BALANCE CONTROL AND STABILITY DURING GAIT - AN EVALUATION OF

FALL RISK AMONG ELDERLY ADULTS

by

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Falls are a significant source of physical, social, and psychological suffering
among elderly adults. Falls lead to morbidity and even mortality. Over one-third of
adults over the age of 65 years will fall within a calendar year, with almost 10,000 deaths
per year attributed to falls. The direct cost of falls exceeds $10 billion a year in the
United States. Fall incidents have been linked to multiple risk factors, including
cognitive function, muscle strength, and balance control. The ability to properly identify
balance impairment is a tremendous challenge to the medical community, with accurate
assessment of fall risk lacking. Therefore, the purpose of this study was to assess balance
control during gait among young adults, elderly adults, and elderly fallers; determine
which biomechanical measures can best identify fallers retrospectively; demonstrate
longitudinal changes in elderly adults and prospectively assess fall risk; and provide a
method for mapping clinical variables to sensitive balance control measures using
artificial neural networks.

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The interaction of the whole body center of mass (CoM) in relation to the base of support (BoS) assessed static and dynamic balance control throughout gait. Elderly fallers demonstrated reduced balance control ability, specifically a decreased time to contact with the boundary of the BoS, when compared to young adults at heel strike. This decreased time might predispose older adults to additional falls due to an inability to properly respond to perturbations or slips.

Inclusion of these balance control measures along with the Berg Balance Scale and spatiotemporal measures demonstrated sensitivity and specificity values of up to 90% when identifying 98 elderly fallers and non-fallers, respectively. Additionally, 27 older adults were followed longitudinally over a period of one year, with only the interaction of the CoM with the BoS demonstrating an ability to differentiate fallers and non-fallers prospectively.

As the collection and analysis of these biomechanics measures can be time consuming and expensive, an artificial neural network demonstrated that clinical measures can accurately predict balance control during ambulation. This model approached a solution quickly and provides a means for assessing longitudinal changes, intervention effects, and future fall risk.

This dissertation includes both previously published and unpublished co-authored material.

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Klausmeier, V., Lugade, V., Collis, D., Jewett, B., Chou, L-S. *Is There Faster Recovery with an Anterior or Anterolateral THA? A Pilot Stody.* Clin Orthop Relat Res, 2010. 468(2):533-541.

Silsupadol, P., Lugade, V., Shumway-Cook, A., van Donkelaar, P., Chou, L-S., Mayr. U., Woolacott, M. *Training-related Changes in Dual-task Walking Performance of Elderly Persons with Balance Impairment: A Double-blind, Randomized Controlled Trial.* Gait Posture, 2009. 29(4):634-9.

Silsupadol, P., Shumway-Cook, A., Lugade, V., van Donkelaar, P., Chou, L-S., Mayr. U., Woolacott, M. *Effects of Single- vs. Dual-task training on Balance Performance in Older Adults: A Double-blind, Randomized Controlled Trial.* Arch Phys Med Rehab, 2009. 90(3):381-7.

Lugade, V., Klausmeier, V., Jewett, B., Collis, D., Chou, L-S. *Short-term Recovery of Balance Control after Total Hip Arthroplasty.* Clin Orthop Relat Res, 2008. 466(12):3051-8.

Siu, K.C., Lugade, V., Chou, L-S.,van Donkelaar, P., Woollacott, M. *Dual-task Interference During Obstacle Clearance in Healthy and Balance-impaired Older Adults.* Aging Clin Exp Res, 2008. 20(4): p. 349-54.

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CHAPTER I

INTRODUCTION

With increasing age, risk of falling among elderly adults becomes a major health concern. A fall, which is often defined as unintentionally coming to the ground or some lower level as the consequence of something other than the impact of a violent blow, loss of consciousness, or sudden onset of paralysis (as in stroke or an epileptic seizure), can lead to fracture, reduced level of activity, fear of future falls and even death.[1] Although falls are often considered accidents, researchers now believe that falls occur due to causal events and are not just due to random chance.

Studies have shown that almost one-third of adults 65 years or older have experienced one or more falls.[2-4] Incidence of falling increases with age, as 40% of adults over the age of 80 report a fall event.[5-7] Falling can occur at any time or place for elderly persons, as studies have shown that 50% of falls occur within the home or in the immediate vicinity of the home. A small number of falls occur in the bathroom or on stairs, while the most common location is on level surfaces in commonly used rooms.[1]

Not only are falls common, but they have often been associated with mortality and serious morbidity.[6, 8] Falls may lead to further complications and injuries, resulting in immobility, restrictions in life style and a decrease in the quality of life of an elderly person. After suffering a fall, elderly persons have demonstrated a likelihood of falling again, impacting their physical, psychological and social lifestyle, due to a correlated reduction in activity that frequent fallers tend to exhibit.[1, 2, 9] Among adults 65 years of age or older, almost 9500 deaths per year can be attributed to falling, with hip injuries

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being the leading cause of mortality.[1, 9] The direct cost of falling exceeds $10 billion a year in the United States, with treatment of hip fractures accounting for $35,000 per patient.[1, 3]

Falls are a complicated phenomenon comprising both intrinsic and extrinsic risk factors. Intrinsic factors, or those related to the individual, include a decreased performance in the balance control system, with loss of mobility being a strong indicator for increasing fall risk.[10] In order to maintain stability, adequate levels of vision, vestibular function, musculoskeletal function and proprioception are all required. Prior studies have shown that decreased lower-extremity muscle strength and cognitive function are significant predictors of falls among older adults.[10-12] Extrinsic factors, or those pertaining to environmental hazards, contribute to the majority of falls and can include objects to trip over, poor lighting, slippery surfaces or inappropriate furniture.[9] Often, the frailty of the individual can determine the susceptibility of falls occurring over even the most minor of hazards, with older frail adults encountering serious hazards from long pant legs or ill-fitting shoes. In addition, experience with an environmental factor can modify the risk of falling among the elderly (i.e. practiced stair climbing).[9]

Among these factors, musculoskeletal weakness, gait and balance deficits, depression, history of falls, number of medications and several other risk factors have all been shown to play a major role in fall related incidents.[5, 13] Due to the high incidence of falls among the elderly population, as well as subsequent dangers and costs, it is important to develop models that might detect the likelihood of falls among older adults. With earlier detection and intervention, clinicians might be able to reduce the incidence of falls and/or reduce the impact of any fall events.

<u>Age-related Changes</u>

Several models have been proposed for the decline in sensory and motor function through aging. These include the accumulation of significant genetic errors through the duplication of DNA, aging being part of specific genetic programming and the hypothesis that cells have a limited number of divisions.[14] Of the two main aging models, the first proposes that aging is due to internal causes such that all systems experience neuronal decline across time until failure. The second model proposes that neuronal activity remains at optimal levels throughout aging until an external stimulus affects the neuronal function.[15, 16] Agreement in both models pertain to age-related changes in adults.

The musculoskeletal system undergoes change during aging, with decreases noticed for maximum strength for lower extremity muscles. In a 7-year longitudinal study older men aged 73 years and over, while body weight was reduced by 2% and body cell mass by 6%, the maximum muscle strength of the vastus lateralis decreased by 10-22%.[17] In addition, both men and women demonstrate age-related reductions in isometric, concentric and eccentric knee extensor peak torque, with age accounting for 11-30% of the variance in peak torque in both genders.[18]

Among nursing home residents with a history of falls, the peak torque and power for the knee extensors, knee flexors, ankle plantarflexors and ankle dorsiflexors were significantly less than those of age-matched controls.[19] This weakness in ankle musculature is of particular importance during falls, because of their critical importance in balance recovery during perturbations to stance. Though there is a lack of consistency in the data, older adults and adults with a history of falls have also demonstrated a

reduced step width during gait when compared to young adults. It was hypothesized that older adults modified their base of support in order to reduce the gravitational moment of the center of mass in the medio-lateral direction and also might reflect a decreased control ability of the hip abductors.[20]

Much of the variability seen in musculoskeletal function in the elderly has also been attributed to changes in the neuromuscular system, which has a role of integrating sensory information and maintaining postural control. The musculoskeletal system is considered the effector system which maintains posture and controls movement, with the nervous system planning and setting posture based on sensory input.[21] Impairments to the sensory systems can affect the way our central nervous system is able to integrate information about our environment.

The somatosensory, vision and vestibular systems all provide information about the environment. Somatosensory input provides the CNS with information relating the position and motion of the body with respect to the supporting surfaces and relationships between body segments. Vision provides the position and motion of the head with respect to surrounding objects as well as a reference to verticality. Vestibular input provides position and movement of the head with respect to gravity and inertial forces.

Proprioception is particularly important during changes in position, walking on uneven surfaces, and when other senses are impaired. Though changes in peripheral nerves have not been confirmed, peripheral neuropathies associated with diabetes and vitamin B12 deficiency are common among the elderly.[9] With such neuropathy, muscle response to perturbation can be significantly delayed.

Older adults and children rely on input from their visual system more than young adults, with unstable older adults showing an even greater reliance on visual input.[16] Nashner and Berthoz (1978) showed that enhancing the visual input reduced the sway amplitude, while reducing vision increased the final amplitude.[22] Thus, the structural changes in the aging eye and the decline in visual field, acuity and contrast sensitivity might lead to additional postural imbalance.

The vestibular system has also been shown to decline with age, with an approximately 40% reduction in vestibular system sensory cells for adults over the age of 70.[23] Age-related changes to balance also occur as a result of the accumulation of minute calciferous granules within the inner ear.[7] With vestibular deficits, many older adults will experience symptoms of dizziness, which can also play a significant role in imbalance. In addition to these factors, other risks such as neurological conditions, bone loss, cardiovascular disease, number of medications and many others have been linked with falling in the elderly, with multiple risk factors increasing the risk.

Balance Control during Gait in Older Adults

Epidemiological studies have shown that 30-70% of all falls occur while walking and thus remains an important area for balance control studies.[20] The basic motor control of stepping is mediated by the spinal cord via signals from the mesencephalic region. Refinements to this walking pattern are made at the cerebellum through the brain stem nuclei via comparison of the afferent signals from the muscles, indicating their position in

space, and the central pattern generator, which indicates the intended movement. The motor cortex also controls precise stepping motions via guidance from visual input.[14, 16] Integration of all these signals allows the central nervous system to properly place the feet and establish the base of support during gait in order to capture the moving center of mass (CoM). Any deficiencies in one of more of the pathways may lead to a reduced ability to control the CoM or Center of Pressure (CoP). Past studies have investigated the end-point control of the CoM and CoP among several populations.

Balance during gait is maintained by regulation of the CoM about the supporting foot,[24] with a safe trajectory of the swing foot providing precise end-point control.[25] In addition, stable gait is achieved as a function of both the CoM position and velocity.[26] The motion of the whole body CoM has been shown to identify elderly people who are at a higher risk of falling,[24, 27] with results showing that a greater medio-lateral motion of the CoM distinguished elderly patients with balance impairment from healthy older adults. When combined with the CoP, a better assessment of balance control during gait could be ascertained.[28, 29] The antero-posterior CoM-CoP distance demonstrated a decreased separation in healthy elderly while obstacle crossing than in young adults.[30] In addition, anterior CoM velocities were reduced among the elderly during this gait condition. It was hypothesized that the elderly demonstrated this conservative strategy due to reduced muscle strength.

Responding to trips and slips also is critical for older adults, as approximately 65% of falls occur in this manner. In responding to a trip, older adults displayed lower magnitudes and a slower rate of muscle activity in the hamstrings and ankle plantarflexors, when compared to young adults.[16] Similar muscle activation patterns

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were noticed during slips, with older adults demonstrating greater trunk hyperextension, higher arm elevation and longer co-activation on the perturbed limb.[31] Older adults also slip faster, longer, and with greater incidence than young adults, due, perhaps to reduced muscle response capacity at heel strike.

Variability and Stability

Another measure of balance control commonly used during locomotion is gait variability. Variability, which is often calculated as the coefficient of variation or standard deviation, indicates a measure's fluctuation over time, across individuals or raters.[32] During gait, an increased step-to-step variability could indicate an inability to compensate for instability and a predisposition to falling.[33] An increase in variability has also been associated with an increased risk of falls in the elderly.[34] In a one-year prospective study of elderly individuals, stride time variability was significantly greater in subjects who consequently fell (106 ± 30 ms), when compared to those who did not fall (49 ± 4ms).[35]

In addition to discriminating fallers from non-fallers, several studies have investigated the age-related differences in gait variability.[33, 36-39] Among these studies, most find that older adults exhibit greater stride-to-stride variability than young adults. In two studies of treadmill locomotion, older adults demonstrated 0.4 cm greater step width variability than young adults, with step width demonstrating 70 % larger variability than step length.[39] Increased step width variability might reflect an accommodation or

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adaptation to the aging of the neuromuscular system and decreased motor skill. Even older adults that had been categorized as having optimal gait and mobility for their age displayed higher step time variability than healthy young adults did when measured during both over-ground walking and walking with a perturbation of an irregular surface.[37]

In contrast to these studies, Gabell and Nayak (1984) showed that older adults did not demonstrate greater variability during locomotion for any temporal-distance measure, explaining variability to be indicative of pathological causes.[33] Such differences in the data could be due to methodology differences but also confounding results such as reduced muscle strength and poor vision among the elderly.[36, 37]

Purpose of the Study

While studies have investigated the role of muscle strength and postural control in the elderly, with gait studies demonstrating differences in the aging populations, few have identified ways in which prospective fall risk can be assessed. This project aims to fill this gap by developing a model than can be used in a clinical setting to diagnose elderly individuals as fallers or non-fallers. To this end, we propose a method for measuring balance control during gait; we examine methods for identifying fallers retrospectively and assessing the relative risk of falls longitudinally; and we establish a model for estimating balance control during gait in the elderly from clinical evaluations.

Bridge

The studies described in Chapters II-V include co-authored material. Dr. Victor Lin, Dr. Arthur Farley and Dr. Li-Shan Chou contributed substantially to the work by providing critique, data analysis, and development of methodologies. I was the primary contributor to the data collections, data analysis, implementation of the procedure, and did all the writing.

The goal of the first study (Chapter II) was to develop a robust means for measuring balance control among adults during ambulation. This was accomplished by defining the base of support throughout the gait cycle as well as by determining the position and velocity of the whole body center of mass. By examining the interaction of the center of mass with the base of support, a thorough understanding of foot placement and postural control during dynamic motion could be determined and possible underlying mechanisms of balance impairment investigated.

CHAPTER II

CENTER OF MASS AND BASE OF SUPPORT INTERACTION DURING GAIT

Introduction

Most falls occur during locomotion,[20, 40, 41] with age-related gait dysfunction being a common risk factor.[2, 7] During ambulation, the body is in a continuous state of imbalance, with each subsequent foot strike preventing a fall.[42] Ability to place the foot properly in order to control the center of mass (CoM) motion and regulate the body's momentum might decline in individuals with gait imbalance.[42, 43] To better understand the underlying mechanisms of gait imbalance and assess the risk of falls in the elderly, a precise analysis of foot placement and CoM movement during locomotion is required.

Stable gait is achieved as a function of the CoM position and velocity at the moment of foot placement.[25, 44] The feasible stability region, defined by the allowable ranges of the CoM position and velocity in relation to the base of support (BoS), was proposed to examine whether a fall might occur.[26] This work was extended by deriving the extrapolated center of mass (XcoM) to quantify gait stability. The condition for stability is described as when the XcoM is confined within the BoS.[45] These model-

based studies demonstrated the importance of the CoM velocity to assess balance control during gait.

The stability margin, defined as the shortest distance from the center of gravity to the support polygon, was used as a measure of balance.[45, 46] While such studies have investigated the CoM and CoM velocity in relation to the center of pressure or BoS during quiet stance, no studies, have investigated this relationship throughout a gait cycle. The instantaneous location of the CoM and CoM velocity vector in relation to the BoS could provide further insights on how static and dynamic balance is maintained during gait. This analysis might elucidate the underlying mechanisms of balance impairment and proper foot placement in order to recover from perturbations and prevent falls.

The purpose of this study was to examine the trajectory of the CoM in relation to the dynamically changing BoS during gait in healthy young adults, healthy elderly adults and elderly patients who reported gait imbalance. In addition to the XcoM and center of pressure (CoP) relationship,[47, 48] the CoM–BoS interaction was quantified in three ways: 1) The shortest distance from the CoM to the boundary of the BoS; 2) The distance from the CoM to the centroid of the BoS polygon; and 3) The distance from the CoM to the BoS boundary along the direction of the CoM velocity.

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Methods

Subjects

This study included 20 healthy young adults (HY; mean age (SD): 23.6 (3.7) years, mean BMI (SD): 23.2 (2.8) kg/m^2), 10 healthy elderly adults (HE; mean age (SD): 75.4 (7.0) years, mean BMI (SD): 24.3 (2.5) kg/m^2), and 10 elderly fallers (EF; mean age (SD): 78.9 (4.9) years, mean BMI (SD): 24.5 (2.7) kg/m^2) recruited from the surrounding community. Subjects reported no history of head trauma, neurological or heart diseases, muscle, joint, or orthopedic disorder, visual impairment that was uncorrected by glasses, persistent vertigo, or lightheadedness. Subjects were evaluated using the Berg Balance Scale (BBS) and questioned about their history of falls. The EF scored 52 or less on the BBS and reported one or more falls in the year previous to the testing date.[10] The study was approved by the university's institutional review board. Subjects were instructed about the procedures and written consent was obtained prior to testing.

Experimental Protocol

All subjects walked barefoot at a self-selected comfortable pace along a 10-meter unobstructed walkway. In addition, ten healthy young adults were asked to walk at a self-selected slower walking speed. Walking trials were recorded after each subject had become familiar with the laboratory setting by performing a few practice trials. Whole body motion was recorded using an 8-camera motion analysis system (Santa Rosa, CA) at 60Hz and low-pass filtered using a fourth-order Butterworth filter with cutoff

frequency set at 8Hz. A total of 29 reflective markers were placed on subjects' bony landmarks to define a 13-segment model.[27]

Data Processing

Whole body CoM position was calculated as the weighted sum of the 13-segment model.[27] Linear CoM velocity was calculated using Woltring's cross validated spline algorithm from the CoM positions.[49] The CoP was calculated from the ground reaction forces and moments of two force plates (Advanced Mechanical Technologies Inc., Watertown, MA) placed in series along the walkway. The two-dimensional BoS area was instantaneously defined based on the configurations of both feet; whether at heel strike, foot flat, heel off, or toe off (Figure 2.1). During single limb support, the boundaries of the BoS were defined by the supporting limb's foot width, ankle width and foot length. The heel marker (taking into account the radius of the marker, marker wand and base) was the demarcation for the posterior boundary. The anterior boundary was defined as the distal end of the toes using the measured foot length along the vector defined by the metatarsal-phalangeal and heel markers. The medial and lateral boundaries were defined using the measured ankle and foot widths at the location of the ankle marker and metatarsal-phalangeal joint marker, respectively.

During double limb support, the BoS was defined similarly to single limb support, while including portions of each foot in contact with the ground as well as the area between the feet (Figure 2.1). At heel strike, only the posterior boundary of the contacting limb was included in the BoS. At foot flat the entire foot was part of the BoS. During heel off, the metatarsal-phalangeal joint became the posterior boundary. At toe

off, the swing limb no longer was included in the BoS and the contralateral limb was in single limb support. The BoS area was calculated throughout the gait cycle.
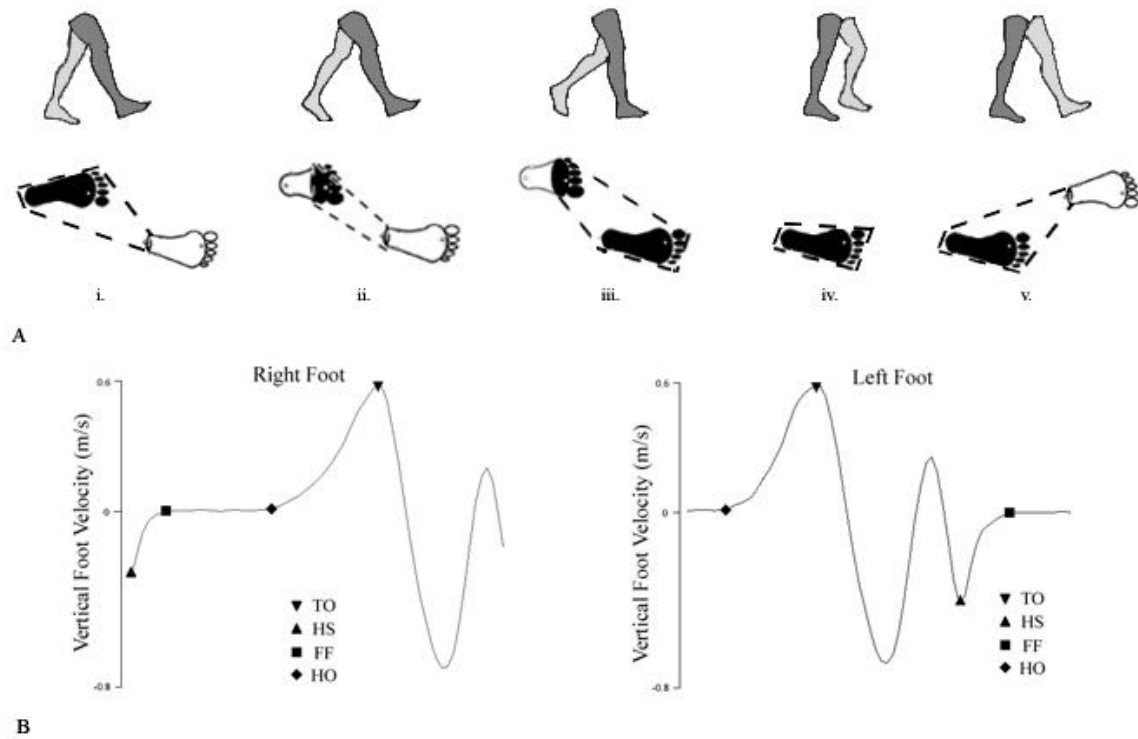
Figure 2.1. The base of support throughout one gait cycle (A) for heel strike (i), heel off (ii), foot flat (iii), toe off (iv) and heel strike (v). The shaded regions of the foot and the dashed lines represent the foot contact area and the boundary of the base of support, respectively. The base of support is determined based on foot positions (B) of heel strike (HS), toe off (TO), foot flat (FF) and heel off (HO) for both limbs.

