ENHANCING POSTUROGRAPHY STABILIZATION ANALYSIS AND LIMITS OF STABILITY ASSESSMENT

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Senia Smoot Reinert, M.S.

Dayton, Ohio

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ENHANCING POSTUROGRAPHY STABILIZATION ANALYSIS AND LIMITS OF STABILITY ASSESSMENT

Name: Reinert, Senia Smoot

APPROVED BY:

_______________________
Kimberly E. Bigelow, Ph.D.
Advisory Committee Chairman
Associate Professor
Department of Mechanical and Aerospace Engineering

_______________________
Wiebke S. Diestelkamp, Ph.D.
Committee Member
Professor
Department of Mathematics

_______________________
Kurt Jackson, PT, Ph.D., GCS
Committee Member
Associate Professor and Neurology Coordinator
Department of Physical Therapy

_______________________
Allison Kinney, Ph.D.
Committee Member
Assistant Professor
Department of Mechanical and Aerospace Engineering

_______________________
Robert J. Wilkens, Ph.D., P.E.
Associate Dean for Research and Innovation
Professor
School of Engineering

_______________________
Eddy M. Rojas, Ph.D., M.A., P.E.
Dean, School of Engineering
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ABSTRACT

ENHANCING POSTUROGRAPHY STABILIZATION ANALYSIS AND LIMITS OF STABILITY ASSESSMENT

Name: Reinert, Senia Smoot
University of Dayton

Advisor: Dr. Kimberly E. Bigelow

Posturography is the study of an individual’s regulation of balance and much posturography research is dedicated to studying the effect of aging on postural control. The study of the postural stability of this population is motivated by a need to understand physiological changes caused by the aging process in older adults. While posturography is commonly used in research with older adults, there is need to improve and enhance current data collection procedures and data analysis approaches. This work identified and addressed four research gaps in current posturography knowledge with an emphasis on older adult populations. A single session of data collection was conducted to obtain the necessary data for each aim which were then each addressed independently. Ninety older adults participated in this research. The objective of the first aim was to evaluate use of Time to Stabilization method to gauge the stabilization time for older adults stepping onto a firm and a compliant surface, with an emphasis on first identifying methods to assess the appropriateness of the data trend and to determine the success of the curve fit.
The results of this study suggest the majority of older adult data is appropriate for this analysis. The authors suggest using a signal-to-noise cutoff of 2.5 when evaluating data trends and a $R^2$ cutoff of .25 when evaluating curve fit. The objective of the second aim was to determine if incorporating a foam surface, nonlinear analysis, and age stratification would improve the insightfulness of the Limits of Stability (LOS) assessment. The findings of this work indicated differences in LOS performance between age groups and that the assessment benefits from nonlinear analysis. The objective of the third aim was to determine whether LOS assessment inertial measurement unit (IMU)-based outcome measures demonstrated greater differences between fallers and non-fallers than the traditional center of pressure (COP)-based outcome measures. The results showed the IMU-based measure of jerk was better than the tradition posturography measures at differentiating between fallers and nonfallers. The final aim’s objective was to assess the degree of correlation between both sensors to evaluate whether the older adults in this study performed the LOS assessment correctly. Results indicated participants moved with a moderately high degree of correlation in the M/L plane but less in the A/P plane. This raises questions regarding implementation of the LOS assessment as it appears the ankle strategy is not being fully adhered to, especially in the A/P plane. Study limitations include only a single curve fitting method was explored, signal-to-noise ratio and $R^2$ values were the only two metrics by which the data trend and curve fit were evaluated, falls were self-reported, and sensor positioning. Future work includes a study evaluating two clinical groups could utilize the time to stabilization method and jerk measures and a study to explore the fact that participants who visually appear to be
correctly conducting the LOS assessment actually display a wide range of correlation between upper and lower body segments.
My dissertation is dedicated to my husband, my family, and my friends—I couldn’t have done this without their love and support.
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CHAPTER 1
INTRODUCTION

1.0 Posturography and Older Adults

Posturography is the study of an individual’s regulation of balance [1]. Balance can be described as the continuous minute adjustments a person makes to maintain upright stance, swaying in any given direction before compensating to move back towards the center of their base of support [2,3]. Postural control is maintained by the integration of input from the nervous, sensory, and motor systems [4]. Posturography measures are calculated from shifts of a subject’s Center of Pressure (COP), which is indicative of the movements of their Center of Gravity (COG), as they stand on a force plate. These measures provide insight into the passive and active techniques individuals employ to maintain upright posture [1,4]. Posturography is used to study how balance and postural control is affected by injuries, neurological disorders, and various pathologies that have physiological symptoms [1,3,5–13]. In the field of posturography, a large body of research has been devoted to the study of how balance changes as humans age [3,5,6,14–20].

Longer life expectancies and the aging of the baby boomer generation is leading to an increase in the older adult population in the United States [21]. The population of older adults is expected to double over the next quarter century, resulting in this
demographic comprising 20% of the U.S. population by 2030 [21]. The study of the postural stability of this population is motivated by a need to understand physiological changes caused by the aging process in older adults. Understanding these changes can lead to improved medical care and, subsequently, quality of life. The high incidence of falls in older adults is one age-related societal concern. Falls often have severe physical and emotional repercussions, resulting in a high physiological, social, and fiscal cost to both the faller and community [1,22]. A third of adults aged 65 and older fall each year, and falls serve as the leading cause of accidental death for this population [23,24]. Nonfatal falls often result in visits to the emergency room and/or institutionalization, an annual medical cost over $30 billion dollars as of 2012, and reductions in quality of life [24,25]. Therefore, one main objective of posturography research when studying older adults has been to find methods to differentiate between fallers and non-fallers so potential at-risk fallers can be identified; this allows interventions to be put in place to reduce the likelihood of a fall occurring [3,5,20,26].

While posturography is commonly used in research with older adults, there still is room to improve and enhance current data collection procedures and data analysis approaches. For example, posturography does not consistently differentiate between individuals who fall and those who do not so there may be room to better identify subtle differences through improved methodologies. For the majority of posturography-based studies, participants stand on the flat plate without moving [4]. Common variations to data collection include incorporating evaluations such as the modified clinical test of sensory interaction on balance—which utilizes an eyes open/eyes closed condition and a firm surface/compliant surface condition—and having a visual target to focus on [15,27–
Participants can also be given a task to do while standing flat on the plate, such as leaning in a certain fashion or undergoing a cognitive challenge [6,26,30]. These modifications are incorporated for many different reasons: to explore the interplay between the postural control system and sensory systems; to understand how an attentional demand affects postural control; to study how postural control during a dynamic movement.

Data analyses, while traditionally including parameters such as sway range, sway speed, and root mean square of sway, have recently expanded to include nonlinear measures of variability such as sample entropy [3,31]. Measures of variability have allowed researchers to analyze the temporal structure of the data, which provides insight on predictability, regularity, and complexity. Although these analyses are becoming more common, they are still not yet widely applied in many posturography assessments. In an effort to improve this research tool, the following work will identify three specific research gaps in current posturography knowledge with an emphasis on older adult populations. These gaps will be explored and developed as specific research aims of this dissertation.

1.1 Improving Current Approach to Determining Stabilization Time

Posturography studies sometimes exclude the first 5-10 seconds of data collected or allow subjects a chance to stabilize on the plate once they step onto it [32]. Researchers have suggested the first 10 seconds of data collection be excluded from analysis due to the fact that the participant is still experiencing a transient effect from stepping onto the plate [32]. This stabilization period, however, could potentially provide
insight regarding reaction time and compensatory strategies. This can allow researchers to better understand how different populations regain postural equilibrium after a movement. This stabilization period has the potential to be especially insightful in the evaluation of older adults as they have been found to have decreased postural performance when exposed to perturbations [33–35].

When using posturography to determine stabilization time after a perturbation or movement, researchers have proposed using a measure of mean velocity to identify the point at which stabilization occurs. Mazza et al. utilized this approach, implementing a sliding window technique to calculate the mean velocity of the COP data for specific time windows of the time series [36]. With this approach, stabilization time was designated as the time window at which the mean COP velocity was lower than that of all following time windows [36]. One limitation with this method, however, was the fact that significant differences in stabilization time occurred when different sized windows were used [37]. Rabufetti et al. then introduced a different time to stabilization analysis method as an alternative to examine how long it takes individuals to restabilize after movements such as stepping and standing from a seated position [38]. Rabufetti et al.’s method suggested fitting a negative exponential curve to the root mean square (RMS) of the acceleration of the COM to determine stabilization time [38]. This method is based on the assumption that the RMS data exhibit a characteristic curve that depicts initial and significant instability that then exponentially decays to a stable, steady state [38].

Since older adults are known to be less steady and since the Time to Stabilization method has not been generally applied to this population, it is important to explore whether this methodology is appropriate for this population and develop guidelines to
help confirm that it is. Similarly, in cases where individuals may be stepping onto a surface that is not flat, such as compliant foam, it is unclear if stabilization will occur according to this assumption. Current publications offer no guidance regarding how to determine whether the RMS curve for a given trial appropriately demonstrates the necessary characteristics required for this analysis. Furthermore, as this analysis requires curve fitting, published research does not suggest how to evaluate the success of the curve fit. As the curve fitting is principle in identifying the stabilization point, a poorly fit curve would result in an inaccurate stabilization time.

Finally, Rabufetti’s method has only been applied to a healthy populations with no specific age-group focus [37,38]. Rabufetti et. al evaluated the stabilization time of 40 healthy adults, ranging in age from 17 to 79 years, with a mean age of 43 [38]. DiDominico evaluated the stabilization time of 45 healthy adults, ranging in age from 18 to 65 years with a mean age of 40 [37]. Therefore, the first aim of this work was to evaluate the use of Rabufetti’s stabilization time analysis on the data of older adults. This will be done with an emphasis on exploring methods to evaluate both the RMS curve and the success of the subsequently fitted curve to the data. In addition to a firm surface, stabilization time will be calculated for trials on a compliant surface to determine whether it is possible to identify a point of stabilization when standing on foam.

1.2 Improving Current Analysis of the Limits of Stability Assessment

The limits of stability (LOS) test is another postural stability test conducted on a balance plate. It is an assessment that has been found to be consistent and reliable when used for older adults [39]. The LOS test requires subjects to lean forwards, backwards,
and side-to-side using only an ankle strategy rather than bending at the waist. This allows the body to be treated as an inverted pendulum in the analysis and provides insight on an individual’s postural control, the range of motion of their ankle, and their own confidence in their ability to move beyond their base of support [15,39,40].

The traditional LOS assessment has not undergone much modification to improve its sensitivity and discrimination. To date, the LOS assessment has only been conducted on a firm surface despite that fact that other posturography tests often include a more compliant foam surface [28,29,41]. Foam pads limit and disrupt the proprioceptive sensory input participants would normally receive from a firm standing surface [41]. This increases the challenge of maintaining postural control, especially for older adults, which could help increase the sensitivity of this assessment to differences between populations [42]. Therefore one potential enhancement to this assessment would be in have participants stand on a foam pad while performing the test.

In addition to incorporating a foam standing surface, it is also worth investigating the assumption that all older adults should be treated as a single group. Age adversely affects physiological and cognitive function and therefore it is possible that there could be significant differences between ‘younger’ older adults and ‘older’ ones. Therefore, it is worth investigating whether older adults of different age ranges perform this test significantly differently.

Another way to potentially improve the insightfulness of the LOS assessment is to incorporate nonlinear movement variability outcome parameters into the analysis. A traditional static posturography trial requires a subject to stand ‘quietly,’ or without making any deliberate movements. Nonlinear variability measures are often used to
evaluate the inherent complexity that exists in this unconstrained sway [43,44]. The LOS test, however, requires subjects to restrict their movements to a set configuration. Due to the constrained nature of the test protocol, only traditional measures have been used for this test (most commonly measures that describe how far the individual sways in each direction). It is not known yet whether these nonlinear outcome measures of human movement variability are appropriate for the LOS test or if they might be able to provide insight into better identifying fallers. Because individuals are asked to move in each direction, there may be information is how smoothly and directly they perform these movements. Nonlinear analyses, which quantify the patterns and regularity of movement, may provide insight regarding this. Therefore, the objective of the second aim is to evaluate the effect of the foam surface on the LOS assessment and to include age stratification and nonlinear measures in the analysis.

1.3 Incorporating Wearable Sensors in the LOS Test to Differentiate Between Fallers and Non-Fallers

The third aim of this work focused on whether the incorporation of wearable sensors while performing the LOS assessment could improve its ability to differentiate between fallers and non-fallers. Inertial Measurement Units (IMUs) worn on the thigh could be used to collect acceleration data during the assessment and see if acceleration-based outcome parameters could enhance the sensitivity of the LOS assessment. Studies utilizing the LOS test to differentiate fallers and non-fallers, however, have found that the LOS assessment does not significantly differentiate between fallers and non-fallers [40,45]. Incorporating the wearable sensors, however, may improve the LOS
assessment’s ability to differentiate between these two populations. Wearable sensors would provide data that could be used to determine the jerk, or movement smoothness, exhibited by participants as they conduct this assessment. Jerk can be used to evaluate how much control a participant exerts over their motion, which may be more insightful than how far they move, the traditional balance plate outcome parameter for this assessment. It is the goal of this aim to evaluate whether the addition of wearable sensors can be used to improve this assessment’s ability to differentiate between fallers and non-fallers.

1.4 Incorporating Wearable Sensors in the LOS Assessment to Evaluate Test Adherence

As a supplementary extension to aim 3, it is also worthwhile to see if wearable sensors could be used to gauge whether the LOS assessment was being appropriately conducted. Currently, the only metric researchers use to determine whether the assessment is being appropriately conducted is by visual inspection. There are two issues concerning whether the test is being conducted correctly. Firstly, the test is designed to measure the deliberate displacement of a participant’s COP; bending at the waist rather than correctly leaning forward would result in collecting data that does not accurately reflect this. In addition, the LOS assessment’s ability to differentiate between various populations would be hindered by participants performing the test in varying degrees of correctness. Placing wearable sensors on both upper and lower body segments would allow for a more precise appraisal of whether the test was conducted correctly—i.e. whether or not the participant was successfully utilizing an ankle strategy by moving both
segments in a similar manner. By examining the correlation of the accelerations experienced by the two sensors, it would be possible to evaluate whether the upper and lower body segments were moving in a similar fashion.

1.5 Dissertation Layout

This work consisted of a single session of data collection to obtain the necessary data for each aim. Each aim was then addressed as an independent study and the four middle chapters of this dissertation are comprised of each of the respective manuscripts. The final chapter reviews each aim, discusses the overarching theme that ties them together, reviews some of the limitations of this work, and presents suggestions for future research.
CHAPTER 2

A METHOD FOR APPLYING TIME TO STABILIZATION ANALYSIS TO OLDER ADULT DATA

2.0 Introduction

Delayed stabilization after a postural perturbation can be indicative of postural instability, slower reaction times, or less efficient compensatory strategies and may contribute to a higher likelihood of falls [36–38]. As such, researchers have explored various methods for evaluating how long it takes for stabilization to occur after a postural perturbation, such as an external disturbance or a self-initiated movement. Posturography data has previously been used to determine this stabilization time [36–38]. Posturography utilizes a force plate to detect shifts of a subject’s center of pressure (COP), which is indicative of the movements of the center of mass (COM), to gain insight into the passive and active techniques individuals employ to maintain upright posture [1,4]. During upright stance an individual’s COM experiences small shifts in all directions, which the postural control system regulates and compensates for. Therefore, when researchers attempt to describe the point of stabilization from a postural stability perspective, they are referring to when an individual reaches a steady state comprised of these small postural oscillations.
When using posturography data to determine stabilization time after a large perturbation or movement, researchers initially employed a sliding window technique to measure changes in mean COP velocity to determine when the velocity stabilized [36]. One limitation with this approach, however, was the fact that window size significantly affected stabilization time [36,37]. A different method, from this point forward referred to as Time to Stabilization, was introduced by Rabufetti et al. in 2011 as an alternative. The method was developed to examine how long it takes individuals to restabilize after movements such as stepping and standing from a seated position [38]. The Time to Stabilization method determines stabilization time by fitting a negative exponential curve to the root-mean-square (RMS) of the COM acceleration data [38]. The Time to Stabilization method is based on the assumption that the RMS of the COM acceleration data exhibits a characteristic curve that depicts initial notable instability that then exponentially decays to a stable, steady state. While the Time to Stabilization method has appeared promising, it has received limited widespread use. This may be in part because to date there has been no published guidance to determine when the Time to Stabilization is an appropriate methodology to apply and whether the curve was successfully fit to the data [37,38]. The Time to Stabilization method has only been applied to young, healthy populations and therefore it is currently unknown how well it will translate to populations who are more frail and/or variable [37,38]. Also the current Time to Stabilization method does not include guidance regarding how to determine whether the negative exponential curve fit the data in a way that allows for an accurate calculation of stabilization time.

