmits EEG frequency bands as well as raw EEG signals. The goal is to determine if similar EEG patterns can be generated using breathwork in less time than traditional meditation methods and whether EDA (exploratory data analysis) can yield insights regarding the specific brainwave changes produced by said breathwork.

This thesis is organized into the following chapters. Chapter 2 details the background and related work. Preliminary works that led to this research is described in Chapter 3. Chapter 4 describes the methodology of the experiments while Chapter 5 presents the results. Finally, Chapter 6 concludes this study and provides future work considerations.

CHAPTER 2: BACKGROUND AND RELATED WORK

2.1 Meditation

2.1.1 Origin of Meditation

Meditation is an ancient practice found throughout history and can be traced to prehistoric era. Unfortunately, during this era, learnings and knowledge are passed on through word of mouth and the exact timing of development cannot be pinpointed. However, the earliest documented evidence of meditation was found on wall arts in India and is commonly believed to have been the birthplace of meditation. (History of meditation, n.d.) Evidences of meditation are also seen largely in religious context, with the earliest discovered being Buddhism.

2.1.2 Benefits of Meditation

While different meditation techniques have developed and existed over time, the main purpose is to train the mind, similar to fitness as an approach to train the body. (IDEA, n.d.) Concentration of mind was viewed as a step toward spiritual growth and emotional freedom. Recent medication methods have repurposed some of those techniques as ways to reduce stress and promote healthy living. Generally, meditation improves your emotional state and relaxes your mind and as a result, gives you a feeling of self-control. (Surangsrirat & Intarapanich, 2015) Herbert Benson, MD, a researcher at Harvard University Medical School, coined the term “relaxation response” to describe the involuntary bodily response when one experiences a focus on breath and relaxation and brings the body back to a healthier balance. This bodily response is a naturally occurring measure against overstress. (Martinez & Zhao, 2018)

Meditation have been studied and shown to have the following short-term benefits to the nervous system (Bushak, 2016) (IDEA, n.d.):

- Lower blood pressure
- Healthier glucose levels
- Improved blood circulation
- Lower heart rate
- Less perspiration
- Slower respiratory rate
- Less anxiety
- Lower blood cortisol levels
- More feelings of well-being
- Less stress
- Deeper relaxation
- Improved sleep quality
- Improved focus
- Reduced dependency on opioid drugs

There has also been researches that demonstrated mindfulness and positive thinking having a beneficial effect on the DNA of breast cancer patients. This remarkable discovery indicates that we may not have seen the extent of the physical effects of mindfulness meditation. (Bushak, 2016)

2.1.3 Meditation Techniques

Meditation techniques or exercises are distinct from the state of meditation that they induce.

Whereas the state of meditation is difficult to define in precise terms, the techniques which induce meditation are in most cases quite easy to describe and practice. It is important to point

out that the stated goal of these meditation techniques is not the same as the state of meditation. For instance, one of the most common meditation techniques, as taught worldwide for centuries (Dass, 2010) (Kornfield, 2010) (Saraswati, 2006) (Sayadaw, 1991) (Sole-Leris), is for the subject to concentrate their mind on the breath as it spontaneously enters and leaves the body. Although focusing the mind on the breath can lead a practitioner to meditation, meditation is not the same as the ability to watch the breath un-disturbed. In fact, the so-called “state of meditation” has been identified as a plurality of states, and researchers have classified these by their psychological characteristics as well as their corresponding tradition (Goleman, 1988).

The various exercises that lead to a state of meditation have been described in many classic and contemporary texts (Dass, 2010) (Goleman, 1988) (Kornfield, 2010) (Saraswati, 2006) (Sayadaw, 1991) (Sole-Leris) and are also taught by a number of oral traditions worldwide (Kornfield, 2010) (Saraswati, 2006) (Sole-Leris). To carefully highlight the contribution of this work, and differentiate it from the state of the art in this field, we summarize the various techniques by family here. We consider meditation techniques popularly taught currently in the traditions of yoga and Buddhism (including Mahayana, Theravada, and Zen practices). Although we do not address other traditions directly, they are known to have analogous practices which can generally be classified by the families listed herein (Goleman, 1988).

The popular contemporary techniques of meditation include:

- **Breath Awareness:** In this family of techniques, as described previously, the subject places their awareness on each breath as it enters and exits the body. The breath can be watched at the entrance of the nostrils (Dass, 2010) (Kornfield, 2010) (Saraswati, 2006) (Sayadaw, 1991) (Sole-Leris) or at the sensation of the stomach rising upon inhalation

and falling upon exhalation (associated with the movement of the diaphragm) (Dass, 2010) (Kornfield, 2010) (Saraswati, 2006) (Sayadaw, 1991). The subject may also count each breath as a mean to enhance concentration (Dass, 2010) (Saraswati, 2006).

- **Body Awareness:** When practicing body awareness meditation, the subject places their awareness on sensations on the surface of or within their body, either as a whole or part-by-part (Dass, 2010) (Kornfield, 2010) (Saraswati, 2006) (Sayadaw, 1991) (Sole-Leris). The starting point of awareness on the body and the resulting pattern it makes as it sweeps/scans the body tends to vary by tradition and by practice (Kornfield, 2010) (Saraswati, 2006) (Sole-Leris).
- **Thought Awareness:** In this family of techniques, the subject tends to watch their own thoughts, regarding them as separate from the subject's awareness, and in some cases watching for (or consciously inducing) gaps between subsequent thoughts (Dass, 2010) (Kornfield, 2010) (Saraswati, 2006) (Sayadaw, 1991).
- **Mantra:** Several traditions of meditation teach the subject a mantra, which can be used to inspired devotional feelings (Dass, 2010) (Goleman, 1988) or as a focus of concentrated awareness (Dass, 2010) (Goleman, 1988) (Kornfield, 2010) (Saraswati, 2006) (Stigsby, Rodenberg, & Moth, 1981). Some traditions, including the contemporary practice of Transcendental Meditation (TM) (Stigsby, Rodenberg, & Moth, 1981), emphasize the subtle effects of the syllabic sounds of the mantra, and the ability of these sounds to directly influence the subject's state of mind (Dass, 2010) (Goleman, 1988) (Saraswati, 2006).

In each of these families of techniques, if the subject finds that their mind has wandered from the object of awareness, they are instructed to return the awareness to that object immediately (perhaps first quickly noting what distracted their attention (Kornfield, 2010) (Sayadaw, 1991)). To the authors' knowledge, all of these traditions emphasize that the subject should avoid feeling guilty or otherwise inadequate for having become distracted, but should rather return their awareness to the object of meditation without emotional concerns. In some traditions, multiple techniques can be used in sequence to enhance or deepen meditation (Dass, 2010) (Kornfield, 2010) (Saraswati, 2006) (Sayadaw, 1991) (Sole-Leris).

2.2 Pranayama

Pranayama is a general name for a family of breathing exercises from the Indian tradition of yoga. The name "pranayama" comes from two Sanskrit words: prana which means vital life force, as experienced through the breath, and ayama which means discipline or control. Thus, pranayama can be defined as control of the vital life force via breath discipline, and yogic theory correspondingly emphasizes that breath-control can influence the subtle energies of the human body (Dass, 2010) (Iyengar, 2005) (Saraswati, 2006). Generally, pranayama exercises are practiced for a few minutes (typically up to half an hour) immediately preceding a formal meditation technique, although in many traditions the subject simply sits or reclines quietly upon completing pranayama (Iyengar, 2005) (Saraswati, 2006).

2.3 Alternate Nostril Breathing

In this study, we consider Alternate nostril breathing, a breathing technique that creates balance and regulates the airflow through your nasal passages and as a result, settles the mind, body, and emotions. Alternate nostril breathing, is also known as Anuloma-Viloma and Nadi Shodhana

(roughly translated as “the meridian cleaner”) in the yogic literature (Dass, 2010) (Iyengar, 2005) (Saraswati, 2006), where the Sanskrit term, Nadi Shodhana, means “clearing the channels of circulation.” The mind and body’s balance and ease can be restored with just a few minutes of this breathwork. (Eisler, Nadi Shodhana: How to Practice Alternate Nostril Breathing, 2015)

Alternate nostril breathing is one of the most fundamental and ubiquitous techniques of pranayama taught throughout India, with details and names varying slightly by region and tradition (Dass, 2010) (Iyengar, 2005) (Saraswati, 2006). In the most basic form of alternate nostril breathing, a subject inhales through one nostril and exhales through the opposite nostril, gently and evenly. The nostril corresponding to inhalation and exhalation is alternated, and the nostril not currently in use is physically blocked by the fingers. In the advanced form of alternate nostril breathing, which is taught once the subject gains comfort controlling their breath, timed breath-retention and muscular contractions are added to the basic form (Iyengar, 2005) (Saraswati, 2006). The basic (beginner) form of this technique, as utilized in this work, is described in detail in the next section.

Although there are various styles of Nadi Shodhana, the ultimate purpose and goal are the same – to restore the necessary balance to the body and mind. This type of breathwork is commonly used in either yoga or meditation but can also be done in moments of stress and anxiety to help calm your mind.

Additional benefits of alternate nostril breathing includes (Eisler, Nadi Shodhana: How to Practice Alternate Nostril Breathing, 2015) (Cronkleton, 2018):

- Relaxes body and mind
- Reduces anxiety and settles stress

- Improves lungs and respiratory functions and endurance
- Expands ability to focus the mind
- Restores balance in left and right hemispheres of the brain
- Rejuvenates the nervous system
- Lowers heart rate

2.3.1 Nadi Shodhana Practice

Below are instructions to one common way to practice Nadi Shodhana, or alternate nostril breathing (Eisler, Nadi Shodhana: How to Practice Alternate Nostril Breathing, 2015) (Cronkleton, 2018):



Figure 1: Alternate nostril breathing (Cronkleton, 2018)

1. Sit in a comfortable position, making sure your spine is straight.
2. Relax your left hand comfortable on your left lap or knee.
3. Lift your right hand to just in front of your face.

4. With your right hand, rest your pointer finger and middle finger between your eyebrows, lightly using them as an anchor (see Figure 1).
5. Close your eyes and take a deep breath in and exhale completely through your nose.
6. Using your right thumb, close your right nostril.
7. Inhale through your left nostril slowly, quietly and steadily. Retain your breath at the top of the inhale for a brief pause.
8. Close your left nostril with your right ring finger. Open your right nostril and exhale slowly through the right side. Pause briefly at the bottom of the exhale.
9. Inhale through your right side slowly and then close this nostril.
10. Open your left nostril and exhale through the left side.
11. This is one cycle. Repeat steps 6 through 10 for up to 5-10 cycles or up to 5 minutes.

It is recommended to take deep breaths, both in and out, and to do so as slowly as possible.

While there are many variations of Nadi Shodhana since its inception, the core is similar across the types and focuses on breathing through your left or right nostril, one side at a given time.

2.4 Electroencephalography (EEG)

Electroencephalography (EEG) is an electrophysiological monitoring method to detect electrical activity of the brain on a millisecond basis. EEG activity stems from the voltage differences within the brain neurons. The waves or oscillations generated by brain activities at a variety of frequencies are representative in two states – active or resting. Synchronized electrical pulses from masses of neurons within the brain communicating with each other produces various bandwidths of brainwaves. These bandwidths can further be divided to describe their functions and reflect different states of brain functions when they occur in different locations of the brain.

Depending on where the voltages are the strongest at a given time, positive and negative poles, the most active brain regions can be inferred. (Farnsworth, 2019) Based on specific frequency ranges, five types of brainwave frequency bands have been identified: delta, theta, alpha, beta, and gamma:

- **Delta (δ , 1-4 Hz):** Delta waves are the slowest and strongest brainwave and usually correlates to deep sleep or non-REM sleep. Delta waves can also be found during deep meditation.
- **Theta (θ , 4-8 Hz):** Theta waves are associated with difficulty of mental operations such as during experiences of drowsiness, light sleep, deep relaxation, or meditation.
- **Alpha (α , 8-12 Hz):** Alpha waves are active when a person is awake, and moderately active when a person is relaxed with eyes closed. Increased level of alpha waves during mental and physical relaxation with eyes closed reflects relaxation and sensory inhibition. As a result, alpha waves can be used to monitor meditation effectiveness, as well as track the relaxation level of a respondent.
- **Beta (β , 12-25 Hz):** Beta waves occur during normal waking consciousness. Most people operate in this frequency during the day. Higher beta waves can also be associated with “heightened state of awareness” during active, busy, or anxious thinking and active concentration.
- **Gamma (γ , >25 Hz):** Gamma waves are the fastest brainwave and relates to feelings of strong capability and occur generally during hyperactivity or processing of information from different brain areas.

EEG provides neurofeedback – a real-time visibility to which areas of the brain is active at a given time. Neurofeedback is often used to try and modify behavior and, as a result, can be used to teach a subject self-regulation and control of their brain functions. (Shaked, 2017)

2.5 Muse

Scientists commonly capture EEG utilizing a 10-20 system to notate where the electrodes are being placed on the scalp. The 10-20 system diagram (Figure 2) shows a top-view of the head with NASION being the middle point of the nasofrontal surface, the sides (A1/A2) are the ears, and INION the projecting point at the base of the skull (Farnsworth, 2019) Traditional EEG systems use electrodes attached to the scalp to pick up brain-generated voltages. These electrodes are flat, metal disks that attach to the scalp and makes contact with the skin via conductive gel, paste or cream, typically based on saline. (Farnsworth, 2019) However, not only is the traditional setup cumbersome and time-consuming to set up, these devices are generally expensive and requires expertise. In the recent years, there has been an increase in more affordable EEG recording systems availability, and while there are tradeoffs for these devices being low-cost and portable, researchers have tested and validated the effectiveness in low-cost, portable EEG systems, such as the Muse headband from InteraXon Inc, for brainwave research. Krigolson's study concluded that they were able to measure and quantify the N200, P300, and reward positivity ERP components with a MUSE EEG system compared with a standard cap. (Krigolson, Williams, Norton, Hassall, & Colino, 2017)

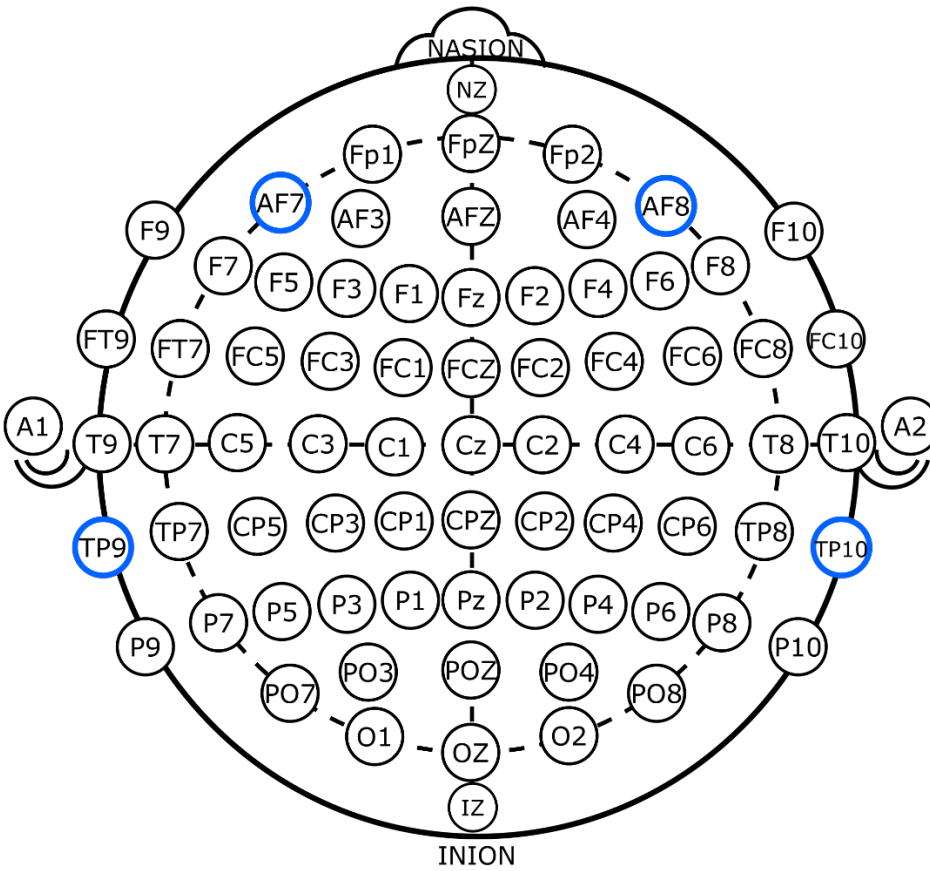


Figure 2: 10-20 System markers, with the ones used by the Muse headset selected in blue. (Shaked, 2017)

The Muse headband, a Bluetooth EEG device, consists of 4 (+1 for ground) finely calibrated EEG brain sensors on the Muse – 2 on the forehead, 2 behind the ears – to detect and measure the brain activity. The 2016 version of the Muse headband targets AF7, AF8, TP9, and TP10 electrodes, as selected in blue in the Figure 2. Data are sampled at 220 Hz and referenced to the Fpz channel.

The headband is placed over the ears and across the forehead. The Muse is also equipped with 3-axis accelerometer for motion input and quantifying head movements. The data is transmitted wirelessly via Bluetooth to the mobile device application, Muse, provided by InteraXon Inc although this device also works in tandem with another third-party mobile app, Muse Monitor.

Muse Monitor app provides real-time feedback on the subject's brain activity and is the primary app used in this study to capture EEG activities.

2.6 Academic Research with Muse and Meditation

Researchers have long been intrigued by the benefits and effectiveness of meditation. With Muse, researchers have a more affordable and portable way of conducting meditation experiments and observing its effects on human brainwave and there have been extensive uses in academic researches.

Neuroscientist Olav Krigolson, co-leader of the research team, traveled all the way to Mount Everest region of Nepal and conducted their research on 27 monks with the aim of exploring how meditation augments brain function. All 27 monks are well-versed and experienced in meditation. (Dipananda, 2016) The study demonstrated that the monks' brains remain active during meditation when compared with the mental state of rest. They found "increased brain signals associated with relaxation, concentration, and synchronization (a brain function during which various parts of the brain work together)" and concluded that meditation has a "carry over effect." (Dipananda, 2016)

Another research also studied Buddhist monks, experienced meditators who have at least 10 years of experiences and no less than 3,000 hours of meditation practice, during meditation and other activities using Muse. This study found "burst of powers in delta band, deep meditation state, during meditation." (Surangsirat & Intarapanich, 2015)

Researchers are not solely fixated on monks and experienced meditators. Muse has also been utilized to study the effects on attentional consequences on both young adolescents and adults who do not have meditational habits. Middle grades students and whether mindfulness training

would decrease their office discipline referrals (Martinez & Zhao, 2018), as well as simple, does mindfulness training decrease stress and thereby improve one's ability to focus.

Although a number of research projects have analyzed the effects of meditation and pranayama on the brain using medical-grade many-channel EEG and GSR sensors (Ghiya & Lee, 2012) (Hoffman, 1998) (Joshi, 2009) (Srivastava, Jain, & Singhal, 2005) (Stigsby, Rodenberg, & Moth, 1981), to our knowledge this is the first study of its type to utilize a simple 5-channel EEG device built for the home market. Moreover, this device is intended to be used in the practice of meditation, with its corresponding stock Muse app measuring a subject's brain activity through stages of active thinking as well as breath awareness, and providing live feedback to the subject to enhance their practice (Muse App, n.d.). In this study, we replicate the functionality of the Muse application, measuring brain activity during a five-minute stage of active thinking, and follow this with 5 minutes of alternate nostril breathing pranayama, followed by 5 minutes of seated relaxation (during which no specific meditation technique is prescribed).

CHAPTER 3: PRELIMINARY WORK

This chapter describes the preliminary work and contributions that have taken place prior to this thesis work and as a result, led to motivation for further research into relations between EEG and meditation.

3.1 Student Response System

3.1.1 Background

Audience response systems, conventionally known as “clickers,” often are promoted to assist with student engagement in large classroom settings. Students often avoid speaking up in larger classroom settings from fear of repercussions. Some possible reasons include students may not want to stand out in the crowd; they may fear of providing the wrong or inadequate answer; they may avoid expressing their true thoughts or feelings due to its controversial nature. These devices permit students to give real-time feedback towards lecture contents, as well as respond to polls and quizzes given by the instructor. The anonymous responses from the clickers allows students to provide feedback regarding their understanding and interest level without any repercussions. Clickers have been proven to improve academic performance and student satisfaction.

This project incorporates clicker into a simple web-service platform and integrates smart room lighting. Proposed features include, but are not limited to:

- The use of lighting to provide immediate feedback to the instructor of the class based on student attitude

- The use of lighting to provide answers to polled questions (i.e. the brightness of a light indicates how many students chose that answer, in a multiple-choice question delivered to the class)
- The use of lighting as a way of providing both student anonymity and student response aggregation, so that students do not feel singled-out
- The use of a multi-modal student attitude assessment system, including
 - Biometric signals taken from wearable technology
 - Student responses manually entered on a mobile web-application, to such questions as “How well do you understand what is being said right now?”
- The generation of temporary session ID that the instructor can distribute to a class at the beginning of a lecture session, ensuring that
 - None (or very few) students outside the class can participate-in or interfere-with the results
 - The recorded data from the lecture session can be uniquely tagged for post-lecture analysis
- A database behind the web service that tracks the state of a lecture session in progress, and saves aggregates for post-lecture analysis

3.1.2 Central Repository

The student response system data will primarily come from student inputs via the web-service platform at this time because the current system have not incorporated wearable technology.

However, once incorporated, students’ biometric signals from the wearable technology will be collected and uniquely tagged with its corresponding session ID. The collected data are written

and stored in the MySQL database on Context-Aware. The database saves aggregates for post-lecture analysis.

The database schema for this project is as follows (Figures 3 thru 10):

#	Name	Type	Collation	Attributes	Null	Default	Extra	Action
1	answer_id	int(11)			No	None	AUTO_INCREMENT	Change Drop Primary Unique Index Spatial Fulltext Distinct values
2	answer	varchar(1000)	latin1_swedish_ci		No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
3	answer_seq	int(11)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
4	correct	tinyint(1)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
5	question_id	int(11)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values

Figure 3: answers table – holds the available answers to the instructor’s question

#	Name	Type	Collation	Attributes	Null	Default	Extra	Action
1	bridge_id	int(11)			No	None	AUTO_INCREMENT	Change Drop Primary Unique Index Spatial Fulltext Distinct values
2	ip_address	char(15)	latin1_swedish_ci		No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
3	auth_key	char(255)	latin1_swedish_ci		No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
4	session_id	int(11)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values

Figure 4: bridge table – holds the information about the bridge for the lights

The column name 'on' is a MySQL reserved keyword.