Toe off and heel strike were detected based on the vertical velocity of the midfoot (Figure 1B).[50] Foot flat was determined based on the anterior velocity of the toe marker dropping below 100 mm/sec.[51] Heel off was determined at the point at which the heel marker exceeded the threshold of 40 mm above its position during foot flat.[52]

The shortest distance from the CoM to the boundary of the BoS was identified and calculated throughout gait (Figure 2.2). When the CoM is within the BoS, the distance is referred to as the stability margin. A smaller stability margin could indicate a

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less stable configuration. When the CoM is located outside the BoS, the distance is referred to as the CoM separation. This CoM separation is used as an indicator to evaluate the individual's ability in dynamic balance maintenance, with a greater distance indicating a better capability to displace and recapture the CoM outside the BoS. Alternatively, it is possible that individuals with poor balance might extend their CoM a greater distance outside the BoS due to an inability to control movement. The centroid of the BoS polygon was calculated based on an equal density distribution across the entire BoS surface. A smaller distance from the CoM to the centroid demonstrates close proximity to the center of the BoS and greater static balance control.

Dynamic balance was determined utilizing the instantaneous direction of the CoM velocity vector. The displacement of the CoM to the boundary of the BoS along the direction of the velocity vector is referred to as the CoMv distance, and is representative of the dynamic distance to the border of the BoS, regardless of whether the CoM is inside or outside the BoS. The time to contact was determined by dividing the CoMv distance by the CoM velocity. This variable described the amount of time needed for the CoM to cross the border of the BoS. In addition, the XcoM was calculated as $XcoM_x = p_x + \dfrac{v_x}{\omega_o}$, where $\omega_o = \sqrt{gravity/vertical\ CoM\ position}$, p is the CoM position and v is the CoM velocity.[45] Lateral and anterior separations between the XcoM and CoP were calculated at heel strike.[48]
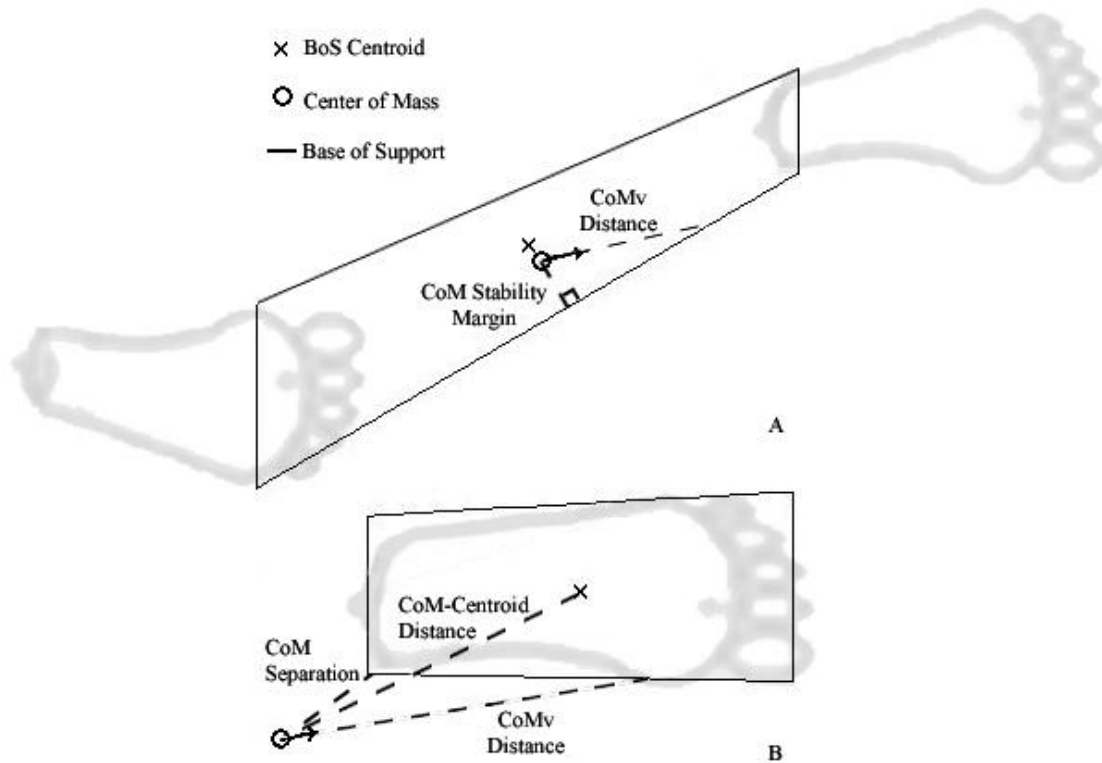
Figure 2.2. Center of mass and base of support interaction during double limb support (A) and single limb (B) support phases.

Custom MATLAB (Mathworks, Natick, MA, USA) programs were used to calculate the BoS, XcoM and the corresponding CoM-BoS and XcoM-CoP interactions. Statistical analyses were performed with SPSS 14.0 (SPSS Inc., Chicago, IL, USA) using a one-way analysis of variance to detect differences among groups for CoM-BoS distances, time to contact and XcoM-CoP distances. Between-group analysis was performed at the transition phases of gait, specifically heel strike and toe off. A Bonferroni correction was used to adjust the alpha level to $P= .0167$. A student T-test with alpha level set at $P= .05$ was used when comparing young adults walking at a slow speed and elderly fallers. Pearson correlations were performed between BBS scores and CoM-BoS interactions for all elderly adults, with alpha level set at $P= .05$.

<u>Results</u>

The CoM-BoS interaction is indicative of both static and dynamic balance control ability (Figure 2.3). During double limb support, the CoM and CoP remains within the boundary of the BoS for all subjects. In contrast, during single limb support, while the CoP remains within the boundary of the BoS, the CoM travels outside of the BoS, with the CoMv vector initially directed towards the medial border of the foot at contralateral toe off and directed away from the boundary from midstance till the subsequent heel strike. When the CoMv vector is directed away from the BoS, the CoMv distance to the border is not calculated. Greatest separation between all CoM variables and the BoS is found at the instant of toe off and prior to heel strike.

EF walked at a slower self-selected gait velocity than both HY ($P< .001$) and HE ($P=.048$; Table 2.1). At heel strike, while the stability margin and distance to centroid was similar for all groups, HY demonstrated a greater CoMv distance to the border than both HE and EF (Table 2.1; Figure 2.3). At toe off, a greater CoM separation and distance to the BoS centroid was demonstrated by HY when compared to both HE and EF (Table 2.1; Figure 2.3). In addition, a larger CoMv distance to the border was shown by HY compared to EF. Throughout gait, HE showed a similar pattern to that seen among HY, while EF maintained their CoM closer to the BoS when compared to the other two groups (Figure 2.3). The CoM was contained within the BoS for all groups when both feet were on the ground.
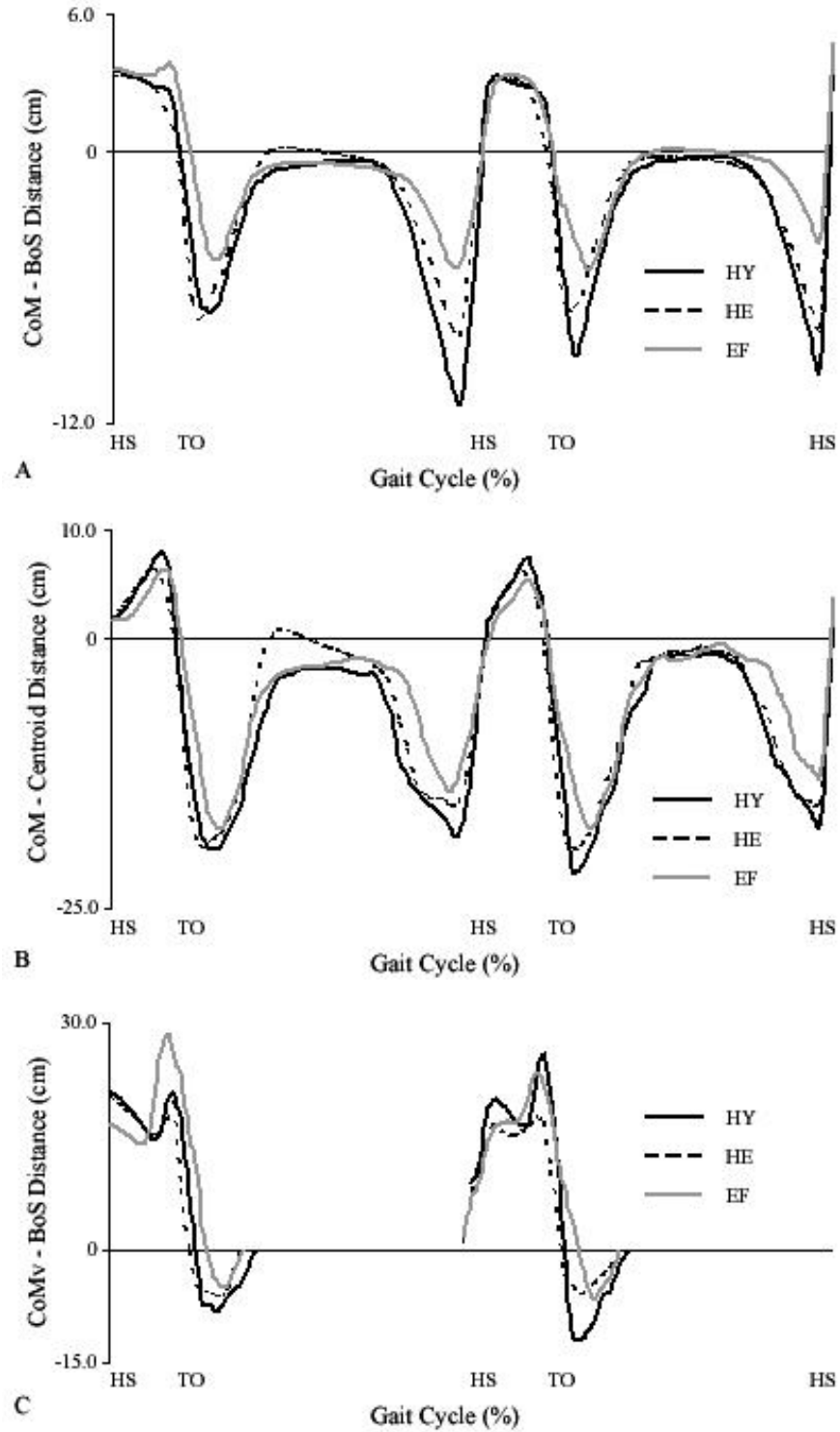
Figure 2.3. Ensemble average of gait cycles for HY, HE, and EF. Positive values occur when the CoM is inside the base of support, and negative values are found when the CoM is outside of the base of support. The instant of heel strike are represented with HS and TO, respectively. The empty sections of (C) represents points when the CoM is outside the BoS and the CoM velocity is directed away from the BoS.

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Young adults who were asked to walk at a slower than comfortable speed demonstrated a similar gait velocity to elderly fallers (Table 2.2) (P= .754). While no differences were seen in the BoS area, the elderly fallers demonstrated a 5 cm smaller distance to the BoS along the CoM velocity vector (P= .007) and 45ms shorter time to contact with the border (P= .003) at heel strike, when compared to HY. No differences were seen among the static CoM-BoS measures at heel strike or during toe off.

No significant group differences were detected for the XcoM-CoP distance in the lateral direction (P = .764; Table 2.3). In the anterior direction, the XcoM-CoP distance at heel strike was approximately 11cm greater in HE than EF (P = .049) and 20cm greater in HY than EF (P < .001). Across all elderly subjects, no significant correlations were found between the BBS and any of the CoM-BoS interactions at either heel strike or toe off (P> .05).

Table 2.1. Group averages (SD) for the CoM and the BoS interaction at heel strike and toe off.

Gait Variable	HY	HE	EF
Gait Velocity (m/s)	1.38 (0.14)	1.26 (0.20)	1.02 *[†] (0.10)
At Heel Strike (CoM inside BoS)			
CoM Stability Margin (cm)	3.5 (0.4)	3.5 (0.6)	3.9 (0.8)
Distance to Centroid (cm)	2.2 (0.7)	2.2 (0.4)	2.5 (0.4)
CoMv Distance to Border (cm)	23.0 (4.1)	18.7 * (4.0)	17.5 * (2.6)
Time to Contact (ms)	157.4 (30.9)	146.0 (39.4)	165.3 (25.9)
BoS Area (cm^2)	475.0 (59.8)	435.4 (57.2)	401.9 * (71.7)
At Toe Off (CoM outside BoS)			
CoM Separation (cm)	12.4 (2.5)	10.4 (2.4)	8.3 * (2.4)
Distance to Centroid (cm)	25.5 (2.6)	23.4 (3.0)	21.4 * (2.4)
CoMv Distance to Border (cm)	17.2 (3.7)	15.3 (6.7)	11.3 * (4.0)
Time to Contact (ms)	117.2 (25.3)	111.0 (39.9)	114.9 (38.9)
BoS Area (cm^2)	218.0 (34.2)	219.8 (35.7)	227.7 (40.0)

* Significant difference from HY (P < .0167).
[†] Significant difference from HE (P < .0167).

Table 2.2. Group averages (SD) for the CoM and the BoS interaction at heel strike and toe off when HY are controlled for speed.

Gait Variable	HY - Slow	EF	P-Value
Gait Velocity (m/s)	1.00 (0.13)	1.02 (0.10)	.754
At Heel Strike (CoM inside BoS)			
CoM Stability Margin (cm)	3.7 (0.7)	3.9 (0.8)	.590
Distance to Centroid (cm)	2.6 (1.1)	2.5 (0.4)	.750
CoMv Distance to Border (cm)	22.5 (4.5)	17.5 (2.6)	.007 *
Time to Contact (ms)	210.0 (31.9)	165.3 (25.9)	.003 *
BoS Area (cm^2)	434.7 (97.7)	401.9 (71.7)	.404
At Toe Off (CoM outside BoS)			
CoM Separation (cm)	8.9 (2.9)	8.3 (2.4)	.638
Distance to Centroid (cm)	21.8 (2.5)	21.4 (2.4)	.727
CoMv Distance to Border (cm)	12.0 (3.6)	11.3 (4.0)	.683
Time to Contact (ms)	112.9 (36.5)	114.9 (38.9)	.909
BoS Area (cm^2)	212.9 (27.10	227.7 (40.0)	.346

* Significant difference between EF and HY slow speed (P < .05)

Table 2.3. Group averages (SD) of the XcoM-CoP interaction in the anterior and lateral directions at heel strike.

Variable	HY	HE	EF
Anterior Separation (cm)	60.9 (7.6)	52.4 (8.6)	41.6 (6.6)* †
Lateral Separation (cm)	6.4 (2.3)	7.3 (2.3)	6.6 (3.3)

* Significant difference from HY (P < .0167).
† Significant difference from HE (P < .0167).

Discussion

The purpose of this study was to propose a method for identifying the dynamically changing BoS during gait, as well as provide static and dynamic balance measures for the interaction of the CoM and BoS. When applied to our subjects, elderly fallers demonstrated a reduced ability to control their CoM in relation to the BoS due to poor balance and possible fear of falling.

By maintaining a shorter separation of the CoM outside the BoS, elderly fallers demonstrated a conservative gait pattern. At toe off, the CoM is medial and posterior to the BoS, with the CoM velocity directed towards the medial border of the supporting limb. At heel strike, EF had a significantly smaller anterior XoM-CoP separation than both HE and HY. These results support prior studies, which demonstrated reduced CoM-CoP separation and CoM anterior velocity among the elderly during level walking.[30] Smaller distances to the border among elderly fallers could be indicative of a fear of a sideways or backwards fall, as well as reduced muscle strength. Adaptations to fear of

sideways falls, which are a factor for hip fractures,[53] could be accomplished by maintaining the CoM closer to the medial boundary before toe off of the swing foot.

Differences in gait velocities between subjects might be a limitation of this study, as velocity affects foot placement and CoM movement in the sagittal and frontal planes. Elderly fallers, who walked slower, demonstrated a larger BoS in the frontal plane, with a reduced BoS in the sagittal plane. Therefore, the effect of speed was tested among young adults. When HY were asked to walk at slower speeds, they demonstrated larger balance control capacities than EF. At heel strike, young adults had a similar BoS area as the elderly fallers, yet controlled their CoM such that the distance to the BoS along the direction of the CoM velocity vector and time to contact with the border was significantly greater than EF. This might be indicative of an elderly faller's inability to properly control the CoM momentum while landing the swing foot. Smaller time to contact will result in a reduced ability to compensate for any perturbations or obstacles that are encountered at foot strike, including slips. Slips have been highly associated with falls in the elderly, with greater hamstring activation and greater ability to reduce heel contact velocity found among young adults when compared to older adults.[54] Such velocity modifications and muscle activation might not be present in our elderly fallers, which might predispose them to greater risk of falling. According to the dynamic walking model, the step-to-step transition may require 60-70% of the overall metabolic energy spent during ambulation, and is responsible for re-directing the CoM velocity.[55] It is possible that weaker musculature and a poorer strategy among elder has resulted in a walking strategy that is redirecting the CoM velocity in a less efficient manner than healthy adults.

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Based on the XcoM concept, a perturbation which causes a change in the CoM velocity will induce a change in foot placement of the subsequent step (or CoP) by $\Delta v/\omega_o$.[47] This "offset-plus-proportional control" of balance was not seen in this study, with similar XcoM-CoP distances observed in the lateral direction among all subjects, while a reduced XcoM-CoP distance was demonstrated in the anterior direction at heel strike among EF. Greater differences in foot placement and the lateral stability margin might be witnessed among the EF if a perturbation is placed during gait.[47]

Defining the base of support during gait further demonstrates foot placement strategies used to capture the dynamically changing center of mass during locomotion, where 50% of all falls occur.[56] A quantitative definition of the BoS was determined previously,[57] however, only double-limb support of a lifting exercise was investigated and dynamic changes to the BoS and its interaction to the CoM during gait were not investigated. Past work has also shown that the CoM-BoS stability margin may be a useful measure during dynamic situations,[45] with the projection of the CoM to the supporting boundary being used as a measure of stability among walking machines.[46, 58] Utilizing the technique presented, it is possible to determine the relative position of the CoM to the border and centroid of the base of support as well as the CoM's distance to the boundary along the direction of velocity. These variables might provide a greater understanding of a person's static and dynamic balance control.

No correlations were found between CoM-BoS measures and the BBS. While most HE scored a maximum of 56 on the BBS, some demonstrated similar CoM-BoS interactions as the EF. Conversely, HY who scored a 56 did not demonstrate similar gait measures to the EF. The BBS, which has a ceiling effect and is a static test of balance,

might not detect an individual's deficiency in dynamic balance control.[59, 60] The CoM-BoS interactions, CoMv-BoS in particular, could be more sensitive in distinguishing deviations in balance control and gait adaptations in the elderly.

In conclusion, we have proposed a method for calculating the base of support and its interaction with the CoM throughout gait. Elderly fallers positioned their CoM and controlled their CoM velocity in a different manner than healthy adults at toe off and heel strike. When young adults walked at a similar gait velocity, they demonstrated greater dynamic stability than the elderly fallers. Knowledge of foot placement and the CoM trajectory could help identify rehabilitation practices for patients with balance disorders.[61] Proper foot placement and BoS changes might elucidate a safer and more efficient gait pattern among elderly fallers.

Bridge

Chapter II demonstrated a novel method for assessing balance control dynamically throughout gait. Additionally, it investigated differences in foot placement and center of mass control among young adults, healthy older adults, and elderly fallers at the moment of heel strike and toe off.

Chapter III investigated the ability of these newly defined balance control measures as well as gait spatiotemporal measures and commonly used clinical tests in assessing the retrospective fall risk in elderly adults. Specifically, clustering algorithms designed to differentiate non-fallers from fallers were assessed based on proper

retrospective classification. Gait and clinical measures that best identified older adults were identified.

CHAPTER III

IMPROVING FALL RISK CLASSIFICATION WITH A COMBINATION OF

CLINICAL AND GAIT BALANCE MEASURES

The study described in this chapter was developed by a number of individuals,

including Dr. Arthur Farley and Dr. Li-Shan Chou. Dr. Farley and Dr. Chou contributed

substantially to this work by providing critique, data analysis, and development of

methodologies. I was the primary contributor to the data collections, data analysis,

implementation of the procedure, and did all the writing.

Introduction

Falls are a major health concern among the elderly. Approximately one third of

adults over the age of 65 will fall each year.[5] Falls lead to severe injuries, a decrease in

activity, loss of confidence, and even death.[2] While past studies have investigated

individual factors that best discriminate between healthy older adults and adults who

sustain a fall,[62, 63] few studies have considered combinations of biomechanical and

clinical factors in assessing and predicting the risk of falls. Among these factors,

musculoskeletal weakness, gait and balance deficits, history of falls, cognitive

impairment, and several other risk factors have all been shown to play a major role in fall

related incidents.[5, 13] Therefore, a thorough analysis of clinical and biomechanical

measures might elucidate those combinations of measures that can best identify fallers.

Since most falls occur during dynamic locomotion,[40, 41] level walking tasks are an appropriate paradigm to assess differences in healthy older adults and fallers. Prior studies have demonstrated the ability to discriminate elderly fallers from healthy young and older adults,[27, 29, 64] though the sensitivity of this classification is unknown. Studies have also indicated that clinical examinations are capable of discriminating older adults and adults with a fall history.[10, 65] Shumway-Cook and colleagues demonstrated that the Berg Balance Scale, Timed Up and Go Test as well as self reported balance ability could properly categorize fallers and non-fallers with sensitivity up to 91% and specificity up to 87%.

To reduce the risk of falls, greater understanding of the underlying biomechanical mechanisms and clinical factors is required. Treatment and intervention options for older adults first require proper identification of at risk older adults. While falls have been shown to be a multifactorial problem, with intrinsic and extrinsic factors playing significant role in fall related incidents,[63] it is unknown which variables can best identify fallers.

