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Nonlinear Analysis of Balance Data in the Easter Seals Adult Day Services Population

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Honors Thesis

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Abstract

81.1 million adults are expected to be affected by dementia in 2040. Individuals with dementia are twice as likely to fall as healthy individuals and three times as likely to sustain an injury during a fall. Unfortunately, current fall prevention techniques in place for cognitively healthy older adults are not as effective for those with dementia. The objective of this study was to examine balance differences between individuals of varying cognitive ability utilizing Easter Seals Adult Day Services. All study participants completed the Montreal Cognitive Assessment (MoCA). Clinical assessments were done in conjunction with static posturography data collection on a balance plate. Four different quiet standing test conditions were used to assess the three sensory systems contributing to postural control. Of the 16 participants able to attempt balance testing, 12 were able to complete all testing conditions. It was found that, due to multiple cofounding variables, it was difficult to identify a specific correlation between MoCA scores and balance parameters. There was also difficulty in correlating age with balance parameters due to the high variance in the study population. When compared to age-matched community-dwelling older adults the Easter Seals population did not show consistent trends in the results of traditional analysis, however, nonlinear results showed very clear and consistent differences. It is hoped that this study can contribute to a better understanding of balance limitations in the adult day services population and inform future interventions.

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Introduction

Background on Falls in Individuals with Dementia

Dementia is a major cause of serious health problems and mortality in adults over the age of 65 [1]. Dementia is a blanket term that describes Alzheimer's disease (AD), vascular dementia, and frontotemporal dementia, among others, though the most common is AD [1, 2, 3]. As of 2010, there were 24.3 million people affected by this disease [2]. In general, dementia is defined by a loss of memory, impairment of cognitive function, and deterioration of motor function [2, 3]. Though there is currently no cure for dementia, there are some medications and treatments that, in the short term, have slowed the progression of the disease [2, 3]. Dementia is an issue with increasing urgency, as the number of people with dementia is predicted to rise to 81.1 million adults by 2040 [2]. Currently, AD is ranked as the fifth leading cause of death in the adult population over 65 in the United States [3].

Dementia is generally progressive, and can be broken into three stages: early, middle, and late [4]. Symptoms present when first diagnosed include mild memory loss, increased difficulty of making decisions, and inability to articulate thoughts [4]. Motor function decline like reduced gait speed is common in older adults, but it also can be a precursory sign of cognitive impairment [5]. In the middle or moderate stage of dementia, individuals begin to lose the ability to complete activities of daily living (ADLs) and need to be reminded to eat, bathe, or even use the bathroom [4]. Motor skills begin to be affected by this stage, and tasks like brushing teeth can become more difficult [6]. By the late (severe) stage, symptoms include inability to recognize people and common objects and greater loss of motor function, causing instinctual tasks like walking or chewing to become more laborious [4, 6, 7, 8,].

There are multiple ways to determine cognitive deficit. Two of the most popular assessments include the Mini Mental Status Exam (MMSE) and the Montreal Cognitive

Assessment (MoCA) [9]. These validated assessments ask the individual to remember and recite items, do basic arithmetic, and draw simple pictures in order to test various aspects of cognition. While the MMSE is more commonly used, the MoCA was more recently developed for a higher sensitivity to identifying mild cognitive impairment (MCI) [9]. Mild cognitive impairment is important to identify, as it often leads to more severe stages of dementia [9]. The MoCA assesses short term memory recall, visuospatial abilities, attention, concentration, and working memory through multiple short tasks to culminate in a score out of 30 possible points. A score of 27 to 30 corresponds to normal cognitive ability, a score of 26-18 corresponds to MCI, and a score of 18 or less is considered a severe cognitive deficit such as Ahlzheimer's disease [9]. The combination of dementia's side effects result in a loss of independence and an increased risk of falls [2, 7, 10, 8]. Falls are a major concern for older adults as they can cause a variety of serious injuries and health problems—sometimes even death [11, 12]. This is especially true of individuals with dementia, as they are twice as likely to fall as the cognitively healthy older population [7, 10]. The severity of falls in those affected by dementia is also greater: an individual with dementia is three times more likely to fracture one of their bones because of a fall [7]. Individuals with dementia also have a higher chance of death after a fall than their cognitively healthy counterparts [8].

Many factors cause falls, some of which are shared between cognitively healthy older adults and those affected by dementia [7]. Some examples of these shared risk factors include gait or balance deficiencies, medications, or visual disorders [13, 7]. Most of the fall risks shared by the entire older adult population are magnified in older adults with dementia [7]. For example, when dementia progresses, it affects the individual's ability to move and causes loss of motor control [7, 8, 14]. When motor function losses become severe, most members of the cognitively healthy older population would begin to use canes or walkers, but those with dementia sometimes have an inability to learn the new motor skills needed to make the assistive devices effective [14]. Dementia patients are also more likely to be taking psychotropic medications like antidepressants and antipsychotics that have been shown to cause increase of fall risk [7]. Visual deficits are an eventual side effect of dementia as well—perception and visuospatial awareness decrease with the progression of the disease [14, 15].

Understanding these risks, particularly the unique risks specific to individuals with dementia, is instrumental in creating preventative measures for falls. However the causes of falls of older adults with cognitive deficits are still fairly ambiguous [8]. This is partially due to the complicated nature of loss of motor function and the close relationship of cognitive and motor decline [5].

Linking Falls to Balance

One of the more statistically significant causes of falls in individuals with dementia is balance impairment [8]. Defined as keeping the body stable, balance depends on three systems: visual, vestibular and proprioception, all of which deteriorate with age [17, 7]. Dementia has been seen to increase the rate of deterioration of the visual system [15, 14]. Some studies have found that individuals with AD have trouble focusing when visually overstimulated, causing increased sway [16]. These systems can also be affected by certain medications commonly prescribed to individuals with dementia, leading to an increased fall risk due to balance impairments [7]. Medication side effects do not account for all of the increased fall-risk individuals with dementia experience, however, as cognitive impairment itself can adversely influence balance [1]. The progression of many kinds of dementia lead to a loss of motor function, making it hard to react to changes in stability [7, 8, 4]. Current research has quantified a lower activity level as well as poorer performance by individuals with mild AD in clinical tests such as the Berg Balance Scale, Timed Up and Go, and Walking in Figure Eight assessments than age and gender matched cognitively healthy participants [18]. Research has also documented changes in equilibrium in individuals with mild cognitive impairment (MCI) as well as those with mild AD [19].

Human balance can be measured using a method called posturography. Posturography can be divided into two different categories: static and dynamic [12]. Static posturography, used in this study, looks at an individual's body in an unchanging, or static, position, while dynamic posturography observes balance when static stance is challenged through external perturbations [12]. Static posturography uses a force plate, much like a bathroom scale to measure center of pressure (COP) and observe how it moves [20]. Center of pressure, which is the location of the ground reaction force of the body, gives a better understanding of how control is maintained over the center of gravity [21]. This provides insight as to how an individual sways while standing [20]. Clinically, posturography has the potential for significant benefits, as it provides a fast and unobtrusive way to measure how steady a subject is under a variety of sensory conditions. The individual being tested must stand on the force plate for 10-60 seconds, and different conditions can be used to examine the different systems that contribute to balance, such as having the individual close their eyes to limit the visual system input [20].

The information gained from posturography assessments can interpreted in many different ways. Traditional, also known as linear, analysis measures examine the amount the COP moves relative to time (sway range, sway velocity, etc.) and are outlined by Prieto et al [21]. Measures such as these reflect how much and how fast COP changes [21]. Smaller amounts and slower speed correlate to better postural control and indicate better stability [21].When studying balance in older adults, Bigelow and Berme found that sway velocity in the medial-lateral direction was the best differentiator of fallers and non-fallers [20].

More recently another method of examining COP data has emerged—nonlinear analysis. Where traditional measures look specifically at quantifying the amount of sway, nonlinear analysis works to identify the underlying patterns of sway in an effort to account for the variability of the balance control system [22]. By looking at how the patterns of sway change over time, the ability of the individual to adapt to the environment around them is more accurately captured [22]. In the past, it has been assumed that the most ideal balance system would be very repeatable (periodic), but more recent studies challenge this assumption [22]. Work is now being done to better understand what the optimal amount of variability is, as it is important to recognize variability as a spectrum [22]. If there is a lack of recognizable pattern in sway of an individual, it is considered “random” and indicates poor postural control because it does not allow for sufficient efficiency in achieving postural goals [22]. Periodic patterns, however, indicates a likely inability of an individual to adapt to unexpected external environmental obstacles [22]. Nonlinear analysis provides a technique to more accurately quantify the meaning of seemingly random data points in an individual’s balance patterns [23]. This makes nonlinear analysis much more sensitive than traditional analysis methods, and nonlinear techniques have been used to examine fall risk in older adults [20].

Many different types of nonlinear analysis exist, but Sample Entropy was the method chosen for this study. Sample Entropy gives a value that quantifies the pattern, and more specifically the regularity or predictability, of a time series [24]. As the SampEn value increases, it correlates to a more chaotic pattern, meaning that the patterns are less regular and predictable [24]. Similarly, as the SampEn value decreases it represents a more periodic pattern, correlating to a more regular, predictable pattern [24]. In recent studies, Sample Entropy has been preferable to a similar method, Approximate Entropy, as it is more consistent and less dependent on the amount of data being processed [24]. Sample Entropy has been used in recent studies to differentiate typically developing children with Cerebral Palsy, to examine athletic ability of gymnasts, and to identify adults with Ehulers-Danlos Syndrome [25, 26, 27].

Purpose of this Study

This work was part of a larger research project with Easter Seals Adult Day Services. Many individuals with dementia utilize adult day services where they can receive supervised care in a group-setting during the day. The purpose of this larger project was to examine fall risk in the adult day services because many individuals in this population have dementia and falls have been identified as a problem. The project’s goal was to isolate factors that best identified individuals with high fall risk who were using Easter

Seals Adult Day Services. It is important to note that while the majority of individuals utilizing Easter Seals' services did have cognitive deficits, many also had serious other physical ailments that drove their need for the services as well. After identifying fall risk factors specific to this population, it was hoped that an intervention plan could be developed to prevent future falls in high fall risk subjects. The entire project encompassed clinical assessments as well as posturographic data collection. The posturography work is the main emphasis of this thesis.

The original purpose of this thesis was to use sample entropy to determine differences in balance between individuals at the Day Services who fell often from those who did not. Unfortunately logistical complications - as described later in this thesis - caused the aim to be altered, and relationships between cognitive ability (MoCA score) and balance performance were instead thoroughly scrutinized. As part of the new direction, cognitively healthy members of the elderly population were also analyzed in order to better understand how varying cognitive ability affects sway pattern regularity. It was hypothesized that balance parameters reflecting poorer postural control would be found in individuals with lower MoCA scores. It was also hypothesized that the heightened sensitivity of nonlinear analysis techniques would be able to more clearly and significantly differentiate the cognitively healthy individuals from the individuals utilizing Easter Seals services as compared to traditional measures.

Methods

Study Participants

Based on the nature of the grant that this project was funded through, only individuals participating at one of three Dayton-area Easter Seals Adult Day Services were eligible to participate in this study. Easters Seals provides a daycare service for adults who are unable to take care of themselves without the aid of a caregiver, usually due to some sort of cognitive deficit. The structure of the services allows for flexible schedules to match the needs of the participants and their caregivers, so an individual utilizing the services does not have to attend every day. It was expected that around 70 to 100 people of the estimated 250 individuals using these services would choose to participate in this study. In order to be considered for the posturographic data collection portion study, individuals had to be able to stand without assistance or upper extremity support for 60 seconds. If the participant demonstrated a lack of ability to safely follow directions or began to show signs of physical fatigue or stress, they were excluded from the study.

Consent and Logistics

Because of the potential vulnerability of participants using Easter Seal Adult Day services due to cognitive deficits, the consent process for this project was lengthy and complex. First, information on the study, as well as an invitation to participate was sent to families utilizing the Easter Seals Adult Day Services by the site coordinators. Once the legal guardian and/or the individual using Easter Services showed interest in the study, a consent form with more detail about the study was sent to them. A member of the research team that was authorized to obtain consent then called the legally authorized representative to verbally go over the consent form and address any questions or concerns they had about the study, and the legally authorized representative could sign the consent form before returning it. If the individual had misplaced the form and did not have it available to follow along with while the researcher verbally reviewed it, a new mailing had to be sent out and the whole process began again. The multi-week process of mailing of these forms and the phone follow-ups became very labor intensive and challenging, causing loss of many potential study participants. After receiving consent from the legally authorized representative, it was also important to obtain assent from the individual completing the testing for the study so as not to collect the data against their will. In carrying out this study, many individuals who used the adult day services did not have a legally authorized representative and were able to sign for themselves. These self-consenters also presented a consent challenge, because great care had to be taken to ensure that they were cognitively able to provide informed consent. Extra comprehension questions were asked after the overview of the consent form to determine if the potential participant understood why we were doing the study, what was being asked of them and what the benefits and risks of participating were. Only those individuals who expressed interest in participating and were able to articulate responses consistent with understanding the consent materials were able to participate in the study. For those individuals that did consent, if at any time they showed discontent with being part of the study, they were able to withdraw. If safety of the participant was ever a concern, they were not asked to complete the remaining testing.

