IDENTIFYING GAIT DEFICITS IN STROKE PATIENTS USING INERTIAL SENSORS

by

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ABSTRACT

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Falls remain a significant problem for stroke patients. Tripping, the main cause of falls, occurs when there is insufficient clearance between the foot and ground. Based on an individual's gait deficits, different joint angles and coordination patterns are necessary to achieve adequate foot clearance during walking. However, gait deficits are typically only quantified in a research or clinical setting, and it would be helpful to use wearable devices – such as accelerometers – to quantify gait disorders in real-world situations. Therefore, the objective of this project was to understand gait characteristics that influence the risk of tripping, and to detect these characteristics using accelerometers.

Thirty-five participants with a range of walking abilities performed normal walking and attempted to avoid tripping on an unexpected object while gait characteristics were quantified using motion capture techniques and accelerometers. Multiple regression was used to identify the relationship between joint coordination and foot clearance, and multiple analysis of variance was used to determine characteristics of gait that differ between demographic groups, as well as those that enable obstacle avoidance. Machine learning techniques were employed to detect joint angles and the risk of tripping from patterns in accelerometer signals.

Measures of foot clearance that represent toe height throughout swing instead of at a single time point are more sensitive to changes in joint coordination, with hip-knee coordination during midswing having the greatest effect. Participants with a history of falls or stroke perform worse than older non-fallers and young adults on many factors related to falls risk, however, there are no differences in the ability to avoid an unexpected obstacle between these groups. Individuals with an inability to avoid an obstacle have lower scores on functional evaluations, exhibit limited sagittal plane joint range of motion during swing, and adopt a conservative walking strategy.

Machine learning processes can be used to predict knee range of motion and classify individuals at risk for tripping based on an ankle-worn accelerometer. This work is significant because a portable device that detects gait characteristics relevant to the risk of tripping without expensive motion capture technology may reduce the risk of falls for stroke patients.

I dedicate this project to the love of my life, Stacey.

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Chapter 1: Introduction

Falls are a major problem for recovering stroke patients, with higher incidences of falls for stroke patients than the general elderly population (Batchelor, Mackintosh, Said, & Hill, 2012). However, interventions have been unsuccessful in preventing falls for stroke patients (Batchelor, Hill, Mackintosh, & Said, 2010; Batchelor, Hill, Mackintosh, Said, & Whitehead, 2012; Batchelor et al., 2012; Dean et al., 2012; Verheyden et al., 2013). Due to a variety of sensorimotor impairments, patients recovering from a stroke typically experience gait deviations that may present a risk for falling, such as spatiotemporal asymmetries and abnormal joint kinematics that could limit foot clearance (Balaban & Tok, 2014; Kim & Eng, 2003; Olney & Richards, 1996; Woolley, 2001).

Insufficient clearance between the foot and the walking surface or an obstacle may result in a trip, one of the greatest causes of falls (W. P. Berg, Alessio, Mills, & Tong, 1997; Blake et al., 1988; Overstall, Exton-Smith, Imms, & Johnson, 1977; Robinovitch et al., 2013; Tuunainen, Rasku, Jantti, & Pyykko, 2014). Low foot clearance and high foot clearance variability is suspected to increase risk of falling (Begg, Best, Dell'Oro, & Taylor, 2007). A low foot clearance value indicates that the foot passes close to the walking surface during swing phase, and high variability in foot clearance suggests an increased probability that the foot will come in contact with the walking surface. Foot clearance is dependent on the extent to which the swing leg shortens during gait. Gait adaptations to accommodate varying walking surfaces (Gates, Wilken, Scott, Sinitski, & Dingwell, 2012) and perform everyday tasks while walking (Schulz, Lloyd, & Lee, 2010) include concurrent changes in joint kinematics and foot clearance. Similarly, foot clearance variability is correlated with joint angle variability (Mills, Barrett, &

Morrison, 2008). Therefore, an understanding of how the joints of the lower extremity are controlled during walking will provide insight about how adequate foot clearance is achieved.

Joint coordination can allow the same goal, such as foot clearance, to be reached within each stride cycle, even if the strategy for achieving adequate foot clearance is different. For example, patients with knee osteoarthritis exhibit similar foot clearance as a control group, but the knee flexion, hip abduction and ankle adduction angles were different between the groups (Levinger et al., 2012). This evidence supports the theory that the lower extremity joints are coordinated to achieve the planned distal endpoint trajectory of the limb (Karst, Hageman, Jones, & Bunner, 1999). In healthy gait, coordination between the joints of the lower extremity enables foot clearance while the leg advances during swing (Moosabhoy & Gard, 2006). Since lack of coordination in the lower extremity has been observed in stroke patients (Barela, Whitall, Black, & Clark, 2000; Little, McGuirk, & Patten, 2014; Moosabhoy & Gard, 2006; Rinaldi & Monaco, 2013), investigation of the coupling of joint segments in stroke patients may yield information regarding the kinematic strategies required to achieve adequate foot clearance during walking.

Despite the obvious consequences of inadequate foot clearance and the incidence of trips, it is unclear how joint kinematics, coordination and foot clearance relate to the ability to avoid unexpected obstacles that could present a tripping hazard. Current clinical evaluations related to falls risk are used to quantify community engagement, fear of falling and gait and balance performance, although they often do not rely on information that can be obtained using equipment found in a 3D motion capture laboratory, and are not based on actual ability to avoid a trip or a fall. There is a push to investigate falls risk using perturbations that are similar to actual falls in an effort to further understand the mechanisms of falls and identify potential interventions that could reduce the incidence of falls (Grabiner, Crenshaw, Hurt, Rosenblatt, &

Troy, 2014). Experiments that challenge the ability to avoid an obstacle will help identify which individual and gait characteristics are relevant to the risk of tripping.

While abnormal joint kinematics and joint coordination patterns are common among stroke patients, the effect of hemiparesis caused by the stroke is different for each patient (Jonsdottir et al., 2009). It has been suggested that an individual-based approach to evaluate a patient's risk of tripping may be more effective than a group-based approach (Begg et al., 2007). The gold standard for detecting individual components of a gait disorder requires the use of motion capture technology, typically found in research labs. More commonly, a stroke patient will receive a gait analysis in a clinical setting. However, the frequency of falls for stroke patients within the first six months following discharge from rehabilitation highlights the need for gait supervision when patients are ambulating on their own (Forster & Young, 1995; Mackintosh, Hill, Dodd, Goldie, & Culham, 2005; Wagner, Phillips, Hunsaker, & Forducey, 2009). The ability to identify in real-time when an individual may be at risk for a fall may reduce the number of falls, particularly in the stroke population.

Wearable sensors are becoming a common way to reliably monitor and evaluate health-related indices (Appelboom et al., 2014; Bassett, 2012; Dobkin, 2013). Although there have been several efforts to quantify joint kinematics outside of a research or clinical setting using wearable inertial sensors, most current methods only identify foot clearance, not the lower extremity kinematics or coordination patterns that may contribute to changes in foot clearance (Hamacher, Hamacher, Taylor, Singh, & Schega, 2014; Mariani, Rochat, Buela, & Aminian, 2012; McGrath, Greene, Walsh, & Caulfield, 2011). Other methods designed to provide accurate information about joint kinematics require the placement of several sensors on multiple body segments (Seel, Raisch, & Schauer, 2014; Slajpah, Kamnik, & Munih, 2014), which may be difficult for the general population to effectively adopt.

Machine learning techniques contain the tools to identify patterns and associations in various types of health-related data (Chawla & Davis, 2013). For quantifying movement, machine learning algorithms are applied to the accelerometer signals from wearable devices to classify different activities, such as walking, running, climbing stairs and sitting (Moncada-Torres, Leuenberger, Gonzenbach, Luft, & Gassert, 2014). The ability to use similar machine learning techniques to classify and predict different walking patterns based on accelerometer signals could be used to quantify joint kinematics related to falls or evaluate the risk of tripping in real-time.

Statement of Purpose

The purpose of the proposed studies is to understand the gait characteristics that influence foot clearance and the ability to avoid obstacles that could present a tripping hazard. The ultimate goal is to use machine learning techniques to detect these falls-related gait abnormalities using a portable inertial sensor.

Specific Aims and Hypotheses

Aim 1: To identify the relationship between joint coordination and foot clearance during walking. This objective will be accomplished by using vector coding to quantify the coordination between the sagittal plane joint motions of the lower extremity, as well as determining foot clearance during normal overground walking for stroke patients, older adults with and without a history of falls, and young adults. It is expected that abnormal and highly variable coordination patterns will be associated with lower and more variable foot clearance.

Aim 2: To identify differences in function and gait characteristics related to falls risk, as well as the ability to avoid an unexpected obstacle, among stroke patients, young adults, older fallers and older non-fallers. This objective will be accomplished by comparing joint kinematics, joint coordination, neuromuscular function, and performance on falls-related evaluations across groups. It is hypothesized that participants with a history of falls and stroke will perform worse on falls-related evaluations and exhibit gait characteristics associated with the risk of falling, and that these participants will also be unable to avoid an obstacle while walking.

Aim 3: To determine gait and individual characteristics that enable successful avoidance of an unexpected object that could present a tripping hazard. This objective will be accomplished by observing participants react to an object that unexpectedly impedes the normal trajectory of the foot. Joint coordination patterns, joint angles, foot clearance, neuromuscular function and evaluations of falls risk will be compared for those who are successful and unsuccessful at avoiding the object. It is hypothesized that participants who do not avoid the object will have abnormal joint coordination and joint coordination variability, reduced sagittal plane joint angles, lower and more variable foot clearance, poor functional gait and balance scores, and lower muscle activity and isometric strength.

Aim 4: To detect gait characteristics related to the risk of tripping and classify individuals likely to contact an unexpected obstacle based on accelerometer signals. This objective will be accomplished by using machine learning algorithms to identify features in data from ankle-worn accelerometers related to specific joint kinematics and gait patterns of individuals who are unable to avoid an unexpected obstacle. It is expected that machine learning algorithms will be more successful in predicting knee joint angles than hip or ankle angles, and that the parameters required for accurate classification of the risk for tripping will be identified.

Delimitations of the Study

Results of this study may only be generalizable to the sample and conditions of the experiment.

1. All participants will be able to ambulate on their own for five minutes at a time without the use of an assistive device; therefore, any identification of abnormal gait may not be generalizable to individuals with more severe gait deficits.
2. Gait characteristics for each participant will be assessed during overground walking, and the ability to avoid obstacles will be evaluated while walking on a treadmill. Kinematic analyses may only be generalizable to each testing condition.

Assumptions of the Study

Some assumptions will be made in conducting this study:

1. Participants will truthfully answer all questions in the questionnaire.
2. Participants will walk in a way that represents their typical gait.
3. Participants will make an effort to avoid the obstacle when it is presented.
4. Walking overground will be similar to walking on treadmill.

5. All lower-extremity segments are rigid bodies.
6. All lower-extremity joints are frictionless.

Significance of the Study

Falls remain a significant problem for stroke patients, and each patient's risk of falling may be based on unique gait deficits. Identifying the characteristics of gait that control foot clearance and those that are associated with the ability to avoid obstacles while walking can inform rehabilitation techniques and interventions designed to reduce the risk of tripping. Developing a convenient way to monitor an individual's gait with wearable sensors and machine learning techniques could eventually be used to predict the risk of tripping in real-time, and allow for an individual to make gait alterations that enable them to avoid an obstacle.

Chapter 2: Predicting Foot Clearance from Joint Coordination

Introduction

Falls are a major problem for stroke survivors, with higher incidences of falls than the general elderly population (Batchelor et al., 2012). Trips are one of the greatest causes of falls, and are the result of insufficient clearance between the foot and floor (Robinovitch et al., 2013). Determining the ability for individuals to achieve adequate foot clearance requires the quantification of the minimum foot clearance (MFC), the lowest point of the toe as it passes the walking surface during the swing phase of gait. Low MFC indicates that the toe is close to the walking surface, and high MFC variability means that a person exhibits a variety of toe heights while walking, presumably some with low foot clearance. Both low MFC and high MFC variability are suspected to increase the risk of falling (Begg et al., 2007). To reduce the risk of falling, it would be beneficial to understand the gait characteristics that contribute to low MFC and high MFC variability.

Individual changes in the sagittal plane ankle, knee and hip angles affect toe clearance throughout swing phase of healthy gait (Gates et al., 2012; Moosabhoy & Gard, 2006; Schulz et al., 2010; Schulz, 2011; Winter, 1992), and MFC variability is correlated with joint angle variability (Mills et al., 2008). However, joint adaptations to achieve MFC may be specific to a patient group or individual (Levinger et al., 2012). Rather than identify distinct joint angles to ensure adequate foot clearance, in healthy gait, a variety of coordination patterns between the joints can result in a consistent end-point trajectory of the lower extremity (Latash, Levin, Scholz, & Schoener, 2010; Latash, 2010). However, abnormal coordination has been observed in stroke survivors (Barela et al., 2000; Chow & Stokic, 2015; Little et al., 2014; Moosabhoy & Gard, 2006). The effect of abnormal joint coordination or joint coordination variability on the magnitude or variability of foot clearance is not known, but it may help to explain a greater incidence of falls among the chronic stroke population.

There have been several methods used to quantify foot clearance and foot clearance variability. MFC and MFC variability are commonly determined as the mean and standard deviation, respectively, of the vertical position of the toe at the local minimum of the toe trajectory during midswing (Moosabhoy & Gard, 2006; Nagano, James, Sparrow, & Begg, 2014). However, it is possible that this local minimum does not exist for every stride, with the toe height increasing throughout swing phase without the inflection point identified as MFC. This has been noted particularly among individuals with a history of stroke (Little et al., 2014). Due to the challenges in identifying MFC from the toe trajectory, MFC has been identified as the toe height at the point of greatest forward velocity of the foot (Winter, 1992). Additionally, the magnitude of MFC and the part of the shoe closest to the walking surface (e.g. toe vs. midfoot vs. heel) varies with task, suggesting that an absolute value for MFC may not be an adequate representation of foot clearance in all circumstances (Loverro, Mueske, & Hamel, 2013; Thies, Jones, Kenney, Howard, & Baker, 2011). Another way of measuring foot clearance is by determining how much the leg shortens during the swing phase (Little et al., 2014; Moosabhoy & Gard, 2006). Maximal limb shortening provides a measure of the capacity for shortening of the leg during swing to facilitate foot clearance. Because maximal limb shortening is based on the distance between the hip and toe, it may be more sensitive to changes in joint coordination as the hip-toe distance relies on concurrent joint motions at the ankle, knee and hip. Nonetheless, maximal limb shortening and maximal limb shortening variability still represent a single point during swing phase and may not adequately describe foot clearance or foot clearance variability. Principle Components Analysis (PCA) can be used to identify modes of variation within a waveform without choosing a discrete point (Daffertshofer, Lamoth, Meijer, & Beek, 2004). By performing PCA on the vertical trajectory of the toe during swing, it is possible to obtain a variable that represents the magnitude of toe height not at one point, but throughout swing phase. The standard deviation of this variable represents the variability in toe height throughout swing.

The purpose of this study was to identify how lower extremity sagittal plane joint coordination and coordination variability influences foot clearance and foot clearance variability for people with a range of walking patterns. Traditional measures of foot clearance were compared with a representation of foot clearance using PCA. It was expected that the PCA method of quantifying foot clearance and foot clearance variability would be more sensitive to changes in joint coordination and joint coordination variability. Additionally, it was anticipated that abnormal gait patterns would play an important role in defining the relationship between joint coordination and foot clearance. Exploring this relationship will provide insight about how to ensure adequate foot clearance, particularly for people with abnormal joint coordination.

Methods

Participants. Thirty-five community-dwelling participants with a range of walking abilities were included in this study (Table 1). Ten participants were healthy young adults age 18-45, ten were healthy older adults age 65 and older without a history of falls, ten were healthy older adults age 65 and older with a history of falls, and five were participants who had experienced a stroke more than six months earlier. Participants were considered as having a falls history if they had experienced a fall in the last six months, defined as unintentionally coming to rest on the ground (Senden, Savelberg, Grimm, Heyligers, & Meijer, 2012). Participants with chronic stroke were recruited from local rehabilitation centers, and their affected side was noted. For all other participants, the ‘affected’ side was assigned randomly. All participants were able to walk without an assistive device for 5 minutes at a time. Mental state was determined using the Mini-Mental State Examination (MMSE), and inclusion was limited to participants with a MMSE score greater than 22 (Savin, Morton, & Whitall, 2014).

Table 1

Participant Characteristics by Group

	Young Adult	Older Adult - Non-faller	Older Adult - Faller	Stroke
N	10	10	10	5
Age (range), yr	30.5 (22-44)	71.9 (65-87)	75.3 (66-91)	61.6 (40-83)
Height (SD), m	1.74 (0.14)	1.68 (0.08)	1.72 (0.12)	1.68 (0.10)
Weight (SD), kg	76.0 (18.1)	75.9 (16.2)	86.3 (23.0)	82.6 (13.4)
Sex	5 M, 5 F	3 M, 7 F	5 M, 5 F	2 M, 3 F
Number of Falls 6 Months (range)	0.1 (0-1)	0	1.4 (1-3)	0.4 (0-1)
Mini Mental State Exam (range)	29.6 (28-30)	29.3 (28-30)	28.6 (27-30)	27.6 (24-30)
LE Fugl-Meyer (range)	--	--	--	24.6 (17-31)
Affected Side	--	--	--	3 R, 2 L
Type of Stroke	--	--	--	5 ischemic
Time since stroke onset (range), mo	--	--	--	43.2 (10-120)

Note. SD = standard deviation; LE = lower extremity.

Each participant was provided a pair of standard laboratory shoes (Saucony Jazz, Lexington, MA) and tight-fitting shorts. The participants with chronic stroke completed the lower extremity sub-scale of the Fugl-Meyer assessment, which has a range of possible scores of 0-34 (Sanford, Moreland, Swanson, Stratford, & Gowland, 1993; Sullivan et al., 2011). Participants wore a gait belt and the evaluator provided assistance for stability only as needed.

Biomechanics assessment. Retroreflective markers used for motion capture were applied bilaterally to track the motion of the thigh, leg and foot. The tracking markers were placed on a the right and left ASIS and PSIS, a four-marker plate on the thighs and the legs, and a rigid four-marker cluster attached to the heel counter of the shoes. A standing calibration was recorded with additional calibration markers on the following bilateral anatomical locations: iliac crest, greater trochanter, lateral and medial femoral epicondyles, malleoli and first and fifth metatarsal heads. An additional calibration marker was placed on the distal end of each shoe. The location of this marker in the local coordinate system of the foot was used to determine the toe position during the movement trials without the need for tracking the toe marker. The distal toe marker position represented the toe's trajectory during swing phase (Nagano, Begg, Sparrow, & Taylor, 2011). A global coordinate system was defined with the origin in the plane of the walking surface, the x-axis pointing laterally to the right of the participant, the y-axis pointing in the direction of walking, and the z-axis perpendicular to the floor pointing superiorly. The calibration markers were removed following a three-second standing calibration trial. During all trials, the three-dimensional positions of each marker were continuously collected at 200 Hz with a ten-camera Eagle system (Motion Analysis, Inc., Santa Rosa, CA). This data was filtered using a 4^{th} order, zero-lag, recursive Butterworth filter with a cutoff at 10 Hz.

From the calibration trial, the joint center of each hip was established as 25% of the distance between the left and right greater trochanters (Weinhandl & O'Connor, 2010), and the knee and ankle joint centers were defined as the midpoint between the lateral and medial femoral epicondyles and malleoli, respectively. Right-handed local coordinate systems were defined for the pelvis, thigh, shank and foot segments as outlined by Wu et al. (2002). Three-dimensional joint angles at the hip, knee and ankle were calculated using a joint coordinate system approach (Grood & Suntay, 1983; Wu et al., 2002). Processing of the kinematic data was done using Visual 3D software (v5.00.24; C-Motion, Inc., Rockville, MD).

Data was collected as each participant walked overground at their normal walking pace. Ten strides were recorded for the affected leg. Participants were allowed to rest if their rating of perceived exertion was above 9 – very light (Borg, 1970). Each stride was time normalized to 100% of the stride cycle (101 data points), with heel-strike and toe-off events determined from the location of a heel marker and the virtual location of the toe marker using the horizontal velocity algorithm (Zeni, Richards, & Higginson, 2008), implemented using custom software (Matlab v8.0.0.783, Mathworks, Inc., Natick, MA, USA).

Data analysis. Coordination and variability of coordination was calculated for the relative sagittal plane motion of the hip and knee, hip and ankle, and knee and ankle using a vector coding technique (Hamill, Haddad, & McDermott, 2000). With the proximal joint angle on the x-axis and the distal joint angle on the y-axis, each point in a stride cycle was plotted. A vector was made between consecutive points, and split into x- and y-components, where the x-component indicates proximal joint motion and the y-component indicates distal joint motion. The relative motion between the joints was established by taking the four-quadrant arctangent of the y-component over the x-component, producing a coupling angle with a range of -180° to 180°. All coupling angles in quadrants II-IV were converted to a corresponding coupling angle in quadrant I by taking the absolute value of angles in quadrant III, and subtracting from or adding to 180° for angles in quadrant II and IV, respectively. The result was a range of coupling angles of 0° to 90° (Ferber, Davis, & Williams, 2005). Circular statistics were used to calculate each participant's mean and standard deviation of the coupling angle at each point in the stride cycle. The stride cycle was split into six sub phases, labeled loading response (ipsilateral heel-strike to contralateral toe-off), midstance (contralateral toe-off to contralateral heel-strike), terminal stance (from contralateral heel-strike to ipsilateral toe-off), and initial swing, midswing and terminal swing (one third each of the swing phase of the ipsilateral leg). The coupling angle and coupling angle variability were averaged across each sub phase, using circular statistics.

Three measures of foot clearance were calculated: two that approximate toe height during swing, and one measure of maximal limb shortening. The standard deviation of each these measures represents foot clearance variability. In the first measure of toe height, MFC was defined as the vertical displacement from the ground of the toe marker at the point of greatest horizontal velocity of the toe marker (Winter, Patla, Frank, & Walt, 1990). The mean and standard deviation of the MFC was calculated for each participant. The second method represented toe height through Principle Components Analysis of the vertical toe marker position waveform during swing phase. All trials of all subjects were organized into *n* rows of a matrix with the vertical toe marker position during swing phase for each trial, time normalized to 101 data points, filling *p* columns of an X_{nxp} matrix. Using eigenvector analysis, the covariance matrix $S_{101 \times 101}$ was orthonormalized to determine the eigenvector matrix $U_{101 \times 101}$. Each eigenvector represents a principle component (PC) that describes one mode of variation within the entire dataset. The eigenvalues, $U'SU = L_{1 \times 101}$, were determined to rank each PC's contribution to the total variation in the data. A parallel analysis with an equivalently-sized input matrix of normally-distributed randomly-generated numbers revealed the variance explained by random error, and therefore a PC was retained only if the variance explained by that PC was greater than this threshold. Each trial was given a score for each of the retained PCs based on how it contributes to that PC's mode of variation (Equation 1), where $\bar{x}_{1\text{x}101}$ is the mean of all trials. The interpretation of each retained PC was determined according to the single PC reconstruction method outlined by Brandon, et al. (2013), and the PCs that represent the magnitude of the vertical toe position during swing were identified. For each participant, the mean and standard deviation of each PC score that represents toe height were evaluated across all trials.

$$Z_{n\times101} = \left(X_{n\times101} - (1_{n\times1} \times \bar{x}_{1\times101})\right) \times U'_{101\times101} \qquad (1)$$

To determine maximal limb shortening, the locations of the hip joint and toe at each point in the stride cycle were considered. The instantaneous distance between the hip and toe was divided by the instantaneous height of the hip joint relative to the ground to determine the normalized limb length. The greatest percent reduction (i.e. the lowest value) of normalized limb length during swing represented the maximal limb shortening (Little et al., 2014). For each participant, the mean and standard deviation of the maximal limb shortening were taken across all trials. All data reduction was done using custom software (Matlab v8.0.0.783, Mathworks, Inc., Natick, MA, USA).

A Pearson correlation was calculated for each pair of foot clearance measures and for each pair of foot clearance variability measures. Three stepwise multiple regression analyses were used to determine the relative contributions of the joint coordination variables in predicting foot clearance: the mean coupling angle for each pair of coupled joints (hip-knee, hip-ankle, knee-ankle) over each sub phase of the stride cycle was used to predict the toe height at the greatest horizontal velocity of the foot, the PC scores that represent toe height during swing, and the maximal limb shortening. Additionally, the relationship of within-subject variability of the coupling angle to within-subject variability of foot clearance was investigated with three similar stepwise multiple regression analyses: the variability in coupling angle for each pair of coupled joints (hip-knee, hip-ankle, knee-ankle) over each sub phase of the stride cycle was used to predict the variability of the toe height at the greatest horizontal velocity of the foot, the standard deviation of the PC scores that represent toe height during swing, and the variability in maximal limb shortening. Stepwise multiple regression was used to control for multicollinearity between the predictor variables, with stepping criteria of a 0.05 probability of F to enter, and a 0.10 probability of F to be removed. For each model that significantly predicted the dependent variable, the predictor variables that contributed significantly and had a variance inflation factor of less than 5 were identified, with significance determined at $p < 0.05$. All statistical analyses were performed in SPSS (v19.0.0.1; SPSS, Inc., Chicago, IL).

Results

The relative motion of each pair of coordinated joints (hip-knee, hip-ankle, knee-ankle) was interpreted using the coupling angle (Figure 1). When the coupling angle is 0°, just the proximal joint is moving, and there is only distal joint motion at 90°. There is equal relative motion of the proximal and distal joints when the coupling angle is 45°.

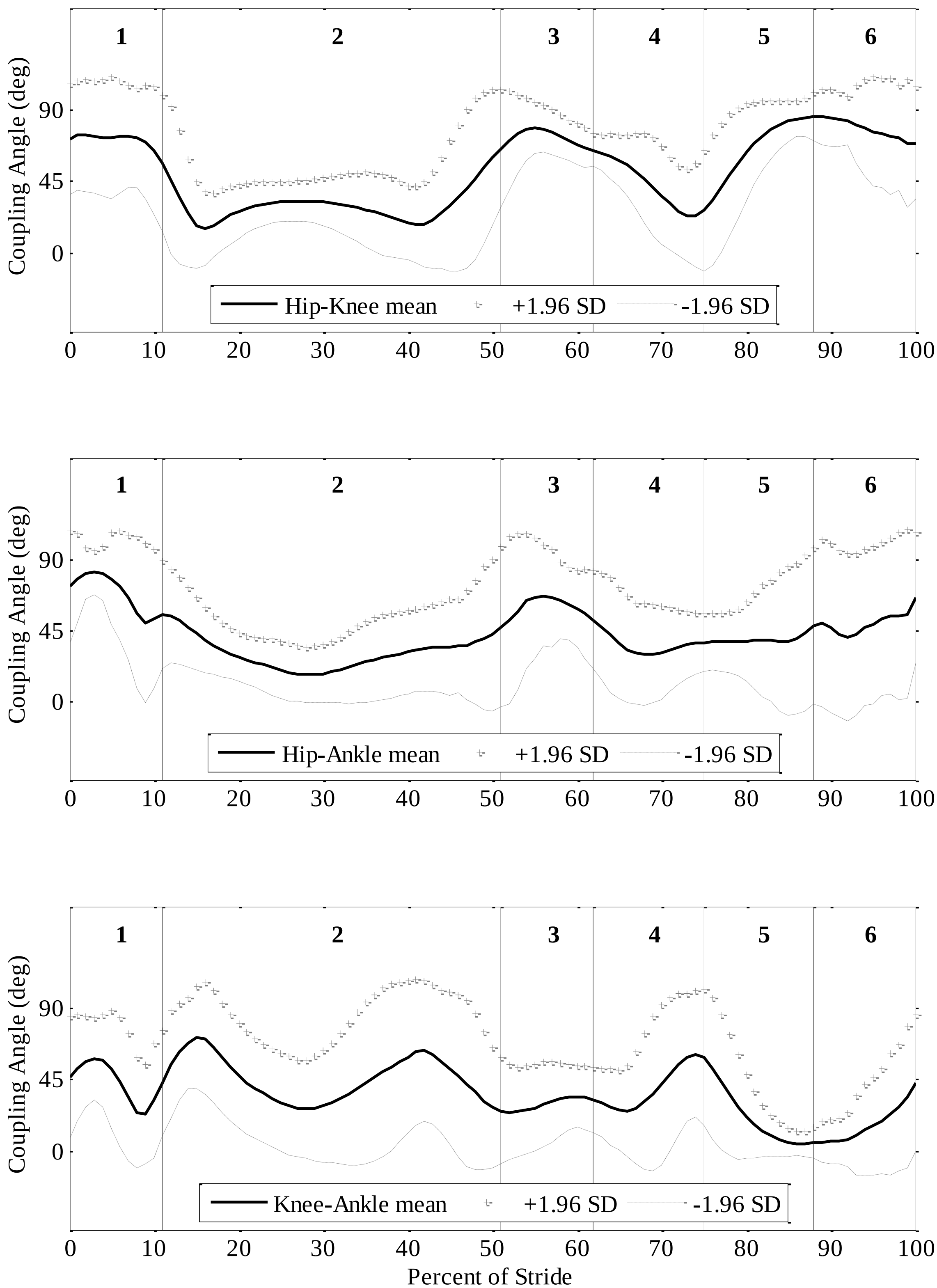

Figure 1. Mean and variability of the coupling angle for each coordination pattern: hip-knee, hip-ankle, knee-ankle. Numbered sections represent the six sub phases of the gait cycle: 1) loading response, 2) midstance, 3) terminal stance, 4) initial swing, 5) midswing and 6) terminal swing.

The mean MFC was 0.026 m (SD = 0.014) (Figure 2), and the mean maximal limb shortening was 0.975 of normalized limb length (SD = 0.013) (Figure 3). Both MFC and maximal limb shortening occurred approximately in the middle of swing (MFC: M = 54.4%, SD = 5.90%; maximal limb shortening: M = 44.2%, SD = 6.98%). The results of the Principle Components Analysis of the vertical toe position during swing yielded three retained PCs. Upon visual inspection of the features of toe height during swing characterized by each PC, it was revealed that PC1 explains 70.42% of the overall variance in the data, and represents the magnitude of toe height during the second half of swing (Figure 4; Table 2). While PC2 only explains 14.33% of the overall variance in the data, and demonstrates a difference in toe height from the beginning to end of swing, most of the variance explained by PC2 occurs during early-to-mid swing when the toe is closest to the ground (Figure 4; Table 2). Therefore, both PC1 and PC2 were used to describe foot clearance.

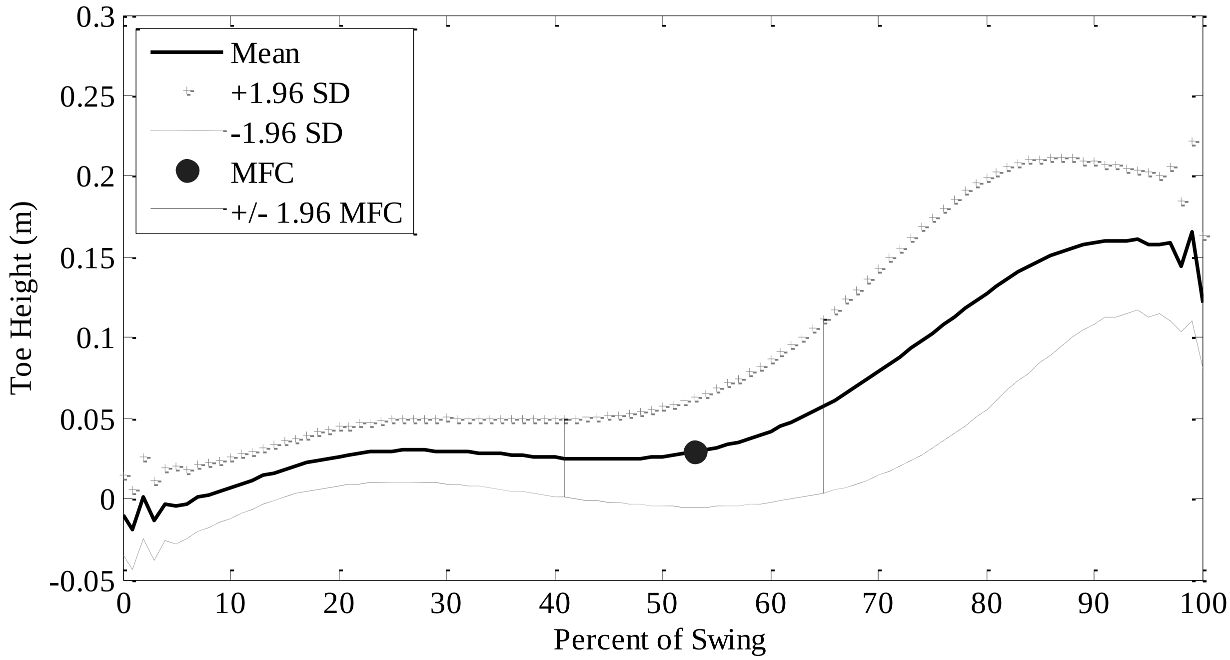

Figure 2. Mean and standard deviation of toe height throughout swing phase. The mean and standard deviation of the MFC location is identified.

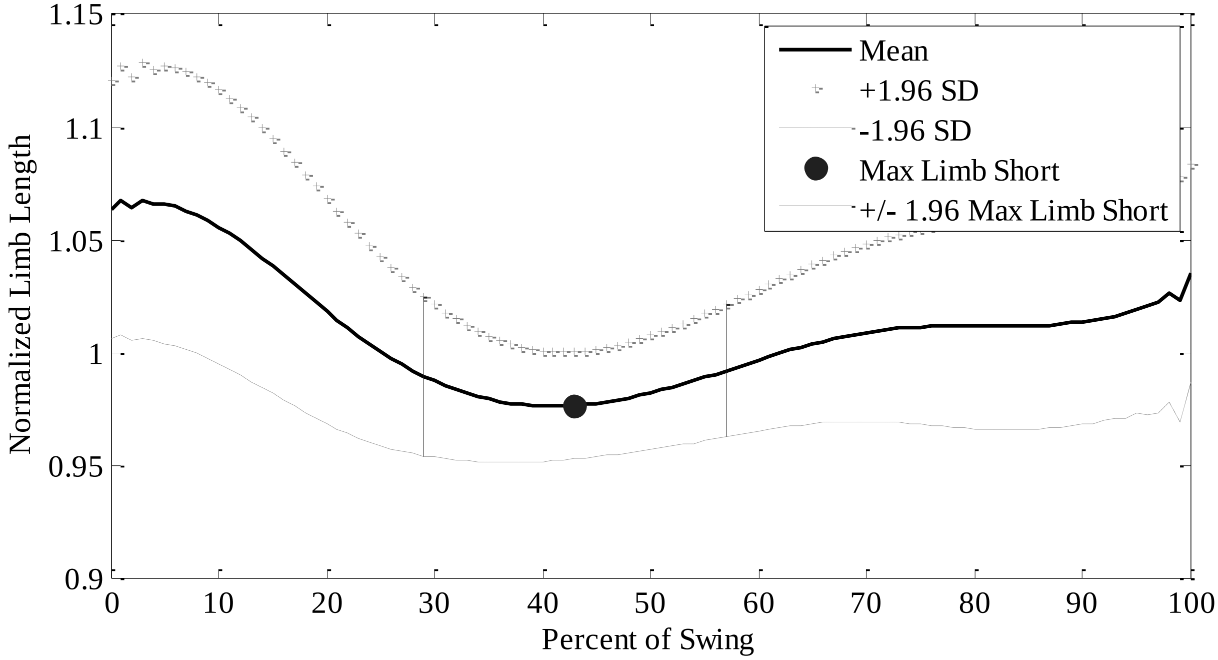

Figure 3. Mean and standard deviation of limb length (hip-toe distance) normalized to hip height throughout swing phase. The mean and standard deviation of the maximal limb shortening is identified.

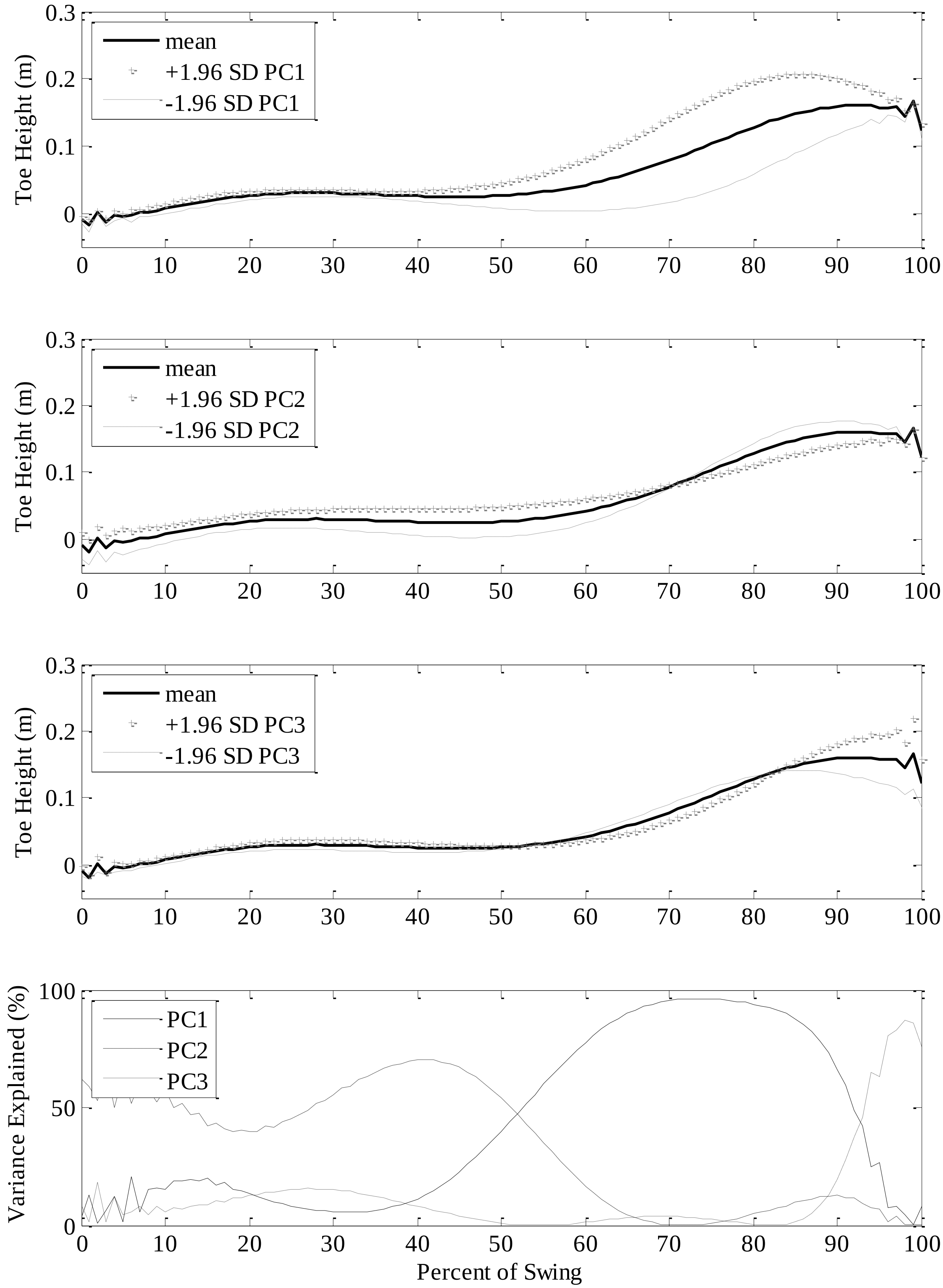

Figure 4. The effect of each of the three retained PCs on toe height during swing, and the variance explained by each retained PC.

Table 2

The Variance Explained and the Feature Represented by Each of the Retained PCs for Toe Height during Swing

PC	Variance Explained (%)	Feature Represented
1	70.42	Magnitude of toe height during swing
2	14.33	Difference in toe height from beginning to end of swing
3	10.79	Timing of minimum foot clearance
Total	95.53	

There was no significant correlation between maximal limb shortening and MFC or PC1, but there was a significant moderate correlation between MFC and both PC scores, and between maximal limb shortening and PC2. By definition, the PC1 and PC2 scores are not correlated. There was a significant and high correlation between MFC variability and maximal limb shortening variability, and between the standard deviations of both PC scores. The moderate correlation between MFC variability and the variability of both PC scores was also significant. There was no significant correlation between maximal limb shortening variability and the variability of either PC score (Table 3).

Table 3

Bivariate Correlation Coefficients and Significance of the Correlation Between Measures of Foot Clearance and Foot Clearance Variability

	Foot Clearance		Foot Clearance Variability	
	r	*p*	*r*	*p*
MFC - Max Limb Shortening	-0.296	0.084	0.777	<0.001*
MFC - PC1	0.493	0.003*	0.550	0.001*
MFC - PC2	0.696	<0.001*	0.564	<0.001*
Max Limb Shortening - PC1	-0.174	0.318	0.017	0.092
Max Limb Shortening - PC2	-0.491	0.003*	0.071	0.685
PC1 - PC2	-0.031	0.858	0.834	<0.001*

* $p < 0.05$

Each predictor model was statistically significant and contained between 1 and 5 of the 18 predictors, with no variables removed for any of the models. A single variable accounted for less than 20% of the variance in MFC ($F_{(1,33)}$ = 6.895, p = 0.013) and MFC variability ($F_{(1,33)}$ = 8.051, p = 0.008), while more than approximately 50% of the variance in the magnitude and variability of maximal limb shortening (Mean: $F_{(5,29)}$ = 11.971, p < 0.001; Standard Deviation: $F_{(2,32)}$ = 21.753, p = <0.001), PC1 (Mean: $F_{(2,32)}$ = 20.856, p < 0.001; Standard Deviation: $F_{(3,31)}$ = 14.214, p = <0.001) and PC2 (Mean: $F_{(2,32)}$ = 13.728, p < 0.001; Standard Deviation: $F_{(3,31)}$ = 12.497, p = <0.001) was explained by their respective models (Table 4).

