ABSTRACT

Quantifying Physiological and Neurological Responses to
Organic Motion Patterns

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The human body was designed to move, and the benefits of exercise and an active lifestyle are well known. However, many individuals live with neuromuscular conditions that limit movement and quality of life. One treatment strategy designed to help such individuals experience the benefits of movement is equine-assisted therapy. Complementing that is a mechanical horse-riding simulator developed to recreate the complex three-dimensional motion patterns of riding. The aim of this study is the development of methodologies to assess physiological effects on the human body from the impartation of riding motions. Areas of assessment investigated include force-plate balance measures, electromyography, and electroencephalography. Assessments were conducted with healthy adult individuals both before and after a session of riding. Methods to process the data are explored, and some results are analyzed. Of particular note, shifts were observed in electroencephalogram alpha power peaks that are associated with cognitive benefits.

Quantifying Physiological and Neurological Responses to
Organic Motion Patterns

by

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A Thesis

Approved by the Department of Mechanical Engineering

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I would like to thank Dr. Garner, Dr. Rylander, and Dr. Fillmore for all their help and support. Also, I would like to thank Dave Lemke for all his expertise and guidance in EMG placement.

DEDICATION

To my family and friends. Thank you for the support

CHAPTER ONE

Introduction

Exercise has many physical and mental benefits. Physically, exercise promotes good muscle, bone, and metabolic health. Mentally, exercise promotes improvements in mood, energy, and sleep [1]. For individuals that are healthy, actively reaping the benefits of exercise is simple. However, not all individuals are in peak health. Those with an underlying disorder may not be able to easily reap the benefits of exercise. For example, those who have a neurodevelopmental disorder, such as autism, or those who have a neurological disorder, such as cerebral palsy, may suffer from social, sensory, and motor impairments that can make active modalities of exercise difficult to implement in their lifestyles. In this way, a passive modality such as hippotherapy may be a better fit.

Hippotherapy, Real and Simulated

Hippotherapy is a therapeutic treatment strategy that utilizes the passive, rhythmic, and repetitive motion provided by equine movement to achieve a functional outcome. The benefits of hippotherapy are numerous ranging from improvements in trunk strength and balance to improvement in confidence and self-esteem [2]. In patient groups such as autism or cerebral palsy, hippotherapy has proven to be a valid therapeutic option [3, 4, 5, 6]. However, factors such as weather, location, and cost may limit access to hippotherapy as a treatment option.

The MiraColt, a mechanical horse-riding simulator designed at Baylor University, offers an accessible way to experience the realistic motion patterns of riding. Derived from organic motion patterns recorded from live horses, the MiraColt is able to mimic equine movement in six degrees of freedom [7]. Just as hippotherapy has research support as a valid therapeutic option, simulated therapy also has a research foundation in autism and cerebral palsy [8, 9].

Objective, Refined

The original objective of this thesis was to uncover the mechanism of action behind hippotherapy. That is, what underlying mechanisms initiate during hippotherapy to produce the variety of benefits? Human subject experiments were begun to provide data for this study. However, due to COVID-19 and the ongoing period of quarantine that followed, the human subjects experimentation phase was shortened, and the overall objective of this thesis was shifted. The refined objective was to create a methodology to direct how the effects of hippotherapy will be studied in future work. Three assessments were used to establish a methodology and begin a normative dataset. Conditions tested in each assessment will be outlined in this chapter. Justification of conditions tested can be found in the assessment-specific chapters. The assessments are pictured in Figure 1.1.

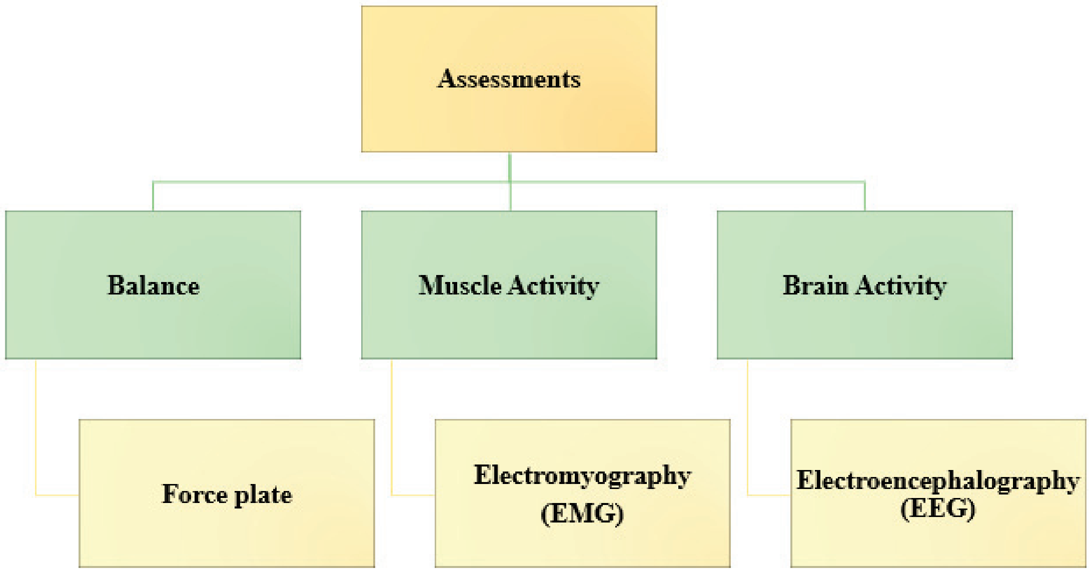

Figure 1.1: Assessments Studied. Balance (via force plate), Muscle Activity (via EMG), Brain Activity (via EEG)

Participants

All testing was done at the Baylor BioMotion lab in the Baylor Research and Innovation Collaborative (BRIC) in Waco, Texas. The lab contains three force plates (Advanced Mechanical Testing, Inc, Watertown, MA) for collecting balance data and eight electrodes (EMGs, Noraxon, Scottsdale, AZ) for recording muscular activity. The study was approved by the Baylor Internal Review Board and written consent was obtained from all six subjects (2 males, 4 females). All subjects were healthy – without disabilities that would prevent them from participating in the study. The subjects ranged in age from 22 to 25 years (average was 23 ± 1.3 years of age) and body mass ranged from 55.4 to 106.6 kg (average was 69.7 ± 18.5 kg). Two subjects had previously experienced simulated hippotherapy, and no subjects had experienced actual horseback riding. The order in which the assessments were conducted is shown in Figure 1.2.

Figure 1.2: Order of Assessments in Study

Sensor Placement

Volunteer subjects were first equipped with EMG electrodes. In a separate dressing room, eight electrodes were placed bilaterally on four different muscle groups: lumbar, gluteus maximus, bicep femoris, and anterior deltoids. These muscles were chosen because they are key muscles in static and dynamic posture. The muscles were individually palpitated and marked to ensure an optimal EMG reading.

Before placing the electrodes, the skin was cleaned of oil and hair using an alcohol pad and razor, respectively. Once the skin dried from the alcohol, the electrodes were placed on the cleaned skin using a conductive adhesive and each electrode was clipped to a signal transmitter.

Each volunteer subject was also outfitted with an EEG headset (DSI-24; Wearable Sensing, Inc.). The headset system uses dry sensors that do not require skin abrasion or conductive media. To don the EEG headset, all hair accessories and earrings were removed. The headset was placed on the subject from back to front, adjusting the crown assembly to align the side sensors with the ears. Using subject-feedback for comfort level, the headset was tightened using the rear adjustment or elastics on the side of the crown assembly. Electrodes were rotated until full contact with the scalp was made. Two additional electrodes were uncoiled out of the headset and clipped to each ear.

Impedances of each electrode were checked using the DSI streaming software and adjusted until an acceptable value was reached.

Balance Protocol

A balance protocol tested four unique quiet standing positions: Feet Together (FT), Single Leg Stance (SLS), Semi-Tandem (ST), and Tandem (T). The names of the positions and their abbreviations can be found in Table 1.1. Each of the conditions were performed either with only eyes open, or only eyes closed, or both visual conditions as separate tasks. Figure 1.3 shows how the feet are positioned, along with the visual conditions tested per stance. Also, for three of the four conditions (ST, T, SLS) the subject was asked to alternate the leading foot. While the leading foot in ST and T stance is the foot that is in front, the leading foot in SLS is the one in contact with the floor. The names of the conditions tested in this study along with their abbreviations are found in Table 1.2.

Table 1.1: Quiet Standing Position Names and Abbreviations

Condition Name	Abbreviation
Feet Together	FT
Single Leg Stance	SLS
Semi-Tandem	ST
Tandem	T

Before balance testing began, a researcher demonstrated the foot position of each condition for the subject. FT had the subject press both feet together from heel-to-toe. SLS had the subject place one foot on the force plate and the other foot hovering in the air. The position of the hovering foot was not controlled. ST had the subject align the heel of the leading foot align with the toes of the rear foot. T had the subject align the leading foot from heel-to-toe of the rear foot. Depending on the foot size of the subject, some conditions (ST, T) required the subject to stand on the force plate at a 45° angle.

The order of the conditions tested was randomized by the researcher. Each condition was performed with arms crossed, gaze forward, a focused mind, and attempting to stand as still as possible. Each condition had one trial that lasted 20-seconds, except for FTEO and FTEC. These two conditions were completed in a single, 20-second trial, where the first ten seconds the subject had their eyes open, and the latter ten seconds the subject had their eyes closed. The researcher gave the subject verbal cues as to when the recording began, and when the recording ended. Once all conditions had been tested, the next assessment began. Further details of the balance assessments are given in Chapter Two.

Figure 1.3: Quiet Standing Positions and the Visual Conditions Tested

Table 1.2: Quiet Standing Conditions Tested and Abbreviations

Condition Name	Abbreviation
Feet Together with Eyes Open	FTEO
Feet Together with Eyes Closed	FTEC
Semi-Tandem Right with Eyes Open	STR EO
Semi-Tandem Left with Eyes Open	STL EO
Tandem Right with Eyes Open	TR EO
Tandem Left with Eyes Open	TL EO

Electromyography (EMG) Protocol

The EMG protocol tested four unique muscle groups bilaterally: lumbar (L), gluteus maximus (GM), bicep femoris (BF), and anterior deltoids (AD). These muscles were activated using four targeted exercises: standing flexion (SF), prone hip extension (HE), single leg raise (SLR), and arm raise (AR). Table 1.3 lists all the relevant muscle terminology and abbreviations. Similar to the protocol of the quiet standing conditions, each targeted exercise was demonstrated to the subject before the assessment began. The order of the targeted exercises was not randomized for this assessment. There was no formal timing for these exercises, only verbal cues, and a set number of repetitions. How each of the targeted exercises are performed is as follows.

Prone hip extension (HE) was executed by having the subject lie prone on a massage table. By verbal cue, the subject raised one leg off the table, holding until a verbal cue, then lowering the leg back onto the table. This action was repeated 3 times per leg. Arm Raise (AR) was executed by having the subject stand upright with arms relaxed. By verbal cue, the subject raised one arm, holding until a verbal cue, then lowering the arm back to their side. This action was repeated once per arm. Once each arm was raised, the exercise finished off with a bilateral arm raise, holding until a verbal cue, then lowering the arms back to their side. Standing flexion (SF) was executed by having the subject stand upright with arms relaxed. By verbal cue, bend at the waist, reaching for their toes with their arms. This position was held until a verbal cue returned them to an upright position. This exercise had 3 repetitions. The last exercise was a Single Leg Raise (SLR), which was executed by having the subject statically stand on one leg. This exercise did not have inherent repetition as the other exercise did. In a separate recording, the hovering leg was alternated. Once all conditions have been tested, the next assessment began. Further details of the EMG data collection and analysis are given in Chapter Three.

Table 1.3: Muscle Terminology and Abbreviations

Muscle Terminology	Abbreviations
Lumbar	L
Gluteus Maximus	GM
Bicep Femoris	BF
Anterior Deltoids	AD
Standing Flexion	SF
Prone Hip Extension	HE
Single Leg Raise	SLR
Arm Raise	AR

Electroencephalography (EEG) Protocol

The EEG protocol tested resting-state at two visual conditions: Eyes Open and Eyes Closed. During the assessment, the subject was instructed to sit on the MiraColt in a forward riding position with their feet placed in the stirrups and arms on the handrail. An EEG recording is suspectable to artifacts from eye, face, and jaw movements; therefore, the subject was instructed to sit as still as possible with their gaze forward. The EEG assessment took a total of ten minutes, where the first five minutes tested eyes open and the latter five minutes, eyes closed. Once those conditions had been tested, both the EEG assessment and the pre-intervention measures were concluded. Further details of the EEG data collection and analysis are given in Chapter Four.

Intervention and Post-intervention Measures

The intervention protocol involved the sequence of assessments described above, followed by a 15-minute riding session on the MiraColt. During riding the subject kept eyes open. The speed of the MiraColt was set in this study to 50 on the display, which corresponds to approximately 30 complete riding motion cycles per minute. Following the riding session a post-intervention assessment sequence was conducted in the following order: visual conditions tested for EEG, targeted exercises tested for EMG, and quiet standing positions tested for balance

CHAPTER TWO

Balance

Introduction

This thesis is focused on assessing the physiological responses and effects in the human body to impartation of organic motion through a mechanical horse-riding simulator. This chapter addresses assessment of effects on postural stability before and after riding sessions, as measured through a force plate. The current study involves human experiments with healthy, non-impaired participants as a way to develop appropriate methodology, and obtain baseline data, with a view toward future experiments and assessments involving participants with a variety of different disabilities or conditions that affect balance, posture, muscle coordination, and neural activity. The aim is that such experiments will inform therapeutic interventions to improve overall quality of life for these individuals.

Postural Control

Maintaining a specific posture or changing from one posture to another is a complex interaction between the muscular, skeletal, sensory, and neural systems of the body [10]. To understand the underlying mechanisms that drive postural control, terms such as center of mass (COM), balance, and base of support (BOS) must be defined first. The center of mass (COM) is the mean position of mass in an object.

If the position of the body changes, the center of mass will encounter perturbations to its position with respect to the body. For a static stance, if the COM remains inside the base of support, which is the area of contact that a person makes with the supporting surface, a balanced state is maintained [11]. Figure 2.1 demonstrates the relationship between position of the body, location of the center of mass, and its position over the base of support. Returning to a state of balance is known as postural control [12].

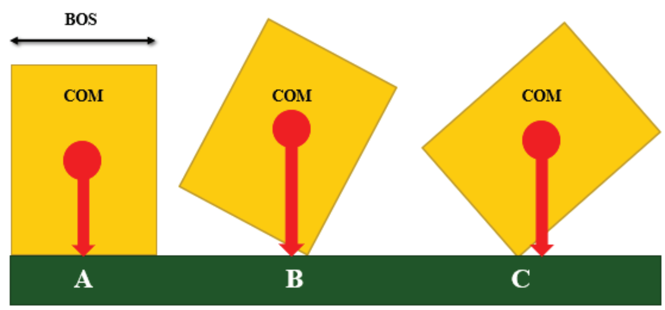

Figure 2.1: Relationship between position of object, location of center of mass, and base of support. Balanced state (A), unstable state (B), loss of balance (C).

There are three main trademarks of good posture and subsequently good balance: 1) The ability to maintain a specific static posture, 2) the ability to transition between postures during movement, and 3) recovering equilibrium in response to an unexpected external event. The first trademark will be the focus of this chapter [13].

Postural Control System

Postural control is an ongoing task given by the postural control system. There are two main functions of this system: maintaining balance and adjusting the position and orientation of the body in space with respect to the surroundings [10]. As previously mentioned, maintaining posture requires compiling sensory input information and appropriately adjusting movement and position of the various major body systems.

Specific sensory inputs are visual, vestibular, and somatosensory feedback [14]. Each input serves a different role in helping to maintain balance.

Visual input informs the brain about where the head and body are located with respect to the world and about the motion between the body and the surroundings. The vestibular system of the inner ear acts as the balance center and sends messages to the cerebellum, which is the location of the body's movement control center. The vestibular system communicates to the brain about the position and movements of the head. Without this system, distinguishing between vertical and horizontal movement would be hard to differentiate. The final input is somatosensory feedback, specifically proprioceptive input. Muscles, tendons, and joints in your body are outfitted with special sensors that can sense changes in pressure and position. This input gives information on where different parts of the body are with respect to itself. Without proprioceptive input, understanding where the head is with respect to the shoulders would be difficult to identify.

All of these inputs work together to create a balanced state. If one of these inputs is impaired, the other inputs can increase their influence and compensate for the deficit, but normal balance may be out of reach. Moreover, the probability of falling due to a balance deficit can increase, as is the case in elderly individuals [15]. Often individuals with poor postural stability will attempt to compensate for their decreased stability by increasing their base of support [16]. If an individual cannot increase the base of support with confidence, devices such as walkers or canes can be used instead. In either case, the individuals' mobility will be restricted as walking requires a flexible base of support. Other inputs into the postural control system include programmed reactions, postural reflexes, and other biomechanical components [10]. These inputs are more difficult to isolate, therefore, they are not as commonly studied in a laboratory setting.

Balance Assessments

Although balance may seem to be an effortless task, it is required for nearly all functional tasks such as walking, sitting, and quiet standing. Having a balance impairment can make these day-to-day activities difficult to accomplish. Since the postural control system deteriorates with age, those who are older are more at risk from a balance deficit, which can increase the risk of falling [10, 13]. In Americans over the age of 65, the risk of falling is one in four each year, and the number of fall-related injuries amounts to 2.8 million each year, all of which required emergency treatment [17]. By 2020, the cost of fall-related injuries is expected to reach 67.7 billion dollars [17]. The risk of falling can be further exacerbated with a sensory impairment. One out of six American adults over the age of seventy have a visual impairment and one out of four adults have a hearing impairment or have a loss of feeling in their feet [18]. To assess the multiple systems that enable postural stability, a clinical balance assessment is required.

The main purposes of clinical balance assessments are to predict the risk of falling and identify the mechanism at fault for a balance impairment [13]. Since maintaining balance is part of an integrated system, clinical balance tests can be divided into three different categories: functional, systematic, and quantitative [13]. The focus of a functional assessment is to identify if there is an underlying balance deficit [13]. An example of a functional assessment is the Tinetti-test, which can grade the gait and balance in elderly individuals [19]. The test has two parts: 1) The subject sits in a chair and is asked to stand-up, turn in a circle and sit back down in the chair; 2) The subject walks for a distance followed by a turn, and then sits in a chair after walking another set distance [20]. Functional tests like the Tinetti-test can predict the fall risk, depending on where the subject's performance lands on a numerical scale [13]. While a functional balance test, at best, can identify the existence of a balance problem, a systematic assessment can categorize the underlying causes of a balance deficit [13] such as "biomechanical constraints, stability limits, anticipatory responses, postural responses, sensory orientation, and stability in gait" as identified by the Balance Evaluation Systems Test (BESTest), which categorizes a balance deficit into one of the above mentioned systems [21].

The final type of clinical balance assessment is quantitative, also known as posturography, which is the main medium of measurement for the balance assessment in this chapter. Unlike the previous clinical assessments that use qualitative means as a method to measure the magnitude of a balance impairment, posturography numerically evaluates postural sway in terms of center of pressure (COP) displacements [10, 13]. The focus of this assessment is not only to evaluate holistic balance, but also to create a more objective balance assessment as compared to a functional or systemic assessment, since those results can vary between examiners [13]. Changes to balance are evaluated by changes to postural sway, which is defined as the variations to the position of the center of gravity. In research, the position of the center of gravity is oftentimes defined indirectly by the center of pressure [10]. Center of pressure is a point that represents where the pressure of the body over the base of support would be if it were projected onto the floor [22]. The reason center of pressure is an indirect measurement of postural sway is that along with the assessment of the center of gravity, the forces a muscle produces to create movement is integrated with the center of pressure evaluation. The center of pressure is typically represented in anterior-posterior and medial-lateral displacements. Displacements of the center of pressure can be collected using a force plate. Although center of pressure is an indirect measurement of overall balance, its measurement is a common outcome variable [10, 23, 24].

Force Plate Protocol

To assess quiet standing conditions, a force plate is used. Subjects are required to wear footwear that is flat-heeled and close-toed. The researcher will demonstrate the quiet standing conditions to the subject. For each of the conditions tested, the researcher will check whether the subject's feet in each condition fit within the boundaries of the force plate. One condition that may require a variation in foot orientation is tandem stance, which requires the subject to stand heel-to-toe. For some subjects, the orientation of the feet may align across the diagonal of the force plate rather than its length. Tandem stance oriented length-wise versus along the diagonal can be seen in Figure 2.2. After demonstrating the quiet standing positions, the subject will be informed how long each condition will last. To obtain the most accurate data, the researcher will instruct the subject to stand as still as possible, with their gaze forward and arms at their sides. The researcher will also request that the subject stay focused on the task. The data obtained from the force plate is center of pressure in the X- and Y-directions.

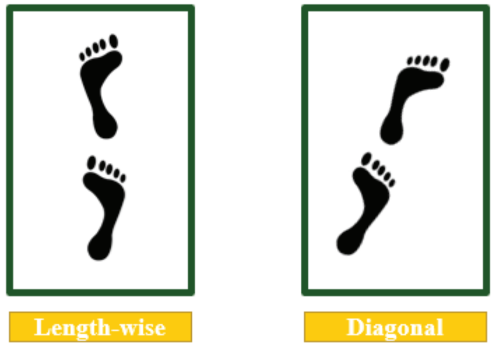

Figure 2.2: Different orientations of tandem stance on a force plate

Applicability of Hippotherapy

Autism Spectrum Disorder (ASD) refers to a set of neurodevelopmental conditions that influences the way an individual perceives and communicates with others [25]. ASD is known as a developmental disorder because it is typically diagnosed within the first two years of life [25]. The diagnosis of ASD can be determined by the following key features: impairments in social communication, repetitive interactions, and stereotypic behavior [26]. In addition to these features, motor impairments in planning and executing tasks, gross or fine motor skills, coordination and others have been demonstrated in ASD [27]. Although motor impairments in ASD are considered as associated symptoms, recent research has shown that motor impairments, such as unusual reactions to sensory stimuli and cognitive deficits, are some of the more common early symptoms in children with ASD [28, 22].

