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Skin-Contact Sensor for Automatic Fall Detection

Ravi Narasimhan

Abstract— **This paper describes an adhesive sensor system worn on the skin that automatically detects human falls. The sensor, which consists of a tri-axial accelerometer, a microcontroller and a Bluetooth Low Energy transceiver, can be worn anywhere on a subject's torso and in any orientation. In order to distinguish easily between falls and activities of daily living (ADL), a possible fall is detected only if an impact is detected *and* if the subject is horizontal shortly afterwards. As an additional criterion to reduce false positives, a fall is confirmed if the user activity level several seconds after a possible fall is below a threshold. Intentional falls onto a gymnastics mat were performed by 10 volunteers (total of 297 falls); ADL were performed by 15 elderly volunteers (total of 315 ADL). The fall detection algorithm provided a sensitivity of 99% and a specificity of 100%.**

I. INTRODUCTION

The world population is aging at an increasing rate. In 2011, there were 784 million people aged 60 years or over; this age group will increase to 22% of the global population in 2050 [1]. As the population ages, healthcare for the elderly becomes increasingly important. Falling down is seen as one of the major risk factors associated with aging. In fact, in the United States, one in three persons aged 65 years or over falls each year, but less than half report their falls to healthcare providers [2]. Falls by the elderly can result in moderate to severe injuries and can sometimes be fatal. Prompt notification of falls to family members or healthcare providers is essential for timely medical attention.

Several approaches have been described in the literature for automatic fall detection. In [3], a piezoelectric shock sensor and a mercury tilt switch are proposed to detect impact and orientation of the subject. Multiple radio tags placed at several locations on the body are used together with machine learning methods in [4] for fall detection. The norms of the acceleration vectors from trunk and thigh tri-axial accelerometers were used for fall detection in [5]. References [6], [7] use tri-axial accelerometers attached to a subject with the z-axis in the vertical direction; falls are detected based on the norms of the acceleration vectors and the acceleration along the z-axis. A mobile application for fall detection using the accelerometer in a smartphone is described in [8].

This paper describes a fall detection system based on a tri-axial accelerometer attached to the subject's skin using an adhesive. The skin-contact sensor helps overcome issues such as the device slipping out of a pocket or sliding along a belt. Furthermore, continuous monitoring can be ensured, including times when the subject changes clothes or is inside a bathroom. Enhanced algorithm performance is achieved by using impact as well as detection of a horizontal position (which includes supine, prone and lateral positions) shortly after the impact. In addition, a fall is confirmed by ensuring that the activity level is below a threshold several seconds after a possible fall. Moreover, a calibration procedure is used to determine the acceleration vector of the vertical position and to allow flexibility in sensor placement on the torso. The fall detection algorithm provided a sensitivity of 99% and a specificity of 100% on subjects participating in intentional falls and activities of daily living (ADL).

R. Narasimhan is with Vital Connect, Inc., 2105 S. Bascom Ave., Ste. 316, Campbell, CA 95008, USA rnarasimhan at vitalconnect.com

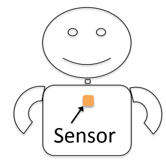

Fig. 1. Illustration of sensor placed on skin of torso.

II. MATERIALS AND METHODS

A. Skin-Contact Sensor

The sensor for fall detection consists of a Bosch BMA250 digital tri-axial accelerometer, a microcontroller and a Bluetooth Low Energy (BLE) wireless transceiver. The acceleration data are sampled at 125 Hz and digitized to 10 bits, with a maximum range of $\pm 4g$ for each axis. As shown in Fig. 1, the sensor is attached to the skin using an adhesive and can be placed anywhere on a subject's torso and in any orientation. The positive z-axis of the tri-axial accelerometer is from the sensor towards the skin (i.e., perpendicular to the surface of the skin). In normal operation, the microcontroller is used to execute the fall detection algorithm using the tri-axial acceleration data, and the BLE transceiver sends an alert if a fall is detected. However, for greater data visibility in this study, the sensor continuously transmitted acceleration data to a computer that executed the fall detection algorithm.

