Portable Preimpact Fall Detector With Inertial Sensors

Ge Wu and Shuwan Xue

Abstract—**Falls and the resulting hip fractures in the elderly are a major health and economic problem. The goal of this study was to investigate the feasibility of a portable preimpact fall detector in detecting impending falls before the body impacts on the ground. It was hypothesized that a single sensor with the appropriate kinematics measurements and detection algorithms, located near the body center of gravity, would be able to distinguish an in-progress and unrecoverable fall from nonfalling activities. The apparatus was tested in an array of daily nonfall activities of young ($n = 10$) and elderly ($n = 14$) subjects, and simulated fall activities of young subjects. A threshold detection method was used with the magnitude of inertial frame vertical velocity as the main variable to separate the nonfall and fall activities. The algorithm was able to detect all fall events at least 70 ms before the impact. With the threshold adapted to each individual subject, all falls were detected successfully, and no false alarms occurred. This portable preimpact fall detection apparatus will lead to the development of a new generation inflatable hip pad for preventing fall-related hip fractures.**

Index Terms—**Elderly, fall detection, inertial sensor, preimpact.**

I. Introduction

FALL-RELATED hip fractures are common among the elderly [1] and present the most serious threat [2], [3]. Each year, more than 200 000 hip fractures occur in people over the age of 65 years as a result of a fall [4], [5]. They are the leading cause of fall-related death, with a mortality rate of 14%–36% one year after hip fracture [6]–[8]. For those elderly people who survive a hip fracture, most never regain their premorbid level of ambulation [9], [10].

Fall-related hip fractures in the elderly also present a tremendous amount of economic burden to the victim, with an annual medical cost of $7–$10 billion on treating fall-related hip fractures, and another $2.5 billion on nursing home care for fall-related hip fractures in the U.S. [11], [12].

Fall-related hip fractures may be prevented by hip protection pads [13]–[15]. However, current designs of these pads are faced with the dilemma of either being made very thick to increase the effectiveness but sacrificing their acceptance by the users [14], [16], [17] or made thin, flexible, and reasonably loose to increase their comfort level and acceptance by the elderly, but sacrificing their effectiveness [18]–[20].

Alternatively, the use of airbag as a hip protection mechanism has been suggested [9], [21]. However, one key problem that remains unresolved to the protection mechanism is the detection of an impending fall well before the hip hits the ground. Given the variety and the complexity of falls among the elderly, the preimpact detection of a fall becomes challenging. To date, few studies are available that address preimpact detection of falls.

Although falls may occur in many ways such as backward falls (e.g., due to a slippery floor), forward falls (due to tripping), sideway falls (due to misstepping), and straight-down falls (due to fainting) [22], studies have shown that there are distinct kinematics characteristics during falls [23]–[28]. Specifically, the inertial velocity profile of the body is of particular interest. For example, the vertical velocity at landing from a standing fall is shown to range between 2–4 m/s [24], [25], which is 2–3 times of the velocity in normal, nonfall activities [29]. There must be a large vertical acceleration that lasts sufficient time during the descending phase of the fall to achieve this velocity. In addition, the vertical velocity during a fall is usually accompanied by a simultaneous increase in the horizontal velocity [30]. This is also different from the majority of normal activities [29]. Based on these observations, we believe that the inertial velocity profile contains sufficient kinematics information during the initiation and descending phase of a fall that can be used for fall detection.

The purpose of this study was to investigate the feasibility of a portable preimpact fall detection apparatus based on the inertial frame velocity profile of the body. It was hypothesized that a single sensor with the appropriate kinematics measurements and detection algorithms, located near the center of gravity of the body, would be able to distinguish an in-progress and unrecoverable fall from nonfalling activities. The apparatus was tested in an array of daily nonfall activities and simulated fall activities with human volunteers. The inertial velocity profiles were measured and compared between the nonfall and fall activities. A preimpact fall detection algorithm based on the inertial frame vertical velocity magnitude was applied to separate the nonfall and fall activities.

II. Method

A. Portable Preimpact Fall Detection Apparatus

The portable preimpact fall detection apparatus consisted of an inertial sensor unit, a data logger, and a real-time fall detection algorithm. A commercially available orientation sensor was used (3DM-G, MicroStrain, Inc., Williston, VT) as the inertial sensor. It included triaxial accelerometers and triaxial angular rate sensors. It was small, light, and battery powered [Fig. 1(b)].

