

# Inertial Sensing-Based Pre-Impact Detection of Falls Involving Near-Fall Scenarios

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**Abstract**—Although near-falls (or recoverable imbalances) are common episodes for many older adults, they have received a little attention and were not considered in the previous laboratory-based fall assessments. Hence, this paper addresses near-fall scenarios in addition to the typical falls and activities of daily living (ADLs). First, a novel vertical velocity-based pre-impact fall detection method using a wearable inertial sensor is proposed. Second, to investigate the effect of near-fall conditions on the detection performance and feasibility of the vertical velocity as a fall detection parameter, the detection performance of the proposed method (Method 1) is evaluated by comparing it to that of an acceleration-based method (Method 2) for the following two different discrimination cases: falls versus ADLs (i.e., excluding near-falls) and falls versus non-falls (i.e., including near-falls). Our experiment results show that both methods produce similar accuracies for the fall versus ADL detection case; however, Method 1 exhibits a much higher accuracy than Method 2 for the fall versus non-fall detection case. This result demonstrates the superiority of the vertical velocity over the peak acceleration as a fall detection parameter when the near-fall conditions are included in the non-fall category, in addition to its capability of detecting pre-impact falls.

**Index Terms**—Elderly, inertial sensor, near-falls, pre-impact fall detection, vertical velocity.

## I. INTRODUCTION

FALLS are the leading cause of injury-related deaths and hospitalization among older adults [1], [2]. Due to the high impact of falls on health and healthcare costs, there has been an increasing attention on automatic fall detection methods in the past decade [3]–[6]. This rapid development has been facilitated by the advent of wearable sensors, MEMS-based miniature inertial sensors (e.g., accelerometers and gyroscopes) in particular. They are rapidly shrinking in size and weight to the extent that they can be unobtrusively attached to the body [7]–[10]. In

fact, automatic fall detection methods can be categorized into the following two methods: 1) detection of a subject who has already fallen (i.e., post-impact fall detection) and 2) detection of a subject who is about to fall (i.e., pre-impact fall detection). A primary goal of the post-impact fall detection method, where the majority of existing algorithms belong to, is to minimize the time between a fall and the arrival of medical attention and prevent long lie times that are potentially fatal. However, this method has the limitation that it cannot prevent injuries from the impact. Thus, more recently, researchers have been working on body protection mechanisms such as an inflatable airbag system in order to avoid or reduce the fall-related injuries [11]–[14]. Note that an important prerequisite for the utilization of a wearable airbag system is the pre-impact fall detection to trigger the airbag inflator. While the post-impact detection method makes use of distinctive “impact” signals (e.g., peak accelerations [3], [15]) and information after falls (e.g., lying posture [16] or altitude [6]), and can be post-processed to determine the fall, the pre-impact detection should be performed in real time by relying on only some characteristic information during the descending phase of the fall as the impact and post-impact information are unavailable. This makes the latter method more challenging than the former method. Hence, to date, only a few studies have explicitly addressed the pre-impact fall detection using wearable inertial sensors (e.g., [13], [17]–[20]).

Among the existing pre-impact fall detection methods, Nyan *et al.* [19] used pretested reference templates for each type of fall by comparing the angles and angular velocities of the thigh segment between falls and normal activities. These templates were obtained from laboratory based falling experiments that try to simulate and capture the angular characteristics and patterns of the complex real-life falls. Shi *et al.* [13] and Shan and Yuan [20] used the support vector machine (SVM) through feature selection procedures among a number of raw signals from the accelerometer and gyro. However, the most popular approach to detect falls involves the threshold-based method due to its low complexity and easy implementation. Our particular interest is the works by Wu and Xue [17] and Bourke *et al.* [18] who used the downward vertical velocity as a discrimination parameter for thresholding. The vertical velocity profile represents the kinematic characteristic of falls during their descending phase. Any faller naturally experiences a certain level of downward vertical velocity that can be effectively used for the pre-impact fall detection. Both algorithms in [17] and [18] require the calculation of vertical velocity based on an inertial sensor comprising of a tri-axial accelerometer and a tri-axial gyroscope.

This work also adopts the vertical velocity profile used in [17] and [18]. Although the effectiveness of the velocity profile for

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the pre-impact fall detection has been proposed earlier, the calculation of the vertical velocity using the inertial sensor signals is not trivial and requires the implementation of the following two steps: i) calculation of the vertical acceleration and ii) calculation of the vertical velocity via numerical integration of the acceleration. To be practical, these two steps should be done in real time.

First, step i) needs the orientation of the sensor in order to compensate for the gravity component in the accelerometer signal and then to calculate the vertical acceleration with respect to the inertial reference frame. This implies that the orientation accuracy has a direct effect on the vertical acceleration accuracy. In [17], the orientation was obtained by a quaternion filter approach. However, the inertial sensor (with the accelerometer and gyro) without a magnetometer cannot correct the yaw (i.e., the heading direction) drift and the drifted yaw component can be fused with the quaternion components, affecting the tilt angle as well [21]. It should be noted that the required orientation for step i) is not the 3-D orientation (i.e., roll, pitch, and yaw) but only the tilt orientation (i.e., roll and pitch). In other words, only the tilt orientation is the necessary and sufficient condition, not the full 3-D orientation. Second, step ii) encounters the “boundless” drift error because the measurement errors in the acceleration will be accumulated in the estimated velocity through the integration. In order to deal with the drift issue, Kangas *et al.* [22] performed the integration only over a short period (i.e., from the beginning of the fall to the impact); Bourke *et al.* [23] used a Butterworth bandpass filter, in addition to the conditional integration (i.e., integrating only during dynamic conditions and setting the velocity to zero during static conditions); and Degen *et al.* [24] applied a damping factor in the integration to bound the drift during static conditions.

