An Investigation of Rambling-Trembling Sway Trajectories with Simulated Somatosensory Deficit

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Abstract

The purpose of this study is to investigate the effects of simulated somatosensory deficit and vision on (1) linear measures and (2) rambling-trembling-derived measures of the COP during quiet standing. It was hypothesized that (1) linear COP measures will show greater changes from baseline as deficit severity increases and there will be an interaction between the deficit severity and visual condition, with the effect greater in the eyes-closed condition compared to the eyes-open, and (2) rambling (RM) and trembling (TR) parameters will show similar trends across deficit and vision conditions, but with different magnitudes, and present greater sensitivity to deficit detection compared to the COP measures. The long-term goal of this study is to understand postural sway from a mechanistic perspective and use this information to develop a clinically-relevant measure of balance that is sensitive to changes in somatosensation abilities.

Fifty-two healthy young adults (aged 22.10 ± 1.88 years, 29 male, 23 female) participated in the study. Participants were asked to stand on two force plates (AMTI, Watertown, MA) with a standardized stance and either eyes open (EO) or closed (EC). Five foam thickness conditions (0”, 1/8”, 1/4”, 1/2”, and 1”, corresponding to F0, F1, F2, F3, and F4, respectively) were used to simulate varying degrees of somatosensory deficit. Participants completed three trials with EO and EC for each randomly-ordered foam condition. Foot-floor kinetic data were filtered with a 10 Hz lowpass Butterworth filter and analyzed using MATLAB software (Mathworks, Natick, MA). Force and COP data were used to calculate RM and TR time series, as detailed by Zatsiorsky & Duarte (1999). Velocity, acceleration, and jerk in the mediolateral (ML) and anteroposterior (AP) directions were calculated for every measure type (COP, RM, and TR). Percent changes

were calculated using F0 as the baseline. MATLAB software was used to perform three-way analyses of variance with Tukey's HSD post hoc tests with p<0.01 to determine analyze effects of vision, foam thickness, and measure type. Linear regression of each parameter across foam thickness was performed to estimate measure means across the full spectrum of simulated deficit.

The EO condition produced no statistically significant differences across any foam condition, often plateauing after F2. Therefore, further analysis was performed primarily using EC data. For EC trials, the F4 condition showed greatest percent changes from baseline for all assessed parameters, with an upward trend in mean values from F1 to F4 for COP, RM, and TR measures. In general, standard deviations were very large, likely due to the large sample size and inherent variability in postural sway between subjects. However, some statistically significant differences between COP, RM, and TR acceleration and jerk were still able to be found.

In terms of sensitivity, COP captures the smallest change in foam thickness, but RM provides a robustness across parameters that is not found in COP or TR. Dependence on sway direction is evident, with AP parameters often showing greater percent changes across foam thickness. RM and TR measures showed different behavior in the AP- and ML-direction, with RM greater than COP and TR in the AP-direction. This result is particularly interesting when considering the physiological mechanisms attributed to RM and TR, as these results suggest that movement in AP-direction may be more heavily influenced by the central nervous system. The findings of this study suggest that RM-TR derived measures may: (1) provide a greater degree of deficit detection ability than traditional linear COP measures, and (2) reveal previously unknown mechanisms of postural control.

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Chapter 1: Introduction

1.1 Background and Motivation

Nearly 30,000 fatal falls occur in America every year, making accidental falls among the leading causes of death in older adults in the United States (Burns & Kakara, 2018; Hartholt, 2016). Medical care from non-fatal falls amount to approximately $50 billion dollars annually, a significant portion of which can be attributed to surgical and rehabilitative efforts (Florence et al., 2018). Even when provided proper medical attention, patients experience considerable challenges in maintaining quality of life and independence.

Falls are often the result of sensory dysfunction and subsequent errors in body position estimation. In healthy individuals, visual, vestibular, and somatosensory feedback mechanisms allow for sophisticated movements. Falls in older adults are often multifactorial and can primarily be attributed to diminished function of one or more of these individual systems in addition to lowered sensorimotor processing rates from age-linked neural degeneration (Speers, Kuo, & Horak, 2002; Wickremaratchi & Llewelyn, 2006).

Fall risk assessments typically consist of a physical examination, medication dosing review, and a falls history (CDC, 2013). Some common risk factors include hip weakness, low balance score, and taking more than 4 medications (Robbins et al., 1989). However, in elderly patients without any identified risk factors, there remains an estimated 12% chance of fall over the course of a year (Robbins et al., 1989). Using these established risk factors, a substantial portion of the population is declared a non-risk and may not receive vital preventative care. If caught early, fall risk can be minimized through various intervention strategies, such as physical therapy. Thus, the need for more sensitive balance measures is evident (Berg, Maki, Williams, Holliday, & Wood-Dauphinee, 1992).

Balance has been studied in a research setting primarily through posturography, which uses reaction forces and moments to calculate center-of-pressure (COP), a point which represents the location of a concentrated sum of bodily pressure under the soles of the feet. COP can be plotted as a time-series, which allows for calculations of linear and nonlinear parameters such as path length, range, velocity, and entropy. These measures have been used extensively in balance research across age and pathology, but lack a connection to the physiological mechanisms that dictate them (Berg et al., 1992; Doyle, Hsiao-Wecksler, Ragan, & Rosengren, 2007; Lin, Seol, Nussbaum, & Madigan, 2008).

It is well documented that COP movement is influenced by the body's center of gravity (COG) and inertial forces, and there has been a significant effort to decompose COP signals into components that describe these control mechanisms (Murray, Seireg, & Scholl, 1967). Zatsiorsky and King developed a method for determining position of the gravity line (GL), a vertical line estimation of the body's COG (Vladimir M. Zatsiorsky & King, 1998). With the goal of differentiating GL movement from inertial forces, Zatsiorsky and Duarte later developed a COP signal decomposition method that calculates rambling (RM), movement of the body's instant equilibrium point, and trembling (TR), oscillations around said reference point (V. M. Zatsiorsky & Duarte, 1999, 2000).

Effects of age, stance position, and vision have all been investigated using RM-TR methods and findings suggest that sensory information: (1) plays a key role in modulating standing balance and (2) influences RM and TR components differently (Ferronato & Barela, 2011; Mochizuki, Duarte, Amadio, Zatsiorsky, & Latash, 2006; Sarabon, Panjan, & Latash, 2013). RM-TR decomposition analysis has the potential to change how sway is analyzed in both research and clinical settings. Expanding knowledge of postural sway mechanisms will aid in our understanding of healthy aging and pathological complications in addition to informing fall risk detection and mitigation strategies.

1.2 Specific Aims

The specific aims of this study are to: investigate the effects of simulated balance deficit and vision on (1) linear measures and (2) RM-TR-derived measures of the COP during quiet standing. It is hypothesized that: (1) linear COP measures will show increasing changes from baseline as deficit severity increases and there will be an interaction between the deficit severity and visual condition, with the effect greater in the eyes-closed condition compared to the eyes-open, and (2) RM and TR parameters will show similar trends across deficit and vision conditions, but with different magnitudes, and present greater sensitivity to deficit detection compared to the linear COP measures.

The long-term goal of this research is to develop a sensitive measure of balance deficit that can be used in a research and clinical setting to better understand postural sway on a population- and patient-scale.

1.3 Thesis Content

This document contains four chapters. Chapter 1 contains a brief introduction to posturography and its shortcomings in research and clinical settings. Chapter 2 details relevant background information regarding physiological dynamics, postural sway feedback mechanisms, existing measures of balance, and medical interventions. Chapter 3 contains a manuscript of the background, motivation, methods, results, and discussion of the study investigating the effects of simulated somatosensory deficit on rambling-trembling sway trajectories. Chapter 4 summarizes the present study and proposes recommendations for future work.

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Chapter 2: Background

2.1 Physiology of Postural Sway

2.1.1 Neural Signaling

The nervous system is divided into the central and peripheral components. The central nervous system (CNS) is comprised of the brain and spinal cord, and the peripheral nervous system (PNS) defines all nerves that extend throughout the body. It communicates through neuronal connections, which relay chemical messages from one neuron to the next in order to provide information from various receptors within the body. The body is constantly collecting data that informs our voluntary (conscious) and involuntary (subconscious) activities. Signals from sensors placed throughout the body are integrated into the PNS and CNS, forming feedback loops that produce appropriate output based on input. Sensory receptors generate signals based on environmental stimuli, which are transmitted through afferent neuronal pathways to the brain for processing.

Neurons, the basic unit of the nervous system, are composed of three essential structures: the postsynaptic terminal, the axon, and presynaptic terminal. They may have multiple pre- and post-synaptic terminals, which are responsible for sending and receiving signals, respectively. The axon lies between the two terminals and propagates the received signal through the neuron and discharges chemical signals that trigger subsequent neurons. Neurons operate through the use of action potential, an all-or-nothing signal that is propagated within and between neurons. To perceive stimuli, the signal must be strong enough to reach the sensation threshold, the minimum signal strength required to activate the receptor and trigger action potential. Stimulus strength can be amplified through spatial or temporal summation (*Figure 1*). Spatial summation occurs when multiple postsynaptic terminals of a single neuron are activated simultaneously, covering a larger area than a single terminal. Together, the potentials can sum to achieve threshold. Temporal summation is the result of repeated discharge from a single presynaptic terminal. If close enough in time, the effects of repeated discharge can summate in the postsynaptic terminal. Sensation threshold is the body's way of filtering stimuli to determine relative importance of the input.

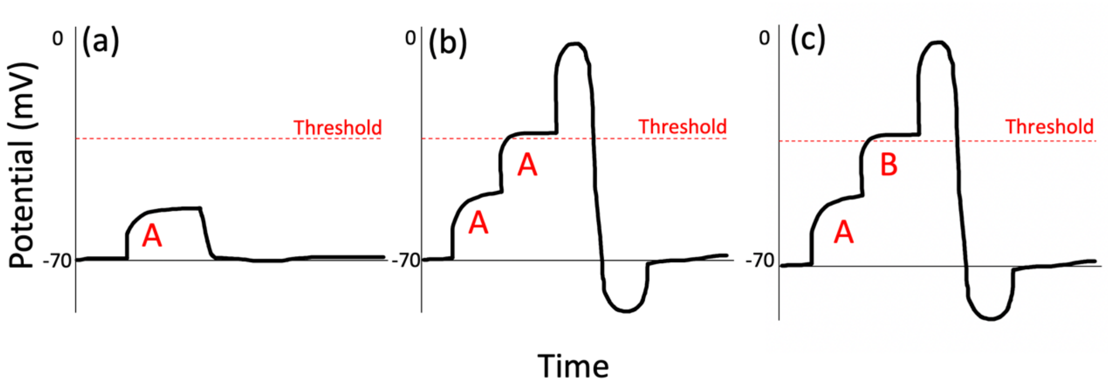

Figure 1. *Depiction of (a) weak signal, resulting in no action potential (b) temporal summation of neuron A, and (c) spatial summation of adjacent neurons A and B. (b) and (c) reach sensation threshold and thus trigger an action potential*

To produce appropriate motion, input from the body and environment, as well as sufficient processing of such input, is vital. The human body utilizes neural input from vestibular, visual, and somatosensory systems to determine body position and environmental conditions to maintain balance. The vestibular system provides information about head position and rotational forces, vision allows input from the environment and body orientation, and somatosensation gathers proprioceptive and cutaneous touch information.

2.1.2 Vestibular System

The vestibular apparatus is located in the inner ear and acts as an accelerometer and inertial sensor for the head. It consists of membranous tubes and cavities, called the membranous labyrinth. Within the labyrinth, the semicircular ducts, the utricle, and the saccule gather information about head position and rotations.

The basic functional unit of the vestibular system is the hair cell (*Figure 2*). Hair cells are comprised of three essential components: the cilia (kinocilium and stereocilia), the cell body, and the nerve. When the hair cell is externally stimulated, an influx of potassium ions depolarizes the hair cell. This causes depolarization of the cell and triggers the opening of voltage-gated ion channels, which causes an influx of calcium ions. In the presence of calcium ions, the hair cell releases vesicles of excitatory neurotransmitters, which are expelled into the synaptic cleft. The adjacent nerve receives the neurotransmitter, which triggers an afferent neural signal cascade and allows for perception of the signal.

Figure 2. *Representative drawing of a typical hair cell that is vital to the vestibular senses.*

There are three semicircular ducts in each ear, oriented in the anterior, posterior, and lateral directions. Each duct has a crest called a crista ampullaris, which is home to the cupula, a gelatinous mass of tissue that connects to innervated hair cells. Semicircular ducts are filled with a fluid called endolymph; when the head is rotated, fluid flow manipulates the shape of the cupula, exciting the hair cell cilia (Hall, 2011; Pfeiffer, Serino,

& Blanke, 2014). The three semicircular ducts are used primarily to detect 3-directional head rotations.

The utricle and saccule are chambers within the ear that house sensory organs called maculae. Maculae in the utricle and saccule determine orientation of the head in the horizontal and vertical plane, respectively. Each macula has hair cells that connect to a gelatinous tissue layer. When the head moves, gravity bends cilia embedded in the gelatinous layer, stimulating the hair cells and generating a neural signal (Hall, 2011; Pfeiffer et al., 2014). The utricle and saccule are particularly important for detecting linear accelerations and modulating static equilibrium during standing (Hall, 2011).

2.1.3 Vision

The body also heavily relies on visual input to coordinate movement. The retina, the light-receptive portion of the eye, is composed of cone and rod cells, which detect color of light and brightness. Each rod and cone is connected to bipolar, amacrine, and ganglion cells that relay signals to the optic nerve (Hall, 2011). To reach the retina at the back of the eye, light passes through the cornea and pupil and refracts on the convex lens to create a focal point. The lens can be manipulated to adjust focal length through a process called accommodation, which allows the eye to switch between focus on near and far objects.

Vision is key to perceiving environmental conditions and the obstacles that accompany them. Information is processed by both focal (central) and ambient (peripheral) mechanisms. The central component primarily processes object recognition and motion, while the peripheral component processes movement and is thought to be responsible for the majority of postural control (Bardy, Warren, & Kay, 1999).

2.1.4 Somatosensation

Within somatosensation, receptors can be classified as mechanoreceptors (touch), thermoreceptors (temperature), nociceptors (pain), chemoreceptors (chemicals), and proprioceptors (body orientation). Within somatosensation, postural control relies most critically on mechanoreceptors and proprioceptors (Speers et al., 2002).

Human skin contains four main types of mechanoreceptors, including Meissner's corpuscles, Pacinian corpuscles, Merkel's disks, and Ruffini's corpuscles. Receptors can be described based on their responsiveness (adaptability) and activation threshold. Based on their adaptive speed and threshold, these four mechanoreceptors allow for different sensation abilities: Meissner corpuscles detect light touch, Pacinian corpuscles detect pressure and high-frequency vibration, Merkel's disks detect hair follicle movement, and Ruffini's corpuscles detect pressure and low-frequency vibration. These sensors are placed throughout the body, including the soles of the feet, and allow for sensation of conditions such as texture and bodily pressure distribution.

Proprioceptors provide information regarding body orientation relative to itself. This ability relies on input from three basic types of receptors: muscle spindles, Golgi tendon organs, and joint receptors. Muscle spindles are responsible for sensing muscle length and velocity. Golgi tendon organs monitor force at the muscle-tendon interface, and allow assessment of force-based resistance to motion. Joint receptors gather information regarding compressive forces within the joint capsules. Together, these sensors provide a sense of joint position, kinesthesia, and resistive force.

2.2 Age-Related Changes

Over the course of a lifetime, many different conditions can disrupt sensory processing. Some of the most notable conditions include stroke, Parkinson's disease, and diabetes, but perhaps the most prevalent is healthy aging. As we age, we experience sensory losses due to degradation in vestibular sense, vision, or somatosensation. This is manifested as heightened sensory thresholds that prevent previously-detectable signals from reaching threshold and triggering action potential. Any one deficit can detrimentally affect postural sway, but more often than not, multiple-system failures are responsible for age-related decline in balance.

2.2.1 Vestibular System

Hair cells within the semicircular ducts, utricle, and saccule convert physical conditions to electrical signals. With age, the number and quality of hair cells decreases, making it more difficult to perceive position and subtle head rotations during quiet standing (Speers et al., 2002).

2.2.2 Vision

It is well known that vision declines with age. Presbyopia, the most common mode of failure with age, is the loss of lens elasticity, which dampens the process of accommodation. This condition is considered a standard symptom of aging and is usually remedied through the use of reading glasses. However, studies have also shown that healthy older adults experience decreases in sensitivity to low-frequency spatial motion (Sekuler & Hutman, 1980). Elderly people are also at heightened risk for diseases such as cataracts, glaucoma, macular degeneration, and diabetic retinopathy, that can severely impact visual acuity and depth perception.

2.2.3 Somatosensation

It is estimated that one in five elderly individuals experiences peripheral neuropathy, the loss of touch sensation in the extremities (Richardson, Ashton-Miller, Lee, & Jacobs, 1996). Neuropathy can be exacerbated by co-morbid conditions, such as diabetes, but can also occur in healthy aging individuals. These deficits arise from a variety of causes, including decreased sensitivity (heightened threshold) of mechanical stimuli and age-linked degeneration of myelinated afferent fibers (Wickremaratchi & Llewelyn, 2006).

2.3 Fall Prevalence

According to the United States Census Bureau, the number of adults aged 65 or older are expected to make up 23.4% of the total population by the year 2060 (United States Census Bureau, 2017). Life expectancy has increased nearly linearly at a rate of two years per decade (Crimmins, 2015; Oeppen & Vaupel, 2002). As life expectancy continues to increase, the population of elderly persons also continues to grow, which presents a unique challenge to healthcare and geriatric medicine.

Between 2007 and 2016, there was a 31% increase in falls in adults aged 65 years and above, making falls the 7th leading cause of death in older adults (Burns & Kakara, 2018). In 2016, falls in older adults resulted in 25,189 deaths in the United States. Among those who survived, medical costs amounted to nearly $50 billion, presenting a significant burden on the healthcare system.

2.4 Fall Risk Detection and Prevention

The CDC outlines four basic steps for preventing falls, including: 1) consulting with a healthcare professional about fall risk, 2) exercising to improve balance and muscle strength, 3) checking eye function and foot sensitivity regularly, and 4) adapting the home to be safer (CDC, 2013). The Center for Disease Control (CDC) recently created an initiative for healthcare providers called Stopping Elderly Accidents, Deaths & Injuries (STEADI), that encourages doctors to carefully screen, assess, and intervene to reduce fall risk (CDC, 2017). STEADI hinges on the validity and detection of established fall risk factors, including prescription history, orthostatic blood pressure, visual acuity, footwear, vitamin D deficiencies, and comorbidities. Based on these risk factors, doctor may prescribe interventions such as altered medication dosing, physical therapy, or dietary supplementation. However, in a study assessing the accuracy of fall risk designation, Robbins et. al (1989) found that in a patient with no commonly-identified fall risk factors, there remains a 12% chance of fall (Robbins et al., 1989). To supplement these risk factors, doctors may choose to employ a variety of clinical balance assessments.

2.5 Clinical Balance Assessment

Physical therapists may utilize a variety of standardized balance tests, including (but not limited to) the dynamic balance test, Berg balance scale (BBS), and timed up and go (TUG) (Dixon, Knight, Binns, Ihaka, & O'Brien, 2017). During a dynamic balance test, participants are asked to walk as quickly and accurately as possible across a five-meter-long beam (Dixon et al., 2017). The Berg Balance Scale is a succession of 14 tasks that increase in difficulty, including single-leg and bipedal stance and moving from a seated to standing position. Performance during each task is ranked from 0-4, with 4 representing successful completion of the task (Dixon et al., 2017). Finally, the TUG test measures the time required to raise from a chair, walk 3 meters, turn around, walk back, and sit down. Patients are designated as healthy or unhealthy based on adherence to a cutoff time. For estimating fall risk, the cutoff time is typically set to 20 seconds, with a time less than 20 seconds signifying no fall risk, 20-30 representing moderate risk, and greater than 30 seconds flagging a significant risk of fall and dependence in activities of daily living (Shumway-Cook, Baldwin, Polissar, & Gruber, 1997). A unifying trend found in most clinical tests is the aim to test functional abilities and limits; outcomes are designed to measure impact on activities of daily living, and not the influence of individual physiological systems. Research-based methods, on the other hand, provide a broader scope of information pertaining to performance on an individual and group scale using a mechanistic approach.

2.6 Research-based Balance Assessment

2.6.1 Postural Sway

Postural sway is the primary method of static balance measurement in a research setting. Quiet standing requires signal integration from the visual, vestibular, and somatosensory systems in order to maintain upright stance (Winter, 1995). Subtle sway movements can be measured using force plates, which collect foot-floor force and moment data. Center of Pressure (COP) is a commonly used measure of balance and can be described as a point which represents the location of a concentrated sum of bodily pressure under the soles of the feet (Winter, 1995). COP can be calculated in the mediolateral and anteroposterior directions according to the following equations:

Equation 1. *Calculations for center-of-pressure (COP) time-series*

$$COP_x = -\frac{M_y + F_x * d_z}{F_z} \qquad COP_y = \frac{M_x - F_y * d_z}{F_z}$$

The reference system used to generate these equations orients the x-axis in the mediolateral direction, with positive x pointing to the lateral right of the body. The y-axis represents the anteroposterior direction, with positive y pointing posteriorly. The z-axis represents the inferior-superior bodily direction, with positive z pointing directly down onto the force plates. M and F represent moments and forces in the designated direction, as measured by the force plate, and dz represents the distance from the top surface of the force plate to the origin of the coordinate system, as provided by the force plate manufacturer. Experimental trials typically last between 30 and 90 seconds and require the subject to stand quietly with arms resting at the sides.

Posturography has the power to reveal valuable information about balance and the control mechanisms that govern it, and has both medical and research applications. Sway analysis has been used extensively to study balance in a wide variety of subject demographics, including, but not limited to, healthy young individuals, the elderly, and individuals with pathological complications such as peripheral neuropathy. To analyze sway, the COP time series is used to calculate various linear measures, depending on the nature of the research. A summary of relevant linear measures can be found in Table 1, below.

Table 1. *Summary of commonly used COP measures, including the time-series, parameter, and a selection of relevant research findings that utilize them.*

Time Series	Measure	Findings
COP	Path Length	- ML-direction reliable with eyes-open or eyes-closed (Li et al., 2016) - Greater in individuals with spinal cord injury (Lemay et al., 2014)
	Range	- Test-retest reliable (Degani et al., 2017) - Can differentiate between healthy young control and non-faller elderly. (Degani et al., 2017)
COP Velocity	Mean	- Sensitive in both eyes-open and eyes-closed conditions (Prieto et al., 1996) - Increases shown in elderly and patients with vestibular deficiency (Baloh et al., 1998)(Prieto et al., 1996) - COP velocity is correlated to center of mass (COM), velocity, but is more correlated with COM acceleration (Masani, Vette, Abe, & Nakazawa, 2014)
	Maximum	- Differentiates between healthy young, elderly non-fallers, and elderly fallers (Hewson et al., 2010)
COP Acceleration	Mean	- Due to high correlation of COP velocity and COM acceleration, derivative of COP acceleration represents COM (body) jerk (Masani et al., 2014)
	Root Mean Square (RMS)	- Lower in persons with Multiple Sclerosis than healthy controls (Huisinga, Mancini, St. George, & Horak, 2013)
COP Jerk	Mean	- Associated with “smoothness” of movement - Decreases shown in older adults with proprioceptive-training intervention (Tai Chi) compared to standard care (Hass et al., 2004) - Increases shown in older adults (Huang & Brown, 2013)

2.6.2 Rambling-Trembling

2.6.2.1 Origins and History

It is well documented that the COP time series is modulated by migration of the center of gravity and inertial forces exerted on the body (Murray et al., 1967; Winter, 1995; Vladimir M. Zatsiorsky & King, 1998). Center of gravity is measured by the gravity line, the estimated location of a vertical line that passes through the body's center of gravity. There has been significant effort in the last two decades to decompose COP signals into static and dynamic components, representing the gravity line and inertial forces, respectively, in order to better understand sway biomechanics and postural control mechanisms (King & Zatsiorsky, 1997).

In 1999, Zatsiorsky and Duarte proposed a new decomposition method, coining the terms "rambling" and "trembling" (V. M. Zatsiorsky & Duarte, 1999). The goal of this method was to develop a measure of two distinct sources of motion: (1) a set, or reference, point that moves with time, called rambling, and (2) oscillation of the COP around such a point, termed trembling. The primary objective of the development of rambling-trembling decomposition was to analyze sway from a mechanistic perspective to better understand postural control and its shortcomings (V. M. Zatsiorsky & Duarte, 1999).

2.6.2.2 Mathematical Calculation

Calculation of the rambling and trembling time series is relatively simple and can be performed using software such as MATLAB (Mathworks, Natick, MA). The process of decomposition is shown in Figure 2 and can summarized in three primary steps:

1. Find instances when $F_{hor} = 0$, known as instant equilibrium points (IEPs).

2. Plot COP values at identified IEPs and interpolate points using a cubic spline function. This interpolated time series represents an estimation of the rambling trajectory.
3. Subtract COP from the rambling trajectory to estimate the trembling time series.

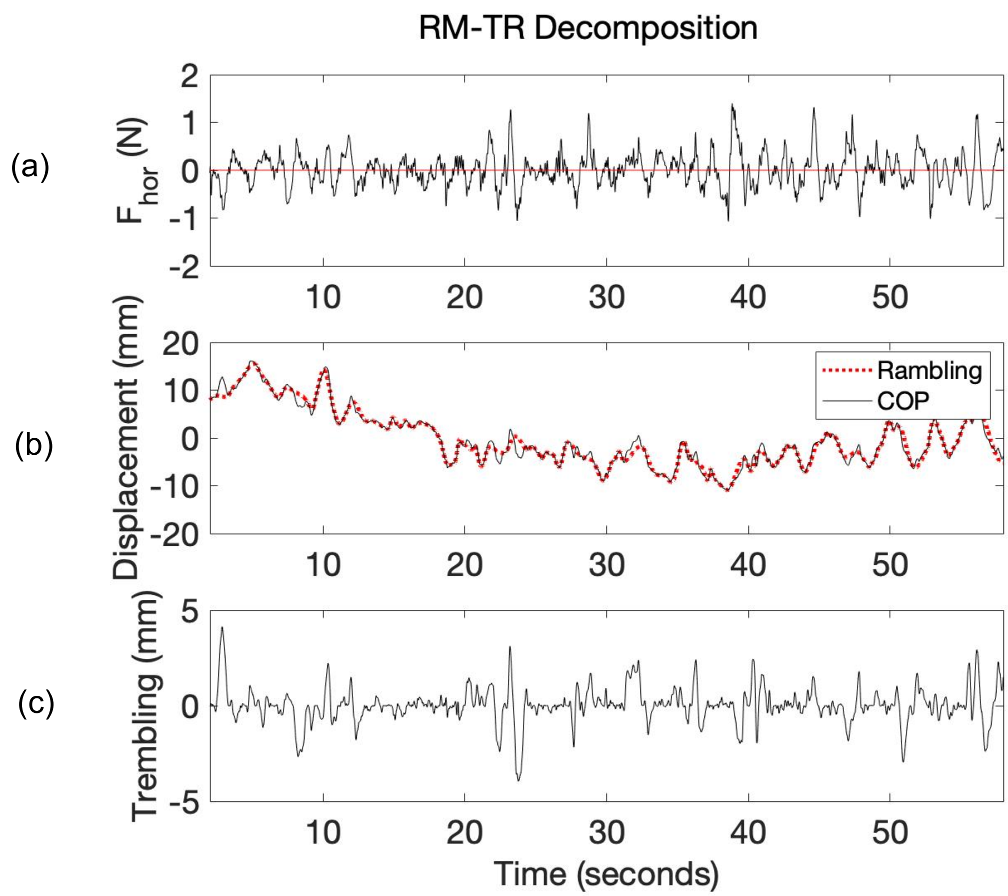

Figure 3. *Sample rambling-trembling decomposition COP data (a) shows the horizontal force with the zero-crossing points. (b) shows the interpolation of F_{hor} =0 timepoints, shown in red. (c) shows trembling, the difference between COP and rambling.*

2.6.2.3 Applications and Secondary Calculations

Just as with the COP time series, rambling and trembling time series can be used to calculate several linear parameters, including velocity, acceleration, and jerk.