Manuscript received January 27, 2007; revised September 30, 2007; accepted November 7, 2007. This work was supported by the National Institute on Aging under Grant 1R43AG022265-01.

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Digital Object Identifier 10.1109/TNSRE.2007.916282

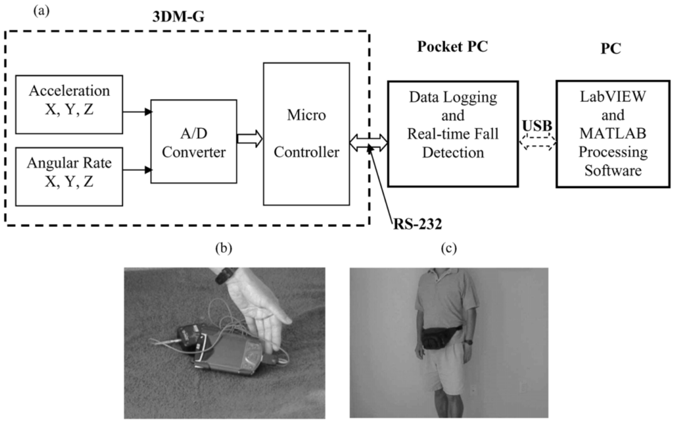

Fig. 1. Illustration of the fall detector system. (a) Block diagram of the sensors and processing system. (b) Photograph of the inertial sensor connected to the pocket PC. (c) Photograph of the sensor attachment to the body.

A pocket PC (HP iPAQ h5550) was used for data logger and for housing the real-time fall detection algorithm [Fig. 1(a)]. The interface between the sensor and the pocket PC was implemented with customized software developed on the National Instruments LabVIEW 7.0 development platform. The pocket PC was able to log over 20 h of raw sensor data from the 3DM-G (nine channels of 12-bit data stream, 57 Hz each channel). The pocket PC also had enough processing power to implement the real-time algorithms. Both orientation sensor and the pocket PC were fitted inside a waist bag that was carried by human subjects on the front of their waist [Fig. 1(c)]. The orientation sensor was adhered firmly to the back side of the waist bag so it was in good contact with subjects' body.

B. Preimpact Fall Detection Algorithm

A simple threshold detection method was used with the magnitude of inertial frame vertical velocity as the main variable to detect falls before impact. The threshold was either set to a fixed value or allowed to vary according to each individual subject's normal activity range (determined after a set of normal activities were performed; see below).

The inertial frame velocity was obtained by first transforming the acceleration and angular velocity measured from the body reference frame to the inertial reference frame, and then integrating the inertial frame acceleration. The transformation was done with the quaternion filter approach [31]–[33] (see Fig. 2: ωB is angular rate in body frame; aI and aB are linear acceleration vectors in inertial and body frames, respectively; aI_v and vI_v are vertical acceleration and velocity in inertial frame, respectively; g is the gravitational acceleration; ωC is corrective angular rate; q and q$^{\sim}$ are Quaternion vectors without and with update, respectively; $\mathrm{D_{B2I}}$ is direction cosine matrix from body to inertial frame; Δq is change of Quaternion vector between two samples; K is proportional gain; and Δt is time interval between two samples). Quaternion filter software was developed using LabVIEW and imported to the pocket PC.

The reference frame transformation algorithm was validated by cross comparison with a theoretical model and a camera-based motion analysis system in two controlled experiments.