Therefore, the objective of this study was to evaluate the use of the Time to Stabilization method to gauge the stabilization time for older adults stepping onto a firm
and a compliant surface, with an emphasis on first identifying methods to assess the appropriateness of the data trend and to determine the success of the curve fit.

2.1 Methods

Ninety older adults who were able to stand unassisted for 5 minutes, walk for 50 feet unassisted, and did not require a lower limb brace, foot orthotic, or prosthesis participated in this study. Thirty-nine of the participants were male and fifty-one were female. The mean age was 76.09±8.4 years, mean height was 169.11±9.72 cm, and mean body mass was 74.0±14.0 kg. This methodology was approved by the Institutional Review Board at the University of Dayton and participants gave written informed consent before data collection began.

Participants wore flat soled, comfortable footwear. They were instructed to stand in front of a force plate and, when told ‘begin,’ step up onto the plate. Once on the plate, they were to look straight ahead, keep their hands at their sides, and not talk for the duration of data collection. Any trials in which participants inadvertently took a third step or moved their feet after stepping were discarded and repeated. Six 70 s trials were conducted in a random order, three on the flat plate and three on a foam pad (Airex AG, Sins, Switzerland). Trial length was selected to allow for the time series to be separated into a stabilizing region and a stabilized region sufficiently long enough for a traditional analysis. Previous work that utilized the Time to Stabilization method found healthy individuals stabilized in under 1 second after a forward step [38]. Therefore, the authors expected the first 10 seconds to contain the stabilization phase and the remaining 60 seconds to capture the stabilized quiet standing. Participants wore a gait belt during
testing and a researcher spotted them for the duration of each trial. Anterior/posterior (A/P) and medial/lateral (M/L) center of pressure (COP) data were collected at 1000 Hz with a Bertec force plate (Model 5046, Bertec Corp., Worthington OH). The COP data were downsampled to 100 Hz and filtered with a 4th order low-pass Butterworth filter at 5 Hz. Firm and foam surface trials were analyzed separately.

A custom MATLAB code (Appendix A) was developed to calculate stabilization time according to the method described by Rabufetti et al. [38]. There was only one difference between the current approach and Rabufetti’s method: while Rabufetti et al. used the COM acceleration, the current study used the COP acceleration. DiDominico et al. previously used COP velocity while following Rabufetti’s approach and Rabufetti et al. also noted in their original paper that both COM and COP acceleration were ‘substantially equivalent’ to each other [37,38].

According to the time to stabilization method, it was first necessary to identify when participants had completed both steps onto the plate or foam. For the stepping movement that participants performed in this study, the maximum downward force peak was used to signify the second heel strike. The next subsequent data point in which the downward vertical force dipped below the participant’s body weight was used to designate the start of the stabilization phase. Next, the COP acceleration was calculated using a central finite difference method from the COP displacement data after the second heel strike; only A/P acceleration was calculated as the majority of the motion occurred in the A/P direction during the forward step. The root mean square (RMS) of the A/P COP acceleration was then calculated for one second windows starting at the beginning of the stabilization phase to the end of the 70-second trial. After the RMS of the A/P COP
acceleration was calculated, it was plotted from the second heel strike to the end of the trial to evaluate the trend in the data.

To determine whether the resulting curve exhibited the necessary characteristic trend for the Time to Stabilization Method to be appropriate to apply, the RMS curve of each trial was evaluated. To exhibit the characteristic pattern on which the Time to Stabilization method is based, the RMS curve should demonstrate an initial peak designating the perturbation, followed by a sharp decline in acceleration, and ending in a period of stabilization with smaller fluctuations in acceleration. To quantify how well each RMS curve demonstrates this behavior, a signal-to-noise ratio was calculated. The signal-to-noise ratio was calculated as the ratio between the highest RMS value peak during the first 10 seconds and the average RMS value of the last 60 seconds of the stabilization region. Data that failed to demonstrate a high signal-to-noise ratio either did not contain a large initial perturbation or the participant failed to reach a stable state by the end of the trial. In addition to the signal-to-noise ratio, visual inspection was conducted to aid in the selection of the ideal signal-to-noise ratio cutoff point. The visual inspection was based on a Good-Moderate-Poor rating system (see Figure 2.1). Several signal-to-noise ratio cutoffs were then evaluated against the visual inspection ratings for this population to identify an ideal cutoff value that would exclude the majority of trials with Poor data trends and keep all trials with Good and Moderate data trends.
Figure 2.1: RMS of A/P COP acceleration curves with Good (top), Moderate (middle), and Poor (bottom) data trends. Data classified as Good displays a high initial peak followed by a sharp decline in acceleration and ending with a period of stabilization with small fluctuations in acceleration; noise is minimal. Data classified as Moderate demonstrates an initial peak but it is not very high in comparison to the overall trial data; there is moderate noise. Data classified as Poor lacks an initial peak, depicts a very large degree of noise, and/or the stabilization phase is not apparent.
Those trials that met the established signal-to-noise ratio cutoff were then advanced to curve fitting step of the time to stabilization calculation. The following negative exponential model was fit to the RMS curve:

\[ Y = k \times e^{-t/\tau} + Y_{inf} \]

where \( Y_{inf} \) is the equivalent asymptotic value to the beginning of the stabilization period, \( T \) is the inverse decay rate, \( t_0 \) is the start of the stabilization period, and \( Y_0 = k + Y_{inf} \) describes the movement at the start of the stabilization phase [38]. Stabilization time was calculated as 3 times the inverse decay rate, \( T \) [38]. The MATLAB functions ‘fittype’ and ‘fit’ were used to fit the negative exponential curve to the data and solve for the unknown values of \( Y_{inf} \), \( T \), and \( k \). The first initial starting points were based on the data collected in a small pilot study. Initial guesses for the unknown values \((k = 16, T=2.5, and Y_{inf}= .3)\) were provided to the fitting function to improve the speed and performance of the algorithm. The initial guesses were refined though the data analysis process to ensure that the final curve fits were robust to the initial guesses. Figure 2.2 depicts a representative trial and its fitted curve.

![Figure 2.2: RMS of A/P COP acceleration with fitted curve.](image-url)
After the curve fitting was completed, it was necessary to evaluate the curve fit for each trial to ensure the fit was successful and therefore an accurate stabilization time was calculated. The fit of the curve was evaluated by calculating the $R^2$ value between the RMS data and the fitted curve for the first 10 seconds of the trial. The first 10 seconds was used instead of the entire trial as that was the region in which the rapid decay from perturbation to stabilization occurred. Including the entire trial would favorably bias the $R^2$ value as the last 60 seconds of the RMS curve for most trials had a $R^2$ value approaching 1. Similar to the visual inspection used in the evaluation of the data trend, a visual inspection was also conducted for the curve fits for the purpose of using its results as a metric to judge appropriate $R^2$ values (See Figure 2.3).
Figure 2.3: RMS of A/P COP acceleration curves with Good (top), Moderate (middle), and Poor (bottom) curve fits. Curves designated as Good fit the data closely, especially the initial peak; the curve demonstrates a significant amount of decay. Curves designated as Moderate fit the data decently well but do not follow the trend of the initial peak; the decay rate is still evident but the slope is more gradual. Curves designated as Poor do not fit the data well; the curve appears to be a straight line or an inverse exponential line.
For possible $R^2$ cutoffs of 0.25, 0.50, and 0.75 the number of Good, Moderate, and Poor fits that would be included versus excluded were determined to try to identify the most appropriate cutoff range. For all of the trials that both met the signal-to-noise ratio cutoff and the $R^2$ value cutoff for the curve fit, the stabilization times were reported. Additionally, the amount of time it took for each participant to complete the step was also calculated.

### 2.2 Results

Four participants were unable to complete the trials on the foam pad. For both surface conditions, signal-to-noise ratios were calculated and compared to the visual rating system to establish a cutoff that allowed the good and moderate trials to advance while ensuring trials with poor data trends were not included in the analysis. For both conditions, signal-to-noise ratios ranges were 2.34 to 24.37, 2.29 to 6.56, and 1.17 to 4.38 respectively for good, moderate, and poor data trends. For the 253 trials completed on the flat plate, 220 were visually classified as good, 25 as moderate, and 8 as poor with regard to demonstrating the characteristic data trend. For the 230 trials on the foam pad, 126 trials were classified as good, 54 as moderate, and 50 as poor A signal-to-noise cutoff of 2 advanced data with good and moderate trends for both surface conditions while a cutoff of 3 resulted in losing 23 trials with either good or moderate fits. Therefore, a signal-to-noise ratio of both 2 and 2.5 were evaluated to determine which cutoff ratio was more appropriate for this population for both flat and foam surfaces.

The signal-to-noise ratios for the flat plate condition ranged from 1.47 to 24.37 with a median value of 6.23. When a signal-to-noise ratio cutoff of 2 was used, all trials with good and moderate data trends would have advanced to curve fitting but 62.5% of
the trials with poor data characteristics (n=5) would also. With a signal-to-noise ratio cutoff of 2.5, all good trials, 23 of 25 moderate trials, and 4 of 8 poor trials would have advanced to curve fitting. For the foam pad condition, the signal-to-noise ratio range was 1.17 to 11.47 with a median value of 4.07. For the foam pad trials, signal-to-noise ratio of 2 would result in advancing all the good trials, all the moderate trials, and 38 of 50 poor trials. A signal-to-noise ratio of 2.5 would advance 124 good trials, 53 moderate trials, and 24 poor trials. Therefore, for both surface conditions, a cutoff signal-to-noise ratio of 2.5 would result in removing the majority of trials with a poor data trend while advancing the majority of trials with either a good or moderate fit. Table 2.1 depicts the percentages for the data trend classifications.

**Table 2.1: Trials with data trends that advance after respective signal-to-noise cutoffs**

<table>
<thead>
<tr>
<th>Signal-to-noise Ratio</th>
<th>Flat Plate</th>
<th>Foam Pad</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Good and Moderate</td>
<td>Poor</td>
</tr>
<tr>
<td>2.0</td>
<td>100%</td>
<td>62.5%</td>
</tr>
<tr>
<td>2.5</td>
<td>99%</td>
<td>50%</td>
</tr>
</tbody>
</table>

All trials that met the signal-to-noise ratio cutoff of 2.5 were then analyzed using the Time to Stabilization method. The $R^2$ calculation the first 10 seconds was determined to aid in curve fit evaluation. The fit of the curve was assessed for $R^2$ cutoffs of 0.25, 0.50, and 0.75 and Table 2.2 depicts the percentage of trials that would advance dependent on the cutoff value. As the objective was to exclude poor curve fits while advancing both good and moderate curve fits, the two were grouped together. The $R^2$
values for good, moderate, and poor fits respectively were [.008 to .972], [0.037 to 0.6875], [.0877 to .52].

**Table 2.2:** Trials with curves that advance after respective $R^2$ cutoffs due to curve fitting.

<table>
<thead>
<tr>
<th>R²</th>
<th>Flat Plate</th>
<th></th>
<th>Foam Pad</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Good and Moderate</td>
<td>Poor</td>
<td>Good and Moderate</td>
<td>Poor</td>
</tr>
<tr>
<td>0.25</td>
<td>97.6%</td>
<td>0.0%</td>
<td>91.2%</td>
<td>14.3%</td>
</tr>
<tr>
<td>0.50</td>
<td>93.9%</td>
<td>0.0%</td>
<td>75.3%</td>
<td>14.3%</td>
</tr>
<tr>
<td>0.75</td>
<td>73.9%</td>
<td>0.0%</td>
<td>50.0%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

The optimal $R^2$ cutoff for this particular data was chosen to be 0.25, as it included the majority of good and moderate curves while excluding the majority of poor curve fits. This resulted in 239 trials of the 247 trials that advanced past the data trend check on the flat plate being included in the final analysis, and 178 trials out of 201 on the foam pad.

Based on this screening process, stabilization time on the flat plate was determined to be $5.48\pm3.9$ s with a stepping time of $2.72\pm0.5$ s. On the foam pad, stabilization time was $7.54\pm6.5$ s and step time was $2.97\pm0.7$ s.

### 2.3 Discussion

The objective of this study was to examine whether the Time to Stabilization analysis was appropriate for the data of older adults and how successfully the curve generated by the method fit the data. The results suggest that while not all data collected from older adults demonstrates the characteristic trend that makes the Time to
Stabilization analysis appropriate, the majority of the data does. Many of the trials on the foam pad did have a lack of characteristic data trend. This is not surprising as the added challenge of the foam creates greater instability and controlled steady state may not occur, especially in older adults. Therefore, the authors do support the use of this analysis for older adults, however care should be taken in applying this methodology, especially if an unstable standing surface is used during data collection.

When evaluating different signal-to-noise ratio cutoffs, results for this study suggested the most appropriate cutoffs for examining older adults was 2.5. While this did result in excluding several trials that appeared to demonstrate an appropriate curve, the majority of the trials that did not advance due to this cutoff had poor data trends. The less conservative 2.0 signal-to-noise ratio cutoff resulted in a reduced percentage of good/moderate trials retained versus the poor trials that were cut. It is the recommendation of the authors that other researchers conducting this stabilization time analysis determine an appropriate signal-to-noise ratio cutoff for their population to ensure that data that does not demonstrate the appropriate trend is not included in the analysis. It is also recommended that if several signal-to-ratio cutoffs are considered, selecting the more conservative one is the better approach. The authors of this study evaluated several methods to characterize the curve and found signal-to-noise ratio to be the most reliable when compared to the visual inspection method. However, future studies could continue to explore options for a better method of evaluating the data trend such as advanced pattern recognition or different signal processing techniques.

Of the three $R^2$ cutoffs evaluated for the curve fits in this study, the cutoff of 0.25 was deemed to be the most appropriate value for this population, excluding the poorly fit
curves while retaining the majority of the curves with a good or moderate fit. This was unexpected as the authors had assumed a high $R^2$ cutoff for the first 10 seconds would be necessary to capture the best curves. The curves that had poor fits however, had extremely low $R^2$ values, making it unnecessary to use a high cutoff $R^2$ value. One contributing factor to this outcome was the use of a signal-to-noise ratio to first exclude the trials with the worst data trends. Because a large degree of noise was one aspect that resulted in a low signal-to-noise ratio, the data that did advance past this cutoff was more likely to demonstrate a more ideal negative exponential trend. As it is more important to first ascertain the quality of the data before fitting the curve, the authors recommend using a more stringent measure to evaluate the data and a lesser one while evaluating curve fit.