Parameter calculations for RM, TR, and COP time series can be studied independently and can be used to better understand the relative contributions of each component to overall balance.

Rambling-trembling decomposition has been used to analyze the postural sway of healthy young subjects, healthy old subjects, and subjects with pathological complications such as multiple sclerosis and spinal cord injury (Sarabon et al., 2013; Shin, Motl, & Sosnoff, 2011; Shin & Sosnoff, 2017). Mochizucki et al. (2006) investigated rambling-trembling patterns in healthy young adults and found rambling velocity to be greater than trembling in the anteroposterior direction, and noted that perception of task difficulty had a significant influence on outcome. Degani et al. (2017) investigated the changes with age and showed larger, faster, and shakier sway in both rambling and trembling components (Degani et al., 2017).

Analysis of these populations has informed several theories of postural control, including the equilibrium point hypothesis and the supraspinal-peripheral control hypothesis. The equilibrium point, or Feldman's Lambda, hypothesis suggests that the central nervous system maintains upright posture by shifting the COP from one equilibrium point to the next, using sensory input to dictate muscular contributions and angular adjustments (Feldman, 1986). This theory aligns with the theoretical framework for rambling-trembling, equating rambling to movement of the equilibrium point, and trembling to the inherent tonic stretch reflex in muscles.

The supraspinal-peripheral control hypothesis goes further to propose that perturbations cause "resetting" of the reference point (rambling) as dictated by the central nervous system. According to this hypothesis, movement of the COP is an attempt to constantly restore torsional balance. This centrally-planned motion is subject to deviations caused by muscle contraction, reflexes, or external perturbations in the periphery. This interference can be measured as the trembling component of sway (Tahayori, Riley, Mahmoudian, Koceja, & Hong, 2012; V. M. Zatsiorsky & Duarte, 1999).

Despite the potential value to the study of postural sway, there remains a significant gap in knowledge regarding rambling-trembling trajectory analyses and their implications for postural control in the presence of visual and somatosensory deficit. Therefore, the goals of the current study are to: investigate the effects of simulated somatosensory deficit and vision on (1) linear COP measures and (2) RM-TR-derived measures of the COP during quiet standing. It was hypothesized that: (1) linear COP measures will show increasing changes from baseline as deficit severity increases and there will be an interaction between the deficit severity and visual condition, with the effect greater in the eyes-closed condition compared to the eyes-open, and (2) RM and TR parameters will show similar trends across deficit and vision conditions, but with different magnitudes, and present greater sensitivity to deficit detection compared to the linear COP measures.

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Chapter 3: An Investigation of Rambling-Trembling Sway Trajectories with Simulated Somatosensory Deficit

Note: Formatted according to Gait & Posture standards, in anticipation for manuscript submission.

3.1 Abstract

Background: Falls in older adults are often multifactorial, but can primarily be attributed to diminished sensory detection abilities from age-linked neural degeneration (Speers, Kuo, & Horak, 2002; Wickremaratchi & Llewelyn, 2006). A novel method for center-of-pressure (COP) analysis, called rambling-trembling (RM-TR) decomposition, has potential to provide valuable information about postural sway, with research- and clinically-relevant applications (Zatsiorsky & Duarte, 1999, 2000).

Research Question: What are the effects of vision and simulated somatosensory deficit on RM-TR-derived measures of COP, as compared to traditional COP measures?

Methods: Fifty-two healthy young adults (aged 22.10 ± 1.88 years) participated in the study. Participants stood on two force plates with a standardized stance with either eyes open (EO) or eyes closed (EC). Five foam thicknesses (F0-F4) were used to simulate somatosensory deficit. Force and moment data were filtered using a 10Hz lowpass Butterworth filter and used to calculate COP, RM, and TR time series, as detailed by Zatsiorsky & Duarte (1999). MATLAB software was used to perform three-way analyses of variance with Tukey's HSD post hoc tests with $p<0.01$ to determine statistical significance. Linear regression of each parameter across foam thickness was performed to estimate measure means across the full spectrum of simulated deficit.

Results: The EO condition showed minimal changes with foam thickness. Therefore, analysis is focused primarily on EC, which showed an upward trend is apparent from F1 to F4 in all measures, with variable magnitudes across measure type. COP captures the smallest change in foam thickness, but RM provides a robustness across parameters that is not found in COP or TR. Dependence on sway direction is evident, with AP parameters often showing greater changes across foam thickness.

Significance: Findings suggest that RM-TR derived measures may act as a compliment to, or provide a greater sensitivity than, traditional COP measures.

Word Count (300 limit): 297

Keywords: Center of pressure; Postural control; Balance; Falls

3.2 Introduction

Nearly 30,000 fatal falls occur in America every year, making accidental falls among the leading causes of death in older adults in the United States (Burns & Kakara, 2018; Hartholt, 2016). Medical care from non-fatal falls amount to approximately $50 billion dollars annually, a significant portion of which can be attributed to surgical and rehabilitative efforts (Florence et al., 2018). Even when provided proper medical attention, patients experience considerable challenges in maintaining quality of life and independence.

Most falls are the result of sensory dysfunction and subsequent errors in body position estimation. In healthy individuals, visual, vestibular, and somatosensory feedback mechanisms allow for sophisticated movements. Falls in older adults are often multifactorial and can be attributed to diminished function within one or more of these individual systems in addition to lowered sensorimotor processing rates from age-linked neural degeneration (Speers et al., 2002; Wickremaratchi & Llewelyn, 2006). In elderly patients without any identified fall risk factors, there remains an estimated 12% chance of a fall over the course of a year (Robbins et al., 1989). If caught early, fall risk can be minimized through various intervention strategies, such as physical therapy. Thus, the need for more sensitive balance measures is evident (Berg, Maki, Williams, Holliday, & Wood-Dauphinee, 1992).

Balance has been studied in a research setting primarily through posturography, which uses reaction forces and moments to calculate center-of-pressure (COP), a point which represents the location of a concentrated sum of bodily pressure under the soles of the feet. COP can be plotted as a time-series, which allows for calculations of linear parameters such as path length, range, and velocity. These measures have been used extensively in balance research across age and pathology, but lack a connection to the physiological mechanisms that dictate them (Berg et al., 1992; Doyle, Hsiao-Wecksler, Ragan, & Rosengren, 2007; Lin, Seol, Nussbaum, & Madigan, 2008).

A novel method for center-of-pressure (COP) analysis, called rambling-trembling (RM-TR) decomposition, has potential to provide valuable information about postural sway, with research- and clinically-relevant applications (Zatsiorsky & Duarte, 1999, 2000). This decomposition method calculates rambling (RM), movement of the body's instant equilibrium point (IEP), and trembling (TR), oscillations around such a point (Zatsiorsky & Duarte, 1999, 2000).

Effects of age, stance position, and vision have all been investigated using RM-TR methods and findings suggest that sensory information: (1) plays a key role in modulating standing balance and (2) influences RM and TR components differently (Ferronato & Barela, 2011; Mochizuki, Duarte, Amadio, Zatsiorsky, & Latash, 2006; Sarabon, Panjan, & Latash, 2013). RM-TR decomposition analysis has the potential to change how sway is analyzed in both research and clinical settings. Expanding knowledge of postural sway mechanisms will aid in our understanding of healthy aging and pathological complications in addition to informing fall risk detection and mitigation strategies.

The purpose of this study is to investigate the effects of simulated balance deficit and vision on (1) linear measures and (2) RM-TR-derived measures of the COP during quiet standing. It is hypothesized that: (1) linear measures will show increasing changes from baseline as deficit severity increases and there will be an interaction between the deficit severity and visual condition, with the effect greater in the eyes-closed condition compared to the eyes-open, and (2) RM and TR parameters will show similar trends across deficit and vision conditions, but with variable magnitudes, and present greater sensitivity to deficit detection compared to the traditional COP measures. The long-term goal of this research is to identify a sensitive measure of balance deficit that can be used in a research and clinical setting to better understand postural sway on a population- and patient-scale.

3.3 Methods

3.3.1 Participants

Fifty-two healthy young adults (aged 22.10 ± 1.88 years, 29 males, 23 females) volunteered to participate in the study. All participants were informed of the study risks and benefits, and provided written consent, as approved by the University of Kansas Institutional Review Board. Participants with a history of neurological disorder, balance problems, and/or significant injury in the back and legs were excluded from participation in the study. One subject (s1022) was removed from the study due to significant deviation from parameter means (> 3 standard deviations) and subsequent classification as an outlier.

3.3.2 Testing Conditions

Participants were asked to stand naturally, with arms at the sides, on two force plates (AMTI, Watertown, MA). A standardized stance width of 17cm with a 20° angle between feet was used (McIlroy & Maki, 1997). Five randomly-ordered foam thickness conditions (no foam, 1/8”, 1/4”, 1/2”, and 1”, corresponding to F0, F1, F2, F3, and F4, respectively) were used to simulate varying degrees of somatosensory deficit. Foam pads utilized in this study were 12”x12” with a density of 2 lbf/ft^3 and pressure to compress 25% of 4 psi (McMaster-Carr, Chicago, IL, USA). Two randomly-ordered visual conditions, eyes-open (EO) and eyes-closed (EC), were also used. During the EO condition, participants were asked to keep their eyes focused on a target, placed at eye level approximately 3 meters from the subject. For the EC condition, participants were asked to keep head upright, as if looking at the target. Three 60-second trials were completed for every foam thickness and visual condition for a total of 30 trials per subject, with a 5-minute seated break after every 6 trials.

3.3.3 Data Collection and Analysis

Participants were recorded with a video camera for the duration of the testing session in order to ensure task instruction compliance. Foot-floor kinetic data were collected at 100 Hz using two 6-axis AMTI force plates (Advanced Mechanical Technology Inc., Watertown, MA, USA) and a 16-bit A/D acquisition system (Cambridge Electronic Design, Cambridge, England, UK). Data were exported as text files and analyzed using MATLAB software (Mathworks, Natick, MA). Force and moment data were filtered using a 10Hz lowpass Butterworth filter and down-sampled to 50 Hz. Signals from the two force plates were combined to form a singular set of force and moment time-series. These combined signals were then used to calculate a 2-D position vector describing the center-of-pressure (COP), the projection of resultant forces on the floor surface. Mediolateral (ML) and anteroposterior (AP) COP were calculated according to the following equations (Winter, Patla, & Frank, 1990):

$$COP_x = -\frac{M_y + F_x * d_z}{F_z} \qquad COP_y = \frac{M_x - F_y * d_z}{F_z}$$

Force and COP position trajectories were used to calculate RM and TR time series in the AP and ML directions, as detailed by Zatsiorsky & Duarte (1999). Briefly, COP positions at instant equilibrium points, the time when horizontal force (F_{hor}) = 0, were found and interpolated to estimate RM trajectory. The RM trajectory was subtracted from the COP to calculate the TR trajectory. For simplicity, these three distinct time series will be referred to as COP, RM, and TR.

COP, RM, and TR time-series were numerically differentiated with 4th order accuracy to calculate COP velocity (1st derivative of position), acceleration (1st derivative of velocity), and jerk (1st derivative of acceleration). Mean values were extracted from these time series. Calculations for each parameter were done separately in the AP- and ML-directions and EO and EC conditions. Relative percent change from baseline (F0, no foam) was used to describe parameter values. Sensitivity was defined by: (1) the number of significant differences between foam conditions for within- and between-measure comparisons, (2) the thinnest detectable foam thickness difference, and (3) the slope of the regression line across simulated deficit.

3.3.4 Statistics

MATLAB software was used to perform two types of statistical analyses. Three-way analyses of variance (ANOVA) with Tukey's HSD post hoc tests were used to determine statistical significance between and within foam thickness, measure type, and vision groups. Statistical significance was set to $p<0.01$.

To perform linear regression, foam thickness was modeled as a dependent variable in order to estimate means across the full length of simulated deficit. Statistical significance of coefficients was set to $p<0.01$ and a 90% confidence interval was calculated for each linear model.

3.4 Results

3.4.1 EO versus EC

The EC condition shows significantly greater changes ($p<0.01$) across foam thickness as compared to EO in all measured parameters. The EO condition resulted in a change of approximately 20% or less from baseline to F1-F4 (*Figure 1).* EC trials show a steady increase in mean percent change from F1 to F4, whereas EO often results in a plateau at F2, leaving all measures relatively unaffected by the F3 and F4 foam thicknesses. Due to the relative lack of sensitivity to foam thickness in the EO condition, further analysis is focused on the EC condition.

3.4.2 RM, TR, and COP Means

COP, RM, and TR parameters are able to differentiate between various levels of foam (*Table 1*). With $p<0.01$ accuracy, the COP time series is able to differentiate between 10 pairs of foam thicknesses, RM between 17, and TR between 8. RM is able consistently distinguish between foam thickness differences of 1/2" or greater. With $p<0.05$ or $p<0.1$, RM can differentiate between a thickness difference as small as 3/8”. COP ML velocity is able to recognize the difference between the smallest change of foam thickness, 1/8”, with $p<0.05$. TR AP velocity shows significant changes for 3/8” differences or larger, but presents minimal significance for TR ML velocity, AP acceleration, or ML acceleration. With $p<0.05$, TR ML jerk can differentiate 1/2" or greater.

Acceleration and jerk show significant COP-RM and RM-TR differences in the AP, but not the ML *(Table 2, Table 3*). A significant difference between COP and TR is found in ML jerk. AP RM means remain relatively constant across velocity, acceleration, and jerk, where other parameters tend to decrease with increasing derivative order.

3.4.3 Linear Regression

Linear regression across foam thickness was performed on velocity, acceleration, and jerk measures (*Figure 2).* All regression models show upward trends with foam and statistically significant slope values, with the exception of ML jerk COP and RM.

<u>AP Velocity:</u> COP, RM, and TR measures all show significant upward trends with the greatest R^2 values attributed to COP and RM. Significant overlap between measures, and therefore insignificant slope differences, is apparent.

<u>ML Velocity:</u> COP and TR have higher R^2 values than RM. Slopes are nearly identical, ranging narrowly from 41.8951 to 43.3057. Confidence intervals show nearly complete overlap, suggesting insignificant slope differences.

<u>AP Acceleration:</u> RM shows the greatest slope. There is no overlap of the RM 90% confidence interval with COP and minimal overlap with TR. A significant difference is found between RM and COP.

<u>ML Acceleration:</u> COP shows the greatest slope, but there is substantial overlap between the three measures. RM shows the narrowest 90% confidence interval and greatest R^2 value.

<u>AP Jerk</u>: RM slope is greater than both COP and TR. COP and TR show similar slopes and overlapping confidence intervals, but neither measure overlaps with RM, indicating significant difference of RM from COP and TR.

ML jerk: COP has the lowest of all R^2 values (0.0021). COP and RM models have insignificant p-values, evidenced by the large confidence intervals. TR, on the other hand, shows a clear upward trend with a significant slope and narrow confidence interval.

3.5 Discussion

The body relies on information collected by the somatosensory, visual, and vestibular sense in order to maintain standing balance. The high measure sensitivity of EC, compared to EO, sheds some light onto the dependence on vision under conditions of somatosensory deficit. When the eyes are open, our healthy participants used vision to compensate for the lack of somatosensory feedback, shifting the sensory weight onto the visual and vestibular systems. When the eyes are closed, the body is forced to shift sensory weight onto the vestibular system, leaving a larger gap in sensory detection abilities. These findings are consistent with the first hypothesis, which stated that there would be an interaction between deficit severity and visual condition, with the effect greater in the eyes-closed condition compared to the eyes-open.

This form of sensory weighting is well known in the literature and presents a substantial challenge to older adults, who feel the compounding effects of somatosensory, visual, and vestibular degeneration. Despite the prevalence, there are very few interventions available for somatosensory or vestibular deficits. Visual aids, such as glasses or contacts, offer the ability to re-shift sensory weighting onto vision, but there is evidence that vision overdependence can lead to falls (Yeh, Cluff, & Balasubramaniam, 2014). For research-based applications, these findings reinforce the use of eyes-closed balance measurement, commonly found in fall risk assessment, as the lack of visual feedback more easily identifies persons experiencing somatosensory and vestibular deficits.

Within- and between-measure comparisons and regression findings support the first part of the second hypothesis, which states that COP, RM, and TR parameters will show similar trends across deficit and vision conditions, but with variable magnitudes. All parameters showed positive upward trends from baseline across foam thickness, but the magnitudes of these changes, demonstrated by regression slope values, are not always equal. AP RM acceleration and jerk exhibit significantly greater slope values than COP and TR. ML TR jerk shows a statistically significant slope, where COP and RM do not. These results demonstrate the direction-dependence of both overall sway and the individual RM and TR components, and may provide insight into postural control mechanisms.

Much debate surrounds the attribution of physiological mechanisms to RM and TR, but a leading theory suggests that RM trajectories are centrally-controlled, while TR trajectories are peripherally-controlled (Tahayori, Riley, Mahmoudian, Koceja, & Hong, 2012). The prominence of RM slopes in the AP direction is particularly interesting when considering the physiological mechanisms attributed to RM and TR, as these results may suggest that movement is more heavily controlled centrally in the AP. These findings highlight the need for further exploration of RM-TR decomposition in the context of postural control.

Conclusions to be made regarding the second part of the second hypothesis are less clear. Sensitivity was defined three separate ways: (1) the number of significant differences between foam conditions for within- and between-measure comparisons, (2) the thinnest detectable foam thickness difference, and (3) the slope of the regression line across simulated deficit.

All parameters, with the exception of ML acceleration and AP jerk, were able to differentiate F1 from F4 (7/8" of foam), which, assuming linearity of parameter change across foam thickness, presents the greatest possible difference and most obvious contrast. Few parameters could detect a foam difference of 3/8", and even fewer could differentiate the smallest change in foam, 1/8". COP showed greater detectability for lower levels of deficit (F1 vs. F2), while RM was able to consistently differentiate between higher levels of deficit (F2 vs F4 and F3 vs F4). The COP time series' ability to differentiate between 1/8" of foam could be crucial in the detection of early-stage somatosensory deficit. However, the RM time series was able to differentiate nearly twice as many foam levels as COP and TR, suggesting that RM may be a more robust measure for intermediate stages of somatosensory loss.

Regression yielded low p-values implying model significance, but low R^2 values signifying relatively poor fit, limiting the implications of these models. This was expected due to large standard deviation measurements. However, these results in combination with 90% confidence intervals may provide valuable diagnostic abilities that span the full length of deficit simulation. The RM time series showed significantly greater slope across foam thickness than COP and TR in AP acceleration and jerk, highlighting this measure's sensitivity to simulated deficit.

Together, these three types of sensitivity can be used to inform the most appropriate measure of postural sway, depending on direction of interest (AP versus ML) and target deficit detectability (early- versus late-stage somatosensory loss).

Limitations

There are several limitations to this study that restrict the implications of our findings. First, and perhaps most restricting, foam was used to model somatosensory deficit by limiting the amount of feedback provided by the ground surface. This technique is common in the study of sway, along with plantar cooling and anesthetics, but is limited in its direct application to patient populations (Hoch & Russell, 2016; Patel, Fransson, Johansson, & Magnusson, 2011). In this case, foam was the most viable option to minimize adverse effects to subjects and this benefit outweighed the marginal differences found in other forms of simulated deficit. Previous work has shown sway response to foam to be highly dependent on foam density and elastic modulus, but nonetheless resulted in altered postural sway patterns (Patel, Fransson, Lush, & Gomez, 2008). While the use of foam does not directly mirror the effects of clinical deficit, it does present a challenge to balance by introducing a degree of instability that requires altered control mechanisms.

Second, the use of healthy individuals also presented difficulties due to the inherent variability in healthy sway. Healthy subjects were used to isolate the effect of the simulated somatosensory deficit and decrease the likelihood of confounding medical conditions, but resulted in high parameter variance that limited the significance of the study's findings. Significance may have also been limited by the robust balance of healthy young individuals, who are able to quickly and efficiently adapt to sensory challenges, minimizing contrast between foam thicknesses. Individuals with clinical deficits, on the other hand, would not possess this same robust adaptability, potentially yielding even greater contrasts, and therefore sensitivity, throughout real-life deficit progression. Third, parameter behavior was assumed to have a linear relationship with simulated deficit, which, given the relatively low R^2 values, is not necessarily true. Finally, only a limited number of parameters were examined in this study. The use of velocity, acceleration, and jerk does not fully capture the potential of rambling-trembling methods and leaves the door open for further analysis.

Future Work

Future work should continue the investigation of rambling-trembling decomposition with patient populations, such as Parkinson's or diabetic peripheral neuropathy, in order to further understand its strengths for deficit detection and research-based analysis. It may also be beneficial to explore the use of different regression models, such as logistic, in search of a better fit of sample data to the model. Researchers may also choose to include a wider variety of sway parameters, both linear and nonlinear, to capture a broader scope of rambling-trembling behavior.

3.6 Conclusions

Further exploration of rambling-trembling analysis is needed, but current findings shed light on the potential value of these methods in both research- and clinically-based applications. Understanding postural sway from a mechanistic perspective and identifying fall risk in a clinical setting are both vital to reducing falls and maintaining high quality of life with age. With this knowledge and improved measure sensitivity, clinicians may soon be able to accurately detect fall risk, preventing falls and saving thousands of lives every year.

Tables and Figures

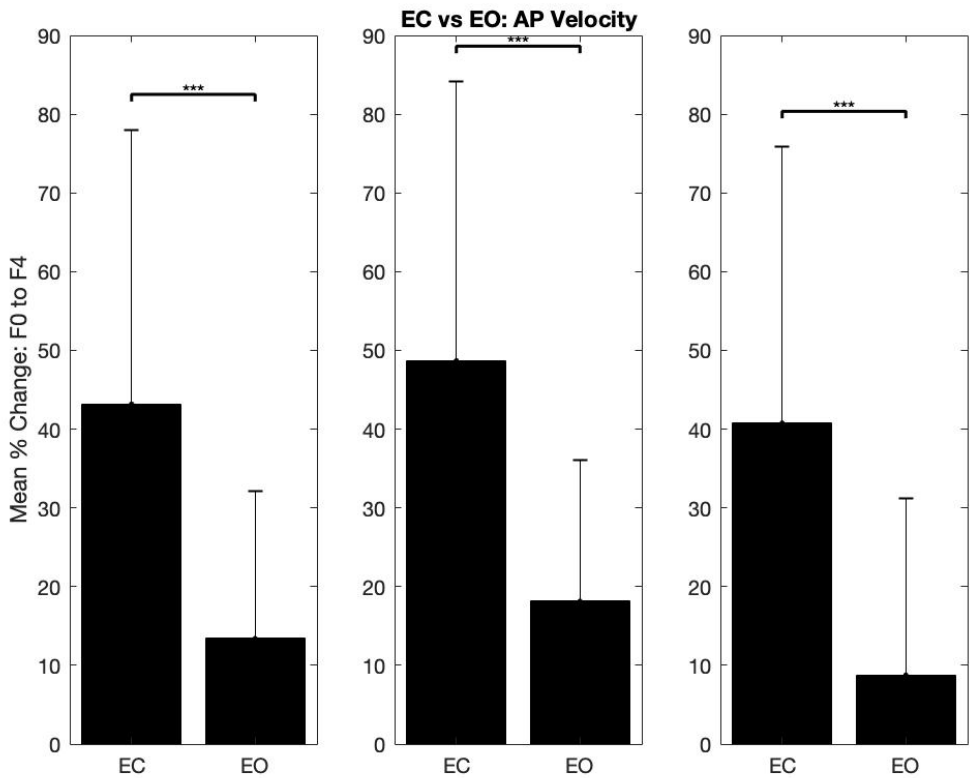


Figure 1. *Representative EC versus EO analysis. EC magnitudes are consistently greater than EO in all parameters, including ML velocity. Significant differences are shown with (***), signifying p < 0.001.*

Table 1. *Within-measure foam comparisons in ascending thickness difference order. Color-coded significant differences are shown.*

