ABSTRACT

BOHLEN, PETER ALEXANDER. Paving the Road for Real Time Fall Prevention (Under the direction of Dr. He (Helen) Huang).

Individuals with gait deficits often experience difficulty walking. These difficulties include unsuccessful foot clearance while walking or failed recovery from an unexpected perturbation. With the development of new measurement systems and assistive devices, it is possible to identify situations where an individual is at high risk of fall and intervene to mitigate the risk in real time. This fall prevention approach is called real-time fall prevention. Two studies were completed to better understand how real-time fall prevention methods can be better employed to reduce the risk of falling.

Functional electrical stimulation (FES) is an example of a real-time fall prevention device used to treat toe drop in individuals with Stroke or Multiple Sclerosis. However questions remain about when FES or similar devices should be implemented in order to avoid fatigue. The initial study presented in this thesis explores predicting intrinsically caused trips (ICTs) before they occur in individuals with chronic stroke. Subjects walked at a constant speed on a treadmill while their lower limb gait kinematics and force plate data were collected. Twelve of the individuals demonstrated ICTs during the treadmill walking. The stance phase gait kinematics of the twelve individuals were segmented, sorted and then analyzed to explore the feasibility of predicting ICTs before they occured. Potential sources were then tested using an outlier-based algorithm. The initial findings of the study found that ICT prediction was feasible 50-260ms before the ICTs occurred using only two sources from the lower limb kinematics. While further work is needed to make our design practical for clinical purposes, the outcome suggests that the implementation of real-time fall prevention methods such as FES may be possible.

Another question that remains for improving real-time fall prevention is how to avoid falls when an individual is at high risk after a perturbation. Amputees rely on their prosthetic device to respond appropriately to a trip, but different environmental factors yield different levels of disturbance and thus makes recovery difficult. The second study used a simple dynamic simulation to better understand the relationship between environmental factors and level of disturbance caused by tripping. Our results suggest that the level of disturbance experienced after a collision is heavily impacted by environmental factors. Additionally, the results suggest that trips occurring in mid to late swing phase may force the foot to make contact with the ground. The relationships observed in this study may help researchers to better understand the difficulties faced in trip recovery procedures for amputees. Additionally, these results will lead towards the development of prosthesis controllers to assist in fall prevention in real-time.

The results from the two studies presented in this thesis will be useful for improving real-time fall prevention methods, thus reducing the risk of unexpected falls for people who show declined upright gait stability.

Paving the Road for Real Time Fall Prevention

by
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BIOGRAPHY

Peter Alexander Bohlen was born on January 26, 1988 in a small town in rural Illinois. He spent much of his youth outdoors, building forts, exploring creeks, and getting into trouble. After graduating from college, Peter worked at Vanderbilt University building custom devices to aid in his labs research efforts. Upon moving back to North Carolina to continue his education, he and his wife bought a 1940s farmhouse that they have been slowly renovating from the foundation up. He enjoys competitive sports, board games with friends, working with his hands, and spending time exploring the world with his incredible wife, Nicole.

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Study Two Experimental Tripping Data: We would like to acknowledge providence VA Medical Center and Dr. Susan D'Andrea for providing the experimental tripping data that was used for study two.

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I. Introduction

Walking is an activity of daily living (ADL) that healthy individuals often take for granted. Besides providing an individual the means to move about, walking is also associated with a great amount of physical and mental health benefits [1]. However, for individuals with gait deficits, ambulation is difficult and even un-safe. The World Health Organization (WHO) estimates that 37.3 million falls each year require medical attention [2]. The WHO further estimates that yearly 424,000 individuals who fall do not survive, making falling the second leading cause of unintentional injury death in the world behind auto-accidents [2].

The consequences of falling in any population are severe with high psychological [3] and physical costs [4]. The psychological costs can include anxiety about walking in public, fear of exploring new places, mistrust of assistive devices, and fear of falling. The physical costs may include broken bones, soft tissue injuries, hospitalization, decreased mobility, greater disability or even death. Additionally, it is estimated that approximately $34 billion is spent annually on fall related medical bills [5]. Because the cumulative costs of falling can be so high it is unsurprising that a great deal of research has been done towards the development of programs and physical therapy routines to aid individuals in the prevention of falls.

Many of the programs towards fall prevention are designed to reduce the risk of fall and increase the capacity to recovery from unexpected disturbance. One of the simplest approaches to reducing the risk of fall is to modify the environment an individual interacts with. Programs that emphasize environment modification use inspections and hazard-reduction efforts to reduce the risk of falls [6]. A second type of program stresses modifying

the individual rather than the environment. Programs that highlight a combination of large doses of exercise and challenging balance exercises such as Thai Chi or Stay Active and Independent for Life have been found to effectively decrease fall rates [7], [8], [9], [10]. Although both of these approaches are effective, they are preventive approaches that do not always provide protection when the subject is facing a scenario with a high risk of falling.

Newly developed measurement systems and assistive devices make it possible to identify scenarios with high risk and intervene to mitigate the risk of fall in real time. We call this strategy: real time fall prevention. However, major questions still remain for real time fall prevention: when should these fall prevention interventions be introduced and what is the most effective way to prevent falls when an individual faces a high risk of fall. Two pilot studies were conducted to pave the road for solving the challenges faced by the real time fall prevention in two specific cases. The first study explores predicting real-time risk of fall in individuals with chronic stroke and the second study explores how environmental factors affect the level of disturbance experienced from a foot-object collision with the goal of advanced prosthesis control. Though each of the studies only focus on an application on a specific population, our hope is that the results of this research may be translational, and assist in fall prevention in additional populations as well.

II. Study One: Can Intrinsically Caused Tripping Events in Stroke Survivors be Predicted?

Note

The work presented in study one, *Prediction of Intrinsically Caused Tripping Events in Individuals with Stroke* has been submitted for review to the IEEE journal *Transactions on Neural Systems and Rehabilitation Engineering*. My contributions to this work include the data pre-processing, analysis, and manuscript preparation of methods and results sections under the guidance of Dr. Helen Huang, Dr. Michael Lewek, and Dr. Fan Zhang.

Introduction

Stroke is a condition that affects 700,000 American patients every year, and is characterized by a region of poor blood flow in the brain resulting in cell death [11]. After suffering a stroke, an individual will typically have neurological deficiencies that lead to gait abnormalities. Gait alterations include, but are not limited to: decreased walking speed, reduced foot clearance, and spatiotemporal gait asymmetry [12]. As a result of the altered gait patterns, falls become much more common in individuals with stroke [12]. A high risk of falling after stroke has been reported during a hospital stay and after discharge. The incidence of falls in inpatient settings has ranged from 14% to as high as 64.5% [13]. Several reports have documented the incidence, risk factors, and consequences of falls for community-dwelling people with stroke as well. In the community, the incidence of one-time falls varies from 23% to 73%, with multiple fall rates ranging from 12% to 47% [14]. Because stroke affects so many individuals, it is clear that finding a solution to assist walking stability and prevent falls is needed.

In order to better understand how to prevent falls, a better understanding of what causes falls must be established. Two different risk factors play a role in falls; extrinsic and intrinsic. Extrinsic factors that lead to falls are typically caused by unpredictable environmental factors that are difficult to traverse. Intrinsic factors include physiological impairments. Intrinsic factors for individuals with stroke are challenging because hemi-paretic gait impairments can affect individuals dramatically differently. Fortunately, despite the differences amongst individuals, there are many common kinematic patterns observed including reductions in hip, knee, and ankle flexion during swing [15], [16], [17]. The resultant combination of the altered lower limb kinematics is a functionally longer limb during swing, which reduces foot clearance during swing phase [18].

These unsuccessful foot clearances caused by intrinsic abnormalities in neuro-motor control during the late stance and early swing phase of gait (also called intrinsically-caused trips (ICT) in this study) are undesirable because they can contribute to stumbles and falls. The critical question we seek to answer is if these ICT's can be predicted before they occur. If prediction of such events is possible, assistive devices (e.g. FES or exoskeletons) may be used to preemptively initiate recovery strategies to prevent falls. The outcomes of this study are expected to inform the future design of assistive devices that can eliminate ICT-caused stumbling and falls and therefore enhance the mobility and stability of individuals with stroke.

Methods

A. Participants

This study was conducted with the approval of the Institutional Review Board (IRB) at the University of North Carolina at Chapel Hill and informed consent was obtained for all subjects. Data were collected from subjects with chronic hemiparesis at least six months post stroke from a larger study examining gait kinematics and kinetics during treadmill ambulation [19], [20]. Each of the subjects showed sensory motor dysfunction consistent with an ischemic or hemorrhagic unilateral brain lesion. Any subjects that required an ankle foot orthosis (AFO) for safe ambulation were excluded or subjects with comorbidities that prevented unassisted walking on a treadmill were excluded from this study. Additionally, subjects were excluded if they had any history of falls, or balance deficits unrelated to the stroke.

Twelve out of forty recruited subjects were observed to demonstrate ICTs in treadmill walking during the experiments. Data was collected from these 12 subjects whose demographic information is summarized in Table I.

TABLE I: Summary of Demographic Information for Twelve Subjects with Chronic Stroke

Subject Number	Age	Gender	Height (inches)	Weight (lbs)	Time since Stroke (month)	Paretic Side	Overground Walking Speed (m/s)	Fugl-Meyer Score
01	54	M	71.5	185	20	R	1.02	25
02	81	F	63	115	18	R	0.47	24
03	57	M	70	175	31	R	0.56	28
04	60	M	74	224	9	R	0.94	26
05	60	F	66	148	222	L	1.15	31
06	41	M	75	205	6	R	0.53	22
07	71	M	63	209	8	L	0.78	28
08	44	M	70	145	43	L	0.68	21
09	53	M	71	165	37	L	1.11	27
10	44	F	64	189	59	L	0.49	16
11	53	F	66	144	19	R	1.23	27
12	48	F	68	215	48	L	0.51	23

B. Experimental Measurements and Protocol

Reflective markers were placed in clusters mounted to rigid thermoplastic shells to the subjects' pelvis, thighs, and shanks. Additional markers were placed over the 2nd metatarsal head, at the 5th metatarsal head, and on the heel counter to track the motion of the feet. Additionally markers were placed at the malleoli, femoral condyles, greater trochanter and bilateral iliac crests to determine the ends of limb segments as described in [21]. Motion data from the lower limb was recorded using an 8-camera motion capture system (Vicon, Denver, CO, USA) at 120 Hz. Ground reaction forces (GRF) were recorded from a dual belt

instrumented treadmill (Bertec Corp., Columbus, OH, USA) and sampled at 960 Hz. The trajectory of markers and GRF data were low-pass filtered at 6Hz and 20Hz respectively. Segment orientations and joint angles were computed by Visual 3D (C-Motion, Germantown, MD, USA).

During the experiments the walking sessions were monitored by Physical therapists, who selected a speed that the participant could maintain for the entirety of the session, targeting 70% of maximum heart rate or a score of 14 on the Borg Rating of Perceived Exertion Scale. The subjects were then asked to walk for 20 minutes at a fixed speed on the treadmill. In order to prevent a fall during walking, each subject wore a harness that did not restrict lower limb movement or provide unweighting. During the experiments, assistive devices were not allowed and the use of treadmill hand rails was discouraged.

C. Data Segmentation

All the collected data were manually segmented before analysis using customized scripts in Matlab. Gait cycles with unsuccessful foot clearance were first sorted by identifying vertical GRFs that exceeded 10N during swing phase on the paretic side. An example that demonstrates the sorting is illustrated in Figure 1 (top), in which the red curve indicated the presence of a vertical GRF when the unsuccessful foot clearance occurred in the swing phase. We then further sorted the unsuccessful foot clearance events into ICTs and 'scuffs'. ICTs were defined as naturally occurring unsuccessful foot clearances that elicited notable recovery reaction in the subjects. The reaction to ICTs was reflected by the dramatic pattern change of the foot's center of gravity in the vertical direction (as demonstrated by the red curve in Figure 1 (bottom)). Note that scuffs were not studied because they did not actually perturb the subject's

balance. Because our goal was to make early predictions of ICTs, we only analyzed data prior to ICTs. In this study, we focused on the last 10% of the stance phase of the paretic leg (immediately prior to the toe-off preceding each ICT). Toe-off was ideal because it is easily identifiable using GRF data in real-time. Additionally, the data in the gait cycles with successful foot clearance (indicated as non-ICT in this study) were segmented and used for building and evaluating the predictive model. Due to the potential confounding effect of a trip recovery process occurring over multiple gait cycles, we avoided using non-ICT data for the four gait cycles following any unsuccessful foot clearance event for analysis.