Stabilization time was determined to be 5.48±3.9 s with a stepping time of 2.72±0.5 s on the flat plate, and 7.54±6.5 s with a stepping time of 2.97±0.7 s on the foam pad. These values are notably larger than the ones determined by Rabufetti et al, who determined a mean stabilization time of .42 s for their participants in the 50th percentile of the experimental group (compared to the stabilization time of .29 s for the participants in the 5th percentile of the experimental group and 1.01 s for participants in the 95% percentile of the experimental group) [38]. As Rabufetti’s study evaluated healthy participant across a wide range of ages (43±21 years) and this work focused on older adults (76±8 years) who were not screened for health issues, the younger and healthier individuals may have had the faster stabilization time. Older adults exhibit decreased postural stability and postural reactions to perturbations and therefore it is not surprising they take longer to stabilize [3,34,35]. Additionally, there was no indication
that Rabufetti et al. used any kind of screening techniques to exclude data with poor trends or curves with poor fits. This disparity between stabilization times highlights the potential stabilization time may have as an analysis tool to explore differences between populations, especially as an impaired population may not be able to normally stabilize or may require a longer period of time to reach stabilization [11,35]. The authors do suggest either controlling for stepping time or calculating it and evaluating any correlations between the stepping time, stabilization time, and any corresponding stability parameters. This is recommended because stabilization time on its own is less meaningful if participants are allowed to select the speed at which they experience the perturbing movement. If stepping time is controlled for, a shorter stabilization time indicates better postural control. If it is not controlled for, however, a frail, unstable participant taking a slow, deliberate step could technically stabilize more quickly than those who confidently complete the motion in a shorter time period.

In conclusion, the methods presented here are one means of establishing how data could be screened and treated to determine appropriateness of Rabufetti’s Time to Stabilization Analysis. While care should be taken to ensure that the Time to Stabilization method is appropriate for the population and test condition being analyzed, it does appear like it could help differentiate between test conditions, and populations with notable differences. Future work should continue to attempt to objectify and automate the process. Appendix A contains the MATLAB programs used in this work and Appendix C contains some additional analysis of the quiet standing portion of data.
3.0 Introduction

Limits of Stability (LOS) testing is commonly used in research and clinical practice to identify impairments in balance [12,15,26,40,46–48]. LOS is a dynamic test of postural control that measures the maximum distance a person can lean in multiple directions at their ankles while keeping their feet flat on the ground [49]. LOS testing has been used to differentiate between clinical populations and healthy controls and to monitor changes in postural control in response to a therapeutic intervention [15,26,40,46,48–50]. Previous studies have demonstrated differences in LOS performance between individuals with conditions such Parkinson’s disease, obesity, chronic pain, and brain injury when compared to healthy controls [9,12,15,26,40,47,51].

While the LOS test has shown differences in performance between different clinical populations and between young and older adults, little is known about its ability to discriminate between sub groups of older adults (e.g. 60-69, 70-79, 80+). Additionally, prior research has shown that the LOS test does not consistently differentiate between older adult fallers and non-fallers [9,12,15,40,46,51]. While it may be that these individuals do not differ in their ability to complete the LOS test, it may also be that the test in its current form is not sensitive enough to identify potential differences
in performance between fallers and non-fallers. Perhaps, by modifying how the LOS test is performed and/or the results are analyzed, differences could be more easily identified.

One potential modification of the LOS test would be to incorporate a foam surface condition. Currently, quiet-standing posturography utilizes both a firm and a foam surface testing condition. The foam is intended to disrupt proprioceptive feedback which makes it harder to detect pressure distribution and body orientation, and thus increases the challenge of maintaining upright posture [41]. In older adults it has been found that postural control is significantly worse on foam than it is for younger adults [42]. It is speculated that standing on the foam pad is difficult for older adults because they often experience a loss of sensory input redundancy and sensitivity due to aging, making it harder to compensate for the reduced sensory input of the foam [18]. Because foam offers a greater challenge, it may be better at differentiating between individuals with and without balance deficits than a firm surface [41]. Additionally, foam may better mimic real world conditions (e.g. thick-soled shoes, grass, soft carpet, etc.) that provide an added challenge to proprioception and postural control. For these reasons, it is of interest to determine if there are meaningful differences in LOS performance between firm and foam testing conditions.

Another area of consideration for improving the utility of the LOS test is in how the data is analyzed and interpreted. Traditionally, LOS testing provides the maximum displacement of an individual’s center of pressure (COP_{max}) from which sway ranges can be determined. It is thought that individuals with good postural control complete these movements in a highly consistent manner while individuals who have poor control exhibit more irregular movement patterns. Traditional measures of sway range do not
capture these underlying differences in movement quality because they only give the maximum displacement of COP. However, newer non-linear analysis methods, such as sample entropy, allow us to explore this. Sample entropy quantifies the underlying regularity of human movements and has been used to study phenomena such as the effect of aging and pathology on postural control [52]. Incorporating sample entropy into an analysis to examine the irregularity of quiet-standing postural sway has provided insight not captured by more traditional parameters regarding the mechanisms of postural control [52–54]. Using it to analyze LOS data may provide additional understanding of the postural control mechanisms employed by an individual as they make the series of deliberate movements required for the LOS assessment.

Therefore, the primary purpose of this study was to determine if a foam testing condition and/or non-linear analysis methods can better differentiate between sub groups of older adults than traditional LOS testing methods. It was hypothesized that differences would be more easily identified using the foam testing condition and that non-linear analysis would have additional benefit. Another goal of this study was to lay the groundwork for future studies using the similar methods for assessing differences in LOS performance between fallers and non-fallers and between clinical populations and healthy controls.

3.1 Methods

Ninety (51 female, 39 male) older adults (mean age = 76.1 ± 8.4, range = 36) were recruited from local community centers, retirement communities, and various interest groups. Participants were divided into groups using the following age
designations: young-old (YO) 60-69 years, middle-old (MO) 70-79 years, and old-old (OO) 80+ years [55]. Table 3.1 depicts characteristics of each age group.

Inclusion criteria included a minimum age of 60 and the ability to stand for at least 5 minutes without support and walk 50 feet without physical assistance but with use of assistive device if needed. Participants were excluded if they had a severe neurological, orthopedic or cognitive impairments that would compromise the safety of testing. Additionally, individuals with a lower limb brace ankle-foot orthotic (AFO) or lower limb prosthesis were excluded from this study. This study was approved by the University of Dayton Institutional Review Board and all participants gave written informed consent before participating.

Table 3.1: Participant Characteristics, organized per age group

<table>
<thead>
<tr>
<th></th>
<th>YO</th>
<th>MO</th>
<th>OO</th>
</tr>
</thead>
<tbody>
<tr>
<td>n</td>
<td>n=22</td>
<td>n=37</td>
<td>n=31</td>
</tr>
<tr>
<td>Age</td>
<td>65.4 ± 2.3</td>
<td>74.6 ± 2.7</td>
<td>85.4 ± 4.4</td>
</tr>
<tr>
<td>Height (cm)</td>
<td>171.0 ± 10.3</td>
<td>167.4 ± 9.2</td>
<td>169.8 ± 9.6</td>
</tr>
<tr>
<td>Body Mass (kg)</td>
<td>74.6 ± 13.3</td>
<td>75.5 ± 14.6</td>
<td>71.8 ± 13.4</td>
</tr>
<tr>
<td>Gender (M/F)</td>
<td>10/12</td>
<td>13/24</td>
<td>15/16</td>
</tr>
</tbody>
</table>

A force plate (Model 5046, Bertec Corp., Worthington OH) was used to collect anterior-posterior (A/P) and medial-lateral (M/L) COP data at 1000 Hz. Each participant performed six LOS trials including three on the firm plate and three on a closed cell foam
pad (Airex AG, Sins, Switzerland) placed on top of the plate. The trials were performed in a random order. Participants began by standing on the plate in a comfortable, self-selected stance and wore comfortable, self-selected footwear. For each trial, subjects were instructed to lean primarily at their ankles forward, backward, and side to side as far as possible without losing their balance while keeping their feet flat on the surface.

Participants were instructed to take as much time as needed to finish the full range of movement but were not required to hold the position once they reached their maximum lean distance. A researcher demonstrated the proper form prior to the test. Participants wore a gait belt during testing and were closely spotted by a researcher but were not touched unless a fall occurred. A researcher watched for any obvious signs of performing the test incorrectly such as bending at the waist or moving their arms from their sides to aid in maintaining balance. If an error was detected the researcher then repeated the instructions and demonstration and the trial was redone.

The COP data was downsampled to 100 Hz and filtered with a 4th order low-pass Butterworth filter. Data from the 3 trials of each testing condition (firm and foam) were averaged separately to determine A/P and M/L sway ranges and sample entropy (SampEn) values. SampEn was calculated according to Ramdani et al. with codes for these calculations included in Appendix A [52]. SampEn is calculated by dividing the time series into vectors of a designated length, m, and systematically comparing the elements of each vector to those in the subsequent vector. The vectors are considered similar if the elements are within the range of a designated tolerance, r. After each vector has been compared to the subsequent one, the conditional probabilities are determined by comparing these results to those obtained when using m+1. A vector size of m=2 and a
tolerance, $r=.2$ was chosen. SampEn scores can range from a minimum of 0 to a maximum of 1.5. Appendix A contains the MATLAB programs used in this work.

For the statistical analysis, a one-way multivariate analysis of variance ($p \leq .05$) was used to determine the effect of age group (YO, MO, OO) and surface condition (Firm, Foam) on A/P and M/L sway ranges and sample entropy values. A post hoc Bonferroni correction was applied to account for the number of comparisons made, resulting in a $p$-value of 0.0125 for significance.

### 3.2 Results

During the testing, 1 participant was unable to perform any portion of the LOS test due to safety and balance concerns, and 3 were unable to perform the foam surface condition. There were several instances where a loss of balance occurred during the LOS assessment and these trials were not included in the analysis. Table 3.2 depicts the results of the COP measures for all participants, separated into the pre designated age groups.
### Table 3.2: Sway Ranges and Sample Entropy Values on Foam and Flat Surface (mean ± SD)

<table>
<thead>
<tr>
<th>Firm Plate</th>
<th>Young-Old (YO)</th>
<th>Middle-Old (MO)</th>
<th>Old-Old (OO)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A/P Sway Range (cm)</td>
<td>13.01 ± 2.90&lt;sup&gt;c&lt;/sup&gt;</td>
<td>11.98 ± 2.57</td>
<td>11.02 ± 2.95&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>M/L Sway Range (cm)</td>
<td>19.53 ± 4.57&lt;sup&gt;c&lt;/sup&gt;</td>
<td>17.49 ± 3.63</td>
<td>16.30 ± 4.87&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>A/P SampEn*</td>
<td>0.049 ± 0.018&lt;sup&gt;b,c&lt;/sup&gt;</td>
<td>0.070 ± 0.026&lt;sup&gt;a,c&lt;/sup&gt;</td>
<td>0.097 ± 0.040&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td>M/L SampEn*</td>
<td>0.021 ± 0.009&lt;sup&gt;c&lt;/sup&gt;</td>
<td>0.029 ± 0.015&lt;sup&gt;c&lt;/sup&gt;</td>
<td>0.039 ± 0.020&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Foam Pad</th>
<th>Young-Old (YO)</th>
<th>Middle-Old (MO)</th>
<th>Old-Old (OO)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A/P Sway Range (cm)</td>
<td>13.00 ± 2.32&lt;sup&gt;c&lt;/sup&gt;</td>
<td>12.84 ± 2.25</td>
<td>11.68 ± 2.37&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>M/L Sway Range (cm)</td>
<td>19.20 ± 4.14&lt;sup&gt;c&lt;/sup&gt;</td>
<td>18.0 ± 3.16</td>
<td>17.01 ± 5.50&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>A/P SampEn*</td>
<td>0.071 ± 0.017&lt;sup&gt;b,c&lt;/sup&gt;</td>
<td>0.092 ± 0.039&lt;sup&gt;a,c&lt;/sup&gt;</td>
<td>0.111 ± 0.040&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
<tr>
<td>M/L SampEn*</td>
<td>0.031 ± 0.012&lt;sup&gt;c&lt;/sup&gt;</td>
<td>0.039 ± 0.018&lt;sup&gt;c&lt;/sup&gt;</td>
<td>0.047 ± 0.022&lt;sup&gt;a,b&lt;/sup&gt;</td>
</tr>
</tbody>
</table>

<sup>a</sup> denotes significance differences when compared to age group young-old (p<.0125)

<sup>b</sup> denotes significance differences when compared to age group middle-old (p<.0125)

<sup>c</sup> denotes significance differences when compared to age group old-old (p<.0125)

<sup>*</sup> denotes significance between surface type (p<.0125)

A/P and M/L sway ranges were significantly greater for YO when compared to the OO age group (p=.005, p=.006). There were no differences in A/P or M/L sway ranges between
the MO and YO or OO age groups. There were also no differences in A/P and M/L sway ranges between the firm and foam surface conditions for any age group.

There were significant differences in A/P SampEn between all age groups, with values increasing with each age group: p=.005 (YO-MO) and p=.000 (MO-OO and YO-OO). There were significant differences in M/L SampEn between the YO and OO and the MO and OO age groups (p=.000, p=.012). Both A/P SampEn (p=.005) and M/L SampEn (p=.005) values were significantly greater during the foam vs. firm surface testing condition for all age groups. There were no interactions between surface and age group.

3.3 Discussion

One of the primary objectives of this study was to identify possible differences in LOS test performance between different age stratified groups of older adults (60-69, 70-79, 80+). The findings of this study show that there are differences in LOS test performance between age groups and that non-linear analysis (SampEn) may be more effective than traditional measures at detecting these differences. In general, during LOS testing on both the firm and foam surfaces, A/P and M/L sway ranges decreased with age, with a significant difference identified between the YO and OO age groups. This was expected since the normal aging process can lead to a reductions in physiological traits such as flexibility, sensation and strength, which are important for balance and could result in lower sway ranges [56]. Aging can also increase fear of falling even when muscle strength is controlled for, and fearful older adults have been found to have smaller sway ranges than those who are more confident in their abilities [57].
These findings indicate that clinicians and researchers should be cautious of grouping older adults into a single population (e.g. 65+) because averaging LOS sway ranges across age groups may mask potentially important normal and pathological changes in postural control. These findings should also be considered when using LOS testing to determine differences between clinical populations (e.g. Parkinson’s) and healthy older adults. In these cases, researchers should ensure that they are using controls that are appropriately aged matched to the clinical population. These findings should also be taken into consideration if LOS testing is being used to monitor or track postural control over extended (years) periods of time in older adults. Additionally, this holds true for this population, which was very diverse regarding health conditions. If all major health conditions had been controlled for (and thus older adults with more health problems were eliminated) this difference may not have been seen.

Another important objective of this study was to determine if non-linear analysis methods could improve the ability of the LOS test to detect differences in performance. The non-linear analysis showed significant differences in A/P SampEn values between all age groups and differences in M/L SampEn between the YO vs. OO and MO vs. OO age groups. This was better than the traditional sway range measures that could only identify differences between the YO and OO age groups. Sample entropy was used in this study as a measure of the predictability of COP movement and is reported as a value between 0 and 1.5. The closer to 0, the more periodic and predictable an individual’s movement are, and the closer to 1.5 the more chaotic they are. A healthy individual falls somewhere between the two values, allowing them to be posturally stable yet still able to adapt to environmental changes [58]. Similar to many physiological processes that experience a
decrease in complexity with age, the postural control of older adults during quiet standing has been found to be less dynamic than that of younger adults; this decrease in complexity of movement has been theorized to result in a decreased ability to adapt to environmental changes that influence postural control [59–61].

Our findings, however, indicated that LOS SampEn values increased with age when participants are conducting a deliberate movement. Although current research using SampEn on dynamic movements is limited, Duarte and Sternad found that older adults demonstrated increased complexity as measured by Multiscale Entropy when compared to younger adults during a period of 30 minutes of prolonged standing in which participants were allowed to move around naturally [16]. It appears that while the predictability of the COP excursion of older adults decrease during quiet standing, the predictability of the COP excursion during a deliberate movement may increase with age. Participants in all age groups also demonstrated significantly larger SampEn values on the foam compared to the firm surface. As the foam surface likely makes it harder to move in a controlled and consistent fashion this finding falls within current understanding of how sample entropy can be used to interpret human movement.