Table 4

Variance in Foot Clearance and Foot Clearance Variability Accounted for by Joint Coordination and Joint Coordination Variability

	Foot Clearance		Foot Clearance Variability	
	# Predictors	Adjusted R^2	# Predictors	Adjusted R^2
MFC	1	0.148	1	0.172
Max Limb Shortening	5	0.617	2	0.550
PC1	2	0.539	3	0.538
PC2	2	0.428	3	0.504

Note. All models were statistically significant at $p < 0.05$.

The effect of each variable on the prediction of foot clearance or foot clearance variability was determined from the standardized coefficients of the predictors for each model (Table 5). MFC was predicted by a lower knee-ankle coupling angle during midstance. Maximal limb shortening was primarily predicted by lower hip-knee coupling angle during initial swing and lower knee-ankle coupling angle during midstance, and to a lesser extent greater coupling angle for knee-ankle during midswing and greater hip-knee and hip-ankle coupling angle during terminal stance. The PC1 score was primarily predicted by a greater hip-knee coupling angle during midswing, and to a lesser extent, a lower hip-knee coupling angle during loading response. The PC2 score was predicted by a lower coupling angle for hip-knee during terminal stance and knee-ankle during initial swing. The variability in MFC was predicted by greater variability in hip-ankle coupling angle during terminal stance. The variability in maximal limb shortening was predicted by greater hip-knee and lower knee-ankle coupling angle variability during initial swing. The variability in PC1 score was primarily predicted by greater knee-ankle variability in midstance, and to a lesser extent, greater hip-ankle coupling angle variability during loading response and greater hip-ankle coupling angle variability during terminal stance. PC2 variability was predicted by lower hip-knee and greater knee-ankle variability during midstance, and greater knee-ankle variability during initial swing.

Table 5

Descriptive Information and Standardized Coefficients for the Predictor Variables Included in Each Multiple Regression Model Predicting Foot Clearance or Foot Clearance Variability from Joint Coordination or Joint Coordination Variability

Sub phase	Joints	Coupling Angle (°)			Model Standardized Coefficients (β)			
		Max	Median	Min	MFC	MLS	PC1	PC2
Loading Response	Hip-Knee	87.39	70.94	37.99			-0.384	
Midstance	Knee-Ankle	62.93	42.47	19.30	-0.416	-0.439		
Terminal Stance	Hip-Knee	77.15	72.67	57.66				-0.371
Initial Swing	Hip-Knee	58.12	42.47	35.99		-0.655		
Initial Swing	Knee-Ankle	50.67	38.98	13.80				-0.446
Midswing	Hip-Knee	77.02	66.70	30.83			0.698	
Midswing	Knee-Ankle	35.17	19.50	8.48		0.266		
Terminal Swing	Hip-Knee	85.53	80.05	54.16		0.310		
Terminal Swing	Hip-Ankle	75.73	48.37	21.32		0.288		

Sub phase	Joints	SD Coupling Angle (°)			Model Standardized Coefficients (β)			
		Max	Median	Min	SD MFC	SD MLS	SD PC1	SD PC2
Loading Response	Hip-Ankle	13.87	7.52	3.48			-0.410	
Midstance	Hip-Knee	11.63	4.90	3.43				-0.640
Midstance	Knee-Ankle	17.83	8.92	5.28			0.636	0.733
Terminal Stance	Hip-Ankle	16.85	6.10	2.30	0.443		0.396	
Initial Swing	Hip-Knee	16.71	4.84	1.67		1.657		
Initial Swing	Knee-Ankle	20.05	7.92	3.54		-1.421		0.500

Note. MLS = maximal limb shortening; SD = standard deviation.

Discussion

The significant correlation between MFC and both PC scores – and the lack of correlation between maximal limb shortening and MFC or PC1 – is likely due to the fact that MFC and the PC scores represent toe height during swing, while maximal limb shortening is based on the hip-toe distance. The moderate correlation between maximal limb shortening and PC2 may be due to the fact that most of the variance explained by PC2 occurs around the point of maximal limb shortening. Regardless of their relationship with each other, each of these measures can be used to quantify foot clearance, with low foot clearance and high foot clearance variability considered risk factors for tripping (Begg et al., 2007). However, to modify foot clearance requires an understanding of the effect of joint coordination on the toe height. The low variance explained in the prediction of MFC and MFC variability from coordination and coordination variability suggests that there is not a strong relationship between sagittal plane joint coordination and foot clearance, determined as MFC. The problem likely lies within identifying a single point during the stride cycle to represent foot clearance, particularly when that point was chosen based on the velocity of the foot, rather than an actual measure of toe height. In contrast, coordination and coordination variability accounted for a greater percentage of the variance in the mean and standard deviation of maximal limb shortening as well as the PC scores. In the case of the PC scores, it appears that a continuous variable that represents toe height has a stronger relationship with joint coordination than the discrete variable of MFC. While maximal limb shortening is also a single point during the stride cycle, it is based on the hip-toe distance, which is determined by the kinematics of the lower extremity joints and likely has a stronger relationship to joint coordination.

With six sub phases of the gait cycle, and three pairs of coupled joints, there were 18 potential predictor variables for each model. The stepwise multiple regression method resulted in five or fewer predictor variables for each of the models. The reduced number of predictor variables may be due to the simplified information from the coordination variables by collapsing the range of coupling angle to 0° to 90°. Each measure of joint coordination reports the relative motion of the proximal and distal joints. The original coupling angle had a range of -180° to 180°, and provided the ability to determine not only which joint had greater motion, but also which direction each joint was moving (e.g. flexion or extension). The result was a circular variable, with values of -180° and 180° representing the same coupling angle. However, to be able to use the coordination variables in the linear multiple regression models, the coupling angle was converted to a scale of 0° to 90°, with the magnitude of the coupling angle simply reporting which joint had more relative motion. It is likely that several of the predictor variables were more similar to each other on this reduced scale than if the coupling angle had been able to indicate the direction of motion as well as the magnitude of relative motion.

To evaluate the effect of individual predictor variables, the sign of the coefficient (β) is used to determine whether an increase in the predictor variable is associated with an increase ($\beta > 0$) or decrease ($\beta < 0$) in the dependent variable. For the coordination variables, an additional interpretation of the magnitude of the coupling angle is necessary to determine the relative motion of the proximal and distal joints during the sub phase of interest. A greater coupling angle specifies more distal joint motion relative to the proximal joint. A greater value for MFC or one of the PC scores means greater toe height, while a greater value for maximal limb shortening means less limb shortening. For the models that predict foot clearance variability, the magnitude of the predictor variable indicates the amount of coupling angle variability for that particular sub phase.

Specific coordination patterns related to foot clearance depend on the measure of foot clearance chosen. For MFC, greater foot clearance is the result of more knee motion relative to ankle motion during midstance. The opposite effect occurred for maximal limb shortening, as greater relative motion of the ankle to the knee during midstance resulted in greater foot clearance. This discrepancy provides further support that the relationship between joint coordination and foot clearance is not same for MFC and maximal limb shortening. However, for maximal limb shortening, PC1 and PC2, it appears that the amount of knee motion relative to hip motion – during initial swing, midswing and terminal stance, respectively – has an effect on the magnitude foot clearance. This is consistent with the results of Little et al. (2014), who noted abnormal hip-knee coordination had a greater effect on foot clearance than ankle dorsiflexion. While the direction of the hip and knee motion cannot be determined from the reported coupling angles, it can be approximated by looking at the overall mean sagittal plane joint angles (Figure 5). During typical gait, both the hip and knee are flexing during terminal stance and initial swing. Hip flexion serves to advance the leg forward, and as evidenced by these results, knee flexion during initial swing controls the magnitude of foot clearance. All participants had more knee motion relative to hip motion (minimum coupling angle > 45°) during terminal stance, with most experiencing a hip-knee coupling angle between 72-77°, although this higher coupling angle results in a lower predicted PC2 score, which represents low foot clearance. Similarly, with a median hip-knee coupling angle of less than 45° during initial swing, most participants had greater hip flexion than knee flexion. The few participants with a greater coupling angle did not have a lower foot clearance as predicted by maximal limb shortening. During midswing, the knee typically extends while the hip continues to flex (Figure 5). Most participants had much greater knee extension than hip flexion during this sub phase (median coupling angle > 45°), however, the minimum coupling angle was as low as 30.83°. From the joint angles of the participant with a history of stroke (Figure 5), it appears that not only was the relative hip-knee motion different from the typical gait pattern, but the knee for this participant is flexing rather than extending during midswing. While the difference in direction of knee motion could not be determined from the coupling angle, this participant with abnormal coordination – less knee motion relative to hip motion – had a lower predicted PC1 score, which corresponds to a lower toe height throughout swing.

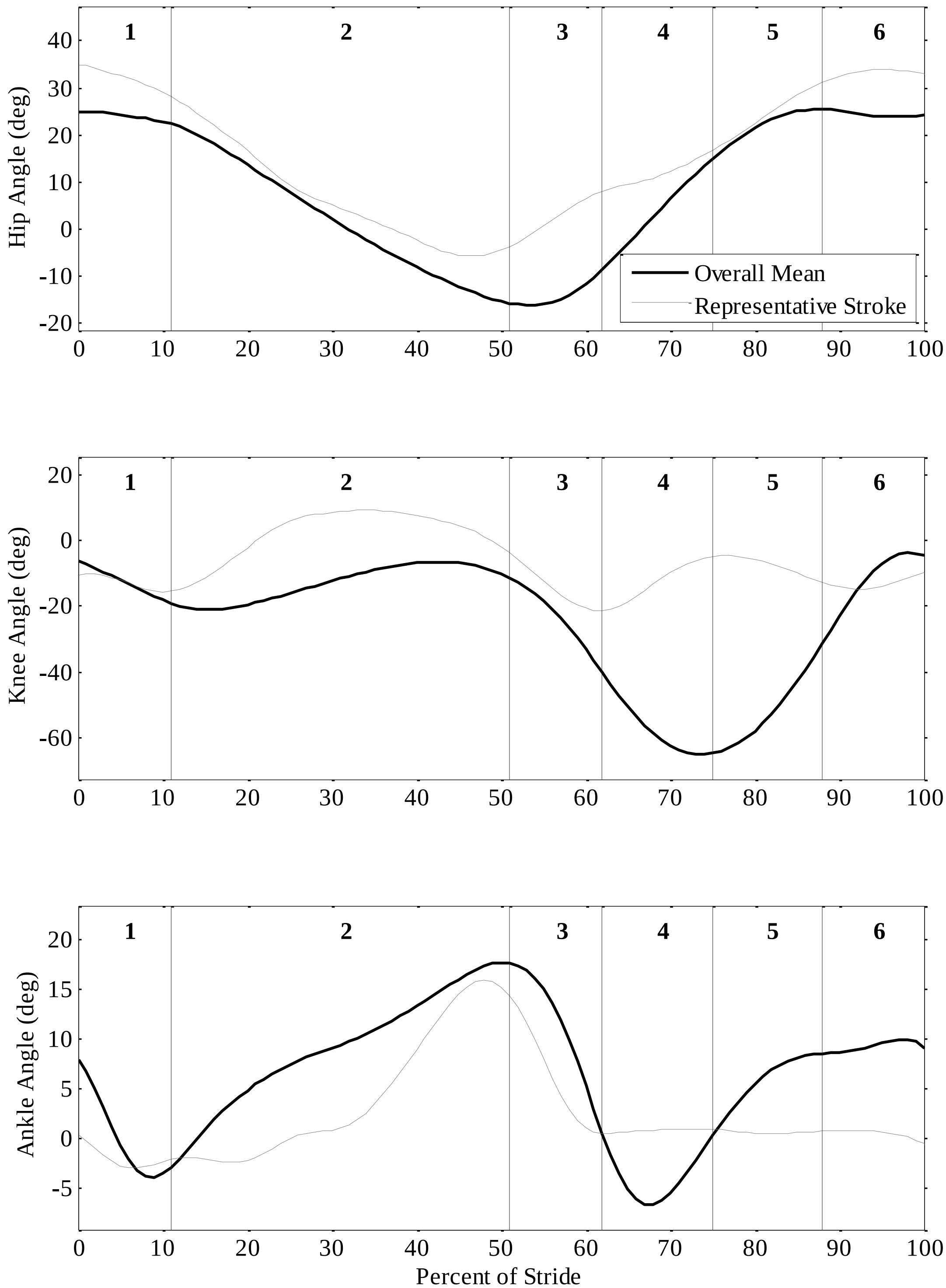

Figure 5. Overall mean sagittal plane hip, knee and ankle angle curves for all participants (black), and individual mean curves for a representative participant with a history of stroke (gray). Positive angles represent hip flexion, knee extension and ankle dorsiflexion. Numbered sections represent the six sub phases of the gait cycle: 1) loading response, 2) midstance, 3) terminal stance, 4) initial swing, 5) midswing and 6) terminal swing.

It was expected that greater joint coordination variability would result in greater predicted variability of foot clearance, regardless of how foot clearance was determined. For all coupling patterns that contributed significantly to the foot clearance variability models, the median coupling angle variability was closer to the minimum than the maximum, indicating that greater coupling angle variability was abnormal. In almost all cases, this led to greater predicted variability in foot clearance, which increases the likelihood that low foot clearance could occur. For MFC, PC1 and PC2, variability in joint coordination during stance had the greatest influence on predicted foot clearance variability. Variability in the relative motion of the hip and ankle during terminal stance – just before toe-off – affects the predicted variability of the toe height during swing for both MFC and PC1. Additionally, knee-ankle variability during midstance has the greatest effect on predicted PC1 and PC2 variability. This is consistent with the observation that joint kinematic variability is related to foot clearance variability (Mills et al., 2008). Similar to the magnitude of foot clearance analysis, hip-knee coordination variability during initial swing has the greatest effect on maximal limb shortening variability.

Three of the predictor variables for the foot clearance variability models have negative standardized coefficients, meaning greater coupling angle variability results in less predicted foot clearance variability. In the maximal limb shortening model, the knee-ankle coordination variability has the opposite effect of the hip-knee coordination variability within the same sub phase. This behavior may be explained by a high variance inflation factor (4.790) for each of these predictor variables, indicating that hip-knee and knee-angle coordination variability during initial swing are highly correlated. To avoid having two correlated predictor variables, it may be reasonable to consider a model for maximal limb shortening variability that includes initial swing hip-knee coupling angle variability only, although this model barely accounts for about

15% of the variance in maximal limb shortening variability ($F_{(1,33)} = 6.026$, $p = 0.020$, $R^2 = 0.154$, Adjusted $R^2 = 0.129$). The negative standardized coefficients for hip-ankle coupling angle variability during loading response in the PC1 variability model and hip-knee coupling angle variability during midstance in the PC2 variability model may exist for a different reason. Having greater coordination variability (i.e. a variety of possible combinations for the relative motion of the lower extremity joints) may allow a person to adapt to unexpected obstacles or perturbations during gait (Latash, 2010). This could be especially important during stance when an individual may have to adjust to inconsistencies in the walking surface. Therefore, in these instances, greater coupling angle variability may be considered a healthy component of gait, and that is reflected in low predicted variability of the PC1 and PC2 scores.

Conclusion

Only a small portion of the variance in MFC, defined at the point of the greatest horizontal velocity of the foot, is explained by joint coordination. Maximal limb shortening may be more sensitive to changes in joint coordination because the hip-toe distance is constrained by the hip, knee and ankle angles. Rather than identifying foot clearance at a discrete time point, PC1 and PC2 quantify toe height throughout swing. Normal hip-knee coordination during midswing, namely more knee extension relative to hip flexion, results in greater predicted toe height as measured by PC1. Abnormal gait that results in high joint coordination variability may yield greater variability in foot clearance during swing. Future studies should examine if training an individual to make changes to joint coordination results in an increase in foot clearance and reduction of foot clearance variability among those with abnormal gait.

Chapter 3: Identifying Group Differences Related to Falls Risk and Obstacle Avoidance

Introduction

Certain demographic groups, such as older adults, recurrent fallers, and people with a history of stroke, are considered to have a high risk of falling. Nearly 40% of older adults fall in a given year (Blake et al., 1988; Hausdorff, Rios, & Edelberg, 2001; Tinetti, Speechley, & Ginter, 1988), and older adults are more likely to trip than young adults (Garman, Franck, Nussbaum, & Madigan, 2015). About half of all fallers will fall recurrently (Stalenhoef, Crebolder, Knottnerus, & VanderHorst, 1997), and so having a history of falls increases falls risk (Deandrea et al., 2010). Despite the prevalence of falls in the elderly population, the risk of falling is even greater among stroke survivors (Batchelor et al., 2012).

The ability to identify and address specific risk factors may prevent falls. Risk factors may include low falls self-efficacy, poor gait and balance ability, abnormal spatiotemporal gait parameters, and insufficient foot clearance during walking. Although there is some evidence to the contrary (Clemson, Kendig, Mackenzie, & Browning, 2015), falls history and low falls self-efficacy have been thought to feed into a downward spiral of mobility limitations, reduced independence and more falls (Belgen, Beninato, Sullivan, & Narielwalla, 2006; Delbaere, Crombez, Vanderstraeten, Willems, & Cambier, 2004; Deshpande et al., 2008; Friedman, Munoz, West, Rubin, & Fried, 2002). Gait and balance disorders are the most significant risk factor for falling among community-ambulating older adults (Deandrea et al., 2010), and are more modifiable than other risk factors, such as medical history or advanced age. A common way to modify gait and balance disorders is through exercise, including strength training, which has been effective at preventing falls in the elderly population (Panel on Prevention of Falls in Older Persons, American Geriatrics Society and British Geriatrics Society, 2011), and reducing gait asymmetries for stroke survivors (Seo & Kim, 2014). Therefore, lower-extremity strength may play a role in preventing falls (Pavol, Owings, Foley, & Grabiner, 2002). Specific gait characteristics have also been considered in relation to falls risk. While most spatiotemporal gait parameters are not related to falls risk (Moreira, Sampaio, & Kirkwood, 2014), greater step width has been used to discriminate fallers from non-fallers (Gehlsen & Whaley, 1990a; Maki, 1997). Additionally, low foot clearance and increased foot clearance variability are suspected to increase the risk of falling (Begg et al., 2007). Foot clearance is determined by the degree of flexion during swing phase of the lower extremity joints, either individually (Little et al., 2014; Moosabhoy & Gard, 2006; Winter, 1992), or in coordination with each other, as shown in Chapter 2.

It is expected that groups considered at risk for falling (e.g. older adults, previous fallers, stroke survivors) would score differently than those not at risk for falling (e.g. young adults) on measures related to each of these factors. However, it is important to determine if an individual is at risk for falling simply by their demographics. Therefore, the purpose of this study was to identify differences among stroke survivors, young adults, older fallers and older non-fallers in function and ability related to measures of falls risk, including falls self-efficacy, gait and balance, neuromuscular function, spatiotemporal gait parameters, foot clearance, joint kinematics and joint coordination. Additionally, group effects of the ability to successfully avoid a tripping hazard while walking were determined. It was anticipated that there would be group differences in measures of falls risk and the ability to avoid an obstacle, with the older fallers and participants with a stroke expected to perform worse than the young adults and older non-fallers.

Methods

Participants. The 35 participants introduced in Chapter 2 were included in this analysis, and split into four groups: young adults, older adult non-fallers, older adult fallers, and chronic stroke participants. A questionnaire was administered to gain demographic information, information about the type and location of the stroke, falls history. Fear of falling was assessed through the Frenchay Activities Index (FAI) (Schepers, Ketelaar, Visser-Meily, Dekker, & Lindeman, 2006), Swedish modification of the Falls Efficacy Scale (FES-S), which has been validated in a stroke population (Hellstrom & Lindmark, 1999), and the Activities-specific Balance Confidence scale (ABC) (Powell & Myers, 1995).

Functional evaluation. The following functional evaluations were administered in order, however, items that were common among different evaluations were not repeated: Performance-Oriented Assessment of Mobility (POMA) Balance Assessment (Tinetti, 1986), Mini-BESTest (Franchignoni, Horak, Godi, Nardone, & Giordano, 2010), POMA Gait Assessment (Tinetti, 1986), fast walking speed (Oken, Yavuzer, Ergocen, Yorgancioglu, & Stam, 2008; Richards & Olney, 1996), and Functional Gait Analysis (FGA) (Wrisley, Marchetti, Kuharshy, & Hitney, 2004). Participants wore a gait belt, and the evaluator held onto the belt in case the participant lost their balance during the tasks, but only provided assistance if necessary.

Biomechanics assessment. Force output and muscle activity were recorded as the participant performed the following maximum voluntary contractions (MVC): isometric knee extension, isometric ankle dorsiflexion and isometric ankle plantar flexion. Each isometric contraction lasted five seconds. Participants wore shoes to protect their feet and they were verbally encouraged to give a maximal effort during each contraction. Each leg was tested separately using a handheld dynamometer (Lafayette Manual Muscle Testing System, Model 01165, Lafayette, IN, USA), and the peak force during the contraction was identified. Electromyogram (EMG) signals were recorded wirelessly (Noraxon, DTS EMG, Scottsdale, AZ, USA) at 1000 Hz from the rectus femoris, tibialis anterior, and medial gastrocnemius of both legs. Prior to application of the surface electrodes (Vermed, NeuroPlus, Bellows Falls, VT, USA), the skin was shaved (if necessary), gently abraded, and wiped with alcohol to reduce electrical impedance. Pairs of electrodes were placed on the skin above each muscle according to the guidelines established by the Surface Electromyography for the Non-Invasive Assessment of Muscles project (Hermens, Freriks, Disselhorst-Klug, & Rau, 2000).

Retroreflective markers used for motion capture were applied and the location of the markers was recorded and processed as described in Chapter 2. Data was collected as each participant walked at their self-selected walking pace (Table 6), both overground (Chapter 2) and on a treadmill (Precor, C964i, Woodinville, WA, USA). During the treadmill walking trials, participants wore a safety harness that provided no support during normal walking, but prevented the participant from landing on the ground in the case of a fall. The treadmill walking began with a one-minute acclimation period that was not recorded. Two treadmill conditions were tested: normal walking, and avoiding an unexpected obstacle. The order of the treadmill conditions was randomized to distribute any learning or fatigue effects across all conditions. Additionally, participants were allowed to rest at any point if their perceived exertion was above what is considered very light based on the Rating of Perceived Exertion scale (Borg, 1970). If the participant was required to rely on the support of the harness and fall-arrest system, the treadmill was stopped immediately.

Table 6

Walking Speed by Group for the Overground and Treadmill Conditions

	Young Adult		Older Adult - Non-faller		Older Adult - Faller		Stroke	
	M	SD	M	SD	M	SD	M	SD
Overground Speed (m/s)	1.48	0.12	1.35	0.16	1.24	0.19	1.02	0.39
Treadmill Speed (m/s)	1.01	0.21	0.74	0.22	0.73	0.27	0.80	0.47

Note. M = mean; SD = standard deviation.

To ensure participants were looking straight ahead and not at their feet, participants were required to complete a concurrent visual task while walking on the treadmill. An arrow appeared on a screen positioned at eye level approximately one meter from the treadmill. The participants were asked to report the direction the arrow was pointing. The verbal response was manually entered into a computer, and the time to produce the response was recorded using custom software (Matlab v8.0.0.783, Mathworks, Inc., Natick, MA, USA). A new arrow appeared one second after each response for a total time of one minute. Each minute of testing was evaluated on the number of responses, percent of correct responses, and the mean, maximum and minimum time for each response. To control for the effects of doing this dual motor and visual task, participants also completed the visual task for one minute while standing on the treadmill but not walking, as well as walking without performing the visual task for one minute while all biomechanical data were recorded.

For normal treadmill walking with the visual task, kinematic data were recorded continuously for one minute. For the obstacle avoidance treadmill condition, participants were instructed to attempt to avoid the obstacle. The obstacle was a lightweight piece of foam cut to length, width and height dimensions of 20 x 16 x 6 cm (Airex AG, Balance-pad, CH-5643 Sins, Switzerland). Similar to the process outlined by Weerdesteyn, et al. (2003), at random heel-strike events, the foam was placed on the belt of the treadmill in front of the foot entering stance phase so that the obstacle would have to be avoided in the subsequent swing phase. Considering typical minimal foot clearance for most elderly adults has been reported to be no more than 5 cm (Begg et al., 2007), using a 6-cm obstacle required the participant to react to the object to avoid coming in contact with it. This is also within the range of obstacle heights used in previous studies of obstacle avoidance in stroke survivors (Said, Goldie, Patla, & Sparrow, 2001). If the foot did come in contact with the side of the block of foam, the obstacle was kicked away so that the progress of the foot was not actually impeded. If the foot stepped down on the obstacle, the block of foam compressed to only minimally disturb the participant's gait cycle. After the foot cleared or came in contact with the obstacle, the block of foam slid off of the treadmill. The participant continued to walk on the treadmill until another obstacle was presented, for a total of six obstacles in a one-minute period. This was repeated for a total of four periods, or 24 obstacles. The number of steps between obstacles was randomized, as was the foot (right or left), however, within each period the obstacle was presented on the right side three times and the left side three times.

All kinematic data were divided into individual strides as described in Chapter 2. The outcome of each stride with an obstacle present was classified as follows: Trip – if the foot kicked the obstacle forward during swing; Step on – if the next heel-strike landed on top of the obstacle rather than on the treadmill belt; Clear – if the foot did not come in contact with the obstacle. The classification was determined by tracking the location of retroreflective markers attached to the obstacle, and using custom software (Matlab v8.0.0.783, Mathworks, Inc., Natick, MA, USA) to identify any changes in velocity of the markers relative to the treadmill belt speed, as well as the location of the toe and heel relative to the position of the obstacle.

Data analysis. All kinematic data were processed as outlined in Chapter 2. The EMG data were full-wave rectified and root mean square values were calculated using a 120-ms window. The greatest muscle activity during the maximal voluntary contraction trial was considered the maximal muscle activity for each muscle (Hassanlouei, Falla, Arendt-Nielsen, & Kersting, 2014). The processed EMG signals were expressed as a percent of the maximal muscle activity, and time-normalized from 1000 Hz to match the 200 Hz recording of the kinematic data.

Data were analyzed to identify differences between groups (young, older non-faller, older non-faller, and stroke) for the following constructs: falls-related evaluations, neuromuscular function, spatiotemporal gait parameters, foot clearance, foot clearance variability, joint kinematics, kinematic timing, initial swing joint coordination, midswing joint coordination and obstacle avoidance. Since each construct can be defined by several variables, for each group of measurements a MANOVA was used to determine the group effect.

Common tests for fear of falling and gait and balance ability were employed as the falls-related evaluations. Measures of falls self-efficacy included total FAI score (Schuling, de Haan, Limburg, & Groenier, 1993), the total FES-S score (Hellstrom & Lindmark, 1999), and the total ABC score (Powell & Myers, 1995). Gait and balance performance was evaluated with the balance component of the POMA (Tinetti, 1986), the total Mini-BESTest score (Franchignoni et al., 2010), and the Functional Gait Analysis score (Wrisley et al., 2004). Measures of neuromuscular function included maximal isometric force output during knee extension, dorsiflexion and plantar flexion, and the peak rectus femoris, tibialis anterior and medial gastrocnemius activity during swing for the affected leg. All strength measures were normalized to body mass.

Several spatiotemporal gait parameters were calculated during each condition of the biomechanics assessment. To simplify the analysis and use data most similar to typical walking, only walking speed (considered separately for overground and treadmill conditions), and overground stance time, swing time and step width were considered. Step width for each stride was calculated as the average horizontal distance between the right and left feet during double support time, and then averaged across all strides of overground walking to get a participant's mean step width.

Four measures of foot clearance for the affected leg during overground walking were calculated as described in Chapter 2: MFC, maximal limb shortening, and PC1 and PC2 scores. The standard deviation of each these measures represents foot clearance variability. Kinematic variables of interest included the sagittal plane peak angle and range of motion for the hip, knee and ankle during swing. Kinematic timing was determined as the time – expressed as a percentage of stride – to the peak joint angle during swing. Joint coordination during initial swing and midswing was quantified as the mean of the coupling angle over the respective subphase of the gait cycle for hip-knee, hip-ankle and knee-ankle coordination. Obstacle avoidance was quantified as the percent of strides with the obstacle present that were classified as a trip or step on, as well as the total percent of strides where the foot came in contact with the obstacle.

Additional information was collected that related to the execution of the experiment. This included performance on the visual task and placement of the obstacle. Visual task performance was quantified with five variables measuring response time (number of responses, and the mean, maximum and minimum time for each response) and percent of correct responses. For the walking with the visual task and the obstacle conditions, each participant's performance on the visual task was expressed relative to their score during the standing baseline visual task. Factor analysis reduced the number of variables needed to describe visual task performance to include only number of responses and maximum time for the walking condition, and mean time and percent correct for the obstacle condition (Appendix F). Using the reduced set of variables, a MANOVA was performed to detect differences in visual task performance across groups. Obstacle placement was measured as the mean and standard deviation of the distance in the direction of walking from the toe to the obstacle at toe-off. An additional MANOVA was used to determine if obstacle placement was different across groups.

The assumptions for using a MANOVA to investigate group differences were checked. Due to unequal sample sizes in each group and a significant ($p < 0.001$) Box's M test for some of the constructs, the results of each MANOVA were reported using Pillai's trace (Tabachnick & Fidell, 2013). For each MANOVA that identified a construct that was significantly different across groups ($p < 0.05$), the follow up test was a one-way ANOVA for each dependent variable that was included in the omnibus test. In the case of a significant ($p < 0.05$) group effect for a dependent variable, all pairwise comparisons across groups were performed using a Tukey correction. All statistical tests were done in SPSS (v19.0.0.1; SPSS, Inc., Chicago, IL).

Results

There were no differences between groups on visual task performance and obstacle placement (Table 7). Results of the omnibus tests for falls-related constructs (

Table *8*), indicated a significant effect of group for falls self-efficacy, gait and balance, maximal isometric strength, spatiotemporal gait parameters, and foot clearance. There was no overall effect of group for midswing joint coordination or obstacle avoidance.

Table 7

Overall Group Effects for Experiment-Related Constructs

Construct	Pillai's Trace	F	df1	df2	p	η_p^2
Visual Task Performance	0.539	1.641	12	90	0.094	0.180
Obstacle Placement	0.278	1.667	6	62	0.144	0.139

Table 8

Overall Group Effects for Each Gait- or Falls-Related Construct

Construct	Pillai's Trace	F	df1	df2	p	η_p^2
Falls-Related Evaluations	1.072	2.596	18	84	0.002*	0.357
Neuromuscular Function	1.094	2.584	18	81	0.002*	0.365
Spatiotemporal Parameters	0.950	2.687	15	87	0.002*	0.317
Foot Clearance	0.607	1.904	12	90	0.044*	0.202
Foot Clearance Variability	0.811	2.781	12	90	0.003*	0.270
Joint Kinematics	1.217	3.186	18	84	<0.001*	0.406
Kinematic Timing	0.815	3.852	9	93	<0.001*	0.272
Initial Swing Coordination	0.785	3.664	9	93	0.001*	0.262
Midswing Coordination	0.433	1.743	9	93	0.090	0.144
Obstacle Avoidance	0.317	1.947	6	62	0.087	0.159

* $p < 0.05$

Follow up tests for falls-related evaluations showed that the total FAI score and all measures of gait and balance were significantly different between groups, and there was a trend toward group differences for total FES-S score and ABC score (Table 9). There were no significant differences between pairs of groups for the total FAI score (p > 0.050). The young participants scored higher than the stroke participants for POMA balance (Young: M = 15.9, SD = 0.3; Stroke: M = 14.4, SD = 0.5; p = 0.009), Mini-BESTest total (Young: M = 27.1, SD = 1.0; Stroke: M = 21.8, SD = 3.8; p = 0.005), and the FGA (Young: M = 29.5, SD = 0.7; Stroke: M = 19.8, SD = 6.1; p = 0.001). The young participants also had a greater score than older fallers on the Mini-BESTest total (Fallers: M = 23.5, SD = 3.0; p = 0.022), and the FGA (Fallers: M = 23.9, SD = 5.1; p = 0.030), and a greater score than non-fallers on the Mini-BESTest total (Non-fallers: M = 23.3, SD = 2.7; p = 0.015) (Figure 6).

Table 9

Group Effects for Each Falls-Related Evaluation

Dependent Variable	F	p	η_p^2
FAI Total	3.464	0.028*	0.241
FES-S Total	2.709	0.062	0.208
ABC	2.793	0.057	0.213
POMA Balance	4.295	0.012*	0.294
Mini-BESTest Total	6.069	0.002*	0.370
Functional Gait Analysis	6.359	0.002*	0.381

Note. df1 = 3 and df2 = 31 for all tests.
* $p < 0.05$

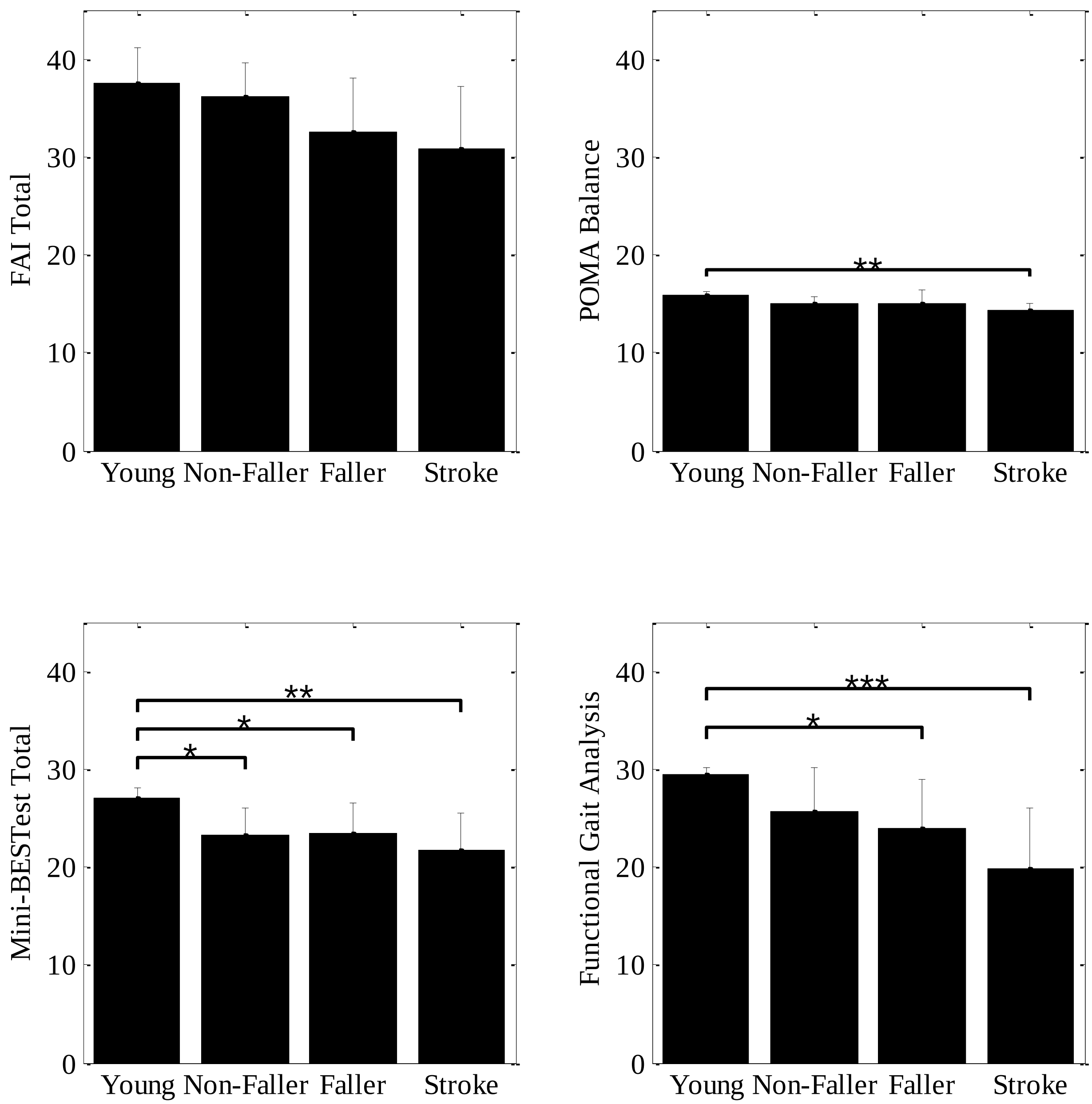

Figure 6. Pairwise comparisons for falls-related evaluations that are significantly different bewtween groups. (*p < 0.05; ***p < 0.001)

The group differences in neuromuscular function of the affected leg were related to strength and not muscle activity (Table 10). The stroke participants were weaker than the young participants for all strength measures (knee extension (Stroke: M = 0.186 kg/kg body mass, SD = 0.062 kg/kg body mass; Young: M = 0.320 kg/kg body mass, SD = 0.051 kg/kg body mass; p =

0.013), plantar flexion (Stroke: M = 0.156 kg/kg body mass, SD = 0.084 kg/kg body mass; Young: M = 0.378 kg/kg body mass, SD = 0.074 kg/kg body mass; $p < 0.001$), dorsiflexion (Stroke: M = 0.177 kg/kg body mass, SD = 0.075 kg/kg body mass; Young: M = 0.361 kg/kg body mass, SD = 0.055 kg/kg body mass; $p < 0.001$)), and they were also weaker than the older non-fallers for all strength measures (knee extension (Non-fallers: M = 0.306 kg/kg body mass, SD = 0.109 kg/kg body mass; p = 0.030), plantar flexion (Non-fallers: M = 0.260 kg/kg body mass, SD = 0.043 kg/kg body mass; p = 0.016), dorsiflexion (Non-fallers: M = 0.314 kg/kg body mass, SD = 0.054 kg/kg body mass; $p < 0.001$)). The young participants were stronger than the older fallers in plantar flexion (Fallers: M = 0.206 kg/kg body mass, SD = 0.040 kg/kg body mass; $p <0.001$) and dorsiflexion (Fallers: M = 0.361 kg/kg body mass, SD = 0.055 kg/kg body mass; $p < 0.001$). The young participants were also stronger than the older non-fallers in plantar flexion (p = 0.001), while the older non-fallers were stronger than the older fallers in dorsiflexion (p = 0.018) (Figure 7).

Table 10

Group Effects for Each Measure of Neuromuscular Function

Dependent Variable	F	p	η_p^2
Knee Extension	5.318	0.004*	0.340
Plantar Flexion	20.940	<0.001*	0.670
Dorsiflexion	16.439	<0.001*	0.614
Peak RF Activity Swing	0.928	0.439	0.085
Peak TA Activity Swing	0.674	0.575	0.063
Peak GAS Activity Swing	2.676	0.065	0.211

Note. df1 = 3 and df2 = 30 for all tests; RF = rectus femoris; TA = tibialis anterior; GAS = medial gastrocnemius.

* $p < 0.05$

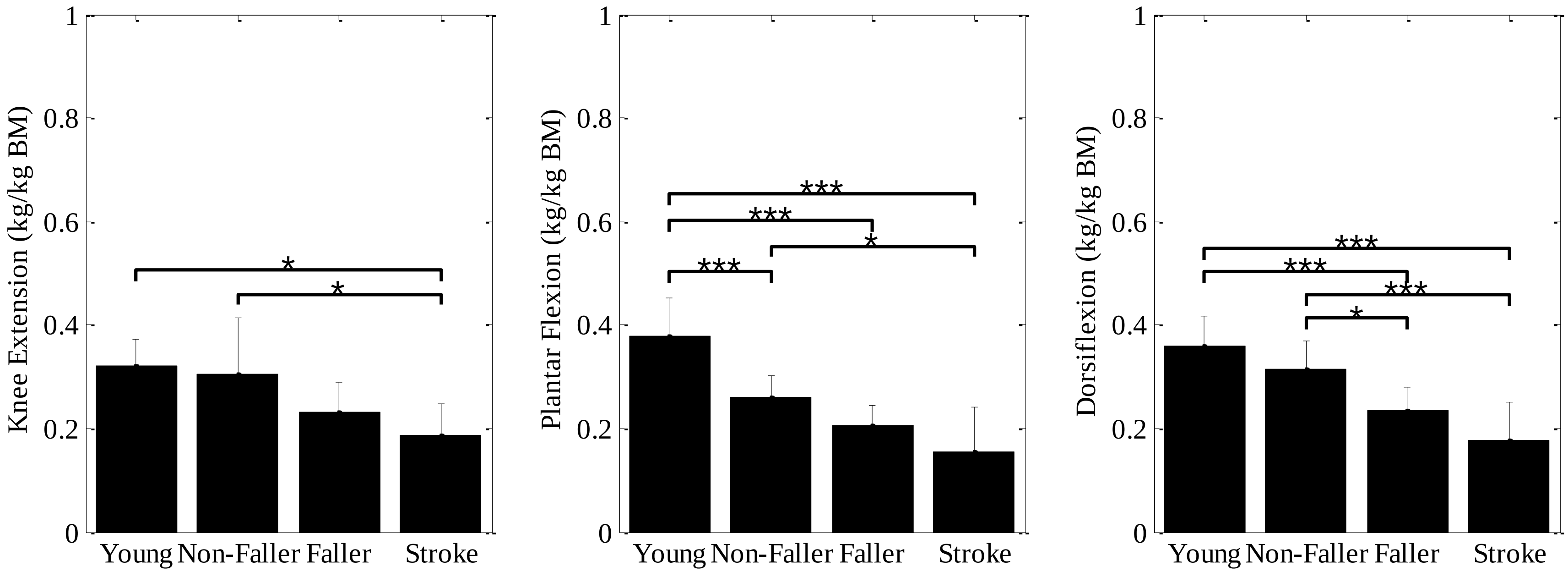

Figure 7. Pairwise comparisons for lower extremity strength on the affected side for motions that are significantly different between groups. (BM = body mass; *p < 0.05; ***p < 0.001)

Spatiotemporal gait parameters that were different between groups included overground speed, stance time and step width (Table 11). The participants with chronic stroke (M = 1.020 m/s, SD = 0.388 m/s) had a slower overground walking speed than the young (M = 1.485 m/s, SD = 0.119 m/s; p = 0.001) and older non-fallers (M = 1.354 m/s, SD = 0.159 m/s; p = 0.025), and the young participants also had a faster overground walking speed than the older fallers (M = 1.236 m/s, SD = 0.186; p = 0.046). There were no significant differences between pairs of groups for stance time (p > 0.050). The stroke participants (M = 0.117 m, SD = 0.060 m) had a greater step width than the older non-fallers (M = 0.041 m, SD = 0.026 m; p = 0.004) and the young participants (M = 0.044 m, SD = 0.028 m; p = 0.005) (Figure 8).

