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An Analysis of the Accuracy of Wearable Sensors for Classifying the Causes of Falls in Humans

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Abstract

Falls are the number one cause of injury in older adults. Wearable sensors, typically consisting of accelerometers and/or gyroscopes, represent a promising technology for preventing and mitigating the effects of falls. At present, the goal of such “ambulatory fall monitors” is to detect the occurrence of a fall and alert care providers to this event. Future systems may also provide information on the causes and circumstances of falls, to aid clinical diagnosis and targeting of interventions. As a first step towards this goal, the objective of the current study was to develop and evaluate the accuracy of a wearable sensor system for determining the causes of falls. Sixteen young adults participated in experimental trials involving falls due to slips, trips, and “other” causes of imbalance. Three-dimensional acceleration data acquired during the falling trials were input to a linear discriminant analysis technique. This routine achieved 96% sensitivity and 98% specificity in distinguishing the causes of a falls using acceleration data from three markers (left ankle, right ankle, and sternum). In contrast, a single marker provided 54% sensitivity and two markers provided 89% sensitivity. These results indicate the utility of a three-node accelerometer array for distinguishing the cause of falls.

Index Terms

Accelerometers; aging; balance; biomechanics; fall detection; falls; injury; linear discriminant analysis (LDA); machine learning; postural stability

I. Introduction

Falls are the number one cause of injuries in older adults, including approximately 90% of hip fractures, 40% of vertebral fractures, and 60% of head injuries [1]–[3]. Wearable kinematic sensors, typically consisting of miniature accelerometers and/or gyroscopes,

represent a promising technology for preventing and mitigating the effects of falls in older adults. While currently in its infancy, the application of such “ambulatory fall monitors” will likely continue to grow as sensor hardware become further miniaturized, and systems emerge for producing reliable and clinically useful information.

At present, the primary goal of ambulatory fall monitors is to detect the occurrence of a fall and alert care providers to this event [4]–[7], who can then commence earlier treatment and prevent the “long lie” that often accompanies falls in older adults. Such systems have been the focus of intense research and development by several groups over the past 10 years, who have examined the accuracy of one or more sensors (accelerometers or gyroscopes) to distinguish falls from daily activities as captured in the laboratory setting. Collectively, these studies indicate that 95%–100% accuracy in fall detection can be achieved from a single sensor mounted at the head, torso, or pelvis, based for example on detecting accelerations applied to the pelvis and torso at impact, or vertical and horizontal velocities of body segments during descent, which exceed the range of values observed during normal activities [8]–[10]. For example, Bourke *et al.* [11] found that a threshold algorithm, focusing on peak values of acceleration from two tri-axial accelerometers mounted on the thigh and sternum, was 100% successful in separating falls (in the forward, backward, and lateral directions) from 10 activities of daily living, based on the high accelerations occurring at impact from the fall. Similarly, Wu [12] found that, based on analysis of the velocity profile of the trunk, she could correctly categorize 45 out of 46 falls from a range of daily activities.

In the present study, we extend our consideration of the role of wearable sensors beyond fall detection, to explore whether body segment movements occurring before impact, during the initiation and descent phases of the fall, can provide insight on the mechanisms (cause and circumstances) of the event. Currently, our understanding of how and why these events occur is based on self-reports, which may be unreliable [13], [14], or witness accounts, which are often unavailable [15], [16]. The ability to provide objective information on fall mechanisms would extend the utility of fall monitoring systems to assist researchers in understanding the contributing role of physiological and environmental variables, and health care providers in the diagnosis and targeting of interventions.

As a first step in the development of such systems, the goal of the current study was to develop a wearable sensor system, and a related data classification scheme, for accurately characterizing the cause of falls due to slips, trips, and other types of imbalance. We addressed this goal by conducting laboratory “falling experiments” with young adults, acquiring whole-body kinematic data for a wide range of fall causes. We then systematically input acceleration data, acquired immediately preceding the fall, into a linear discriminant analysis classification routine, to determine how system accuracy in predicting the cause of fall depended on the number and location of accelerometer sensors. Our methods serve as a template for the development of additional applications of wearable sensors in falls research and prevention.

II. Material and Methods

A. Participants

Sixteen healthy young adults (12 of whom were men) participated in this study, ranging in age between 20 and 35 years (mean = 25.6 years, SD = 3.8 years). All participants were students at Simon Fraser University, recruited through advertisements and flyers on university notice boards. The experiment protocol was approved by the Research Ethics Committee at Simon Fraser University and all participants provided informed written consent.