#	Name	Type	Collation	Attributes	Null	Default	Extra	Action
1	light_id	int(11)			No	None	AUTO_INCREMENT	Change Drop Primary Unique Index Spatial Fulltext Distinct values
2	light_num	tinyint(3)		UNSIGNED	No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
3	on	tinyint(1)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
4	hue	smallint(5)		UNSIGNED	No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
5	brightness	tinyint(3)		UNSIGNED	No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
6	mode	tinyint(1)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
7	time	timestamp		on update CURRENT_TIMESTAMP	No	CURRENT_TIMESTAMP	ON UPDATE CURRENT_TIMESTAMP	Change Drop Primary Unique Index Spatial Fulltext Distinct values
8	bridge_id	int(11)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values

Figure 5: lights table – holds the information about individual lights and its status

#	Name	Type	Collation	Attributes	Null	Default	Extra	Action
1	question_id	int(11)			No	None	AUTO_INCREMENT	Change Drop Primary Unique Index Spatial Fulltext Distinct values
2	question	varchar(1000)	latin1_swedish_ci		No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
3	start_time	timestamp			No	0000-00-00 00:00:00		Change Drop Primary Unique Index Spatial Fulltext Distinct values
4	end_time	timestamp			No	0000-00-00 00:00:00		Change Drop Primary Unique Index Spatial Fulltext Distinct values
5	session_id	int(11)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values

Figure 6: questions table – holds instructor’s question with its corresponding session ID

#	Name	Type	Collation	Attributes	Null	Default	Extra	Action
1	session_id	int(11)			No	None	AUTO_INCREMENT	Change Drop Primary Unique Index Spatial Fulltext Distinct values
2	class_key	varchar(6)	latin1_swedish_ci		No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
3	start_time	timestamp			Yes	NULL		Change Drop Primary Unique Index Spatial Fulltext Distinct values
4	end_time	timestamp			Yes	NULL		Change Drop Primary Unique Index Spatial Fulltext Distinct values

Figure 7: session table – holds the information about the particular lecture session

#	Name	Type	Collation	Attributes	Null	Default	Extra	Action
1	answer_id	int(11)			No	None	AUTO_INCREMENT	Change Drop Primary Unique Index Spatial Fulltext Distinct values
2	answer	int(11)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
3	submit_time	timestamp			Yes	NULL		Change Drop Primary Unique Index Spatial Fulltext Distinct values
4	question_id	int(11)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values

Figure 8: student_answer table – holds the student's response to the instructor's questions

#	Name	Type	Collation	Attributes	Null	Default	Extra	Action
1	interest_id	int(11)			No	None	AUTO_INCREMENT	Change Drop Primary Unique Index Spatial Fulltext Distinct values
2	interest_rating	int(11)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
3	submit_time	timestamp			Yes	NULL		Change Drop Primary Unique Index Spatial Fulltext Distinct values
4	session_id	int(11)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values

Figure 9: student_interest table – holds the current student interest level data

#	Name	Type	Collation	Attributes	Null	Default	Extra	Action
1	understanding_id	int(11)			No	None	AUTO_INCREMENT	Change Drop Primary Unique Index Spatial Fulltext Distinct values
2	understanding_rating	int(11)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
3	submit_time	timestamp			Yes	NULL		Change Drop Primary Unique Index Spatial Fulltext Distinct values
4	session_id	int(11)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values

Figure 10: student_understanding table – holds the current student understanding level data

3.1.3 Project Status

The team was able to complete the web platform creation for the Student Response System from front end to backend and delivered minimum viable product (MVP) within the expected time frame. The next phase of the project is to test out in actual classroom settings, perform analysis on the data collected and add additional features to the web platform. This project is currently waiting for IRB approval.

3.2 Spinal Cord Injury VR Recovery

3.2.1 Background

There has been research on implementing Virtual Reality (VR) into spinal cord injury (SCI) patients' rehabilitation exercise routines to see how quickly and effectively the patients improve afterwards. However, these researches generally concentrate on the overall progress of the patients. As SCI patients tend to endure pain and fatigue when it comes to rehabilitation exercising, this research will focus on the effects of VR during these sessions, emphasizing on pain and fatigue. We hypothesize that VR helps decrease the amount of pain and fatigue during these exercises.

The main issue, nonetheless, is that kinesiology researchers presently use a Visual Analogue Pain and Fatigue Scale (Figure 11) to collect qualitative data from SCI patients. These measures are subjective and often biased at times due to the subject's current state of mind, mood and emotion. Furthermore, subjects often have varied tolerance in pain and fatigue – a pain scale 6 for one subject may be a pain scale 2 for another subject.

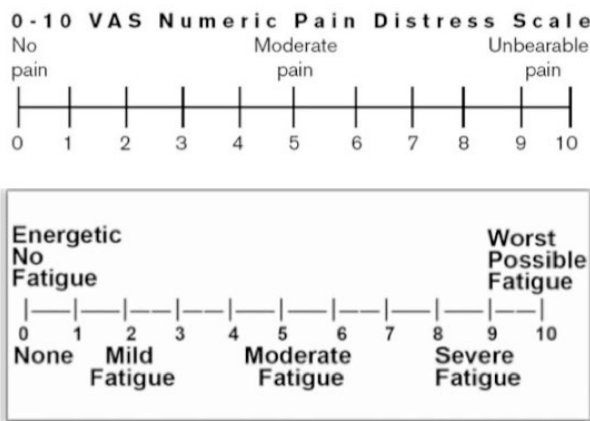


Figure 11: VAS Numeric Pain Distress Scale

This research, a collaborative work between Computer Science and Kinesiology department, intends to instead collect quantitative data using wearable technology. The objective, neuropsychology-oriented, approach focuses on collecting, monitoring and analyzing biometric signals such as heart rate, Galvanic skin response (GSR), and skin temperature.

Recorded GSR and skin temperature signals were first used to evaluate the test subjects' emotional status. The study concluded that GSR signal of each test subject can be used to identify stress- or effort- related emotional events, which are indicated as short-duration peaks of the GSR signal itself. Using the same GSR measurements, we hope these signals will determine whether autonomic nervous signals can indicate areas of pain or fatigue during a VR implemented exercise for SCI patients and as a result, can be used to adjust or customize better rehabilitation exercises for SCI patients.

3.2.2 Central Repository

Microsoft bands were used to collect biotelemetry user data such as GSR rate, heartrate, and skin temperature in the SCI research. The band is connected via Bluetooth to an Android app and the collected data are written to and stored in the MySQL database on Context-Aware via the Web Server. These data can be extracted from the database to a CSV file using a Python script.

The database schema for this project is as follows (Figures 12 thru 16):

#	Name	Type	Collation	Attributes	Null	Default	Extra	Action
<input type="checkbox"/>	1	id			No	0		Change Drop Primary Unique Index Spatial More
<input type="checkbox"/>	2	data			Yes	NULL		Change Drop Primary Unique Index Spatial More
<input type="checkbox"/>	3	time			No	0		Change Drop Primary Unique Index Spatial More

Figure 12: skin_temp_table

#	Name	Type	Collation	Attributes	Null	Default	Extra	Action
1	time	int(11)			No	0		Change Drop Primary Unique Index More
2	ip	varchar(20)	latin1_swedish_ci		No	None		Change Drop Primary Unique Index More

Figure 13: players table

#	Name	Type	Collation	Attributes	Null	Default	Extra	Action
1	id	int(11)			No	0		Change Drop Primary Unique Index Spatial More
2	data	int(11)			Yes	NULL		Change Drop Primary Unique Index Spatial More
3	time	bigint(20)			No	0		Change Drop Primary Unique Index Spatial More

Figure 14: heart_rate_table

#	Name	Type	Collation	Attributes	Null	Default	Extra	Action
1	id	int(11)			No	0		Change Drop Primary Unique Index Spatial More
2	data	int(11)			Yes	NULL		Change Drop Primary Unique Index Spatial More
3	time	bigint(20)			No	0		Change Drop Primary Unique Index Spatial More

Figure 15: gsr_rate_table

#	Name	Type	Collation	Attributes	Null	Default	Extra	Action
1	id	int(11)			No	0		Change Drop Primary Unique Index Spatial More
2	dataX	float			Yes	NULL		Change Drop Primary Unique Index Spatial More
3	dataY	float			Yes	NULL		Change Drop Primary Unique Index Spatial More
4	dataZ	float			Yes	NULL		Change Drop Primary Unique Index Spatial More
5	time	bigint(20)			No	0		Change Drop Primary Unique Index Spatial More

Figure 16: accelerometer_table

3.2.3 Unified Analysis Over Biotelemetry User Data

Once the biotelemetry user data has been migrated into the central repository and extracted, we analyzed the data on whether pain or strenuous activities can be detected from these biometric signals, with emphasis on GSR. This part of the project utilized a combination of Microsoft Excel and MATLAB to preprocess the raw data, extract the features, and plot the data for visual graphs. We were specifically interested to identify any spikes or dips in the biometric signals and

determine if they correspond to the events during the sessions, such as increase in physical activity or pain.

Data processing algorithms such as Fast Fourier Transform (FFT) and wavelet transform were explored to convert the signals from its original domain to a representation in the frequency domain in order to further breakdown the discrete frequencies for GSR and EEG. The hope was to identify and isolate the signals and thereby be able to detect pain from these signals.

3.2.4 Project Design

The experiment was set up for subjects to pedal on table-mounted Saratoga cycles (Figure 17) for a predetermined period of time while wearing a VR headset. The VR headset displays pleasant sceneries to give subjects illusions that they are pedaling through outdoor nature.

The intensity of the arm bikes increased as experiment continued; timestamps were recorded when the intensity level increased. Additionally, the subjects were pinched by the researcher on their arms, both announced or unannounced; timestamps were recorded when these pinches were performed. We hoped to differentiate biotelemetry user data when subjects performed more strenuous activities or when pain was inflicted upon them.



Figure 17: Arm bikes (Exercise Cycles, n.d.)

3.2.5 Project Status

We were able to set up a preliminary experiment to record some data for testing purposes from two subjects. However, we had various technical difficulties. We have prepared two Microsoft band for this experiment, one in Medium size and one in Large size, for our subjects. However, the Medium band had connection issues and thus, we were forced to use the Large band for both subjects. Because the oversized band was unable to make proper contact with one of the two subjects, the subject's data was not recorded successfully. We had further technical difficulty where the other subjects' data had noise that made data analysis challenging.

As GSR refers to the change in sweat gland activity as a reflection of the intensity of our emotional state, we attempted to identify signs during strenuous activities and/or pain events through GSR. However, from the visual graphs created in Microsoft Excel (Figure 18), we were unable to identify either events based on the GSR data we have collected against the time we have recorded for when those events occur. Figure 18 was plotted with time in the x-axis and μS for GSR rate in the y-axis. There was also a sudden drop in GSR readings between time 3:02PM and 3:23PM, which we believed to have been caused by the improper contact between the subject and the Microsoft Band. The Microsoft Band used in the experiment was not properly sized to the subject as the one intended for the subject had connection difficulties. As such, the band was significantly larger than that of subject's wrist and potentially caused contact issues during the experiment due to the arm movements. We further explored utilizing either FFT or wavelet transform to gain insights into the GSR readings we have collected but that also proved to be inconclusive.

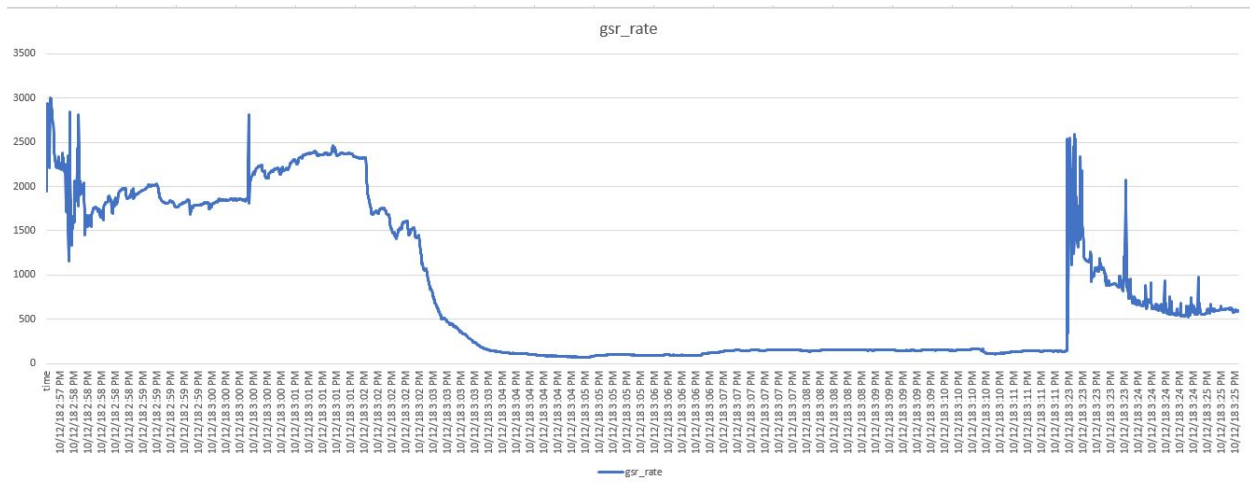


Figure 18: GSR readings

Our lack of ability to identify a pattern in the limited test subject data we collected from GSR signals, paired with cross-departmental coordination challenges, led to this project to be put on hold.

3.2.6 EEG Interest

We began exploring EEG once our efforts with GSR was put on hold. The original intent was to research into being able to identify pain events in EEG readings. In the process of that, we became curious of the accuracy surrounding consumer-grade EEG devices, such as the Muse headband, and whether it can be used to differentiate and examine the different states of mind.

Our interest also shifted from experimenting with pain, to being able to identify the effects of meditation and relaxation through EEG. There has been plenty of prior works regarding meditation and breathwork utilizing expensive, full-cap EEG sensors. We were intrigued to explore the proximation of that feedback, but from a consumer-grade device. We wanted to see if we can obtain the same amount of information of how well subjects are able to relax based on the 5-channels available on the consumer-grade devices. As a result, the remainder of this thesis is inspired by this study.

CHAPTER 4: METHODOLOGY

This chapter consists of four parts. Section 4.1 describes the hardware equipment used in this thesis, while section 4.2 discusses the software components required to gather the data needed for analysis. Last but not least, section 4.3 of this chapter provides the design of the study for this thesis.

4.1 Hardware

4.1.1 Computer

Table 1 details the specifications of the computer used in this thesis:

Manufacturer	Apple
Model	MacBook Pro (Retina, 13-inch, Mid 2014)
Model Number	A1502
Operating System	macOS Mojave Version 10.14.6
Processor	Intel Core i5 (“Haswell”)
Processor Speed	2.6 GHz
Architecture	64-bit
Memory	8 GB 1600 MHz DDR3

Table 1: Computer Specifications

The computer was connected to the Internet using either wired or wireless connection. If utilizing wired connection, an Apple Thunderbolt to Gigabit Ethernet Adapter was used. Local WiFi network (WAN) was used if the computer connects to the Internet via wireless connection.

4.1.2 Smartphone

Table 2 details the specifications of the smartphone used in this thesis:

Manufacturer	Apple
Model	iPhone XS Max
Model Number	A1921
Operating System	iOS 13.4 (Original OS iOS 12.0)

Processor	Apple A12 Bionic
Processor Speed	2.5 GHz
Architecture	64-bit
Memory	4 GB LPDDR4X

Table 2: Smartphone Specifications

4.1.3 Muse Headband

The Muse headband, a Bluetooth EEG device, consists of 4 (+1 for ground) finely calibrated EEG brain sensors on the Muse – 2 on the forehead, 2 behind the ears – to detect and measure the brain activity. This device works in tandem with Muse Monitor app on the iPhone and provides real-time feedback on the subject’s brain activity. The 2016 model was used in this thesis.

4.2 Software

4.2.1 Muse OSC Specifications

The Muse Monitor app on the iPhone was connected to the Muse headband over Bluetooth. The app recorded the data and can either be exported to CSV or streamed directly from the app to an OSC data receiver utilizing OSC Streaming. Server IP/Name and Port were preset in [Settings] within the app.

The following data can be streamed and recorded:

- Absolute – Brainwave values are absolute band powers, based on the logarithm of the Power Spectral Density (PSD) of the EEG data for each channel. The frequency spectrums of these are:
 - Delta(δ) 1-4 Hz
 - Theta(θ) 4-8 Hz
 - Alpha(α) 7.5-13 Hz

- Beta(β) 13-30 Hz
- Gamma(γ) 30-44 Hz
- Raw – Raw EEG values show each sensors raw data in microvolts (μV), the range of which is $\{0:\sim 1682\}$. The sensors are:
 - TP9 – Left ear
 - AF7 – Left forehead
 - AF8 – Right forehead
 - TP10 – Right ear
 - AUXR – Right Auxiliary (MU-02 only)
- AUX Right (MU-02 only)
- Accelerometer – The effect of gravity on the headband, measured in g (9.81m/s^2)
- Gyro (MU-02 only) – The amount of rotation from the last position the headband was in. This will always return to zero.
- Headband On
- HIS (Horse Shoe Indicator / Sensor connectivity)
- Marker button presses

“By default Muse Monitor will output a single combined average value for the five absolute brain wave values. This can be toggled to output separate values for each sensor, via Muse Monitor settings.” (Muse Monitor FAQs, n.d.)

Item	OSC Path	Values	Description	Range / Units	Data rate
RAW EEE	/muse/eeg	f f f f {+f}	TP9, AF7, AF8, TP10 {+AUX on MU-02}	0.0 – 1682.815 uV	220 Hz 256 Hz
Delta Absolute	/muse/elements/delta_absolute	f f f f f	One Average or Four Float values	Bels	10 Hz
Theta Absolute	/muse/elements/theta_absolute	f f f f f	One Average or Four Float values	Bels	10 Hz
Alpha Absolute	/muse/elements/alpha_absolute	f f f f f	One Average or Four Float values	Bels	10 Hz
Beta Absolute	/muse/elements/beta_absolute	f f f f f	One Average or Four Float values	Bels	10 Hz
Gamma Absolute	/muse/elements/gamma_absolute	f f f f f	One Average or Four Float values	Bels	10 Hz
Horseshoe	/muse/elements/horseshoe	f f f f	TP9, AF7, AF8, TP10 fit	1=Good, 2=Medium, 4=Bad	10 Hz
Touching Forehead	/muse/elements/touching_forehead	i	Forehead fit	1=True, 0=False	10Hz
Battery info	/muse/batt	i i i i	Batt Level, Batt Voltage, ADC Voltage, Temp	%100, mV, {-1 N/A}, C	0.1 Hz
Gyroscope	/muse/gyro	f f f	X, Y, Z	degrees/seconds {-245:+245}	52 Hz
Accelerometer	/muse/acc	f f f	X, Y, Z	g {-2:+2}	52 Hz
Blink	/muse/elements/blink	i	Blink detected	1=Blink	10 Hz (if true)
Jaw Clench	/muse/element/jaw_clench	i	Jaw Clench detected	1=Jaw Clench	10 Hz (if true)
Markers	/Marker/{1,2,3,4,5}	i	Marker Button Pressed	1=True	Instant

Table 3: OSC Specifications

(Muse Monitor FAQs, n.d.)

4.2.2 Homebrew

Homebrew is a package manager for macOSX and is used in this thesis to install the dependencies to compile and install Python.

4.2.3 Python 3.8

The programming language Python, version 3.8, was used in this thesis to communicate with the OSC server as well as the database hosted on Context-Aware. Python was also used to process the data exported from the Context-Aware database.

4.2.3.1 py3server.py

This script captures Raw EEG and EEG frequency bands data streams from the Muse headband via Muse Monitor app through OSC Server. The captured data is posted to Context-Aware database using PHP functions.

We originally scripted for both Raw EEG readings and EEG frequency bands data streams to post to Context-Aware in real-time. While we had no issues with EEG frequency bands data, the high volume of Raw EEG signals per second overwhelmed Context-Aware database and resulted in session time-out errors. The script thus was modified to take the average of every 50 raw EEG readings with the timestamp of the 50th reading.

We encountered yet another obstacle with Raw EEG signals when we performed test runs of the experiment on-site on campus. The network detected high volume of network traffic from the sheer amount of Raw EEG signal readings attempting to post to Context-Aware database and as a result, throttled the network connection. We consequently further modified the script to take

the average of every 100 raw EEG readings with the timestamp of the 100th reading. The complete final script is available in Appendix D.

4.2.3.2 *sql2stats.py*

This script uses PHP functions to retrieve the Raw EEG and EEG frequency bands data from the Context-Aware database and processes the timestamps from Epoch nanoseconds to local human readable time. The data is exported and outputted in Excel Worksheet (.xlsx). This script was repurposed from the SCI/VR Recovery study. The complete script is available in Appendix E.

4.2.3.3 *intervalAverage.py*

This script imports the data from an Excel Worksheet (.xlsx) and aggregates the data over a specified time interval in either seconds or minutes, taking inputs from the command line. The data is exported and outputted in a new Excel Worksheet (.xlsx). The complete script is available in Appendix F.

4.2.4 SQL Database

We created two tables in Context-Aware database – one for Raw EEG signals and one for EEG frequency bands. The database schema is as follows (Figures 19 and 20):

#	Name	Type	Collation	Attributes	Null	Default	Extra	Action
1	id	int(11)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
2	alpha	float			Yes	NULL		Change Drop Primary Unique Index Spatial Fulltext Distinct values
3	beta	float			Yes	NULL		Change Drop Primary Unique Index Spatial Fulltext Distinct values
4	gamma	float			Yes	NULL		Change Drop Primary Unique Index Spatial Fulltext Distinct values
5	delta	float			Yes	NULL		Change Drop Primary Unique Index Spatial Fulltext Distinct values
6	theta	float			Yes	NULL		Change Drop Primary Unique Index Spatial Fulltext Distinct values
7	time	bigint(20)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values

Figure 19: *eeg_table* for EEG frequency bands

#	Name	Type	Collation	Attributes	Null	Default	Extra	Action
1	id	int(11)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values
2	TP9	float			Yes	NULL		Change Drop Primary Unique Index Spatial Fulltext Distinct values
3	AF7	float			Yes	NULL		Change Drop Primary Unique Index Spatial Fulltext Distinct values
4	AF8	float			Yes	NULL		Change Drop Primary Unique Index Spatial Fulltext Distinct values
5	TP10	float			Yes	NULL		Change Drop Primary Unique Index Spatial Fulltext Distinct values
6	REF	float			Yes	NULL		Change Drop Primary Unique Index Spatial Fulltext Distinct values
7	time	bigint(20)			No	None		Change Drop Primary Unique Index Spatial Fulltext Distinct values

Figure 20: eegraw_table for raw EEG signals

4.3 Study Design

This section discusses the procedural design of the study.

We designed our study in an attempt to emulate the proprietary method in the stock Muse app from InteraXon Inc. The stock Muse app provides a guided pre-session calibration to customize neurofeedback to match the participant’s experience prior to the actual meditation training session. The calibration consists of 2 brief exercises and lasts 1 minute: in the first exercise, participants were asked to perform a word association task to simulate a period of busy-thinking. In the second exercise, participants were asked to clear their minds as a brief induction to a focused attention state. The data from these two calibration sessions were entered into a machine learning algorithm to generate a session-specific signature of concentration and distraction customized to this particular participant. The guided meditation instructions were then delivered after this calibration.

While InteraXon Inc did not specify how the stock app differentiates between an active versus a relaxed mind, we speculated that some form of analysis on beta and alpha brainwaves were used. As such, our study was designed to replicate that of the stock app.

The study was designed to last approximately 20 to 30 minutes in its entirety per participant, including walking the participants through the flow of the study (PRE), 5 minutes of baseline-

setting interview, a short break, followed by 15 minutes of meditation experiment and concluded with a questionnaire (Figure 21). The study was timed by the researcher and performed on one participant at a time. EEG recordings were taken continuously in the 5-minute Interview and during the 15-minute Meditation Experiment as shown in Figure 21.

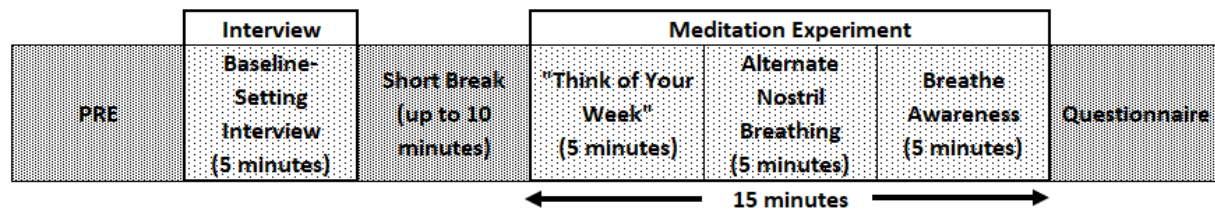


Figure 21: A schematic representation of the study design

At the start of the study, each participant was instructed to put on the Muse headband, they were then asked to sit quietly with their eyes closed, gently, without effort, for the duration of the interview and the experiment. Participants sat with their back straight in as harmonious a pose as possible. All participants sat in the same chair, so that the type of chair is not a variable in the study setting.