Therefore, the purpose of this study was twofold: 1) to determine which combinations of balance control, spatiotemporal and clinical balance examinations can best distinguish between fallers and non-fallers retrospectively; and 2) to determine the probability distribution for older adults to be either a faller or a non-faller. Since gait and clinical measures provide differing analysis of an elderly person's balance ability, we hypothesized that a combination of the Berg Balance scale, gait spatiotemporal and balance control measures would better identify elderly fallers, compared to any single measure.

Methods

This study included a retrospective analysis on data collected from several studies

conducted in the Motion Analysis Laboratory at the University of Oregon between 2005

and 2010. Among the 98 older adults who participated in this study, 32 reported one or

more falls in the previous year [23 females/9 males; average (SD) age = 76.7 (6.3) years;

body mass index (BMI) = 26.7 (5.1) kg/m^2; fall history = 2.2 (1.2) falls]. The remaining

66 older adults reported no accidental falls [41 females/25 males; average (SD) age =

74.2 (5.9) years; BMI = 26.4 (4.1) kg/m^2]. Prior to testing, all subjects provided written

consent to the study procedures which were approved by the institutional review board.

Subjects were screened using the Berg balance scale (BBS).[66] The BBS is scored

on a scale of 0-56, with subjects asked to perform several static balance tests. The BBS

was included in the clustering and classification analysis as a measure of clinical balance

performance.

Gait parameters were obtained during over-ground level walking trials. During

biomechanical gait testing, all adults were asked to walk at a self-selected comfortable

pace across a 10-meter walkway. Reflective markers were placed on 29 bony landmarks

of the body, with three dimensional marker trajectories captured using an 8-camera

motion analysis system (Motion Analysis Corp, Santa Rosa, CA, USA) at 60Hz.[27] Data

were filtered using a fourth-order low pass Butterworth filter with an 8-Hz cutoff

frequency.

Gait characteristics were assessed using spatiotemporal and balance control

measures. Spatiotemporal measures included gait velocity, cadence, single support time,

stride length and step width.[70] Balance control measures included the interaction of the CoM with the base of support (BoS) at heel strike.[64] The shortest distance of the CoM to the BoS boundary (CoM-BoS distance) represents the static balance control ability. The displacement of the CoM along the direction of the CoM velocity vector to the BoS (CoMv-BoS distance) represents dynamic balance control ability. Time to contact with the BoS, which describes the amount of time the CoM can remain within the base of support before contacting the border, was calculated as the CoMv-BoS distance divided by the instantaneous CoM velocity. The BoS area was also calculated.

K-means clustering was utilized to determine which combinations of the above relevant measures were particularly effective at discriminating between fallers and non-fallers among the 98 older adults.[71] Heuristic methods for 2-means clustering searches for the best separation of the input parameter values into two sets, based upon the Euclidean distance from each instance to the mean values of the two corresponding clusters. A heuristic method starts with two arbitrary means and assigns each instance to the cluster associated with the nearest mean. As an iterative method, the mean of each cluster is then updated based on its associated instances. The assignment and update cycle is repeated until no change in cluster membership occurs (Figure 3.1). This process does not guarantee the optimum clustering of instances, as the procedure is sensitive to the randomly chosen initial means. Therefore, the process is repeated five times with each dataset to determine a most accurate cluster, as quantified by the minimum within
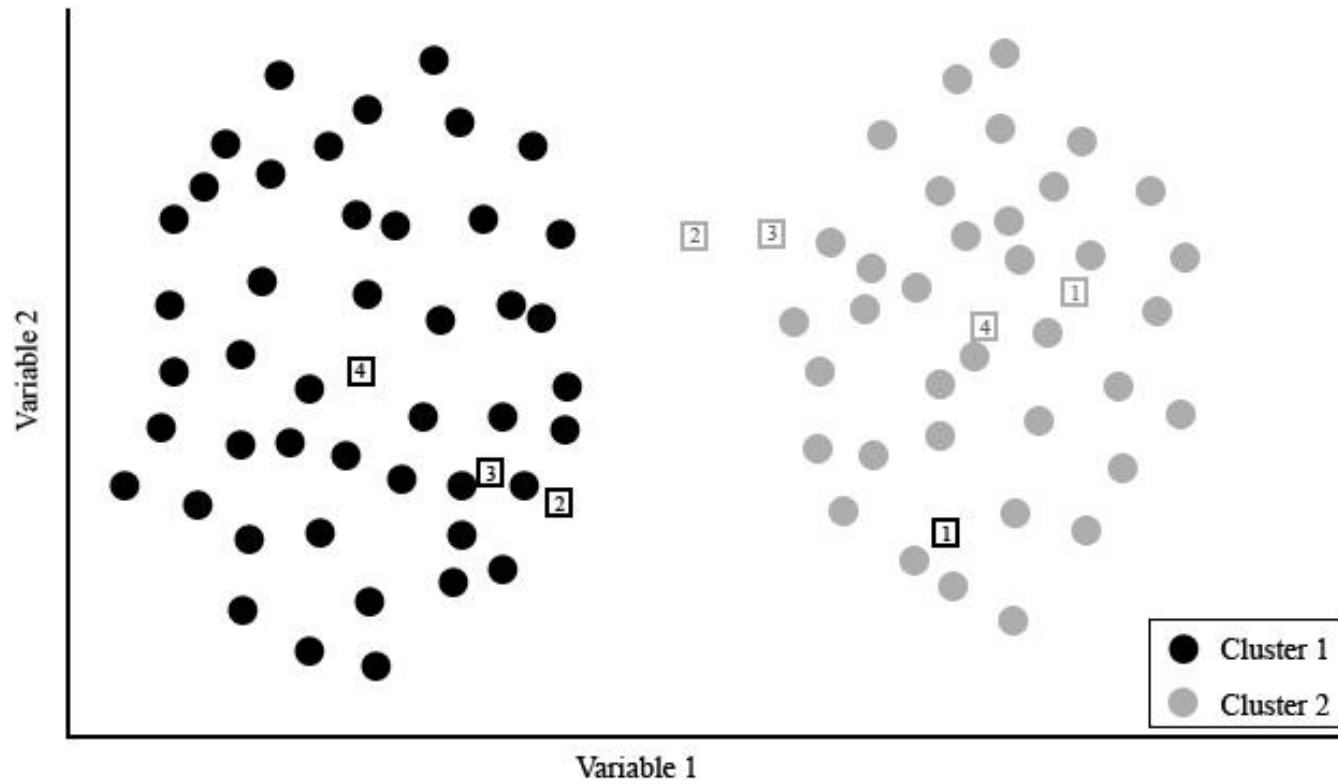
Figure 3.1. Example classification of each of the 98 subjects into two clusters using k-means clustering. Each axis represents the use of z-scored measures to discriminate groups (in this case two). Circles represent each individual, while the squares represent the calculated centroid of the clusters through iterations of the algorithm (in this case 1 through 4).

cluster sum of squared distances to the mean. The procedure is implemented in Matlab (Mathworks, Natick, MA, USA).

After clustering is complete, we assign the cluster with the preponderance of fallers to be the faller cluster. The second cluster is assigned to be the non-faller cluster. Sensitivity and specificity of the resultant classification is determined based on the membership of the resultant two clusters. The means of the two clusters can be considered to be a model of fallers and non-fallers, respectively, for the given data. The gold standard used was a self-report of prior falls.

A total of 5 gait spatiotemporal measures, 4 gait balance control measures, and the BBS were normalized using a z-score reflecting the number of standard deviations of an instance value from the mean. All combinations of these measures were explored during k-means clustering, with 31 combinations of gait spatiotemporal measures and 10 combinations of the CoM-BoS utilized as grouping variables to assess the sensitivity and specificity of group assignment. Furthermore, sampling all 10 possible measures provided 1023 combinations of measures to investigate the ability for all groupings to properly identify fallers and non-fallers.

While k-means clustering provides a binary classification of fallers and non-fallers, the use of Gaussian mixture models (GMM) can describe the probability that an individual is a member of either cluster. Similar to k-means, two clusters are specified a priori, with the expectation maximization algorithm used to estimate the maximum likelihood of individuals belong to either the faller cluster or non-faller cluster. Once again, this iterative algorithm is repeated until convergence reaches local optima, based on best fit likelihood of two Gaussian distributions. All 1023 combinations of measures

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were investigated using GMM, with the probability of each subject belonging to the falling group derived. This process was implemented in Matlab. The results allowed us to provide a graded estimate of fall risk. Those subjects who had a probability score of greater than 70% were considered high risk fallers; those between 30 and 70% medium risk; and those less than 30% low risk fallers.

An independent samples t-test was used to detect differences in group (fallers vs non-fallers) on anthropometric, clinical, and gait parameters. Analysis was performed using SPSS 14.0 (SPSS Inc., Chicago, IL, USA). Significance was set at alpha levels of $P < .05$.

<center>Results</center>

Several of the clinical and gait measures showed group differences in value between fallers and non-fallers. Fallers were approximately 2 years older (P = .052) than non-fallers with similar BMI for both groups (Table 3.1). Subjects who reported a prior fall demonstrated significantly lower BBS (P <.001) scores when compared to older adults without a prior fall. In addition, fallers demonstrated slower gait velocity (P <.001), with a reduced base of support area and separation distance of the CoM to the BoS along the direction of the CoMv vector at heel strike (P < .001)

Utilizing the k-means clustering algorithm and prior fall history as the gold standard for categorizing non-fallers and fallers, most of the individual variables showed only a poor to moderate ability to categorize older adults (Table 3.2). Nevertheless, the BBS,

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normalized stride length and CoMv-BoS distance at heel strike all demonstrated

sensitivity and specificity scores greater than 0.70.

Utilizing different combinations of spatiotemporal gait measures, CoM-BoS

interactions at heel strike, or the BBS, the ability to predict group membership of healthy

adults and fallers demonstrated good sensitivity and specificity (Figure 3.2). When

considering subsets out of the 10 possible measures, the best performing combinations

determined by the k-means algorithm provided specificity and sensitivity scores greater

than 0.85 (Table 3.3). The BBS, stride length, and balance control measures at heel strike

were most commonly associated with high sensitivity and specificity clusters.

Through the GMM algorithm, the ability for a single variable to have a high

probability of falling among those who actually reported a fall was greater than 80% for

only the BBS, normalized stride length, and BoS Area (Table 3.2). Among those

combinations with the best binary classification, the fall risk approached 90% for

measures that included the BBS (Table 3.3). Selected measures that included a

combination of the BBS, gait spatiotemporal, and balance control measures also

demonstrated the ability to classify fallers at a high risk of falling (Figure 3.3). Even so,

several adults who are classified as low risk individuals did report a fall in the prior 12

months and several adults categorized as high risk adults did not report a fall.

Table 3.1. Clinical, spatiotemporal and balance control measures of older adults

Variable	Non-Fallers (n = 66)	Fallers (n = 32)	P-value
Age (yrs)	74.2 (5.9)	76.7 (6.3	.052
BMI (kg/m^2)	26.4 (4.1)	26.7 (5.1)	.743
BBS (/56)	54.2 (3.2)	47.7 (4.7)	<.001
TUG (sec)	9.3 (2.0)	9.8 (3.5)	.500
ABC (%)	92.2 (10.5)	77.2 (17.9)	.001
TMT (sec)	56.5 (26.1)	66.8 (42.1)	.403
Spatiotemporal Measures			
Gait Velocity (m/s)	1.21 (0.19)	0.99 (0.18)	<.001
Cadence (steps/min)	119.0 (10.9)	112.7 (12.9)	.013
Single Support (%)	38.9 (1.9)	37.5 (1.9)	.001
Stride Length [a]	0.75 (0.07)	0.65 (0.08)	<.001
Step Width [b]	0.32 (0.10)	0.32 (0.08)	.917
CoM-BoS At Heel Strike			
CoM-BoS distance (cm)	3.52 (0.59)	3.24 (0.56)	.030
CoMv-BoS distance (cm)	20.3 (4.8)	15.7 (3.9)	<.001
BoS Area (cm^2)	424.3 (76.8)	337.7 (51.8)	<.001
Time to Contact (ms)	160.2 (31.5)	157.2 (33.9)	.667

[a] Normalized to body height; [b] Normalized to ASIS width

Table 3.2. Ability of single variables to predict prior falls**.**

Variable	Sensitivity [a]	Specificity [a]	Fall Risk [b]
Age (years)	62.5	50.0	76.0
BMI (kg/m^2)	28.1	78.8	37.1
BBS (/56)	71.9	90.9	89.9
Spatiotemporal			
Gait Velocity (m/s)	68.8	76.9	31.2
Cadence (step/min)	84.4	36.9	39.8
Single limb support (%)	59.4	69.2	17.9
Stride Length [c]	71.9	78.5	87.6
Step Width [d]	53.1	58.5	71.4
CoM-BoS At Heel Strike			
CoM-BoS distance (cm)	71.9	45.3	7.2
CoMv-BoS distance (cm)	71.9	73.4	22.7
BoS Area (cm^2)	46.9	67.2	27.3
Time to Contact (ms)	87.5	40.6	80.0

[a] Sensitivity and Specificity refer to correct identification of fallers and non-fallers, respectively, using K-means clustering. [b] Fall Risk refers to the probability of being categorized as a faller using GMM clustering for those subjects who reported a fall; [c] Normalized to body height; [d] Normalized to ASIS width.

Table 3.3. Combination of variables which best categorizes prior fallers and non-fallers.

Variables	Sensitivity [a]	Specificity [a]	Fall Risk [b]
Stride Length [c], Step Width [d], BBS	87.5	86.2	90.4
CoMv-BoS, BoS Area, BBS	90.6	82.8	89.7

[a] Sensitivity and Specificity refer to correct identification of fallers and non-fallers, respectively, using K-means clustering; [b] Fall Risk refers to the probability of being categorized as a faller using GMM clustering for those subjects who reported a fall; [c] Normalized to body height; [d] Normalized to ASIS width.
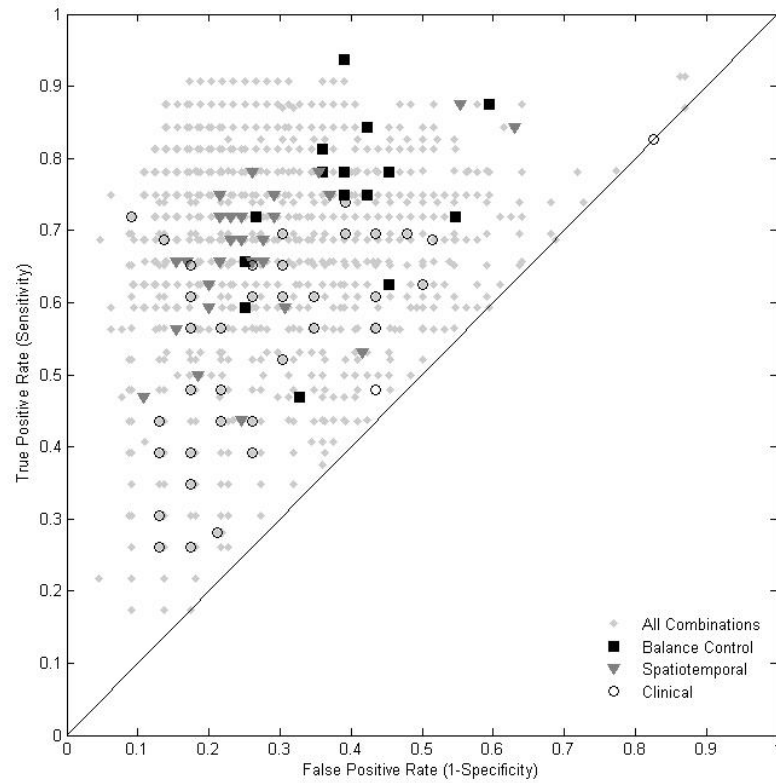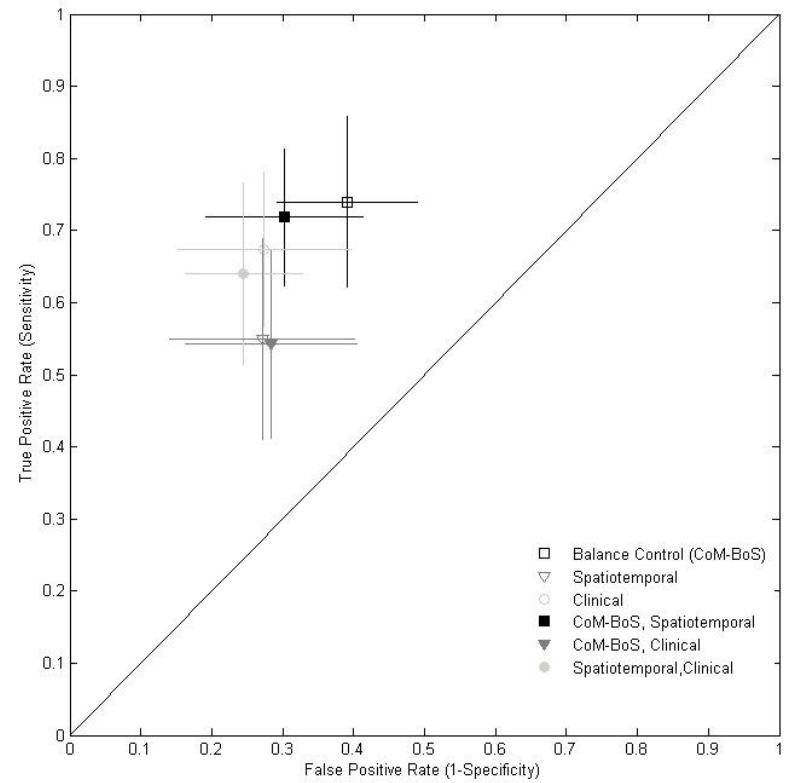
Figure 3.2. Ability to categorize adults as non fallers or fallers based on gait characteristics, using individual k-means clusters (A) and the average (SD) of the sensitivity and specificity for each grouping type (B).

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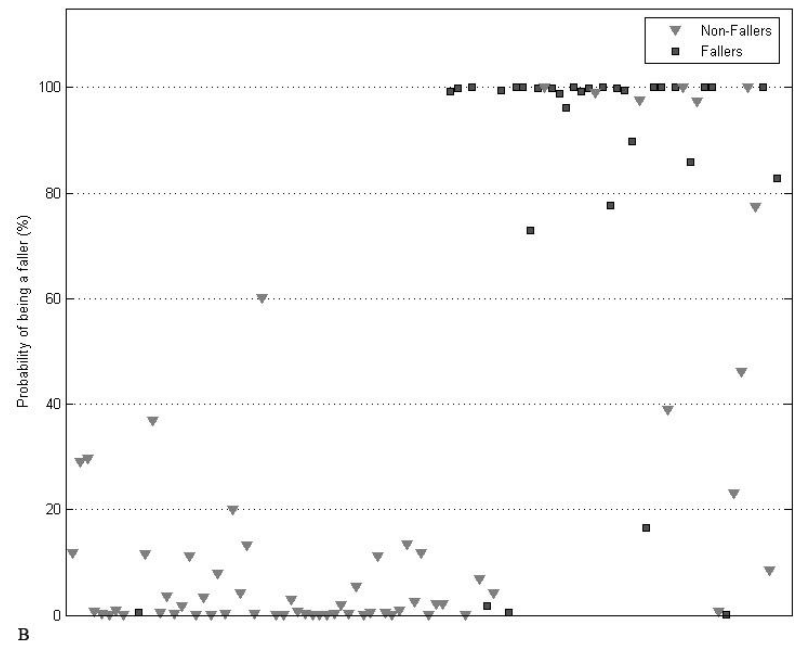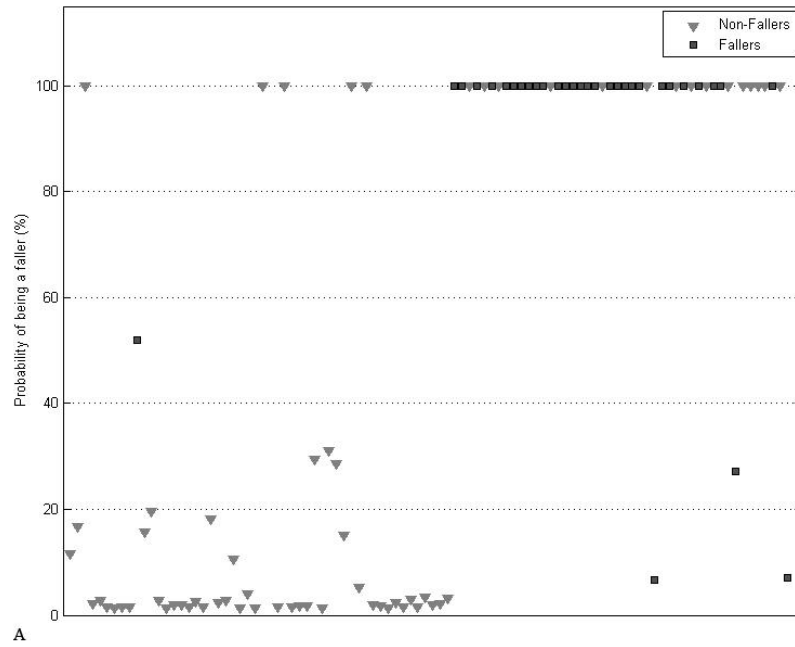
Figure 3.3. Probability of being in the falling group among all elderly adults, utilizing the Stride Length, Step Width, and BBS (A), as well as the CoM-BoS distance, CoMv-BoS distance, BoS Area, and BBS (B).

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The purpose of this study was to determine subsets of clinical and laboratory measures that could distinguish between fallers and non-fallers retrospectively. The ability to accurately categorize, determine the probability, and predict those older adults at risk of falling could significantly improve treatment options, medical costs, and quality of life. We found that a combination of clinical, gait spatiotemporal, and balance control measures better discriminated elderly fallers, with the BBS, stride length, and step width as well as the BBS, BoS area, and CoMv-BoS distance providing the best sensitivity, specificity, and fall risk probability.

In our study, using a single measure to categorize adults performed poorly, though the BBS did demonstrate sensitivity and specificity values greater than 70%. Results of the BBS classification were similar to those reported by Shumway Cook and colleagues who demonstrated 77 and 86% sensitivity and specificity, respectively.[10] While the BBS demonstrated high results using both the k-means clustering and GMM methods, it does not identify specific impairment, has a ceiling effect on healthier adults and is often dichotomous in how it differentiates older adults.[59] Thus, when using the GMM method, adults were often categorized as either 0 or 100% faller.