	Foam		Thickness Difference	AP Vel	ML Vel	AP Acc	ML Acc	AP Jerk	ML Jerk
COP	1	2	1/8"	-15.9703	-21.2044	-4.8486	-2.8398	-3.1401	1.1786
	2	3	1/4"	-9.4006	-11.9066	-6.5432	-5.5126	-3.5700	-13.9659
	1	3	3/8"	-25.3710	-33.1110	-11.3917	-8.3524	-6.7101	-12.7872
	3	4	1/2"	-34.0337	-13.7039	-14.4753	-14.5273	-10.5651	-23.2811
	2	4	3/4"	-43.4343	-25.6105	-21.0185	-20.0399	-14.1351	-37.2469
	1	4	7/8"	-59.4047	-46.8149	-25.8670	-22.8797	-17.2751	-36.0683
RM	1	2	1/8"	-1.7323	-2.0305	-1.5303	-1.8283	-4.9513	-4.4218
	2	3	1/4"	-7.0819	-5.6769	-7.0331	-6.9828	-9.5236	-11.5084
	1	3	3/8"	-8.8142	-7.7074	-8.5634	-8.8112	-14.4749	-15.9302
	3	4	1/2"	-12.3436	-12.6222	-11.8766	-12.1725	-23.7055	-24.5876
	2	4	3/4"	-19.4255	-18.2991	-18.9097	-19.1553	-33.2291	-36.0960
	1	4	7/8"	-21.1578	-20.3296	-20.4400	-20.9836	-38.1805	-40.5178
TR	1	2	1/8"	-8.5812	-3.9050	-5.5734	0.0839	-5.1361	-1.1613
	2	3	1/4"	-13.2351	-7.7458	-8.4381	-0.2703	-4.1207	-5.8869
	1	3	3/8"	-21.8163	-11.6508	-14.0115	-0.1864	-9.2568	-7.0483
	3	4	1/2"	-22.1350	-19.4351	-9.9494	-4.1258	-3.4914	-10.4743
	2	4	3/4"	-35.3701	-27.1809	-18.3875	-4.3961	-7.6121	-16.3613
	1	4	7/8"	-43.9513	-31.0859	-23.9609	-4.3122	-12.7483	-17.5226

p < 0.01
p < 0.05
p < 0.1

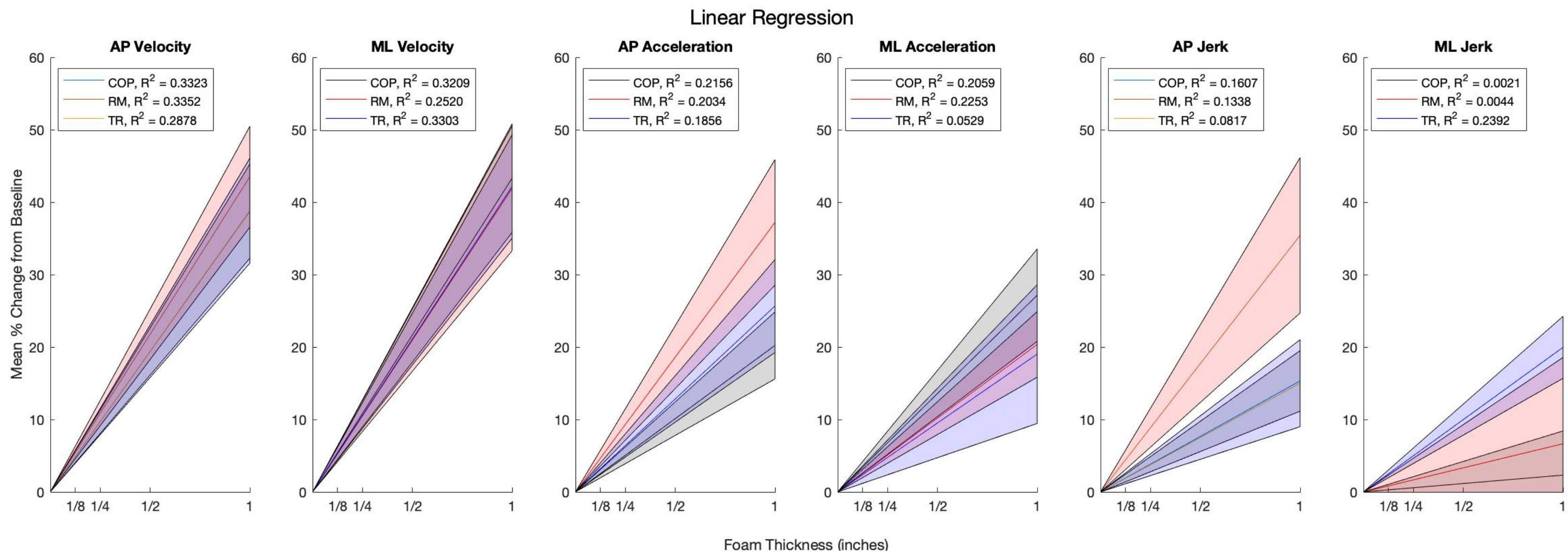
Table 2. *Mean changes in velocity, acceleration, and jerk from baseline (F0) to F4.*

	COP	RM	TR
AP Vel	43.186	48.687	40.766
ML Vel	46.526	48.011	45.712
AP Acc	24.043	42.380	20.425
ML Acc	22.009	24.260	26.059
AP Jerk	20.329	43.779	13.860
ML Jerk	5.987	16.3444	23.905

Table 3. *P-values for measure-type comparisons for mean change from baseline to F4.*

		Mean Velocity			Mean Acceleration			Mean Jerk		
AP		**COP**	**RM**	**TR**	**COP**	**RM**	**TR**	**COP**	**RM**	**TR**
	COP		0.7086	0.9355		0.0255	0.8653		0.0161	0.7272
	RM			0.4901			0.0053			0.0013
	TR									
ML		**COP**	**RM**	**TR**	**COP**	**RM**	**TR**	**COP**	**RM**	**TR**
	COP		0.9776	0.9932		0.9376	0.8118		0.2756	0.0218
	RM			0.9471			0.9597			0.5024
	TR									

p < 0.01
p < 0.05
p < 0.1



`	AP Vel			ML Vel			AP Acc			ML Acc			AP Jerk			ML Jerk		
	COP	RM	TR	COP	RM	TR	COP	RM	TR	COP	RM	TR	COP	RM	TR	COP	RM	TR
slope	38.7619	43.5121	38.8259	43.3057	41.8951	42.1613	20.2253	37.2058	25.664	27.163	20.3609	19.0297	15.326	35.4285	15.0114	3.3233	6.6506	19.9578
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.0012	<0.001	<0.001	<0.001	0.529	0.3574	<0.001
lower 90% CI	32.2592	36.5558	31.5793	35.8105	33.2857	35.0185	15.6988	28.5352	19.2508	20.7834	15.8332	9.4479	11.1474	24.7047	9.0081	-3.7657	-5.2642	15.678
upper 90% CI	45.2645	50.4684	46.0725	50.8008	50.5045	49.4041	24.8517	45.8764	32.0771	33.5426	24.8886	28.6114	19.5045	46.1523	21.0148	8.4122	18.5654	24.2377

Figure 2. *Linear regression of velocity, acceleration, and jerk for the COP, RM, and TR time series. 90% confidence intervals are shown by shaded regions. Regression models are based on slope values alone, as y-intercept values were found to be insignificant.*

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Chapter 4: Summary

4.1 Summary of Study

The purpose of this study is to investigate the effects of simulated somatosensory deficit and vision on center-of-pressure (COP) and rambling-trembling-derived measures of sway during quiet standing. Fifty-two healthy young adult volunteers (aged 22.10 ± 1.88 years) were asked to stand with arms at their sides, with either eyes-closed (EC) or eyes-open (EO), on two force plates. A stance width of 17cm with a 20° angle between feet was used. Five randomly-ordered foam thicknesses (no foam, 1/8”, 1/4”, 1/2”, and 1”, corresponding to F0, F1, F2, F3, and F4) were used to simulate varying degrees of somatosensory deficit. Percent change from baseline (F0) of mean velocity, acceleration, and jerk were extracted from COP, rambling, and trembling time-series.

As expected, the EC condition exhibited significantly greater changes across foam thickness as compared to EO in all measured parameters, showing EC conditions to be more sensitive to changes in simulated somatosensory deficit. With EC, COP, rambling, and trembling parameters all showed positive, upward trends with increasing deficit, but with variable magnitudes. Anteroposterior rambling is shown to have a greater magnitude of change across deficit severity in acceleration and jerk parameters. Mediolateral trembling jerk exhibited greater changes than COP or rambling. Overall, the rambling time-series was able to differentiate the greatest number of foam level comparisons.

4.2 Conclusions and Recommendations

In research-based applications, rambling is thought to represent centrally-controlled movement of a non-stationary COP equilibrium point, while trembling captures small, peripherally-controlled muscular adjustments and reflexes. Our findings suggest that these components of sway are influenced differently in the presence of somatosensory deficit. Further exploration of rambling-trembling is needed, but these differences highlight the potential directionality of postural control mechanisms, linking anteroposterior movement to the central nervous system and mediolateral to the peripheral nervous system. From a clinical perspective, rambling may serve as a robust measure of somatosensory loss-induced balance changes. However, the most sensitive measure for an individual may depend on direction of interest (anteroposterior versus mediolateral) and target deficit detectability (early- versus late-stage somatosensory loss).

4.3 Limitations and Future Work

Findings from this study are limited by several factors, including the use of foam as a deficit model, variability and adaptability of healthy young subjects, assumption of a linear relationship between deficit and parameter magnitude, and limited number of parameters studied. Future work should continue the investigation of rambling-trembling decomposition with patient populations, such as Parkinson's or diabetic peripheral neuropathy, in order to further understand its strengths for deficit detection and research-based analysis. It may also be beneficial to explore the use of different regression models, such as logistic, in search of a better fit of sample data to the model. Researchers may also choose to include a wider variety of sway parameters, both linear and nonlinear, to capture a broader scope of rambling-trembling behavior. Expansion of this study may lead to identification of highly sensitive sway measures that could be used to better understand postural sway from a mechanistic approach and mitigate fall risk in a clinical setting.

Appendix A: Supplementary Materials

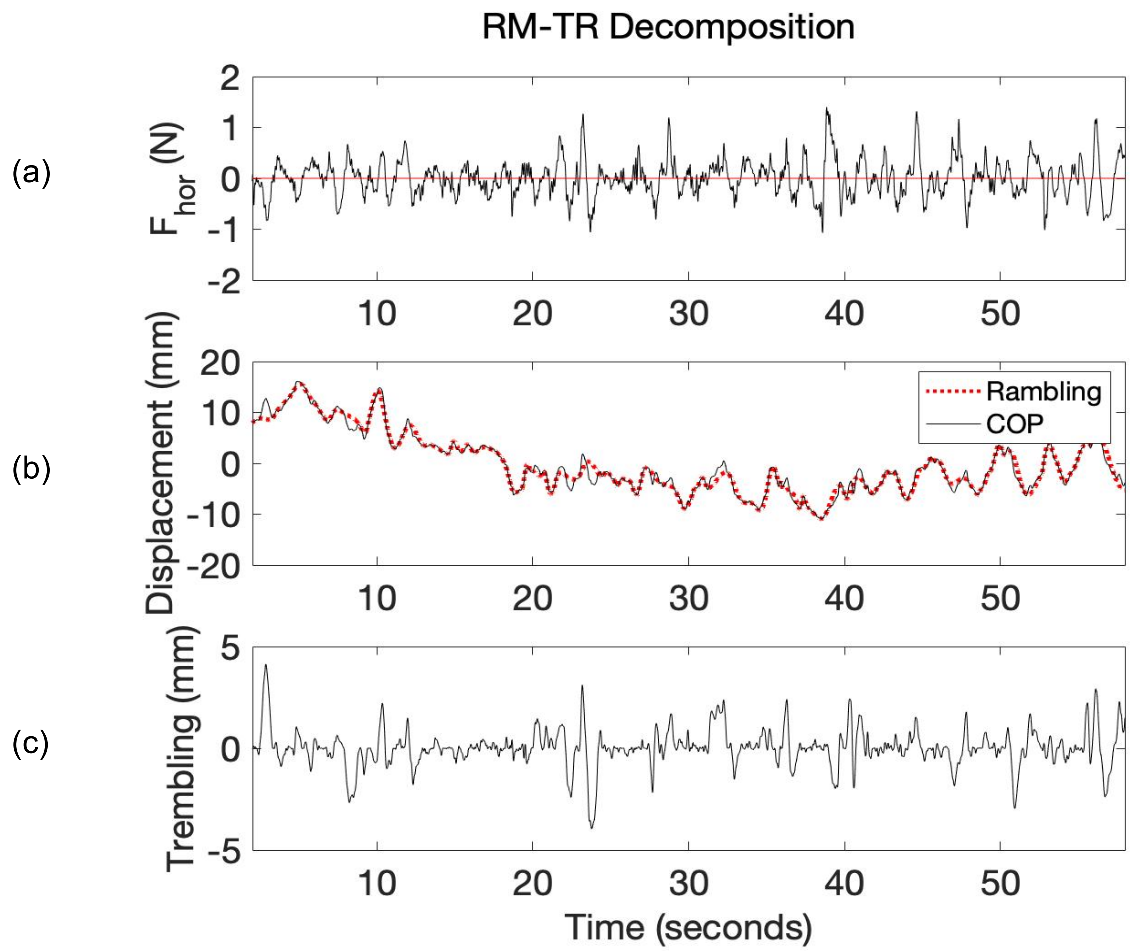

Figure 1. *Sample RM-TR decomposition using data from s1052. Plots are representative of the study data.*

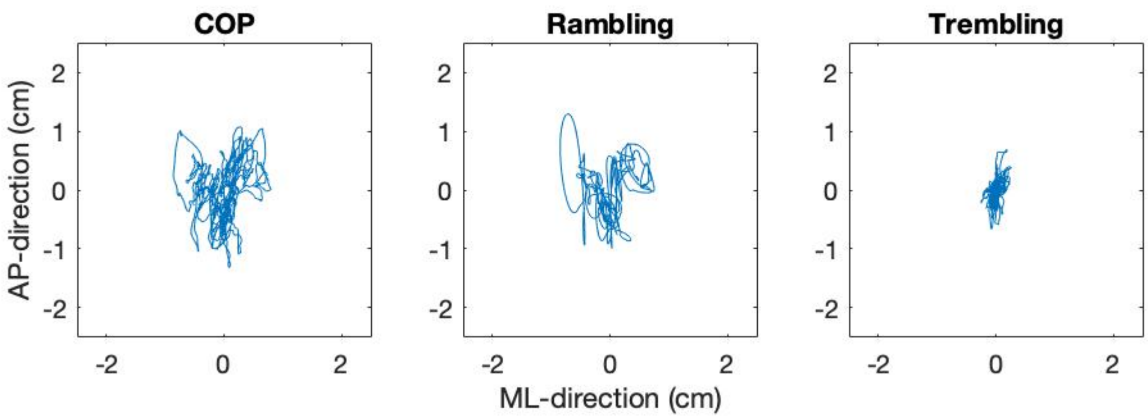

Figure 2. *Sample stabilogram from RM-TR decomposition using data from s1052.*

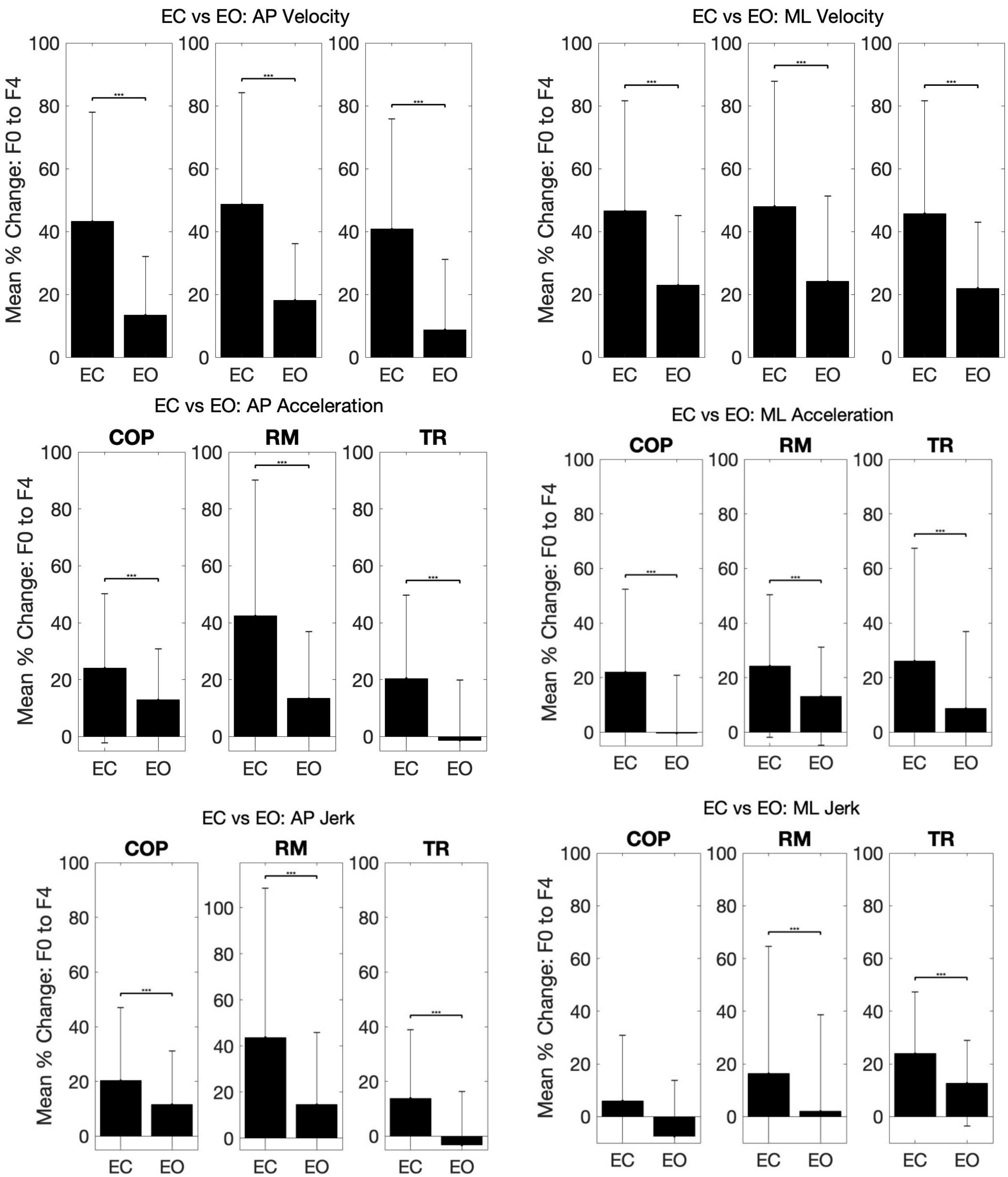

Figure 3. *Eyes closed (EC) versus eyes-open (EO) averages for each parameter and measure type, including standard deviation and significant differences (* p<0.1, ** p<0.05, *** p<0.01)*

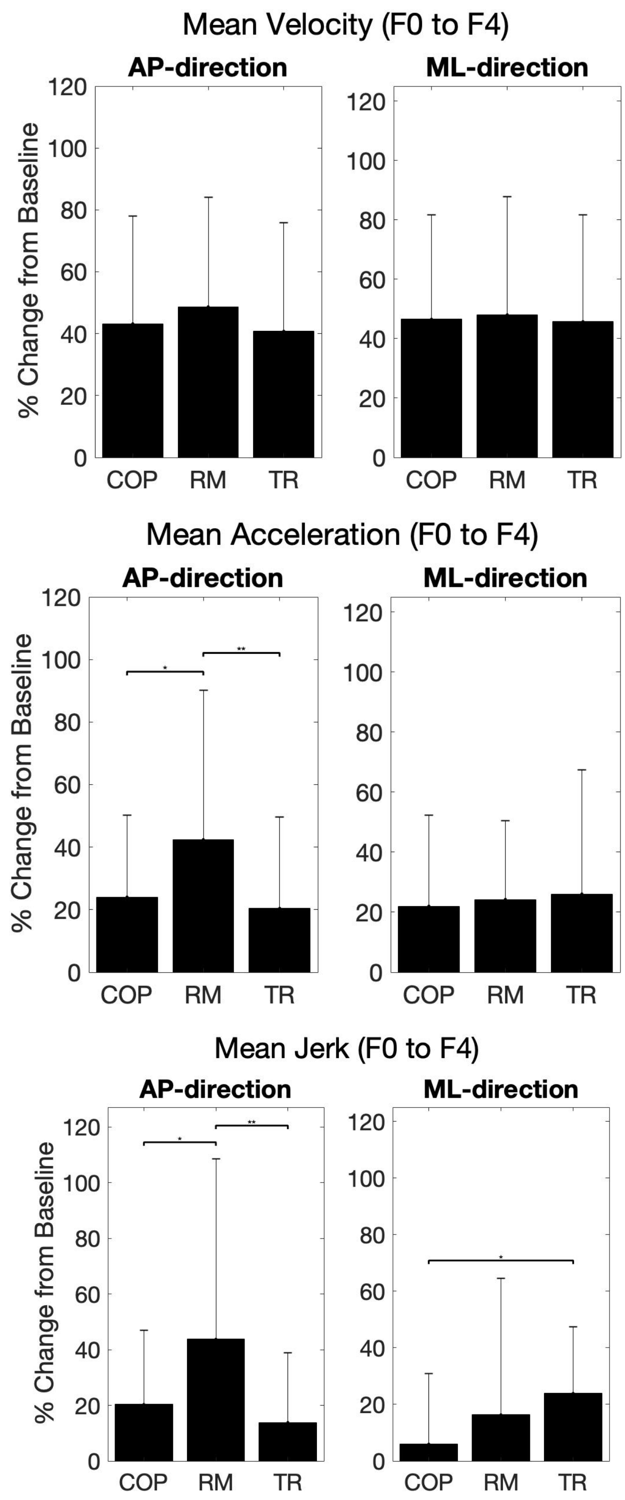

Figure 4. *Mean percent changes from baseline to F4, including standard deviation and significant differences (* p<0.1, ** p<0.05, *** p<0.01)*

Appendix B: Experimental Protocol Documents

Verbal Prompts

Biodynamics Prompts for Sway Task - updated 8/31/19

This experiment involves a standing task, which involves:

- Multiple trials, each lasting 1 minute.
    - You will say “ready” when you are ready for a trial to begin,
    - We will say “begin” at the start of a trial and “done” at the end of the trial.
- We will ask you to stand on a variety of foam pads. We will ask you to take a step backwards when we change the foam pad.
- Some trials will be done with your eyes open and others will be done with your eyes closed.
    - For the eyes open trials, please keep your eyes focused on the target directly in front of you for the entire 1 minute trial.
    - For the eyes closed trials, please keep your eyes closed for the entire 1 minute trial. You may open your eyes between the trials.
- During each 1 minute trial, please:
    - Stand relaxed and as naturally as possible, be careful not to lock your knees,
    - Keep your arms at your side, breathe normally, and
    - Do not turn your head or speak. If you feel uncomfortable or fatigued, please tell us immediately.
- When a trial is done, feel free to relax, move your arms and bend your legs, but please do not move your feet.
- After doing 6 trials, we will change the foam pads and you will have the option to sit down and take a break.
- “We are not testing how good your balance is, we are just testing how the foam affects your natural balance”
- Do you have any questions?

We are ready to start our first/next trial.

- This is an **eyes open trial**: please breathe normally, focus on the target, and say “ready” when you are ready to begin … “ready” … “begin” … “done”
- This is an **eyes closed trial**: please close your eyes, breathe normally, and say “ready” when you are ready to begin … “ready” … “begin” … “done”

Reminders:

- Eyes open: Please keep your feet in place, your arms at your side, and your eyes focused on the target in front of you. Breathe normally and please say “ready” when you are ready to begin the next trial.
- Eyes closed: Please keep your feet in place, your arms at your side, and your eyes closed. Breathe normally and say “ready” when you are ready to begin the next trial.

Signed Consent Form

KU SCHOOL OF ENGINEERING
The University of Kansas

Adult Informed Consent Statement

"Quiet Standing Analysis during Somatosensory and Visual Deficiencies"

INTRODUCTION
The Biodynamics Research Laboratory at the University of Kansas supports the practice of protection for human subjects participating in research. The following information is provided for you to decide whether you wish to participate in the present study. You may refuse to sign this form and not participate in this study. You should be aware that even if you agree to participate, you are free to withdraw at any time. If you do withdraw from this study, it will not affect your relationship with this unit, the services it may provide to you, or the University of Kansas.

PURPOSE OF THE STUDY
The purpose of this project is to collect quiet standing data on healthy adults under different levels of somatosensory feedback deficiency (standing on various thickness of foam) with either eyes open or closed. This data will be used to develop new measurement and analysis techniques used to detect somatosensory deficits patients with various pathologies. It is expected that the results from this study will help us to better understand the contribution of the somatosensory feedback in quiet standing, and how the body maintains its balance under a somatosensory deficiency. In the future, we hope to investigate the application or our new measurement and analysis techniques on patient populations (e.g. diabetes, stroke, Parkinson's disease) to determine how well they work to detect somatosensory deficits. Our long-term goal is to improve the physician's tool for detecting somatosensory deficits, so that an intervention can be introduced which would reduce the risk of the patient experiencing a fall.

In this project, movement, force, and electromyography (EMG - muscle and heart activity) data will be collected from healthy adults while each stand quietly on foam of different thicknesses. All tests are non-invasive and considered to be low-risk to the participant. The testing will provide the investigators with information about the how the participant's motor control system controls balance while standing on foam.

PROCEDURES
For this study, we will look at your quiet standing balance. First, you will be asked to change into your personal attire (shorts and t-shirt) that will allow us to easily place the sensors on your skin in the correct location. Next, we will record the following demographic and physical information:

- Name
- Gender
- Height
- Weight
- Age
- Email address and/or phone number
- Distance from ankle to bottom of the foot
- Distance from ankle to knee
- Distance from knee to hip

We will also ask you to review your phone screen answers, and confirm that the answers have not changed since the phone call.

KU Lawrence IRB # STUDY00141250 | Approval Period 9/20/2019 – 9/19/2020

Sensors will be placed on your feet, calves, quads and around your sternum. We will place the kinematic and EMG sensors with adhesive tape. Once the sensors are confirmed to be working properly, you will stand relaxed on the force plates while we record the natural sway of your body. You will wear a safety harness and will be under close supervision by a research associate to aid in the case of a very unlikely fall. While wearing the harness, you will be asked to stand with your eyes open or closed, and on a varying thickness of foam that will range from no foam to a maximum of 2.4" of foam. Trials will be 60 seconds in duration and you will be given at least 30 seconds of rest between sets of six trials. You will also be given the opportunity for seated rest whenever you choose. Each of the conditions will be repeated three times. During these trials, we will monitor muscle activity, movement, and forces, as described below. In addition, we will use a video camera to record all trials. The trials are being recorded so that the investigators can view them if any trials produce unexpected results. These recordings will be completely secured and only accessible by members of the research team. These recording will have sound due to the nature of the video camera, but the audio recordings will not be used for any purpose.

Assessment of Muscle Activity: Our EMG system (Bagnoli™ Desktop EMG – 8 Channels) measures your muscle activity. Non-invasive surface electrodes are applied on your skin over your muscle. Alcohol wipes and/or a pumice stone are used to clean your skin and then an electrode unit is placed over each area. Lower leg and thigh muscles will be monitored, including anterior tibialis, gastrocnemius, quadriceps, and hamstrings. Our EMG system gathers information from your muscles but does not give any feedback back to you. Application of the electrodes takes 10-15 minutes.

Assessment of Heart Activity: Similar to the assessment of muscle activity, heart activity will be assessed using our EMG system (Bagnoli Desktop EMG – 8 Channels). Alcohol wipes and/or a pumice stone are used to clean your skin and then an electrode unit is placed around your sternum to record your pulse. Our EMG system gathers information from your muscles but does not give any feedback back to you. Application of the electrodes takes 5 minutes.

Assessment of Movement: Our motion capture system (NDI Optotrak Certus) measures the movement of your body while you perform a task. We will place markers on your skin and record the movement of those markers. The location of the markers will be feet, calves, quadriceps, sternum, and lower back. The application of the markers takes approximately 15 minutes.

Assessment of Force: Our force plate system (AMTI OR6) measures the forces your feet exert on the floor while you perform a task. The force plates are mounted in the floor. You will be standing barefoot on the force plates or standing on top of foam that is placed on top of the force plate. The surfaces are sterilized in between each subject.