An additional purpose of this study was to assess the effects of a foam surface condition on LOS testing. This was the first study that the authors are aware of to incorporate foam to determine if the increased challenge provided by the compliant surface would influence performance. When using the traditional LOS outcome measures of A/P and M/L sway range, no differences in performance were identified. This was somewhat unexpected as a compliant surface has been shown to have a significant effect on quiet standing posturography and was hypothesized to have a significant effect on
how far individuals undergoing the LOS assessment could lean [28,41]. One rationale for the lack of difference could be that although the compliant foam theoretically would allow for an increase in sway range, it was offset by the reduced proprioceptive feedback provided by the foam as well as a fear of falling that may have prevented participants from achieving any net increases in sway range.

Although the sway ranges were not different between surface types, the SampEn values were significantly higher for the foam condition for all age groups. This finding supported our original hypothesis that SampEn and a foam surface condition may identify differences in LOS performance not seen with traditional testing. As the foam is more challenging, this falls in line with current understanding of sample entropy—people were less predictable with their movements when proprioceptive feedback was disrupted. Additionally, it appears that with increasing age, participants were less able to control their postural response to the difficulty in standing on the foam, resulting in increased complexity.

In conclusion, the findings of this study indicate that when interpreting and comparing LOS test results among older adults, clinicians and researchers should use closely matched age groups when possible. Additionally, the use of non-linear analysis methods may improve the ability of the LOS assessment to identify differences in performance that are not currently revealed by traditional sway ranges. Lastly, while using a foam surface during LOS testing may not enhance the findings provided by traditional sway ranges, it may provide additional insight when combined with non-linear analysis methods. Based on these findings, future research investigating the ability of
non-linear analysis and compliant surface conditions to predict falls, monitor disease progression, and quantify treatment response in older adults may be warranted.
CHAPTER 4
FALLERS DEMONSTRATE DECREASED MOVEMENT QUALITY AS MEASURED BY JERK COMPARED TO NON-FALLERS DURING THE LIMITS OF STABILITY TEST

4.0 Introduction

One third of older adults experience a fall every year, giving rise to high physical, social, and fiscal costs to both the faller and society [1,22–24]. Falls are the leading cause of accidental death for older adults; nonfatal falls often result in admission to emergency rooms and/or institutionalization, reductions in quality of life of the faller, and an annual medical cost over $30 billion dollars as 2012 [23–25]. Due to the severity of physical and emotional repercussions that often occur as a result of a fall, it is important to reduce the incidence of falls in older adults. One way to reduce falls is to identify at-risk older adults before they fall and implement preventative measures such as exercise regimes, physical therapy, or medication changes [62–64].

In an effort to decrease the incidence of falls, a large body of postural control research is dedicated to identifying at-risk fallers by better understanding differences between older adults who have and have not experienced a fall [5,62,65]. One postural research assessment that has been evaluated as a potential measure to differentiate between fallers and non-fallers is the Limits of Stability (LOS) assessment [15,40,45,66].
The LOS assessment is traditionally conducted on a force plate and requires an individual to lean as far as they can in multiple directions while utilizing only an ankle strategy. The most commonly reported outcome measure of the LOS assessment is the maximum displacement of the center of gravity (COG) or center of pressure (COP) [39,40,45,66]. Previous studies of older adults have not identified differences in LOS values between fallers and non-fallers [40,66]. While maximum sway values may not be useful in identifying differences between fallers and non-fallers, it is not known whether measures that assess the relative quality of movement such as the “smoothness” may provide greater insight. It is worth evaluating modifications to this test that could improve the assessment’s ability to discriminate between these two groups.

With this in mind, wearable inertial measurement unit (IMU) sensors may have the potential to enhance the LOS assessment by providing data on how individuals move during the test. IMUs consist of tri-axial accelerometers, gyroscopes, and magnometers and can measures changes in acceleration, angular velocity, and magnetic fields. IMUs have recently been used to augment postural stability studies and have been proposed as a potentially less expensive alternative to force plates [67]. While there is limited guidance regarding which IMU-based sway measures are more insightful when trying to differentiate between clinical populations, Mancini et al. proposed using a measure known as “jerk” to compare movement smoothness between clinical populations and healthy controls [12]. Jerk, the time derivative of acceleration, is a measure of dynamic stability that is used to describe the ability to regulate acceleration or deceleration of a movement [12]. Jerk is used to characterize a movement’s smoothness, which is an indicator of healthy motor function and sensorimotor control [68,69].
Therefore, the objective of this study was to determine whether LOS assessment IMU-based outcome measures demonstrated greater differences between fallers and non-fallers than the traditional COP-based outcome measures. We hypothesized that while traditional COP parameters would not differentiate between fallers and non-fallers, fallers would demonstrate significantly decreased smoothness, as measured by jerk calculated from acceleration data from an IMU, in their movements.

4.1 Methods

Eighty-one older adults (mean age of 75.6 ± 8.1) recruited from local retirement communities and groups participated in this study. Participants were required to be able to stand for a minimum of 5 minutes, walk 50 feet unassisted, and not require the use of a limb brace, ankle-foot orthosis, or lower limb prosthesis. Twenty-nine participants self-reported experiencing at least one fall in the 12 months prior to testing, with a fall defined as anytime an individual unintentionally came to rest on a lower surface[65]. The University of Dayton Institutional Review Board approved this study and participants gave written informed consent before testing began. Participant characteristics are described in Table 4.1.
Table 4.1: Participant Characteristics for IMU Limits of Stability Study (mean±SD)

<table>
<thead>
<tr>
<th></th>
<th>Fallers</th>
<th>Non-fallers</th>
</tr>
</thead>
<tbody>
<tr>
<td>n</td>
<td>29</td>
<td>52</td>
</tr>
<tr>
<td>Age (years)</td>
<td>78.52 ± 8.3</td>
<td>73.96 ± 7.5</td>
</tr>
<tr>
<td>Height (cm)</td>
<td>165.96 ± 9.4</td>
<td>170.19 ± 9.0</td>
</tr>
<tr>
<td>Body Mass (kg)</td>
<td>70.04 ± 15.7</td>
<td>76.44 ± 13.1</td>
</tr>
<tr>
<td>Gender (M/F)</td>
<td>9/20</td>
<td>22/29</td>
</tr>
</tbody>
</table>

Participants were fitted with an IMU on the left mid-thigh, approximately 3 inches above the knee, to capture the ankle strategy employed during the assessment (Opal Model, APDM, Portland, Oregon). The thigh IMU was positioned flat against the body and held in place with elastic straps provided by the manufacturer. The IMU had a tri-axial accelerometer that recorded linear acceleration data in all three planes of motion. Participants stood on a force plate (Model 5046, Bertec Corp., Worthington OH) that collected center of pressure (COP) data in both the A/P and M/L directions at 1000 Hz.

Prior to data collection, a researcher explained and demonstrated the LOS movement. When told ‘begin,’ the participant leaned as far as they could in the anterior-posterior (A/P) and then, the medial-lateral (M/L) directions [26]. Participants were
instructed to keep their feet in place and flat on the floor for the duration of the LOS assessment. They were told to bend at the ankle, rather than the waist, and to take as much time as necessary to complete the movement. Six trials were conducted in a randomized order, three on a firm surface and three on a foam surface (Airex closed cell foam pad). Both surfaces were evaluated to investigate differences between standing surface on the LOS assessment. All participants wore a gait belt and were spotted by a researcher during data collection. Trials in which a participant lost their balance, rocked up on their toes or heels, bent at the waist, or extended arms for balance were repeated.

The COP data were downsampled to 100 Hz and filtered with a 4th order low-pass Butterworth filter with a 5 Hz cutoff. Maximum excursion in the horizontal plane was determined from the COP data and reported as A/P and M/L Sway [15,49,66]. Appendix A contains the MATLAB programs used in this work.

The acceleration data collected by the IMU was filtered with a fourth-order Butterworth filter with a 5 Hz cut-off. The filter cutoff was determined after a Fast Fourier Analysis was conducted to produce a power spectral density plot which depicted the frequency that contained approximately 99% of the signal. The jerk \( \left( \frac{m^2}{s^5} \right) \) experienced by each sensor was calculated according to Flash and Hogan and is depicted below, where \( ACC_{ML} \) was the linear acceleration experienced by the IMUs in the M/L direction \( \left( \frac{m}{s^2} \right) \), \( ACC_{AP} \) was the acceleration experienced by the IMUs in the A/P direction \( \left( \frac{m}{s^2} \right) \), \( t \) was time (seconds), and \( t_f \) was the length of the entire time period of data collection (seconds) [70]. Jerk is a measure of dynamic stability and a movement with a small amount of jerk is smoother and more controlled than one with a higher degree of jerk [71].
\[ \text{Jerk} = \frac{1}{2} \int_{0}^{t_f} \left( \left( \frac{dACC_{AP}}{dt} \right)^2 + \left( \frac{dACC_{ML}}{dt} \right)^2 \right) dt \]

A one-way multivariate analysis of variance (p ≤ .05) was used to determine the effect of fall status (faller, non-faller) on COP sway ranges and thigh jerk for each trial.

4.2 Results

Participants completed 90.5\% of the trials on the flat plate and 85.2\% of the trials on the foam pad due to fatigue and/or inability to complete the test. Fallers conducting the assessment took a significantly longer time to perform the LOS assessment (p=.003). Fallers took 23.22 ± 9.1 s to complete the assessment on the flat surface and 24.93 ± 10.6 seconds on the foam pad. Nonfallers took 20.68 ± 7.8 s to complete the assessment on the flat surface and 22.43 ± 8.7 seconds on the foam pad. Table 4.2 depicts the M/L and A/P sway ranges and the jerk experienced by both groups.
Table 4.2: COP Sway Ranges and Thigh Jerk (mean±SD)

<table>
<thead>
<tr>
<th></th>
<th>Fallers</th>
<th>Non-fallers</th>
<th>p-value</th>
<th>Effect Size</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Flat Plate</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M/L COP Sway Range (cm)</td>
<td>17.39 ± 5.3</td>
<td>17.61 ± 4.5</td>
<td>0.514</td>
<td>0.045</td>
</tr>
<tr>
<td>A/P COP Sway Range (cm)</td>
<td>11.48 ± 3.5</td>
<td>12.03 ± 3.1</td>
<td>0.076</td>
<td>0.166</td>
</tr>
<tr>
<td>Thigh Jerk (m²/s⁵)</td>
<td>12.68 ± 11.1</td>
<td>11.61 ± 8.1</td>
<td>0.030</td>
<td>0.11</td>
</tr>
<tr>
<td><strong>Foam Pad</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M/L COP Sway Range (cm)</td>
<td>17.80 ± 5.1</td>
<td>18.15 ± 4.2</td>
<td>0.514</td>
<td>0.075</td>
</tr>
<tr>
<td>A/P COP Sway Range (cm)</td>
<td>12.00 ± 2.9</td>
<td>12.51 ± 2.3</td>
<td>0.076</td>
<td>0.195</td>
</tr>
<tr>
<td>Thigh Jerk (m²/s⁵)</td>
<td>31.27 ± 69.6</td>
<td>19.27 ± 15.5</td>
<td>0.030</td>
<td>0.238</td>
</tr>
</tbody>
</table>

There were no differences between fallers and non-fallers (p>0.05) for A/P and M/L sway ranges on both surfaces. When the IMU-based measure of jerk was evaluated, fallers experienced a significantly higher degree of thigh jerk than non-fallers on both surfaces (p=0.030).
4.3 Discussion

The main aim of this study was to evaluate whether the LOS assessment accelerometer based outcome parameter of jerk could differentiate between fallers and non-fallers better than traditional COP based measures. As expected, the COP results did not show significant differences between fallers and non-fallers. This finding is consistent with the results of previous LOS-based research [15,40,45,66]. The IMU-based measure of thigh jerk, however, was significantly different between the two groups. This could be due to the fact that fallers took significantly longer to conduct the assessment or that they were moving with a decreased amount of motor control. Higher degrees of jerk imply the faller group was experiencing steeper rates of accelerations and decelerations as they performed the LOS assessment, suggesting a decreased degree of motor control [12].

Decreased smoothness of motion in arm movement has been associated with several other clinical populations with balance impairments, such as individuals who had experienced a stoke or individuals with pre-symptomatic Huntington’s disease [72,73].

Measures of jerk may be more insightful in this application than COP-based measures because of the inherent differences of what the parameters characterize. For the LOS assessment, COP sway range is how researchers describe how far an individual can deliberately move within their base of support [74]. Measures of jerk evaluate the control exercised while conducting the movements towards that maximum excursion [69]. This finding has potential for rehabilitation efforts as smoothness of movement has the potential to be improved, as demonstrated by stroke patients exhibiting increased smoothness in their arm movement as they recover [23]. Therefore, researchers
attempting to incorporate lifestyle changes in at-risk older adult fallers may consider utilizing jerk as a metric by which to measure any physiological improvements.

The results of this study and the calculated effect size also suggest that both groups exhibited more jerk on the foam surface than the flat plate, likely due to the fact that the foam pad is a highly unstable surface and it reduces the ability of the participants to maintain postural stability as it limits proprioceptive input [41]. Therefore future work attempting to differentiate between these populations should continue to utilize a compliant testing surface.

As the results were limited to the thigh, it is also worth evaluating whether this trend is observed when evaluating other body segments for this population. The thigh was selected as it best captured the motion of an appropriately conducted lean from the ankle. It may be of interest to evaluate the jerk experienced by the trunk, the lower back, and head during the LOS assessment. Ideally, all segments should demonstrate a similar degree of jerk during the LOS assessment and measuring multiple segments may help illuminate differences between clinical groups with different degrees of motor control.

There are several implications of this work. The insightfulness of the jerk outcome measure coupled with the lack of significance of the sway parameters indicates the LOS assessment benefits from incorporating wearable sensors or possibly replacing the force plate with wearable sensors altogether. In addition to improved sensitivity to differences between these two groups, wearable sensors are much less expensive than posturography equipment and only a single tri-axial accelerometer may be required. Therefore, the authors suggest future work evaluating older adult fallers and non-fallers consider utilizing measures of jerk measured by accelerometers. A next step would be to
establish a range of values of normative values for fallers and non-fallers so a single accelerometer could be used as a screening tool for older adult fallers. This would be a less expensive and faster alternative to using posturography-based measures as a screening tool.

One limitation with this work was the fact that forty-one of the participants were unable to conduct all three trials on both surfaces. The main issue was fatigue and/or discomfort conducting the LOS assessment on the foam pad. With this in mind, future work that involves the LOS assessment on a compliant surface may need to reduce the number of trials when working with frailer populations. Or utilizing a less compliant foam may decrease the difficulty of the task.

In conclusion, there is evidence that the LOS assessment benefits from the incorporation of accelerometer-based measures of jerk. Further research is needed to explore jerk as a metric for identifying at-risk fallers.
CHAPTER 5
EVALUATION OF TEST ADHERENCE DURING THE LIMITS OF STABILITY ASSESSMENT

5.0 Introduction

One potential issue with the Limits of Stability (LOS) assessment, detailed in chapters 3 and 4 of this dissertation, is the fact that the main method to determine whether the test is being conducted properly is visual inspection. Researchers are required to make a subjective judgement call whether or not research participants are appropriately bending at the ankle rather than the hips. If IMUs are placed on both the upper and lower body of the participants this could provide data on whether the LOS test is being performed appropriately. Participants who correctly utilize an ankle strategy during the leaning movements and refrain from bending at the waist would experience a higher degree of correlation between the signals of the IMUs on the thigh and the sternum. To the authors’ knowledge, only visual inspection has been used to date to affirm whether the LOS assessment was being performed as intended.