B. Intentional Falls and ADL

Intentional falls onto a gymnastics mat were performed by 10 volunteers (7 male, 3 female). The falls listed in Table I were performed three times by each subject. The total number of falls was 297 since one subject did not perform Fall Test Case 2. The subjects ranged in age from 23 to 46 years (32.7 ± 6.7 years), body mass from 52.6 to 90.7 kg (75.4 ± 14.2 kg) and height from 1.57 to 1.83 m (1.72 ± 0.09 m). Most of the subjects fell onto pillows placed on the mat to cushion the falls. For ADL, 15 elderly volunteers (10 male, 5 female) performed each ADL listed in Table II three

TABLE I

INTENTIONAL FALLS

Test Case	Description
1	Fall forward with legs straight
2	Fall backward with legs straight
3	Fall to the left with legs straight
4	Fall to the right with legs straight
5	Fall forward with knees bent
6	Falls backward with knees bent
7	Fall to the left with knees bent
8	Fall to the right with knees bent
9	Trip over a small object
10	Fall while sitting on a chair

TABLE II

ACTIVITIES OF DAILY LIVING (ADL)

Test Case	Description
1	Sitting down and standing up from an armchair
2	Sitting down and standing up from a low stool
3	Sitting down and standing up from a bed
4	Lying down and standing up from a bed
5	Walking 10 m
6	Stretching while standing
7	Picking up an object from the floor

times at a community center. The ADL subjects ranged in age from 63 to 91 years (74.3 ± 9.2 years), body mass from 61.2 to 98.4 kg (78.4 ± 10.4 kg) and height from 1.42 to 1.80 m (1.68 ± 0.11 m). The total number of ADL tasks was 315. The intentional falls and ADL were video recorded.

C. Fall Detection Algorithm

Since most subjects are horizontal after an injurious fall, a main feature of the fall detection algorithm is identifying the subject's horizontal position after an impact. Furthermore, most subjects lie on the floor for a significant time after a serious fall. Hence, false positives are further decreased by requiring a low activity level several seconds after a possible fall. An activity metric is defined as a moving average of the L^1-norm of the bandpass-filtered acceleration vector.

The horizontal position is identified by computing the angle of the acceleration vector shortly after an impact with an acceleration vector obtained when the subject was vertical. In order to compute this angle and provide flexibility in sensor placement and orientation on the torso, a calibration procedure is needed to determine the acceleration vector of the vertical position before the fall detection algorithm is executed. Several methods for calibration are possible. For instance, implicit calibration can be achieved by measuring the acceleration vector when the subject is walking. Alternatively, explicit calibration involves the subject notifying the system (e.g., using a mobile phone) when he or she is vertical. In case a subject has a stooped posture, the algorithm uses impact alone for fall detection and disregards the horizontal position requirement. A stooped posture is inferred if the magnitude of the z-axis component of the acceleration vector measured during calibration is greater than a threshold.