Many studies have compared the postural sway of children with ASD versus children who are typically developing (TD). One study found that age-matched children with ASD versus children who are TD had higher postural sway, regardless of the visual and somatosensory inputs tested [29]. These results can indicate that age-matched children with ASD versus those who are typically developing have a postural control system that is less developed. Another study found that the symptom severity was a significant factor in postural sway in children with ASD as compared to typically developing children [27]. This can suggest that symptoms severity can perhaps affect allocation of resources, which make producing a static posture difficult.

Unlike in autism, where motor impairments are associated symptoms, motor impairments in cerebral palsy is a defining characteristic. Cerebral palsy refers to a set of neurological disorders that can permanently affect body movement due to an injury to the developing brain [30]. Characteristics of cerebral palsy include ataxia, spasticity, body tremors, and a “scissor-ed” gait [30]. To mitigate these characteristics, one type of balance training is improving reactive balance control, which is defined as the automatic movements the body makes in order to control the center of gravity. Postural control is maintaining or recovering the state of balance [31]. Improving reactive balance control can improve overall postural control because it can help an individual recover the state of balance. Ideal reactive balance control would be for the subject to not fall from a perturbation, because the subject would be able to make the necessary automatic movements to recover the state of balance. Although this would be a near impossible goal for a subject with cerebral palsy, some research studies have shown that reactive balance control is modifiable [32, 33]. In children with varying levels of cerebral palsy severity, reactive balance control was trained using a movable force plate. The intervention involved exposing the subjects to a set number of perturbations for the length of the study. All subjects saw sustained (i.e. 30 days) reduction in the center of pressure area [32].

Current medical knowledge is not able to provide a cure for these disorders. Therefore, the efficacy of treatments that can mitigate the symptoms become vital for those who are diagnosed. Hippotherapy as an intervention to improve postural stability has shown favorable results. In terms of motor control, the effect of hippotherapy in children with autism decreased postural sway significantly from pre-intervention to post-intervention in terms of center of pressure displacements. Sway length in centimeters decreased approximately from 34 cm to 26 cm from pre- to post-intervention. Sway Area in square centimeters decreased 0.075 to 0.04 [3]. Regarding non-motor features of autism, subjects have also shown improvement in social behaviors [4] and motivation for self-improvement [5]. The effect of hippotherapy in cerebral palsy has shown evidence towards improved gross motor activity, which could mitigate abnormal gait and balance [6]. This intervention has also shown improvement in postural alignment of the upper body, which could facilitate the alignment of the center of gravity as a whole [34]. Between these groups, hippotherapy as a therapeutic intervention has shown both physical, mental improvements and the quality of life in the respective subject pools. In order to understand the full advantages of hippotherapy, efforts to isolate and identify the influence of specific inputs into the postural control system must be made.

Common Methods in Literature

Typical instrumental balance assessments concentrate on controlling visual input and the base of support. Visual input is controlled by having the eyes open or the eyes closed. A variable base of support directly involves the feet position in a balance assessment. Since good balance in a static stance is achieved when the center of mass is aligned over the base of support, having a variable BOS can create a more difficult task.

Positions that are commonly used for assessing balance are feet together, feet in tandem, and single leg stance. Each of these conditions are pictured in Figure 2.3. Examples of the use of these foot conditions in literature are found in Table 2.1. Derivatives of each of these unique foot conditions involve alternating the leading foot in semi-tandem and tandem stance or allowing a known distance between the two feet. In terms of difficulty, feet together with its widest base of support is the easiest condition. As the base of support decreases from semi-tandem to tandem to single leg stance, the difficulty of the condition increases. Besides common quiet standing positions, the literature was also used to identify a common trial length for each conditions, which were 20 seconds or 30 seconds. Examples of the use of these trials length are found in Table 2.2.

Figure 2.3: Quiet Standing Positions. Feet Together (FT), Semi-Tandem (ST), Tandem (T), and Semi-Tandem (ST)

Table 2.1: Relevance of Quiet Standing Conditions in Literature

Condition	Reference
Feet Together	[35, 36]
Semi-tandem	[37]
Tandem	[35]
Single Leg Stance	[38]

Table 2.2: Relevance of 20 second and 30 second Trial Lengths in Literature

Condition	Reference
20 seconds	[39, 40]
30 seconds	[29, 41, 42]

Objective of a Balance Assessment

The aim of the balance assessment in this study is to create a methodology that can be used to accurately describe a subject's balance ability before and after an intervention. A sound experimental methodology should account for the effects of learning and order. The two ways that the methodology was refined in this study was comparing different processing techniques and experimental methods in regard to conditions tested. The second aim of the balance assessment in this study is to provide preliminary results on pre- and post-intervention differences and report trends across multiple variables.

Outcome Variables

Starting with the raw data of center of pressure coordinates over time, common outcome variables of postural stability that are calculated from this data include center of pressure amplitude, velocity, excursion, and sway area as seen in Figure 2.4 [10, 43, 44]. Sway area is often represented as the area of a fitted ellipse. Total excursion is the total distance traveled by the center of pressure if the sway path were straightened out and velocity is the total excursion over time. Velocity can be represented in a single direction or as a mean. Center of pressure amplitude can be represented in anterior-posterior and medial-lateral directions.

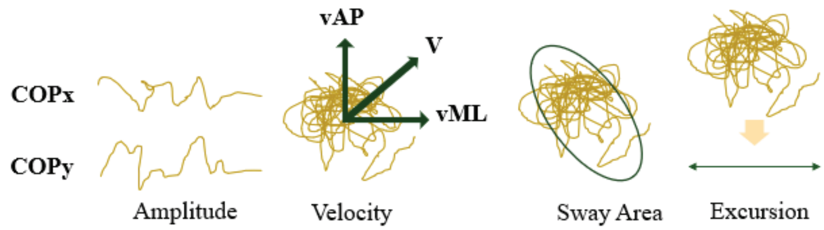

Figure 2.4: Common Balance Parameters. Center of Pressure Amplitude (left most), Center of Pressure velocity (second), Sway Area (third), Excursion (right most)

Methodology for Balance Assessment One

All testing was completed at the Baylor BioMotion lab in the Baylor Research and Innovation Collaborative in Waco, Texas. The BioMotion lab contains three AMTI force plates (Advanced Mechanical Testing, Inc, Watertown, MA) that were used to collect center of pressure data during the balance assessments. The study was approved by the Baylor Internal Review Board and written consent was obtained from all six subjects (2 males, 4 females). All subjects were healthy, meaning that they had no disabilities that would prevent them from performing a balance assessment. The subjects ranged in age from 22 to 25 years (average was 23 ± 1.3 years of age) and body mass ranged from 55.4 to 106.6 kg (average was 69.7 ± 18.5 kg). Two subjects had experienced simulated hippotherapy and no subjects had experience with actual horseback riding. Due to time constraints, for one subject full pre and post data was not documented. Therefore, a total of five subjects were available for analysis.

The balance assessment tested four unique stances, which included Feet Together, Single Leg Stance, Tandem, Semi-Tandem stances. The balance assessment came first in the pre-intervention measures and last in the post-intervention measures as seen in Figure 2.5. While feet together and single leg stances were tested with eyes open and eyes closed, tandem and semi-tandem stances were only tested with eyes open. Additionally, in single leg, tandem, and semi-tandem stances the leading foot was alternated, making a total of ten unique conditions as seen in Figure 2.6. Each of these positions and variations were explained to each subject before the balance assessment began. Each trial for each condition was 20 seconds long. Feet together and single leg stances had eyes open for the first ten seconds and eyes closed for the last ten seconds. The subject was given verbal cues on when to close their eyes during the trial. The balance assessment was repeated pre- and post- a 15-minute riding session on the mechanical horse.

After all data had been collected, different processing techniques were used to best represent the total sway area. The processing techniques used were two variations of least squares and principal component analysis to fit the data with an ellipse that would then be used to quantify area. The first least squares method (Least Squares Criterion) used existing MATLAB code to calculate the length of the major axis, minor axis, orientation, and coordinates of the centroid to configure an ellipse around the sway path as seen in Figure 2.7 [45]. A separate MATLAB code was used to plot an ellipse over the sway area using those ellipse parameters [46]. The second ellipse method (Direct Fit Least Squares) used existing MATLAB to calculate the vector of coefficients that best fits the general conic representation of an ellipse over the sway area [47, 48]. The final method used is principle component analysis, which determines the direction along which the majority of the variation occurs. This method also used existing MATLAB code to estimate an ellipse over the sway area [49]. Finally, common balance parameters were calculated for each condition across subjects. Those parameters are the standard deviations of center of pressure in anterior-posterior and medial-lateral direction, mean velocity, total excursion, and ellipse area, all of which are shown in Figure 2.8 adapted from source article, Moghadam et al., 2011 [43].

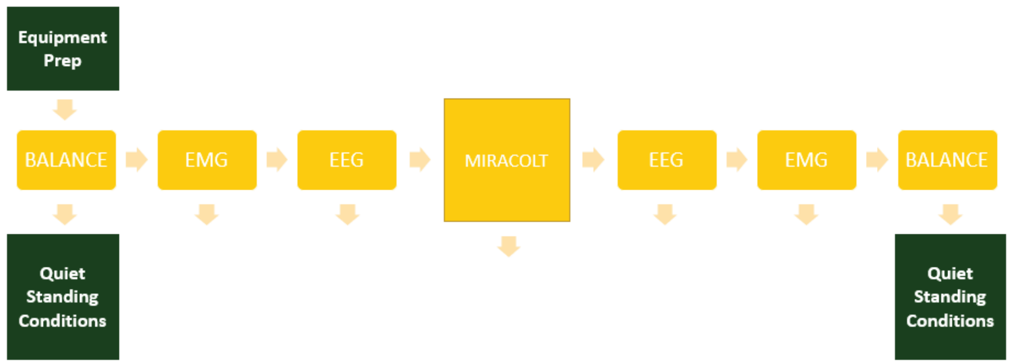

Figure 2.5: Balance Assessment Placement in Overall Methodology. Quiet Standing Conditions Tested: Feet Together (FT), Single Leg Stance (SLS), Semi-Tandem (ST), and Tandem (T)

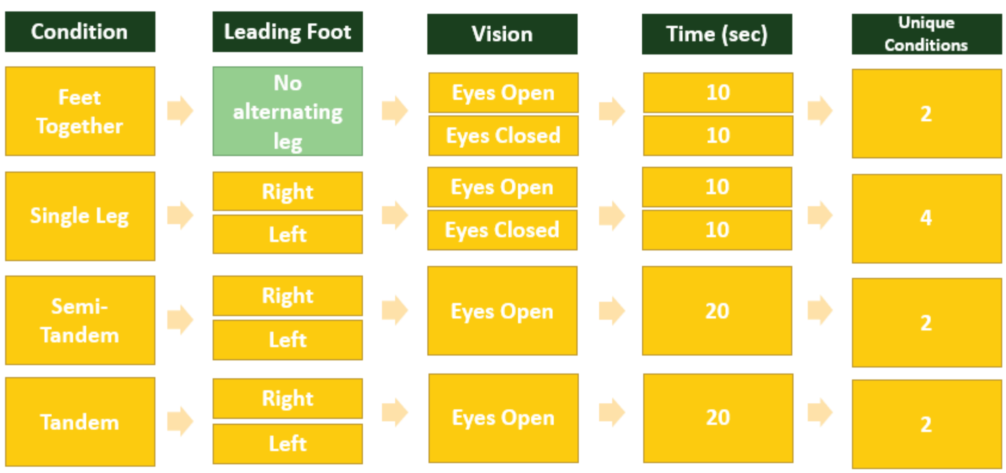

Figure 2.6: Derivatives of Condition, Foot Position, Visual Condition, and Time for the first balance assessment.

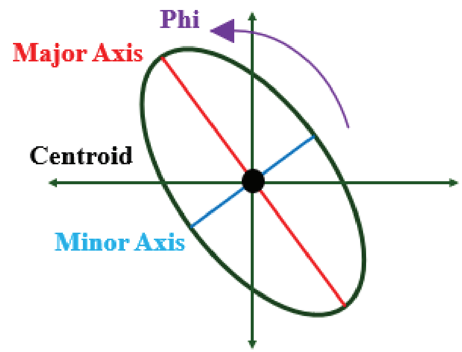

Figure 2.7: Ellipse Parameters. Major Axis (red), Minor Axis (blue), Centroid (center coordinates, black), Phi (purple)

Table 1
The formulae for calculating the COP measures.

Parameter	Formula
SD of amplitude (mm)	
AP	$\sigma_x = \sqrt{\frac{\sum (x_i - \bar{x})^2}{N-1}}$
ML	$\sigma_y = \sqrt{\frac{\sum (y_i - \bar{y})^2}{N-1}}$
SD of velocity (mm/s)	
AP	$\sigma_{v_x} = \sqrt{\frac{\sum (v_{x_i} - \bar{v})^2}{N-1}}$ where $v_{x_i} = \frac{x_{i+1} - x_i}{t_{i+1} - t_i}$
ML	$\sigma_{v_y} = \sqrt{\frac{\sum (v_{y_i} - \bar{v})^2}{N-1}}$ where $v_{y_i} = \frac{y_{i+1} - y_i}{t_{i+1} - t_i}$
Phase plane portrait (arbitrary unit)	
AP	$\sigma_{r_x} = \sqrt{\sigma_x^2 + \sigma_{v_x}^2}$
ML	$\sigma_{r_y} = \sqrt{\sigma_y^2 + \sigma_{v_y}^2}$
Total	$\sigma_{r_x} = \sqrt{\sigma_{r_x}^2 + \sigma_{r_y}^2}$
Mean velocity (mm/s)	$\bar{v} = \frac{1}{T} \sum_1^T \sqrt{(x_{t+1} - x_t)^2 + (y_{t+1} - y_t)^2}$
Area (mm^2)	$A = 2\pi F_{0.05[2,N-2]} \sqrt{\sigma_x^2 \sigma_y^2 + \sigma_{xy}^2}$ where $\sigma_{xy} = \frac{(x_i - \bar{x})(y_i - \bar{y})}{N-1}$

COP: center of pressure; SD: standard deviation; AP: anteroposterior; ML: mediolateral.

Figure 2.8: Common Balance Parameters as described in Literature [43]

Methodology for Balance Assessment Two

Whether or not fatigue, learning effects, or ordering effects were factors in the results of the first balance assessment was not accounted for. These effects could not be accounted for due to the intermixing of three different assessments and time constraints that only allowed one trial. After searching common stances in both a healthy and patient population, a new methodology was created. Only two stances, feet together (FT) and tandem (T), along with both visual conditions (eyes open, EO; and eyes closed, EC) were tested, making a total of four conditions. A total of eight sets were completed, where each set tested the four unique conditions in a randomized order to account for a possible ordering effect. The number of sets and repetition of conditions was to uncover a possible learning effect or fatigue. There was one trial for each condition per set that lasted 30 seconds. The first four sets were separated from the latter four sets by a 15-minute riding session on the mechanical horse. Each one of the four sets in the pre- and post-intervention were separated from each other by a break with alternating length. The first and third break lasted seven minutes and the second break lasted 15 minutes of both the pre- and post-intervention. With IRB approved consent, a total of twelve subjects were assessed, ranging from 20 to 25 years (average from 22.3 ± 1.1 years). The breakdown of the methodology with an example of a randomized order of conditions can be seen in Figure 2.9. Like the first balance assessment, the same balance parameters were computed for each condition.

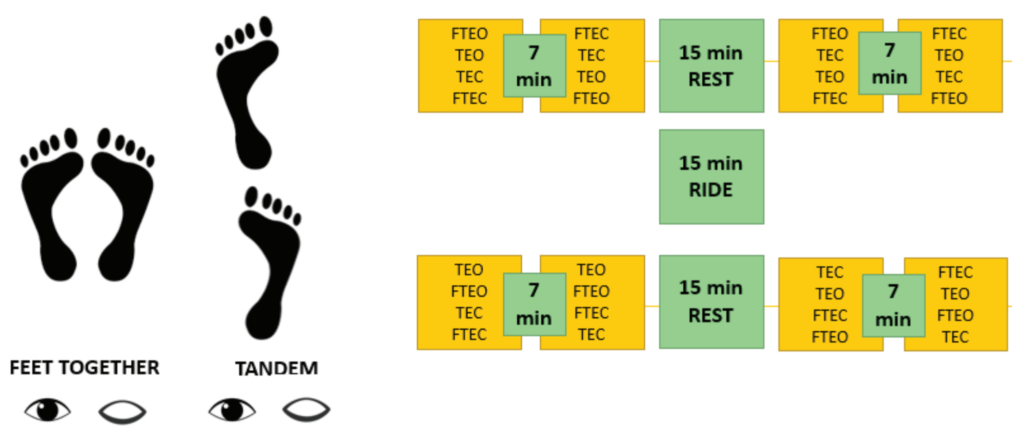

Figure 2.9: Balance Assessment Two. Conditions tested (left), Organization of Methods (right)

Results for Balance Assessment One

One of the objectives of this assessment and the thesis is how to study the motions imparted by hippotherapy. The first method used to explore postural sway is a least squares ellipse fit. However, the application across all conditions and subjects did not yield correctly fitted ellipses. Therefore, a new method had to be researched, such as PCA. Figure 2.10 shows the comparison of FTEO post-riding for one subject, using least squares and PCA. In the least squares fit, the incorrect tilt of ellipse was corrected in PCA. The next test of validity for these methods was attempting to fit an ellipse to a postural sway graph that was parabolic in nature, which was found during single leg stance with eyes closed for one subject. In this case, a method known as direct fit least squares was used. Figure 2.11 shows the comparison of these three methods with a parabolic sway path. As seen in the figure, all three methods were unable to capture the erratic sway path. However, it raised the question of if a better trial of single leg stance was used, which method would provide a better fit. In Figure 2.12, three different ellipse methods are compared graphically side by side. The condition displayed in each plot is Single Leg Stance with eyes open of a one subject. The first plot represents the least squares criterion. The second plot represents PCA, and the third plot represents a direct ellipse fit method. Common ellipse parameters could not be extracted from all ellipse-fit methods, so only area of the ellipse is reported. Table 2.3 shows the area of each fitted ellipse. The fourth column of Table 2.3 shows the area of the ellipse as calculated by Moghadam et al. [43]. In comparing the areas produced by an ellipse-fit method as compared to a formulaic calculation of ellipse area, the third plot, Direct Fit, had the closest fit. Common balance parameters are reported for FTEO, FTEC, and TEO from Tables 2.4 to 2.6 for the first balance assessment according to Moghadam et al. [43]. The purpose of the first balance study is to explore processing techniques. Only quiet standing conditions that overlap with the upcoming iteration of the balance assessment will be shown.