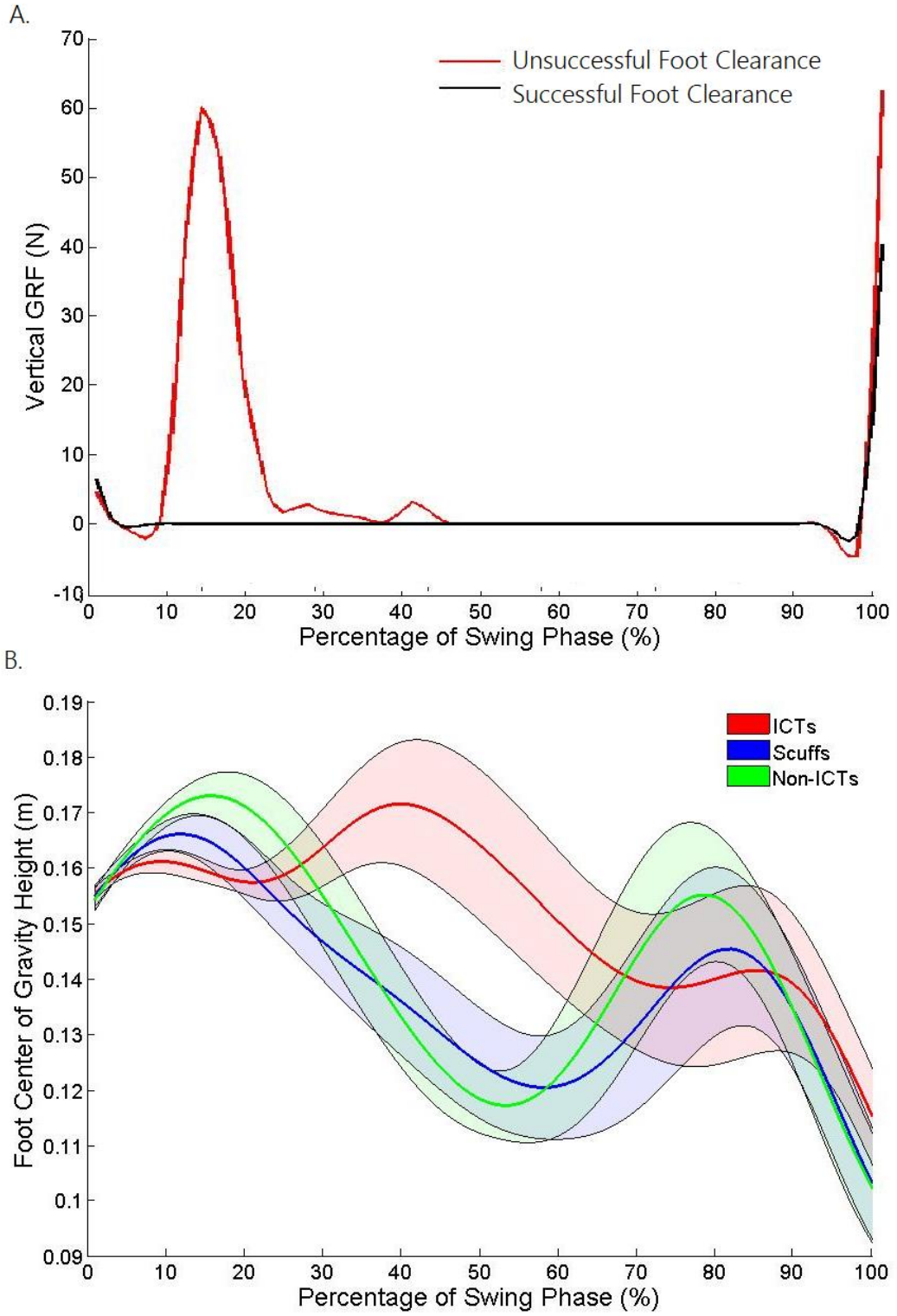

Figure 1: (Top)) One example of identifying an unsuccessful foot clearance based on ground reaction force during swing phase. (Bottom) Pattern change of height of foot's center of gravity when ICT occurred versus successful clearance and scuffs.

D. Investigated Data Sources and Source Selection Analysis

For this study, only kinematics were considered as potential data sources for ICT prediction. The reason for this is because kinematic information is easily measurable in the community with wearable sensors. Sixty unique kinematic measurements from each leg were included in this study. These sources included 9 segmental orientations ($Thigh_{x, y, z}$, $Shank_{x, y, z}$, $Foot_{x, y, z}$), 7 joint angles ($Hip_{x, y, z}$, $Knee_{x}$, $Ankle_{x, y, z}$), and the angular velocities and accelerations derived from these segmental and joint angles. The subscripts *x*, *y*, and *z* represent angular data from the sagittal plane, frontal plane and transverse plane, respectively. Additionally, we included 3 measures of limb length ($LL_{x,y,z}$), which were measured in Visual 3D using estimates of the hip joint center to the center of gravity of the foot. Lastly, the foot's center of gravity vertical position ($Foot_{COG\_z}$), velocity ($Foot'_{COG\_z}$), and acceleration ($Foot''_{COG\_z}$) were included as sources. The foot's center of gravity was directly obtained from Visual 3D software using measures of the subjects' foot and marker placement. The foot's elevation velocity and acceleration were derived from the first and second time derivative.

In order to find the most informative data sources for ICT prediction, source selection analysis was performed on all the considered data sources. We used two efficient and commonly used source selection approaches: a wrapper method and a filter method [22]. In order to use a wrapper method, a pre-determined prediction algorithm is required to be in place to measure the discriminability of sources. Sequential forward selection (SFS) is one of the most common wrapper methods used. Unlike wrapper methods, filter methods need no prediction algorithm in place. Instead, they use discriminating criteria, such as correlation coefficients [23] and mutual information [24] to rank sources. Minimum-redundancy-

maximum-relevance (mRMR) is a type of discriminating criteria that simultaneously considers the redundancy and relevance of sources [24]. Both methods have been successfully applied to source or feature selection for estimation of user intent and movement state for prosthesis control [25], [26], [27]. Comparing both methods, we found that bother methods were efficient in selecting critical sources for user intent recognition [27]. In our study, we used and compared these two source selection methods: SFS and mRMR. The source selection for accurate ICT prediction was conducted on the data collected from all the subjects and/or the data from each individual subject.

The SFS algorithm is initialized with two data source sets: the selected set, *A*, which was initially empty; and the remaining set, *B*, which included all the considered data sources. In the first iteration, each individual source was used for ICT prediction using our prediction algorithm. The data source that yielded the highest prediction performance was added into set *A* and removed from set *B*. In the following rounds, each remaining source in set *B* was combined with sources already selected in set *A* and evaluated for ICT prediction. The source that generated the highest prediction performance was selected and added into set *A* and removed from set *B*. Only one source was selected in each iteration and this procedure was repeated until all the data sources were selected. The sequence in which the sources were selected determined the rank of the sources in terms of their importance for ICT prediction.

The mRMR approach was also used to determine a rank of sources for the ICT prediction. To simultaneously maximize the relevance and minimize the redundancy among data sources, the mRMR approach selected data sources based on the mRMR score which was defined as:

$$mRMR = D_{BC} / D_{WC} \tag{1}$$

Distance between case, or D_{BC}, represented the Euclidean distance [28] of data source (d) between two difference cases (i.e. ICT and non-ICT); Distance within case, or D_{WC}, denoted the Euclidean distance of data source (d) within the same case (either ICT or non-ICT). They were calculated as following:

$$D_{BC} = \frac{1}{n*m}\sum_{i=1}^{n}\sum_{j=1}^{m} dist(d_{ICT}^{i}, d_{non-ICT}^{j}) \quad (2)$$

$$D_{WC} = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} dist(d_{ICT}^{i}, d_{ICT}^{j}) + \sum_{k=1}^{m-1}\sum_{l=k+1}^{m} dist(d_{non-ICT}^{k}, d_{non-ICT}^{l}) \quad (3)$$

where n was the number of gait cycles containing ICT; m was the number of gait cycles containing non-ICT; and *dist* represented the Euclidean distance. The sources were then ranked based on the descending order of mRMR scores for each individual subject. The larger the mRMR score was, the more useful the data source was for ICT prediction. In order to use mRMR across multiple subjects, sources were ranked by calculating the frequency of occurrence of each possible source from the top 15 sources across each subject of interest.

E. ICT Prediction Algorithm

Mahalanobis distance (M-distance) was used to distinguish gait cycles with or without ICTs in this study. The M-distance based algorithm was used because (1) it is a widely used algorithm for prediction/detection problem [29], (2) the computational efficiency of this algorithm makes it practical for real-time implementation, and (3) this prediction strategy only requires a normal dataset (i.e. non-ICTs) to build the predictive model in real application, which enhances its practical value. In order to use M-distance, features that represented the characteristics of each data source were extracted from each individual source. In this study, a

set of third-order polynomial regression coefficients were used as the features for each data source [30]. The feature set from each data source was then concatenated into a single feature vector for prediction. Data that was associated with successful foot clearances (i.e. non-ICT) were used to build the normal model. The M-distance from a new observation to the normal model was calculated and compared to a pre-defined threshold to predict an ICT. The threshold was determined based on the maximum value of M-distance derived from observations in the normal model multiplied by a scale factor. In order to generate the receiver operatic characteristic (ROC) curve used to evaluate prediction performance, different prediction thresholds were tested. The optimal threshold was chosen based on the ROC curve to guarantee high prediction accuracy and low false alarm rate.

F. Evaluation of Prediction Performance

Two different evaluation metrics were used to quantify the prediction performance: (1) the area under the ROC curve (AUROC) [31], and (2) prediction time. An ROC curve is a graph where the y-axis represents the prediction accuracy and the x-axis denotes the false alarm rate. AUROC is a metric that indicates overall prediction performance. An ROC curve represented by a diagonal line with an area of .5 suggests that two data sets are inseparable, whereas an ROC curve with area of 1 suggests that data two data sets are completely separable. The prediction accuracy (y-axis) measures the percentage of correctly predicted ICTs in the total number of ICTs. The false alarm rate (x-axis) quantifies the ratio of the successful foot clearances that were falsely predicted as ICTs to the total number of the successful foot clearances. Prediction time was defined as the time elapsed from the moment that an ICT was

correctly predicted (toe-off) to the time that the ICT actually happened. A positive time value indicates that the ICT was predicted before the ICT occurred.

The occurrence of ICT and non-ICT gait cycles varied across subjects. One hundred and ten non-ICT gait cycles for each subject were randomly selected. Ten of the non-ICT gait cycles were left out as catch-trial data, and the remaining 100 non-ICT trials were used as the normal data set. The distance of ICT and catch-trial from the normal set were measured and recorded. Then, a new rotation was initiated using 10 new catch data and a new normal dataset. Figure 2 shows a sample histogram of non-ICT, ICT and catch trial M-Distances from a single rotation. A total of 11 rotations were performed, using all 110 non-ICT cycles as catch-trial data just once. ROC analysis was then performed on the cumulative catch trial and ICT distances to get the AUROC. This cross validation process was repeated 30 times, randomly selecting 110 new non-trip trials, and repeating analysis to get an average AUROC for each source to reduce noise in the data.

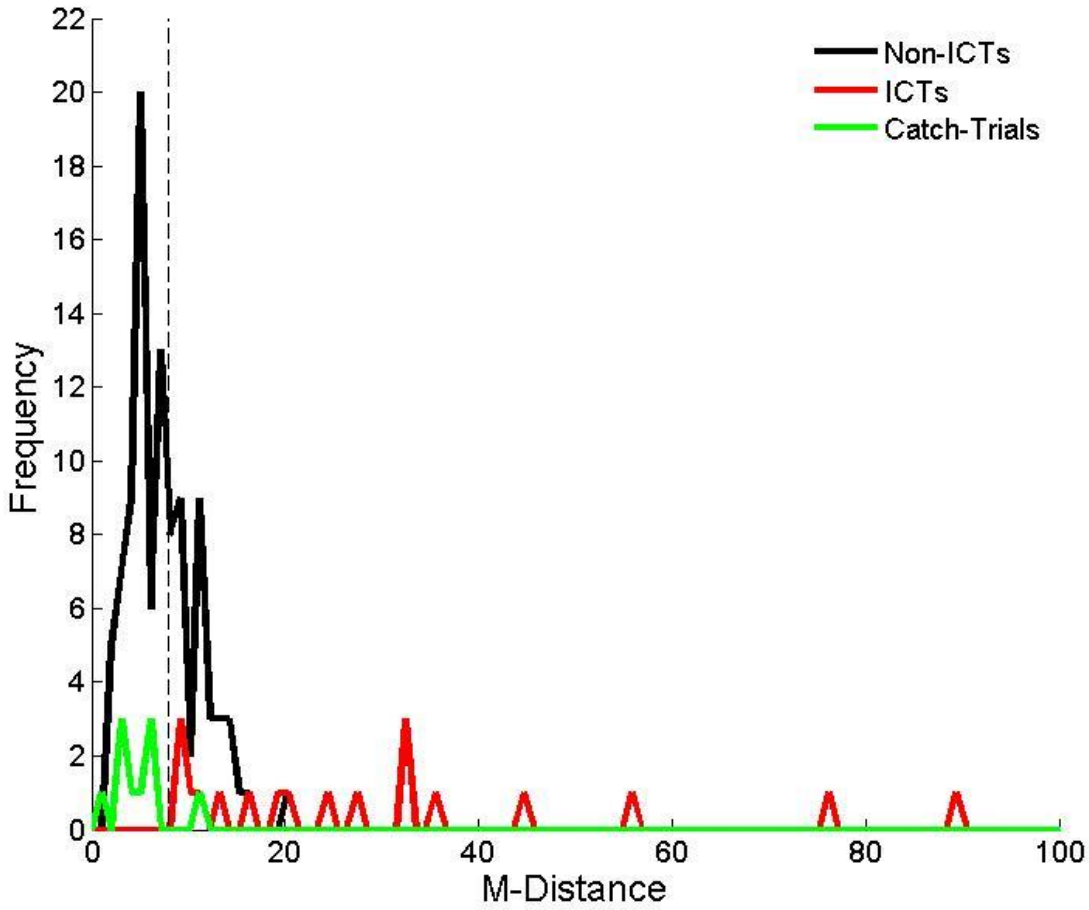

Figure 2: Histogram of ICT and Catch-Trial distances to Non-ICT data. M-distances of the Non-ICT data to itself are shown as well for reference. ICTs or Catch trials above an M-Distance threshold are predicted to be ICT's. Data below the threshold are predicted to not be ICTs. For this example, a threshold M-distance of 8 shown as a dashed line would predict all ICTs correctly (Prediction accuracy of 1) with only a single catch trial labeled as an ICT (False alarm rate of 0.1).