There is a need to better understand how closely participants adhere to the directions of the assessment to ensure the LOS test is actually evaluating what it is intended to; this could also aid in the assessment’s ability to differentiate between subject groups. Therefore, the objective of this secondary aim was to assess the degree of
correlation between both sensors to evaluate whether the older adults in this study performed the LOS assessment correctly, bending from the ankle rather than the hips.

5.1 Methods

This was a secondary analysis conducted from another study. Eighty-one older adults (mean age of 75.6 ± 8.1 years) without significant mobility impairments participated. The University of Dayton Institutional Review Board approved this study and participants gave written informed consent before data collection began.

Participants were fitted with two IMUs: one on the sternum and one on the left mid-thigh, approximately 3 inches above the knee (Opal Model, APDM, Portland, Oregon). Both sternum and thigh IMUs were positioned flat against the body and held in place with elastic straps provided by the manufacturer. Each IMU has a tri-axial accelerometer that recorded linear acceleration data in all three planes of motion.

Participants were given instructions and a demonstration of the LOS assessment. The instructions were to lean as far as possible in the anterior/posterior (A/P) and the medial-lateral (M/L) direction [26]. While leaning, participants were told to use an ankle strategy rather than bending at the waist. They were also instructed to keep their feet flat on the floor and their arms at their sides. Three trials were conducted on a firm surface.

Participants were fitted with a gait belt and spotted during data collection. Trials in which a participant lost their balance, failed to keep their feet flat on the floor, or extended their arms for balance were repeated. As an aim of this study was to evaluate how closely participants adhered to the requirements of the assessment, any trials in which participants visibly bent at the waist were also discarded and repeated.
The correlation coefficient of the acceleration in the A/P and M/L directions were then used as outcome measures to gauge the degree of similar movement experienced by the upper and lower segments of the participants’ bodies. A higher R value indicates a participant is moving both segments more similarly, and therefore more correctly utilizing an ankle strategy, than a participant with a lower degree of correlation between the two sensors.

5.2 Results

The correlation coefficient between the trunk and thigh sensor was determined for each trial. In the M/L direction, the correlation coefficient was $0.73 \pm 0.34$ with a range of $[-0.96$ to $0.98]$. In the A/P direction, the correlation coefficient was $0.44 \pm 0.41$ with a range of $[-0.94$ to $0.94]$.

5.3 Discussion

The aim of this study was to use the correlation coefficient between the IMUs strapped to the participants’ trunk and thigh to examine how closely participants were adhering to the LOS assessment’s instruction to use an ankle strategy. Results indicated participants were moving with a moderately high degree of correlation in the M/L direction. However, the correlation coefficient in the A/P direction was lower and had larger standard deviations in comparison to the mean. The decreased correlation in this direction could be related to the fact that participants reported that it was more difficult to lean forwards and backwards than side to side. Additionally, as there was a high degree
of standard deviation, it appears there was a wide range of how well individuals conducted this assessment.

This raises questions regarding implementation of the LOS assessment as it appears the ankle strategy is not being fully adhered to, especially in the A/P direction. More importantly, the researcher visually monitoring the participants perceived that the assessment was being conducted correctly. All trials included in this analysis were ones in which participants had appeared to only use an ankle strategy.

It is therefore the recommendation of the authors that other researchers using the LOS assessment strongly stress the importance of leaning correctly, i.e. with an ankle strategy, rather than attempting to lean as far as possible, especially in the A/P direction, as it may be a factor contributing to accidentally bending at the waist. This finding also highlights the need for future work to continue to evaluate differences between someone who appears to be visually performing the LOS assessment correctly and someone who actually utilizing a true ankle strategy. It is even necessary to determine what range of movement between the upper and lower body segments is acceptable with an appropriately conducted lean. For example, participants with a correlation coefficient between .7 and 1 could be classified as performing the assessment ideally. It is consequently the suggestion of the authors that a similar study is conducted on a young, healthy population and other clinical populations to explore this further.

Some of the limitations of this work include the fact that only the correlation coefficient was evaluated as an outcome parameter. Future work could evaluate additional means to study the motion the of the upper and lower body segments.
Techniques such as motion capture may be a more reliable and insightful method to move forward with.

In conclusion, researchers who utilize the LOS assessment are strongly encouraged to ensure that the test is being performed correctly by quantitative means rather than purely visual assessment. This will ensure that the research question is being correctly addressed and improve the insightfulness of the LOS assessment as a measure used to differentiate between clinical populations.
CHAPTER 6
CONCLUSION

6.0 Summary of Motivation for Research

Posturography research has given the field of biomechanics insight into the process by which humans maintain balance, improved understanding of various pathologies, aided in the tracking of therapy efficacy, and enhanced understanding of physiological processes such as aging. Despite its widespread and established use in biomechanical research it is important to continue to explore new methods to improve the sensitivity and insightfulness of posturography. This dissertation sought to improve the utility of this tool to allow for continued improvement of understanding postural behavior and ultimately improve identification of individuals who have subtle deficits that may indicate risk of fall or onset of disease.

6.1 Review of Research

The objective of the first aim was to apply the Time to Stabilization method as described by Rabufetti et al. to the data of older adults to ascertain whether this approach was appropriate for an older adult population [38]. The goal of this work was also to establish a set of guidelines for posturography analysis by identifying methods to assess how data could be screened and treated to ensure the method was successfully applied. Center of pressure data were collected from 90 older adults as participants stepped up
onto a force plate with and without a foam pad. A recommendation of a signal-to-noise ratio cutoff of 2.5 and a $R^2$ cutoff of at least .25 was made after evaluating multiple signal-to-noise ratios and $R^2$ cutoffs to ensure only trials with appropriate data trends and curve fits were included. It was found a conservative cutoff regarding the data trend and a lenient one for the curve fitting resulted in the largest number of trials with good trends and well fit curves to advance. The older adults in this study took longer to stabilize than the younger, healthier adults of other studies that used this method. As the data of older adults was suitable for this analysis with the Time to Stabilization method, indicating this method may have uses with other clinical populations.

The objective of the second aim was to evaluate differences in the Limits of Stability (LOS) performance between older adults of different age ranges and explore whether incorporating a foam surface condition and nonlinear analysis could highlight differences in these sub-groups. 90 older adults participated in this study, conducting the LOS assessment on force plate. The three age categories participants were grouped into were young-old (60-69 years), middle-old (70-79 years), and old-old (80+ years). A/P and M/L sway range and sample entropy values were calculated. The results indicated significant differences in sway ranges between the young-old and old-old age groups for both surfaces, significant differences in A/P SampEn between all groups, and significant differences in M/L SampEn between the young-old and old-old and the middle-old and old-old groups.

The implication of these results is that older adults of different ages do perform the LOS assessment differently and this should be taken into account in future research. Additionally, sample entropy appears to be more sensitive to differences between groups...
than sway range. This could be due to the fact that while sway range measures the distance an individual leans in each direction, sample entropy looks at the underlying predictability of the actual movement itself. In other words, it captures how the movement was conducted rather than simply describing how far the movement displaced the individual’s COP. As sample entropy appears to be more adept at highlighting subtle, underlying differences between groups, nonlinear parameters should be incorporated into future LOS-based work.

The objective of the third aim of this study was to explore whether the LOS assessment IMU-based outcome measure of jerk was more sensitive to differences between fallers and non-fallers than the traditional COP-based outcome measures. There were no significant differences between groups when traditional parameters were compared. When the IMU-based measure of jerk was evaluated, however, fallers demonstrated significantly larger thigh jerk than non-fallers on both surfaces. This indicates that the fallers were demonstrating decreased smoothness, and therefore decreased movement control, compared to the non-fallers group. Therefore, the LOS assessment’s sensitivity appears to be improved by the accelerometer-based measure of jerk, especially as it is a parameter that describes the quality of the movement rather than just how far of a distance the movement resulted in.

The objective of the fourth aim was to evaluate whether older adults performed this assessment correctly by assessing the degree of correlation between IMUs placed on two different segments of the body. The LOS assessment should be performed by the individual bending from the ankle rather than the hips. The results of the fourth aim indicted a better adherence to the test requirements in the M/L plane than in the A/L
plane. Further work is needed to explore how correctly the assessment is actually being conducted.

6.2 Research Theme

The overarching theme of this study was to explore, improve and enhance the current posturography based data collection and analysis methods. The first study examined a published stabilization methodology, with the intent to explore its application for analyzing older adult data and to suggest guidelines to others hoping to utilize this method. The second study took a traditional LOS test and explored how to improve its insightfulness by evaluating the conventional practice of treating older adults as a homogeneous population simply based on the metric of age. This study also was the first that the author is aware of that utilizing a nonlinear measure to evaluate data collected in the LOS assessment. The third and fourth study in this dissertation took the novel approach of utilizing supplemental data collection tool than traditional studies that have used the LOS assessment. Rather than only collecting center of pressure (COP) data, wearable sensors were placed on the thigh and the jerk experienced by the thigh was determined, and found to be more sensitive than traditional measures when differentiating between two populations.

The results of these studies showcase the benefits of continuing efforts to improve existing data collection and analysis approaches in posturography work. Once an analysis methodology such as the Time to Stabilization method proposed by Rabufetti et. al. is published, the research field experiences the most benefit when that methodology is evaluated to improve its current approach and adopt it for a wide range of use. This study
also shows that examining age groups of older adults is a beneficial addition. Depending on the research question at hand, a study could neglect to pick up on differences between groups or fail to notice important trends if care is not taken to evaluate the initial assumptions about a subject pool.

It is also apparent that nonlinear measures of variability, such as sample entropy, can increase the insightfulness of certain methodologies and pick up on differences, such as those between age ranged, not captured by more traditional parameters. There is benefit to be gained from adding a measure of nonlinear variability to a test that traditionally only evaluated parameters such as sway length; this supports the continued work of incorporating nonlinear measures in posturography-based studies, especially when differences between clinical groups may be subtle. As nonlinear measures become more mainstream in the field of posturography, however, it is important to continue to revisit assumptions—in the case of sample entropy vector size or tolerance—and evaluate which measure best addresses specific research question.

Finally, combining posturography data with other data, such acceleration data collected by an IMU, does appear to enhance the LOS assessments abilities to pick up on subtle differences between two populations. In addition, the IMU data provides one way to study how closely participants are adhering to test directions. These findings perhaps best highlight how the sensitivity and insightfulness of posturography-based studies can benefit from innovative approaches to traditional data collection and analysis methods.
6.3 Study Limitations

There were several limitations of this work. A main overarching limitation was the fact that the only exclusion criteria for the research participants were whether a mobility impairment was present. As this did not control for potential health conditions, there could have been potentially confounding factors within the subject population itself. Although this was not ideal, it was also necessary as the researchers wanted to test a representative population of older adults. In addition, as focus of this work was older adults, it is highly unlikely that a large subject population could have obtained if individuals with health problems were excluded. Also, participants were allowed to wear their own shoes as long as they were flat-soled.

For the stabilization methodology in aim 1, only a single curve fitting method was explored (the MATLAB functions ‘fittype’ and ‘fit’). It could be possible that a better curve fitting method would improve this analysis, prove to be more consistent when analyzing trials with less suitable curve trends, or be less sensitive to initial guesses. Additionally, signal-to-noise ratio and $R^2$ values were the only two metrics by which the data trend and curve fit were evaluated. Other methods of trend evaluation, such as identifying a cutoff threshold at which standard deviations of the mean are within, are worth exploring. The second study’s main limitations was the fact that the parameter of sample entropy is dependent on data length and the trials were not identical in length of time. Although the datasets were large enough this was not a big issue, it still was not ideal for this analysis.

For the third study, the first main limitation was that participant self-reported any falls, potentially resulting in a misidentification of a faller or non-fallers if a participant
misremembers or forgets an incident. Additionally, the main IMU parameter, jerk, was calculated as the time derivative of acceleration according to Mancini et al [75]. Other authors, however, have suggested that dimensionless jerk is more appropriate measure to quantify deviations from smoothness when conducting a movement [70]. Dimensionless jerk was not used, however, as it required the calculation of peak velocity. As the original signal was acceleration, integrating the signal to obtain this parameter would introduce too much error. Finally, the position of the thigh sensor could be an area in which consistency is improved. The sensor was placed flat on the frontal plane of the thigh, however additional safeguards were not taken to ensure it was as perfectly oriented as possible. The chest sensor does not have this limitation as it had a strap configuration that resulted in a much more consistent placement.

6.4 Future Work

Based on the results of the three aims of this dissertation, two separate avenues of future work are proposed. Firstly, stabilization time and jerk both were promising measures. A study evaluating two clinical groups could utilize the time to stabilization method to evaluate both groups. It would be especially beneficial to use these parameters to enhance a slip or trip study by evaluating how long it took for participants to restabilize after experiencing a trip. In addition to determining how long it took for stabilization to occur, wearable sensors on the trunk and various external limbs could be used to analyze the degree of jerk experienced by the participant during the slip, recovering, and subsequent stabilization. Comparing the jerk experienced by the trunk to
the jerk experienced by the legs and arms could provide interesting input regarding recovery strategies.

A second study is needed to explore the fact that the participants who visually appear to be correctly conducting the LOS assessment actually are displaying a wide range of correlation between upper and lower body movement. A study that collected LOS from multiple healthy age ranges could be the first step to address this. Information gained from this study could be then used to provide recommendations concerning LOS assessment instruction, visual monitoring, and guidelines for analyzing trials to account for differences in how correctly the test was conducted.
REFERENCES


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APPENDIX A:

MATLAB PROGRAMS

Batched Time to Stabilization and Traditional Posturography Outcome Parameters

The following code was used to complete Aim 1. This code takes COP data collected from the force plate and first processes it (down samples, filter) and then runs the Time to Stabilization analysis described in Chapter 2 of this dissertation. The author of this method is Rabufetti et al [38]. The only changes made to the method compared to the way it was described by Rabufetti are the fact that COP data was used instead of COG. The output is the Time to Stabilization value, denoted as TS and this is saved into an Excel file that the user is prompted to define the name of. This code is written to be appropriate for the motion of stepping up onto the plate. Other perturbing motions, such as kneeling and standing will require modification but guidance can be found in Rabufetti’s original manuscript. This modification will focus mostly on identifying the time through focusing on Fz.