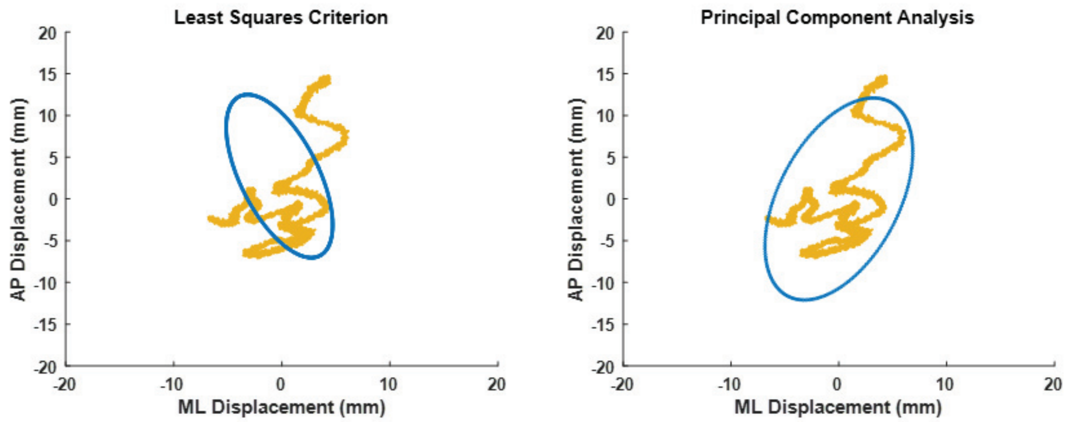

Figure 2.10: Comparing the fit between Least Squares and PCA for Feet Together Eyes Open (FTEO) post-riding for One Subject

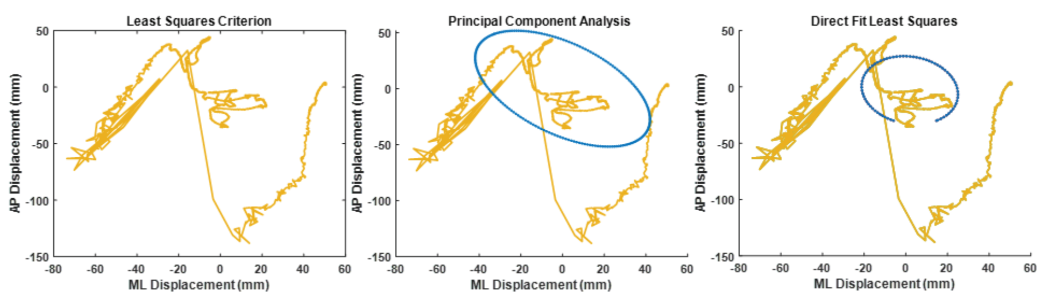

Figure 2.11: Parabolic sway path against different ellipse methods

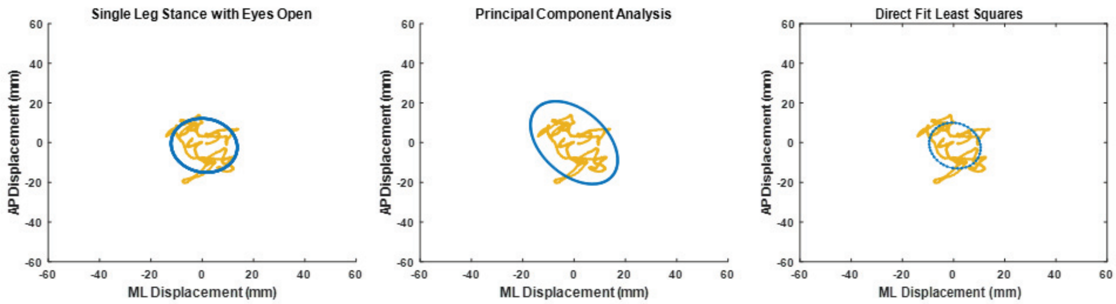

Figure 2.12: A graphical representation of three ellipse-fitting methods for single leg stance post-intervention for one subject

Table 2.3: Area of each ellipse-fit method

Statistic	Least Squares	PCA	Direct Fit	Formula
Ellipse Area (mm^2)	549.64	1007.53	362.72	402.72

Table 2.4: Means of Common Balance Parameters for FTEO

Statistic	Pre Mean	Post Mean
SD in AP (mm)	3.33	4.54
SD in ML (mm)	3.39	4.46
Mean Velocity (mm/s)	31.86	31.74
Total Excursion (mm)	3342.45	3062.76
Ellipse Area (mm^2)	68.19	152.77

Table 2.5: Means of Common Balance Parameters for FTEC

Statistic	Pre Mean	Post Mean
SD in AP (mm)	7.39	5.41
SD in ML (mm)	5.17	5.50
Mean Velocity (mm/s)	20.86	37.11
Total Excursion (mm)	3366.14	3017.29
Ellipse Area (mm^2)	256.97	184.99

Table 2.6: Means of Common Balance Parameters for TEO

Statistic	Pre Mean	Post Mean
SD in AP (mm)	3.95	5.85
SD in ML (mm)	4.59	5.48
Mean Velocity (mm/s)	30.43	22.36
Total Excursion (mm)	3774.13	3902.96
Ellipse Area (mm^2)	123.09	205.4

Results for Balance Assessment Two

The objective of the second balance assessment is to explore the refined methodology. The main difference between the two balance methodologies is that multiple trials of the same condition were spread over intervals of rest. Figures 2.13 to 2.16 represents the group mean across all subjects over the pre- and post-intervention sets. The value of the average slope is reported for each balance parameter for each condition. The main reason that the second balance assessment was pursued is that there was a possibility of a learning effect or fatigue. By looking at the values for average slope, across all conditions, and for each balance parameter, the average slope is close to zero. This means from Set 1 to Set 4 and Set 5 to Set 8 of any condition, the trials can be seen as not different. Therefore, they can be averaged. The exception is total excursion in FTEO, FTEC, and TEO. In these conditions, the average slope is negative. This can suggest that more trials of these conditions enabled a learning effect, since the total distance traveled grew shorter. Unsurprisingly, the average slope for TEC for total excursion is positive. TEC being the most difficult position, it is understandable that maintaining that position was not easy and did not become easy over numerous trials. In fact, the condition grew to be more difficult with each successive trial. Tables 2.7 to 2.10 report common balance parameters across all subjects.

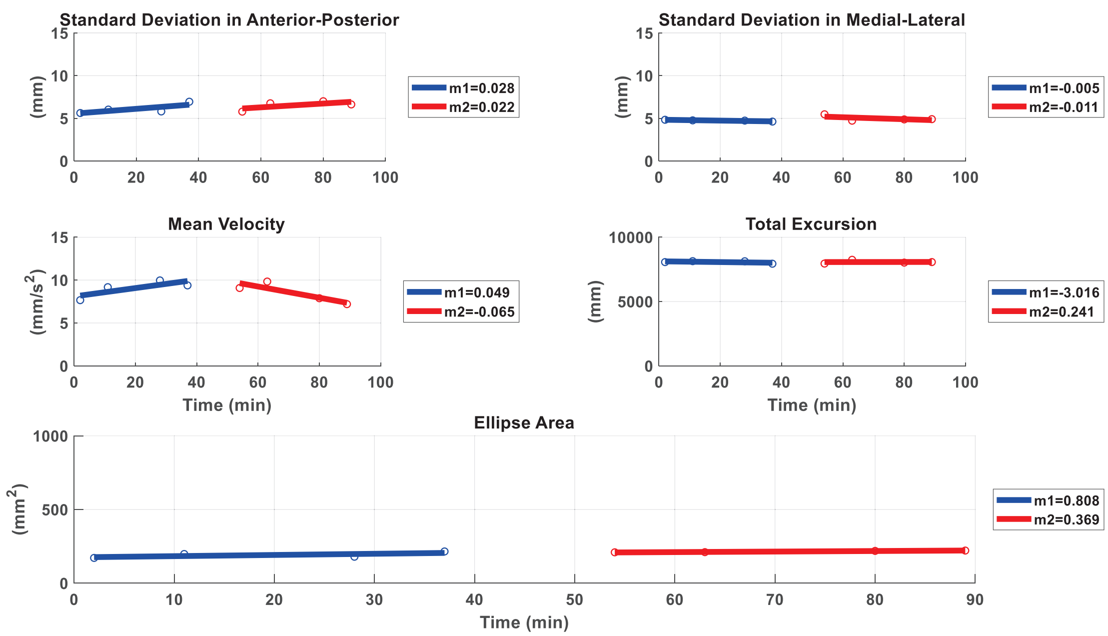

Figure 2.13: Common Balance Parameters for FTEO. SD in AP (top left), SD in ML (top right), Mean Velocity, (middle left), total excursion (middle right), and ellipse area (bottom

Table 2.7: Means and Standard Deviations of Common Balance Parameters for FTEO

Statistic	Pre Mean	Post Mean
SD in AP (mm)	6.10(0.59)	6.54(0.53)
SD in ML (mm)	4.74(0.09)	4.99(0.33)
Mean Velocity (mm/s)	9.04(0.98)	8.50(1.18)
Total Excursion (mm)	8065.08(92.07)	8069.03(124.07)
Ellipse Area (mm^2)	191.22(19.62)	215.24(5.94)

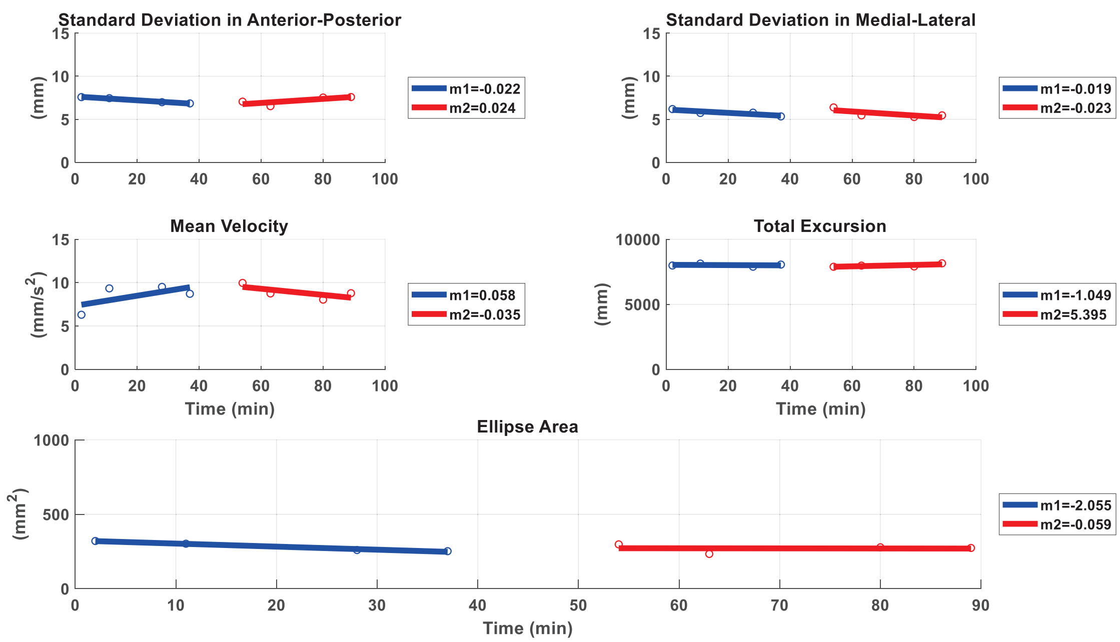

Figure 2.14: Common Balance Parameters for FTEC. SD in AP (top left), SD in ML (top right), Mean Velocity, (middle left), total excursion (middle right), and ellipse area (bottom)

Table 2.8: Means and Standard Deviations of Common Balance Parameters for FTEC

Statistic	Pre Mean	Post Mean
SD in AP (mm)	7.22(0.35)	7.18(0.49)
SD in ML (mm)	5.76(0.35)	5.64(0.50)
Mean Velocity (mm/s)	8.46(1.49)	8.88(0.80)
Total Excursion (mm)	8015.08(102.53)	7981.83119.93)
Ellipse Area (mm^2)	283.65(32.95)	270.77(26.96)

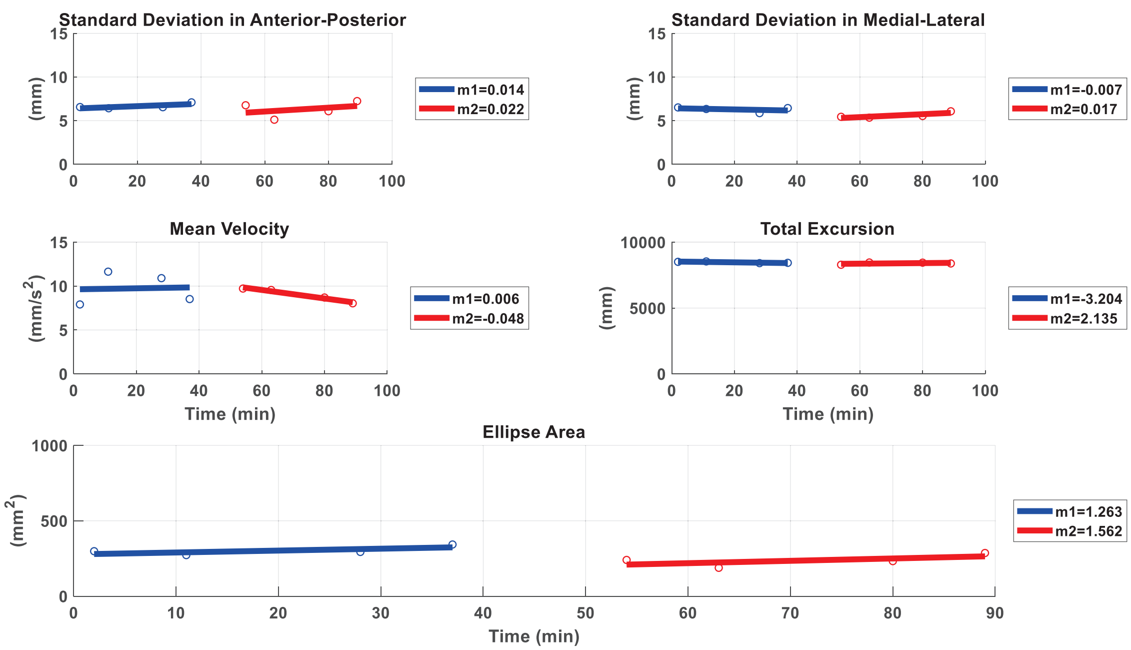

Figure 2.15: Common Balance Parameters for TEO. SD in AP (top left), SD in ML (top right), Mean Velocity, (middle left), total excursion (middle right), and ellipse area (bottom)

Table 2.9: Means and Standard Deviations of Common Balance Parameters for TEO

Statistic	Pre Mean	Post Mean
SD in AP (mm)	6.65(0.30)	6.30(0.93)
SD in ML (mm)	6.29(0.29)	5.60(0.33)
Mean Velocity (mm/s)	9.74(1.81)	9.00(0.78)
Total Excursion (mm)	8472.05(61.28)	8394.71(78.14)
Ellipse Area (mm^2)	301.87(29.55)	236.98(40.21)

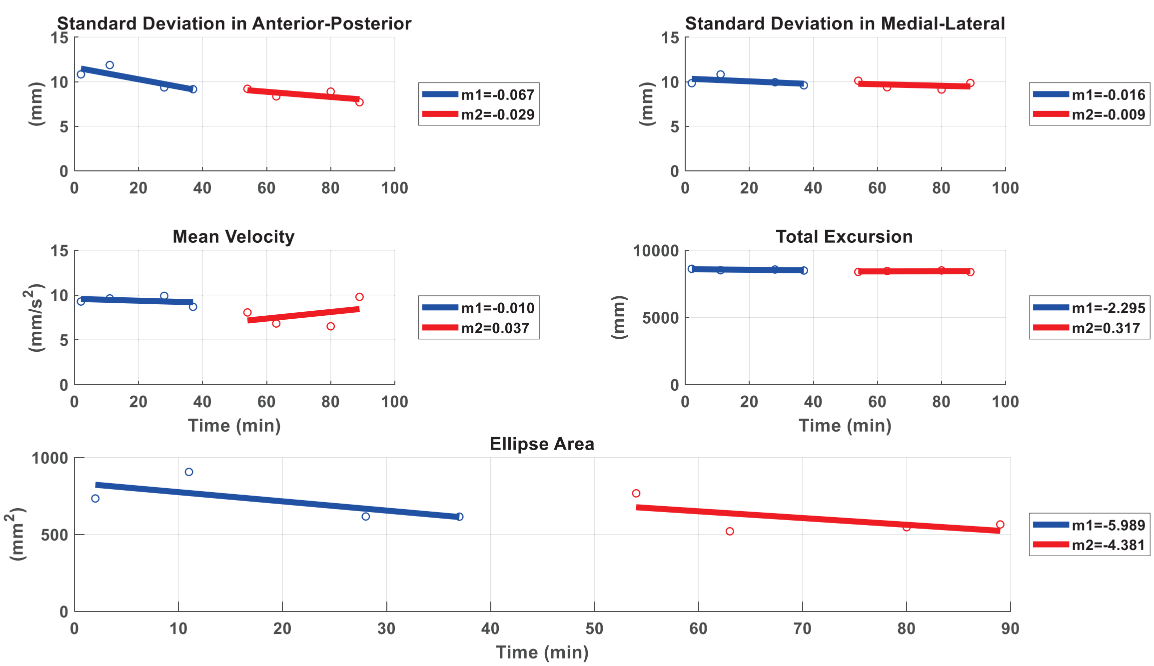

Figure 2.16: Common Balance Parameters for TEC. SD in AP (top left), SD in ML (top right), Mean Velocity, (middle left), total excursion (middle right), and ellipse area (bottom)

Table 2.10: Means and Standard Deviations of Common Balance Parameters for TEC

Statistic	Pre Mean	Post Mean
SD in AP (mm)	10.25(1.28)	8.54(0.66)
SD in ML (mm)	10.05(0.54)	9.62(0.45)
Mean Velocity (mm/s)	9.37(0.53)	7.80(1.49)
Total Excursion (mm)	8545.97(44.54)	8429.76(57.08)
Ellipse Area (mm^2)	718.12(137.17)	600.03(113.05)

Discussion

The purpose of this study was to explore and refine a methodology that will help understand how to study the passive movements imparted by hippotherapy. A secondary objective was to begin a normative dataset specific to the derivatives of the methodology presented in this thesis. The refinement of methodology was conducted in two ways: 1) through different ellipse-fit methods; 2) through the implemented protocol.

The ellipse-fit methods include Least Squares Criterion, Principal Component Analysis, and Direct Fit Least Squares. As a first pass measure, the Least Squares Criterion provided a way to analyze the sway area through phi, and lengths of the major and minor axis, and subsequently area. However, with a phi value that is not correctly oriented on the sway path, the area that can be calculated would not be representative of the sway area it is attempting to encapsulate. Therefore, ellipse parameters were not calculated since it could not be done for all conditions correctly. It is important to note that the incorrect phi value is more likely to be the result of the execution of the code that calculates phi rather than a problem with the method itself. Although the code could have been corrected to correct phi, an ellipse method that can work correctly without modification and does not need multiple source codes to work is preferable. The second method, PCA, was compared against the same scenario, a correctly oriented ellipse was produced.

The next hurdle for the ellipse-fit methods is fitting an ellipse to an erratic sway path that describes a parabolic sway path rather than one that is an ellipsoid. In this case, not only did both these methods fail, but also the third method, Direct Fit Least squares could not capture the entire sway area. However, with only one trial per condition in the first balance assessment, a bad trial is likely, especially during the most difficult stance, single leg with eyes closed. On the positive side, three ellipse-fit methods that work reasonably well given good data are available for comparison. Using the sway paths for single leg stance eyes open, the areas encompassed by each of the methods were compared to a formulaic calculation of ellipse area. Before comparing the actual values, it can be hypothesized that the areas produced by the two ellipse areas will be smaller compared to that produced by PCA. This is because the least squares method in both its variations is designed to minimize the distance between the given points and the fitted curve [50]. Moreover, the design behind PCA is to calculate the principal directions in which the dataset varies. As a result, you have an ellipse that is fitted to the inherent variation of the sway area. The calculation of each of the areas supports the hypothesis as the least squares method had lower values for area than PCA. Also, the formulaic calculation of the sway area is closer to the Direct Fit Least Squares than any of the other methods. More in-depth comparisons and larger datasets need to be analyzed for any other obstacles to arise and the need for a new ellipse method is required. However, with these comparisons the first goal of the balance assessment is achieved in that a better picture of how to represent sway area is realized.

The second way the methodology was refined is through the conditions tested. While the first balance assessment has ten conditions, the second had four conditions. This change was made so that this methodology can be used in both a healthy and patient population. For example, the use of single leg stance is a difficult task for even a healthy person. In a study with over 100 subjects, the longest an individual in the relevant age group can hold a single leg stance is just under ten seconds [38]. In the first balance study, single leg stance with both eye conditions was a combined trial, meaning the subject by the end of the trial had held a single leg stance for twenty seconds, the latter ten seconds with eyes closed. Unsurprisingly, subjects required many retrials during this condition. Moreover, tandem stance can be used as a replacement for single leg stance [10]. Therefore, the number of conditions were narrowed down to the most unique of the original set, and can be carried forward into a clinical study.

Common balance parameters were generated for FTEO, FTEC, TEO for the first and the second balance assessment. From pre to post, the mean post values for each of the common balance parameters is often larger or similar to the mean pre values in the first balance assessment for FTEO and TEO. This trend persists for FTEO, but not TEO in the second balance assessment. In fact, TEO improved in all parameters, which could be attributed to the difficulty of the stance. FTEO is an easy, almost boring task for a healthy individual that little effort may have been given to the task. TEO is a strange task that may present as a fun challenge. With long breaks between sets, TEO may have engaged the subject better than FTEO could. In fact, TEC also sees improvement from pre to post in every balance parameter for the second balance assessment. Additionally, between the first and second balance assessment, FTEC improved from pre to post in the same parameters.

In one study that compares the changes in the mean center of balance in young adults, similar results were found in the second balance assessment for FTEO for the standard deviation of the amplitude [51]. The conditions tested that overlap with the conditions tested in the second balance assessment are FTEO, FTEC, TEO, and TEC on a stable platform. However, only FTEO in the x-direction matches the results of this study.

Regarding trends across the assessments for the SD in AP for FTEC compared to TEO, the values of the former are higher than the latter. One would hypothesize that since the base of support is larger for FTEC than TEO, subjects would be more balanced. However, the results suggest the opposite. This trend may suggest that visual condition maybe a more important input into the postural control system than the base of support.

Both balance studies from the refinement of processing techniques to amassing a normative dataset will help to create a methodology than can efficiently study the motions imparted by hippotherapy. The future application of these techniques and the current methodology will be for a study that aims to better understand how simulated hippotherapy might impact the postural stability of kids with autism. As a neurodevelopmental disorder that is known for its idiosyncrasies in social behavior, emotion, and mood, good use of time is important to collecting pre- and post-intervention data. By having conditions that have been refined to the pertinent ones, producing common balance parameters, and representing data in a literature-backed way, advances can be made in finding the mechanism of action behind hippotherapy.

CHAPTER THREE

Electromyography

Introduction

This thesis is focused on assessing the physiological responses and effects in the human body to impartation of organic motion through a mechanical horse-riding simulator. This chapter addresses assessment of effects on muscle activation and coordination before and after riding sessions, as measured through electromyogram sensors. This assessment involves human experiments with healthy, non-impaired participants as a way to develop appropriate methodology, and obtain baseline data, with a view toward future experiments and assessments involving participants with a variety of different disabilities or conditions that affect balance, posture, muscle coordination, and neural activity. The aim is that such experiments, by revealing the muscle coordination of healthy activities, will inform therapeutic interventions to improve overall quality of life for these individuals.