With regards to the experimental fall test protocols of the existing works, they have been focused on simulating falls and normal activities of daily living (ADLs) in laboratory settings. However, near-falls (or recoverable imbalances) are common events for many older adults and are clinically relevant markers of falls worthy of further study [25], [26]. For example, investigators have found that older adults who report multiple near falls (such as missteps or stumbles) are more likely to go on to fall [27]. One particular issue associated with the near-fall cases comes from the fact that, although near-falls are not actual falls and thus should be categorized as non-falls, they have a higher chance of causing false alarms in the detection system (i.e., classifying near-falls as falls). This is mainly due to the fact that near-falls may accompany abrupt movements that produce sensor values that go over the preset fall thresholds. Therefore, near-falls should be differentiated from falls and normal activities. In [17], three types of near-fall tests were included in the non-fall data set without discriminating them from ADLs. In [25], an automatic detection of near-falls compared to non-near-falls was investigated using treadmill walking tests under various conditions. They achieved 85.71% sensitivity and 88.02% specificity using the maximum peak-to-peak vertical acceleration derivative parameter. However, to date, the effect of the inclusion of near falls to a non-fall dataset on the fall detection performance has not been investigated yet.

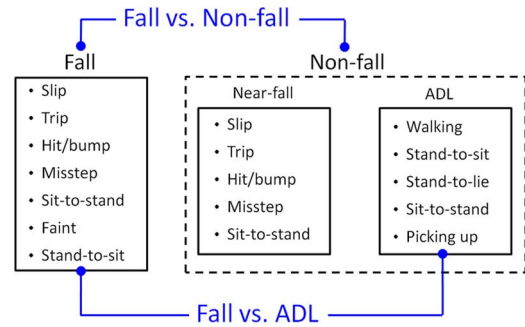


Fig. 1. Three categories of laboratory experiments (fall, near-fall, and ADL) and two classification cases (fall versus non-fall and fall versus ADL) carried out in this study.

The main contribution of this paper is therefore twofold. First, it introduces a novel vertical velocity-based pre-impact fall detection algorithm structured with a Kalman filter using a wearable inertial sensor, which can work in real-time for practical implementation. Second, this work investigates the effect of near-fall scenarios on the detection performance and the feasibility of the vertical velocity thresholding in comparison to the peak acceleration thresholding.

## II. MATERIALS AND METHODS

### A. Subjects and Data Collection

Eleven healthy young male adults participated in this study: mean age 27.6 (SD 4.3) years; height 176 (SD 8) cm; weight 71.3 (SD 9.7) kg. All participants were students at Simon Fraser University, recruited through advertisements and flyers on university notice boards.

We employed a wireless OPAL inertial sensor (APDM, Inc., USA) attached on the anterior side of the waist. The waist-attached inertial sensor in this study as well as in [17] is located near the body's center of gravity, providing reliable information on subject body movements [28]. The OPAL sensor includes a tri-axial accelerometer, a tri-axial gyroscope, and a tri-axial magnetometer. However, the magnetometer signals were not needed (thus not used) and only the signals from the accelerometer and gyroscope recorded at 128 Hz were used for the analysis. The experiment protocol that we carried out was approved by the Research Ethics Board at Simon Fraser University and all participants provided informed written consent.

### B. Experimental Protocol

There were three categories in the experimental protocol: falls, near-falls, and ADLs (see Fig. 1). First, in the fall experiments, participants fell onto a 30-cm thick gymnasium mattress, onto which we laid a 1.3 cm top layer of high density ethylene vinyl acetate foam. 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. In order to ensure that the falls we simulated were typical of those experienced by older adults, we selected seven types of fall experiments based on the findings in [29] conducted by our research team, which identifies major causes and activities of falls by investigating a library of video sequences of 227 real-life falls captured in local long-term care facilities (LTC). The seven types of causes

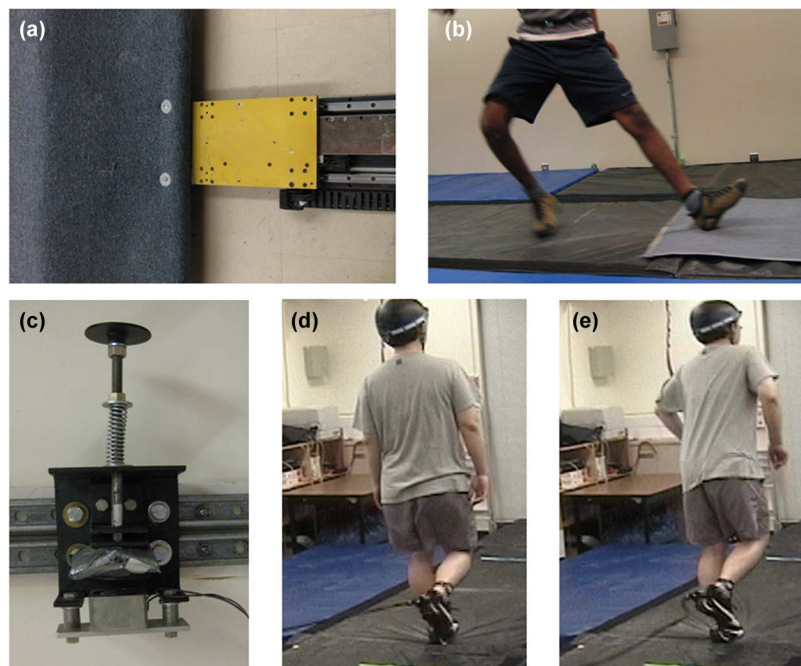


Fig. 2. Fall triggering procedures for (a) and (b) slip and (c)–(e) trip trials. (a) Translational carpet fastened to a linear motor; (b) snapshot of the sheet being translated to cause a slip; (c) tether releasing device controlled by a switch; (d) snapshot of a tether becomes taut during the swing phase of walking; and (e) snapshot of the tether being released by the device after the trip fall triggering.