Results

A. Generalized Source Selection Results: Sequential Forward Selection Method

The sequential forward selection algorithm was initially applied on the data collected from the paretic limbs from all 12 subjects. In each selection iteration, the data source, which in combination with previously selected data sources generated the highest averaged value of AUROC across all the subjects, was defined as the important data source for ICT prediction. It was observed that for 3 out of 12 subjects (Subject 03-05), AUROC values were significantly lower if the data sources selected based on all 12 subjects were used for ICT prediction. Therefore, in this study, these three subjects were treated as outlier subjects in the following analysis. The aforementioned forward selection procedure was repeated on the data collected from the remaining 9 subjects. Results from the first rotation of the generalized sequential forward selection are shown in Table II. The mean AUROC values for the first rotation of the SFS gives us the rank of each source if it were used alone.

TABLE II: Sequential Forward Selection First Rotation Source Ranking

Source	Mean AUROC
$Shank_x$	0.915
$Foot_{COG\_z}$	0.912
$Foot''_{COG\_z}$	0.909
$Foot_{COG'\_z}$	0.906
LL_z	0.899
$Shank'_x$	0.888
$Foot_x$	0.884
$Knee_x$	0.878
$Shank''_x$	0.863
$Shank_y$	0.856

The sources selected based on the averaged results across these 9 subjects were defined as the generalized sources in this study. Figure 3 shows the first 6 generalized sources from the SFS selection algorithm. The black curve indicated the averaged AUROC value across the 9 subjects. Higher values indicate better prediction performance. It can be seen that as the number of selected data sources increased, the prediction performance initially improved dramatically and then gradually saturated or even decreased. We used the value of 0.95 as a threshold for picking the number of sources, which selected two data sources as the most informative sources, including the paretic shank angle in the sagittal plane (i.e. $Shank_x$) and the elevation velocity of the paretic foot's center of gravity of (i.e. $Foot'_{COG\_z}$).

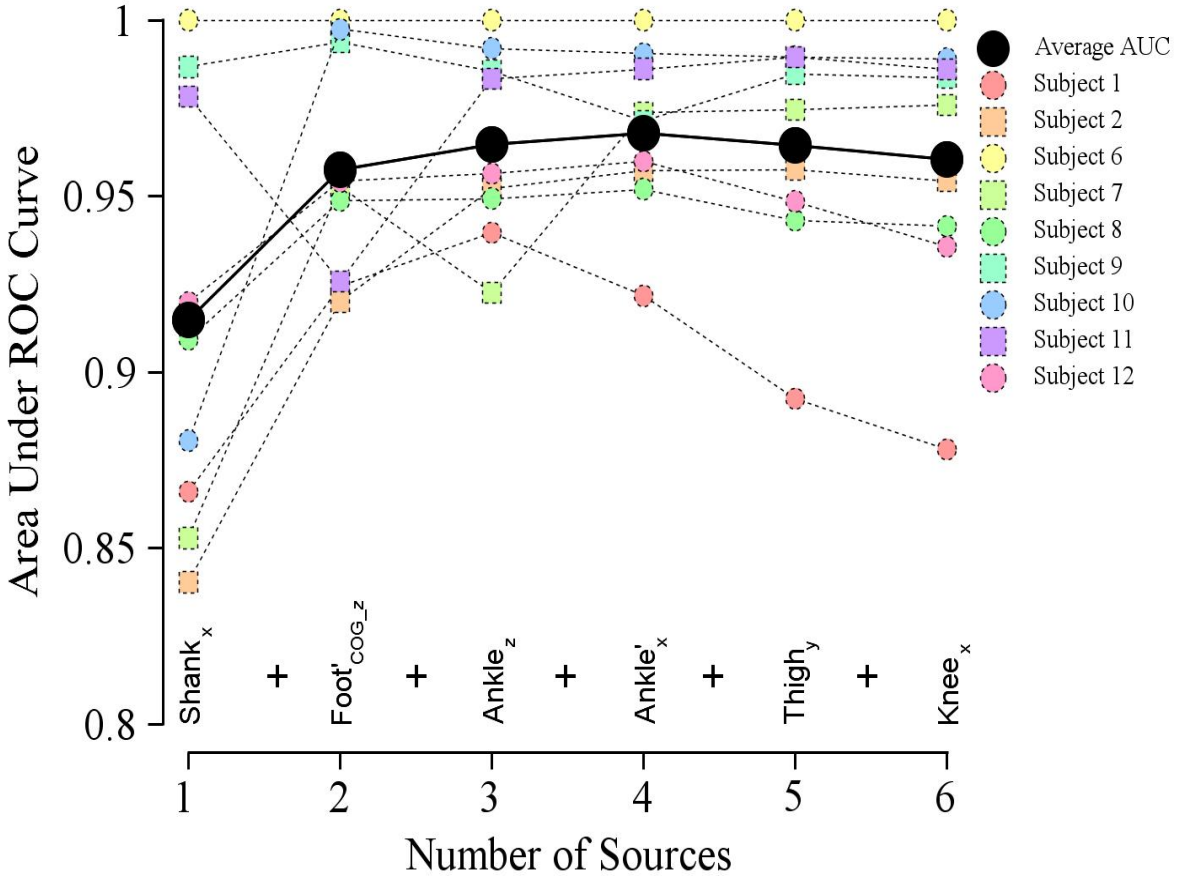

Figure 3: Generalized sequential forward selection results for 9 subjects. The black solid line indicates the averaged AUROC across the 9 subjects.

The ROC curve of ICT prediction using the top 2 data sources generalized from 9 subjects was shown in Figure 4. The top left corner of the ROC curve is the point where prediction accuracy reaches 100% and false alarm rate equals 0%, which represents an ideal prediction performance. The closer the ROC curve gets to the top left corner, the better the prediction performance is overall. The range of ROC curves across all 9 subjects was highlighted in the shaded area.

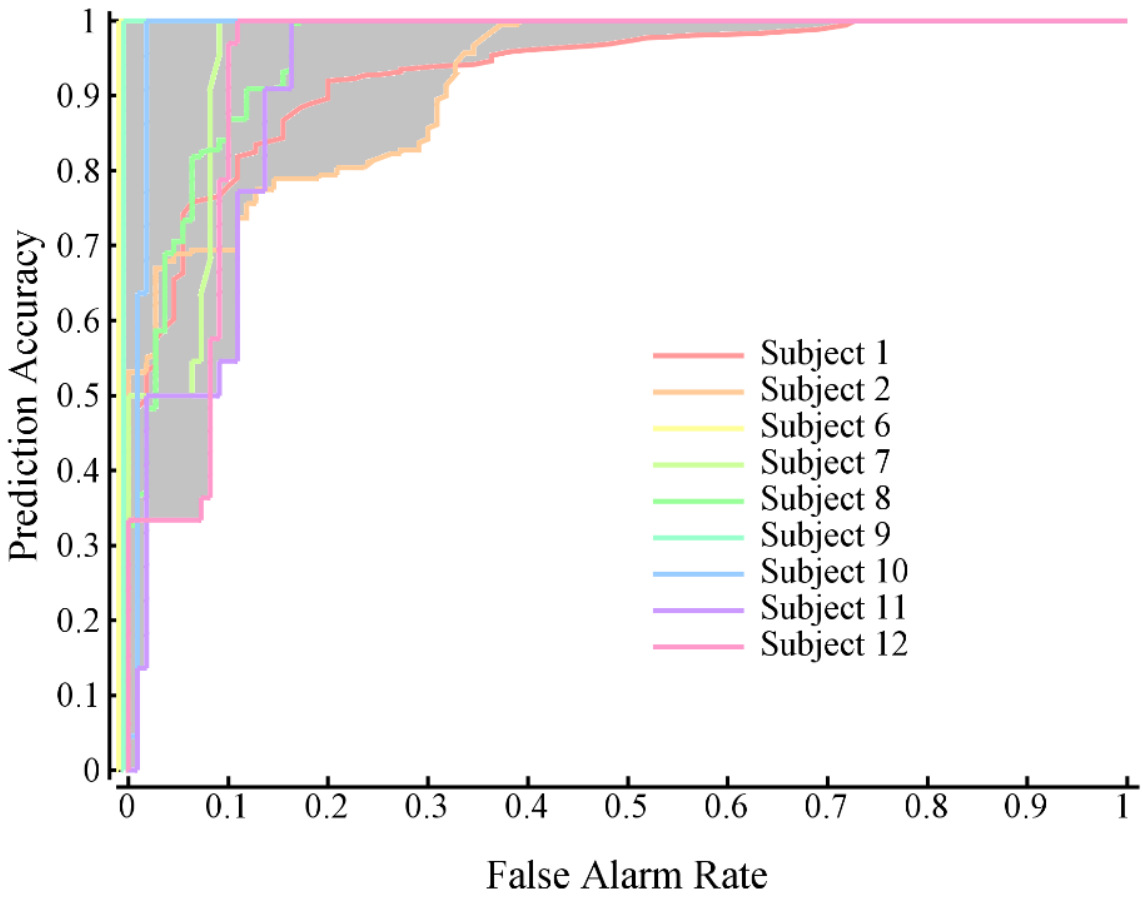

Figure 4: ROC curves for 9 subjects using top 2 precursors selected by SFS algorithm.

B. Source Selection Results Using Different Methods: SFS vs mRMR

By using mRMR method, the shank angle in the sagittal plane (i.e. $Shank_x$) was the most frequently selected data source (8 out of 9 subjects), and therefore was identified as the most important precursor for ICT prediction. It is noteworthy that this source was also selected as the top one precursor by SFS approach, which may imply that this selected data source was valid and robust. The height of the paretic foot's center of gravity (i.e. $Foot_{COG\_z}$), the foot angle in the sagittal plane (i.e. Foot_x), and the vertical limb length (i.e. LL_z) were tied in the

second place of source ranking, which were selected in 7 out of 9 subjects. However, $Foot_{COG\_z}$ was identified as the second important source by mRMR, because it produced a slightly higher AUROC value than the other two sources. The prediction performance using these top 2 sources selected by mRMR (i.e. $Shank_x$ and $Foot_{COG\_z}$) was compared to the performance derived from SFS selected sources (i.e. $Shank_x$ and $Foot'_{COG\_z}$), as shown in Figure 5. The averaged AUROC value across 9 subjects based on SFS sources yielded a slightly better performance than the one based on mRMR. However, the difference was not statistically significant based on one-way ANOVA ($p>0.05$). Since the data sources selected by SFS yielded a slightly better performance, only the sources selected based on SFS will be used and analyzed in the following sections.

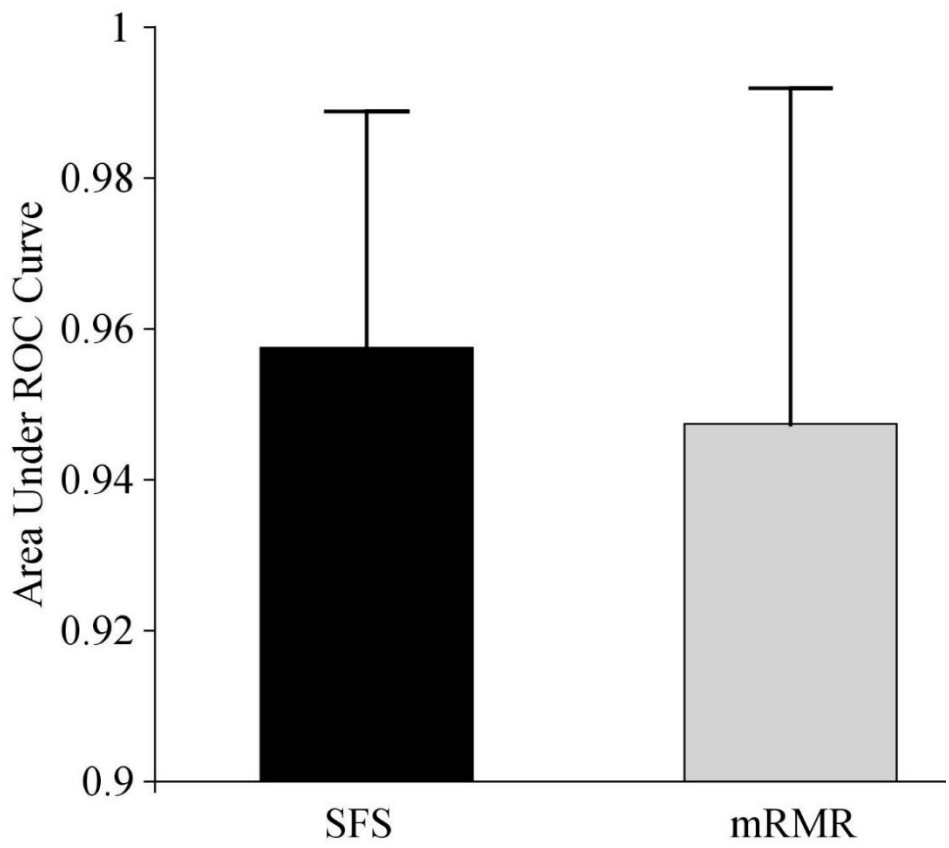

Figure 5: Comparison of the averaged value of AUROC for ICTs prediction performance: SFS vs. mRMR.