Role of Muscles in Posture

While visual, vestibular, and somatosensory feedback are important sensory inputs into the postural control system, maintaining a specific posture or changing from one posture to another would be impossible without the timely input of the muscular system. Good posture in terms of the musculoskeletal system can be defined as the state in which the surrounding structures of the body are protected from immediate injury or latent injury regardless of the functional position of the body [52]. On the other hand, bad posture is better defined with examples rather than a general definition.

There are four common deformations in body posture: lordotic, kyphotic, flat-back, and sway-back [52]. While lordosis is categorized by an excessive inward curve of the spine, kyphosis is the excessive outward curve of the spine and flat-back is a condition in which the normal curvature of the spine is lost. Lastly sway-back is characterized by a posterior tilt of the pelvis and kyphosis of the upper spine [53]. To prevent these spinal deformities, postural muscles need to work in coordination. Postural muscles are typically found surrounding the trunk and neck [54]. The energy cost of maintaining a postural activity is low, as postural activity typically activates slow muscle fibers. These types of fibers are naturally fatigue-resistant and are the first type of muscle fibers recruited when contractile activity occurs [54]. Beyond posture, muscles have many other important roles in the body, including, of course, movement. Even muscle tone, which is the tension in muscles at rest, aids in various types of physiological processes such as creating a natural reflex response and controlling the digestive system [55].

Impaired Muscle Activity

Some disorders such as autism and cerebral palsy are characterized by impaired muscle activity. As mentioned in the previous chapter, one of the associated symptoms in individuals with autism is motor impairment. These motor impairments can be partially attributed to low muscle tone. In children with autism, 30% have exhibited some level of muscle tone reduction, [56] which affects static and dynamic balance, is also linked to language impairments and adaptive function [57]. While low muscle tone is exhibited in children with autism, children with spastic cerebral palsy are restricted by excessive muscle tone resulting in stiffness of movements [58]. These motor impairments in both autism and cerebral palsy affect the muscle's ability to function properly, which can have a major impact on mobility, coordination, and bodily functions.

Treatment Strategies for Muscles

Many common treatment strategies for these kinds of muscle impairments involve passive motion to get the body moving. Treatment strategies include such things as a wedge cushion and wobble stool, and real and simulated hippotherapy. Those with low muscle tone may find it difficult to sit in a single position for long periods of time. Thus, to promote better posture, equipment such as a wedge cushion or a wobble stool can be used to keep the muscles engaged. The wedge cushion promotes better posture by requiring the activation of core muscles while sitting. The wobble stool promotes better posture by providing an unstable surface that requires constant adjustment, and therefore constant activation of muscles, to keep upright [59].

While the wobble cushion and wobble stool provide a form of passive challenge to muscles and posture, real and simulated hippotherapy provide an active form of challenge by imparting motion to which the rider's body must respond. During hippotherapy the center of gravity of a horse will move in the sagittal, transverse, and frontal planes [60]. As a result, the rider will have to adjust his or her own center of gravity to stay balanced on the horse. This requires the activation of several core muscle groups and postural muscles. As with real hippotherapy, a mechanical horse also imparts a passive and rhythmic motion that has been shown to produce similar activation patterns as real hippotherapy [61].

Electromyography (EMG) Assessment

Electromyography (EMG) is used to measure the electrical potential of muscles as they contract. EMG is able to record muscular activity by using electrodes to convert electrical potential into a voltage [62]. There are two types of EMG, surface and needle. While surface EMG can detect superficial muscular activity, needle EMG is used to detect deep muscle activity. Each of these types has its advantages and disadvantages. Whereas surface EMG is relatively painless, needle EMG is invasive and can be a factor in participation for a subject. However, surface EMG is more susceptible to misplacement, resulting in the recording of the wrong signal or recording the activity of multiple muscles. Also surface EMG naturally yields low voltage readings which require amplification, and inherent noise that requires filtering. For the purposes of this study surface EMG was used as it is more accessible and commonly used in general practice. Surface EMG can provide useful information on muscle coordination and firing patterns, which can be used to guide muscle rehabilitation.

Objective of the EMG Assessment

The long-term objectives of this study are to assess the effects of riding on muscle activation amplitude, symmetry, and coordination pattern for a few basic muscles associated with posture, balance, and gait. The immediate goal of the EMG assessment in this study is to create a methodology that can be used to accurately describe a subject's muscular activity before and after hippotherapy. To that end, experiments were performed to record EMG of targeted muscles during targeting exercises both before, and after, a session of riding on the mechanical horse. The focus of this thesis is the process to analyze such EMG data, while the specific results of the experiments themselves is left for future work. To truly understand the results obtained from an EMG recording, the raw EMG must be processed correctly. This chapter will focus on several ways to process and analyze the EMG data. A secondary aim of the EMG assessment in this study is to begin a normative baseline dataset for future comparison with a patient population.

Targeted Muscles

Specific muscle groups that are important to posture include lumbar, gluteus maximus, bicep femoris, and anterior deltoids. To prevent spinal deformities such as sway-back, the physiological loading of the lumbar muscles must be synchronized and appropriate to prevent excessive curvature of the spine. Gluteus maximus is one of the largest muscles in the body, and its activation is important in dynamic posture such as sitting, walking, running, and standing on one leg [63]. Also important in dynamic posture is the bicep femoris, which plays a key role in activities such as standing up, and walking [64]. Although its purpose in posture may not be immediately evident, the anterior deltoids helps to prevent kyphosis. Kyphosis can be characterized by rounded shoulders, which enables a hunchback posture. By activating the anterior deltoids, posture can be more easily maintained as loading will be more evenly distributed across the other postural muscles. In this chapter, these muscles will be the focus. To get a closer look at muscle activity, eight electrodes (EMGs, Noraxon, Scottsdale, AZ) were placed bilaterally on the lumbar, gluteus maximus, bicep femoris, and anterior deltoids.

Targeted Exercises

Several targeted exercises were used in this study to challenge the targeted muscle groups for EMG assessment. These exercises include hip extension, standing flexion, single leg stance, and arm raise. The hip extension exercise is executed while laying prone on a padded bench, and lifting each leg in turn into full extension, holding it momentarily, and then lowering it back to rest position. The standing flexion exercise begins in an upright standing posture, followed by bending at the waist with the head moving toward the floor, holding momentarily, and then raising back up to standing posture. The single leg stance also begins in an upright standing position. In this exercise, each leg in turn is lifted off the floor and held momentarily while remaining balanced on the other leg. The arm raise exercise begins in an upright standing position with arms relaxed by the side. Each arm is then raised in turn to shoulder level and then lowered. In the final iteration both arms are raised together to shoulder level, held, and then lowered.

Electrode Placement

Surface EMG measurements of muscle activation signals are read through sensors placed on the skin over the targeted muscles. To prepare the skin for placement, the skin was first inspected for any fine hairs. If hairs were present, a razor was used to clear the area in which the electrode would be placed. Next, an alcohol wipe was used to vigorously scrub the skin clean of dirt and oils that would impede the data collection. Each muscle was palpated in order to identify the correct sensor placement location. When placing the electrodes for the anterior deltoids, the subject was asked to raise each arm during palpation. The electrodes placed on the gluteus maximus used the recognition of the hip pocket, which is found just below the waistline. The electrodes placed on the bicep femoris were placed while the subject was slightly extending each leg. Finally, the electrodes placed on the lumbar muscles were placed lateral to the spine and corrected with a slight flexion at the waist.

Protocol

Six human volunteers were tested for these EMG assessment experiments, which were approved by the Internal Review Board of Baylor University. The subjects ranged in age from 22 to 25 years (average was 23 ± 1.3 years of age), and body mass ranged from 55.4 to 106.6 kg (average was 69.7 ± 18.5 kg). Two subjects had experienced riding on the mechanical horse, and none of the subjects had experienced actual horseback riding. Due to time constraints, one subject was unable to complete the full pre- and post-data collections. Therefore, a total of five subjects were available for analysis. Figure 3.1 shows the EMG assessment and progression of the study as a whole.

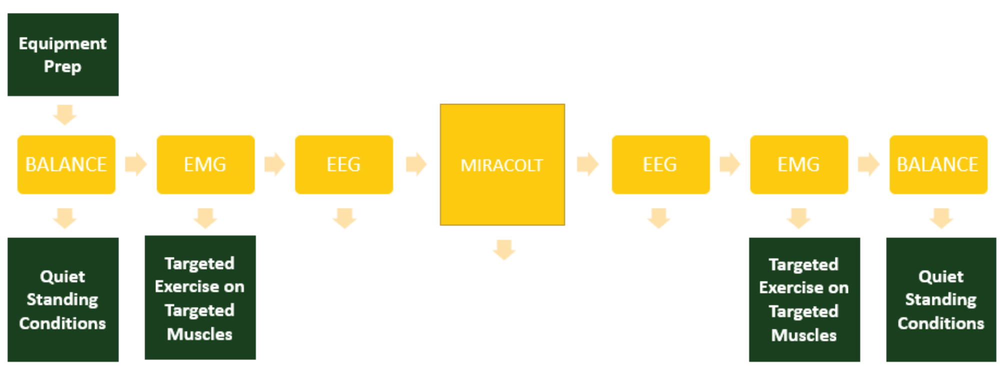

Figure 3.1: EMG Assessment Placement in Overall Methodology

After each of the electrodes were placed, the subject was instructed on how to perform each of the targeted exercises. During this instruction, each of the electrodes were checked for the expected EMG signal. Once all electrodes were checked and the subject was taught the exercises, the EMG assessment began with hip extension. During the exercise, the subjects were asked to lay prone on their stomachs with legs extended behind them, and their arms by their sides. The subject was given verbal cues to direct movement. First, the subject was asked to raise their left leg in the air, while their right leg was lying flat. When the researcher gave a verbal cue, the subject lowered their raised leg and returned to a resting position. The same was repeated for the other leg, and back and forth until both legs had been extended a total of three times each. The next exercise was standing flexion. The subject was asked to stand with feet flat on the floor. Then the subject was asked to bend at the waist and aim to touch their hands towards their feet, although it was not necessary to touch the feet. After a brief hold the subject was asked to extend back to a standing position. Each subject repeated a standing flexion a total of three times. The subject was given verbal cues on when to bend down, how long to hold the position, and when to return to a straight standing posture. The next exercise tested was single leg stance. In this exercise the subject was asked to stand with feet flat on the floor and lift one leg in a static hold. In a separate trial, the other leg was tested. The final exercise tested is an arm raise. In this exercise, the subject was asked to raise one arm to shoulder height, and then lower the arm after a verbal cue. This action was repeated for the other arm. After both arms had been raised once, then both arms were raised together. In all the exercises tested, no formal timing was used, only verbal cues from the researcher with momentary holds. These exercises and recordings were performed both before, and after, a session of riding on the mechanical horse. In the progression of the combined methodology, it was decided that the EEG assessment should take precedence over the other assessments in regard to being most immediately before and after the riding intervention. Moreover, the EMG and balance assessments took approximately five minutes each to complete, therefore, the order in which these assessments took place pre- and post-intervention were not deemed critical.

Data Processing Methods

The objective of the data processing methods was to quantify a level of activation for each muscle during the targeting exercise, and particularly during any hold phase of the exercise. The outcome variables used to quantify the level of muscular activity during targeted exercises were the root mean square (RMS) and the absolute mean value (AMV). These outcome variables are well-known time domain parameters commonly used in EMG processing [65, 66]. The root mean square is a measure of the magnitude of a set of numbers, and quantifies the typical size of a set of numbers. RMS is different than a simple calculation of the mean. Where the mean is the average of a set of numbers, RMS is calculated by squaring all the values, averaging the squares, and computing the square root of that average. For simplification MATLAB's rms() function was used. The result is a value typically higher than a simple mean calculation. The absolute mean value (AMV) is simply the mean of the rectified signal. These outcome variables (RMS and AMV) were calculated over segments of trial data representing various periods of activity, and periods of rest.

Pre-Processing

The first steps in pre-processing the EMG data are shown in Figure 3.2 below. An explanation of each plot in the Figure is as follows. The first row shows the raw EMG signal. The signal shows intervals of active muscle contraction and intervals of rest. The rest periods may be completely flat, or they may display a small amount of noise, which can be seen as random spikes or a signal with a constant amplitude. The amount of noise present in the signal is dependent on many external factors such as equipment, electrode location, and muscle type. Before any other processing is completed, low and high frequencies must be removed from the signal. These frequencies were removed using MATLAB's lowpass() and highpass() functions. The purpose of removing low frequencies is to remove any DC offset and baseline drift due to movement [67]. Removing high frequencies from the signal is meant to remove aliasing. Following the viable frequency range for surface EMG, the cut off frequencies were set to 10 Hz and 500 Hz [67]. The filtered EMG signal is found in the second-row plot. The next step in processing is to rectify the signal. Full wave rectification is the same as converting all the negative EMG signal values into positive values. Rectification is necessary so that parameters such as the AMV can be calculated. Otherwise, the mean value would approach zero [67].

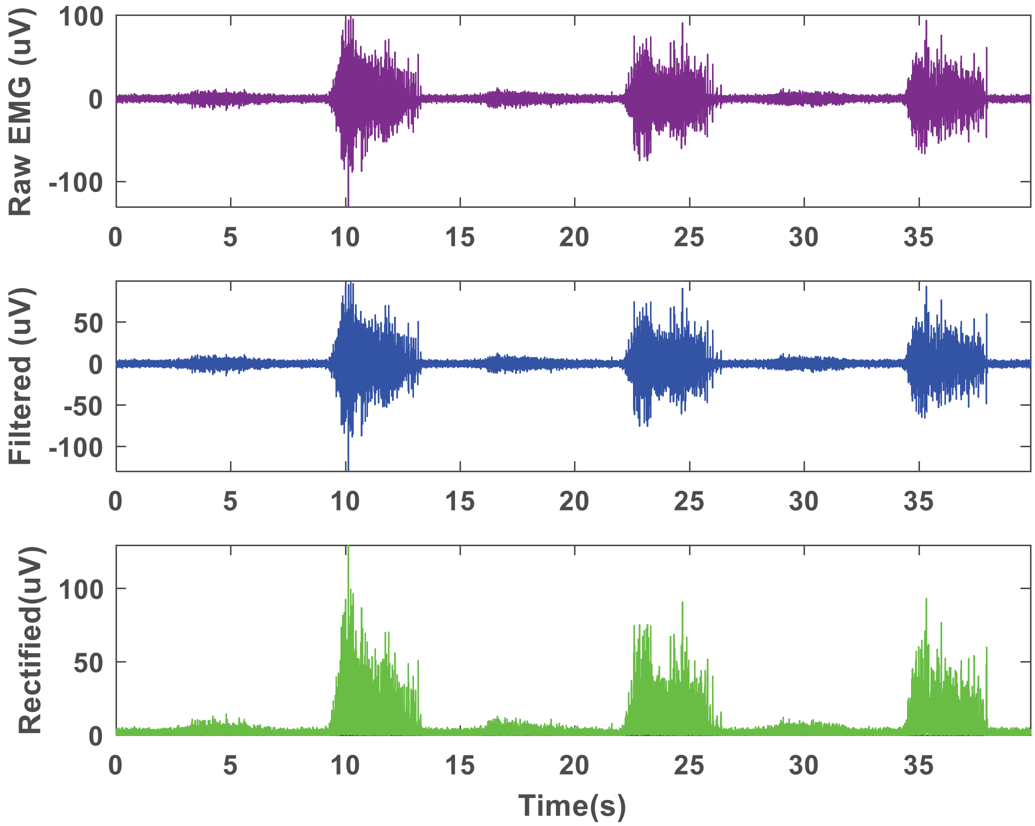

Figure 3.2: First three steps of processing an EMG signal. Sample raw EMG (purple), band-pass filtered EMG (blue, 10-500Hz), rectified EMG (green).

Manual Versus Automated Task Segmentation

A key aspect of processing the EMG data is identifying the various segments of the recorded data associated with periods of activity, and periods of rest. These segments can be described in terms of timestamps, marking the onset frame and offset frame of each period, within the samples of data. Manual timestamping involves watching the recording of the EMG assessment and noting the timestamps of each contractile activity. This type of marking method is subjective, time-consuming, and prone to human error. Moreover, with multiple subjects, tasks, trials, and muscles, having an automated marking pipeline would enable efficiency and objectivity, comparatively. In this study an automated segmentation algorithm is sought to consistently and objectively identify EMG data within periods of rest, and within periods of sustained, stable muscle activity. Such automation will allow easy calculation of such measures as RMS and AMV for those periods separately. A natural place to begin with such an automated algorithm is by identifying a threshold value distinguishing EMG activity levels and inactivity levels.

Thresholding Algorithm

For the purposes of this study the threshold is an EMG voltage value used for the purpose of distinguishing segments of signal data representing when a muscle is generally activated and when a muscle is generally at rest. The data signal itself consists of a sequence of EMG voltage values recorded over time at 1200 Hz for each muscle. Thus, each frame of data represents the EMG sensor recording at that instant of time. Due to the variable nature of muscle activation, and the tendency for noise to be recorded in the data, spikes (brief pulses of elevated voltage) in the data may appear even during periods when a muscle is generally at rest. The segmenting algorithm must therefore be able to parse out those spikes to distinguish activity periods and rest periods.

Given a threshold value, the algorithm used in this study works as follows. The rectified EMG signal was passed through a moving average with a window length of 100 frames. For each window, the EMG signal value of each frame was compared to the threshold value, and the number of window frames above and below the threshold were counted, respectively. If the number of frames falling below the threshold exceeded the number of frames rising above the threshold, the entire interval of 100 frames was assumed to represent a muscle generally at rest, or at least not generally active. Alternatively, if there were found more frames above the threshold than below, then the entire interval of 100 frames was assumed to represent a muscle generally active. In this way, the entire EMG signal is segmented into periods of either rest or muscle activity.

Figure 3.3 shows a sampling of results from the automatic algorithm segmenting the right glute during prone hip extension for one subject. The threshold was set manually to 5uV, since the rest periods seemed very small. Active periods are designated with the black background shading. The signal of this muscle for this subject and exercise represents a relatively clean signal with easily distinguishable active and rest periods; therefore, marking of intervals was simple. As another example, Figure 3.4 shows the left gluteal muscle during standing flexion for one subject. The threshold was set again to 5uV. This time, with the manually set threshold, the algorithm was not able to catch all peaks in the signal. Visually it is observable that between 15 and 20 seconds through the trial, there appears a period of activity, but its signal is not consistent enough for the algorithm to categorize the period as active, and thus it is missed.

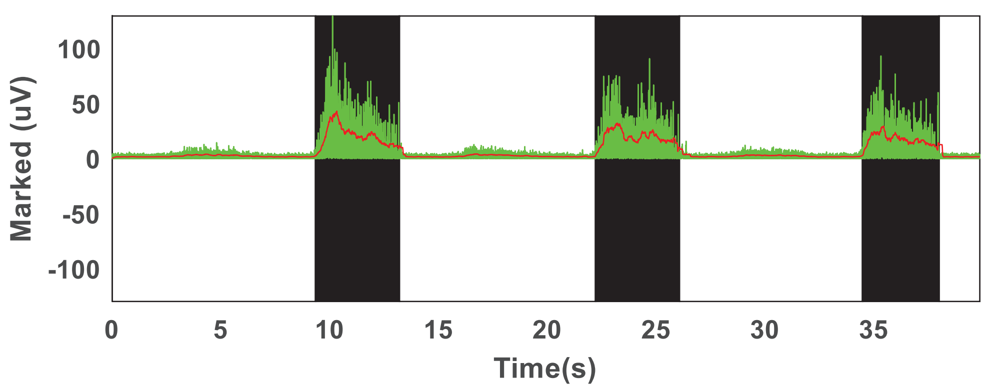

Figure 3.3: Automatic Segmentation of the Right Glute During Hip Extension for One Subject

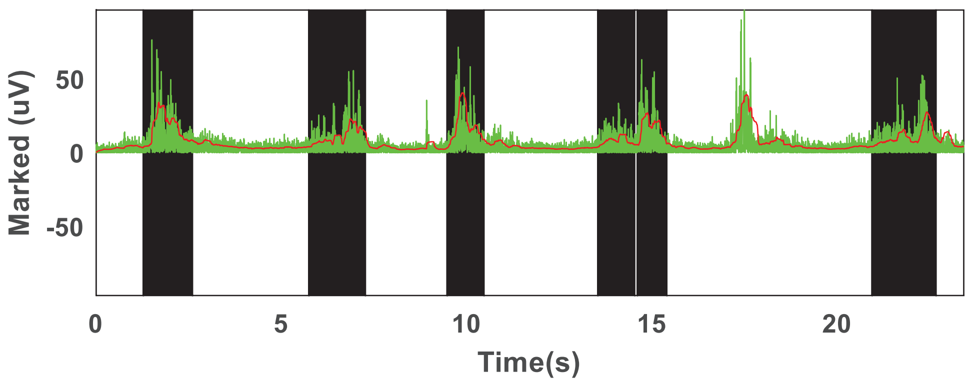

Figure 3.4: Example of Automatic Segmentation Failure of Left Gluteal Muscle During Standing Flexion for One Subject

An alternative to setting the threshold manually is to use some sort of algorithm to set the threshold, such as using a histogram approach. A histogram displays the number of frames falling within each of several voltage ranges, or bins. In Figure 3.5 below, a histogram of voltages from the data signal of Figure 3.4 above is presented. From this histogram it is shown that a vast majority of frames have voltages that lie between 0 and 5 uV, thus suggesting a reasonable threshold within that range. This is important because it shows that our initial guess of a threshold at 5uV was probably a little on the high side. Resetting the threshold to 4 uV gives Figure 3.6, where all active periods are marked. Of course, the resolution (e.g., bin size) of the histogram can also be varied to provide more detail on potential threshold values.