we considered are: 1) *slips*; 2) *trips*, and the following five other combinations of cause and activity: 3) loss of balance after being hit/bump by another person (denoted as *hit/bump*); 4) loss of balance due to misstep or gait variability (denoted as *misstep*); 5) incorrect weight transfer while rising from sitting (denoted as *sit-to-stand* fall); 6) falls due to fainting (denoted as *faint*); and 7) incorrect weight transfer while sitting down on a chair (denoted as *stand-to-sit* fall). We conducted training sessions with each participant, where video segments of the real-life falls from our previous work [29] were used to train young participants by asking them to mimic the falling behavior of the LTC residents in the videos. In the *slip* fall trials, the participants were instructed to walk up to a carpet placed over the gym mattress, and they were made to slip backward by having the carpet translate rapidly from underneath their feet [see Fig. 2(a) and (b) and also Fig. 3(a)]. The *trip* fall trials were simulated by having a tether attached to the participants' right ankles become taut during the swing phase of walking, initiating a forward fall. Once the trip falls were triggered, the tether was quickly released so that the participants' falls were not constrained by it [see Fig. 2(c)–(e) and also Fig. 3(b)]. In the *hit/bump* falls, a sudden sideways force was applied to the participants' trunks using a soft boxing glove, initiating loss of balance and the participants were instructed to act out a sideways fall. In the *misstep* falls, the participants were instructed to walk forward with high variability in their gaits by taking a narrow step, cross-step or misstep that caused loss of balance and fall. In the *sit-to-stand* falls, the participants initially sat on a chair and were instructed to lose their balance while attempting to stand up. In the *faint* trials, the participants were instructed to act out a “collapse” or “legs giving away” by falling down [see Fig. 3(c)]. For the *hit/bump*, *misstep*,

*sit-to-stand*, and *faint* falls, no specific instruction was given about the direction of the fall. Lastly, in the *stand-to-sit* falls, 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 the chair, to lose their balance and fall backward [see Fig. 3(d)]. We acquired three trials for each fall type. Therefore, a total of 231 trials were collected for the fall test category from 11 participants.

Second, in the near-fall experiments, we conducted the following five types of near-fall trials: slip, trip, hit/bump, misstep, and sit-to-stand. The experimental procedures are equal to the fall experiments above but the participants were instructed to recover balance instead of falling. Note that the faint and stand-to-sit trials were omitted from the near-fall experiments as participants cannot recover their balances in those trials. In total, 165 trials were analyzed for the near-fall test category by acquiring three trials for each near-fall type, over 11 participants.

Third, all eleven subjects also performed three trials of the following five types of ADLs: walking 5 m, descending from standing to sitting on a chair, descending from standing to lying on the ground, rising from sitting to standing, picking an object from the ground. Again, 165 trials were obtained in total for the ADL test category.

### C. Method

1) *Calculation of the Vertical Velocity*: In order to obtain the vertical velocity from the inertial sensor signals, first, we need to calculate the vertical acceleration. The sensor signals from the accelerometer ( $A$ ) and the gyroscope ( $G$ ) can be modeled as  $\mathbf{s}_A = {}^S \mathbf{g} + {}^S \mathbf{a} + \mathbf{n}_A$  and  $\mathbf{s}_G = {}^S \boldsymbol{\omega} + \mathbf{n}_G$ , respectively, where  $\mathbf{g}$  is the gravitational acceleration;  $\mathbf{a}$  is the body acceleration of

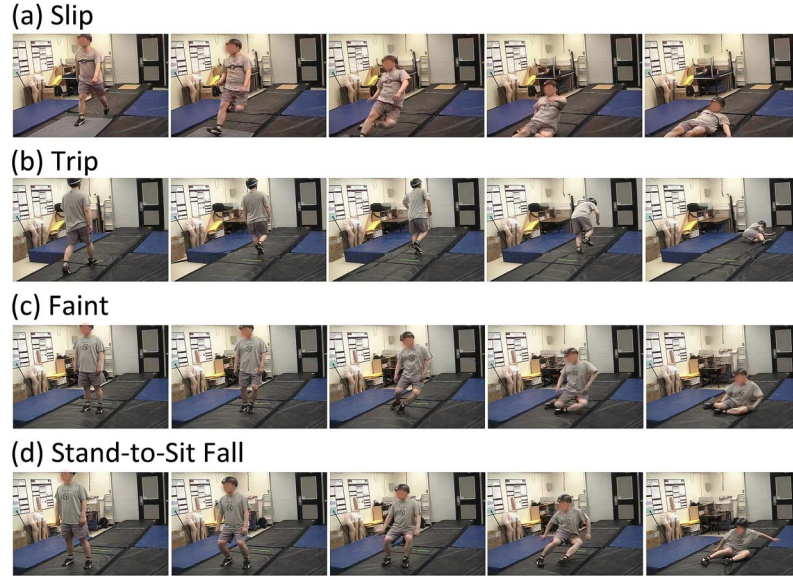


Fig. 3. Laboratory simulation of falls mimicking the falling behavior of older adults due to (a) slips, (b) trips, (c) faint, and (d) incorrect weight transfer while sitting down on a chair.