C. Customized Source Selection Results for Outlier Subjects

The informative data sources for outlier subjects (Subjects 03-05) were customized and investigated separately using the SFS algorithm. In addition, for these three subjects, the data sources on the contralateral side were also included for consideration. Table III listed the top 2 customized data sources for Subject 03-05 using the SFS algorithm, in comparison to the sources generalized from other 9 subjects. The selected sources from Subject 03-05 were very different from the generalized sources determined based on the averaged results across the other 9 subjects. For example, kinematics of the less affected limb (e.g. $Foot_{COG\_z}$ and $Foot_x$"

on the contralateral side in Subject 05) or proximal joints in the paretic lower limb (e.g. LL_z in Subject 03 that represents hip and knee kinematics) were identified as the precursors.

TABLE III. Generalized and Customized Forward Source Selection Results for 9 Subjects and 3 Outlier Subject.

Source Rank	**Generalized**	**Customized**		
	9 Subjects	**Subject 3**	**Subject 4**	**Subject 5**
Primary Source	$Shank_x$	LL_z	$Ankle_y$”	C $Foot_{COG\_z}$”
Secondary Source	$Foot'_{COG\_z}$	C $Thigh_x$”	$Foot_{COG\_z}$”	C $Foot_x$”

Note: C represents contralateral side.

The ROC curve of ICT prediction performance based on the generalized and customized sources for Subjects 03-05 is shown in Figure 6. The ROC curves of the customized sources (indicated in solid lines) are closer to the left top corner than the generalized sources (represented in dotted lines), which indicates that the customized sources generated better prediction performance than the generalized sources for these three subjects. The performance improvement was further highlighted in Figure 7. Figure 7 compared the AUROC using the generalized and customized sources. By using the customized sources, the ICT prediction performance was improved for these three outlier subjects. For example, in Subject 05, the AUROC value was increased approximately from 0.45 to 0.9 by using the customized sources.

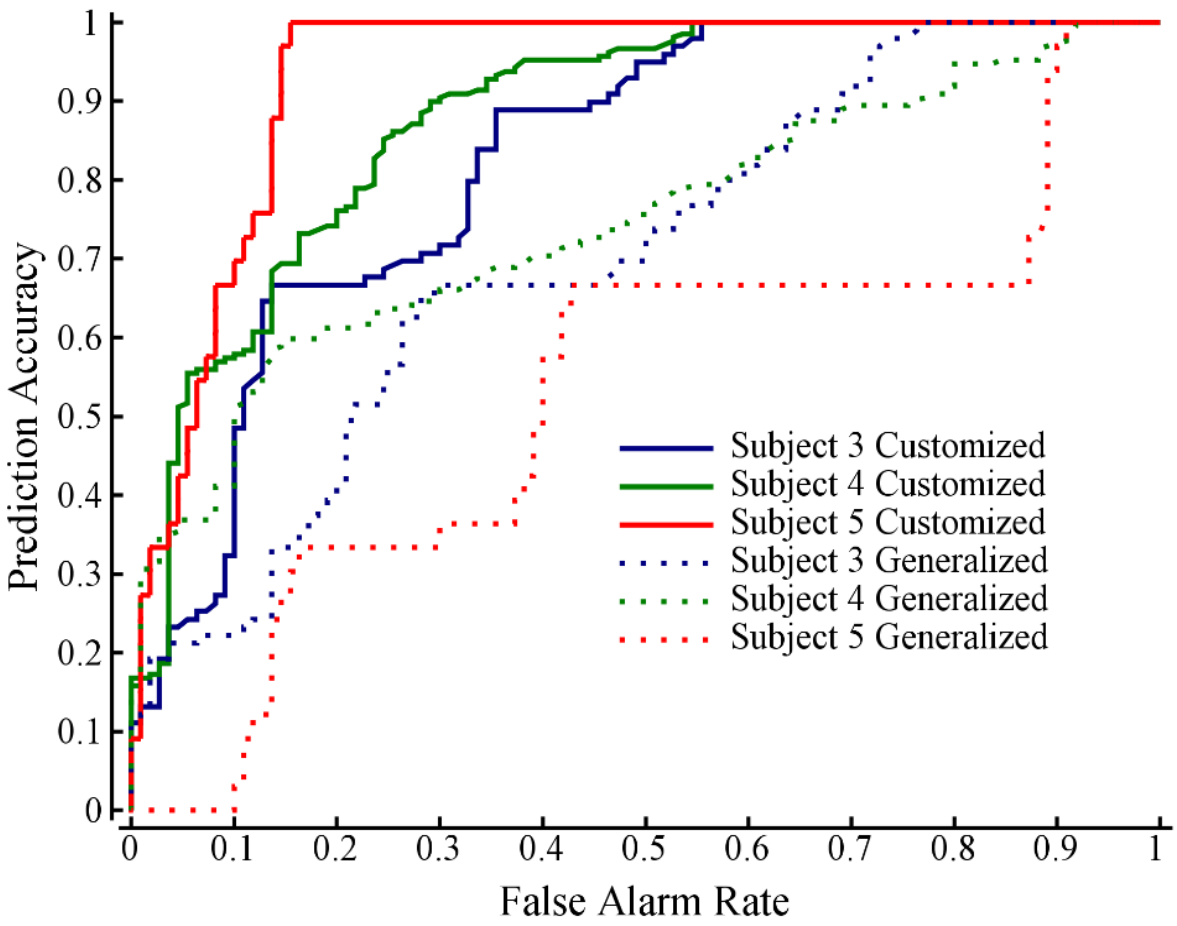

Figure 6: ROC curves for 3 outlier subjects (Subject 03-05) using top 2 generalized and customized ICT precursors.

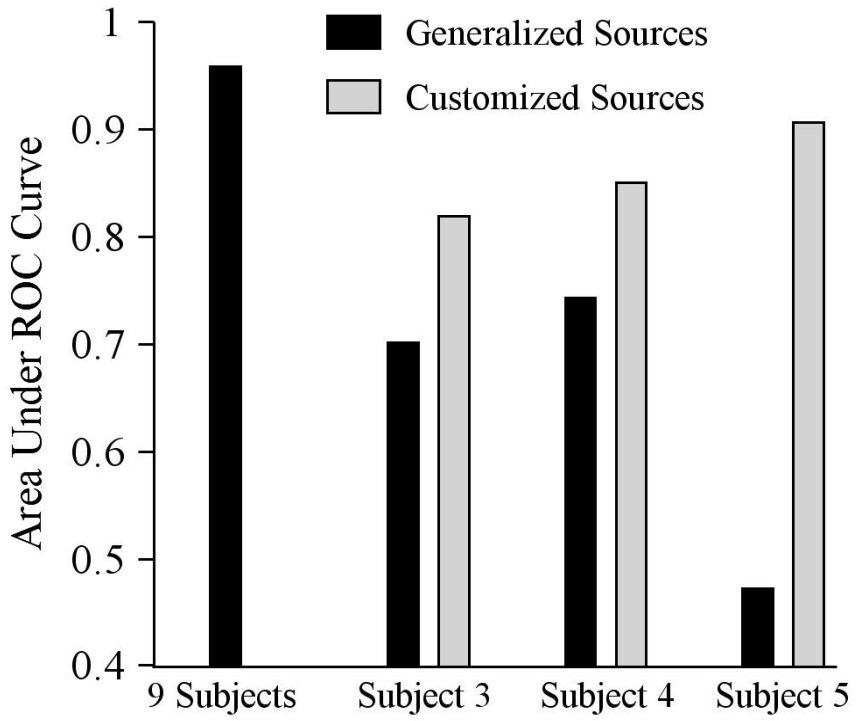

Figure 7: AUROC value of ICT prediction performance using the generalized sources vs. the customized sources selected by SFS algorithm.

A. ICT Prediction Time

The elapsed time between the moment that the ICT was predicted and the moment that the foot actually made contact with the ground was calculated for all 12 subjects and summarized in Table IV. Across the 12 subjects, the mean value of prediction time ranged from 49.7ms to 260ms. The positive value indicated that the ICT event was predicted before the trip happened.

TABLE IV- Mean Value and Standard Deviation of ICT Prediction Time for All 12 Subjects

Subject Number	Mean of ICT Prediction Time (ms)	Standard Deviation of Prediction Time (ms)	Number of ICTs
01	104.1	25.6	118
02	118.4	35.5	19
03	133.3	33.9	9
04	76.3	19.2	19
05	260.0	10.0	3
06	220.0	0	2
07	115.0	21.2	2
08	49.7	10.2	29
09	120.0	34.6	3
10	120.0	28.3	2
11	135.0	7.1	2
12	60.0	10.0	3
Average	**126.0**	**-**	**-**

Discussion

The results of this study are very promising groundwork for the prevention of falls for individuals with stroke. The neurological deficiencies that lead to gait abnormalities make safe ambulation a difficult task for stroke survivors, even with smooth level walking conditions. Previous work has suggested that ICTs during swing phase of gait are caused by movement abnormalities that are initiated during the stance phase [18]. However, there are currently no

methods that predict ICT's before they occur. The results of this study show that the prediction of naturally occurring tripping events is possible. In fact, we were able to successfully predict trips by monitoring only the kinematics of the lower limbs during the preceding stance phase. Early prediction of intrinsically caused tripping events promises further proactive engineering mechanisms for ICT avoidance and therefore reduces the risks of fall in individuals with stroke.

The ICT's observed during this study were all naturally induced, and caused by insufficient foot clearance during swing phase. Reduced foot clearance during the swing phase of walking is caused by an insufficient shortening of the leg. Shortening of the leg is achieved by a combination of joint kinematics, most notably knee flexion and ankle dorsiflexion. Though there are many parameters that lead to a successful shortening of the limb, we found that by using only two kinematic sources, we were able to accurately predict an ICT. For 9 of the 12 subjects, we found that the elevation velocity of the foot's center of gravity and sagittal shank angle were able to provide sufficient information to predict a trip at the time of toe off. Additionally, both sagittal shank angle and the elevation velocity of the foot's center of gravity can be easily obtained using accelerometers and gyroscopes [32].

The results from the first rotation of the SFS presented in Table III further emphasize the importance of sources obtained from the shank and the foots' center of gravity. These two sources along with their first and second time derivatives made up 6 of the top 10 standalone sources, suggesting that the sagittal shank angle and foot height before toe-off are strong precursors for ICTs. The top 10 standalone sources for the first rotation all had mean AUROC greater than 0.85, which is significantly better than chance. This suggests that by only using a

single source, the prediction of ICTs is still plausible. In fact, with the exception of LL_z, each of the top 10 standalone sources came from the knee, shank or foot.

Unsurprisingly, the generalized source selection did not work well for everyone. The neurological deficiencies caused by stroke affect everyone differently. Our results suggest that customized approaches may be necessary for trip prediction in some individuals. The advantage of a customized approach is that trip prediction would use the optimal sources for each individual. In this study, we limited the sources per subject to only two sources. By allowing more sources, trip prediction may increase for some individuals. In fact the addition of more sources actually decreased the detection performance for some subjects, suggesting additional sources may add more noise than useful information for predicting ICTs for some individuals. This trend can be seen in the generalized source detection for subject 11 and 12 in figure 4. While such trends suggest a customized optimization for everyone would be ideal, such an approach would be time consuming and costly.

The implications of predicting an ICT before it occurs suggests that a new proactive approach to fall prevention may be possible. Currently, proactive fall prevention strategies are limited. The use of a functional electrical stimulation (FES) device is often employed for individuals with stroke or MS in order to provide ankle dorsiflexion during swing phase [33]. This elicited ankle dorsiflexion effectively shortens the limb, and provides the necessary swing clearance. However, in order to avoid trips, such a device is used for every step and fatigues the targeted muscles very quickly [34]. If an ICT predictor was used in conjunction with an FES device, the device would only need to be active when a trip was predicted.

One of the most exciting results from this study is that Sagittal Shank Angle was the first source selected from both of our source selection methods. When used as a standalone source, the mean AUROC curve for sagittal shank angle for the 9 subjects was 0.915. The shank angle is an ideal source because current FES devices are already worn on the shank, just below the knee joint. In fact, many FES devices that provide ankle dorsiflexion utilize a tilt sensor, which determines the timing of the stimulation. While a tilt sensor would likely not be sensitive enough to work with our algorithm, an Inertial Measurement Unit (IMU) could easily be integrated into current FES devices. In addition to sagittal shank angle, timing of gait events is also important. Heel-strike and Toe-off information could be obtained from insole force measurements from devices similar to Pedar insoles (Novel, Germany) or foot switches. An additional IMU could be placed on the foot to give an estimate of the vertical velocity of the foot center of gravity. Therefore, integration of our algorithm is certainly plausible.