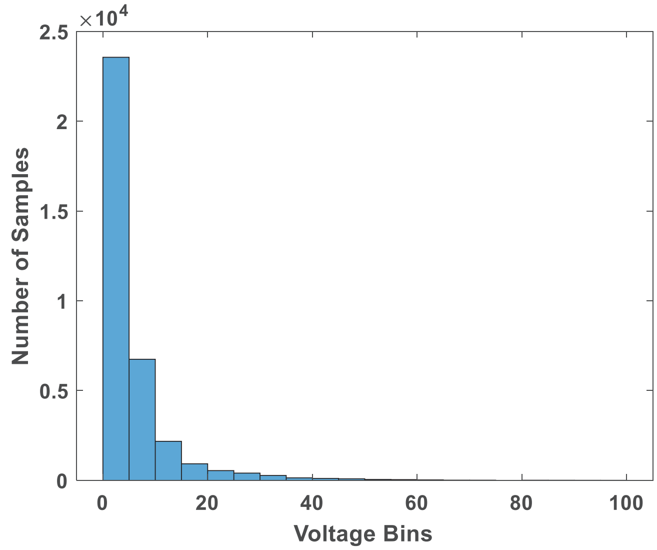

Figure 3.5: Example of a Histogram of Voltages Left Gluteal Muscle During Standing Flexion for One Subject

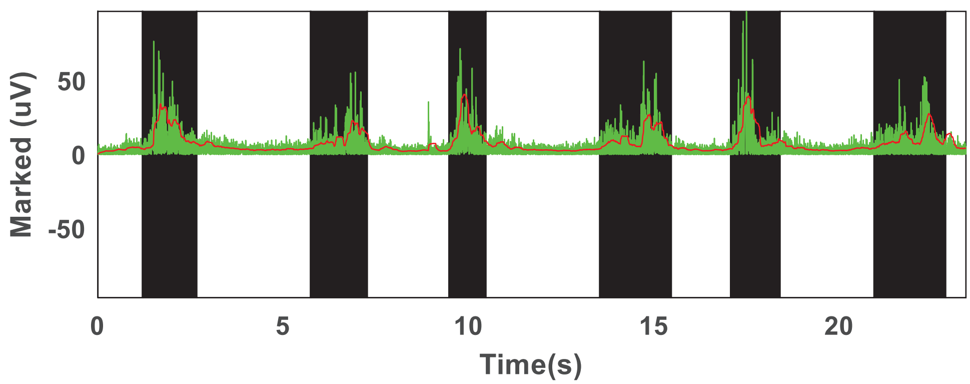

Figure 3.6: Successful Automatic Segmentation using a Histogram of Common Voltages of Left Gluteal Muscle During Standing Flexion for One Subject

Modulating Interval Length

Another phase of the automatic segmentation algorithm is filtering out transitions between rest periods and periods of muscle activity. Especially for the types of exercises in this study, which involve distinct periods of rest, with transitions into held positions of activity, the aim is to capture muscle activation levels during those periods of held activity. Two basic approaches are explored in this study, with the interval length of a held contractile period determined as either a set number of frames or a percentage of active period between rests. That is, once a region of activity is automatically detected, it is cropped to remove either a fixed number of frames, or a fixed percentage of the whole. The resulting cropped section is assumed to represent a steady level of activation during a held exercise, and those frames cropped out are assumed to be transitional.

Figure 3.7 and Figure 3.8 show the set frame approach cutting 500 and 1500 frames, respectively, and are comprised of similar plots. The first row in each of the figures represents the rectified signal of the left Lumbar muscle. The black and yellow rectangles indicate the alternating activation of the left Lumbar muscle during alternating hip extension. The second row in each plot represents the RMS values of the active periods and rest periods, respectively. The third row in each plot represents the AMV values of the same periods. Comparing Figure 3.7 and Figure 3.8, the distinction between an “active” period becomes less distinct from the “rest” period in Figure 3.8 (1500 frames cut). Without a unique activity period that represents the frames being cut or additional marking to separate from the rest periods and active periods, the distinction will be less clear.

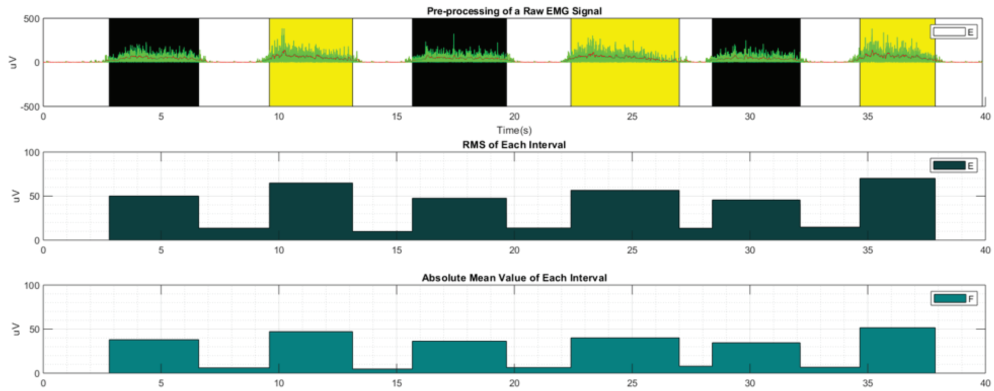

Figure 3.7: Left Lumbar during Hip Extension with 500 frames cut

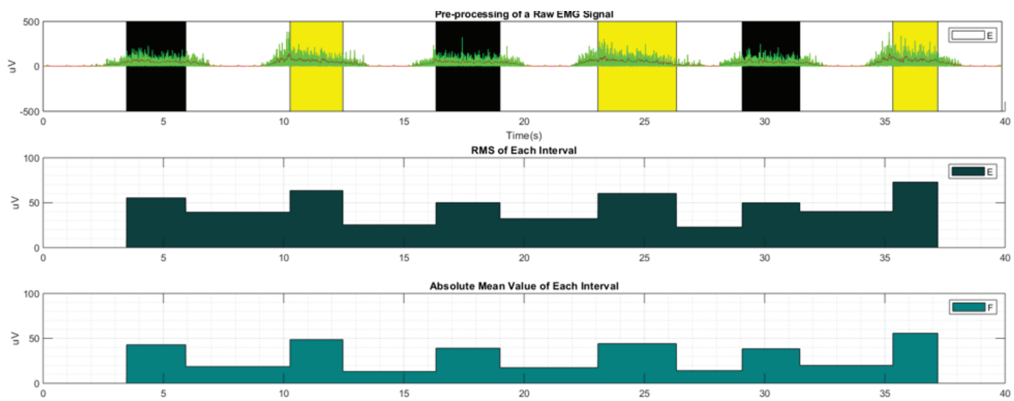

Figure 3.8: Left Lumbar during Standing Flexion with 1500 frames cut

The concept of cropping data signals using a percentage of the active period is derived from the set frame approach but builds on what it lacks. This feature is also meant to distinguish between the held contractile activity and contractile activity during the transition periods, but by using a percentage it can adjust to the duration of the activity period. That is, while the first phase of the segmenting algorithm segments periods of rest from periods of activity, in this phase the activity period is segmented proportionally into transitions (onset and offset) and, more importantly, the period of sustained, held activity. There is still a question on what percentage to use for a specific muscle for a specific exercise. One way to find a percentage that will give a period of sustained activity is to investigate the RMS and AMV sensitivity. For the results that follow, a percentage of 55% was decided based on the above-mentioned parameters.

Results

Figures 3.9 to 3.12 represent each one of the four muscles assessed in this study. The muscles are located in various places, have different uses and activation levels, but the algorithm, defined by a threshold set by a histogram was able to identify the rest periods; and therefore, the activated periods. Figures 3.9 to 3.12 have the same organization. The top row of each figure represents the rectified signal. Each activation period in the rectified signal is colored black, which describes the essence of the held activity and red during the transition periods. These red lateral endpoints of the activity segment are representative of onset and offset periods. The length of the transition periods cropped from the sustained activity period is dependent on the percentage used, which varies from figure to figure. By inspection, the RMS (second rows) and AMV (third rows) sensitivity looks to remain stable across repetitions for each muscle for each of the activity periods. The last plot of each of these figures is the average of each of the onset, offset, and active periods. In order to make quick comparisons, Tables 3.1 and 3.2 represent the group means across all subjects for the biceps femoris during hip extension, for RMS and AMV, respectively. Each of the activity periods is represented as a mean and standard deviation.

Looking at the table data an interesting trend is seen immediately. The standard deviation of AMV for the offset periods is substantially less than for the onset periods in every case. Low standard deviation can represent more steadiness and stability in muscle activation. In the context of the exercise, this could simply mean that the amplitude of the bicep femoris did not vary as much when working with gravity lowering the leg as it did working against gravity raising the leg. Or, perhaps the contributions of other muscles such as glutes and lumbar helped steady it. Another trend seen within the RMS data is the difference from pre to post, and from left to right. The left bicep femoris activation levels (means) decreased from pre to post riding for all activity periods, while the right biceps femoris activation levels increased from pre to post riding for all activity periods. This interesting trend may be a reflection of how commonly the left and right legs were used. Assuming that most subjects used their right foot more often perhaps the riding session tended to stimulate the regularly-used dominant muscle, and relax the non-dominant muscle.

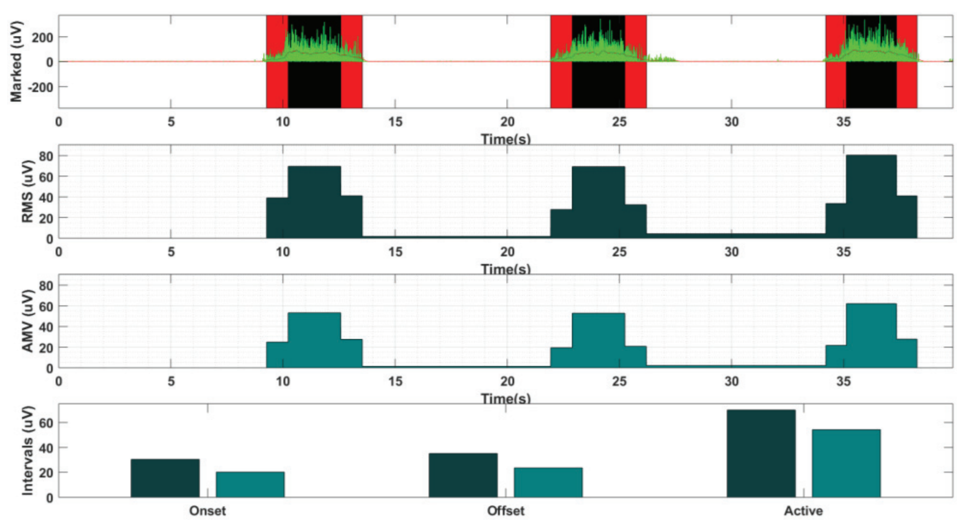

Figure 3.9: Bicep Femoris during Prone Hip Extension for One Subject

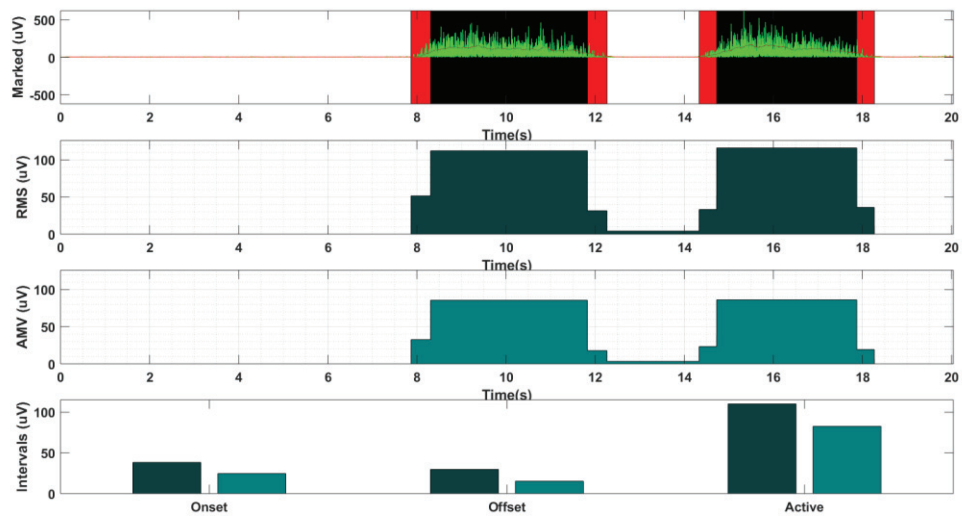

Figure 3.10: Anterior Deltoids during Arm Raise for One Subject

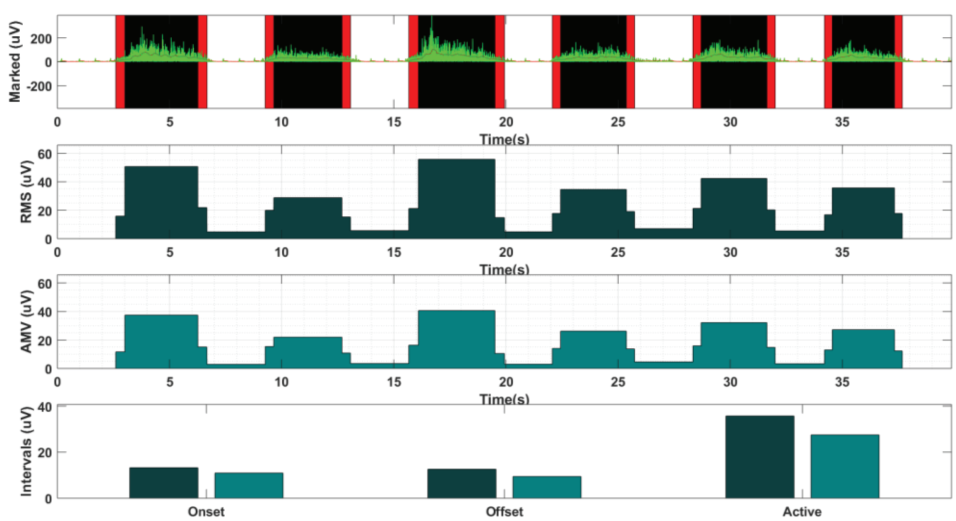

Figure 3.11: Lumbar during Prone Hip Extension for One Subject

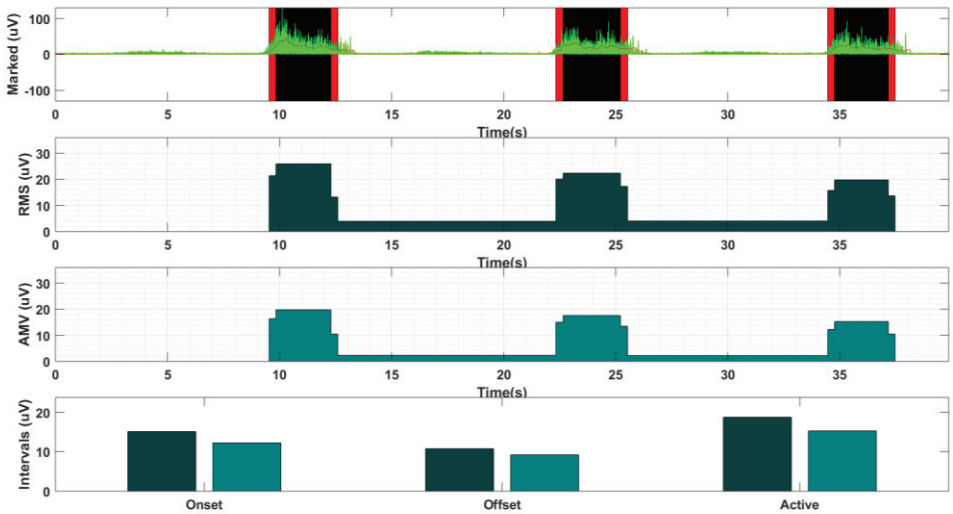

Figure 3.12: Gluteus Maximus during Prone Hip Extension for One Subject

Table 3.1: Group RMS Mean and Standard Deviations of the Bicep Femoris during Hip Extension Pre and Post Riding (uV)

Statistic	Pre Biceps Femoris (L)	Post Biceps Femoris (L)	Pre Biceps Femoris (R)	Post Bicep Femoris (R)
Onset (mean)	44.22	36.63	39.36	39.64
Onset (SD)	24.89	14.29	15.32	9.64
Offset (mean)	28.99	27.63	33.12	42.49
Offset (SD)	9.96	8.33	9.25	6.50
Active (mean)	87.03	71.87	80.24	94.97
Active (SD)	56.97	29.15	29.18	26.61

Table 3.2: Group AMV Mean and Standard Deviations of the Bicep Femoris during Hip Extension Pre and Post Riding (uV) (elephant)

Statistic	Pre Lumbar (L)	Post Lumbar (L)	Pre Lumbar (R)	Post Lumbar (R)
Onset (mean)	31.38	26.50	27.85	26.61
Onset (SD)	17.31	10.34	10.18	7.11
Offset (mean)	19.21	19.44	22.12	26.77
Offset (SD)	4.97	5.27	5.84	2.28
Active (mean)	62.88	51.52	59.18	67.13
Active (SD)	40.69	18.26	20.64	14.44

Discussion

The long-term purpose of EMG study toward which this thesis is aimed is to understand the effect on muscle activity and coordination from a program of simulated riding therapy. To achieve this purpose, the objective of the EMG assessment in this study is to establish an appropriate EMG data processing methodology using healthy participants, and to begin a baseline data base for future comparison to a patient population. The targeted exercises studied in this assessment were designed to have fairly distinct intervals of sustained, held muscle activity, and of muscle rest, within the EMG signal. A key contribution of this study is an algorithm for identifying EMG signal values during those distinct activity periods. The algorithm proved capable of automatically segmenting the ON/OFF intervals for RMS and AMV calculations, which are common EMG outcome variables.

One hallmark of the algorithm proposed in this study is objective, automated segmentation of rest and held activity periods. Manual segmentation approaches, whether by observational timestamping during the exercise trials, or by visual inspection of the graphed data, is time-consuming, subjective, and prone to error and intermixing of distinct intervals. This is important because if the intervals contain a mix of rest, transition, or active EMG data values, the calculation of RMS and AMV will represent the interval activation level incorrectly. The proposed algorithm automatically looks for windows of data with a majority of frames either above or below a threshold value. As the window scans across the data set frame by frame, each frame is marked as being within a region of rest, or not. This first phase of automation targets rest periods strategically because: 1) rest periods occupy a larger part of each targeted exercise as compared to contractile periods, and 2) the amplitude range of a rest period is lower and more stable, with few spikes of higher amplitude data frames. These two characteristics make thresholding the rest periods more straightforward, and then assuming the contractile periods occur in the other segments of the data set. However, this first phase of automation depends on a proper selection for the threshold value.

Another hallmark of the algorithm is the refinement of the threshold value used to auto segment the data. Though somewhat reasonable threshold values may be obtained manually by observation of the resting EMG periods, a histogram approach may prove useful as an automated way to determine threshold values when processing many sets of data from many muscles, participants, and exercise trials. A histogram shows the distribution of voltages in bins from lowest voltage range to highest voltage range. A histogram will also report how common are values in each range (bin). The histogram approach assumes that there will be a high number of data frames with a resting value. Rest periods are lower and more stable in voltage, therefore, a histogram will be able to identify the range of voltages in which most rest period samples reside. Thus, the algorithm seeks a threshold value on the high end of the range of values containing this high number of frames. This approach is valuable because it opens the possibility for an objectively-determined, unique threshold value for each data set, attuned for variations in noise and amplitude across the different muscles, subjects, and activities. Future work on this algorithm could investigate effects of window sizes and bin numbers of the histogram on threshold accuracy.

The advantages of the algorithm of this study are the speed, versatility, and objectivity for processing EMG signals from basic, ON/OFF type exercises. Using this algorithm provides benefits over manual approaches, especially when many EMG data sets from multiple muscles, exercises, and participants need to be processed. Future steps to refine the algorithm are to further automate the threshold selection, and creating sensitivity measures so that even noisy signals can tell a story.

Finally, the algorithm provides for cropping of frames within suspected transition periods to focus on muscle activity during periods of held exercise. As mentioned, intermixing of EMG data values across distinct activity periods poses a problem of distorting the perceived muscle activation level. However, if the interval lengths are cropped by a set number of frames or by a percentage, the risk of computing RMS or AMV over intermixed values is reduced. Additionally, in this way the transitional activity periods can be segmented, namely the onset and offset periods, which may have value for analysis. These additional activity periods can provide insights on muscle coordination, firing patterns, and synchronization of rest periods, which can point to the goodness of integration of neuromuscular input during distinct, on/off type tasks.

The EMG data values observed in this study are consistent with other values reported in the literature. Kellis et al., 2017 reported biceps femoris EMG RMS values averaging 82.96 ± 35.56 uV, which compares well to the value of 80.24 ± 29.18 uV observed in this study [68]. Although the hip flexion angle, and the degree of eccentric contraction was not recorded in this thesis, the EMG values reported for this study fall close to the mean activity level, supporting the approach of the presented algorithm.

CHAPTER FOUR

EEG

What is EEG

Electroencephalography (EEG) is the study of the changes in electrical potential that occur due to the synchronous firing of large populations of neurons within the brain [69]. Electrical potentials are primarily produced by the movement of ions across the cell membrane. The direction of this movement is coordinated by the membrane potential [70].