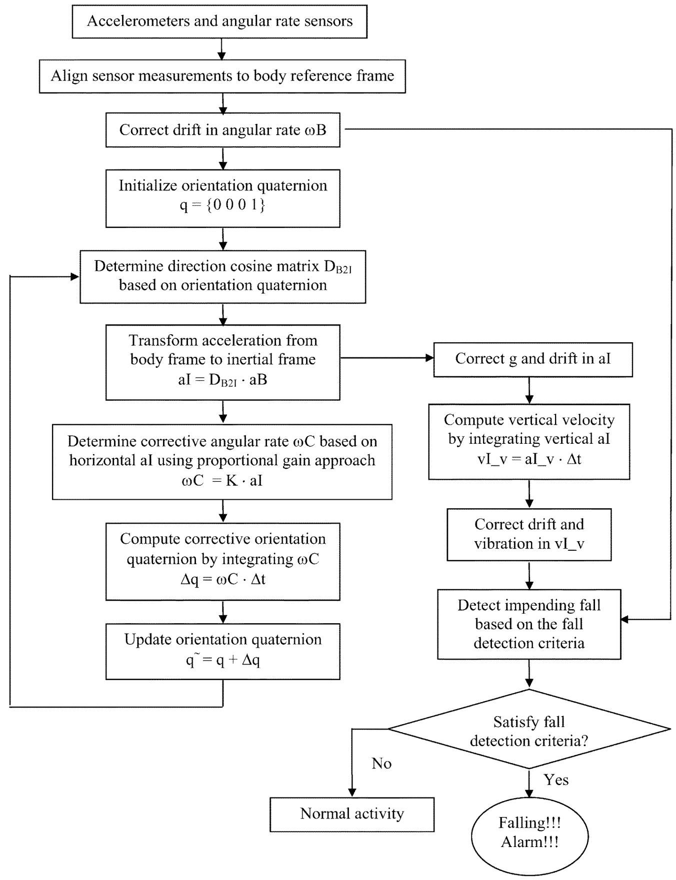

Fig. 2. Block diagram of the fall detection algorithm.

The first controlled experiment was a free fall motion where the sensor was set to fall freely from a known height (H) to a soft cushion, with no particularly fixed orientation of the sensor at the start of and during the fall. The computed vertical acceleration and velocity profiles of the sensor during the free fall. That is

$$a\mathrm{I\_v} = g \tag{1}$$

$$v\mathrm{I\_}v = gt \tag{2}$$

$$T_{\mathrm{air}} = (2H/g)^{1/2} \tag{3}$$

where $a\mathrm{I\_v}$ and $v\mathrm{I\_v}$ are the inertial frame vertical acceleration and velocity, respectively, T_{air} the time the free-fall body is in the air, H the height of free-fall, and g the gravity acceleration.

The second controlled experiment was a pendulum motion where the sensor was suspended at a known pendulum length (2.06 m) and initially displaced a known angle from vertical (10°–50°). The inertial frame vertical velocity at the sensor location was obtained by the inertial sensor measurement, and was compared to that obtained by two other methods: a theoretical pendulum model and a camera-based motion analysis system. The theoretical pendulum model was a classical second-order differential equation as: $\theta'' = g/L \sin\theta$ (where θ is the pendulum angle with respect to the line of gravity, and L the pendulum length). By numerical integration of θ'', the inertial frame velocity was calculated as $v\mathrm{I\_v} = L\theta' \sin\theta$. The camera-based motion analysis system had three 50-Hz infrared sensitive cameras (Elite, Bioengineering Technology and Systems (BTS), Milan, Italy) which measured the spatial position (i.e., $x-y-z$) of a reflective marker attached to the center of the inertial sensor. The cameras were calibrated using a calibration grid (BTS) with one cardinal axis aligned with the line of gravity. The velocity of the marker was computed by numerical differentiation of the displacement of the marker (i.e., $x' - y' - z'$).

C. Normal and Simulated Fall Activities in Human Volunteers

Ten young adults (19–43 years of age) and 14 older adults (72–91 years of age) participated in the testing. They were recruited through flyers. All subjects signed a consent form that was approved by the Institutional Review Board.

The preimpact fall detector apparatus was attached to each subject at the waist as shown in Fig. 1(c). Once the apparatus was powered on, subjects were instructed to perform a series of normal activities, including walking inside a three story building at a strolling pace with combinations of descending and ascending three flights of stairs and taking the elevator up and down the three-story building; sitting down on and rising from three different chairs with a leisure speed; untying and retying shoe laces with any posture; picking up from the floor a 3.7 kg weight at 50% and 100% arm length, respectively; stepping into a bathtub, sitting down, standing up, and stepping out of the tub at a leisure speed; and lying down on a mattress, turning to the side, and getting up at a leisure speed. Young subjects were also asked to perform near fall activities including sway walking (i.e., turning around in place about five turns while eyes were closed, and then walking along a line with eyes open); being tripped unexpectedly while walking; and being pushed unexpectedly while walking. Two of the young subjects were also asked to drive on local streets and on highways, and to go up and down an escalator in a local bookstore. All young subjects were then instructed to perform a series of simulated falls including forward falls, backward falls, sideway falls, and downward falls, three times each. All simulated falls were triggered externally by being pushed suddenly by another person. A thick foam pad (height of 0.12 m) was used for subjects to land their falls. The total recording time for each subject ranged from 40 to 60 min.