Additional clinical evaluations were performed on some elderly subjects with classification results for these variables also examined. Among the 98 elderly subjects, only 46 subjects completed the Timed Up and Go (TUG), Trail Making Test (TMT) and Activities Specific Balance Confidence Scale (ABC). Unlike the BBS, the TUG, TMT and ABC demonstrated low sensitivity (52%, 82.6% and 43.5%, respectively) and

specificity (69.6%, 17.4 % and 78.3%, respectively). The TMT difference score reflects a person's inability to perform multiple tasks and a decrement in executive function. It has been hypothesized that slower scores on the TMT might be due to an impaired ability to modify plans of action or to maintain two thoughts simultaneously.[72] The ability to perform gait and perform a secondary task is often cited as a cause of distraction and falls.[13] Clinical tests such as the TUG have demonstrated good sensitivity and specificity when identifying fallers.[65] Among our subjects only a smaller proportion of elderly adults completed the TMT and TUG tests, thereby reducing the strengths of these clinical tests. Among active elderly adults, a battery of tests, including clinical balance examinations was not capable of predicting fall risk.[73] Laessoe and colleagues hypothesized that due to the multifactorial mechanisms of falls, the influence of environmental factors, difficulty of daily tasks performed, along with individual physiological factors must be considered in order to predict fall risk. Measures of physical performance, based on their study, could not predict fall risk in the elderly.

Among the gait spatiotemporal and balance control measures, only the normalized stride length and CoMv-BoS distance were capable of categorizing both fallers and non-fallers at a high sensitivity and specificity. When combining balance and clinical tests in this study, the ability to identify past fallers (Figure 3.2B; Table 3.3) was significantly improved. By including measures of balance control during gait, impairment to the underlying balance mechanisms among older adults can be evaluated. An inability to properly maintain the CoM position and velocity as well as an appropriate placement of the foot to create a safe base of support, might predispose older adults to further fall risk.

The CoM distance to boundary of the base of support along the direction of the CoM velocity at heel strike was a common measure among well performing combinations. The distance to the border is indicative of a person's ability to respond to possible perturbations and maintain the CoM within the boundaries of the base of support. If the distance is reduced, it is possible that imbalance and falls might occur in the presence of a smaller disturbance. By modifying other balance control measures such as the position and velocity of the CoM within the base of support as well as the BoS area, it might be possible to avoid possible falls. Therefore, understanding the manner in which these measures are controlled among elderly adults along with their clinical history can provide a better understanding of fall risk.

By investigating numerous combinations of balance control and clinical measures, a few combinations performed much better than others in identifying retrospective fallers. Nevertheless, this study had a few limitations. While a large cohort of elderly adults has been tested, many did not have all of the clinical examinations performed. Additionally, older adults were classified for fall risk based on retrospective results, though research needs to investigate the ability to identify future fallers. Current findings can offer encouragement for further studies which investigate falls among older adults longitudinally using a combination of variables. Scott and colleagues (2007) have stated that few studies assess the predictive validity of fall-risk tools, with no single tool demonstrating strong predictive values across multiple settings or an ability to generalize the findings.[74] Therefore, a tool that can accurately and repeatedly assess and reduce the risk of falling in the elderly is needed.

The use of GMM and k-means clustering with two means are just two algorithms by which categorization and identification of fallers can be performed. While both methodologies require that the number of clusters be specified a priori,[71] the algorithms are robust and readily implemented through Matlab. Other techniques such as hierarchical clustering or fuzzy clustering as well as statistical techniques such as regression analysis might also provide means for discriminating fallers from non-fallers. The strength of this study though, is through the combination of multiple clinical, anthropometric, and balance control measures in discriminating older adults.

In conclusion, combinations of relevant measures should be utilized when attempting to identify fallers among a group of older adults. While a single variable might indicate that an older adult is healthy or not, additional measures might elucidate reasons for fall incidents. In this study, we found that selected combinations of tests, particularly the CoM-BoS interaction, gait performance and the BBS can be strong indicators of past fall history. Knowing which variables can properly identify fallers can help us eventually reduce health care costs, improve quality of life for the elderly and allow for individualized treatment and intervention.

<div align="center">Bridge</div>

Chapter III demonstrated the ability of clustering models in discriminating older adults as fallers and non-fallers, while also providing the fall risk of individuals. This

methodology utilized a combination of gait balance control, spatiotemporal, and clinical measures in generating two clusters retrospectively.

Chapter IV investigated the ability to classify older adults prospectively utilizing the cluster means generated previously. Additionally, elderly adults were followed longitudinally in order to investigate age-related changes in gait balance control and clinical performance.

CHAPTER IV

A COMBINATION OF GAIT MEASURES BETTER IDENTIFIES ELDERLY

FALLERS: LONGITUDINAL CHANGES IN CLINICAL AND GAIT MEASURES

The study described in this chapter was developed by number of individuals, including Dr. Arthur Farley, Dr. Victor Lin, and Dr. Li-Shan Chou. Dr. Farley and Dr. Chou contributed substantially to this work by providing critique, data analysis and development of methodologies. Dr. Lin performed clinical evaluations and provided interpretation of clinical results. I was the primary contributor to the data collections, data analysis, implementation of the procedure, and did all the writing.

Introduction

One-third of adults over the age of 65 will experience one or more falls.[2] While 50% of falls occur within the home or in the immediate vicinity of the home,[1] the most common location is on level surfaces in commonly used rooms. Falls lead to immobility, decrease the quality of life, and impact the physical, psychological, and social lifestyle of an elderly person.[1,9] Over 9500 deaths and $10 billion in direct costs a year can be attributed to falls.[1,3]

Musculoskeletal weakness, gait and balance deficits, depression, history of falls, number of medications, and several other risk factors have all been shown to play a major

role in fall related incidents.[5, 13] Due to the high incidence of falls among the elderly

population, as well as subsequent dangers and costs, it is important to follow adults

longitudinally in order to investigate cognitive, musculoskeletal, and balance control

changes.

Aging studies have demonstrated decreased muscle strength, loss in bone density,

and reduced sensory integration via the somatosensory, vision, and vestibular systems.[16]

Often, detrimental changes can increase frailty in elderly adults, making them more

susceptible to fall events. The musculoskeletal system is considered the effector system

which maintains posture and controls movement, with the nervous system planning and

setting posture based on sensory input.[21] Impairments to the sensory systems can affect

the way our central nervous system is able to integrate information about our

environment. Reduced capacity in either system can contribute to increased balance

impairment and fall risk, therefore understanding longitudinal changes in the elderly via

clinical and gait examinations can provide further ways to evaluate the underlying

mechanisms of falling.

While gait and balance studies have shown the ability to discriminate healthy

adults from fallers, few studies have investigated longitudinal gait and clinical changes in

the elderly, in particular as it related to the risk of prospective falls. Risk assessment of

falls using clinical examinations such as the trail-walking test[75] or a 15-predictor model[76]

have been shown to discriminate participants who fell during follow-up visits, though

generalizability of these tests and understanding the mechanisms of a fall event are

unknown. Among gait studies, in a one-year prospective study of elderly adults,

Hausdorff and colleagues demonstrated that stride time variability was 50ms greater in

subjects who consequently fell, when compared to those who did not fall.[35] The one-leg stance test, limits of stability test and a self-report of balance problems have also been shown to be associated with an increased fall risk among community dwelling older adults.[77]

By performing a full gait and clinical analysis of elderly adults, we hope to provide information in regards to the longitudinal changes with aging. In this study, we investigated changes in sensory input, clinical examination, balance control and stability as well as number of fall incidents across a 12 month period. In addition, we investigated the ability of a combination of clinical and gait variables to discriminate prospective fallers and non-fallers. To that purpose, this study had 3 main hypotheses. First, we hypothesized that older adults would demonstrate reductions longitudinally in clinical and gait balance control performance over a one year period. Second, we hypothesized that individuals who sustained future falls would demonstrate a reduced ability to maintain balance and stability during gait at baseline testing. Third, we hypothesized that a combination of clinical balance control measures and gait measures would better differentiate prospective fallers from non-fallers than any single clinical or gait measurement.

<center>Methods</center>

<center>*Subjects*</center>

This study included 27 older adults (9 males; mean age (SD): 74.6 (7.7) years;

mean BMI (SD): 29.5 (7.6) kg/m^2) recruited from the surrounding community. Subjects

were evaluated for clinical and gait performance during three visits six months apart

across a year. Clinical evaluations were performed by a physician or physical therapist,

while gait performance was quantified in a motion analysis laboratory. Throughout a one

year period following baseline testing, the number of prospective falls was recorded for

all subjects. Falls were recorded by providing subjects with self-addressed fall postcards

and by phone interview each month. A fall was defined as an unintentional coming to

rest on the ground or lower level with or without the loss of consciousness.[78]

Furthermore, the fall could not be due to sudden onset of paralysis, epileptic seizure,

excess alcohol intake or overwhelming external force. This study was approved by the

university's institutional review board. Subjects instructed about the procedures and

experiment length, with written consent obtained prior to testing.

<center>*Clinical Evaluation*</center>

Subjects were evaluated using the Berg balance scale (BBS) and Timed up and go

(TUG) to estimate static and dynamic balance control, respectively. Each subject's self

confidence in balance ability was scored using the Activities-specific Balance Confidence

Scale (ABC). Cognitive ability was evaluated through the use of the Saint Louis

University Mental Status (SLUMS) and the Trail Making Task (TMT). Subjects were

<center>47</center>

also evaluated for vision and hearing ability using a Snellen chart and 128Hz tuning fork, respectively.

Biomechanics Evaluation

Following clinical evaluations, all subjects walked barefoot continuously around an approximately 30-meter circular walkway at a self-selected comfortable pace for up to 10 minutes. A total of 29 reflective markers were placed on subjects' bony landmarks to define a 13-segment model. When subjects were within the 10-meter long capture volume, whole body motion was recorded using an 8 camera motion analysis system (Santa Rosa, CA). The three dimensional marker trajectories were collected at 60 Hz and low-pass filtered using a fourth order Butterworth filter at a cutoff frequency of 8 Hz. Whole body CoM position was calculated as the weighted sum of the 13-segment model.[27] Linear CoM velocity was calculated using Woltring's cross validated spline algorithm.[49]

Gait balance control was examined using the interaction of the CoM and the base of support (BoS) at heel strike.[64] As previously described, the interaction is based on the distance from the CoM to the closest border of the BoS (CoM-BoS distance), the distance from the CoM to the border of the BoS along the instantaneous CoM velocity (CoMv-BoS distance), the time to contact with the BoS border as well as the BoS area. Gait spatiotemporal measures of gait velocity, cadence, single support time, step width and stride length were also calculated.[70] The stride length and step width were normalized to the body height and ASIS width, respectively.

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A tri-axial MSR accelerometer (Henggart, Switzerland) with data logger, collecting at 50 Hz, was placed on the L4-L5 junction in order to estimate center of mass (CoM) acceleration throughout walking. The Lyapunov exponent was calculated as previously described[79] using the accelerations in the anterior-posterior, superior-inferior and medial-lateral directions. These values are indicative of a person's stability, with exponential divergence seen when the Lyapunov exponent $\lambda > 1$, a stable limit cycle when $\lambda = 0$ and a stable fixed point when $\lambda < 0$.

Lower extremity muscle strength was evaluated using a BIODEX System 3 Dynamometer (Shirley, NY). Bilateral maximum torque of the ankle platarflexors, knee extensors and hip abductors were measured isometrically. Values were normalized to the subject's body mass. Hip abductor strength was measured with the subject in the neutral position while standing. Knee extensors strength was determined with the subject in the seated position at 60 degrees of knee flexion. Ankle plantarflexor strength was measured in the seated position with the ankle at a neutral position and the knee flexed to 20 degrees.

Older adults were categorized as either 1) healthy non-fallers or 2) at-risk fallers based on their associated Euclidean distance to the centroid of the two k-means clusters that were previously derived.[80] These clusters were iterative determined based on the Euclidean distance from each normalized subset of measures to the nearest cluster mean. Utilizing retrospective fall data from 98 elderly subjects, the method begins by randomly selecting two means and assigning each instance to the corresponding closest cluster. The mean of each cluster is then updated based upon assigned instances, and the process

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repeated until there is no change in cluster membership. The means of the two clusters were considered to be suitable models for predicting fallers and non-fallers.

Among the current 27 older adults, subjects were assigned as fallers or non-fallers based on the shortest Euclidean distance to either cluster mean. Sensitivity, specificity and relative risk (RR) were assessed using self-reported prospective falls. Sensitivity and specificity refers to properly identifying prospective fallers and non-fallers, respectively. RR was calculated as the probability of falling among those categorized as "at-risk fallers" versus the probability of falling among adults categorized as "healthy non-fallers" as defined by Equation (1):

$$RR = \frac{p_{faller}}{p_{non-faller}} \tag{4.1}$$

with

$$p_{faller} = \frac{k_{fallers}}{n_{fallers}} \tag{4.2}$$

and

$$p_{non-faller} = \frac{k_{non-fallers}}{n_{non-fallers}} \tag{4.3}$$

where p indicates the probability of falling, k indicates the number of subjects in either group that reported a fall, and n indicates the number of subjects categorized as a faller or non-faller. A RR value of 1 would indicate that the risk classification is not better than randomly guessing, while values larger than 1 indicate that the subjects categorized in the at-risk group demonstrated a much greater risk of falling than the adults who were categorized as healthy.

Differences in muscle strength, gait measures and clinical evaluations were examined across visits (baseline, 6 months and 12 months) using a mixed model repeated measures ANOVA. Differences between prospective fallers and non-fallers were evaluated at baseline testing using an independent samples t-test. All analysis was performed in SPSS 14.0 (Chicago, IL).

<u>Results</u>

Out of the 27 subjects, 11 reported a fall, with 4 reporting multiple falls 6 months after baseline testing (Figure 4.1). By one year, 16 of the adults had experienced a fall, with 8 being recurrent fallers. Out of the 40 total events reported during phone interviews of postcard submission, 8 were not considered falls due to the incident occurring following changes in medication, dizziness, during a recreational activity and in one case, a large external force perturbing the individual. Of the 32 non-accidental falls during daily activity, most were due to unknown imbalance reasons, trips or slips, often while performing a secondary task, in the bathtub or while gardening and walking outdoors.

Across a one year period, older adults demonstrated an increase in cognitive ability, as indicated by a 3 point average increase in the SLUMS (Table 4.1). Older adults did not demonstrate differences in any other clinical or muscle strength measure.

Similarly, no differences were seen across time for gait spatiotemporal, balance control

and stability measures (Table 4.2).

At baseline testing, only the CoMv-BOS showed significant differences between

prospective fallers and non-fallers (P = .015). Across the 16 fallers, an approximately

3cm greater distance was demonstrated for this distance, when compared to the non-

fallers. No other balance control or clinical measure, including prior fall history (P =

0.189) demonstrated differences between future fallers and non-fallers. On average,

among all subjects, older adults demonstrated 20/40 vision, with unimpaired hearing in

both ears, an average intake of 5 medications and reported 1 fall in the prior year.
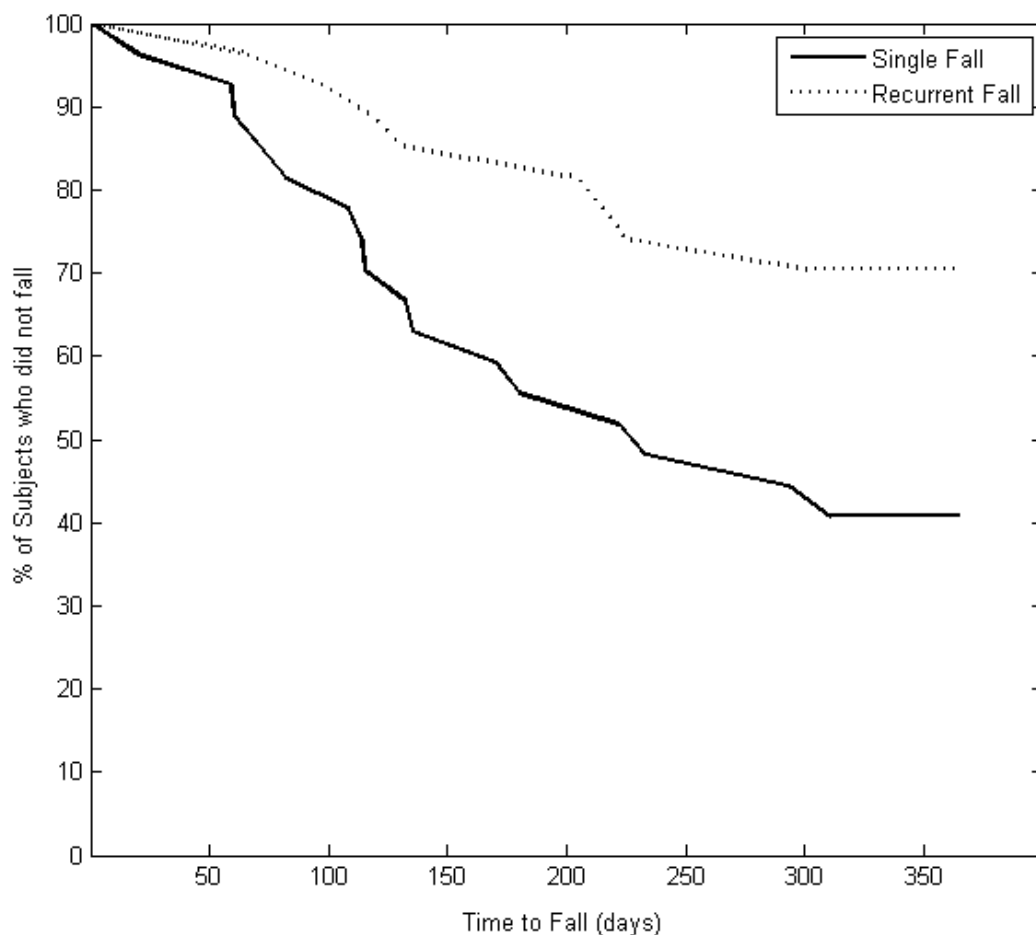
Figure 4.1. Among all 27 subjects the amount of time from baseline testing until a fall
incident was reported. During a year, 16 adults reported a fall, with recurrent falls
occurring in 8 individuals.

Table 4.1. Clinical and muscle strength performance (SD) for older adults.

Variable	Baseline	6 months	12 months	P Value *
Clinical Examinations				
TUG (sec)	8.8 (2.1)	9.5 (1.9)	8.5 (0.9)	.203
ABC (%)	79.5 (16.9)	83.7 (17.3)	77.7 (15.6)	.635
BBS (/56)	53.3 (3.2)	53.6 (2.3)	53.8 (1.8)	.809
TMT (sec)	55.7 (57.1)	65.0 (56.3)	42.1 (43.9)	.499
SLUMS	25.5 (3.9)	27.5 (3.7)	28.3 (1.8)	.019
Muscle Strength (Nm/kg)				
Hip Abductor	0.61 (0.21)	0.52 (0.14)	0.53 (0.14)	.229
Knee Extensor	1.07 (0.29)	1.05 (0.27)	1.12 (0.27)	.806
Ankle Plantarflexor	0.88 (0.27)	1.11 (0.36)	0.98 (0.38)	.100

* Visit main effect

The ability to predict prospective falls up to 6 months and 12 months post baseline testing was poor when using a single variable, as demonstrated by sensitivity, specificity and relative risk values (Table 4.3). Through the use of k-means clustering, categorization of at-risk fallers and healthy adults using a combination of variables was able to predict prospective fallers by 6 months and 12 months with up to 80% and 70% sensitivity and specificity, respectively (Table 4.4). The favorable combination of variables included measures of clinical balance, gait spatiotemporal performance and balance control during ambulation. Specifically, the distance from the CoM to the boundary of the BoS, age and self reported balance ability demonstrated favorable results, with relative risk values of those classified as fallers approaching 4.0.

Table 4.2. Gait performance (SD) across one year for older adults.

Gait Performance	Baseline	6 months	12 months	P value *
Spatiotemporal				
Gait Velocity (m/s)	0.97 (0.20)	1.04 (0.18)	1.07 (0.18)	.332
Cadence (steps/min)	107 (11)	113 (12)	115 (11)	.114
Single Support Time (%)	37.1 (2.5)	37.5 (1.9)	38.0 (2.0)	.492
Stride Length	0.66 (0.09)	0.67 (0.07)	0.68 (0.07)	.684
Step Width	0.36 (0.10)	0.34 (0.10)	0.33 (0.12)	.682
Balance Control				
CoM-BoS (cm)	4.0 (1.3)	3.6 (1.4)	3.6 (0.9)	.504
CoMv-BoS (cm)	18.4 (3.8)	17.3 (3.2)	18.3 (3.8)	.540
Time to Contact (ms)	189 (43)	167 (35)	174 (44)	.167
BoS Area (cm^2)	447 (103)	438 (107)	433 (69)	.896
Lyapunov exponents				
Medio-Lateral	0.07 (0.04)	0.06 (0.03)	0.05 (0.02)	.085
Superior-Inferior	0.08 (0.04)	0.08 (0.03)	0.08 (0.03)	.994
Anterior-Posterior	0.09 (0.03)	0.09 (0.03)	0.09 (0.02)	.844

* Visit effect

Table 4.3. Ability of variables to predict future falls.

Variable	6 Months			12 Months		
	Sensitivity	Specificity	Relative Risk	Sensitivity	Specificity	Relative Risk
Age	27.3	43.8	0.47	31.3	36.4	0.57
BMI	54.6	56.3	1.29	50.0	54.6	1.08
BBS	0	75.0	0	0	63.6	0
TUG	20.0	69.2	0.71	15.4	60.0	0.52
TMT	9.1	75.0	0.44	6.3	63.6	0.29
ABC	27.3	66.7	0.84	26.7	63.6	0.82
Spatiotemporal						
GV	72.7	18.8	0.76	81.3	27.3	1.24
Cadence	100	12.5	Inf*	93.8	9.1	1.20
SS	63.6	43.8	1.20	56.3	36.4	0.88
SL [a]	63.6	25.0	0.74	68.8	27.3	0.93
SW [b]	63.6	25.0	0.74	62.5	18.2	0.70
Balance Control						
CoM-BoS	36.4	50.0	0.71	50.0	63.6	1.25
CoMv-BoS	36.4	43.8	0.62	43.8	45.5	0.84
Time to Contact	0	68.8	0	12.5	72.7	0.63
BoS Area	45.5	37.5	0.67	56.3	45.5	1.03

* Relative risk of infinity indicates that the probability of falling among those categorized as non-fallers was zero; [a] Normalized to body height; [b] Normalized to ASIS width

Table 4.4. Using k-means clusters to determine prospective fallers.