The final part of the study focused on the timing of the prediction time of the trips. According to data reported in [35], the electromechanical delay from an elicited electrical stimulation was approximately 17.2ms, half the reported time for a voluntary response. The subject with the earliest mean ICT onset in this study was just over 49ms after toe-off. This suggests that an electrically elicited muscle contraction directly after toe off for predicted trips should in fact be sufficient to avoid an unsuccessful foot clearance. In fact the mean ICT prediction time across all subjects was 126ms. For this study, we only considered the final 10% of stance phase for predicting ICTs. This timing was ideal because it could be easily obtained from heel strike and toe-off events. However the observed large ICT prediction time suggests that exploring data after toe-off should be emphasized in future studies as well.

III. Study Two: Effects of Material Properties of Foot and Obstacles on the Level of Tripping Disturbance: A Simulation Study

Note: The work presented in study two, *Material Properties of Foot and Obstacles Affect Level of Tripping Disturbance: A Simulation Study* has been submitted for review a conference paper to the 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. My contributions to this work include the build and integration of the collision model, data collection, analysis of data, and assistance in writing and preparation of the manuscript, under the guidance of Dr. Helen Huang and Dr. Ming Liu.

Introduction

There are approximately 2 million individuals living in the US with amputation [36], with approximately 185,000 additional lower limb amputations occurring every year [37]. Individuals with lower limb amputation often rely on prostheses in order to ambulate. However, the resultant gait deficits from a lower limb amputation leaves amputees much more susceptible to trips and slips, which often lead to falls. In inpatient rehabilitation settings, one in five patients with lower limb amputation will experience at least one fall with approximately 18% of the falls resulting in an injury [38]. Falls in the community are common as well, studies have shown that 27% of unilateral amputees and 58% of bilateral amputees report at least one fall in the last 12 months [39]. It was also reported that up to 22% of the falls were related to environmental factors alone and 48% were a result of intrinsic patient related factors [39].

One factor that makes lower limb amputees more susceptible to trips and falls is that their prosthesis is limited in function and capability. Although prostheses have made great advancements over the past years, inadequate patient-device interactions and lack of sensory feedback make amputees more susceptible to trips. Additionally, when amputees are

introduced to unpredictable environments or terrains, the chance of a tripping event is further increased. Because trips cannot always be prevented, amputees must rely on the successful implementation of a recovery strategy to avoid falling. For able-bodied individuals, two common recovery strategies are often observed after a tripping event, an elevation strategy and a lowering strategy.

The first strategy is an elevation strategy in which the subject flexes both the hip and knee of the affected foot in order to avoid a second collision [40]. This recovery strategy is usually observed for trip recoveries occurring early on in swing phase. The second recovery strategy, which is observed more frequently in mid and late swing is the lowering strategy. A successful lowering strategy consists of the subject placing the obstructed leg on the ground, and stepping over the obstacle with the contralateral leg [40]. Unfortunately, commercially available computer controlled prosthetics only offer the lowering strategy [41], [42], by increasing the impedance of the prosthesis upon detection of a trip. However, research reported by Crenshaw et al. found that when subjects' computer-controlled prostheses were blocked by an obstacle during walking, attempted lowering strategies failed leading to a fall, or assisted support [43].

Powered prosthetic devices offer a great deal of potential to further mitigate the risk of falls for amputees. The advantage of powered devices is that they can be programed to perform tasks that passive prostheses are unable to [44], [45], [46]. The programmable nature of powered prosthetics allow for control algorithms to be designed to adjust and respond to perturbations experienced by the user. Several different studies have used wearable sensors in

order to detect when a tripping event has occurred [47], [48]. Additionally, efforts are being made to make more robust prosthesis controllers that more readily reject abnormal walking gaits such as those encountered during a trip [49]. However, these preliminary designs have not been used in commercial powered prostheses.

In order to design an effective control strategy for powered prostheses that increases chance of recovery, we need a better understanding of how environmental factors affect the level of disturbance experienced from a collision event. In order to create an effective recovery control procedure, it should be able to cover most of the tripping scenarios. This is a difficult task because there are multiple factors that determine how a collision will disturb an individual while walking. For instance, the distance between an obstacle and the foot at toe-off determines the relative speed of the toe when the trip happens. Additionally, variable material properties of the foot and an obstacle further affect the duration of the trip and relative speed between the toe and the obstacle when the trip ends. The wide variability in environmental factors makes it challenging to study the relationship between environmental factors and the level of disturbance experienced experimentally. Collection of authentic experimental collision data is further complicated because it has been shown that subjects alter their kinematics and kinetics when anticipating a trip [50], [51]. To overcome these difficulties, we propose a dynamic biomechanics simulation to better understand the relationship between environmental factors and the level of disturbance caused by tripping. Successful implementation of a collision simulation would be useful because it would remove artifact from anticipation of a collision, and be able to explore unlimited environmental factors. By quantifying this information future

studies will be better informed which will assist in creating robust real-time fall prevention control methods for powered prostheses.

Methods

We constructed a simplified dynamical model to simulate a collision event to better understand the interaction between the foot and an obstacle in the sagittal plane. The model was built under the environment of SimMechanics, a toolbox of Simulink (MathWork, MA, US) and included two submodels: a rigid body model to simulate locomotion and a nonlinear spring-damper model to simulate a foot-object collision (Figure 8).

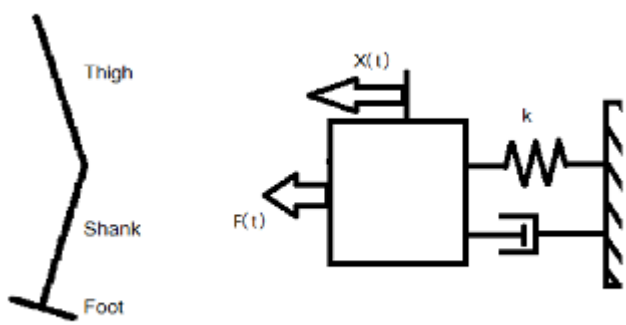

Figure 8 (Left) Rigid body model for locomotion simulation (Right) a nonlinear spring-damper model for collision simulation

Rigid Model for Locomotion

We constructed a simplified rigid body model in order to represent the motion of the leg, which experienced the tripping. In order represent locomotion of above knee amputees, who usually rely on fixed passive ankle joints, two segments, thigh and shank-foot, are modeled as rigid bodies. The motion of the leg was described by coordinates of the hip center, hip joint angle, and knee joint angle. The inertial properties of each segment were decided by measuring the height and weight of an able-bodied subject and then using the formulas reported in [52]. The interaction force of the simulated trip acted on the distal end of the foot of the model.

Nonlinear Spring-Damper Model for Tripping

In order to estimate the level of disturbance generated during a trip, a simple nonlinear spring-damper model [53] was integrated to simulate the collision between the foot and the obstacle. An obstacle was defined as a rigid body fixed on the ground with one of its surface perpendicular to the ground. The normal forces (F_{normal}), which was paralleled with the ground, are calculated using the following non-linear spring damper expression adapted from [53]:

$$F_{normal} = kx^{e} + Step(x, 0,0, d_{max}, c_{max})\dot{x} \qquad (4)$$

where x is the distance penetrated by the toe, and $\dot{x}$ is penetration speed of the toe, e is the spring coefficient, and d_{max} and c_{max} are the max damping penetration and max damping coefficient respectively. The *Step* function allows a smooth transition of the damping term as the collision is initiated and terminated. This equation is further explained in [53]. Frictional forces ($F_{Friction}$) during the collision was simulated as Coulomb friction and calculated using:

$$F_{Friction} = \mu F_{Normal} * sgn(\dot{y}) \quad (5)$$

where $\dot{y}$ is the vertical velocity of the toe, and μ is the coefficient of friction, which is a static coefficient (μ_{static}) when vertical velocity is less than .05 m/s or dynamic ($\mu_{dynamic}$) when the velocity is greater than or equal to .05 m/s. The *sgn* term from equation 5 outputs a 1 or -1 to ensure that the frictional force is in the correct direction.

Although more sophisticated collision models [54] are available, this model is chosen due to its simple structure and wide acceptance. The same model has been used in commercial rigid body simulation software Adams (MacNeal-Schwendler Coporation, Califorina) for collision simulations.

Simulation Procedure

A forward dynamic simulation was conducted to illustrate the influence of environmental factors on the level of gait disturbance (see Figure 9). This simulation was conducted based on kinematic and kinetic data collected from an able-bodied subject (80 kg body weight and 1.74 meter height) during treadmill walking at the self-selected walking speed. The data collection procedure was conducted under a protocol approved by IRB at the University of North Carolina – Chapel Hill. A video based motion capture system (Vicon, British) was used to collect the motion data and torque at different joints was calculated based on inverse dynamics.

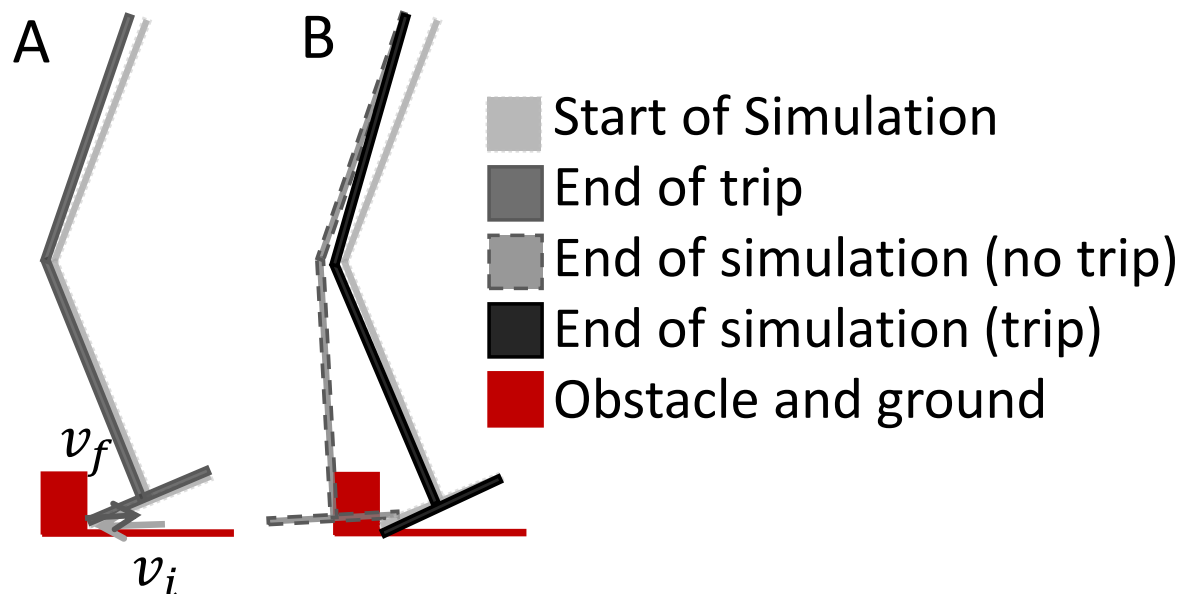

Figure 9: An example case of the forward dynamic simulation. A: before collision and after collision; B: Influence of the collision at the end of the simulation.

The elasticity properties between the foot and the obstacle were defined by parameters, which were adjusted in the simulation. A total of six parameters were used as variables for the study, each with 5 potential values evenly spaced between the min and max values shown in Table V. The range of each parameter was chosen based on the values reported in [55] and further expanded to cover more elastic and inelastic scenarios.

TABLE V. PARAMETER VALUE RANGES

Variable	***Min Value***	***Max Value***
Spring Coefficient (k)	$1x10^4$	$2x10^5$
Spring Exponent (e)	100	1500
Max Damping Coefficient (c_{max})	1	2.2
Max Damping Penetration (d_{max})	.001	.02
Static Friction Coefficient ($\boldsymbol{\mu_{static}}$)	.2	.8
Dynamic Friction Coefficent (μ_{Dynamic})	.1	.2

To align with existing studies, which uses time information to choose recovery strategy, we defined the location of the obstacle based time of trip (using percentage of swing time) instead of the distance between the obstacle and a reference point, location of ipsilateral toe at previous toe off. Because the toe moved forward during the swing, the high percentage of the swing phase indicates that the obstacle is far from the reference point.

The tripping events happened at 15%, 30%, 45%, 60%, and 75% of swing time were studied in the simulation. We used the measured joint angle and angular velocity at the hip and knee joints at the selected the trip time as initial conditions for the forward simulation. The obstacle was set 0.01 mm ahead of the toe at the selected trip time.

Several assumptions were involved to simplify the model. 1) The joint torques were constant during the simulation. Because trips were never anticipated, it was reasonable to

assume that torque acted on each joint was not alternated during and just after the trip until subjects react to the trip through reflex and/or voluntary reaction. Here, the torque at each joint was calculated based on the inverse dynamics at the trip time using the collected motion data. 2) The trajectory of the hip center was not affected by the trip.

The simulation duration was set as 100ms to fully illustrate the influence of the environmental factors. Based on the data reported in [40], [56], and [57] EMG responses were observed in the swing leg biceps femoris 60-80ms after a trip and 110-130ms after trip in rectus femoris and vastus lateralis. Considering 20ms electromechanical delay commonly seen in the lower limb [50], we concluded that in the first 100ms after trip, no correction torque from human subjects were present.