%TTS Analysis and Posturography
%Written by Senia Smoot Reinert

clc; close all; clear all;

%Manually change the name of how you want your excell spreadsheet to save
output_name='TTS_posturography.xls';

%Select Folder where trials are saved as text files
directory_name=uigetdir(pwd,'Select data directory');
directory_name=[directory_name '\']
files=dir([directory_name,'*.csv'])
if isempty(files)
    msgbox('No raw files in this directory')
end

% Batching

%build place holder matrix for all sampen values for batching
output=zeros(length(files),13);
FileName=cell(length(files),1);
for i=1:length(files)
    filename=files(i).name;
    data_all = csvread(fullfile(directory_name, filename),1,0);
    FileName{i,1}=filename;
    Matr = data_all(:,:);
    %specify a downsampling rate, m
    m = 10;
    %Downsample the data to 100 Hz
    Matr = downsample(Matr,m);
    %Assign column names
    t = Matr(:,1);
    Fz = Matr(:,8);
    COPx = Matr(:,15);
    COPy = Matr(:,16);
    %calculate N
    n= length(t);

    %apply 5th order low-pass Butterworth Filter with a 3 Hz cutoff
    freq
    Fs = 1/mean(diff(t));
    Fcutoff = 5;
    fnorm = Fcutoff/(Fs/2);
    %use a second order filter since filtfilt runs it twice
    [b,a] = butter(2,fnorm);
    COPy = filtfilt(b,a,COPY);
    COPx = filtfilt(b,a,COPx);
    Fz = filtfilt(b,a,Fz);

    %find weight of subject (avg last 10 seconds of Fz)
    BW = mean(Fz(1000:end));

    %find final (i.e. max) peak in data
    MaxPeak=max(Fz);

    %Find the indices of max peak
    MaxPeakPosition = find(Fz==MaxPeak);

    %Find where Fz goes lower than Body weight
    BelowBW=find(Fz(MaxPeakPosition:end)< BW, 'first');

    %Find the indices of where Fz goes lower than BW
    BelowBWPosition= BelowBW + MaxPeakPosition;

    %plot Fz
    % figure(1);
    % subplot(2,2,1)
    % plot(Fz)
    % axis([0,n, 0-.05*BW, BW+.15*BW])
    % title('Fz')
    %
    %plot Fz and highlight location of max peak and Fz shift
    below BW
    % subplot(2,2,2)

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%% plot(Fz)
%% axis([0,n, 0-.05*BW, BW+.15*BW])
%% hold on
%% plot(MaxPeakPosition,MaxPeak,'xr-','linewidth', 2,'Markersize',10)
%% hold on
%% plot(BelowBWPosition, Fz(BelowBWPosition),'go-','linewidth', 2,'Markersize',5)
%% title('Step onto plate complete(x), start of settling(o)')
%% % zoom in plot 1
%% subplot(2,2,3)
%% plot(Fz)
%% hold on
%% plot(MaxPeakPosition,MaxPeak,'xr-','linewidth', 2,'Markersize',10)
%% hold on
%% plot(BelowBWPosition, Fz(BelowBWPosition),'go-','linewidth', 2,'Markersize',5)
%% axis([MaxPeakPosition-.5*MaxPeakPosition,MaxPeakPosition+.5*MaxPeakPosition,BW-.1*BW, BW+.05*BW])
%% title('Close up')
%% %delete' all data before the point where Fz goes below BW
%% t0=t(BelowBWPosition:n);
%% t0_Fz=Fz(BelowBWPosition:n);
%% t0_COPx=COPx(BelowBWPosition:n);
%% t0_COPy=COPy(BelowBWPosition:n);
%% t0_n=length(t0_Fz);
%% %plot all data points of Fz from where it shifted below 0 to end
%% subplot(2,2,4)
%% plot(t0_Fz)
%% axis([0,t0_n, BW-.0075*BW,BW+.0075*BW])
%% title('All data after start of settling')
%% hold on

%% figure
%% subplot(2,1,1)
%% plot(t0,t0_COPx)
%% subplot(2,1,2)
%% plot(t0,t0_COPy)

%% Rabuffetti
%% calculate the RMS of the COP AP velocity

%%get vector for AP Velocity for each time step
%% AV = 0;
%% for ii = 2:t0_n-1
%% AV(ii) = mean(((sqrt((t0_COPy(ii-1)-t0_COPy(ii+1))^2))/(t0(ii+1)-t0(ii-1))));
%% end

%%Calculate RMS of AP velocity for each 1 second window
for jj = 1:length(AV)-100
    RMS(jj)=sqrt((sum(AV(jj:jj+100).^2))/length(AV(jj:jj+100)));
end

% fit RMS to an exponential curve example
x=t0(2:length(t0)-100);
y=RMS;
myfittype = fittype('k*exp(-x/tau)+Yinf',...  
    'dependent','y','independent','x',...  
    'coefficients',{'k','tau', 'Yinf'})
% initial guesses based on pilot (1, 1.5, .02)
myfit = fit(x,y', myfittype,  
    'startpoint', [1.5 1.2 .02]);
figure
    plot(myfit)
hold on
plot(x,RMS,'bo');
title('Rabufetti')
hold on
coeff =coeffvalues(myfit);
k=coeff(1);
T=coeff(2);
Yinf=coeff(3);
Stab_time=3*T;
plot(myfit, 'r')
ylim([0 .5])

% 'delete' all data before the point where Fz goes below BW
 t0=t(BelowBWPosition:n);
 t0_Fz=Fz(BelowBWPosition:n);
 t0_COPx=COPx(BelowBWPosition:n);
 t0_COPy=COPy(BelowBWPosition:n);
 t0_n=length(t0_Fz);
 T3=find(t0>3*T,1, 'first');

% COP redesignation -- before stabilization in mm
 COPx1=t0_COPx(1:T3)*1000;
 COPy1=t0_COPy(1:T3)*1000;
 t1=t0(1:T3);

% COP redesignation -- after 10 s and make in mm
 COPx2=COPx(1000:end)*1000;
 COPy2=COPy(1000:end)*1000;
 t2=t(1000:end);
 n=length(t2);

% COP parameters after stabilization

% posturography parameters after stabilization reached

% Shifts graph to 0
 x_bar = mean (COPx2);
 y_bar = mean(COPY2);
for ii = 1: length(COPx2)
    y_n(ii) = COPy2(ii) - y_bar;
    x_n(ii) = COPx2(ii) - x_bar;
end

COPy2=y_n;
COPx2=x_n;

% A/P Sway Range (mm)
AP_Sway = abs(max(COPy2) - min(COPy2));

% M/L Sway Range (mm)
ML_Sway = abs(max(COPx2) - min(COPx2));

%Mean Velocity (mm/s)
Mean_Vel_loop = 0;
for ii = 1:length(COPx2)-1;
    Mean_Vel_loop = Mean_Vel_loop + (sqrt((COPx2(ii+1)-...
    COPx2(ii))^2+(COPy2(ii+1)-COPy2(ii))^2));
end

Mean_Vel = (Mean_Vel_loop/(max(t2)-min(t2)));

% RMS (mm)
RMS = sqrt((sum(COPy2.^2+COPx2.^2))/n);

%Confidence Ellipse
sig_x = sqrt((sum(COPx2.^2))/n);
sig_y = sqrt((sum(COPy2.^2))/n);
sig_xy = (sum(COPx2.*COPy2))/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));
CI = a*b*pi;
x1 = EigV(1,1);
x2 = EigV(2,1);

% Angular deviation from AP Sway (deg)
theta_dev = acosd(x1/sqrt(x1^2 + x2^2))-180;

% Mean Frequency (Hz)
MF = Mean_Vel/(2*pi*sum(sqrt(COPx2.^2+COPy2.^2))/n);

% M/L Mean Velocity (mm/s)
ML_Vel_loop = 0;
for ii = 1:length(COPx2)-1;
    ML_Vel_loop = ML_Vel_loop + (sqrt((COPx2(ii+1)-...
    COPx2(ii))^2));
end

ML_V = (ML_Vel_loop/(max(t2)-min(t2)));

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% AP Mean Velocity (mm/s)
AP_Vel_loop = 0;
for ii = 1:length(COPx2)-1;
    AP_Vel_loop = AP_Vel_loop + (sqrt((COPy2(ii+1)-COPy2(ii))^2));
end

AP_V = (AP_Vel_loop/(max(t2)-min(t2)));

% stance percentage (weight symmetry)
FzR1= Matr(:,2);
FzR=FzR1(T3:n);
FzL1=Matr(:,5);
FzL=FzL1(T3:n);
sub=FzR-FzL;
zcount=0;
Rcount=0;
Lcount=0;
for j=1:length(sub)
    if sub(j) == 0
        zcount=zcount+1;
    elseif sub(j) > 0
        Rcount=Rcount+1;
    else
        Lcount=Lcount+1;
    end
end

total=zcount+Rcount+Lcount;
P_R=Rcount/total;
P_L=Lcount/total;

output(i,:) = [k T Yinf Stab_time AP_Sway ML_Sway Mean_Vel RMS CI ML_MV AP_MV P_R P_L];
clearvars -except output i FileName directory_name output_name files end

%output data in an excel file
header={'Filename' 'k' 'T' 'Yinf' 'Stab_time' 'AP_Sway' 'ML_Sway' 'Mean_Vel' 'RMS' 'CI' 'ML_MV' 'AP_MV' 'P_R' 'P_L'};
range=['A2:A',num2str(length(files)+1)];
xlswrite([directory_name output_name],header,'A1:N1')
xlswrite([directory_name output_name],FileName,range)
range2=['B2:N',num2str(length(files)+1)];
xlswrite([directory_name output_name],output,range2)
Batched Sample Entropy
This code was used to calculate the sample entropy values reported in aim 3. Appendix D provides a comprehensive breakdown of how to use this code and what it does.

% SampEn Code
% This code will batch run COP data and is currently set up for text files
% where the 11 and 12 columns contain the COPx and COPy data respectively.

clear all
close all
clc

% Set m, vector size, and r factor, for tolerance size
m = 2;
rf=.2;

% Manually change the name of how you want your excel spreadsheet to save
output_name='SampenOutput1027';

% Select Folder where trials are saved as text files
directory_name=uigetdir(pwd,'Select data directory');
directory_name=[directory_name '\'];
% make text for final data collection
files=dir([directory_name, '*.csv']);
if isempty(files)
    msgbox('No raw files in this directory')
end

% Batching

% Build placeholder matrix for all sampen values for batching
output=zeros(length(files),2);
FileName=cell(length(files),1);

for i=1:length(files)
    % run a for loop for COPx and COPy vectors to get SampEn for both
    for j=1:2

        filename=files(i).name;
        data_all=load([directory_name filename]);
        data_all = csvread([directory_name filename],1,0);
        FileName(i,1)=filename;
        % Selects the COPx column on the first pass of the for loop, % and the COPy column on the second pass of the for loop (j = 1:2)
        % start reading file 10 seconds into data collection (way after
%stabilization
data=data_all(10000:end,j+14);
data=data_all(:,end-2+j);
%Downsamples data by a factor of 10%
%downsample by 20 to get to 50 Hz?
data=downsample(data,10);
%Sets the tolerance, r (When r =0.2, the tolerance level is within
%20% of the standard deviation of all step lengths within the entire
time series.);
r = rf*std(data);
%N = number of data points in the set
N = length(data);

%Initialize counters for m length vectors
%originally was length(data)-m-1 to get the 25
%vectors but removed the '-1' to drop the last vector
count_m_vectors = zeros(length(data)-m,1);
vector_count = 1;
m_vectors = zeros(length(data)-m,m);

%Breaks COP data into vectors of length m
%originally was vector_count <= length(data)-m-1 to get the 25
%vectors but removed the '-1' to drop the last vector
%want to have the same amount of comparisons
while vector_count <= length(data)-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,:),1,length(m_vectors),1);
    %determibe 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_pl_vectors = zeros(length(data)-m,1);
vector_count_pl = 1;
m_vectors_pl = zeros(length(data)-m,m+1);

% Get vectors of length m+1
while vector_count_p1 <= length(data)-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)
end

% Calculate probabilities
prob_m_vectors = matched_vectors/(vector_count-1);
prob_m_p1_vectors = matched_vectors_p1/(vector_count_p1-1);

% Calculate A and B
B = sum(prob_m_vectors)/(N-m);
A = sum(prob_m_p1_vectors)/(N-m);

%be consistant with Ramdani
Br=(1/2)*(N-m-1)*(N-m)*B;
Ar=(1/2)*(N-m-1)*(N-m)*A;
SampEn = -log(Ar/Br);
output(i,j)=SampEn;
clearvars -except output i j m rf directory_name output_name
files FileName
end
end

%output data in an excel file
header={'Filename' 'SampEn COPx' 'SampEn COPy'};
range=['A2:A',num2str(length(files)+1)];
xlswrite([{directory_name output_name},header,'A1:C1']
xlswrite([{directory_name output_name},FileName,range]
range2=['B2:C',num2str(length(files)+1)];
xlswrite([{directory_name output_name},output,range2)}]
Batched Limits of Stability (LOS) Assessment Center of Pressure (COP) Analysis

This program was used to calculate the maximum COP excursion during the LOS assessment. The program first downsamples and filters the COP data and then calculates the A/P and M/L COP excursions and outputs them in an excel program.

```matlab
% LOS analysis
% Written by Senia Smoot Reinert
clc; close all; clear all;

% Manually change the name of how you want your excel spreadsheet to save
output_name='LOS_traditional_data.xls';

directory_name=uigetdir(pwd,'Select data directory');
directory_name=[directory_name '\'];
files=dir([directory_name '*csv']);
if isempty(files)
    msgbox('No raw files in this directory')
end

% Batching
output=zeros(length(files),7);
FileName=cell(length(files),1);

for i=1:length(files)
    filename=files(i).name;
    data_all = csvread([directory_name filename],1,0);
    FileName{i,1}=filename;
    Matr = data_all(:,:);
    % transpose it to get it in the correct format
    % specify a downsampling rate, m
    m = 10;
    % Downsample the data
    Matr = downsample(Matr,m);
    % Assign column names
    t = Matr(:,1);
    Fz = Matr(:,8);
    COPx = Matr(:,15);
    COPy = Matr(:,16);

    % calculate N
    n = length(t);
    % Shifts graph to 0
    x_bar = mean (COPx);
```
y_bar = mean(COPy);

for ii = 1:length(COPx)
    y_n(ii) = COPy(ii) - y_bar;
    x_n(ii) = COPx(ii) - x_bar;
end

% apply 4th order low-pass Butterworth Filter
Fs = 1/mean(diff(t));
Fcutoff = 5;
fnorm = Fcutoff/(Fs/2);
[b,a] = butter(2,fnorm);
y_nF = filtfilt(b,a,y_n);
x_nF = filtfilt(b,a,x_n);

T = (max(t)-min(t));

% A/P Sway Range (cm)
% get equilibrium position to maximum (how much to each side)?
AP_Sway = abs(max(y_nF) - min(y_nF))*100;

% M/L Sway Range (cm)
ML_Sway = abs(max(x_nF) - min(x_nF))*100;

% RMS (cm)
% RMS = sqrt((sum(y_n.^2+x_n.^2))/n)*100;

% find center points for both vectors
x_initial = mean(x_nF(1:5));
y_initial = mean(y_nF(1:5));

distance=sqrt(abs(x_initial)^2+abs(y_initial)^2)*100;

% + max AP sway
% LOS-- negative means forward and when you lean left

% + max AP sway (- direction)
if y_initial < 0
    pos_maxAP=abs(min(y_nF))+y_initial;
else
    pos_maxAP=abs(min(y_nF))-y_initial;
end

% - in AP sway (+ direction)
if y_initial < 0
    neg_maxAP=abs(max(y_nF))+y_initial;
else
    neg_maxAP=abs(max(y_nF))-y_initial;
end

% - min ML sway (- direction)
if x_initial < 0

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neg_maxML = abs(min(x_nF)) + x_initial;
else
    neg_maxML = abs(min(x_nF)) - x_initial;
end

%+ max ML sway (+ direction)
if x_initial < 0
    pos_maxML = abs(max(x_nF)) + x_initial;
else
    pos_maxML = abs(max(x_nF)) - x_initial;
end

pos_maxAP = pos_maxAP * 100;
neg_maxAP = neg_maxAP * 100;
pos_maxML = pos_maxML * 100;
neg_maxML = neg_maxML * 100;

output(i,:) = [AP_Sway ML_Sway pos_maxAP neg_maxAP pos_maxML neg_maxML distance];
end

% output data in an excel file
header = {'Filename', 'AP Sway Range', 'ML Sway Range', 'pos_maxAP', 'neg_maxAP', 'pos_maxML', 'neg_maxML', 'distance'};
range = ['A2:A', num2str(length(files)+1)];
xlswrite(fullfile(directory_name, output_name), header, 'A1:H1')
xlswrite(fullfile(directory_name, output_name), FileName, range)
range2 = ['B2:H', num2str(length(files)+1)];
xlswrite(fullfile(directory_name, output_name), output, range2)
Batched Limits of Stability (LOS) Assessment OPAL Analysis

This program was used to calculate the jerk experienced by the chest and trunk sensors during the LOS assessment. It reads csv files and output an excel file.