Table 11

Group Effects for Each Spatiotemporal Gait Parameter

Dependent Variable	F	p	η_p^2
Overground Speed	6.502	0.002*	0.386
Treadmill Speed	2.269	0.100	0.180
Stance Time	3.142	0.039*	0.233
Swing Time	1.979	0.138	0.161
Step Width	5.478	0.004*	0.346

Note. df1 = 3 and df2 = 31 for all tests.

* $p < 0.05$

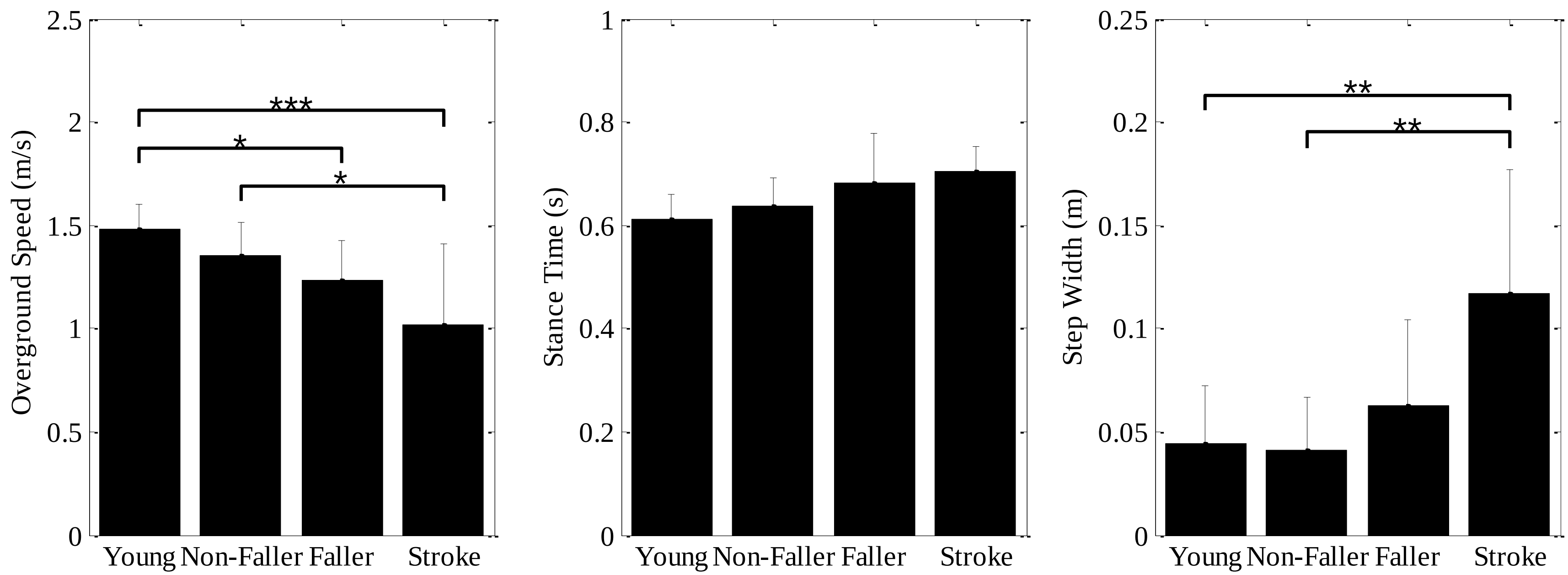

Figure 8. Pairwise comparisons for spatiotemporal gait parameters that are significantly different between groups. (*p < 0.05; **p < 0.01; ***p < 0.001)

While there was a trend toward group differences for MFC, the only measure of foot clearance that was different between groups was PC2 score, which represents toe height in early swing (Table 12). The participants with chronic stroke (M = 0.144, SD = 0.096) had a greater PC2 score than the young (M = -0.039, SD = 0.048; $p < 0.001$), older fallers (M = -0.014, SD = 0.056; $p = 0.001$), and older non-fallers (M = -0.001, SD = 0.070; $p = 0.002$) (Figure 9).

Table 12

Group Effects for Each Measure of Foot Clearance

Dependent Variable	F	p	η_p^2
MFC	2.763	0.059	0.211
Maximal Limb Shortening	2.612	0.069	0.202
PC1	0.384	0.765	0.036
PC2	9.570	<0.001*	0.481

Note. df1 = 3 and df2 = 31 for all tests.
* $p < 0.05$

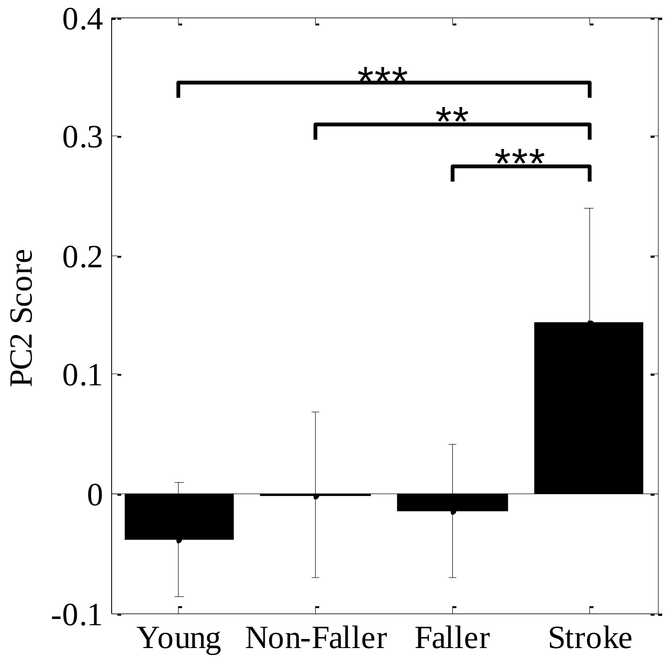

Figure 9. Pairwise comparisons for PC2 score, the only measure of foot clearance that is significantly different between groups. (**p < 0.01; ***p < 0.001)

The standard deviation of MFC and PC2 score were different across groups, with a trend towards differences for maximal limb shortening variability (Table 13). Participants with chronic stroke (M = 0.015 m, SD = 0.010 m) had greater MFC variability than older fallers (M = 0.006 m, SD = 0.005 m; p = 0.004), older non-fallers (M = 0.004 m, SD = 0.001 m; p = 0.001), and young participants (M = 0.003 m, SD = 0.001 m; p < 0.001). The participants with chronic stroke (M = 0.047, SD = 0.036) also had a greater standard deviation of PC2 score than the older non-fallers (M = 0.022, SD = 0.004; p = 0.018) (Figure 10).

Table 13

Group Effects for Each Measure of Foot Clearance Variability

Dependent Variable	F	p	η_p^2
MFC SD	8.026	<0.001*	0.437
Maximal Limb Shortening SD	2.844	0.054	0.216
PC1 SD	2.337	0.093	0.184
PC2 SD	3.502	0.027*	0.253

Note. df1 = 3 and df2 = 31 for all tests; SD = standard deviation.
* $p < 0.05$

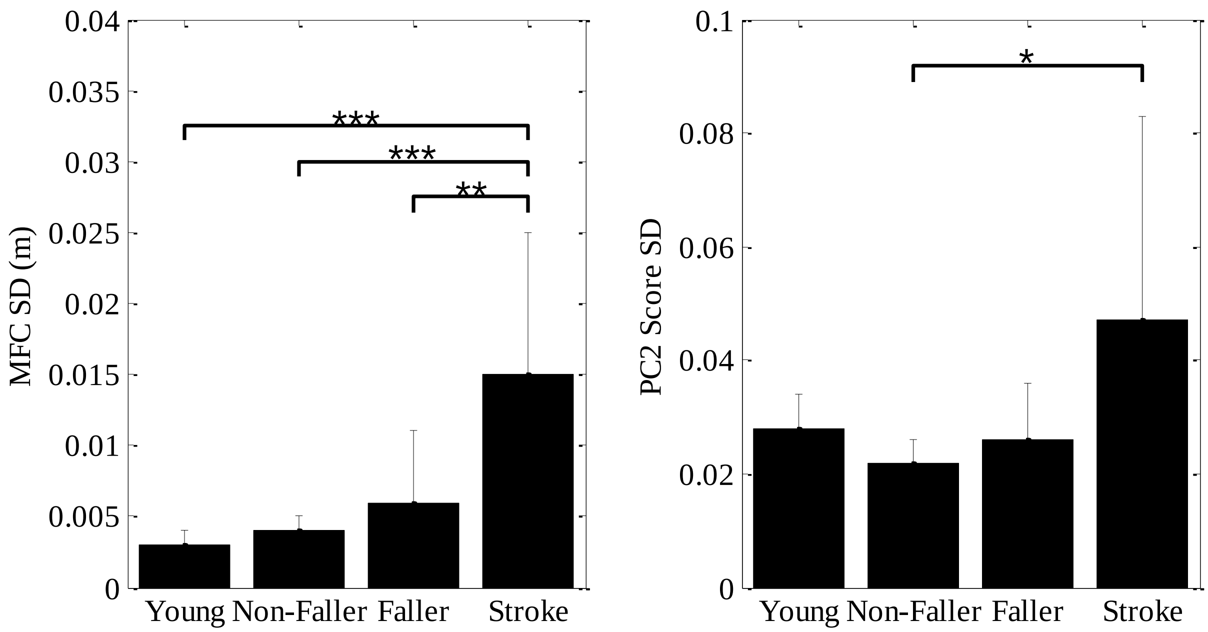

Figure 10. Pairwise comparisons for measures of foot clearance variability that are significantly different between groups. (*p < 0.05; **p < 0.01; ***p < 0.001)

Between-group kinematic differences during swing were observed for peak knee flexion and range of motion at the knee and ankle (Table 14). The participants with chronic stroke (Peak: M = 53.15°, SD = 17.87°; ROM: M = 48.00°, SD = 18.85°) had a lower peak knee flexion and knee range of motion than the young (Peak: M = 67.00°, SD = 3.53°, p = 0.011; ROM: M = 67.86°, SD = 2.91°, p < 0.001), older fallers (Peak: M = 66.86°, SD = 5.74°, p = 0.013; ROM: M = 65.08°, SD = 5.58°, p = 0.002), and older non-fallers (Peak: M = 69.76°, SD = 3.36°, p = 0.002; ROM: M = 64.64°, SD = 4.12°, p = 0.003). Ankle range of motion during swing was greater for young (M = 26.59°, SD = 7.90°) than participants with chronic stroke (M = 10.48°, SD = 5.81°; p < 0.001) and older non-fallers (M = 18.66°, SD = 5.37°; p = 0.029). Older fallers (M = 19.76°, SD = 4.20°) had a greater ankle range of motion during swing than participants with chronic stroke (p = 0.039).

Table 14

Group Effects for Swing Phase Joint Kinematics at the Hip, Knee and Ankle

Dependent Variable		F	p	η_p^2
Hip	Peak	0.429	0.734	0.040
	ROM	1.877	0.154	0.154
Knee	Peak	5.679	0.003*	0.355
	ROM	7.586	0.001*	0.423
Ankle	Peak	1.442	0.249	0.122
	ROM	8.389	<0.001*	0.448

Note. df1 = 3 and df2 = 31 for all tests; ROM = range of motion.
* $p < 0.05$

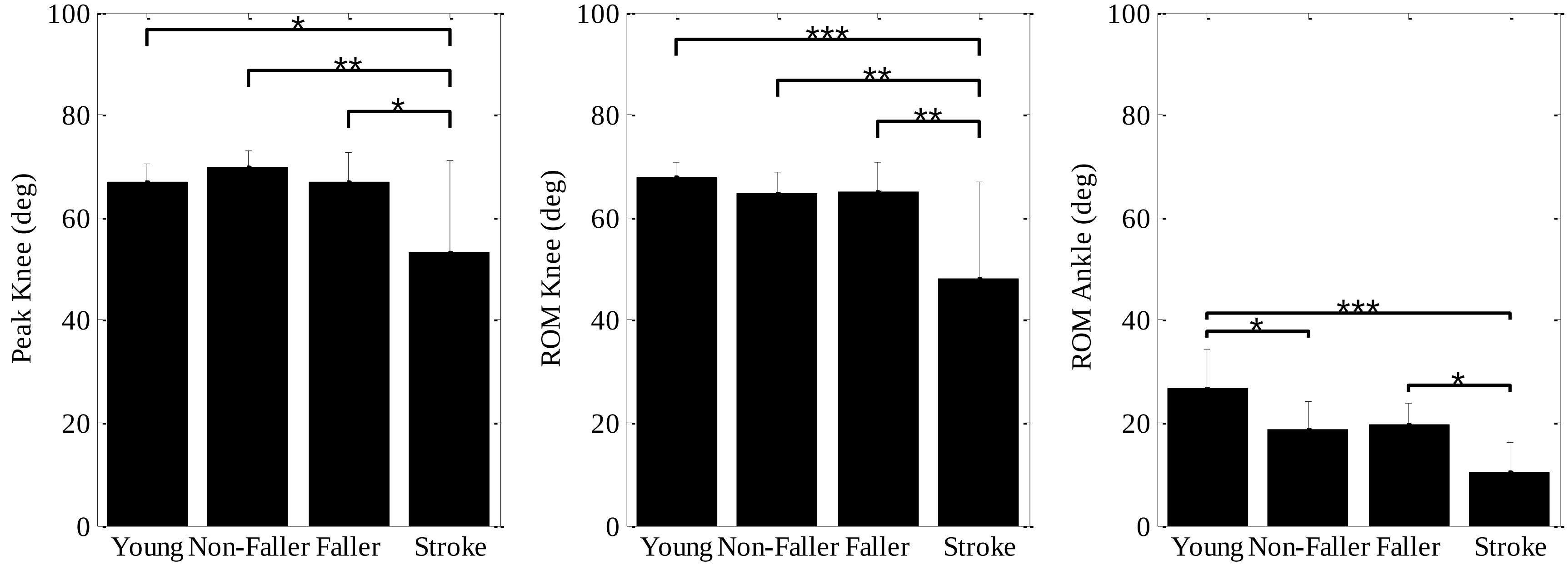

Figure 11. Pairwise comparisons of sagittal plane joint kinematics during swing that are significantly different between groups. (*p < 0.05; **p < 0.01; ***p < 0.001)

The only difference between groups for kinematic timing was the time to peak ankle angle during swing (Table 15). Participants with chronic stroke (M = 79.68%, SD = 11.84%) reached peak dorsiflexion earlier during the stride cycle than young (M = 96.99%, SD = 2.55%; $p < 0.001$), older fallers (M = 94.87%, SD = 5.56%; $p < 0.001$), and older non-fallers (M = 95.53%, SD = 4.59%; $p < 0.001$) (Figure 12).

Table 15

Group Effects for Time to Peak Hip, Knee and Ankle Angle during Swing

Dependent Variable	F	p	η_p^2
Hip	0.867	0.468	0.077
Knee	0.913	0.446	0.081
Ankle	11.108	<0.001*	0.518

Note. df1 = 3 and df2 = 31 for all tests.
* $p < 0.05$

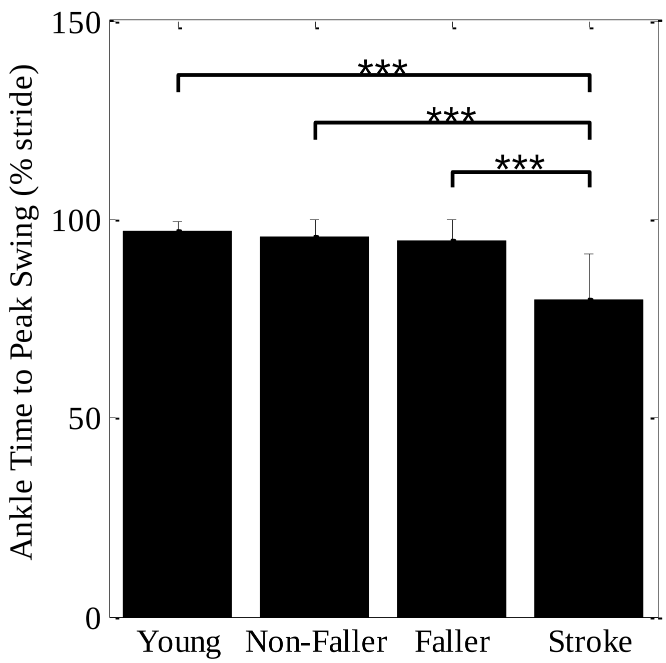

Figure 12. Pairwise comparisons for time to peak dorsiflexion during swing, the only measure of kinematic timing that is significantly different between groups. (***$p < 0.001$)

Joint coordination during initial swing was different between groups for hip-ankle and knee-ankle coupling patterns (Table 16). Participants with chronic stroke (M = 27.29°, SD = 7.51°) had a smaller hip-ankle coupling angle than young (M = 38.99°, SD = 3.98°; p = 0.001) and older fallers (M = 38.25°, SD = 6.33°; p = 0.002). The participants with chronic stroke (M = 30.14°, SD = 10.02°) also had a smaller knee-ankle coupling angle than young (M = 41.13°, SD = 3.55°; p = 0.004), older fallers (M = 43.30°, SD = 5.94°; p = 0.001), and older non-fallers (M = 38.88°, SD = 3.02°; p = 0.030) (Figure 13).

Table 16

Group Effects for Hip-Knee, Hip-Ankle and Knee-Ankle Joint Coordination during Initial Swing

Dependent Variable	F	p	η_p^2
Hip-Knee	2.880	0.052	0.218
Hip-Ankle	7.846	<0.001*	0.432
Knee-Ankle	6.925	0.001*	0.401

Note. df1 = 3 and df2 = 31 for all tests.
* $p < 0.05$

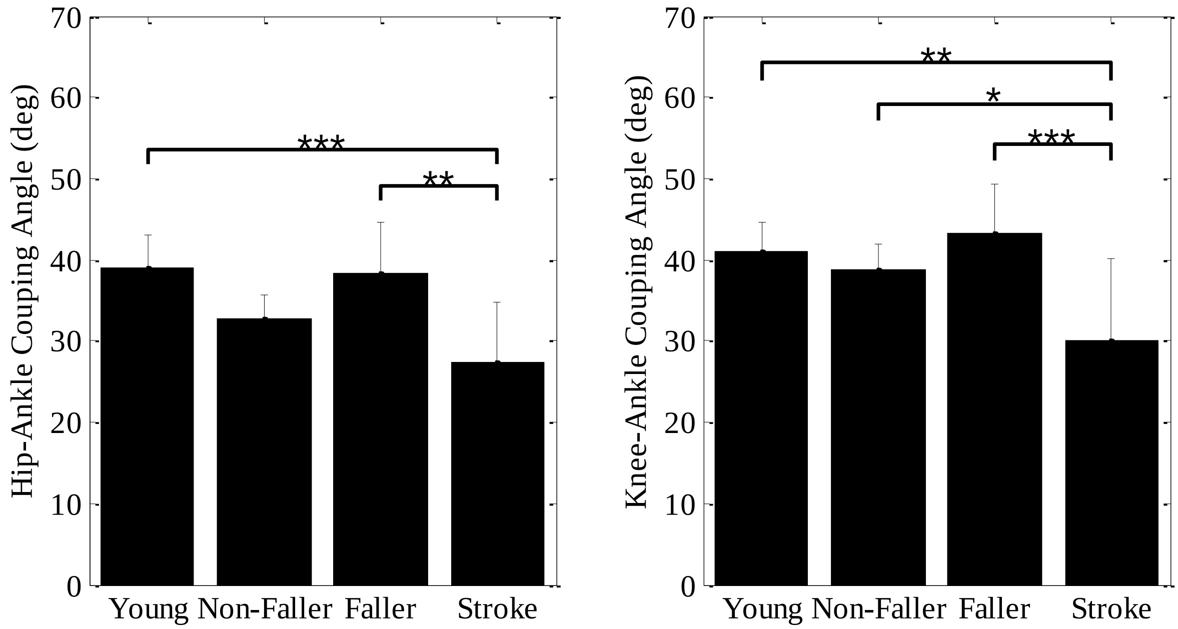

Figure 13. Pairwise comparisons of coupling angle during initial swing for coordination patterns that are significantly different between groups. (*p < 0.05; **p < 0.01; ***p < 0.001)

Discussion

This study examined measures of falls risk, gait characteristics, and the ability to avoid an object presented as a tripping hazard. The main result was that the ability to avoid an obstacle was not different between groups of young adults, older non-fallers, older fallers, and stroke survivors. There were, however, group differences for common measures of falls risk, including falls self-efficacy, gait and balance, lower extremity strength, spatiotemporal gait parameters, foot clearance, and foot clearance variability. Additionally, the groups exhibited different joint kinematics and coordination during swing. The lack of correspondence between group effects for obstacle avoidance and falls risk suggests that all measures of falls risk included in this study are not directly related to the ability to avoid an obstacle. While trips are one of the greatest causes of falls (W. P. Berg et al., 1997; Blake et al., 1988; Overstall et al., 1977; Robinovitch et al., 2013; Tuunainen et al., 2014), other reasons for falling may be explained by common falls risk measures, including the ability to recover from a trip. Additionally, the gait characteristics that were different between groups may not be relevant to avoiding an obstacle. It is likely that an individual-based approach is more relevant in determining ability to avoid an obstacle than membership in an at-risk group.

Differences between young and older adults in their ability to avoid an obstacle while walking has been shown to depend on time as well as the avoidance strategy employed by each individual. In situations where ample time is allowed to adjust foot placement, there is no difference between young and older adults in obstacle avoidance (Galna, Peters, Murphy, & Morris, 2009). Additionally, when attention is divided, such as when providing a verbal response to a visual task, the risk of coming in contact with an unexpected obstacle increases for both young and older adults, though more so for older adults (H. C. Chen et al., 1996). Therefore, many older adults adopt a conservative obstacle avoidance strategy that consists of a slower walking pace, and/or taking shorter steps. A shorter step adaptation may not completely eliminate obstacle contact, however, since it increases the risk of stepping on the obstacle (H. C. Chen, Ashtonmiller, Alexander, & Schultz, 1994), which was measured in this study. Since all participants were allowed to walk at a self-selected pace, it was possible that older adults walking significantly slower than young participants could explain why there were no differences in obstacle avoidance between the groups. The older fallers and the participants with chronic stroke did walk at a slower speed during the overground trials. However, there were no group differences in treadmill walking speed, which is the condition where the obstacles were presented. The absence of group differences on the visual task suggests the task had a similar result on divided attention for all groups. Additionally, the placement of the obstacles was consistent across groups. Based on the similar treadmill speed, divided attention task and obstacle placement, it would be expected that older adults would contact obstacles more frequently than young participants. However, this was not the case, as obstacle avoidance was not different across groups. Further analysis revealed that for all groups except the stroke participants, the self-selected treadmill speed was significantly slower than the self-selected overground walking pace (Table 6; Young: $F_{(1,9)} = 79.607$, $p < 0.001$, partial $\eta^2 = 0.898$; Non-fallers: $F_{(1,9)} = 102.297$, $p < 0.001$, partial $\eta^2 = 0.919$; Fallers: $F_{(1,9)} = 45.855$, $p < 0.001$, partial $\eta^2 = 0.836$; Stroke: $F_{(1,4)} = 2.432$, $p = 0.194$, partial $\eta^2 = 0.378$). It may be that the relatively slower treadmill speed reduced the time constraint on the obstacle avoidance task and leveled the playing field across groups.

Adequate foot clearance is necessary for stepping over an obstacle while walking. Consistent with the lack of group differences in obstacle avoidance, the toe height and variability throughout swing phase – measured by PC1 score – was not different between groups. The only measure of foot clearance that was different between groups was PC2 score, which represents toe height in the first half of swing, and the only differences were between the participants with chronic stroke and each of the other groups. In fact, the participants in the stroke group had a greater PC2 score, indicating greater foot clearance during the first half of swing. The same participants also had greater MFC variability than all other groups, and greater standard deviation of PC2 score than non-fallers. The greater foot clearance variability observed for stroke participants relative to the other groups may be a consequence of the more variable walking patterns commonly observed in hemiparetic gait (Balasubramanian, Neptune, & Kautz, 2008). The lack of other group differences in the magnitude and variability of toe height is consistent with the results of several studies that have found no difference in foot clearance between older and younger adults under normal walking conditions, (Bunterngchit, Lockhart, Woldstad, & Smith, 2000; Elble, Thomas, Higgins, & Colliver, 1991). It is only walking over a period of time that older adults adopt risky walking patterns that include lower MFC paired with lower MFC variability (Nagano et al., 2014), and effects of fatigue on foot clearance were not investigated in this study.

Stroke survivors often exhibit abnormal joint kinematics on the affected side – reduced hip and knee flexion resulting in toe drag, decreased knee extension prior to heel strike due to insufficient acceleration of the leg, and reduced ankle dorsiflexion – which may limit foot clearance during swing phase (Balaban & Tok, 2014; Olney & Richards, 1996). Similar kinematic patterns were observed in this study, particularly at the knee and ankle. It is possible that the greater PC2 score for the participants with chronic stroke could be explained by the time to peak ankle dorsiflexion. The stroke survivors reached peak dorsiflexion at around 80% of the stride cycle, which is within the first half of swing. Meanwhile, the other groups of participants continued to dorsiflex until nearly the end of swing. It could be that the participants with chronic stroke were overcompensating for limitations in ankle dorsiflexion by using hip and knee flexion to produce more than adequate foot clearance immediately after toe-off. The results from the analysis of joint coordination during initial swing showed that the participants with chronic stroke exhibit less ankle motion relative to the proximal joints than the other groups. Overall, the participants with chronic stroke displayed an inability to dorsiflex the ankle throughout swing phase along with reduced knee flexion compared to the other groups. While compensation for these deficits may have resulted in greater foot clearance at the beginning of swing (prior to the occurrence of the peak joint angles), other measures of foot clearance were not different between groups, and these particular gait characteristics did not affect the ability to avoid an obstacle.

Due to the abnormal gait patterns observed in the stroke group, concurrent differences in muscle activation might be expected. Previous work has identified a variety of abnormal muscle activation characteristics for individuals with stroke, including reduced magnitude of muscle activity (Woolley, 2001). Interestingly, in this study there were no differences in peak muscle activity during swing for any of the muscles, including tibialis anterior which contributes to ankle dorsiflexion. While the peak muscle activity during swing was the only component of EMG signal investigated, it may be that group differences exist for other measures of muscle activation, including the timing of muscle onset and offset. The neuromuscular factors that did reveal group differences were measures of lower extremity strength. As expected, the young participants were the strongest. The participants with chronic stroke were the weakest, but not significantly different from the fallers.

The greater step width for participants with chronic stroke than the older non-fallers and young adults is consistent with other studies that have shown that stroke survivors tend to have greater step width relative to normal, healthy older adults (Woolley, 2001). A wider step may be employed to compensate for reduced balance ability, suggests a history of falls (Gehlsen & Whaley, 1990a), and can be an indicator of future falls (Maki, 1997). In this case, the participants that employed a wider step did not come in contact with an obstacle more frequently. Therefore, step width may be more associated with the ability to prevent fall following a perturbation than the ability to avoid an obstacle.

Gait and balance measures have often been used to determine falls risk, however, differences in these measures among groups in the current study did not correspond with the ability to avoid an obstacle. As such, these methods of evaluating gait and balance function among older adults or stroke patients may be useful in determining levels of recovery and the extent of community engagement, though they may not be useful when trying to predict trips, particularly among high-functioning individuals. The POMA balance score is correlated with other measures of function and activity, including the timed up and go, function reach, walking speed, and ABC (Lin et al., 2004). More so than the POMA gait component or the total POMA score, the POMA balance score has been used to predict falls in patients with Parkinson's disease (Contreras & Grandas, 2012), and a cutoff score of 11 has been used to separate fallers and non-fallers (Thomas & Lane, 2005). In the current study, stroke participants scored below this threshold. Likewise, the mean stroke score on the FGA was below the threshold of 22 for distinguishing between fallers and non-fallers established by Wrisley et al. (2010). Yet the stroke participants did not perform differently than other groups on the obstacle avoidance task. This suggests that the POMA balance and FGA scores may be predicting other types of falls besides a trip.

In general, the participants in this study appear to be high-functioning. Tsang et al. (2013) showed that a cutoff score of less than 17.5 on the Mini-BESTest would predict fallers among a stroke group. However, the stroke participants in this study scored on average 21.8. Additionally, there were no significant differences in any gait and balance scores between older fallers and older non-fallers, although gait and balance measures have been used to distinguish these groups in the past. The relatively high functionality of the participants in this study could account for the fewer than expected group differences in gait and balance scores, and could explain why all groups performed similarly on the obstacle avoidance task.

Fear of falling can be defined as "low perceived self-confidence at avoiding falls during essential, relatively nonhazardous activities" (Tinetti & Powell, 1993), and has frequently been associated with falls and falls risk. Fear-related activity restriction has been observed in up to

25% percent of older adults (Reelick, van Iersel, Kessels, & Rikkert, 2009; Tinetti et al., 1988), and fear of falling is greater among stroke survivors, particularly among those with a history of falls (Belgen et al., 2006; Mackintosh et al., 2005). Measures such as the FES-S and ABC chronicle fear of falling while performing certain tasks, and the FAI is used to record a recent (within three to six months) history engaging in activities that require some initiative, such as housework or gardening. Neither the FES-S nor ABC were significantly different across groups, and the group difference in FAI total score did not translate into any pairwise differences. Further, the average total FAI score for the stroke participants was greater than the normative score for chronic stroke participants reported by Schepers et al. (2006), suggesting that the stroke participants in this study had greater community engagement than typical chronic stroke patients.

A limitation of this study is the way MFC was used to quantify foot clearance and foot clearance variability. MFC was defined as the toe height at the point of greatest horizontal velocity of the foot. Using MFC as a measure of foot clearance, therefore, relies on the assumption that there is a local minimum in toe height at this point. Deviations from this relationship may affect the magnitude of MFC. Additionally, it is likely that the MFC standard deviation is a reflection of the variability of when the point of greatest forward velocity of the foot occurs within the stride cycle. The other measures of foot clearance and foot clearance variability may be more accurate representations of the distance between the floor and the foot.

The prevalence of high-functioning participants in all groups may be considered a limitation of this study. It is possible that group differences in obstacle avoidance between the groups would exist if the older faller and stroke participants exhibited greater functional impairments. Nevertheless, the observed differences in measures of falls risk did not correspond with differences in the ability to avoid an obstacle. This suggests that an individual in a group that is not considered at risk may still experience a trip. Of course not all trips result in falls. It is impossible to know from the observations in this study what determines whether a person will fall after coming in contact with an obstacle because this controlled setting (i.e. lightweight obstacle that was free to move, and available support from the harness) was designed to prevent falls. Investigations of factors that contribute to a reduced capacity to maintain balance after a perturbation and not an inability to avoid obstacles are key to developing fall prevention programs. Yet the results of this study indicate that the ability to successfully avoid a tripping hazard cannot be determined simply by inclusion within an at-risk group.

Conclusion

While measures of falls risk were higher for stroke participants and to a lesser extent older fallers, the inability to distinguish between groups on obstacle avoidance suggests that the risk of tripping should be evaluated on an individual, and not group, basis.

Chapter 4: Determining Factors that Affect Obstacle Avoidance Ability

Introduction

As shown in Chapter 3, certain demographic groups – including stroke survivors and older adults with a history of falls – score higher on measures of falls risk, but the ability to avoid an obstacle while walking was not dependent on group. This underscores the conclusion reached by Begg et al. (2007) that an individual-based approach to evaluate a patient's risk of tripping may be better than a group-based approach. Evaluations of an individual's function, including measures of falls self-efficacy, gait and balance performance, and walking speed, have been linked to falls risk (Belgen et al., 2006; Campbell, Borrie, & Spears, 1989; Deandrea et al., 2010; Delbaere et al., 2004; Deshpande et al., 2008; Gehlsen & Whaley, 1990b; Stalenhoef et al., 1997). It is likely that lower-functioning individuals are less likely to avoid obstacles, and therefore are at greater risk of tripping. Therefore, these measures of function can be useful for identifying at-risk individuals. However, as shown in Chapter 3, being labeled at-risk for falling does not necessarily predict the ability to avoid an obstacle. It is possible that specific gait characteristics have a more relevant relationship with obstacle avoidance.

Achieving adequate foot clearance is crucial for avoiding obstacles while walking, and foot clearance can be accounted for by each of the lower extremity joints individually (Winter, 1992). Yet the hip, knee and ankle all contribute concurrently to this task. It has been shown that limb movements are planned for the distal endpoint trajectory, not specific joint trajectories (Karst et al., 1999), which suggests that coordination of the lower extremity joints plays a role in the ability to avoid obstacles. How this is achieved appears to depend on the individual, as different strategies are employed to achieve adequate foot clearance (Levinger et al., 2012; Little et al., 2014). Each strategy for avoiding an obstacle relies on the magnitude of lower extremity joint angles, the relative motion between joints, and the muscle activity that causes joint motion.

The purpose of this study was to determine individual and gait characteristics related to the ability to avoid an unexpected obstacle that could present a tripping hazard. It was expected that participants who were able to avoid an obstacle would score higher on measures of function, and have different gait characteristics than those who were not able to avoid the obstacle. In particular, it was projected that successful obstacle avoidance would be associated with greater foot clearance, and greater peak flexion and sagittal plane range of motion for the lower extremity joints. Additionally, differences in lower extremity joint coordination and neuromuscular function during swing were expected.

Methods

Participants. The 35 participants introduced in Chapter 2 were included in this analysis. According to performance on the obstacle avoidance task in Chapter 3, the participants were split into two groups: those that came in contact with an obstacle multiple times (N = 10), and those that came in contact with an obstacle one or no times (N = 25).

Biomechanics assessment. The same procedures for collecting data from Chapters 2 and 3 were used in this analysis.

Data analysis. Data were analyzed to identify factors related to the ability to avoid an obstacle while walking. The factors tested were the same as outlined in Chapter 3, and included scores on falls-related evaluations, neuromuscular function, spatiotemporal gait parameters, foot clearance, foot clearance variability, lower extremity sagittal plane kinematics, the timing of kinematics during swing phase, and lower extremity joint coordination during initial swing and midswing. The falls-related evaluations were performed prior to the biomechanics assessment, and all measures of gait characteristics were recorded during overground walking. The ability to avoid an obstacle was assessed on a treadmill. For each group of measurements, a MANOVA was used to identify significant differences between participants that came in contact with more than one obstacle, and participants that came in contact with just one or no obstacles ($p < 0.05$). When the assumptions for using a MANOVA were checked, a significant ($p < 0.001$) Box's M test for some of the constructs was found indicating heterogeneity of the variance-covariance matrix. Therefore, the results of each MANOVA were reported using Pillai's trace (Tabachnick & Fidell, 2013). The follow up test was a one-way ANOVA for each dependent variable that was included in the omnibus test. All statistical tests were done in SPSS (v19.0.0.1; SPSS, Inc., Chicago, IL).

Results

There were significant differences between participants that came in contact with multiple obstacles and participants that came in contact with one or no obstacles for falls-related evaluations, spatiotemporal gait parameters, foot clearance, and joint kinematics (Table 17). Differences were not observed for neuromuscular function, which included measures of strength as well as peak muscle activity of the hip, knee and ankle during swing. Measures of foot clearance variability, the time to peak flexion during swing, and joint coordination during initial swing and midswing were also not different based on ability to avoid an obstacle.

Table 17

Overall Effect of Each Gait- or Falls-Related Construct to Distinguish Participants with Multiple Instances of Obstacle Contact from Participants with One or No Instances of Obstacle Contact

Construct	Pillai's Trace	F	df1	df2	p	η_p^2
Falls-Related Evaluations	0.754	14.285	6	28	<0.001*	0.754
Neuromuscular Function	0.206	1.168	6	27	0.352	0.206
Spatiotemporal Parameters	0.572	7.751	5	29	<0.001*	0.572
Foot Clearance	0.393	4.855	4	30	0.004*	0.393
Foot Clearance Variability	0.060	0.480	4	30	0.750	0.060
Joint Kinematics	0.408	3.220	6	28	0.016*	0.408
Kinematic Timing	0.181	2.277	3	31	0.099	0.181
Initial Swing Coordination	0.111	1.289	3	31	0.296	0.111
Midswing Coordination	0.169	2.102	3	31	0.120	0.169

* $p < 0.05$

There were significant differences for all falls-related evaluations except for the total score for the FAI (Table 18). Participants that came in contact with the obstacle once or not at all scored higher than participants with repeated contact on measures of falls self-efficacy including total score for the FES-S and the ABC, as well as all measures of gait and balance.

Table 18

Differences in Scores on Each Falls-Related Evaluation Between Participants with Multiple Instances of Obstacle Contact and Participants with One or No Instances of Obstacle Contact

Dependent Variable	One or No Contact		Multiple Contact		ANOVA Results		
	M	SD	M	SD	F	p	η_p^2
FAI Total	50.24	4.94	48.30	5.48	1.036	0.316	0.030
FES-S Total	9.99	0.03	9.65	0.36	23.217	<0.001*	0.413
ABC	97.51	3.75	88.22	11.85	12.718	0.001*	0.278
POMA Balance	15.56	0.65	14.40	0.97	17.089	<0.001*	0.341
Mini-BESTest Total	25.40	2.20	21.30	3.40	18.003	<0.001*	0.353
Functional Gait Analysis	27.87	2.59	19.30	5.03	44.554	<0.001*	0.574

Note. df1 = 1 and df2 = 33 for all tests; M = mean; SD = standard deviation.
* $p < 0.05$

Participants that contacted the obstacles multiple times walked slower, both overground and on the treadmill. The difference in speed was expressed as greater stance time, while swing time was the same. Additionally, participants that came in contact with the obstacle multiple times also had a greater step width (Table 19).

Table 19

Differences in Each Spatiotemporal Gait Parameter Between Participants with Multiple Instances of Obstacle Contact and Participants with One or No Instances of Obstacle Contact

Dependent Variable	One or No Contact		Multiple Contact		ANOVA Results		
	M	SD	M	SD	F	p	η_p^2
Overground Speed (m/s)	1.40	0.15	1.09	0.31	17.042	<0.001*	0.341
Treadmill Speed (m/s)	0.94	0.25	0.54	0.16	22.531	<0.001*	0.406
Stance Time (s)	0.63	0.06	0.71	0.08	11.409	0.002*	0.257
Swing Time (s)	0.41	0.04	0.41	0.06	0.082	0.776	0.002
Step Width (m)	0.05	0.03	0.09	0.05	7.464	0.010*	0.184

Note. df1 = 1 and df2 = 33 for all tests; M = mean; SD = standard deviation.
* $p < 0.05$

Participants with multiple obstacle contacts exhibited greater MFC, and a greater toe height in early swing, as measured by PC2 score. The PC1 score, which quantifies toe height during the second half of swing, and maximal limb shortening were not different between individuals that avoided the obstacles and those that did not (Table 20).

Table 20

Differences in Each Measure of Foot Clearance Between Participants with Multiple Instances of Obstacle Contact and Participants with One or No Instances of Obstacle Contact

Dependent Variable	One or No Contact		Multiple Contact		ANOVA Results		
	Mean	SD	Mean	SD	F	p	η_p^2
MFC (m)	0.021	0.010	0.036	0.013	13.008	0.001*	0.283
Max Limb Shortening	0.967	0.061	0.924	0.101	2.373	0.133	0.067
PC1	-0.002	0.162	0.008	0.175	0.028	0.869	0.001
PC2	-0.027	0.053	0.085	0.101	18.346	<0.001*	0.357

Note. df1 = 1 and df2 = 33 for all tests; M = mean; SD = standard deviation; Units of maximal limb shortening are normalized limb length; Units of PC1 and PC2 have no biological meaning.
* $p < 0.05$

Significant differences in sagittal plane joint angles were observed between the two groups. Participants who contacted the obstacle multiple times had reduced range of motion at the hip, knee and ankle. The same participants also had lower peak knee flexion during swing (Figure 14; Table 21).