EEG can be viewed as the graphical representation of changes in electrical potential generated by the brain in real time. However, the activity that an EEG records does not represent all neuronal activity, instead it represents pooled electrical activity [69]. In reality, the electrical potential produced by an individual neuron is small [69]. Moreover, the production of electrical potentials is found deep within the brain structures, so until large synchronized neuronal activity is initiated, an EEG will not be able to detect changes in brain activity. The resulting EEG recording is also dictated by the electrodes used to record the changing electrical potential. Once a detectable electrical potential is produced, the closest electrode to the recordable potential will measure it. Additionally, as these signals are quite small (measured in microvolts), these potentials are amplified via hardware as they are recorded. They also eliminate environmental noise by subtracting the electrical activity at each electrode from a point of reference for every time point, so that noise common to both points is removed [69]. This point of reference can be another electrode, or pair of electrodes, or the average of the signal at all electrodes.

The number of electrodes used to record an EEG signal can vary according to the electrode placement system used. For the purposes of this study the standardized international 10-20 system was used, and 19 electrodes were utilized [69]. Of the 19 electrodes used, there are six common anatomical locations, which include frontopolar (Fp), frontal (F), temporal (T), occipital (O), central (C), and parietal (P). Each of these abbreviations will also be concatenated with an odd or even number (e.g. Fp2, or F3) to identify if the electrode is placed on the left or right side of the brain, respectively [69]. Some types of electrodes used to record neuronal activity require the scalp to be cleaned with abrasive gel, so that the impedance produced by the outer layer of skin is minimized. Then, a conductive gel will be applied to ensure good contact and transfer of potential [71]. Although electrodes that use a conductive media are still considered a gold standard in EEG acquisition, the preparation is time-consuming [71] and messy, and alternate methods have been developed in recent years. Dry electrodes are one such method, which uses pins that can make direct contact with the scalp, and they generally require no skin preparation or conductive media. These types of electrodes are the medium in which EEG data was collected in this study.

Waveforms

The signal that an EEG sensor records is not a random signal, but one that has recognizable patterns and waveforms. Historically, one of the primary methods of EEG characterization has been to classify it according to its predominant frequencies or waves. Mathematically, this is often accomplished via methods such as the Fast Fourier

Transform (FFT), which approximates the EEG signal via sine waves, to quantify the amplitude of various EEG frequencies. The five basic types of brain waves are delta (0.5-4Hz), theta (4-8Hz), alpha (8-13Hz), and beta (13-30Hz) [70]. Each of these waves have a place of origin in the brain. Alpha waves are best observed in the posterior and occipital regions of the brain [70]. These waves are commonly seen when a subject is quietly resting with their eyes closed, and are indicative of a relaxed state [72]. In contrast to alpha wave origination, beta waves are commonly found in the frontal or central areas [73]. Beta waves are waves best observed during an alert and wakeful state with eyes open. Therefore, beta waves are the dominant waves in a focused mind. Unlike alpha and beta waves, theta waves are slower in frequency and indicative of drowsiness and deep meditation [74]. Theta waves can originate along the hippocampal region or the frontal midline [75]. Although fleeting theta waves during a sleepy or meditative state are not cause for concern, persistent theta waves during wakefulness is an abnormality and can be indicative of brain dysfunction [74]. The last type of wave is delta waves, which is found frontally in adults and posteriorly in children. These waves are common in infants and stages of deep sleep.

Visual Condition

As mentioned in the description of the four basic waveforms found in an EEG recording, alpha waves are prevalent while eyes are closed and are inhibited otherwise. Similarly, beta waves are dominant while eyes are open and are restricted otherwise. One of the first papers to cite the effect of a visual condition on the presence of alpha waves was published in the 1930s [76]. When subjects were exposed to light, researchers observed a patterned decrease in electrical activity in the occipital lobes. Moreover, researchers found that if the visual field was empty, the alpha waves, or Berger rhythm as coined in the study, was observable. However, if the visual field contained details, a subject could look at the details and the Berger rhythms disappeared [76].

The influence of a visual condition was further solidified when researchers added more complex eye conditions. Gale et al., 1971, tested five visual conditions: eyes closed, eyes closed in the dark, eyes observing a blank screen, eyes observing a pattern, and eyes viewing a complex pattern [77]. The results of this study showed that as the eyes were increasingly used, the amplitude of alpha waves decreased. On the other hand, as alpha waves decreased with visual stimulation, the amplitude of beta waves increased. Although alpha waves are indicative of a relaxed mind, peak alpha frequency (10-11Hz) has been shown to affect memory, emotional states, and cognitive preparedness [78]. The amplitude of peak alpha frequency is distinguishable between a healthy and patient population. A healthy population tends to have a higher peak alpha frequency, whereas a population that has sustained a traumatic brain injury (TBI), for example, has a lower peak alpha frequency [78]. Since these waves can be isolated by a visual condition, it is important to include varying levels of visual stimulation in the methodology in order to speak directly about the pre- and post-effects of hippotherapy in terms of alpha and beta waves.

Quantitative EEG

Analyzing EEG is a skill that requires understanding of the subject matter and hands-on experience, thus making the analysis process subjective and susceptible to human error. The development of quantitative EEG (qEEG) helped to automate EEG analysis and make the process more objective. qEEG is a diagnostic technique that applies mathematical methods to digitized EEG to evaluate dynamic cognitive brain function through quantitative metrics. While FFT and other methods can estimate raw amplitudes for various frequencies, the uniqueness of qEEG is its use of a normative database that can be used as a comparison within each individual. This database is large enough to use as a representative population, and direct comparisons can be made between samples or within individuals over time, because the normative database follows a Gaussian distribution. Therefore, by calculating the Z-score for EEG metrics of interest, aberrant values can be identified, which are commonly defined as Z-scores more extreme than plus or minus 2.

There are multiple normative databases available to use for comparison. The database used in this study is Neuroguide (Applied Neurosciences, Inc.), which contains 625 individuals that range in age from 2 months to 82 years old. Some of the important settings this database features are the ability to set the visual condition, either eyes open or eyes closed, in a resting state. The inclusion criteria for the database had multiple parameters for defining normal function, which include but are not limited to neuropsychological, neurological, school achievement, demographic and other factors [79]. The distribution of the database in terms of gender and ethnicity is males (58.9%), females (41.1%), whites (71.4%), blacks (24.2%), and oriental (3.2%) [79]. This database can be used in confidence for valid comparisons because it has been thoroughly cross-validated [80]. Comparisons made with this database will identify significant pre and post changes with regards to hippotherapy.

Importance of EEG Assessments

Surface EEG is a safe diagnostic technique that does not require foreign instruments to be introduced into the body [81]. The impedance and signal quality of an EEG may require time and preparation to account for, but EEG is a valid method in diagnosing dysfunction of the brain. A few examples of abnormal brain activity that an EEG can detect include cognitive engagement, localized damage to brain structures, and brain death [70].

Cognitive engagement can be defined as the capacity of an individual to take on a learning task, the amount of effort an individual can apply toward fulfilling the task, and for how long they can keep working on the task [82]. Other factors of cognitive engagement include an individual's interest in self-improvement via knowledge or skills and an individual's perception of their ability to complete the task successfully [83]. One way to report these trademarks of cognitive engagement are to get self-reported scores from the subject in regard to how difficult they thought the task was, and how long it took to finish the task [82, 83]. However, cognitive engagement can be reported objectively by observing the amplitude and presence of alpha and beta waves. In a study comparing a concentrated mental state versus an immersed mental state, alpha waves decreased for each state with respect to rest, while beta waves had varying levels of augmentation and reduction depending on the lobe [84]. With respect to sensitivity, the evidence suggests that EEG is capable of discerning between similar mental states.

EEG can also be used to identify damaged brain structures and states of alertness. Two trademarks of cerebral dysfunction include focal slowing and generalized slowing. Focal slowing is a result of focal lesions, which are injuries to the brain tissue after an injury. These types of injuries to brain tissue can negatively affect cognitive, lexical, and sensory abilities [85]. Focal lesions are apparent in EEG when the signals in the suspected area of injury have slower activity than an undamaged area. Causes of a focal lesion includes but is not limited to stroke, traumatic brain injury, and tumors [86]. Unlike focal slowing which is due to a specific event, generalized slowing can be due to drugs, underdevelopment of neural systems or infections. Where the slowing occurs depends on the spread of the cerebral pathology [86]. Some types of damage may not be permanent but a temporary state of lowered alertness, such as a subject in a coma. The irreversibility of a comatose state can be identified in an EEG signal by the lack of variability and the varying levels of reactivity in the signal. With respect to diagnosis, EEG can identify the general area or region of damage and the severity of the damage. However, due to spatial smearing, specific locations are not possible.

When the damage to brain tissue is too severe or pervasive that brain activity ends, EEG can be used as an indicator of brain death [87]. Specifically, brain death is defined as the permanent end of all central nervous system activity with no possibility of regaining those functions [87]. While it is not the entire criteria, when EEG signals are absent, brain death can be diagnosed [88]. Other EEG-criteria are present to ensure the diagnosis of brain death is accurate. Those criteria are as follows. The first supplementary criteria is that electrodes must be placed on all major brain regions to ensure that the absence of an EEG signal is not a localized effect, which may not be possible due to an injury [89]. Second, the impedance for each electrode should be matched. If not, artifacts could hide a low but potentially viable signal. Third, reactivity tests in the matter of somatosensory, visual, and auditory inputs should be conducted on the subject and distinguished between a viable cerebral signal versus a physiological signal that is not cerebral and artifacts that are not physiological [89]. Other uses of an EEG assessment include diagnosing sleep disorders, prescribing the correct amount of anesthesia, and receiving biofeedback [70].

Objective of EEG Assessment

Similar to the purposes of the other assessments in this study, the purpose of the EEG assessment is to establish a methodology. Having a written and clear methodology will help to provide a template for future studies, which may or may not modify aspects of the methodology, but will nonetheless provide a solid platform for valid comparisons. An encompassing objective across all assessments is to find evidence that identifies the mechanism of action behind hippotherapy. Although there are many studies that evaluate the brain after hippotherapy through self-reported scores, the current approach is important because it evaluates brain activity directly through an EEG signal. Therefore, this assessment can highlight waveform types and brain regions that are influenced by hippotherapy.

Outcome Variables

There are many ways to quantify EEG signals, but the four outcome variables that will be presented in the current results are absolute power, relative power, and the z-scores of the two. Absolute power is defined as the total energy density of a certain region, which is dictated by electrode location, and a range of frequencies. The output of absolute power is displayed across all channels and frequencies ranging from 1 to 50 Hz. Relative power is related to absolute power in that it is the percentage of the total power of the signal. The output of Z-scored absolute & relative power is displayed across all channels and frequencies ranging from 1 to 30 Hz. These metrics of interest will be represented in numerous ways. When presenting methods or results over frequency bands, absolute and relative power will be visually and numerically quantified. When presenting across individual frequencies, all the metrics will be represented graphically.

Methodology

All testing was completed at the Baylor BioMotion lab in the Baylor Research and Innovation Collaborative in Waco, Texas. The EEG headset (DSI-24; Wearable Sensing, Inc.) had 19 channels and did not need conductive media. The study was approved by the Baylor Internal Review Board and written consent was obtained from all six subjects (2 males, 4 females). The subjects ranged in age from 22 to 25 years (average was 23 ± 1.3 years of age) and body mass ranged from 55.4 to 106.6 kg (average was 69.7 ± 18.5 kg). However, only 4 subjects (1 male, 3 female) had viable data. All subjects were healthy, meaning that they had no disabilities that would prevent them from performing an EEG assessment. Three of the six subjects were familiar with the processing of placing and preparing an EEG headset. Figure 4.1 shows the EEG assessment's place in the overall methodology.

Figure 4.1: EEG Assessment Placement in Overall Methodology. Pre Conditions (EC, EO), Intervention Conditions (EO), Post Conditions (EC, EO)

The EEG assessment was completed after the balance and EMG assessment, and directly before and after the hippotherapy session. The methodology was designed as such so that the EEG signal recorded would reflect the effects of hippotherapy and not another external factor. Once subjects came in and were outfitted with EMG electrodes, they were also fitted with the EEG headset. If the subject had long hair tied in a ponytail, they were asked to remove it, so that the headset could be correctly placed. The hair was also moved out of the way of the sensors to obtain good contact. Electrode impedances were shown graphically through the DSI software. The contact of the electrodes was adjusted until the software showed acceptance of the electrode impedance.

The EEG assessment pre and post hippotherapy lasted 10 minutes each and was conducted while sitting on the mechanical horse. For the first 5 minutes, the subject was instructed to have their eyes open. For the second 5 minutes the subject was asked to close their eyes. During the ten minutes, the subject was asked to sit as still as possible and minimize any facial movement or eye movement as this would create artifacts in the data. In order to keep the subjects focused but relaxed on the task during the eyes open period, the subject was instructed to keep their gaze on a colored sheet on the wall in front of them. Since the riding session had the subjects riding with eyes open, the EEG assessment post riding had the subject start with eyes closed for the first 5 minutes and then eyes open for the latter 5 minutes. The subject was informed of the passage of time every few minutes to ease any restlessness. After the post EEG assessment, the subject completed post balance and EMG assessments and the headset was taken off.

EEG Processing

The initial step in EEG processing was to re-reference the raw signal from a Pz reference to a linked ears reference using Neuroguide. Because the EEG data was recorded continuously throughout the assessment session, the second step was to separate out the pre-ride and post-ride data, and the eyes open and eyes closed data, into unique files. The third step was the removal of artifacts. Artifacts arise in an EEG signal in the form of eye, facial, and jaw movements, and other physiological artifacts. To convert the raw EEG signal into EEG metrics, Neuroguide was used to separate good data from artifacts. Using the automatic detection feature, at least ten seconds of artifact-free data was manually selected and used as a template for Neuroguide to detect additional artifact-free data in the rest of the EEG recording. Once >30 seconds of good data was selected, qEEG comparisons with the normative database were generated. A sampling of such data is shown in Figure 4.2.

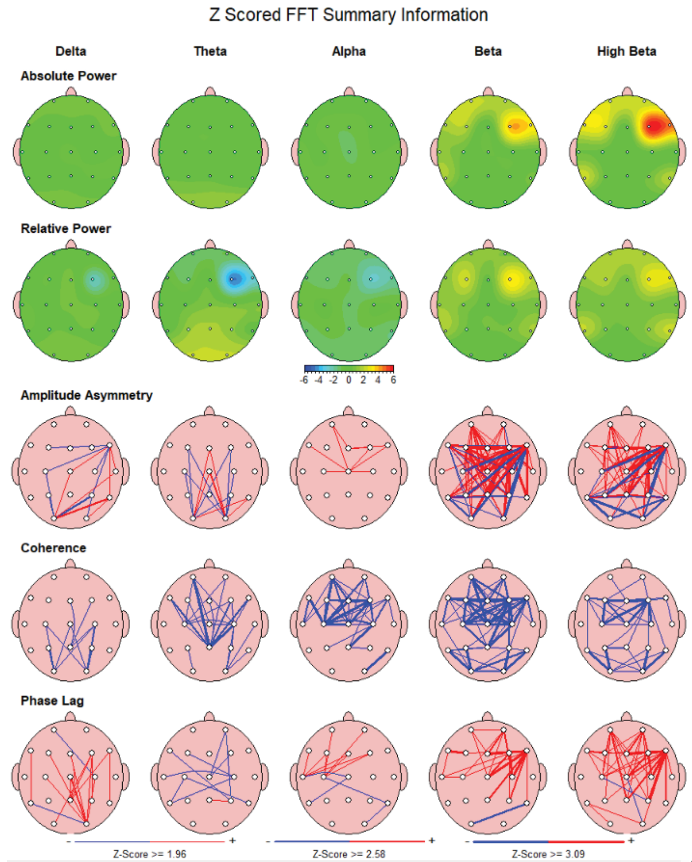

Figure 4.2: Example of a qEEG report for One Subject

Aberrance

Although qEEG allows comparisons to be made for each individual, quantifying the significance of changes across conditions requires additional analysis. Krigbaum and Wigton et al, 2015 present a method to quantify significance of changes from qEEG. Their method describes the variable sites-of-interest (SoI) as an electrode site (i.e. channel) at any one of the major frequency bands when it has a Z-score greater than or equal to one, or less than or equal to negative one. If the SoI exceeds this threshold, the SoI is considered aberrant. The SoIs that meet the Z-score threshold are summed and averaged by channel or frequency for the EEG metric of interest [90]. In this study, the metrics chosen were absolute and relative power. As described in the method above, the raw values (normalized by the software) from the absolute power and relative power were averaged across all channels per major frequency band for pre- and post-riding data. For each metric at each frequency band, pre-riding values were subtracted from post-riding values. If the difference was greater than zero, it would be counted as an improvement. Next, the mean pre-riding values for each metric were compared to the aberrant threshold. In this study, aberrance was set to the absolute value of the Z-score greater than 2, which corresponds to a level of significance just less than 0.05. We chose the threshold of $Z > 2$ (rather than $Z > 1$, as in Krigbaum and Wigton et al., 2015) as this is a more standard definition of aberrance. Since this study is based on a therapeutic intervention, whether or not aberrance pre-intervention is meaningfully improved or resolved by the post-intervention measurement is a factor to document. Values are considered meaningful improvements when there is improvement from pre- to post-intervention (e.g. a lower Z-score) and pre-intervention values were aberrant. The final statistic calculated was the number of resolved values. A value is resolved if aberrant pre-values become non-aberrant post-values.

Frequencies can be categorized into common bands, but also can be looked at individually. The processing methods described above, such as the qEEG output and aberrant metrics, were calculated on frequency bands. In order to identify which frequencies and brain regions are affected by hippotherapy, the rest of the analysis will describe individual frequencies.

Results

In Figure 4.3 the top row shows absolute power according to the frequency band of major wave types, and the bottom row shows the same for relative power. The data is visualized through topographic scalp maps, where each of the colors used indicates a level of significance. Comparing the top row, which represents a subject pre-riding eyes closed, with the bottom row, which represents the same subject post-riding eyes closed, an immediate visual change in each of the scalp maps can be seen. In order to quantify the changes from pre to post riding, the number of aberrant and resolved values are represented in Tables 4.1 and 4.2. From the tables below, large changes in the number of aberrant values to the number of resolved metrics can be observed for absolute power in eyes open and in eyes closed. However, these values represent the number of changes across all frequencies. In order to identify which frequencies and brain regions are affected by hippotherapy, individual frequency analysis will take precedent.

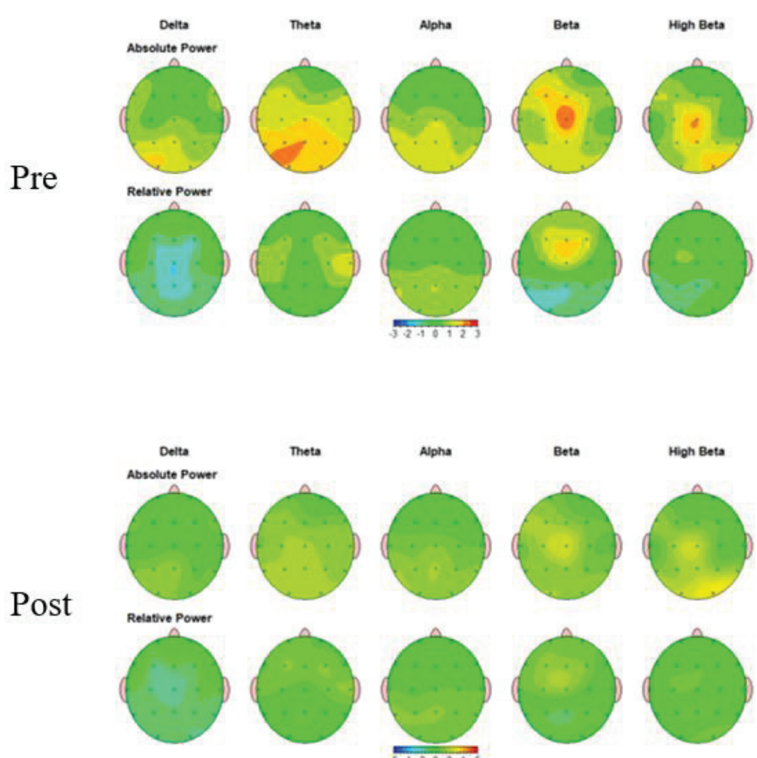

Figure 4.3: Pre versus Post qEEG Data for One Subject

Table 4.1: Quantifying the Number of Resolved Metrics for Absolute Power, Eyes Closed

Statistic	Aberrant	Meaningful Improvements	Resolved
Subject 1	47	32	17
Subject 2	9	9	9
Subject 3	29	13	11
Subject 4	5	5	4

Table 4.2: Quantifying the Number of Resolved Metrics for Absolute Power, Eyes Open

Statistic	Aberrant	Meaningful Improvements	Resolved
Subject 1	137	111	45
Subject 2	60	14	4
Subject 3	36	27	22
Subject 4	2	1	1

The following Figure 4.4 graphs all channels over frequency for absolute power for one subject. Each channel is represented by a colored line. The plots in column one show the EEG data for eyes closed pre-riding, post-riding, and the subtraction of the two. The second column shows a similar configuration for eyes open. The third column shows the subtraction of the data at the two visual conditions during pre- and post-riding. The plot in the last row of the last column represents a summary plot that represents the difference from eyes closed to eyes open, from post to pre. The importance of the summary plot is that it represents the overall changes due to the riding intervention.

Figure 4.5 shows the repetition of the summary plot to identify changes due to riding for all subjects and all metrics. A feature that can be seen across most subjects of the raw absolute and relative power metrics is a change in the alpha frequency band when eyes are closed. Figures 4.6 to 4.9, for each subject, shows the pre, post, and the of the two of eyes closed from eyes open. A shift, not only in amplitude but also frequency is observed in every subject from pre- to post-intervention. Figure 4.10 is the average of the data represented in Figures 4.6 to 4.9. The shift in alpha peak frequency is sustained.