% OPAL jerk and correlation code
% written by Senia Smoot Reinert
% edited by Dr. Allison Kinney

clc; close all; clear all;

% Manually change the name of how you want your excel spreadsheet to save
output_name = 'OPAL_LOS_48.xls';

% Select Folder where trials are saved as text files
directory_name = uigetdir(pwd,'Select data directory');
directory_name = [directory_name '\'];
files = dir(fullfile(directory_name, '*.csv'));
if isempty(files)
    msgbox('No raw files in this directory')
end

% Batching

% Build placeholder matrix for batching
output = zeros(length(files), 5);
FileName = cell(length(files), 1);

for i = 1:length(files)
    filename = files(i).name;
gait_data = csvread(fullfile(directory_name, filename), 1, 1);
FileName{i, 1} = filename;
Matr = gait_data(:, :);

% z+ is forward direction, z-, backwards (M/L rotation)
% y+ points LEFT, y-, RIGHT (A/P rotation)
% x(-) points down, x(+) points up

% Trunk angular velocity
thigh_acc_x = gait_data(:, 18);
thigh_acc_y = gait_data(:, 19);
thigh_acc_z = gait_data(:, 20);

% Thigh angular velocity
trunk_acc_x = gait_data(:, 49);
trunk_acc_y = gait_data(:, 50);
trunk_acc_z = gait_data(:, 51);
%calculate time (get frequency and multiple it by count);
frames=1:length(trunk_acc_y);
t=frames/128;

%Filter data with a fourth-order lowpass Butterworth filter (5 Hz cut-off)
Fs = 1/mean(diff(t));
Fcutoff = (5)/2;
fnorm = Fcutoff/(Fs/2);
[b,a] = butter(2,fnorm);
trunk_acc_x = filtfilt(b,a,trunk_acc_x);
trunk_acc_y = filtfilt(b,a,trunk_acc_y);
trunk_acc_z = filtfilt(b,a,trunk_acc_z);
thigh_acc_x = filtfilt(b,a,thigh_acc_x);
thigh_acc_y = filtfilt(b,a,thigh_acc_y);
thigh_acc_z = filtfilt(b,a,thigh_acc_z);

%plot M/L rotation for trunk (b) and thigh (r) segments
figure
subplot(3,1,1)
plot(t,thigh_acc_x, 'b', t,trunk_acc_x, 'r')
title('acc_x (vertical direction) thigh=blue, trunk=red')
hold on
subplot(3,1,2)
plot(t,thigh_acc_y, 'b', t,trunk_acc_y, 'r')
title('acc_y (A/P rotation-- left/right)')
hold on
subplot(3,1,3)
plot(t,thigh_acc_z, 'b', t,trunk_acc_z, 'r')
title('acc_z (M/L rotation--forward/backwards)')
hold on

%calculate jerk for thigh
%y
for ii=1:length(thigh_acc_y)-2
    thigh_jerk_y(ii) = (thigh_acc_y(ii+2)-thigh_acc_y(ii))/(t(ii+2)-t(ii));
end

%z
for ii=1:length(thigh_acc_z)-2
    thigh_jerk_z(ii) = (thigh_acc_z(ii+2)-thigh_acc_z(ii))/(t(ii+2)-t(ii));
end

%remove last 2 data points from time vector so it equals
thigh_jerk1,
%trunk_jerk1
tt=t(1:end-2);

%normalize thigh
%    n_thigh_jerk_z=thigh_jerk_z-mean(thigh_jerk_z);
%    n_thigh_jerk_y=thigh_jerk_y-mean(thigh_jerk_y);
%thigh jerk
thigh_jerk1 = ((thigh_jerk_y).^2+(thigh_jerk_z).^2);

%calculate jerk for trunk
%y
for ii=1:length(trunk_acc_y)-2
    trunk_jerk_y(ii) = (trunk_acc_y(ii+2)-trunk_acc_y(ii))/(t(ii+2)-t(ii));
end

%z
for ii=1:length(trunk_acc_z)-2
    trunk_jerk_z(ii) = (trunk_acc_z(ii+2)-trunk_acc_z(ii))/(t(ii+2)-t(ii));
end

%normalize trunk
%    n_trunk_jerk_z=trunk_jerk_z-mean(trunk_jerk_z);
%    n_trunk_jerk_y=trunk_jerk_y-mean(trunk_jerk_y);

%trunk jerk
trunk_jerk1 = ((trunk_jerk_y).^2+(trunk_jerk_z).^2);
trunk_jerk = (1/2)*trapz(tt,trunk_jerk1);

%plot thigh jerk
figure
plot(tt, thigh_jerk_z, 'b', tt, thigh_jerk_y, 'r')

%get correlations for acceleration
%x
regres_acc_x = corrcoef(thigh_acc_x, trunk_acc_x);
r_acc_x = regres_acc_x(1,2);

%y
regres_acc_y = corrcoef(thigh_acc_y, trunk_acc_y);
r_acc_y = regres_acc_y(1,2);

%z
regres_acc_z = corrcoef(thigh_acc_z, trunk_acc_z);
r_acc_z = regres_acc_z(1,2);

output(i,:) = [thigh_jerk trunk_jerk r_acc_x r_acc_y r_acc_z];

clearvars -except i files directory_name output_name header

%output data in an excel file
header = [{'filename' 'thigh_jerk' 'trunk_jerk' 'r_acc_x' 'r_acc_y' 'r_acc_z'}];
range = ['A2:A', num2str(length(files)+1)];
xlswrite([directory_name output_name],header,'A1:F1')
xlswrite([directory_name output_name],FileName,range)
range2 = ['B2:F', num2str(length(files)+1)];

%output is the matrix of the nymbers we want to put out
Batched Fast Fourier Transfer (FFT) Analysis
Runs a FFT to obtain the power spectral density plot for a dataset.

%Original Code by Dr. Nick Stergiou’s Lab, modified by Senia Smoot
%%Fourier Transform
close all; clc; clear;
%Get the data from the file and subtract the mean
[filename,path]=uigetfile('*.*.csv','CSV file');
%data=dlmread([path filename]);
directory_name=uigetdir(pwd,'Select data directory');
directory_name=(directory_name '\');
data= csvread([directory_name filename],10000,10);
%Prompt User to Enter Sampling Frequency
% prompt = {'Enter Sampling Frequency'};
% dlg_title = 'Enter Sampling Frequency';
% num_lines = 1;
% def = {'60'};
% answer = inputdlg(prompt,dlg_title,num_lines,def);
% Fs = str2double(answer{1});
%Set the sampling frequency of the data
Fs = 1000;
%Calculate the FFT
T = 1/Fs;
L = length(data);
t = (0:L-1)*T;
NFFT = 2^nextpow2(L);
Spect = fft(data,NFFT)/L;
f = Fs/2*linspace(0,1,NFFT/2+1);
data2=2*abs(Spect(1:NFFT/2+1));
% Plot Power Spectrum
bar(f,data2)
axis([0 20 0 (max(abs(data2)))])
title('PowerSpectra using fft function')
xlabel('Frequency (Hz)')
ylabel('Power')
**Batched Surrogation Analysis Code**

This program was used to test the validity of the sample entropy analysis. This program generates 19 randomly scrambled data sets so they can be run through the sample entropy program. The 19 random values should be significantly different from the 1 ‘real’ value.

```matlab
%%
% Program for producing Phase randomized surrogate time series.
% Original Code by Dr. Nick Stergiou’s Lab, modified by Senia Smoot
clc; close all; clear all;

[filename,path]=uigetfile('*.csv','CSV file');
directory_name=uigetdir(pwd,'Select data directory');
directory_name=[directory_name \ ']
balance_data= csvread([directory_name filename],1,0);
balance_data=balance_data(1:end,:);

% output=zeros(length(balance_data),2);
% FileName=cell(length(filename),1);

for f=1:19
    for j=1:2

        %Manually change the name of how you want your excell spreadsheet to save
        output_name=[filename '_Surg' num2str(f)];

        %Selects the COPx column on the first pass of the for loop, and the COPy column on the second pass of the for loop (j = 1:2)
        data=balance_data(:,j);
        %Downsamples data by a factor of 10%
        s=data;

        %Length of data
        N=length(s);
        %Imaginary number
        im=sqrt(-1);
        %Define pi
        twopi=2*pi;
        %Round each element toward zero
        half=fix((N+1.1)/2);

        %Take the fast fourier transform of the original data
        z=fft(s);
        %Loop for half the data
        for i=2:half;
            r=rand*twopi;
            z(i)=z(i)*(cos(r)+im*sin(r));
        end
```

83
for i=2:half
    z(N+2-i)=conj(z(i));
end
zz=ifft(z);
%take the real part of a complex number for the series
output(:,j)=real(zz);
end

%output data in an excel file
outputname=strcat(filename,'_Surg',num2str(f),'.txt');
save (outputname, 'output', '-ascii')

%output data in an excel file
% header={'Filename' 'COPx' 'COPy'};
% range=['A2:A',num2str(length(filename)+1)];
% xlswrite([directory_name output_name],header,'A1:C1')
% xlswrite([directory_name output_name],FileName,range)
% range2=['B2:C',num2str(length(files)+1)];
% xlswrite([directory_name output_name],output,range2)
end
APPENDIX B
SAMPLE ENTROPY MATLAB CODE
INSTRUCTIONAL GUIDE

Code name: SampEn

Instructional Guide for using the Sample Entropy Code.

Pre-running checks:

- This code requires “.txt” files. The code is written to work with files from Acquire 4 software.
- This code is currently set up to run COP files with 12 data inputs (in columns). This can be changed on line 39 (data=data_all(:,j+10);) if your data is saved differently.
- This code runs batch samples – i.e. it will run every text file in the selected folder and output an excel spreadsheet in the same directory as the files with the COPx and COPy Sample Entropy (SampEn) values for each file.
- The name of the excel spreadsheet can be changed by altering the quotes text in ‘output_name=’Subject1_SampenOutput’ on line 15
- You need to specify your m and r values (on lines 11 and 12). The code is sent to run the default m=2 and the r factor=.2, common choices for clinical data. The r factor is than multiplied with the standard deviation of the data set to get r.
- Code set up to downsample data by a factor of 10 (line 40).
- Add comments to code

Steps: Run SampenDayton code. This code opens the data files, selects the correct column of data to be analyzed, calculates Sampen for both COPx and COPy data, and outputs the values in an excel spreadsheet.

Breakdown of code logic:
<table>
<thead>
<tr>
<th>Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>m = 2;</code></td>
<td>User can specify <code>m</code> and <code>r</code> values</td>
</tr>
<tr>
<td><code>rf=.2;</code></td>
<td></td>
</tr>
<tr>
<td><code>output_name='Subject1_SampenOutput';</code></td>
<td>User can rename name of excel file with outputs</td>
</tr>
<tr>
<td><code>directory_name=uigetdir(pwd,'Select data directory');</code></td>
<td>User selects folder with text files to analyze</td>
</tr>
<tr>
<td><code>directory_name=[directory_name '\'];</code></td>
<td></td>
</tr>
<tr>
<td><code>files=dir([directory_name,'*txt']);</code></td>
<td></td>
</tr>
<tr>
<td><code>if isempty(files)</code></td>
<td></td>
</tr>
<tr>
<td><code>msgbox('No raw files in this directory')</code></td>
<td></td>
</tr>
<tr>
<td><code>end</code></td>
<td></td>
</tr>
<tr>
<td><code>output=zeros(length(files),2);</code></td>
<td>Creates a place holder matrix for all sampen values for batching</td>
</tr>
<tr>
<td><code>FileName=cell(length(files),1);</code></td>
<td></td>
</tr>
<tr>
<td><code>data=data_all(:,j+10);</code></td>
<td>Selects the COPx column on the first pass of the for loop, and the COPy column on the second pass of the for loop (j = 1:2)</td>
</tr>
<tr>
<td><code>data=downsample(data,10);</code></td>
<td>Downsamples data by a factor of 10</td>
</tr>
<tr>
<td><code>r = rf*std(data);</code></td>
<td>Sets the tolerance, <code>r</code> (When <code>r = 0.2</code>, the tolerance level is within 20% of the standard deviation of all step lengths within the entire time series.)</td>
</tr>
<tr>
<td><code>N = length(data);</code></td>
<td><code>N = number of data points in the set</code></td>
</tr>
<tr>
<td><code>count_m_vectors = zeros(length(data)-m+1,1);</code></td>
<td>Initializes counters for ‘m’ length vectors</td>
</tr>
<tr>
<td><code>vector_count = 1;</code></td>
<td></td>
</tr>
<tr>
<td><code>m_vectors = zeros(length(data)-m+1,m);</code></td>
<td></td>
</tr>
<tr>
<td><code>while vector_count &lt;= length(data)-m+1</code></td>
<td></td>
</tr>
<tr>
<td>`m_vectors(vector_count,:) = data(vector_count:vector_count+m-1,1)'</td>
<td></td>
</tr>
<tr>
<td><code>vector_count = vector_count + 1;</code></td>
<td></td>
</tr>
<tr>
<td><code>end</code></td>
<td></td>
</tr>
</tbody>
</table>
matched_vectors=zeros(N-m+1,1);

for vector_count = 1:length(m_vectors)
    vector_to_match=repmat(m_vectors(vector_count,:), length(m_vectors), 1);
    comparisons =(abs(vector_to_match-m_vectors)<= r);
    matches = all(comparisons,2);
    matched_vectors(vector_count,1) =sum(matches)-1;
end

while vector_count_p1 <= length(data)-m
    m_vectors_p1(vector_count_p1,:) =
    data(vector_count_p1:vector_count_p1+m,1)';
    vector_count_p1 = vector_count_p1 + 1;
end

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

prob_m_vectors = matched_vectors/(vector_count-1);
prob_m_p1_vectors = matched_vectors_p1/(vector_count_p1-1);

Builds an empty matrix for the vectors that are matches

Identifies the matches for vectors of length m. m_vectors are each pre-defined vector in the data set, and the vectors_to_match is a vector comprised entirely of the vector currently being matched. Vectors_to_match is then subtracted from m_vectors, the absolute value is then taken, and if it is within tolerance, r, it is stored as a match. The number of matches are stored in matched_vectors (1 value is subtracted to account of a self-match).

Repeats the same steps for ‘m+1’ vectors that are used for ‘m’ size vectors

Calculates the
\( C_i^m = \frac{\text{Vectors of } m \text{ within tolerance } r}{\text{Total vectors compared}} \)

\( C_i^{m+1} = \frac{\text{Vectors of } m + 1 \text{ within tolerance } r}{\text{Total vectors compared}} \)

\( B^m(r) = C_1^m, C_2^m, C_3^m, \ldots, C_{N-m}^m \)

\( A^m(r) = C_1^{m+1}, C_2^{m+1}, C_3^{m}, \ldots, C_{N-m}^{m+1} \)

\( B^m(r) = \frac{C_1^m + C_2^m + C_3^m + \ldots + C_{N-m}^m}{N - m} \)

\( A^m(r) = \frac{C_1^{m+1} + C_2^{m+1} + C_3^m + \ldots + C_{N-m}^{m+1}}{N - m} \)

\( \text{SampEn}(m, r, N) = -\log \left( \frac{A^m(r)}{B^m(r)} \right) \)
APPENDIX C

CONSENT FORM, QUESTIONNAIRE, DATA COLLECTION SHEETS, RECRUITMENT FLYER

UNIVERSITY OF DAYTON - CONSENT TO PARTICIPATE IN RESEARCH

TITLE OF STUDY: Identification of More Discriminative Posturography Protocols to Better Identify Older Adults’ Fall Risk: Phase II

We are inviting you to be a part of a research study led by Senia Smoot Reinert at the University of Dayton. Your participation in this study is voluntary. Please review the information below to learn more about the study. Before participating, ask questions about anything you do not understand.