B. Experimental Protocol

In the experimental trials, participants fell to the ground from standing height, simulating various underlying causes of imbalance (Fig. 1). In all trials, participants fell onto a 30-cm-thick gymnasium mattress, into which we inserted a 1.3-cm top layer of high density ethylene vinyl acetate foam, so the composite structure was stiff enough to allow for stable standing and walking, but soft enough to reduce the forces during impact to a safe level.

Given our long-term goal of designing a wearable sensor system for classifying falls in older adults, a major concern in our experimental design was to best ensure that the falls we simulated were typical of those experienced by older adults. To address these concerns, we examined a library of video sequences of 227 real-life falls in older adults, acquired as part of an ongoing project by our research team to examine the mechanisms of falls in long-term care facilities [17]. We found that 75% of falls were collectively due to slips, trips, and five other combinations of cause and activity: fainting, incorrect weight transfer while sitting down on a chair, incorrect weight transfer while rising from sitting, losing balance while reaching for an object, and losing balance while turning. As further described below, we conducted training sessions with each participant, where we displayed representative video of a real-life fall (Fig. 2) and instructed them fall in a fashion similar to that observed in the older adult.

In slipping trials [Fig. 2(a)], participants walked over a low friction plastic sheet, and were made to slip backward by either rapidly translating the sheet ($n = 3$) or by simply instructing them to act out a backward slip ($n = 3$) without translation of the sheet. Tripping trials [Fig. 2(b)] were simulated either by having a rope attached to the participant's right ankle become taut during the swing phase of walking ($n = 3$) or by instructing the participant to simply act out a trip over an obstacle ($n = 3$; a wooden block of approximately 10 cm width and 15 cm height), initiating a forward fall. In falls due to other causes, the participant was instructed to act out falls due to fainting ($n = 3$), incorrect weight transfer while sitting down on a chair ($n = 3$), incorrect weight transfer while rising from sitting ($n = 3$), loss of balance while reaching for an object ($n = 3$), and loss of balance while turning ($n = 3$). In fainting trials, participants were instructed to stand on the gym mat and then suddenly relax (or collapse) the legs to act out a faint as naturally as possible. No instruction was given about the direction of the fall. In falls caused by loss of balance while reaching, participants were instructed to reach and pick up an object placed on the ground in front of them, primarily by bending at the waist and, after retrieving the object, to lose balance upon rising and fall

backward. In falls due to loss of balance while turning, participants were instructed to turn 180 from standing, lose balance and fall. No instruction was provided on the desired fall direction. In falls due to incorrect weight transfer while sitting, we instructed participants to begin in a standing position, and then lower the body in a controlled manner to simulate sitting down on a fictitious chair, and at the expected contact position, to lose their balance and fall backward. In falls due to incorrect transfer while rising, participants initially sat on a chair and were instructed to lose their balance while attempting to stand up. Again, no instruction was provided on the fall direction. In the current analysis, we considered trials that resulted in falls (successful recoveries will be analyzed in a future publication). Therefore, over the 16 participants, a total of 96 slips, 96 trips, and 240 “other cause” trials were analyzed.

C. Data Collection

During each trial, we used an eight-camera motion analysis system (Eagle system, Motion Analysis Corp.) recording at 120 Hz to acquire the three-dimensional positions of 22 reflective skin markers. Markers were located bilaterally over the ankles (lateral malleoli), knees (lateral femoral epicondyles), hips (greater trochanters), waist [right and left anterior superior iliac spine (ASIS)], wrists (dorsal surface), elbows (olecranon), shoulders (lateral humeral epicondyles), and scapulae. Markers were also located at the sternum, C7 vertebrae, sacrum and the front, top, and back of the head. Position data were low pass filtered using a recursive, fourth-order Butterworth filter having a cutoff frequency of 20 Hz [4], [18] and double differentiated to estimate accelerations.

D. Data Analysis

Data analysis focused on determining whether the cause of falls could be accurately predicted from 3D acceleration data from five key anatomical locations (markers at the left ankle, right ankle, waist (right ASIS), sternum, and top of the head), selected based on their feasibility for sensor placement on the human body. In the single marker category, we included only waist, sternum, and head, and not right ankle or left ankle markers, based on the consideration that the asymmetry in foot movements associated with trips and slips would necessitate bilateral placement in any real life application of our sensor technology.