4.3.1 Baseline-Setting Interview

In order to measure each participants' baseline frequencies, participants were asked the following 3 questions by the researcher:

- (1) What's the most interesting thing you've read or seen this week?
- (2) You're a mad scientist, what scientific experiment would you run if money and ethics weren't an issue?
- (3) What's a body part you wouldn't mind losing and why?

The participants were instructed to think of their answers internally without any movements or vocalization. The researcher gave the participants approximately 90 to 100 seconds per question

before moving onto the next question. At the end of the 5 minutes baseline-setting interview, participants opened their eyes and took a short break of up to 10 minutes, without taking off the Muse headband.

4.3.2 Meditation Experiment

After the short break, the participants were directed to again close their eyes before moving onto the meditation experiment. During the 15-minute meditation experiment, participants were provided three sets of instructions, 5 minutes each, and switched from one to another consecutively for the duration of the experiment. The researcher provided the instructions as a reminder at the beginning of each switch of instructions.

Experiment Part 1: “Think of Your Week”

Participants were asked to start off the experiment with the following prompt for the first 5 minutes – “in 1-hour intervals, traverse back in time and think of what you’ve done this week.” This helped further characterize the participant’s beta frequency signals when the participant is not in a meditational state, as a result, established the participant’s brainwave baseline.

Experiment Part 2: Alternate Nostril Breathing

After 5 minutes of baseline establishment, participants were instructed to switch over to alternate nostril breathing technique for the next 5 minutes of the experiment. Participants were instructed to use their right hand and close their nostrils alternatively with their thumb and ring finger. The index and long finger rested on their forehead. The participants were asked to keep their left hand on their left knee.

First, participants closed their right nostril with their thumb and inhaled completely, slowly and soundlessly through their left nostril. Then they closed the left nostril with their ring finger and opened their right nostril by lifting their thumb to exhale. One cycle of breathing went like the follow:

- Inhale through left nostril (close right nostril with right thumb)
- Exhale through right nostril (close left nostril with right ring finger)
- Inhale through right nostril (close left nostril with right ring finger)
- Exhale through left nostril (close right nostril with right thumb)

Experiment Part 3: Breath Awareness

After 5 minutes of alternate nostril breathing meditation, participants were instructed to switch over to breath awareness meditation at the end of their current alternate nostril breathing cycle. For the remainder of the experiment, participants meditated while inhaling and exhaling slowly without manipulation of the nostrils. Participants were asked to direct their attention to the movement of air into and out of their nostrils, and focus their awareness to the movement of air through their nasal passages. Participants were informed that it was acceptable if they find their minds began to wander, as long as they bring their attention back to their breathing. The meditation experiment concluded in its entirety after 5 minutes of breath awareness meditation.

4.3.3 Questionnaire

After the meditation experiment concluded, the participants were asked to fill out a questionnaire (Figure 22). The study for the participant was finished once the participants completed the questionnaire.

	1	2	3	4	5
	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
	Never	Rarely	Sometimes	Often	Always
Prior to this experiment:					
1. My moods are stable.					
2. My body and mind are always comfortable.					
3. I can handle setbacks and cope with angry and sad emotions.					
4. I can keep my emotions calm when faced with matters which makes me angry.					
5. I believe that meditation has emotional and physical benefits.					
6. I have meditated in the past.					
After the experiment:					
7. The experiment was easy to follow.					
8. The experiment was a relaxing or calming experience.					
9. The sense of relaxation became stronger as the experiment progressed.					
10. After the experiment, I believe that meditation has emotional and physical benefits.					
11. I would consider meditating regularly/irregularly after this experiment.					
12. From the following adjectives, choose one(s) that best describe your overall experience.	Stressful	Anxious	Boring	Relaxing	Exciting
13. Which segment of the experiment was the most relaxing?	Interview	Think of Your Walk	Alternate Breathing	Breathe Awareness	
14. Which segment of the experiment was the least relaxing?	Interview	Think of Your Walk	Alternate Breathing	Breathe Awareness	

Figure 22: Participant Questionnaire

CHAPTER 5: EXPERIMENTAL RESULTS

A total of 6 participants were studied: 3 participants on February 14, 2020 (participants #1-3) and 3 more participants on March 6, 2020 (participants #4-6).

Each participant's data was streamed and posted to Context-Aware database to their corresponding tables in real-time during the study. Each participant was assigned an unique numeric ID to preserve anonymity whilst keeping the datapoints distinguishable between different participants.

5.1 Data Extraction and Storage Consideration

With the Python script, the data was extracted using Epoch time from the study, processed to obtain local California Pacific Time and outputted to an Excel Workbook. Each Excel Workbook contained the EEG frequency bands and raw EEG signals from one participant for either their interview or the experiment. The EEG frequency bands were recorded in Hz and raw EEG signals were recorded in μV .

Table 4 provides the statistics pertaining to the data collected per participant per segment of the study. We yielded approximately 2 to 4 rows of raw EEG and 9 to 10 rows of EEG frequency readings per second.

Participant #	Interview or Experiment	Start Time	End Time	# of Raw EEG Readings	# of EEG Frequency Readings	File Size
1	Interview	12:40PM	12:45PM	759	2950	271 KB
1	Experiment	12:54PM	1:09PM	2270	8850	797 KB
2	Interview	1:13PM	1:18PM	760	2952	270 KB
2	Experiment	1:24PM	1:39PM	2277	8845	798 KB
3	Interview	1:46PM	1:51PM	758	2946	271 KB
3	Experiment	2:00PM	2:15PM	2275	8841	792 KB
4	Interview	11:27AM	11:32AM	759	2947	211 KB
4	Experiment	11:37AM	11:52AM	2277	8838	623 KB
5	Interview	1:45PM	1:50PM	759	2948	212 KB
5	Experiment	1:54PM	2:09PM	2275	8833	615 KB
6	Interview	2:25PM	2:30PM	759	2947	212 KB
6	Experiment	2:35PM	2:50PM	2271	8817	623 KB

Table 4: Statistics of data collected per participant per segment.

For the 5-minute baseline-setting interviews, an average of 241 KB of data was collected per participant, equating to an average of 2,892 KB per participant per hour. An average of 759 raw EEG readings and 2,948 EEG frequency readings were posted per participant for the interview, equating to an average of 9,108 raw EEG readings and 35,380 EEG frequency readings per participant per hour.

Similarly, an average of 708 KB of data was collected per participant for the 15-min meditation experiment, equating to an average of 2,832 KB per participant per hour. An average of 2,274 raw EEG readings and 8,837 EEG frequency readings were posted per participant for the experiment, equating to an average of 9,097 raw EEG readings and 35,349 EEG frequency readings per participant per hour.

As can be seen, the average amount of data collected per participant per hour from the interview and the experiment were approximately the same. With this in mind, we explored hosting these data in Cloud Storage with Amazon Web Services (AWS) in order to support the experiment on a larger scale in the future. The experiments conducted for this thesis was hosted for free on a CSUN server under auspices of @dvancing Technology Lab.

We anticipated to host only the raw data of raw EEG signals and EEG frequency bands in the cloud storage. All data processing will be done locally on premise. Thus, specifically of the AWS Cloud Storage Products, we looked into Amazon Simple Storage Service (Amazon S3) Standard for its simple and scalable platform that allows data accessible from any Internet location. Amazon S3 Glacier were originally considered as well for its affordable long-term storage access. However, the cost proved to be infeasible due to the large amount of POST requests expected from raw EEG and EEG frequency readings. While the cost for S3 Standard was priced at \$0.0055 per 1,000 POST requests, the cost for S3 Glacier increased tenfold to \$0.055 per 1,000 POST requests.

Given the above averages, rounding up as buffer, we estimated approximately 3 MB of data consisting of 9,200 raw EEG readings and 35,400 EEG frequency readings (a total of 44,600 POST requests) per participant per hour of experiment. A GET request each is needed for raw EEG readings and EEG frequency readings, equating to 2 GET requests per participant per hour of experiment. We calculated estimates based on 300 participants (approximately 1 GB of data) as well as 1,000 participants (approximately 3 GB of data) to account for any volume discounts. As a result, an estimate of 13,380,000 POST requests and 600 GET requests are expected for 300 participants and 44,600,000 POST request and 2,000 GET requests for 1,000 participants.

Utilizing the AWS pricing calculator for US West (N. California) region, we obtained the following tiered estimates:

	1 GB	3 GB
S3 Standard storage	0.03 USD	0.08 USD
PUT, COPY, POST, LIST requests to S3 Standard	73.59 USD	245.30 USD
GET, SELECT, and all other requests from S3 Standard	0.0003 USD	0.0009 USD
Data returned by S3 Select	0.0008 USD	0.0024 USD
Data scanned by S3 Select	0.0022 USD	0.0067 USD
S3 Standard cost (monthly)	73.62 USD	245.39 USD
Cost per Participant per Hour	0.2454 USD	0.24539 USD

Table 5: AWS Pricing Estimates, Amazon S3 Standard

We had thought there might be a volume discount from 1GB to 3GB. Yet based on the above monthly costs, it actually costs slightly more per GB if we opted for the 3GB, or 1,000 participants plan. The cost per participant per hour, however, does equate to be approximately the same at \$0.245.

5.2 Preliminary Plots

Initially, EEG frequency bands and raw EEG signals from the baseline-setting interview and the meditation experiment were plotted in MATLAB for each participant and scaled across all participants for easier side-by-side comparison. Stacked plot was used for better visibility of each frequency bands and signals at a glance.

5.2.1 EEG Frequency Bands from Baseline-Setting Interviews

Figures 23 through 28 shows the MATLAB stacked plot consisting of the participants' EEG frequency bands from the baseline-setting interviews. All graphs were plotted with time in the x-axis and Hz for EEG frequency bands in the y-axis. The 5 distinguished EEG frequency bands are aligned vertically on top of one another to observe how it changed over time.



Figure 23: Participant 1's EEG frequency bands

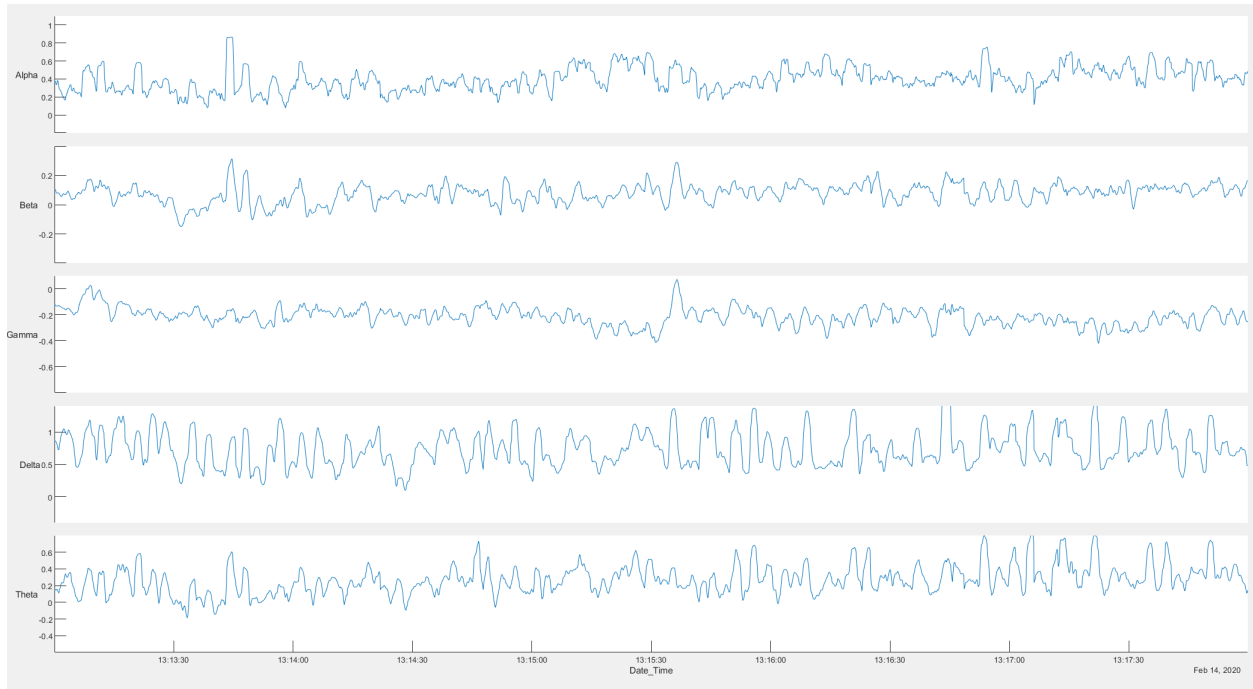


Figure 24: Participant 2's EEG frequency bands

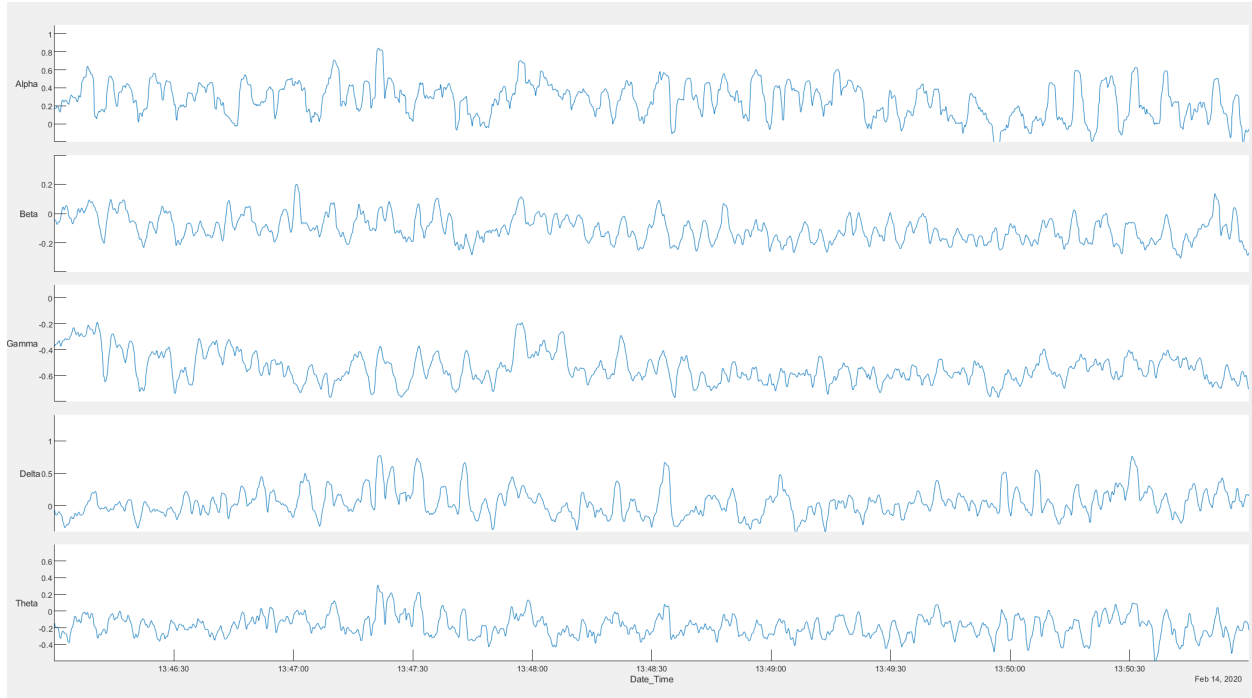


Figure 25: Participant 3's EEG frequency bands

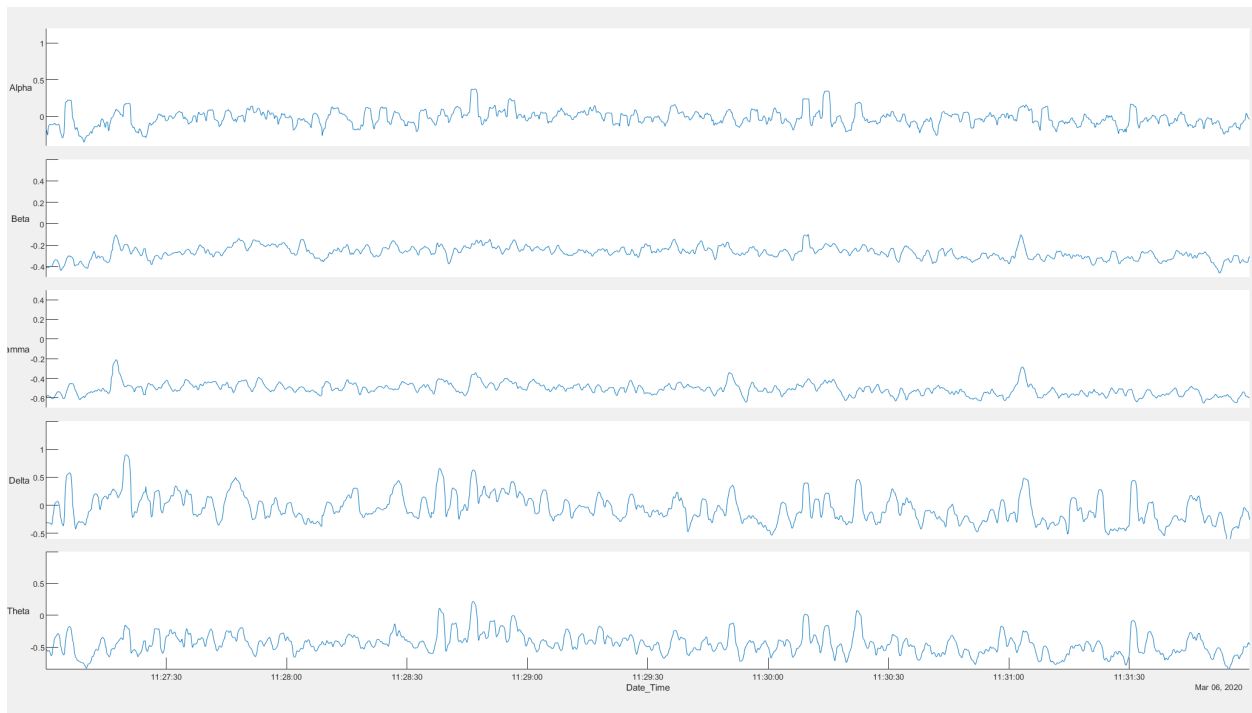


Figure 26: Participant 4's EEG frequency bands

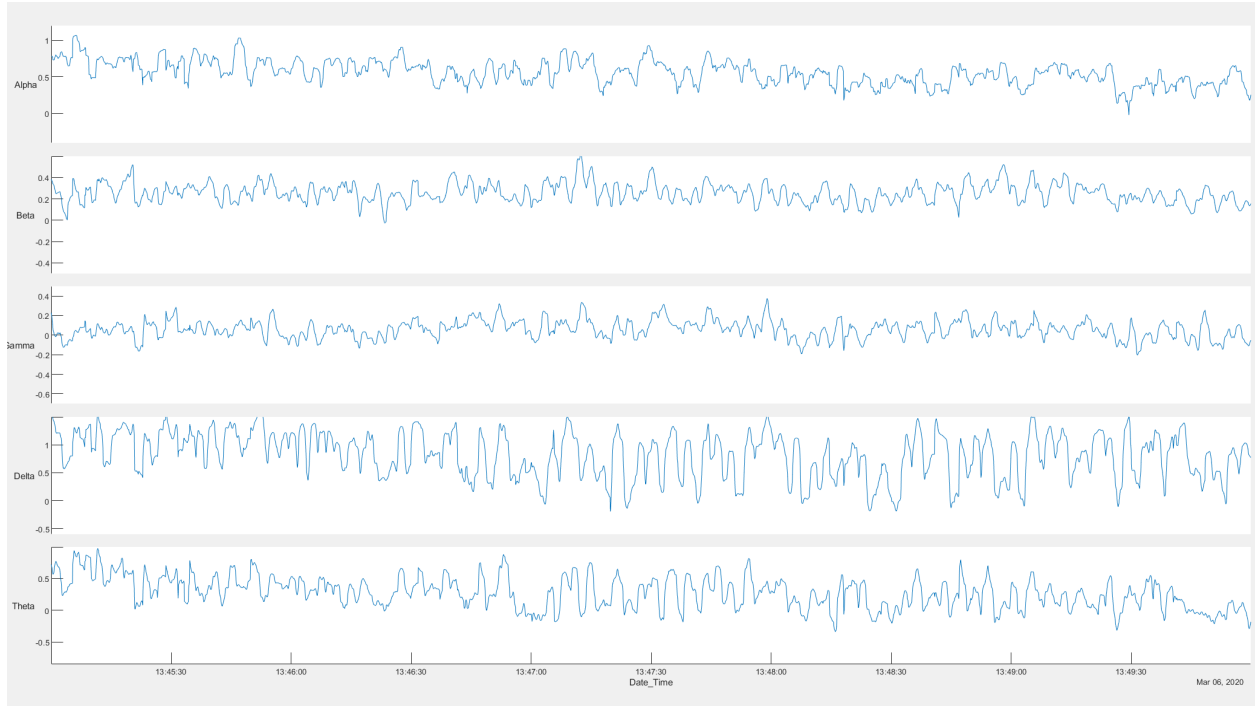


Figure 27: Participant 5's EEG frequency bands



Figure 28: Participant 6's EEG frequency bands

5.2.2 Raw EEG Signals from Baseline-Setting Interviews

Figures 29 through 34 shows the MABLAB stacked plot consisting of the participants' raw EEG signals from the baseline-setting interviews. All graphs were plotted with time in the x-axis and μV for raw EEG signals in the y-axis. The 4 sensors plus 1 referential sensor are aligned vertically on top of one another to observe how it changed over time.