The preimpact fall detection algorithm was applied to the inertial frame velocity profiles of all activities. For each trial, following outputs were generated: 1) activity classification: nonfall or fall and 2) if identified as a fall, the time at which the fall was detected ($T_{\text{detection}}$) and the time at which the maximum vertical acceleration occurred (T_{landing}, indicating the time of the fall impact). The lead time for fall detection (T_{lead}) was computed as $T_{\text{lead}} = T_{\text{detection}} - T_{\text{landing}}$. A negative T_{lead} indicated the detection of the fall occurred before the fall impact. The predicted activity status was compared to the true activity status to determine the predictive qualities as follows.

True positive = (Number of true predicted falls/Number of actual falls) $\times$ 100%.

True negative = (Number of true predicted nonfalls/Number of actual nonfalls) $\times$ 100%.

False positive = (Number of unpredicted falls/Number of actual falls) $\times$ 100%.

False negative = (Number of unpredicted nonfalls/Number of actual nonfalls) $\times$ 100%.

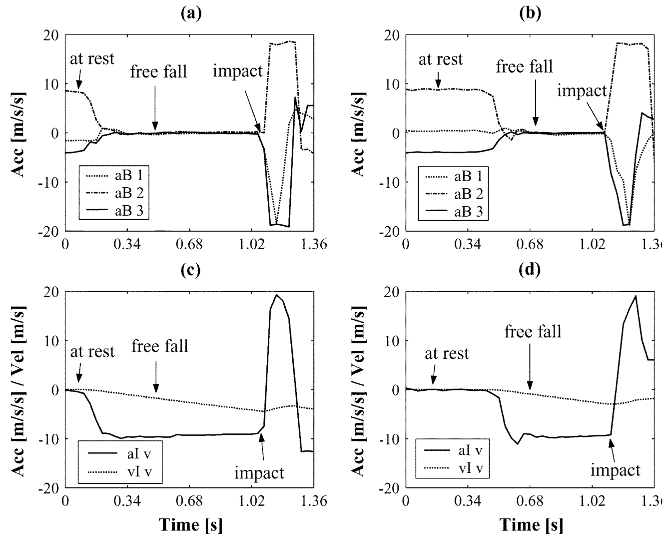

Fig. 3. Time trajectories of acceleration and velocity from the preimpact fall detection apparatus during free falls from a height of 1.22 m (a), (c) and 0.61 m (b), (d), respectively. (a) and (b): Accelerations in the body reference frame (aB1, aB2, and aB3). (c) and (d): Vertical acceleration (aI_v) and vertical velocity (vI_v) in the inertial reference frame.

III. RESULTS

Free-Fall Experiment: The free-fall experiment was done with two different heights: 1.22 and 0.61 m, respectively. Theoretically during a free fall, the vertical acceleration was expected to be the magnitude of gravity g (1) and the horizontal accelerations to be zero. In addition, the time the free-fall body in air (T_{air}) was expected to be 50 and 35 ms for the 1.22- and 0.61-m free-falls, respectively, (3). Fig. 3 shows the time trajectory of inertial frame accelerations (both vertical and horizontal) from the preimpact fall detection apparatus before, during and after these free falls. Both the magnitude and timing of the inertial frame acceleration matched well with the theoretical values. For the inertial frame velocity, since it was simply the integration of the inertial frame acceleration (2), its time trajectory followed the expected linear slope (9.8 m/s^2) during the free falls [as shown in Fig. 3(c) and (d)]. At the end of the 1.22- and 0.61-m free falls, the vertical velocity was 4.6 and 3.3 m/s, respectively, as compared to the theoretical predictions of 4.8 and 3.5 m/s, respectively.

Pendulum Experiment: The inertial frame vertical velocity from the preimpact fall detection apparatus showed close agreements to that calculated from a second-order pendulum model [Fig. 4(a)], and to that derived from the motion analysis system [Fig. 4(b)]. The largest deviations were observed with respect to the theoretical model simulation. This was mainly due to the fact that the damping in the pendulum was unknown and could not be modeled accurately in the theoretical model. The deviation observed with respect to the motion analysis system was mainly due to the digital low-pass filtering of the velocity data which contains larger high-frequency noises than the displacement data.