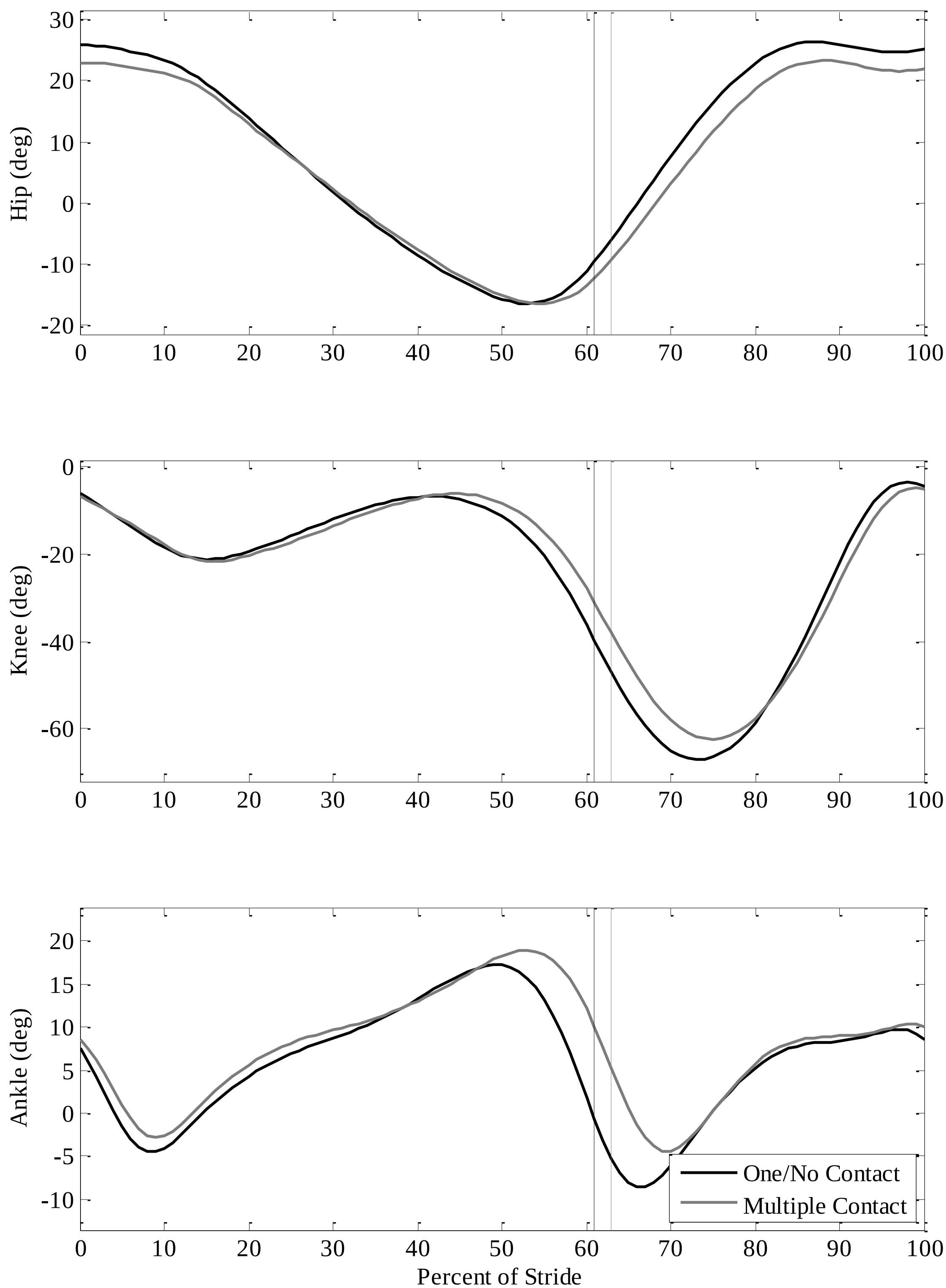

Figure 14. Mean sagittal plane joint hip, knee and ankle angles for participants that contacted the obstacle multiple times (gray), and those that did not (black). Positive angles represent hip flexion, knee extension and ankle dorsiflexion. Vertical lines represent toe-off.

Table 21

Differences in Sagittal Plane Joint Kinematics during Swing Between Participants with Multiple Instances of Obstacle Contact and Participants with One or No Instances of Obstacle Contact

Dependent Variable		One or No Contact		Multiple Contact		ANOVA Results		
		Mean	SD	Mean	SD	F	p	η_p^2
Hip	Peak (°)	27.26	10.01	24.46	9.71	0.570	0.456	0.017
	ROM (°)	37.27	5.70	32.42	4.75	5.626	0.024*	0.146
Knee	Peak (°)	67.89	4.63	60.48	14.39	5.437	0.026*	0.141
	ROM (°)	66.07	4.83	56.41	15.45	8.126	0.007*	0.198
Ankle	Peak (°)	11.27	4.12	10.72	3.69	0.135	0.716	0.004
	ROM (°)	22.37	7.41	14.33	5.20	9.770	0.004*	0.228

Note. df1 = 1 and df2 = 33 for all tests; M = mean; SD = standard deviation; ROM = range of motion.
* $p < 0.05$

Discussion

Most of the falls-risk evaluations examined in this study were successful at distinguishing between participants that came in contact with the obstacle multiple times, and those that did not. FAI was not differenct in this case, but was the only measure of falls self-efficacy that distinguished demographic groups in Chapter 3. Taken together, these results indicate that FAI serves as a measure of community engagement, and is not related to falls as much as FES-S and ABC, which assess fear of falling. Considering there were differences for the FES-S and ABC scores, it appears that participants with a greater fear of falling were more likely to come in contact with the obstacle multiple times. It has been suggested that fear of falling causes a reduction in activity that leads to decreased physical function and an increased risk of falling. However, a greater fear of falling among participants that came in contact with the obstacle multiple times without a concurrent difference in community engagement reveals that even individuals with a high level of community engagement may have limitations that affect their ability to avoid an unexpected obstacle while walking.

Based on the physical measures of function, it appears that poor balance or gait performance is related to an inability to avoid an obstacle while walking. The mean score of the Functional Gait Analysis for participants that made contact with the obstacle multiple times was lower than the cutoff reported by Wrisley & Kumar (2010) that distinguishes fallers from non-fallers. While the mean score for participants that contacted the obstacle multiple times was not below the threshold established in the literature to separate fallers and non-fallers for the POMA balance (Thomas & Lane, 2005) or Mini-BESTest total (Tsang et al., 2013), those participants scored significantly lower than the participants that avoided the obstacle. Participants that came in contact with the obstacle multiple times exhibited a more conservative walking strategy, with a wider step width, longer stance times, and a slower walking speed overground and on the treadmill. This walking pattern is common among individuals that are fearful about falling (Maki, 1997). Nevertheless, this approach did not prevent participants in this study from contacting the obstacle multiple times.

By definition, adequate foot clearance is necessary to avoid a trip, which is why low foot clearance is considered a risk for falling (Begg et al., 2007). The results of this study, however, did not support that theory. The participants that came in contact with the obstacle multiple times actually had a greater foot clearance during overground walking. It has already been established that these participants adopt a conservative walking strategy, and ensuring greater foot clearance may be another component of that strategy. Regardless, the mean MFC of 0.036 m (SD = 0.013 m) was not enough to avoid the obstacles, which were approximately 0.06 m high. Therefore, the ability to avoid an obstacle is not reliant on foot clearance during normal overground walking, but rather the ability to adjust toe height in proportion to the obstacle height. It appears that elevated foot clearance during normal walking may serve as an indication of a conservative walking strategy common among individuals that do not have the capacity to avoid an obstacle.

The ability to achieve adequate foot clearance when necessary appears to be related to sagittal plane lower extremity joint motion. Flexion of the hip, knee and ankle occur concurrently during swing phase to enable foot clearance. It was expected that joint coordination during swing would be related to the ability to avoid an obstacle, but none of the variables that represent joint coordination during initial swing and midswing were significantly different between the two sets of participants. Thus, gait characteristics that are relevant to obstacle avoidance appear to be confined to sagittal plane lower extremity joint kinematics. Greater range of motion in the hip, knee and ankle as well as greater peak knee flexion was observed for the participants that did not come in contact with the obstacle multiple times, and the difference is greater than the reported minimal detectable change for each angle (Wilken, Rodriguez, Brawner, & Darter, 2012). Some of the kinematic differences between participants can be attributed to the effects of walking at a slower speed (Kirtley, 2006; Kwon, Son, & Lee, 2014; Stansfield et al., 2001), and may serve as another indication of a conservative walking strategy for those who came in contact with the obstacle multiple times. Since speed was not controlled in this study, it cannot be determined whether the kinematic differences were solely due to speed effects, or if the participants that came in contact with the obstacle multiple times have a physical limitation in their ability to produce hip, knee and ankle flexion. Of note is the fact that a reduction in joint motion due to slower walking speeds typically affects the knee and ankle but not the hip (Kirtley, 2006; Kwon et al., 2014; Stansfield et al., 2001). Even so, regardless of the reason for the kinematic differences, a lower range of motion may contribute to the inability to avoid an obstacle. With less available range of motion in the lower extremity joints, a participant may not be able to react to an unexpected obstacle, which could result in a trip.

While measures of falls self-efficacy, physical function and walking strategy are useful to identify individuals at risk for tripping, a trip does not occur every time that someone walks. It is possible that risky walking behavior only occurs some of the time, and so specific gait characteristics within a stride cycle may be more helpful than a general designation of falls risk at detecting exactly when an individual may be unable to avoid an obstacle. It would be beneficial to be able detect gait characteristics such as limited sagittal plane range of motion in real time as part of a falls prevention program.

Conclusion

Participants that repeatedly came in contact with an unexpected obstacle could be classified as being at risk for tripping based on functional evaluations. Specific gait characteristics that were related to their inability to avoid the obstacle included limited sagittal plane joint range of motion during swing at the hip, knee and ankle, and in general a conservative walking strategy that consisted of slower walking speed, greater step width, and elevated foot clearance.

Chapter 5: Using Accelerometers and Machine Learning to Detect Gait Characteristics Related to Obstacle Avoidance

Introduction

In the previous chapters, factors related to the risk of falling and the ability to avoid unexpected obstacles were identified, however, these factors are typically only detected in a controlled setting. Measures of function (e.g. gait and balance ability) rely on evaluations by a trained observer or a clinician, and the kinematic measures of gait (e.g. peak ankle and knee angle and hip and knee range of motion during swing) are the product of expensive equipment and time-consuming data processing done in a motion capture lab. Despite the wealth of information that can be produced using these techniques, the analysis may not represent everyday gait patterns or behavior. As a result, there has been a surge in the development of wearable devices that can track movement in real time and in natural settings. The global market for all wearable devices is expected to grow 800% from 2012 to 2018, with a value close to $6 billion (Transparency Market Research, 2015). Wearable devices that track information about the body have been developed for multiple purposes, including the tracking of physical activity, temperature, blood pressure, heart rate, weight, and glucose (Appelboom et al., 2014).

A common method used to analyze human gait through wearable devices is to apply machine learning algorithms to signals obtained from a tri-axial accelerometer. This technique has been employed extensively to classify different activities (e.g. walking, running, climbing stairs, sitting, etc.) (Bao & Intille, 2004; Mannini & Sabatini, 2010; Mannini, Intille, Rosenberger, Sabatini, & Haskell, 2013; Moncada-Torres et al., 2014; Preece, Goulermas, Kenney, & Howard, 2009). Additionally, walking events and walking speed have been detected from accelerometers placed on both shanks (Dobkin, Xu, Batalin, Thomas, & Kaiser, 2011), and idiopathic toe walking can be distinguished from normal gait by analyzing accelerometer data at the heel (Pendharkar, Percival, Morgan, & Lai, 2012). Several machine learning algorithms applied to accelerometer data have also been used to classify older adults at risk for falling, however, the risk of falling was not determined by actual prospective falls, and the accelerometer system contained 10 sensors distributed over the body (Caby, Kieffer, de Saint Hubert, Cremer, & Macq, 2011). Related to the risk of tripping, foot clearance can be estimated using wireless inertial sensors, with placement on the foot or shank (Hamacher et al., 2014; Mariani et al., 2012; McGrath et al., 2011), although these methods do not consider the joint kinematics that influence foot clearance. Other inertial sensor systems have been constructed to make accurate joint angle measurements, based on placement of several sensors on multiple body segments (Seel et al., 2014; Slajpah et al., 2014). Although these methods are designed to provide accurate information about joint kinematics outside of a laboratory setting, it may be difficult for the general population to effectively adopt a multiple-sensor system (Ward, Evenson, Vaughn, Rodgers, & Troiano, 2005).

The success of these many applications indicates that applying machine learning algorithms to accelerometer signals may have a role in preventing falls by detecting gait characteristics related to the ability to avoid an obstacle. A significant contribution to this field would be to develop a single device that is capable of detecting specific gait patterns, as well as predict individuals at risk for tripping based on actual trip history. The first goal of this study was to predict joint angles (peak ankle and knee angle, and hip and knee range of motion during swing) for a given stride from a single ankle-worn accelerometer. The second goal was to determine ability to avoid an obstacle based on features from accelerometers worn on a single or both ankles. Various machine learning algorithms were evaluated to determine optimal performance in terms of accuracy. Computational load was also calculated, as the time required to make a prediction could be an important consideration if this technology was used in a real-time gait detection wearable device. It was expected that the prediction of joint angles would be most successful for the knee joint since the accelerometer was placed on the distal segment of the joint. A positive predictive value near 1 when classifying participants at risk for tripping was expected for the best-performing algorithms, with the simplest algorithms expected to have the worst classification accuracy. Demonstrating successful prediction and/or classification ability indicates that an accelerometer could be incorporated into a wearable device that alerts an individual when they may be at risk for tripping.

Methods

Participants. The 35 participants introduced in Chapter 2 were included in this analysis. According to performance on the obstacle avoidance task in Chapter 3, the participants were split into two groups: those that came in contact with an obstacle more than one time (N = 10), and those that came in contact with an obstacle one or no times (N = 25).

Biomechanics assessment. During the biomechanics analyses performed in Chapters 2 and 3, inertial sensors containing a tri-axial accelerometer (Noraxon Inc, DTS 3D Accelerometer 518, Scottsdale, AZ, USA) were worn on both legs just above the lateral ankle, to record accelerations at 1000 Hz. The orientation of both accelerometers was adjusted so that the positive x-axis pointed anteriorly, the positive y-axis pointed superiorly and the positive z-axis pointed laterally (Figure 15). Each accelerometer had a sensitivity of 24 g, with a maximum input voltage of 4 V. The accelerometer signal was converted from volts to accelerations using the conversion factor 0.167 V/g.

Figure 15. Orientation of the axes for each accelerometer.

Data analysis. The accelerometer data were used in machine learning algorithms with two specific goals: predict lower extremity joint angles and classify individuals likely to come in contact the obstacle multiple times or not (Table 22). All algorithms were executed using the free machine learning software package, Weka (v.3.6.13; The University of Waikato, Hamilton, New Zealand).

Table 22

Framework of the Machine Learning Process for Predicting Kinematics and Classifying Obstacle Contact

Goal	Method	Raw Data	Window	Overlap	Segment Label	Feature extraction	Feature Selection	Prediction
Predict Kinematics	1	1 sensor: left and right separate	Individual strides	--	Hip ROM Knee Peak Knee ROM Ankle ROM	Time- and frequency-domain	Correlation-based	Linear Regression
	2	1 sensor: left and right separate	Individual strides	--	Hip ROM Knee Peak Knee ROM Ankle ROM	PCA	--	Linear Regression
Classify Obstacle Contact	1	1 sensor: left and right separate 2 sensors: left and right together	0.256 s 0.512 s 1.024 s 2.048 s 4.096 s	0% 50%	Obstacle contact or no contact	Time- and frequency-domain	Correlation-based	1R C4.5 Tree Best-First Tree Random Forest Decision Table Naïve Bayes Instance-Based k-Nearest Neighbor

Joint Angle Prediction. All kinematic and accelerometer data were divided into individual strides using the horizontal velocity algorithm employed in Chapters 2-4 (Zeni et al., 2008). Based on the results from Chapter 4, lower extremity joint kinematics related to the ability to avoid an obstacle – peak knee angle and hip, knee and ankle range of motion during swing – were identified for each stride. Also for each stride, two sets of features were extracted from the three-dimensional accelerometer signal. The first method of feature extraction was based on previous work regarding activity recognition using accelerometers. This set of 48 features (Table 23) was selected from the time- and frequency-domain features outlined by Preece, et al. (2009). The mean, standard deviation, median, 25th percentile and 75th percentile of the accelerometer signal was calculated for each axis (Ermes, Parkka, Mantyjarvi, & Korhonen, 2008; Pirttikangas, Fujinami, & Nakajima, 2006). The correlation of the accelerometer signals between axes (x-y, x-z, y-z) was also determined (Bao & Intille, 2004). For additional time-domain features, the accelerometer signal was separated into accelerations due to gravity (DC) and body accelerations (AC) using a median filter (n=3), followed by a low pass filter (third-order elliptical infinite impulse response, cut-off frequency = 0.25 Hz, passband ripple = 0.01 dB, stopband = -100 dB) (Karantonis, Narayanan, Mathie, Lovell, & Celler, 2006). The mean of the DC signal and the mean of the rectified AC signal were calculated for each axis. The frequency-domain features were a product of a fast Fourier transform (FFT) performed on each stride of accelerometer data. The following features were determined for each accelerometer axis: principal frequency (Foerster & Fahrenberg, 2000), spectral energy (sum of the squared FFT coefficients, normalized by signal length) (Bao & Intille, 2004), entropy (A. Zhang, B. Yang, & L. Huang, 2008; Bao & Intille, 2004), and the sum of FFT coefficients grouped in five exponential bands (2^1, 2^2, 2^3, 2^4, 2^5) to avoid using each coefficient separately or in pairs (Huynh & Schiele, 2005).

A subset of relevant features that were not redundant with other features in the subset was selected using the correlation-based feature selection algorithm in Weka (Hall et al., 2009; Maurer, Smailagic, Siewiorek, & Deisher, 2006). This algorithm was performed using a greedy forward stepwise search method: starting with an empty subset, features were added when they had a high correlation with the dependent variable, but also a low correlation with features previously added to the subset. A separate subset of features was chosen for each of the four joint angles based on the relationship between the feature and the given angle.

Table 23

Full Set of Features Determined for Each Window of Data from a Single Sensor

Time Domain	Frequency Domain
Mean	Principal Frequency
Standard Deviation	Spectral Energy
Median	Entropy
25th Percentile	Sum of FFT Coefficients 1-2
75th Percentile	Sum of FFT Coefficients 3-6
Mean DC	Sum of FFT Coefficients 7-14
Mean Rectified AC	Sum of FFT Coefficients 15-30
X-Y Correlation	Sum of FFT Coefficients 31-62
X-Z Correlation	
Y-Z Correlation	

Note. All features were calculated separately for all three axes (X, Y, Z) except for the correlations between axes in the time domain, which were only calculated once.

The second set of features was derived based on an analysis of the relationship between the accelerometer signals and the joint kinematics. Since the predicted angles were based on swing phase, the accelerometer signals and joint angles were time normalized to 101 data points representing 0-100% of swing phase. A principal components analysis of each accelerometer axis and the hip, knee and ankle waveforms during swing was performed according to the methods outlined in Chapter 2. The results of the principal components analysis were principal components (PCs) that identified the major modes of variance within the data. Each stride was given a PC score for each of the retained PCs for the accelerometer signal in the x-, y- and z-directions, as well as the hip, knee and ankle angles. The PCs that represented peak knee angle and hip, knee and ankle range of motion during swing were identified visually (Brandon et al., 2013). PCs from the accelerometer signals that had the highest correlations with the relevant angle PCs were also identified and interpreted. Based on the interpretation of the accelerometer PCs, discrete variables were chosen as features of the accelerometer signal relevant for the prediction of a joint angle (Appendix G). For example, a PC that represented the magnitude of the accelerometer signal throughout swing could be characterized by the mean accelerometer signal. The result was a subset of features unique to each predicted angle.

For the computer-selected and PC-selected subsets of features, the linear regression algorithm in Weka was used to predict each of the four joint angles of a single stride (Hall et al., 2009). Performance of the linear regression model was evaluated using ten runs of 10-fold cross validation, with measures of error reported as mean absolute error, root mean squared error, relative-absolute error, root relative squared error, and the correlation between the actual and predicted angles. Computational load was calculated as the total time testing divided by the number of strides in the testing dataset for a given fold. The linear regression performance was averaged across all repetitions of training and testing for each of the four angles.

Obstacle Contact Classification. To classify an individual participant based on their ability to avoid an obstacle, all accelerometer data were collected as a continuous waveform for each walking condition. It was then divided into windows of 256, 512, 1024, 2048, and 4096 frames, which, with a sampling rate of 1000 Hz, corresponds to window lengths of 0.256, 0,512, 1.024, 2.048 and 4.096 seconds, respectively (Huynh & Schiele, 2005). The number of frames in each window was a power of two to facilitate the FFT during feature extraction. The windows of accelerometer data were also computed using both no overlap and a 50% overlap (Bersch, Azzi, Khusainov, Achumba, & Ries, 2014). For each window of accelerometer data, time- and frequency-domain features were extracted as outlined in the first method above. Since there were two accelerometers, one on each ankle, feature extraction was done twice: on individual sensors separately and both sensors together. The full vector of features for the single sensor was identical to the 48-feature vector described above (Table 23). The double sensor vector had 105 features. The number of features was more than double that of the single sensor due to nine additional correlations of the accelerometer signal between sensors (X1-X2, X1-Y2, X1-Z2, Y1-X2, Y1-Y2, Y1-Z2, Z1-X2, Z1-Y2, Z1-Z2; for the x-, y-, and z-axes of the same (1) and opposite (2) sensors). Using the same correlation-based feature selection algorithm method described previously (Hall et al., 2009), a subset of features relevant to the classification of obstacle contact was selected. In an activity prediction experiment, a window size of 1 s was identified as the cut-off where any increase in window size did not result in improved performance (Banos, Galvez, Damas, Pomares, & Rojas, 2014), therefore the feature selection algorithm was run separately for single and double sensors using the datasets constructed with windows of length 1.024 s with 50% overlap.

All windows for a given participant were labeled based on that participant's ability to avoid an obstacle, with windows from participants that came in contact with the obstacle multiple times labeled "contact", and with windows from those that did not labeled "no contact". Classification of obstacle contact was done using a variety of classification algorithms on each window size, percent of window overlap, and number of sensors combination. The classifiers included 1-Rule, Decision Table, C4.5 Decision Tree, Best-First Decision Tree, Random Forest, Naïve Bayes, Instance-Based, and k-Nearest Neighbor. All classifiers were implemented using the default settings in Weka, with k set to three in the k-Nearest Neighbor algorithm (Hall et al., 2009). Performance for each algorithm and combination of data was evaluated using 10-fold cross-validation (Banos et al., 2014). Performance was reported as recall, also known as sensitivity (percent of "contact" cases that were identified), and precision (percent of correct "contact" cases that were identified). Recall and precision across all window/overlap/sensor combinations were examined to determine the ideal parameters for segmenting the accelerometer data. At those parameters, positive predictive value (PPV) and computational load were compared for each classifier. PPV was calculated from sensitivity, specificity (percent of "no contact" cases that were identified), and prevalence of trips in the older adult population (Equation 1) (Altman, Machin, Bryant, & Gardner, 2000). Prevalence was determined to be 0.15, based on the number of trips reported in studies of the incidence of falls among older adults (Appendix H) (W. P. Berg et al., 1997; Blake et al., 1988; Robinovitch et al., 2013; Talbot, Musiol, Witham, & Metter, 2005). Computational load was reported as time required for testing for each window.

$$PPV = \frac{sensitivity \times prevalence}{sensitivity \times prevalence + (1 - specificity) \times (1 - prevalence)} \tag{1}$$

Results

The correlation-based feature selection method resulted in 7, 14, 18 and 7 time- and frequency-domain features in the subsets for hip range of motion, knee peak, knee range of motion and ankle range of motion, respectively (Table 24). The Principal Components Analysis to determine relevant features in the hip, knee and ankle waveforms and the accelerometer signals resulted in 7, 10, 10, and 13 PC-based features in the subsets for hip range of motion, knee peak, knee range of motion and ankle range of motion, respectively (Table 25), with the same subset used for both the peak angle and range of motion at the knee.

Table 24

Axes of the Time- and Frequency-Domain Features Selected for the Prediction Model of Each Angle

	Hip ROM	Knee Peak	Knee ROM	Ankle ROM
Mean		Z	Y,Z	
Standard Deviation	Y,Z	Z	X,Z	Z
Median	Y	Y	Y	Y
25th Percentile			Y	X
75th Percentile	Z	Z	Y,Z	Z
Mean DC		Z	Y,Z	
Mean Rectified AC	X,Y,Z	X,Z	X	Y,Z
Principal Frequency		Z	X	Y
Spectral Energy				
Entropy		X,Y	X,Y,Z	
Sum of FFT Coefficients 1-2		Y		
Sum of FFT Coefficients 3-6		Y	Y	
Sum of FFT Coefficients 7-14				
Sum of FFT Coefficients 15-30				
Sum of FFT Coefficients 31-62				
X-Y Correlation			✓	
X-Z Correlation		✓		
Y-Z Correlation		✓	✓	
Number of Features Selected	7	14	18	7

Note. ROM = range of motion; ✓ indicates correlation was selected.

Table 25

Axes of the PC-based Features Extracted for the Prediction Model of Each Angle

	Hip ROM	Knee Peak	Knee ROM	Ankle ROM
Mean	Z	X,Z	X,Z	X,Z
Max	Z	X,Y,Z	X,Y,Z	X,Y,Z
Min		Z	Z	Z
Mean First 25%	Z			
Mean First 50%	X			X
Value at 50%	X	X,Z	X,Z	X,Z
Value at 60%				Z
Value at 75%	X			X
Value at 80%				Z
Value at 100%		X	X	Y
Number of Peaks		Y	Y	
Zero Cross Rate	Z			
Number of Features Selected	7	10	10	13

Note. ROM = range of motion; percentages refer to percent of swing.

The time- and frequency-domain feature subset performed better than the PC-based features for each of the four datasets (Table 26). Examining performance for each of the individual angles using the time- and frequency-domain feature subset, the ankle peak model performed the best on absolute measures of error (mean absolute error and root mean squared error), but was among the worst on relative measures of error. The predicted knee angle range of motion had the best performance on relative measures of error, and a strong correlation to the actual knee angle range of motion (Table 26). Computational load was similar for each feature set and angle model (Table 26).

Table 26

Results of the Linear Regression Models Using Both Feature Selection Methods

	Mean Absolute Error (°)		Root Mean Squared Error (°)		Relative-Absolute Error (%)		Root Relative Squared Error (%)		Correlation Coefficient		Time Testing (ms)	
	TF	PC	TF	PC	TF	PC	TF	PC	TF	PC	TF	PC
Hip ROM	5.24	6.21	7.10	8.21	73.86	87.61	77.91	90.16	0.627	0.433	0.164	0.155
Knee Peak	5.68	5.71	8.09	8.80	95.43	95.84	78.44	85.28	0.621	0.523	**0.141**	**0.139**
Knee ROM	6.18	8.19	8.09	10.71	**49.94**	**66.18**	**52.06**	**68.97**	**0.854**	**0.724**	0.168	0.160
Ankle ROM	**4.89**	**4.79**	**6.75**	**6.71**	93.09	91.32	93.67	93.20	0.350	0.363	0.158	0.152

Note. TF = time- and frequency-domain features; PC = PC-based features; ROM = range of motion.

The correlation-based feature selection algorithm for the obstacle avoidance classification resulted in a subset of 17 features for the single sensor and 15 features for the double sensor (Table 27). The Instance-Based and k-Nearest Neighbor classifier had the best recall across all conditions (Figure 16). All tree-based classifiers (C4.5, Best-First and Random Forest) had similar performance, while the simplest classifiers (1-Rule, Decision Table and Naïve Bayes) performed the worst. In general, two sensors were better than one, 50% overlap was better than no overlap, and performance improved as window size increased. Recall and precision plateaued with a window size of approximately one second, particularly for the Instance-Based, k-Nearest Neighbor and decision tree algorithms. Additionally, with a window size of around one second, the difference between no overlap and 50% overlap appears to be negligible.

With a window size of 1.024 s, 50% overlap and one sensor, the Instance-Based and k-Nearest Neighbor classifiers had the best PPV, but also the greatest computational loads (Table 28). Random Forest had a lower computational load while maintaining high PPV. The C4.5 and Best-First Trees were among the fastest classifiers and produced a PPV of around 0.85. The simplest classification algorithms had the lowest PPV. Performance was better for two sensors than one sensor for each classification algorithm.

Table 27

Axes of the Time- and Frequency-Domain Features Selected for the Obstacle Avoidance Classification Models

	Single Sensor	Double Sensor
Mean	Y	
Standard Deviation	X,Y,Z	Y1,Y2,Z2
Median	X,Y	X1,Y2
25th Percentile	X,Z	X2,Z2
75th Percentile	X,Y	X1,Y1,Y2
Mean DC	Y	
Mean Rectified AC	Z	
Principal Frequency	Z	Z2
Spectral Energy	Y	Y1
Entropy	X,Y,Z	Y1,Z1
Sum of FFT Coefficients 1-2		
Sum of FFT Coefficients 3-6		
Sum of FFT Coefficients 7-14		
Sum of FFT Coefficients 15-30		
Sum of FFT Coefficients 31-62		
X1-Y1 Correlation		
X1-Z1 Correlation		
Y1-Z1 Correlation		
X1-X2 Correlation		
X1-Y2 Correlation		
X1-Z2 Correlation		
Y1-X2 Correlation		
Y1-Y2 Correlation		✓
Y1-Z2 Correlation		
Z1-X2 Correlation		
Z1-Y2 Correlation		
Z1-Z2 Correlation		
Number of Features Selected	17	15

Note. Numbered axes indicate the sensor; ✓ indicates correlation was selected.

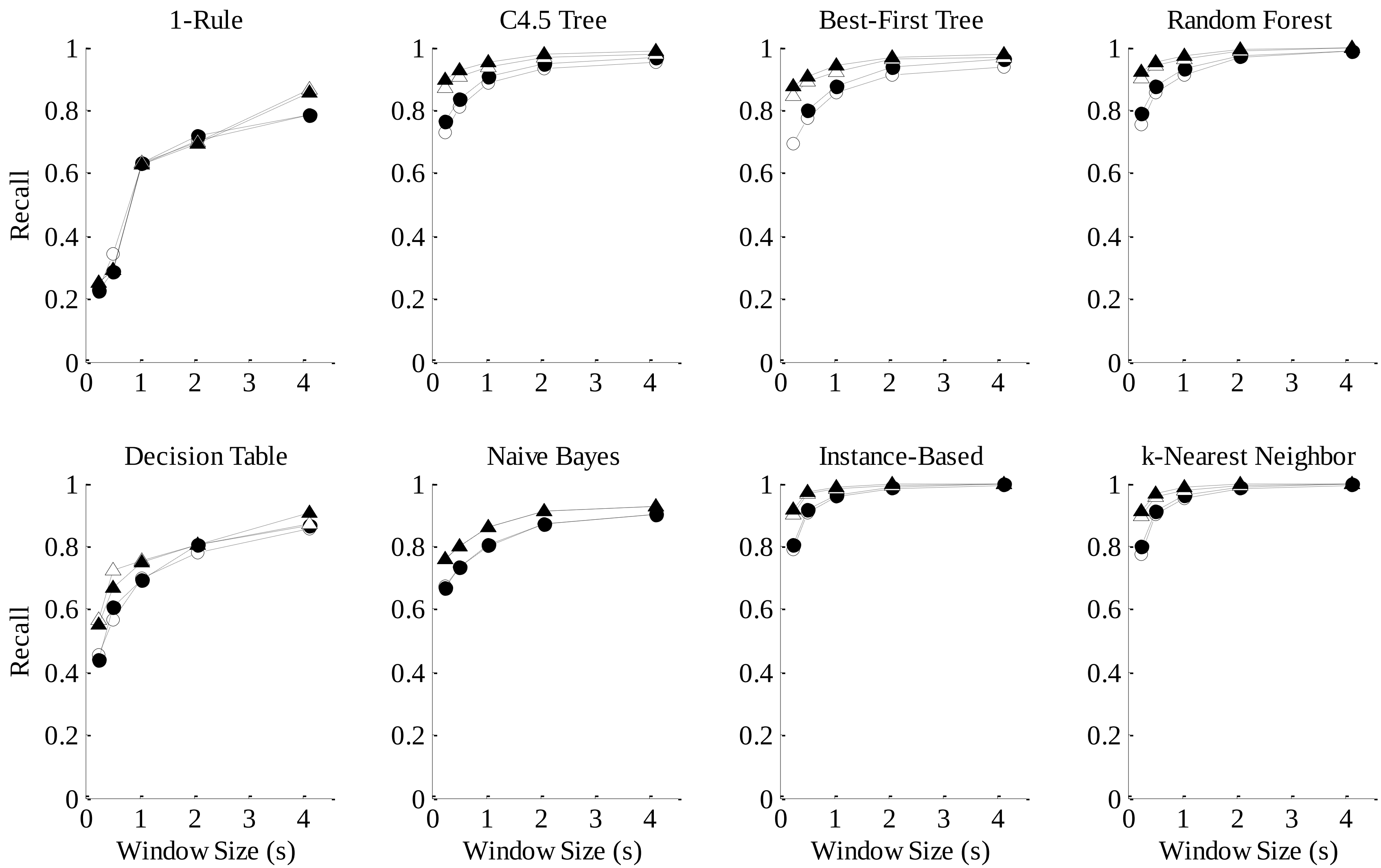

Figure 16. Recall for each classifier based on window size, one sensor (circles), two sensors (triangles), no overlap (empty), and 50% overlap (filled).

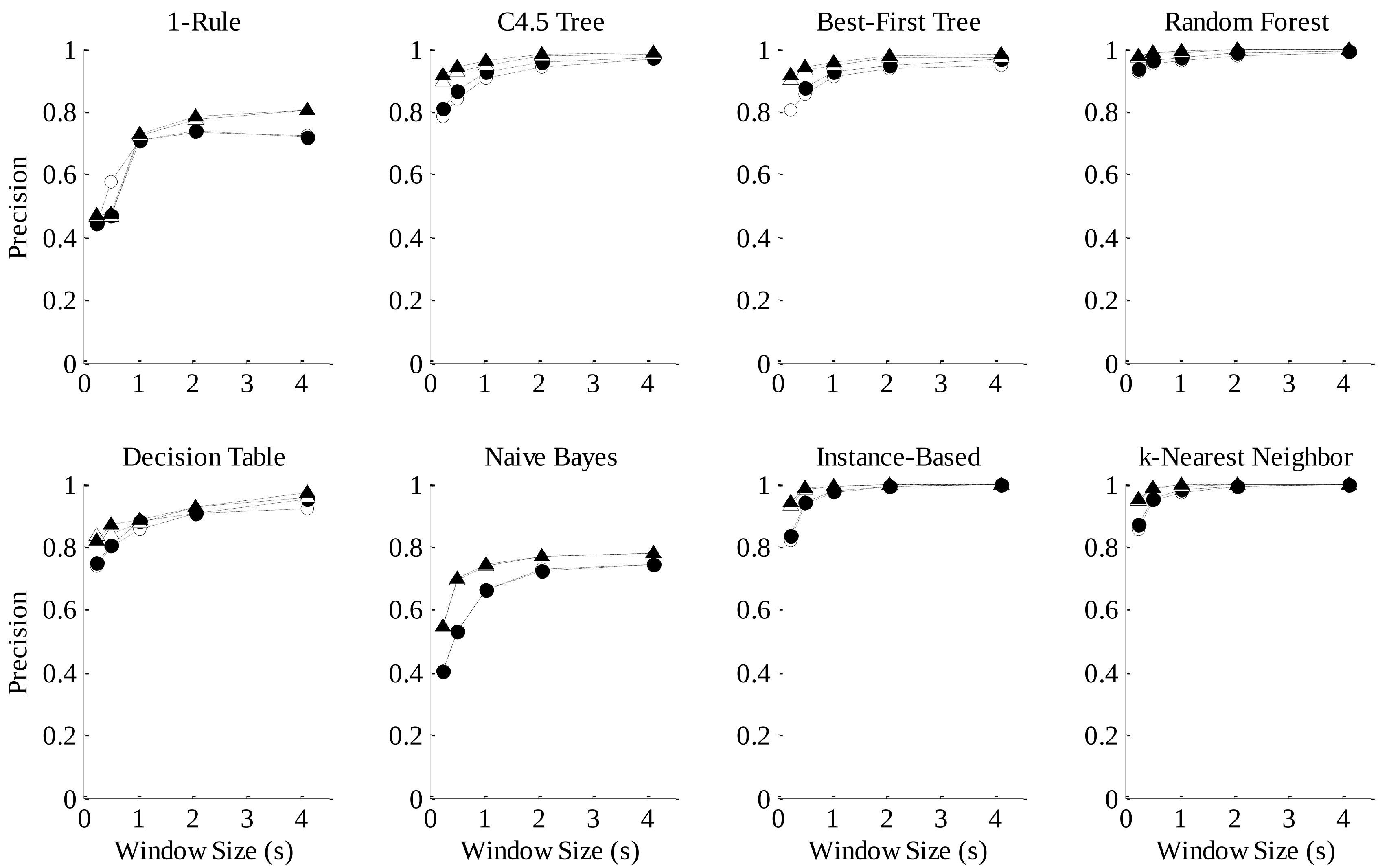

Figure 17. Precision for each classifier based on window size, one sensor (circles), two sensors (triangles), no overlap (empty), and 50% overlap (filled).

Table 28

Positive Predictive Value and Computational Load for Each Classifier and Number of Sensors

Classifier	PPV		Time (ms)	
	One Sensor	Two Sensors	One Sensor	Two Sensors
1-Rule	0.536	0.559	**3.58E-04**	4.56E-04
C4.5 Tree	0.854	0.920	6.53E-04	5.87E-04
Best-First Tree	0.857	0.915	5.22E-04	**2.61E-04**
Random Forest	0.940	0.981	3.00E-02	1.84E-02
Decision Table	0.776	0.792	4.05E-03	1.96E-03
Naive Bayes	0.486	0.583	8.52E-03	7.11E-03
Instance-Based	0.956	0.986	1.04E+01	4.65E+00
k-Nearest Neighbor	**0.961**	**0.990**	5.47E+00	1.43E+01

Note. Window size = 1.024 s; Overlap = 50%.

Discussion

The results of this study indicate that it is possible to use an ankle-worn accelerometer to anticipate and individual's risk of tripping, by both predicting joint angles and identifying walking patterns that are associated with the inability to avoid an unexpected obstacle. The various machine learning techniques that were used to train and test the regression and classification models provided a range of performance outcomes, however, a strong correlation between the predicted and actual knee range of motion and a high positive predictive value for detecting individuals at risk for tripping were achieved.

For the regression analyses, using the correlation-based feature selection algorithm on a large set of features from both the time and frequency domain was more successful than identifying a set of time-domain features through Principal Components Analysis. The goal of the PC-based features was to visually identify components of the accelerometer signal that were related to the joint angles of interest. However, this method relied on the interpretation of multiple PCs, as well as translating the meaning of relevant PCs into discrete variables that could be computed for each stride independently. The reduced performance from the PC-based feature set compared to the time- and frequency-domain feature set could be due to inadequate representation of the relevant PCs. It is also possible that the addition of frequency-domain features is crucial to predicting kinematic behavior from an accelerometer signal. Preece et al. (2009) and Huynh & Schiele (2005) also reported good machine learning performance when using frequency-domain features of an accelerometer signal. Including frequency-domain features does add to the computational load in the feature extraction stage of the machine learning process. In this study, the feature extraction and machine learning were done separately using Matlab and Weka, respectively, and so the time cost of the feature extraction was not included in the computational load analysis. As a result, the reported time testing per stride was similar for models using the two different feature sets.

Considering only models that used a combination of time- and frequency-domain features extracted from the accelerometer signal, the most successful regression model was the prediction of the knee joint range of motion, based on measures of relative error and the correlation coefficient. The kinematic differences between participants who were likely to trip and those who did not were highlighted in Chapter 4, where peak knee flexion was significantly lower for participants that came in contact with the obstacles multiple times, but the reduction in knee range of motion was even greater. So while inadequate peak knee flexion may have contributed to the inability to avoid an obstacle, the same participants also did not achieve the same degree of knee extension during swing. Despite having similar measures of absolute error as the peak knee angle model – and greater absolute error than the ankle and hip range of motion – the greater variance in the knee range of motion likely contributed to the smaller relative error terms in the knee range of motion regression model.

The accelerometer used in the prediction models was placed just above the ankle, recording shank accelerations. As the ankle angle is calculated as the displacement of the foot relative to the shank, the placement of the accelerometer was not conducive to predicting ankle range of motion. Similarly, the shank is not one of the segments determining the hip angle, which likely explains the poor hip range of motion predictions. With the accelerometer on the distal segment of the knee, the knee angle predictions were more successful. Previous studies have utilized sensors on multiple segments to quantify joint kinematics (Seel et al., 2014; Slajpah et al., 2014), and additional sensors may have improved prediction accuracy in this case. However, the goal was to accomplish kinematic prediction using a single sensor, which was done for knee range of motion. Adjustments to sensor position and feature selection could be used to improvement prediction performance for other joints. It is also possible that approaching joint angle prediction as a classification problem may be more successful. For example, if it was determined that everyone with a knee range of motion less than a certain value was considered at risk for tripping, machine learning algorithms may be more adept at predicting high and low classes, rather than the actual joint angle.

The second goal of this study was to use classification algorithms on accelerometer signals to identify individuals at risk for tripping, regardless of other measures of kinematics or walking ability. Of all the classifiers used in this study, the simplest (1-Rule, Decision Table and Naïve Bayes) performed the worst. The best performance based on recall and PPV belonged to the Instance-Based and k-Nearest Neighbor algorithms, although the large computational load may be discouraging when trying to implement a similar system in real time. The relatively high

PPV and low computational load for the decision tree algorithms (C4.5, Best-First, and Random Forest) indicates that this type of algorithm should be considered when looking for a classifier with high accuracy and low computational load, which may be the case when using these algorithms to predict the risk of tripping in real-time. The accuracy performance of the classifiers in this study was similar to results from Bao & Intille (2004) who showed that Instance-Based/Nearest Neighbor and C4.5 Decision Tree outperformed Decision Table and Naïve Bayes during activity recognition tasks using accelerometer signals. Another similarity with the activity recognition literature is that classification performance begins to plateau at a window size around one second, with smaller window sizes resulting in worst performance (Banos et al., 2014). One second appears to be a reasonable window size as the typical walking stride rate is approximately one stride per second (Kirtley, 2006). Allowing for overlapping windows avoids a situation where relevant information may be split between two windows and not fully captured during the feature extraction phase (Bersch et al., 2014).