the object/body that the accelerometer is attached to;  $\omega$  is the angular velocity; and  $\mathbf{n}$ 's are the measurement noises [30]. The left superscript  $S$  implies that the corresponding vectors are expressed with respect to the sensor reference frame  $S$ , whereas the left superscript  $I$  denotes the inertial reference frame  $I$ . Note that the accelerometer signal includes not only the body acceleration that we are interested in but also the gravity component. The gravity with respect to the inertial frame ( ${}^I\mathbf{g}$ ) is a known value (i.e.,  ${}^I\mathbf{g} = [0, 0, g]^T$  where  $g = 9.8 \text{ m/s}^2$ ). However, since the accelerometer reading is inherently expressed with respect to the sensor frame,  $S$ , the gravity with respect to the sensor frame ( ${}^S\mathbf{g}$ ) changes according to the changes in the sensor orientation. Thus, in order to extract the body acceleration from the accelerometer signal by compensating for the gravity component, one needs to calculate the sensor orientation.

The coordinate transformation of a  $3 \times 1$  vector  $\mathbf{x}$  between the sensor frame  $S$  and the inertial frame  $I$  is  ${}^I\mathbf{x} = {}^I_S\mathbf{R} {}^S\mathbf{x}$  where  ${}^I_S\mathbf{R}$  is the orientation matrix of the frame  $S$  with respect to the frame  $I$ . The orientation matrix  ${}^I_S\mathbf{R}$  contains the three unit column vectors of the inertial coordinate system expressed in the sensor coordinate system, i.e.,  ${}^I_S\mathbf{R} = [{}^S\mathbf{X} \ {}^S\mathbf{Y} \ {}^S\mathbf{Z}]^T$  where  ${}^S\mathbf{X}$ ,  ${}^S\mathbf{Y}$ , and  ${}^S\mathbf{Z}$  are the  $3 \times 1$  unit vectors of X, Y, and Z axes of the frame  $I$  observed with respect to the frame  $S$ . Note that  ${}^S\mathbf{g}$  (the gravity vector with respect to the sensor frame) can be expressed in terms of the last row of the matrix  ${}^I_S\mathbf{R}$  (i.e.,  ${}^S\mathbf{Z}^T$ ) as  ${}^S\mathbf{g} = g \times {}^S\mathbf{Z}$ . Therefore,  ${}^S\mathbf{Z}$  is sufficient information to compensate for the gravity effect in the accelerometer signal (i.e., does not require the full 3-D orientation,  ${}^I_S\mathbf{R}$ ). In this study, the vector  ${}^S\mathbf{Z}^+$  is obtained by the Kalman filter proposed recently by the authors [30], where the plus superscript denotes the *a posteriori* estimate after the filter correction and the minus superscript denotes the *a priori* estimate. The Kalman filter algorithm is summarized in the Appendix. Once the vector  ${}^S\mathbf{Z}^+$  is available, the body acceleration with respect to  $S$  is  ${}^S\mathbf{a}^+ = \mathbf{s}_A - g \times {}^S\mathbf{Z}^+$ , and the vertical body acceleration with respect to the

inertial frame can be obtained as  ${}^Ia_z^+ = ({}^S\mathbf{a}^+)^T {}^S\mathbf{Z}^+$  where  ${}^I\mathbf{a}^+ = [{}^Ia_x^+ \ {}^Ia_y^+ \ {}^Ia_z^+]^T$  is used.

The vertical velocity  ${}^Iv_z$  is obtained through a numerical integration of the vertical acceleration. However, it is well known that the numerical integration suffers from a boundless drift. This is because the exact vertical acceleration is not available in practice and, instead, an estimated acceleration is used for the integration, i.e.,  ${}^Ia_z^+$ , which contains the measurement errors. In order to overcome this difficulty, the following conditional damping-based integration technique was used in this study:

$${}^Iv_{z,t} = \begin{cases} \alpha \times {}^Iv_{z,t-1}, & \text{if } |{}^Ia_{z,t}| \leq \varepsilon_{\text{accel}} \text{ AND } |{}^I\dot{a}_{z,t}| \leq \varepsilon_{\text{jerk}} \forall \tau \in [t - n\Delta t, t] \\ {}^Iv_{z,t-1} + \Delta t \times {}^Ia_{z,t}, & \text{otherwise} \end{cases} \quad (1)$$

where  $\alpha$  is a damping factor which slowly resets the integral to zero, and  $\varepsilon_{\text{accel}}$  and  $\varepsilon_{\text{jerk}}$  are the thresholds for the magnitudes of the body acceleration and its time derivative (i.e., jerk  ${}^I\dot{a}_z$ ), respectively. The jerk is obtained from a simple numerical differentiation without noise filtering. This conditional equation is based on the assumption that a quasi-static motion (i.e., non-zero velocity with zero acceleration) is rare in human motions. Therefore, if the acceleration is near zero, the velocity begins converging to zero as well by the damping factor. It should be noted that, even during dynamic conditions, the norm of the body acceleration can shortly lie within the range designated as the static condition (i.e.,  $[-\varepsilon_A - \varepsilon_A]$ ). An example of this case would be when the accelerometer quickly alternates between acceleration and deceleration, resulting in  $|{}^Ia_z|$  passing in and out of the range [30]. Accordingly, the condition related to the jerk was added. Furthermore, the two conditions are assured for a certain amount of time (i.e.,  $n\Delta t$ ). In this study, the following values were experimentally chosen by trial and error and used for the data analysis:  $\alpha = 0.9$ ,  $\varepsilon_{\text{accel}} = 0.5 \text{ m/s}^2$ ,  $\varepsilon_{\text{jerk}} = 2 \text{ m/s}^3$ , and  $n = 10$ .