RISKS

Understand that there may be possible risks for participating.

- Postural Control: There may be a risk of falling during the balance testing but this risk will be minimized by close monitoring from a research associate and a safety harness that will catch you in the event of a fall.
- EMG: There are no known risks to the use of EMGs. There may be skin irritation under the electrodes.
- Movement testing: There are no known risks to movement tracking. You may experience mild skin irritation in the area the markers were applied.
- Force testing: There are no known risks to force testing.

BENEFITS
There are no direct benefits to you for participating in this study. It is anticipated that information gathered in this study will contribute to current scientific knowledge of quiet standing in healthy individuals under normal stance conditions and more challenging conditions created by the foam surface.

PAYMENT TO PARTICIPANTS
There are no costs or payments for participating in this study.

PARTICIPANT CONFIDENTIALITY
The researchers will protect your information, as required by law. Absolute confidentiality cannot be guaranteed because persons outside the study team may need to look at your study records. Your name or any information that reveals your identity will not be associated in any report, publication or presentation with the information collected about you or with the research findings from this study. Instead, the researcher(s) will use a study number rather than your name. Your identifiable information will not be shared unless (a) it is required by law or university policy, or (b) you give written permission.

Your study-related health information will be used at the Biodynamics Research Lab by Dr. Luchies, members of the research team, the KU Human Subjects Committee and other committees and offices that review and monitor research, if a regulatory review takes place.

All study information that is sent outside the Biodynamics Research Lab will have your name and all other identifying characteristics removed, so that your identity will not be known. Because identifiers will be removed, your health information will not be re-disclosed by outside persons or groups and will not lose its federal privacy protection.

Your permission to use and disclose your health information remains in effect until the study is complete and the results are analyzed. After that time, information and video recordings that personally identifies you will be removed from the study records.

INSTITUTIONAL DISCLAIMER STATEMENT
In the event of injury, the Kansas Tort Claims Act provides for compensation if it can be demonstrated that the injury was caused by the negligent or wrongful act or omission of a state employee acting within the scope of his/her employment.

REFUSAL TO SIGN CONSENT AND AUTHORIZATION
You are not required to sign this Consent and Authorization form and you may refuse to do so without affecting your right to any services you are receiving or may receive from the University of Kansas or to participate in any programs or events of the University of Kansas. However, if you refuse to sign, you cannot participate in this study.

CANCELLING THIS CONSENT AND AUTHORIZATION
You understand that your participation in this study is voluntary and that the choice not to participate or to quit at any time can be made without penalty or loss of benefits. The entire study may be discontinued for any reason without your consent by the investigator conducting the study.

You have a right to change your mind about allowing the research team to have access to your health information. If you want to cancel permission to use your health information, you should send a written request to Dr. Luchies. The mailing address is Carl Luchies PhD, 3135B Learned Hall, Lawrence, KS 66045.

If you cancel permission to use your health information, you will be withdrawn from the study. The research team will stop collecting any additional information about you. The research team may use and share information that was gathered before they received your cancellation.

QUESTIONS ABOUT PARTICIPATION

You have read the information in this from. Dr. Luchies or his associates have answered your questions to your satisfaction. You know that if you have more questions after signing this form, you may contact Dr. Luchies at (785) 864-2993 or luchies@ku.edu. If you have questions about your rights as a research subject, you may call or write the Human Research Protection Program (HRPP) at (785) 864-7429 or 2385 Irving Hill Road, Lawrence, KS 66045.

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KEEP THIS SECTION FOR YOUR RECORDS. IF YOU WISH TO PARTICIPATE, PLEASE TEAR OFF THE FOLLOWING PAGE AND RETURN IT TO THE RESEARCHER(S).

KU Lawrence IRB # STUDY00141250 | Approval Period 9/20/2019 – 9/19/2020

"Quiet Standing Analysis during Somatosensory and Visual Deficiencies"

IRB # 00141250

PARTICIPANT CERTIFICATION:

If you agree to participate in this study please sign where indicated, then tear off this section and return it to the investigator(s). Keep the consent information for your records.

I have read this Consent and Authorization form. I have had the opportunity to ask, and I have received answers to, any questions I had regarding the study and the use and disclosure of information about me for the study.

I agree to take part in this study as a research participant. By my signature, I affirm that I am at least 18 years old and that I have received a copy of this Consent and Authorization form.

_______________________________________	______________________________
Type/Print Participant's Name	Participant Number
_______________________________________	______________________________
Participant's Signature	Date

KU Lawrence IRB # STUDY00141250 | Approval Period 9/20/2019 – 9/19/2020

Phone Screen Questionnaire

Phone Screen Answers

Healthy Foam Study

Interviewer:
____

Date:
____

Oral Consent: YES NO

Participant Information
Name:
____

Email Address or Phone Number:
____

Gender: Male Female Other

Question	**YES**	**NO**	**When? Or Notes**
Have you had any head injuries or concussions?			
Have you ever experienced any dizziness or fainting spells?			
Do you have osteoporosis in lower extremity joints (hip, knees, ankles, foot)?			
Have you had, or do you have arthritis in your legs that limits mobility or causes pain?			
Have you had, or do you have any hip, knee, ankle, or foot problems or injuries that limit mobility or cause pain?			
Do you have back problems that limit mobility or cause pain?			
Do you have nerve damage that is affecting your legs?			
Have you had, or do you have muscle problems in your legs that limit mobility or causes pain?			
Have you ever broken any bones in your legs, ankles, or feet?			
have you ever broken any bones in your spine?			
Have you had, or do you suffer from fibromyalgia? Or, have you had, or do you have constant muscle fatigue or aches in your body?			
Do you have any joint replacement in your leg joints?			
Do you have any joint fusion?			
Have you had, or do you have poor circulation in your legs that causes them to be cold or numb?			
Have you had, or do you have any lung disease (besides asthma?)			

Have you had, or do you have any heart problems?			
Have you had, or do you have any chest pain from heart disease?			
Have you had, or do you have any vascular problems?			
Have you ever had a heart attack?			
Do you have high blood pressure? If yes, are you taking medication?			
Do you have any neurological disease?			
Do you suffer from Parkinson's disease?			
have you ever had a stroke?			
If subject is female : Are you pregnant?			
Any other issues we haven't mentioned that we should know about?			

Phone Screen Inclusion/Exclusion Criteria

Standing Foam Study				
Inclusion/Exclusion Criteria: Phone Screen				
Question	YES	NO	When?	Exclude?
Have you had any head injuries or concussions?				Yes if less than 1 yr ago
Have you ever experienced any dizziness or fainting spells?				Case-by-case decision
Do you have osteoporosis in lower extremity joints (hip, knees, ankles, foot)?				Yes
Have you had, or do you have arthritis in your legs that limits mobility or causes pain?				Yes if less than 1 yr ago
Have you had, or do you have any hip, knee, ankle, or foot problems or injuries that limit mobility or cause pain?				Yes if less than 1 yr ago
Do you have back problems that limit mobility or cause pain?				Yes if less than 1 yr ago
Do you have nerve damage that is affecting your legs?				Yes
Have you had, or do you have muscle problems in your legs that limit mobility or causes pain?				Yes if less than 1 yr ago
Have you ever broken any bones in your legs, ankles, or feet?				Yes if less than 2 yr ago
have you ever broken any bones in your spine?				Yes if less than 2 yr ago
Have you had, or do you suffer from fibromyalgia? Or, have you had, or do you have constant muscle fatigue or aches in your body?				Yes
Do you have any joint replacement in your leg joints?				Yes
Do you have any joint fusion?				Yes
Have you had, or do you have poor circulation in your legs that causes them to be cold or numb?				Yes
Have you had, or do you have any lung disease (besides asthma?)				Yes if severe
Have you had, or do you have any heart problems?				Yes if also yes to below
Have you had, or do you have any chest pain from heart disease?				Yes
Have you had, or do you have any vascular problems?				Yes
Have you ever had a heart attack?				Yes if less than 6 mo ago
Do you have high blood pressure? If yes, are you taking medication?				No by itself
Do you have any neurological disease?				Yes
Do you suffer from Parkinson's disease?				Yes
have you ever had a stroke?				Yes
If subject is female : Are you pregnant?				Yes
Any other issues we haven't mentioned that we should know about?				Case-by-case decision

Participant Information Collection Sheet

Participants Information

Healthy Foam Study

Interviewer: ______________________________

Date: ______________________________

Signed Consent: YES NO

Phone Screen Answers Review

Have the answers from the phone screen changed from the day of the coversation to today? YES NO

If yes, what has changed?