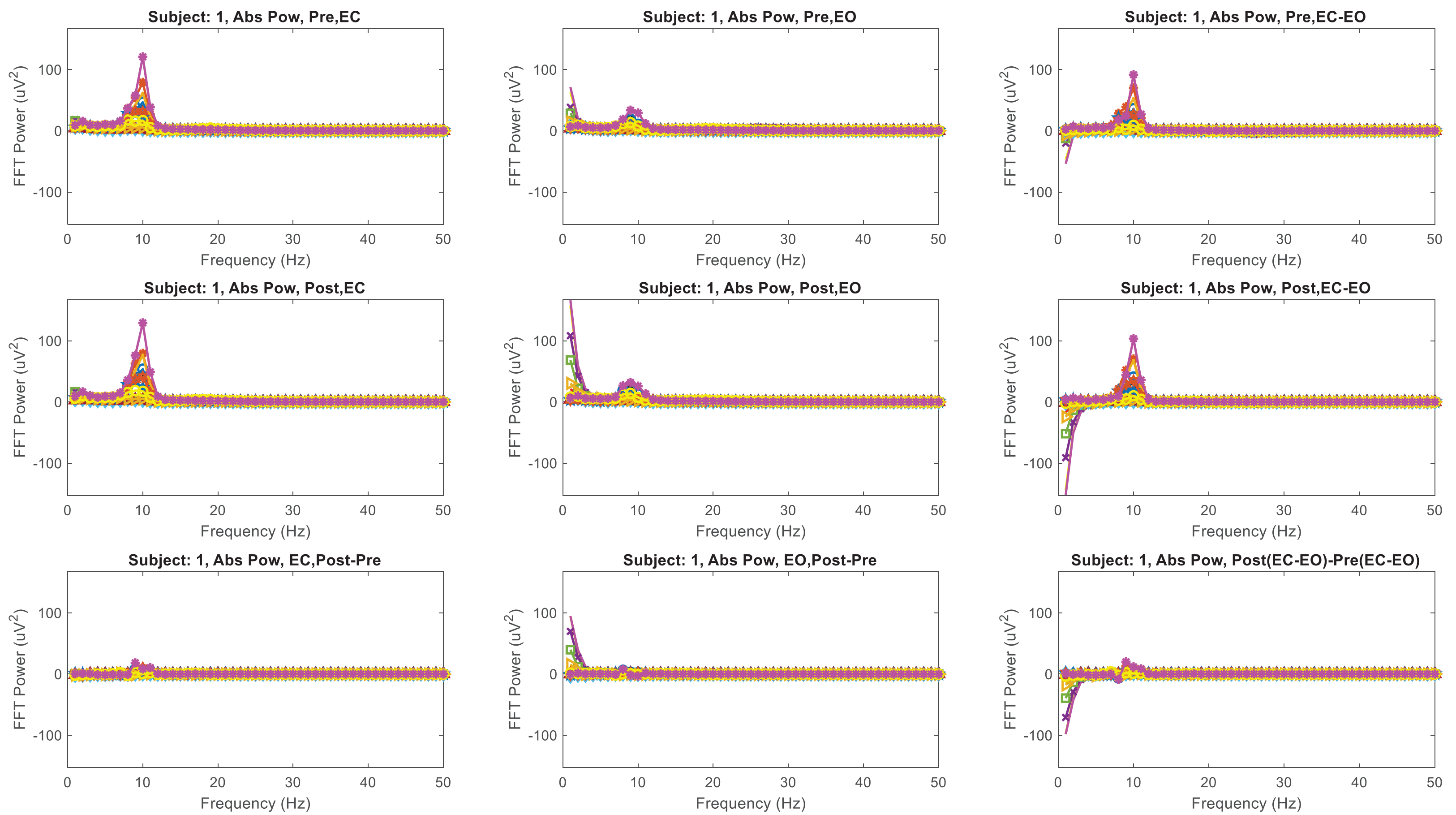

Figure 4.4: Individual Channels plotted over Frequency for Absolute Power for One Subject

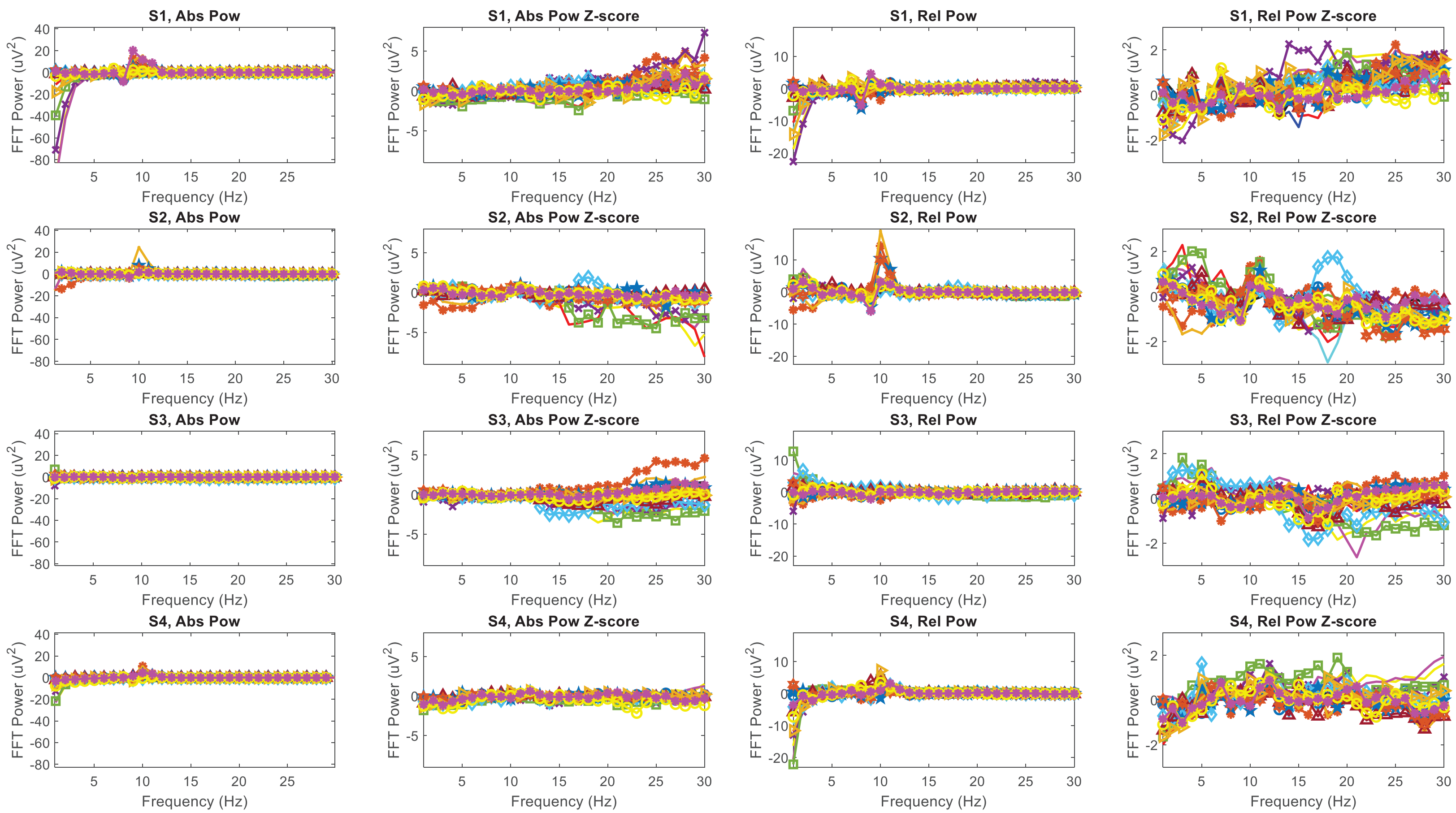

Figure 4.5: Changes due to Hippotherapy for Each Subject and Each Metri

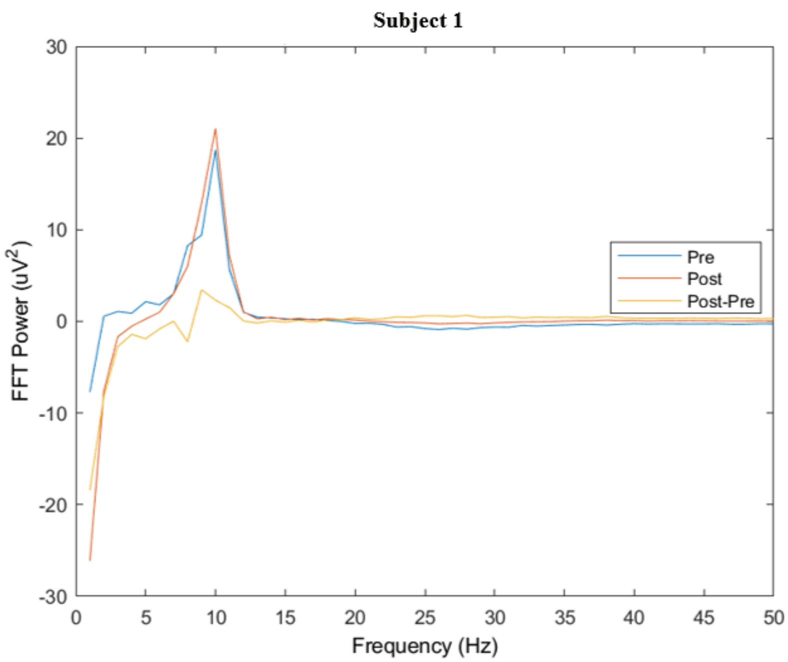

Figure 4.6: Subject One, EC versus EO at Each Timepoint

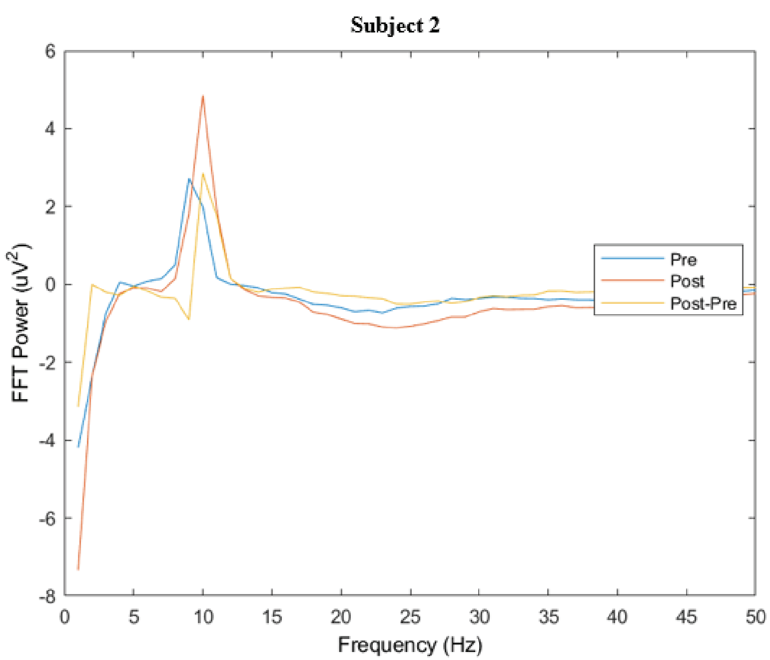

Figure 4.7: Subject Two, EC versus EO at Each Timepoint

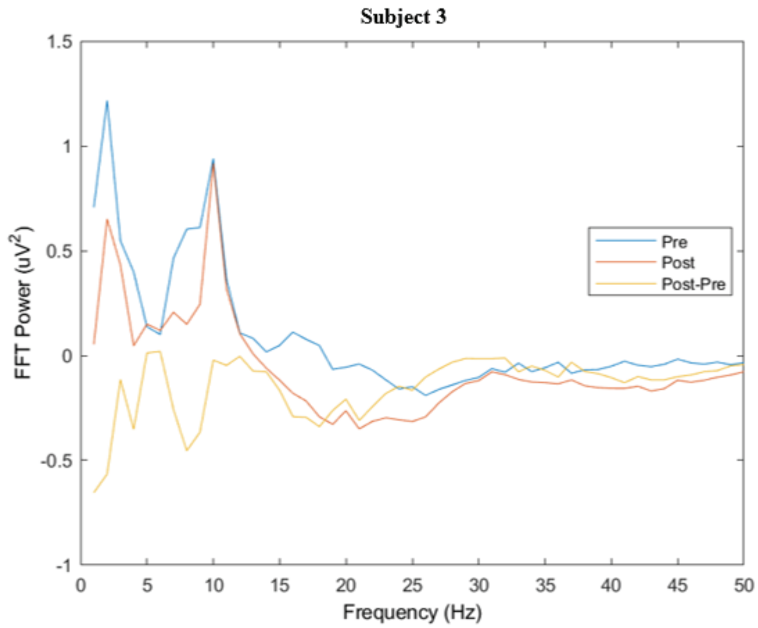

Figure 4.8: Subject Three, EC versus EO at Each Timepoint

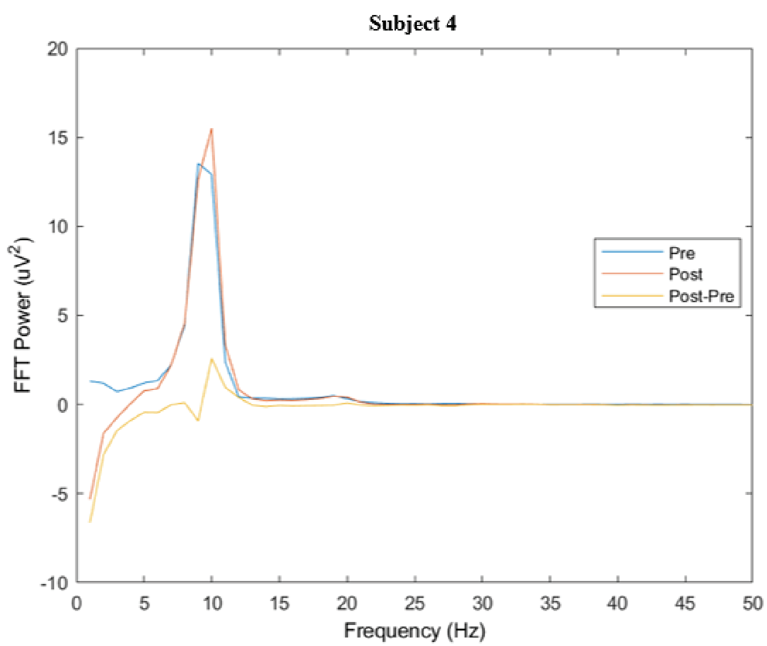

Figure 4.9: Subject Four, EC versus EO at Each Timepoint

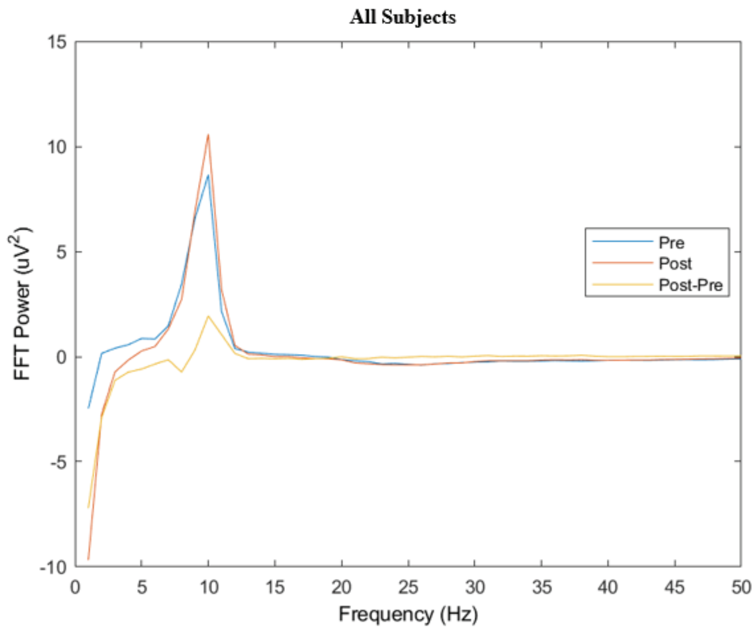

Figure 4.10: Group Data Showing the Mean of All Channels, EC vs EO at Each Timepoint

Discussion

In this study EEG data was measured and analyzed from four human volunteers during rest periods with eyes opened and eyes closed, immediately before and immediately after a 15-minute session of riding on the mechanical horse, MiraColt. The EEG data was first analyzed through the normative database, provided by Neuroguide. Topographic scalp maps showed clear changes from pre- to post- riding. To understand those changes, aberrant metrics were calculated at a significance level ($Z > 2$). Results of aberrance analyses showed many resolved metrics, which were abnormal prior to intervention and within normal range afterward. To precisely characterize these changes, we analyzed individual frequencies, in addition to effects seen in broad frequency bands . By calculating summary plots that showed the frequency-specific differences between eyes closed and eyes open, from pre to post, shifts in alpha amplitude and/or peak frequency were observed across all participants after riding.

In interpreting these shifts in the alpha peak after riding, there are many findings in the literature to draw from. Alpha waves are commonly most prominent when a subject is quietly resting with their eyes closed, and are indicative of a relaxed, or idle, state of mind [72,91]. Alpha waves are also associated with cognitive preparedness and memory [78]. Further, a decrease in alpha wave magnitudes tends to occur when the eyes are open, and when the eyes are engaged with a task [77]. Higher alpha peak frequency is associated more with healthy individuals, whereas lower peak alpha frequency is associated more in clinical cases [78].

The shift in alpha peak frequency and amplitude observed in this study between the pre-riding assessment and the post-riding assessment is considered a positive effect, because of the association of higher alpha peak frequency with greater health. It is theorized that the riding intervention may have helped the participants move toward a state of cognitive preparedness and familiarity with the riding motion, and with the assessments. This shift being observed in a healthy pool of volunteers is notable. In a patient population an increase in alpha peak frequency may be even more prominent and help lead to improved functional outcomes in other areas.

To our knowledge, this is the first study to incorporate EEG as a pre- and post-assessment on the effects of equine riding motion either by live horse or mechanical horse simulation. Also, this study is unique in its combined overall inclusion of varied assessment mechanisms including balance data, EMG data, and EEG data, which will facilitate future cross-correlation of the effects of riding on these metrics. Future progression of the work of this study should include analysis of additional physiological measures of arousal (cardiac, skin conductance, etc.), as well as analysis of data collected during the riding periods of hippotherapy sessions.

CHAPTER FIVE

Conclusion

The objective of this study was to investigate how to study the effects of hippotherapy on the body, which was completed through three different types of assessments: balance, muscular activity, and brain activity. Six individuals were used in the combined three-prong assessment. Additionally, twelve subjects were recruited for an exploratory balance-specific study to investigate the potential presence of a learning effect or delayed reaction from the therapeutic riding intervention.

The results of the first balance assessment (n=6) and the second balance assessment (n=12) were compared across several common balance parameters. An interesting finding was the changes in FTEO versus TEO from pre-intervention to post-intervention from the first to the second balance assessment. While only one balance parameter changed for FTEO in the first and second balance assessments, total excursion and mean velocity, respectively, TEO saw improvement in mean velocity to improvement in all balance parameters across the balance assessments. Additionally, all balance parameters of the TEC condition improved from pre-intervention to post-intervention. Evidence can suggest that cognitive engagement may be the source of improvement. Cognitive engagement can be defined as the amount of which an individual is able to take on a learning task, the amount of effort an individual puts into fulfilling the task, and for how long they keep working on the task [82]. Standing with your feet together with your eyes open is not rigorous or engaging. However, standing in an unnatural position, like tandem stance, requires more effort from the subject. The harder conditions (TEO, TEC, FTEC) in the second balance assessment showed more improvement than the easiest condition, FTEO. The hypothesis that cognitive engagement in terms of effort was a factor in this study may be corroborated by the EEG assessment results. The results of the EEG assessment uncovered a higher shift in alpha peak and in alpha frequency following the riding intervention. An increase in alpha peak frequency has been connected to cognitive preparedness [78] which may suggest that simulated hippotherapy drove neural activity.

The work presented in this thesis is unique in that multiple assessments were combined to quantify the physiologic and neural responses to a novel therapeutic riding device. This work details the methodology evolution that took place during the course of this pilot study to ensure that usable outcome values can be obtained for future clinical trials. The methodology evolution involved the refinement of processing techniques. The first balance assessment compared multiple ellipse-fit methods for best fit. A literature-based ellipse-fit method was established and validated mathematically and was then used to report the area of the ellipse for all conditions. The result of the EMG assessment produced an automated task segmentation algorithm that can capture activity periods by marking rest periods. The key feature of this algorithm is the threshold value that is extracted through a histogram of common voltages found in the signal. The algorithm has been able to produce common outcome variables found in the literature, underscoring the effort made to create a unique code. Additionally, normative data for a healthy population was obtained and described and can be used as the start of a comparison control group moving forward. Although the sample size is small in the combined assessment, the results validate the methodology to incorporate into future studies, namely a patient population with autism.

In an autistic population trends that exist pre-assessment, post-assessment, and across the two are theorized to be different, when compared to a typically developing population. The results provided from an autistic population will give clearer insight into the underlying mechanism of action of hippotherapy through its dysfunction. However, careful thought needs to be given when choosing the assessments to be tested.

In the balance assessment of this study, the number of conditions were refined to be applicable to both populations. When conducting a balance assessment, quiet standing conditions feet together and tandem stance with both visual conditions will be sufficient for representing changes in balance due to hippotherapy. The other conditions tested, such as semi-tandem and single leg stances, are good variations of basic stances. However, time and efficiency are important in any study, but more so when working with a sensitive population.