Variables	6 Months			12 Months		
	Sensitivity	Specificity	Relative Risk	Sensitivity	Specificity	Relative Risk
CoM-BoS, Age, ABC	72.7	50.0	1.83	75.0	63.6	2.06
CoMv-BoS, SS, Age, BBS, ABC	81.8	68.8	4.18	62.5	63.6	1.55

Loss of balance and subsequent falls are a major source of morbidity and mortality in older adults. The ability to longitudinally test older adults for changes in clinical and gait measures might reveal factors that best identify risk of falling. Contrary to our first hypothesis, no longitudinal changes were demonstrated by elderly adults, with no significant changes in individual clinical measures, gait spatiotemporal, or balance control and stability measures found during a one-year follow-up. Similarly, for our second hypothesis, only a single baseline balance control measure was able to differentiate prospective fallers from non-fallers during the one year follow-up period. While only a one-year longitudinal study was conducted, a longer period might demonstrate different results.

A combination of clinical, gait spatiotemporal and balance control measures was able to separate prospective fallers and non-fallers with high sensitivity and specificity. These results are in support of the hypothesis that a combination of measures could better differentiate fallers than any single clinical or gait measure. As falls have been shown to be a multi-factorial problem,[5] these results strengthen the case for thorough evaluations of elderly adults based on multiple performance measures.

Approximately 60% of our community-dwelling elderly subjects suffered a fall during a 1-year period, with 30% suffering recurrent falls. This falling rate is higher than those previously reported, where only one-third of elderly adults suffered a fall in a one year period.[7, 75] The results reported here however are similar to those reported by Maki and colleagues who investigated ambulatory and independent elderly adults for 1 year.[81]

As this cohort of elderly remained active throughout the study and reported no injurious falls, it is possible that increased environmental exposure could explain the higher fall rate.

Age-related neurological changes have been demonstrated in the elderly, including increased reaction times with decreased acuity of the auditory, vestibular, visual and somatosensory systems.[82] In this study, no such differences were seen among the elderly subjects, with similar corrected vision, hearing and TMT scores demonstrated across visits. Interestingly, the SLUMS test was the only examination that showed differences over time, though an increase in performance was demonstrated by the elderly from baseline to 12 months follow up. Such improvement might be due to familiarization with the task. Other clinical examinations, such as the TUG and BBS, have previously been shown to identify retrospective fallers and non-fallers with high sensitivity and specificity.[10, 65] When utilized in this study for prospective analysis, no such ability was demonstrated. As the BBS has a ceiling effect and evaluates static balance, it is possible that the ability to categorize moderate risk elderly and the lack of locomotion with the test does not allow for proper classification.[83] Similarly, while the TUG includes locomotion, it might not be appropriate for community dwelling adults.[83]

Gait adaptations among the elderly have also been hypothesized to be due to a decrease in muscle strength, muscle fibers and range of motion.[82] In this study, while subjects did demonstrate consistently strong ankle, knee and hip isometric strength, many fall events were still reported.

Similarly, while no differences were observed over the year in gait balance control and stability among the elderly, the only measure that differentiated the non-

fallers from fallers at baseline was the CoMv-BoS distance. Maintaining a greater distance might be a conservative strategy adopted by these patients with a greater fall risk due to underlying balance impairment. An inability to quickly respond to perturbations might compel individuals to generate a greater distance at heel strike and therefore increase the response time before the CoM reaches the border of the base of support. Values for the CoM-BoS interaction were similar to those reported previously for elderly fallers,[64] as elderly adults maintained a CoMv distance and time to contact of approximately 18cm and 170ms, respectively, across all visits.

When considering all combinations of clinical, gait spatiotemporal and balance control measures, the best performing combinations of measures for identifying elderly fallers and non-fallers all included the CoM-BoS interactions. When combined with a subject's age and self report of balance ability, sensitivity values approached 75%. Further including single support time and the BBS resulted in similarly high scores in sensitivity, with specificity values approaching 70% and relative risk approaching 4.2. It is possible that inclusion of CoM-BoS variables with clinical variables provides more thorough information in regards to the underlying mechanism of falls, as the interaction of the CoM-BoS has previously been shown to indicate an inability to respond quickly to perturbations at heel strike.[64] Additionally, older adults have previously demonstrated a conservative gait pattern at toe off, as demonstrated by the CoM distance to the base of support. This adaptation might be due to self-perceived balance impairment, with a conservative distance adopted in order to maintain the center of mass in manageable proximity to the base of support. The inclusion of ABC scores in the high performing

combinations also demonstrates an elderly individual's fear of falling and possible reason for adapting a conservative gait pattern.

While the use of several variables was able to discriminate fallers from non-fallers, there are still limitations to this study. First, we have only followed 27 older adults living in the community so far. The ability to generalize results to a larger group of elderly adults from a greater spectrum of activity levels and lifestyles will allow for a more robust categorization of fall risk. Secondly, the participants in this study are likely to be more motivated and interested in fall risk than the general population of older adults. Investigating subjects at risk for injurious falls and those less active might allow for more generalizability of results. Longitudinal testing of elderly adults remain a major strength of this study, with prospective evaluations of fall risk providing additional information on which gait variables best identify fallers.

While investigations into age-related decreases in gait performance and functional ability might reveal differences in fall risk among the elderly, the inherent variability among individuals and the heterogeneous nature of aging between subjects might not allow for single variable analysis of longitudinal change and fall risk.[84] Among a cohort of 70-year-olds, physical performance was found to both decline among some subjects and maintained or improved among other subjects.[84]

In this study, while no significant changes in selected clinical and gait measures over a one-year follow-up were seen among elderly adults, the ability to identify prospective falls could be enhanced when using a combination of variables. In order to properly evaluate and provide intervention for elderly adults, it is recommended that

clinicians perform dynamic evaluations along with clinical evaluations in order to reveal the underlying mechanisms of balance impairment.

<div align="center">Bridge</div>

Chapter IV investigated one year longitudinal changes in clinical and gait measures for older adults. Additionally, the ability of a combined group of balance control and clinical measures to identify prospective fallers was demonstrated, with the relative risk of falls quantified.

Chapter V established a model for mapping clinical measures obtained by physicians to biomechanical balance control measures. Specifically, the ability of an artificial neural network to learn the interactions between input and output measures based on different model architecture parameters was examined.

CHAPTER V

DETERMINATION OF GAIT BALANCE CONTROL IN THE ELDERLY USING

CLINICAL EVALUATIONS AND AN ARTIFICIAL NEURAL NETWORK

The study described in this chapter was developed by number of individuals,

including Dr. Arthur Farley and Dr. Li-Shan Chou. Dr. Farley and Dr. Chou contributed

substantially to this work by providing critique, data analysis and development of

methodologies. I was the primary contributor to the data collections, data analysis,

implementation of the procedure, and did all the writing.

Introduction

While past research has found ways to identify those adults who are more

susceptible to falling than a matching group of elderly individuals, the equipment

necessary to make such predictions can be both expensive and time inefficient for

clinicians. Models that characterize gait balance and stability might be a useful and

efficient tool in providing physicians with identification and interventions for elderly

individuals who are at risk of falling. Having a model that could predict the fall risk of

elderly individuals based on calculated gait balance control and stability parameters

would be a clinically viable and inexpensive solution. In order to achieve this, models

are needed which can find a link between clinical and biomechanical measures.

Previous models have used logistic regression models that utilized static posture variables and clinical measures to determine fall risk. These included predictions based on Berg balance scores, timed up-and-go tests and self reported history of imbalance and history of falls to determine the risk of falling among a group of elderly individuals.[10, 65] Such models require that input predictors explain a high degree of variability and make the assumption that linear relationships exist between variables. Another approach which would allow for non-linear relationships and include a number of input variables is an artificial neural network (ANN).[85] An advantage of ANN models is that they can be built to infer a function simply from observation or training. By exposing the model to set of elderly adult data, with known input and output values, the ANN can be trained to an appropriate level.

Artificial neurons, or nodes, are the basic units in the ANN. Similar to biological nervous systems, connections (or synapses) are established through a learned iterative process. Upon receiving one or more inputs (or dendrites), a node is able to compute a weighted sum and pass a value through a non-linear transfer function to establish an output function. Training, or learning and the establishment of synapses, occurs by using a set of data, and solving for the inputs and outputs in an optimal manner. Inferring the mapping implied by the data and finding the solution that has the smallest possible cost allows the ANN to arrive at a satisfactory weighting level. Once an ANN model has been trained, it can then be used to predict outputs for a new set of inputs.

Though several others researchers have used ANN models to estimate joint kinetics and kinematics, Hahn and Chou have used such ANN models to investigate the interactions between temporal-distance gait measures and dynamic gait stability.[85, 86]

Their studies have shown that an ANN model can predict certain gait variables among elderly adults. Since complete and highly accurate measurement of temporal distance gait variables is not possible in the clinical environment, we propose a study to test the feasibility of such a model in mapping clinical measures to lab measures.

The purpose of this study is to demonstrate that given clinical measures, an artificial neural network can eventually predict the risk of falling, as demonstrated in a previous study among elderly individuals,[80] by determining balance control during gait. Clinical measures that will be utilized come from a complete medical history and subject examination. These include a history of falls, deficits in sensory motor function, visual and hearing impairment, presence of chronic disease or depression, number of medications and clinical balance examinations. We hypothesize that an ANN model can determine the balance control of elderly individuals given easily assessable clinical measures.

<u>Methods</u>

Subjects

A total of 27 elderly subjects (age (SD) = 74.6 (7.7) years; 9 males) were recruited for this study. Volunteers were recruited from the community with a phone screen performed prior to recruitment. All subjects reported no history of head trauma, neurological disease, heart disease or visual impairment that was uncorrected by glasses. In addition, subjects confirmed that they were able to ambulate for up to 10 minutes

without the use of an assistive device. A clinical and biomechanical evaluation was then

performed on all subjects by a physician and trained researchers, respectively. Each

subject signed an informed consent statement, in accordance with ethics approval granted

from the university's institutional review board, prior to participation in the study.

Clinical Evaluation

The body mass index (BMI) was computed for each subject along with a full

medical history of prior fall history, the number of medications taken and co-morbidities.

In addition, physicians evaluated proprioceptive ability, vision and hearing. The

Geriatric Depression Scale (GDS) was used to evaluate depression.[87] The Activities

Specific Balance Confidence Scale (ABC) provided information on a person's self

perception of balance ability.[68] Static balance was evaluated using the Berg Balance

Scale (BBS).[66] Dynamic balance was recorded through the Timed Up and Go test

(TUG).[67] Cognitive ability was estimated using the Trail Making Test (TMT) A and B,

as well as the Saint Louis University Mental Status (SLUMS). The TMT test was

evaluated based on the difference in scores on the B and A test.[69] This difference has

been shown to demonstrate the task switching cost.

Muscle Strength

Bilateral isometric muscle strength of the hip abductors, knee extensors and ankle

plantarflexors was tested using a Biodex System 3 dynamometer (Biodex Medical

Systems, NY). For hip strength, the subject was instructed to abduct while standing in

the neutral position. Knee extensor strength was evaluated in the seated position at 60

degrees of knee flexion. Ankle plantorflexor strength was tested in the seated at 20

degrees of knee flexion and in a neutral ankle position. The peak torque value for each

joint was recorded and normalized to a person's body mass.

Gait Assessment

Subjects were asked to walk at a self-selected comfortable speed across a 10-

meter walkway. During ambulation 29 retro reflective markers were placed on bony

landmarks of the body,[27] with three dimensional marker trajectories captured with an 8-

camera motion analysis system (Motion Analysis Corp, Santa Rosa, CA). Data were

filtered using a fourth-order low pass Burtterworth filter with an 8-Hz cutoff frequency.

Ground reaction forces and moments were captured from three floor-embedded force

plates (Advanced Mechanical Technologies Inc., Watertown, MA). Marker and force

plate data were collected at 60Hz and 960Hz, respectively.

Balance control during gait was assessed using the position and velocity of the

center of mass (CoM) in relation to the base of support (BoS) at heel strike.[64] The

distance from the CoM position to the closest border of the BoS (CoM-BoS) represents

static balance control. The displacement of the CoM along the direction of the CoM

velocity to the boundary of the BoS (CoMv-BoS) represents dynamic balance control.

The BoS area was calculated based on foot anthropometrics and configuration.

ANN Development

The ANN used in this study was designed to calculate the balance control

measures of each subject. Input data sets included subject characteristics (age, BMI,

gender, fall history, medications, vision, hearing), clinical evaluations (BBS, TUG, TMT, ABC, GDS, SLUMS) and muscle strength (ankle, knee, hip). Selected combinations of these 4 input data sets were also evaluated.

A three-layer, feed-forward back-propagation ANN was constructed in Matlab (Mathworks Inc., Natick, MA; Figure 5.1). The first layer of the network consisted of different combinations of normalized clinical inputs. The second layer included a 5, 10 or 20 hidden neurons. The third or output layer included the three balance control variables. Out of the 27 subjects, 24 were randomly selected for training, with testing performed on the other 3 subjects. This process was repeated 9 times in order to test the network on all 27 subjects, with training stopped when the mean squared error (MSE) error reached 0.1, 0.01 or 0.001. Error correction during training was conducted with the Levenberg-Marquardt algorithm. Weighted incoming signals were summed at the hidden and output units, with a tangential sigmoid transfer function and pure linear transfer function used at each layer, respectively. Details of the network architecture have been described previously by Hahn and colleagues.[86]

After successful training, all data was converted back to real world units of cm and cm^2, for the distance and area measures, respectively. The ability of the ANN model to accurately calculate CoM-BoS balance control measures to actual measurements was assessed via correlation analysis. Differences in accuracy in the correlation coefficient (R) between the number of hidden units (5, 10 or 20), between the error goal (0.1, 0.01 and 0.001) and across grouping type were assessed with a 3 way ANOVA in SPSS 14.0.
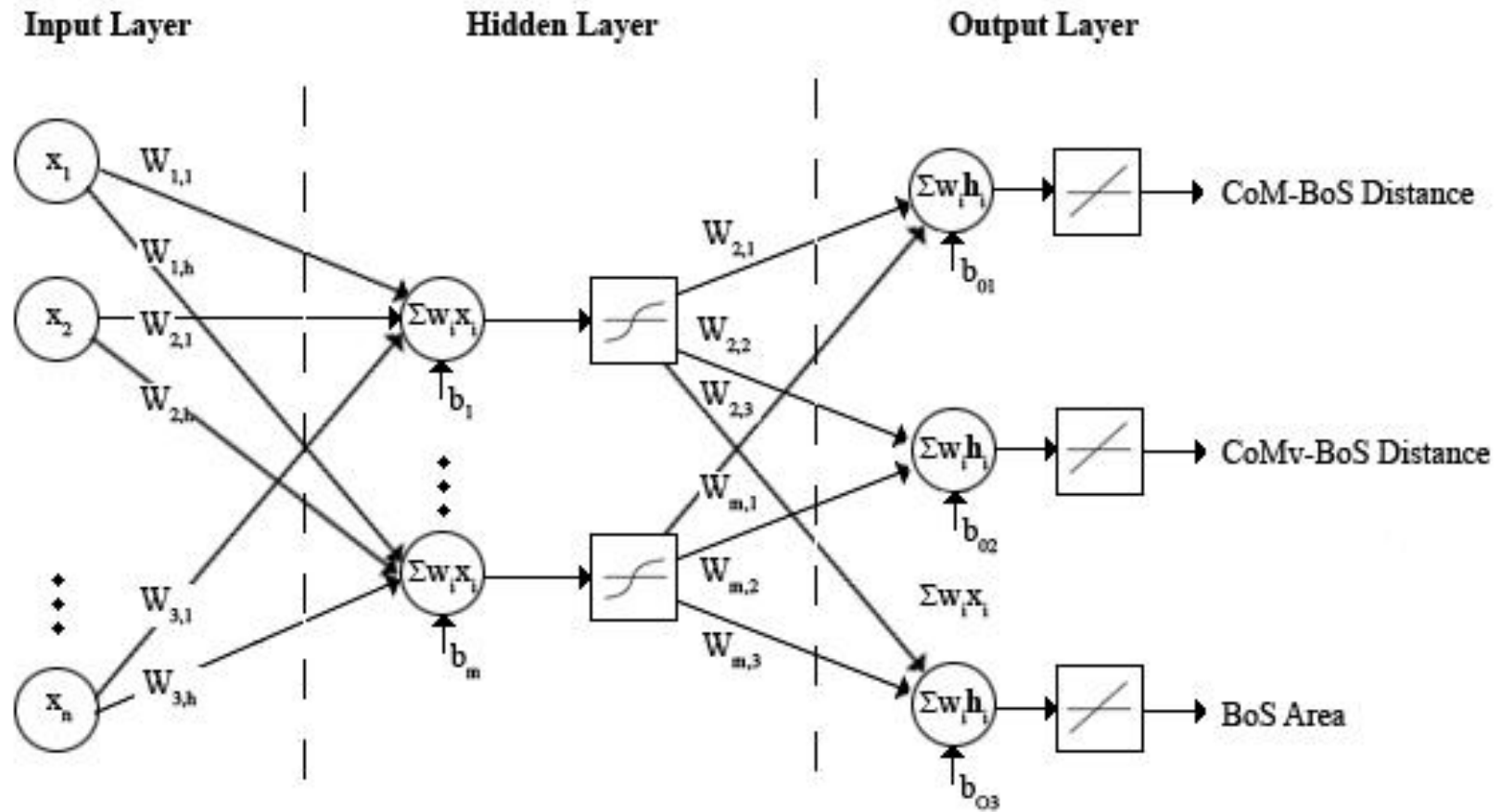
Figure 5.1. Neural network architecture representing the three layers as well as the tangential sigmoid and pure linear transfer functions in the hidden and output layers, respectively. All nodes are not represented in this diagram, though a weighted sum of all inputs and the bias is performed at each node in the hidden and output layers.

The ability to calculate CoM-BoS balance control using three different variable input types as well as a combination of all clinical variables were investigated. In addition, 3 different hidden node sizes and 3 MSE error goals were assessed for a total of 36 network iterations. Minimal processing time was required for network training on all these combinations. When 5 hidden nodes were used, much greater time was needed for the solution to converge to an MSE error of less than 0.01 or 0.001, with much of the samples reaching the maximum limit of 500 epochs before failing to reach the goal (Table 5.1). The use of 10 or 20 hidden was much more efficient in training the data sets at all error goals.

The input type by error goal by hidden nodes interaction was not detected for the CoM-BoS (P = .526), CoMv-BoS (P = .580) or BoS Area (P = .154) correlations. Alternatively, an error goal by hidden nodes interaction was detected for all three balance control dependent variables (P < .001; Table 5.2). For all three output variables, at the error goals of 0.01 and 0.001, as the number of hidden nodes increased from 5 to 10 or from 5 to 20, there was an increase in the correlation coefficient (P < .029). In addition, for the CoMv-BoS distance at the 0.001 error goal, there was approximately a 0.14 increase in the R value when the number of hidden nodes was increased from 10 to 20 (P =.011).

Table 5.1. Number of epochs (SD) for the neural network to learn the data set.

| Variables	Error Goal	Training Convergence (epochs)		
		5 Hidden	10 Hidden	20 Hidden
Subject Characteristics				
	0.1	17.4 (18.7)	7.7 (1.5)	5.0 (0.7)
	0.01	500 (0.0)	14.1 (5.5)	6.0 (1.0)
	0.001	500 (0.0)	21.9 (8.7)	6.4 (0.53)
Clinical Evaluation				
	0.1	61.6 (129.3)	8.3 (1.9)	6.4 (1.0)
	0.01	500 (0.0)	18.6 (18.7)	6.4 (0.7)
	0.001	500 (0.0)	31.0 (10.3)	8.3 (1.6)
Muscle Strength				
	0.1	42.8 (66.6)	7.4 (1.9)	4.6 (0.5)
	0.01	500 (0.0)	11.1 (2.8)	5.7 (1.0)
	0.001	500 (0.0)	22.9 (12.9)	6.3 (0.5)
All Variables				
	0.1	76.4 (163.6)	4.7 (0.5)	3.3 (0.5)
	0.01	151.4 (204.8)	6.1 (0.8)	4.1 (0.3)
	0.001	203.9 (193.9)	7.7 (3.0)	4.3 (0.5)

Table 5.2. Correlation values for balance control measures based on the number of hidden units and the error goal.