Part of the study included a summary of participant's medical conditions that have a known relationship to fall risk. Based on the consent of the participant or their legal guardian, the Easter Seals nurse on staff reviewed the individual's medical records kept at the day service and documented information for the research team on past and present medical conditions known to be related to falls such as dementia, dizziness, visual problems, foot problems, or major surgeries. Medication and dosage information was collected if permitted. History of falls were asked for on the medical history form. The compilation of this information revealed that the majority of individuals utilizing the Adult Day Services had other chronic health conditions in addition to dementia. While more in-depth analysis was attempted, various logistical challenges (such as nursing turnover, medical records that did not reflect recent changes, or fall history that was dependent on information reported by caregivers) meant that this data was not entirely reliable or useful as is. To be as accurate as possible, this was not used further for this portion of the project.

Participants or their legal representatives were also attempted to be asked about their fall history directly. A fall was defined as "any time an individual unintentionally came to rest on the ground or another lower level, including tripping on hazards, falling off ladders, or falling when getting out of bed." Participants were asked how many falls they had had in the last 12 months, how many times they had been hospitalized in the past 12 months because of falls, and how many times they had fallen in the past 6 months. They were also asked to describe when their last fall was and what the circumstances were for that fall. The purpose of doing this was to elicit information that would allow dividing individuals up based on fall history and look at how their performance was related to this fall status. Unfortunately, the information collected from this portion of the study was also deemed unreliable based on the large number of self-consenters with demonstrated difficulty recalling past events.

Data Collection Protocol

This thesis is one significant aspect of a larger study. The larger study's goal was to investigate the fall risk factors unique to individuals utilizing Adult Day Services compared to community dwelling older adults without dementia or other health conditions. All testing took place at an Easter Seals Adult Day Services location when participants were already scheduled to be there. Data collection for the complete study took place during a single test session that lasted approximately 45 minutes. Testing was administered by trained students and faculty from the Physical Therapy and Mechanical Engineering departments at the University of Dayton.

The first assessment conducted during the testing session was the Montreal Cognitive Assessment (MoCA) test. This was done as a way to quantify the cognitive abilities of each participant. The methods of this test are outlined in "Nasreddine et al. JAGS 2005" [9]. A copy of the MoCA test can be seen in the Appendix.

Heart rate, sitting blood pressure, and standing blood pressure were recorded before any other tests were done to ensure the safety of the participant. If these values were considered out of a safe range, participants were excluded from the study and did no further testing.

Clinical assessments that were part of the larger study were then done prior to posturography data collection. Due to the postural control focus of this work, these are not included in this study's analysis. The clinical assessments performed included a 4-m walk to measure self-selected gait speed, a Timed-Up-and-Go (TUG) test to measure agility in coherence with gait speed, Sit to Stand Repetitions to measure lower body strength, and grip strength. Gait assistive devices, if needed, were allowed during all clinical assessments.

The posturography assessment to measure balance was conducted last. Participants were asked to quietly stand on a balance plate (Bertec Corporation, Columbus, OH, Model BP5050) without shoes or external assistance for 30 seconds at a time while spotted by a trained research assistant. Individuals were able to choose a self-defined comfortable stance, with feet approximately shoulder-width apart. Figure 1 shows an individual standing on a balance plate.

Figure 1: Individual Standing on Bertec Balance Plate (Image from Bertec Corporation).

Each individual was asked to attempt four test conditions, described in Table 1. These test conditions are known as the Modified Test of Sensory Integration on Balance (mCTSIB) [28]. They are used to assess how an individual is able to perform under manipulated sensory conditions, providing insight into how the individual sensory systems contributing to balance are working independently and together [28]. The combination of these test conditions allow the isolation of each of the systems in order to determine their interaction with one another. For example, in test condition where eyes are closed and the individual is standing on a foam pad, both proprioception and vision are challenged to allow evaluation of the vestibular system contribution to overall balance.

Table 1: Balance Plate Test Conditions

Test Number	Test Description	Test Abbreviation	Senses Isolated
1	Eyes open on a firm surface	EO-Flat	Visual, Vestibular, Proprioceptive
2	Eyes closed on a firm surface	EC-Flat	Vestibular and Proprioceptive
3	Eyes open on a foam surface	EO-Foam	Visual, Vestibular
4	Eyes closed on a foam surface	EC-Foam	Vestibular

The foam surface used for test conditions 2 and 4 was a closed-cell foam pad. If at any point the participant felt unsteady or showed signs of physical fatigue, they were given time to rest before the next trial was attempted.

The balance plate measures downward force (F_z) and moments along two axes (M_x and M_y). From this, the software calculates and outputs the anterior-posterior (A/P) (front-to-back) center of pressure displacement and medial-lateral (M/L) (side-to-side) center of pressure displacement over the duration of the trial. All data was collected at 1000 Hz.

Data Analysis

All of the balance data was first analyzed using traditional means. There are many different parameters that can be calculated to traditionally analyze data, so the parameters need to be selected carefully to avoid redundancies in results.

Sway range shows maximum distance the participant swayed. Medial/ Lateral (M/L) Sway Range describes peak distance from side to side. Smaller sway ranges are indicative of better postural control, and therefore better balance. Equations for M/L sway range can be seen in equation (1).

$$\text{M/L Sway Range} = |(x_n)_{max} - (x_n)_{min}| \quad (1)$$

where: $(x_n)_{max}$ corresponds to the highest value in the M/L data set and $(x_n)_{min}$ corresponds to the lowest value in the M/L data set.

Sway velocity reflects how fast an individual sways during a trial. Sway velocity in the M/L direction has been shown be the best indicator of fall risk in previous studies [20]. High sway velocities are usually correlated with poor postural control. For this study, M/L sway velocity was calculated. Mean velocity in the medial-lateral direction can be calculated using equation (3).

$$\text{M/L Mean Velocity} = \frac{\sum_{n=1}^{N-1} \sqrt{((x_{n+1}) - (x_n))^2}}{T} \quad (2)$$

where: N is the total number of data points in the COP data set, n is the data point of interest, x corresponds the M/L data set and T represents the total time duration of the trial.

Additionally, A/P sway range, mean velocity, A/P mean velocity, RMS distance, and 95% confidence ellipse were calculated based on their standard use in current literature, however because of the importance of M/L direction in identification of fall risk, only M/L sway range and M/L mean velocity were emphasized in this study. The Matlab code used to calculate these and the previously mentioned traditional measures can be found in the appendix.

Data was then analyzed using nonlinear methods, specifically sample entropy. Sample Entropy Value was calculated for Medial/Lateral (M/L) and Anterior/Posterior (A/P) directions for each participant. This was done by determining a user input of vector length (m) to break up the time series of length (N) into vectors of length (m), which are called template vectors [24]. These template vectors are then compared to each other to determine how many matches there are based on a tolerance (r), also defined by a user input [24]. The vector is not counted as matching itself (in other words, self-matching was not included). This is a key difference between Sample Entropy and Approximate Entropy, which is a slightly different nonlinear analysis method. The number of matches for a specific vector correlates to a conditional probability (Ci^m) where number of matches are divided by the total number of vectors of length m. These conditional ratios are all added together, then divided by (N-m) to get the value Bi.

$$Bi = \frac{(\Sigma Ci^{m})}{(N-m)} \tag{3}$$

Value of B can be calculated once Bi is determined.

$$\mathrm{B} = \frac{(\mathrm{N-m-1}) * (N-m)}{2} * Bi \tag{4}$$

This process is then repeated with vector length increased by 1 (m+1) to get another set of conditional probabilities ($Ci^{(m+1)}$). Only the first (N-m) vectors of length (m) are considered so that the same number of vectors of length (m) are consistent with the number of vectors of length (m+1). These probabilities are again added together and divided by (N-m) to get Ai.

$$Ai = \frac{(\Sigma Ci^{(m+1)})}{(N-m)} \tag{5}$$

Value of A is then calculated in the same way as B using Ai.

$$\mathrm{A} = \frac{(\mathrm{N-m-1}) * (N-m)}{2} * Ai \tag{6}$$

These two numbers are used to calculate the sample entropy value (SampEn) with formula (8).

$$SampEn = -ln(\frac{A}{B}) \tag{7}$$

It is important to note that, due to the omission of self-matches, time series with no similar matches (Ai=0 or Bi=0) SampEn is undefined [29].

Values of m and r were chosen to be 2 based on its accepted use and success in previous studies [28, 24]. The Matlab code used to calculate the Sample Entropy values can be found in the appendix.

Results from these analysis methods were further processed to better understand the general implications of the study. Due to small sample size, statistical analysis was not performed, but data was averaged for each condition for each participant. These averages were used to create scatter plots so correlation between balance parameters and MoCA score could be examined. The same process was repeated to analyze the relationship between balance parameters and age. When a trend was visually identified, linear regressions were performed to better quantify any existing relationship between the two variables.

For further understanding of the results, each participant utilizing Easter Seals Day Services was age-matched with a cognitively healthy community-dwelling older adult data that had been collected for a previous study. All of these individuals were non-fallers. The balance parameters of both groups were compared through the use of bar graphs for the EO-Flat and EC-Flat balance test conditions.

Results

Summary of Study Participants

20 individuals chose to participate in the study, however only 16 of these participants were able to attempt balance testing. The demographic information for all participants able to complete at least one balance test trial are summarized in Table 2. Participants ranged in age from 68 to 88, with MoCA scores ranging from 6 to 29. Average height of participants was 162.54±9.95 cm. Average weight was 76.14±14.54 kg. 43.8% of participants were male.

Table 2: Participant Demographic Information Summary

Subject No.	Sex	Age	Height (cm)	Weight (kg)	MoCA Score	Assistive Device
P1	F	68	166	92.8	25	rollator
P2	F	80	171	50.6	11	cane
P3	M	82	168.6	90.6	6	--
P4	F	83	149.6	81.5	18	rollator
P5	M	64	165	99.8	19	--
P7	F	67	156	91	18	walker
P9	F	66	151	62.5	17	--
P10	F	68	160.1	89.1	16	--
P12	F	67	166	78.4	11	--
D2	M	66	158.4	79.3	11	--
D3	F	70	168	70.8	29	--
D4	M	88	172.7	58.3	16	--
D5	F	83	142.2	73.5	21	--
D6	M	77	152	51.4	24	cane
D7	M	74	176	67.5	23	cane
D8	M	86	178	81.1	13	--

All 16 of these individuals were able to complete the Eyes Open Flat Plate condition, 15 were able to complete the Eyes Closed Flat Plate condition, and 15 were able to complete the Eyes Open Foam condition. Only 12 participants were able to complete the Eyes Closed Foam condition—3 of which were only able to complete 1 trial instead of 2. These numbers are summarized in Table 3.

Table 3: Number of Participants Out of 16 by Balance Test Condition

Test Condition	No. of Subjects able to Complete 1 Trial	No. of Subjects able to Complete 2 Trials
Eyes Open Flat Plate	16	16
Eyes Closed Flat Plate	15	15
Eyes Open Foam	15	15
Eyes Closed Foam	12	9

Summary of Traditional Descriptive Balance Data

A visual representation of how the center of pressure (COP) changes over the time of the trial can be seen in COP plots like the ones shown in Figure 2. The top plot shows better postural control than the bottom plot, demonstrated by the smaller amplitude of sway in the M/L and A/P directions. These plots are examples from the same participant during different test conditions, where the top plot represents data collected during the easiest test condition (Eyes Open Flat Plate) and the bottom plot is data collected during the most challenging test condition (Eyes Closed Foam).