Results Presentation

The level of disturbance of the trip was presented as the change of angle and angular velocity at the hip and knee joint at the end of the simulation compared with measured non-collision data. Because multiple combinations of environmental parameters were used to define the material properties of the foot and the obstacle, it was hard to interpret the influence of each parameter. Therefore, we used coefficient of restitution (COR), a well-defined physical concept, to generalize the material properties [58], [59]. COR is a measure of the relative velocity between two bodies (A and B) before and after they collide and is calculated by:

$$COR = \frac{v_{Af} - v_{Bf}}{v_{Bi} - v_{Ai}} \qquad (6)$$

where v_{Af} and v_{Bf} are velocity of object A and object B after collision respectively and v_{Ai} and v_{Bi} are velocity of the object A and object B before the collision respectively. COR is often used to describe the elasticity between two collided objects. When the COR equals one, it indicates the collision is elastic and no energy is lost during the collision. When the COR equals zero, it indicates the collision is inelastic and the two objects end up moving together. Because the obstacle was fixed in our simulation, the COR was calculated based on toe velocity before the trip and after the trip.

Model Validation

In order to validate our model, we used experimental data collected from a single collision. The data was originally gathered from the University of Rhode Island and the Providence VA Medical Center with the approval of the IRB and informed consent of all subjects. The tripping data was collected from the healthy side of a single amputee level-ground-walking in a lab setting. As the subject walks across the room, a rope is pulled, raising a plastic acrylic plate perpendicular to the floor through a slit in the ground, thus inducing a trip (Figure 10). Subjects' lower limb kinematic data were monitored by a marker based motion capture system (Oqus, Qualisys, Sweden).

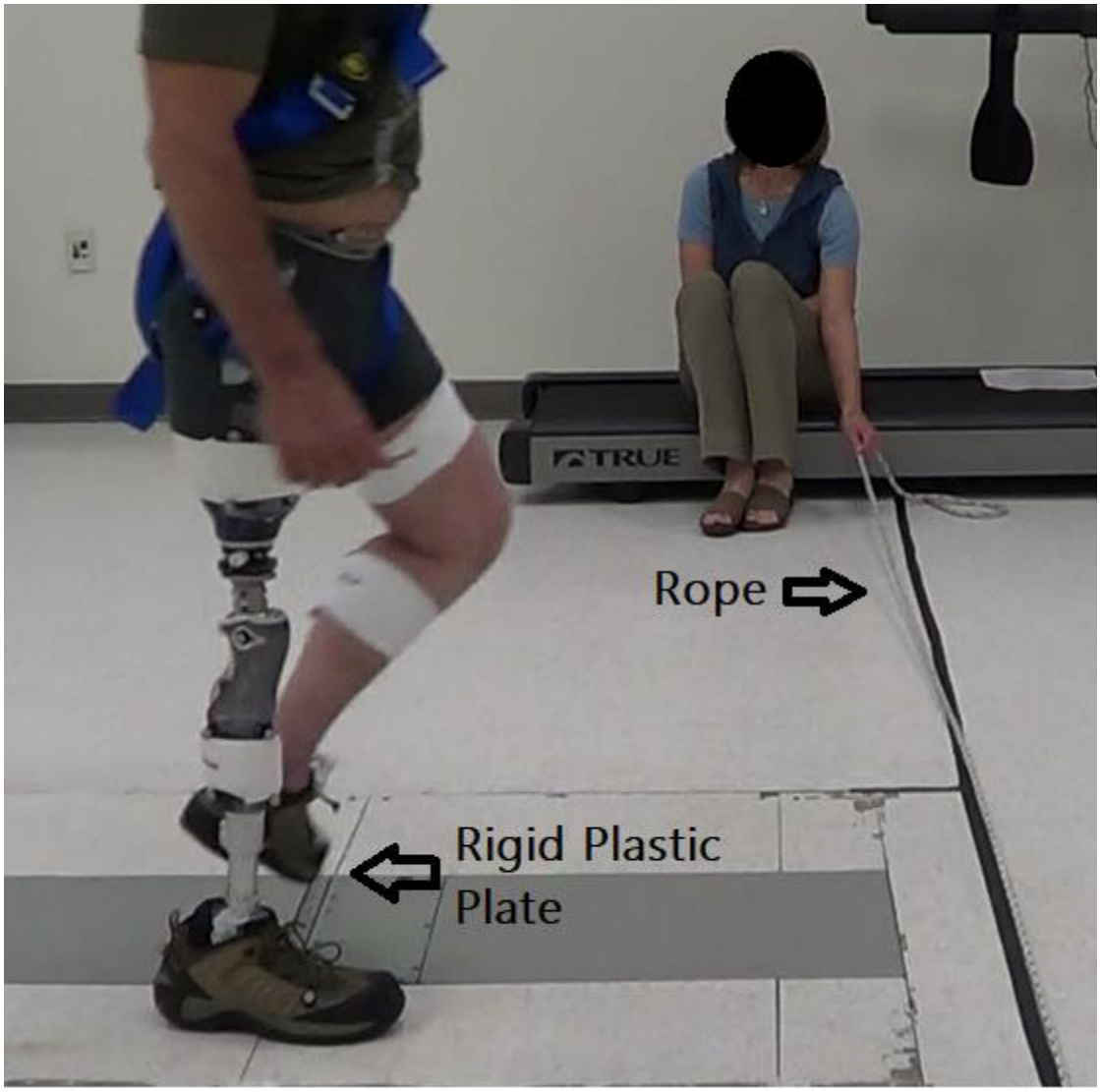

Figure 10: Experimental setup for Inducing trip

Results

The simulation results showed that the level of disturbance was heavily affected by the environmental factors. Figure 11 illustrated the level of disturbance related with obstacle locations and material properties of the foot and the obstacle. Although the simulation results

generated cases for COR was smaller than 0.1 and larger than 0.8, these cases were ignored because such cases were not commonly seen. COR smaller than 0.1 mean that the foot was stuck on the obstacle, and COR larger than 0.8 were only reported for highly elastic objects, such as a ping-pong ball.

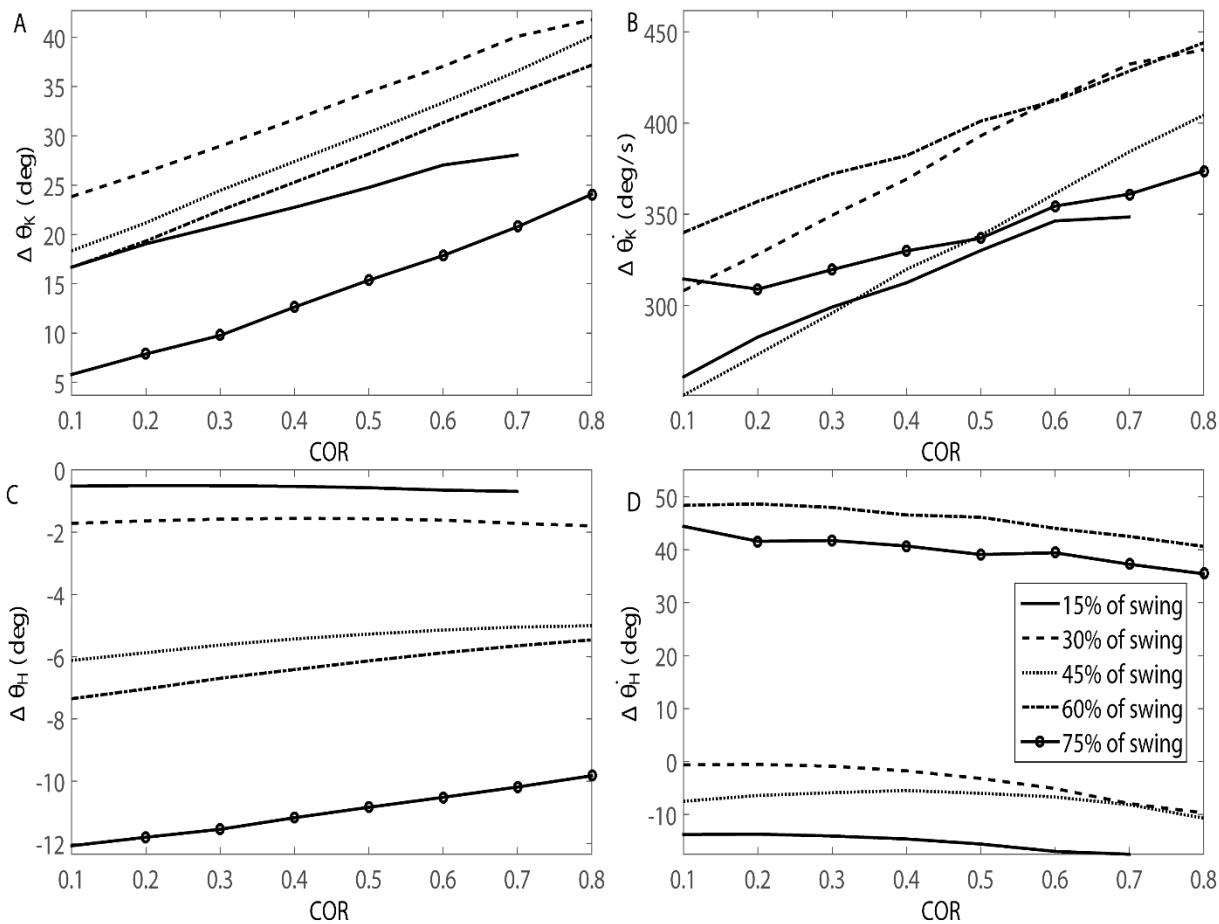

Figure 11: Average level of disturbance caused by tripping. A depicted the change in the knee angle $\Delta\theta_K$; B depicted changes of hip angle, $\Delta\theta_H$; C depicted change of knee angular velocity, $\Delta\dot{\theta}_K$; and D depicted change of hip angular velocity, $\Delta\dot{\theta}_H$. Flexion is positive for both knee and hip joints.

Figure 11 shows that as the elasticity of the collision increased (Increase in COR), the disturbance at the knee joint increased linearly. The disturbance at the hip joint was more dominated by swing phase timing. Additional knee flexion and hip extension were observed, which was caused by the trip. This observation was aligned with the fact that the interaction force between the foot and the obstacle was majorly pointed against the direction of locomotion, which would cause knee flexion and hip extension.

Because both joints changed its rotation direction during the swing phase due to the collision, the angular velocity changed significantly at both joints. We did not see a clear relationship between the absolute value of disturbance on angle and angular velocity with the obstacle locations except for the hip joint angle, of which changed the least among for kinematics used to qualify the disturbance. The extension disturbance increased when the trip happened at the later of the swing phase.

Figure 12 showed the average minimum foot clearance with the ground during the simulation. During the middle swing, negative foot clearance was observed, which indicates risks of uncontrolled contact of the foot and the ground.

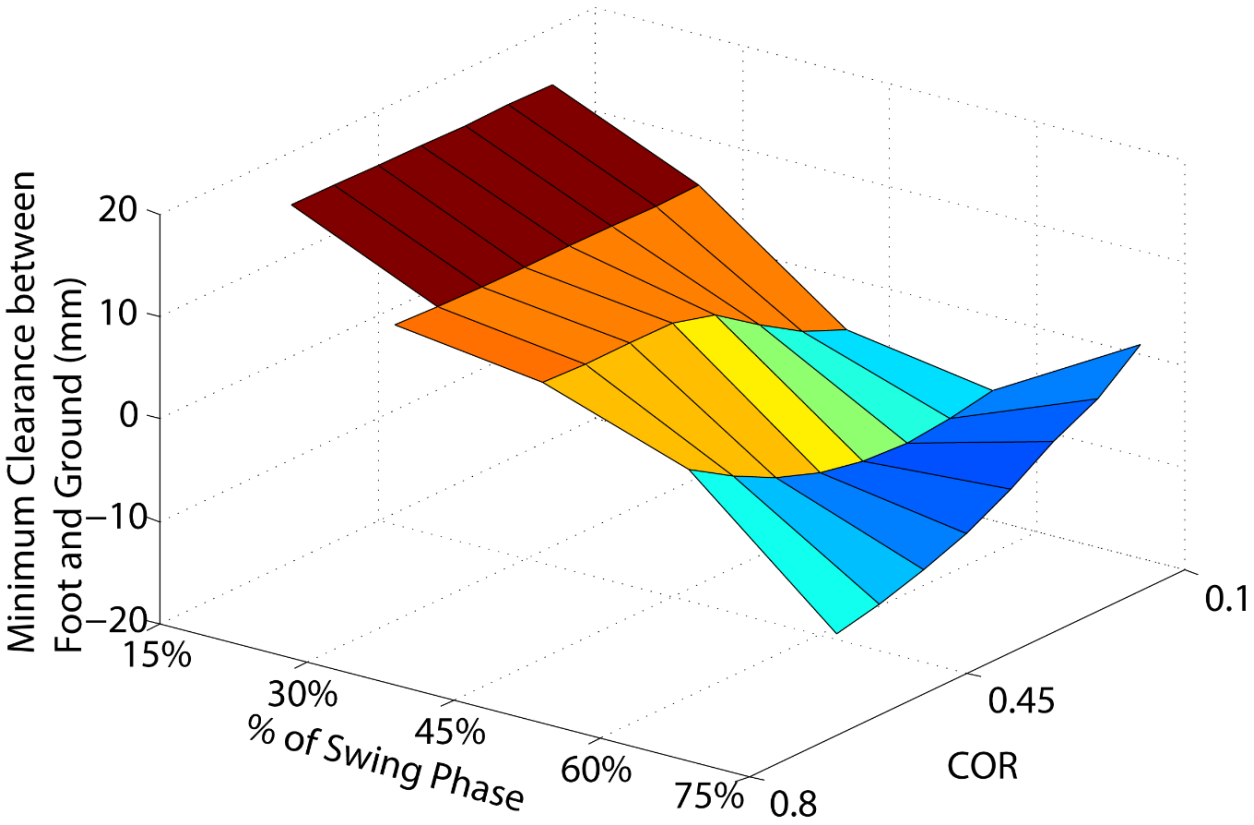

Figure 12: Average minimum foot clearance during the simulation.