Almost all of the features selected for the single sensor were also selected when data from both sensors were included. The relevant additional information from using both sensors appears to be related to differences in y-axis (vertical) accelerations between the sensors. The standard deviation and 75th percentile of the y-axis acceleration was selected for both sensors, as well as the correlation between the y-axes of both sensors. The feature selection algorithm chose relevant features that were not correlated with each other, suggesting that having vertical accelerations that are different between legs is relevant to obstacle avoidance. For all other features that were selected, only one of the axes in a given direction was included. In terms of performance, inclusion of data from two sensors was better than one, particularly for small window sizes. However, with a window size of about one second, it was possible to achieve a PPV of over 0.9 for detecting the risk of tripping with the use of just one sensor.

Three limitations to the procedures used in this study are highlighted. First, in the prediction of joint angles from each stride of accelerometer data, a kinematic algorithm was used to split the data into individual strides (Zeni et al., 2008). Although identifying gait events using ankle-worn accelerators was previously completed (Sant'Anna & Wickstrom, 2010), this study identified these events via an approach not based on accelerometer measurements. Second, for both the regression and classification analyses, the feature extraction was performed in Matlab, and then relevant features were subsequently selected using Weka. The full feature set was then reduced using Matlab before the regression and classification algorithms were run in Weka. Although the back-and-forth between different programs likely did not affect the results of this study, for this technology to be used in the real world, all components of the machine learning process from data acquisition to segmentation to feature extraction/selection to prediction should occur in seamless sequence on one device. Future studies that utilize this approach will be able to provide a better picture of the computational load for each algorithm as all aspects of the machine learning process will be considered. A third limitation of this study was that only one dataset was used to train and test the models. To perform a statistical comparison between different algorithms requires many different datasets (Demšar, 2006). The inclusion of participants with a range of ages and falls history, as well as participants with a history of stroke suggests that the results of this study may be generalizable to a diverse population. However, comparisons of the machine learning algorithms across many independent datasets is necessary to confirm the differences in performance observed here.

In the future, the ability to predict joint kinematics and classify individuals at risk for tripping needs to be tested in real-time as well as in a non-laboratory setting. The algorithms could then be paired with a program designed to suggest changes in observed walking mechanics that are associated with the risk of tripping. A prospective study should also be done to determine if this technology can be used to successfully prevent trips.

Conclusion

In conclusion, this study identified machine learning processes that can be used to predict knee range of motion and classify individuals at risk for tripping based on an accelerometer worn just above the ankle. Placement of the accelerometer on the distal joint segment appears beneficial for lower extremity joint angle prediction. Identifying gait patterns of individuals at risk for tripping can be done using the signal from a single accelerometer with features extracted in overlapping windows of about one second in length. Simple classification algorithms have low accuracy, and excellent accuracy with an instance-based approach can come with a high computational cost, but a high PPV for the risk of tripping and low-to-moderate computational load can be achieved using decision tree classifiers.

Chapter 6: Summary and Conclusions

The objectives of this study were to (a) identify the relationship between joint coordination and foot clearance during walking; (b) identify differences in function and gait characteristics related to falls risk, as well as the ability to avoid an unexpected obstacle, among stroke patients, young adults, older fallers and older non-fallers; (c) determine gait and individual characteristics that enable successful avoidance of an unexpected object that could present a tripping hazard; (d) detect gait characteristics related to the risk of tripping and classify individuals likely to contact an unexpected obstacle based on accelerometer signals.

Thirty-five community-dwelling participants including young adults, older adults without a history of falls, older adults with a history of falls, and chronic stroke patients were included in this study. Participants completed written and physical evaluations of falls risk. Each participant walked at a self-selected pace both overground and on a treadmill. During the treadmill walking condition, participants were exposed to a series of unexpected obstacles, which they attempted to avoid. Performance on the obstacle avoidance task was recorded, and three-dimensional lower extremity kinematics, bilateral muscle activity of rectus femoris, tibialis anterior and medial gastrocnemius, and accelerations of the distal shank were captured during all walking conditions. Kinematic data were used to calculate foot clearance and joint coordination. Falls-related evaluations, neuromuscular function, spatiotemporal gait parameters, foot clearance, foot clearance variability, joint kinematics, kinematic timing, joint coordination and obstacle performance were compared across demographic groups. Comparisons were also made between participants that successfully avoided the obstacles, and those that came in contact with the obstacle multiple times. Machine learning algorithms were used to predict joint angles and gait characteristics associated with the ability to avoid an obstacle based solely on accelerometer data.

Sagittal plane joint coordination can predict measures of foot clearance that rely on concurrent motion at the hip, knee and angle, as well as measures of toe height throughout swing phase. In particular, hip-knee coordination from terminal stance throughout swing appears to have the greatest effect on foot clearance. Individuals that have approximately equal hip and knee motion during terminal stance and initial swing, and more knee extension relative to hip flexion during midswing and terminal swing are predicted to have greater toe height. Additionally, high joint coordination variability may yield greater variability in foot clearance during swing. Future studies should examine if changes to hip-knee joint coordination result in an increase in foot clearance and a reduction of foot clearance variability.

Falls-related evaluations and gait characteristics are different among demographic groups. Participants with chronic stroke perform the worst on the functional evaluations, followed by older adults with a history of falls. The participants with chronic stroke also exhibit gait characteristics that may indicate an increased risk of tripping. However, there are no differences between the groups on the ability to avoid an unexpected obstacle. These results suggest that all common measures of falls risk included in this study are not directly related to the ability to avoid an obstacle, and that membership in an at-risk group is not the best way to identify individuals who are likely to trip. When individuals were classified by their ability to avoid an obstacle and not by their group, factors related specifically to obstacle avoidance emerged. In general, participants with an inability to avoid an obstacle score lower on functional evaluations that assess fear of falling and gait and balance performance. These individuals also adopt a more conservative walking strategy that includes slower walking speed, greater step width and elevated foot clearance. Reduced range of motion of the swing phase hip, knee and ankle angles may also contribute to the inability to avoid an unexpected obstacle.

Detection of gait characteristics associated with obstacle avoidance can be achieved by applying machine learning algorithms to signals from ankle-worn accelerometers. When considering individual walking strides, a linear regression model applied to features from the accelerometer signal can predict joint range of motion during swing. Predicting range of motion at the knee is more successful than at the hip or ankle, although it is possible that better performance at the hip or ankle could be achieved if the accelerometer was attached to the distal segment of those joints. Binary classification algorithms can be used to identify an individual that is unable to avoid an unexpected obstacle based on windows of raw accelerometer data. In general, classification performance is better when longer window lengths and a 50% overlap is used to segment the accelerometer signal. Using information from two sensors, one on each ankle, has better classification performance than one sensor, but this difference is small for larger window sizes. Simple classification algorithms have low accuracy. In spite of a higher computational cost, excellent classification performance can be achieved using decision tree and instance-based classifiers. Future work should examine the feasibility of using these machine learning algorithms as part of a wearable device that detects gait characteristics relevant to the risk of tripping, with the goal of reducing the incidence of falls for stroke patients.

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Appendix A: Literature Review

Falls

Falls are the second greatest cause of accidental or unintentional injury deaths worldwide, behind traffic accidents (World Health Organization, 2012), accounting for 40% of all injury deaths (World Health Organization, 2008). Among older adults, falls are the greatest cause of accidental death (Hausdorff et al., 2001; Hornbrook et al., 1994). Each year, 37.3 million falls require medical attention (World Health Organization, 2012), and the annual direct cost of falls is expected to reach $240 billion by 2040 (World Health Organization, 2008). This is in addition to the indirect costs of loss of productivity and expenses related to caregivers (World Health Organization, 2008).

Falls Risk. The risk of falling can be determined using a number of metrics that assess an individual's function and environment. Falls are also more prevalent among certain demographic groups, such as older adults and people who have experienced a stroke. An individual may be considered at risk for falling simply by being a member of these groups.

Older Adults. Nearly 40% of older adults fall in a given year (Blake et al., 1988; Hausdorff et al., 2001; Tinetti et al., 1988), about half of fallers will fall recurrently (Stalenhoef et al., 1997), and about one quarter of falls result in a serious injury (Tinetti et al., 1988). The majority of falls occur during walking (Hausdorff et al., 2001; Robinovitch et al., 2013), and trips are one of the greatest causes of falls, comprising up to 53% of falls among older adults (W. P. Berg et al., 1997; Blake et al., 1988; Overstall et al., 1977; Robinovitch et al., 2013; Tuunainen et al., 2014). Older adults are more likely to trip than young adults (Garman et al., 2015).

Older adults have described reasons for tripping to include: not lifting their feet as high as they used to, difficulty recovering at the onset of a trip, and alterations in gait when tired or in a hurry that make them more susceptible for tripping (Sheldon, 1960). Despite these insights, identifying factors that can be used to predict falls risk is challenging. Extrinsic risk factors suggest falls are more likely to occur at home than away, outside than inside, and alone versus with someone else (W. P. Berg et al., 1997). In addition, there may be a greater ratio of female to male fallers, although this difference decreases with age (Blake et al., 1988). There are several intrinsic risk factors that have been associated with falls among older adults, with varying levels of support. These include history of falls, fear of falling, cognitive impairment, balance and gait disorders, vertigo, use of sedatives, hypnotics or antiepileptic drugs, history of stroke, Parkinson's disease, advanced age, arthritis, a high level of dependence, weak handgrip strength, giddiness, use of a walking aid, and foot difficulties (Blake et al., 1988; Deandrea et al., 2010; Stalenhoef et al., 1997; Tuunainen et al., 2014). Using a falls risk assessment tool, the probability of a fall ranges from 7% with no or just one risk factor identified, up to 49% when six or more risk factors are present (Tiedemann, Lord, & Sherrington, 2010). Of the identified risk factors for falls, gait and balance disorders have received a lot of attention, because behind history of falls, they are the most significant risk factor for falling among community-ambulating older adults (Deandrea et al., 2010). Another potential reason for the attention paid to balance and gait disorders is that they may be seen as more modifiable than other risk factors, such as medical history or advanced age.

A common measure of balance disorders is to determine postural sway during a standing task, with greater sway indicating poor balance. Overstall et al. (1977) reported no difference in postural sway among non-fallers and those who fell as a result of a trip, however, those who fell for other reasons had greater postural sway. A more recent study confirmed that traditional measures of postural stability (e.g. area of body sway and center of pressure velocity) are not helpful in determining falls risk. Rather, it was suggested that balance-related risk of falls and fear of falling is associated with the critical time, or the time using a preplanned strategy as opposed to relying on vestibular, visual and somatosensory feedback to maintain balance (Tuunainen et al., 2014). Another posture-related task, the choice stepping reaction time test, can be used to predict fallers in an older adult population, though it requires equipment that might not be readily available such as illuminated floor panels that contain pressure switches (Lord & Fitzpatrick, 2001).

Since most falls occur during walking, spatiotemporal gait parameters that describe walking patterns such as velocity, cadence, stance time, swing time, double support time, step length and heel width, have been investigated. Additionally, some kinematic variables including toe height, and hip, knee and ankle angular excursion in the sagittal plane have been considered. However, greater heel width while walking at a fast speed was the only variable to distinguish between older adults with a history a falls and non-fallers (Gehlsen & Whaley, 1990a), and spatiotemporal gait parameters have not been shown to discriminate recurrent fallers from non-recurrent fallers (Moreira et al., 2014). While the magnitude of spatiotemporal gait parameters and sagittal plane walking kinematics have not been successful in identifying those at risk for falling, the variability in these measures may be a more accurate determination of falls risk. Even though increased age is associated with greater variability in spatiotemporal gait parameters (Callisaya, Blizzard, Schmidt, McGinley, & Srikanth, 2010), greater stride time variability can be used to discriminate fallers from non-fallers (Hausdorff et al., 2001), and stride-to-stride variability in walking speed was shown to be the best predictor of falling among spatiotemporal gait parameters (Maki, 1997). Using a principal components analysis approach, it was also determined that fallers have greater joint kinematic variability than non-fallers, suggesting that reductions in joint kinematic variability may reduce the risk of falling (Kobayashi, Hobara, Matsushita, & Mochimaru, 2014).

Stroke Patients. Although the risk of falls increases with age (World Health Organization, 2008), the risk of falling is even greater in the stroke population than the general elderly population (Batchelor et al., 2012). Up to three-quarters of stroke patients who live at home having some residual disability related to stroke fall within 6 months of discharge from a rehabilitation facility (Forster & Young, 1995; Mackintosh et al., 2005; Wagner et al., 2009). Despite the increased risk of stroke with age, about a quarter of strokes occur in people under the age of 65 (Daniel, Wolfe, Busch, & McKevitt, 2009). The 45-64 age group will account for half of the total cost of strokes by the year 2050 (Brown et al., 2006), with financial and social consequences due to loss of productivity at a working age (Brown et al., 2006; G. Wang et al., 2014). Therefore, reducing the risk of falling for stroke patients of all ages is important to lowering the cost of stroke-related disabilities.

There are different types of stroke that cause damage to a portion of the brain (American Stroke Association, 2012). An ischemic stroke is the most common type of stroke, and is characterized by an obstruction or clot in a blood vessel that halts the supply of blood to a brain. When a stroke is caused by a temporary clot, it is called a transient ischemic attack and considered a mini-stroke or a warning sign for a potential larger stroke in the future. A hemorrhagic stroke occurs when a blood vessel ruptures and the accumulating blood compresses the brain tissue. The location of the lesion or brain damage determines the effect of the stroke on the patient's function. There is some evidence that falls risk is greater for stroke patients with left hemisphere lesions, potentially because stroke patients with right hemisphere lesions tend to need greater supervision (Alemdaroglu, Ucan, Topcuoglu, & Sivas, 2012). However, there is generally no association between falls among stroke patients and age, gender, stroke location, or stroke type (Batchelor et al., 2012). Therefore, when stroke patients are discharged from the hospital, the basic information available is typically not helpful in distinguishing first-time fallers from non-fallers (Wagner et al., 2009). Balance and gait analyses, functional assessments and falls history are tools that can be used to identify stroke patients who are at risk for falling (Forster & Young, 1995).

Stroke patients typically exhibit deviations from normal gait that may indicate a risk of falling. Spatiotemporal gait disturbances that are frequently identified among stroke patients include slow walking speeds, prolonged stance phase on the unaffected side, increased double support time, reduced cadence, and early foot contact on the unaffected side (Balaban & Tok, 2014; Kim & Eng, 2003; Olney & Richards, 1996; Woolley, 2001). Additionally, stroke patients exhibit abnormal kinematics on their affected side during both stance and swing phases of gait. Stance is typically characterized by decreased hip extension, reduced knee flexion or knee hyperextension, foot flat at initial contact due to lack of dorsiflexion during swing, and reduced plantar flexion at toe-off (Balaban & Tok, 2014; Kinsella & Moran, 2008; Olney & Richards, 1996; Woolley, 2001; Yavuzer, Oeken, Elhan, & Stam, 2008). Other aberrant joint kinematics on the affected side – reduced hip and knee flexion resulting in toe drag, decreased knee extension prior to heel strike due to insufficient acceleration of the leg, and reduced ankle dorsiflexion – may limit foot clearance during swing phase (Balaban & Tok, 2014; Olney & Richards, 1996). To ensure sufficient foot clearance, a common compensation is leg circumduction and an elevated pelvis on the affected side (Balaban & Tok, 2014; C. L. Chen et al., 2003; Olney & Richards, 1996). These spatiotemporal and kinematic gait adjustments not only produce asymmetric gait patterns, but also contribute to a greater metabolic cost of walking (Balaban & Tok, 2014; Olney & Richards, 1996; Woolley, 2001). While gait asymmetries are common among stroke patients, the effect of hemiparesis caused by the stroke is different for each patient, particularly for slow walkers and women (Jonsdottir et al., 2009; Oken et al., 2008). This underscores the conclusion reached by Begg et al. (2007) that an individual-based approach to evaluate a patient's risk of tripping is better than a group-based approach.

Because stroke patients often fall while walking, and commonly fall forward or to their affected side (Batchelor et al., 2012; Mackintosh et al., 2005), rehabilitation efforts have historically been aimed at correcting asymmetry in gait patterns. However, due to a lack of strength or function on the affected side, asymmetry may be appropriate for hemiplegic subjects, particularly at walking at fast speeds (Griffin, Olney, & McBride, 1995; Olney & Richards, 1996). Evidence supporting a normal, albeit asymmetric, gait pattern for stroke patients showed that stroke patients guided by a Lokomat to have similar gait kinematics to control subjects had abnormal joint torques when producing those movements (Neckel, Blonien, Nichols, & Hidler, 2008). Although gait asymmetry may be a normal component of stroke recovery, a gait pattern that presents a risk of falling deserves attention.

Minimum Foot Clearance. A trip occurs when the progress of the foot during swing phase of gait is impeded by an external force. This force may be due to insufficient clearance between the foot and the walking surface or an obstacle. As such, the magnitude of minimum foot clearance (MFC), which typically occurs at the point of greatest forward velocity of the foot (Winter, 1992), is often studied. Low MFC and high MFC variability is suspected to increase risk of falling (Begg et al., 2007). A low MFC value indicates that the foot passes close to the walking surface during swing phase, and high variability in MFC height suggests an increased probability that the foot will come in contact with the walking surface.

Because falls risk increases with age, there have been some comparisons of MFC between young and older adults. Several studies have found no difference in MFC between older and younger adults, (Bunterngchit et al., 2000; Elble et al., 1991). However, older adults reduced MFC, and also reduced MFC variability, following six minutes of fast treadmill walking, while there was no change in young adults (Nagano et al., 2014). Additionally, when adequate time is provided to avoid to an obstacle in a walking path, both young and older adults adjust their gait and rarely come in contact with the object. However, when less time is provided, older adults contact the obstacle more frequently than the younger adults, and the older adults have a more conservative strategy for avoiding the obstacle (Galna et al., 2009). These examples suggest that MFC is similar between young and older adults in normal walking conditions, but older adults adopt more risky behavior in challenging situations.

Strategies to avoid tripping include increasing median MFC and reducing MFC variability (Begg et al., 2007). However, the magnitude of MFC and the part of the shoe closest to the walking surface (e.g. toe vs. midfoot vs. heel) varies with task, suggesting that an absolute value for MFC may not be adequate to ensure foot clearance in all circumstances (Loverro et al., 2013; Thies et al., 2011). Gait adaptations to accommodate varying walking surfaces (Gates et al., 2012) and perform everyday tasks while walking (Schulz et al., 2010) include concurrent changes in joint kinematics and MFC height. For example, to adapt gait to avoid contact with visible objects by doubling MFC height, healthy young adults utilize up to 10% more ankle dorsiflexion and knee and hip flexion (Schulz, 2011). Similarly, MFC variability is correlated with joint angle variability (Mills et al., 2008). Therefore, another way of measuring trip avoidance is by determining how much the leg shortens during swing phase (Little et al., 2014; Moosabhoy & Gard, 2006).

Winter (1992) quantified the range of joint angles at the ankle, knee and hip that would independently account for the variability observed in MFC height. More recently, Moosabhoy and Gard (2006) developed a theoretical model to determine how changes in the sagittal plane ankle, knee and hip angles affect toe clearance throughout swing phase of healthy gait. Their results suggested that ankle dorsiflexion has a greater effect on toe clearance during mid-swing than knee or hip flexion, while knee and hip flexion have the greatest effect on toe clearance at the beginning and end of swing phase. Little et al. (2014) found that the knee has the greatest influence on toe clearance and limb shortening at the lowest trajectory of the toe, regardless of the time during swing. It has been shown that different patient populations may use different strategies to achieve adequate MFC. For example, patients with knee osteoarthritis had similar MFC height as a control group, but their knee flexion, hip abduction and ankle adduction angles were different (Levinger et al., 2012). Stroke patients diagnosed with "foot drop" are suspected to have weak dorsiflexors that contribute to limited foot clearance, yet impaired coordination of hip and knee flexion had a greater effect on MFC than ankle dorsiflexion (Little et al., 2014). This evidence supports the theory that limb movements are planned for the distal endpoint trajectory, not joint trajectories (Karst et al., 1999). Overall, the achievement of adequate MFC relies on contributions from all of the joints in the lower extremity.

Fear of Falling. Fear of falling can be defined as "low perceived self-confidence at avoiding falls during essential, relatively nonhazardous activities" (Tinetti & Powell, 1993), and has frequently been associated with falls and falls risk. The theory behind this association is that a history of falls – or knowledge of the debilitating consequences of falls – instills a fear of falling, which leads to reduced activity. The decrease in physical and social activities results in declining physical function and an increased risk of falling (Belgen et al., 2006; Delbaere et al., 2004; Deshpande et al., 2008). This fear-related activity restriction has been observed in up to 25% percent of older adults (Reelick et al., 2009; Tinetti et al., 1988). In stroke patients, fear of falling is much more prevalent, approaching 50%, and those with a history of falls have even lower falls-related self-efficacy (Belgen et al., 2006; Mackintosh et al., 2005). Historically, these investigations supported the theory that falls history and fear of falling fed a downward spiral into mobility limitations, reduced independence and more falls (Friedman et al., 2002). However, a recent publication of an 11-year study of falls in older adults has shown that fear of falling does not lead to more injurious falls, and a history of falling does not increase fear of falling (Clemson et al., 2015). Among stroke patients, it has been suggested that those with reduced function and balance ability, as well reduced cognitive function, could be at greater risk for falls (Chin, Wang, Ong, Lee, & Kong, 2013). Conversely, increased mobility among stroke patients could result in more opportunities for falling, and stroke patients that overestimate their walking ability by having greater walking speeds for short distances could have a higher risk of falling (Morone, Iosa, Pratesi, & Paolucci, 2014).

The relationship between fear of falling and falls is complicated by other factors that may contribute to anxiety about falling, such as vision impairments, as well as gait adaptations as a result of that fear. Self-reported poor vision is associated with low falls self-efficacy and activity restriction related to fear of falling, but actual measures of poor vision do not support this association. However, poor vision among those with a fear of falling is associated with poor mobility (Donoghue et al., 2014). Those who report a fear of falling often adopt a stiffening posture during balance and gait tasks, or visual behavior, such as not properly fixating gaze on an obstacle, that could increase the risk of falling while walking. These adaptations may be used to improve head stability, which has been shown to decrease in older adults (Young & Williams, 2015). Other adjustments may be made with the intention of stabilizing gait, including reduced stride length, reduced gait speed, increased double support time, and increased stride width, with increased stride width the only adjustment to also have an independent association with falls risk (Maki, 1997). In stroke patients, it is possible that temporal gait parameters may be more associated with fear of falling than spatial gait parameters (Park & Yoo, 2014). Another analysis showed that fear of falling is associated with an increase in variability of a variety of spatiotemporal gait parameters (Ayoubi, Launay, Annweiler, & Beauchet, 2015). Using different gait-related measures, variability of the medial-lateral accelerations of the trunk was not associate with fear of falling. However, dynamic stability and maximum voluntary knee extension torque were associated with fear of falling, with decreased dynamic stability and low knee extensor strength indicating a greater fear of falling among older adults without a history of falls (Toebes, Hoozemans, Furrer, Dekker, & van Dieen, 2015). While a clear cause-and-effect relationship between fear of falling and falls risk lacks support, it is evident that having a low falls-related self-efficacy can lead to changes in gait patterns.

Interventions. In an effort to reduce falls among older adults, several programs have been created that seek to address commonly identified risk factors for falling. Interventions are typically multifactorial and include any of the following: creating an exercise plan, assessment and adjustment of medications, modifying the environment to remove hazards, vision treatment, providing education about falls risk, and vitamin D supplementation (Panel on Prevention of Falls in Older Persons, American Geriatrics Society and British Geriatrics Society, 2011). Focusing specifically on gait deficits, a balance or weight training program may be successful in reducing gait asymmetries among older adults (Seo & Kim, 2014). However, a limitation of this approach is using outcome measures that are commonly associated with falls risk, and not an actual record of whether the participants experienced falls following the program (Seo & Kim, 2014). In general, programs with high intensity and that include multiple components and balance exercises have been shown to reduce the risk of falls, improve balance, and decrease fear of falling (Arantes et al., 2015; Batchelor et al., 2012). Despite the successes of some program in reducing falls risk, it is possible that additional gains can be made. It has been proposed that task-specific perturbations during training may improve the effectiveness of falls-prevention interventions (Grabiner et al., 2014). Specifically, a program that exposes a participant to a trip while in a safe environment allows the participant to practice recovering from that perturbation, a skill that may be beneficial when transferred to a real-life situation.

In contrast, most proposed interventions have been unsuccessful in preventing falls for stroke patients (Batchelor et al., 2010; Batchelor et al., 2012; Batchelor et al., 2012; Dean et al., 2012; Hornbrook et al., 1994; Verheyden et al., 2013). This is especially true for chronic stroke patients, as a plateau in recovery typically occurs at about six months post-stroke (Richards & Olney, 1996). The improvements observed in stroke patients following the completion of proposed programs have included better mobility and a decreased fear of falling (Dean et al., 2012; Jung, Lee, Shin, & Lee, 2015; Shaughnessy & Michael, 2012). Functional electrical therapy has been used to correct gait deficits, resulting in improved preferred walking velocity and fast walking velocity, longer duration of stance on the paretic side, shorter duration of gait cycle, and better stance time symmetry ratio. However, there was no observed effect on ability to function independently during walking (Spaich, Svaneborg, Jorgensen, & Andersen, 2014). Multifactorial exercise programs, which have shown a decrease in falls in the general elderly population, have not had similar success among stroke patients (Batchelor et al., 2012). An individualized approach is likely the best way to prevent falls among stroke patients, with emphasis on specific intrinsic and extrinsic risk factors unique to an individual patient. For example, vitamin D supplementation has been shown to be an effective intervention for female stroke patients in an institutionalized setting (Batchelor et al., 2010; Verheyden et al., 2013). One limitation to determining effective falls prevention interventions for stroke patients is a lack of consistency in how falls are defined and measured (Batchelor et al., 2010). Additionally, studies that evaluate the effectiveness of falls interventions do not often include stroke patients (Verheyden et al., 2013).

Measuring Gait Deficits

Identifying gait deficits or functional losses is often the first step of a rehabilitation program. The goal is to correct the abnormalities that may present a risk of falling. It has been shown that older adults with more than one type of gait assessment that is abnormal are at greater risk of falling, as the combined information provides a more holistic mobility evaluation (Allali, Ayers, & Verghese, 2015). There are several ways to measuring gait deficits. A variety of tests and scales, some administered by clinicians and others used in research laboratories, have been developed to determine a patient's gait function. Research labs may have equipment available to record 3D joint kinematics and kinetics, or even the MFC during walking. The results obtained by motion capture techniques can be used in a variety of ways, such as determining joint coordination patterns or gait stability. Despite the wealth of information that can be produced in a motion capture lab, the analysis is limited to movements in a controlled environment, and may not represent everyday gait patterns or behavior. As a result, there has been a surge in the development of in-home systems or wearable devices that can track movement in a natural setting.

Evaluating Function. Stroke patients often deal with a loss of function, and so tests and scales that monitor function can be used to track the progress made in recovery. Recovery is typically characterized by three phases: acute (up to one month post-stroke), subacute (one to six months post-stroke) and chronic (more than six months post-stroke) (Harris, Eng, Marigold, Tokuno, & Louis, 2005). Functional recovery post-stroke can be determined using the Fugl-Meyer Sensorimotor Scale, where a trained evaluator assesses sensation, balance, and upper and lower extremity function (Richards & Olney, 1996; Sanford et al., 1993). Other common clinical measures of functional independence are the Barthel Index, which focuses on self-care and mobility (Richards & Olney, 1996), and Brunnstrom's Motor Recovery Stage (BMRS) which evaluates lower extremity function (C. L. Chen et al., 2003; Oken et al., 2008). The majority of the recovery on these scales occurs within the first 6 weeks to 3 months post-stroke, so the use of other measures of recovery are needed to provide the responsiveness required to track long-term improvements (Schepers et al., 2006). For example, significant improvements in gait speed, cadence and stride length can be observed well beyond a year after baseline evaluations (Richards & Olney, 1996).

Self-selected walking speed is a particularly common evaluation due to the ease of measuring the time it takes a patient to walk a fixed distance. Oken et al. (2008) used gait speed faster or slower than 0.34 m/s to divide a sample of stroke patients into fast and slow subgroups. In another classification, Perry et al. (1995) determined that stroke patients with severe impairment resulting in household ambulation only had walking speeds of less than 0.4 m/s, while mild impairment and full community ambulation required gait speed of at least 0.8 m/s, and those with moderate impairment and limited community ambulation walked between 0.4 and 0.8 m/s. Walking speed was validated as a way to distinguish homebound stroke patients from those who walk in the community (Bowden, Balasubramanian, Behrman, & Kautz, 2008). In analyzing muscle activity and lower extremity motion, stroke patients who are able to walk faster exhibit mechanics that are most similar to a control group (Richards & Olney, 1996). Categorizing function based on gait speed should be used with caution, however, as older adults may choose a different walking speed depending on the distance they are expected to travel (Najafi, Helbostad, Moe-Nilssen, Zijlstra, & Aminian, 2009). Additionally, it may take older adults up to 2.5 m to achieve steady state walking, which should be considered when evaluating gait parameters (Lindemann et al., 2008).

Several methods of evaluating function have combined gait speed with other tasks that are easily measured in a laboratory setting. The Dynamic Gait Index was developed to determine postural stability during walking (Wrisley et al., 2004). It is an eight-item scale consisting of a simple walking task with modifications to make it more challenging, such as speed changes, head turns, stairs, and navigation over and around an obstacle. A modified version using only four of the original eight items has been validated in a sample of patients with balance and vestibular disorders (Marchetti & Whitney, 2006). The Dynamic Gait Index is considered an acceptable way to measure function, though it is susceptible to ceiling effects. To avoid this, the Functional Gait Analysis includes seven of the items from the Dynamic Gait Index and adds an additional three items that are greater challenges to balance during walking, including a narrow base of support, eyes closed, and backwards walking conditions (Wrisley et al., 2004). The Performance-Oriented Mobility Assessment evaluates balance and gait in separate assessments (Tinetti, 1986), while the Berg Balance Scale contains some similar balance items and adds other dynamic tasks such as placing a foot on a stool while standing unassisted (K. Berg, Wooddauphinee, & Williams, 1995). Modified from the BESTest, the mini-BESTest is a more recently developed functional assessment that is valid in the chronic stroke population repeats some of the anticipatory, sensory orientation, and dynamic gait tasks that are found in other evaluations, but adds a reactive postural control component as well as a dual-task timed up and go test (Franchignoni et al., 2010; Tsang et al., 2013).

Since fear of falling is suggested to have an influence on function as well as activity, assessments related to falls self-efficacy have been created. The simplest way to evaluate of fear of falling is to ask, “Are you afraid of falling?” and recording the answer of “yes” or “no” (Ayoubi et al., 2015). The Falls Efficacy Scale created by Tinetti et al. (1990) determines confidence in ability to perform common activities of daily living, and is a reliable tool in the stroke population (Hellstrom & Lindmark, 1999). When evaluating function related to fear of falling, the association between fear of falling and gait variability may be better detected by using the Falls Efficacy Scale, rather than simply asking the participant if they are afraid of falling (Hausdorff et al., 2001). Other measures of falls self-efficacy are the Activities-specific Balance Confidence Scale (Ayoubi et al., 2015; Powell & Myers, 1995) and the Survey of Activities and Fear of Falling in the Elderly (Lachman et al., 1998), which also chronicle a patient's fear of falling while performing certain tasks. While not explicitly measuring fear of falling, the Frenchay Activities Index is used to record a patient's recent (within three to six months) history engaging in activities that require some initiative, such as housework or gardening. It has been shown to be responsive to improvements made in the chronic phase of stroke recovery (Schepers et al., 2006). Measures of willingness to participate in community or household activities can provide information about how fear of falling might contribute to activity restriction.

In addition to evaluating function among older adults and specific patient populations, it has been attempted to use several of these measures to predict falls. Healthy older adults that scored low on the Berg Balance Scale and Dynamic Gait Index did have an increased risk of falling, with a model that included the Berg Balance Score and self-reported history of imbalance serving as the best method to predict fallers (Shumway-Cook, Baldwin, & Polissar, 1997). However, the Berg Balance Scale and gait speed are not great predictors of future fallers among stroke patients (Harris et al., 2005). Conversely, study by Shumway-Cook et al. (2000) showed that falls risk in older adults can be predicted by performance on a simple three-meter Timed Up and Go Test with a cutoff of 13.5 seconds. An additional dual-task during the Timed Up and Go Test, either manual or cognitive, was not necessary for accurate falls prediction (Shumway-Cook et al., 2000). These equivocal results indicate that methods of evaluating function among older adults or stroke patients may be useful in determining levels of recovery and the extent of community engagement, though they may not be useful when trying to predict falls.

Motion Capture. To get more specific about abnormal gait patterns that may result in poor performance during functional evaluations, joint kinematics can be recorded using 3D motion capture technology. There are a few limitations to this approach that suggest that the recorded kinematics are not an exact representation of the motion of the body. For example, improper identification of anatomical landmarks, particularly at the knee, can influence how the joint angles are calculated (Della Croce, Leardini, Chiari, & Cappozzo, 2005). Additionally, the assumption that each segment can be modeled as a rigid body is not correct for segments that contain multiple articulations like the trunk or foot, and for segments with a lot of soft tissue such as the thigh. Kinematic errors occur when the rigid-body assumption is not met because markers that move due to skin motion do not represent the true motion of the underlying bone (Cappozzo, Della Croce, Leardini, & Chiari, 2005; Leardini, Chiari, Della Croce, & Cappozzo, 2005; Li, Zheng, Tashman, & Zhang, 2012; Reinschmidt et al., 1997). Nevertheless, 3D motion capture technology remains the gold standard for detecting the individual components of gait and identifying gait disorders. If the equipment is available, this technique is relatively simple. Aside from placing markers on anatomical landmarks, quantification of kinematics does not require any measurements of the subject or specific body segments ahead of time, and the techniques used for measuring kinematics are not restrictive so participants are free to move as they typically would.

Once joint kinematics are recorded, they can be used to identify the results of an intervention on changes in joint angles, or the data can be analyzed further. A review of the reliability of 3D motion capture in reporting joint angles suggests that errors of less than 2° are clinically acceptable, and are regularly reported for sagittal and frontal plane kinematics, although errors of greater than 5° have been reported for hip and knee rotation (McGinley, Baker, Wolfe, & Morris, 2009). This result is supported by an analysis of the minimal detectable change not being less than 2° for common sagittal and frontal plane joint angles (Wilken et al., 2012). For chronic stroke patients, however, the minimal detectable change in sagittal plane kinematics ranges from 4.9° at the ankle to 11.5° at the hip (Kesar, Binder-Macleod, Hicks, & Reisman, 2011). Differences in minimal detectable change between healthy people and stroke patients may be due to greater variability in the gait patterns of stroke patients. Other uses of kinematics beyond raw joint angles include determining MFC, joint coordination, and gait stability.

Minimal Foot Clearance. Much of the research on trip avoidance has been focused on quantifying and manipulating MFC height or MFC variability, and so MFC has to be quantified. In a laboratory with motion capture equipment available, geometric models can be used to predict lowest point on the shoe (Begg et al., 2007), and foot clearance can be measured using digitization of marker clusters on the foot (Telonio, Blanchet, Maganaris, Baltzopoulos, & McFadyen, 2013). This information can be helpful to walkers as they adjust their gait to change MFC. Providing real-time visual feedback about the vertical displacement of the toe results in an increase in mid-swing toe height for healthy young adults (Tirosh, Cambell, Begg, & Sparrow, 2013) as well as older adults and a stroke patient (Begg et al., 2014). This is a promising result, however, the method is confined to gait analysis performed in a biomechanics lab.

Coordination. Joint angles obtained using motion capture techniques can be used to analyze the coordination of the joints throughout the stride cycle. In normal gait, there is significant coordination that occurs between the segments of the lower extremity. These coordinative structures, or muscle synergies, can allow the same goal to be reached by using different degrees of freedom, and they can use the same degrees of freedom to reach the same goals (Latash, Scholz, & Schoner, 2002). Intra-limb coordination of joints or segments can be assessed by either discrete or continuous methods. Discrete methods are used to determine relative timing of joints or segments at one point in a movement cycle. An advantage to using discrete methods to evaluate movement coordination is that the data does not need to be manipulated beyond normal calculation of joint angles. The disadvantage of using discrete methods is that they evaluate coordination at only one point during the cycle (Hamill et al., 2000).

Continuous methods are used to determine coordination or coupling of movement over a period of time. Therefore, a continuous measure of coupling is important for determining coordination throughout the stride cycle (Hamill, van Emmerik, Heiderscheit, & Li, 1999; Hamill et al., 2000). Traditionally, two types of continuous methods are used for determining coordination: continuous relative phase (CRP) and relative motion, also known as vector coding. While both methods are valid for measuring coordination and variability, they do not convey the same information at all times. The differences between the methods are most obvious when determining variability at specific instances or portions of a movement cycle (Miller, Chang, Baird, Van Emmerik, & Hamill, 2010). The decision of which method to use depends on the research question being asked (Hamill et al., 2000; Miller et al., 2010).

CRP is useful because it provides continuous information that is both spatial and temporal. CRP is calculated by creating a parametric phase plot – velocity plotted as a function of position – for each segment. Phase angles are then determined from the arctangent of this plot. After time-normalizing the phase angle, CRP is found by subtracting the phase angle of one segment from the other at every time point. When CRP is 0° the segments are in-phase, and when CRP is 180° the segments are anti-phase. CRP variability is the standard deviation of the CRP at each point in the cycle (Hamill et al., 1999; Hamill et al., 2000).

An additional normalization step must be taken for CRP before calculation of the phase angles. This will account for the frequency differences between waves. The goal of normalization should be to make the phase-plane more circular and center the phase plot about an origin. Different results will be obtained depending on the normalization procedures utilized (Hamill et al., 2000; Peters, Haddad, Heiderscheit, Van Emmerik, & Hamill, 2003; Wheat & Glazier, 2006).

CRP is used to compare the degree of in-phase or out-of-phase relationships for various coupling relationships. This has been done with mixed results. The use of angular velocity in the computation of phase angles provides temporal as well as spatial information, and may make CRP a more sensitive measurement of variability. However, the higher derivative of angular velocity may propagate errors in the displacement data. Additionally, it has been shown that normalization alters the data, and so some authors do not normalize, making comparisons between studies difficult (DeLeo, Dierks, Ferber, & Davis, 2004; Wheat & Glazier, 2006). It is also difficult to generalize the in- or out-of-phase coupling for multiple joint segments or joint combinations throughout stance. Another limitation of CRP is that it is traditionally used for predominantly sinusoidal oscillators. However, most lower extremity joint movements – with the exception of the sagittal plane motion of the hip – are non-sinusoidal, which may affect the results of CRP (DeLeo et al., 2004; Heiderscheit, Hamill, & van Emmerik, 2002; Peters et al., 2003; Wheat & Glazier, 2006).

Vector coding is a way to determine continuous coordination for non-sinusoidal data. Using relative motion or a vector coding method to determine coordination is convenient because no normalization of data is required. It may be useful as a clinical tool because the original kinematic data are used in the analysis (Miller et al., 2010). However, only spatial, and not temporal, information is presented. Relative motion measures coordination by using angle-angle plots. With the proximal segment or joint angle on the x-axis and the distal segment or joint angle on the y-axis, each point in the time-series is plotted. A vector is made between consecutive points, and the orientation of the vector relative to the right horizontal is called the coupling angle. The coupling angle describes the relative motion of the joints or segments, and can be plotted as a function of the stride cycle. The variability of the coupling angle can be used to assess variability across multiple trials and/or between subjects (DeLeo et al., 2004; Hamill et al., 2000; Sparrow, Donovan, Vanemmerik, & Barry, 1987; Wheat & Glazier, 2006).

Coordination across different limbs has been studied in stroke patients, using a variety of methods. A cross-correlation of the sagittal plane angles of the shoulder and contralateral hip joints showed that the upper limb motion coordinated with the lower limb (Bovonsunthonchai, Hiengkaew, Vachalathiti, Vongsirinavarat, & Tretriluxana, 2012). CRP was used to quantify the bilateral coordination of lower extremity segments during the course of an intervention, which yielded improvements in bilateral coordination (Combs, Dugan, Ozimek, & Curtis, 2013). Additionally, walking speed is related to limb coordination for tasks that require coordinated motion of different limbs, such as sliding the heel of one foot along the shin of another (Hollman et al., 2013).

Because stroke patients exhibit a disruption in the “phasic interdependence” of hip and knee sagittal plane excursions (Little et al., 2014), it is beneficial to examine the coordination between body segments on the same limb. Coordination between the joints of the lower extremity is crucial for gait, and enables foot clearance while leg advances during swing

(Moosabhoy & Gard, 2006). While lack of coordination was observed in stroke patients by Little et al. (2014) and Moosabhoy and Gard (2006), it was quantified during the swing phase of gait using a CRP analysis (Barela et al., 2000). Another CRP measure of intersegment coordination indicated that stroke patients exhibit more in-phase coordination between the thorax and pelvis when walking at their preferred slow speed as opposed to a fast walking pace. Additionally, thoracic and pelvic coordination is correlated with Functional Gait Assessment scores and performance on the BESTest balance evaluation (Hacmon, Krasovsky, Lamontagne, & Levin, 2012). Coordination in joint kinematics for stroke patients has also been quantified using the planar law of intersegmental coordination. Under planar law for healthy gait, plotting the elevation angles (the inclination angle of the segment relative to vertical) of the thigh, shank and foot in 3D space results in a teardrop-shaped plane. Although the gait of both stroke patients and controls followed the planar law, the timing of the segment motion was abnormal in stroke patients (Chow & Stokic, 2015). The significance of these few studies that have examined coordination in stroke gait is that coordination of coupled segments within a limb may provide an understanding of the pathology that is causing hemiparetic gait, more so than spatiotemporal gait parameters (Rinaldi & Monaco, 2013). Further investigation of the coupling of joint segments using a vector coding technique could provide additional information about how stroke patients coordinate the segments of their lower extremity during walking.