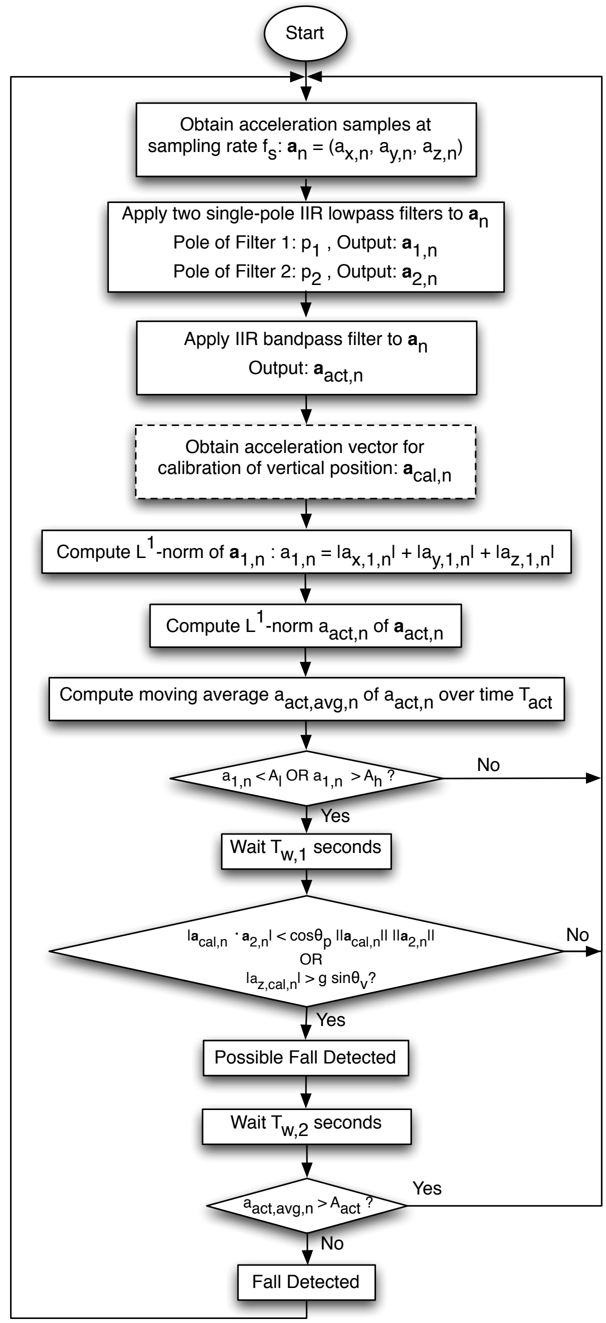

Fig. 2. Fall detection algorithm.

Fig. 2 is a flowchart of the fall detection algorithm. The acceleration vector $\mathbf{a}_n = (a_{x,n}, a_{y,n}, a_{z,n})$ consists of the x, y and z components from the tri-axial accelerometer obtained at the n-th time instant with sampling rate $f_s =$ 125 Hz. The acceleration vector $\mathbf{a}_n$ is passed through two single-pole infinite impulse response (IIR) lowpass filters with poles $p_1 = 13.8$ Hz and $p_2 = 0.8$ Hz, respectively, to produce the vectors $\mathbf{a}_{1,n}$ and $\mathbf{a}_{2,n}$. The vector $\mathbf{a}_{1,n}$ is used to track large changes in acceleration from impacts, while the vector $\mathbf{a}_{2,n}$, which contains only very low frequencies, is used to obtain stable measurements for horizontal position

TABLE III

PARAMETERS FOR FALL DETECTION

Parameter	Value
A_l	$0.3g$
A_h	$3.0g$
A_{act}	$0.2g$
θ_p	60^o
θ_v	20^o
$T_{w,1}$	2 s
$T_{w,2}$	5 s
T_{act}	1 s

determination. Also, an IIR bandpass filter is applied to $\mathbf{a}_n$ to produce the vector $\mathbf{a}_{\text{act},n}$, which is a measure of activity level. The bandpass filter is a sixth-order elliptic filter with a passband ripple of 0.1 dB, a stopband attenuation of 100 dB and a passband of 0.25 Hz to 20 Hz.

During the initialization of the algorithm, a calibration vector $\mathbf{a}_{\text{cal},n}$ is obtained via explicit calibration using $\mathbf{a}_{2,n}$. In continuous operation, the L^1-norm of $\mathbf{a}_{1,n}$ is computed:

$$a_{1,n} = \|\mathbf{a}_{1,n}\|_1 = |a_{x,1,n}| + |a_{y,1,n}| + |a_{z,1,n}|. \tag{1}$$

For the activity level measurement, the L^1-norm $a_{\text{act},n}$ of $\mathbf{a}_{\text{act},n}$ is computed; the activity metric is defined as $a_{\text{act,avg},n}$, which is a T_{act}-second moving average of $a_{\text{act},n}$.

An impact is detected if $a_{1,n} < A_l$ or $a_{1,n} > A_h$. The first condition detects the near "free fall" before impact, while the second condition detects the large acceleration magnitude caused by the impact. If an impact is detected, the algorithm waits for a time period of $T_{w,1}$ seconds, after which the horizontal position criterion is checked. The horizontal position criterion is satisfied if the angle between the calibration vector and $\mathbf{a}_{2,n}$ is larger than θ_p, i.e.

$$|\mathbf{a}_{\text{cal},n} \cdot \mathbf{a}_{2,n}| < \cos\theta_p \|\mathbf{a}_{\text{cal},n}\|_2 \|\mathbf{a}_{2,n}\|_2 \tag{2}$$

where the L^2-norm of $\mathbf{a}_n$ is given by $\|\mathbf{a}_n\|_2 = \sqrt{a_{x,n}^2 + a_{y,n}^2 + a_{z,n}^2}$. As mentioned earlier, the horizontal position criterion is ignored if a stooped posture is detected during calibration, i.e., if $|a_{z,\text{cal},n}| > g\sin\theta_v$, where $\theta_v = 0$ corresponds to a completely vertical posture. A possible fall is detected if the impact criteria are satisfied and either the horizontal position criterion is satisfied or a stooped posture is identified during calibration.