The kinematic data collected experimentally from the single tripping trial is shown in figure 13. The red curves represents the single trip data, and the black curve represents the mean healthy walking data. The onset of the trip, represented by the dashed vertical green line, occurred around 35% of swing phase. The red dashed line represents 100ms after the trip onset for comparison to the simulation data. Based on the experimental tripping data collected, the trip disrupted the trajectory of both the hip and knee angle.

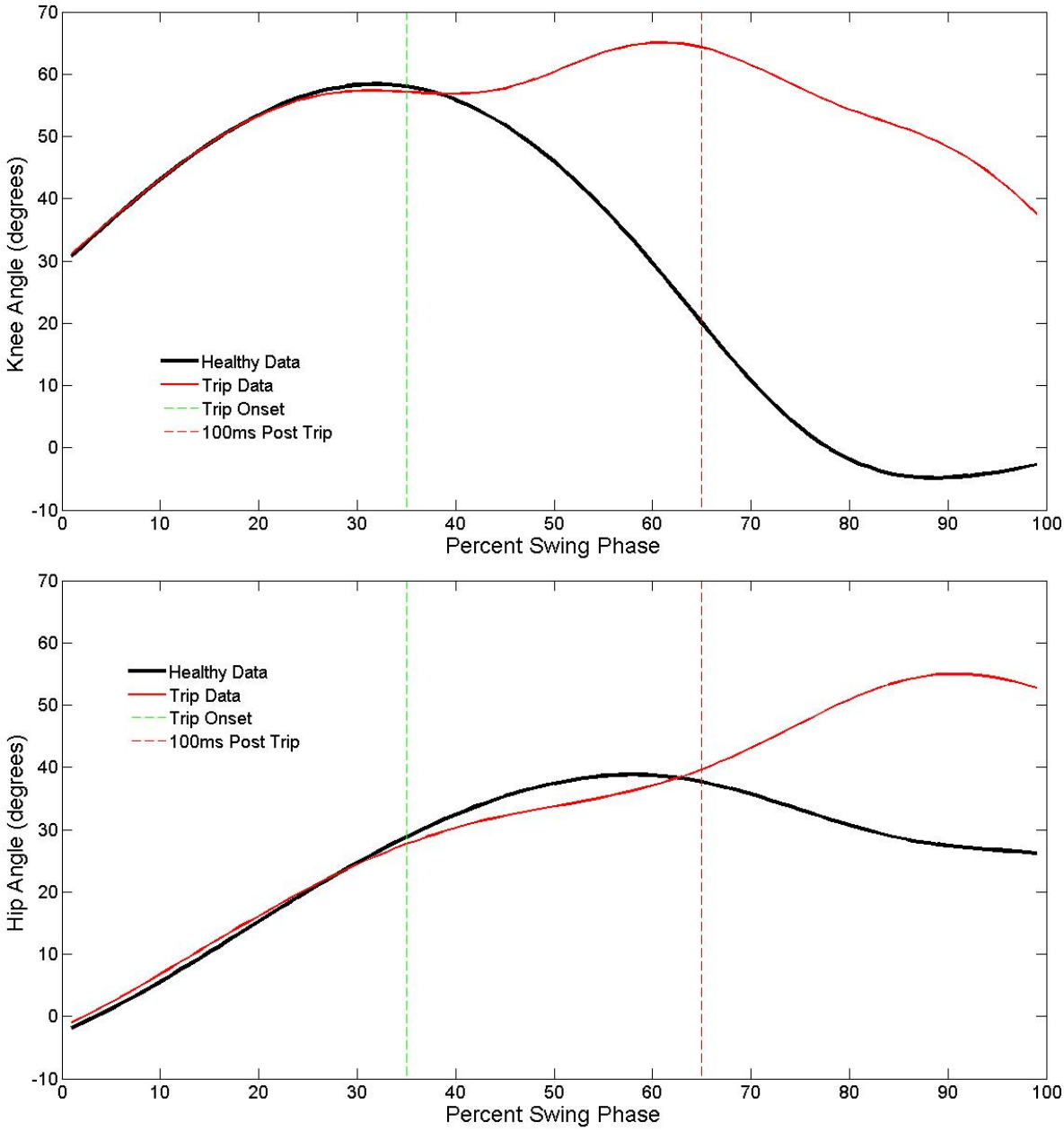

Figure 13: Knee (Top) and Hip (Bottom) Angles collected from an induced trip in lab. The solid black curve represents an average of the subjects hip and knee angles across multiple gait cycles. The red curve represents a single trip, and shows the disturbance in both hip and knee angle after collision with an object.

For fair comparison of the results from the experimental data, we ran the model again at 35% swing phase. The simulated hip and knee angles are compared to the experimental hip

and knee angles in figure 14. The red lines in figure 14 represents the tripping data collected experimentally. Due to low sampling rate of the collected kinematic data and lack of force data at the toe, we were unable to calculate a value for COR. Based on where the data falls however, we estimate that the COR for the experimental data probably falls between 0.6 and 0.7.

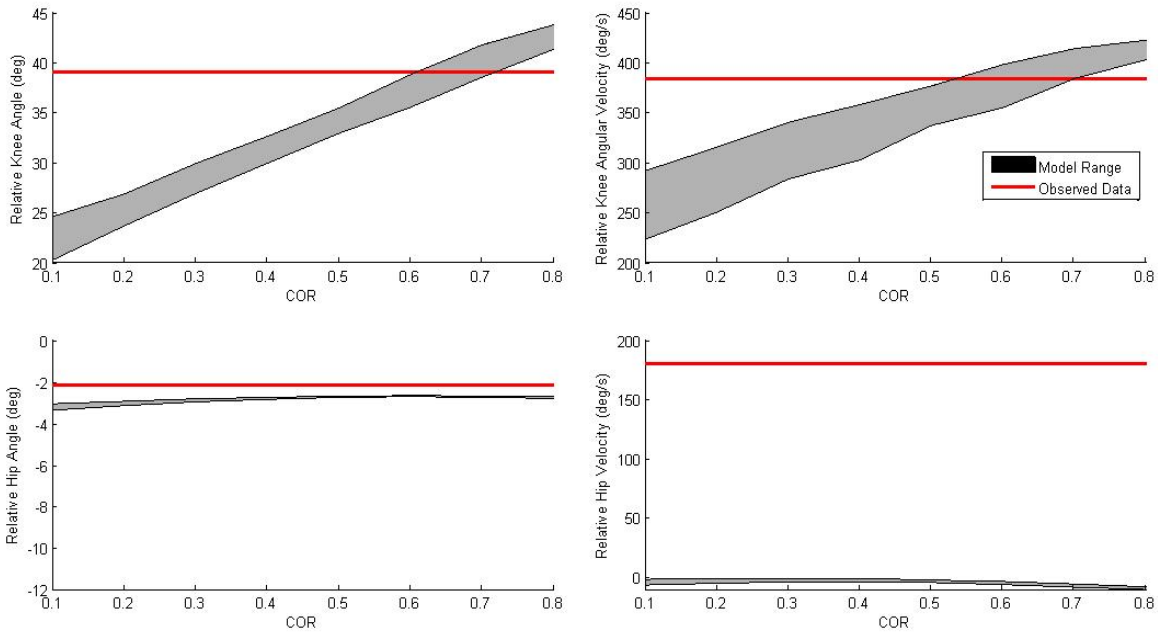

Figure 14: Model kinematics vs observed kinematics from single tripping trial. Black lines represent ranges predicted from model. Red line represents value observed from single tripping trial.

Discussion

The results from this study present a novel solution to a challenging problem in research. Previous studies have shown that if a subject anticipates a trip, they will alter their gait in order to improve chances of recovery [50], [51]. These anticipatory changes in gait alter both kinetics and kinematics of lower limb joints, which contaminates experimental results. By introducing this simulation model, we can use normal walking data collected from a subject and eliminate noise created from the anticipation of a trip or fall.

Another difficulty with collecting real tripping data is that there are many different environmental variables that are difficult to manage and quantify. The use of a simulation allows us to test against all potential tripping scenarios. This is important because the results from our simulation study clearly show that the level of disturbance depends on the environmental factors and timing of the trip. This estimation of disturbance level will help researchers better understand the challenges in creating successful control strategies for amputees.

While the collision model was a good predictor of knee angle and angular velocity, the hip angle and angular velocity values were significantly different than those collected experimentally. Despite the difference in values, the inconsistencies are not too surprising. As mentioned previously, anticipation of trips has been shown to alter gait kinematics. Additionally the tripping data was collected from a single amputee subject whereas the model data was collected from an able-bodied subject. Research has shown that amputees demonstrated a lesser degree of lower limb symmetry than the non-amputees [60], [61]. Furthermore, differences in hip data may be caused by over simplification of a two-dimensional model, or the assumption

in our simulation that the hip moves at a fixed trajectory. However, the observed differences suggest further investigation and validation is certainly needed, ideally using data from a single subject.

Based on our results, the hip angle is not affected very much by collisions that occur early in swing phase. Unlike the hip, collisions in early swing cause the knee to become more flexed from the resultant forces of the collision. This additional flexion may be useful in the facilitation of the elevation recovery strategy observed in early swing. However, when the collision occurs in mid or late swing phase, the hip becomes more extended. This greater extension may make foot clearance more difficult, and as a result the elevation strategy may become a less viable option. Although we did not simulate foot-ground contact forces during this simulation, our results suggest that in mid to late swing, the foot would be forced to make uncontrolled contact with the ground. The uncontrolled contact observed in the simulation might further reduce the chance of using the elevation strategy and make lowering strategy mandatory.

The of this study help give us a better understanding of how environmental factors affect the level of disturbances an individual may experience during a collision event. Understanding the level of disturbance experienced may give us a better understanding of how to employ appropriate prosthesis control strategies to prevent falls in real-time. For example, by knowing the knee and hip motion right after the trips, we can estimate the level of perturbations based on the results in this study and predict the recovery strategy used by prosthesis users. The predicted result can be fused with the recognition of the patient's intended stumble recover strategy (either elevation or lowing strategy), obtained by EMG-based neural-machine interface that has been

developed in our lab [62], [63], [64]. This will enable the prosthesis to cooperate with the amputee user to generate appropriate reaction in human-prosthesis system and recover from trips. Of course, implementing this idea requires significant additional engineering efforts in the future.

Finally, there are many recognized limitations of this study. The motion data collected in this study was only collected from a single able-bodied subject. In order to test the consistency of our results, we will include more subjects in future studies. With the inclusion of more data for validation, we hope that this model can be used as a novel approach to simulate human reaction to trips. This model will be very useful for the development of trip recovery strategies without heavy involvement of human subjects.

Conclusions

Real-time fall prevention is crucial for protecting individuals when they are at risk of falling. By preventing disturbances completely, or assisting in the recovery from a perturbation, we can prevent injuries and deaths that result from falls. While further research is needed, the results of these two studies help pave the way towards two unique real-time fall prevention methods.

The first study aimed to identify kinematic predictors of ICTs. This research is important for the future exploration of engineering solutions to prevent ICTs in individuals with stroke. To do this, gait kinematics collected from twelve individuals with chronic stroke, who demonstrated ICTs in treadmill walking, were captured and analyzed. An ICT prediction algorithm based on outlier principle was employed. The results of this study demonstrated that it was feasible to predict ICTs before they occurred in the swing phase. For nine out of twelve subjects, the shank orientation in the sagittal plane and the elevation velocity of foot's center of gravity from the paretic lower limb provided sufficient information for accurate ICT prediction. The ICTs in the other three stroke patients were attributed to the movement patterns in the non-paretic limb or proximal joints in the paretic limb. The outcomes of this study may inform future design of proactive mechanism in assistive devices for ICT and therefore fall prevention in individuals with stroke. This work is meaningful because it provides an answer to the question of when real-time fall prevention should be implemented.

The second study explored how the level of disturbance from a collision event during swing phase was heavily dependent on environmental factors. We used a simple simulation to

model collisions between a foot and an object during swing phase. This model was partially validated using real trip data collected from a single subject. Because a large amount of environmental factors were considered, we pooled results by a measure of the elasticity of the simulated collisions. Simulated collisions caused additional knee flexion, and hip extension. The additional observed knee flexion was dependent on both the timing of the trip and the elasticity of the collision, while the additional hip extension appeared to be dependent on the timing of collision. The results of the collision simulation also suggest that an elevation strategy in early swing may be facilitated with additional knee flexion caused by the collision, while lowering strategy in late swing may become necessary as a result of uncontrolled contact with the floor. The results of the second study may influence future designs of prosthesis controllers which will be used to assist in real-time fall prevention for amputees.

It is our hope that the results from these studies may also aid other populations that experience higher risk of falls. Though we only looked at predicting ICTs in individuals with strokes, many other populations such as individuals with Multiple Sclerosis or the elderly have gait deficits that make them more susceptible to ICTs as well. Our ICT prediction method may be translational to these other populations which could have a great impact scientifically. Additionally, a better understanding of how environmental factors affect the level of disturbance is useful for other populations as well. While our study only focused on modeling collisions for amputees, simple modifications of the model could provide information that would be useful for designing controllers for individuals who rely on FES devices or exoskeletons for ambulation.