For each trial, we identified the approximate pelvic impact time (T_0) as the time of maximum vertical (downward) velocity of the right ASIS during descent, as determined through the graphical user interface of EVaRT motion capture software (EVaRT, Motion Analysis Corporation, Santa Rosa, CA). Acceleration data for the 1.500 s up to and including T_0 were input to our fall classification procedure, as described in the next paragraph. Previous studies have shown that the time interval during a fall between loss of balance and impact to the pelvis averages 0.715 s, with a standard deviation of 0.100 s [18], [19]. Thus, we regarded a time window of 1.500 s prior to pelvis impact as sufficient to capture the initiation and descent phase of each fall, and this was indeed shown to be the case for all falls (Fig. 3). We used linear discriminant analysis (LDA) and Fisher’s criterion to classify the causes of falls. The features input to these routines were the mean acceleration and variance in acceleration for each of the X, Y, and Z axes (commonly used features for recognizing human posture and activities of daily living [20]–[23]), from each of

the five markers, calculated over the 1.5 s preceding pelvis impact. This resulted in a 30 dimension “feature vector.” We then split this feature vector into model training and testing sets of equal size by choosing data from the first eight participants for training and the following eight for testing. The LDA procedure applies a set of operations to the feature space, which results in optimal separability between classes [24]–[26].

We conducted linear discriminant analysis using acceleration data from each marker, and for each possible combination of 2, 3, 4, and 5 markers. In each case, we then constructed confusion matrices and used these to calculate sensitivity, specificity, precision and accuracy (Fig. 4) as shown in

$$\begin{aligned}\text{Sensitivity} &= \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \times 100 \\ \text{Specificity} &= \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}} \times 100 \\ \text{Precision} &= \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \times 100\end{aligned}$$

and

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}} \times 100$$

We ranked each marker location or combination of markers based on the highest minimum sensitivity observed across the three conditions.

III. Results

The accuracy of the linear discriminant classification algorithm in classifying the cause of falls depended strongly on the location and number of markers, and varied considerably between the different types of falls (Table I). With a single marker, the highest minimum sensitivity was observed for the head and waist markers, which provided at least 54% sensitivity. The worst minimum sensitivity was provided by the sternum (31%). Each of the head, sternum and waist markers were relatively successful in classifying slips (with sensitivities of 77%, 77%, and 96%, respectively) and even better at distinguishing other causes of falls (with sensitivities of 82%, 92%, and 98%), but relatively poor in classifying trips (with sensitivities of 54%, 31%, and 54%).

With two markers, the highest minimal sensitivity was observed for the combination of left ankle + right ankle, which distinguished slips, trips and other falls with 89%, 94%, and 97% sensitivity, respectively. Markers combinations of waist + sternum, waist + head and sternum + head were also effective in detecting slips and other causes of falls (with at least 87% sensitivity), but had no better than 53% sensitivity in distinguishing trips.

The best overall performance was observed with the three marker combination of left ankle + right ankle + sternum, which provided at least 96% sensitivity in classifying all three fall types. The next best three-marker combinations were left ankle + right ankle + head and left

ankle + right ankle + waist, which provided at least 94% and 87% sensitivities. The combination of waist + sternum + head was successful in distinguishing slips and falls due to other causes (with 96% and 97% sensitivities, respectively) but provided only 60% sensitivity for trips. This reflects the general trend of upper body markers being successful in classifying falls due to slips and other causes, foot markers were essential for accurate classification of trips.

The minimum sensitivity was no better with four and five markers than with three. The highest minimum sensitivity for the combination of left ankle + right ankle + sternum + head was 92%, but this decreased to 89% for the other two four-marker combinations.

Specificity (risks for fall positives) was generally high, decreasing below 80% only for the case of a single sternum marker used to classify falls due to other causes. Precision (proportion of true positives against all positive results) was generally lower for slips than trips and other causes. For the “best performing” combination of left ankle + right ankle + sternum, precision was 92%, 90%, and 100% for slips, trips and other causes, respectively, and accuracy (proportion of true results in the overall sample) was at least 97%.

IV. Discussion

Ambulatory fall monitors based on miniature wearable sensors represent a promising approach for detecting and distinguishing the mechanisms of falls in older adults. Previous studies have shown that a single 3D accelerometer, mounted at the head, torso or pelvis, can detect the occurrence of a fall with high accuracy [5]–[12]. In the current study, we extended this line of research by examining the utility of wearable sensors for providing information on the causes of falls acquired in a laboratory setting. Our results indicate that 3D acceleration data from three markers (the left ankle, right ankle, and sternum), acquired at 120 Hz for 1.5 s before impact, and entered into a linear discriminant model, provides at least 96% sensitivity in distinguishing falls due to slips, trips, and other causes. In contrast, the best two-marker combination (left ankle and right ankle) provided a minimum sensitivity of 89%, and the best single marker (head or waist) provided only 54% sensitivity.