TABLE I  
SENSITIVITY AND SPECIFICITY OF FALL DETECTION ALGORITHMS

| Parameters             | Classification    | Threshold           | Sensitivity | Specificity |
|------------------------|-------------------|---------------------|-------------|-------------|
| Vertical velocity      | Fall vs. ADL      | -1.2 m/s            | 97.4 %      | 99.4 %      |
|                        | Fall vs. Non-fall | -1.4 m/s            | 95.2 %      | 97.6 %      |
| Acceleration magnitude | Fall vs. ADL      | 16 m/s <sup>2</sup> | 98.7 %      | 99.4 %      |
|                        | Fall vs. Non-fall | 26 m/s <sup>2</sup> | 84.0 %      | 85.5 %      |

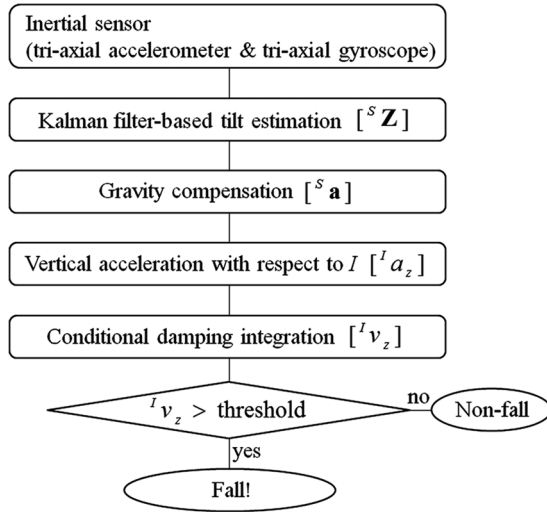


Fig. 4. Flowchart of the proposed pre-impact fall detection algorithm.

In this vertical velocity-based method (Method 1) that we are proposing, the condition in which the vertical velocity (which has a negative sign) exceeds a threshold was determined as a fall. A flowchart of the proposed method is shown in Fig. 4.

2) *Threshold-Based Fall Detections and Analysis:* For comparison purposes, the acceleration magnitude-based method (Method 2) was also used, in which the gravity-subtracted magnitude of the accelerometer signal (i.e.,  $\|s_A\| - g$ ) was used for the thresholding of the fall detection. The magnitude of the accelerometer signal (i.e.,  $\|s_A\|$ ) is one of the most commonly used fall detection parameters in low-complexity accelerometer-based fall detection methods with no gyroscope (e.g., employed by [3], [5], [8], and [15]). This parameter is related to the peak acceleration experienced mostly at the impact of the fall. Note that, while these previous works used  $\|s_A\|$  as the fall detection parameter, Method 2 in this study uses  $\|s_A\| - g$  to set the parameter to become zero at rest.

The classifying abilities of the two pre-impact fall detection methods were investigated in terms of the sensitivity (or true positive rate) and the specificity (or true negative rate). Also, the investigation was performed with respect to the following two classification categories: 1) “falls versus ADLs” where near-fall data were not considered and 2) “falls versus non-falls” where the near-fall data were included in the non-fall group in addition to the ADL data.

The use of the negative downward vertical velocity as a fall detection parameter in Method 1 (using both the accelerometer and gyroscope signals) is associated with the descending

TABLE II  
MEAN AND ONE STANDARD DEVIATION OF  
LEAD TIMES (MSEC) FOR FALL TRIALS

| Fall types   | Fall vs. ADL<br>(threshold: -1.2 m/s) | Fall vs. Non-fall<br>(threshold: -1.4 m/s) |
|--------------|---------------------------------------|--------------------------------------------|
| Slip         | 206 ± 127                             | 182 ± 79                                   |
| Trip         | 300 ± 223                             | 179 ± 146                                  |
| Hit/bump     | 301 ± 100                             | 259 ± 98                                   |
| Mis-step     | 228 ± 112                             | 190 ± 117                                  |
| Sit-to-stand | 187 ± 64                              | 152 ± 51                                   |
| Faint        | 226 ± 90                              | 192 ± 92                                   |
| Stand-to-sit | 156 ± 68                              | 118 ± 62                                   |
| Total        | 231 ± 127                             | 184 ± 104                                  |

phase of the fall before impact, while the use of the acceleration magnitude in Method 2 (using only the accelerometer signal) is related to the peak impact acceleration experienced mostly at the impact of the fall. Accordingly, only for Method 1 which has the capability of detecting falls before the impact, the lead time  $T_{\text{lead}}$  was also obtained from the fall data. The lead time was defined as  $T_{\text{lead}} = T_{\text{impact}} - T_{\text{detect}}$  where  $T_{\text{detect}}$  and  $T_{\text{impact}}$  denote the time when the fall was detected and the time of the impact when the maximum negative vertical velocity was achieved, respectively [20]. The data analysis was performed using C programming.