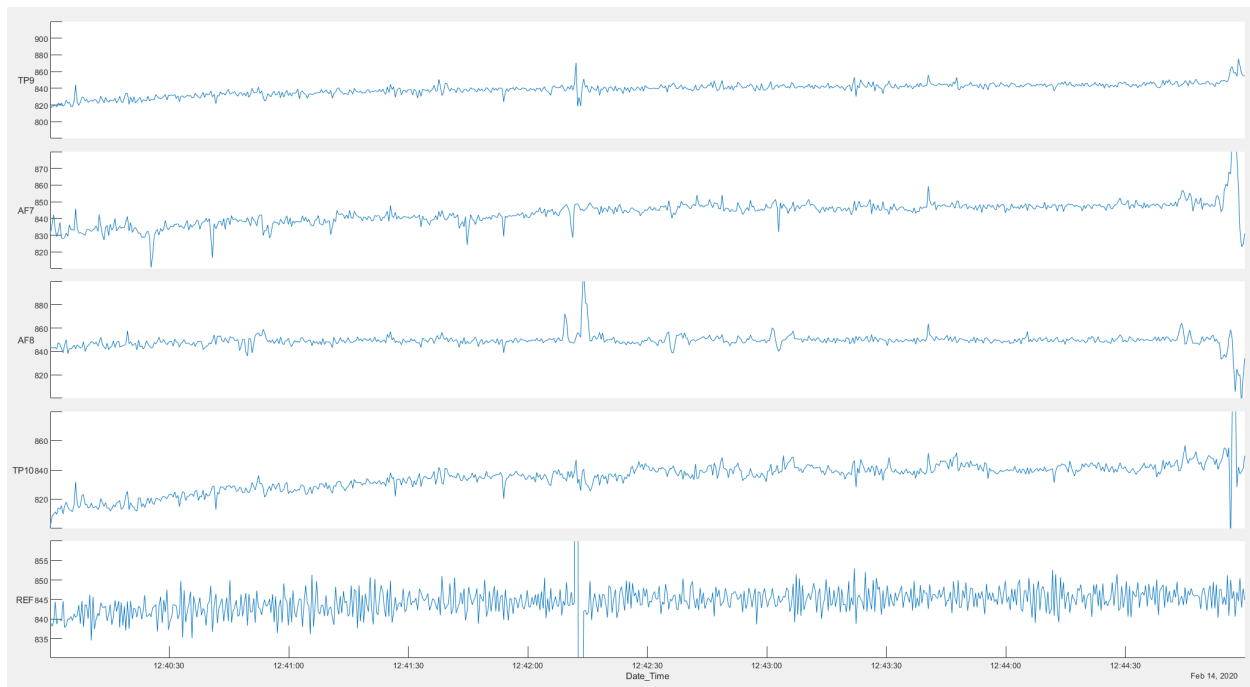


Figure 29: Participant 1's raw EEG signals

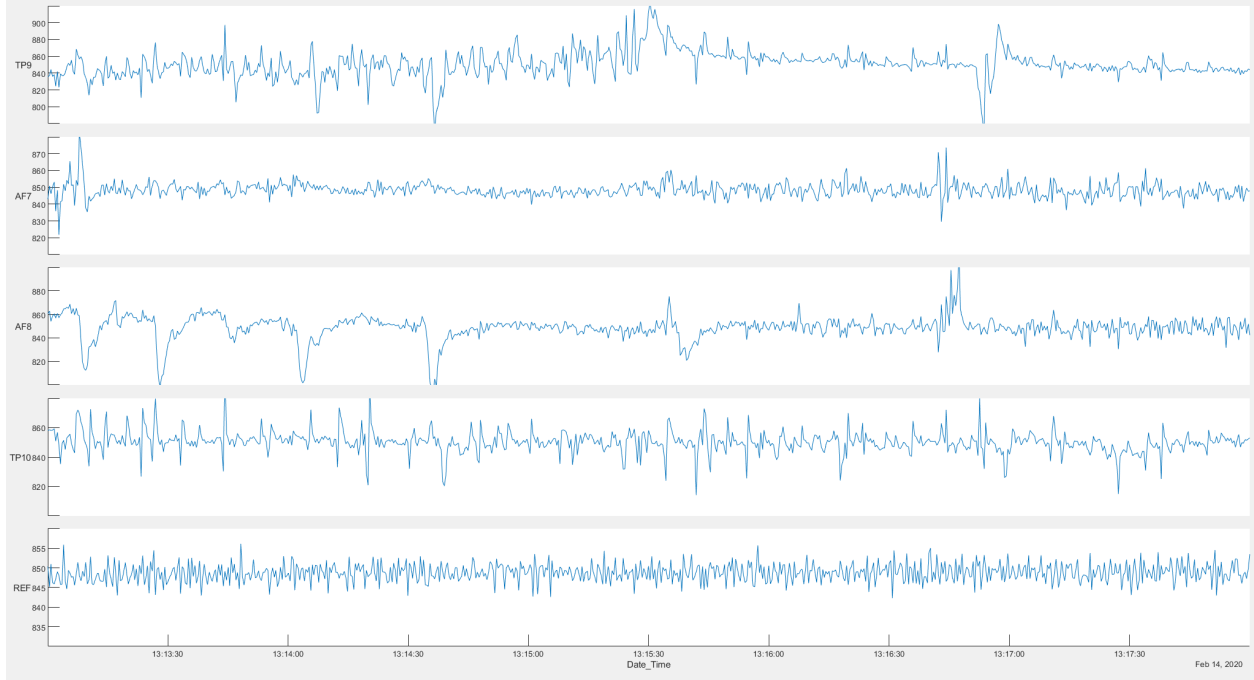


Figure 30: Participant 2's raw EEG signals

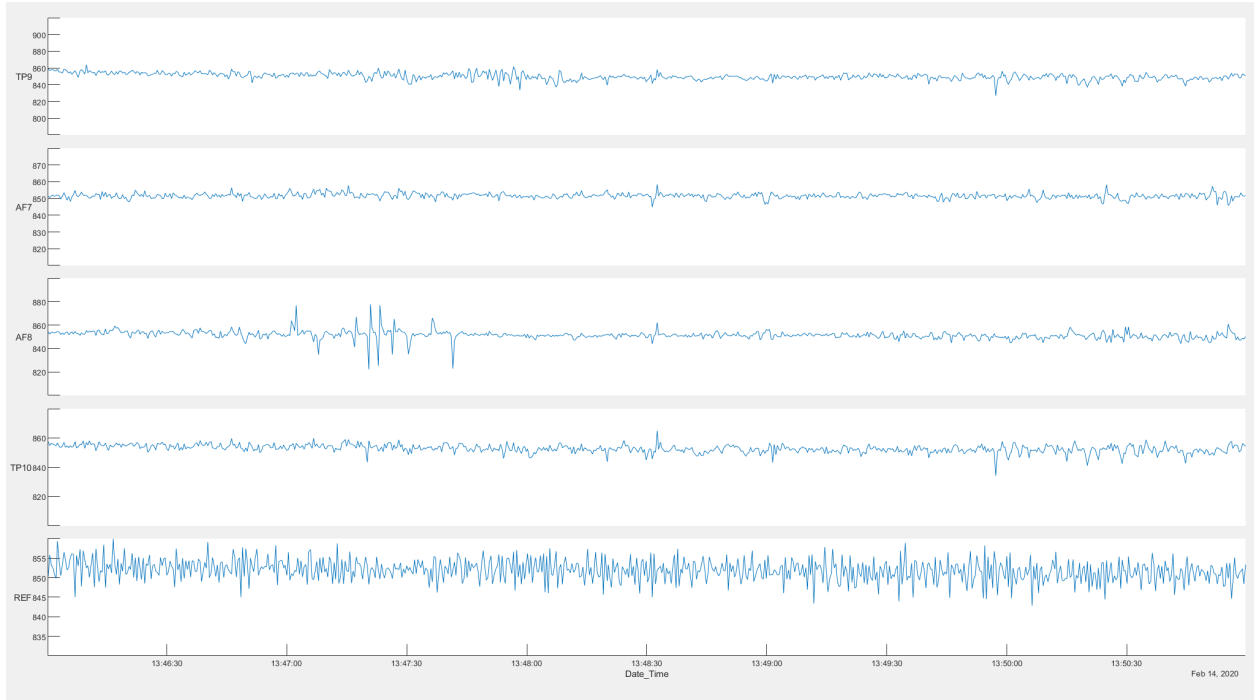


Figure 31: Participant 3's raw EEG signals

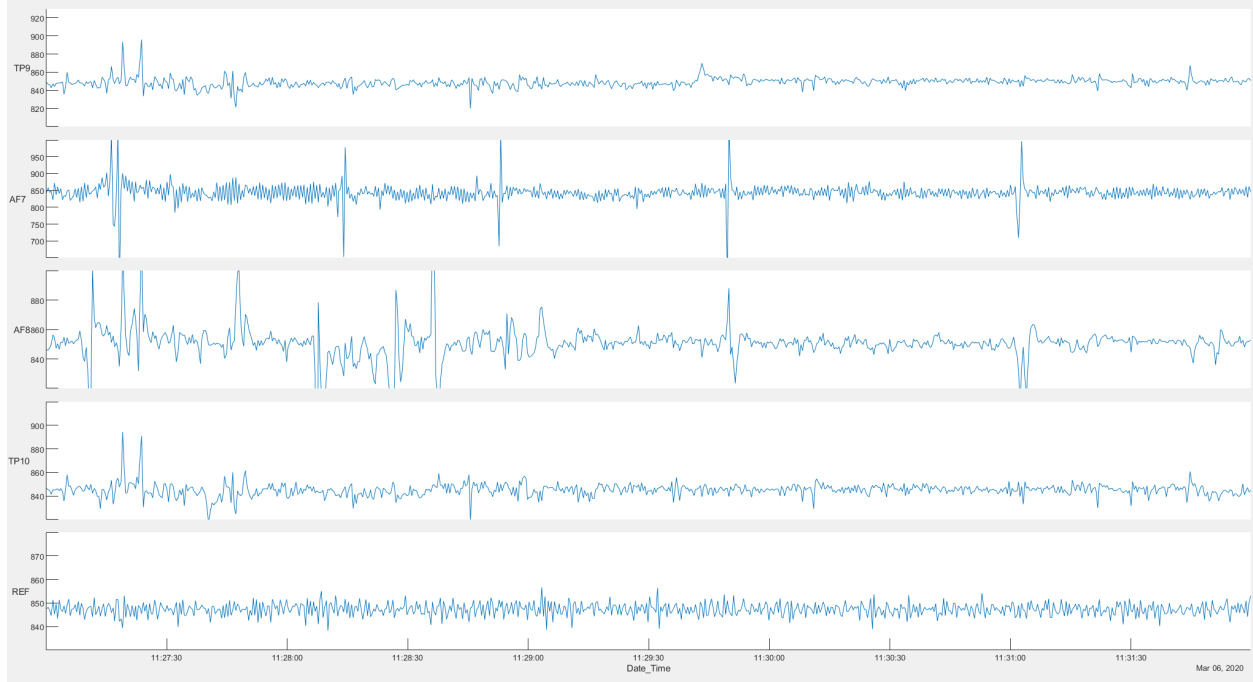


Figure 32: Participant 4's raw EEG signals

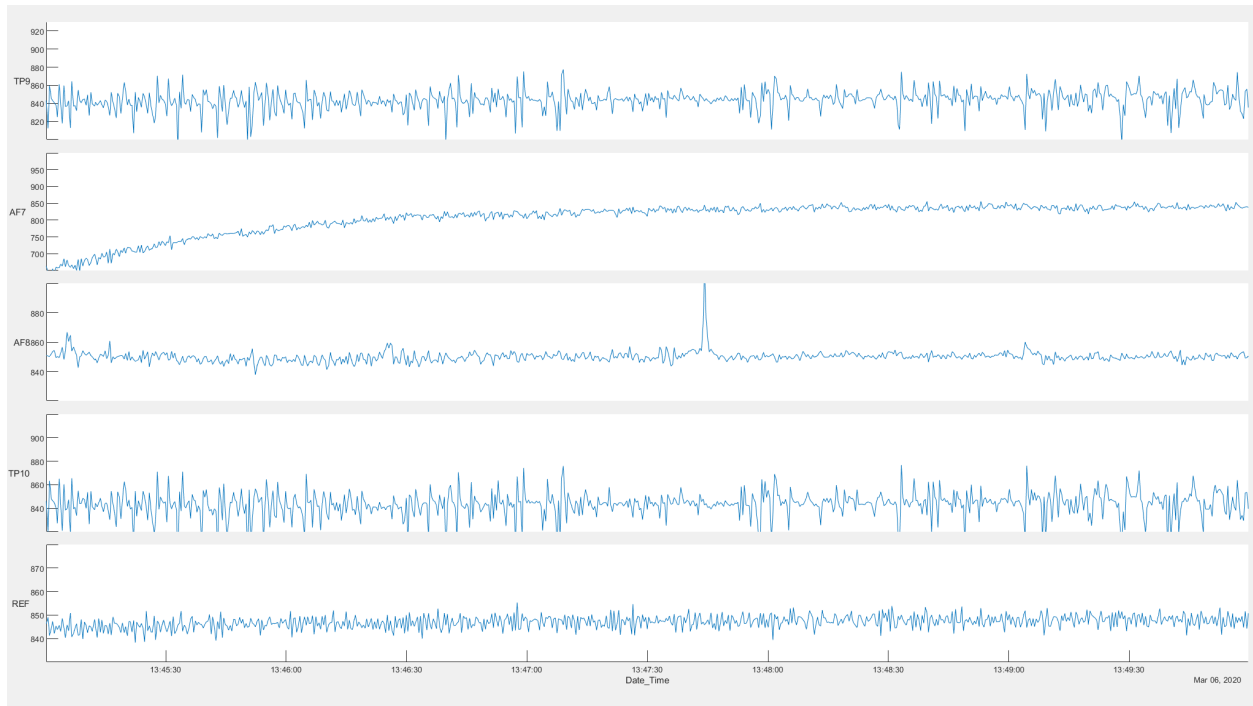


Figure 33: Participant 5's raw EEG signals

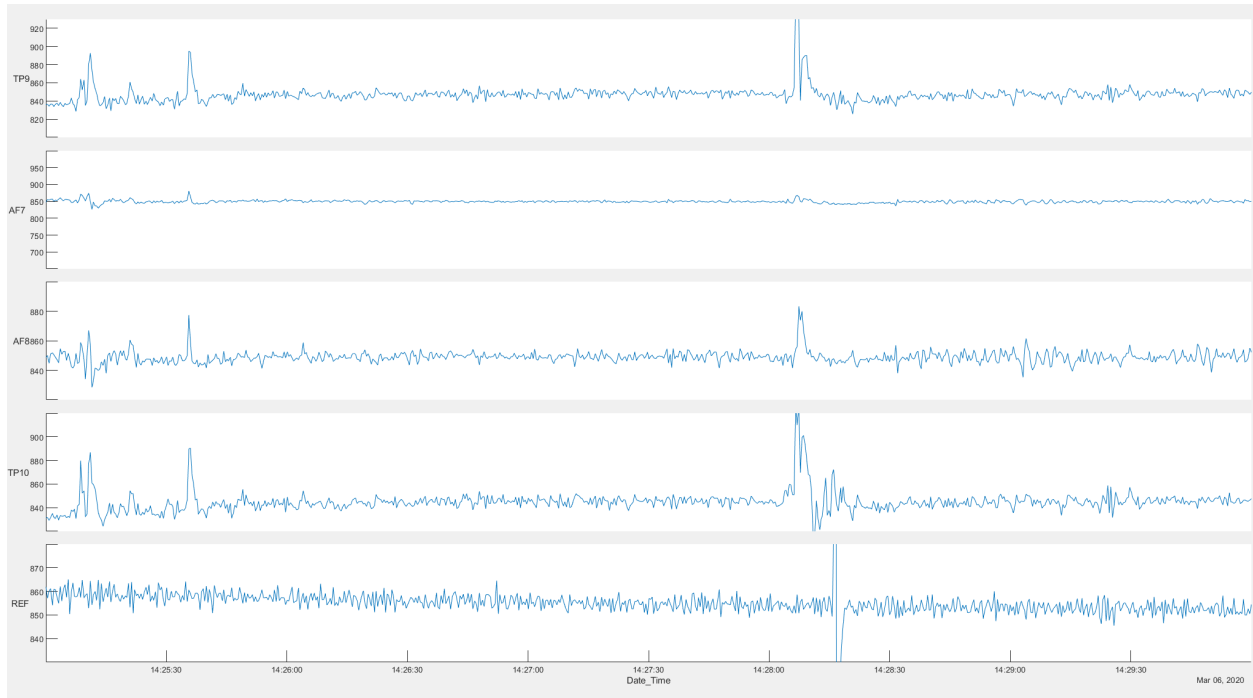


Figure 34: Participant 6's raw EEG signals

5.2.3 EEG Frequency Bands from Meditation Experiment

Figures 35 through 40 shows the MATLAB stacked plot consisting of the participants' EEG frequency bands from the meditation experiments. All graphs were plotted with time in the x-axis and Hz for EEG frequency bands in the y-axis. The 5 distinguished EEG frequency bands are aligned vertically on top of one another to observe how it changed over time.