The improvement in performance provided by three anatomical sites reflects the observation that no two-site combination was able to capture body kinematics unique to each of the three fall types. Slips are initiated just after heel strike, and involve forward sliding of the foot along the ground, resulting typically in a backward fall. We found these falls could be accurately detected with a single marker at the waist (96% sensitivity) and with combinations of “waist and sternum,” or “waist and head.” On the other hand, trips are caused by obstruction of forward movement of the foot during walking, usually due to contact with an obstacle, and typically involve subsequent anterior rotation of the torso and a forward fall. A single marker had poor sensitivity (54%) for detecting such falls, which require sensors on both the right and left feet. In contrast, all two-marker combinations were accurate in distinguishing falls due to “other causes” from those due to slips and trips. These observations help to explain why acceleration data from both feet and the waist (or sternum) are required for comprehensive “cause of fall” detection.

In general, our model predictions had greater specificity than sensitivity, which suggests that our system was better at classifying “negatives” than “positives” (Fig. 5). One exception to this trend was predictions from a single sternum marker, where falls due to slips and trips were often misclassified as due to other causes. Also, precision was generally lower than sensitivity, suggesting a higher number of false positives than false negatives.

There are important limitations to this study. Our participants were healthy young adults, who fell onto a soft landing surface, and initiated their falls voluntarily (although 50% of our tripping and slipping trials involved suddenly applied perturbations). Therefore, an important unanswered question is the extent to which our classification procedure and results will transfer to unexpected falls on a hard surface by older adults, including those with specific disease conditions or neuromuscular impairments who make them prone to falls. Ultimately, this issue can only be addressed by testing the system with older adults as they go about their daily activities. However, several aspects of our experimental design enhance the validity of our results in this population. Most importantly, before commencing a given series of trials, each of our participants studied representative video clips of real-life falls experienced by older adults residing in long-term care, and were instructed to “act out” a similar fall. Despite the inevitable variability in the acting style of participants, we believe this approach to fall simulation substantially enhanced the validity of our results for older adults. We also utilized a ground surface that was soft enough to ensure minimal risk for injury during landing from a fall, but stiff enough to prevent excessive compression during walking or standing. This helped to ensure that body segment kinematics during fall initiation and descent were similar to what would be expected for a fall onto a rigid surface.

Another possible limitation of this study is the fact that the acceleration data input to our fall classification routine were derived by double differentiating position data obtained from our video-based motion analysis system, and will differ in nature from those provided by wearable accelerometers which have a moving reference frame, and measure the vector sum of sensor accelerations plus gravity. While we see little reason for a reduction with accelerometers in the accuracy of our machine learning algorithm (LDA), this remains to be verified through future studies. Additional studies are also required to compare the accuracy of LDA to alternative data classification schemes [such as support vector machine (SVM) or hidden Markov models (HMM)], incorporating various time and frequency domain features, and decision thresholds.

Finally, given the current size of self-contained wearable 3D sensors with on-board data storage and power supply (which are at least the size of large wrist watches), there is a legitimate concern that routine wear may be met with low user compliance in the target population. However, given the rapid rate of miniaturization of these components, one might expect that sufficient performance will soon be achieved with units the size of plasters.

Given the multifactorial etiology of falls and fall-related injuries in older adults, clinicians and researchers need to consider a comprehensive range of information on intrinsic and environmental contributors in designing and selecting interventions. The potential utility of wearable kinematic sensors in this regard extends beyond detecting the causes of fall, to applications such as detecting “near falls,” prompting and monitoring balance recovery

responses, triggering the deployment of protective clothing (such as inflatable hip and head protectors), or providing information on injury severity. Data from kinematic sensors can also be integrated with synchronized measures from physiological sensors (e.g., electromyograms, electrocardiogram, and blood pressure) for an improved understanding of fall mechanisms. The methods employed here provide a useful template for the development and evaluation of such applications.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Biographies

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Stephen N. Robinovitch received the B.App.Sc. degree in 1988 from the University of British Columbia, the M.S. degree in 1990 from Massachusetts Institute of Technology, and the Ph.D. degree in 1995 from Harvard/Massachusetts Institute of Technology.

He is a Professor and Canada Research Chair in Injury Prevention and Mobility Biomechanics at Simon Fraser University. His research focuses on improving our understanding of the cause and prevention of fall-related injuries (especially hip fracture) in older adults, through laboratory experiments, mathematical modeling, field studies in residential care facilities, and product design.

Fig. 1.

Experiment protocol, indicating the various types of falls experienced by each participant. Sixteen participants (12 males and 4 females) experienced three repeated trials for each type of fall, resulting in a total of 96 falls due to slips, 96 due to trips, and 240 due to “other causes.”

Fig. 2.