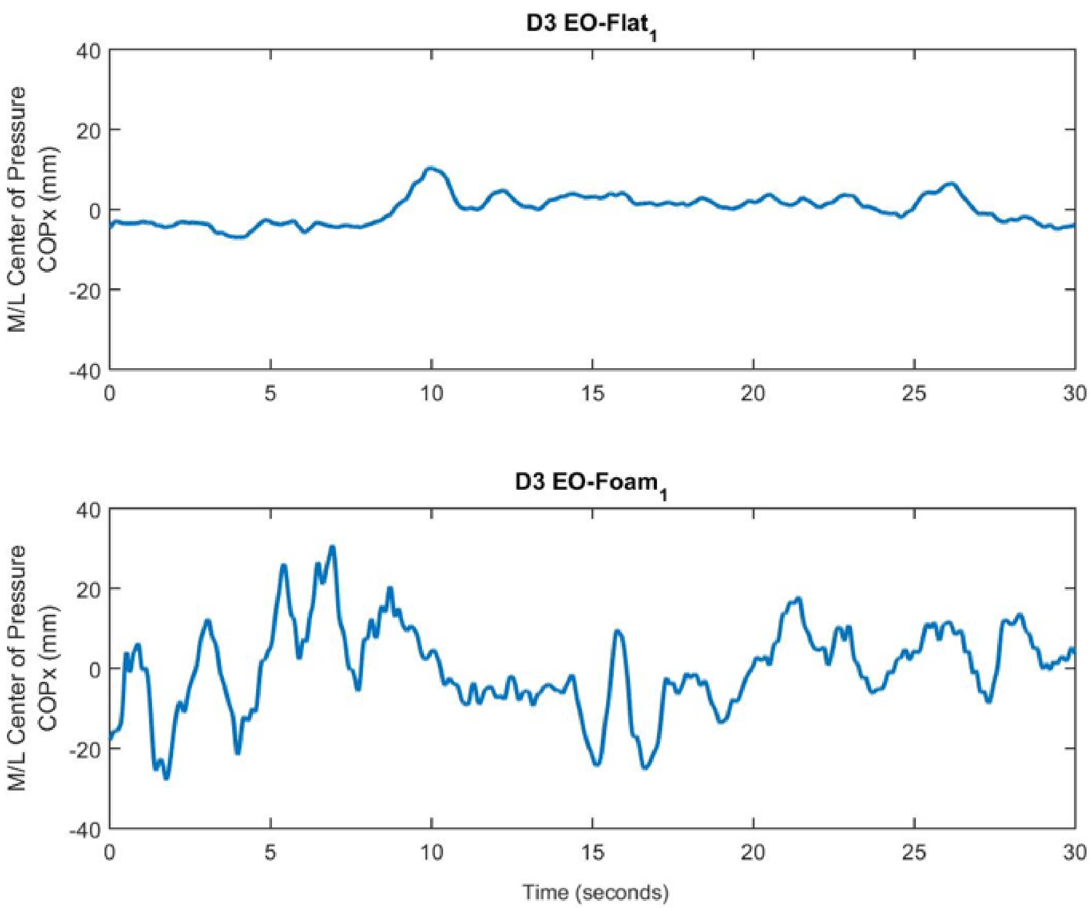

Figure 2: Example COP Plots

Traditional results were calculated for each trial for each participant and then averaged. These averages for each participant were then averaged again to get the generalized result for the test condition. A summary of these results can be seen in Table 4. Averages generally increase progressively from Eyes Open, Flat test condition to Eyes Closed, Foam, which was expected due to the increasing difficulty of each test condition.

Table 4: Summary of Traditional Analysis Results

	EO-Flat (16)	**EC-Flat (15)**	**EO-Foam (15)**	**EC-Foam (12)**
A/P Sway Range (mm)	25.36±9.89	34.90±11.97	49.55±14.50	73.92±39.15
M/L Sway Range (mm)	19.39±15.35	17.06±10.01	42.15±15.35	55.86±53.63
Mean Velocity (mm/s)	16.59±12.96	20.83±10.51	31.10±12.12	57.60±30.16
A/P Mean Velocity (mm/s)	14.03±11.22	18.23±9.05	24.72±9.84	48.15±22.36
M/L Mean Velocity (mm/s)	6.23±4.58	7.02±4.24	14.11±5.88	22.87±15.75
RMS Distance (mm)	5.82±2.17	7.27±2.62	11.98±3.41	17.91±9.31
95% Confidence Ellipse Sway Area (mm2)	201.95±164.65	264.53±220.12	889.52±485.95	1959.78±1778.34

Summary of Nonlinear Descriptive Balance Data

Sample Entropy values (SampEn) were calculated to better understand the patterns of sway. Figure 3 below visually demonstrates the difference between a low Sample Entropy Value (M/L SampEn=0.06) and a high Sample Entropy Value (M/L SampEn=0.51). As can be seen from the figure, the pattern of the frequency in the top plot from subject D7 looks more regular or predictable than that of the bottom plot from subject D3. Both of these plots show data from the most difficult test condition (Eyes Closed Foam).

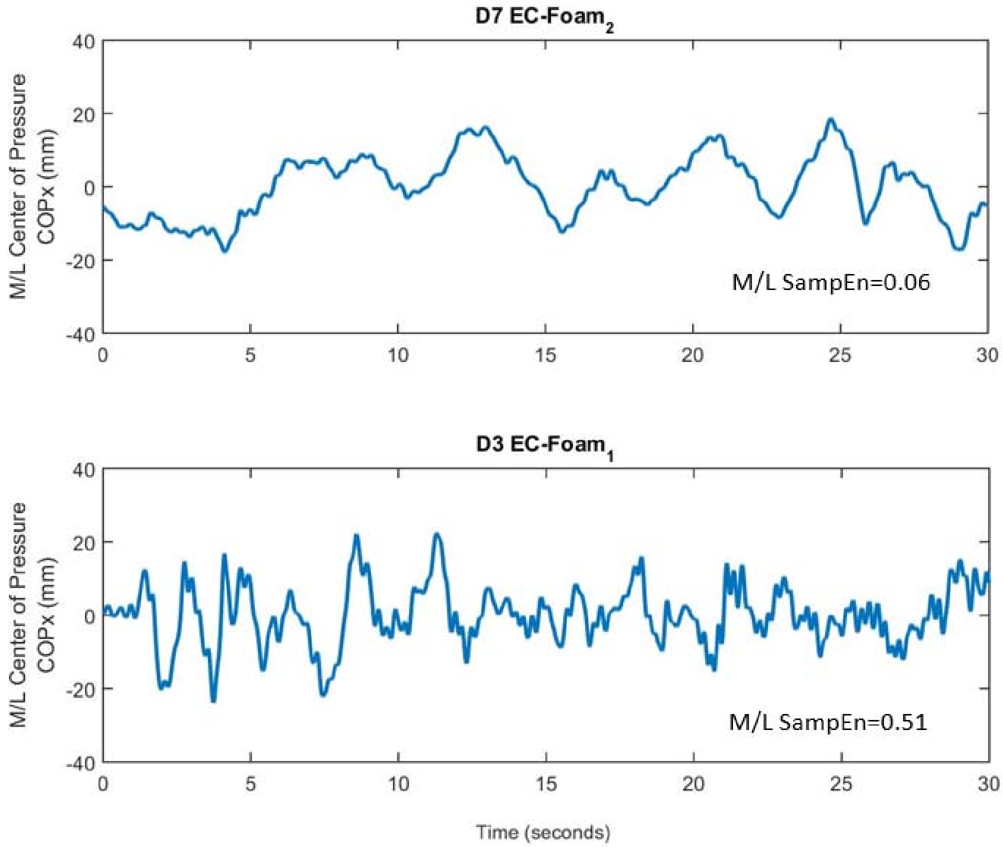

Figure 3: Differences between High and Low Sample Entropy Values

Nonlinear results are summarized in Table 5 below. Unlike the traditional methods, Sample Entropy analysis did not yield generally recognizable trends.

Table 5: Sample Entropy Results Summary

	EO Flat Plate (16)	EC Flat Plate (15)	EO Foam (15)	EC Foam (12)
M/L SampEn Value	0.17±0.06	0.21±0.07	0.13±0.05	0.20±0.09
A/P SampEn Value	0.27±0.14	0.25±0.09	0.25±0.11	0.30±0.14

Relationship between Balance Performance and Cognitive Ability

M/L Sway Range was calculated based on its ability to identify cognitively healthy elderly with high fall risk [20]. Figure 4 shows each participant's M/L Sway Range during all four test conditions as related to cognitive ability (MoCA score). Eyes Closed Foam revealed a moderately strong relationship ($R^2 = 0.63$) such that individuals with lower cognitive function swayed more.

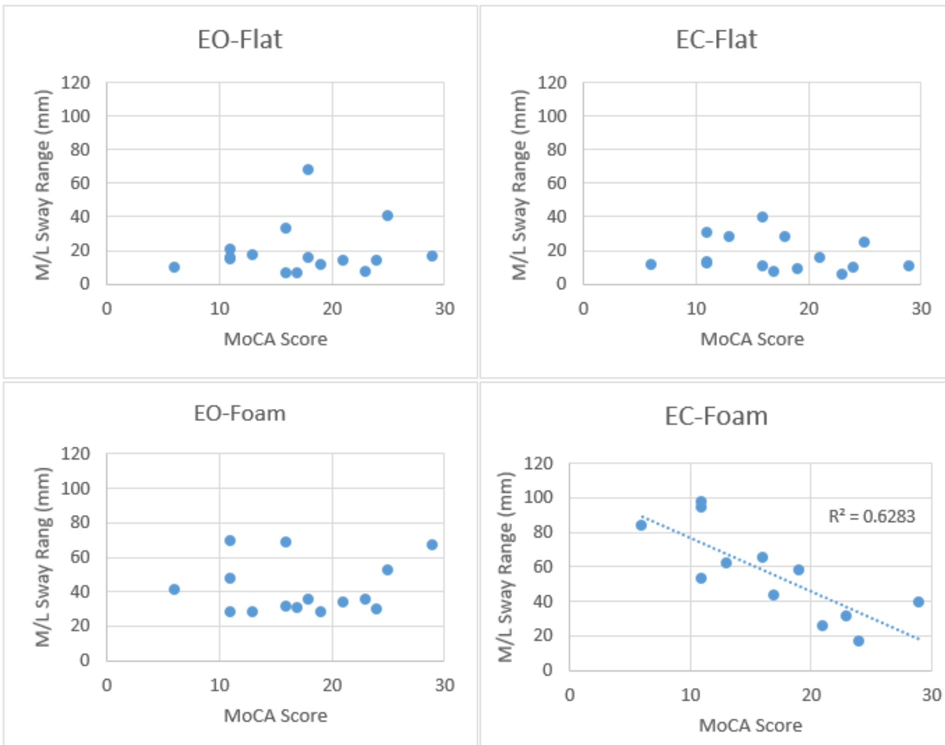

Figure 3: M/L Sway Range in Relation to MoCA Score

M/L Mean Velocity was calculated based on its ability to identify cognitively healthy elderly with high fall risk [20]. Figure 5 shows each participant's M/L Mean Velocity relative to their MoCA score for each test condition. The EC-Foam appeared to show the most definitive trend, however had a very weak correlation between MoCA and (R^2=0.14).

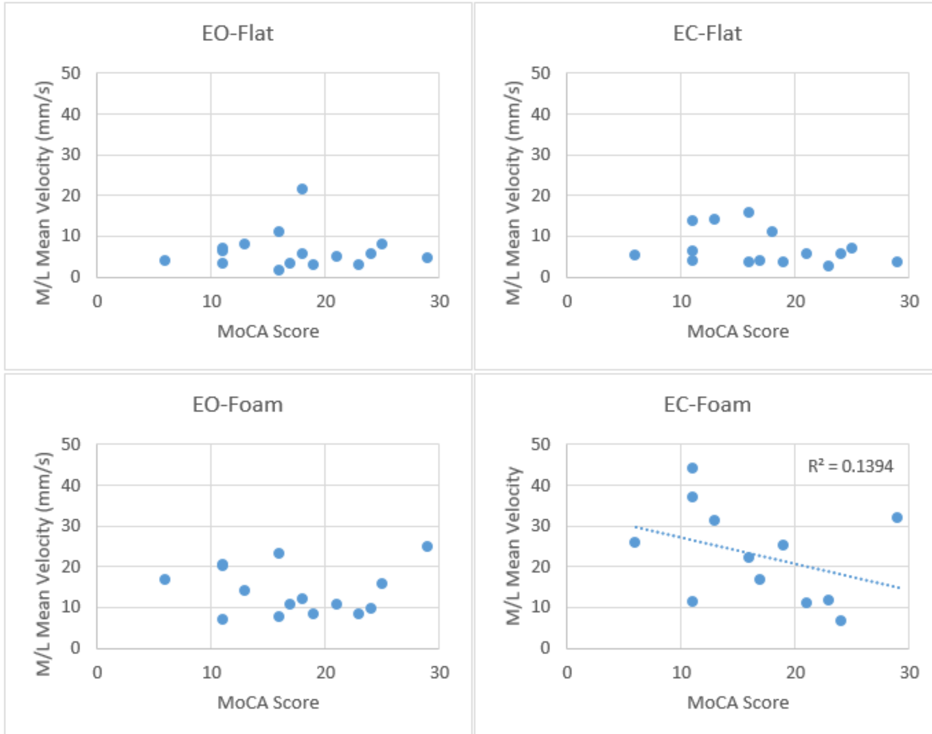

Figure 5: M/L Mean Velocity in Relation to MoCA Score

Nonlinear results relative to MoCA score are summarized in Figures 6 and 7. No discernable trends were identified.

