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Falls Event Detection using Triaxial Accelerometry and Barometric Pressure Measurement

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***Abstract*— A falls detection system, employing a Bluetooth-based wearable device, containing a triaxial accelerometer and a barometric pressure sensor, is described. The aim of this study is to evaluate the use of barometric pressure measurement, as a surrogate measure of altitude, to augment previously reported accelerometry-based falls detection algorithms. The accelerometry and barometric pressure signals obtained from the waist-mounted device are analyzed by a signal processing and classification algorithm to discriminate falls from activities of daily living. This falls detection algorithm has been compared to two existing algorithms which utilize accelerometry signals alone. A set of laboratory-based simulated falls, along with other tasks associated with activities of daily living (16 tests) were performed by 15 healthy volunteers (9 male and 6 female; age: 23.7 ± 2.9 years; height: 1.74 ± 0.11 m). The algorithm incorporating pressure information detected falls with the highest sensitivity (97.8%) and the highest specificity (96.7%).**

I. Introduction

FALLS and fall induced injuries among elderly people are a major cause of morbidity. One in three elderly people living in the community are at risk of falling one or more times in a year; one in four end up with serious injuries. Moreover, falls constitute a significant health care cost [1], [2]. Recent data, which considers the changing Australian age demographic, estimates that falls injury costs will increase twofold over the next 50 years [3].

During the last decade, technological advances in microcontrollers, miniaturization of transduction sensors and wireless communication have permitted the development of wearable devices for clinical applications [4]. A number of wearable devices based on accelerometers have previously been used to detect falls [5-7].

An accelerometry-based falls detector, worn on the belt was developed by Noury *et al.* [5]. The system is capable of recognizing different body postural orientations and detecting when the rotational speed of the trunk exceeds a fixed threshold.

Zhang *et al.* [6] developed a falls detection system based on a triaxial accelerometer embedded in a mobile-phone. The testing protocol consisted of simulated falls and high intensity daily activities performed by young volunteers, in addition to ordinary activities of daily living performed by elderly subjects. Some falls were also simulated using an anthropomorphic test device.

Another system, implemented by Karantonis *et al*. [7], is a waist-mounted triaxial accelerometer unit used to classify different human movement. The algorithm has been tested on different kinds of movement including a limited number of different types of falls. In this paper we compare the proposed system to that of Karantonis *et al*. [7].

The aim of this study is to evaluate an algorithm for falls detection using a wireless waist-mounted device which contains both a triaxial accelerometer and an atmospheric air pressure sensor. Without the information about the change in altitude associated with falling, some events that may occur during daily life, such as sitting heavily into a chair, transitioning down a step or ledge, or climbing into bed, could be indistinguishable from a real fall, when classified using solely accelerometry data. Moreover, using only accelerometry signals, even a necessary act like placing or removing the device from the belt could be falsely detected as a possible fall. Finally, in a realistic scenario, an elderly person could attempt to break the fall and the impact may therefore not be characterized by an extreme acceleration peak.

Only limited reports of combined accelerometric and barometric pressure signals have appeared in the literature. For example, Ohtaki *et al.* [8] used such signals to classify different types of ambulatory physical activities. The initial hypothesis of our study was that determining a change in altitude associated with falling would improve falls detection accuracy.

II. Methods

A. System design

The data acquisition device consists of a triaxial micromachined accelerometer (MMA7260, Freescale) which measures the acceleration along three orthogonal axes with a sampling rate of 40 Hz and an adjustable full-scale deflection between ±1.5 G and ±6 G (where G represents acceleration due to gravity: 9.81 m/s/s), an atmospheric air pressure sensor (SCP1000, VTI Technologies) with a resolution of 1.5 Pa (which corresponds to about 10 cm at

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sea level) and a sampling rate of 1.8 Hz, a microprocessor (MSP430F149, Texas Instruments), a Bluetooth module (WML-C30AH, Mitsumi) and a Li-Pol rechargeable battery. The small wireless device measures 70×54×14 mm and weighs 57.5 g. The device can be attached to the subject's belt in correspondence to the right anterior iliac crest of the pelvis, and measures the barometric pressure and the accelerations relative to the trunk along the vertical, mediolateral and anteroposterior directions.