### III. RESULTS

Table I shows the classifying abilities of the resulting four cases (i.e., each of the two methods evaluated with respect to the two classification categories) and the thresholds were determined so the summation of sensitivity and specificity has the maximum value for each case. For the fall versus ADL detection, both methods produced similar accuracies but, for the fall versus non-fall detection, Method 1 showed a much higher accuracy than Method 2. This result was clearly supported by receiver operating characteristic (ROC) curves shown in Fig. 5. The ROC curves depict the classifier sensitivity versus 1-specificity at different detection thresholds and thus one can find a different sensitivity and specificity combination (e.g., specificity with 100% sensitivity).

Table II shows mean and one standard deviation of the lead times for the fall trials. The average lead times were 231 and 184 ms for the thresholds -1.2 m/s (used in the fall versus ADL classification) and -1.4 m/s (used in the fall versus non-fall

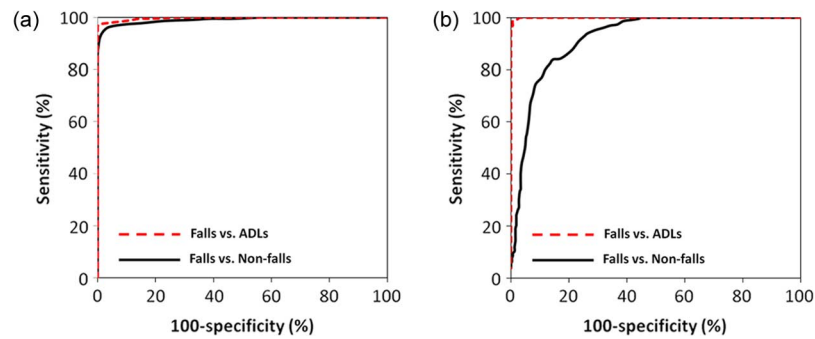


Fig. 5. ROC curves from (a) proposed vertical velocity-based method and (b) acceleration-based method.

TABLE III  
COMPARISON OF PRE-IMPACT FALL DETECTION METHODS

| References                | Sensors and their attachment locations                                                              | Basic principles                                                                                                                                                                                                                 | Sensitivity / Specificity | Lead time   |
|---------------------------|-----------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------|-------------|
| Wu and Xue (2008) [17]    | A tri-axial accelerometers and a tri-axial gyro at anterior waist                                   | Threshold based on a vertical velocity                                                                                                                                                                                           | 100 % / See §.            | 70 ~ 375 ms |
| Bourke et al. (2008) [18] | A tri-axial accelerometers and a tri-axial gyro at anterior chest                                   | Threshold based on a vertical velocity                                                                                                                                                                                           | 100 % / 100 %             | 314 ms      |
| Nyan et al. (2008) [19]   | A tri-axial accelerometer and a bi-axial gyro at right thigh and a tri-axial accelerometer at waist | (i) Threshold based on the sagittal and lateral angles of the thigh segment, (ii) high correlation of angles between thigh and torso, and (iii) high correlation of angular velocities between thigh and a pre-defined template. | 95.2 % / 100 %            | 700 ms      |
| Shan and Yuan (2010) [20] | A tri-axial accelerometer at posterior waist                                                        | Support vector machine classifier                                                                                                                                                                                                | 100 % / 100 %             | 203 ms      |

§ No information of the specificity in the reference. Three false detections during 13 hours test.

classification). For both threshold values, the stand-to-sit falls had the shortest lead time. In fall injury prevention systems using airbags, the required lead time should be longer than the inflation time of airbag system which is about 100 ms (e.g., an average of 120 ms in [14]). From the comparison of the results between Fall versus ADL and Fall versus Non-fall, it can be seen that the inclusion of the near-fall cases in the data set affects the detection accuracy (see Table I) and lead time (see Table II).

Table III summarizes the existing pre-impact fall detection methods in the literature. All of the methods except [19] in Table III achieved 100% sensitivity while our method obtained 97.4% sensitivity and 99.4% specificity for the Fall versus ADL classification. Note that our fall test protocol included the incorrect weight transfer while sitting down on a chair (denoted as *stand-to-sit fall*) based on the findings in [29]. While all of the false negatives in our results came from the stand-to-sit falls, none of the references in Table III dealt with the stand-to-sit falls. If this type of fall is excluded from our data set, our fall versus ADL detection performance also improves to 100% sensitivity and 99.4% specificity with the same threshold of  $-1.2$  m/s.

#### IV. DISCUSSION

Many fall detection algorithms utilize the posture information derived from the accelerometer signals as a determinant

parameter, based on the fact that the accelerometer can be used as an inclinometer in static conditions (e.g., [5], [22], and [31]). In the case of the post-impact fall detection, the information may provide a reasonable indication whether the subject wearing the accelerometer is in lying posture. This is logical since the faller lying down after the fall would be in nearly static conditions. However, in the case of the pre-impact fall detection, we are interested in the falling phase before the impact and the accelerometer is in dynamic condition. In other words, the use of the accelerometer as an inclinometer is no longer appropriate. The addition of a gyroscope provides a solution to this problem. Even in this case, however, the use of body posture represented by the sensor orientation still needs to be paid careful attention during the interpretation of the data. Because of the interposition of the soft tissue between the target body segment and the segment-mounted sensor and the misalignment of the sensor from its initial/calibrated attachment location, there is a concern as to the extent of the error in the “surface” measurements obtained by these sensors. They may not accurately measure the underlying true segmental movements and the degree of the error may vary between subjects according to the mounting location (e.g., the waist in our case) and obesity (see, for example, [32] for artifact effects of skin-mounted inertial sensors). Due to this reason, we did not use the posture information as a fall