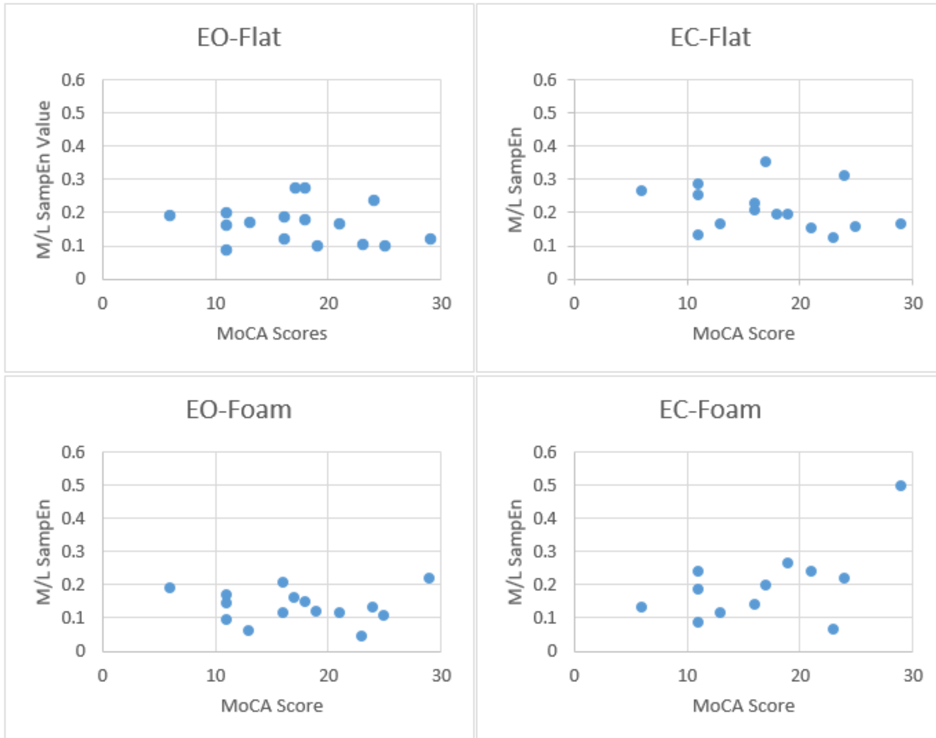

Figure 6: M/L SampEn in Relation to MoCA Score

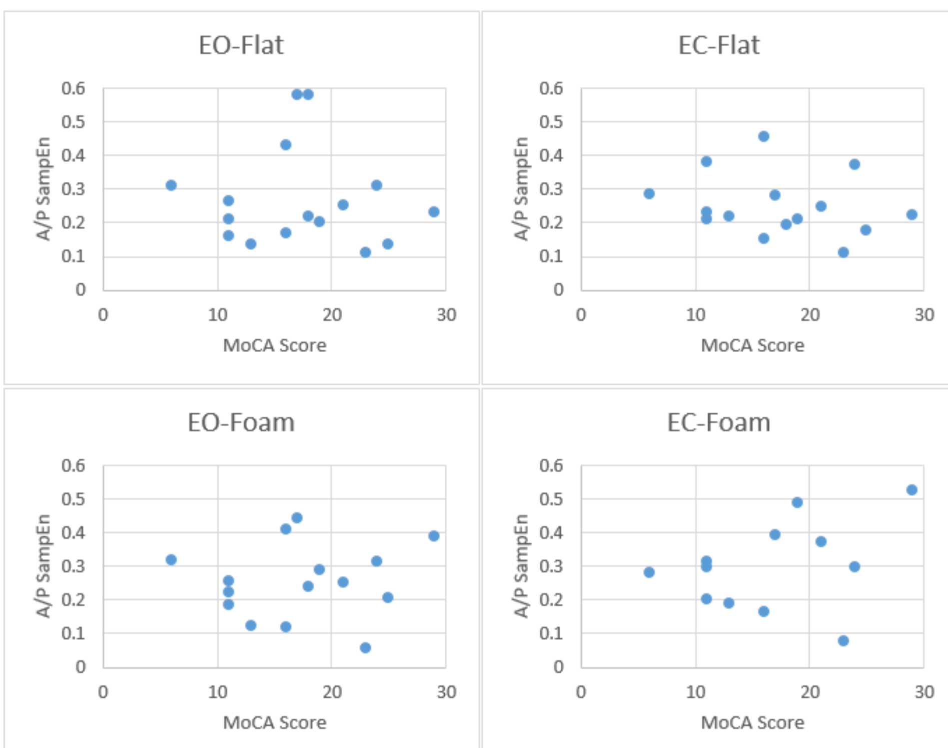

Figure 7: A/P SampEn in Relation to MoCA Score

Relationship between Balance Performance and Age

Balance parameters were then compared with age to determine if there appeared to be a relationship. Traditional measures of M/L Sway Range and M/L Velocity in relation to age can be seen in Figures 8 and 9 respectively. Nonlinear measures in relation to age are summarized in Figures 10 and 11. Variation in age did not correlate to a specific trend in any of the measures calculated.