B. Subject database

Fifteen healthy volunteers (9 male and 6 female; age: 23.7 ± 2.9 years; height: 1.74 ± 0.11 m) participated in this study. All data were collected in a controlled laboratory setting with the University of New South Wales (Sydney, Australia) Ethics Committee approval.

C. Trial experiment protocol

A set of 16 different ambulatory and fall sequences (see first three columns of Table I) were designed to test the performance of each falls detection algorithm. Specifically, the sequences include intentional falls performed onto a mattress (thickness 18 cm) and a set of activities of daily living.

Falls in three different directions (forward, backward and lateral) were evaluated (sequences 1, 2 and 3). Sequence 4 simulated the situation where the subject, after falling, tries to recover without success (active lying). Assuming that, in a more realistic scenario, some elderly people may attempt to break their fall, sequence 5 was introduced. The system was also tested on cases where the subject eventually falls to the floor, after first resting against a wall and then sliding vertically down to the end in the sitting position (sequence 6), which we assume mimics an individual who slowly loses consciousness. To test the ability of the system to distinguish events whose classification are dependent on related events, the subject performed two falls in the forward direction, followed (after 5 s) by a recovery: in one case the subject was asked to rise and walk and in the other case was asked to rise and stand still (sequences 7 and 8 respectively). In addition, seven activities of daily living were performed (from sequence 9 to 16).

Each subject performed one instance of each sequence. The data recording included 20 s and 60 s respectively before and after each event. Fig. 1 shows a sample output of a simulated lateral fall.

D. Feature extraction

In order to develop an algorithm to detect falls, several features of interest are extracted from the accelerometry and barometric pressure signals. The two preprocessing steps performed by Karantonis *et al.* [7] on the raw data are used in the current analysis. The first step is median filtering (n=3). The second step is low-pass filtering, whereby a third-order elliptical infinite response (IIR) filter with a pass-band edge-frequency of 0.25 Hz is applied to the median-filtered signal. The low-pass filtered signal is an estimation

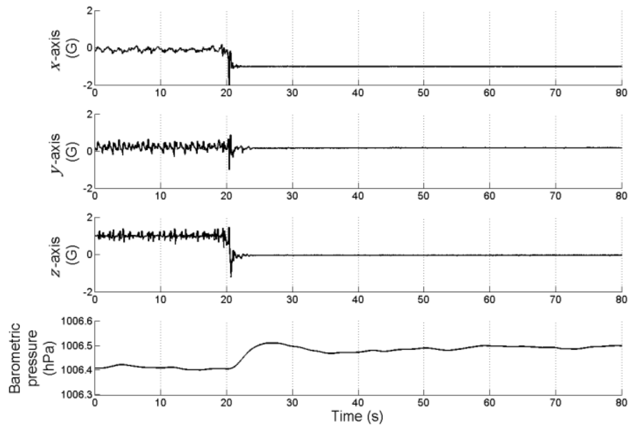

Fig. 1. Data obtained during a simulated lateral fall. The accelerations along x-, y- and z-axis were median filtered (n=3 at 40 Hz), while the barometric pressure signal was low-pass filtered (second order Butterworth filter with cut-off frequency at 0.1 Hz).

of the gravitational acceleration (GA) component and is subtracted from the median filtered signal to obtain an estimation of body acceleration (BA).

1) Acceleration peak: The signal magnitude vector (SVM) provides a measure of the degree of movement intensity and it is derived from the BA component. The SVM can be calculated as following:

$$\mathrm{SVM}[i] = \sqrt{x^2[i] + y^2[i] + z^2[i]} \qquad (1)$$

where $x[i]$ is the i^{th} sample of the BA component along the x-axis samples (similarly for $y[i]$ and $z[i]$).