Detection of Fall Events: The inertial frame vertical velocity trajectories of the preimpact fall detector during various nonfall and fall activities are shown in Fig. 5. For the majority of the

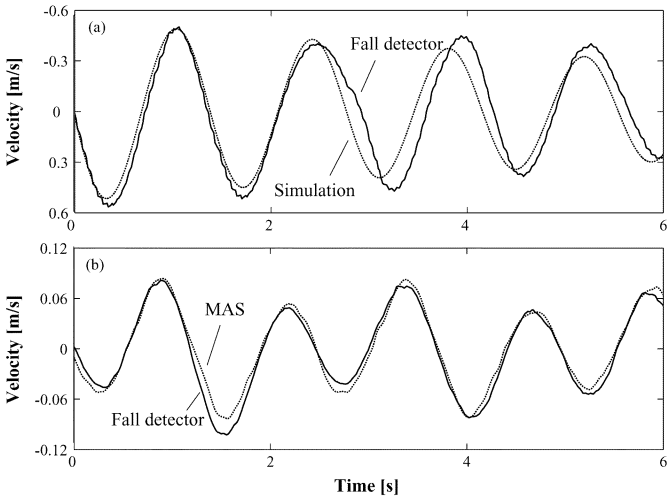

Fig. 4. Time trajectories of inertial frame vertical velocity at the tip of a pendulum during swing, measured from the preimpact fall detection apparatus and (a) calculated from a theoretical model with an initial release angle of 10° from vertical or (b) calculated from the motion analysis system (MAS) with an initial release angle of 34° from vertical.

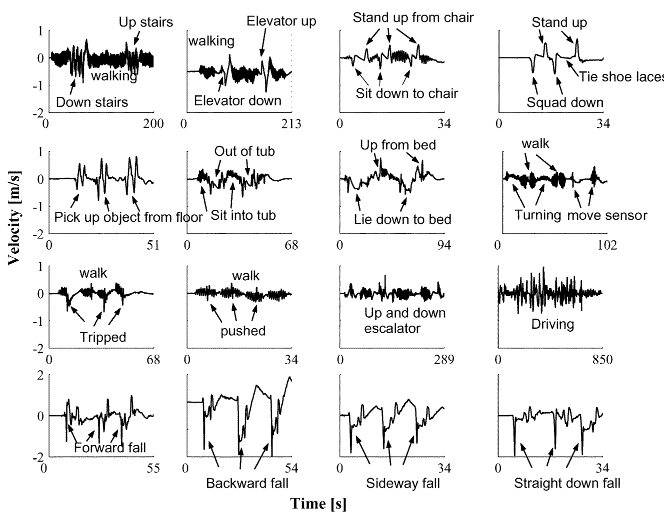

Fig. 5. Representative time trajectories of inertial frame vertical velocity at the waist of one subject during various nonfall activities and fall events.

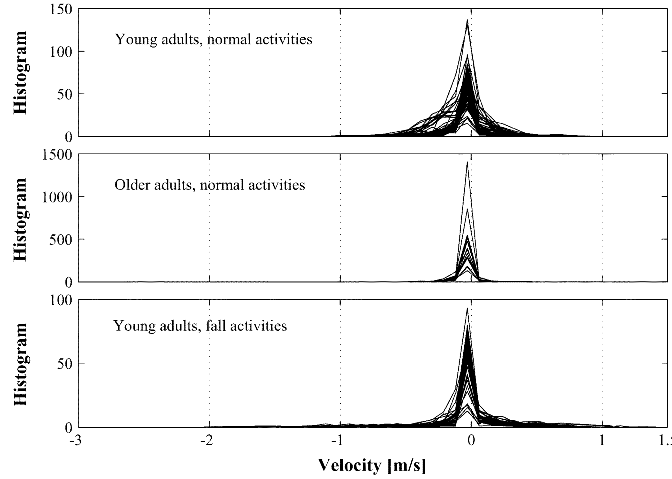

Fig. 6. Histogram of inertial frame vertical velocity of all recordings during nonfall activities of both young and older adults, and fall activities of young adults. The fall activities included the duration from standing (the initiation of the fall trials) to landing impact.