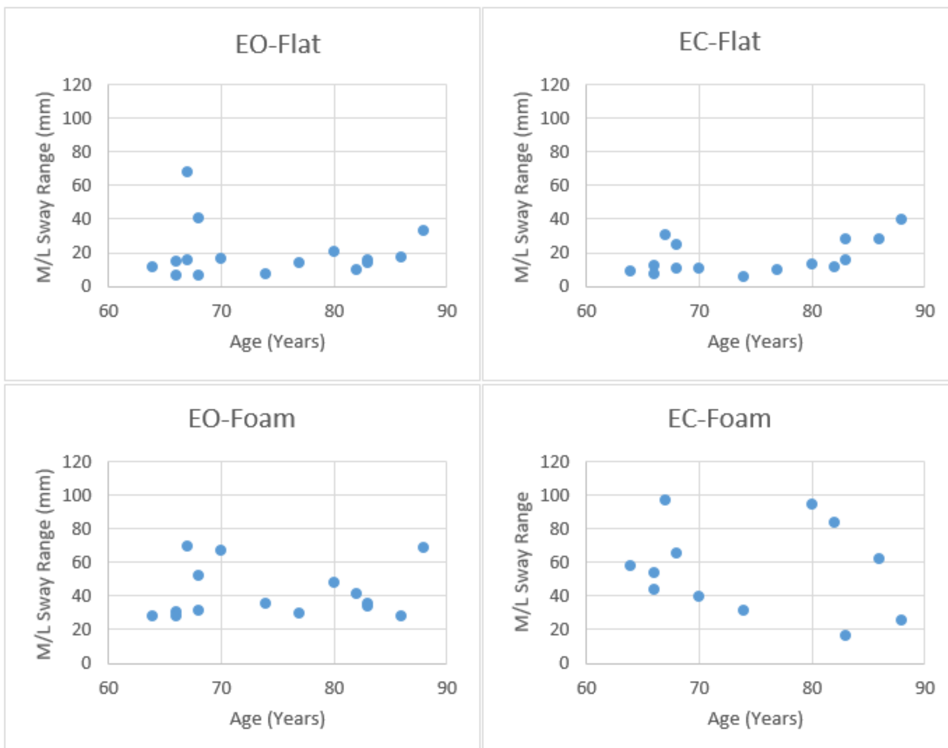

Figure 8: M/L Sway Range in Relation to Age

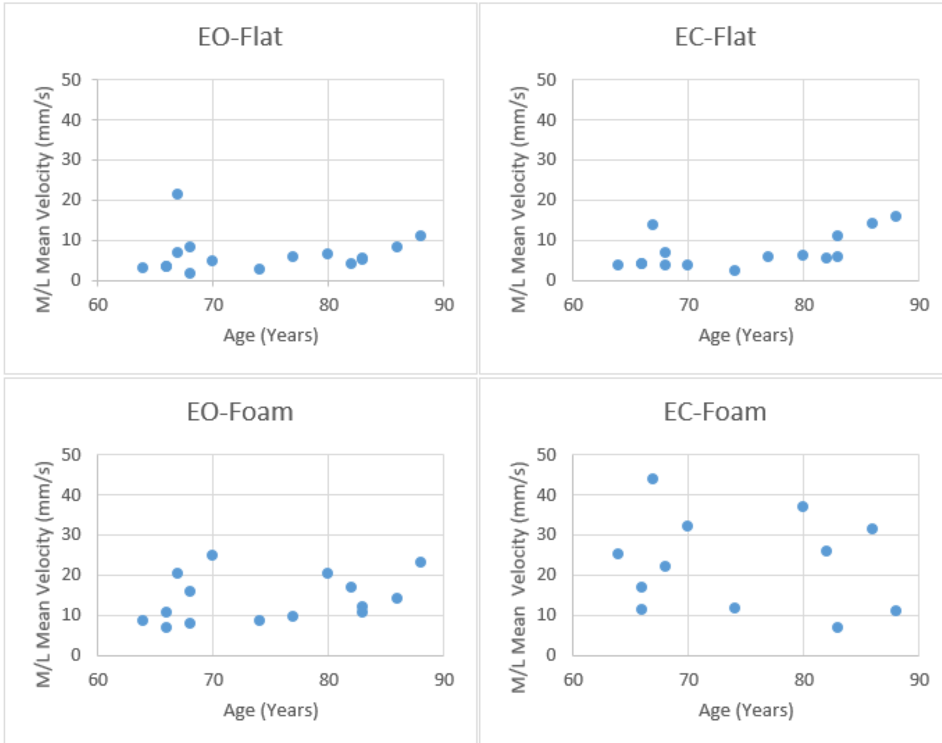

Figure 9: M/L Mean Velocity in Relation to Age

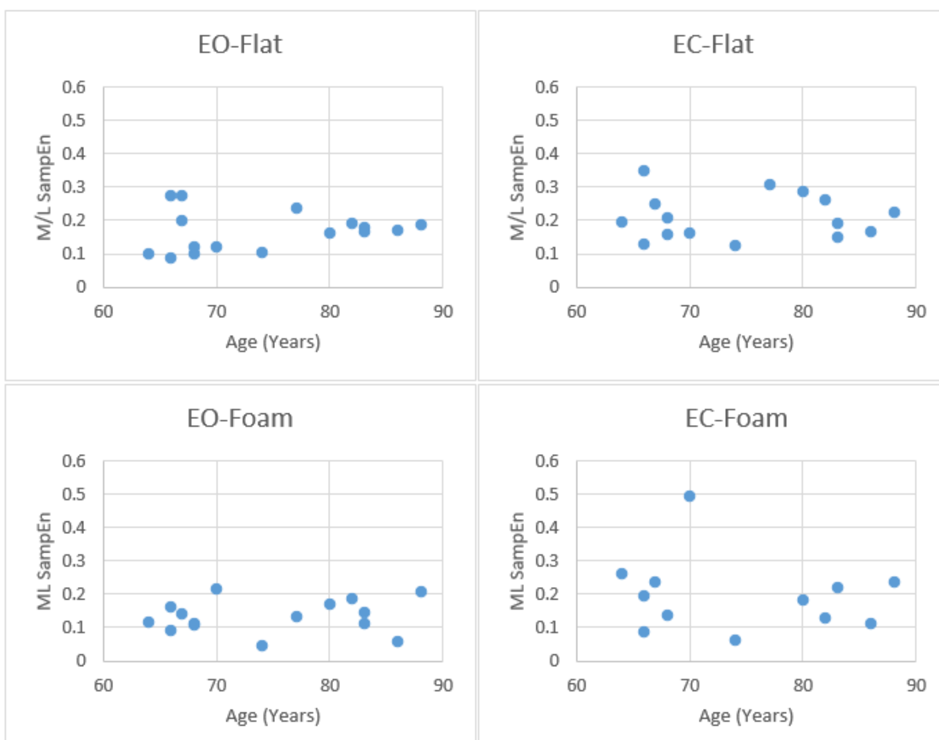

Figure 10: M/L SampEn in Relation to Age

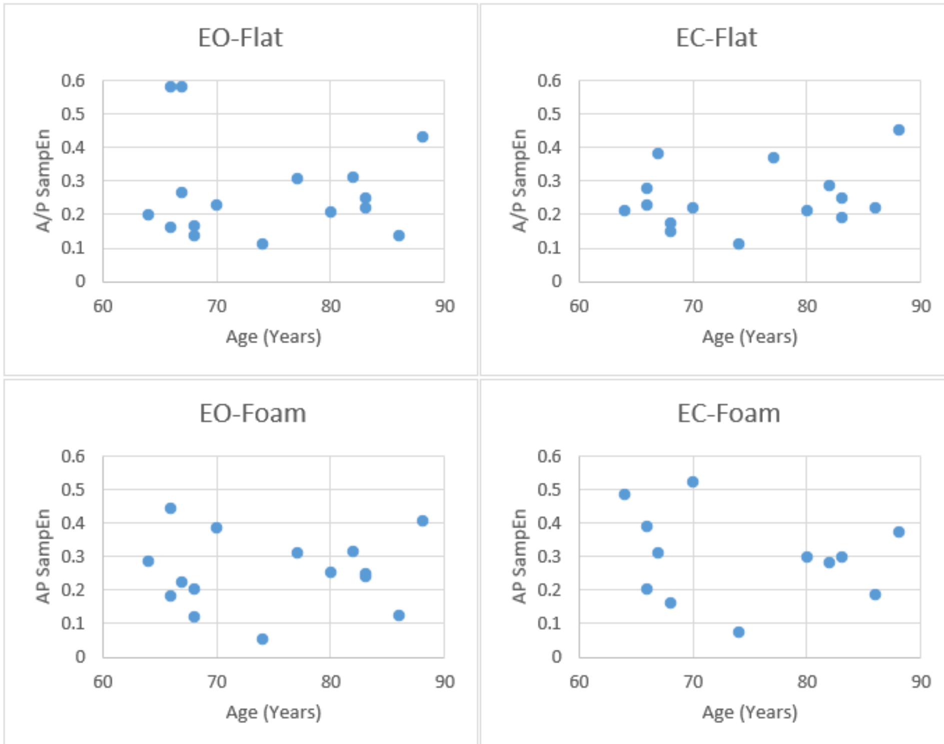

Figure 11: A/P SampEn in Relation to Age

Comparison of Results to Healthy Older Individuals

Balance test results of the individuals utilizing Easter Seals Adult Day Services were compared to age-matched community dwelling adults that were cognitively healthy. M/L sway range and M/L mean velocity results can be seen in Figures 12 and 13, respectively. Neither of these traditional measures seemed to demonstrate any noticeable trend.

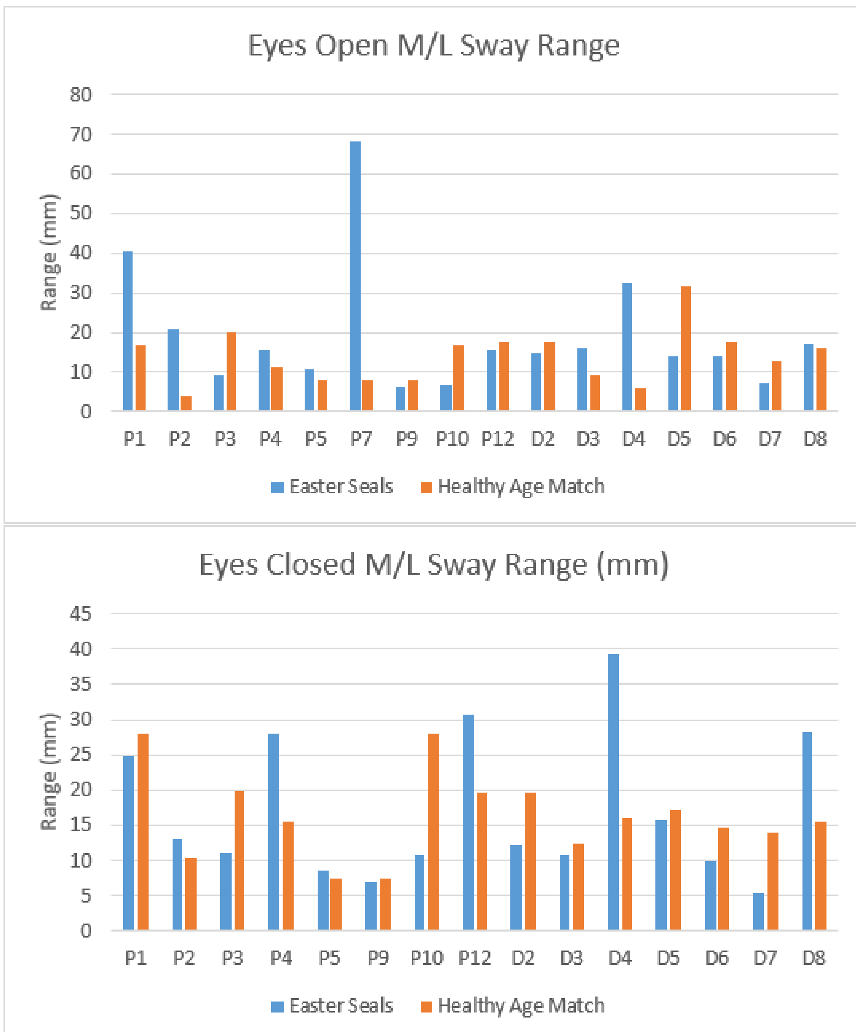

Figure 12: M/L Sway Range Comparison

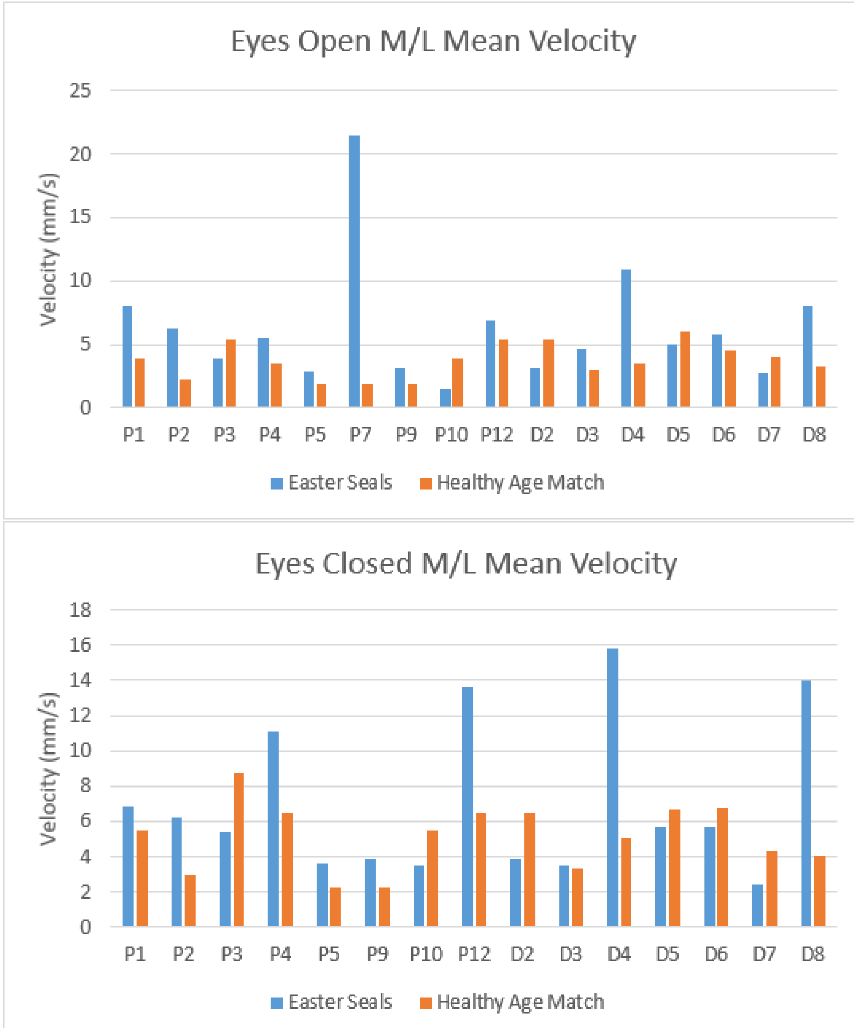

Figure 13: M/L Mean Velocity Comparison

Nonlinear result comparisons can be seen in Figures 14 and 15. Easter Seals participants had higher SampEn values in all cases but two. The M/L EC-Foam condition showed that adult day services participants had M/L SampEn Values that increased by an average of 44.01%. A/P SampEn values followed the same trend.