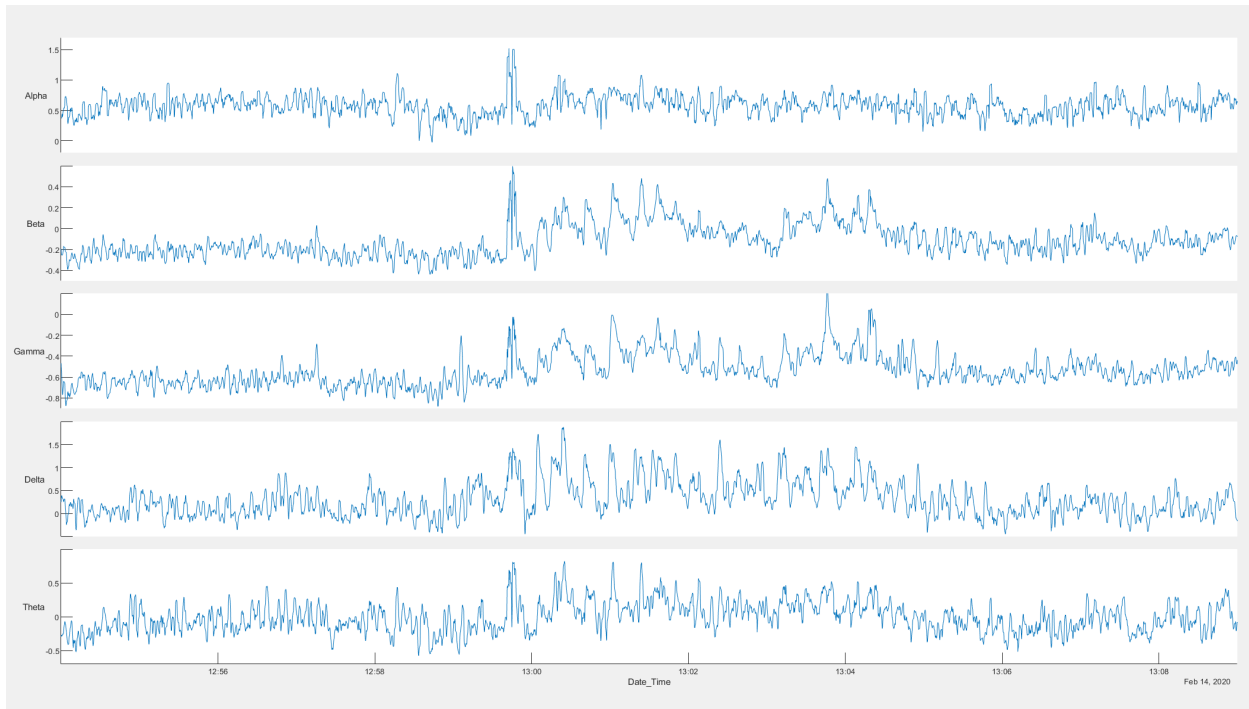


Figure 35: Participant 1's EEG frequency bands

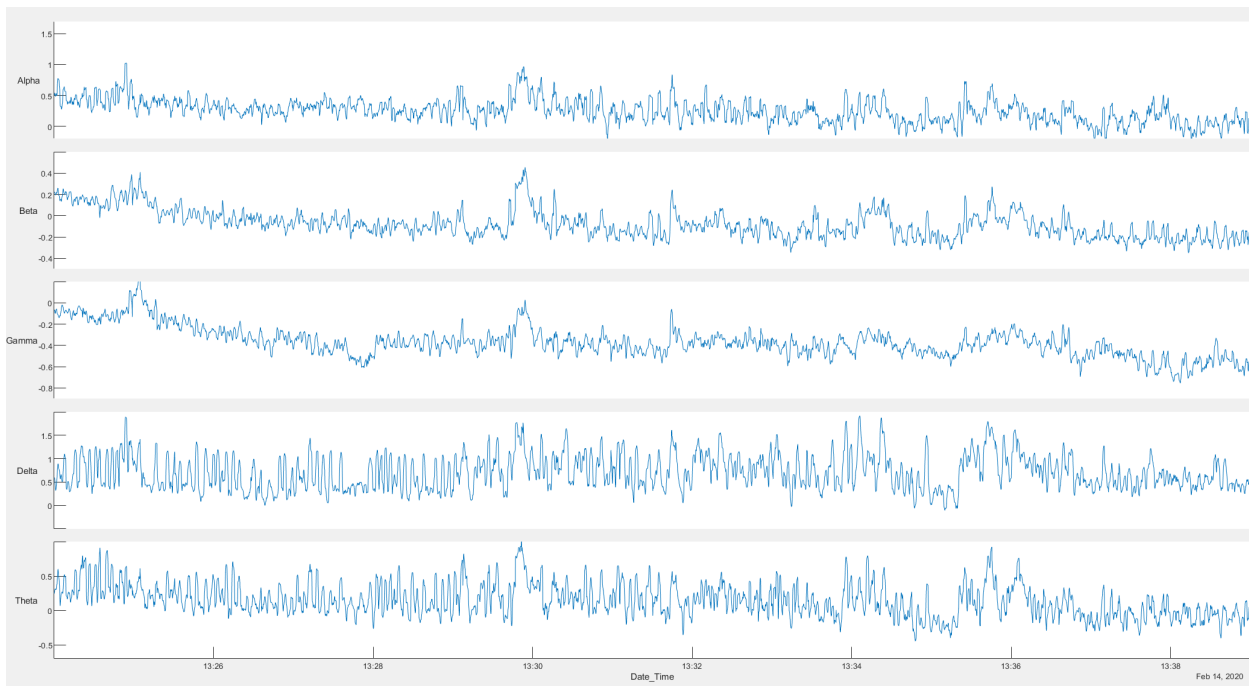


Figure 36: Participant 2's EEG frequency bands

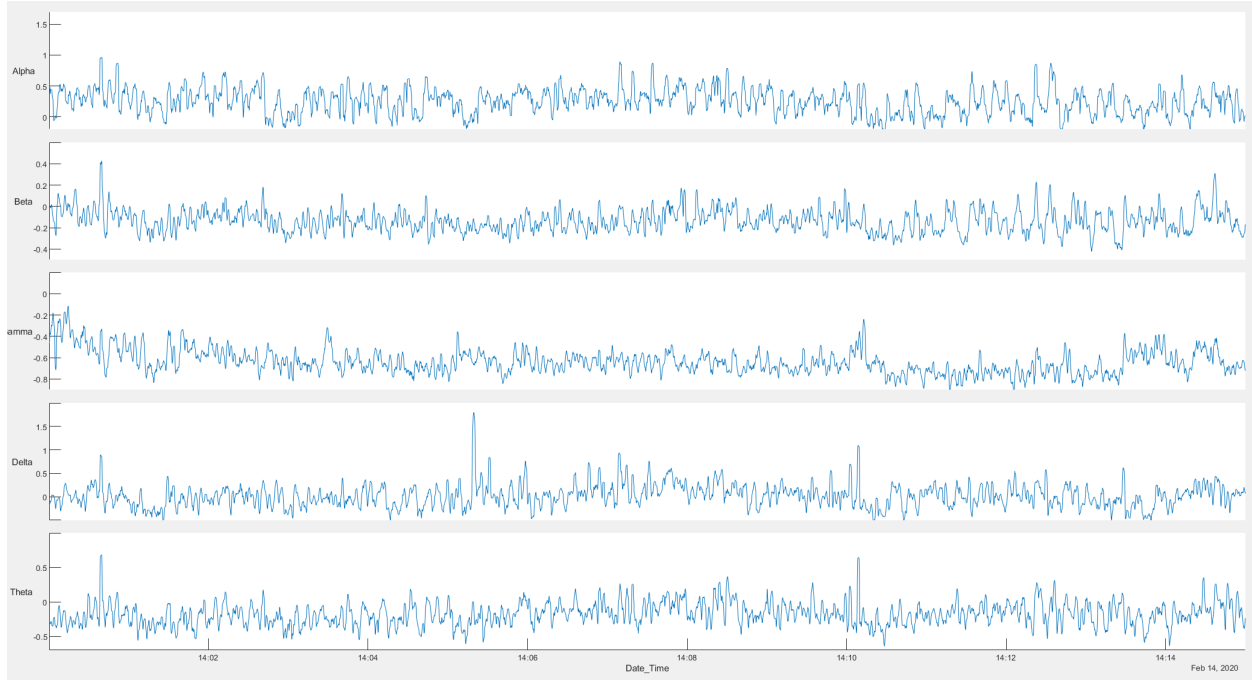


Figure 37: Participant 3's EEG frequency bands

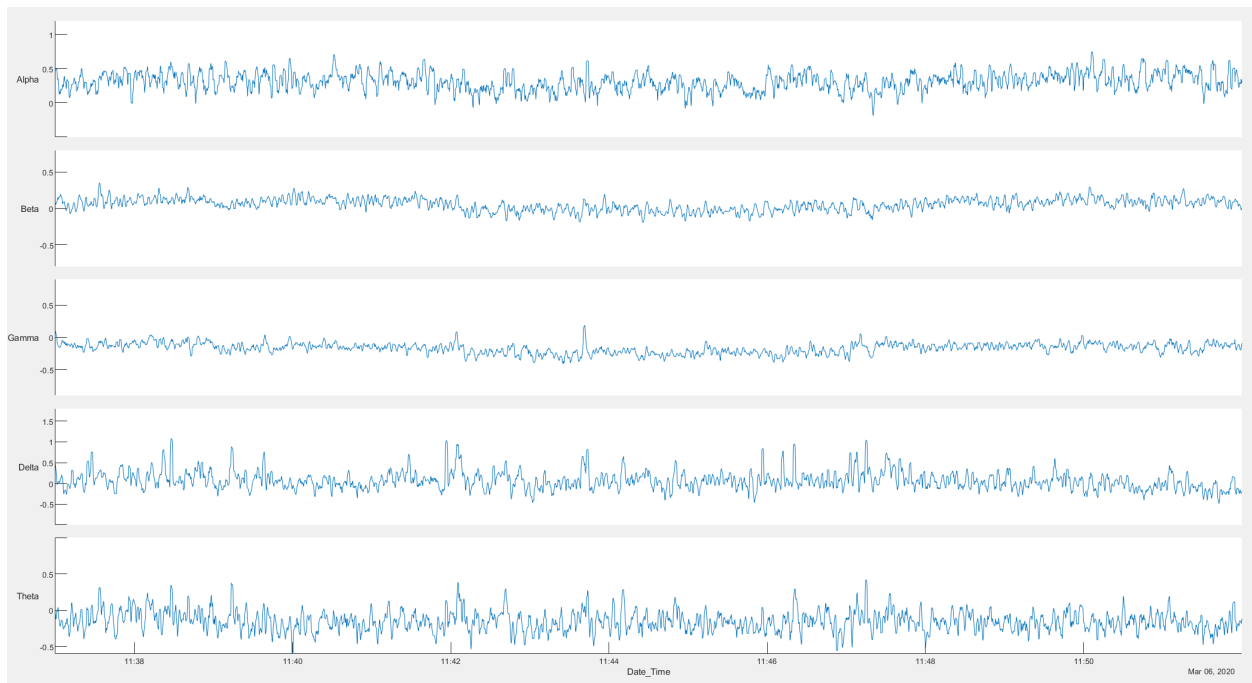


Figure 38: Participant 4's EEG frequency bands

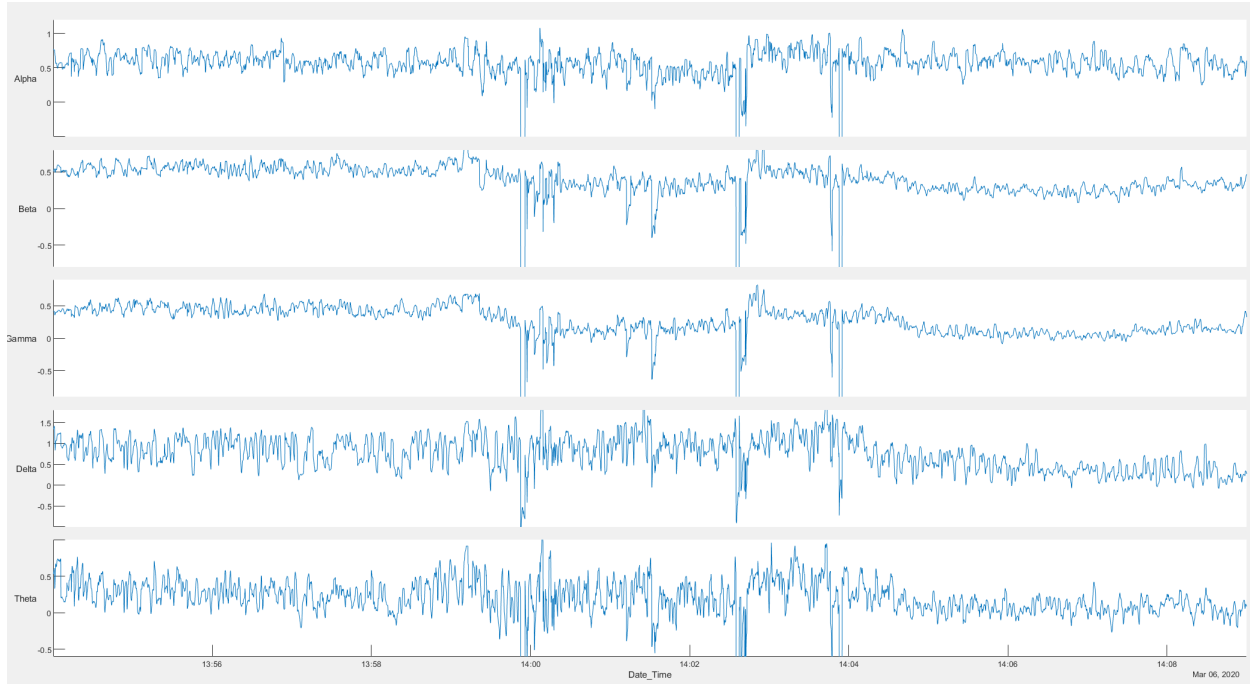


Figure 39: Participant 5's EEG frequency bands

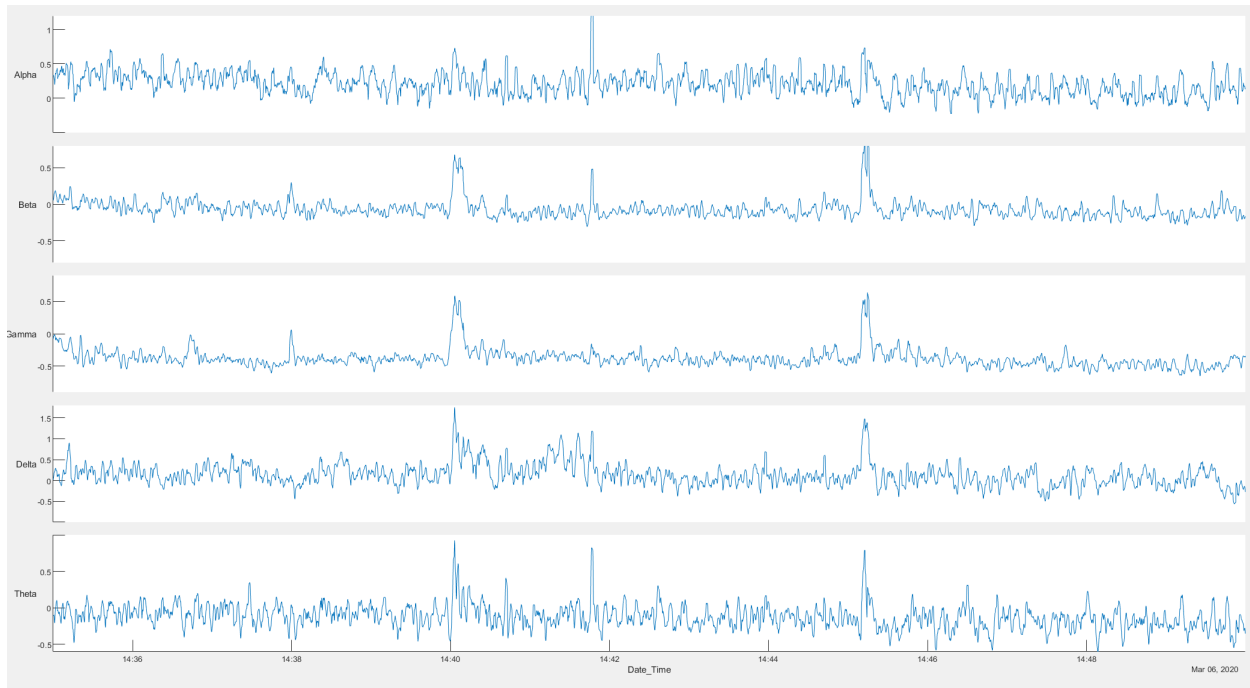


Figure 40: Participant 6's EEG frequency bands

While we hypothesized a decrease in beta frequency bands during meditation phases (Alternate Nostril Breathing and Breath Awareness) when participants were no longer “busy thinking,” our

results showed quite the contrary. The participants' beta frequency bands either had no change, or even increased during meditation phases. We speculated that this might be because most participants are not regular meditators. As such, even while meditating, the participants had to actively think about the unfamiliar instructions, thus contributing to "busy thinking" or active concentration.

On the other hand, we observed a rise in delta frequency bands across participants during the middle 5-minutes of the meditation experiment when participants were instructed to meditate using the alternate nostril breathing technique. The rise in delta bands may be more apparent in some participants (e.g., participant 1) than others (e.g., participant 6), which are more subtle.

5.2.4 Raw EEG Signals from Meditation Experiment

Figures 41 through 46 shows the MABLAB stacked plot consisting of the participants' raw EEG signals from the meditation experiments. All graphs were plotted with time in the x-axis and μV for raw EEG signals in the y-axis. The 4 sensors plus 1 referential sensor are aligned vertically on top of one another to observe how it changed over time.

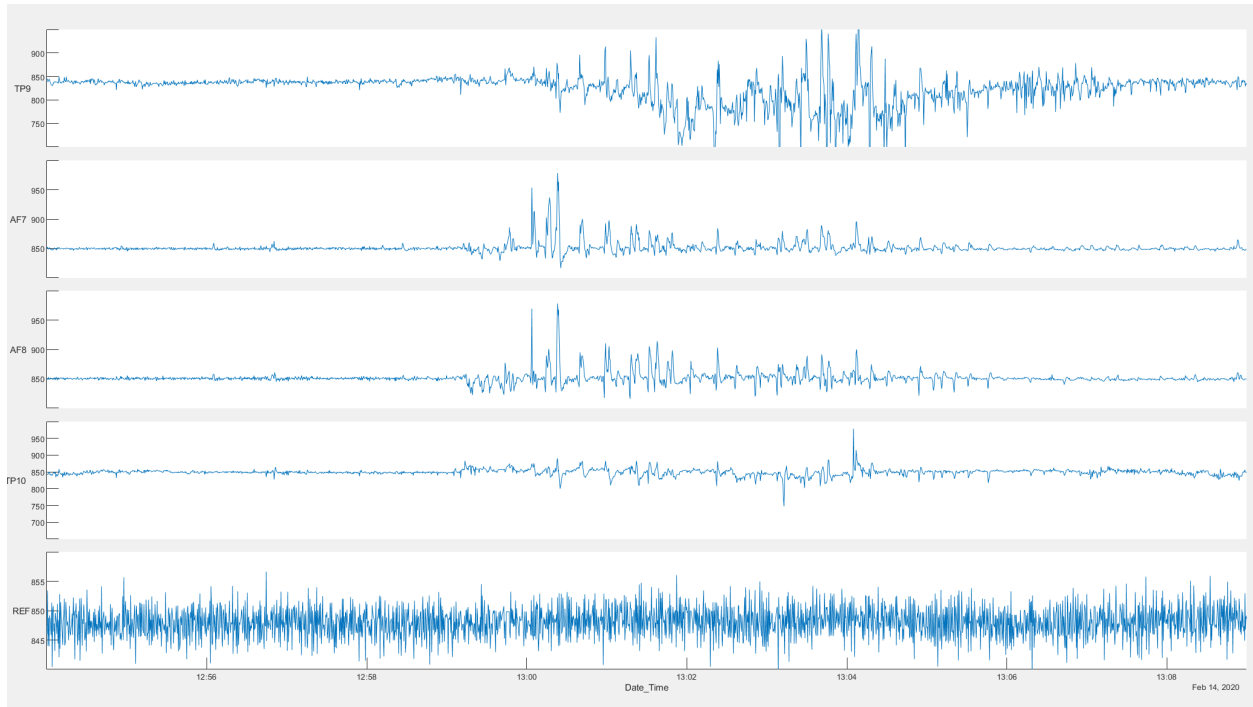


Figure 41: Participant 1's raw EEG signals

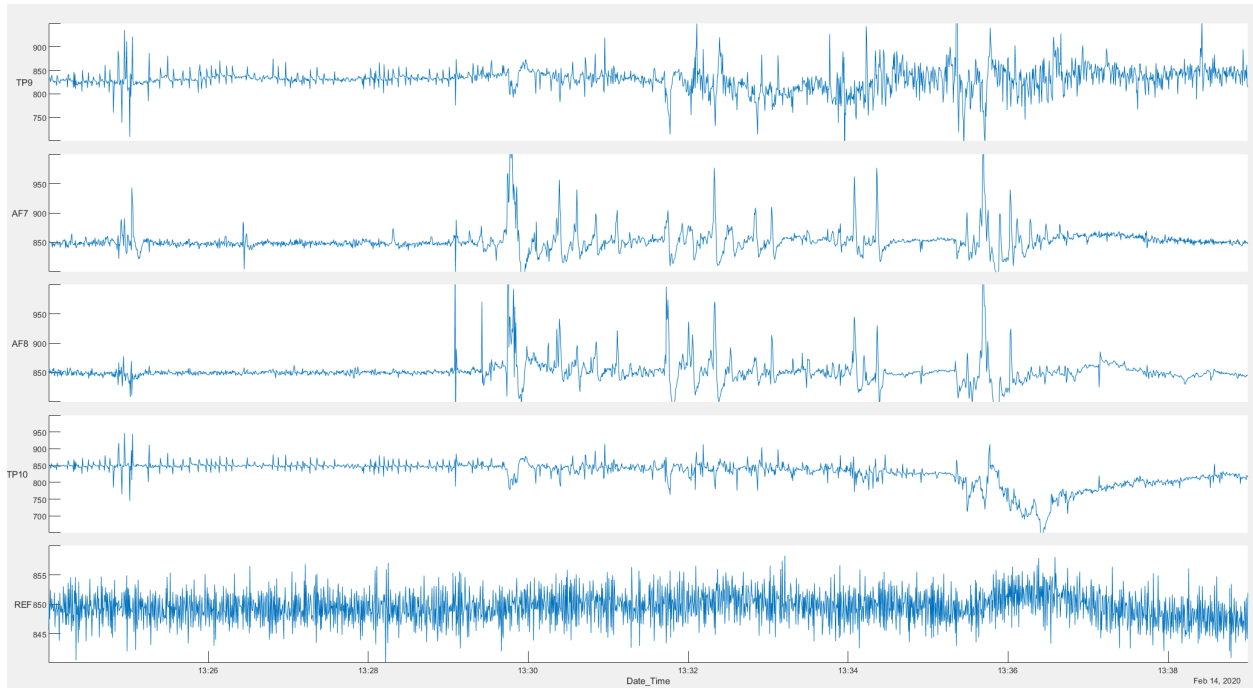


Figure 42: Participant 2's raw EEG signals

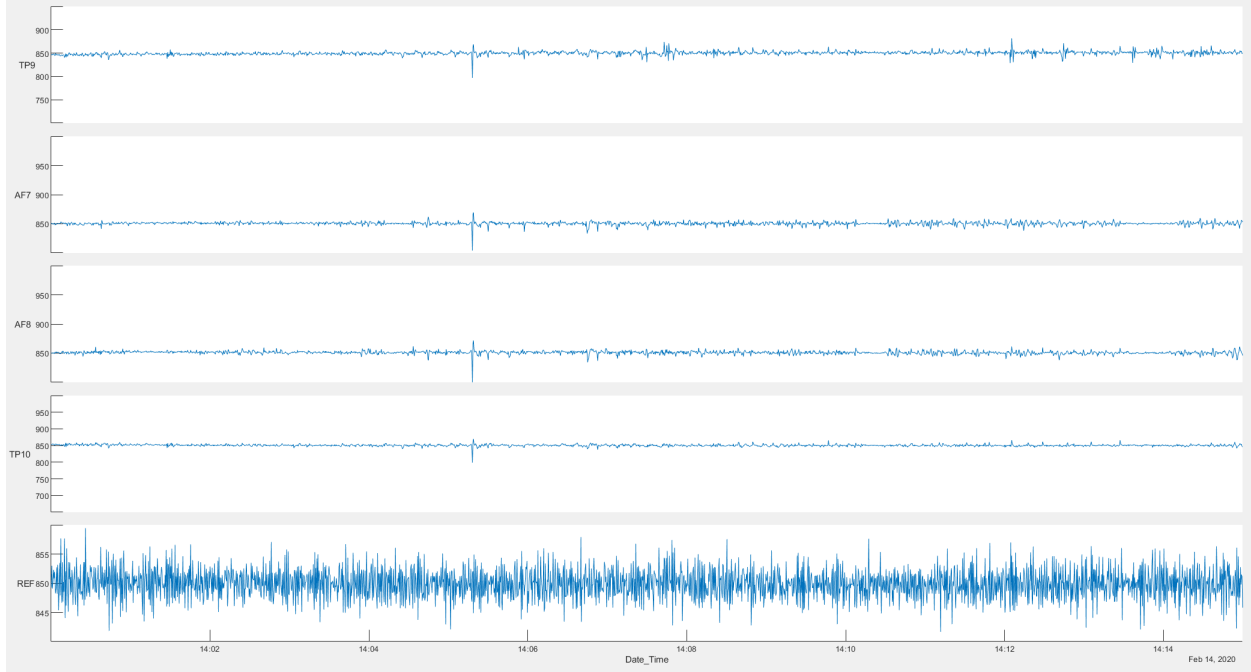


Figure 43: Participant 3's raw EEG signals

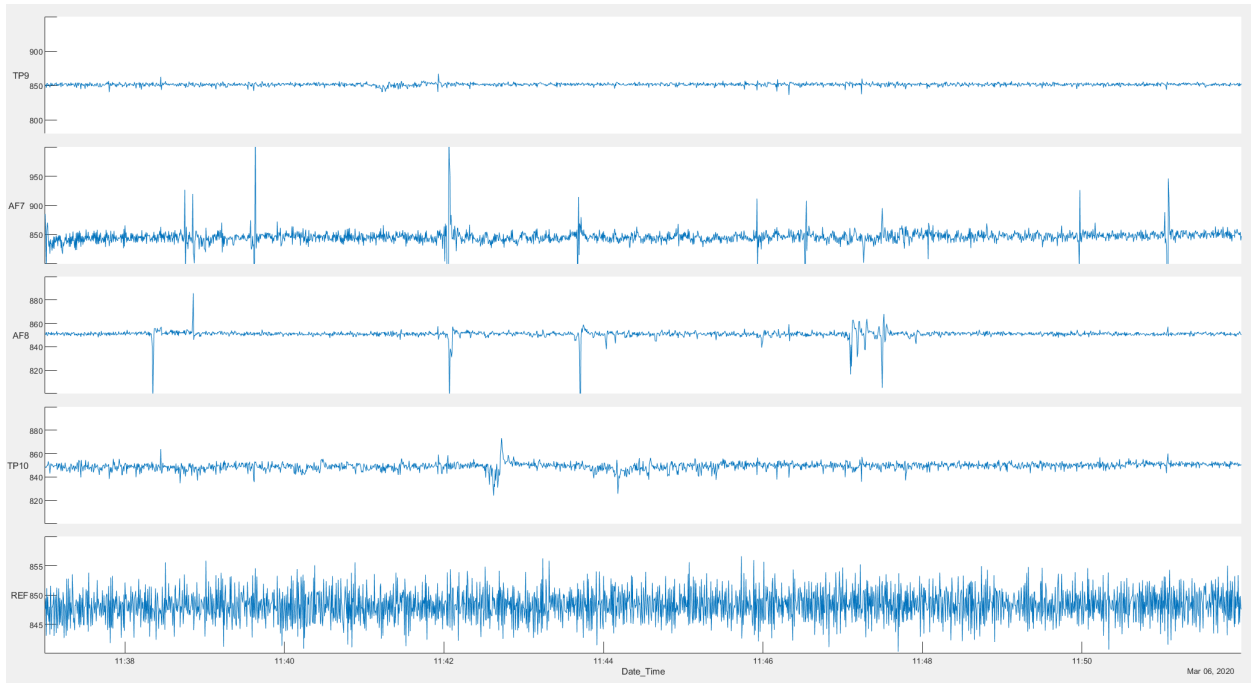


Figure 44: Participant 4's raw EEG signals

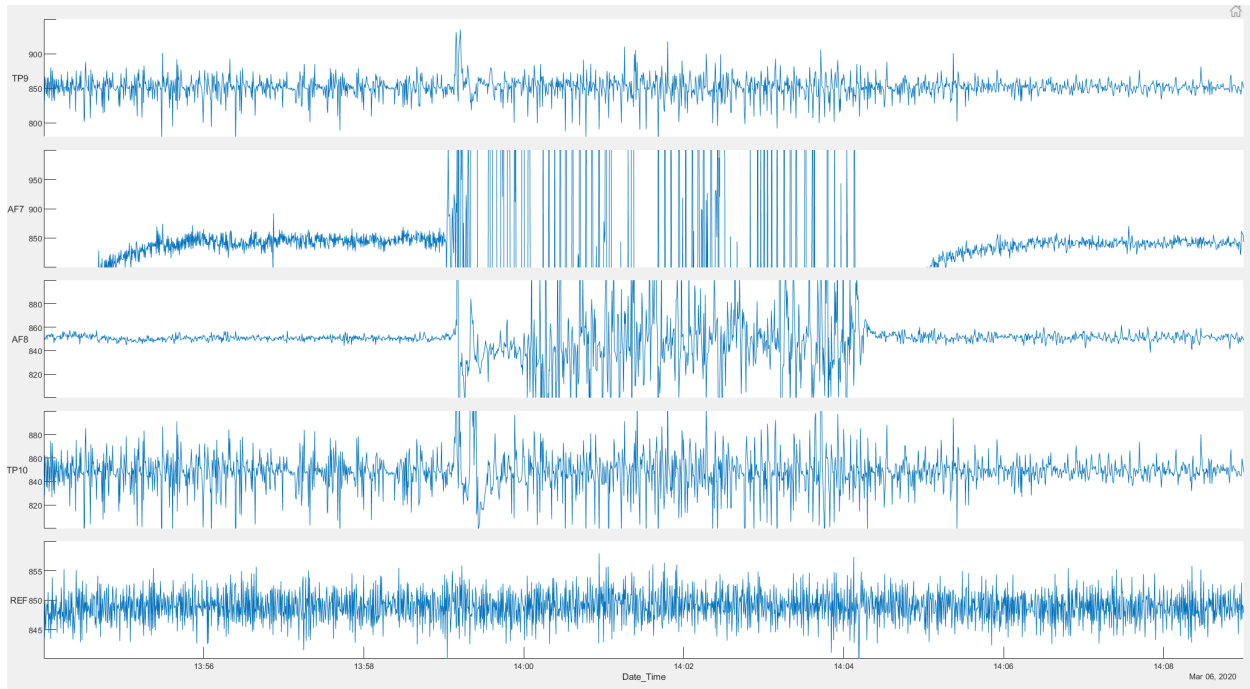


Figure 45: Participant 5's raw EEG signals

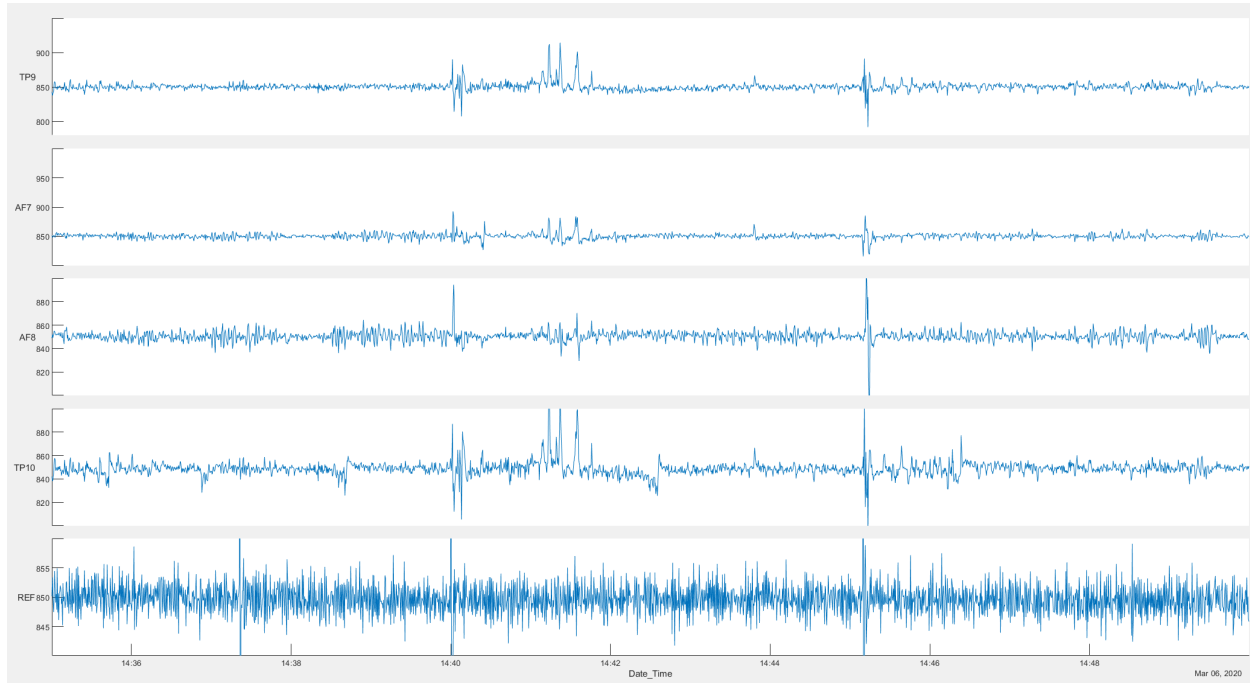


Figure 46: Participant 6's raw EEG signals

5.3 Data Aggregation and Secondary Plots

The number of readings that were recorded per second varied between participants – the total number of readings within a 15-minute interval varied anywhere from 8817 to 8850 readings (Table 4). As a result, it was difficult to compare all 6 participants' EEG frequency bands against one another data point to data point to observe the accurate impact each phases of the meditation experiment had on the participants.