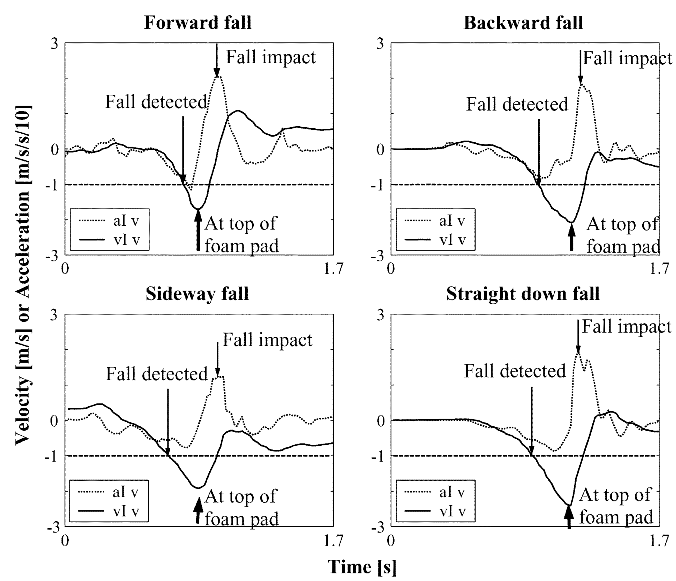

Fig. 7. Representative time trajectories of inertial frame vertical velocity ($\mathrm{vI_v}$) and acceleration ($\mathrm{aI_v}$) during four different falls. The timing of each fall detected and the impact of each fall are shown.

nonfall activities, including those near fall activities, the magnitude of inertial frame vertical velocity was mainly within ± 1 m/s (see Fig. 6). This is particularly true for the older subjects. In contrast, for those fall activities, the magnitude of the inertial frame vertical velocity well exceeded -1 m/s (downward).

With a threshold value of -1 m/s, the preimpact fall detection apparatus detected all fall events (a total of 117) before the largest impact acceleration occurred (see Fig. 7). The lead time (T_{lead}) ranged from 70 to 375 ms (Fig. 8). There were three false alarms during all recorded nonfall activities (a total of 13+ h of data). Two of them occurred in an elevator, and one occurred during a sway walking of a young subject.

When the threshold value was set individually to the maximum value of all nonfall activities of each subject, all falls were detected successfully (100% true positive detection value), and no false alarm occurred (100% true negative detection value).

IV. Discussion

The main purpose of this study is to investigate the feasibility of a portable preimpact fall detection apparatus in detecting impending falls using the inertial frame velocity profile of the body. Different from most currently available fall detectors which detect falls after the impact on the ground, the preimpact fall detector is able to detect falls before landing impact. The results from this study have demonstrated that a simple threshold detection method based on the inertial frame vertical velocity magnitude is capable of separating falls from nonfall activities and of detecting falls before the landing impact.

The use of inertial frame velocity to distinguish falls from nonfall activities, and to identify falls before impact is fundamentally different from other mechanisms for early fall detection. Among these mechanisms, for example, the electromyo-

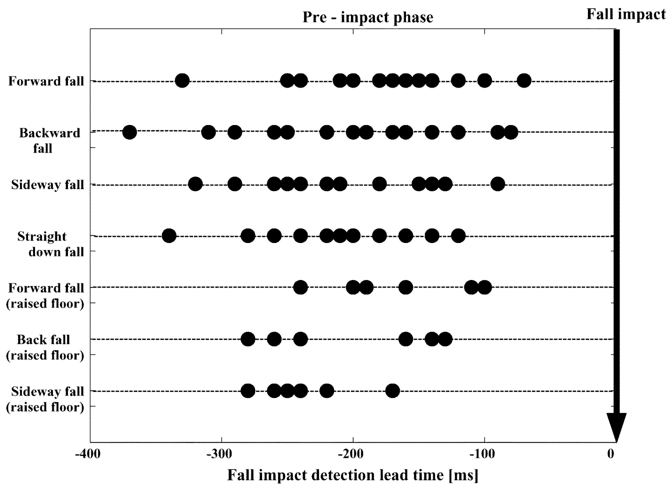

Fig. 8. Fall detection lead time for all subjects.

graphy (EMG) of a series of arm muscles is used in detecting impending falls during seizures in epileptic patients [34]. However, this mechanism is designed specifically for the epileptic patients who would completely lose normal muscle tone and lose consciousness before an impending fall. The use of EMG as a fall detection sensor for the normal elderly population is unrealistic. Another mechanism is the use of a Smart Room [35] that is equipped with a multisensory device to detect patients' movement. These detected movements are processed by a "reasoning agent" to determine if a fall has occurred. A fall decision will lead to an action such as triggering an alarm or sending a message to medical staff. However, the Smart Room has the limitation of physical boundaries.