Laboratory simulation of falls in older adults due to (A) slips, (B) trips, and (C) collapse (one of the five examined other causes of imbalance). Video segments of real-life falls in older adults captured by digital video networks in long term care facilities (top panels) were used to train young participants to mimic the falling behavior of older adults (bottom panels).

Fig. 3.

Acceleration traces in the x, y, and z directions from a typical participant in falls due to slip, trip and collapse. Data from each of the three falls are aligned so pelvis impact occurs at $t = 1.5$ s. Acceleration data for the 1.5 s preceding pelvis impact were input to our fall classification algorithm. The legends explain the coordinate reference frame for each fall e.g., in a slip, the x-axis represents is medial/lateral (positive left), the y-axis represents posterior/anterior (positive posterior), and the z-axis represents superior/inferior movement (positive superior); refer also to the coordinate system axes at the bottom left in Fig. 2(a)–(c). The vertical dashed line indicates the instant of impact (note the correspondingly high acceleration of the waist and sternum markers). Note also the characteristic stepping behaviors in the trip and slip.

A

Slip				Trip				Other Loss-of-Balance			
actual	predicted			actual	predicted			actual	predicted		
	Slip	Trip	Other		Slip	Trip	Other		Slip	Trip	Other
Slip	TP	FN	FN	Slip	TN	FP	TN	Slip	TN	TN	FP
Trip	FP	TN	TN	Trip	FN	TP	FN	Trip	TN	TN	FP
Other	FP	TN	TN	Other	TN	FP	TN	Other	FN	FN	TP

B

Sensor array: Left ankle + Right ankle + Sternum			
actual	predicted		
	Slip	Trip	Other
Slips (n=48)	46	2	0
Trips (n=48)	2	46	0
Other (n=48)	0	3	115

Fig. 4.

(A) For each of the three general causes of falls, definitions of true positive (TP), true negative (TN), false positive (FP), and false negative (FN). Note the differences between the three causes in the cases (matrix cells) that represent TPs, FNs, TNs, and FPs. These parameters, in turn, define the sensitivity and specificity of the model for each cause of fall, as defined in the data analysis section of the text. (B) Confusion matrix, displaying the ability of the three-marker combination of left ankle + right ankle + sternum to distinguish falls due to slips, trips, and other causes.

Fig. 5.

Comparison of the sensitivity of various marker combinations for correctly classifying the causes of falls. H = Head, S = Sternum, W = Waist, LA = Left Ankle, RA = Right Ankle. We regarded the three-marker combination of LA+RA+S as providing the best performance, since it the highest minimum sensitivity (96%) among all combinations examined.

TABLE I

Sensitivity, Specificity, Precision, and Accuracy of Various Marker Arrays in Detecting the Cause of Falls

Marker Combination	Slips (n = 48)				Trips (n = 48)				Other loss of balance (n = 120)			
	Sens(%)	Spec(%)	Prec(%)	Acc(%)	Sens(%)	Spec(%)	Prec(%)	Acc(%)	Sens(%)	Spec(%)	Prec(%)	Acc(%)
One marker												
Head	77	85	60	83	54	93	68	84	82	82	85	82
Sternum	77	87	63	85	31	99	94	84	92	68	78	81
Waist	96	90	74	92	54	98	90	88	98	93	94	96
Two markers												
Left Ankle + Right Ankle	89	98	93	96	94	95	83	94	97	100	100	98
Waist + Sternum	100	92	77	93	52	98	89	88	97	91	93	94
Waist + Head	96	90	74	92	53	98	90	89	97	94	95	86
Sternum + Head	87	90	71	89	50	94	70	84	91	85	89	88
Three markers												
Left Ankle + Right Ankle + Waist	96	97	90	97	87	98	93	96	99	99	99	99
Left Ankle + Right Ankle + Sternum	96	98	92	97	96	97	90	97	96	100	100	98
Left Ankle + Right Ankle + Head	96	97	90	97	94	97	90	96	96	100	100	98
Waist + Sternum + Head	96	92	77	92	60	98	91	90	97	92	93	94
Four markers												
Left Ankle + Right Ankle + Waist + Sternum	96	97	90	97	89	98	91	96	98	100	100	99
Left Ankle + Right Ankle + Waist + Head	98	96	89	97	89	99	95	97	98	100	100	99
Left Ankle + Right Ankle + Sternum + Head	94	97	90	96	92	96	88	95	97	100	100	98
Five markers												
Left Ankle + Right Ankle + Waist + Sternum + Head	87	96	87	94	93	97	88	93	97	100	100	96

NOTES: Sens = sensitivity; Spec = specificity; Prec = precision; Acc = accuracy.