2) Activity and rest: A suitable measure to distinguish periods of subject activity and rest is the signal magnitude area (SMA) obtained using the BA component [9]. The j^{th} sample ($j = 0,1,2, \ldots n$) of SMA parameter can be calculated as following:

$$\mathrm{SMA[j]} = T \sum_{i=j}^{i=j+\frac{1}{T}} (|x[i]| + |y[i]| + |z[i]|) \qquad (2)$$

where $x[i]$, $y[i]$ and $z[i]$ are the BA components of the x-, y- and z-axis samples, respectively, and T is the sampling period. The SMA was calculated by summing each sample value progressively over a 1 s interval, without overlapping the windows.

3) Postural orientation: The GA component provides information on the tilt angle of the subject wearing the device. The tilt angle, Φ, is defined as the angle between the gravitational vector, $\boldsymbol{g}$, derived from the GA, its magnitude (G=9.81 m/s/s) and the acceleration component measured along the positive z-axis by the relation:

$$\Phi = \cos^{-1}(z/\mathrm{G}) \qquad (3)$$

In this study, we define that a tilt angle between 0° and 20° indicates a standing position, while values greater than 20° indicate a non-standing body orientation.

4) Differential pressure: The pressure sensor signal was low-pass filtered using a second order Butterworth filter with cut-off frequency at 0.1 Hz and up-sampled using linear interpolation to the acceleration sampling rate of 40 Hz. The resulting signal was used to calculate the differential pressure parameter ($\Delta\mathrm{P}[k]$). The k^{th}sample of $\Delta\mathrm{P}$ signal was

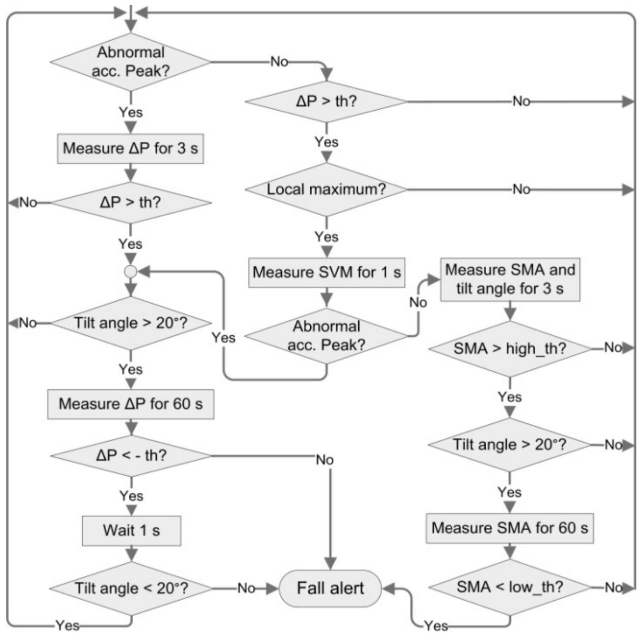

Fig. 2. Flow chart for the falls detection process (Algorithm 3). SVM is analyzed to detect abnormal acceleration peaks, while the thresholding of ΔP indicates if the device altitude has significantly changed and the tilt angle indicates the postural orientation. The two thresholds (high_th and low_th) on SMA indicate the grade of measured activity.

obtained considering the average pressure during the 2 s before and the 2 s after each sample (overlapping the windows):

$$\Delta \mathrm{P}[k] = T/2 \sum_{i=k}^{i=k+2/T} p[i] - T/2 \sum_{i=k-2/T}^{i=k} p[i] \quad (4)$$

where $p[i]$ is the i^{th} sample of the barometric signal and T is the sampling period. The ΔP signal was then normalized by dividing by the subject's height.

E. Fall detection algorithms

Three different falls detection algorithms were investigated. These algorithms were all tested on the same set of data.

Algorithm 1, derived from the classification algorithm implemented by Karantonis *et al.* [7], was based on the detection of an impact by the comparison of the SVM to a preset threshold. The optimal threshold was found to be 1.8 G, and the signal was required to exceed the threshold for at least two consecutive samples. When such a fall event occurs, the current time period is classified as a possible fall. If a possible fall is detected, the SMA of the subject is measured to determine the amount of movement generated by the subject during the 60 s postfall-interval (ignoring the first 5 s due to potential residual movement relating to the fall). If the system recognizes that no activity has occurred during this post-fall interval, i.e. SMA does not exceed the fixed low threshold, the event is upgraded to a fall.