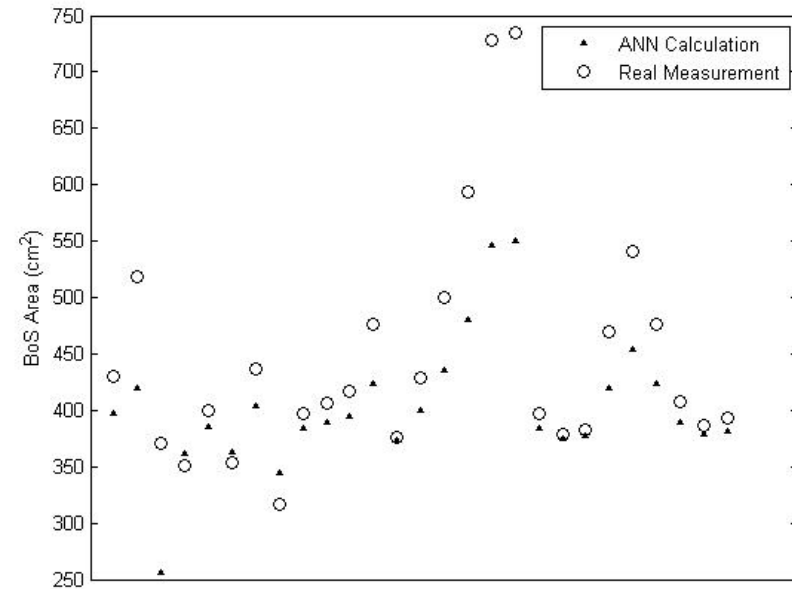| Variables	CoM-BoS Distance		CoMv-BoS Distance		BoS Area	
Error Goal	10 Hidden Unites	20 Hidden Units	10 Hidden Units	20 Hidden Units	10 Hidden Units	20 Hidden Units
Subject Characteristics						
0.1	0.33 (0.23)	0.54 (0.21)	0.72 (0.17)	0.67 (0.14)	0.51 (0.16)	0.76 (0.20)
0.01	0.62 (0.32)	0.47 (0.22)	0.68 (0.18)	0.69 (0.21)	0.71 (0.22)	0.58 (0.19)
0.001	0.33 (0.19)	0.54 (0.22)	0.60 (0.24)	0.71 (0.13)	0.57 (0.12)	0.66 (0.16)
Clinical Evaluation						
0.1	0.77 (0.14)	0.63 (0.19)	0.63 (0.24)	0.48 (0.28)	0.69 (0.17)	0.55 (0.16)
0.01	0.71 (0.14)	0.60 (0.41)	0.53 (0.25)	0.61 (0.30)	0.63 (0.19)	0.68 (0.25)
0.001	0.61 (0.21)	0.75 (0.14)	0.52 (0.28)	0.59 (0.15)	0.59 (0.25)	0.64 (0.15)
Muscle Strength						
0.1	0.48 (0.16)	0.56 (0.16)	0.54 (0.22)	0.60 (0.32)	0.46 (0.13)	0.76 (0.13)
0.01	0.54 (0.20)	0.61 (0.22)	0.62 (0.29)	0.60 (0.23)	0.63 (0.16)	0.68 (0.17)
0.001	0.60 (0.29)	0.57 (0.22)	0.40 (0.31)	0.70 (0.21)	0.50 (0.25)	0.70 (0.22)
All Variables						
0.1	0.80 (0.13)	0.70 (0.13)	0.63 (0.15)	0.69 (0.10)	0.64 (0.19)	0.63 (0.23)
0.01	0.72 (0.10)	0.75 (0.20)	0.68 (0.15)	0.77 (0.10)	0.60 (0.17)	0.71 (0.16)
0.001	0.66 (0.14)	0.61 (0.23)	0.64 (0.19)	0.73 (0.20)	0.69 (0.19)	0.66 (0.24)

Input variable differences were also demonstrated, as greater correlations were demonstrated by using all variables or the clinical examinations, when compared to the subject information input variables or muscle strength tests for the CoM-BoS distance and CoMv-BoS distance (P < .008). No differences were found in the assessment of the BoS Area between input variables. In addition, on average a 0.12 greater correlation was found when using all input variables to determine the CoMv-BoS distance, when compared to the clinical examinations (P = .001). No differences in performance were detected between the clinical measures and all input types for the CoM-BoS distance (P = .189) or BoS area (P = .128).

The combination of all input variables, with 20 hidden nodes and a 0.01 error goal resulted in the best training across all three dependent variables (Table 5.2). The use of these parameters provided convergence within an average of 4 epochs to finish training the network and provided R values between 0.71 and 0.77 for the CoM-BoS distance, CoMv-BoS distance and the BoS Area. On average, using the MSE, the ANN was able to calculate the CoMv-BoS distance to within 1cm and the BoS Area to within 75 cm^2 for all elderly adults (Figure 5.2).

Utilizing all input variables, variability in input weights were demonstrated across all learning iterations of the neural network. While the predictive nature of the input weights is unknown, nonetheless, the largest weights in the input layer were found for the ABC test, vision performance and hip abductor strength.
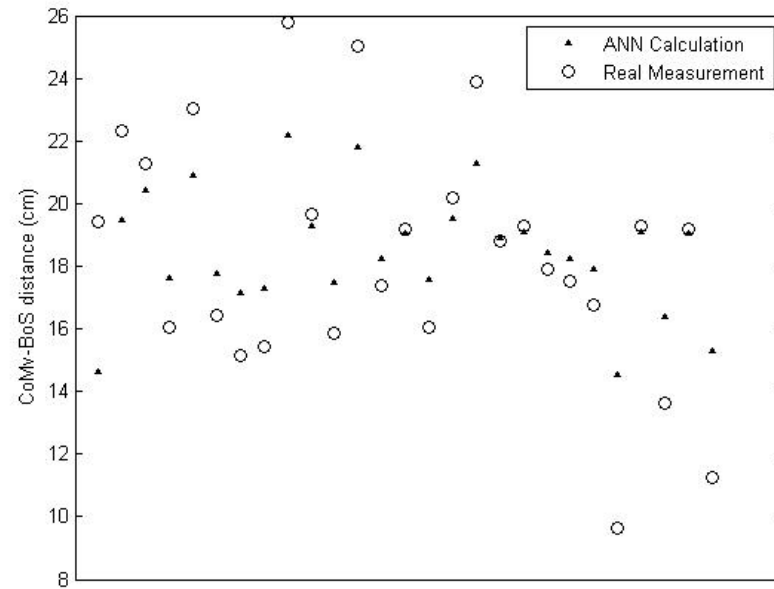
Figure 5.2. Representative data for the CoMv-BoS distance (A) and the BoS Area (B), as calculated by a neural network (triangles) with 20 hidden nodes and an error goal of 0.01. All input variables were included in this training set, with the actual values for these balance control measures represented by the open circles.

Discussion

The purpose of this study was to demonstrate that given clinical measures collected by a physician, an artificial neural network can determine gait balance control among elderly adults, as normally calculated by biomechanical assessment. In support of our hypothesis, by investigating subject characteristics, medical information, clinical evaluations and muscle strength, we were able to demonstrate that ANN model could determine the balance control of elderly individuals.

Improvement in the ability to properly determine balance control measures were demonstrated with an increased number of hidden units. The use of additional hidden nodes has previously been hypothesized to be an indicator of enhanced generality, with greater plasticity and pathways to a solution.[86] Similar network architecture has been successful in gait research. The ability to characterize lower extremity joint kinematics and kinetics based on electromyographic muscle activity was shown to confirm with physiological expectations.[88] Prior studies have also utilized two hidden layer architectures and shown an ability to correctly identify gait conditions using fast Fourier transform of lower extremity kinematics as inputs, with up 83% accuracy.[89] In the current study, single hidden layer architecture was utilized as this has been shown to be computationally faster and sufficient for learning functional relationships.[90]

The use of clinical evaluations resulted in greater balance control predictions than the use of subject information such as age, gender and BMI or lower extremity muscle strength alone. With all three input types, the ability to learn and calculate balance control parameters in elderly subjects improved significantly. While neural network

weights are variable and the predictive strengths unknown, the ABC score, vision and hip abductor strength demonstrated the greatest weighting when all three groupings were included as network inputs. The ABC, which is sometimes used as an indicator of fear of falling, has also been shown previously to be sensitive in discriminating fallers from non-fallers.[91] Similarly, the ability to maintain balance is a function of adequate visual information, with Nashner and Berthoz (1978) demonstrating that reduction in vision increased sway amplitude among older adults.[22] Furthermore, the hip abductor has been shown to be important in maintaining lateral stability, with changes in the base of support adapted by older adults in order to control the CoM and compensate for decreased hip abductor strength.[20]

The use of biomechanics laboratory equipment to assess gait performance can be time consuming and expensive. In addition to the approximately two hours spent within the laboratory by the subjects, much time is expended in data analysis by trained investigators. While such data is essential for determining the underlying mechanisms of balance impairment and possible fall incidents,[83] the ability to categorize and identify community dwelling elderly fallers at risk of falls in a quick and inexpensive manner is needed. As clinical examinations for this study took approximately 30 minutes with interpretation and analysis of the data quickly performed, the ability to use such data and correlate the findings to biomechanical measures for those adults unable to be evaluated in the laboratory setting is essential.

Limitations of this study included the small sample size. Though only 27 adults have thus far been fully screened by a physician, the use of a neural network still demonstrated the ability to quickly be trained and showed high correlation values of up to

0.80. This provides further evidence that an ANN can successfully be used to assess a person's gait balance control, without the need for full assessment within a laboratory setting. Future research can investigate the ability for a neural network to predict changes in balance control ability and eventually fall risk in the elderly based on different interventions. The ability for the network to provide differences in output conditions based on improvements at the input layer, such as in muscle strength gains or losses, alterations in medication or due to changes in cognitive ability will provide older adults and physicians with a quick and useful way to assess gait performance, where the majority of falls occur in the elderly population.

In conclusion, results from this study demonstrated that an artificial neural network could be trained to map clinical variables to biomechanical measures of gait balance control. While further studies should investigate the generalizability of the network to a larger group of subjects, these initial findings suggest that an ANN can be used to assess balance impairment and fall risk in the elderly. Investigating a combination of muscle strength, clinical examinations and subject medical history, this network approached a solution quickly and accurately. Following training, the ability to predict balance control measures among our subjects reached correlation values of R = 0.80. These findings demonstrate that ANN models can be used to assess longitudinal changes, understand the effects of personalized intervention and predict future fall risk in the elderly.

Bridge

Chapter V investigated the ability of artificial neural networks to learn mappings from clinical evaluations to gait balance control measures. Utilizing multiple input types and investigating various network settings, recommendations were made for setting up a model that can estimate the interaction of the center of mass with the base of support during gait. The ability for a neural network to predict balance control measures reached correlation values of $R = 0.80$ when utilizing a combination of muscle strength, clinical evaluations and medical history. Chapter VI summarizes the findings and provides a general discussion and conclusion from all the studies in this dissertation.

CHAPTER VI

DISCUSSION AND CONCLUSION

Falls remain a serious medical concern among the elderly, with incidence of falls

leading to morbidity and mortality. As falls have been correlated to changes in cognitive

function, muscle strength, balance control, as well as several other intrinsic and extrinsic

factors, there remains a need to properly identify balance impairment and fall risk.

Therefore, the aim of this study was to develop a model that could be used in a clinical

setting to diagnose elderly individuals as fallers or non-fallers. To that end, this study

investigated a method for measuring balance control during gait among young and older

adults; examined methods for identifying fallers retrospectively using a combination of

clinical and gait measures; assessed the longitudinal changes in older adults and

estimated the relative risk of falls prospectively; and established a model for estimating

balance control during gait in the elderly from clinical evaluations.

Main Findings

In the first study, the interaction of the whole body center of mass position and

velocity in relation to the base of support assessed static and dynamic balance control

throughout gait. Elderly fallers demonstrated reduced balance control ability, specifically

a decreased time to contact with the boundary of the BoS, when compared to young

adults at heel strike. This decreased time might predispose older adults to additional falls due to an inability to properly respond to perturbations or slips. When young adults walked at a similar gait velocity, they demonstrated greater dynamic balance control than the elderly fallers. Proper foot placement and understanding BoS changes might elucidate a safer and more efficient gait pattern among elderly fallers.

In the second study, clustering algorithms demonstrated that a combination of gait and clinical measures should be utilized when attempting to identify retrospective fallers. Inclusion of CoM-BoS balance control measures, along with the Berg Balance Scale and spatiotemporal measures, such as stride length and single support time, demonstrated sensitivity and specificity values of up to 90% when identifying 98 elderly fallers and non-fallers, respectively. Knowing which variables can properly identify fallers can allow for individualized treatment and intervention.

In the third study, a longitudinal analysis of 27 older adults demonstrated few changes in clinical and gait measures across a one year period. Among those adults who reported a prospective fall, only the CoM displacement to the boundary of the BoS along the CoM velocity vector demonstrated an ability to differentiate fallers from non-fallers. Similar to the previous study, a combination of balance control measures, the ABC, BBS, age and single support time demonstrated almost 80% sensitivity and 70% specificity in identifying older adults who fell in the following 6 months.

As the collection and analysis of these biomechanics measures can be time consuming and expensive, the final study investigated the ability of artificial neural networks to map clinical variables to balance control measures. The use of three layer feed-forward ANN with back propagation demonstrated that clinical measures can

accurately predict balance control during ambulation. Utilizing 20 nodes in the hidden layer, a combination of muscle strength, clinical examinations and subject medical history, this network approached a solution quickly and accurately. The ability to predict balance control measures reached correlation values of R = 0.80, and demonstrates that ANN architecture can be a powerful tool in providing a means for assessing longitudinal changes, intervention effects and future fall risk in the elderly.

<u>Limitations of the Study</u>

Although this study provided interesting findings regarding balance control and fall risk in the elderly, several limitations do exist. First, the number of subjects in the study may have limited the statistical power to detect group and time differences in the elderly. While differences were detected between groups and the ability to identify individuals remained strong, a larger number of subjects would have provided greater training to the artificial neural network model and allowed for additional testing and generalizability. Second, many of the subjects who volunteered for the study were active in the community and/or interested in examining their own balance ability. The ability to generalize to all elderly adults still needs to be investigated. Further work should also be conducted to quantify activity level among the elderly, and across a wide spectrum of individuals based on age, gender, body composition, race and activity level.

A one year longitudinal assessment of balance control and changes due to aging did not demonstrate across time differences. While physiological tests have

demonstrated age-related musculoskeletal and neurological change, longer periods of testing is possibly required to demonstrate similar changes among our population. Controlling for a vast number of external factors is a confounding issue in such a longitudinal study as well. Additionally, even though the primary outcome measures of the neural network have been shown to distinguish young adults, older healthy adults and elderly fallers, additional data is needed to validate the accuracy and assess the repeatability of these measures across a spectrum of adults.

During human movement analysis there is also the potential for error in estimating body motion. While the markers are placed on bony landmarks of the body, estimations and assumptions are made in order to quantify body segment parameters. Additionally, elderly adults who are obese will commonly have greater adipose tissue, thereby making accurate placement of markers difficult, particularly those on the lower extremity and pelvis. While skin motion artifact is a limitation to any marker based system, this technology has been validated and tested in the researcher community.

Finally, anthropometric data was utilized in this study to estimate center of mass locations of subjects. While these data sets represent a small group of individuals, they have been used extensively in the literature and been commonly accepted due to a lack of robust anthropometric information. The ability to calculate body segment parameters based on gender, age, body composition will validate human movement studies further.

Balance control and stability in the elderly remains a critical medical concern. While balance control has been accepted as the ability to maintain the center of mass within the base of support, there is still disagreement on proper quantification of variability or stability. In a traditional view of CoM motion, greater variability was an indicator of a degenerative system of posture control and increased risk of falling. However, Hamill and colleagues propose that variability can also be healthy and exploratory. A tradeoff between stability and variability might exist such that once a stable posture can be achieved or recovered, the system may utilize variability as an exploratory tool.[92]

Stability refers to the system's ability to recover (or diverge for instability) from perturbations or inherent variability in order to maintain posture.[93] To date, there remains disagreement on the physiological interpretation of non-linear measures of stability, including the Lyapunov exponent. The ability to demonstrate its usefulness can allow for further improvement in understanding human movement.

The ability to quantify age-related changes in balance control needs to be investigated further. While most studies have remained retrospective in nature, the ability to accurately assess fall risk should continue to demonstrate its effectiveness prospectively. Therefore, research that follows older adults for greater than one year needs to continue.

The effectiveness of using a neural network to assess gait balance control needs further study. The findings from this study demonstrate that this model is suitable for

mapping clinical to biomechanical measures in a small subset of individuals, but its ability to correctly map a new and larger set of data is still unknown. While results are favorable, a greater variability of subjects will provide a more robust model.

Finally, the ability to provide individualized intervention and treatment based on clinical examinations should allow for models to predict biomechanical changes in balance control, stability and fall risk in the elderly. Development of such models that allow for targeted intervention should be investigated.

APPENDIX A

INFORMED CONSENT FORM

Research Project Title: Detecting and Simulating Falls Risk in the Elderly

You are invited to participate in a research study conducted by Dr. Li-Shan Chou, of the University of Oregon, Department of Human Physiology. We hope to gain a better understanding of the mechanisms underlying the increased incidences of falls in the elderly and factors that are important for the maintenance of balance during walking.

If you decide to participate, you will be tested in the Motion Analysis Laboratory (Room B52, Gerlinger Annex). You will be invited to engage in the research activities (laboratory testing described below) every 6 months over the course of two years (5 visits – baseline, 6 months, 12 months, 18 months, 24 months).

In the first part of this study, a clinical evaluation will be performed at the Senior Health and Wellness Center with Richard Brunader, MD or in the Motion Analysis Lab by Victor Lin, MD. You will be asked about your current health condition, and evaluated for neurological and sensory-motor function. We expect the clinical visit will take approximately 45 minutes.

Any information that is obtained in connection with this clinical visit will remain confidential and will be disclosed only when you are qualified as a study subject and with your permission as granted in this consent form and its attachment. In order to do this research, you must also authorize us to access and use the above health information. An authorization form to allow Drs. Brunader or Lin to release that health information is attached for you to review and sign as an addendum to this consent form. The purpose of the form entitled "Authorization Form for Research Disclosure of Personal Health Information" is to allow Drs. Brunader and Lin to share medical history and exam results with Dr. Chou.

The laboratory testing will include three sections. Body movement will be recorded by our motion capture cameras (or maybe video cameras with your approval) while you are 1) walking barefoot around an approximately 40-meter walkway, 2) while walking barefoot on a treadmill set to your comfortable walking speed and 3) while standing up from, walking 6 meters and sitting back on the chair. Reflective markers will be placed on your skin at selected bony landmarks to record the motion of each individual body segment. An acceleration sensor will also be placed at the sacrum to record accelerations of the body. Surface electrodes will be placed on muscle surfaces to record activity of three muscles from one leg.

Before any walking trials, electromyographic (EMG) data and muscle strength of each selected muscle group (medial gastrocnemius, vastus lateralis, and gluteus medius) will be recorded on a strength testing device. Strength of your hip abductor will be measured in a standing position using a frame with a padded adjustable height board with arm supports that allow subjects to stand with support for testing. You will be instructed to abduct the hip against the application pad without rotating the lower extremity or moving the trunk. Strength of the knee extensor will be measured in a seated position at 60 degrees of knee flexion, and strength of the ankle plantarflexor will be measured in a seated position at 20 degrees of knee flexion and neutral ankle position. To stabilize the trunk during testing, Velcro straps will be tightened across your chest and waist, in addition to tilting of the chair 10 degrees backward from the vertical. You will be instructed to push as hard as you can for a period of 5 seconds for 3 contractions. A rest period of 5 seconds will be given between these 3 repetitions.

You will be asked to wear a pair of paper physical therapy shorts and sleeveless shirt (tank top) during testing. It will take approximately 2 hours to perform all of the above-mentioned tests.

We expect that there will be no more risk for you during testing than there normally is for you when outside of the laboratory. However, you may feel fatigue during or after muscle strength testing. Our staff members will check with you frequently and provide any required assistance. You will be given frequent breaks as requested. There is also possibility of discomfort involved in removing adhesive tape (used for marker placement) from skin at the end of the experiment. Although you personally may not receive any benefits from this research, based on results of this study, more effective therapies, rehabilitation programs, or balance assistive devices for the prevention of falls in the elderly may be designed and implemented.

Any information that is obtained in connection with this study and that can be identified with you will remain confidential and will be disclosed only with your permission. Subject identities will be kept confidential by coding the data with the study, subject pseudonyms, and collection date. The code list will be kept separate and secure from the actual data files. Furthermore, all videotaped data (collected upon your approval) will be kept confidential and will be reported in anonymous fashion (with face masked). The videotapes will be erased after an appropriate period of time after the completion of the study.

You will be reimbursed with $20 for your laboratory visit to compensate for the time spent. Your participation is voluntary. Your decision whether or not to participate will not affect your relationship with the Department of Human Physiology or the University of Oregon. If you decide to participate, you are free to withdraw your consent and discontinue participation at any time without penalty.

If you have any questions, please feel free to contact Dr. Li-Shan Chou, (541) 346-3391, Department of Human Physiology, 112C Esslinger Hall, University of Oregon, Eugene, OR, 97403-1240. If you have questions regarding your rights as a research subject,

contact Human Subjects Compliance, University of Oregon, Eugene, OR 97403, (541) 346-2510. You will be given a copy of this form to keep. Your signature indicates that you have read and understand the information provided above, understand the procedures that you will be experiencing, and willingly agree to participate, that you may withdraw your consent at any time and discontinue participation without penalty, that you will receive a copy of this form, and that you are not waiving any legal claims, rights or remedies.
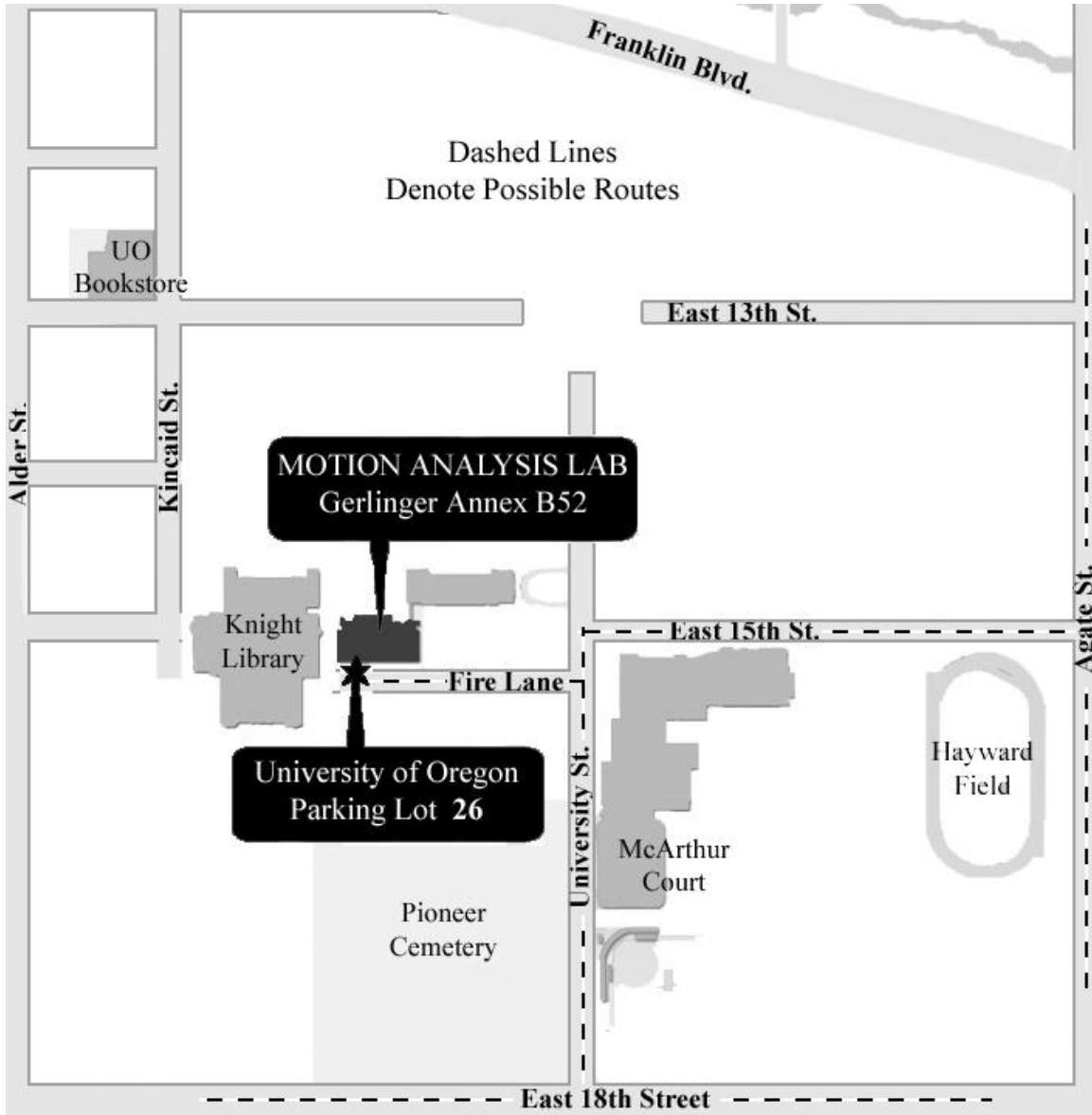
Name: _____

Signature: _____

Date: _____

APPENDIX B

DIRECTIONS

From 18th St:
- Turn onto University St. towards McArthur Court.
- Take the first left turn after Pioneer Cemetery

From Franklin Blvd:
- Turn onto Agate St towards Hayward Field.
- Take a right turn onto 15th St.
- Take a left turn onto University St.
- Take the first right turnA green University of Oregon sign will be visible for parking lot 26. Someone will be waiting for you at the end of this fire lane/parking lot. Testing will occur in Gerlinger Annex B52. If further directions are needed, feel free to contact us at 541-346-1033.