We aggregated each participant's EEG frequency band reading by averaging the data on a per-second basis using a Python script. This allowed us to compare each participants' EEG readings on a per-second basis and gain a better view on the overall impact of the different phases of the study.

We were particularly interested in the effects of beta and delta frequency bands that we observed in the previous sections. These frequency bands were plotted as stacked plot in MATLAB for better visibility of each participant's corresponding beta and delta frequency bands during baseline-setting interviews and meditation experiment. Graphs were plotted with seconds in the x-axis and Hz for EEG frequency bands and μV for raw EEG signals, respectively, in the y-axis. Each row shows the readings for each of the 6 participants.

5.3.1 Beta and Delta Frequency Bands from Baseline-Setting Interviews

Figures 47 and 48 depicts the beta and delta frequency bands for all participants during the baseline-setting interviews.

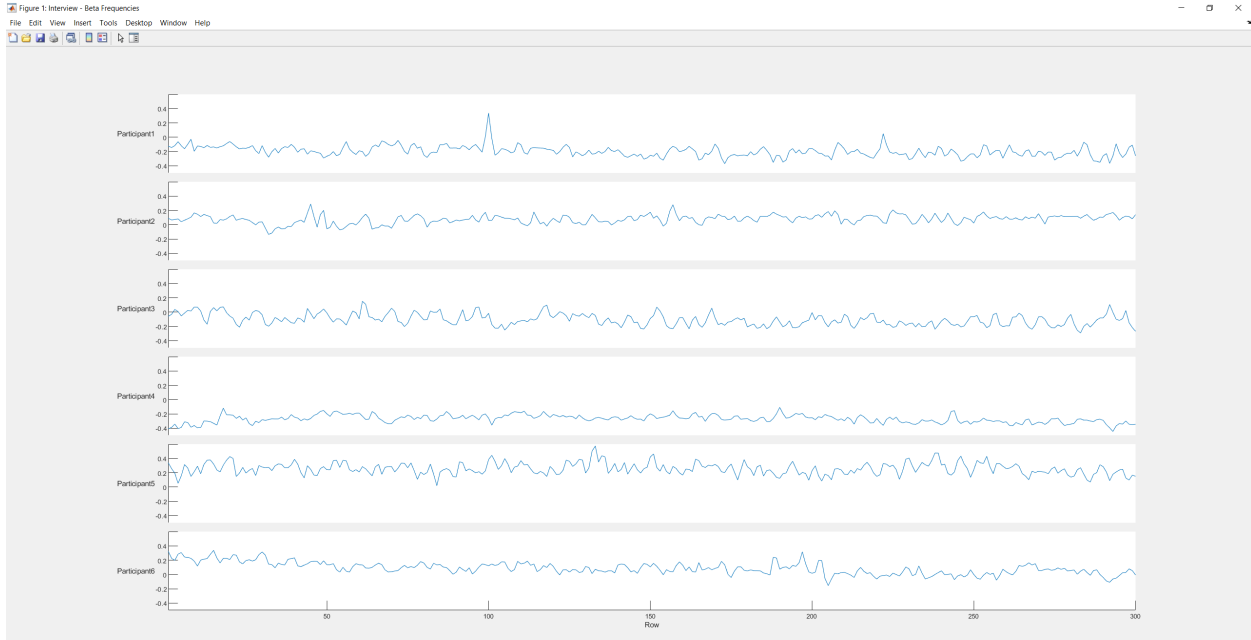


Figure 47: Beta frequency bands for all participants

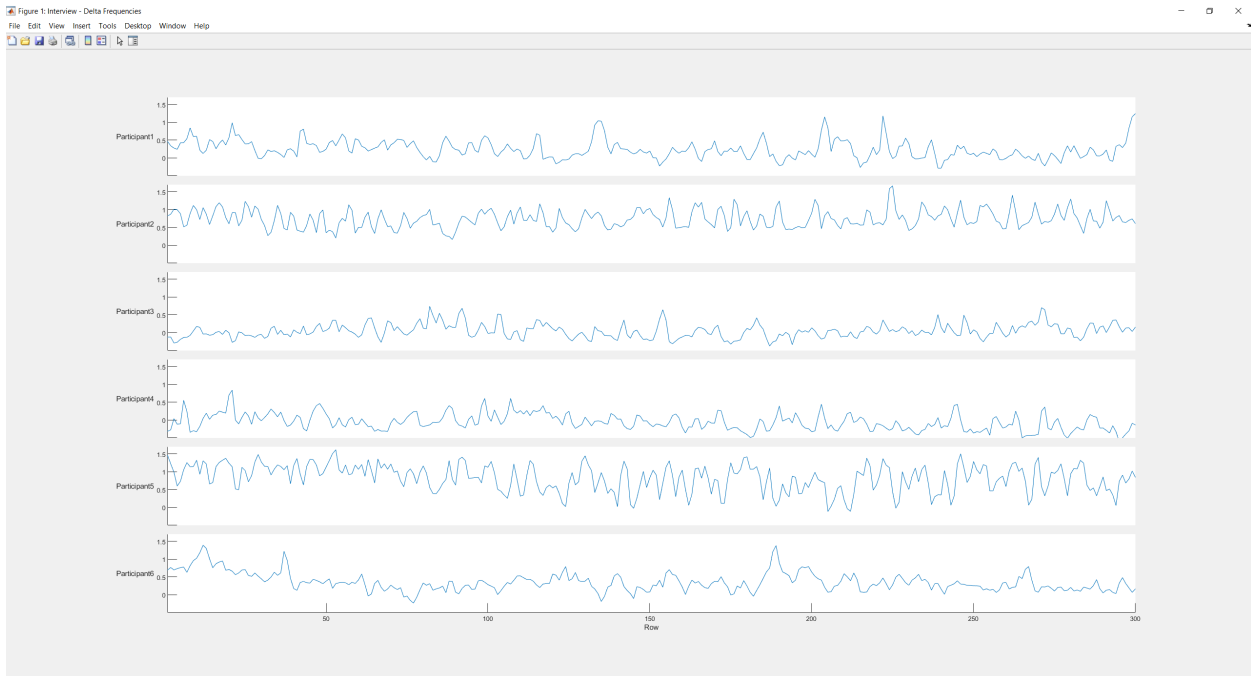


Figure 48: Delta frequency bands for all participants

5.3.2 Beta and Delta Frequency Bands from Meditation Experiments

Figures 49 and 50 depicts the beta and delta frequency bands for all participants during the meditation experiments. As the x-axis are in seconds, the participants switched from ‘Think of

Your Week' to alternate nostril breathing technique at 300 seconds (first 5-minute mark), and to breath awareness at 600 seconds (second 5-minute mark). The study concluded at 900 seconds, or 15 minutes.

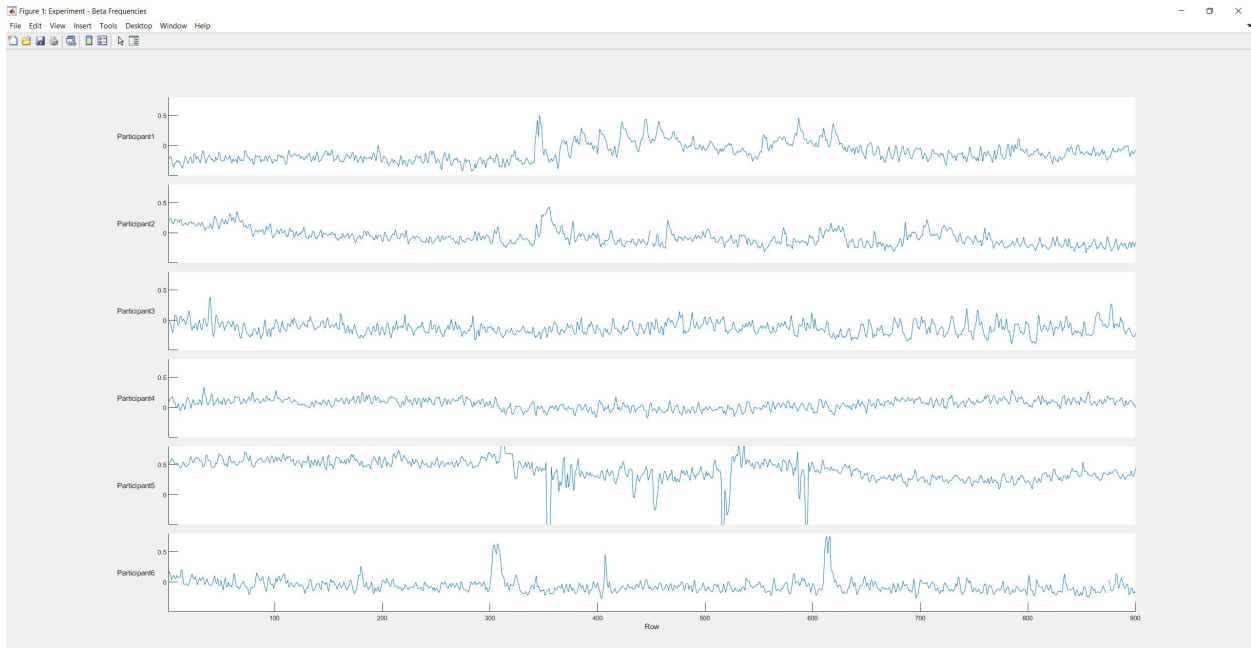


Figure 49: Beta frequency bands for all participants

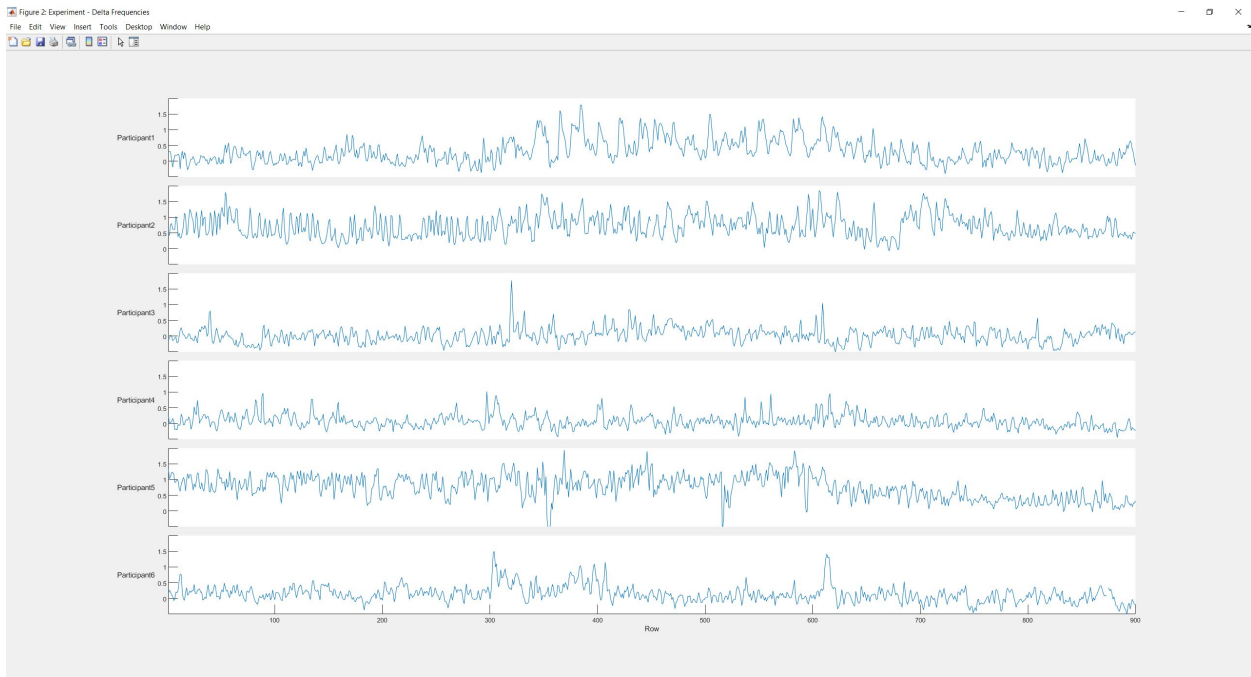


Figure 50: Delta frequency bands for all participants

Similar to our preliminary plots, we observed either no change or a slight increase in beta frequency bands across the participants, particularly during Alternate Nostril Breathing phase. Participant 1 and 2 have the most pronounced rise in beta during the Alternate Nostril Breathing phase. Both Participant 1 and 2 also have meditated more regularly than other participants in the past based on their questionnaire responses (Figure 61). Their beta frequency bands calmed down once they entered into the Breath Awareness phase.

With respect to delta frequency bands, we observed a rise across participants during the middle 5-minutes, 300 second mark to 600-second mark, of the meditation experiment when participants were instructed to meditate using the alternate nostril breathing technique. We once again notice the most pronounced results in Participant 1 and 2 during Alternate Nostril Breathing phase, who meditated on a more regular basis than other participants. We can see their delta frequency bands continued strong even as they switch to breath awareness meditation, contrary to their beta frequency bands.

5.4 Average Across All Participants

In order to further obtain a clearer picture of the overall effect of the study across all participants, we averaged across all 6 participants per reading per second for beta and delta frequency bands.

These frequency bands were plotted in MATLAB for beta and delta frequency bands during baseline-setting interviews and meditation experiment. Graphs were plotted with seconds in the x-axis and Hz for EEG frequency bands and μV for raw EEG signals, respectively, in the y-axis.

5.4.1 Beta and Delta Frequency Bands from Baseline-Setting Interviews

Figures 51 and 52 depicts the beta and delta frequency bands for the average of all 6 participants during the baseline-setting interviews.

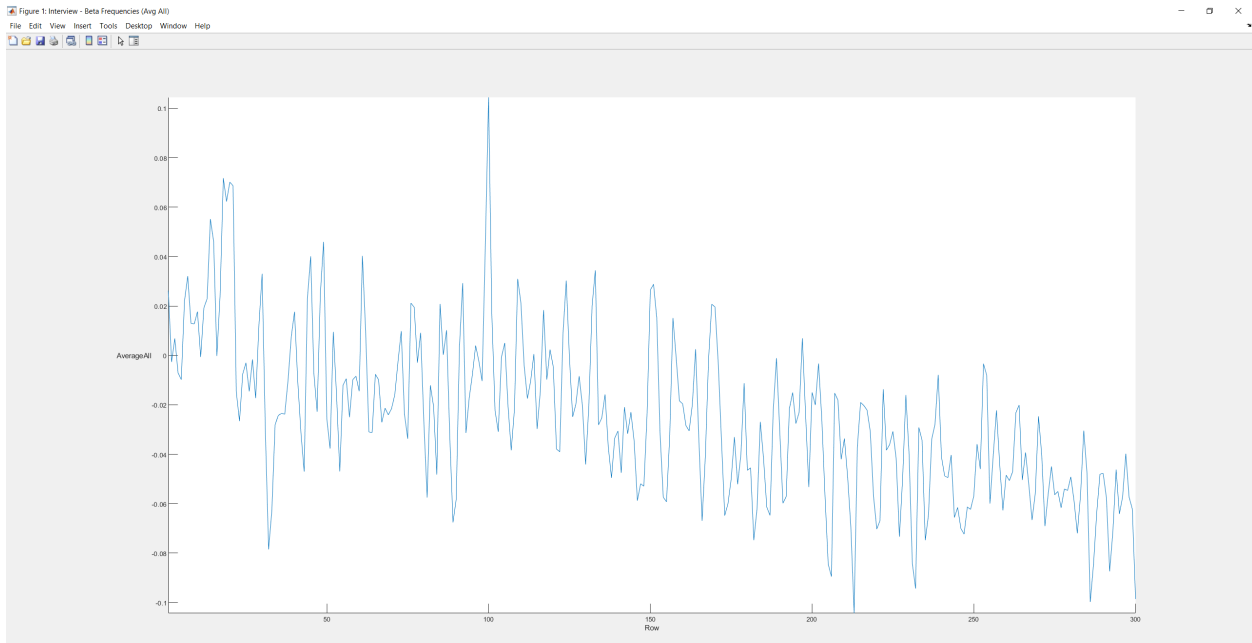


Figure 51: Beta frequency bands averaged across all participants

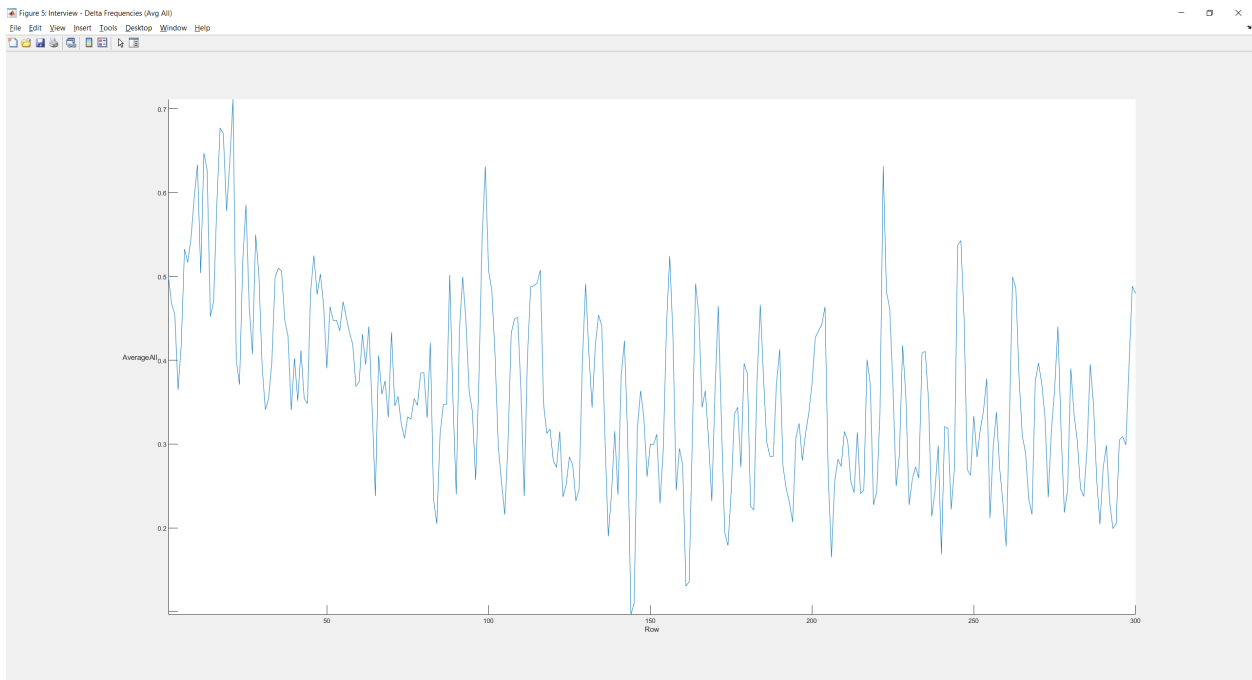


Figure 52: Delta frequency bands averaged across all participants

5.4.2 Beta and Delta Frequency Bands from Meditation Experiments

Figures 53 and 54 depicts the beta and delta frequency bands for the average of all 6 participants during the meditation experiments. As the x-axis are in seconds, the participants switched from

‘Think of Your Week’ to alternate nostril breathing technique at 300 seconds (first 5-minute mark), and to breath awareness at 600 seconds (second 5-minute mark). The study concluded at 900 seconds, or 15 minutes.