The inertial frame velocity profiles contain not only sufficient information for preimpact fall detection, but also crucial information related to fall-related injuries such as hip fractures. It is estimated that for a fall to break the hip, there must be a sufficient amount of impact when the person lands on the hip [36]. The magnitude of the impact is proportional to the body mass and the vertical velocity. Indeed, the fall severity, as defined by the configuration and velocity of the body at impact, is found to be the primary predictor of hip fracture risk [24], [25]. Therefore, using the magnitude of inertial frame vertical velocity as a prefall detection criterion provides a sense of fall severity, which is crucial for preventing fall-related injuries. Furthermore, the velocity profile can provide crucial information about the direction of falls. It is documented that among all falls the sideway falls pose the highest risk of hip fracture. It is thus desirable that the preimpact fall detector not only detects the impending fall but also provides specific information about the fall such as whether the fall is a sideway fall and to which side. Although this study did not attempt to identify fall directions, the preimpact fall detection sensor will have the capacity for this feature in future studies.

As all detection mechanisms do, with a simple threshold detection mechanism, maximizing the true positive prediction value (i.e., identified as a fall when is) and the lead-time will likely increase the chance of false alarms (i.e., identified as a fall when not). However, it is found that the use of adaptive threshold is successful in decreasing the chance of false alarms. In general, older adults move relatively slower than young adults during daily activities, as evidenced by the smaller magnitude of the inertial frame vertical velocity (Fig. 6). This reduced magnitude will widen the gap between nonfall activities and fall events. This gap is perhaps even wider in frail elders who are at risk for falls, thus further deceasing the chance of false alarm when used in this population. Nevertheless, the nonfall activities tested in this study are at leisure speed and are in a controlled environment. Future studies should be done to determine the performance of the preimpact fall detector during faster speeds of normal activities, and in real life environments.

The successful detection of an impending fall before landing impact has significant clinical applications. One immediate application is to trigger a fall alarm in order to mobilize help for the victim. Another direct application is to lead to a new generation of hip protection mechanism, i.e., the inflatable hip pad. Because of its invisibility when dormant and sufficient compliance when inflated, the inflatable hip pad will be more attractive to elders, and be more effective in preventing hip fractures than existing hip protectors. In fact, using inflatable airbags in preventing crash injuries is not a new concept. The inflatable airbags are the standard safety feature in motor vehicles. The airbag concept also has been used in the design of protective motorcycle suit [37], avalanche life-preserving jacket [38], and head and cervical protector in sports [39]. Clearly, the inflatable hip pad depends largely on the success of preimpact fall detection. Although in this study a simple threshold method was used, the lead time of the fall detection was 70 ms or longer, sufficient for triggering an airbag (usually less than 25 ms). With the success of preimpact fall detection apparatus, the inflatable hip pad for preventing fall-related hip fractures in elders can become a reality.

The portability of the preimpact fall detection apparatus can also be a valuable diagnosis and research tool. It can be worn by high-risk individuals on their belts during their daily activities. The motion of real-life falls, not the ones simulated in the laboratory environments, can be "caught" by the apparatus. This would not be possible with the laboratory-based motion analysis systems. The kinematics data can be uploaded to computers for diagnosis of high risk of falls.

An effective fall detection and injury prevention system can increase the confidence and independence of elderly during exercise or recovery from illness, and improve their quality of life. We can imagine the scenario that elders in nursing homes or community dwellings who are prone to falling can safely venture out to yard or even on streets when wearing a fall detection and airbag system, instead of being physically restricted indoors. As Josephson *et al.* stated, "any intervention that can make inroads on this major cause of death and disability in the elderly population will clearly have major impact" [40].

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