Bibliography

1. Lee, I-Min, and David M. Buchner. "The importance of walking to public health." *Medicine and science in sports and exercise* 40.7 Suppl (2008): S512-8.

2. WHO. (2002). The Injury Chart Book A graphical Overview of the Global Burden of Injuries. Geneva: Department of Injuries and Violence Prevention, World Health Organization.

3. Tinetti, Mary E., et al. "Fear of falling and fall-related efficacy in relationship to functioning among community-living elders." *Journal of gerontology* 49.3 (1994): M140-M147.

4. Tinetti, Mary E. "Factors associated with serious injury during falls by ambulatory nursing home residents." *Journal of the American Geriatrics Society* 35.7 (1987): 644-648.

5. Stevens JA, Corso PS, Finkelstein EA, Miller TR. The costs of fatal and nonfatal falls among older adults. Injury Prevention 2006a;12:290–5.

6. Rubenstein, Laurence Z. "Falls in older people: epidemiology, risk factors and strategies for prevention." *Age and ageing* 35.suppl 2 (2006): ii37-ii41.

7. Sherrington, Catherine, et al. "Effective exercise for the prevention of falls: a systematic review and meta-analysis." *Journal of the American Geriatrics Society* 56.12 (2008): 2234-2243.

8. Gillespie, Lesley D., et al. "Interventions for preventing falls in elderly people." *Cochrane Database Syst Rev* 4.4 (2003).

9. Laing, Sharon S., et al. "Fall prevention knowledge, attitude, and practices of community stakeholders and older adults." *Journal of aging research*2011 (2011).

10. York, Sally C., et al. "A translational research evaluation of the Stay Active and Independent for Life (SAIL) community-based fall prevention exercise and education program." *Health promotion practice* (2010): 1524839910375026.

11. Hinkle, Janice L., and Mary McKenna Guanci. "Acute ischemic stroke review." *Journal of Neuroscience Nursing* 39.5 (2007): 285-293.

12. Vivian Weerdesteyn PhD, P. T., et al. "Falls in individuals with stroke."*Journal of rehabilitation research and development* 45.8 (2008): 1195.

13. Nyberg, Lars, and Yngve Gustafson. "Patient falls in stroke rehabilitation a challenge to rehabilitation strategies." *Stroke* 26.5 (1995): 838-842.

14. Hyndman, Dorit, Ann Ashburn, and Emma Stack. "Fall events among people with stroke living in the community: circumstances of falls and characteristics of fallers." *Archives of physical medicine and rehabilitation*83.2 (2002): 165-170.

15. I. A. K. DE QUERVAIN, S. R. Simon, S. Leurgans, W. S. Pease, and D. McALLISTER, "Gait Pattern in the Early Recovery Period after Stroke*," *The Journal of Bone & Joint Surgery*, vol. 78, no. 10, pp. 1506-14, 1996.

16. S. Mulroy, J. Gronley, W. Weiss, C. Newsam, and J. Perry, “Use of cluster analysis for gait pattern classification of patients in the early and late recovery phases following stroke,” *Gait & posture,* vol. 18, no. 1, pp. 114-125, 2003.

17. S. J. Olney, and C. Richards, “Hemiparetic gait following stroke. Part I: Characteristics,” *Gait & Posture,* vol. 4, no. 2, pp. 136-148, 1996.

18. Burpee, Jessica L., and Michael D. Lewek. "Biomechanical gait characteristics of naturally occurring unsuccessful foot clearance during swing in individuals with chronic stroke." *Clinical Biomechanics* 30.10 (2015): 1102-1107.

19. J. Feasel, M. C. Whitton, L. Kassler, F. P. Brooks, and M. D. Lewek, “The integrated virtual environment rehabilitation treadmill system,” Neural Systems and Rehabilitation Engineering, IEEE Transactions on, vol. 19, no. 3, pp. 290-297, 2011.

20. C. K. Rhea, C. J. Wutzke, and M. D. Lewek, “Gait dynamics following variable and constant speed gait training in individuals with chronic stroke,” Gait & posture, vol. 36, no. 2, pp. 332-334, 2012.

21. M. Murray, A. Hardee, R. L. Goldberg, and M. D. Lewek, “Loading and knee flexion after stroke: Less does not equal more,” Journal of Electromyography and Kinesiology, vol. 24, no. 1, pp. 172-177, 2014.

22. J. Liu, S. Ranka, and T. Kahveci, “Classification and feature selection algorithms for multi-class CGH data,” Bioinformatics, vol. 24, no. 13, pp. i86-i95, 2008.

23. T. R. Golub, D. K. Slonim, P. Tamayo, C. Huard, M. Gaasenbeek, J. P. Mesirov, H. Coller, M. L. Loh, J. R. Downing, and M. A. Caligiuri, “Molecular classification of cancer: class discovery and class prediction by gene expression monitoring,” science, vol. 286, no. 5439, pp. 531-537, 1999.

24. C. Ding, and H. Peng, “Minimum redundancy feature selection from microarray gene expression data,” Journal of bioinformatics and computational biology, vol. 3, no. 02, pp. 185-205, 2005.

25. Huang, He, et al. "An analysis of EMG electrode configuration for targeted muscle reinnervation based neural machine interface." *Neural Systems and Rehabilitation Engineering, IEEE Transactions on* 16.1 (2008): 37-45.

26. Farrell, M. Todd, and Hugh Herr. "A method to determine the optimal features for control of a powered lower-limb prostheses." *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*. IEEE, 2011.

27. Zhang, Fan, and He Huang. "Source selection for real-time user intent recognition toward volitional control of artificial legs." *Biomedical and Health Informatics, IEEE Journal of* 17.5 (2013): 907-914.

28. D. L. Davies, and D. W. Bouldin, “A cluster separation measure,” Pattern Analysis and Machine Intelligence, IEEE Transactions on, no. 2, pp. 224-227, 1979.

29. V. J. Hodge, and J. Austin, “A survey of outlier detection methodologies,” Artificial Intelligence Review, vol. 22, no. 2, pp. 85-126, 2004.

30. J. L. Lelas, G. J. Merriman, P. O. Riley, and D. C. Kerrigan, “Predicting peak kinematic and kinetic parameters from gait speed,” Gait & posture, vol. 17, no. 2, pp. 106-112, 2003.

31. J. A. Hanley, and B. J. McNeil, “The meaning and use of the area under a receiver operating characteristic (ROC) curve,” Radiology, vol. 143, no. 1, pp. 29-36, 1982.

32. Luinge, Henk J., and Peter H. Veltink. "Measuring orientation of human body segments using miniature gyroscopes and accelerometers."*Medical and Biological Engineering and computing* 43.2 (2005): 273-282.

33. Yan, Tiebin, Christina WY Hui-Chan, and Leonard SW Li. "Functional electrical stimulation improves motor recovery of the lower extremity and walking ability of subjects with first acute stroke a randomized placebo-controlled trial." Stroke 36.1 (2005): 80-85.

34. Maneski, Lana Z. Popović, et al. "Surface-distributed low-frequency asynchronous stimulation delays fatigue of stimulated muscles." Muscle & nerve 48.6 (2013): 930-937.

35. Zhou, Shi, et al. "Electromechanical delay in isometric muscle contractions evoked by voluntary, reflex and electrical stimulation."European journal of applied physiology and occupational physiology70.2 (1995): 138-145.

36. Ziegler-Graham K, MacKenzie EJ, Ephraim PL, Travison TG, Brookmeyer R. Estimating the Prevalence of Limb Loss in the United States: 2005 to 2050. Archives of Physical Medicine and Rehabilitation2008;89(3):422-9.

37. Owings M, Kozak LJ, National Center for Health S. Ambulatory and Inpatient Procedures in the United States, 1996. Hyattsville, Md.: U.S. Dept. of Health and Human Services, Centers for Disease Control and Prevention, National Center for Health Statistics; 1998.

38. Pauley, Tim, Michael Devlin, and Kathleen Heslin. "Falls sustained during inpatient rehabilitation after lower limb amputation: prevalence and predictors." American journal of physical medicine & rehabilitation 85.6 (2006): 521-532.

39. Kulkarni, J., et al. "Falls in patients with lower limb amputations: prevalence and contributing factors." Physiotherapy 82.2 (1996): 130-136.

40. Eng, Janice J., David A. Winter, and Aftab E. Patla. "Strategies for recovery from a trip in early and late swing during human walking."Experimental Brain Research 102.2 (1994): 339-349.

41. Össur, "PROPRIO FOOT® Technical manual," Össur.

42. OttoBock, "C-Leg 4 Microprocessor-Controlled Prosthetic Knee," OttoBock2015.

43. Crenshaw, Jeremy R., Kenton R. Kaufman, and Mark D. Grabiner. "Failed Trip Recoveries of Above-knee Amputees Suggest Possible Fall-Prevention Interventions." annual conference of the American Society of Biomechanics, Providence, RI. 2010.

44. Sup, Frank, et al. "Preliminary evaluations of a self-contained anthropomorphic transfemoral prosthesis." Mechatronics, IEEE/ASME Transactions on 14.6 (2009): 667-676.

45. Eilenberg, Michael F., Hartmut Geyer, and Hugh Herr. "Control of a powered ankle–foot prosthesis based on a neuromuscular model." Neural Systems and Rehabilitation Engineering, IEEE Transactions on 18.2 (2010): 164-173.

46. Liu, Ming, et al. "Improving finite state impedance control of active-transfemoral prosthesis using dempster-shafer based state transition rules." Journal of Intelligent & Robotic Systems 76.3-4 (2014): 461-474.

47. Zhang, Fan, et al. "Towards design of a stumble detection system for artificial legs." Neural Systems and Rehabilitation Engineering, IEEE Transactions on 19.5 (2011): 567-577.

48. B. E. Lawson, H. A. Varol, F. Sup, and M. Goldfarb, "Stumble detection and classification for an intelligent transfemoral prosthesis," in Engineering in medicine and biology society (EMBC), 2010 annual international conference of the IEEE, 2010, pp. 511-514.

49. Thatte, Nitish, and Hartmut Geyer. "Towards local reflexive control of a powered transfemoral prosthesis for robust amputee push and trip recovery." Intelligent Robots and Systems (IROS 2014), 2014 IEEE/RSJ International Conference on. IEEE, 2014.

50. McFadyen, B. J., and H. Carnahan. "Anticipatory locomotor adjustments for accommodating versus avoiding level changes in humans."Experimental brain research 114.3 (1997): 500-506.

51. Austin, Gary P., Gladys E. Garrett, and Richard W. Bohannon. "Kinematic analysis of obstacle clearance during locomotion." Gait & posture 10.2 (1999): 109-120.

52. Zatsiorsky, V., and V. Seluyanov. "The Mass and Inertia Characteristics of the Main Segments of the Human Body, Biomechanics VIII-B, Matsui, H. and Kobayashi, K.(eds.),(1983)." 1152-1159.

53. Peasgood, Mike, Eric Kubica, and John McPhee. "Stabilization of a dynamic walking gait simulation." Journal of computational and nonlinear dynamics 2.1 (2007): 65-72.

54. Marhefka, Duane W., and David E. Orin. "A compliant contact model with nonlinear damping for simulation of robotic systems." Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on 29.6 (1999): 566-572.

55. MSC, "Help document for Adams/View - Adams 2012.1.2," 2012.

56. Schillings, A. M., et al. "Muscular responses and movement strategies during stumbling over obstacles." Journal of Neurophysiology 83.4 (2000): 2093-2102.

57. Schillings, A. M., Th Mulder, and Jaak Duysens. "Stumbling over obstacles in older adults compared to young adults." Journal of neurophysiology 94.2 (2005): 1158-1168.

58. Thornton, C. "Coefficient of restitution for collinear collisions of elastic-perfectly plastic spheres." Journal of Applied Mechanics 64.2 (1997): 383-386.

59. Jackson, Robert L., Itzhak Green, and Dan B. Marghitu. "Predicting the coefficient of restitution of impacting elastic-perfectly plastic spheres."Nonlinear Dynamics 60.3 (2010): 217-229.

60. Hurley, G. R. B., et al. "The role of the contralateral limb in below-knee amputee gait." Prosthetics and orthotics international 14.1 (1990): 33-42.

61. Huang, He, et al. "A Cyber Expert System for Auto-Tuning Powered Prosthesis Impedance Control Parameters." Annals of Biomedical Engineering (2015): 1-12.

62. F. Zhang, W. DiSanto, J. Ren, Z. Dou, Q. Yang, H. Huang, “A Novel CPS System for Evaluating a Neural-Machine Interface for Artificial Legs”, in Proceeding of 2nd ACM/IEEE International Conference on Cyber-Physical Systems, Chicago, IL, pp 67-76, 2011

63. Huang,He, Todd A. Kuiken, and Robert D. Lipschutz. "A strategy for identifying locomotion modes using surface electromyography."Biomedical Engineering, IEEE Transactions on 56.1 (2009): 65-73.

64. Hefferman, Gerald M., et al. "Integration of surface electromyographic sensors with the transfemoral amputee socket: A comparison of four differing configurations." Prosthetics and orthotics international 39.2 (2015): 166-173.