In the EMG portion of the study, the number of exercises may be refined to one or two targeted exercises. One exercise that consistently gave clean data is prone hip extension. This exercise activates many muscles (lumbar, glutes, biceps femoris) and can easily be converted, by addition of a flexion angle, to target specific muscles. A simple pilot study using a similar format of the second balance study for the EMG assessment may reveal more about muscular activity before and after riding and can refine the number of exercises in a research-oriented mindset.

In the EEG portion of the study, more thought must be given to the methodology when working with an autistic population. To collect EEG data, a subject is required to sit still for ten minutes before and after a riding session. Steps should be taken to engage the subjects during the recording, but in a way that minimizes the effects on brain waves, such as the attention-sensitive alpha waves.

BIBLIOGRAPHY

[1] “7 Great Reasons Why Exercise Matters,” from https://www.mayoclinic.org/healthy-lifestyle/fitness/in-depth/exercise/art-20048389.

[2] Govender (nee’ Naidoo), P., Barlow, C., and Ballim, S., 2016, “Hippotherapy in Occupational Therapy Practice,” South African Journal of Occupational Therapy, **46**, pp. 31–36.

[3] Ajzenman, H. F., Standeven, J. W., and Shurtleff, T. L., 2013, “Effect of Hippotherapy on Motor Control, Adaptive Behaviors, and Participation in Children With Autism Spectrum Disorder: A Pilot Study,” American Journal of Occupational Therapy, **67**(6), pp. 653–663.

[4] Bass, M. M., Duchowny, C. A., and Llabre, M. M., 2009, “The Effect of Therapeutic Horseback Riding on Social Functioning in Children with Autism,” J Autism Dev Disord, **39**(9), pp. 1261–1267.

[5] Taylor, R. R., Kielhofner, G., Smith, C., Butler, S., Cahill, S. M., Ciukaj, M. D., and Gehman, M., 2009, “Volitional Change in Children With Autism: A Single-Case Design Study of the Impact of Hippotherapy on Motivation,” Occupational Therapy in Mental Health, **25**(2), pp. 192–200.

[6] Sterba, J. A., Rogers, B. T., France, A. P., and Vokes, D. A., 2002, “Horseback Riding in Children with Cerebral Palsy: Effect on Gross Motor Function,” Developmental Medicine & Child Neurology, **44**(5), pp. 301–308.

[7] Garner, B. A., and Rigby, B. R., 2015, “Human Pelvis Motions When Walking and When Riding a Therapeutic Horse,” Human Movement Science, **39**, pp. 121–137.

[8] Wuang, Y.-P., Wang, C.-C., Huang, M.-H., and Su, C.-Y., 2010, “The Effectiveness of Simulated Developmental Horse-Riding Program in Children With Autism,” Adapted Physical Activity Quarterly, **27**(2), pp. 113–126.

[9] Choi, H.-J., Kim, K.-J., and Nam, K.-W., 2014, “The Effects of a Horseback Riding Simulation Exercise on the Spinal Alignment of Children with Cerebral Palsy,” J Kor Soc Phys Ther, **26**(3), pp. 209–215.

[10] Palmieri, R. M., Ingersoll, C. D., Stone, M. B., and Krause, B. A., 2002, “Center-of-Pressure Parameters Used in the Assessment of Postural Control,” Journal of Sport Rehabilitation, **11**(1), pp. 51–66.

[11] Palmieri, R. M., Ingersoll, C. D., Stone, M. B., and Krause, B. A., 2002, “Center-of-Pressure Parameters Used in the Assessment of Postural Control,” Journal of Sport Rehabilitation, **11**(1), pp. 51–66.

[12] Pollock, A. S., Durward, B. R., Rowe, P. J., and Paul, J. P., 2000, “What Is Balance?,” Clin Rehabil, **14**(4), pp. 402–406.

[13] Mancini, M., and Horak, F. B., 2010, “The Relevance of Clinical Balance Assessment Tools to Differentiate Balance Deficits,” Eur J Phys Rehabil Med, **46**(2), pp. 239–248.

[14] Chiba, R., Takakusaki, K., Ota, J., Yozu, A., and Haga, N., 2016, “Human Upright Posture Control Models Based on Multisensory Inputs; in Fast and Slow Dynamics,” Neuroscience Research, **104**, pp. 96–104.

[15] Prevention, I. of M. (US) D. of H. P. and D., Berg, R. L., and Cassells, J. S., 1992, *Falls in Older Persons: Risk Factors and Prevention*, National Academies Press (US).

[16] Collins B, and Miller L.J., 2012, “Sensory Based Motor Disorder: Postural Disorder,” from https://www.spdstar.org/sites/default/files/publications/3.%20Jul.-Aug.%202012%20-%20SBMD%2C%20PD_0.pdf.

[17] 2015, “Falls Prevention Facts,” from https://www.ncoa.org/news/resources-for-reporters/get-the-facts/falls-prevention-facts/.

[18] Dillon, C. F., Gu, Q., Hoffman, H. J., and Ko, C.-W., 2010, “Vision, Hearing, Balance, and Sensory Impairment in Americans Aged 70 Years and Over: United States, 1999-2006: (665372010-001).”

[19] Tinetti, M. E., Williams, T. F., and Mayewski, R., 1986, “Fall Risk Index for Elderly Patients Based on Number of Chronic Disabilities,” Am. J. Med., **80**(3), pp. 429–434.

[20] “Tinetti Test,” from https://www.physio-pedia.com/Tinetti_Test#cite_note-1.

[21] Horak, F. B., Wrisley, D. M., and Frank, J., 2009, “The Balance Evaluation Systems Test (BESTest) to Differentiate Balance Deficits,” Phys Ther, **89**(5), pp. 484–498.

[22] Ruhe, A., Fejer, R., and Walker, B., 2011, “Center of Pressure Excursion as a Measure of Balance Performance in Patients with Non-Specific Low Back Pain Compared to Healthy Controls: A Systematic Review of the Literature,” Eur Spine J, **20**(3), pp. 358–368.

[23] Mettler, A., Chinn, L., Saliba, S. A., McKeon, P. O., and Hertel, J., 2015, “Balance Training and Center-of-Pressure Location in Participants With Chronic Ankle Instability,” J Athl Train, **50**(4), pp. 343–349.

[24] Smart, L. J., Stoffregen, T. A., and Bardy, B. G., 2002, "Visually Induced Motion Sickness Predicted by Postural Instability," Hum Factors, **44**(3), pp. 451–465.

[25] "Autism Spectrum Disorder - Symptoms and Causes," from, https://www.mayoclinic.org/diseases-conditions/autism-spectrum-disorder/symptoms-causes/syc-20352928. [Accessed: 19-Jul-2020].

[26] Fournier, K. A., Kimberg, C. I., Radonovich, K. J., Tillman, M. D., Chow, J. W., Lewis, M. H., Bodfish, J. W., and Hass, C. J., 2010, "Decreased Static and Dynamic Postural Control in Children with Autism Spectrum Disorders," Gait & Posture, **32**(1), pp. 6–9.

[27] Memari, A. H., Ghanouni, P., Gharibzadeh, S., Eghlidi, J., Ziaee, V., and Moshayedi, P., 2013, "Postural Sway Patterns in Children with Autism Spectrum Disorder Compared with Typically Developing Children," Research in Autism Spectrum Disorders, **7**(2), pp. 325–332.

[28] Chang, C.-H., Wade, M. G., Stoffregen, T. A., Hsu, C.-Y., and Pan, C.-Y., 2010, "Visual Tasks and Postural Sway in Children with and without Autism Spectrum Disorders," Research in Developmental Disabilities, **31**(6), pp. 1536–1542.

[29] Molloy, C. A., Dietrich, K. N., and Bhattacharya, A., 2003, "Postural Stability in Children with Autism Spectrum Disorder," J Autism Dev Disord, **33**(6), pp. 643–652.

[30] 2013, "Cerebral Palsy: Hope Through Research." NIH Publication No. 13-159, from https://www.ninds.nih.gov/Disorders/Patient-Caregiver-Education/Hope-Through-Research/Cerebral-Palsy-Hope-Through-Research.

[31] Pollock, A. S., Durward, B. R., Rowe, P. J., and Paul, J. P., 2000, "What Is Balance?," Clin Rehabil, **14**(4), pp. 402–406.

[32] Shumway-Cook, A., Hutchinson, S., Kartin, D., Msme, R. P., and Woollacott, M., 2003, "Effect of Balance Training on Recovery of Stability in Children with Cerebral Palsy," Developmental Medicine & Child Neurology, **45**(9), pp. 591–602.

[33] El-Shamy, S. M., and Kafy, E. M. A. E., 2014, "Effect of Balance Training on Postural Balance Control and Risk of Fall in Children with Diplegic Cerebral Palsy," Disability and Rehabilitation, **36**(14), pp. 1176–1183.

[34] Martín-Valero, R., Vega-Ballón, J., and Perez-Cabezas, V., 2018, "Benefits of Hippotherapy in Children with Cerebral Palsy: A Narrative Review," Eur. J. Paediatr. Neurol., **22**(6), pp. 1150–1160.

[35] Le Clair, K., and Riach, C., 1996, "Postural Stability Measures: What to Measure and for How Long," Clinical Biomechanics, **11**(3), pp. 176–178.

[36] Lin, D., Seol, H., Nussbaum, M., and Madigan, M., 2008, “Reliability of COP-Based Postural Sway Measures and Age-Related Differences,” Gait & posture, **28**, pp. 337–42.

[37] Frzovic, D., Morris, M. E., and Vowels, L., 2000, “Clinical Tests of Standing Balance: Performance of Persons with Multiple Sclerosis,” Archives of Physical Medicine and Rehabilitation, **81**(2), pp. 215–221.

[38] Springer, B. A., Marin, R., Cyhan, T., Roberts, H., and Gill, N. W., 2007, “Normative Values for the Unipedal Stance Test with Eyes Open and Closed:,” Journal of Geriatric Physical Therapy, **30**(1), pp. 8–15.

[39] Radonovich, K. J., Fournier, K. A., and Hass, C. J., 2013, “Relationship between Postural Control and Restricted, Repetitive Behaviors in Autism Spectrum Disorders,” Front Integr Neurosci, **7**.

[40] Ferdjallah, M., Harris, G. F., Smith, P., and Wertsch, J. J., 2002, “Analysis of Postural Control Synergies during Quiet Standing in Healthy Children and Children with Cerebral Palsy,” Clinical Biomechanics, **17**(3), pp. 203–210.

[41] Prieto, T., Myklebust, J., Hoffmann, R., Lovett, E., and Myklebust, B., 1996, “Measures of Postural Steadiness: Differences Between Healthy Young and Elderly Adults,” IEEE transactions on bio-medical engineering, **43**, pp. 956–66.

[42] Bauer, C., Gröger, I., Rupprecht, R., and Gaßmann, K. G., 2008, “Intrasession Reliability of Force Platform Parameters in Community-Dwelling Older Adults,” Archives of Physical Medicine and Rehabilitation, **89**(10), pp. 1977–1982.

[43] Moghadam, M., Ashayeri, H., Salavati, M., Sarafzadeh, J., Taghipoor, K. D., Saeedi, A., and Salehi, R., 2011, “Reliability of Center of Pressure Measures of Postural Stability in Healthy Older Adults: Effects of Postural Task Difficulty and Cognitive Load,” Gait Posture, **33**(4), pp. 651–655.

[44] Doyle, R., Hsiao-Wecksler, E., Ragan, B., and Rosengren, K., 2007, “Generalizability of Center of Pressure Measures of Quiet Standing,” Gait & posture, **25**, pp. 166–71.

[45] Gal O., 2020, “Fit_ellipse.” from https://www.mathworks.com/matlabcentral/fileexchange/3215-fit_ellipse), MATLAB Central File.

[46] Narayan R., 2020, ‘Ellipseselect.” from https://www.mathworks.com/matlabcentral/fileexchange/12569-ellipseselect.

[47] Chernov N., 2020, “Ellipse Fit (Direct method).” from https://www.mathworks.com/matlabcentral/fileexchange/22684-ellipse-fit-direct-method.

[48] Fitzgibbon, A. W., Pilu, M., and Fisher, R. B., 1996, “Direct Least Squares Fitting of Ellipses,” *Proceedings of 13th International Conference on Pattern Recognition*, IEEE, Vienna, Austria, pp. 253–257 vol.1.

[49] Schwarz, D., “Confellipse.”

[50] Gander, W., Golub, G. H., and Strebel, R., 1994, “Least-Squares Fitting of Circles and Ellipses,” BIT, **34**(4), pp. 558–578.

[51] Nichols-Larsen, D., Glenn, T., and Hutchinson, K., 1995, “Changes in the Mean Center of Balance During Balance Testing in Young Adults,” Physical therapy, **75**, pp. 699–706.

[52] Czaprowski, D.,Stoliński, Ł., Tyrakowski, M., Kozinoga, M., and Kotwicki, T., 2018, “Non-Structural Misalignments of Body Posture in the Sagittal Plane,” Scoliosis Spinal Disord, **13**.

[53] “Sway Back Posture,” from https://www.physiopedia.com/Sway_Back_Posture.

[54] Ivanenko, Y., and Gurfinkel, V. S., 2018, “Human Postural Control,” Front. Neurosci., **12**.

[55] 2018, “9.3D:Muscle Tone.” From, https://med.libretexts.org/Bookshelves/Anatomy_and_Physiology/Book%3A_Anatomy_and_Physiology_(Boundless)/9%3A_Muscular_System/9.3%3A_Control_of_Muscle_Tension/9.3D%3A_Muscle_Tone.

[56] “Related Conditions,” from https://www.autism-society.org/what-is/diagnosis/related-conditions/.

[57] Wilson, R. B.,McCracken, J. T., Rinehart, N. J., and Jeste, S. S., 2018, “What’s Missing inAutism Spectrum Disorder Motor Assessments?,” J Neurodevelop Disord, **10**(1),p. 33.

[58] Alliance, C.P., “Spastic Cerebral Palsy,” from https://cerebralpalsy.org.au/our-research/about-cerebral-palsy/what-is-cerebral-palsy/types-of-cerebral-palsy/spastic-cerebral-palsy/.

[59] Andrew Caws, 2018, “6 STRATEGIES TO COMBAT LOW MUSCLE TONE IN AUTISTIC CHILDREN,” from http://www.sensorydirect.com/2018/09/6-strategies-to-combat-low-muscle-tone-in-autistic-children/.

[60] Moraes, A. G.,Copetti, F., Angelo, V. R., Chiavoloni, L. L., and David, A. C., 2016, “The Effects of Hippotherapy on Postural Balance and Functional Ability in Children with Cerebral Palsy,” J Phys Ther Sci, **28**(8), pp. 2220–2226.

[61] Kim, M. J., Kim,T., Oh, S., and Yoon, B., 2018, "Equine Exercise in Younger and Older Adults: Simulated Versus Real Horseback Riding," Percept Mot Skills, **125**(1), pp. 93–108.

[62] Halaki, M., and Ginn, K., 2012, "Normalization of EMG Signals: To Normalize or Not to Normalize and What to Normalize To?," Computational Intelligence in Electromyography Analysis - A Perspective on Current Applications and Future Challenges.

[63] Elzanie, A., and Borger, J., 2020, "Anatomy, Bony Pelvis and Lower Limb, Gluteus Maximus Muscle," *StatPearls*, StatPearls Publishing, Treasure Island, FL.

[64] Vaughn, J. E., and Cohen-Levy, W. B., 2020, "Anatomy, Bony Pelvis and Lower Limb, Posterior Thigh Muscles," *StatPearls*, StatPearls Publishing, Treasure Island, FL.

[65] De Luca, C. J., 1997, "The Use of Surface Electromyography in Biomechanics," Journal of Applied Biomechanics, **13**(2), pp. 135–163.

[66] Asghari Oskoei,M., and Hu, H., 2007, "Myoelectric Control Systems—A Survey," Biomedical Signal Processing and Control, **2**(4), pp. 275–294.

[67] Konrad, P., 2006, *The ABC of EMG: A Practical Introduction to Kinesiological Electromyography*, Noraxon USA, Inc.

[68] Kellis, E., Galanis, N., Kofotolis, N., and Hatzi, A., 2017, "Effects of Hip Flexion Angle on Surface Electromyographic Activity of the Biceps Femoris and Semitendinosus during Isokinetic Knee Flexion," Muscles Ligaments Tendons J, **7**(2), pp. 286–292.

[69] IV, W. O. T., 2014, *Handbook of EEG Interpretation, Second Edition*, Demos Medical Publishing.

[70] Teplan, M., 2002, "FUNDAMENTALS OF EEG MEASUREMENT," MEASUREMENT SCIENCE REVIEW, **2**, p. 11.

[71] Lopez-Gordo, M.A., Sanchez-Morillo, D., and Valle, F. P., 2014, "Dry EEG Electrodes," Sensors(Basel), **14**(7), pp. 12847–12870.

[72] Kirstein, C., 2007, "Sleeping and Dreaming," *XPharm: The Comprehensive Pharmacology Reference*, S.J. Enna, and D.B. Bylund, eds., Elsevier, New York, pp. 1–4.

[73] Kropotov, Juri D., 2007, *Beta Rhythms, 1st ed.*, Clinical Neurology for Psychiatrists, London, UK, Chap. 3.

[74] Louis, E. K. S., Frey, L. C., Britton, J. W., Frey, L.C., Hopp, J. L., Korb, P., Koubeissi, M. Z., Lievens, W. E., Pestana-Knight, E.M., and Louis, E. K. S., 2016, *TheNormal EEG*, American Epilepsy Society.

[75] "Understanding brain waves," from http://neurofeedbackalliance.org/understanding-brain-waves/.

[76] Adrian, E. D., "THE BEBGER RHYTHM : POTENTIAL CHANGES FROM THE OCCIPITAL LOBES IN MAN.," p. 31.

[77] Gale, A., Dunkin, N., and Coles, M., 1969, "Variation in Visual Input and the Occipital EEG," Psychon Sci, **14**(6), pp. 262–263.

[78] Angelakis, E., Lubar, J., Stathopoulou, S., and Kounios,J., 2004, "Peak Alpha Frequency: An Electroencephalographic Measure of Cognitive Preparedness," Clinical neurophysiology : official journal of the International Federation of Clinical Neurophysiology, **115**, pp. 887–97.

[79] Thatcher, R., BS, R., PhD, C., MS, D., and MA, R., 2003, "Quantitative EEG Normative Databases: Validation and Clinical Correlation," Journal of Neurotherapy, **7**, pp. 87–121.

[80] "After 25 Years the NeuroGuide Normative Databases are Accepted Science," from https://www.appliedneuroscience.com/PDFs/25_year_old_and_independently_evaluated_normative_database.pdf.

[81] Siddiqui, M. A., and Siddiqui, M. M., 2014, "EEG SIGNALS AND ITS RECORDING HELP IN DIFFERENT DISEASE," **3**(1). No, pp. 5.

[82] Rotgans, J. I., and Schmidt, H. G., 2011, "Cognitive Engagement in the Problem-Based Learning Classroom," Adv Health Sci Educ Theory Pract, **16**(4), pp. 465–479.

[83] Greene, B. A., and Miller, R. B., 1996, "Influences on Achievement:Goals, Perceived Ability, and Cognitive Engagement," Contemporary Educational Psychology, **21**(2), pp. 181–192.

[84] Lim, S., Yeo, M., and Yoon, G., 2019, "Comparison between Concentration and Immersion Based on EEG Analysis," Sensors (Basel), **19**(7).

[85] Rush, B., 2011, "Focal Lesion, Contusion," *Encyclopedia of Clinical Neuropsychology*, J.S. Kreutzer, J. DeLuca, and B. Caplan, eds., Springer, New York, NY, pp. 1065–1065.

[86] Louis, E. K. S., Frey, L. C., Britton, J. W., Frey, L.C., Hopp, J. L., Korb, P., Koubeissi, M. Z., Lievens, W. E., Pestana-Knight, E.M., and Louis, E. K. S., 2016, *The Abnormal EEG*, American Epilepsy Society.

[87] Chen, Z., Cao, J., Cao, Y., Zhang, Y., Gu, F., Zhu, G.,Hong, Z., Wang, B., and Cichocki, A., 2008, "An Empirical EEG Analysis in Brain Death Diagnosis for Adults," Cogn Neurodyn, **2**(3), pp. 257–271.

[88] Lee, S.-Y., Kim, W.-J., Kim, J. M., Kim, J., Park,S., and The Korean Society of Clinical Neurophysiology Education Committee, 2017, "Electroencephalography for the Diagnosis of Brain Death," Ann Clin Neurophysiol, **19**(2), p. 118.

[89] Stecker, M. M.,Sabau, D., Sullivan, L. R., Das, R. R., Selioutski, O., Drislane, F. W.,Tsuchida, T. N., and Tatum, W. O., 2016, "American Clinical Neurophysiology Society Guideline 6: Minimum Technical Standards for EEG Recording in Suspected Cerebral Death," Neurodiagn J, **56**(4), pp. 276–284.

[90] Krigbaum, G., and Wigton, N. L., 2015, "A Methodology of Analysis for Monitoring Treatment Progression with 19-Channel Z-Score Neurofeedback (19ZNF) in a Single-Subject Design," Appl Psychophysiol Biofeedback, **40**(3), pp. 139–149.

[91] Magosso, E.,Ricci, G., and Ursino, M., 2019, "Modulation of Brain Alpha Rhythm and Heart Rate Variability by Attention-Related Mechanisms," AIMS Neurosci, **6**(1), pp. 1–24.