Comparison of treadmill and overground walking. In a laboratory gait analysis, it is common for walking to be done on a treadmill. When the desired number of gait cycles are recorded in consecutive steps, the data collection process is much quicker than if only a couple strides can be used during each trial of overground walking. Additionally, it is common to use a harness when conducting experiments on people with gait deficits as a safety precaution, and a harness stationed over a treadmill is easier to manage than if the support was necessary while walking overground. Yet overground walking is typically how people ambulate, and differences in gait analyses from the treadmill to overground could limit the generalizability of discoveries made during treadmill walking.

Spatiotemporal gait parameters have high between- and within-day reliability for healthy older adults during treadmill walking (Faude, Donath, Roth, Fricker, & Zahner, 2012), but are different on an instrumented treadmill compared to overground walking (Wearing, Reed, & Urry, 2013). For example, it has been shown that preferred walking speed is slower on a treadmill than overground (Nagano et al., 2011). When the treadmill is set to the preferred overground walking speed, cadence increases and stance time decreases (Warabi, Kato, Kiriyama, Yoshida, & Kobayashi, 2005). However, there is some evidence that training on a treadmill may have carry-over effects to overground walking. Adaptation to a swing phase perturbation on the affected side while walking on an instrumented treadmill could be generalized to overground walking for both stroke patients and controls. Both sets of participants showed improved step length symmetry, increased overground gait velocity, increased stride length and decreased stride duration after the treadmill intervention (Savin et al., 2014). MFC and gait stability are also affected depending on whether walking is recorded overground or on a treadmill. Treadmill walking results in improved local dynamic stability compared with overground walking (Dingwell, Cusumano, Cavanagh, & Sternad, 2001), and MFC is lower on the treadmill compared to overground for both limbs of young and older adults, except for older adults' non-dominant leg (Nagano et al., 2011).

From a kinematics perspective, both healthy older adults and healthy young adults have similar joint angles during treadmill and overground walking, and except for transverse plane rotation at the hip and the ankle, the differences between the two modes of walking is less than 2-3° (Parvataneni, Ploeg, Olney, & Brouwer, 2009; Riley, Paolini, Della Croce, Paylo, & Kerrigan, 2007; Watt et al., 2010). This is typically considered to be within the range of clinically acceptable error in kinematic measurements (McGinley et al., 2009). However, older adults have about a 23% higher metabolic cost of walking on a treadmill than overground (Parvataneni et al., 2009), and the differences in spatiotemporal gait parameters suggests that an acclimatization period may be useful when analyzing gait on a laboratory treadmill (Watt et al., 2010).

Wearable Devices. While a gait analysis obtained using motion capture provides the most accurate information about a gait deficit, a major limitation is that it must be done in a setting where the expensive equipment is available. This means that knowledge of joint kinematics is restricted to patients who are able to access this type of facility, and the motion examined is restricted by the laboratory setup and may not be generalizable to everyday activities. An alternative is the development of in-home systems that can be installed in a location outside of a laboratory to track gait during rehabilitation. In one such system, components for constant monitoring of rehabilitation progress includes a step counter, photo-emitting detectors, a data collection and processing center, and a software interface (Giansanti, Morelli, Maccioni, & Grigioni, 2013; Giansanti, Morelli, Maccioni, & Brocco, 2013). Another web-cam based system is designed to capture walking speed, step time and step length in a home environment (F. Wang et al., 2013). However, these systems are still limited by the place of installation, and the assumption that the user will have the ability to control and troubleshoot the system. Perhaps the best alternative to using motion capture equipment to monitor gait in natural settings is to use wearable devices that can convey the same information without requiring a contrived setting or expensive and complicated equipment. Wearable devices that track information about the body have been developed for multiple purposes, and future improvements in this technology can help to monitor stroke patients at risk for falling.

General Use. The global wearable wireless device market is booming, and is expected to continue to grow, particularly in tech-savvy, health-conscious and affluent countries like the U.S. and Canada (Transparency Market Research, 2015). The demand for this type of technology across all platforms was 14 million devices in 2011; that number is projected to be 171 million in 2016 (Appelboom et al., 2014). Likewise, the global market is expected to grow 800% from 2012 to 2018, with a value close to $6 billion (Transparency Market Research, 2015). The healthcare field has begun using mobile health (mHealth) technology consisting of accelerometers, gyroscopes, GPS and other sensors to monitor and report aspects of patient's lives in real-time. Common analyses include physical activity, temperature, blood pressure, heart rate, electrocardiogram, weight, and glucose (Appelboom et al., 2014). The benefits of mHealth include: reliable information in contrast to a self-report by the patient that is not always accurate, identification of patients in need of treatment, streamlined communication between the patient and healthcare professional, and personal engagement and behavior change by the patient (Appelboom et al., 2014; Bassett, 2012; Dobkin, 2013).

These devices have already been designed for specific populations to aid in health care outcomes. Older adults are at risk for heart failure, and there are over a hundred different mobile electrocardiogram systems that can provide continuous monitoring of heart function and detection of heart arrhythmia (Baig, Gholamhosseini, & Connolly, 2013; Tanantong, Nantajeewarawat, & Thiemjarus, 2014). A system has even been developed to monitor the fetal heart (Signorini, Fanelli, & Magenes, 2014). A wireless electrocardiogram monitor can also be used to detect epileptic seizures (Masse, Van Bussel, Serteyn, Arends, & Penders, 2013), or episodes of obstructive sleep apnea (Sannino, De Falco, & De Pietro, 2014) based on changes in cardiac rhythm. Wearable devices can be used to monitor heart rate and respiratory rate, and this has been applied to firefighters, athletes, and other workers at risk for sudden health impairment (Lukocius, Vaitkunas, Virbalis, Dosinas, & Vegys, 2014; Smith, Haller, Dolezal, Cooper, & Fehling, 2014). Activity monitors can be used to quantify sedentary behavior within certain populations, and have had success in detecting changes in physical activity behavior (Bassett, 2012; Swartz, Rote, Cho, Welch, & Strath, 2014). A clinical trial is in place to determine if measuring walking activity with accelerometers during rehabilitation alters physical activity behavior and improves walking function after discharge (Mansfield et al., 2013). The use of wearable devices offers a more ecologically sound alternative to the questionnaires and scales that are used to quantify physical function (Dobkin, 2013). While constant monitoring by body-worn sensors may be considered a violation of privacy, it is a tradeoff that has to be considered if wearable devices are going to be used to enhance diagnosis, treatment and rehabilitation of pressing health issues (Dobkin, 2013). However, if the use of wearable devices to monitor health and function is to be successful, it is reliant on the patients to wear the device. A study that investigated stroke patients' adherence to the use of a step activity monitor found greater adherence in older patients, those with greater balance self-efficacy, and those with better walking endurance. Additionally, adherence was lower on the second day than the first day, suggesting that strategies for ensuring adherence are necessary when gait is to be monitored for more than one day (Barak et al., 2014). It appears that the use of wearable devices for healthcare is a valuable tool with a variety of potential applications for health improvement.

Falls risk. An ideal use of wearable devices is to detect the risk of falls, and several studies have examined the feasibility of this by using inertial measurement units. Inertial sensors can provide measures of position, angle, angular velocity, or linear acceleration, depending on the type of device (Howcroft, Kofman, & Lemaire, 2013). Accelerometers, which record linear acceleration, are a good choice for monitoring gait because they can be small and do not require a lot of power (Rueterbories, Spaich, Larsen, & Andersen, 2010). Also, the type of accelerometer appears to be flexible: a high test-retest reliability has been reported for using smart phone accelerometers compared with tri-axial accelerometers to quantify gait parameters (Nishiguchi et al., 2012). However, accelerometer reliability is better when using the mean of two walking trials rather than a single trial (Bautmans, Jansen, Van Keymolen, & Mets, 2011).

In the absence of motion capture equipment, gait dysfunction can be detected with inertial sensors as asymmetry in spatiotemporal gait parameters (Dobkin et al., 2011; Punt et al., 2014). The sensors are commonly placed on the lower back or pelvis, near the body's center of mass, however, some protocols apply the sensor to the shank, while others involve multiple sensors placed on various body parts. Obtaining information requires analysis of the accelerometer signal: peak frequency represents the gait cycle or the time for one step, root mean square indicates the degree of gait instability where a high root mean square corresponds with low stability, autocorrelation peak is the degree of gait balance where a high score means greater balance, and coefficient of variance represents the degree of gait variability or the variability in time between consecutive footfalls (Nishiguchi et al., 2012; Senden et al., 2012). These variables can be used to detect subtle changes in gait patterns (Isho, Tashiro, & Usuda, 2015). The subsequent challenge, however, is to parlay these variables into clinically meaningful information about gait. For example, triaxial accelerometers worn on the ankles can accurately predict walking speed and identify bouts of walking as distinct from other activities (Dobkin et al., 2011), while a triaxial accelerometer worn on the lower back can be used to quantify number of steps, mean step length, and walking distance in chronic stroke patients (Punt et al., 2014).

It has been the focus of a few experiments to relate data obtained from wearable devices to falls risk. With a triaxial accelerometer on the back of the pelvis, gait speed was used to discriminate falls risk in older adults in studies by Bautmans et al. (2011) and Senden et al. (2012). Additional discriminators of falls risk in the Senden et al. (2012) paper were step length and root mean squared. A potential reason for the discrepancy between the two experiments is how falls risk was classified. In the Bautmans et al. (2011) study, falls risk was evaluated by a six-month history of falls, a timed up and go test time of greater than 15s, or a Tinetti score less than or equal to 24. The Senden et al. (2012) study used only the Tinetti scale to determine falls risk. Among stroke patients, smart-phone based accelerometers were used to measure trunk accelerations during walking. Interstride variability of mediolateral trunk acceleration could distinguish between self-reported fallers and non-fallers, but traditional clinical evaluations could not (Isho et al., 2015). While these successes suggest that falls risk may be identified using wearable devices, the results should be validated using an actual measure of falls rather than scales or relying on a patient's self-report.

In some cases, kinematic information can be obtained using wearable devices. Related to the risk of tripping, foot clearance can be estimated using wireless inertial sensors, with placement on the foot or shank (Hamacher et al., 2014; Mariani et al., 2012; McGrath et al., 2011). The method proposed by McGrath et al. (2011) was successful in predicting MFC in "non-normal" gait. However, these gait aberrations were not consistent with any clinical population, rather they were a healthy individual's interpretation of "shuffling gait." Despite the convenience of using wearable technology to monitor MFC outside of a clinic or lab, most current methods only identify foot clearance, not the lower extremity kinematics that may contribute to changes in foot clearance. Other inertial sensor systems have been constructed to make accurate joint angle measurements, based on placement of several sensors on multiple body segments (Seel et al., 2014; Slajpah et al., 2014). Walking kinematics can be determined from a system of wearable sensors that includes seven inertial measurement units and two instrumented shoe insoles (Slajpah et al., 2014). Most methods of using inertial measurement units require that each device be placed on specific locations with a specific orientation to calculate joint kinematics. A new approach can get the same information with arbitrary placement of the inertial measurement units by taking advantage of the mechanical constraints of the joints (Seel et al., 2014). Although this method is be designed to provide accurate information about joint kinematics outside of a laboratory setting, it may be difficult for the general population to effectively adopt the multiple-sensor system. A better solution would be to have a single device that is capable of detecting specific gait patterns.

Machine Learning

Wearable devices can produce a large amount of data, and when machine learning algorithms are applied to that data, it is possible to produce information well beyond the actual measurement that is recorded. For example, linear accelerations obtained from an accelerometer are used to classify types of physical activity such as gardening, walking, or cycling (Moncada-Torres et al., 2014). There are three main ways that machine learning algorithms can be used: anomaly detection (e.g. support vector machines, Markov models and wavelet analysis), which separates the data into normal and abnormal sets; prediction (e.g. supervised learning), which aims to identify future events based on the data; and diagnosis or decision making (e.g. neural networks or decision trees), which involves classifying the data based on a large database of labeled information (Banaee, Ahmed, & Loutfi, 2013).

Algorithms. Regardless of the algorithm used to get higher level information out of the data, the approach is the same. This approach, outlined by Banaee et al. (2013) requires raw sensor data that is labeled according to the desired classification, and then split into a training set and a testing set. The training set is preprocessed and then key features are detected and selected. Then a model can be built on the training data as it learns which features correspond to which labels. When the model is created, it can be tested with the test data set. The test data set is also preprocessed and the key features are extracted. Based on the features and the model, the data are classified according to the desired data mining technique: anomaly detection, prediction, or diagnosis. Once the classification occurs, the model can be checked by comparison to the labels associated with the original data. Machine learning performance depends on decisions made at each step of the process: data acquisition, preprocessing, segmentation, feature extraction and selection, classification, and evaluation (Banos et al., 2014).

Data acquisition. During the data acquisition phase, the accelerometer signal is affected by the sampling rate. According to the Nyquist sampling theorem, the sampling rate should be at least twice the maximum frequency in the data. For gait, 99% of the frequency of gait is below 15 Hz, requiring a minimum sampling rate of 30 Hz, though a higher rate is necessary to improve beyond what would be a crude estimate at 30 Hz (Antonsson & Mann, 1985). In a review of the literature on activity recognition, Bersch et al. (2014) found the highest sampling frequency to be 512 Hz. Typically, the sampling rate is chosen based on the capacity of the accelerometer, and 50 Hz is common among off-the-shelf monitors (Bersch et al., 2014). A higher sampling frequency improves classification accuracy up to 20 Hz, but improvements are not significant beyond 20 Hz (Maurer et al., 2006). After data acquisition, preprocessing such as filtering may occur, however, if preprocessing can be avoided, it will prevent the removal of relevant information from the raw data (Banos et al., 2014).

Segmentation. Once the data has been collected, several methods can be used to segment the data into smaller, more manageable windows. These methods fall into one of two categories: they can be used online (the data can be segmented before the entire data collection is complete) or they need to be used offline (after all of the data has been collected). When designing a system to be used in real time, only online segmentation methods should be considered. Some methods of segmenting data rely on accompanying knowledge of the beginning and end of an activity (e.g. rigorously shaking the accelerometer between bouts of walking, sitting, running, etc.) (Moncada-Torres et al., 2014), or specific events such as heel-strike and toe-off during gait (Banos et al., 2014). A common online technique is to use a fixed-size sliding window, with either non-overlapping or overlapping data (Bersch et al., 2014). Overlapping allows some, but not all, data that appeared in one window to be included again in the subsequent window. The sliding window method of segmentation is beneficial for periodic activities such as gait, as long as each window captures a full period of the activity being captured (Banos et al., 2014).

Therefore, the size of the window needs to be considered. A smaller window size typically leads to more frequent analysis of the data. However, there may need to be a tradeoff between performance and speed. With small windows, more windows need to be processed which affects the computational load, and less data is included in each winsow which may reduce performance (Banos et al., 2014). A window size of 1 s appears to yield the best performance in classifying activities (walking vs. running vs. stairs etc.), with no significant benefits of using a larger window size, and a 30% increase in performance compared to a window size of 0.25 s, but the optimal window size is dependent on the activity being recognized (Banos et al., 2014).

Feature extraction. Rather than using the raw accelerometer signal, for each window of data, features are extracted to be used in the machine learning algorithms. Typically, the features are based on the time domain or the frequency domain. Time-domain features include statistics such as the mean and standard deviation of the signal, or the correlation between different axes of an accelerometer (Bao & Intille, 2004; Bersch et al., 2014). Additionally, the accelerometer signal is sometimes separated into components that represent acceleration due to gravity and body acceleration (Karantonis et al., 2006). To obtain frequency-domain features requires the use of a discrete Fourier transform, which has a high computation cost (Maurer et al., 2006). The use of a fast Fourier transform helps reduce the time required for the transform, but relies on a window size that is a power of 2. From the fast Fourier transform, common features include spectral energy, entropy, principal frequency, and combinations of the fast Fourier transform coefficients (Bersch et al., 2014; Preece et al., 2009).

Feature selection. While a large range of features can be extracted, the complete feature space can be reduced to eliminate irrelevant or redundant features that do not contribute to the classification accuracy. The presence of irrelevant features causes machine learning algorithms to deteriorate. This is even true for algorithms such as decision trees that theoretically only choose features that help the algorithm because in some situations, the unhelpful features may appear to be as good as a truly helpful feature, and will be included in the algorithm (Witten & Frank, 2005). Several algorithms exist that will aid in feature selection. A forward wrapper can be used in conjunction with a specific classification algorithm to select features that will aid the performance of that particular classification scheme (Caby et al., 2011). A correlation-based feature selection algorithm is used independent of the classification algorithm to select features that are highly correlated with the classes to be detected, but are not correlated with other selected features (Maurer et al., 2006; Witten & Frank, 2005).

Classification. Many classification algorithms have been developed to perform machine learning, and most fall into groups including, among others, decision trees, classification rules, instance-based learning, numeric prediction, and Bayesian networks (Witten & Frank, 2005). Classifiers range from simple to complex, though an increase in complexity does not always equate to better performance. Decision trees use a divide-and-conquer approach to sort the data based on the values of the features. The simplest and most rudimentary application of a decision tree is 1R or 1-rule. Each feature is branched according to the different values of the feature, and each branch is assigned to the class that occurs most often within that branch. The error rate of this classification is calculated for all of the features, and the feature that has the least error is chosen as the 1R classifier (Witten & Frank, 2005). More complex decision tree algorithms involve multiple features and branches. One feature is selected as the first node, with branches for each value of that feature. Each branch is then split further with additional features until all instances at a node have the same classification, which is known as a pure node. Once a tree is constructed, postpruning is often used to simplify the tree and prevent overfitting. This practice always results in errors based on the training data, but might result in better performance when applied to a different testing data set (Witten & Frank, 2005). Standard decision tree algorithms use a depth-first expansion, using a fixed order to expand nodes of the tree until a pure node is reached. Postpruning is then applied to the full tree. A common depth-first algorithm is called C4.5. Decision trees can also be constructed using best-first expansion, where the order of expansion is dependent on the best available nodes for splitting with the goal of finding pure nodes as quickly as possible (Shi, 2007). The full trees for both depth-first and best-first expansion are identical, however, both pre- and postpruning are used to construct a tree using best-first expansion, and so the pruned structure is different. A Random Tree is constructed using a random number of features at each node with no pruning. Regardless of the method used to construct a tree, it is likely that different training sets will yield different models, and the classification of the test data depends on which tree is used for the classification. Bagging is a machine learning technique that involves each tree considering the same test instance and voting on the classification, then the class that receives the most votes is chosen. The Random Forest decision tree algorithm uses bagging on ensembles of Random Trees (Witten & Frank, 2005), and has been successful in detecting falls (Gjoreski, Gams, & Lustrek, 2014).

Other types of classifiers are based on rules or probabilities. A Decision Table is a simple rule-based classifier that uses a subset of features. A table is constructed from the training data that contains all instances and their values for each feature in the subset, as well as their class. For each instance in the testing data set, the table is searched for an exact match of features. If no exact match is found, the assigned class is the majority class. Otherwise, the majority class of the matches from the table is assigned (Kohavi, 1995). Naïve Bayes is another simple classifier, but rather than using just one feature as in 1R, or a subset of features like a Decision Table, it uses all features with equal importance and independent of each other (Witten & Frank, 2005). The classification is made based on the probability of each class occurring with the given feature set. The Naïve Bayes algorithm is based on the assumptions of conditional independence between features and normal distribution of feature values, and relies on large amounts of data to accurately model feature value distributions (Bao & Intille, 2004; Witten & Frank, 2005). However, this simple classifier often yields good performance in activity recognition in spite of these assumptions not being met (Caby et al., 2011).

Another example of each feature having equal influence on the classification decision is nearest-neighbor instance-based learning (IB1) (Witten & Frank, 2005). In this algorithm, the training data is stored, and the distance (typically Euclidean) between the features of each instance of the training data set and the features of a given test instance are calculated. The classification for the test instance is identified as the class of the training instance that is the shortest distance away. While IB1 is a simple and effective algorithm, a major problem with instance-based learning is that it is slow, with a time proportional to the number of training instances times the number of testing instances. Speed is an issue particularly when there are a large (>10) number of features. Additionally, noise within the training data can corrupt the classification. A solution to this problem is to use a k-nearest-neighbor (kNN) approach, where a small value for k is chosen, and then the k nearest neighbors for each test instance vote to determine the test instance class.

Numeric prediction. Numeric prediction is a special case of machine learning that occurs when the outcome is numeric and all of the features are numeric. During training, all of the features are given weights so that when the weights are multiplied by the value of the feature and added together the result is the predicted value of the outcome class (Witten & Frank, 2005). In simple regression, only one feature is used in the prediction model, namely the feature that has the greatest influence on the outcome class. Linear regression involves a linear combination of all of the features.

Evaluation. Testing classification algorithms involves building a model with training data and testing it on an independent data set. Ideally, there would be separate training and testing data sets, both of which contain a large number of instances. However, the amount of data this requires is often impractical. A common solution for smaller data sets is to use 10-fold cross validation repeated for a pre-defined number of runs, typically 10 (Witten & Frank, 2005). With 10-fold cross validation, the entire data set is randomly split into 10 folds of approximately the same size. Training is done using nine of the folds, and testing is done on the fold that was not involved in training. For one run, the process is repeated so each fold serves as the test data set exactly once. In subsequent runs, the data set is divided into 10 different folds, with training and testing done according to the same procedure. In total, a 10-fold cross validation with 10 runs yields 100 model building and testing events.

Each time a model is tested, there are a number of ways to evaluate model performance. For linear regression, performance can be evaluated using absolute or relative measures of error, as well as the correlation between the predicted and actual values of the test data (Witten & Frank, 2005). Absolute measures of error (e.g. mean absolute error, root mean squared error) quantify the error in prediction using units of the predicted value. Low values for absolute measures of error indicate good model performance. Mean absolute error is the average magnitude of the difference between actual and predicted values. Root mean squared error is the square root of the average squared difference between actual and predicted values. Relative measures of error (e.g. relative-absolute error, root relative squared error) compute the prediction error of the regression model as a percentage of the prediction error of a simple model. The simple model is usually the mean of the actual values. It is hoped that the model produced by linear regression performs better than simply predicting all values to be the mean, and so relative measures of error compare the size of the error from the regression model to the size of the error if the mean was predicted in each case. Low values for relative measures of error indicate good model performance. Relative-absolute error is the total absolute error in the regression model divided by the total absolute error when using the mean as the predictor, multiplied by 100. Root relative squared error is the square root of the total squared error in the regression model divided by the total squared error when using the mean as the predictor, multiplied by 100. Rather than quantifying an error value, the correlation coefficient is the correlation between the actual values and the predicted values. A high correlation coefficient indicates good model performance. There are differences in how each of these measures evaluate performance. The root squared errors (both absolute and relative) have a greater weight for large differences due to the squared error term. Additionally, the relative error measures depend on the variability in the actual data, which makes it difficult to compare performance across different data sets.

Binary classification – assigning data to one of two classes – has a different set of metrics used to evaluate model performance that depend on whether the correct classification was made (Witten & Frank, 2005). A common way to depict model performance is through a confusion matrix (Figure 18), where the columns represent the predicted class (negative or positive) and the rows represent the actual class (negative or positive). The cells of the confusion matrix contain the number of instances that correspond to true negatives (actual negative, predicted negative), false positives (actual negative, predicted positive), false negative (actual positive, predicted negative), and true positive (actual positive, predicted positive) (Chawla, 2010). Since reporting a set of four values to evaluate a model can be cumbersome, additional measures have been developed to provide a comprehensive picture of the model performance. Classification accuracy (Table 29) is a simple and common way to evaluate performance as it reports the percent of correct classifications (Bersch et al., 2014). A limitation to using the classification accuracy exists for imbalanced data sets, which are situations when the classification categories are not equally represented in the data. This is illustrated in an example where the majority class occurs close to 100% of the time. A classification model that simply chooses the majority class would therefore be correct close to 100% of the time without considering any of the features within the data (Bersch et al., 2014; Chawla, 2010). Imbalanced data sets are common among real world machine learning problems (Chawla, 2010), so alternatives to classification accuracy, such as recall, precision and F-measure (Table 29), are necessary for evaluating classification performance. Recall is a measure of the percent of positive cases identified, while precision measures the percent of correct positive predictions. F-measure combines the tradeoff between precision and recall and presents an overall measure of performance for imbalance data sets (Chawla, 2010). Overall, the goal is to improve recall without hurting precision. However, the measure of performance chosen should depend on the impact of the problem. For example, a good recall score occurs when the number of false negatives is small, while a good recall score occurs when the number of false positives is small. When detecting the risk of tripping, it could be argued that it is better to avoid false negatives (predicting no risk of tripping when the risk exists) than to avoid false positives (predicting a risk of tripping when there is no risk). In that case, recall is a more important measure of classification performance.

	Predicted Negative	*Predicted Positive*
Actual Negative	**True Negative**	**False Positive**
Actual Positive	**False Negative**	**True Positive**

Figure 18. Confusion matrix (adapted from Chawla (2010)).

Table 29

Measures of Binary Classification Performance in Machine Learning and Clinical Terms

	Measure	Formula
Machine Learning	Classification Accuracy	(TP+TN)/(TP+FP+TN+FN) * 100
	Recall	(TP)/(TP+FN)
	Precision	(TP)/(TP+FP)
	F-measure	(2*TP)/(2*TP+FP+FN)
Clinical	Sensitivity	(TP)/(TP+FN)
	Specificity	(TN)/(TN+FP)
	PPV	(sensitivity*prevalence)/ (sensitivity*prevalence+(1-specificity)*(1-prevalence))

Note. TP = true positive; TN = true negative; FP = false positive; FN = false negative; PPV = positive predictive value.

Clinically, diagnostic tests are evaluated in a similar way to the binary classification results from machine learning, albeit with a different vocabulary. Sensitivity is the same as recall, or the percent of positive cases identified. A common complement to sensitivity is specificity, or the percent of negative cases identified. In clinical terms, precision is represented as the positive predictive value, or the probability that a positive result is actually true. The positive predictive value is the ratio of true positives to the total number of positive test results. Generalization of the positive predictive value beyond the sample population depends on the prevalence of classification being identified within the target population (Table *29*). The prevalence can be included in the equation for positive predictive value if the prevalence within the sample is not the same as the target population (Altman et al., 2000).

Another measure of performance for a classification algorithm is its computational load. Computational load is based on the time for processing the algorithms. The time can be considered in two stages: the time required for the data preprocessing – including segmentation and windowing – and feature extraction, and the time required for classification (Bersch et al., 2014). A greater time means a greater computational load. This can be an important factor when considering a machine learning algorithm, particularly one that is to be used in real time.

While measures of performance are useful for evaluating a particular machine learning algorithm, it is often necessary to compare performance across multiple algorithms. However, problems arise when attempting to use traditional statistical tests for this task (Demšar, 2006). The results of a machine learning algorithm typically include many (100 for a 10-fold cross validation run 10 times) iterations of training and testing a model. Since the same data is used multiple times in this type of analysis, estimations of variance may be biased. Therefore, only the performance score and not the variance of the performance score can be used from the results of repetitive testing on a single data set. Variance can only be considered for differences in performance across independent data sets, and so the number of data sets in a comparison is considered the sample size.

In spite of this limitation, several non-parametric tests can be used to compare performance across multiple machine learning algorithms. The sign test is a way of comparing performance for pairs of classification algorithms (Demšar, 2006). For each data set, the classifier that had the best performance is recorded. The null hypothesis for equal performance is that both algorithms would "win" on an equal number of data sets. An algorithm is considered significantly better with $p < 0.05$ if the number of wins is greater than $N/2 + 1.96\sqrt{N}/2$, where N is the total number of data sets. According to this formula, significance at $p < 0.05$ can be determined with a minimum of five data sets. Another method of comparing performance for pairs of classification algorithms is the Wilcoxon signed ranks test, which is a non-parametric alternative to the paired t-test (Demšar, 2006). The absolute value of the difference in performance between the two algorithms (|algorithm 1 – algorithm 2|) is ranked, and the ranks are then summed separately for the positive (algorithm 1 > algorithm 2) and negative (algorithm 2 > algorithm 1) and differences. The smaller of the two sums is then used to compute a z-statistic based on the number of data sets. The Friedman test is an omnibus test for multiple comparisons, and is considered a non-parametric analog to repeated-measures ANOVA (Demšar, 2006). The Friedman test is also based on ranking the performance of the algorithms on each data set. The average ranking is included in the test statistic. Follow up tests for a significant Friedman test are all pairwise comparisons using the Nemenyi test, where a pair of classifiers is significantly different if the difference in their average ranks is greater than a critical difference (Demšar, 2006).

Movement Applications. There are several ways this data mining framework has been applied to human gait classification. Data from a motion capture system that tracked a series of markers representing key anatomical landmarks during walking was classified into one of five conditions: normal, hemiplegia, Parkinson's disease, back pain or leg pain. Several machine learning algorithms were used, including support vector machines, decision tree, k-nearest neighbors, random forest, naïve Bayes, neural network, and majority class. All but the majority class, which was the baseline algorithm, had above 90% accuracy when classifying types of patients (Pogorelc, Bosnic, & Gams, 2012). Examples of this technique on classifying data from wearable devices include: correctly identifying walking, running and ascending or descending stairs from an insole device (Zhang et al., 2005), detecting walking events and walking speed from triaxial accelerometers place on both shanks (Dobkin et al., 2011), distinguishing idiopathic toe walking from normal gait by analyzing accelerometer data at the heel (Pendharkar et al., 2012), and classifying the MFC of young and older adults (Begg, Palaniswami, & Owen, 2005). Several pattern recognition algorithms applied to accelerometer data have been used to classify older adults at risk for falling, however, the risk of falling again was not determined by actual prospective falls, and the accelerometer system contained 10 sensors distributed over the body (Caby et al., 2011). A novel application of this technology suggests data mining algorithms applied to a single accelerometer signal may be used to accurately predict joint kinematics for stroke patients with gait deficits. Successful classification of joint kinematics could then be used to identify adaptations that should be made (e.g. greater knee flexion during swing), to reduce the likelihood of falling.

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Appendix B: Protocol Summary

Instructions: Each Section must be completed unless directed otherwise. Incomplete forms will delay the IRB review process and may be returned to you. Enter your information in the **colored boxes** or place an **"X"** in front of the appropriate response(s). If the question does not apply, write **"N/A."**

SECTION A: Title

A1. Full Study Title: Identifying Gait Deficits In Stroke Patients Using Inertial Sensors

SECTION B: Study Duration

B1. What is the expected start date? *Data collection, screening, recruitment, enrollment, or consenting activities may not begin until IRB approval has been granted. Format: 07/05/2011*

12/1/2015

B2. What is the expected end date? *Expected end date should take into account data analysis, queries, and paper write-up. Format: 07/05/2014*

12/1/2016

SECTION C: Summary

C1. Write a brief descriptive summary of this study in Layman Terms (non-technical language):

Gait deficits are a common and costly problem among stroke patients, and they increase a person's risk for falling. In this study, the gait of stroke patients, older adults with and without a history of falls, and younger adults will be analyzed with 3D motion capture equipment and using portable, wearable inertial sensors. The goals of this project are to identify gait patterns that are associated with an increased risk of falling, and to detect poor gait patterns in stroke patients using signals from the accelerometer sensors. If the goals of the proposed project are met, it may be possible to determine when a stroke patient is at an increased risk of falling, thus improving their quality of life and longevity.

C2. Describe the purpose/objective and the significance of the research:

Purpose

The purpose of the proposed studies is to understand the gait characteristics that influence foot clearance and the ability to avoid obstacles that could present a tripping hazard. The final goal is to use data mining techniques to detect these falls-related gait abnormalities among stroke patients using a portable inertial sensor. This will be achieved through the following specific aims:

Aim 1: To identify the relationship between joint coordination patterns and minimal foot clearance during walking for chronic stroke patients and healthy controls.

This objective will be accomplished by using vector coding to quantify the coordination between the sagittal plane joint motions of the lower extremity, as well as determining the minimal foot clearance during normal walking for stroke patients and healthy controls. It is expected that abnormal coordination patterns and those with high variability will be associated with lower and more variable foot clearance.

Aim 2: To determine characteristics of gait that enable stroke patients and healthy controls to successfully avoid an unexpected object that could present a tripping hazard.

This objective will be accomplished by recording kinematics during walking trials where participants will have to react to an object that unexpectedly impedes the normal trajectory of the foot. Joint coordination patterns, joint angles, minimal foot clearance and functional balance and gait scores will be compared for those who are successful and unsuccessful at avoiding an unexpected object. It is hypothesized that participants who do not avoid the object will have more variable joint coordination, reduced sagittal plane joint angles, lower and more variable foot clearance, and poor functional gait and balance scores.

Aim 3: To detect gait abnormalities and the risk of tripping for stroke patients and healthy controls using patterns in accelerometer signals.

This objective will be accomplished by simultaneously recording joint kinematics and lower extremity accelerations during the typical gait of stroke patients and healthy controls. Pattern recognition algorithms will be used to create a model that classifies a training subset of the accelerometer signals according to the gait patterns observed in a kinematic analysis (e.g. reduced knee flexion, out-of-phase knee and hip coordination). This model will be tested on a different subset of the accelerometer signals, and a comparison between the pattern-recognized gait profile and the actual joint kinematics will be made. It is expected that stroke patients' lower extremity accelerations, as recorded by a portable accelerometer, have distinct and predictable patterns based on specific deviations from normal gait.

Significance

Falls remain a significant problem for stroke patients, and each patient's risk of falling may be based on unique gait deficits. Identifying the characteristics of gait that control foot clearance and those that are associated with the ability to avoid obstacles while walking can inform rehabilitation techniques and interventions designed to reduce the risk of falls. Developing a convenient way to monitor an individual's gait with wearable sensors and data mining techniques could eventually be used to predict falls risk in real-time, and allow for the patient to make corrections to prevent falling.

C3. Cite the most relevant literature pertaining to the proposed research:

Falls are a major problem for recovering stroke patients, with higher incidences of falls for stroke patients than the general elderly population (Batchelor et al., 2012). However, interventions have been unsuccessful in preventing falls for stroke patients (Batchelor et al., 2010; Batchelor et al., 2012; Batchelor et al., 2012; Dean et al., 2012; Verheyden et al., 2013). Due to a variety of sensorimotor impairments, patients recovering from a stroke typically experience gait deviations that may present a risk for falling, such as spatiotemporal asymmetries and abnormal joint kinematics that could limit foot clearance (Balaban & Tok, 2014; Kim & Eng, 2003; Olney & Richards, 1996; Woolley, 2001).

Insufficient clearance between the foot and the walking surface or an obstacle may result in a trip, one of the greatest causes of falls (W. P. Berg et al., 1997; Blake et al., 1988; Overstall et al., 1977; Robinovitch et al., 2013; Tuunainen et al., 2014). As such, the magnitude of minimum foot clearance (MFC) is often studied. Low MFC and high MFC variability is suspected to increase risk of falling (Begg et al., 2007). A low MFC value indicates that the foot passes close to the walking surface during swing phase, and high variability in MFC height suggests an increased probability that the foot will come in contact with the walking surface. MFC is dependent on the extent to which the swing leg shortens during gait. Gait adaptations to accommodate varying walking surfaces (Gates et al., 2012) and perform everyday tasks while walking (Schulz et al., 2010) include concurrent changes in joint kinematics and MFC height. Similarly, MFC variability is correlated with joint angle variability (Mills et al., 2008). Therefore, an understanding of how the joints of the lower extremity are controlled during walking will provide insight about how MFC is achieved.

Joint coordination can allow the same goal, such as foot clearance, to be reached with each stride cycle, even if the strategy for achieving adequate MFC is different. For example, patients with knee osteoarthritis exhibit similar MFC height as a control group, but the knee flexion, hip abduction and ankle adduction angles were different between the groups (Levinger et al., 2012). This evidence supports the theory that the lower extremity joints are coordinated to achieve the planned distal endpoint trajectory of the limb (Karst et al., 1999). In healthy gait, coordination between the joints of the lower extremity enables foot clearance while the leg advances during swing (Moosabhoy & Gard, 2006). Since lack of coordination in the lower extremity has been observed in stroke patients (Barela et al., 2000; Little et al., 2014; Moosabhoy & Gard, 2006; Rinaldi & Monaco, 2013), investigation of the coupling of joint segments in stroke patients may yield information regarding the kinematic strategies required to achieve adequate MFC during walking.

Despite the obvious consequences of inadequate foot clearance and the incidence of falls, it is unclear how joint kinematics, coordination and MFC relate to the ability to avoid unexpected obstacles that could present a tripping hazard. There is a push to investigate task-specific falls risk perturbations in an effort to further understand the mechanisms of falls and identify potential interventions that could reduce the incidence of falls (Grabiner et al., 2014). Experiments that challenge the ability to avoid an obstacle will help identify which kinematic and coordination patterns are relevant to the risk of tripping.

While abnormal joint kinematics and intralimb joint coordination patterns are common among stroke patients, the effect of hemiparesis caused by the stroke is different for each patient (Jonsdottir et al., 2009). This underscores the conclusion reached by Begg et al. (2007) that an individual-based approach to evaluate a patient's risk of tripping is better than a group-based approach. The gold standard for detecting individual components of a gait disorder requires the use of motion capture technology, typically found in research labs. More commonly, a stroke patient will receive a gait analysis in a clinical setting under trained supervision. However, the frequency of falls for stroke patients within the first six months following discharge from rehabilitation highlights the need for gait supervision when patients are ambulating on their own (Forster & Young, 1995; Mackintosh et al., 2005; Wagner et al., 2009). The ability to identify in real-time when a stroke patient may be at risk for a fall may reduce the number of falls in this population.

Wearable sensors are becoming a common way to reliably monitor and evaluate health-related indices (Appelboom et al., 2014; Bassett, 2012; Dobkin, 2013). Although there have been several efforts to quantify joint kinematics outside of a research or clinical setting using wearable inertial sensors, most current methods only identify foot clearance, not the lower extremity kinematics or coordination patterns that may contribute to changes in foot clearance (Hamacher et al., 2014; Mariani et al., 2012; McGrath et al., 2011). Other methods designed to provide accurate information about joint kinematics require the placement of several sensors on multiple body segments (Seel et al., 2014; Slajpah et al., 2014), which may be difficult for the general population to effectively adopt.

Data mining techniques contain the tools to identify patterns and associations in various types of health-related data (Chawla & Davis, 2013). For quantifying movement, pattern recognition algorithms are applied to the accelerometer signals from wearable devices to classify different activities, such as walking, running, climbing stairs and sitting (Moncada-Torres et al., 2014). The ability to use similar data mining techniques to classify different walking patterns based on accelerometer signals could eliminate the need to directly measure joint kinematics for people with gait deficits. It would be beneficial if a single wearable inertial sensor could be used to detect specific abnormalities in lower extremity joint kinematics and coordination patterns that influence MFC, particularly for clinical populations such as stroke patients.

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SECTION D: Subject Population

Section Notes…

- D1. If this study involves analysis of de-identified data only (i.e., no human subject interaction), IRB submission/review may not be necessary. **Please review the UWM IRB Determination Form for more details.**

D1. Identify any population(s) that you will be specifically targeting for the study. Check all that apply: (Place an "X" in the column next to the name of the special population.)

	Existing Dataset(s)	**X**	Institutionalized/ Nursing home residents recruited in the nursing home
X	UWM Students of PI or study staff		Diagnosable Psychological Disorder/Psychiatrically impaired
X	UWM Students (but not of PI or study staff)		Decisionally/Cognitively Impaired

	Non-UWM students to be recruited in their educational setting, i.e. in class or at school		Economically/Educationally Disadvantaged
X	UWM Staff or Faculty		Prisoners
	Pregnant Women/Neonates		International Subjects (residing outside of the US)
	Minors under 18 and ARE NOT wards of the State		Non-English Speaking
	Minors under 18 and ARE wards of the State		Terminally ill
X	Other (Please identify): People with chronic stroke		

D2. Describe the subject group and enter the total number to be enrolled for each group. For example: teachers-50, students-200, parents-25, student control-30, student experimental-30, medical charts-500, dataset of 1500, etc. Then enter the total number of subjects below. Be sure to account for expected drop outs. For example, if you need 100 subjects to complete the entire study, but you expect 5 people will enroll but "drop out" of the study, please enter 105 (not 100).	
Describe subject group:	**Number:**
People with chronic stroke	10
Older adults with a history of falls	12
Older adults with no history of falls	12
Young adults	12
TOTAL # OF SUBJECTS:	46
TOTAL # OF SUBJECTS (If UWM is a collaborating site for a multi institutional project):	

D3. For each subject group, list any major inclusion and exclusion criteria (e.g., age, gender, health status/condition, ethnicity, location, English speaking, etc.) and state the justification for the inclusion and exclusion criteria:

Chronic stroke

- Inclusion: experienced a stroke more than 6 months earlier; able to walk without an assistive device for 5 minutes at a time
- Exclusion: cognitively impaired and unable to follow a three-step command

- Justification: People with chronic stroke are at risk of falling, so investigating gait deficits within this population may be key to reducing the risk of falls. To participate in the tasks involved in this study, all participants must be able to walk without an assistive device for 5 minutes at a time, and must not be cognitively impaired so they can successfully follow all of the directions for completing the study.