If a possible fall is detected, the algorithm waits for another $T_{w,2}$ seconds, after which the activity criterion $a_{\text{act,avg},n} > A_{\text{act}}$ is checked. If the activity criterion is satisfied, the subject was active after a possible fall; hence, the possible fall is not upgraded to a fall. However, if $a_{\text{act,avg},n} \leq A_{\text{act}}$, the subject was most likely injured because of a fall; hence, a fall is detected.

III. RESULTS

The fall detection algorithm was evaluated using the parameters given in Table III. No fall was detected for all 315 ADL, resulting in 100% specificity. Two cases of ADL recorded a possible fall, but no fall was detected because

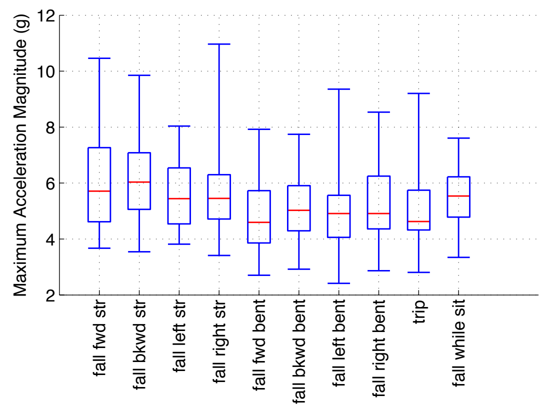

Fig. 3. Box plot of maximum acceleration magnitude for intentional falls.

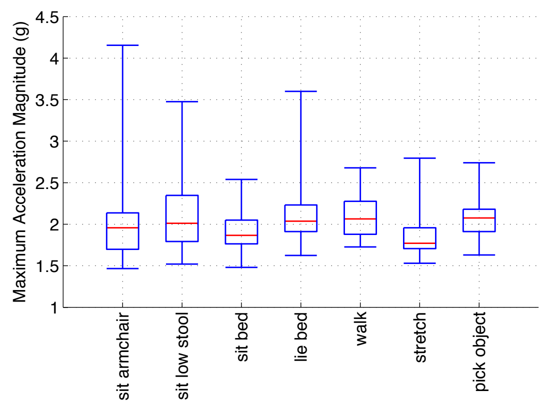

Fig. 4. Box plot of maximum acceleration magnitude for ADL.

of the activity criterion. Out of the 297 intentional falls performed, 294 were correctly detected, which corresponds to a sensitivity of 99%.

Figs. 3 and 4 are box plots of the maximum value of the acceleration magnitude $a_{1,n}$ for intentional falls and ADL, respectively. For the intentional falls, the maximum acceleration magnitude ranges from $2.4g$ to $11.0g$. The median of the maximum acceleration magnitude is larger when the legs are straight compared to when the legs are bent for falls forward, backward and to the sides. For ADL, the maximum acceleration magnitude ranges from $1.5g$ to $4.2g$.

A box plot of the angle between the calibration acceleration vector and the z-axis is shown in Fig. 5 for ADL. The angle ranges from -9.4^o to 54.4^o. Fig. 6 is a box plot of the angle between the calibration acceleration vector ($\mathbf{a}_{\text{cal},n}$) and the final acceleration vector ($\mathbf{a}_{2,n}$) $T_{w,1}$ seconds after impact for the intentional falls. The angle ranges from 64.2^o to 114.8^o. A box plot of the activity measure $a_{\text{act,avg},n}$ $T_{w,2}$ seconds after a possible fall is given in Fig. 7 for intentional falls. The activity measure ranges from $0.037g$ to $0.198g$.