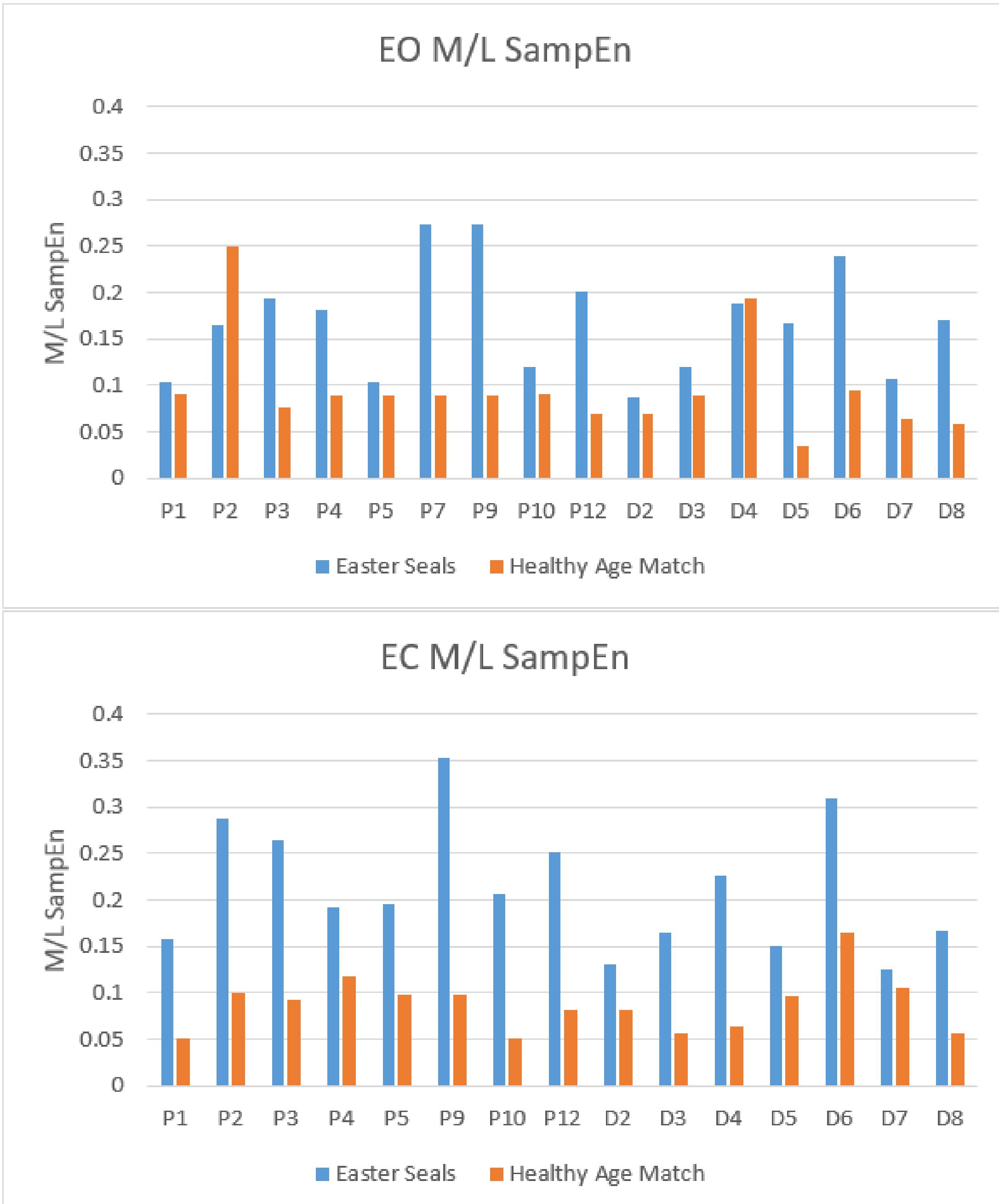

Figure 14: M/L SampEn Comparison

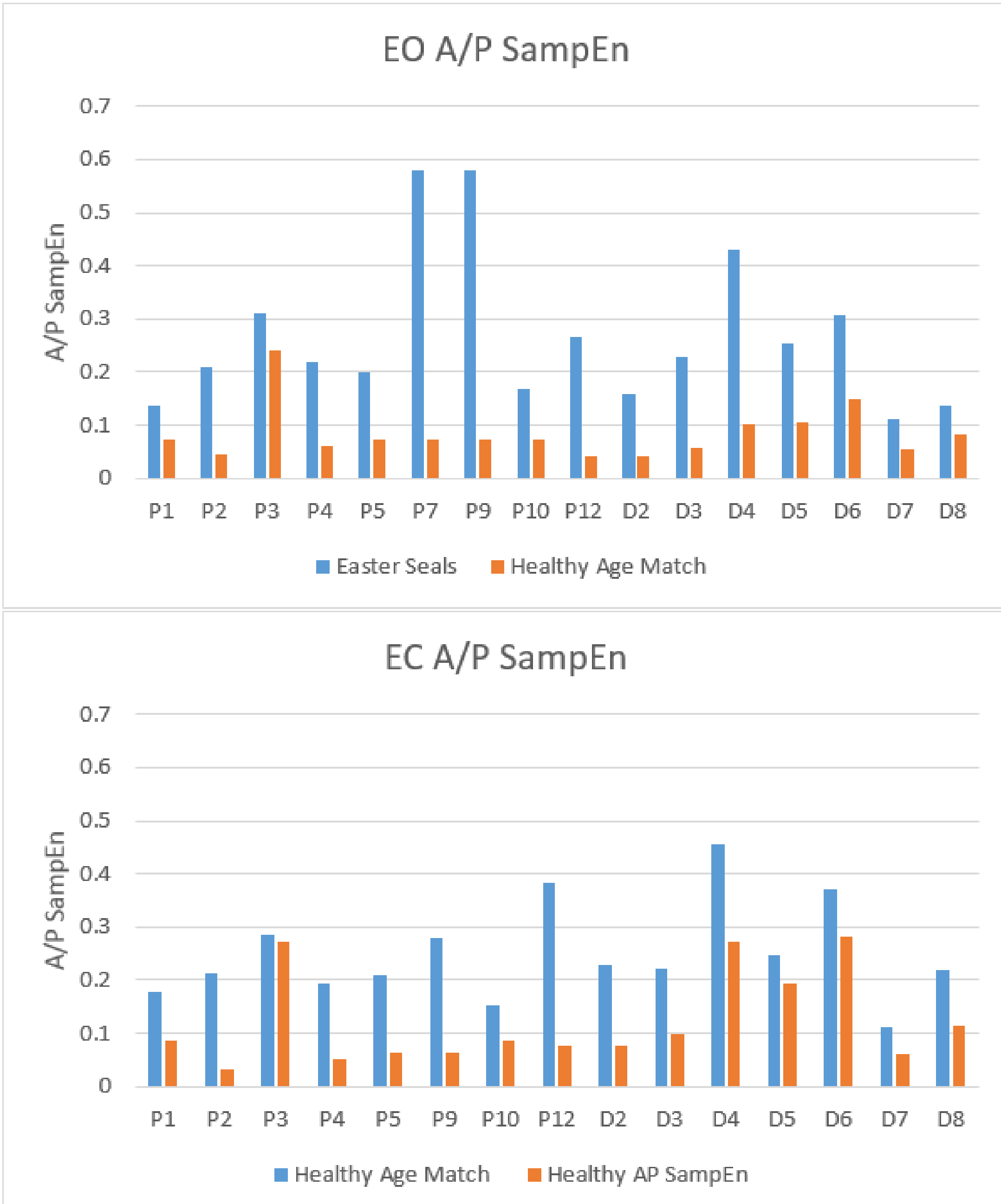

Figure 15: A/P SampEn Comparison

Discussion

Summary of Participants

There were numerous obstacles encountered during this study due to the nature of the larger project that was being done. The most significant part of this was the pool of people the recruiting process included. As previously mentioned, it was expected that 70-100 people of the 250 individuals utilizing the Easter Seals Adult Day Services were expected to choose to participate in this study, however data was collected for only 20 individuals.

It was also difficult to arrange data collection times because of the lengthy and complicated consent process. While some participants had legally authorized representatives, there were many self-consenters, meaning that the utmost care had to be taken to ensure all participants could fully comprehend potential risks as well as benefits of the study. This consent process could take almost as much time as the data collection process itself, which added a level of unpredictability to test session duration. In addition to this, if a participant's legal representative had given consent, it could not be assumed that the individual would be willing to take part in the study that day, making it hard to schedule testing appointments ahead of time. If a study like this were to be attempted again, it is suggested that the recruitment and consent process be revised. It was originally assumed that caregivers lived with the individuals under their care, however this was not always the case. Bringing the informational packets and consent forms door to door once potential participants had been identified by the Easter Seals staff would create a more laborious recruitment process, but would eliminate communication confusion and mail delay. It would also potentially be beneficial to hold informational sessions at the Easter Seals Adult Day Services locations for all potential participants and their caregivers. These sessions could be strategically timed to overlap with other events so the greatest number of people could be reached. Overall, it is suggested that personal face-to-face contact be made with caregivers to better convey the intentions and motivation of the study.

These logistical limitations were also compounded by the population using the Easter Seals Adult Day Services. While most of the participants had diagnoses of dementia, not all did. It is suspected that some individuals were using the services because of a physical need rather than a cognitive one, which changed the understanding of the population that was being addressed in this study. This, in combination with the long and complicated medical histories of some of the participants, made it difficult to generalize results because of the variations between individuals. It is important to consider that the small sample size of this study may be an accurate representation of the variation in adults utilizing the adult day services, which may affect future studies. Future studies could benefit from a more well-defined population, as the population observed in this study had much variability that made it difficult to isolate fall risk factors. If a broad look at the adult day services population is desired, future work may also benefit from a larger sample sized scaled appropriately to the variation common in the individuals utilizing adult day care services. As much medical information as possible should be collected so all fall risk factors and balance deficits can be fully understood. There may also be other factors, such as economic background, that may have affected past medical care and as well as current caregiver involvement.

Only 75% of individuals participating in the Del Mar Project were able to attempt balance testing, and only 45% of individuals were able to complete all balance testing conditions. The individuals who were not able to complete balance testing were heavily dependent on gait assistive devices such as canes or rollators, and in most cases were not able to stand independently for the 30 second trial. All but one balance testing participant were able to complete EO-Flat, EC-Flat, and even EO-Foam conditions without a strenuous level of difficulty. The EC-Foam condition presented problems for 6 out of the 15 participants able to complete the EO-Foam condition. Because of high level of difficulty associated with the EC-Foam test condition, the use of posturography might not necessarily be conducive for use in a clinical environment. However, the results of participants who were able to complete the balance testing may provide valuable insight for clinicians. This will be addressed further in later sections of this discussion.

Summary of Traditional Descriptive Balance Data

While all standard traditional balance parameters were calculated as part of the data analysis process, M/L Sway Range and M/L Mean Velocity interpretation will be the focus of this study because of previous studies' implications of these measures in identifying fall risk [20]. Current literature has very little information on the normative values for the testing conditions of EO-Foam and EC-Foam conditions, as past studies have concentrated most on EO-Flat and EC-Flat conditions. As such, comparison to healthy values can only be done for the flat plate conditions.

Past research has shown that healthy older adults have a M/L Sway Range of 12.5+-7.50 mm during EO-Flat condition and 12.3+-6.84 mm during EC-Flat condition, reflecting a relatively small difference between the two conditions [21]. The results in Table 4 reflect the same trend with slightly higher values of 19.39±15.35 mm for the EO-Flat condition and 17.06±10.01 mm for the EC-Flat test condition. These higher values show decreased postural control when compared to past studies' results for healthy older adults, however the implications from this finding are slightly diluted by the higher standard deviation between the participants of this study.

In addition M/L Mean Velocity for the average healthy older adult was previously found to be 5.34+-2.56 mm/s for the EO-Flat condition and 6.27+-3.70 mm/s for the EC-Flat condition [21]. These values are much lower than the 16.59±12.96 mm/s for the EO-Flat condition and the 20.83±10.51 mm/s for the EC-Flat condition found in this study, but, again, the standard deviations between the participants must be acknowledged. The higher values of the Easter Seals population still correlate to poorer postural control in the adult day services population.

In this study all of the balance parameters increased in value between EC-Flat to EO-Foam and continued to increase in value for the EC-Foam condition. The one exception to this general trend was the M/L Sway Range, which dropped in value between the EO-Flat and EC-Flat condition before rising substantially between the EC-Flat and EO-Foam condition. The reasons for this trend in the adult day services population are unclear, so it is suggested that a larger sample size be observed to determine if the pattern persists.

It is important to note the relatively high standard deviation for each balance parameter summarized in Table 4. The standard deviation seemed to increase in the same patterns as the values of the balance parameters themselves, meaning that as postural control weakened, variation between participants increased. While this could potentially be attributed to differences in balance abilities, based on the individuals tested it seems that that it is more likely a difference in overall health, physical abilities, and comorbidities that were observed in this population.

EC-Foam was the most challenging condition. In addition to having the lowest number of participants able to complete both trials, EC-Foam had the highest sway ranges and sway velocities—as well as the highest standard deviation. The standard deviation of the M/L Sway Range was 96.0% of the actual M/L Sway Range average for this test condition, which indicative of extremely low reliability between the relatively few participants. These findings suggest that individuals exhibit worse postural sway than previously tested healthy older adults. Increased values in postural sway parameters have been correlated to those with higher fall rates in past studies [20]. This risk of fall is increased by environmental conditions such as dark rooms (which inhibit the visual system), or padded flooring (which inhibits the proprioceptive system), as these factors are replicated by the more difficult test conditions performed as part of this study.

Though this study is one of the first to look at posturography in the adult day services population, the results support work done by Manckoundia, who has shown that individuals with Alzheimer’s disease (AD) have increased sway range when compared with healthy elderly subjects [30]. While the participants of Manckoundia’s study did not use adult day services, AD represents another population with impaired balance. The relationship between these two populations demonstrate an opportunity for the use of posturography to fill the need for unique intervention for fall prevention, as well as quantifiable evaluation of such interventions.

Summary of Nonlinear Descriptive Balance Data

Nonlinear results are important to interpret as well because the description of patterns of sway help enhance and support the description of balance given by traditional measures. This is also a more recent analysis method that has not been used before with the adult day services population. Sample Entropy quantifies the sway patterns and predictability of the data in both the M/L and A/P direction by assigning a number value to it (SampEn). This scale starts at 0, meaning the pattern is periodic and completely regular. As SampEn increases, the sway pattern is considered more variable. It is currently unknown what the optimal amount of variability is, however past research has indicated that cognitively older adults who are recurrent fallers have higher SampEn values than cognitively healthy older adults who do not fall [31].

Interestingly the results of the Sample Entropy analysis done in this study demonstrate more noticeable trends between the repression of the visual system (Eyes Open vs. Eyes Closed) than the repression of the proprioceptive system (Flat Plate vs. Foam). This is good information to have, as most participants who struggled to complete all balance test conditions had the most difficulty completing the foam conditions. Because of this EO-Flat and EC-Flat represent the easiest conditions to use in a clinical setting. The M/L SampEn values summarized in Table 5 seem to show that patterns of sway during Eyes Closed conditions were less predictable than those of the Eyes Open conditions. This trend does not appear in the A/P direction, as the A/P SampEn values for each condition were very close together and had fairly high standard deviations. The A/P SampEn values were so similar that no trends can be appropriately generalized from them. These results seem to support current literature, as the M/L direction has been seen to be the impaired direction for fallers in previous studies [20]. The heightened variability of sway pattern in EC conditions reflect an increased fall risk when in an environment with vision-inhibiting conditions.

Relationship between Balance Performance and Cognitive Ability

It was expected that low MoCA scores would correspond to higher values of sway range and velocity, indicating poorer postural control for individuals with lower cognitive function. The data from this study revealed, as seen in Figures 3 through 6, that there was not as strong of a correlation as expected between most balance parameters and cognitive ability. While traditional measures seemed to have extremely weak correlations, nonlinear measures showed almost no measurable correlation when using a simple linear regression. The balance parameter that seemed to demonstrate the most clear correlation (R^2=0.63) to MoCA score was M/L Sway Range for the EC-Foam condition. Interestingly, the EC-Foam test condition was the most difficult for participants of this study to complete evidenced by the fact that only 56.25% of individuals who did balance testing were able to fully complete both trials, however, it seemed to provide the trends that most clearly follow the trend expected. Upon further reflection, it was not surprising that cognitive ability was not individually strong enough to differentiate individuals with poor postural control from individuals with good postural control in most balance parameters due to the diverse and complicated medical history for each participant utilizing the adult day services. In order to clearly define the potential relationship between cognitive ability and COP measures, it is necessary to further isolate cognitive deficit in the study population.

Relationship between Balance Performance and Age

It is known that as people age typically balance declines, especially after the age of 65 [13]. With this decline, it is expected that M/L Sway Range and Mean Velocity values should increase with age, however both of these parameters show a lack of differentiation between the oldest participant and the youngest. This could be attributed to comorbidities in the adult day services population such as strokes, past physical injury, or dementia.