Older adults with a history of falls

- Inclusion: age 65 and older; able to walk without an assistive device for 5 minutes at a time; have fallen in the last six months, with a fall being defined as unintentionally coming to rest on the ground [1]
- Exclusion: cognitively impaired and unable to follow a three-step command
- Justification: Older adults with a history of falls are likely to fall again, so investigating gait deficits within this population may be key to reducing the risk of recurring falls. To participate in the tasks involved in this study, all participants must be able to walk without an assistive device for 5 minutes at a time, and must not be cognitively impaired so they can successfully follow all of the directions for completing the study.

Older adults with no history of falls

- Inclusion: age 65 and older; able to walk without an assistive device for 5 minutes at a time; have not fallen in the last six months, with a fall being defined as unintentionally coming to rest on the ground [1]
- Exclusion: cognitively impaired and unable to follow a three-step command
- Justification: To identify gait deficits associated with older adults who have fallen, it is important to make comparisons to the gait patterns of older adults who have not fallen. To participate in the tasks involved in this study, all participants must be able to walk without an assistive device for 5 minutes at a time, and must not be cognitively impaired so they can successfully follow all of the directions for completing the study.

Young adults

- Inclusion: age 18-45
- Exclusion: cognitively impaired and unable to follow a three-step command
- Justification: To identify gait deficits associated with older adults and those who have fallen, it is important to make comparisons to the gait patterns of younger adults who have a lower risk of falling. To participate in the tasks involved in this study, all participants must be able to walk without an assistive device for 5 minutes at a time, and must not be cognitively impaired so they can successfully follow all of the directions for completing the study.

Reference for Inclusion Criteria

[1] Senden R, Savelberg HHCM, Grimm B, Heyligers IC, Meijer K. Accelerometry-based gait analysis, an additional objective approach to screen subjects at risk for falling. Gait Posture 2012;362:296-300.

SECTION E: Study Activities: Recruitment, Informed Consent, and Data Collection
Section Notes…

- Reminder, all recruitment materials, consent forms, data collection instruments, etc. should be attached for IRB review.
- The IRB welcomes the use of flowcharts and tables in the consent form for complex/ multiple study activities.

In the table below, chronologically describe all study activities where human subjects are involved.

- In **column A**, give the activity a short name. Please note that Recruitment, Screening, and consenting will be activities for almost all studies. Other activities may include: Obtaining Dataset, Records Review, Interview, Online Survey, Lab Visit 1, 4 Week Follow-Up, Debriefing, etc.
- In **column B**, describe who will be conducting the study activity and his/her training and/or qualifications to complete the activity. You may use a title (i.e. Research Assistant) rather than a specific name, but training/qualifications must still be described.
- In **column C**, describe in greater detail the activities (recruitment, screening, consent, surveys, audiotaped interviews, tasks, etc.) research participants will be engaged in. Address **where**, **how long**, and **when** each activity takes place.
- In **column D,** describe any possible risks (e.g., physical, psychological, social, economic, legal, etc.) the subject may ***reasonably*** encounter. Describe the **safeguards** that will be put into place to minimize possible risks (e.g., interviews are in a private location, data is anonymous, assigning pseudonyms, where data is stored, coded data, etc.) and what happens if the participant gets hurt or upset (e.g., referred to Norris Health Center, PI will stop the interview and assess, given referral, etc.).

A. Activity Name:	**B. Person(s) Conducting Activity**	**C. Activity Description (Please describe any forms used):**	**D. Activity Risks and Safeguards:**
Recruitment	Lauren Benson – Completed IRB training, Constructed study design, Research Assistant in Neuromechanics Lab	A Recruitment Flyer will be posted around the UWM campus, in public locations, and at local nursing homes to encourage potential participants to contact the investigators about participation.	N/A

	Sharon Feldmann - Manager, SCIC/Neuro Rehab at Froedert Hospital, licensed Physical Therapist, **trained in IRB practices at Froedert Hospital**	Additionally, flyers will be distributed to patients at Froedert Hospital who are eligible to participate. **Protected Health Information (history of stroke, ability to walk for 5 minutes at a time without an assistive device, and no cognitive impairment) will be obtained by therapist with access to a patient's medical history. That patient will then be given information about the study, and can choose to contact the investigators at UWM about participation in the study.**	
Screening	Lauren Benson – Completed IRB training, Constructed study design, Research Assistant in Neuromechanics Lab	Participants will be given the Screening Questionnaire to determine if they are eligible for the study, and their eligible group.	N/A
Obtaining Consent	Lauren Benson – Completed IRB training, Constructed study design, Research Assistant in Neuromechanics Lab	Participants will be informed about the study and asked for consent to participate via the Consent Form.	N/A
Demographic and Fear of Falling Questionnaire	Lauren Benson – Completed IRB training, Constructed study design, Research Assistant in Neuromechanics Lab	Participants will be given a Questionnaire to gather demographic information (height, weight, age, sex, dominant side), as well as information about their walking ability, falls history. Fear of falling will be assessed using the Frenchay Activities Index (Schepers et al., 2006), Swedish	Since private information will be collected, there is a risk of breach of confidentiality. (Very unlikely) All data will be stored in a locked filing cabinet in a locked room. All data will be

		modification of the Falls Efficacy Scale (Hellstrom & Lindmark, 1999), and the Activities-specific Balance Confidence scale (Powell & Myers, 1995). Additionally, stroke patients will be asked about the nature of their stroke. If needed, help will be provided for completing the surveys.	given a letter and number that is uniquely associated with each participant. This code will not contain any partial identifiers (i.e. last four digits of SSN) and will be stored in a separate locked office in a locked filing cabinet. No identifiers will be stored with the research data. Only those individuals with an active role in this study will have access to the research data and identifying information. When all participants have completed active participation in the study and data collection is completed, the code will be destroyed. All appropriate measures to protect private information will be taken.
Mini-Mental State Examination	Lauren Benson – Completed IRB training, Constructed study design, Research Assistant in Neuromechanics Lab	Participants will be given the Mini-Mental State Examination (Savin et al., 2014) to assess their ability to understand and perform the tasks required to complete the study	N/A
Fugl-Meyer Lower Extremity Motor Evaluation	Thomas Almonroeder – Completed IRB training, Doctor of Physical Therapy, Research Assistant in	The motor function of the participants' lower extremity will be assessed by a licensed physical therapist using the Fugl-Meyer scale (Sanford et al., 1993).	There is a risk of muscle soreness or injury such as muscle strain or muscle tightness as a result of the testing. (Unlikely)

	Neuromechanics Lab		To reduce the above risks, practice trials will be performed prior to data collection to allow participants to become familiar with each procedure prior to performing a maximal effort trial. Participants will be allowed to stop at any point if they feel uncomfortable. If participants are injured while participating in this research study, they will initially be provided care by the investigator(s), who are all trained in first aid and CPR. Students will then be referred to the Norris Health Center for follow-up care. Non-students will be referred to their primary care physician and will be responsible for all expenses incurred. In the case of an emergency, 911 will be called.
Functional Gait and Balance Evaluation	Lauren Benson – Completed IRB training, Constructed study design, Research Assistant in Neuromechanics Lab	Each participant's functional gait and balance ability will be evaluated with the activities in the Functional Evaluation, consisting of the Mini-BESTest (Franchignoni et al., 2010), Functional Gait Analysis (Wrisley et al., 2004), Performance-Oriented Assessment of Mobility (Tinetti, 1986), and fast walking speed (Oken et al., 2008; Richards & Olney, 1996) scales. Participants will wear a gait belt, and the	There is a risk of muscle soreness or injury such as muscle strain or muscle tightness as a result of the testing. (Unlikely) There is a risk of falling during tasks that challenge gait and balance ability. (Unlikely) To reduce the above risks, practice trials will be performed prior

		evaluator will provide contact guard assistance, holding onto the belt in case the participant loses their balance during the tasks.	to data collection to allow participants to become familiar with each procedure prior to performing a maximal effort trial. Participants will be allowed to stop at any point if they feel uncomfortable. Participants will wear a gait belt, and the evaluator will provide contact guard assistance, holding onto the belt in case participants lose their balance during the tasks that challenge gait and balance ability. If participants are injured while participating in this research study, they will initially be provided care by the investigator(s), who are all trained in first aid and CPR. Students will then be referred to the Norris Health Center for follow-up care. Non-students will be referred to their primary care physician and will be responsible for all expenses incurred. In the case of an emergency, 911 will be called.
Strength Assessment	Lauren Benson – Completed IRB training, Constructed study design, Research Assistant in Neuromechanics Lab	A pair of electrodes (Vermed, NeuroPlus, Bellows Falls, VT, USA) will be applied to the skin over each of three muscles (rectus femoris, tibialis anterior, and medial gastrocnemius) of each leg. Prior to electrode placement,	There is a risk of muscle soreness or injury such as muscle strain or muscle tightness as a result of the testing. (Unlikely) There is also a risk of minor skin irritation

		the skin will be shaved (if necessary) and rubbed with alcohol. Muscle activity will be wirelessly recorded (Noraxon, DTS EMG, Scottsdale, AZ, USA) from each pair of electrodes. To quantify the maximum amount of muscle activation and isometric force that can be produced by each muscle, a series of maximal contraction exercises will be performed. Participants will be seated and will try to extend their knee, and plantar flex and dorsiflex their ankle while being met with resistance from a dynamometer (BTE Technologies, Inc., PrimusRS, Hanover, MD, USA). This series of exercises will be performed three times for each muscle.	due to the spray tape adhesive or tape. (Unlikely) To reduce the above risks, practice trials will be performed prior to data collection to allow participants to become familiar with each procedure prior to performing a maximal effort trial. Participants will be allowed to stop at any point if they feel uncomfortable. If participants are injured while participating in this research study, they will initially be provided care by the investigator(s), who are all trained in first aid and CPR. Students will then be referred to the Norris Health Center for follow-up care. Non-students will be referred to their primary care physician and will be responsible for all expenses incurred. In the case of an emergency, 911 will be called.
Overground Walking	Lauren Benson – Completed IRB training, Constructed study design, Research Assistant in Neuromechanics Lab	Retroreflective markers will be applied over the skin to the trunk, pelvis and both legs at biological landmarks. A force plate (Bertec Corp., Columbus, OH, USA) will record force data while the electrodes on the skin record muscle activity and a 10-camera motion analysis system (Motion Analysis,	There is a risk of muscle soreness or injury such as muscle strain or muscle tightness as a result of the testing. (Unlikely) There is also a risk of minor skin irritation due to the spray tape adhesive or tape. (Unlikely)

		Inc., EVART 4.6, Santa Rosa, CA, USA) will track three-dimensional position data of the retroreflective markers throughout the trial. Additionally, inertial sensors containing a tri-axial accelerometer (GT3X; ActiGraph Corp., Pensacola, FL) will be worn on both wrists, thighs just above the knee, and legs just above the lateral ankle, and the right, center and left pelvis to record accelerations at 100 Hz. Data will be collected as each participant walks at their normal walking pace for about 10 meters, with one foot landing completely inside the force plate. This will be repeated for 10 trials on each leg.	To reduce the above risks, practice trials will be performed prior to data collection to allow participants to become familiar with each procedure prior to performing a maximal effort trial. Participants will be allowed to stop at any point if they feel uncomfortable. If participants are injured while participating in this research study, they will initially be provided care by the investigator(s), who are all trained in first aid and CPR. Students will then be referred to the Norris Health Center for follow-up care. Non-students will be referred to their primary care physician and will be responsible for all expenses incurred. In the case of an emergency, 911 will be called.
Treadmill walking	Lauren Benson – Completed IRB training, Constructed study design, Research Assistant in Neuromechanics Lab	The same data that is collected during the overground trials will also be recorded as the participant walks at their normal walking pace on a treadmill (C964i; Precor, Woodinville, WA, USA) while attached through a harness to a fall-arrest system. Two conditions will be tested: Normal walking, and avoiding an unexpected obstacle. To ensure participants are looking	There is a risk of muscle soreness or injury such as muscle strain or muscle tightness as a result of the testing. (Unlikely) There is also a risk of minor skin irritation due to the spray tape adhesive or tape. (Unlikely) There is a risk of falling during the treadmill conditions.

		straight ahead, participants will be required to complete a concurrent visual task. An arrow will appear on a screen positioned at eye level 1 m from the treadmill. The participants will be asked to report the direction the arrow is pointing. The verbal response and the time to produce a response will be recorded using custom software (Matlab v8.0.0.783, Mathworks, Inc., Natick, MA, USA), and a new arrow will appear one second after their response. To control for the effects of doing this dual motor and visual task, participants will also complete the visual task for one minute while sitting, and will walk without performing the visual task for one minute while all biomechanical data are recorded. For normal walking with the visual task, kinematic, EMG and accelerometer data will be recorded continuously for one minute. For the obstacle avoidance conditions, participants will be instructed to avoid the obstacle as well as they can. The obstacle will be a lightweight piece of foam cut to length, width and height dimensions of 20 x 16 x 6 cm (Airex AG, Balance-pad, CH-5643 Sins, Switzerland). Similar to the process outlined by Weerdesteyn, et al. (2003), at random toe-off events, the foam will be placed on the belt of the treadmill so that the obstacle will appear in	To reduce the above risks, practice trials will be performed prior to data collection to allow participants to become familiar with each procedure prior to performing a maximal effort trial. Participants will be allowed to stop at any point if they feel uncomfortable. The fall-arrest system will prevent participants from falling to the ground during the treadmill trials, and the emergency stop on the treadmill will be activated in case participants stumble. The unexpected obstacle is a lightweight soft foam that can be kicked out of the way or will compress if stepped on. If participants are injured while participating in this research study, they will initially be provided care by the investigator(s), who are all trained in first aid and CPR. Students will then be referred to the Norris Health Center for follow-up care. Non-students will be referred to their primary care physician and will be responsible for all expenses incurred. In the case of

		front of the foot that is in swing. The height of the obstacle will be 6-cm above the treadmill belt. Considering typical minimal foot clearance for most elderly adults has been reported to be up to 5 cm (Begg et al., 2007), using a 6-cm obstacle should require the participant to react to the object to avoid coming in contact with it. This is also within the range of obstacle heights used in previous studies of obstacle avoidance in stroke patients (Said, Goldie, Patla, & Sparrow, 2001). If the foot does come in contact with the side of the block of foam, the obstacle will be kicked away so that the progress of the foot is not actually impeded. If the foot steps down on the obstacle, the block of foam will be crushed to only minimally disturb the participant's gait cycle. As soon as the foot clears or comes in contact with the obstacle, the block of foam will slide off of the treadmill so that the obstacle will be removed during the stance phase of walking. The participant will continue to walk on the treadmill for up to a minute at a time while kinematic, EMG and accelerometer data is collected continuously and the obstacle is presented at random toe-off events. This will be repeated as necessary until the obstacle is presented for a total of ten trials on both	an emergency, 911 will be called.

		the affected and unaffected sides. The outcome of each trial will be classified as a trip if the foot comes into contact with the obstacle, and not a trip if the foot clears the obstacle. This will be detected by tracking the location of retroreflective markers attached to the obstacle, and identifying any changes in velocity of the markers relative to the treadmill belt speed, or by detecting the intersection of the foot segment with the shape of the foam block. If a fall occurs requiring the participant to rely on the support of the harness and fall-arrest system, the treadmill will be stopped immediately. The order of the treadmill conditions will be randomized to avoid a fatigue effect. Additionally, each participants' rating of perceived exertion will be taken before each condition, and the participant will be allowed to rest between conditions until their rating of perceived exertion is at or below 9 – very light (Borg, 1970).	

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[14] Borg G. Perceived exertion as an indicator of somatic stress. Scand J Rehabil Med 1970;22:92-8.

E2. Explain how the data will be analyzed or studied (i.e. quantitatively or qualitatively) and how the data will be reported (i.e. aggregated, anonymously, pseudonyms for participants, etc.):

All data will be aggregated and stored anonymously so it is not possible to connect an individual with their data.

Aim 1:
The coordination and variability of coordination will be calculated for the relative sagittal plane motion of the hip and knee, hip and ankle, and knee and ankle. The stride cycle will be split into six sub phases, and the coordination and variability will be averaged across each sub phase. Minimum foot clearance and minimum foot clearance variability will be determined using two methods. In the first method, minimal foot clearance will be defined as the vertical displacement from the ground of the toe marker at the point of greatest horizontal velocity of the toe marker. The second method will determine minimal foot clearance through Principle Components Analysis of the vertical toe marker position waveform during swing phase. The instantaneous distance between the hip and toe will be divided by the instantaneous height of the hip joint to determine the normalized limb length. The greatest percent reduction in normalized limb length during swing represents the maximal limb shortening. The mean and standard deviation of the maximal limb

shortening will be taken across all trials for each walking condition. Multiple regression will be used to determine the relative contributions of the joint coordination variables in predicting foot clearance as determined by minimal foot clearance or maximal limb shortening.

Aim 2:

The data from the obstacle avoidance trials will be split into trials where a trip occurred and trials where a trip did not occur. A multivariate analysis of variance (MANOVA) will be used to determine how kinematic characteristics of the strides that result in tripping differ from those where a trip was avoided. If the MANOVA indicates a significant difference between the tripping and non-tripping trials, follow-up independent t-tests will be done for all dependent variables to determine significant kinematic markers of tripping risk. Two additional MANOVAs will be performed to determine if measures of fear of falling, and functional gait and balance evaluations, or muscle activity and isometric strength can discriminate those who come in contact with the unexpected obstacle from those who successfully avoid the obstacle. The participants will be split into groups of those who came in contact with the obstacle at least once, and those who avoided the obstacle every time. For the first analysis, the dependent variables will be scores for the functional evaluations. For the second analysis, the dependent variables will be each participant's mean force output from each of the MVC trials, and mean muscle activity for each muscle during each of the sub phases of the stride cycle. In either analysis, if the MANOVA indicates a significant difference between participants who come in contact with the obstacle and those that avoid it, follow-up independent t-tests will be done for all dependent variables to determine which functional evaluations or muscle properties significantly identify tripping risk.

Aim 3:

The Apriori association mining algorithm will be used to determine how the accelerometer signals are associated with joint kinematics and joint coordination by identifying sets of items or features within the dataset, and then determining inferences from the identified sets. For each association, the confidence will be reported as the probability of observing the kinematic features from the given set of accelerometer features. Additionally, accelerometer signals will be used to predict the trials where the foot came in contact with the object versus those where the object was avoided by using the accelerometer signals. Several different algorithms will be employed to classify the accelerometer features, including SVM, decision tree, and Bayesian network. The performance of the different algorithms will be compared, as well as the performance of the algorithms for different accelerometer locations, or combinations of locations, on the body.

SECTION F: Data Security and Confidentiality
Section Notes… • Please read the IRB Guidance Document on Data Confidentiality for more details and recommendations about data security and confidentiality.

F1. Explain how study data/responses will be stored in relation to any identifying information (name, birthdate, address, IP address, etc.)? Check all that apply.

[__] Identifiable - Identifiers are collected and stored with study data.
[__] Coded - Identifiers are collected and stored separately from study data, but a key exists to link data to identifiable information.
[X] De-identified - Identifiers are collected and stored separately from study data without the possibility of linking to data.
[__] Anonymous - No identifying information is collected.

If more than one method is used, explain which method is used for which data.

F2. Will any recordings (audio/video/photos) be done as part of the study?

[__] Yes
[X] No [SKIP THIS SECTION]

If yes, explain what activities will be recorded and what recording method(s) will be used. Will the recordings be used in publications or presentations?

F3. In the table below, describe the data storage and security measures in place to prevent a breach of confidentiality.

- In **column A**, clarify the type of data. Examples may include screening data, paper questionnaires, online survey responses, EMG data, audio recordings, interview transcripts, subject contact information, key linking Study ID to subject identifiers, etc.
- In **column B**, describe the storage location. Examples may include an office in Enderis 750, file cabinet in ENG 270, a laptop computer, desktop computer in GAR 420, Qualtrics servers, etc.

- In **column C**, describe the security measures in place for each storage location to protect against a breach of confidentiality. Examples may include a locked office, encrypted devices, coded data, non-networked computer with password protection, etc.
- In **column D**, clarify who will have access to the data.
- In **column E**, explain when or if data will be discarded.

A. Type of Data	B. Storage Location	C. Security Measures	D. Who will have access	E. Estimated date of disposal
Paper questionnaires	Filing cabinet in Enderis 132	The filing cabinet will be locked	Directors of the Neuromechanics Lab and their research assistants	12/1/16
Raw EMG, kinematic, kinetic and accelerometer data	Desktop computer in Enderis 132	The computer is password protected, the data will be de-identified with no key connecting subject names with subject numbers	Directors of the Neuromechanics Lab and their research assistants	N/A
Processed EMG, kinematic, kinetic and accelerometer data	Desktop computer in Enderis 132	The computer is password protected, the data will be de-identified with no key connecting subject names with subject numbers	Directors of the Neuromechanics Lab and their research assistants	N/A

F4. Will data be retained for uses beyond this study? If so, please explain and notify participants in the consent form.

No.

SECTION G: Benefits and Risk/Benefit Analysis

Section Notes…

- Do not include Incentives/ Compensations in this section.

G1. Describe any benefits to the individual participants. If there are no anticipated benefits to the subject directly, state so. Describe potential benefits to society (i.e., further knowledge to the area of study) or a specific group of individuals (i.e., teachers, foster children).

There are no direct benefits to the individual participants. There are potential benefits to society and in particular to those at risk of falling if the outcomes of this study indicate ways to prevent falls.

G2. Risks to research participants should be justified by the anticipated benefits to the participants or society. Provide your assessment of how the anticipated risks to participants and steps taken to minimize these risks (as described in Section E), balance against anticipated benefits to the individual or to society.

The risks to participants are minimal. Participants will be informed that they may discontinue their participation within this study at any time. Participants may experience minor muscle soreness as a result of the biomechanics testing. Participants may suffer musculoskeletal injury such as muscle strain as a result of the biomechanics testing. Participants may also experience minor skin irritation due to the spray tape adhesive (very unlikely). There are no anticipated psychosocial or privacy risks due to participation in the study. Because participants are required to be able to walk without assistive devices for 5 minutes at a time, they will be accustomed to the type of activity performed during the testing session. The fall-arrest system will prevent participants from falling to the ground during the treadmill trials, and the emergency stop on the treadmill will be activated in case participants stumble. The unexpected obstacle is a soft foam that can be kicked out of the way or will compress if stepped on, reducing the negative effects its presence may have on a participant's walking ability. First-aid medical treatment will be provided in the unlikely event of physical injury resulting from participation in this study. In case of basic first-aid, all research personnel involved are trained in basic first-aid and CPR and will provide appropriate care. In the event that some emergency treatment may be necessary, 911 will be called as a standard operation procedure and the subject will be individually responsible for the cost(s) associated with that treatment. If this event is unexpected, a full report will be submitted to the IRB. All data will be stored in a locked filing cabinet in a locked room. All data will be given a letter and number that is uniquely associated with each participant. This code will not contain any partial identifiers (i.e. last four digits of SSN) and will be stored in a separate locked office in a locked filing cabinet. No identifiers will be stored with the research data. Only those individuals with an active role in this study will have access to the research data and identifying information. When all participants have completed active participation in the study and data collection is completed, the code will be destroyed. All appropriate measures to protect private information will be taken.
Given the minimal risks for participating in this study, and the steps that will be taken to reduce the risk of injury or a breach of confidentiality, the potential benefits to society

outweigh these risks. This study has the potential to lead to a reduced number of falls, particularly for people at risk of falling.

SECTION H: Subject Incentives/ Compensations

Section Notes…

- H2 & H3. The IRB recognizes the potential for undue influence and coercion when extra credit is offered. The UWM IRB, as also recommended by OHRP and APA Code of Ethics, agrees when extra credit is offered or required, prospective subjects must be given the choice of an equitable, non-research alternative. The extra credit value and the non-research alternative must be described in the recruitment material and the consent form.
- H4. If you intend to submit to Accounts Payable for reimbursement purposes make sure you understand the UWM "Payments to Research Subjects" Procedure 2.4.6 and what each level of payment confidentiality means **(click here for additional information).**

H1. Does this study involve incentives or compensation to the subjects? For example cash, class extra credit, gift cards, or items.

[X] Yes
[__] No [SKIP THIS SECTION]

H2. Explain what (a) the item is, (b) the amount or approximate value of the item, and (c) when it will be given. For extra credit, state the number of credit hours and/or points. (e.g., $5 after completing each survey, subject will receive [item] even if they do not complete the procedure, extra credit will be award at the end of the semester)**:**

Participants will receive a $50 gift card at the completion of the data collection.

H3. If extra credit is offered as compensation/incentive, please describe the specific alternative activity which will be offered. The alternative activity should be similar in the amount of time involved to complete and worth the same number of extra credit points/hours. Other research studies can be offered as additional alternatives, but **a non-research alternative is required**.

H4. If cash or gift cards, select the appropriate confidentiality level for payments (see section notes):

[X] Level 1 indicates that confidentiality of the subjects is not a serious issue, e.g., providing a social security number or other identifying information for payment would not pose a serious risk to subjects.

- For payments over $50, choosing Level 1 requires the researcher to collect and maintain a record of the following: The payee's name, address, and social security number, the amount paid, and signature indicating receipt of payment (for cash or gift cards).
- When Level 1 is selected, a formal notice is not issued by the IRB and the Account Payable assumes Level 1.
- Level 1 payment information will be retained in the extramural account folder at UWM/Research Services and attached to the voucher in Accounts Payable. These are public documents, potentially open to public review.

[__] Level 2 indicates that confidentiality is an issue, but is not paramount to the study, e.g., the participant will be involved in a study researching sensitive, yet not illegal issues.

- Choosing a Level 2 requires the researcher to maintain a record of the following: The payee's name, address, and social security number, the amount paid, and signature indicating receipt of payment (for cash or gift cards).
- When Level 2 is selected, a formal notice will be issued by the IRB.
- Level 2 payment information, including the names, are attached to the PIR and become part of the voucher in Accounts Payable. The records retained by Accounts Payable are not considered public record.

[__] Level 3 indicates that confidentiality of the subjects must be guaranteed. In this category, identifying information such as a social security number would put a subject at increased risk.

- Choosing a Level 3 requires the researcher to maintain a record of the following: research subject's name and corresponding coded identification. This will be the only record of payee names, and it will stay in the control of the PI.
- Payments are made to the research subjects by either personal check or cash. Gift cards are considered cash.
- If a cash payment is made, the PI must obtain signed receipts.
- If the total payment to an individual subject is over $600 per calendar year, Level 3 cannot be selected.

If Confidentiality Level 2 or 3 is selected, please provide justification.

SECTION I: Deception/ Incomplete Disclosure (INSERT “NA” IF NOT APPLICABLE)
Section Notes… • If you cannot adequately state the true purpose of the study to the subject in the informed consent, deception/ incomplete disclosure is involved.

I1. Describe (a) what information will be withheld from the subject (b) why such deception/ incomplete disclosure is necessary, and (c) when the subjects will be debriefed about the deception/ incomplete disclosure.

N/A

Appendix C: Recruitment Flyers

YOUNG ADULTS NEEDED FOR RESEARCH STUDY

Title: Identifying Gait Deficits In Stroke Patients Using Inertial Sensors

Purpose: To understand the gait characteristics that influence foot clearance and the ability to avoid obstacles that could present a tripping hazard, and to detect these falls-related gait abnormalities using a portable inertial sensor.

Who Can Participate?

- Males and Females
- Age 18-45
- Must be able to walk without assistive devices for 5 minutes at a time
- Must be able to follow three-step commands

What Would I Have To Do?

- One Testing Session (2 hours)
  - Fill out questionnaires
  - Perform cognitive, motor, gait and balance evaluations
  - Maximally active your leg muscles against resistance
  - Walk across the floor
  - Walk on a treadmill in 4 different conditions:
    - Normal walking
    - Walking while performing a cognitive task
    - Walking and avoiding an unexpected obstacle
    - Walking and avoiding an unexpected obstacle while performing a cognitive task

Compensation

- $50 gift card

In case of any questions or to volunteer, please contact:

Lauren Benson
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This research project has been approved by the University of Wisconsin-Milwaukee Institutional Review Board for the Protection of Human Subjects (IRB Protocol Number16.153 approved on 11/25/2015)

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OLDER ADULTS
NEEDED FOR RESEARCH STUDY

Title: Identifying Gait Deficits In Stroke Patients Using Inertial Sensors

Purpose: To understand the gait characteristics that influence foot clearance and the ability to avoid obstacles that could present a tripping hazard, and to detect these falls-related gait abnormalities using a portable inertial sensor.

Who Can Participate?

- Males and Females
- Age 65 and over
- Must be able to walk without assistive devices for 5 minutes at a time
- Must be able to follow three-step commands

What Would I Have To Do?

- One Testing Session (2 hours)
  - Fill out questionnaires
  - Perform cognitive, motor, gait and balance evaluations
  - Maximally active your leg muscles against resistance
  - Walk across the floor
  - Walk on a treadmill in 4 different conditions:
    - Normal walking
    - Walking while performing a cognitive task
    - Walking and avoiding an unexpected obstacle
    - Walking and avoiding an unexpected obstacle while performing a cognitive task

Compensation

- $50 gift card

In case of any questions or to volunteer, please contact:

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CHRONIC STROKE PARTICIPANTS NEEDED FOR RESEARCH STUDY

Title: Identifying Gait Deficits In Stroke Patients Using Inertial Sensors

Purpose: To understand the gait characteristics that influence foot clearance and the ability to avoid obstacles that could present a tripping hazard, and to detect these falls-related gait abnormalities using a portable inertial sensor.

Who Can Participate?

- Males and Females
- Experienced a stroke over 6 months ago
- Must be able to walk without assistive devices for 5 minutes at a time
- Must be able to follow three-step commands

What Would I Have To Do?

- One Testing Session (2 hours)
    - Fill out questionnaires
    - Perform cognitive, motor, gait and balance evaluations
    - Maximally active your leg muscles against resistance
    - Walk across the floor
    - Walk on a treadmill in 4 different conditions:
        - Normal walking
        - Walking while performing a cognitive task
        - Walking and avoiding an unexpected obstacle
        - Walking and avoiding an unexpected obstacle while performing a cognitive task

Compensation

- $50 gift card

In case of any questions or to volunteer, please contact:

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Appendix D: Consent Forms
Version 1

UNIVERSITY OF WISCONSIN – MILWAUKEE
CONSENT TO PARTICIPATE IN RESEARCH

THIS CONSENT FORM HAS BEEN APPROVED BY THE IRB FOR A ONE YEAR PERIOD

1. General Information

Study title: Identifying Gait Deficits In Stroke Patients Using Inertial Sensors

Person in Charge of Study (Principal Investigator):
- The Principal Investigator (PI) for this study is Kristian O'Connor, PhD., a faculty member in the Department of Kinesiology. The co-PI on this study is Lauren Benson, a PhD student in the Department of Kinesiology.

2. Study Description

You are being asked to participate in a research study. Your participation is completely voluntary. You do not have to participate if you do not want to.

Study description:
- The purpose is to understand the walking characteristics that influence the risk of falling, and to detect walking characteristics using portable sensors.
- This investigation may reduce the number of falls in stroke patients and people at risk for falling.
- The goals of this study are: to identify the relationship between walking mechanics and foot height during walking; to determine characteristics of walking that enable people to successfully avoid an unexpected tripping hazard; and to detect the risk of tripping using accelerometer signals.
- The study is being done at UW Milwaukee, where there will be 46 participants.
- Participants will be tested during one 2-hour session.

3. Study Procedures

What will I be asked to do if I participate in the study?
If you agree to participate you will be asked to go to the Neuromechanics Laboratory at UW Milwaukee (Enderis Hall, Room 132) for one testing session.
You will be asked to wear clothing appropriate for physical activity; however, clean, tight-fitting shorts will be provided for you during the testing session. The tasks you perform include:

1. You will be given a questionnaire to collect demographic information, as well as information about walking ability, falls history, and fear of falling. Additionally, stroke patients will be asked about the nature of their stroke. (10 minutes)
2. You will be evaluated on your ability to understand and perform the tasks required to complete the study. (5 minutes)
3. You will be asked to put on tight-fitting shorts and a generic pair of athletic shoes, which will be provided for the testing session. (5 minutes)
4. Your ability to produce specific movements and reflexes in your legs will be assessed by a licensed physical therapist. (10 minutes)
5. Your walking and balance ability will be evaluated with a variety of walking and balance tasks. (20 minutes)
6. Electrodes will be applied to the skin above three muscles on each leg. Prior to electrode placement, the skin in that area may need to be shaved, and it will be rubbed with alcohol. These electrodes will track your muscle activity, but you will not feel anything or be harmed in any way by the electrodes. (10 minutes)
7. You will perform three sets of three distinct motions with each leg (straighten knee, bring toes up, bring heel up) against resistance, trying to activate your muscles as much as possible for 5 seconds at a time. (10 minutes)
8. Markers will be applied to your head, trunk, pelvis and both legs at specific landmarks. The location of these markers will be recorded as you stand still. (10 minutes)
9. Lightweight, portable sensors will be attached to your wrists, ankles, thighs and hips. (5 minutes)
10. You will walk at your normal pace along a 10-m walkway 20 times while movement and muscle activity data are recorded. (15 minutes)
11. You will perform a visual task, which will require you to say the direction an arrow is pointing while arrows are presented randomly. (5 minutes)
12. You will be secured in a fall-arrest system that will prevent you from falling. After acclimating to the treadmill and choosing a comfortable walking speed, you will walk at your chosen pace on a treadmill for up to 3 minutes at a time in three different conditions. The order of the conditions will be randomized and include:
    a. Normal walking
    b. Walking while performing the visual task
    c. Walking and avoiding an unexpected obstacle while performing the visual task

    You will be allowed to rest whenever you feel it is necessary. Movement and muscle activity data will be recorded during each trial. (15 minutes)

4. Risks and Minimizing Risks

What risks will I face by participating in this study?

Physical risks

- Muscle soreness as a result of the testing. (Unlikely)
- Injuries such as muscle strain or muscle tightness as a result of the testing session. (Unlikely)
- Injuries such as bruises or cuts due to the risk of falling while walking overground or on the treadmill. (Unlikely)
- Minor skin irritation due to the spray tape adhesive or tape. (Unlikely)

Psychological, social, economic risks

- None

Protection of Physical Risks:

To reduce the above risks, practice trials will be performed prior to data collection to allow you to become familiar with each procedure prior to performing a maximal effort trial. You will be allowed to stop at any point if you feel uncomfortable. You will wear a belt with handles during the functional evaluations, and the evaluator will hold onto the handles in case you lose your balance during the tasks that challenge your walking and balance ability. The fall-arrest system will prevent you from falling to the ground during the treadmill trials, and the emergency stop on the treadmill will be activated in case you stumble. The unexpected obstacle is a lightweight soft foam that can be kicked out of the way or will compress if stepped on. If you feel any soreness or irritation while participating in this study, please tell the investigators as soon as possible. If you are injured while participating in this research study, you will initially be provided care by the investigator(s), who are all trained in first aid and CPR. Students will then be referred to the Norris Health Center for follow-up care. Non-students will be referred to their primary care physician and will be responsible for all expenses incurred.

Risks to Privacy and Confidentiality:

Since your private information will be collected for this study, there is always a risk of breach of confidentiality. (Very unlikely)

Protection of Risks to Privacy and Confidentiality:

All data will be stored in a locked filing cabinet in a locked room. All data will be given a letter and number that is uniquely associated with you. This code will not contain any partial identifiers (i.e. last four digits of your SSN) and will be stored in a separate locked office in a locked filing cabinet. No identifiers will be stored with the research data. Only those individuals with an active role in this study will have access to the research data and only the PI and Co-PI will have access to identifying information. When all participants have completed active participation in the study and data collection is completed, the code will be destroyed. All appropriate measures to protect your private information will be taken.

5. Benefits

Will I receive any benefit from my participation in this study?

There are no benefits to you other than to further research. The information which is obtained may be useful scientifically and possibly helpful to others.

6. Study Costs and Compensation

Will I be charged anything for participating in this study?
You will not be responsible for any of the costs from taking part in this research study. You are responsible for your own transportation to and from UWM and for any parking costs for the testing session.

Are subjects paid or given anything for being in the study?
There is no compensation for participating in this study.

7. Confidentiality

What happens to the information collected?
All information collected about you during the course of this study will be kept confidential to the extent permitted by law. We may decide to present what we find to others, or publish our results in scientific journals or at scientific conferences. Only the PI and co-PI will have access to the information. However, the Institutional Review Board at UW-Milwaukee or appropriate federal agencies like the Office for Human Research Protections may review this study's records. The confidentiality of your data and information will be safeguarded as outlined in "Risks & Minimizing Risks" section under the "Protection of Risks to Privacy and Confidentiality" header.

8. Alternatives

Are there alternatives to participating in the study?
There are no known alternatives available to you other than not taking part in this study.

9. Voluntary Participation and Withdrawal

What happens if I decide not to be in this study?
Your participation in this study is entirely voluntary. You may choose not to take part in this study. If you decide to take part, you can change your mind later and withdraw from the study. You are free to not answer any questions or withdraw at any time. Your decision will not change any present or future relationships with the University of Wisconsin- Milwaukee. If you choose to withdraw, we will use the information collected about you to that point. If you are a student, your refusal to take part in the study will not affect your grade or class standing.

10. Questions

Who do I contact for questions about this study?
For more information about the study or the study procedures or treatments, or to withdraw from the study, contact:

Kristian O'Connor, PhD
Department of Kinesiology
Enderis 471
P.O. Box 413
Milwaukee, WI 53201
414-229-2680

Who do I contact for questions about my rights or complaints towards my treatment as a research subject?
The Institutional Review Board may ask your name, but all complaints are kept in confidence.

Institutional Review Board
Human Research Protection Program
Department of University Safety and Assurances
University of Wisconsin – Milwaukee
P.O. Box 413
Milwaukee, WI 53201
(414) 229-3173

11. Signatures

Research Subject's Consent to Participate in Research:
To voluntarily agree to take part in this study, you must sign on the line below. If you choose to take part in this study, you may withdraw at any time. You are not giving up any of your legal rights by signing this form. Your signature below indicates that you have read or had read to you this entire consent form, including the risks and benefits, and have had all of your questions answered, and that you are 18 years of age or older.

____
Printed Name of Subject/ Legally Authorized Representative

____ ______________________
Signature of Subject/Legally Authorized Representative Date

Principal Investigator (or Designee)
I have given this research subject information on the study that is accurate and sufficient for the subject to fully understand the nature, risks and benefits of the study.

____ ______________________
Printed Name of Person Obtaining Consent Study Role

____ ______________________
Signature of Person Obtaining Consent Date

Version 2

UNIVERSITY OF WISCONSIN – MILWAUKEE
CONSENT TO PARTICIPATE IN RESEARCH

THIS CONSENT FORM HAS BEEN APPROVED BY THE IRB FOR A ONE YEAR PERIOD

1. General Information

Study title: Identifying Gait Deficits In Stroke Patients Using Inertial Sensors

Person in Charge of Study (Principal Investigator):

- The Principal Investigator (PI) for this study is Kristian O'Connor, PhD., a faculty member in the Department of Kinesiology. The co-PI on this study is Lauren Benson, a PhD student in the Department of Kinesiology.

2. Study Description

You are being asked to participate in a research study. Your participation is completely voluntary. You do not have to participate if you do not want to.

Study description:

- The purpose is to understand the walking characteristics that influence the risk of falling, and to detect walking characteristics using portable sensors.
- This investigation may reduce the number of falls in stroke patients and people at risk for falling.
- The goals of this study are: to identify the relationship between walking mechanics and foot height during walking; to determine characteristics of walking that enable people to successfully avoid an unexpected tripping hazard; and to detect the risk of tripping using accelerometer signals.
- The study is being done at UW Milwaukee, where there will be 46 participants.
- Participants will be tested during one 2-hour session.

3. Study Procedures

What will I be asked to do if I participate in the study?

If you agree to participate you will be asked to go to the Neuromechanics Laboratory at UW Milwaukee (Enderis Hall, Room 132) for one testing session.

You will be asked to wear clothing appropriate for physical activity; however, clean, tight-fitting shorts will be provided for you during the testing session. The tasks you perform include:

13. You will be given a questionnaire to collect demographic information, as well as information about walking ability, falls history, and fear of falling. Additionally, stroke patients will be asked about the nature of their stroke. (10 minutes)
14. You will be evaluated on your ability to understand and perform the tasks required to complete the study. (5 minutes)
15. You will be asked to put on tight-fitting shorts and a generic pair of athletic shoes, which will be provided for the testing session. (5 minutes)
16. Your ability to produce specific movements and reflexes in your legs will be assessed by a licensed physical therapist. (10 minutes)
17. Your walking and balance ability will be evaluated with a variety of walking and balance tasks. (20 minutes)
18. Electrodes will be applied to the skin above three muscles on each leg. Prior to electrode placement, the skin in that area may need to be shaved, and it will be rubbed with alcohol. These electrodes will track your muscle activity, but you will not feel anything or be harmed in any way by the electrodes. (10 minutes)
19. You will perform three sets of three distinct motions with each leg (straighten knee, bring toes up, bring heel up) against resistance, trying to activate your muscles as much as possible for 5 seconds at a time. (10 minutes)
20. Markers will be applied to your head, trunk, pelvis and both legs at specific landmarks. The location of these markers will be recorded as you stand still. (10 minutes)
21. Lightweight, portable sensors will be attached to your wrists, ankles, thighs and hips. (5 minutes)
22. You will walk at your normal pace along a 10-m walkway 20 times while movement and muscle activity data are recorded. (15 minutes)
23. You will perform a visual task, which will require you to say the direction an arrow is pointing while arrows are presented randomly. (5 minutes)
24. You will be secured in a fall-arrest system that will prevent you from falling. After acclimating to the treadmill and choosing a comfortable walking speed, you will walk at your chosen pace on a treadmill for up to 3 minutes at a time in three different conditions. The order of the conditions will be randomized and include:
    a. Normal walking
    b. Walking while performing the visual task
    c. Walking and avoiding an unexpected obstacle while performing the visual task

    You will be allowed to rest whenever you feel it is necessary. Movement and muscle activity data will be recorded during each trial. (15 minutes)

4. Risks and Minimizing Risks

What risks will I face by participating in this study?