We are excited to meet you and for you to be a part of our project.
Sincerely,
Vipul Lugade & Betty Chen

BROCHURE

Falling

Approximately one-third of older adults will experience a fall once a year.

These falls can often occur while performing routine activities such as walking, turning or getting up from bed.

Falls Evaluation

Lower limb muscular strength testing and whole body motion analysis while walking will be performed during your visit to the Univerity of Oregon.

Motion Analysis

During your visit you will be asked to walk in the laboratory at your comfortable speed.

The visit takes about 2 hours.

You will be compensated for your time spent in the laboratory.

Research Goals

* Identify risk factors for falling in the elderly.

* Determine possible links between clinical evaluations and biomechanical quantification of gait balance control and stability.

* Provide possible interventions to adults with balance impairment.

* Longitudinally assess balance control changes for elderly adults over the age of 70.

* Develop a model for risk of falling among older adults in the community based on clinical evaluations.

Referrals
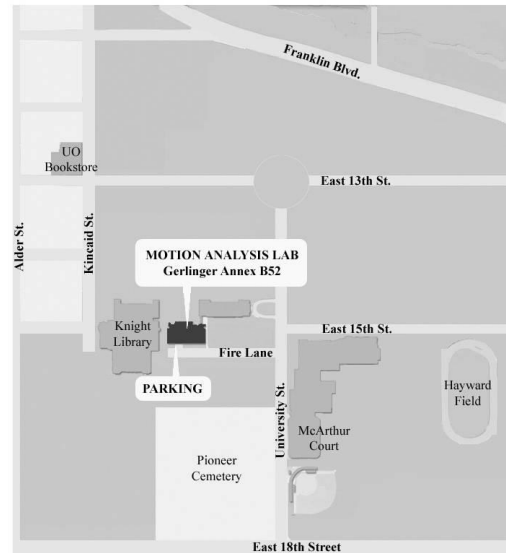
Contact:
Vipul Lugade
Betty Chen

University of Oregon
Motion Analysis Laboratory
Gerlinger Annex B52
Eugene, OR 97403

(541) 346-1033 (phone)
(541) 346-2841 (fax)

Fall Risk Evaluation

UNIVERSITY OF OREGON
MOTION ANALYSIS LAB

APPENDIX D

ACTIVITIES SPECIFIC BALANCE CONFIDENCE SCALE

For each of the following activities, please indicate your level of self-confidence by choosing a corresponding number from the following rating scale:

0%   10   20   30   40   50   60   70   80   90   100%
No Confidence   Completely Confident

"How confident are you that you will not lose your balance or become unsteady when you …"

1. … walk around the house?   _____%

2. … walk up and down stairs?   _____%

3. … bend over and pick up a slipper from the front of a closet floor?   _____%

4. … reach for a small can off a shelf at eye level?   _____%

5. … stand on your tip toes and reach for something above your head?   _____%

6. … stand on a chair and reach for something?   _____%

7. … sweep the floor?   _____%

8. … walk outside the house to a car parked in the driveway?   _____%

9. … get into or out of a car?   _____%

10. … walk across a parking lot to the mall?   _____%

11. … walk up or down a ramp?   _____%

12. … walk in a crowded mall where people rapidly walk past you?   _____%

13. … are bumped into by people as you walk through the mall?   _____%

14. … step onto or off of an escalator while you are holding on to a railing?   _____%

15. … step onto or off an escalator while holding onto parcels such that you cannot hold onto the railing?   _____%

16. … walk outside on icy sidewalks?   _____%

BERG BALANCE SCALE

Name _____   Date: _____

Grading: Please mark the lowest category that applies.

1. Sitting to standing
  Instruction: Ask the patient to please stand up. Try not to use hands for support.
  (4) able to stand, no hands and stabilize independently
  (3) able to stand independently using hands
  (2) able to stand using hands after several tries
  (1) needs minimal assist to stand or to stabilize
  (0) needs moderate or maximal assist to stand   _____

2. Standing unsupported
  Instruction: Stand for 2 minutes without holding on to any external support.
  (4) able to stand safely 2 minutes
  (3) able to stand 2 minutes with supervision
  (2) able to stand 30 seconds unsupported
  (1) needs several tries to stand 30 seconds unsupported
  (0) unable to stand 30 seconds unassisted   _____

IF SUBJECT IS ABLE TO STAND 2 MINUTES SAFELY, SCORE FULL MARKS
FOR SITTING UNSUPPORTED. PROCEED TO POSITION CHANGE STANDING
TO SITTING.

3. Sitting unsupported feet on floor
  Instruction: Sit with arms folded for 2 minutes.
  (4) able to sit safely and securely 2 minutes
  (3) able to sit 2 minutes under supervision
  (2) able to sit 30 seconds
  (1) able to sit 10 seconds
  (0) unable to sit without support 10 seconds   _____

4. Standing to sitting
  Instruction: Please sit down.
  (4) sits safely with minimal use of hands
  (3) controls descent by using hands
  (2) uses back of legs against chair to control descent
  (1) sits independently but has uncontrolled descent
  (0) needs assistance to sit   _____

5. Transfers
   Instruction: Please move from a chair with arm rests to a chair without arm rests
   and back again.
   (4) able to transfer safely with only minor use of hands
   (3) able to transfer safely with definite need of hands
   (2) able to transfer with verbal cueing and/or supervision
   (1) needs one person to assist
   (0) needs two people to assist or supervise to be safe   _____

6. Standing unsupported with eyes closed
   Instruction: Close your eyes and stand still for 10 seconds.
   (4) able to stand 10 seconds safely
   (3) able to stand 10 seconds with supervision
   (2) able to stand 3 seconds
   (1) unable to keep eyes closed 3 seconds but stays steady
   (0) needs help to keep from falling   _____

7. Standing unsupported with feet together
   Instruction: Place your feet together and stand without holding on to any external
support.
   (4) able to place feet together independently and stand 1 minute safely
   (3) able to place feet together independently and stand 1 minute with supervision
   (2) able to place feet together independently but unable to hold for 30 seconds
   (1) needs help to attain position but able to stand 15 seconds with feet together
   (0) needs help to attain position and unable to hold for 15 seconds   _____

THE FOLLOWING ITEMS ARE TO BE PERFORMED WHILE STANDING
UNSUPPORTED

8. Reaching forward with outstretched arm
   Instruction: Lift arm to 90 degrees. Stretch out your fingers and reach forward as far
as you can. Examiner places a ruler at end of fingertips when arm is at 90 degrees.
Fingers should not touch the ruler while reaching forward. The recorded measure is the
distance forward that the fingers reach while the subject is in the most forward leaning
position.
   (4) can reach forward confidently >10 inches
   (3) can reach forward >5 inches safely
   (2) can reach forward >2 inches safely
   (1) reaches forward but needs supervision
   (0) needs help to keep from falling   _____

9. Pick up object from the floor
   Instruction: Pick up the shoe/slipper that is placed in front of your feet
   (4) able to pick up slipper safely and easily
   (3) able to pick up slipper but need supervision
   (2) unable to pick up but reaches 1-2 inches from slipper and keeps balance
independently
   (1) unable to pick up and needs supervision while trying
   (0) unable to try - needs assist to keep from falling   _____

10. Turning to look behind over left and right shoulders
   Instruction: Turn to look behind you over your left shoulder. Repeat to the right.
   (4) looks behind from both sides and weight shifts well
   (3) looks behind one side only, other side shows less weight shift
   (2) turns sideways only but maintains balance
   (1) need supervision when turning
   (0) needs assist to keep from falling   _____

11. Turn 360 degrees
   Instruction: Turn around in a full circle, then turn a full circle in the other direction.
   (4) able to turn 360 safely in <4 seconds each side
   (3) able to turn 360 safely one side only in <4 seconds
   (2) able to turn 360 safely but slowly
   (1) needs close supervision or verbal cueing
   (0) needs assistance while turning   _____

12. Count number of times step stool is touched
   Instruction: Place each foot alternately on the stool. Continue until each foot has
touched the stool
   four times for a total of eight steps.
   (4) able to stand independently and safely and complete 8 steps in 20 seconds
   (3) able to stand independently and complete 8 steps in >20 seconds
   (2) able to complete 4 steps without aid with supervision
   (1) able to complete < 2 steps, needs minimal assist
   (0) needs assistance to keep from falling/ unable to try   _____

13. Standing unsupported, one foot in front
   Instruction: (Demonstrate) Place one foot directly in front of the other. If you feel
that you can't place your foot directly in front, try to step far enough ahead that the heel
of your forward foot is ahead of the toes of the other foot.
   (4) able to place foot tandem independently and hold 30 seconds
   (3) able to place foot ahead of other independently and hold 30 seconds
   (2) able to take small step independently and hold 30 seconds
   (1) needs help to step but can hold 15 seconds
   (0) loses balance while stepping or standing   _____

14. Standing on one leg

Instruction: Stand on one leg as long as you can without holding on to an external support.

    (4) able to lift leg independently and hold >10 seconds
    (3) able to lift leg independently and hold 5-10 seconds
    (2) able to lift leg independently and hold up to 3 seconds
    (1) tries to lift leg, unable to hold 3 seconds, but remains standing independently
    (0) unable to try or needs assist to prevent fall   _____

TOTAL SCORE   _____/56

APPENDEX F

GERIATRIC DEPRESSION SCALE

Name _____   **Date**_____

1. Are you basically satisfied with your life?	Yes ☐	No ☐
2. Have you dropped many of your activities and interests?	Yes ☐	No ☐
3. Do you feel that your life is empty?	Yes ☐	No ☐
4. Do you often get bored?	Yes ☐	No ☐
5. Are you in good spirits most of the time?	Yes ☐	No ☐
6. Are you afraid that something bad is going to happen to you?	Yes ☐	No ☐
7. Do you feel happy most of the time?	Yes ☐	No ☐
8. Do you often feel helpless?	Yes ☐	No ☐
9. Do you prefer to stay at home, rather than going out and doing things?	Yes ☐	No ☐
10. Do you feel you have more problems with memory than most?	Yes ☐	No ☐
11. Do you think it is wonderful to be alive now?	Yes ☐	No ☐
12. Do you feel pretty worthless the way you are now?	Yes ☐	No ☐
13. Do you feel full of energy?	Yes ☐	No ☐
14. Do you feel that your situation is hopeless?	Yes ☐	No ☐
15. Do you think that most people are better off than you?	Yes ☐	No ☐
TOTAL SCORE	Yes ☐	No ☐

APPENDIX G

TRAIL MAKING TEST A
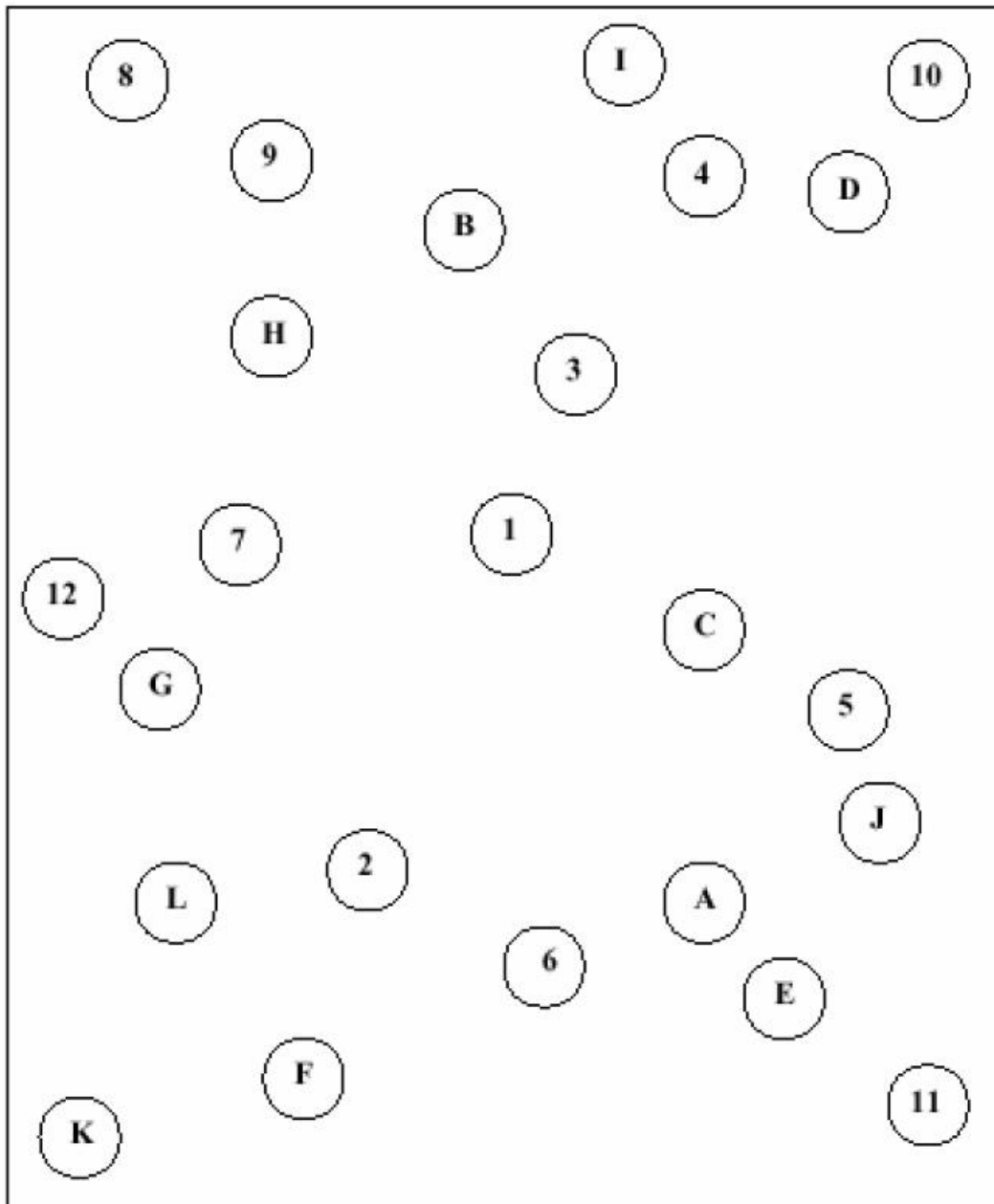
Patient's Name: _____   Date: _____
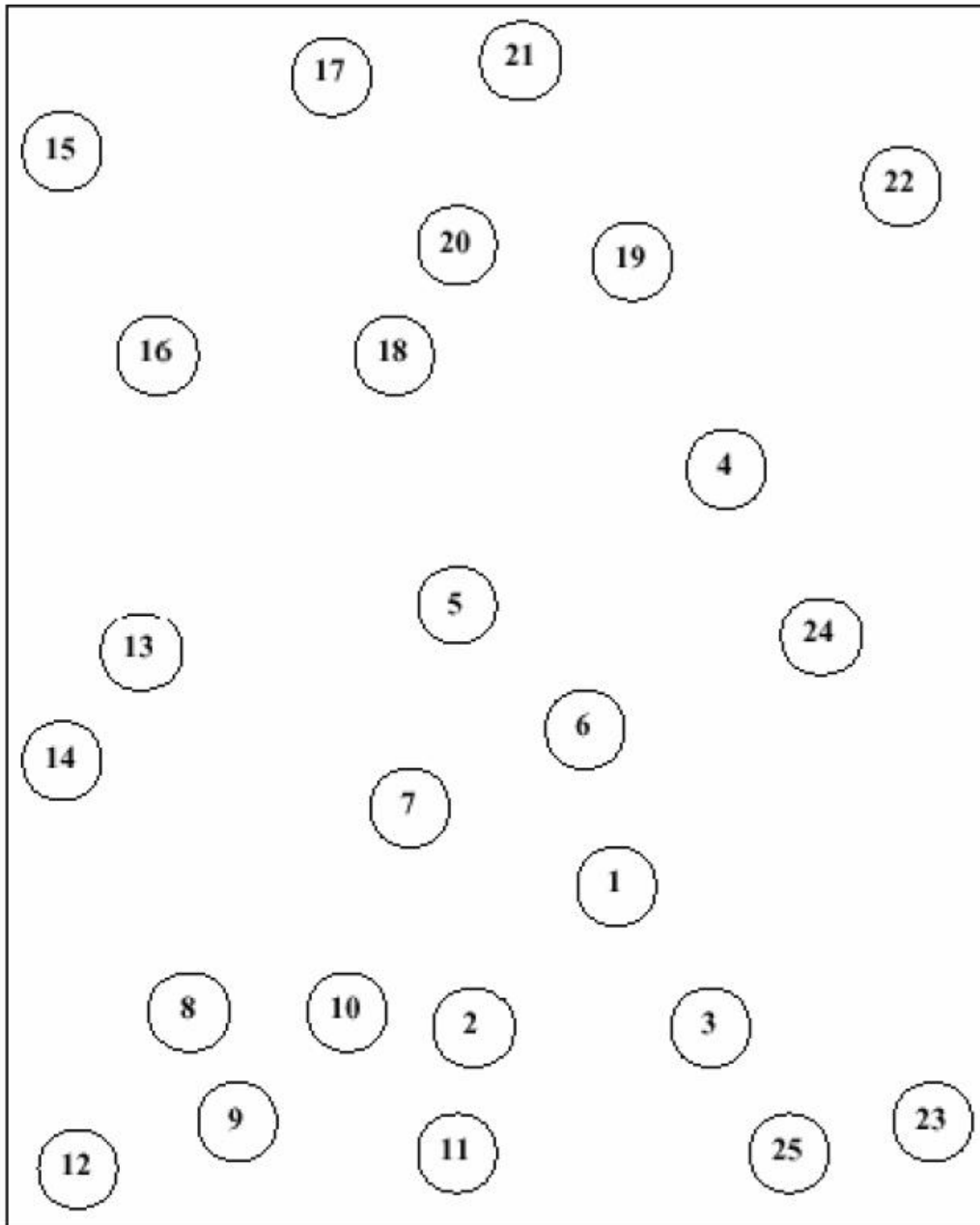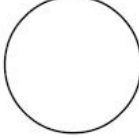
APPENDIX H

TRAIL MAKING TEST B

Patient's Name: _____   Date: _____

SAINT LOUIS UNIVERSITY MENTAL STATUS

Name _____ Age _____
Is patient alert? _____ Level of education _____

___/1	❶ 1. What day of the week is it?
___/1	❶ 2. What is the year?
___/1	❶ 3. What state are we in?
	4. Please remember these five objects. I will ask you what they are later.
	Apple Pen Tie House Car
	5. You have $100 and you go to the store and buy a dozen apples for $3 and a tricycle for $20.
	❶ How much did you spend?
___/3	❷ How much do you have left?
	6. Please name as many animals as you can in one minute.
___/3	❶ 0-4 animals ❶ 5-9 animals ❷ 10-14 animals ❸ 15+ animals
___/5	7. What were the five objects I asked you to remember? 1 point for each one correct.
	8. I am going to give you a series of numbers and I would like you to give them to me backwards.
	For example, if I say 42, you would say 24.
___/2	❶ 87 ❶ 649 ❶ 8537
	9. This is a clock face. Please put in the hour markers and the time at
	ten minutes to eleven o'clock.
	❷ Hour markers okay
___/4	❷ Time correct
___/2	❶ 10. Please place an X in the triangle.
	❶ Which of the above figures is largest?
	11. I am going to tell you a story. Please listen carefully because afterwards, I'm going to ask you some questions about it.
	Jill was a very successful stockbroker. She made a lot of money on the stock market. She then met Jack, a devastatingly handsome man. She married him and had three children. They lived in Chicago. She then stopped work and stayed at home to bring up her children. When they were teenagers, she went back to work. She and Jack lived happily ever after.
	❷ What was the female's name? ❷ What work did she do?
___/8	❷ When did she go back to work? ❷ What state did she live in?

_____   **TOTAL SCORE**

CLINICAL INTAKE FORM

Subject ID:

Evaluation Date:

Height [____] cm.

Weight [____] kg.