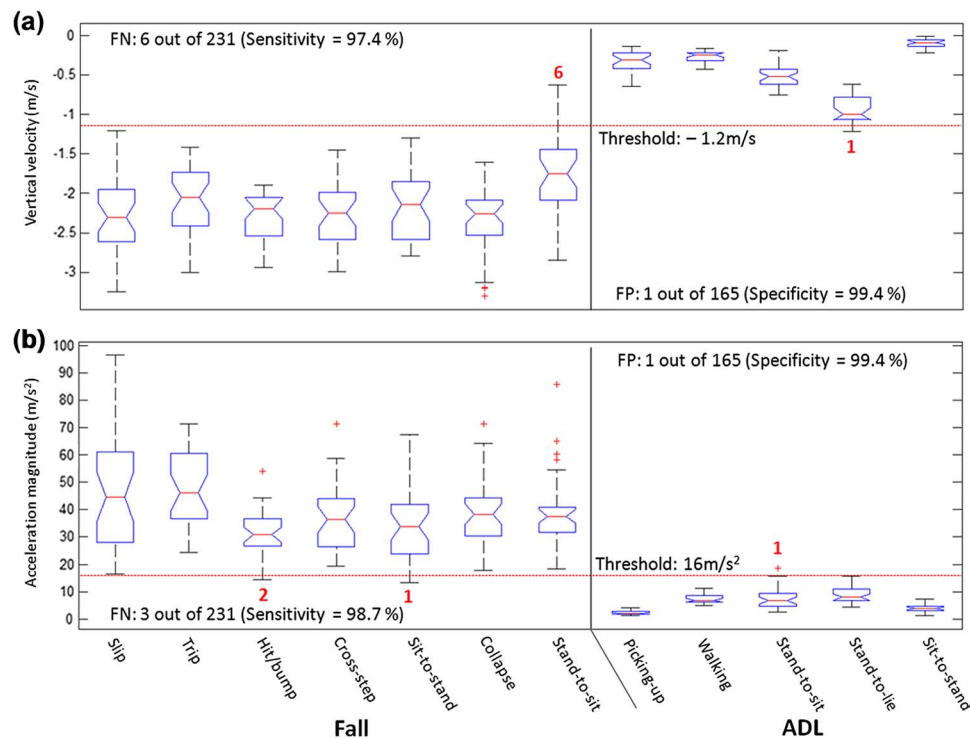


Fig. 6. Boxplots of the maximum values of (a) vertical velocity and (b) acceleration magnitude, for the discrimination of falls from ADLs. Horizontal dotted lines indicate the thresholds used. In the plots, the FN and FP indicate the false negatives and false positives, respectively, and the numbers above or below the boxes indicate the number of false detections of each trials.

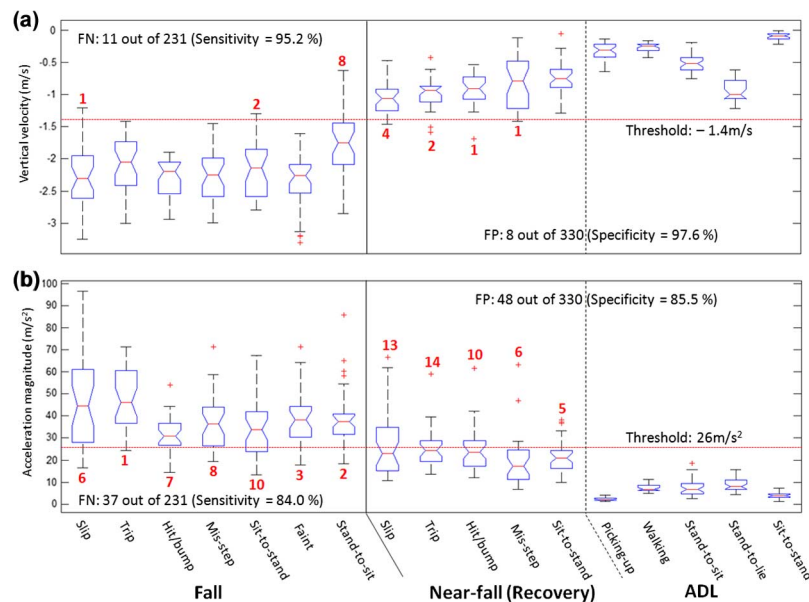


Fig. 7. Boxplots of the maximum values of (a) vertical velocity and (b) acceleration magnitude, for the discrimination of falls from non-falls. Horizontal dotted lines indicate the thresholds used. In the plots, the FN and FP indicate the false negatives and false positives, respectively, and the numbers above or below the boxes indicate the number of false detections of each trials.

detection parameter for thresholding and the proposed method is independent of this issue.

For the fall versus ADL detection (see Fig. 6), the proposed method produced six false negatives out of the 231 fall trials and one false positive out of the 165 ADL trials. Note that all of the false negatives came from the stand-to-sit falls and the only false positive came from the stand-to-lie ADLs. These results are as expected because, in the case of stand-to-sit falls,

the fall is initiated at relatively lower location and thus the time duration from the fall initiation to the impact is short and the vertical velocity may not reach to the threshold value. In contrast, the stand-to-lie ADL may accompany fast downward velocity depending on the subject. Since the false detections are concentrated on a few particular movements, the detection accuracy has much room for further improvement if those particular cases are resolved.