These findings seem to further support the unique variation in individuals of the adult day services population demonstrated in other results of this study.

Comparison of Results to Healthy Older Individuals

Traditional parameter results did not have a visually identifiable trend when comparing older healthy adults to adults currently utilizing adult day services. With few exceptions, the nonlinear analysis seemed to demonstrate a more definitive trend for the comparison. Based on this result, it seems that nonlinear measures were able to identify a difference between community dwelling older adults and adults using adult day services where traditional methods did not, suggesting that nonlinear techniques provide a unique and potentially valuable perspective to the description of balance.

Figures 15 and 16 show that in both the EO-Flat and EC-Flat conditions the adult day services population had much higher A/P and M/L SampEn values that the community-dwelling older adults. Higher SampEn values are indicative of more variable patterns. There were two exceptions to this general trend in the EO-Flat M/L SampEn values (seen in Figure 15). The most definitive results seemed to be supplied by the EC-Flat M/L SampEn values. The individuals utilizing adult day services had M/L SampEn values that were 24.87%-84.58% higher than their age-matched community-dwelling counterparts. The average difference between the two groups was 44.01%. A/P SampEn values followed the same trends as the M/L SampEn values, but due to past M/L direction importance the M/L results might have stronger implications.

In current literature it has been shown that elderly fallers have more irregular patterns (shown by higher SampEn values) than healthy elderly non-fallers in the A/P direction, but this pattern was not nearly as noticeable in the M/L direction [31]. This study is the first that extends the use of Sample Entropy to the adult day services population, which is a population known to have increased fall risk due to dementia and physical comorbidities.

Limitations and Future Directions

The main limitation of this study was sample size. Though variation between participants was a limitation of the implication of results in this study, it is probable that diverse medical histories and cognitive abilities represent differences extremely common in the adult day services population. Because of this understanding, the ideal sample size for a study like this would have been at least 70-100 participants. Recruitment techniques and consent process could be adjusted in future work to better suit the needs of the individuals utilizing adult day services as well as the needs of their caregivers. Results from a study of larger scope could lead to better understanding of balance of the individuals in need of these services. Larger sample size could also allow for appropriate use of statistical analysis for a better interpretation of results and the significance of their implications.

If variation was minimized through a more specifically defined population, a smaller sample size could be used. Future studies could attempt to better isolate dementia as a fall risk. In order for this to be effective, study population would have to be more specifically defined to include only individuals with dementia. Scrutiny of medical records would also be needed to ensure participants had similar medical histories.

The large project that encompassed this study is currently developing an intervention program to address individuals utilizing Easter Seals Adult Day Services with high fall risk. The program will take into account the clinical measures collected along with the posturographic data to tailor intervention techniques best suited to the unique needs of the adult day services population. It is hoped that further posturography assessments could also contribute to the evaluation of such interventions.

Conclusion

This study is among the first to analyze the balance of individuals using adult day services, and many unexpected obstacles were encountered due to the unique challenges faced by this population. One such obstacle was the variability of cognitive and physical ability between the individuals that participated in this study.

Results showed that the addition of balance testing utilizing the balance plate supported results of the clinical assessments done as part of the larger project, however further research would have to been done to confirm whether benefits of the insight gained was enough to outweigh the inability to accommodate the use of gait assistive devices. When compared to age-matched cognitively healthy adults, Sample Entropy analysis was better able to differentiate between the Easter Seals population and the cognitively healthy population than traditional methods. The adult day services population demonstrated more variable sway patterns in Sample Entropy analysis results, which may suggest that future interventions should target movement regularity and control. In a previous study, Harbourne explored the potential effects of using the results of nonlinear analysis to guide new physical therapy techniques that focus on facilitating more regular movements when attempting everyday tasks, such as getting up from a chair [22]. It is possible that the findings of this study could be similarly leveraged to design interventions that best address the differences observed in postural control strategies in this population.

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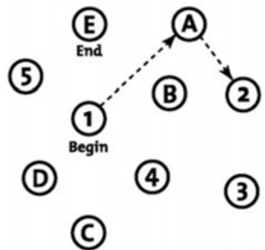
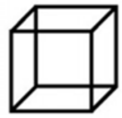
Appendix

1. MoCA Test

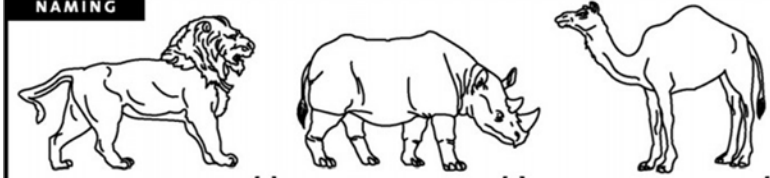
MONTREAL COGNITIVE ASSESSMENT (MOCA)

NAME :
Education :
Sex :

Date of birth :
DATE :

		POINTS
VISUOSPATIAL / EXECUTIVE  [ ]	Copy cube  [ ]	Draw CLOCK (Ten past eleven) (3 points) [ ] Contour [ ] Numbers [ ] Hands	___/5

NAMING



[ ] [ ] [ ] ___/3

MEMORY		FACE	VELVET	CHURCH	DAISY	RED	
Read list of words, subject must repeat them. Do 2 trials. Do a recall after 5 minutes.	1st trial						No points
	2nd trial						

ATTENTION	Read list of digits (1 digit/ sec.). Subject has to repeat them in the forward order [ ] 2 1 8 5 4 Subject has to repeat them in the backward order [ ] 7 4 2	___/2
	Read list of letters. The subject must tap with his hand at each letter A. No points if ≥ 2 errors [ ] F B A C M N A A J K L B A F A K D E A A A J A M O F A A B	___/1
	Serial 7 subtraction starting at 100 [ ] 93 [ ] 86 [ ] 79 [ ] 72 [ ] 65 4 or 5 correct subtractions: **3 pts**, 2 or 3 correct: **2 pts**, 1 correct: **1 pt**, 0 correct: **0 pt**	___/3
LANGUAGE	Repeat : I only know that John is the one to help today. [ ] The cat always hid under the couch when dogs were in the room. [ ]	___/2
	Fluency / Name maximum number of words in one minute that begin with the letter F [ ] ____ (N ≥ 11 words)	___/1
ABSTRACTION	Similarity between e.g. banana - orange = fruit [ ] train – bicycle [ ] watch - ruler	___/2

DELAYED RECALL	Has to recall words WITH NO CUE	FACE [ ]	VELVET [ ]	CHURCH [ ]	DAISY [ ]	RED [ ]	Points for UNCUED recall only	___/5
Optional	Category cue							
	Multiple choice cue							

ORIENTATION	[ ] Date [ ] Month [ ] Year [ ] Day [ ] Place [ ] City	___/6

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Add 1 point if ≤ 12 yr edu

Administered by: ____________________

2. Traditional Analysis Matlab Code prepared by Dr. Allison Kinney

```
% Postural stability data analysis code
% This code reads data files from the Bertec Acquire software and
% calculates traditional postural stability measures. The code can read
in
% more than one input file. You will be prompted to select the files.
You
% can select any type of file (.txt, .csv, or .mat) that the Acquire
% software produces. The code can read files from any version of the
% Acquire software (with different column numbers). The code will
output an
% Excel spreasheet containing the outcome measures for all files
selected.
% Therefore, it is suggested that you select all data files for one
subject
% when you run this code.
%
% You will be prompted to enter 3 inputs. The inputs are described in
% detail below.

% UPDATE HISTORY
% Original Version: June 2015
% Update 1: Feb 2016 - Fixed Fz column number for input files with 16
columns of data

clc; close all; clear;

% Prompt the user for the 3 inputs. Inputs are explained in detail
below.
prompt={'Enter the output spreadsheet file name:',...
        'Enter the downsampling rate:',...
        'Enter the 4th order low-pass Butterworth filter cutoff
frequency:'};
name='Input';
numlines=1;
defaultanswer={'Subject1_Output','10','5'};
answer=inputdlg(prompt,name,numlines,defaultanswer);

% Select the name of the output spreadsheet file
% Suggestion: If all data files are selected for a subject, name the
output
% file to reflect the subject code/ID number.
outputFileName = answer{1};

% Specify a downsampling rate for the data, m
% Suggestion: The rate should be selected such that the data has a
sampling
% rate of 100 Hz after downsampling. If the data were collected at 1000
Hz,
% then m = 10 would result in a sampling rate of 100 Hz after
downsmapling.
m = str2double(answer{2});

% Specify a cutoff frequency (Hz) for the 4th order low-pass
Butterworth
```

```
% Filter that will be applied to the data
Fcutoff = str2double(answer{3});

% Specify if plots should be generated for each file opened.
plotOption = questdlg('Would you like to plot the data? If yes is
selected, a plot of A/P and M/L COP for each file will be created and
saved in the current file directory.', ...
    'Plot option', ...
    'Yes','No','No');

% Read the data from the file
[fileName,directoryName,~] =
uigetfile({'*.*';'*.txt';'*.csv';'*.mat'},'Select the file(s) to
analyze. You may select more than one file.', 'Multiselect','on');

% If they only select 1 file, a cell needs to be created
if ~iscell(fileName)
    temp = fileName;
    clear fileName
    fileName{1} = temp;
    clear temp
end
[~,numFiles] = size(fileName);
TrialNames = cell(1,numFiles);

% Check if the output file already exists. Ask the user to change the
file
% name if they do not want to write over the file.
while exist([directoryName outputFileName '.xlsx'], 'file')
    fileOption = questdlg(['Output file ' outputFileName ' already
exists in the current directory. The data in the file will be replaced.
Would you like to change the output file name?'], ...
        'Output file warning', ...
        'Yes','No','Yes');

    switch fileOption
        case 'Yes'
            prompt={'Enter the output spreadsheet file name:'};
            name='Input 2';
            numlines=1;
            defaultanswer={'Subject2_Output'};
            answer2=inputdlg(prompt,name,numlines,defaultanswer);
            answer(1) = answer2;
            outputFileName = answer{1};
        case 'No' % don't change the file name, so delete the old
version of the file
            % Deletes file if it already exists
            delete([directoryName outputFileName '.xlsx'])
    end
end

% Column headers for output spreadsheet
output = {'Trial Name','Body Mass (kg)','Total Trial Time
(seconds)','AP Sway Range (mm)',...
    'ML Sway Range (mm)', 'Mean Velocity (mm/s)', ...
```

```
    'AP Mean Velocity (mm/s)', 'ML Mean Velocity (mm/s)', 'RMS Distance
(mm)',...
    '95% Confidence Ellipse Sway Area (mm^2)','Mean Frequency (Hz)'};

% For loop to repeat data processing for each file opened
for f = 1:numFiles
    % Open data file. Can open .csv, .mat, or .txt files
    if ~isempty(strfind(char(fileName(f)),'.csv'))
        rawData = csvread([directoryName fileName{f}],1,0);
        TrialNames(f) = regexprep(fileName(f), '.csv','');
    elseif ~isempty(strfind(char(fileName(f)),'.mat'))
        temp = load([directoryName fileName{f}]);
        % Transpose the mat file data
        rawData = temp.data';
        TrialNames(f) = regexprep(fileName(f), '.mat','');
    elseif ~isempty(strfind(char(fileName(f)),'.txt'))
        rawData = dlmread([directoryName char(fileName(f))]);
        TrialNames(f) = regexprep(fileName(f), '.txt','');
    else
        fid=fopen(fileName, 'r');
        if fid == -1
            errordlg('File could not be opened, check name or
path.','File Import Error')
        end
    end

    % Downsample the data based on the downsample rate set at the top
of
    % the code
    data = downsample(rawData,m);

    % Extract data from the data file
    % Time is always the first column
    t = data(:,1);
    if size(data,2) == 16
        % Fz is 8th column when there are 16 columns of data
        Fz = data(:,8);
    else
        % Fz is 5th column from end when there are 6 or 12 columns of
data
        Fz = data(:,end-4);
    end

    % Calculate body mass in kg from Fz data
    bodyMass = mean(Fz)/9.81;

    % COPx and COPy are always the last 2 columns (regardless of
new/old plate)
    % Coverts from m to mm
    % COPx - ML direction
    COPx = data(:,end-1)*1000;
    % COPy - AP direction
    COPy = data(:,end)*1000;

    % calculate N
    N = length(t);
```

```
% De-means COPx and COPy data
COPx_mean = mean(COPx);
COPy_mean = mean(COPy);
COPy_n = COPy - COPy_mean;
COPx_n = COPx - COPx_mean;

% Apply 4th order low-pass Butterworth Filter at cut-off frequency
% specified at the top of the code
Fs = 1/mean(diff(t));
fnorm = Fcutoff/(Fs/2);
[b,a] = butter(2,fnorm);
COPy_nF = filtfilt(b,a,COPy_n);
COPx_nF = filtfilt(b,a,COPx_n);

% If the user chooses to generate plots, plot the filtered COP data
switch plotOption
    case 'Yes'
        h=figure;
        subplot(2,1,1)
        plot(t,COPx_nF,'LineWidth',2)
        ylabel({'M/L Center of Pressure','COPx (mm)'})
        title(TrialNames(f))
        limits [0 30 -30 30]

        subplot(2,1,2)
        plot(t,COPy_nF,'LineWidth',2)
        ylabel({'A/P Center of Pressure','COPy (mm)'})
        xlabel('Time (seconds)')

        saveas(h,[directoryName TrialNames{f} '.jpg'])
end

% Time Range (seconds)
T = max(t)-min(t);

% A/P Sway Range (mm)
AP_Sway = abs(max(COPy_nF) - min(COPy_nF));

% M/L Sway Range (mm)
ML_Sway = abs(max(COPx_nF) - min(COPx_nF));

% Mean Velocity (mm/s)
Totex = sum(sqrt(diff(COPx_nF).^2 + (diff(COPy_nF).^2)));
Mean_Vel = Totex/T;

% ML Mean Velocity (mm/s)
ML_MV = sum(abs(diff(COPx_nF)))/T;

% AP Mean Velocity (mm/s)
AP_MV = sum(abs(diff(COPy_nF)))/T;

% RMS Distance (mm)
RD = sqrt(COPx_nF.^2 + COPy_nF.^2);
```

```
    RMS = sqrt((sum(RD.^2))/N);

    % 95% Confidence Ellipse Sway Area (mm^2)
    sig_x = sqrt((sum(COPx_nF.^2))/N);
    sig_y = sqrt((sum(COPy_nF.^2))/N);
    sig_xy = (sum(COPx_nF.*COPy_nF))/N;
    CoVa = [sig_x.^2 sig_xy; sig_xy sig_y.^2];
    [EigV,Eig] = eig(CoVa);
    a = 1.96*sqrt(Eig(1,1));
    b = 1.96*sqrt(Eig(2,2));
    Percent_Confidence_Ellipse_Sway_Area = a*b*pi;

    % Mean Frequency (Hz)
    MF = Mean_Vel/(2*pi*sum(sqrt(COPx_nF.^2+COPy_nF.^2))/N);

    % Matrix of outcome variables
    outTemp = [bodyMass, T, AP_Sway, ML_Sway, Mean_Vel, AP_MV, ML_MV,
RMS,...
        Percent_Confidence_Ellipse_Sway_Area,MF];

    % Create output matrix
    for o = 1:length(outTemp)
        output{f+1, o+1} = outTemp(o);
    end

    output{f+1, 1} = TrialNames{f};

    clearvars -except f fileName directoryName outputFileName output m
Fcutoff TrialNames plotOption
end

% Writes output data file
xlswrite([directoryName outputFileName '.xlsx'],output)
```