Date of Birth [____]

Respiration [____] /min

Temperature [____] °C

Vision:

20/ [____] OD

20/ [____] OS

Hearing:

Left Ear: ☐ OK ☐ Impaired

Right Ear: ☐ OK ☐ Impaired

Medications:

Total Number [____]

Types ☐ Psychotropics ☐ Steroids

☐ Cardiac Drugs ☐ NSAIDs

Daily Function:

ADL [____] /6   IADL [____] /8

Depression Screen:

☐ Neg ☐ Pos GDS [____] /15

Dementia Screen:

☐ Neg ☐ Pos SLUMS [____] /30

Co- Morbidities

Notes:

☐	Osteoporosis	[____]
☐	Osteopenia	[____]
☐	Arthritis	[____]
☐	Dizziness	[____]
☐	Peripheral Neuropathy	[____]
☐	ASPVD	[____]
☐	Orthostatic	[____]
☐	History of Stroke	[____]
☐	History of Falls	[____]
☐	Hip Fracture	[____]
☐	Spine Fracture	[____]
☐	Forearm Fracture	[____]
☐	Parental Hip Fracture	[____]
☐	Smoker	[____]
☐	Drink Alcohol	[____]
☐	Coronary Artery Disease	[____]
☐	Cardiac Arrhythmias	[____]
☐	CVD Symptomatic	[____]
☐	Thyroid Dysfunction	[____]
☐	Renal Insufficiency	[____]
☐	Anemia	[____]
☐	Vitamin D deficiency	[____]
☐	Impaired Coordination	[____]

Balance Tests:

Trail Making (A)	☐	sec
Trail Making (B)	☐	sec
Timed up and Go	☐	sec
ABC	☐	%
Berg Balance Scale	☐	/56
Dynamic Gait Index	☐	/24
Sit to Stand (x5)	☐	sec

mcTSIB

Open Firm	☐ OK	☐ Impaired
Closed Firm	☐ OK	☐ Impaired
Open Foam	☐ OK	☐ Impaired
Closed Foam	☐ OK	☐ Impaired

Range of Motion: Normal/Abnormal (1/0)

Right Limb

Hip:	Ab/Add	☐	Flex/Ext	☐
	Int/Ext Rot	☐		
Knee:	Flex/Ext	☐		
Ankle:	Inv/Ever	☐	Dorsi/Plantar	☐

Left Limb

Hip:	Ab/Add	☐	Flex/Ext	☐
	Int/Ext Rot	☐		
Knee:	Flex/Ext	☐		
Ankle:	Inv/Ever	☐	Dorsi/Plantar	☐

Manual Muscle Test: Grade (0-5)

Right Limb

Hip:	Flexion	☐	Extension	☐
	Abduction	☐	Adduction	☐
Knee:	Flexion	☐	Extension	☐
Ankle:	Plantarflexion	☐	Dorsiflexion	☐

Left Limb

Hip:	Flexion	☐	Extension	☐
	Abduction	☐	Adduction	☐
Knee:	Flexion	☐	Extension	☐
Ankle:	Plantarflexion	☐	Dorsiflexion	☐

REFERENCES CITED

1. Lord, S.R., *Falls in Older People*. 2001: Cambridge University Press.

2. Campbell, A.J., M.J. Borrie, G.F. Spears, S.L. Jackson, J.S. Brown, and J.L. Fitzgerald, *Circumstances and consequences of falls experienced by a community population 70 years and over during a prospective study*. Age Ageing, 1990; **19**(2): p. 136-141.

3. Sattin, R.W., D.A. Lambert Huber, C.A. DeVito, J.G. Rodriguez, A. Ros, S. Bacchelli, J.A. Stevens, and R.J. Waxweiler, *The incidence of fall injury events among the elderly in a defined population*. Am J Epidemiol, 1990; **131**(6): p. 1028-1037.

4. Tinetti, M.E., *Instability and falling in elderly patients*. Semin Neurol, 1989; **9**(1): p. 39-45.

5. Campbell, A.J., J. Reinken, B.C. Allan, and G.S. Martinez, *Falls in old age: a study of frequency and related clinical factors*. Age Ageing, 1981; **10**(4): p. 264-270.

6. Prudham, D. and J.G. Evans, *Factors associated with falls in the elderly: a community study*. Age Ageing, 1981; **10**(3): p. 141-146.

7. Tinetti, M.E., M. Speechley, and S.F. Ginter, *Risk factors for falls among elderly persons living in the community*. New Engl J Med, 1988; **319**(26): p. 1701-1707.

8. Ashley, M.J., C.I. Gryfe, and A. Amies, *A longitudinal study of falls in an elderly population II. Some circumstances of falling*. Age Ageing, 1977; **6**(4): p. 211-220.

9. Tinetti, M.E. and M. Speechley, *Prevention of falls among the elderly*. New Engl J Med, 1989; **320**(16): p. 1055-1059.

10. Shumway-Cook, A., M. Baldwin, N.L. Polissar, and W. Gruber, *Predicting the probability for falls in community-dwelling older adults*. Phys Ther, 1997; **77**(8): p. 812-819.

11. Gabell, A., M.A. Simons, and U.S. Nayak, *Falls in the healthy elderly: predisposing causes*. Ergonomics, 1985; **28**(7): p. 965-975.

12. Guralnik, J.M., L. Ferrucci, E.M. Simonsick, M.E. Salive, and R.B. Wallace, *Lower-extremity function in persons over the age of 70 years as a predictor of subsequent disability*. N Engl J Med, 1995; **332**(9): p. 556-561.

13. Nevitt, M.C., et al., *Risk factors for recurrent nonsyncopal falls. A prospective study*. JAMA, 1989; **261**(18): p. 2663-2668.

14. Kandel, J.G., J.H. Schwartz, and T.M. Jessell, *Principles of Neural Science*. 4th ed. 2000, New York: McGraw-Hill.

15. Horak, F.B., C.L. Shupert, and A. Mirka, *Components of postural dyscontrol in the elderly: a review.* Neurobiol Aging, 1989; **10**(6): p. 727-738.

16. Shumway-Cook, A. and M.H. Woollacott, *Motor Control - Translating Research into Clinical Practice*. 3rd ed. 2007, Philadelphia: Lippincott Williams & Wilkins.

17. Aniansson, A., M. Hedberg, G.B. Henning, and G. Grimby, *Muscle morphology, enzymatic activity, and muscle strength in elderly men: a follow-up study.* Muscle Nerve, 1986; **9**(7): p. 585-591.

18. Lindle, R.S., E.J. Metter, N.A. Lynch, J.L. Fleg, J.L. Fozard, J. Tobin, T.A. Roy, and B.F. Hurley, *Age and gender comparisons of muscle strength in 654 women and men aged 20-93 yr.* J Appl Physiol, 1997; **83**(5): p. 1581-1587..

19. Whipple, R.H., L.I. Wolfson, and P.M. Amerman, *The relationship of knee and ankle weakness to falls in nursing home residents: an isokinetic study.* J Am Geriatr Soc, 1987; **35**(1): p. 13-20.

20. Woollacott, M.H. and P.F. Tang, *Balance control during walking in the older adult: research and its implications.* Phys Ther, 1997; **77**(6): p. 646-660.

21. Patla, A.E., J.S. Frank, and D.A. Winter, *Balance control in the elderly: implications for clinical assessment and rehabilitation.* Can J Public Health, 1992; **83 Suppl 2**: p. S29-S33.

22. Nashner, L. and A. Berthoz, *Visual contribution to rapid motor responses during postural control.* Brain Res, 1978; **150**(2): p. 403-407.

23. Manchester, D., M. Woollacott, N. Zederbauer-Hylton, and O. Marin, *Visual, vestibular and somatosensory contributions to balance control in the older adult.* J Gerontol, 1989; **44**(4): p. M118-M127.

24. MacKinnon, C.D. and D.A. Winter, *Control of whole body balance in the frontal plane during human walking.* J Biomech, 1993; **26**(6): p. 633-644.

25. Winter, D.A., *Foot trajectory in human gait: a precise and multifactorial motor control task.* Phys Ther, 1992; **72**(1): p. 45-56.

26. Pai, Y.C. and J. Patton, *Center of mass velocity-position predictions for balance control.* J Biomech, 1997; **30**(4): p. 347-354.

27. Chou, L.S., K.R. Kaufman, M.E. Hahn, and R.H. Brey, *Medio-lateral motion of the center of mass during obstacle crossing distinguishes elderly individuals with imbalance.* Gait Posture, 2003; **18**(3): p. 125-133.

28. Jian, Y., D. Winter, M. Ishac, and L. Gilchrist, *Trajectory of the body COG and COP during initiation and termination of gait.* Gait Posture, 1993; **1**(1): p. 9-22.

29. Lee, H.J. and L.S. Chou, *Detection of gait instability using the center of mass and center of pressure inclination angles.* Arch Phys Med Rehabil, 2006; **87**(4): p. 569-575.

30. Hahn, M.E. and L.S. Chou, *Age-related reduction in sagittal plane center of mass motion during obstacle crossing.* J Biomech, 2004; **37**(6): p. 837-844.

31. Tang, P.F. and M.H. Woollacott, *Inefficient postural responses to unexpected slips during walking in older adults.* J Gerontol A Biol Sci Med Sci, 1998; **53**(6): p. M471-M480.

32. Chau, T., S. Young, and S. Redekop, *Managing variability in the summary and comparison of gait data.* J Neuroeng Rehabil, 2005; **2**: p. 22-41.

33. Gabell, A. and U.S. Nayak, *The effect of age on variability in gait.* J Gerontol, 1984; **39**(6): p. 662-666.

34. Brach, J.S., J.E. Berlin, J.M. VanSwearingen, A.B. Newman, and S.A. Studenski, *Too much or too little step width variability is associated with a fall history in older persons who walk at or near normal gait speed.* J Neuroeng Rehabil, 2005; **2**: p. 21-28.

35. Hausdorff, J.M., D.A. Rios, and H.K. Edelberg, *Gait variability and fall risk in community-living older adults: a 1-year prospective study.* Arch Phys Med Rehabil, 2001; **82**(8): p. 1050-1056.

36. Kang, H.G. and J.B. Dingwell, *Separating the effects of age and walking speed on gait variability.* Gait Posture, 2008; **27**(4): p. 572-577.

37. Menz, H.B., S.R. Lord, and R.C. Fitzpatrick, *Age-related differences in walking stability.* Age Ageing, 2003; **32**(2): p. 137-142.

38. Owings, T.M. and M.D. Grabiner, *Variability of step kinematics in young and older adults.* Gait Posture, 2004; **20**(1): p. 26-29.

39. Owings, T.M. and M.D. Grabiner, *Step width variability, but not step length variability or step time variability, discriminates gait of healthy young and older adults during treadmill locomotion.* J Biomech, 2004; **37**(6): p. 935-938.

40. Berg, W.P., H.M. Alessio, E.M. Mills, and C. Tong, *Circumstances and consequences of falls in independent community-dwelling older adults.* Age Ageing, 1997; **26**(4): p. 261-268.

41.   Lord, S.R., J.A. Ward, P. Williams, and K.J. Anstey, *An epidemiological study of falls in older community-dwelling women: the Randwick falls and fractures study.* Aust J Public Health, 1993; **17**(3): p. 240-245.

42.   Winter, D.A., A.E. Patla, and J.S. Frank, *Assessment of balance control in humans.* Med Prog Technol, 1990; **16**(1-2): p. 31-51.

43.   Pratt, J.E. and R. Tedrake, *Velocity-Based Stability Margins for Fast Bipedal Walking*, Fast Motions Biomech Robotics. 2006; Springer Berlin. p. 299-324.

44.   Townsend, M.A., *Biped gait stabilization via foot placement.* J Biomech, 1985; **18**(1): p. 21-38.

45.   Hof, A.L., M.G. Gazendam, and W.E. Sinke, *The condition for dynamic stability.* J Biomech, 2005; **38**(1): p. 1-8.

46.   Garcia, E., J. Estremera, and P.G.d. Santos, *A comparative study of stability margins for walking machines.* Robotica, 2002; **20**: p. 596-606.

47.   Hof, A.L., *The 'extrapolated center of mass' concept suggests a simple control of balance in walking.* Hum Mov Sci, 2008; **27**(1): p. 112-125.

48.   Hof, A.L., R.M. van Bockel, T. Schoppen, and K. Postema, *Control of lateral balance in walking. Experimental findings in normal subjects and above-knee amputees.* Gait Posture, 2007; **25**(2): p. 250-258.

49.   Woltring, H.J., *A FORTRAN package for generalized, cross-validatory spline smoothing and differentiation.* Adv Eng Software, 1986; **8**: p. 104-113.

50.   O'Connor, C.M., S.K. Thorpe, M.J. O'Malley, and C.L. Vaughan, *Automatic detection of gait events using kinematic data.* Gait Posture, 2007; **25**(3): p. 469-474.

51.   Ghoussayni, S., C. Stevens, S. Durham, and D. Ewins, *Assessment and validation of a simple automated method for the detection of gait events and intervals.* Gait Posture, 2004; **20**(3): p. 266-72.

52.   Pappas, I.P., M.R. Popovic, T. Keller, V. Dietz, and M. Morari, *A reliable gait phase detection system.* IEEE Trans Neural Syst Rehabil Eng, 2001. 9(2): p. 113-125.

53.   Greenspan, S.L., E.R. Myers, D.P. Kiel, R.A. Parker, W.C. Hayes, and N.M. Resnick, *Fall direction, bone mineral density, and function: risk factors for hip fracture in frail nursing home elderly.* Am J Med, 1998; **104**(6): p. 539-545.

54.   Lockhart, T.E. and S. Kim, *Relationship between hamstring activation rate and heel contact velocity: factors influencing age-related slip-induced falls.* Gait Posture, 2006; **24**(1): p. 23-34.

55.   Kuo, A.D., *The six determinants of gait and the inverted pendulum analogy: A dynamic walking perspective.* Hum Mov Sci, 2007; **26**(4): p. 617-656.

56.   Winter, D.A., *Human balance and posture control during standing and walking.* Gait Posture, 1995; **3**(4): p. 193-214.

57.   Delisle, A., M. Gagnon, and P. Desjardins, *Knee flexion and base of support in asymmetrical handling: effects on the worker's dynamic stability and the moments of the L5/S1 and knee joints.* Clin Biomech, 1998; **13**(7): p. 506-514.

58.   Huang, Q., S. Kajita, N. Koyachi, K. Kaneko, K. Yokoi, H. Arai, K. Komoriya, and K. Tanie. *A High Stability, Smooth Walking Pattern for a Biped Robot* in *Internation Conference on Robotics and Automation*. 1999; Detroit, Michigan.

59.   Bogle Thorbahn, L.D. and R.A. Newton, *Use of the Berg Balance Test to predict falls in elderly persons.* Phys Ther, 1996; **76**(6): p. 576-585.

60.   Geiger, R.A., J.B. Allen, J. O'Keefe, and R.R. Hicks, *Balance and mobility following stroke: effects of physical therapy interventions with and without biofeedback/forceplate training.* Phys Ther, 2001; **81**(4): p. 995-1005.

61.   Chang, J.T., S.C. Morton, L.Z. Rubenstein, W.A. Mojica, M. Maglione, M.J. Suttorp, E.A. Roth, and P.G. Shekelle, *Interventions for the prevention of falls in older adults: systematic review and meta-analysis of randomised clinical trials.* BMJ, 2004. **328**(7441): p. 680-686.

62.   Davison, J. and S. Marrinan, *Falls.* Rev Clin Geron, 2007; **17**(02): p. 93-107.

63.   Rubenstein, L.Z., *Falls in older people: epidemiology, risk factors and strategies for prevention.* Age Ageing, 2006; **35**(suppl 2): p. ii37-ii41.

64.   Lugade, V., V. Lin, and L.S. Chou, *Center of mass and base of support interaction during gait.* Gait Posture, 2011; **33**(3): p. 406-411.

65.   Shumway-Cook, A., S. Brauer, and M. Woollacott, *Predicting the probability for falls in community-dwelling older adults using the Timed Up & Go Test.* Phys Ther, 2000; **80**(9): p. 896-903.

66.   Berg, K., *Measuring balance in the elderly: preliminary development of an instrument.* Phys Ther Canada, 1989; **41**(6): p. 304-311.

67.   Podsiadlo, D. and S. Richardson, *The timed" Up & Go": a test of basic functional mobility for frail elderly persons.* J Am Geriatr Soc, 1991; **39**(2): p. 142-148.

68.   Powell, L.E. and A.M. Myers, *The Activities-specific Balance Confidence (ABC) Scale.* J Gerontol A Biol Sci Med Sci, 1995; **50A**(1): p. M28-M34.

69.   Corrigan, J.D. and N.S. Hinkeldey, *Relationships between parts A and B of the Trail Making Test.* J Clin Psych, 1987; **43**(4): p. 402-409.

70.   Lugade, V., A. Wu, B. Jewett, D. Collis, and L.S. Chou, *Gait asymmetry following an anterior and anterolateral approach to total hip arthroplasty.* Clin Biomech, 2010; **25**(7): p. 675-680.

71.   MacKay, D.J.C., *Information theory, inference, and learning algorithms.* 2003: Cambridge Univ Pr.

72.   Crowe, S.F., *The differential contribution of mental tracking, cognitive flexibility, visual search, and motor speed to performance on parts A and B of the Trail Making Test.* J Clin Psych, 1998; **54**(5): p. 585-591.

73.   Laessoe, U., H.C. Hoeck, O. Simonsen, T. Sinkjaer, and M. Voigt, *Fall risk in an active elderly population – can it be assessed?* J Neg Results BioMedicine, 2007; **6**(1): p. 2-12.

74.   Scott, V., K. Votova, A. Scanlan, and J. Close, *Multifactorial and functional mobility assessment tools for fall risk among older adults in community, home-support, long-term and acute care settings.* Age Ageing, 2007; **36**(2): p. 130-139.

75.   Yamada, M. and N. Ichihashi, *Predicting the probability of falls in community-dwelling elderly individuals using the trail-walking test.* Environ Health Prev Med, 2010; **15**: p. 386-391.

76.   Sherrington, C., S.R. Lord, J.C.T. Close, E. Barraclough, M. Taylor, S. O'Rourke, S. Kurrle, A. Tiedemann, R.G. Cumming, and R.D. Herbert, *A simple tool predicted probability of falling after aged care inpatient rehabilitation.* J Clin Epidem, 2011; **64**(7): p. 779-786.

77.   Muir, S.W., K. Berg, B. Chesworth, N. Klar, and M. Speechley, *Balance impairment as a risk factor for falls in community-dwelling older adults who are high functioning: a prospective study.* Phys Ther, 2010; **90**(3): p. 338-347.

78.   Carter, N.D., K.M. Khan, H.A. McKay, M.A. Petit, C. Waterman, A. Heinonen, P.A. Janssen, M.G. Donaldson, A. Mallinson, and L. Riddell, *Community-based exercise program reduces risk factors for falls in 65-to 75-year-old women with osteoporosis: randomized controlled trial.* J Canadian Med Assoc, 2002; **167**(9): p. 997-1004.

79.   Buzzi, U.H., N. Stergiou, M.J. Kurz, P.A. Hageman, and J. Heidel, *Nonlinear dynamics indicates aging affects variability during gait.* Clin Biomech, 2003; **18**(5): p. 435-443.

80.   Lugade, V., A.M. Farley, and L.S. Chou. *Fall Risk Analysis using K-means Clustering on Gait Balance Measures.* in *ISB2011.* 2011. Brussels.

81.   Maki, B.E., P.J. Holliday, and A.K. Topper, *A prospective study of postural balance and risk of falling in an ambulatory and independent elderly population.* J Gerontol, 1994; **49**(2): p. M72-M84.

82.   Prince, F., H. Corriveau, R. Hébert, and D.A. Winter, *Gait in the elderly.* Gait Posture, 1997; **5**(2): p. 128-135.

83.   Bhatt, T., D. Espy, F. Yang, and Y.C. Pai, *Dynamic gait stability, clinical correlates, and prognosis of falls among community-dwelling older adults.* Arch Phys Med Rehabil, 2011; **92**(5): p. 799-805.

84.   Seeman, T.E., P.A. Charpentier, L.F. Berkman, M.E. Tinetti, J.M. Guralnik, M. Albert, D. Blazer, and J.W. Rowe, *Predicting changes in physical performance in a high-functioning elderly cohort: MacArthur studies of successful aging.* J Gerontol, 1994; **49**(3): p. M97-M108.

85.   Hahn, M.E. and L.S. Chou, *A model for detecting balance impairment and estimating falls risk in the elderly.* Ann Biomed Eng, 2005; **33**(6): p. 811-820.

86.   Hahn, M.E., A.M. Farley, V. Lin, and L.S. Chou, *Neural network estimation of balance control during locomotion.* J Biomech, 2005; **38**(4): p. 717-724.

87.   Sheikh, J.I. and J.A. Yesavage, *Geriatric Depression Scale (GDS): Recent evidence and development of a shorter version.* Clin Geront: J Aging Mental Health, 1986; **5**(1-2): p. 165-173.

88.   Sepulveda, F., D.M. Wells, and C.L. Vaughan, *A neural network representation of electromyography and joint dynamics in human gait.* J Biomech, 1993; **26**(2): p. 101-109.

89.   Barton, J.G. and A. Lees, *An application of neural networks for distinguishing gait patterns on the basis of hip-knee joint angle diagrams.* Gait Posture, 1997; **5**(1): p. 28-33.

90.   Chau, T., *A review of analytical techniques for gait data. Part 2: neural network and wavelet methods.* Gait Posture, 2001; **13**(2): p. 102-120.

91.   Herman, T., A. Mirelman, N. Giladi, A. Schweiger, and J.M. Hausdorff, *Executive control deficits as a prodrome to falls in healthy older adults: a prospective study linking thinking, walking, and falling.* J Gerontol A Biol Sci Med Sci, 2010; **65**(10): p. 1086-1092.

92.   Hamill, J., J. Haddad, B. Heiderscheit, R. Van Emmerik, and L. Li, *Movement System Variability*, K. Davids, S. Bennett, and K. Newell, Editors. 2006, Human Kinetics: Champaign. p. 153-165.

93. Dingwell, J.B. and L.C. Marin, *Kinematic variability and local dynamic stability of upper body motions when walking at different speeds.* J Biomech, 2006; **39**(3): p. 444-452.