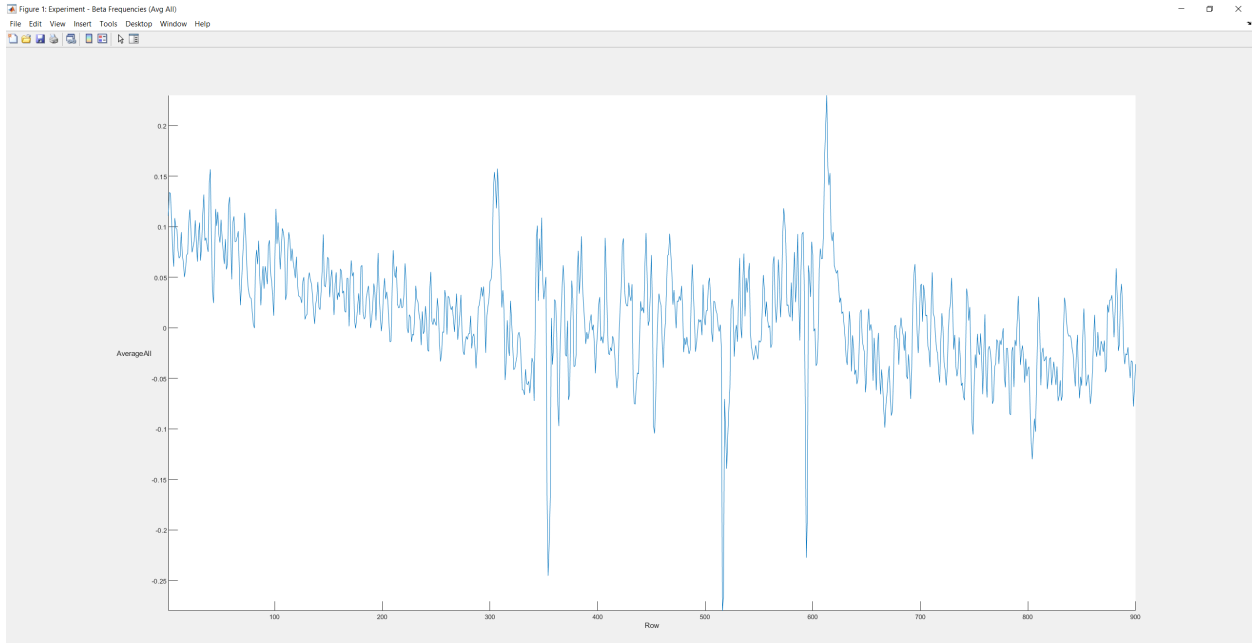


Figure 53: Beta frequency bands averaged across all participants

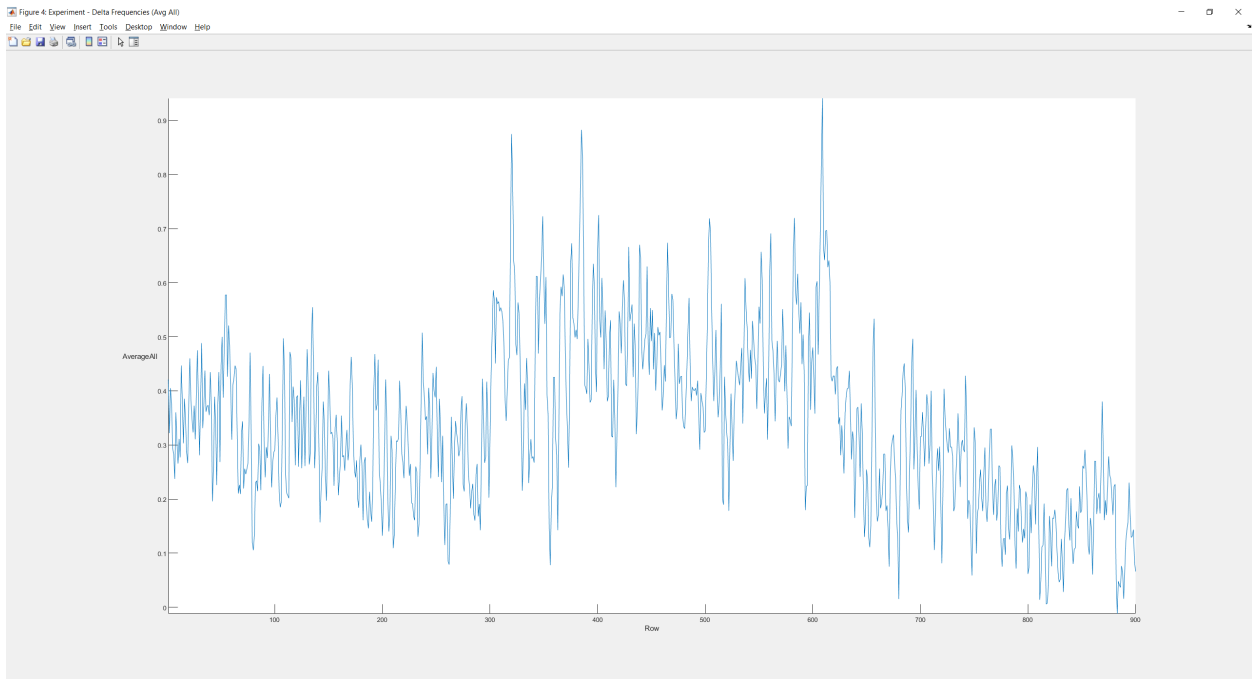


Figure 54: Delta frequency bands averaged across all participants

We noticed a slight decrease in beta frequency band (Figure 53) between 0 and 300 seconds when participants were to traverse back in time to think of their week. The sudden uptick at 300- and 600-second marks may be due to the researcher's instructions to the participants for that particular phase of the experiment, as a result, contributed to participants' active thinking in regards to the instructions. Contrary to what we thought were no change or slight increase in beta frequency bands during meditation phases from previous analysis, we see a slight decrease in beta going from Think of Your Week to Alternate Nostril Breathing, as well as Think of Your Week to Breath Awareness. In order to quantify the change, we took an average of the beta frequency band readings for each experiment phase. The beta frequency band saw an 87.8% decrease during Alternate Nostril Breathing phase versus Think of Your Week phase, and a 137.1% decrease during Breath Awareness phase versus Think of Your Week. We also compared the Interview phase with Think of Your Week phase, and observed a 275.6% decrease during Think of Your Week phase.

As for delta frequency band in Figure 54, there is a noticeable rise between 300 and 600 seconds, when participants were instructed to meditate using the alternate nostril breathing technique. Similar to beta, we took an average of the delta frequency band readings for each experiment phase. The delta frequency band saw a 50.8% increase during Alternate Nostril Breathing phase versus Think of Your Week phase, and a 21.3% decrease during Breath Awareness versus Think of Your Week phase. Between the Interview phase and Think of Your Week phase, we saw a 14.8% decrease during Think of Your Week phase.

The results of delta frequency bands were particularly intriguing for us. The delta plots has been the biggest find in this study because to our knowledge, we were the first study to show an increase in delta activities with alternate nostril breathing technique.

5.5 Fast Fourier Transform (FFT)

We further analyzed the data using FFT on the average across all participants' beta and delta frequency band readings. We separated each 300 seconds of experiment phase so that we can see if there are any noticeable amplitude changes between the phases for these two frequency bands. All FFT plots (Figure 55 through 60) were plotted in MATLAB with frequency in Hz in the x-axis and amplitude in the y-axis.

Figure 55 shows the FFT plot of beta frequency bands during Think of Your Week phase. To our surprise, this phase had fewer cumulative beta sum across all frequencies. Yet, there are more beta amplitude in the lower frequency domains while the higher frequency domains are more evenly distributed.

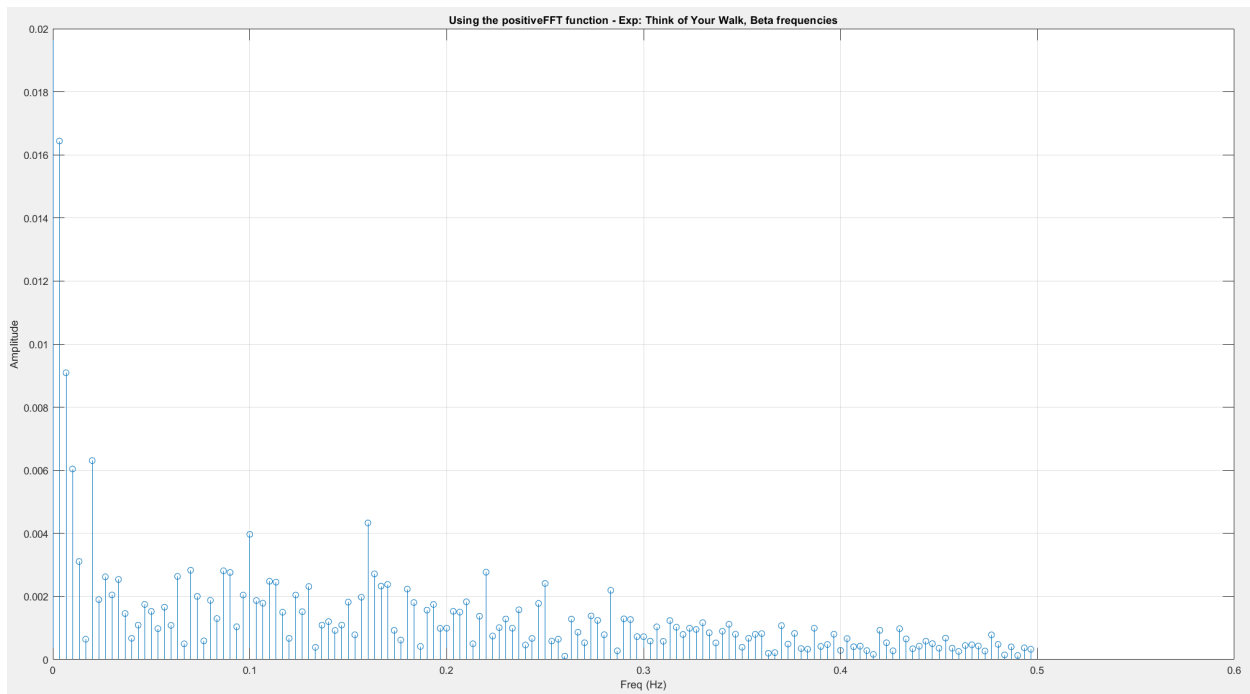


Figure 55: FFT - Beta during Think of Your Week

Figure 56 depicts the FFT plot of beta frequency bands during Alternate Nostril Breathing phase. Compared against Think of Your Week phase, we can see a higher amplitude of beta. We speculated that this may have been contributed from the participants' heightened sense of awareness and active concentration on following the instructions to alternate nostril breathing.

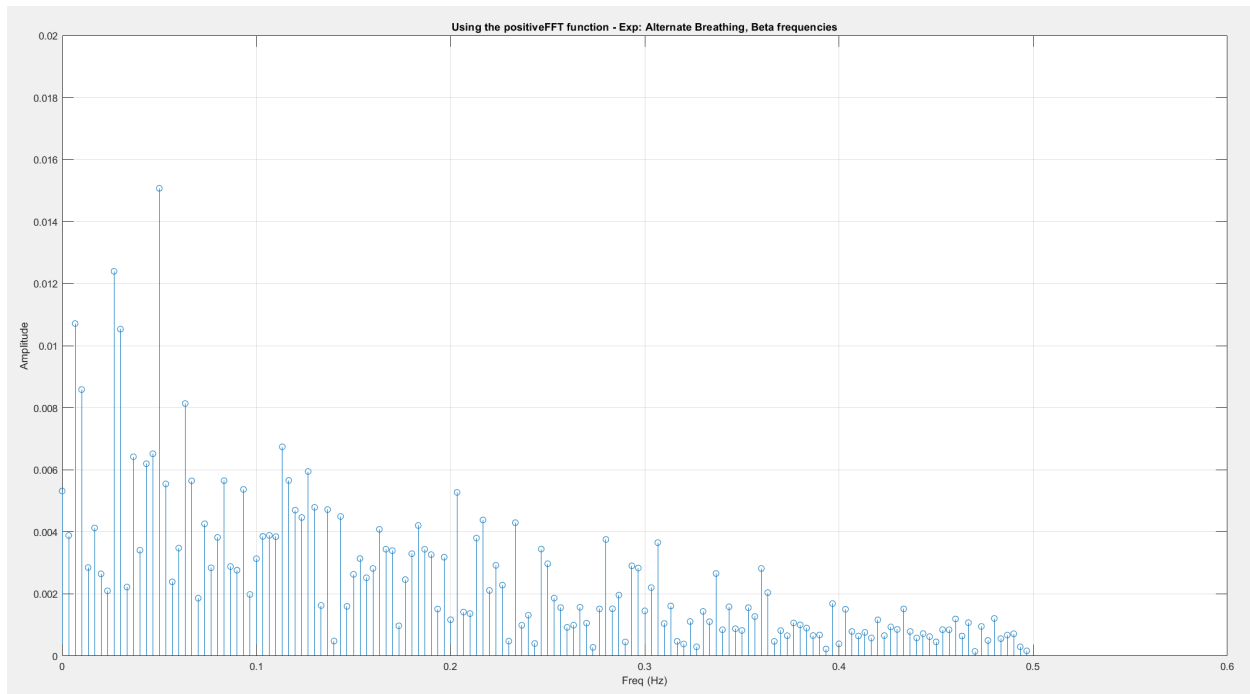


Figure 56: FFT - Beta during Alternate Nostril Breathing

Figure 57 shows the FFT plot of beta frequency bands during Breath Awareness phase. This phase has a lower cumulative beta sum across frequencies when compared against Alternate Nostril Breathing phase but higher than Think of Your Week phase. Overall, there is a lower amplitude of beta when compared with Alternate Nostril Breathing phase and we suspected that it may be because this phase required less thinking in relation to instructions.

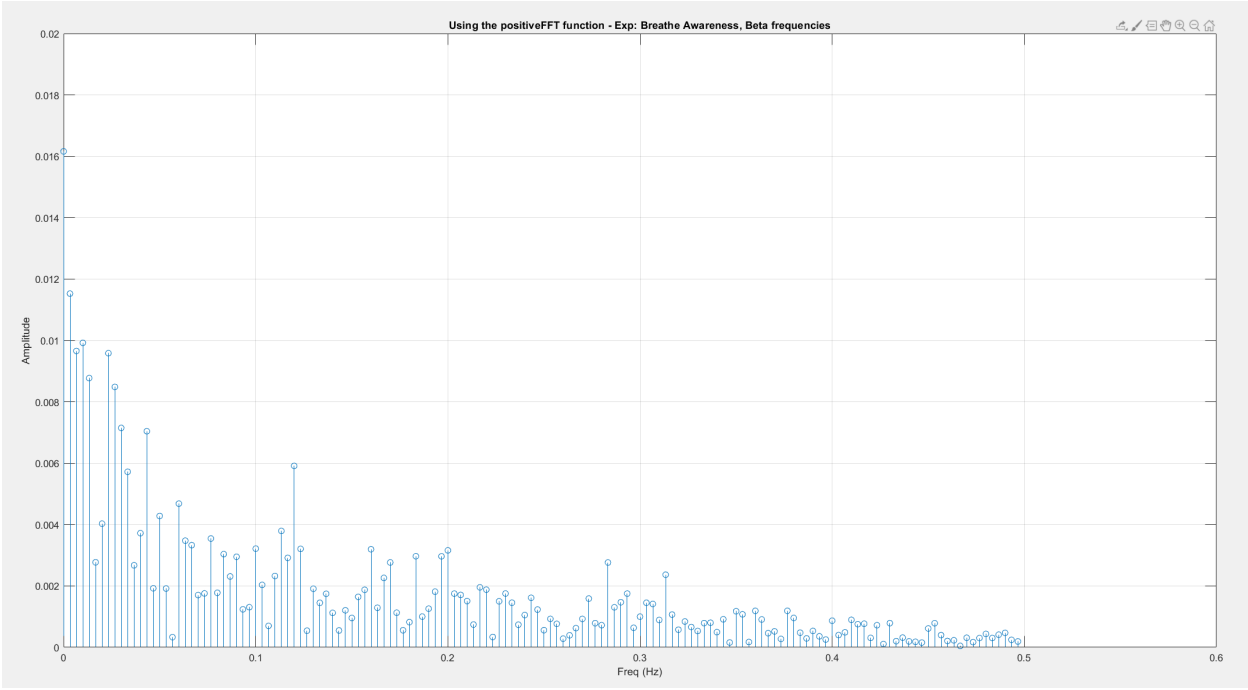


Figure 57: FFT - Beta during Breath Awareness

Moving onto delta frequency bands. Figure 58 depicts the delta frequency bands during Think of Your Week phase. When compared against Alternate Nostril Breathing phase and Breath Awareness phase, there is a fairly even distribution across the different frequency domains even though there are fewer cumulative delta sum across all frequency domains.

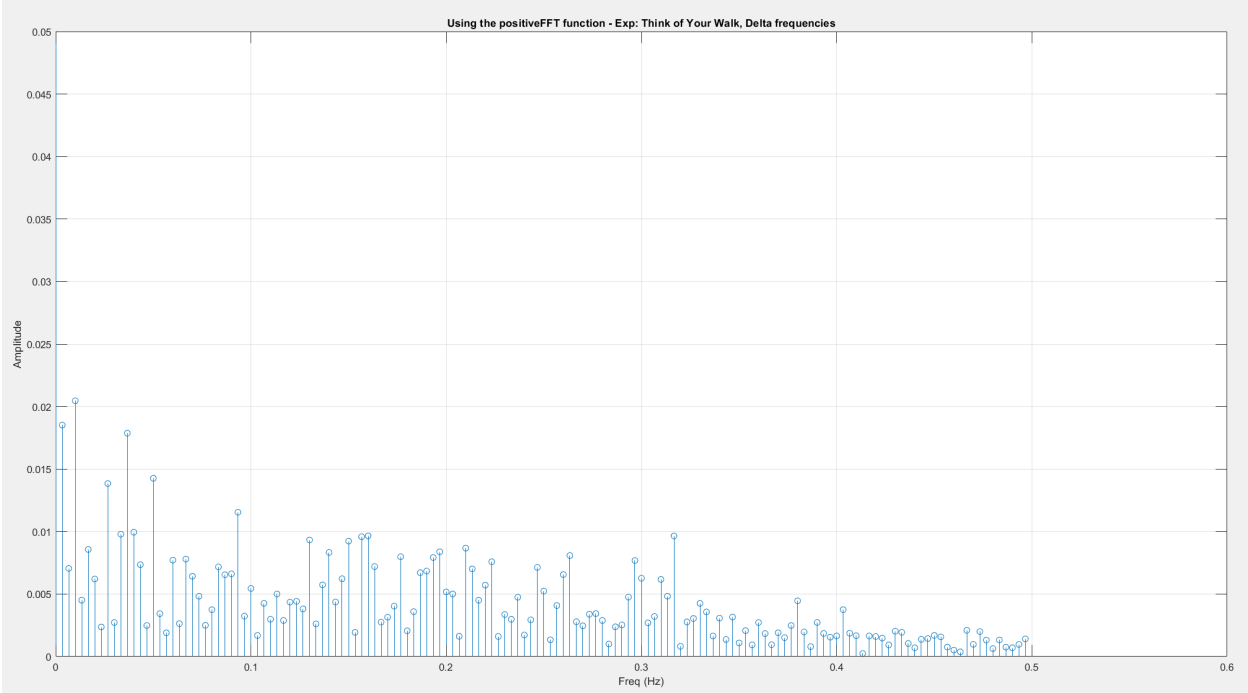


Figure 58: FFT - Delta during Think of Your Week

Figure 59 shows the FFT plot of delta frequency bands during Alternate Nostril Breathing phase. Compared to Think of Your Week phase and Breath Awareness phase, this phase appears to have the largest cumulative sum across all frequency domains.

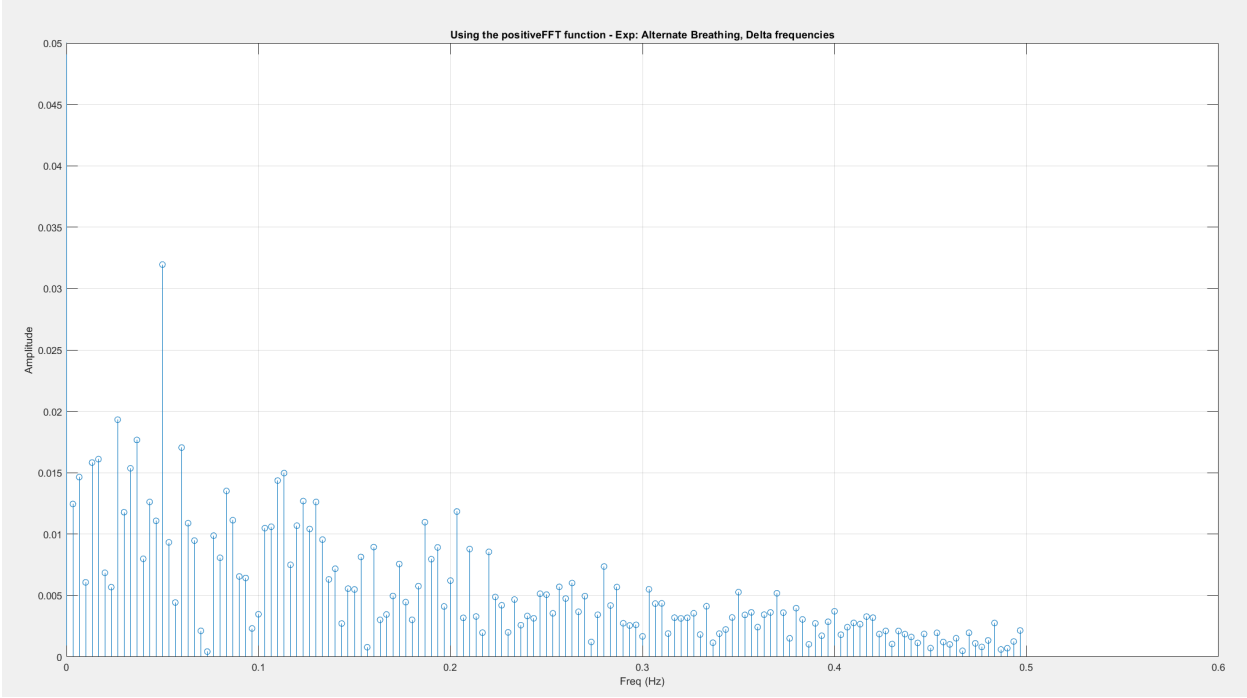


Figure 59: FFT - Delta during Alternate Nostril Breathing

Figure 60 depicts the FFT plot of delta frequency bands during Breath Awareness phase. Compare to the previous 2 phases of the experiment, this phase has higher amplitude at lower frequencies, as well as the most lower frequency delta signals.

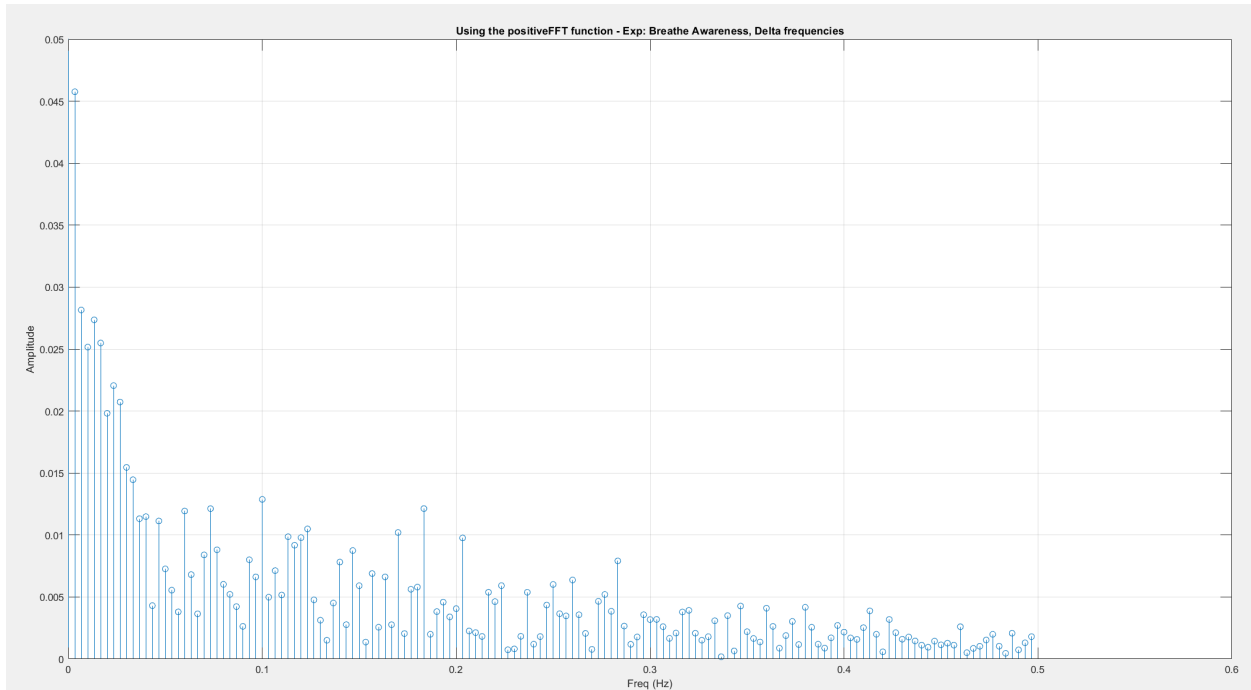


Figure 60: FFT - Delta during Breath Awareness

5.6 Questionnaire Results

Participants were asked to complete a questionnaire after the meditation experiment. Figure 55 shows the participants' responses. Numeric responses were on a 5-point scale, from 1 to 5 as follows: Strongly Disagree / Never – Disagree / Rarely – Neutral / Sometimes – Agree / Often – Strongly Agree / Always.

	Participant Number					
	1	2	3	4	5	6
Prior to this experiment:						
1. My moods are stable.	3	4	3	4	4	4
2. My body and mind are always comfortable.	2	4	3	4	4	5
3. I can handle setbacks and cope with angry and sad emotions.	2	4	2	4	5	3
4. I can keep my emotions calm when faced with matters which makes me angry.	4	4	2	5	3	3
5. I believe that meditation has emotional and physical benefits.	4	5	4	5	Not Available	5
6. I have meditated in the past.	4	5	3	3	2	3
After the experiment:						
7. The experiment was easy to follow.	5	5	3	5	5	5
8. The experiment was a relaxing or calming experience.	4	5	4	5	3	5
9. The sense of relaxation became stronger as the experiment progressed.	4	5	4	4	4	5
10. After the experiment, I believe that meditation has emotional and physical benefits.	4	5	4	5	3	5
11. I would consider meditating regularly/irregularly after this experiment.	4	5	4	5	3	5
12. From the following adjectives, choose one(s) that best describe your overall experience.	Relaxing	Relaxing	Relaxing	Relaxing	Relaxing	Relaxing
13. Which segment of the experiment was the most relaxing?	Breathe Awareness	Breathe Awareness	Breathe Awareness	Alternate Breathing	Breathe Awareness	Alternate Breathing
14. Which segment of the experiment was the least relaxing?	Interview	Think of Your Walk	Think of Your Walk	Think of Your Walk	Think of Your Walk	Interview

Figure 61: Participants' questionnaire responses

Prior to this study, on average, the participants rated themselves 3.67 for their moods being stable and their body and mind are always comfortable. Participants scored an average of 3.33 on whether they can handle setbacks and cope with negative emotions (e.g., angry and sad) and 3.50 on whether they can keep their emotions calm when faced with upsetting matters. In terms of meditation, participants scored an average of 4.60 in believing the emotional and physical benefit of meditation and 3.33 on whether they have meditated in the past. However, participant 5 did not answer whether they believe in meditational benefits prior to the study and as such, the average does not fully reflect all participants' responses for this question.