____

____

Participant Information

Name: ______________________________

Number: ______________

Email Address or Phone Number: ______________________________

Gender: Male Female Other

Height: ______________________________

Weight: ______________________________

Age: ______________________________

Distance from ankle to bottom of the foot: ______________________________

Distance from ankle to knee: ______________________________

Distance from knee to hip: ______________________________

Appendix C: MATLAB Codes

```
%% Main_Sway_Analysis
% Written by Logan Sidener (lsidener@ku.edu)
% The University of Kansas - Biodynamics Lab
% Modified by Eryn Gerber (eryngerber@ku.edu)
% Last updated 2/19/2020
%
% Purpose: This is the main script used to analyze the foam study data
clear; clc; close all;

% Sampling Parameters
fsample = 100; %[Hz]
fdown = 50; %The desired frequency (in Hz) after downsampling the data
trial_time = 60; %[s]
trial_dt = 1/fsample; %[s]
g = 9.80665; %[m/s^2]

% Force plate information
gain_fp = 1000;

%% Load Subject Information
subject_info = xlsread('/Users/eryngerber/Documents/Biodynamics Lab/Foam
2.0/Subject_Data.xlsx',1,'B3:G55');
%% Establish the path to the data
path = '/Users/eryngerber/Documents/Biodynamics Lab/Foam 2.0/Raw Data/s';

% Choose the conditions of the trial(s) to be analyzed
maxsubj = 1052;
maxfoam = 4;
maxvision = 1; % EC=0,EO=1
maxtrial = 3;

% Initialize empty results matrices
final_data = zeros(3,72);
final_data_avg = zeros(5,72);
all_data=zeros(900,73);

ii=0;
for subject = 1001:maxsubj

    % Code progress updates (during run)
    fprintf([datestr(clock,21) ' \n']);
    fprintf('subject %d\n',subject)

    % Read the zeros file and calculate the mean for each channel
    zeromean = mean(dlmread([path int2str(subject)
'/zeros000.txt'],'\t',1,0));

    % Initialize the count and set figure number to match subject number
    fignum=subject;
    count = 0;
    for numvision = 0:maxvision
        fprintf('vision %d\n',numvision);
```

```
        if numvision == 0
            vision = 'EC';
        else
            vision = 'EO';
        end
        for foam = 0:maxfoam
            fprintf('foam %d\n',foam);
            for trial = 1:maxtrial
                ii=ii+1;
                % Define the file to be analyzed and read the data
                fname = [path int2str(subject) '/Foam_' int2str(foam) '_'
vision '_' int2str(trial) '.txt'];
                data = dlmread(fname,'\t',1,0);

                % Apply a 10 Hz lowpass filter to the raw data, as used in
                order = 2; %2nd order filter
                cutoff_freq_max = 10; %cutoff frequency in Hz
                data=Low_Pass_Filt(order,cutoff_freq_max,fsample,data);


                % Downsample the time series to the desired sampling
frequency
                ratio = fsample/fdown;
                if length(data)==6001
                    data = downsample(data, ratio);
                    time = data(:,1);
                end

                % EAPtract the appropriate subject info
                info=subject_info(subject-1000,:);
                age=info(2);
                gender=info(3); %0 or 1, 0=male
                height=info(4); %given in cm
                weight=info(5); %kg
                bmi=info(6);

                % Add to the count, used for the subplot function
                count = count+1;

                % Calibrate data from volts to force and moments for both FPs
                force_right = V2f_fp3364(data,zeromean,2:7);    %FP 3364
                force_left = V2f_fp3477(data,zeromean,8:13);   %FP 3477

                % ApplML a 90deg CCW rotation about the z-axis to make +AP
the
                % anterior direction and +ML to subject's right
                force_right=[-force_right(:,2) force_right(:,1)
force_right(:,3) ...
                    -force_right(:,5) force_right(:,4) force_right(:,6)];
%FP3364
                force_left=[-force_left(:,2) force_left(:,1) force_left(:,3)
...
                    -force_left(:,5) force_left(:,4) force_left(:,6)];
%FP3477
```

```
                % Combine calibrated force plate data together
                % Coordinate sMLstem is as above: +AP=anterior, +ML=subject's
right
                force_comb = comb_FPs(force_left, force_right);


                force_ML_avg = mean(force_comb(:,1));
                force_AP_avg = mean(force_comb(:,2));
                force_ML_cent = force_comb(:,1)-force_ML_avg;
                force_AP_cent = force_comb(:,2)-force_AP_avg;

                % Calculate COPAP and COPML (centered)
                COP_comb = comb_FPs_COP(force_comb);
                COP_AP=COP_comb(:,1)-mean(COP_comb(:,1)); % + = anterior
                COP_ML=COP_comb(:,2)-mean(COP_comb(:,2)); % + = subject's
right

                % Calculate linear COP pos parameters
                [COP_tot_path_length, COPAP_path_length, COPML_path_length,
COP_SD, ...
                    COP_range_AP, COP_range_ML, RMS_COP, RMS_COP_AP,
RMS_COP_ML]=sway_process_pos(COP_AP(100:2901), COP_ML(100:2901), fdown);

                % Calculate linear COP vel and acc parameters
                a=2; %Fourth order accuracy differentiation
                [vel_mean, vel_AP_mean, vel_ML_mean, vel_max, vel_AP_max,
vel_ML_max ...

,acc_AP_max,acc_ML_max,jerk_ML_max,jerkrate_ML_max,jerk_AP_max,jerkrate_AP_ma
x,acc_ML_mean,acc_AP_mean,jerk_ML_mean,jerk_AP_mean] =
sway_process_velacc(COP_AP(100:2901),COP_ML(100:2901), fdown, a);

                % Calculate Non-linear parameters (SE and DFA parameters)
                [SampEntAP] = sway_process_nonlinear(COP_AP(100:2901),
fdown);
                [SampEntML] = sway_process_nonlinear(COP_ML(100:2901),
fdown);

                % Calculate Rambling and Trembling parameters using
                % centered force data

[F_zero_index,F_zero_COP,F_zero_time,ML_Rambling,ML_Trembling,ML_RMS_Ram,ML_R
MS_Trem,ML_path_length_Ram,ML_path_length_Trem,ML_max_vel_Trem,ML_max_acc_Tre
m,ML_max_vel_Ram,ML_max_acc_Ram,ML_COP_SD_Trem,ML_COP_SD_Ram,ML_max_jerk_Trem
,ML_max_jerk_Ram,ML_max_jerkrate_Trem,ML_max_jerkrate_Ram,ML_mean_vel_Trem,ML
_mean_vel_Ram,ML_mean_acc_Trem,ML_mean_acc_Ram,ML_mean_jerk_Trem,ML_mean_jerk
_Ram] = RamblingTrembling(force_ML_cent,COP_ML,time,fdown);

[F_zero_index,F_zero_COP,F_zero_time,AP_Rambling,AP_Trembling,AP_RMS_Ram,AP_R
MS_Trem,AP_path_length_Ram,AP_path_length_Trem,AP_max_vel_Trem,AP_max_acc_Tre
m,AP_max_vel_Ram,AP_max_acc_Ram,AP_COP_SD_Trem,AP_COP_SD_Ram,AP_max_jerk_Trem
,AP_max_jerk_Ram,AP_max_jerkrate_Trem,AP_max_jerkrate_Ram,AP_mean_vel_Trem,AP
_mean_vel_Ram,AP_mean_acc_Trem,AP_mean_acc_Ram,AP_mean_jerk_Trem,AP_mean_jerk
_Ram] = RamblingTrembling(force_AP_cent,COP_AP,time,fdown);
```

```
                % Trim first and last 2 seconds of time
                time = time(100:2901);

                % Store parameters in matrix
                % final data = 3 trials for 1 foam (1 subject)
                final_data(trial,:)=[subject, foam, numvision, age, gender,
COP_tot_path_length, ...
                    COPAP_path_length, COPML_path_length, COP_SD,
COP_range_AP, COP_range_ML, RMS_COP, RMS_COP_AP, RMS_COP_ML, ...
                    vel_mean, vel_AP_mean, vel_ML_mean, vel_max, vel_AP_max,
vel_ML_max,
acc_AP_max,acc_ML_max,jerk_ML_max,jerkrate_ML_max,jerk_AP_max,jerkrate_AP_max
,...
                    SampEntAP,
SampEntML,AP_RMS_Ram,AP_RMS_Trem,AP_path_length_Ram,AP_path_length_Trem,ML_RM
S_Ram,ML_RMS_Trem,ML_path_length_Ram,ML_path_length_Trem,...

AP_max_vel_Trem,AP_max_acc_Trem,AP_max_vel_Ram,AP_max_acc_Ram,AP_COP_SD_Trem,
AP_COP_SD_Ram,ML_max_vel_Trem,ML_max_acc_Trem,ML_max_vel_Ram,ML_max_acc_Ram,.
..

ML_COP_SD_Trem,ML_COP_SD_Ram,ML_max_jerk_Trem,ML_max_jerk_Ram,ML_max_jerkrate
_Trem,ML_max_jerkrate_Ram,...

AP_max_jerk_Trem,AP_max_jerk_Ram,AP_max_jerkrate_Trem,AP_max_jerkrate_Ram,acc
_ML_mean,acc_AP_mean,jerk_ML_mean,jerk_AP_mean...

ML_mean_vel_Trem,ML_mean_vel_Ram,ML_mean_acc_Trem,ML_mean_acc_Ram,ML_mean_jer
k_Trem,ML_mean_jerk_Ram,...

AP_mean_vel_Trem,AP_mean_vel_Ram,AP_mean_acc_Trem,AP_mean_acc_Ram,AP_mean_jer
k_Trem,AP_mean_jerk_Ram];
                % all data = 3 trials, all foams, all subject averages
                all_data(ii,:)=[subject, foam, numvision, trial, age,
gender,COP_tot_path_length,  ...
                    COPAP_path_length, COPML_path_length, COP_SD,
COP_range_AP, COP_range_ML, RMS_COP, RMS_COP_AP, RMS_COP_ML, ...
                    vel_mean, vel_AP_mean, vel_ML_mean, vel_max, vel_AP_max,
vel_ML_max, acc_AP_max,acc_ML_max,
jerk_ML_max,jerkrate_ML_max,jerk_AP_max,jerkrate_AP_max,...
                    SampEntAP,
SampEntML,AP_RMS_Ram,AP_RMS_Trem,AP_path_length_Ram,AP_path_length_Trem,ML_RM
S_Ram,ML_RMS_Trem,ML_path_length_Ram,ML_path_length_Trem,...

AP_max_vel_Trem,AP_max_acc_Trem,AP_max_vel_Ram,AP_max_acc_Ram,AP_COP_SD_Trem,
AP_COP_SD_Ram,ML_max_vel_Trem,ML_max_acc_Trem,ML_max_vel_Ram,ML_max_acc_Ram,.
..

ML_COP_SD_Trem,ML_COP_SD_Ram,ML_max_jerk_Trem,ML_max_jerk_Ram,ML_max_jerkrate
_Trem,ML_max_jerkrate_Ram,...

AP_max_jerk_Trem,AP_max_jerk_Ram,AP_max_jerkrate_Trem,AP_max_jerkrate_Ram,acc
_ML_mean,acc_AP_mean,jerk_ML_mean,jerk_AP_mean...

ML_mean_vel_Trem,ML_mean_vel_Ram,ML_mean_acc_Trem,ML_mean_acc_Ram,ML_mean_jer
k_Trem,ML_mean_jerk_Ram,...
```

```
AP_mean_vel_Trem,AP_mean_vel_Ram,AP_mean_acc_Trem,AP_mean_acc_Ram,AP_mean_jer
k_Trem,AP_mean_jerk_Ram];

            end
            % Store the calculated data in the final results matrix
            final_data_avg(foam+1,1:3)=final_data(1,1:3);

final_data_avg(foam+1,4:size(final_data,2))=mean(final_data(:,4:size(final_da
ta,2)));
        end
        index=5*(subject-1001)+1;
        if numvision==0
            final_data_EC(index:index+4,:)=final_data_avg;
        else
            final_data_EO(index:index+4,:)=final_data_avg;
        end
    end
end
%% Save Data
save('all_data.mat','all_data')
save('final_data.mat','final_data_EC', 'final_data_EO')

%% Organize Results
% Sort final_data_EC and EO by foam (ordered 0-4)
load('final_data.mat')
load('all_data.mat')
final_data_EC_byfoam = sortrows(final_data_EC,2);
final_data_EC_Foam0 = final_data_EC_byfoam(1:52,:);
final_data_EC_Foam1 = final_data_EC_byfoam(53:104,:);
final_data_EC_Foam2 = final_data_EC_byfoam(105:156,:);
final_data_EC_Foam3 = final_data_EC_byfoam(157:208,:);
final_data_EC_Foam4 = final_data_EC_byfoam(209:260,:);

final_data_EO_byfoam = sortrows(final_data_EO,2);
final_data_EO_Foam0 = final_data_EO_byfoam(1:52,:);
final_data_EO_Foam1 = final_data_EO_byfoam(53:104,:);
final_data_EO_Foam2 = final_data_EO_byfoam(105:156,:);
final_data_EO_Foam3 = final_data_EO_byfoam(157:208,:);
final_data_EO_Foam4 = final_data_EO_byfoam(209:260,:);

% Sort all_data by EC/EO
all_data_EC=zeros(780,73);
all_data_EO=zeros(780,73);
j=1;
k=1;
for i=1:length(all_data)
    if all_data(i,3)==0
        all_data_EC(j,:)=all_data(i,:);
        j=j+1;
    elseif all_data(i,3)==1
        all_data_EO(k,:)=all_data(i,:);
        k=k+1;
    end
end
```

```
save('all_data_EC.mat','all_data_EC')
save('all_data_EO.mat','all_data_EO')

%% Remove Outlier Subjects
% delete outlier subjects (>=30% of data > 3 std devs from sample mean;
outlier - 1022 pregnancy)
delete_subject = 1022;
[delete_rows1] = find(final_data_EC==delete_subject);
[delete_rows2] = find(all_data_EC==delete_subject);
final_data_EC_removed = final_data_EC([1:delete_rows1(1)-
1,delete_rows1(5)+1:end],:);
final_data_EC_removed_TOT_avg = mean(final_data_EC_removed);
final_data_EO_removed = final_data_EO([1:delete_rows1(1)-
1,delete_rows1(5)+1:end],:);
final_data_EO_removed_TOT_avg = mean(final_data_EO_removed);
all_data_EC_removed = all_data_EC([1:delete_rows2(1)-
1,delete_rows2(15)+1:end],:);
all_data_EO_removed = all_data_EO([1:delete_rows2(1)-
1,delete_rows2(15)+1:end],:);

num_subjects = length(final_data_EC_removed)/5;

final_data_EC_removed_byfoam = sortrows(final_data_EC_removed,2);
final_data_EC_removed_Foam0 = final_data_EC_removed_byfoam(1:num_subjects,:);
final_data_EC_removed_0_avg = mean(final_data_EC_removed_Foam0);
final_data_EC_removed_0_std = std(final_data_EC_removed_Foam0);
final_data_EC_removed_Foam1 =
final_data_EC_removed_byfoam(num_subjects+1:2*num_subjects,:);
final_data_EC_removed_1_avg = mean(final_data_EC_removed_Foam1);
final_data_EC_removed_1_std = std(final_data_EC_removed_Foam1);
final_data_EC_removed_Foam2 =
final_data_EC_removed_byfoam(2*num_subjects+1:3*num_subjects,:);
final_data_EC_removed_2_avg = mean(final_data_EC_removed_Foam2);
final_data_EC_removed_2_std = std(final_data_EC_removed_Foam2);
final_data_EC_removed_Foam3 =
final_data_EC_removed_byfoam(3*num_subjects+1:4*num_subjects,:);
final_data_EC_removed_3_avg = mean(final_data_EC_removed_Foam3);
final_data_EC_removed_3_std = std(final_data_EC_removed_Foam3);
final_data_EC_removed_Foam4 =
final_data_EC_removed_byfoam(4*num_subjects+1:5*num_subjects,:);
final_data_EC_removed_4_avg = mean(final_data_EC_removed_Foam4);
final_data_EC_removed_4_std = std(final_data_EC_removed_Foam4);

final_data_EO_removed_byfoam = sortrows(final_data_EO_removed,2);
final_data_EO_removed_Foam0 = final_data_EO_removed_byfoam(1:num_subjects,:);
final_data_EO_removed_0_avg = mean(final_data_EO_removed_Foam0);
final_data_EO_removed_0_std = std(final_data_EO_removed_Foam0);
final_data_EO_removed_Foam1 =
final_data_EO_removed_byfoam(num_subjects+1:2*num_subjects,:);
final_data_EO_removed_1_avg = mean(final_data_EO_removed_Foam1);
final_data_EO_removed_1_std = std(final_data_EO_removed_Foam1);
final_data_EO_removed_Foam2 =
final_data_EO_removed_byfoam(2*num_subjects+1:3*num_subjects,:);
final_data_EO_removed_2_avg = mean(final_data_EO_removed_Foam2);
```

```
final_data_EO_removed_2_std = std(final_data_EO_removed_Foam2);
final_data_EO_removed_Foam3 =
final_data_EO_removed_byfoam(3*num_subjects+1:4*num_subjects,:);
final_data_EO_removed_3_avg = mean(final_data_EO_removed_Foam3);
final_data_EO_removed_3_std = std(final_data_EO_removed_Foam3);
final_data_EO_removed_Foam4 =
final_data_EO_removed_byfoam(4*num_subjects+1:5*num_subjects,:);
final_data_EO_removed_4_avg = mean(final_data_EO_removed_Foam4);
final_data_EO_removed_4_std = std(final_data_EO_removed_Foam4);

save('final_data_EC_removed_avg.mat','final_data_EC_removed_0_avg','final_dat
a_EC_removed_1_avg','final_data_EC_removed_2_avg','final_data_EC_removed_3_av
g','final_data_EC_removed_4_avg')
save('all_data_removed.mat','all_data_EC_removed','all_data_EO_removed')
%% Add headers to final results tables
load('final_data.mat');
load('all_data.mat');

col_headers1={'Subject', 'Foam', 'Vision', 'Age', 'Gender','Total Length',
'AP Length', 'ML Length', 'COP SD', 'Range_AP',...
    'Range_ML', 'COP RMS', 'COP RMS_AP', 'COP RMS_ML', 'Mean Velocity', 'Mean
Vel_AP', 'Mean Vel_ML', 'max Velocity', 'max Vel_AP', 'max
Vel_ML','acc_AP_max','acc_ML_max','max jerk ML','max jerk rate ML','max jerk
AP','max jerk rate AP'...
    'Samp En_AP', 'Samp En_ML','RMS_RM_AP','RMS_TR_AP','Length RM_AP','Length
TR_AP','RMS_RM_ML','RMS_TR_ML','Length RM_ML','Length
TR_ML','AP_vel_Trem','AP_acc_Trem','AP_vel_Ram','AP_acc_Ram',...

'AP_COP_SD_Trem','AP_COP_SD_Ram','ML_vel_Trem','ML_acc_Trem','ML_vel_Ram','ML
_acc_Ram','ML_COP_SD_Trem','ML_COP_SD_Ram',...

'ML_max_jerk_Trem','ML_max_jerk_Ram','ML_max_jerkrate_Trem','ML_max_jerkrate_
Ram','AP_max_jerk_Trem','AP_max_jerk_Ram','AP_max_jerkrate_Trem','AP_max_jerk
rate_Ram','acc_ML_mean','acc_AP_mean','jerk_ML_mean','jerk_AP_mean'...

'ML_mean_vel_Trem','ML_mean_vel_Ram','ML_mean_acc_Trem','ML_mean_acc_Ram','ML
_mean_jerk_Trem','ML_mean_jerk_Ram',...

'AP_mean_vel_Trem','AP_mean_vel_Ram','AP_mean_acc_Trem','AP_mean_acc_Ram','AP
_mean_jerk_Trem','AP_mean_jerk_Ram'};
col_headers2={'Subject', 'Foam', 'Vision', 'Trial', 'Age', 'Gender','Total
Length', 'AP Length', 'ML Length', 'COP SD', 'Range_AP',...
    'Range_ML', 'COP RMS', 'COP RMS_AP', 'COP RMS_ML','Mean Velocity', 'Mean
Vel_AP', 'Mean Vel_ML', 'max Velocity', 'max Vel_AP', 'max
Vel_ML','acc_AP_max','acc_ML_max','max jerk ML','max jerk rate ML','max jerk
AP','max jerk rate AP'...
    'Samp En_AP', 'Samp En_ML','RMS_RM_AP','RMS_TR_AP','Length RM_AP','Length
TR_AP','RMS_RM_ML','RMS_TR_ML','Length RM_ML','Length
TR_ML','AP_vel_Trem','AP_acc_Trem','AP_vel_Ram','AP_acc_Ram',...

'AP_COP_SD_Trem','AP_COP_SD_Ram','ML_vel_Trem','ML_acc_Trem','ML_vel_Ram','ML
_acc_Ram','ML_COP_SD_Trem','ML_COP_SD_Ram',...

'ML_max_jerk_Trem','ML_max_jerk_Ram','ML_max_jerkrate_Trem','ML_max_jerkrate_
Ram','AP_max_jerk_Trem','AP_max_jerk_Ram','AP_max_jerkrate_Trem','AP_max_jerk
rate_Ram','acc_ML_mean','acc_AP_mean','jerk_ML_mean','jerk_AP_mean'...
```

```
'ML_mean_vel_Trem','ML_mean_vel_Ram','ML_mean_acc_Trem','ML_mean_acc_Ram','ML
_mean_jerk_Trem','ML_mean_jerk_Ram',...

'AP_mean_vel_Trem','AP_mean_vel_Ram','AP_mean_acc_Trem','AP_mean_acc_Ram','AP
_mean_jerk_Trem','AP_mean_jerk_Ram'};

% 261 x 72 matrices (with labels) averaged trials for every subject
final_data_EC_cell=[col_headers1; num2cell(final_data_EC)];
final_data_EO_cell=[col_headers1; num2cell(final_data_EO)];
all_data_cell=[col_headers2; num2cell(all_data)];
all_data_EC_cell = [col_headers2; num2cell(all_data_EC)];
all_data_EO_cell = [col_headers2; num2cell(all_data_EO)];

save('data_cells.mat','final_data_EC_cell', 'final_data_EO_cell',
'all_data_cell','all_data_EC','all_data_EO');

% 5 x 67 matrices (no labels) averaged for all subjects
final_data_EC_avg =
[final_data_EC_removed_0_avg(6:end);final_data_EC_removed_1_avg(6:end);final_
data_EC_removed_2_avg(6:end);final_data_EC_removed_3_avg(6:end);final_data_EC
_removed_4_avg(6:end)];
final_data_EO_avg =
[final_data_EO_removed_0_avg(6:end);final_data_EO_removed_1_avg(6:end);final_
data_EO_removed_2_avg(6:end);final_data_EO_removed_3_avg(6:end);final_data_EO
_removed_4_avg(6:end)];
final_data_EC_std =
[final_data_EC_removed_0_std(6:end);final_data_EC_removed_1_std(6:end);final_
data_EC_removed_2_std(6:end);final_data_EC_removed_3_std(6:end);final_data_EC
_removed_0_std(6:end)];
final_data_EO_std =
[final_data_EO_removed_0_std(6:end);final_data_EO_removed_1_std(6:end);final_
data_EO_removed_2_std(6:end);final_data_EO_removed_3_std(6:end);final_data_EO
_removed_0_std(6:end)];

save('data_avg_std.mat','final_data_EC_avg',
'final_data_EO_avg','final_data_EC_std','final_data_EO_std')
```

```
function y_filt=Low_Pass_Filt(order,cutoff_freq,freq,y)
%% y_filt=Low_Pass_Filt(order,cutoff_freq,freq,y)
%COP Linear Measures Calculator
%Camilo Giraldo (c318g339@ku.edu)
%Updated by Logan Sidener
%The University of Kansas - Biodyanmics Lab
%Last Update: 3/7/2017
%
%Purpose: This function uses a low pass filter to filter the time series y
using the order specified
%by the user
%
%Inputs:
%   order:       order of the filtering function
%   cutoff_freq: maximum frequency that will be allowed in filtered time
%                series [Hz]
```

```
%   freq:        sampling frequency of time series
%   y:           raw time series
%
%Outputs:
%   y_filt: filtered time series
%
%Future Work:
%   - Add more type of filters to this function, and allow user to choose

%% Beginnning of Function
%Low-Pass Filter Parameters
nyquist_freq=freq/2;                    %Nyquist freq [hz]
norm_cutoff=cutoff_freq/nyquist_freq;   %Normalized cutoff frequency

%Design of nth order digital low-pass filter
[b,a]=butter(order,norm_cutoff,'low');

%Filtering time series
y_filt=filtfilt(b,a,y);

end
```

```
function fm_3364=V2f_fp3364(volt,zeross,cols)
%% fm_3364=V2f_fp3364(volt,zeross,cols)
%Force Plate 3364 Volts to Force and Moments
%Camilo Giraldo (c318g339@ku.edu)
%The University of Kansas - Biodynamics Lab
%Last Update: 11/03/2016
%
%Purpose: This function turns the voltage data of 3364 into N and N-m
%
%Inputs:
%   Volt: Force plate 3364 data in volts
%   Zero: 1x6 vector with the mean volts for no load on force plate
%   Cols: Columns where force plate 3364 is located
%
%Outputs:
%   fm_3364: force and moments columns in a matrix (Fx,Fy,Fz,Mx,My,Mz)
%
%Future Work; modify the function so it does not need the variable "cols"

%% Beginning of function
%Gain of the force plate in [Amps]
gain=1000;

%KU Biomechanics Lab Force Plate 3364 Calibration Matrix
SIcalmat_3364=[1.506 0.003  0.01  -0.003 -0.013  0.006;
              -0.012 1.513 -0.01   0.01   0.001  0.009;
               0.001 0.002  5.895 -0.002  0.008  0.017;
              -0.001 0.0    0.0    0.732 -0.002 -0.001;
               0.0   0.0    0.0    0.001  0.732  0.003;
               0.001 0.004 -0.02  -0.001 -0.001  0.385];
```

```
% Substract zeros from force plate volts data
[volt_rows,~]=size(volt);                              %Number of rows in data
zero_offset=(zeross'*ones(1,volt_rows))';                %Zero offset in matrix
volt_rowsx6 [Volts]
volt(:,cols)=volt(:,cols)-zero_offset(:,cols);         %Volt data minus the zero
values

%Converting volt data of FP 3364 to N and N-m
GF=(1.e6)/(gain*10);                                   %Equation given by AMTI
fm_3364=GF.*volt(:,cols)*SIcalmat_3364';               %FP 3364 data in N and N-
m

end
```

```
function fm_3477=V2f_fp3477(volt,zeross,cols)
%% fm_3477=V2f_fp3477(volt,zeross,cols)
%Force Plate 3477 Volts to Force and Moments
%Camilo Giraldo (c318g339@ku.edu)
%The University of Kansas - Biodynamics Lab
%Last Update: 11/03/2016
%
%Purpose: This function turns the voltage data of 3477 into N and N-m
%
%Inputs:
%   Volt: Force plate 3477 data in volts
%   Zero: 1x6 vector with the mean volts for no load on force plate
%   Cols: Columns where force plate 3477 is located
%
%Outputs:
%   fm_3477: force and moments columns in a matrix (Fx,Fy,Fz,Mx,My,Mz)
%
%Future Work; modify the function so it does not need the variable "cols"

%% Beginning of function
%Gain of the force plate in [Amps]
gain=1000;

%KU Biomechanics Lab Force Plate 3364 Calibration Matrix
SIcalmat_3477=[1.498 -0.002  0.004  0.003 -0.006  0.011;
               0.006  1.500  0.001 -0.014  0.003  0.015;
              -0.002  0.016  5.930 -0.001  0.003  0.000;
               0.001 -0.001  0.0    0.740 -0.003 -0.001;
              -0.001  0.0    0.0    0.002  0.740  0.001;
               0.0    0.003 -0.002  0.0    0.001  0.383];

% Substract zeros from force plate volts data
[volt_rows,~]=size(volt);                              %Number of rows in data
zero_offset=(zeross'*ones(1,volt_rows))';                %Zero offset in matrix
volt_rowsx6 [Volts]
volt(:,cols)=volt(:,cols)-zero_offset(:,cols);         %Volt data minus the zero
values
```

```
%Converting volt data of FP 3364 to N and N-m
GF=(1.e6)/(gain*10);                              %Equation given by AMTI
fm_3477=GF.*volt(:,cols)*SIcalmat_3477';          %FP 3477 data in N and N-
m

end
```

```
function FP = comb_FPs(fp_left, fp_right)
%% FP = comb_FPs(fp_left, fp_right)
%Combination of Force Plates into One Force Plate
%Camilo Giraldo (c318g339@ku.edu)
%Modified by Logan Sidener
%The University of Kansas - Biodynamics Lab
%Last Update: 3/7/2016
%
%Purpose: this function combines the analog data (already converted to SI
%units) of two force plates labeled as left and right foot. It is assumed
%that the coordinate systems of both force plates are: +x is to the
%anterior direction, +y is to the right hand of the subject, and +z is
%into the ground.
%
%Inputs:
%   fp_right: calibrated analog data of FP1 3364 (Fx,Fy,Fz,Mx,My,Mz)
%   fp_left:  calibrated analog data of FP2 3477 (Fx,Fy,Fz,Mx,My,Mz)
%
%Outputs:
%   FP: Combined force plate data (Fx,Fy,Fz,Mx,My,Mz)

%% Beginning of function
%Distance from center of force plates to middle of force plates
d = 231.5/1000;         %[m]

%Combined force plate components
    %Fx component [N]
    FP(:,1)=fp_left(:,1)+fp_right(:,1);

    %Fy component [N]
    FP(:,2)=fp_left(:,2)+fp_right(:,2);

    %Fz component [N]
    FP(:,3)=fp_left(:,3)+fp_right(:,3);

    %Mx component [N-m]
    FP(:,4)=fp_left(:,4)+fp_right(:,4)-d*fp_left(:,3)+d*fp_right(:,3);

    %My component [N-m]
    FP(:,5)=fp_left(:,5)+fp_right(:,5);

    %Mz component [N-m]
    FP(:,6)=fp_left(:,6)+fp_right(:,6)+d*fp_left(:,1)-d*fp_right(:,1);

% New coordinate system
```

```
%               x
%               ^
%               |
%               |
%               |
%               |
%               X- - - - - - - > y

end
```

```
function COP=comb_FPs_COP(data_cal)
%% COP=COP_mild_xy(data_cal)
%COP Calculator for PD Mild Study
%Camilo Giraldo (c318g339@ku.edu)
%Modified by Logan Sidener
%The University of Kansas - Biodynamics Lab
%Last Update: 3/7/2017
%
%Purpose:
%Calculates COP in x and y axis using data that is already in N and N-m.
%
%Inputs:
%   data_cal: force plate calibrated data in the order of columns Fx,Fy,Fz,
%             Mx,My,Mz
%
%Outputs:
%   COP: two column matrix with COP in the x and y direction (columns 1 and
%        2 respectively)

%% Beginning of function
%Location of origin below the combined force plate surface
dz=0.0375;          %Mean of dz from FP3477 and FP3364 in [m]

%COP Calculations [m]
COP(:,1)=-(data_cal(:,5)+data_cal(:,1)*dz)./data_cal(:,3);     %X-dir, AP
COP(:,2)= (data_cal(:,4)-data_cal(:,2)*dz)./data_cal(:,3);     %Y-dir, ML

% %Subtract off the mean of the COP data to center the plot around zero
% ONLY USE IF PLOTTING COPX VS COPY FOR DATA CHECK
% means=mean(COP);
% COP=COP-means;


%Coordinate system
%               x
%               ^
%               |
%               |
%               |
%               |
%               X- - - - - - - > y

end
```

```matlab
function [COP_tot_path_length, COPx_path_length, COPy_path_length, COP_SD, ...
    COP_range_x, COP_range_y, RMS_COP, RMS_COP_x, RMS_COP_y]=
sway_process_pos(COPx, COPy, sampling_freq)
%sway_process - Function designed to calculate various parameters
%   related to the displacement of the COP time series
% Written by Logan Sidener
% Started 3/6/2018
% Last updated: 1/17/2020 by Eryn Gerber

%
% Inputs:
% COPx: The unfiltered time series of the COP position in the x-direction
% COPy: The unfiltered time series of the COP position in the y-direction
% sampling_freq: The sampling frequency used to collect the data
%
% Outputs:
% wiofj
% fwioefj

[m, ~]=size(COPx);

% DISTANCE TRAVELED
% Find the distance traveled in both directions between each time point
COPx_dist=COPx(2:m)-COPx(1:m-1);
COPy_dist=COPy(2:m)-COPy(1:m-1);
% Calculate magnitude of distance traveled in x, y, and total
distance_tot=sqrt(COPx_dist.^2 + COPy_dist.^2);
distance_x=sqrt(COPx_dist.^2);
distance_y=sqrt(COPy_dist.^2);
% Add each value from above together
COP_tot_path_length=sum(distance_tot);
COPx_path_length = sum(distance_x);
COPy_path_length = sum(distance_y);

% Calculate St. Dev. of the segment lengths for COP magnitude
COP_SD = std(distance_tot);

% SWAY RANGE
COPx_max        = max(COPx);
COPx_min        = min(COPx);
COPy_max        = max(COPy);
COPy_min        = min(COPy);
COP_range_x    = COPx_max - COPx_min;
COP_range_y    = COPy_max - COPy_min;

% RMS ERROR OF COP
% Magnitude of COP
COP = sqrt(COPx.^2+COPy.^2);
COP_dist_center_sway = COP - mean(COP);
abs_COP_dist_center_sway =sqrt(COP_dist_center_sway.^2);
RMS_COP = mean(abs_COP_dist_center_sway);

% x-direction
```

```
COP_dist_center_sway_x = COPx - mean(COPx);
abs_COP_dist_center_sway_x =sqrt(COP_dist_center_sway_x.^2);
RMS_COP_x = mean(abs_COP_dist_center_sway_x);

% y-direction
COP_dist_center_sway_y = COPy - mean(COPy);
abs_COP_dist_center_sway_y =sqrt(COP_dist_center_sway_y.^2);
RMS_COP_y = mean(abs_COP_dist_center_sway_y);

% COP DISPLACEMENT - distance from individual point to mean
% Subtract the mean value from the COP time series to get the COP
displacement
COPx_mean = mean(COPx);
COPy_mean = mean(COPy);
COPx_disp = COPx-COPx_mean;
COPy_disp = COPy-COPy_mean;

% Find mean, max and SD of displacement values in both directions
Dispx_max = max(abs(COPx_disp));
Dispx_mean = mean(abs(COPx_disp));
Dispx_sd = std(COPx_disp);
Dispy_max = max(abs(COPy_disp));
Dispy_mean = mean(abs(COPy_disp));
Dispy_sd = std(COPy_disp);


end
```

```
function [vel_mean, vel_x_mean, vel_y_mean, vel_max, vel_x_max, ...

vel_y_max,acc_x_max,acc_y_max,jerk_x_max,jerkrate_x_max,jerk_y_max,jerkrate_y
_max,acc_x_mean,acc_y_mean,jerk_x_mean,jerk_y_mean] = sway_process_velacc(
COPx_filt, COPy_filt, fsample, a )

% sway_process_velacc - Function designed to calculate various parameters
% related to the velocity and acceleration of the COP time series
% Written by Logan Sidener
% Started 3/6/2018
% Modified by Eryn Gerber (eryngerber@ku.edu)
% Last updated: 2/19/2020

dt=1/fsample;

% Numerically differentiate the filtered time series to find the vel and acc
[vel_x,acc_x]=dxdt_d2xdt2(COPx_filt,a,dt);
[vel_y,acc_y]=dxdt_d2xdt2(COPy_filt,a,dt);
[jerk_x,jerkrate_x]=dxdt_d2xdt2(acc_x,a,dt);
[jerk_y,jerkrate_y]=dxdt_d2xdt2(acc_y,a,dt);

% Compute the magnitude of the COP_vel and COP_acc time series
COP_vel = sqrt(vel_x.^2+vel_y.^2);
COP_acc = sqrt(acc_x.^2+acc_y.^2);
```

```
% Compute the mean (magnitude) of each time series
vel_mean = mean(COP_vel);
vel_x_mean = mean(sqrt(vel_x.^2));
vel_y_mean = mean(sqrt(vel_y.^2));

acc_mean = mean(COP_acc);
acc_x_mean = mean(sqrt(acc_x.^2));
acc_y_mean = mean(sqrt(acc_y.^2));

jerk_x_mean = mean(sqrt(jerk_x.^2));
jerk_y_mean = mean(sqrt(jerk_y.^2));

% Compute the maximum (magnitude) of each time series
vel_max = max(COP_vel);
vel_x_max = max(sqrt(vel_x.^2));
vel_y_max = max(sqrt(vel_y.^2));

acc_max = max(COP_acc);
acc_x_max = max(sqrt(acc_x.^2));
acc_y_max = max(sqrt(acc_y.^2));

jerk_x_max = max(sqrt(jerk_x.^2));
jerkrate_x_max = max(sqrt(jerkrate_x.^2));
jerk_y_max = max(sqrt(jerk_y.^2));
jerkrate_y_max = max(sqrt(jerkrate_y.^2));

end
```

```
% Rambling-Trembling Analysis Function
% Purpose: Decompose COP signals into rambling and trembling components,
% and calculate relevant parameters (velocity, acc, jerk, etc.)
% Written by: Eryn Gerber, erynbgerber@ku.edu
% Last Updated Feb 24, 2020

function [F_zero_index,F_zero_COP,F_zero_time,Rambling,Trembling,RMS_Ram,...
    RMS_Trem,path_length_Ram,path_length_Trem,max_vel_Trem,max_acc_Trem,...

max_vel_Ram,max_acc_Ram,COP_SD_Trem,COP_SD_Ram,max_jerk_Trem,max_jerk_Ram,...
    max_jerkrate_Trem,max_jerkrate_Ram,mean_vel_Trem,mean_vel_Ram,...
    mean_acc_Trem,mean_acc_Ram,mean_jerk_Trem,mean_jerk_Ram] =
RamblingTrembling(force_comb,COP_series,time,fdown)

len = length(force_comb);
F_zero_index=[];
F_zero_COP=[];
F_zero_time=[];

for i=1:len-1
    if
or(and(force_comb(i)<0,force_comb(i+1)>0),and(force_comb(i)>0,force_comb(i+1)
<0))
        [F_zero_index] = [F_zero_index;i];
        [F_zero_COP] = [F_zero_COP;COP_series(i)];
```

```
        [F_zero_time] = [F_zero_time;time(i)];
    end
end

% Function will return if there are <2 zero-crossing points in the dataset
if or(isempty(F_zero_index)== 1,size(F_zero_index)<2)
    disp('F never crosses 0')
    Rambling = NaN;
    Trembling = NaN;
    RMS_Ram = NaN;
    RMS_Trem = NaN;
    path_length_Ram = NaN;
    path_length_Trem = NaN;
    return
end

% Function will return calculated parameters if zero crossing points are
% found
if isempty(F_zero_index) == 0
    F_zero_COP_spline = spline(F_zero_time,F_zero_COP,time);
    Rambling = F_zero_COP_spline;
    Rambling = Rambling(100:2901);
    Trembling = COP_series(100:2901)-Rambling;

    % Calculate RMS values for Ram and Trem
    COP_dist_center_sway_Ram = Rambling - mean(Rambling);
    abs_COP_dist_center_sway_Ram =abs(COP_dist_center_sway_Ram);
    RMS_Ram = mean(abs_COP_dist_center_sway_Ram);

    COP_dist_center_sway_Trem = Trembling - mean(Trembling);
    abs_COP_dist_center_sway_Trem =abs(COP_dist_center_sway_Trem);
    RMS_Trem = mean(abs_COP_dist_center_sway_Trem);

    % Calculate COP distance for RM and TR
    [m1,~]=size(Trembling);
    [m2,~]=size(Rambling);
    COP_dist_Trem=Trembling(2:m1)-Trembling(1:m1-1);
    COP_SD_Trem = std(COP_dist_Trem);
    COP_dist_Ram=Rambling(2:m2)-Rambling(1:m2-1);
    COP_SD_Ram = std(COP_dist_Ram);

    % Calculate magnitude of distance traveled in x, y, and total
    distance_Trem=sqrt(COP_dist_Trem.^2);
    path_length_Trem = sum(distance_Trem);
    distance_Ram=sqrt(COP_dist_Ram.^2);
    path_length_Ram = sum(distance_Ram);

    % Calculate Velocity and Acceleration of RM and TR
    dt = 1/fdown;
    a = 2;
    [vel_Trem,acc_Trem]=dxdt_d2xdt2(Trembling,a,dt);
    vel_Trem = abs(vel_Trem);
    acc_Trem = abs(acc_Trem);
    max_vel_Trem = max(vel_Trem);
    mean_vel_Trem = mean(vel_Trem);
```

```
    max_acc_Trem = max(acc_Trem);
    mean_acc_Trem = mean(acc_Trem);
    [vel_Ram,acc_Ram]=dxdt_d2xdt2(Rambling,a,dt);
    vel_Ram = abs(vel_Ram);
    acc_Ram = abs(acc_Ram);
    max_vel_Ram = max(vel_Ram);
    mean_vel_Ram = mean(vel_Ram);
    max_acc_Ram = max(acc_Ram);
    mean_acc_Ram = mean(acc_Ram);

    % Jerk
    [jerk_Trem,jerkrate_Trem]=dxdt_d2xdt2(acc_Trem,a,dt);
    jerk_Trem = abs(jerk_Trem);
    jerkrate_Trem = abs(jerkrate_Trem);
    max_jerk_Trem = max(jerk_Trem);
    mean_jerk_Trem = mean(jerk_Trem);
    max_jerkrate_Trem = max(jerkrate_Trem);
    mean_jerkrate_Trem = mean(jerkrate_Trem);
    [jerk_Ram,jerkrate_Ram]=dxdt_d2xdt2(acc_Ram,a,dt);
    jerk_Ram = abs(jerk_Ram);
    jerkrate_Ram = abs(jerkrate_Ram);
    max_jerk_Ram = max(jerk_Ram);
    mean_jerk_Ram = mean(jerk_Ram);
    max_jerkrate_Ram = max(jerkrate_Ram);
    mean_jerkrate_Ram = mean(jerkrate_Ram);

end
```

```
%% Perc_Normalize
% Written by Eryn Gerber (eryngerber@ku.edu)
% The University of Kansas - Biodynamics Lab
% Last updated 2/19/2020
%
% Purpose: Calculate normalized values for parameters.
% 100*(foamN-foam0)/foam0 and save as .mat file
% Code part 3 of 5
%% Normalized percent changes
load('final_data_EC_removed_avg.mat')
Foam10_EC_removed = zeros(51,72);
Foam10_EC_removed(:,1:5) = final_data_EC_removed_Foam1(:,1:5);
Foam10_EC_removed(:,6:end) = 100.*(final_data_EC_removed_Foam1(:,6:end)-
final_data_EC_removed_Foam0(:,6:end))./final_data_EC_removed_Foam0(:,6:end);
Foam10_EC_removed_avg = mean(Foam10_EC_removed);
Foam10_EC_removed_std = std(Foam10_EC_removed);
Foam20_EC_removed = zeros(51,72);
Foam20_EC_removed(:,1:5) = final_data_EC_removed_Foam2(:,1:5);
Foam20_EC_removed(:,6:end) = 100.*(final_data_EC_removed_Foam2(:,6:end)-
final_data_EC_removed_Foam0(:,6:end))./final_data_EC_removed_Foam0(:,6:end);
Foam20_EC_removed_avg = mean(Foam20_EC_removed);
Foam20_EC_removed_std = std(Foam20_EC_removed);
Foam30_EC_removed = zeros(51,72);
Foam30_EC_removed(:,1:5) = final_data_EC_removed_Foam3(:,1:5);
Foam30_EC_removed(:,6:end) = 100.*(final_data_EC_removed_Foam3(:,6:end)-
final_data_EC_removed_Foam0(:,6:end))./final_data_EC_removed_Foam0(:,6:end);
```

```
Foam30_EC_removed_avg = mean(Foam30_EC_removed);
Foam30_EC_removed_std = std(Foam30_EC_removed);
Foam40_EC_removed = zeros(51,72);
Foam40_EC_removed(:,1:5) = final_data_EC_removed_Foam4(:,1:5);
Foam40_EC_removed(:,6:end) = 100.*(final_data_EC_removed_Foam4(:,6:end)-
final_data_EC_removed_Foam0(:,6:end))./final_data_EC_removed_Foam0(:,6:end);
Foam40_EC_removed_avg = mean(Foam40_EC_removed);
Foam40_EC_removed_std = std(Foam40_EC_removed);

Norm_EC_removed_changes_avg =
[Foam10_EC_removed_avg(6:end);Foam20_EC_removed_avg(6:end);Foam30_EC_removed_
avg(6:end);Foam40_EC_removed_avg(6:end)];
Norm_EC_removed_changes_std =
[Foam10_EC_removed_std(6:end);Foam20_EC_removed_std(6:end);Foam30_EC_removed_
std(6:end);Foam40_EC_removed_std(6:end)];

Norm_EC_removed_changes =
[Foam10_EC_removed;Foam20_EC_removed;Foam30_EC_removed;Foam40_EC_removed];
save('Perc_changes_EC.mat','Norm_EC_removed_changes','Norm_EC_removed_changes
_avg','Norm_EC_removed_changes_std','Foam10_EC_removed','Foam20_EC_removed','
Foam30_EC_removed','Foam40_EC_removed','Foam10_EC_removed_avg','Foam10_EC_rem
oved_std','Foam20_EC_removed_avg','Foam20_EC_removed_std','Foam30_EC_removed_
avg','Foam30_EC_removed_std','Foam40_EC_removed_avg','Foam40_EC_removed_std')

Foam10_EO_removed = 100.*(final_data_EO_removed_Foam1-
final_data_EO_removed_Foam0)./final_data_EC_removed_Foam0;
Foam10_EO_removed_avg = mean(Foam10_EO_removed);
Foam10_EO_removed_std = std(Foam10_EO_removed);
Foam20_EO_removed = 100.*(final_data_EO_removed_Foam2-
final_data_EO_removed_Foam0)./final_data_EC_removed_Foam0;
Foam20_EO_removed_avg = mean(Foam20_EO_removed);
Foam20_EO_removed_std = std(Foam20_EO_removed);
Foam30_EO_removed = 100.*(final_data_EO_removed_Foam3-
final_data_EO_removed_Foam0)./final_data_EC_removed_Foam0;
Foam30_EO_removed_avg = mean(Foam30_EO_removed);
Foam30_EO_removed_std = std(Foam30_EO_removed);
Foam40_EO_removed = 100.*(final_data_EO_removed_Foam4-
final_data_EO_removed_Foam0)./final_data_EC_removed_Foam0;
Foam40_EO_removed_avg = mean(Foam40_EO_removed);
Foam40_EO_removed_std = std(Foam40_EO_removed);

Norm_EO_removed_changes_avg =
[Foam10_EO_removed_avg(6:end);Foam20_EO_removed_avg(6:end);Foam30_EO_removed_
avg(6:end);Foam40_EO_removed_avg(6:end)];
Norm_EO_removed_changes_std =
[Foam10_EO_removed_std(6:end);Foam20_EO_removed_std(6:end);Foam30_EO_removed_
std(6:end);Foam40_EO_removed_std(6:end)];

Norm_EO_removed_changes =
[Foam10_EO_removed;Foam20_EO_removed;Foam30_EO_removed;Foam40_EO_removed];
save('Perc_changes_EO.mat','Norm_EO_removed_changes','Norm_EO_removed_changes
_avg','Norm_EO_removed_changes_std','Foam10_EO_removed','Foam20_EO_removed','
Foam30_EO_removed','Foam40_EO_removed','Foam10_EO_removed_avg','Foam10_EO_rem
oved_std','Foam20_EO_removed_avg','Foam20_EO_removed_std','Foam30_EO_removed_
avg','Foam30_EO_removed_std','Foam40_EO_removed_avg','Foam40_EO_removed_std')
```

```
%% Results_Plots
% Written by Eryn Gerber (eryngerber@ku.edu)
% The University of Kansas - Biodynamics Lab
% Last updated 2/17/2020
%
% Purpose: This is the main script used to plot the foam study data
% Code part 2 of 5
%% Data Check (Plot all Subjects)
plot(final_data_EC_removed_Foam0(:,1),final_data_EC_removed_Foam0(:,52),'-
ok')
hold on
%plot(final_data_EC_removed_Foam1(:,1),final_data_EC_removed_Foam1(:,29),'-
or')
%plot(final_data_EC_removed_Foam2(:,1),final_data_EC_removed_Foam2(:,29),'-
ob')
%plot(final_data_EC_removed_Foam3(:,1),final_data_EC_removed_Foam3(:,29),'-
og')
plot(final_data_EC_removed_Foam4(:,1),final_data_EC_removed_Foam4(:,52),'-
om')

%% Decomposition time-series
subplot(3,1,1)
sgtitle('RM-TR Decomposition','FontSize',20)
plot(time, force_AP_cent(100:2901),'k',time,zeros(2802),'r')
xlim([2 58])
xticks([10 20 30 40 50])
yticks([-2 -1 0 1 2])
set(gca,'FontSize',20)
ylim([-2 2])
ylabel('F_{hor} (N)','FontSize',20)
subplot(3,1,2)
plot(time,AP_Rambling.*1000,':r','LineWidth',2)
hold on
plot(time,COP_AP(100:2901).*1000,'-k')
legend('Rambling','COP','FontSize',15)
xlim([2 58])
xticks([10 20 30 40 50])
yticks([-20 -10 0 10 20])
set(gca,'FontSize',20)
ylim([-20 20])
ylabel('Displacement (mm)','FontSize',20)
subplot(3,1,3)
plot(time,AP_Trembling.*1000,'-k')
xlim([2 58])
xticks([10 20 30 40 50])
yticks([-5 0 5])
set(gca,'FontSize',20)
ylim([-5 5])
ylabel('Trembling (mm)','FontSize',20)
xlabel('Time (seconds)','FontSize',20)
savefig('Decomposition')


%% COP Plots - RM, TR, COP
```

```
figure()
subplot(1,3,1)
plot(ML_Rambling*100,AP_Rambling*100)
title('RM (cm)')
axis square
axis([-2 2 -2 2])
subplot(1,3,2)
plot(ML_Trembling*100, AP_Trembling*100)
title('TR (cm)')
axis square
axis([-0.5 0.5 -0.5 0.5])
subplot(1,3,3)
plot(COP_ML*100,COP_AP*100)
title('COP (cm)')
axis square
axis([-2 2 -2 2])

%% ML Mean Velocity w StDev EC
figure()
hold on
errorbar([0 1 2 3 4],final_data_EC_avg(:,12),final_data_EC_std(:,12))
errorbar([0 1 2 3 4],final_data_EC_avg(:,57),final_data_EC_std(:,57))
errorbar([0 1 2 3 4],final_data_EC_avg(:,56),final_data_EC_std(:,56))
title('Mean Velocity (ML,EC)')
legend('COP','RM','TR')

%% AP Mean Velocity w StDev EC
figure()
hold on
errorbar([0 1 2 3 4],final_data_EC_avg(:,11),final_data_EC_std(:,11))
errorbar([0 1 2 3 4],final_data_EC_avg(:,63),final_data_EC_std(:,63))
errorbar([0 1 2 3 4],final_data_EC_avg(:,62),final_data_EC_std(:,62))
title('Mean Velocity (AP,EC)')
legend('COP','RM','TR')

%% ML Mean Acc w StDev EC
figure()
hold on
errorbar([0 1 2 3 4],final_data_EC_avg(:,52),final_data_EC_std(:,52))
errorbar([0 1 2 3 4],final_data_EC_avg(:,58),final_data_EC_std(:,58))
errorbar([0 1 2 3 4],final_data_EC_avg(:,59),final_data_EC_std(:,59))
title('Mean Velocity (ML,EC)')
legend('COP','RM','TR')
```

```
%% Results_Plots_Norm
% Written by Eryn Gerber (eryngerber@ku.edu)
% The University of Kansas - Biodynamics Lab
% Last updated 2/19/2020
%
% Purpose: Plot the normalized (percent change) in comp, 2x3, and bar chart
% arrangements
```

```
%% Mean Velocity Comparison
load('data_avg_std.mat')
figure()
subplot(1,2,1)
sgtitle('Norm Mean Velocity')
errorbar([1 2 3
4],Norm_EC_removed_changes_avg(:,12),Norm_EC_removed_changes_std(:,12),'-ok')
hold on
errorbar([1 2 3
4],Norm_EC_removed_changes_avg(:,56),Norm_EC_removed_changes_std(:,56),'-or')
errorbar([1 2 3
4],Norm_EC_removed_changes_avg(:,57),Norm_EC_removed_changes_std(:,57),'-ob')
axis([1 4 -40 100])
xticks([1 2 3 4])
title('ML-direction')

subplot(1,2,2)
errorbar([1 2 3
4],Norm_EC_removed_changes_avg(:,11),Norm_EC_removed_changes_std(:,11),'-ok')
hold on
errorbar([1 2 3
4],Norm_EC_removed_changes_avg(:,62),Norm_EC_removed_changes_std(:,62),'-or')
errorbar([1 2 3
4],Norm_EC_removed_changes_avg(:,63),Norm_EC_removed_changes_std(:,63),'-ob')
title('AP-direction')
legend('COP','TR','RM')
axis([1 4 -40 100])
xticks([1 2 3 4])
savefig('Norm Mean Vel Comp')

%% Shaded Error Plot: Norm Mean Vel EC Comp
x = [1/8 1/4 1/2 1];
y = [Norm_EC_removed_changes_avg(:,12)]';
stdv = [Norm_EC_removed_changes_std(:,12)]';

y2 = [Norm_EC_removed_changes_avg(:,56)]';
stdv2 = [Norm_EC_removed_changes_std(:,56)]';

y3 = [Norm_EC_removed_changes_avg(:,57)]';
stdv3 = [Norm_EC_removed_changes_std(:,57)]';

y4 = [Norm_EC_removed_changes_avg(:,11)]';
stdv4 = [Norm_EC_removed_changes_std(:,11)]';

y5 = [Norm_EC_removed_changes_avg(:,62)]';
stdv5 = [Norm_EC_removed_changes_std(:,62)]';

y6 = [Norm_EC_removed_changes_avg(:,63)]';
stdv6 = [Norm_EC_removed_changes_std(:,63)]';

subplot(1,2,2)
title('ML-direction')
sgtitle('Changes in Normalized Mean Vel Across Foam Thickness','FontSize',25)
```

```
shadedErrorBar(x,y,stdv,'lineprops',{'-k','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
hold on
shadedErrorBar(x,y2,stdv2,'lineprops',{'-b','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
shadedErrorBar(x,y3,stdv3,'lineprops',{'-r','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
axis([0.125 1 0 100])
xticks([1/8 1/4 1/2 1])
yticks(linspace(-100,100,11))
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'},'FontSize',20)
legend('COP','TR','RM','Location','northwest')

subplot(1,2,1)
title('AP-direction')
shadedErrorBar(x,y4,stdv4,'lineprops',{'-k','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
hold on
shadedErrorBar(x,y5,stdv5,'lineprops',{'-b','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
shadedErrorBar(x,y6,stdv6,'lineprops',{'-r','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
axis([0.125 1 0 100])
xticks([1/8 1/4 1/2 1])
yticks(linspace(-100,100,11))
ylabel('Mean % Change from Baseline','FontSize',35)
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'},'FontSize',20)

[a,h1]=suplabel('Foam Thickness (inches)');
set(h1,'FontSize',20)

savefig('Norm Mean Vel EC Comp_shaded')

%% Shaded Error Plot: Norm Mean Vel EO
x = [1/8 1/4 1/2 1];
y = [Norm_EO_removed_changes_avg(:,12)]';
stdv = [Norm_EO_removed_changes_std(:,12)]';

y2 = [Norm_EO_removed_changes_avg(:,56)]';
stdv2 = [Norm_EO_removed_changes_std(:,56)]';

y3 = [Norm_EO_removed_changes_avg(:,57)]';
stdv3 = [Norm_EO_removed_changes_std(:,57)]';

y4 = [Norm_EO_removed_changes_avg(:,11)]';
stdv4 = [Norm_EO_removed_changes_std(:,11)]';

y5 = [Norm_EO_removed_changes_avg(:,62)]';
stdv5 = [Norm_EO_removed_changes_std(:,62)]';

y6 = [Norm_EO_removed_changes_avg(:,63)]';
stdv6 = [Norm_EO_removed_changes_std(:,63)]';

subplot(1,2,2)
```

```
title('ML-direction')
sgtitle('Changes in Normalized Mean Vel Across Foam Thickness
EO','FontSize',25)
shadedErrorBar(x,y,stdv,'lineprops',{'-k','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
hold on
shadedErrorBar(x,y2,stdv2,'lineprops',{'-b','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
shadedErrorBar(x,y3,stdv3,'lineprops',{'-r','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
axis([0.125 1 0 100])
xticks([1/8 1/4 1/2 1])
yticks(linspace(-100,100,11))
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'},'FontSize',20)
legend('COP','TR','RM','Location','northwest')

subplot(1,2,1)
title('AP-direction')
shadedErrorBar(x,y4,stdv4,'lineprops',{'-k','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
hold on
shadedErrorBar(x,y5,stdv5,'lineprops',{'-b','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
shadedErrorBar(x,y6,stdv6,'lineprops',{'-r','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
axis([0.125 1 0 100])
xticks([1/8 1/4 1/2 1])
yticks(linspace(-100,100,11))
ylabel('Mean % Change from Baseline','FontSize',35)
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'},'FontSize',20)

[a,h1]=suplabel('Foam Thickness (inches)');
set(h1,'FontSize',20)

savefig('Norm Mean Vel EO Comp_shaded')

%% Mean Acceleration Comparison EC
figure()
subplot(1,2,1)
sgtitle('Norm Mean Acceleration')
errorbar([1 2 3
4],Norm_EC_removed_changes_avg(:,52),Norm_EC_removed_changes_std(:,52),'-ok')
hold on
errorbar([1 2 3
4],Norm_EC_removed_changes_avg(:,59),Norm_EC_removed_changes_std(:,59),'-or')
errorbar([1 2 3
4],Norm_EC_removed_changes_avg(:,58),Norm_EC_removed_changes_std(:,58),'-ob')
title('ML-direction')
axis([1 4 -40 100])
xticks([1 2 3 4])

subplot(1,2,2)
errorbar([1 2 3
4],Norm_EC_removed_changes_avg(:,53),Norm_EC_removed_changes_std(:,53),'-ok')
hold on
```

```
errorbar([1 2 3
4],Norm_EC_removed_changes_avg(:,64),Norm_EC_removed_changes_std(:,64),'-or')
errorbar([1 2 3
4],Norm_EC_removed_changes_avg(:,65),Norm_EC_removed_changes_std(:,65),'-ob')
title('AP-direction')
legend('COP','TR','RM')
axis([1 4 -40 100])
xticks([1 2 3 4])
sigstar({[4],},[0.0255]);
savefig('Norm Mean Acc Comp')

%% Shaded Error Plot: Norm Mean Acc EC Comp
x = [1/8 1/4 1/2 1];
y = [Norm_EC_removed_changes_avg(:,52)]';
stdv = [Norm_EC_removed_changes_std(:,52)]';

y2 = [Norm_EC_removed_changes_avg(:,59)]';
stdv2 = [Norm_EC_removed_changes_std(:,59)]';

y3 = [Norm_EC_removed_changes_avg(:,58)]';
stdv3 = [Norm_EC_removed_changes_std(:,58)]';

y4 = [Norm_EC_removed_changes_avg(:,53)]';
stdv4 = [Norm_EC_removed_changes_std(:,53)]';

y5 = [Norm_EC_removed_changes_avg(:,64)]';
stdv5 = [Norm_EC_removed_changes_std(:,64)]';

y6 = [Norm_EC_removed_changes_avg(:,65)]';