Algorithm 2 was developed by augmenting the previous algorithm to consider the postural orientation of the wearer. In addition to the comparison of the SVM to a preset threshold, an event is classified as a possible fall only if the detection of the impact is followed by a non-standing classification of body orientation. If the subject is still lying or sitting during the 60 s post-fall interval, then the event is upgraded to a fall.

Algorithm 3 (Fig. 2) was developed using all the parameters considered in the previous two algorithms (SVM, SMA and Φ). In addition the ΔP signal was employed to improve classification performance. If an abnormal acceleration peak is detected, by thresholding the SVM value (1.8 G), ΔP is monitored for a 3 s interval. If the thresholding of ΔP (with a heuristically determined threshold) indicates that the device altitude has significantly changed and if the subject's tilt angle indicates a non-standing position, the event is classified as a possible fall. If the system recognizes that no pressure change has occurred during the 60 s post-fall interval and the subject is still in a non-standing position, then the classification is upgraded to a fall (Fig. 3). The system is able to recognize if the subject was able to rise again during the 60 s period after the event classified as a possible fall. If the system recognizes that the device altitude is significantly changed, even without detecting an abnormal acceleration peak, but the SMA exceeds a high threshold and the subject is in a non-standing position, the event is classified as a possible fall. If no activity (low threshold on SMA) has occurred during the 60 s post-fall interval, the classification is upgraded to a fall.

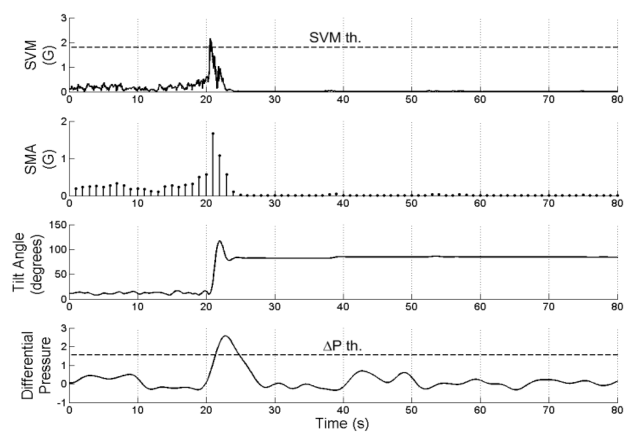

Fig. 3. Sample output of a simulated backward fall. SVM threshold (SVM th.) detects abnormal acceleration peaks. The Differential Pressure has been normalized by dividing by the subject's height; its thresholding (ΔP th.) indicates change in altitude.

III. RESULTS

A total data set of 240 sequences was analyzed retrospectively in MATLAB version 7.5 to determine the sensitivity, specificity and accuracy of the three algorithms. The overall accuracy of each sequence is calculated as the percentage of correct classifications made, taken across the fifteen subjects (Table I). The sequences classified by Algorithm 1 as a possible fall are considered incorrect if the subjects recover after the fall, or no fall occurs. If a fall is classified as a possible fall by Algorithm 1, the classification is considered correct. In order to compare the performance of the three algorithms, the accuracy, sensitivity and specificity were considered (Table II). The results show that falls can be detected with the highest sensitivity (97.8%) and the highest specificity (96.7%) by Algorithm 3, which