Physical risks

- Muscle soreness as a result of the testing. (Unlikely)
- Injuries such as muscle strain or muscle tightness as a result of the testing session. (Unlikely)
- Injuries such as bruises or cuts due to the risk of falling while walking overground or on the treadmill. (Unlikely)
- Minor skin irritation due to the spray tape adhesive or tape. (Unlikely)

Psychological, social, economic risks

- None

Protection of Physical Risks:
To reduce the above risks, practice trials will be performed prior to data collection to allow you to become familiar with each procedure prior to performing a maximal effort trial. You will be allowed to stop at any point if you feel uncomfortable. You will wear a belt with handles during the functional evaluations, and the evaluator will hold onto the handles in case you lose your balance during the tasks that challenge your walking and balance ability. The fall-arrest system will prevent you from falling to the ground during the treadmill trials, and the emergency stop on the treadmill will be activated in case you stumble. The unexpected obstacle is a lightweight soft foam that can be kicked out of the way or will compress if stepped on. If you feel any soreness or irritation while participating in this study, please tell the investigators as soon as possible. If you are injured while participating in this research study, you will initially be provided care by the investigator(s), who are all trained in first aid and CPR. Students will then be referred to the Norris Health Center for follow-up care. Non-students will be referred to their primary care physician and will be responsible for all expenses incurred.

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There are no benefits to you other than to further research. The information which is obtained may be useful scientifically and possibly helpful to others.

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Will I be charged anything for participating in this study?
You will not be responsible for any of the costs from taking part in this research study. You are responsible for your own transportation to and from UWM and for any parking costs for the testing session.

Are subjects paid or given anything for being in the study?
You will receive a $50 gift card as compensation for participating in this study.

7. Confidentiality

What happens to the information collected?
All information collected about you during the course of this study will be kept confidential to the extent permitted by law. We may decide to present what we find to others, or publish our results in scientific journals or at scientific conferences. Only the PI and co-PI will have access to the information. However, the Institutional Review Board at UW-Milwaukee or appropriate federal agencies like the Office for Human Research Protections may review this study's records. The confidentiality of your data and information will be safeguarded as outlined in "Risks & Minimizing Risks" section under the "Protection of Risks to Privacy and Confidentiality" header.

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I have given this research subject information on the study that is accurate and sufficient for the subject to fully understand the nature, risks and benefits of the study.

____ ______________________
Printed Name of Person Obtaining Consent Study Role

____ ______________________
Signature of Person Obtaining Consent Date

Appendix E: Questionnaires and Forms

Screening Questionnaire

Please answer the following two questions to the best of your ability. Eligible participants will answer "yes" to the first question and "no" to the second question.

☐ Yes ☐ No Can you walk for five minutes at a time without the use of an assistive device?

☐ Yes ☐ No Are you cognitively impaired such that you cannot follow three-step commands?

Please answer the following questions to determine the study group for which you may be eligible.

☐ Yes ☐ No Have you experienced a stroke more than six months ago?
[If "yes", you qualify for the stroke group. If "no", continue to the next question.]

☐ Yes ☐ No Are you between the ages 18-45?
[If "yes", you qualify for the young adult group. If "no", continue to the next question.]

☐ Yes ☐ No Are you age 65 or older?
[If "yes", continue to the next question. If "no", you are not eligible to participant in this study.]

☐ Yes ☐ No Have you fallen (defined as unintentionally coming to rest on the ground) in the last six months?
[If "yes", you qualify for the falls history group. If "no", you qualify for the no falls history group.]

Comments/Notes:
____

____

____

Demographic Questionnaire

Age	
Gender	
Height	
Weight	
Dominant side (left or right)	
Do you have any difficulties when walking? If so, what?	
Do you use an assistive device or orthotic or brace when walking? If so, what?	
Can you walk for 5 minutes at a time without an assistive device?	
How many times have you fallen in the last 6 months? (A fall is defined as unintentionally coming to rest on the ground.)	

Stroke Patients Only	
Type of stroke (ischemic or hemorrhagic)	
Time since stroke	
Location of lesion	
Affected side	
Dominant side before stroke	

Frenchay Activities Index (FAI)

In the last 3 months, how often have you undertaken:

Preparing main meals	Never	Less than once a week	1-2 times per week	Most days
Washing up after meals	Never	Less than once a week	1-2 times per week	Most days
Washing clothes	Never	1-2 times in 3 months	3-12 times in 3 months	At least weekly
Light housework	Never	1-2 times in 3 months	3-12 times in 3 months	At least weekly
Heavy housework	Never	1-2 times in 3 months	3-12 times in 3 months	At least weekly
Local shopping	Never	1-2 times in 3 months	3-12 times in 3 months	At least weekly
Social occasions	Never	1-2 times in 3 months	3-12 times in 3 months	At least weekly
Walking outside for > 15 minutes	Never	1-2 times in 3 months	3-12 times in 3 months	At least weekly
Actively pursuing a hobby	Never	1-2 times in 3 months	3-12 times in 3 months	At least weekly
Driving a car/going on a bus	Never	1-2 times in 3 months	3-12 times in 3 months	At least weekly

In the last 6 months, how often have you undertaken:

Travel outing/car ride	Never	1-2 times in 6 months	3-12 times in 6 months	At least weekly
Gardening	Never	1-2 times in 6 months	3-12 times in 6 months	At least weekly
Household maintenance	Never	Light	Moderate	Heavy/All necessary
Reading books	None	1 in 6 months	Less than 1 in 2 weeks	More than 1 every 2 weeks
Gainful work	None	Up to 10 hours/week	10-30 hours/week	Over 30 hours/week

Swedish Modification of the Falls Efficacy Scale (FES-S)

Not confident at all					Fairly confident					Completely confident
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**

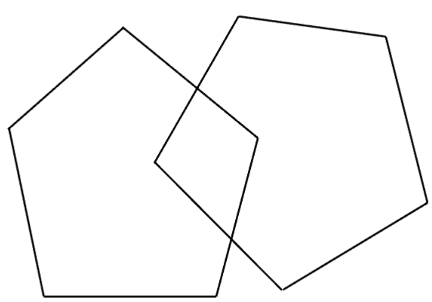
On a scale of 0-10, how confident are you that you do the following activities without falling?	Confidence
Get in and out of bed	
Get on and off the toilet	
Personal grooming	
Get in and out of chair	
Get dressed and undressed	
Take a bath or a shower	
Go up and down stairs	
Walk around neighborhood	
Reach into cupboards/closets	
Housecleaning	
Prepare simple meals	
Answer the telephone	
Simple shopping	

Activities-specific Balance Confidence (ABC)

No confidence										**Completely confident**
0%	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100%**

How confident are you that you will not lose your balance or become unsteady when you…	**Confidence**
Walk around the house	
Walk up or down stairs	
Bend over and pick up a slipper from the front of a closet floor	
Reach for a small can off a shelf at eye level	
Stand on your tip toes and reach for something above your head	
Stand on a chair and reach for something	
Sweep the floor	
Walk outside the house to a car parked in the driveway	
Get into or out of a car	
Walk across a parking lot to the mall	
Walk up or down a ramp	
Walk in a crowded mall where people rapidly walk past you	
Are bumped into by people as you walk through the mall	
Step onto or off of an escalator while you are holding onto a railing	
Step onto or off of an escalator while holding onto parcels such that you cannot hold onto the railing	
Walk outside on icy sidewalks	

Mini-Mental State Examination

Questions	**Possible**	**Score**
"What is the year? Season? Date? Day of the week? Month?"	5	
"Where are we now: State? County? Town/city? Building? Floor?"	5	
The examiner names three unrelated objects clearly and slowly, then asks the patient to name all three of them. The patient's response is used for scoring. The examiner repeats them until patient learns all of them, if possible. *[flag, water, shirt]* Number of trials: ____________	3	
"I would like you to count backward from 100 by sevens." (93, 86, 79, 72, 65, …) Stop after five answers. Alternative: "Spell WORLD backwards." (D-L-R-O-W)	5	
"Earlier I told you the names of three things. Can you tell me what those were?"	3	
Show the patient two simple objects, such as a wristwatch and a pencil, and ask the patient to name them.	2	
"Repeat the phrase: 'No ifs, ands, or buts.'"	1	
"Take the paper in your right hand, fold it in half, and put it on the floor." (The examiner gives the patient a piece of blank paper.)	3	
"Please read this and do what it says." (Written instruction is "Close your eyes.")	1	
"Make up and write a sentence about anything." (This sentence must contain a noun and a verb.)	1	
"Please copy this picture." (The examiner gives the patient a blank piece of paper and asks him/her to draw the symbol below. All 10 angles must be present and two must intersect.) 	1	
TOTAL	30	

Functional Evaluation

Task	**Description**	**Possible**	**Score**
Sitting down	Unsafe (misjudged distance, falls into chair)	0	
	Uses arms or not a smooth motion	1	
	Safe, smooth motion	2	
Sitting Balance	Lean or slides in chair	0	
	Steady, safe	1	
Arises: “Cross your arms across your chest. Try not to use your hands unless you must. Do not let your legs lean against the back of the chair when you stand. Please stand up now.”	Unable without help	0	
	Able, uses arms to help	1	
	Able without using arms	2	
Attempts to rise	Unable without help	0	
	Able, requires > 1 attempt	1	
	Able to rise, 1 attempt	2	
Immediate standing balance (first 5 seconds)	Unsteady (swaggers, moves feet, trunk sway)	0	
	Steady but uses walker or other support	1	
	Steady without walker or other support	2	
Standing balance	Unsteady	0	
	Steady but wide stance (medial heels > 4 inches apart) and uses cane or other support	1	
	Narrow stance without support	2	
Nudged (subject at max position with feet as close together as possible, examiner pushes lightly on subject’s sternum with palm of hand 3 times)	Begins to fall	0	
	Staggers, grabs, catches self	1	
	Steady	2	
Eyes closed (at maximum position)	Unsteady	0	
	Steady	1	
Turning 360°	Discontinuous steps	0	
	Continuous steps	1	
	Unsteady (grabs, swaggers)	0	
	Steady	1	

Task	Description	Possible	Score
Rise to toes: “Place your feet shoulder width apart. Place your hands on your hips. Try to rise as high as you can onto your toes. I will count out loud to 3 seconds. Try to hold this pose for at least 3 seconds. Look straight ahead. Rise now.” [allow 2 attempts, score best]	< 3 s	0	
	Heels up, but not full range (smaller than when holding hands), OR noticeable instability for 3 s	1	
	Stable for 3 s with maximum height	2	
Stand on one leg: “Look straight ahead. Keep your hands on your hips. Lift your leg off of the ground behind you without touching or resting your raised leg upon your other standing leg. Stay standing on one leg as long as you can. Look straight ahead. Lift now.” [allow 2 attempts each side, score best attempt from worst side]	Unable	0	
	< 20 s	1	
	20 s	2	
Compensatory stepping correction - forward: “Stand with your feet shoulder width apart, arms at your sides. Lean forward against my hands beyond your forward limits. When I let go, do whatever is necessary, including taking a step, to avoid a fall.” [hands on shoulders, shoulders and hips in front of toes]	No step, OR would fall if not caught, OR falls spontaneously	0	
	More than one step used to recover equilibrium	1	
	Recovers independently with a single, large step (realignment step OK)	2	
Compensatory stepping correction - backward: “Stand with your feet shoulder width apart, arms at your sides. Lean backward against my hands beyond your backward limits. When I let go, do whatever is necessary, including taking a step, to avoid a fall.” [hands on scapulae, hips behind heels]	No step, OR would fall if not caught, OR falls spontaneously	0	
	More than one step used to recover equilibrium	1	
	Recovers independently with a single, large step	2	
Compensatory stepping correction - lateral: “Stand with your feet together, arms down at your sides. Lean into my hand beyond your sideways limit. When I let go, do whatever is necessary, including taking a step, to avoid a fall.” [test both sides, score lowest]	Falls, or cannot step	0	
	Several steps to recover equilibrium	1	
	Recovers independently with 1 step (crossover or lateral OK)	2	

Task	Description	Possible	Score
Stance (feet together); eyes open, firm surface: "Place your hands on your hips. Place your feet together until almost touching. Look straight ahead. Be as stable and still as possible, until I say stop."	Unable	0	
	< 30 s	1	
	30 s	2	
Stance (feet together); eyes closed, foam surface: "Step onto the foam. Place your hands on your hips. Place your feet together until almost touching. Be as stable and still as possible, until I say stop. I will start timing when you close your eyes."	Unable	0	
	< 30 s	1	
	30 s	2	
Incline - eyes closed: "Step onto the incline ramp. Please stand on the incline ramp with your toes toward the top. Place your feet shoulder width apart and have your arms down at your sides. I will start timing when you close your eyes."	Unable	0	
	Stands independently < 30 s OR aligns with surface	1	
	Stands independently 30 s and aligns with gravity	2	
Timed up & go with dual task: "When I say 'go', stand up from chair, walk at your normal speed across the tape on the floor, turn around and come back to sit in the chair." "Count backwards by threes starting at _________. When I say 'go', stand up from chair, walk at your normal speed across the tape on the floor, turn around and come back to sit in the chair. Continue counting backwards the entire time."	Stops counting while walking OR stops walking while counting	0	
	Dual task affects either counting OR walking (>10%) when compared to without dual task	1	
	No noticeable change in sitting, standing or walking for dual task compared to without dual task	2	
		TUG time	
		Dual task time	

Task	Description	Possible	Score
Gait level surface: “When I say go, walk at your normal speed from here to the mark” [10 m, time middle 6 m]	Cannot walk 6 m without assistance, severe gait deviations or imbalance, deviates greater than 15 in outside 12-in walkway	0	
	Walks 6 m, slow speed, abnormal gait pattern, evidence for imbalance, deviates 10-15 in outside 12-in walkway	1	
	5.5-7 s, uses assistive device, slower speed, mile gait deviations, deviates 6-10 in outside 12-in walkway	2	
	< 5.5 s, no assistive devices, good speed, no evidence for imbalance, normal gait pattern, deviates 0-6 in outside 12-in walkway	3	
		Time 1	
		Time 2	
		Time 3	
Fast walking speed: “When I say go, walk as fast as you safely can from here to the mark” [10 m, time middle 6 m]		Time 1	
		Time 2	
		Time 3	

ALSO FILL OUT EVALUATION ON NEXT PAGE

Task	Description	Possible	Score
Gait evaluation: Initiation of gait	Any hesitancy or multiple attempts to start	0	
	No hesitancy	1	
Gait evaluation: Step length and height	Right swing foot does not pass left stance foot with step	0	
	Right foot passes left stance foot	1	
	Right foot does not clear floor completely with step	0	
	Right foot completely clears floor	1	
	Left swing foot does not pass right stance foot with step	0	
	Left foot passes right stance foot	1	
	Left foot does not clear floor completely with step	0	
	Left foot completely clears floor	1	
Gait evaluation: Step Symmetry	Right and left step length not equal (estimate)	0	
	Right and left step appear equal	1	
Gait evaluation: Step Continuity	Stopping or discontinuity between steps	0	
	Steps appear continuous	1	
Path (estimated in relation to 12-in width)	Marked deviation	0	
	Mild/moderate deviation or uses walking aid	1	
	Straight without walking aid	2	
Trunk	Marked sway or uses walking aid	0	
	No sway but flexion of knees or back, or spreads arms out while walking	1	
	No sway, no flexion, no use of arms, and no use of walking aid	2	
Walking stance	Heels apart	0	
	Heels almost touching while walking	1	

Task	Description	Possible	Score
Change in gait speed: "Begin walking at your normal speed. When I say 'fast', walk as fast as you can. When I say 'slow', walk as slowly as you can." [3 steps each]	Cannot change speeds, deviates greater than 15 in outside 12-in walkway, or loses balance and needs assistance	0	
	Makes only minor adjustments to walking speed, or accomplishes a change in speed with significant gait deviations, deviates 10-15 in outside 12-in walkway, or changes speed but loses balance, but is able to recover	1	
	Is able to change speed but demonstrates mild gait deviations, deviates 6-10 in outside 12-in walkway, or no gait deviations but unable to achieve a significant change in velocity, or uses an assistive device	2	
	Able to smoothly change walking speed without loss of balance or gait deviation. Shows a significant difference in walking speeds. Deviates 0-6 in outside 12-in walkway.	3	

Task	Description	Possible	Score
Gait with horizontal head turns: "Begin walking at your normal speed. When I say 'right', turn your head and look to the right. When I say 'left', turn your head and look to the left. Try to keep walking in a straight line." [3 steps each; 2 turns each side]	Severe disruption of gait, loses balance, stops, needs assistance, deviates greater than 15 in outside 12-in walkway	0	
	Performs head turns with moderate change in gait velocity, slows down, deviates 10-15 in outside 12-in walkway, but recovers	1	
	Performs head turns smoothly with slight change in gait velocity, deviates 6-10 in outside 12-in walkway, or uses an assistive device	2	
	Performs head turns smoothly with no change in gait. Deviates 0-6 in outside 12-in walkway.	3	
Gait with vertical head turns: "Begin walking at your normal speed. When I say 'up', tip your head up. When I say 'down, tip your head down. Try to keep walking in a straight line." [3 steps each; 2 turns each direction]	Severe disruption of gait, loses balance, stops, needs assistance, deviates greater than 15 in outside 12-in walkway	0	
	Performs head turns with moderate change in gait velocity, slows down, deviates 10-15 in outside 12-in walkway, but recovers	1	
	Performs head turns smoothly with slight change in gait velocity, deviates 6-10 in outside 12-in walkway, or uses an assistive device	2	
	Performs head turns smoothly with no change in gait. Deviates 0-6 in outside 12-in walkway.	3	

Task	Description	Possible	Score
Gait and pivot turn: "Begin walking at your normal speed. When I say 'turn and stop', turn as quickly as you can to face the opposite direction and stop." [time after saying 'turn']	Cannot turn safely, requires assistance to turn and stop	0	
	Turns slowly, requires verbal cueing, or requires several small steps to catch balance following turn and stop	1	
	Turns safely in > 3 s and stops with no loss of balance, or turns safely in < 3 s and stops with mild imbalance, requires small steps to catch balance	2	
	Turns safely < 3 s and stops quickly with no loss of balance	3	
Step over obstacle: "Begin walking at your normal speed. When you come to the shoe box, step over it, not around it, and keep walking." [2 boxes at 6 m, 9 in. total height]	Cannot perform without assistance	0	
	Is able to step over one shoe box but must slow down and adjust steps to clear box safely. May require verbal cueing.	1	
	Is able to step over one shoe box without changing gait speed, no evidence of imbalance	2	
	Is able to step over two shoe boxes without changing gait speed, no evidence of imbalance	3	
Gait with narrow base of support: "Walk with arms folded across chest, feet aligned heel to toe in tandem." [count steps up to 10]	< 4 steps or cannot perform without assistance	0	
	4-7 steps	1	
	7-9 steps	2	
	10 steps with no staggering	3	

Task	Description	Possible	Score
Gait with eyes closed: “Walk at your normal speed with your eyes closed” [time after ‘go’; 6 m (20 ft)]	Cannot walk 6 m without assistance, severe gait deviations or imbalance, deviates greater than 15 in outside 12-in walkway, or will not attempt task	0	
	Walks 6 m, slow speed, abnormal gait pattern, evidence for imbalance, deviates 10-15 in outside 12-in walkway. > 9 seconds	1	
	Walks 6 m, uses assistive device, slower speed, mild gait deviations, deviates 6-10 in outside 12-in walkway. 7-9 s	2	
	Walks 6 m, no assistive devices, good speed, no evidence of imbalance, normal gait pattern, deviates 0-6 in outside 12-in walkway. < 7 s	3	
Ambulating backwards: “Walk backwards until I tell you to stop.” [6 m (20 ft)]	Cannot walk 6 m without assistance, severe gait deviations or imbalance, deviates greater than 15 in outside 12-in walkway, or will not attempt task	0	
	Walks 6 m, slow speed, abnormal gait pattern, evidence for imbalance, deviates 10-15 in outside 12-in walkway	1	
	Walks 6 m, uses assistive device, slower speed, mild gait deviations, deviates 6-10 in outside 12-in walkway	2	
	Walks 6 m, no assistive devices, good speed, no evidence for imbalance, normal gait pattern, deviates 0-6 in outside 12-in walkway	3	
Steps: “Walk up these stairs as you would at home (i.e. using the rail if necessary). At the top, turn around and walk down.”	Cannot do safely	0	
	Two feet to a stair, must use rail	1	
	Alternating feet, must use rail	2	
	Alternating feet, no rail	3	

Lower Extremity Fugl-Meyer

Test	Item	Description	Possible	Score
Reflex Activity	Achilles	No reflex activity can be elicited	0	
		Reflex activity can be elicited	2	
	Patellar	No reflex activity can be elicited	0	
		Reflex activity can be elicited	2	
Flexor Synergy (in supine)	Hip flexion	Cannot be performed at all	0	
		Partial motion	1	
		Full motion	2	
	Knee flexion	Cannot be performed at all	0	
		Partial motion	1	
		Full motion	2	
	Ankle dorsiflexion	Cannot be performed at all	0	
		Partial motion	1	
		Full motion	2	
Extensor Synergy (in side lying)	Hip extension	Cannot be performed at all	0	
		Partial motion	1	
		Full motion	2	
	Adduction	Cannot be performed at all	0	
		Partial motion	1	
		Full motion	2	
	Knee extension	Cannot be performed at all	0	
		Partial motion	1	
		Full motion	2	
	Ankle plantar flexion	Cannot be performed at all	0	
		Partial motion	1	
		Full motion	2	

Test	Item	Description	Possible	Score
Movement combining synergies (sitting: knees free of chair)	Knee flexion beyond 90°	No active motion	0	
		From slightly extended position, knee can be flexed, but not beyond 90°	1	
		Knee flexion beyond 90°	2	
	Ankle dorsiflexion	No active flexion	0	
		Incomplete active flexion	1	
		Normal dorsiflexion	2	
Movement out of synergy (standing, hip at 0°)	Knee flexion	Knee cannot flex without hip flexion	0	
		Knee begins flexion without hip flexion, but does not reach to 90°, or hip flexes during motion	1	
		Full motion as described	2	
	Ankle dorsiflexion	No active motion	0	
		Partial motion	1	
		Full motion	2	
Normal Reflexes (sitting) [This item is only included if the patient achieves a maximum score on all previous items, otherwise score 0]	Knee flexors Patellar Achilles	At least 2 of the 3 phasic reflexes are markedly hyperactive	0	
		One reflex is markedly hyperactive, or at least 2 reflexes are lively	1	
		No more than one reflex is lively and none are hyperactive	2	
Coordination/speed - Sitting: Heel to opposite knee (5 repetitions in rapid succession)	Tremor	Marked tremor	0	
		Slight tremor	1	
		No tremor	2	
	Dysmetria	Pronounced or unsystematic dysmetria	0	
		Slight or systematic dysmetria	1	
		No dysmetria	2	
	Speed	Activity is more than 6 seconds longer than unaffected side	0	
		2-5.9 seconds longer than unaffected side	1	
		Less than 2 seconds difference	2	

Strength Evaluation

Exercise	Trial	Right Leg	Left Leg
Knee extension	Trial 1		
	Trial 2		
	Trial 3		
Plantar flexion	Trial 1		
	Trial 2		
	Trial 3		
Dorsiflexion	Trial 1		
	Trial 2		
	Trial 3		

Rating of Perceived Exertion

6	
7	Very, very light
8	
9	Very light
10	
11	Fairly light
12	
13	Somewhat hard
14	
15	Hard
16	
17	Very hard
18	
19	Very, very hard
20	

Appendix F: Visual Task Performance Factor Analysis

A factor analysis was done in an attempt to reduce the number of variables representing the visual task performance construct. Factors were extracted using Principle Axis Factoring with a varimax rotation and Kaiser normalization.

The factors extracted during the factor analysis of the visual task performance measures accounted for 69.73% of the variance (Table 30). Factor 1 represented the response time during the obstacle condition, while factors 2 and 3 represented response time during walking. Factor 4 represented the percent of correct responses during the obstacle condition. Group differences in visual task performance were evaluated using the highest-loading variable for each of the four extracted factors: number of responses and mean time for the walking condition, and mean time and percent correct for the obstacle condition.

Table 30

Extracted Factors and the High Loadings (> 0.5) of Each Measure of Visual Task Performance in Two Walking Conditions Relative to Baseline Performance

Condition	Variable	Factor			
		1	2	3	4
Treadmill Walking	Number of responses		-0.720		
	Mean time		0.574	0.705	
	Max time			0.842	
	Min time		0.573		
	Percent correct				
Obstacle	Number of responses	-0.802	-0.567		
	Mean time	0.903			
	Max time	0.875			
	Min time				
	Percent correct				0.912

Appendix G: Accelerometer Feature Extraction Principal Components Analysis

Principal Components Analysis was used to identify major modes of variation within the swing phase sagittal plane lower extremity joint angles and the accelerometer signal during swing in each of the three axes. Visual inspection of the retained principal components (PCs) of the hip, knee and ankle waveforms revealed the PCs relevant to each peak joint angle and range of motion (Table 31). Each stride for all participants and all walking conditions (N = 20093) was given a score for each of the retained angle and accelerometer PCs. Bivariate correlations were done for each angle-accelerometer pair of PCs. For each relevant angle PC, the accelerometer PCs with the greatest correlation coefficients were chosen as features for that angle. The chosen accelerometer PCs were interpreted with discrete variables that could be extracted from the accelerometer signal (Table 32).

Table 31

Retained PCs of the Swing Phase Sagittal Plane Joint Angles

Joint	PC	Feature Represented
Hip	1*	Magnitude throughout swing
	2*	Range of motion
Knee	1*	Magnitude throughout swing
	2*	Range of motion
	3	Timing of peak
	4	Magnitude at beginning and end of swing
Ankle	1*	Magnitude throughout swing
	2*	Range of motion
	3	Timing of peak
	4*	Magnitude at end of swing

* PC is relevant to angle peak or range of motion.

Table 32

Retained PCs of the Swing Phase Accelerometer Signals Correlated with Peak and Range of Motion Angle PCs

Axis	PC	Feature Represented	Feature Discrete Variables
X	1	Magnitude throughout swing	Mean, Max
	2	Timing of peak	Mean First 50%, Value at 50%, 75%
	3	Timing of peak	Mean First 50%, Value at 50%, 75%
Y	1	Magnitude/timing of peak	Max
	2	Magnitude of peak and at end of swing	Max, Value at 100%
	3	Timing of peak	Value at 50
	4	One peak or two peaks	Number of Peaks
Z	1	Magnitude throughout swing	Mean, Max
	2	Magnitude/timing of peak	Value at 60%, 80%
	3	Magnitude of trough	Min, Value at 50%
	4	Number of oscillations	Zero Cross Rate
	6	Timing of peak	Mean First 25%

Note. Percentages refer to percent of swing.

Appendix H: Trip Prevalence Calculation

The prevalence of trips among older adults (age 65 and older) was calculated based on the reported number of trips in four studies (W. P. Berg et al., 1997; Blake et al., 1988; Robinovitch et al., 2013; Talbot et al., 2005). For each study, prevalence was calculated at the number of participants that tripped divided by the total number of participants (Table 33). The prevalence was averaged across all four studies to get a mean prevalence of tripping for older adults. In two cases, the number of participants that tripped was estimated based on the assumption that the average number of falls per faller was the same rate as the number of trips per tripper.

Table 33

Calculation of Prevalence of Trips Based on Studies Reporting Number of Trips for Older Adults

Study	Number of Incidents		Number of Participants			Prevalence of trips
	Falls	Trips	Fallers	Trippers	Total	
Blake et al. (1988)				147	1042	0.14
Berg, et al. (1997)	91	31[a]	50	17[b]	96	0.18
Talbot et al. (2005)				125	589	0.21
Robinovitch et al. (2013)	227	48	130	27[c]	371	0.07
Average						0.15

[a] 34% of falls were classified as a trip.

[b] Average number of falls per faller: 91/50 = 1.82;
Estimated number of participants that tripped: 31/1.82 = 17.

[c] Average number of falls per faller: 227/130 = 1.75;
Estimated number of participants that tripped: 48/1.75 = 27.

Curriculum Vitae

EDUCATION

University of Wisconsin-Milwaukee, Milwaukee, WI Expected date of graduation: August 2016
Degree Program: PhD in Health Sciences
Major: Biomechanics

University of Wisconsin-Milwaukee, Milwaukee, WI Date of graduation: May 2013
Degree Program: Master's in Kinesiology
Major: Biomechanics

Amherst College, Amherst, MA Date of graduation: May 2008
Honors: cum laude, Sigma Xi
Major: Chemistry

RESEARCH EXPERIENCE

University of Wisconsin-Milwaukee, Milwaukee, WI September 2011-present
PhD Dissertation: "Identifying Gait Deficits in Stroke Patients Using Inertial Sensors"
- Quantify deficits in stroke gait using machine learning applied to accelerometer signals.

Research Assistant
- Investigate biomechanical factors of sports injuries, such as fatigue, orthotics, balance training.
- Developed software to score and produce reports for injury-risk assessment of all UWM athletes.

Master's Thesis: "The Effect of Fatigue on Intra-Limb Joint Coordination Variability during Running Using a Waveform Analysis Approach"
- Examined the effect of running in an exerted state on joint coordination variability of runners.

Amherst College, Amherst, MA September 2007-May 2008
Honors Thesis: "A Fluorescence Spectroscopy Investigation of Ruthenium Anticancer Compounds"
- Synthesized ruthenium-based compounds that mimicked an anticancer drug.
- Examined ruthenium compound interactions with proteins by fluorescence spectroscopy.

National Cancer Institute, Frederick, MD May 2007-August 2007
Amherst College Kauffman Fellowship
- Investigated the pathway of degradation for the tumor suppressor *Programmed cell death 4*.

FUNDING

International Society of Biomechanics December 2015
The Matching Dissertation Grant Program
- Recipient of **$2000** award, "Identifying Gait Deficits in Stroke Patients Using Inertial Sensors".

University of Wisconsin-Milwaukee, Milwaukee, WI November 2012-present
College of Health Sciences Student Research Grant
- Recipient of **$1900** award, "Identifying Gait Deficits in Stroke Patients Using Inertial Sensors".
- Recipient of **$2000** award, "The Effect of Balance Training on Knee Kinematics and Kinetics for Athletes with Previous Overuse Knee Injury".
- Recipient of **$500** award, "The Effect of Fatigue on Intra-Limb Joint Coordination Variability during Running Using a Waveform Analysis Approach".

PUBLICATIONS

1. **Benson, L. C.**, Almonroeder, T.G., & O'Connor, K. M. Balance exercises with only anterior-posterior motion may be best suited for overuse knee injury rehabilitation. *Human Movement Science*, Submitted for publication.
2. Almonroeder, T. G. & **Benson, L. C.** Gender Differences in Lower Extremity Kinematics and Patellofemoral Kinetics During Running. *Journal of Sports Sciences*, Submitted for publication.
3. Almonroeder, T. G., **Benson, L. C.**, & O'Connor, K. M. (2015). The effect of a prefabricated foot orthotic on lower extremity mechanics during running in individuals with varying rearfoot dynamics. *Journal of Orthopaedic & Sports Physical Therapy*, Accepted for publication.
4. Almonroeder, T. G., **Benson, L. C.**, & O'Connor, K. M. (2015). Changes in patellofemoral joint stress during running with the application of a prefabricated foot orthotic. *International Journal of Sports Physical Therapy*, *10*(7), 967.
5. Almonroeder, T. G., **Benson, L. C.**, & O'Connor, K. M. (2015). The effect of a prefabricated foot orthotic on frontal plane joint mechanics in healthy runners. *Journal of Applied Biomechanics*, *31*(3).
6. **Benson, L.** & O'Connor, K. (2015). Running in an exerted state: mechanical effects. *Lower Extremity Review*, *7*(10).
7. **Benson, L. C.**, & O'Connor, K. M. (2015). The effect of exertion on joint kinematics and kinetics during running using a waveform analysis approach. *Journal of Applied Biomechanics, 31*(4), 250-257.
8. O'Connor, K. M., Johnson, C., & **Benson, L. C.** (2015). The effect of isolated hamstrings fatigue on landing and cutting mechanics. *Journal of Applied Biomechanics*, *31*(4), 211-220.
9. Almonroeder, T. G., **Benson, L. C.**, & O'Connor, K. M. (2015). The effect of a prefabricated foot orthotic on frontal plane joint mechanics in healthy runners. *Journal of Applied Biomechanics, 31*(3), 149-158. doi:10.1123/JAB.2014-0100
10. Blees, J. S., Schmid, T., Thomas, C. L., Baker, A. R., **Benson, L.**, Evans, J. R., . . . Henrich, C. J. (2010). Development of a high-throughput cell-based reporter assay to identify stabilizers of tumor suppressor Pdcd4. *Journal of Biomolecular Screening, 15*(1) doi: 10.1177/1087057109351028
11. Bringmann, G., Ruedenauer, S., Bruhn, T., **Benson, L.**, & Brun, R. (2008). Total synthesis of the antimalarial naphthylisoquinoline alkaloid 5-epi-4 '-O-demethylancistrobertsonine C by asymmetric suzuki cross-coupling. *Tetrahedron, 64*(23) doi: 10.1016/j.tet.2008.03.087

PRESENTATIONS

1. **Benson, L.**, Cobb, S., Hyngstrom, A., Keenan, K., Luo, J., & O'Connor, K. (2016). Predicting walking foot clearance from sagittal plane joint coordination. Abstract for podium and poster presentations, **Second Place in Student Competition** University of Wisconsin-Milwaukee College of Health Sciences Spring Research Symposium, Milwaukee, WI
2. **Benson, L.**, Almonroeder, T., & O'Connor, K.M. (2015). Making it count: using number of touch-downs during eyes closed single-leg stance to evaluate balance performance. Abstract for podium and poster presentations, University of Wisconsin-Milwaukee College of Health Sciences Fall Research Symposium, Milwaukee, WI
3. **Benson, L.** & O'Connor, K.M. (2015). Assessment of knee mechanics and muscle activity during balance exercises. Abstract for poster presentation, Annual Meeting of the American Society of Biomechanics, Columbus, OH
4. **Benson, L.** & O'Connor, K.M. (2015). Assessment of knee mechanics and muscle activity during balance exercises. Abstract for podium and poster presentations, **Second Place in Student Competition** University of Wisconsin-Milwaukee College of Health Sciences Spring Research Symposium, Milwaukee, WI

PRESENTATIONS CONTINUED

5. Almonroeder, T., **Benson, L.**, & O'Connor, K.M. (2015). The effect of a foot orthotic on frontal plane joint mechanics during running in groups with varying rearfoot motion. Abstract for poster presentation. American Physical Therapy Association Combined Sections Meeting, Indianapolis, IN
6. **Benson, L.**, & O'Connor, K.M. (2014). The effect of fatigue on joint kinematics during running using a waveform analysis approach. Abstract for poster presentation, **Finalist in the International Master's Student Paper Competition**, World Congress of Biomechanics, Boston, MA
7. Almonroeder, T., **Benson, L.**, & O'Connor, K.M. (2015). The effect of a prefabricated foot orthotic on frontal plane joint mechanics during running. Abstract for poster presentation, World Congress of Biomechanics, Boston, MA
8. **Benson, L.**, & O'Connor, K.M. (2014). The effect of fatigue on joint kinematics during running using a waveform analysis approach. Abstract for podium and poster presentations, University of Wisconsin-Milwaukee College of Health Sciences Spring Research Symposium, Milwaukee, WI
9. Almonroeder, T., **Benson, L.**, & O'Connor, K.M. (2014). The effect of a prefabricated foot orthotic on frontal plane joint mechanics during running. Abstract for podium and poster presentations, University of Wisconsin-Milwaukee College of Health Sciences Spring Research Symposium, Milwaukee, WI
10. **Benson, L.**, & O'Connor, K.M. (2013). The effect of fatigue on intra-limb joint coordination variability during running using a waveform analysis approach. Abstract for podium and poster presentations, University of Wisconsin-Milwaukee College of Health Sciences Spring Research Symposium, Milwaukee, WI
11. **Benson, L.**, & O'Hara, P.B. (2008). A fluorescence spectroscopy investigation of ruthenium anticancer compounds. Abstract for poster presentation. Smith College Intercollegiate Poster Session, Northampton, MA

TEACHING EXPERIENCE

University of Wisconsin-Milwaukee, Milwaukee, WI — September 2011-December 2015

Kinesiology Department Ad hoc Instructor (Spring and Fall 2014, Fall 2015)

- Developed lessons for and instruct students in undergraduate Biomechanics course.

Kinesiology Department Lecture and Laboratory Teaching Assistant (2011-12 and 2012-13)

- Led two laboratory sections per semester in Biomechanics.
- Assisted students during lectures and out of class in introductory Kinesiology courses.

Center for Talented Youth, Baltimore, MD — Summers 2009, 2011, 2012

Chemistry Instructor

Williston Northampton School, Easthampton, MA — August 2008-June 2011

Chemistry Teacher
Head of Track & Field Program
Assistant Varsity Field Hockey Coach
Assistant Varsity and JV Skiing Coach
Dorm Head
Advisor
Athletic Committee, Williston+ Task Force, Classroom Technology Project

Amherst College, Amherst, MA — September 2005-May 2008

Chemistry Department Lecture and Laboratory Teaching Assistant, Tutor

PROFESSIONAL EXPERIENCE

Exercise Instructor, Milwaukee, WI September 2015-present

- Lead biweekly exercise class for older adults.

USA Field Hockey, Colorado Springs, CO October 2013-June 2013

Head Futures Coach, Wisconsin

- Coached elite field hockey student-athletes in the state of Wisconsin.

University School of Milwaukee, River Hills, WI August 2012-October 2016

Head Varsity Reserve/JV Field Hockey Coach

- Coached student-athletes in varsity- and JV-level field hockey

Nomads Field Hockey Club, Northampton, MA December 2008-March 2011

U-19/U-14 Coach

- Coached a local indoor field hockey team in tournaments throughout New England and nationally.

PROGRAMMING SKILLS

Titanium Certified Developer December 2013-present

- Certified to create and distribute mobile applications for all smart phones.

MATLAB September 2011-present

- Proficient in using MATLAB to create custom software for data analyses.

AWARDS

University of Wisconsin-Milwaukee, Milwaukee, WI May 2013-present

- Distinguished Graduate Student Fellowship awarded to UWM's most academically excellent graduate students (2015-16)
- College of Health Sciences Alumni Chapter Scholarship for strong academic work (2015-16)
- Chancellor's Graduate Student Award for scholarly activity in the College of Health Sciences (2014-15)
- Georgio Sanna Memorial Scholarship for graduate studies in Kinesiology (2013-2014 and 2014-2015)

Amherst College, Amherst, MA May 2006-May 2008

- Everett H. Pryde Research Award for outstanding teaching assistance and research (2008)
- Computer Center Prize for outstanding contributions in the Computer Center (2008)
- Eugene Wilson Award for preeminent student-athlete in sportsmanship at Amherst (2008)
- Samuel Bowles Prize for proficiency in journalism (2008)
- Sphinx Spoon Award for student that best promotes Amherst Athletics (2005-06, 2006-07)
- Friends of Amherst Field Hockey Award (2007)
- Friends of Amherst Track and Field Award (2007-08)
- NESCAC All-Sportsmanship team for Field Hockey (2007)
- NESCAC All-Sportsmanship team for Track and Field (2007-08)
- NESCAC and NFHCA All-Academic team for Field Hockey (2006, 2007)
- NESCAC All-Academic team for Indoor (2007, 2008) and Outdoor Track and Field (2007, 2008)

LEADERSHIP ROLES

University of Wisconsin-Milwaukee, Milwaukee, WI
2012-present

- President of Kinesiology Graduate Association (2013-present)
- Vice President of Kinesiology Graduate Association (2012-2013)
- Black & Gold Committee representative to the College of Health Sciences (2012-present)

Metro Milwaukee Women's Ice Hockey, Milwaukee, WI September 2013-March 2014

- Captain of traveling women's ice hockey team

LEADERSHIP ROLES CONTINUED

Amherst College, Amherst, MA September 2006-May 2008

- Tri-Captain of varsity field hockey team (2007)
- Tri-Captain of varsity track and field indoor and outdoor teams (2007-08)
- President/Founder of Student-Athlete Advisory Committee (SAAC) (2007-08, 2006-07)
- Chair/Vice Chair of New England Small College Athletic Conference SAAC (2007-08, 2006-07)
- Editor-in-Chief of weekly school newspaper. (2006-07)

RECENT VOLUNTEER WORK

Fuel Up. Go! Fitness and Nutrition, Milwaukee, WI April 2013-October 2014
Strength and Conditioning Intern

- Organize weekly metabolic circuit conditioning workouts to help people reach their fitness goals.

University School of Milwaukee, River Hills, WI March 2013-May 2013
Volunteer Track & Field Coach

- Coached student-athletes in track and field.

Aurora Sports Medicine Institute, Milwaukee, WI
Fall 2012
Volunteer

- Prepared treatment areas and assisted Physical Therapists with patient visits.

Kingo Lutheran Church, Shorewood, WI October 2011-May 2015
Tutor

- Assist disadvantaged students with homework and study skills.

INTERESTS

Running

- Compete in races at distances from 5K to marathon. (2008-present)

Ice hockey

- Member of the Metro Milwaukee traveling women's ice hockey team. (2011-2014)
- Member of the Pioneer Valley Vipers traveling women's ice hockey team. (2009-2011)

Music

- Member of the Milwaukee American Legion Band trumpet section. (2013-present)

Traveling

- Toured 18 countries during a nine-week around the world excursion. (Summer 2010)