stdv6 = [Norm_EC_removed_changes_std(:,65)]';

subplot(1,2,2)
title('ML-direction')
sgtitle('Changes in Normalized Mean Acc Across Foam Thickness','FontSize',25)
shadedErrorBar(x,y,stdv,'lineprops',{'-k','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
hold on
shadedErrorBar(x,y2,stdv2,'lineprops',{'-b','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
shadedErrorBar(x,y3,stdv3,'lineprops',{'-r','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
axis([0.125 1 0 100])
xticks([1/8 1/4 1/2 1])
yticks(linspace(-100,100,11))
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'},'FontSize',20)
legend('COP','TR','RM','Location','northwest')

subplot(1,2,1)
title('AP-direction')
shadedErrorBar(x,y4,stdv4,'lineprops',{'-k','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
hold on
shadedErrorBar(x,y5,stdv5,'lineprops',{'-b','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
```

```
shadedErrorBar(x,y6,stdv6,'lineprops',{'-r','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
axis([0.125 1 0 100])
xticks([1/8 1/4 1/2 1])
yticks(linspace(-100,100,11))
ylabel('Mean % Change from Baseline','FontSize',35)
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'},'FontSize',20)

[a,h1]=suplabel('Foam Thickness (inches)');
set(h1,'FontSize',20)

savefig('Norm Mean Acc EC Comp_shaded')
%% Shaded Error Plot: Norm Mean Acc EO Comp
x = [1/8 1/4 1/2 1];
y = [Norm_EO_removed_changes_avg(:,52)]';
stdv = [Norm_EO_removed_changes_std(:,52)]';

y2 = [Norm_EO_removed_changes_avg(:,59)]';
stdv2 = [Norm_EO_removed_changes_std(:,59)]';

y3 = [Norm_EO_removed_changes_avg(:,58)]';
stdv3 = [Norm_EO_removed_changes_std(:,58)]';

y4 = [Norm_EO_removed_changes_avg(:,53)]';
stdv4 = [Norm_EO_removed_changes_std(:,20)]';

y5 = [Norm_EO_removed_changes_avg(:,64)]';
stdv5 = [Norm_EO_removed_changes_std(:,64)]';

y6 = [Norm_EO_removed_changes_avg(:,65)]';
stdv6 = [Norm_EO_removed_changes_std(:,65)]';

subplot(1,2,2)
title('ML-direction')
sgtitle('Changes in Normalized Mean Acc Across Foam Thickness
EO','FontSize',25)
shadedErrorBar(x,y,stdv,'lineprops',{'-k','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
hold on
shadedErrorBar(x,y2,stdv2,'lineprops',{'-b','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
shadedErrorBar(x,y3,stdv3,'lineprops',{'-r','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
axis([0.125 1 -5 100])
xticks([1/8 1/4 1/2 1])
yticks(linspace(-100,100,11))
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'},'FontSize',20)
legend('COP','TR','RM','Location','northwest')

subplot(1,2,1)
title('AP-direction')
shadedErrorBar(x,y4,stdv4,'lineprops',{'-k','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
hold on
```

```
shadedErrorBar(x,y5,stdv5,'lineprops',{'-b','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
shadedErrorBar(x,y6,stdv6,'lineprops',{'-r','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
axis([0.125 1 -5 100])
xticks([1/8 1/4 1/2 1])
yticks(linspace(-100,100,11))
ylabel('Mean % Change from Baseline','FontSize',35)
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'},'FontSize',20)

[a,h1]=suplabel('Foam Thickness (inches)');
set(h1,'FontSize',20)

savefig('Norm Mean Acc EO Comp_shaded')


%% Shaded Error Plot: Norm Mean Jerk EC Comp
x = [1/8 1/4 1/2 1];
y = [Norm_EC_removed_changes_avg(:,54)]';
stdv = [Norm_EC_removed_changes_std(:,54)]';

y2 = [Norm_EC_removed_changes_avg(:,60)]';
stdv2 = [Norm_EC_removed_changes_std(:,60)]';

y3 = [Norm_EC_removed_changes_avg(:,61)]';
stdv3 = [Norm_EC_removed_changes_std(:,61)]';

y4 = [Norm_EC_removed_changes_avg(:,55)]';
stdv4 = [Norm_EC_removed_changes_std(:,55)]';

y5 = [Norm_EC_removed_changes_avg(:,66)]';
stdv5 = [Norm_EC_removed_changes_std(:,66)]';

y6 = [Norm_EC_removed_changes_avg(:,67)]';
stdv6 = [Norm_EC_removed_changes_std(:,67)]';

subplot(1,2,2)
title('ML-direction')
sgtitle('Changes in Normalized Jerk Across Foam Thickness','FontSize',25)
shadedErrorBar(x,y,stdv,'lineprops',{'-k','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
hold on
shadedErrorBar(x,y2,stdv2,'lineprops',{'-b','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
shadedErrorBar(x,y3,stdv3,'lineprops',{'-r','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
axis([0.125 1 0 108])
xticks([1/8 1/4 1/2 1])
yticks([0 20 40 60 80 100])
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'},'FontSize',20)
legend('COP','TR','RM','Location','northwest')

subplot(1,2,1)
title('AP-direction')
```

```
shadedErrorBar(x,y4,stdv4,'lineprops',{'-k','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
hold on
shadedErrorBar(x,y5,stdv5,'lineprops',{'-b','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
shadedErrorBar(x,y6,stdv6,'lineprops',{'-r','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
axis([0.125 1 0 108])
xticks([1/8 1/4 1/2 1])
yticks([0 20 40 60 80 100])
ylabel('Mean % Change from Baseline','FontSize',35)
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'},'FontSize',20)

[a,h1]=suplabel('Foam Thickness (inches)');
set(h1,'FontSize',20)

savefig('Norm Mean Jerk EC Comp_shaded')

%% Shaded Error Plot: Norm Mean Jerk EO Comp
x = [1/8 1/4 1/2 1];
y = [Norm_EO_removed_changes_avg(:,54)]';
stdv = [Norm_EO_removed_changes_std(:,54)]';

y2 = [Norm_EO_removed_changes_avg(:,60)]';
stdv2 = [Norm_EO_removed_changes_std(:,60)]';

y3 = [Norm_EO_removed_changes_avg(:,61)]';
stdv3 = [Norm_EO_removed_changes_std(:,61)]';

y4 = [Norm_EO_removed_changes_avg(:,55)]';
stdv4 = [Norm_EO_removed_changes_std(:,55)]';

y5 = [Norm_EO_removed_changes_avg(:,66)]';
stdv5 = [Norm_EO_removed_changes_std(:,66)]';

y6 = [Norm_EO_removed_changes_avg(:,67)]';
stdv6 = [Norm_EO_removed_changes_std(:,67)]';

subplot(1,2,2)
title('ML-direction')
sgtitle('Changes in Normalized Jerk Across Foam Thickness EO','FontSize',25)
shadedErrorBar(x,y,stdv,'lineprops',{'-k','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
hold on
shadedErrorBar(x,y2,stdv2,'lineprops',{'-b','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
shadedErrorBar(x,y3,stdv3,'lineprops',{'-r','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
axis([0.125 1 -10 100])
xticks([1/8 1/4 1/2 1])
yticks(linspace(-100,100,11))
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'},'FontSize',20)
legend('COP','TR','RM','Location','northwest')
```

```
subplot(1,2,1)
title('AP-direction')
shadedErrorBar(x,y4,stdv4,'lineprops',{'-k','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
hold on
shadedErrorBar(x,y5,stdv5,'lineprops',{'-b','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
shadedErrorBar(x,y6,stdv6,'lineprops',{'-r','LineWidth',3,'LineStyle','-
'},'transparent',true,'patchSaturation',0.05)
axis([0.125 1 -10 100])
xticks([1/8 1/4 1/2 1])
yticks(linspace(-100,100,11))
ylabel('Mean % Change from Baseline','FontSize',35)
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'},'FontSize',20)

[a,h1]=suplabel('Foam Thickness (inches)');
set(h1,'FontSize',20)

savefig('Norm Mean Jerk EO Comp_shaded')
%% 2x3 Plot: Norm Mean Jerk
% AP Rambling
subplot(2,3,1)
sgtitle('Percent Change from Baseline: Mean Jerk')
errorbar([1/8 1/4 1/2
1],Norm_EC_removed_changes_avg(:,55),Norm_EC_removed_changes_std(:,55),'-ok')
hold on
errorbar([1/8 1/4 1/2
1],Norm_EO_removed_changes_avg(:,55),Norm_EO_removed_changes_std(:,55),'-x')
ylabel('AP-direction')
axis([0 1.125 -40 80])
xticks([1/8 1/4 1/2 1])
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'})
title('Rambling')
% AP Trembling
subplot(2,3,2)
errorbar([1/8 1/4 1/2
1],Norm_EC_removed_changes_avg(:,66),Norm_EC_removed_changes_std(:,66),'-ok')
hold on
errorbar([1/8 1/4 1/2
1],Norm_EO_removed_changes_avg(:,66),Norm_EO_removed_changes_std(:,66),'-x')
title('Trembling')
axis([0 1.125 -40 80])
xticks([1/8 1/4 1/2 1])
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'})
legend('EC','EO')
% AP COP
subplot(2,3,3)
errorbar([1/8 1/4 1/2
1],Norm_EC_removed_changes_avg(:,55),Norm_EC_removed_changes_std(:,55),'-ok')
hold on
errorbar([1/8 1/4 1/2
1],Norm_EO_removed_changes_avg(:,55),Norm_EO_removed_changes_std(:,55),'-x')
axis([0 1.125 -40 80])
xticks([1/8 1/4 1/2 1])
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'})
title('COP')
```

```
% ML Rambling
subplot(2,3,4)
errorbar([1/8 1/4 1/2
1],Norm_EC_removed_changes_avg(:,61),Norm_EC_removed_changes_std(:,61),'-ok')
hold on
errorbar([1/8 1/4 1/2
1],Norm_EO_removed_changes_avg(:,61),Norm_EO_removed_changes_std(:,61),'-x')
ylabel('ML-direction')
axis([0 1.125 -60 80])
xticks([1/8 1/4 1/2 1])
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'})
% ML Trembling
subplot(2,3,5)
errorbar([1/8 1/4 1/2
1],Norm_EC_removed_changes_avg(:,60),Norm_EC_removed_changes_std(:,60),'-ok')
hold on
errorbar([1/8 1/4 1/2
1],Norm_EO_removed_changes_avg(:,60),Norm_EO_removed_changes_std(:,60),'-x')
axis([0 1.125 -40 80])
xticks([1/8 1/4 1/2 1])
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'})
% ML COP
subplot(2,3,6)
errorbar([1/8 1/4 1/2
1],Norm_EC_removed_changes_avg(:,54),Norm_EC_removed_changes_std(:,54),'-ok')
hold on
errorbar([1/8 1/4 1/2
1],Norm_EO_removed_changes_avg(:,54),Norm_EO_removed_changes_std(:,54),'-x')
axis([0 1.125 -40 80])
xticks([1/8 1/4 1/2 1])
set(gca, 'XTickLabel', {'1/8' '1/4' '1/2' '1'})
suplabel('Foam Thickness (inches)')
savefig('NormMeanJerk2x3')


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% BAR CHARTS %%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% Bar Chart: Norm Mean Vel Foam 4 EC
% COP RM TR
subplot(1,2,1)
y1 =
[Norm_EC_removed_changes_avg(4,11);Norm_EC_removed_changes_avg(4,63);Norm_EC_
removed_changes_avg(4,62)];
std =
[Norm_EC_removed_changes_std(4,11);Norm_EC_removed_changes_std(4,63);Norm_EC_
removed_changes_std(4,62)];
BarPlot_KU_EG(y1,std,[{'COP'},{'RM'},{'TR'}])
ylim([0 120])
xlim([0.5 3.5])
yticks(0:20:120)
ylabel('% Change from Baseline','FontSize',20)
title('AP-direction','FontSize',25)
set(gca,'FontSize',20)
```

```
subplot(1,2,2)
y2=[Norm_EC_removed_changes_avg(4,12);Norm_EC_removed_changes_avg(4,57);Norm_
EC_removed_changes_avg(4,56)];
std2 =
[Norm_EC_removed_changes_std(4,12);Norm_EC_removed_changes_std(4,57);Norm_EC_
removed_changes_std(4,56)];
BarPlot_KU_EG(y2,std2,[{'COP'},{'RM'},{'TR'}])
ylim([0 125])
xlim([0.5 3.5])
yticks(0:20:120)
title('ML-direction','FontSize',25)
sgtitle('Change in Mean Acc (F0 to F4)','FontSize',25)
set(gca,'FontSize',20)
savefig('Bar_AP_4_Norm Mean Vel EC')

%% Bar Chart: Norm Mean Vel Foam 4 EO
% COP RM TR
subplot(1,2,1)
y1 =
[Norm_EO_removed_changes_avg(4,11);Norm_EO_removed_changes_avg(4,63);Norm_EO_
removed_changes_avg(4,62)];
std =
[Norm_EO_removed_changes_std(4,11);Norm_EO_removed_changes_std(4,63);Norm_EO_
removed_changes_std(4,62)];
BarPlot_KU_EG(y1,std,[{'COP'},{'RM'},{'TR'}])
ylim([0 120])
xlim([0.5 3.5])
yticks(0:20:120)
ylabel('% Change from Baseline','FontSize',20)
title('AP-direction','FontSize',25)
set(gca,'FontSize',20)

subplot(1,2,2)
y2=[Norm_EO_removed_changes_avg(4,12);Norm_EO_removed_changes_avg(4,57);Norm_
EO_removed_changes_avg(4,56)];
std2 =
[Norm_EO_removed_changes_std(4,12);Norm_EO_removed_changes_std(4,57);Norm_EO_
removed_changes_std(4,56)];
BarPlot_KU_EG(y2,std2,[{'COP'},{'RM'},{'TR'}])
ylim([0 125])
xlim([0.5 3.5])
yticks(0:20:120)
title('ML-direction','FontSize',25)
sgtitle('Change in Mean Acc (F0 to F4)','FontSize',25)
set(gca,'FontSize',20)
savefig('Bar_AP_4_Norm Mean Vel EO')

%% Bar Chart: Norm Mean Acc Foam 4 EC
% COP RM TR
subplot(1,2,1)
y1 =
[Norm_EC_removed_changes_avg(4,53);Norm_EC_removed_changes_avg(4,65);Norm_EC_
removed_changes_avg(4,64)];
std =
[Norm_EC_removed_changes_std(4,53);Norm_EC_removed_changes_std(4,65);Norm_EC_
removed_changes_std(4,64)];
```

```
BarPlot_KU_EG(y1,std,[{'COP'},{'RM'},{'TR'}])
ylim([0 120])
xlim([0.5 3.5])
yticks(0:20:120)
ylabel('% Change from Baseline','FontSize',20)
title('AP-direction','FontSize',25)
set(gca,'FontSize',20)

subplot(1,2,2)
y2=[Norm_EC_removed_changes_avg(4,52);Norm_EC_removed_changes_avg(4,58);Norm_
EC_removed_changes_avg(4,59)];
std2 =
[Norm_EC_removed_changes_std(4,52);Norm_EC_removed_changes_std(4,58);Norm_EC_
removed_changes_std(4,59)];
BarPlot_KU_EG(y2,std2,[{'COP'},{'RM'},{'TR'}])
ylim([0 125])
xlim([0.5 3.5])
yticks(0:20:120)
title('ML-direction','FontSize',25)
sgtitle('Change in Mean Acc (F0 to F4)','FontSize',25)
set(gca,'FontSize',20)
savefig('Bar_AP_4_Norm Mean Acc EC')

%% Bar Chart: Norm Mean Acc Foam 4 EO
% COP RM TR
subplot(1,2,1)
y1 =
[Norm_EO_removed_changes_avg(4,53);Norm_EO_removed_changes_avg(4,65);Norm_EO_
removed_changes_avg(4,64)];
std =
[Norm_EO_removed_changes_std(4,53);Norm_EO_removed_changes_std(4,65);Norm_EO_
removed_changes_std(4,64)];
BarPlot_KU_EG(y1,std,[{'COP'},{'RM'},{'TR'}])
ylim([-30 40])
xlim([0.5 3.5])
ylabel('% Change from Baseline','FontSize',20)
title('AP-direction','FontSize',25)
set(gca,'FontSize',20)

subplot(1,2,2)
y2=[Norm_EO_removed_changes_avg(4,52);Norm_EO_removed_changes_avg(4,58);Norm_
EO_removed_changes_avg(4,59)];
std2 =
[Norm_EO_removed_changes_std(4,52);Norm_EO_removed_changes_std(4,58);Norm_EO_
removed_changes_std(4,59)];
BarPlot_KU_EG(y2,std2,[{'COP'},{'RM'},{'TR'}])
ylim([-30 40])
xlim([0.5 3.5])
title('ML-direction','FontSize',25)
sgtitle('Change in Mean Acc (F0 to F4)','FontSize',25)
set(gca,'FontSize',20)
savefig('Bar_AP_4_Norm Mean Acc EO')

%% Bar Chart: Norm Mean Jerk Foam 4 EC
% COP RM TR
subplot(1,2,1)
```

```
y1 =
[Norm_EC_removed_changes_avg(4,55);Norm_EC_removed_changes_avg(4,67);Norm_EC_
removed_changes_avg(4,66)];
std =
[Norm_EC_removed_changes_std(4,55);Norm_EC_removed_changes_std(4,67);Norm_EC_
removed_changes_std(4,66)];
BarPlot_KU_EG(y1,std,[{'COP'},{'RM'},{'TR'}])
ylim([0 120])
xlim([0.5 3.5])
yticks(0:20:120)
ylabel('% Change from Baseline','FontSize',20)
title('AP-direction','FontSize',25)
set(gca,'FontSize',20)
sigstar({[1,2],[2,3]},[0.05,0.01]);

subplot(1,2,2)
y2=[Norm_EC_removed_changes_avg(4,54);Norm_EC_removed_changes_avg(4,61);Norm_
EC_removed_changes_avg(4,60)];
std2 =
[Norm_EC_removed_changes_std(4,54);Norm_EC_removed_changes_std(4,61);Norm_EC_
removed_changes_std(4,60)];
BarPlot_KU_EG(y2,std2,[{'COP'},{'RM'},{'TR'}])
ylim([0 125])
xlim([0.5 3.5])
yticks(0:20:120)
title('ML-direction','FontSize',25)
sigstar({[1,3]},[0.05]);
sgtitle('Change in Mean Jerk (F0 to F4)','FontSize',25)
set(gca,'FontSize',20)
savefig('Bar_AP_4_Norm Mean Jerk EC')

%% Bar Chart: Norm Mean Jerk EO Foam 4
subplot(1,2,1)
y1 =
[Norm_EO_removed_changes_avg(4,55);Norm_EO_removed_changes_avg(4,67);Norm_EO_
removed_changes_avg(4,66)];
std =
[Norm_EO_removed_changes_std(4,55);Norm_EO_removed_changes_std(4,67);Norm_EO_
removed_changes_std(4,66)];
BarPlot_KU_EG(y1,std,[{'COP'},{'RM'},{'TR'}])
xlim([0.5 3.5])
ylim([-50 50])
ylabel('% Change from Baseline','FontSize',20)
title('AP-direction','FontSize',25)
set(gca,'FontSize',20)

subplot(1,2,2)
y2=[Norm_EO_removed_changes_avg(4,54);Norm_EO_removed_changes_avg(4,61);Norm_
EO_removed_changes_avg(4,60)];
std2 =
[Norm_EO_removed_changes_std(4,54);Norm_EO_removed_changes_std(4,61);Norm_EO_
removed_changes_std(4,60)];
BarPlot_KU_EG(y2,std2,[{'COP'},{'RM'},{'TR'}])
xlim([0.5 3.5])
ylim([-50 50])
title('ML-direction','FontSize',25)
```

```
sgtitle('Change in Mean Jerk (F0 to F4)','FontSize',25)
set(gca,'FontSize',20)

savefig('Bar_AP_4_Norm Mean Jerk EO')
```

```
%% RMTR_Stats_ANOVA2
% Written by Eryn Gerber (eryngerber@ku.edu)
% The University of Kansas - Biodynamics Lab
% Last updated 3/17/2020
%
% Purpose: Run two-way ANOVAs on foam data

%% Generate "measure" array for comparison of COP, RM, and TR parameters
clc;
% raw measure list, 5 foam levels (1x765)
Measure = num2cell(zeros(765,1));
for i = 1:length(Measure)
    for i = 1:255
        Measure(i)={'C'};
    end
    for i = 256:510
        Measure(i)={'R'};
    end
    for i = 511:765
        Measure(i)={'T'};
    end
end

% full normalized measure list, 4 foam levels (1x612)
Measure_norm = num2cell(zeros(612,1));
for j = 1:length(Measure)
    for j = 1:204
        Measure_norm(j)={'C'};
    end
    for j = 205:408
        Measure_norm(j)={'R'};
    end
    for j = 409:612
        Measure_norm(j)={'T'};
    end
end

% single foam comparison, 1 foam level (1x153)
Measure_single = num2cell(zeros(153,1));
for k = 1:length(Measure_single)
    for k = 1:51
        Measure_single(k)={'C'};
    end
    for k = 52:102
        Measure_single(k)={'R'};
    end
    for k = 103:153
        Measure_single(k)={'T'};
    end
```

```
end

Foam=[Norm_EC_removed_changes(:,2);Norm_EC_removed_changes(:,2);Norm_EC_remov
ed_changes(:,2)];

%% Mean Vel AP vs ML

Perc_change_COP_AP =
[Norm_EC_removed_changes(1:51,11),Norm_EC_removed_changes(52:102,11),Norm_EC_
removed_changes(103:153,11),Norm_EC_removed_changes(154:204,11)];
Perc_change_COP_ML =
[Norm_EC_removed_changes(1:51,12),Norm_EC_removed_changes(52:102,12),Norm_EC_
removed_changes(103:153,12),Norm_EC_removed_changes(154:204,12)]
[p,anovatbl_AP_nm_vel2_Foam,stats]=anova2([Perc_change_COP_AP;Perc_change_COP
_ML],51);

%% AP Mean Vel

Perc_change_COP =
[Norm_EC_removed_changes(1:51,11),Norm_EC_removed_changes(52:102,11),Norm_EC_
removed_changes(103:153,11),Norm_EC_removed_changes(154:204,11)];
Perc_change_RM =
[Norm_EC_removed_changes(1:51,63),Norm_EC_removed_changes(52:102,63),Norm_EC_
removed_changes(103:153,63),Norm_EC_removed_changes(154:204,63)];
Perc_change_TR =
[Norm_EC_removed_changes(1:51,62),Norm_EC_removed_changes(52:102,62),Norm_EC_
removed_changes(103:153,62),Norm_EC_removed_changes(154:204,62)];

[p,anovatbl_AP_nm_vel2_Foam,stats]=anova2([Perc_change_COP;Perc_change_RM;Per
c_change_TR],51);

[p1,anovatbl_AP_nm_vel_Foam,stats1]=anova1(Perc_change_COP);
[results_AP_nm_vel_Foam_COP,means]=multcompare(stats1,'CType','hsd');

[p1,anovatbl_AP_nm_vel_Foam,stats2]=anova1(Perc_change_RM);
[results_AP_nm_vel_Foam_RM,means]=multcompare(stats2,'CType','hsd');

[p1,anovatbl_AP_nm_vel_Foam,stats3]=anova1(Perc_change_TR);
[results_AP_nm_vel_Foam_TR,means]=multcompare(stats3,'CType','hsd');
%% ML Mean Vel
Perc_change_COP =
[Norm_EC_removed_changes(1:51,12),Norm_EC_removed_changes(52:102,12),Norm_EC_
removed_changes(103:153,12),Norm_EC_removed_changes(154:204,12)];
Perc_change_RM =
[Norm_EC_removed_changes(1:51,57),Norm_EC_removed_changes(52:102,57),Norm_EC_
removed_changes(103:153,57),Norm_EC_removed_changes(154:204,57)];
Perc_change_TR =
[Norm_EC_removed_changes(1:51,56),Norm_EC_removed_changes(52:102,56),Norm_EC_
removed_changes(103:153,56),Norm_EC_removed_changes(154:204,56)];

[p,anovatbl_ML_nm_vel2_Foam,stats]=anova2([Perc_change_COP;Perc_change_RM;Per
c_change_TR],51);

[p1,anovatbl_ML_nm_vel_Foam,stats1]=anova1(Perc_change_COP);
```

```
[results_ML_nm_vel_Foam_COP,means]=multcompare(stats1,'CType','hsd');

[p1,anovatbl_ML_nm_vel_Foam,stats2]=anova1(Perc_change_RM);
[results_ML_nm_vel_Foam_RM,means]=multcompare(stats2,'CType','hsd');

[p1,anovatbl_ML_nm_vel_Foam,stats3]=anova1(Perc_change_TR);
[results_ML_nm_vel_Foam_TR,means]=multcompare(stats3,'CType','hsd');
%% AP Mean Acc
Perc_change_COP =
[Norm_EC_removed_changes(1:51,53),Norm_EC_removed_changes(52:102,53),Norm_EC_
removed_changes(103:153,53),Norm_EC_removed_changes(154:204,53)];
Perc_change_RM =
[Norm_EC_removed_changes(1:51,65),Norm_EC_removed_changes(52:102,65),Norm_EC_
removed_changes(103:153,65),Norm_EC_removed_changes(154:204,65)];
Perc_change_TR =
[Norm_EC_removed_changes(1:51,64),Norm_EC_removed_changes(52:102,64),Norm_EC_
removed_changes(103:153,64),Norm_EC_removed_changes(154:204,64)];

[p,anovatbl_AP_nm_acc2_Foam,stats]=anova2([Perc_change_COP;Perc_change_RM;Per
c_change_TR],51);

[p1,anovatbl_AP_nm_acc_Foam,stats1]=anova1(Perc_change_COP);
[results_AP_nm_acc_Foam_COP,means]=multcompare(stats1,'CType','hsd');

[p1,anovatbl_AP_nm_acc_Foam,stats2]=anova1(Perc_change_RM);
[results_AP_nm_acc_Foam_RM,means]=multcompare(stats2,'CType','hsd');

[p1,anovatbl_AP_nm_acc_Foam,stats3]=anova1(Perc_change_TR);
[results_AP_nm_acc_Foam_TR,means]=multcompare(stats3,'CType','hsd');

%% ML Mean Acc
Perc_change_COP =
[Norm_EC_removed_changes(1:51,52),Norm_EC_removed_changes(52:102,52),Norm_EC_
removed_changes(103:153,52),Norm_EC_removed_changes(154:204,52)];
Perc_change_RM =
[Norm_EC_removed_changes(1:51,58),Norm_EC_removed_changes(52:102,58),Norm_EC_
removed_changes(103:153,58),Norm_EC_removed_changes(154:204,58)];
Perc_change_TR =
[Norm_EC_removed_changes(1:51,59),Norm_EC_removed_changes(52:102,59),Norm_EC_
removed_changes(103:153,59),Norm_EC_removed_changes(154:204,59)];

[p,anovatbl_ML_nm_acc2_Foam,stats]=anova2([Perc_change_COP;Perc_change_RM;Per
c_change_TR],51);

[p1,anovatbl_ML_nm_acc_Foam,stats1]=anova1(Perc_change_COP);
[results_ML_nm_acc_Foam_COP,means]=multcompare(stats1,'CType','hsd');

[p1,anovatbl_ML_nm_acc_Foam,stats2]=anova1(Perc_change_RM);
[results_ML_nm_acc_Foam_RM,means]=multcompare(stats2,'CType','hsd');

[p1,anovatbl_ML_nm_acc_Foam,stats3]=anova1(Perc_change_TR);
[results_ML_nm_acc_Foam_TR,means]=multcompare(stats3,'CType','hsd');

%% AP Mean Jerk
```

```
Perc_change_COP =
[Norm_EC_removed_changes(1:51,55),Norm_EC_removed_changes(52:102,55),Norm_EC_
removed_changes(103:153,55),Norm_EC_removed_changes(154:204,55)];
Perc_change_RM =
[Norm_EC_removed_changes(1:51,67),Norm_EC_removed_changes(52:102,67),Norm_EC_
removed_changes(103:153,67),Norm_EC_removed_changes(154:204,67)];
Perc_change_TR =
[Norm_EC_removed_changes(1:51,66),Norm_EC_removed_changes(52:102,66),Norm_EC_
removed_changes(103:153,66),Norm_EC_removed_changes(154:204,66)];

[p,anovatbl_AP_nm_jerk_Foam2,stats]=anova2([Perc_change_COP;Perc_change_RM;Pe
rc_change_TR],51);

[p1,anovatbl_AP_nm_jerk_Foam,stats1]=anova1(Perc_change_COP);
[results_AP_nm_jerk_Foam_COP,means]=multcompare(stats1,'CType','hsd');

[p1,anovatbl_AP_nm_jerk_Foam,stats2]=anova1(Perc_change_RM);
[results_AP_nm_jerk_Foam_RM,means]=multcompare(stats2,'CType','hsd');

[p1,anovatbl_AP_nm_jerk_Foam,stats3]=anova1(Perc_change_TR);
[results_AP_nm_jerk_Foam_TR,means]=multcompare(stats3,'CType','hsd');

%% ML Mean Jerk
Perc_change_COP =
[Norm_EC_removed_changes(1:51,54),Norm_EC_removed_changes(52:102,54),Norm_EC_
removed_changes(103:153,54),Norm_EC_removed_changes(154:204,54)];
Perc_change_RM =
[Norm_EC_removed_changes(1:51,61),Norm_EC_removed_changes(52:102,61),Norm_EC_
removed_changes(103:153,61),Norm_EC_removed_changes(154:204,61)];
Perc_change_TR =
[Norm_EC_removed_changes(1:51,60),Norm_EC_removed_changes(52:102,60),Norm_EC_
removed_changes(103:153,60),Norm_EC_removed_changes(154:204,60)];

[p,anovatbl_ML_nm_jerk_Foam2,stats]=anova2([Perc_change_COP;Perc_change_RM;Pe
rc_change_TR],51);

[p1,anovatbl_ML_nm_jerk_Foam,stats1]=anova1(Perc_change_COP);
[results_ML_nm_jerk_Foam_COP,means]=multcompare(stats1,'CType','hsd');

[p1,anovatbl_ML_nm_jerk_Foam,stats2]=anova1(Perc_change_RM);
[results_ML_nm_jerk_Foam_RM,means]=multcompare(stats2,'CType','hsd');

[p1,anovatbl_ML_nm_jerk_Foam,stats3]=anova1(Perc_change_TR);
[results_ML_nm_jerk_Foam_TR,means]=multcompare(stats3,'CType','hsd');
```

```
%% RMTR_Regression AP Mean Vel
% Written by Eryn Gerber (eryngerber@ku.edu)
% The University of Kansas - Biodynamics Lab
% Last updated 4/1/2020
%
```

```
% Purpose: Run regression statistics on foam data
%
%%
load('Perc_changes_EC.mat')
clear thickness
foam1 = Norm_EC_removed_changes(1:51,:);
foam2 = Norm_EC_removed_changes(52:102,:);
foam3 = Norm_EC_removed_changes(103:153,:);
foam4 = Norm_EC_removed_changes(154:204,:);