TABLE I
NUMBER OF CORRECT AND INCORRECT CLASSIFICATIONS AND ACCURACY CALCULATED FOR EACH SEQUENCE

			Algorithm 1			Algorithm 2			Algorithm 3		
No	Category	Instructions	Overall Correct	Overall Incorrect	Accuracy (%)	Overall Correct	Overall Incorrect	Accuracy (%)	Overall Correct	Overall Incorrect	Accuracy (%)
1	Fall	Forward fall, ending lying	15	0	100	15	0	100	15	0	100
2	Fall	Backward fall, ending lying	15	0	100	15	0	100	15	0	100
3	Fall	Lateral fall, ending lying	15	0	100	15	0	100	15	0	100
4	Fall	Forward fall, ending active lying	15	0	100	15	0	100	14	1	93.3
5	Fall	Forward fall with attempt to break the fall	7	8	46.7	7	8	46.7	15	0	100
6	Fall	Resting against a wall, then sliding vertically down to the end in the sitting position	1	14	6.7	1	14	6.7	14	1	93.3
7	Fall with recovery	Forward fall, recovery and walking	0	15	0	15	0	100	15	0	100
8	Fall with recovery	Forward fall, recovery and standing	0	15	0	15	0	100	15	0	100
9	No fall	Sitting on a chair	15	0	100	15	0	100	15	0	100
10	No fall	Collapse into a chair	4	11	26.7	4	11	26.7	12	3	80
11	No fall	Climbing into bed	12	3	80	12	3	80	13	2	86.7
12	No fall	Jump in vertical direction	8	7	53.3	15	0	100	15	0	100
13	No fall	Pick up something from the floor	15	0	100	15	0	100	15	0	100
14	No fall	Bend down and doing own laces	15	0	100	15	0	100	15	0	100
15	No fall	Taking the lift	15	0	100	15	0	100	15	0	100
16	No fall	Walk down the stairs (6 steps)	15	0	100	15	0	100	15	0	100

incorporates pressure information. Algorithm 1 can distinguish falls with 75.5% sensitivity, while the addition of postural orientation in Algorithm 2 does not improve sensitivity but specificity increases from 66% to 90.7%.

TABLE II
ACCURACY, SENSITIVITY AND SPECIFICITY OF THE THREE ALGORITHMS

	Algorithm 1	Algorithm 2	Algorithm 3
Accuracy (%)	69.6	85.0	97.1
Sensitivity (%)	75.5	75.5	97.8
Specificity (%)	66.0	90.7	96.7

IV. DISCUSSION

The purpose of this study was to evaluate the performance of a falls detection system based on a triaxial accelerometer and a barometric pressure sensor. An existing algorithm, based on the use of a triaxial accelerometer was evaluated. The augmentation of this existing algorithm, through the inclusion of information regarding postural orientation, gleaned from the triaxial accelerometry signal, was also evaluated. Finally, a measure of barometric pressure was employed, as a surrogate measure of altitude, to improve upon the previous algorithms.

A significant limitation in the system implemented by Noury *et al*. [5] was the inability to detect falls where the subject falls to the floor, after first resting against a wall and then sliding vertically down to the end in the sitting position. In these kinds of falls, the authors report less than 19% accuracy. By including pressure information it is possible to detect a fall followed by loss of consciousness, even if the fall is not characterized by a considerable trunk rotation speed, or by an abnormal acceleration peak.

Zhang *et al.* [6] achieved an overall accuracy of 93.3% in falls detection but obtained only 84.4% accuracy when high-intensity daily activities (e.g. running, or jumping) were performed and 89.1% accuracy when the subject handled the mobile-phone causing acceleration (e.g. turning the hand, tremble). Results show that using the information about the change in altitude associated with falling could help to decrease the number of events associated with a relevant acceleration and incorrectly classified as a fall.

Compared to the system developed by Karantonis *et al.* [7] this approach, which included the pressure information, demonstrated an improved performance in detecting recoveries from falls events. The authors [7] proposed to add a user input to their system in order to reduce the incidence of false alarms. Results show that using a barometric pressure sensor could make that alteration less critical.

About 40% of the sequences in which the subject climbed into bed were not classified as a fall, even if the ΔP signal exceeded the threshold, only because the system detected some activity during the 60 s post-fall interval. If the individual enters the bed and immediately remains motionless, a false detection may occur. Also, a finer resolution pressure transducer might help discriminate the altitude difference between lying on a bed and lying on the ground.

Finally, it is necessary to test the system on elderly people and to evaluate the system sensitivity and specificity in a real environment, where unpredictable changes in pressure may generate false alarms.

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