For the fall versus non-fall detection (see Fig. 7), Method 1 maintained a high detection accuracy (i.e., >95% in both sensitivity and specificity) but the detection accuracy of Method 2 was significantly reduced. Method 2 produced false negatives across all types of falls and false positives in all types of near-falls. During the near-fall trials, the falls were triggered experimentally or by self-generated perturbations and the participants regained their postural stability from the imbalances by quickly moving their center of mass. However, even the movements involved in these recoverable imbalances can result in a considerable increase in the peak acceleration levels, for example, in the case of Method 2. In the case of Method 1, on the other hand, since the velocity is obtained by integrating the acceleration with respect to time, it is inherently less affected by these short and abrupt movements.

We paid particular attention to the experimental protocol in order to improve the reality of the falling tests. As previously mentioned, our protocols were obtained from a detailed analysis of the real-world fall videos. Furthermore, during the participants' trials, no instruction was given about the fall direction and impact location, which can increase the complexity and variability of the falling kinematics. Nevertheless, the proposed algorithm has been evaluated using the simulated falls which may have differences with real falls as discussed in [33]. Bagala *et al.* [34] shows that the performances of the existing fall detection algorithms may be affected when real-world fall data are applied, and this may be true for our method as well. Therefore, as discussed in [34], a large, shared real-world fall database could provide an enhanced understanding of the fall process for evaluation of fall detection performance.

In conclusion, this paper proposed a novel vertical velocity-based pre-impact fall detection method using a wearable inertial sensor. The feasibility of the vertical velocity as a fall detection parameter and the detection performance of the proposed method were evaluated by comparing it with the performance of the acceleration-based method. Importantly, this paper dealt with near-fall situations in addition to the falls and ADLs. The experiments showed that both methods produced similar accuracies for the fall versus ADL detection, while Method 1 produced much higher accuracy than Method 2 for the fall versus non-fall detection. The results show the advantage of the vertical velocity over the peak acceleration in terms of the robustness for the pre-impact fall detection against both the ADL near-fall trials. The consideration of near-fall conditions for the performance evaluation of the pre-impact fall detection method may provide insight into the future development of a real-world pre-impact fall detection system.

#### APPENDIX

In the fall detection algorithm, a linear Kalman filter is used to estimate the unit vector  ${}^S\mathbf{Z}$ , in the course of calculation of the vertical acceleration. The Kalman filter can be defined by the following process and measurement models:

$$\begin{cases} {}^S\mathbf{Z}_t = \Phi_{t-1}^S \mathbf{Z}_{t-1} + \mathbf{w}_{t-1} \\ \mathbf{z}_t = \mathbf{H}^S \mathbf{Z}_t + \mathbf{v}_t \end{cases} \quad (\text{A1})$$

where  ${}^S\mathbf{Z}$  is designated as the state vector;  $\mathbf{z}$  is the measurement vector that is defined as  $\mathbf{s}_A - {}^S\mathbf{a}^-$  (i.e., the accelerometer signal

minus the *a priori* estimate of the body acceleration);  $\Phi$  is the state transition matrix;  $\mathbf{H}$  is the observation matrix; and  $\mathbf{w}$  and  $\mathbf{v}$  are the white Gaussian process and measurement noises, respectively. Once the process and measurement models are set, the procedure of the Kalman filter is as follows.

- Step 1: Compute the *a priori* state estimate,  ${}^S\mathbf{Z}_t^- = \Phi_{t-1}^S \mathbf{Z}_{t-1}^+$  where  $\Phi_{t-1} = \mathbf{I} - \Delta t[\mathbf{s}_{G,t-1} \times]$  and  $\Delta t$  is the time sampling rate. The vector cross product operator  $[\mathbf{s} \times]$  is defined as  $\begin{bmatrix} 0 & -s_z & s_y \\ s_z & 0 & -s_x \\ -s_y & s_x & 0 \end{bmatrix}$  if  $\mathbf{s} = [s_x \ s_y \ s_z]^T$ .
- Step 2: Compute the *a priori* error covariance matrix,  $\mathbf{P}_t^- = \Phi_{t-1} \mathbf{P}_{t-1}^+ \Phi_{t-1}^T + \mathbf{Q}_{t-1}$  where  $\mathbf{Q}$  is the process noise covariance matrix and is defined as  $\mathbf{Q}_{t-1} = E[\mathbf{w}_{t-1} \mathbf{w}_{t-1}^T]$  where  $E$  is the expectation operator.
- Step 3: Compute the Kalman gain,  $\mathbf{K}_t = \mathbf{P}_t^- \mathbf{H}^T (\mathbf{H} \mathbf{P}_t^- \mathbf{H}^T + \mathbf{M}_t)^{-1}$  where  $\mathbf{M}$  is the measurement noise covariance matrix and is defined as  $\mathbf{M}_t = E[\mathbf{v}_t \mathbf{v}_t^T]$ .
- Step 4: Compute the *a posteriori* state estimate,  ${}^S\mathbf{Z}_t^+ = {}^S\mathbf{Z}_t^- + \mathbf{K}_t (\mathbf{z}_t - \mathbf{H}^S \mathbf{Z}_t^-)$ .
- Step 5: Compute the *a posteriori* error covariance matrix,  $\mathbf{P}_t^+ = (\mathbf{I} - \mathbf{K}_t \mathbf{H}) \mathbf{P}_t^-$ .

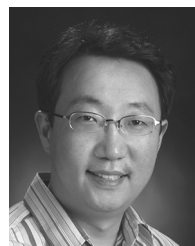
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