After the study, most participants found the instructions of the experiment easy to following, giving an average score of 4.67. The participants thought the experiment to be calming or relaxing and found the sense of relaxation increased as the experiment progressed, both scoring an average of 4.33. Interestingly, the study did not alter the participants' belief in meditation's emotional and physical benefits as participants gave the same rating prior to and after the experiment, with the exception of participant 5 due to missing response. Most participants would consider meditating regularly/irregularly after this experience, giving it a rating of 4.33. Overall ratings after the experiment were between 4.33 and 4.67, indicating a positive experience to the participants.

For multiple choice responses, all 6 participants found the overall study experience to be relaxing. Given this fact, it speaks to meditation having calming effects.

2 of the 6 participants found alternate breathing segment to be the most relaxing while the other 4 participants found breath awareness segment to be the most relaxing. This might be due to the fact that alternate nostril breathing requires some concentration and focus on the orders of which nostril to breath from and as such, may not be as relaxing as breath awareness where it's simply taking deep breaths in and out without nostril manipulation.

4 of the 6 participants thought of 'Think of Your Week' segment of the study to be the least relaxing while the other 2 participants thought the baseline-setting interviews were the least relaxing. We found this result interesting on its own since we had expected the interview questions to be more thought provoking and therefore, the least relaxing. However, perhaps having to traverse back in one's week may have caused unintentional stress, in that some may struggle to remember what they've done this past week and as a result, found this part of the study less relaxing than simply answering some interview questions.

CHAPTER 6: CONCLUSION AND FUTURE WORK

6.1 Conclusion

Our goal for this thesis to determine if similar EEG patterns can be generated using breathworks in less time, whether consumer-grade device can capture enough information to determine that, and whether EDA (exploratory data analysis) can yield insights regarding the specific brainwave changes produced by said breathworks.

Based on our experimental results, we were able to observe decreased beta during meditation and breathwork, indicating a decrease in active thinking. We were also able to observe increased delta during meditation and breathwork with the most pronounced increase during alternate nostril breathing, suggesting possible achievement of deep meditation in a short period of time.

6.2 Future Work

Deeper data analysis on the collected data can be performed. Combined with machine learning, we would like to see what precision is necessary for raw EEG and EEG frequency bands to make predictions, as well as at what precision do the predictions start to stray. Different stages and phases of frequency band activities can also be classified in order to reason on the subject's emotions states and stress levels. This would provide real data analysis when a human feels a certain way, and we are beginning with just a relaxed versus a busy mind.

The data collection we've done is a step forward into producing a more empathetic computing environment. We attempted to reproduce the Muse stock app and differentiate busy versus relaxed thinking. This data would feed into empathetic computing and the combination of EEG and machine learning would in turn produce human computer interfaces with empathy.

Danielle Krettek, the founder and principal of Google Empathy Lab, believes that “intelligence should come from an understanding of basic human response that are precursors to empathy, like the mimicry that happens when one person yawns and other people instinctively yawn.”

(Johnson, 2020) Google Empathy Lab is an ongoing project to make AI more empathetic. With EEG and machine learning, there are potentials in the ability to work empathy into ongoing interactive AI projects such as Siri, Cortana, and Alexa. There is also the ability to use a home EEG system like the Muse to measure and respond to a customer’s needs with recommendations and customizations to trigger relaxation response.

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APPENDIX A: EXPERIMENT SETUP

Preliminary Setup

The instructions listed below are required to setup the environment for this thesis.

1. Launch Terminal and install Homebrew

```
/usr/bin/ruby -e "$(curl -fsSL
```

2. Using Homebrew, install (or reinstall) python3:

```
# Install python 3.x  
brew install python
```

3. Using python package manager pip3, update it and use it to install the virtual environment

library

```
$ pip3 install -U pip3  
$ pip3 install virtualenv  
$ pip3 install virtualenvwrapper
```

4. Open your `.bash_profile` in any text editor and add the following:

```
source /usr/local/bin/virtualenvwrapper.sh  
export PIP_REQUIRE_VIRTUALENV=true
```

5. Close Terminal. Open a new Terminal, then (`mkdir` and) `cd` to your workspace.

6. Create a new virtual environment in your workspace:

```
$ mkvirtualenv -p python3  
osc-server
```

7. You are now in a virtual python environment and may install any libraries within it. This will not be visible by other programs on your Mac. To return to this environment from another directory, type:

```
$ workon osc-server
```

8. Using python manager pip3, install the python-osc libraries:

```
$ pip3 install python-osc
```

Muse Setup

This section describes the initial setup necessary to pair Muse headband with Muse Monitor app on the smartphone.

1. Using your smartphone of choice, purchase and download Muse Monitor app from either the iOS App Store (\$14.99) or Google Play (\$14.99).
2. Pair your Muse headband to your smartphone
3. Launch Muse Monitor app.
4. Wait for the Muse headband to begin transmitting data to Muse Monitor app. Graphs of brainwave data should begin to appear within the app within 30 seconds.
5. Click on the [Settings] icon.
6. Enter your computer's WAN or Ethernet IP address in the field: OSC Stream Target IP.
7. Confirm that OSC Stream PORT is 5000.
8. Exit [Settings].

APPENDIX B: EXPERIMENT INSTRUCTIONS

OSC Server: Usage Instructions

The following describes the usage instructions when running a meditation experiment.

1. Adjust the computer and smartphone's display and power settings to ensure neither device will go to sleep while the experiment runs.
2. Determine your computer's WAN or Ethernet IP address. (For Macs, go to System Preferences > Network > WiFi or Ethernet and take note of the IP address.)
3. Open Terminal and cd to your work directory.
4. Launch your virtual environment by typing:

```
$ workon osc-server
```

5. Launch the server and start listening for data stream by typing:

```
$ python3 py3server.py --ip=<your IP> --player=<insert participant id here>
```

6. Launch Muse Monitor app.
7. Turn on the Muse headband and turn it on.
8. In Muse Monitor app, wait for the connection, then tap the broadcast icon to start streaming data to OSC server.
9. The OSC Server is now collecting and streaming data to Context-Aware database. Press Ctrl-C to quit.

Data Extraction

To extract the data to a .xlsx file (separating RAW EEG and EEG frequency bands to their corresponding sheets within the Excel workbook), launch Terminal and type the following arguments:

```
$ python3 sql2stats.py --start=<time experiment started in epoch time>  
--end=<time experiment ended in epoch time> --outfile=<filename>
```

Data Analysis

To aggregate the data on a specified time interval, launch Terminal and type the following arguments:

```
$ python3 intervalAverage.py --interval=<the time interval to  
aggregate on; use 'xS' for seconds and 'xT' for minutes> --  
infile=<filename> --outfile=<filename>
```


APPENDIX C: ADDITIONAL INFORMATION TO SUBJECTS

Subjects

Inclusion Requirements

Subjects are eligible to participate in this study if he/she is:

- Age: 18-64 years old
- Gender: Male or Female
- Physique: Healthy

Exclusion Requirements

Minors will not be included in this study.

Subjects are not eligible to participate in this study if he/she have any history of mental or psychiatric diagnosis including: depression, anxiety, bipolar, autism, schizophrenia, ADHD, any personality or obsessive-compulsive disorder, PTSD, substance abuse, learning disorder, brain or head injury or any other psychiatric disorders. If subject thinks he/she might be vulnerable to mental health issues or have found meditation to be disturbing, subject should NOT participate in this study.

Time Commitment

This study will involve approximately 20 to 30 minutes of time.

Risks and Discomforts

The possible risks and/or discomforts associated with the procedures described in this study include: fatigue, boredom, and minor emotional discomfort. Meditation, in some cases, may

affect participants' emotions and psychology. If participants require care, medical services, or psychological services as a consequence of the research, they will be referred to local medical, or psychological services at their own expense.

The Muse headband is made of materials commonly used in consumer wearable electronic devices. However, certain people may develop skin irritation due to allergies or sensitivities.

There are precautionary actions that can be taken, such as avoiding any type of moisture between the skin and the device. Minor risks such as the above can and will be addressed by the supervised nature of the study, which preclude dangerous physical preconditions.

Benefits

Subject Benefits

The possible benefits subjects may experience from the procedures described in this study include revitalization, enhanced mental function, calmness and better sleep.

Benefits to Others or Society

This research will help determine if similar EEG patterns can be generated using breathing exercises in less time and whether EDA (exploratory data analysis) can yield insights regarding the specific brainwave changes produced by said breathing exercise.

Compensation, Costs and Reimbursements

Compensation for Participation

Subjects will not be paid for their participation in this research study.

Costs

There is no cost to subjects for participation in this study.

Reimbursement

Subjects will not be reimbursed for any out of pocket expenses, such as parking or transportation fees.

Confidentiality

Subject Identifiable Data

All identifiable information that will be collected about subjects will be removed at the end of data collection.

Data Storage

All research data collected will be stored electronically without any personally identifying information in a database hosted on a secure server, requiring a combination of CSUN network access and password-based authentication to access.

Data Access

The researcher and faculty advisor named on the first page of this form will have access to subjects' study records. All research data will be stored anonymously into a database on a secure network with password-based authentication. No personally identifying information will be stored. Publications and/or presentations that result from this study will not include identifiable information about the subjects.

Data Retention

The researchers intend to keep the research data in a repository indefinitely. Other researchers will have access to the data for future research.

Mandated Reporting

Under California law, the researcher is required to report known or reasonably suspected incidents of abuse or neglect of a child, dependent adult or elder, including, but not limited to, physical, sexual, emotional, and financial abuse or neglect. If any researcher has or is given such information in the course of conducting this study, she may be required to report it to the authorities.

APPENDIX D: *py3server.py*

```
import argparse
import math
import time
import datetime
import requests
import numpy as np
import atexit

from pythonosc import dispatcher
from pythonosc import osc_server

#initialize variables for raw eeg capture
counter = 0
raw_eeg_data = [] #list of raw eeg readings

def init_freq_globals():
    global alph, beta, gamm, delt, thet, packet_counter, timestamp
    alph = 0
    beta = 0
    gamm = 0
    delt = 0
    thet = 0
    packet_counter = 5
    timestamp = 0

def raw_eeg_handler (unused_addr, args, ch1, ch2="", ch3="", ch4="", ch5=""):
    global raw_tp9, raw_af7, raw_af8, raw_tp10, ref, raw_eeg_timestamp, counter, raw_eeg_data

    #take in reading
    raw_eeg_timestamp = time.time()
    raw_eeg_reading = [ch1, ch2, ch3, ch4, ch5, raw_eeg_timestamp]
    counter += 1

    if (counter < 101):
        #add raw eeg readings into raw eeg data list
        raw_eeg_data.append(raw_eeg_reading)
        print(str(counter) + ": added to raw eeg data list")
    elif (counter == 101):
        #every 100 instances of raw eeg readings are averaged and posted to
context-aware
        #once posted, raw eeg data list is cleared
        #raw eeg readings in raw eeg buffer list is copied to raw eeg data
list
        #raw eeg buffer list is cleared and counter is reset

        print("counter at " + str(counter) + ": averaging...")
        #calculate average of the 100 readings in raw eeg data list and post
to context-aware
        post_raw_eeg(raw_eeg_data)
```

```

        #raw eeg buffer list copied to raw eeg data list
        while (len(raw_eeg_buffer) > 100):
            #buffer has more than 100 readings, copy first 100 readings, post
and delete from buffer
            print("Buffer at " + str(len(raw_eeg_buffer)) + " and counter at
" + str(counter))
            raw_eeg_data = raw_eeg_buffer[0:100]
            post_raw_eeg(raw_eeg_data)
            del raw_eeg_buffer[0:100]
            counter -= 100
            print("Posted to context-aware, BUFFER now at " +
str(len(raw_eeg_buffer)) + " and counter now at " + str(counter))
        else:
            #less than 100 readings in buffer, copy entire list and clear
buffer; reset counter to current # of data list items
            print(str(len(raw_eeg_buffer)) + " items in BUFFER, copying to
raw eeg data list")
            raw_eeg_data = raw_eeg_buffer.copy()
            raw_eeg_buffer.clear()
            counter = len(raw_eeg_data)
            print ("counter reset to " + str(counter))
    elif (counter > 101):
        #add raw eeg readings to raw eeg buffer list while there are more
than 100 instances of readings in raw eeg data list
        raw_eeg_buffer.append(raw_eeg_reading)
        print(str(counter) + ": added to raw eeg BUFFER list")

def post_raw_eeg(x):
    #calculate average of the 100 readings in raw eeg data list
    avg = np.mean(x, axis = 0, dtype = float)
    raw_tp9 = avg[0]
    raw_tp9 = str(raw_tp9)
    raw_af7 = avg[1]
    raw_af7 = str(raw_af7)
    raw_af8 = avg[2]
    raw_af8 = str(raw_af8)
    raw_tp10 = avg[3]
    raw_tp10 = str(raw_tp10)
    ref = avg[4]
    ref = str(ref)
    raw_eeg_timestamp = (x[len(x)-1][5]*1000)
    raw_eeg_timestamp = str(raw_eeg_timestamp)

    #post to context-aware
    response = requests.post(url = "http://context-aware.sand-
box.csun.edu/php/insertPlayers.php?func=eegraw&player=" + playernum + "&TP9="
+ raw_tp9 + \
        "&AF7=" + raw_af7 + "&AF8=" + raw_af8 + "&TP10=" + raw_tp10 + "&REF="
+ ref + "&time=" + raw_eeg_timestamp)
    if "failed" in response.text:
        print ("The following eeg insertion failed: TP9=" + raw_tp9 + "&AF7="
+ raw_af7 + "&AF8=" + raw_af8 + "&TP10=" + raw_tp10 + "&REF=" \
        + ref + "&time=" + str(raw_eeg_timestamp))
        print("Posted avg of " + str(len(x)) + " items in data list")

```

```

def freq_handler(UNUSED_ADDR, args, ch1):
    global alph, beta, gamm, delt, thet, packet_counter, timestamp
    if args[0] is 'alpha':
        # We expect alpha packet to arrive first
        init_freq_globals()
        alph = ch1
        alph = str(alph)
        timestamp = (time.time())*1000
        timestamp = str(timestamp)
        packet_counter -= 1
    elif args[0] is 'beta':
        beta = ch1
        beta = str(beta)
        packet_counter -= 1
    elif args[0] is 'delta':
        delt = ch1
        delt = str(delt)
        packet_counter -= 1
    elif args[0] is 'theta':
        thet = ch1
        thet = str(thet)
        packet_counter -= 1
    elif args[0] is 'gamma':
        gamm = ch1
        gamm = str(gamm)
        packet_counter -= 1
        if packet_counter is not 0:
            print( "Somehow a packet was dropped!" )
            response = requests.post(url = "http://context-aware.sand-
box.csun.edu/php/insertPlayers.php?func=eeg&player=" + playernum + "&alpha="
+ alph + \
            "&beta=" + beta + "&gamma=" + gamm + "&delta=" + delt + "&theta="
+ thet + "&time=" + timestamp)
        else:
            print( "FAIL" )

#record last raw eeg reading when exiting program
#average out by however many instances of raw eeg recorded since last post to
context aware
@atexit.register
def exit_handler():
    if counter == 0:
        print( "Nothing to post, goodbye!")

```

```

else:
    avg = np.mean(raw_eeg_data, axis = 0, dtype = float)
    raw_tp9 = avg[0]
    raw_tp9 = str(raw_tp9)
    raw_af7 = avg[1]
    raw_af7 = str(raw_af7)
    raw_af8 = avg[2]
    raw_af8 = str(raw_af8)
    raw_tp10 = avg[3]
    raw_tp10 = str(raw_tp10)
    ref = avg[4]
    ref = str(ref)
    raw_eeg_timestamp = (raw_eeg_data[len(raw_eeg_data)-1][5]*1000)
#decided to use last timestamp of 50 readings
    raw_eeg_timestamp = str(raw_eeg_timestamp)
    response = requests.post(url = "http://context-aware.sandbox.csun.edu/php/insertPlayers.php?func=eegraw&player=" + playernum
+ "&TP9=" + raw_tp9 + \
        "&AF7=" + raw_af7 + "&AF8=" + raw_af8 + "&TP10=" + raw_tp10 +
"&REF=" + ref + "&time=" + raw_eeg_timestamp)
    print ("Average of " + str(counter) + " raw eeg data averaged and
posted. Goodbye!")
    if "failed" in response.text:
        print ("The final following eeg insertion failed: TP9=" + raw_tp9
+ "&AF7=" + raw_af7 + "&AF8=" + raw_af8 + "&TP10=" + raw_tp10 + "&REF=" \
            + ref + "&time=" + str(raw_eeg_timestamp))

if __name__ == "__main__":
    parser = argparse.ArgumentParser()
    parser.add_argument("--ip",
                        default="130.166.12.164",
                        help="The ip to listen on")
    parser.add_argument("--port",
                        type=int,
                        default=5000,
                        help="The port to listen on")
    parser.add_argument("--player",
                        type=str,
                        default="1",
                        help="Player #")
    args = parser.parse_args()
    playernum = args.player

    dispatcher = dispatcher.Dispatcher()
    dispatcher.map("/debug", print)
    dispatcher.map("/muse/eeg", raw_eeg_handler, "raw_eeg")
    dispatcher.map("/muse/elements/alpha_absolute", freq_handler, "alpha")
    dispatcher.map("/muse/elements/beta_absolute", freq_handler, "beta")
    dispatcher.map("/muse/elements/gamma_absolute", freq_handler, "gamma")
    dispatcher.map("/muse/elements/delta_absolute", freq_handler, "delta")
    dispatcher.map("/muse/elements/theta_absolute", freq_handler, "theta")

    server = osc_server.ThreadingOSCUDPServer(
        (args.ip, args.port), dispatcher)
    print("Serving on {}".format(server.server_address))
    server.serve_forever()

```


APPENDIX E: *sql2stats.py*

```
import argparse
import requests
import json
import pandas as pd
import numpy as np
import datetime

#take argument from command line the start and end time to extract
if __name__ == "__main__":
    parser = argparse.ArgumentParser()
    parser.add_argument("--start",
                        default="1570520640",
                        help="The time experiment started in epoch time")
    parser.add_argument("--end",
                        default="1570520700",
                        help="The time experiment ended in epoch time")
    parser.add_argument("--outfile",
                        default="summary-1",
                        help="The filename to dump to (.xlsx will be
appended; file must not exist)" )
    args = parser.parse_args()
    starttime = args.start
    endtime = args.end
    outfile = args.outfile

starttime = starttime + "000"
endtime = endtime + "000"

#extract frequency eeg data
# api-endpoint
URL = "http://context-
aware.sandbox.csun.edu/php/getPlayers.php?func=allEEGTime&start=" + starttime
+ "&end=" + endtime

#sending get request and saving the response object as list in list
freq_data = requests.get(url = URL).json()

#create Pandas Dataframe with data, including corresponding header
df_freq = pd.DataFrame(freq_data, columns=['Player', 'Alpha', 'Beta',
'Gamma', 'Delta', 'Theta', 'Time'])

#extract raw eeg data
# api-endpoint
URL = "http://context-
aware.sandbox.csun.edu/php/getPlayers.php?func=allEEGRawTime&start=" +
starttime + "&end=" + endtime

#sending get request and saving the response object as list in list
raweeg_data = requests.get(url = URL).json()
```

```

#create Pandas Dataframe with data, including corresponding header
df_raw = pd.DataFrame(raw_eeg_data, columns=['Player', 'TP9', 'AF7', 'AF8',
'TP10', 'REF', 'Time'])

#convert time to numeric first
#also change back raw_eeg time from nanosecond to EPOCH time in seconds
df_freq['Time'] = pd.to_numeric(df_freq['Time'])/1000
df_raw['Time'] = pd.to_numeric(df_raw['Time'])/1000

#add column Date_Time column converting EPOCH time to Pacific time
df_freq['Date_Time'] = pd.to_datetime(df_freq['Time'], unit='s',
origin='unix').dt.tz_localize('UTC').dt.tz_convert('US/Pacific')
df_raw['Date_Time'] = pd.to_datetime(df_raw['Time'], unit='s',
origin='unix').dt.tz_localize('UTC').dt.tz_convert('US/Pacific')

#remove time zone info due to Excel's inability to handle time zones
df_freq['Date_Time'] = df_freq['Date_Time'].dt.tz_localize(None)
df_raw['Date_Time'] = df_raw['Date_Time'].dt.tz_localize(None)

#drop EPOCH time column for readability
df_freq = df_freq.drop(['Time'], axis=1)
df_raw = df_raw.drop(['Time'], axis=1)

with pd.ExcelWriter(outfile + '.xlsx') as writer:
    df_freq.to_excel(writer, sheet_name='eeg_freq')
    df_raw.to_excel(writer, sheet_name='raw_eeg')

```

APPENDIX F: *intervalAverage.py*

```
import pandas as pd
import numpy as np
import datetime
import argparse

#take argument from command line the time interval to aggregate on
#use 'xxS' for seconds
#use 'xxT' for minutes
#default is 30-seconds
if __name__ == "__main__":
    parser = argparse.ArgumentParser()
    parser.add_argument("--interval",
                        default="30S",
                        help="The time interval to aggregate on; use 'xS' for
seconds and 'xT' for minutes")
    parser.add_argument("--infile",
                        default="eeg-1",
                        help="The filename to import from (.xlsx will be
appended; file must exist)" )
    parser.add_argument("--outfile",
                        default="summary-1",
                        help="The filename to dump to (.xlsx will be
appended; file must not exist)" )
    args = parser.parse_args()
    interval = args.interval
    infile = args.infile
    outfile = args.outfile

#load data from excel file
#read in each participant data sheets separately
data = pd.ExcelFile(infile + '.xlsx')
par_1 = pd.read_excel(data, 'participant_1', index_col=0)
par_2 = pd.read_excel(data, 'participant_2', index_col=0)
par_3 = pd.read_excel(data, 'participant_3', index_col=0)
par_4 = pd.read_excel(data, 'participant_4', index_col=0)
par_5 = pd.read_excel(data, 'participant_5', index_col=0)
par_6 = pd.read_excel(data, 'participant_6', index_col=0)

#create summary dataframe and aggregate mean over x-sec or x-min intervals
avg_1 = par_1.set_index('Date_Time').resample(interval).mean()
avg_2 = par_2.set_index('Date_Time').resample(interval).mean()
avg_3 = par_3.set_index('Date_Time').resample(interval).mean()
avg_4 = par_4.set_index('Date_Time').resample(interval).mean()
avg_5 = par_5.set_index('Date_Time').resample(interval).mean()
avg_6 = par_6.set_index('Date_Time').resample(interval).mean()
```

```
#export to xlsx
with pd.ExcelWriter(outfile + '.xlsx') as writer:
    avg_1.to_excel(writer, sheet_name='participant_1')
    avg_2.to_excel(writer, sheet_name='participant_2')
    avg_3.to_excel(writer, sheet_name='participant_3')
    avg_4.to_excel(writer, sheet_name='participant_4')
    avg_5.to_excel(writer, sheet_name='participant_5')
    avg_6.to_excel(writer, sheet_name='participant_6')
```