PURPOSE OF THE STUDY

The aim of this study is to identify better ways to measure balance of older adults to indicate that someone is at higher risk of falling.

PROCEDURES

If you decide to be a part of this study, please do the following:

1. You will answer a few questions concerning your health.
2. You will be asked questions to measure your ability to think and remember.
3. You will be asked questions about your history of falls.
4. You will be asked questions regarding your daily activity levels.
5. You will fill out a form answering questions about how confident you are in your balance during tasks that you do every day.
6. You will have your height, weight, and age recorded.

7. You will step up onto a balance plate (similar in look and function to a bathroom scale) and have your balance measured while you stand as still as possible for 70 seconds. You will repeat this 3 times on the flat plate and on a foam pad placed on the flat plate.

8. You will stand on the force plate and have your balance measured as you lean forward, backwards, and side to side.

9. You will wear two small sensors around your chest and lower back or mid-thigh. They will be attached by an elastic strap and worn over your clothing.

You can rest as much as you would like during testing. Testing will take approximately 30-45 minutes to complete.

Several of the tests above that involve physical contact will be performed by a female researcher. If you would prefer a male researcher please let me know so that I can meet your request.

In order to participate in this study, you must be at least 60 years old. You must be able to walk 50 feet unassisted, be able to stand without assistance for 5 minutes, and not require the use of a lower limb brace ankle/foot orthotic (AFO) or a lower limb prosthesis.

POTENTIAL RISKS AND DISCOMFORTS

There may be a risk of losing your balance or falling during testing. To lower this risk you will wear a gait belt that a researcher can use to help slow your fall. You will also be spotted by a researcher during each test and the balance plate will be positioned so you can use a wall for support if needed.

There is also a risk you may become fatigued during this study. You will get a break halfway through data collection, but additional breaks may be taken as needed. Please inform the researcher if you feel the need to take a break.

ANTICIPATED BENEFITS TO PARTICIPANTS

There are no direct benefits to you. It is hoped that the findings of this study will aid in the decrease of falls in older adults by developing a better clinical screening methodology.
PAYMENT FOR PARTICIPATION

There is no payment for participation in this study.

IN CASE OF RESEARCH RELATED INJURY

If you become ill or are injured as a result of this study, you should seek medical treatment through your doctor or treatment center of choice. You agree to promptly tell the Principal Investigator about any illness or injury: Senia Smoot Reinert at 304-533-6378. You do not waive any liability rights for personal injury by signing this form.

CONFIDENTIALITY

When the results of the research are published or discussed in conferences, no information will be included that would reveal your identity. Photographs may be taken during testing and used in presentations or publications about this research with your permission. We will make every effort to protect your identity using techniques such as blurring or blacking out any identifying features. Nevertheless, use of these recordings does increase the risk that your identity may be compromised. No records of helping in this research will be shared with others. Your personal information and results will also not be shared with others.

PARTICIPATION AND WITHDRAWAL

Your participation in this research is voluntary. If you choose not to participate, that will not affect your relationship with The University of Dayton or other services to which you are otherwise entitled. If you decide to participate, you are free to withdraw your consent and discontinue participation at any time without prejudice or penalty. The investigator may withdraw you from participating in this research if circumstances arise which warrant doing so.

IDENTIFICATION OF INVESTIGATORS

Please contact one of the investigators listed below if you have any questions about this research.

Senia Smoot Reinert, Principal Investigator, University of Dayton, Mechanical and Aerospace Engineering Department, 304-533-6378, smoots1@udayton.edu

Dr. Kimberly Bigelow, Faculty Advisor, University of Dayton, Mechanical and Aerospace Engineering Department, 937-229-2918, kbigelow1@udayton.edu.
RIGHTS OF RESEARCH PARTICIPANTS

You may contact the Chair of the Institutional Review Board (IRB) at the University of Dayton if you have questions about your rights as a research participant: Dr. Mary Connolly, (937) 229-3493, Mconnolly1@udayton.edu.

SIGNATURE OF RESEARCH PARTICIPANT (or legal guardian)

I have read the information above. I have had a chance to ask questions and all of my questions have been answered to my satisfaction. I have been given a copy of this form. I certify that I am at least 18 years of age.

Name of Participant (please print)
____________________________________________

Address
_____________________________________________________________________

Signature of Participant ___________________________________________ Date___________

SIGNATURE OF WITNESS

My signature as witness certifies that the Participant signed this consent form in my presence.

Name of Witness (please print)
____________________________________________________

Signature of Witness __________________________________________ Date___________

(Must be same as participant signature date)
CONSENT TO USE IMAGES OR RECORDINGS FROM RESEARCH

I consent and give permission for the researcher to use photographs taken during the course of this research. My identity will be protected or disguised by the researcher prior to publication or use in presentations of their results. By signing below, I confirm that I understand that these images may compromise the confidentiality of my participation in this research. You may still participate in this research if you do not allow the use of your photos.

Name of Participant (please print)
_____________________________________________

Address
_____________________________________________________________________

Signature of Participant
___________________________________________ Date___________
UNIVERSITY OF DAYTON – FALL HISTORY AND HEALTH

QUESTIONNAIRE

Subject Code: _________________________________

Age: _________________________________

Height: _______________________________

Gender:  M  F

Testing Facility Name: __________________________________________________________

Testing Facility Type: __________________________________________________________

Have you fallen in the past year, with a fall being defined as any time you come to rest on a lower surface unintentionally, including slips, trips, falling down the stairs:  YES  NO

If yes, how many falls have you had in the past year?

If yes, did any of these falls occur in the past 6 months?

If yes, where did the fall(s) happen?

If yes, please describe the circumstances when the fall(s) occurred.

If yes, please describe any injuries you may have incurred.

Does you have any of the following? (Check all that apply)

___ 1. Any diagnosed balance disorders, such as inner ear problems, ear infections, crystals in your ears (BPPV), or vertigo

___ 2. Any known neurological disorders, such as Multiple Sclerosis or Parkinson’s Disease

___ 3. Any orthopedic disorders (such as arthritis) or muscle weakness that affects your balance or walking

___ 4. Balance problems when standing

___ 5. Balance problems when walking

___ 6. Seizures in the last year

___ 7. Fainting or persistent dizziness within the last year
8. Dizziness when you stand up too quickly
9. Visual problems other than need for glasses/contacts
10. Numbness of the feet
11. Any total joint replacements
12. Any lower leg surgery that affected your balance or walking post-surgery
13. Any lower leg surgery that still affects your balance or walking today
14. A stroke
15. Use a mobility aid (walker, cane, etc.)
16. Taking 4 or more medications
17. Do any of your medications come with a warning to avoid driving/operating heavy machinery after taking?
18. Do any of these make you noticeably sleepy or dizzy?

Physical Activity Questions:
20. Have you seen a PT in the last year that included a focus on improving balance or how you walk
21. Have you participated in fall prevention training (i.e. Matter of Balance, etc.) during the last year
22. Describe your weekly physical activities: NONE/LIGHT/MODERATE INTENSE
23. Days/minutes each week do you do these activities: ________/_________
24. Do you do activities to increase muscle strength once a week or more: YES NO
25. Do you do activities to increase flexibility once a week or more: YES NO
Participan Code: __________________________
Date: __________________________

Circle One:  NON-FALLER  Faller

Circle One:  MALE  FEMALE

CHECK WHEN COMPLETE:

_____ 1. Consent Form

_____ 2. Fall History Survey

_____ 3. Activities Specific Balance Confidence Test

_____ 4. Height ___________  Weight ___________ Age ___________

<table>
<thead>
<tr>
<th>Order</th>
<th>Trial Name</th>
<th>Testing Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>STEP_FLAT_1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>STEP_FLAT_2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>STEP_FLAT_3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>STEP_BLUE_1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>STEP_BLUE_2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>STEP_BLUE_3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>LOS_FLAT_1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>LOS_FLAT_2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>LOS_FLAT_3</td>
<td></td>
</tr>
<tr>
<td>LOS_BLUE_1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LOS_BLUE_2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LOS_BLUE_3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Volunteers Needed For Fall Prevention Research

We are looking for volunteers for a balance study. As a participant in this study, your balance and/or walking would be measured by University of Dayton researchers. Fallers (individuals who have fallen in the past year) and non-fallers are being sought.

Looking for adults:

- Ages 60+ years of age
- Who can stand unassisted for 5 minutes
- Who can walk unassisted for 50 feet
- Who do not require the use of a lower limb brace, orthotic, or prosthesis

This is a one-time study and testing sessions will last 30-45 minutes. Tests can be scheduled at your convenience. Participation is voluntary.

Please contact Senia Smoot Reinert at XXX-XXX-XXX or Renee Beach Sample at XXX-XXX-XXX for information

Thank you!

Image: http://campus.udayton.edu/~rugbym/redbluep1.gif
APPENDIX D
TIME TO STABILIZATION, STEP TIME, AND QUIET STANDING FINDINGS

While the main focus of the time to stabilization research was to improve the currently published methodology and investigate its application to older adult data, differences between older adult fallers and non-fallers were also investigated, for both the time to stabilization and the minute of quiet standing data that followed the completion of the step. This appendix contains the results of these evaluations and some author thoughts on the implications of these results.

Table 1: Stabilization Times According to Fall Status on Foam and Flat Surface

<table>
<thead>
<tr>
<th></th>
<th>Firm Plate</th>
<th>Foam Pad</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fallers</td>
<td>Non-fallers</td>
</tr>
<tr>
<td>Stabilization Time (&gt;10s)</td>
<td>5.042± 2.17 (^b)</td>
<td>5.070 ± 1.741 (^b)</td>
</tr>
<tr>
<td>Stabilization Time (&lt;10s)</td>
<td>15.55± 1.26</td>
<td>12.21±1.76</td>
</tr>
</tbody>
</table>

\(^a\) denotes significance between groups (p > .05)

\(^b\) denotes significance differences between flooring type (p > .05)

There were no significant differences between fallers and non-fallers regarding stabilization time for both groups but there were significant differences between
stabilization times on the respective flooring types for the group who stabilized within the first 10 seconds. Traditional outcome measures and nonlinear measures of variability were calculated for the participants who all stabilized in the first 10 seconds (Table 2). Those who took longer to stabilize were not included in this analysis to remove any additional sway artifact caused by the participants still undergoing stabilization.

**Table 2:** Posturography Parameters for 60 seconds of Quiet Standing According to Fall Status on Foam and Flat Surface

<table>
<thead>
<tr>
<th></th>
<th>Firm Plate</th>
<th>Foam Pad</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fallers</td>
<td>Non-fallers</td>
</tr>
<tr>
<td><strong>A/P Sway Range</strong></td>
<td>42.496± 13.92</td>
<td>39.518± 11.69</td>
</tr>
<tr>
<td><strong>M/L Sway Range</strong></td>
<td>19.822± 6.33&lt;sup&gt;a&lt;/sup&gt;</td>
<td>19.860± 6.71&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td><strong>Mean Velocity</strong></td>
<td>21.279± 7.88</td>
<td>22.511± 11.08</td>
</tr>
<tr>
<td><strong>RMS</strong></td>
<td>8.227± 2.39&lt;sup&gt;a&lt;/sup&gt;</td>
<td>7.723± 1.94&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td><strong>95% CI</strong></td>
<td>311.846± 169.9&lt;sup&gt;a&lt;/sup&gt;</td>
<td>274.445± 132.05&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td><strong>SampEnX</strong></td>
<td>.096± 0.039&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.104± 0.047&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td><strong>SampEnY</strong></td>
<td>0.125± 0.046&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.144± 0.060&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
</tbody>
</table>

<sup>a</sup> denotes significance between groups (p > .05)

There were significant differences between groups in the 60 seconds of quiet standing. On both surfaces, fallers demonstrated significantly different M/L sway ranges than non-fallers (p=.044), larger RMS values (p=.030), larger sway areas on both surfaces (p=.036), and smaller M/L and A/P SampEn (p=.013, p=.038) Surface type
significantly affected all parameters (p=.000-.004) except stabilization time and A/P sample entropy.

The correlation analysis indicated highly significant (p<.001) weak to moderate negative correlations between stabilization time and the five traditional posturography outcome parameters. Correlations ranged from -.271 to -.306 with mean velocity having the strongest correlation coefficient.

**Implications of these findings**

The objective of this research was to explore the use of stabilization time as calculated by Rabufetti et al.’s could serve as a tool to differentiate between fallers and non-fallers and if there were any correlations between stabilization time and subsequent postural control during quiet standing. To address this objective, the time it took for an older adult to stabilize after taking a step and analyzing postural sway parameters as individuals stood quietly for a minute were calculated. The findings of this study indicate that there does not appear to be differences in stabilization time between older adult fallers and non-fallers but that there were some weak to moderate correlations between stabilization time and the posturography parameters. Finally, during the period of quiet standing, significant differences did occur between fallers and non-fallers.

One explanation for the lack of significance between the stabilization time of fallers and non-fallers could be the fact that the stepping speed was not controlled for—stabilization time could have been affected by how slowly participants took the step onto the plate, allowing for a less stable participant to potentially compensate by stepping more carefully. Fallers may have taken the step slower than non-fallers, causing their
results to be appear much more similar than they would have been otherwise. Other than controlling for stepping time, only a MATLAB function was used to fit the negative exponential curve to the data, there could be potential methods to improve the fit and thus more accurately determine stabilization time.

It did appear that there would be a relationship between stabilization time and the postural parameters, however the correlations were negative rather than positive. Although it was a weak to moderate degree of correlation, the results indicate that the faster the stabilization time, the less posturally stable individuals were during the 60 second period of quiet standing. This further supports the theory that fallers were being more deliberate while stepping and thus stabilizing fast enough to be undistinguishable from non-fallers; and that those who likely completed the step faster, and thus took longer to stabilize, were actually more stable overall as determined by the quiet standing outcome parameters. It was notable that stabilization correlated only with the traditional posturography parameters and not any of the measures of complexity calculated for this study. The reason for this is unknown but it is possible that the underlying postural control strategies for stabilizing after a movement are inherently different than those utilized to maintain upright posture.

Several of the traditional posturography parameters during the 60 second quiet standing trial did differentiate between fallers and non-fallers. These parameters included M/L sway, RMS, and 95% CI on both the flat and foam surfaces. When compared to published literature, Stel et al. also identified significant differences between the M/L sway range of fallers and non-fallers and Bigelow found significant differences in a related variable, M/L velocity, between the two groups during quiet standing. Maki et al.
also found sway range was a significantly different between fallers and non-fallers. The increased sway range, RMS, and sway areas demonstrated by the fallers when compared to their non-fallers counterparts indicate a lesser degree of stability. The decrease in postural stability of the participants in the study supports current understanding of factors that lead to a fall in older populations. As the difference in M/L sway range was more pronounced on the foam surface, continuing to use foam could improve the clinical utility of a fall screening test. This is further supported by Anacker et al. who found that on a complaint surface fallers had a decreased stance duration when compared to non-fallers.

Fallers also demonstrate decreased predictability as measured by SampEn on both surfaces in comparison to non-fallers, indicating they are swaying in a more periodic and less complex fashion, and that they would be less able to react to environmental changes. Potentially, therapy could be used to improve the level of complexity/adapability. Gatts et al. found that Tai Chi significantly enhanced trip prevention strategies among sensory impaired older adults. Therefore, the authors recommend therapy efficacy studies begin incorporating nonlinear measures of complexity into their analysis approached to determine if the effect goes beyond fall prevention strategies to the underlying complexity of the postural control system. In conclusion, the authors recommend further exploring the use of Rabufetti et al.’s stabilization time method, with the caveat that it is worth exploring ways to measure the success of the curve fit and introducing methodologies such as incorporating a metronome into testing to ‘force’ participants to step at the same rate. The authors also think it is worth further looking into the relationship between stabilization time and subsequent postural control measures.