byfoam=[foam1;foam2;foam3;foam4];

thickness = zeros(204,1);
thickness(1:51)=0.125;
thickness(52:102)=0.25;
thickness(103:153)=0.5;
thickness(154:204)=1;


%% AP Mean Vel
% Define terms
X = linspace(0,1);
thickness=[ones(204,1) thickness];
thickness_COP=thickness;
thickness_RM=thickness;
thickness_TR=thickness;

byfoam_COP = byfoam(:,16);
byfoam_RM = byfoam(:,68);
byfoam_TR = byfoam(:,67);

%% Linear Regression

% Perform regression and find outliers
[x1_COP,int_COP,r,rint1,stats_COP] = regress(byfoam_COP,thickness);
y_COP = X.*x1_COP(2,1);

i1=[];
for i = 1:length(rint1)
    if or(and(rint1(i,1)>0,rint1(i,2)<0),and(rint1(i,1)<0,rint1(i,2)>0))
    else
        i1 = [i1; i];
        byfoam_COP(i)=NaN;
        thickness_COP(i,:)=NaN;
    end
end

[x1_RM,int_RM,r,rint2,stats_RM] = regress(byfoam_RM,thickness);
y_RM = X.*x1_RM(2,1);

i2=[];
for i = 1:length(rint2)
    if or(and(rint2(i,1)>0,rint2(i,2)<0),and(rint2(i,1)<0,rint2(i,2)>0))
    else
```

```
        i2 = [i2; i];
        byfoam_RM(i)=NaN;
        thickness_RM(i,:)=NaN;
    end
end

[x1_TR,int_TR,r,rint3,stats_TR] = regress(byfoam_TR,thickness);
y_TR = X.*x1_TR(2,1);

i3=[];
for i = 1:length(rint3)
    if or(and(rint3(i,1)>0,rint3(i,2)<0),and(rint3(i,1)<0,rint3(i,2)>0))
    else
        i3 = [i3; i];
        byfoam_TR(i)=NaN;
        thickness_TR(i,:)=NaN;
    end
end

plot(X,y_COP,X,y_RM,X,y_TR)
xticks([0.125 0.25 0.5 1])
legend('COP, R^2 = ','RM, R^2 = ','TR, R^2 = ')


%% Remove outliers
byfoam_COP = rmmissing(byfoam_COP);
thickness_COP=rmmissing(thickness_COP);
byfoam_RM = rmmissing(byfoam_RM);
thickness_RM=rmmissing(thickness_RM);
byfoam_TR = rmmissing(byfoam_TR);
thickness_TR=rmmissing(thickness_TR);

%% Linear Regression with removed outliers
X = linspace(0,1);

% Perform regression and find outliers
[x1_COP,int_COP,~,rint1,stats_COP] = regress(byfoam_COP,thickness_COP);
y_COP = X.*x1_COP(2,1);


[x1_RM,int_RM,~,rint2,stats_RM] = regress(byfoam_RM,thickness_RM);
y_RM = X.*x1_RM(2,1);


[x1_TR,int_TR,~,rint3,stats_TR] = regress(byfoam_TR,thickness_TR);
y_TR = X.*x1_TR(2,1);


plot(X,y_COP,X,y_RM,X,y_TR)
xticks([0.125 0.25 0.5 1])
%% Linear Regression with 90% CI
X = linspace(0,1);

[m_COP] = fitlm(thickness_COP(:,2),byfoam_COP);
```

```
int_COP = table2array(m_COP.Coefficients(1,1));
x1_COP = table2array(m_COP.Coefficients(2,1));
y_COP = int_COP + X*x1_COP;
ci_COP = coefCI(m_COP,0.1)
[m_RM] = fitlm(thickness_RM(:,2),byfoam_RM);
int_RM = table2array(m_RM.Coefficients(1,1));
x1_RM = table2array(m_RM.Coefficients(2,1));
y_RM = int_RM + X*x1_RM;
ci_RM = coefCI(m_RM,0.1)
[m_TR] = fitlm(thickness_TR(:,2),byfoam_TR);
int_TR = table2array(m_TR.Coefficients(1,1));
x1_TR = table2array(m_TR.Coefficients(2,1));
y_TR = int_TR + X*x1_TR;
ci_TR = coefCI(m_TR,0.1)

%% Plot Linear Regression with 90% CI
y_COP = X*x1_COP;
y_COP_low = X*ci_COP(2,1);
y_COP_high = X*ci_COP(2,2);
y_RM = X*x1_RM;
y_RM_low = X*ci_RM(2,1);
y_RM_high = X*ci_RM(2,2);
y_TR = X*x1_TR;
y_TR_low = X*ci_TR(2,1);
y_TR_high = X*ci_TR(2,2);
plot(X,y_COP,'k',X,y_RM,'r',X,y_TR,'b')
hold on
fill([X,fliplr(X)],[y_COP_low,fliplr(y_COP_high)],'k','facealpha',.15)
fill([X,fliplr(X)],[y_RM_low,fliplr(y_RM_high)],'r','facealpha',.15)
fill([X,fliplr(X)],[y_TR_low,fliplr(y_TR_high)],'b','facealpha',.15)

legend('COP, R^2 = 0.3323','RM, R^2 = 0.3352','TR, R^2 =
0.2878','Location','northwest')
xlabel('Foam Thickness')
ylim([-5 50])
ylabel('Percent Change from Baseline')
title('Linear Regression of Change in AP Velocity across Foam Thickness')
savefig('APVel_CI')
```

```
%% RMTR_Regression ML Mean Vel
% Written by Eryn Gerber (eryngerber@ku.edu)
% The University of Kansas - Biodynamics Lab
% Last updated 4/1/2020
%
% Purpose: Run regression statistics on foam data


%%
load('Perc_changes_EC.mat')
clear thickness
foam1 = Norm_EC_removed_changes(1:51,:);
foam2 = Norm_EC_removed_changes(52:102,:);
foam3 = Norm_EC_removed_changes(103:153,:);
foam4 = Norm_EC_removed_changes(154:204,:);
```

```
byfoam=[foam1;foam2;foam3;foam4];

thickness = zeros(204,1);
thickness(1:51)=0.125;
thickness(52:102)=0.25;
thickness(103:153)=0.5;
thickness(154:204)=1;


%% AP Mean Vel
% Define terms
X = linspace(0,1);
thickness=[ones(204,1) thickness];
thickness_COP=thickness;
thickness_RM=thickness;
thickness_TR=thickness;

byfoam_COP = byfoam(:,17);
byfoam_RM = byfoam(:,62);
byfoam_TR = byfoam(:,61);

%% Linear Regression

% Perform regression and find outliers
[x1_COP,int_COP,r,rint1,stats_COP] = regress(byfoam_COP,thickness);
y_COP = X.*x1_COP(2,1);

i1=[];
for i = 1:length(rint1)
    if or(and(rint1(i,1)>0,rint1(i,2)<0),and(rint1(i,1)<0,rint1(i,2)>0))
    else
        i1 = [i1; i];
        byfoam_COP(i)=NaN;
        thickness_COP(i,:)=NaN;
    end
end

[x1_RM,int_RM,r,rint2,stats_RM] = regress(byfoam_RM,thickness);
y_RM = X.*x1_RM(2,1);

i2=[];
for i = 1:length(rint2)
    if or(and(rint2(i,1)>0,rint2(i,2)<0),and(rint2(i,1)<0,rint2(i,2)>0))
    else
        i2 = [i2; i];
        byfoam_RM(i)=NaN;
        thickness_RM(i,:)=NaN;
    end
end

[x1_TR,int_TR,r,rint3,stats_TR] = regress(byfoam_TR,thickness);
y_TR = X.*x1_TR(2,1);
```

```
i3=[];
for i = 1:length(rint3)
    if or(and(rint3(i,1)>0,rint3(i,2)<0),and(rint3(i,1)<0,rint3(i,2)>0))
    else
        i3 = [i3; i];
        byfoam_TR(i)=NaN;
        thickness_TR(i,:)=NaN;
    end
end

plot(X,y_COP,X,y_RM,X,y_TR)
xticks([0.125 0.25 0.5 1])
legend('COP, R^2 = ','RM, R^2 = ','TR, R^2 = ')


%% Remove outliers
byfoam_COP = rmmissing(byfoam_COP);
thickness_COP=rmmissing(thickness_COP);
byfoam_RM = rmmissing(byfoam_RM);
thickness_RM=rmmissing(thickness_RM);
byfoam_TR = rmmissing(byfoam_TR);
thickness_TR=rmmissing(thickness_TR);

%% Linear Regression with removed outliers
X = linspace(0,1);

% Perform regression and find outliers
[x1_COP,int_COP,~,rint1,stats_COP] = regress(byfoam_COP,thickness_COP);
y_COP = X.*x1_COP(2,1);


[x1_RM,int_RM,~,rint2,stats_RM] = regress(byfoam_RM,thickness_RM);
y_RM = X.*x1_RM(2,1);


[x1_TR,int_TR,~,rint3,stats_TR] = regress(byfoam_TR,thickness_TR);
y_TR = X.*x1_TR(2,1);


plot(X,y_COP,X,y_RM,X,y_TR)
xticks([0.125 0.25 0.5 1])
%% Linear Regression with 90% CI
X = linspace(0,1);

[m_COP] = fitlm(thickness_COP(:,2),byfoam_COP);
int_COP = table2array(m_COP.Coefficients(1,1));
x1_COP = table2array(m_COP.Coefficients(2,1));
y_COP = int_COP + X*x1_COP;
ci_COP = coefCI(m_COP,0.1)
[m_RM] = fitlm(thickness_RM(:,2),byfoam_RM);
int_RM = table2array(m_RM.Coefficients(1,1));
x1_RM = table2array(m_RM.Coefficients(2,1));
y_RM = int_RM + X*x1_RM;
ci_RM = coefCI(m_RM,0.1)
```

```
[m_TR] = fitlm(thickness_TR(:,2),byfoam_TR);
int_TR = table2array(m_TR.Coefficients(1,1));
x1_TR = table2array(m_TR.Coefficients(2,1));
y_TR = int_TR + X*x1_TR;
ci_TR = coefCI(m_TR,0.1)

%% Plot Linear Regression with 90% CI
y_COP = X*x1_COP;
y_COP_low = X*ci_COP(2,1);
y_COP_high = X*ci_COP(2,2);
y_RM = X*x1_RM;
y_RM_low = X*ci_RM(2,1);
y_RM_high = X*ci_RM(2,2);
y_TR = X*x1_TR;
y_TR_low = X*ci_TR(2,1);
y_TR_high = X*ci_TR(2,2);
plot(X,y_COP,'k',X,y_RM,'r',X,y_TR,'b')
hold on
fill([X,fliplr(X)],[y_COP_low,fliplr(y_COP_high)],'k','facealpha',.15)
fill([X,fliplr(X)],[y_RM_low,fliplr(y_RM_high)],'r','facealpha',.15)
fill([X,fliplr(X)],[y_TR_low,fliplr(y_TR_high)],'b','facealpha',.15)

legend('COP, R^2 = 0.3209','RM, R^2 = 0.2520','TR, R^2 =
0.3303','Location','northwest')
xlabel('Foam Thickness')
ylim([-5 50])
ylabel('Percent Change from Baseline')
title('Linear Regression of Change in ML Velocity across Foam Thickness')
savefig('MLVel_CI')
```

```
%% RMTR_Regression AP Mean Acc
% Written by Eryn Gerber (eryngerber@ku.edu)
% The University of Kansas - Biodynamics Lab
% Last updated 3/18/2020
%
% Purpose: Run regression statistics on foam data


%%
load('Perc_changes_EC.mat')
clear thickness
foam1 = Norm_EC_removed_changes(1:51,:);
foam2 = Norm_EC_removed_changes(52:102,:);
foam3 = Norm_EC_removed_changes(103:153,:);
foam4 = Norm_EC_removed_changes(154:204,:);

byfoam=[foam1;foam2;foam3;foam4];

thickness = zeros(204,1);
thickness(1:51)=0.125;
thickness(52:102)=0.25;
thickness(103:153)=0.5;
thickness(154:204)=1;


%% AP Mean Acc
```

```
% Define terms
X = linspace(0,1);
thickness=[ones(204,1) thickness];
thickness_COP=thickness;
thickness_RM=thickness;
thickness_TR=thickness;

byfoam_COP = byfoam(:,58);
byfoam_RM = byfoam(:,70);
byfoam_TR = byfoam(:,69);

%% Linear Regression

% Perform regression and find outliers
[x1_COP,int_COP,r,rint1,stats_COP] = regress(byfoam_COP,thickness);
y_COP = X.*x1_COP(2,1);

i1=[];
for i = 1:length(rint1)
    if or(and(rint1(i,1)>0,rint1(i,2)<0),and(rint1(i,1)<0,rint1(i,2)>0))
    else
        i1 = [i1; i];
        byfoam_COP(i)=NaN;
        thickness_COP(i,:)=NaN;
    end
end

[x1_RM,int_RM,r,rint2,stats_RM] = regress(byfoam_RM,thickness);
y_RM = X.*x1_RM(2,1);

i2=[];
for i = 1:length(rint2)
    if or(and(rint2(i,1)>0,rint2(i,2)<0),and(rint2(i,1)<0,rint2(i,2)>0))
    else
        i2 = [i2; i];
        byfoam_RM(i)=NaN;
        thickness_RM(i,:)=NaN;
    end
end

[x1_TR,int_TR,r,rint3,stats_TR] = regress(byfoam_TR,thickness);
y_TR = X.*x1_TR(2,1);

i3=[];
for i = 1:length(rint3)
    if or(and(rint3(i,1)>0,rint3(i,2)<0),and(rint3(i,1)<0,rint3(i,2)>0))
    else
        i3 = [i3; i];
        byfoam_TR(i)=NaN;
        thickness_TR(i,:)=NaN;
    end
end

plot(X,y_COP,X,y_RM,X,y_TR)
xticks([0.125 0.25 0.5 1])
```

```
legend('COP, R^2 = ','RM, R^2 = ','TR, R^2 = ')


%% Remove outliers
byfoam_COP = rmmissing(byfoam_COP);
thickness_COP=rmmissing(thickness_COP);
byfoam_RM = rmmissing(byfoam_RM);
thickness_RM=rmmissing(thickness_RM);
byfoam_TR = rmmissing(byfoam_TR);
thickness_TR=rmmissing(thickness_TR);

%% Linear Regression with removed outliers
X = linspace(0,1);

% Perform regression and find outliers
[x1_COP,int_COP,~,rint1,stats_COP] = regress(byfoam_COP,thickness_COP);
y_COP = X.*x1_COP(2,1);


[x1_RM,int_RM,~,rint2,stats_RM] = regress(byfoam_RM,thickness_RM);
y_RM = X.*x1_RM(2,1);


[x1_TR,int_TR,~,rint3,stats_TR] = regress(byfoam_TR,thickness_TR);
y_TR = X.*x1_TR(2,1);


plot(X,y_COP,X,y_RM,X,y_TR)
xticks([0.125 0.25 0.5 1])
%% Linear Regression with 90% CI
X = linspace(0,1);

[m_COP] = fitlm(thickness_COP(:,2),byfoam_COP);
int_COP = table2array(m_COP.Coefficients(1,1));
x1_COP = table2array(m_COP.Coefficients(2,1));
y_COP = int_COP + X*x1_COP;
ci_COP = coefCI(m_COP,0.1)
[m_RM] = fitlm(thickness_RM(:,2),byfoam_RM);
int_RM = table2array(m_RM.Coefficients(1,1));
x1_RM = table2array(m_RM.Coefficients(2,1));
y_RM = int_RM + X*x1_RM;
ci_RM = coefCI(m_RM,0.1)
[m_TR] = fitlm(thickness_TR(:,2),byfoam_TR);
int_TR = table2array(m_TR.Coefficients(1,1));
x1_TR = table2array(m_TR.Coefficients(2,1));
y_TR = int_TR + X*x1_TR;
ci_TR = coefCI(m_TR,0.1)

%% Plot Linear Regression with 90% CI
y_COP = X*x1_COP;
y_COP_low = X*ci_COP(2,1);
y_COP_high = X*ci_COP(2,2);
y_RM = X*x1_RM;
y_RM_low = X*ci_RM(2,1);
```

```
y_RM_high = X*ci_RM(2,2);
y_TR = X*x1_TR;
y_TR_low = X*ci_TR(2,1);
y_TR_high = X*ci_TR(2,2);
plot(X,y_COP,'k',X,y_RM,'r',X,y_TR,'b')
hold on
fill([X,fliplr(X)],[y_COP_low,fliplr(y_COP_high)],'k','facealpha',.15)
fill([X,fliplr(X)],[y_RM_low,fliplr(y_RM_high)],'r','facealpha',.15)
fill([X,fliplr(X)],[y_TR_low,fliplr(y_TR_high)],'b','facealpha',.15)

legend('COP, R^2 = 0.2156','RM, R^2 = 0.2034','TR, R^2 =
0.1856','Location','northwest')
xlabel('Foam Thickness')
ylabel('Percent Change from Baseline')
title('Linear Regression of Change in AP Acceleration across Foam Thickness')
savefig('APAcc_CI')
```

```
%% RMTR_Regression ML Mean Acc
% Written by Eryn Gerber (eryngerber@ku.edu)
% The University of Kansas - Biodynamics Lab
% Last updated 3/18/2020
%
% Purpose: Run regression statistics on foam data


%%
load('Perc_changes_EC.mat')
clear thickness
foam1 = Norm_EC_removed_changes(1:51,:);
foam2 = Norm_EC_removed_changes(52:102,:);
foam3 = Norm_EC_removed_changes(103:153,:);
foam4 = Norm_EC_removed_changes(154:204,:);

byfoam=[foam1;foam2;foam3;foam4];

thickness = zeros(204,1);
thickness(1:51)=0.125;
thickness(52:102)=0.25;
thickness(103:153)=0.5;
thickness(154:204)=1;


%% AP Mean Acc
% Define terms
X = linspace(0,1);
thickness=[ones(204,1) thickness];
thickness_COP=thickness;
thickness_RM=thickness;
thickness_TR=thickness;

byfoam_COP = byfoam(:,57);
byfoam_RM = byfoam(:,63);
byfoam_TR = byfoam(:,64);
```

```
%% Linear Regression

% Perform regression and find outliers
[x1_COP,int_COP,r,rint1,stats_COP] = regress(byfoam_COP,thickness);
y_COP = X.*x1_COP(2,1);

i1=[];
for i = 1:length(rint1)
    if or(and(rint1(i,1)>0,rint1(i,2)<0),and(rint1(i,1)<0,rint1(i,2)>0))
    else
        i1 = [i1; i];
        byfoam_COP(i)=NaN;
        thickness_COP(i,:)=NaN;
    end
end

[x1_RM,int_RM,r,rint2,stats_RM] = regress(byfoam_RM,thickness);
y_RM = X.*x1_RM(2,1);

i2=[];
for i = 1:length(rint2)
    if or(and(rint2(i,1)>0,rint2(i,2)<0),and(rint2(i,1)<0,rint2(i,2)>0))
    else
        i2 = [i2; i];
        byfoam_RM(i)=NaN;
        thickness_RM(i,:)=NaN;
    end
end

[x1_TR,int_TR,r,rint3,stats_TR] = regress(byfoam_TR,thickness);
y_TR = X.*x1_TR(2,1);

i3=[];
for i = 1:length(rint3)
    if or(and(rint3(i,1)>0,rint3(i,2)<0),and(rint3(i,1)<0,rint3(i,2)>0))
    else
        i3 = [i3; i];
        byfoam_TR(i)=NaN;
        thickness_TR(i,:)=NaN;
    end
end

plot(X,y_COP,X,y_RM,X,y_TR)
xticks([0.125 0.25 0.5 1])
legend('COP, R^2 = ','RM, R^2 = ','TR, R^2 = ')


%% Remove outliers
byfoam_COP = rmmissing(byfoam_COP);
thickness_COP=rmmissing(thickness_COP);
byfoam_RM = rmmissing(byfoam_RM);
thickness_RM=rmmissing(thickness_RM);
byfoam_TR = rmmissing(byfoam_TR);
```

```
thickness_TR=rmmissing(thickness_TR);

%% Linear Regression with removed outliers
X = linspace(0,1);

% Perform regression and find outliers
[x1_COP,int_COP,~,rint1,stats_COP] = regress(byfoam_COP,thickness_COP);
y_COP = X.*x1_COP(2,1);


[x1_RM,int_RM,~,rint2,stats_RM] = regress(byfoam_RM,thickness_RM);
y_RM = X.*x1_RM(2,1);


[x1_TR,int_TR,~,rint3,stats_TR] = regress(byfoam_TR,thickness_TR);
y_TR = X.*x1_TR(2,1);


plot(X,y_COP,X,y_RM,X,y_TR)
xticks([0.125 0.25 0.5 1])
%% Linear Regression with 90% CI
X = linspace(0,1);

[m_COP] = fitlm(thickness_COP(:,2),byfoam_COP);
int_COP = table2array(m_COP.Coefficients(1,1));
x1_COP = table2array(m_COP.Coefficients(2,1));
y_COP = int_COP + X*x1_COP;
ci_COP = coefCI(m_COP,0.1)
[m_RM] = fitlm(thickness_RM(:,2),byfoam_RM);
int_RM = table2array(m_RM.Coefficients(1,1));
x1_RM = table2array(m_RM.Coefficients(2,1));
y_RM = int_RM + X*x1_RM;
ci_RM = coefCI(m_RM,0.1)
[m_TR] = fitlm(thickness_TR(:,2),byfoam_TR);
int_TR = table2array(m_TR.Coefficients(1,1));
x1_TR = table2array(m_TR.Coefficients(2,1));
y_TR = int_TR + X*x1_TR;
ci_TR = coefCI(m_TR,0.1)

%% Plot Linear Regression with 90% CI
y_COP = X*x1_COP;
y_COP_low = X*ci_COP(2,1);
y_COP_high = X*ci_COP(2,2);
y_RM = X*x1_RM;
y_RM_low = X*ci_RM(2,1);
y_RM_high = X*ci_RM(2,2);
y_TR = X*x1_TR;
y_TR_low = X*ci_TR(2,1);
y_TR_high = X*ci_TR(2,2);
plot(X,y_COP,'k',X,y_RM,'r',X,y_TR,'b')
hold on
fill([X,fliplr(X)],[y_COP_low,fliplr(y_COP_high)],'k','facealpha',.15)
fill([X,fliplr(X)],[y_RM_low,fliplr(y_RM_high)],'r','facealpha',.15)
fill([X,fliplr(X)],[y_TR_low,fliplr(y_TR_high)],'b','facealpha',.15)
```

```
legend('COP, R^2 = 0.2059','RM, R^2 = 0.2253','TR, R^2 =
0.0529','Location','northwest')
xlabel('Foam Thickness')
ylabel('Percent Change from Baseline')
title('Linear Regression of Change in AP Jerk across Foam Thickness')
savefig('MLAcc_CI')
```

```
%% RMTR_Regression AP Mean Jerk
% Written by Eryn Gerber (eryngerber@ku.edu)
% The University of Kansas - Biodynamics Lab
% Last updated 3/17/2020
%
% Purpose: Run regression statistics on foam data


%% Normalized percent changes and thickness arrays
load('Perc_changes_EC.mat')
clear thickness
foam1 = Norm_EC_removed_changes(1:51,:);
foam2 = Norm_EC_removed_changes(52:102,:);
foam3 = Norm_EC_removed_changes(103:153,:);
foam4 = Norm_EC_removed_changes(154:204,:);

byfoam=[foam1;foam2;foam3;foam4];

thickness = zeros(204,1);
thickness(1:51)=0.125;
thickness(52:102)=0.25;
thickness(103:153)=0.5;
thickness(154:204)=1;

%% Linear Regression
X = linspace(0,1);
thickness=[ones(204,1) thickness];
thickness_COP=thickness;
thickness_RM=thickness;
thickness_TR=thickness;

byfoam_COP = byfoam(:,60);
byfoam_RM = byfoam(:,72);
byfoam_TR = byfoam(:,71);

% Perform regression and find outliers
[x1_COP,int_COP,r,rint1,stats_COP] = regress(byfoam(:,60),thickness);
y_COP = X.*x1_COP(2,1);

i1=[];
for i = 1:length(rint1)
    if or(and(rint1(i,1)>0,rint1(i,2)<0),and(rint1(i,1)<0,rint1(i,2)>0))
    else
        i1 = [i1; i];
        byfoam_COP(i)=NaN;
```

```
        thickness_COP(i,:)=NaN;
    end
end

[x1_RM,int_RM,r,rint2,stats_RM] = regress(byfoam(:,72),thickness);
y_RM = X.*x1_RM(2,1);

i2=[];
for i = 1:length(rint2)
    if or(and(rint2(i,1)>0,rint2(i,2)<0),and(rint2(i,1)<0,rint2(i,2)>0))
    else
        i2 = [i2; i];
        byfoam_RM(i)=NaN;
        thickness_RM(i,:)=NaN;
    end
end

[x1_TR,int_TR,r,rint3,stats_TR] = regress(byfoam(:,71),thickness);
y_TR = X.*x1_TR(2,1);

i3=[];
for i = 1:length(rint3)
    if or(and(rint3(i,1)>0,rint3(i,2)<0),and(rint3(i,1)<0,rint3(i,2)>0))
    else
        i3 = [i3; i];
        byfoam_TR(i)=NaN;
        thickness_TR(i,:)=NaN;
    end
end

plot(X,y_COP,X,y_RM,X,y_TR)
xticks([0.125 0.25 0.5 1])
legend('COP','RM','TR')

%% Remove outliers
byfoam_COP = rmmissing(byfoam_COP);
thickness_COP=rmmissing(thickness_COP);
byfoam_RM = rmmissing(byfoam_RM);
thickness_RM=rmmissing(thickness_RM);
byfoam_TR = rmmissing(byfoam_TR);
thickness_TR=rmmissing(thickness_TR);

%% Linear Regression with removed outliers
X = linspace(0,1);

% Perform regression and find outliers
[x1_COP,int_COP,~,rint1,stats_COP] = regress(byfoam_COP,thickness_COP);
y_COP = X.*x1_COP(2,1);


[x1_RM,int_RM,~,rint2,stats_RM] = regress(byfoam_RM,thickness_RM);
y_RM = X.*x1_RM(2,1);
```

```
[x1_TR,int_TR,~,rint3,stats_TR] = regress(byfoam_TR,thickness_TR);
y_TR = X.*x1_TR(2,1);


plot(X,y_COP,X,y_RM,X,y_TR)
xticks([0.125 0.25 0.5 1])
legend('COP','RM','TR')

%% Linear Regression with 90% CI
X = linspace(0,1);

[m_COP] = fitlm(thickness_COP(:,2),byfoam_COP);
int_COP = table2array(m_COP.Coefficients(1,1));
x1_COP = table2array(m_COP.Coefficients(2,1));
y_COP = int_COP + X*x1_COP;
ci_COP = coefCI(m_COP,0.1)
[m_RM] = fitlm(thickness_RM(:,2),byfoam_RM);
int_RM = table2array(m_RM.Coefficients(1,1));
x1_RM = table2array(m_RM.Coefficients(2,1));
y_RM = int_RM + X*x1_RM;
ci_RM = coefCI(m_RM,0.1)
[m_TR] = fitlm(thickness_TR(:,2),byfoam_TR);
int_TR = table2array(m_TR.Coefficients(1,1));
x1_TR = table2array(m_TR.Coefficients(2,1));
y_TR = int_TR + X*x1_TR;
ci_TR = coefCI(m_TR,0.1)

%% Plot Linear Regression with 90% CI
y_COP = X*x1_COP;
y_COP_low = X*ci_COP(2,1);
y_COP_high = X*ci_COP(2,2);
y_RM = X*x1_RM;
y_RM_low = X*ci_RM(2,1);
y_RM_high = X*ci_RM(2,2);
y_TR = X*x1_TR;
y_TR_low = X*ci_TR(2,1);
y_TR_high = X*ci_TR(2,2);
plot(X,y_COP,'k',X,y_RM,'r',X,y_TR,'b')
hold on
fill([X,fliplr(X)],[y_COP_low,fliplr(y_COP_high)],'k','facealpha',.15)
fill([X,fliplr(X)],[y_RM_low,fliplr(y_RM_high)],'r','facealpha',.15)
fill([X,fliplr(X)],[y_TR_low,fliplr(y_TR_high)],'b','facealpha',.15)

legend('COP, R^2 = 0.1607','RM, R^2 = 0.1338','TR, R^2 =
0.0817','Location','northwest')
xlabel('Foam Thickness')
ylim([-5 50])
ylabel('Percent Change from Baseline')
title('Linear Regression of Change in AP Jerk across Foam Thickness')
savefig('APJerk_CI')
```

```
%% RMTR_Regression ML Mean Jerk
% Written by Eryn Gerber (eryngerber@ku.edu)
% The University of Kansas - Biodynamics Lab
```

```
% Last updated 3/17/2020
%
% Purpose: Run regression statistics on foam data

%%
load('Perc_changes_EC.mat')
clear thickness
foam1 = Norm_EC_removed_changes(1:51,:);
foam2 = Norm_EC_removed_changes(52:102,:);
foam3 = Norm_EC_removed_changes(103:153,:);
foam4 = Norm_EC_removed_changes(154:204,:);

byfoam=[foam1;foam2;foam3;foam4];

thickness = zeros(204,1);
thickness(1:51)=0.125;
thickness(52:102)=0.25;
thickness(103:153)=0.5;
thickness(154:204)=1;

%% ML Mean Jerk
% Define terms
X = linspace(0,1);
thickness=[ones(204,1) thickness];
thickness_COP=thickness;
thickness_RM=thickness;
thickness_TR=thickness;

byfoam_COP = byfoam(:,59);
byfoam_RM = byfoam(:,66);
byfoam_TR = byfoam(:,65);

%% Linear Regression

% Perform regression and find outliers
[x1_COP,int_COP,r,rint1,stats_COP] = regress(byfoam_COP,thickness);
y_COP = X.*x1_COP(2,1);

i1=[];
for i = 1:length(rint1)
    if or(and(rint1(i,1)>0,rint1(i,2)<0),and(rint1(i,1)<0,rint1(i,2)>0))
    else
        i1 = [i1; i];
        byfoam_COP(i)=NaN;
        thickness_COP(i,:)=NaN;
    end
end

[x1_RM,int_RM,r,rint2,stats_RM] = regress(byfoam_RM,thickness);
y_RM = X.*x1_RM(2,1);

i2=[];
for i = 1:length(rint2)
    if or(and(rint2(i,1)>0,rint2(i,2)<0),and(rint2(i,1)<0,rint2(i,2)>0))
```

```
    else
        i2 = [i2; i];
        byfoam_RM(i)=NaN;
        thickness_RM(i,:)=NaN;
    end
end

[x1_TR,int_TR,r,rint3,stats_TR] = regress(byfoam_TR,thickness);
y_TR = X.*x1_TR(2,1);

i3=[];
for i = 1:length(rint3)
    if or(and(rint3(i,1)>0,rint3(i,2)<0),and(rint3(i,1)<0,rint3(i,2)>0))
    else
        i3 = [i3; i];
        byfoam_TR(i)=NaN;
        thickness_TR(i,:)=NaN;
    end
end

plot(X,y_COP,X,y_RM,X,y_TR)
xticks([0.125 0.25 0.5 1])
legend('COP, R^2 = ','RM, R^2 = ','TR, R^2 = ')


%% Remove outliers
byfoam_COP = rmmissing(byfoam_COP);
thickness_COP=rmmissing(thickness_COP);
byfoam_RM = rmmissing(byfoam_RM);
thickness_RM=rmmissing(thickness_RM);
byfoam_TR = rmmissing(byfoam_TR);
thickness_TR=rmmissing(thickness_TR);

%% Linear Regression with removed outliers
X = linspace(0,1);

% Perform regression and find outliers
[x1_COP,int_COP,~,rint1,stats_COP] = regress(byfoam_COP,thickness_COP);
y_COP = X.*x1_COP(2,1);


[x1_RM,int_RM,~,rint2,stats_RM] = regress(byfoam_RM,thickness_RM);
y_RM = X.*x1_RM(2,1);


[x1_TR,int_TR,~,rint3,stats_TR] = regress(byfoam_TR,thickness_TR);
y_TR = X.*x1_TR(2,1);


plot(X,y_COP,X,y_RM,X,y_TR)
xticks([0.125 0.25 0.5 1])
%% Linear Regression with 90% CI
X = linspace(0,1);
```

```
[m_COP] = fitlm(thickness_COP(:,2),byfoam_COP);
int_COP = table2array(m_COP.Coefficients(1,1));
x1_COP = table2array(m_COP.Coefficients(2,1));
y_COP = int_COP + X*x1_COP;
ci_COP = coefCI(m_COP,0.1)
[m_RM] = fitlm(thickness_RM(:,2),byfoam_RM);
int_RM = table2array(m_RM.Coefficients(1,1));
x1_RM = table2array(m_RM.Coefficients(2,1));
y_RM = int_RM + X*x1_RM;
ci_RM = coefCI(m_RM,0.1)
[m_TR] = fitlm(thickness_TR(:,2),byfoam_TR);
int_TR = table2array(m_TR.Coefficients(1,1));
x1_TR = table2array(m_TR.Coefficients(2,1));
y_TR = int_TR + X*x1_TR;
ci_TR = coefCI(m_TR,0.1)

%% Plot Linear Regression with 90% CI
y_COP = X*x1_COP;
y_COP_low = X*ci_COP(2,1);
y_COP_high = X*ci_COP(2,2);
y_RM = X*x1_RM;
y_RM_low = X*ci_RM(2,1);
y_RM_high = X*ci_RM(2,2);
y_TR = X*x1_TR;
y_TR_low = X*ci_TR(2,1);
y_TR_high = X*ci_TR(2,2);
plot(X,y_COP,'k',X,y_RM,'r',X,y_TR,'b')
hold on
fill([X,fliplr(X)],[y_COP_low,fliplr(y_COP_high)],'k','facealpha',.15)
fill([X,fliplr(X)],[y_RM_low,fliplr(y_RM_high)],'r','facealpha',.15)
fill([X,fliplr(X)],[y_TR_low,fliplr(y_TR_high)],'b','facealpha',.15)

legend('COP, R^2 = 0.0021','RM, R^2 = 0.0044','TR, R^2 =
0.2392','Location','northwest')
xlabel('Foam Thickness')
ylabel('Percent Change from Baseline')
title('Linear Regression of Change in AP Jerk across Foam Thickness')
savefig('MLJerk_CI')
```