IV. DISCUSSION AND CONCLUSION

It can be seen from Figs. 3 and 4 that there is considerable overlap in the maximum acceleration magnitude for intentional falls and ADL. Therefore, fall detection based

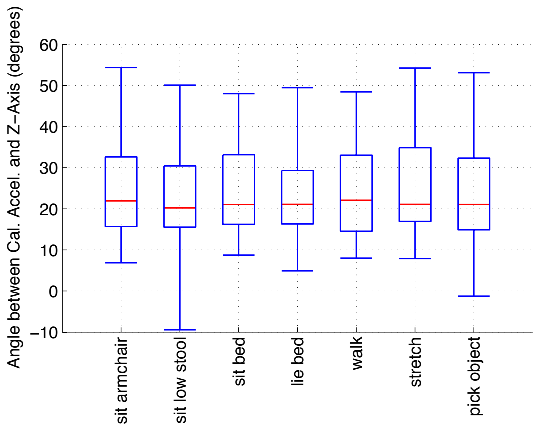

Fig. 5. Box plot of angle between calibration acceleration vector and z-axis for ADL.

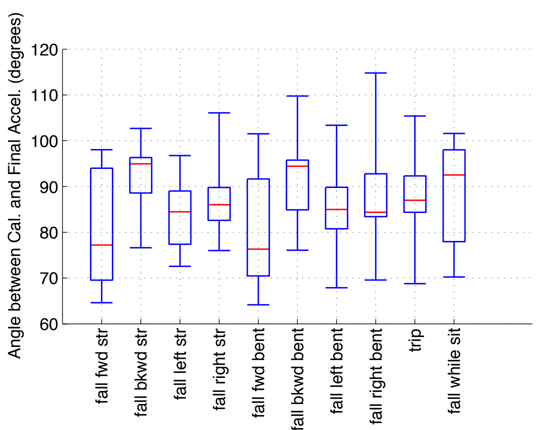

Fig. 6. Box plot of angle between calibration acceleration vector and final acceleration vector $T_{w,1}$ seconds after impact for intentional falls.

on acceleration magnitude alone does not provide sufficient sensitivity and specificity for a skin-contact sensor worn on the torso. The horizontal position detection after impact and activity criterion provide necessary additional information for fall detection. It can be seen from Fig. 6 that an angular tolerance of 30^o from vertical (i.e., $\theta_p = 60^o$) accounts for the range of horizontal positions after impact. As evident from Fig. 7, the activity measure threshold of $0.2g$ was found to capture all the cases of intentional falls while increasing the specificity of the fall detection algorithm.

Two of the three falls that were not detected were Fall Test Case 8 (fall to the right with knees bent) from two different subjects, where the maximum acceleration magnitude was $2.9g$; the other undetected fall was Fall Test Case 7 (fall to the left with knees bent) from a third subject, where the maximum acceleration magnitude was $2.4g$. Since the subjects fell onto pillows placed on the gymnastics mat, it is predicted that the maximum acceleration magnitudes recorded in this study for intentional falls are lower than the the corresponding quantities measured in spontaneous falls on hard surfaces. Hence, the sensitivity of the fall detection algorithm is expected to increase in actual usage.

In conclusion, detection of a horizontal position after

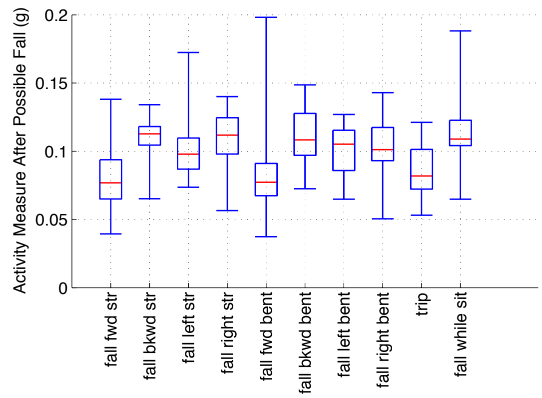

Fig. 7. Box plot of activity measure for intentional falls $T_{w,2}$ seconds after a possible fall.

impact and fall confirmation based on an activity measure provide enhanced sensitivity and specificity for automatic fall detection using a sensor worn on the torso. Future work includes conducting additional ADL and fall test cases, preferably replacing pillows and gymnastics mats with helmets and limb protection to obtain more accurate impact data. Additional areas of research include the effect of sensor position on the torso and power consumption and latency of the sensor for real-time fall detection.

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