3. Sample Entropy Matlab Code prepared by Dr. Allison Kinney

```
% Sample Entropy Code
% This code reads data files from the Bertec Acquire software and
% calculates Sample Entropy. The code can read in
% more than one input file. You will be prompted to select the files.
You
% can select any type of file (.txt, .csv, or .mat) that the Acquire
% software produces. The code can read files from any version of the
% Acquire software (with different column numbers). The code will
output an
% Excel spreasheet containing the outcome measures for all files
selected.
% Therefore, it is suggested that you select all data files for one
subject
% when you run this code.

% You will be prompted to enter 4 inputs. The inputs are described in
% detail below.

% Sample Entropy calculations are based on methods in the following
papers:
%   Richman JS, Moorman JR. Physiological time-series analysis using
%       approximate entropy and sample entropy. Am J Physiol Heart Circ
%       Physiol 2000;278:H2039–49.
%   Ramdani S, Seigle B, Lagarde J, Bouchara F, Bernard PL. On the use
of
%       sample entropy to analyze human postural sway data. Med Eng
Phys
%       2009;31:1023–31. doi:10.1016/j.medengphy.2009.06.004.

% UPDATE HISTORY
% Original Version: July 2015 - Written by Allison Kinney, edited by
Senia
%   Reinert
% Update 1: March 2016 - Added ability to read different file types,
%   re-organization of output file

clear
close all
clc

% Prompt the user for the 4 inputs. Inputs are explained in detail
below.
prompt={'Enter the output spreadsheet file name:',...
        'Enter the downsampling rate:',...
        'Enter the vector size (m):',...
        'Enter the tolerance size factor (rf):'};
name='Input';
numlines=1;
defaultanswer={'Subject1_SampEn_Output','10','2','0.2'};
answer=inputdlg(prompt,name,numlines,defaultanswer);

% Select the name of the output spreadsheet file
```

```
% Suggestion: If all data files are selected for a subject, name the
output
% file to reflect the subject code/ID number.
outputFileName = answer{1};

% Specify a downsampling rate for the data, m
% Suggestion: The rate should be selected such that the data has a
sampling
% rate of 100 Hz after downsampling. If the data were collected at 1000
Hz,
% then m = 10 would result in a sampling rate of 100 Hz after
downsmapling.
ds = str2double(answer{2});

% Specify the vector size used during Sample Entropy calculations. A
vector
% size of 2 means that vectors of 2 values will be compared. A vector
size
% of 2 is recommended (based on information from Nebraska group).
m = str2double(answer{3});

% Specify the tolerance size factor (rf) used during Sample Entropy
% calculations. This tolerance is multiplied by the standard deviation
of
% the data to determine the tolerance size (r = rf*std(data)).
% When rf = 0.2, the tolerance level is 20% of the standard deviation
of
% the data. A vector will be considered a match if it falls within the
% tolerance.
% A tolerance size factor of 0.2 is recommended (based on information
from
% Nebraska group).
rf = str2double(answer{4});

% Read the data from the file
[fileName,directoryName,~] =
uigetfile({'*.*';'*.txt';'*.csv';'*.mat'},'Select the file(s) to
analyze. You may select more than one file.', 'Multiselect','on');

% If they only select 1 file, a cell needs to be created
if ~iscell(fileName)
    temp = fileName;
    clear fileName
    fileName{1} = temp;
    clear temp
end
[~,numFiles] = size(fileName);
TrialNames = cell(1,numFiles);

% Check if the output file already exists. Ask the user to change the
file
% name if they do not want to write over the file.
while exist([directoryName outputFileName '.xlsx'], 'file')
    fileOption = questdlg(['Output file ' outputFileName ' already
exists in the current directory. The data in the file will be replaced.
Would you like to change the output file name?'], ...
```

```
        'Output file warning', ...
        'Yes','No','Yes');

    switch fileOption
        case 'Yes'
            prompt={'Enter the output spreadsheet file name:'};
            name='Input 2';
            numlines=1;
            defaultanswer={'Subject2_SampEn_Output'};
            answer2=inputdlg(prompt,name,numlines,defaultanswer);
            answer(1) = answer2;
            outputFileName = answer{1};
        case 'No' % don't change the file name, so delete the old
version of the file
            % Deletes file if it already exists
            delete([directoryName outputFileName '.xlsx'])
    end
end

% Initialize size of output matrix (1 row for each file, 1 column for
COPx
% and COPy data) and output trial name matrix
output = zeros(numFiles,2);
outputTrialNames = cell(numFiles,1);

% For loop to repeat data processing for each file opened
for f=1:numFiles
    %run a for loop for COPx and COPy vectors to get SampEn for both
    for c=1:2

        % Open data file. Can open .csv, .mat, or .txt files
        if ~isempty(strfind(char(fileName(f)),'.csv'))
            rawData = csvread([directoryName fileName{f}],1,0);
            TrialNames(f) = regexprep(fileName(f), '.csv','');
        elseif ~isempty(strfind(char(fileName(f)),'.mat'))
            temp = load([directoryName fileName{f}]);
            % Transpose the mat file data
            rawData = temp.data';
            TrialNames(f) = regexprep(fileName(f), '.mat','');
        elseif ~isempty(strfind(char(fileName(f)),'.txt'))
            temp = importdata([directoryName char(fileName(f))]);
            if isstruct(temp)
                rawData = temp.data;
            else
                rawData = temp;
            end
            TrialNames(f) = regexprep(fileName(f), '.txt','');
        else
            fid=fopen(fileName, 'r');
            if fid == -1
                errordlg('File could not be opened, check name or
path.','File Import Error')
            end
        end
```

```
        % Downsample the data based on the downsample rate set at the
top
        % of the code
        data_all = downsample(rawData,ds);

        % Extract data from the data file
        % COPx and COPy are always the last 2 columns (regardless of
new/old plate)
        % Extract either COPx or COPy based on c for loop above
        data = data_all(:,end-2+c);

        % Set the tolerance, r
        r = rf*std(data);
        % Number of data points in the set
        N = length(data);

        % Initialize counters for m length vectors. There are N-m
vectors.
        % The same number of vectors are used for both m and m+1 length
        % vectors. This follows the methods presented by Richman and
        % Ramdani, but is different than the methods presented by the
        % Nebraska group.
        count_m_vectors = zeros(N-m,1);
        vector_count = 1;
        m_vectors = zeros(N-m,m);

        % Breaks COP data into N-m vectors of length m
        while vector_count <= N-m
            m_vectors(vector_count,:) =
data(vector_count:vector_count+m-1,1)';
            vector_count = vector_count + 1;
        end

        %Builds an empty matrix for the vectors that are matches
        matched_vectors=zeros(N-m,1);
        %look for matches for vectors of length m
        for vector_count = 1:length(m_vectors)
            %build a vector comprised entirely of the vector currently
being matched
            vector_to_match=repmat(m_vectors(vector_count,:),
length(m_vectors), 1);
            % deterine if corresponding elements of each vector are
within
            % tolerance, r
            comparisons =(abs(vector_to_match-m_vectors)<= r);
            matches = all(comparisons,2);
            % Subtract 1 from vector_count(s) to remove the self-match
count
            matched_vectors(vector_count,1) = sum(matches)-1;
        end

        % Initialize counters for m+1 length vectors
        count_m_p1_vectors = zeros(N-m,1);
        vector_count_p1 = 1;
        m_vectors_p1 = zeros(N-m,m+1);
```

```
        % Get vectors of length m+1
        while vector_count_p1 <= N-m
            m_vectors_p1(vector_count_p1,:) =
data(vector_count_p1:vector_count_p1+m,1)';
            vector_count_p1 = vector_count_p1 + 1;
        end

        %look for matches for vectors of length m+1 (same logic as m
vector
        %for loop above)
        matched_vectors_p1=zeros(N-m,1);
        for vector_count_p1 = 1:length(m_vectors_p1)
            vector_to_match_p1=repmat(m_vectors_p1(vector_count_p1,:),
length(m_vectors_p1), 1);
            comparisons_p1 =(abs(vector_to_match_p1-m_vectors_p1)<= r);
            matches_p1 = all(comparisons_p1,2);
            matched_vectors_p1(vector_count_p1,1) = sum(matches_p1)-1;
        end

        % Calculate probabilities as number of matches divided by
number of
        % vectors minus 1 (to exclude self-match) (N-m)-1 or
vector_count-1
        % The same number of vectors (N-m) are used for both m and m+1
        % length vectors (see comment above).
        prob_m_vectors = matched_vectors/(vector_count-1);
        prob_m_p1_vectors = matched_vectors_p1/(vector_count_p1-1);

        % Calculate A and B as the sum of probabilities divided by N-m
        B = sum(prob_m_vectors)/(N-m);
        A = sum(prob_m_p1_vectors)/(N-m);

        % Br and Ar are the total number of vector matches within the
        % tolerance r. Calculation of Br and Ar are consistent with
        % equations in Ramdani paper.
        Br=(1/2)*(N-m-1)*(N-m)*B;
        Ar=(1/2)*(N-m-1)*(N-m)*A;

        % Calculate Sample Entropy
        SampEn = -log(Ar/Br);

        output(f,c)=SampEn;
        outputTrialNames{f, 1} = TrialNames{f};
        clearvars -except output f ds m rf directoryName outputFileName
outputTrialNames fileName numFiles
    end
end

%output data in an excel file
header={'Filename' 'SampEn COPx' 'SampEn COPy'};
range=['A2:A',num2str(numFiles+1)];
xlswrite([directoryName outputFileName '.xlsx'],header,'A1:C1')
xlswrite([directoryName outputFileName '.xlsx'],outputTrialNames,range)
range2=['B2:C',num2str(numFiles+1)];
xlswrite([directoryName outputFileName '.xlsx'],output,range2)
```