Direction Sensitive Fall Detection Using a Triaxial Accelerometer and a Barometric Pressure Sensor

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Abstract— **Falling is one of the leading causes of serious health decline or injury-related deaths in the elderly. For survivors of a fall, the resulting health expenses can be a devastating burden, largely because of the long recovery time and potential comorbidities that ensue. The detection of a fall is, therefore, important in care of the elderly for decreasing the reaction time by the care-givers especially for those in care who are particularly frail or living alone. Recent advances in motion-sensor technology have enabled wearable sensors to be used efficiently for pervasive care of the elderly. In addition to fall detection, it is also important to determine the direction of a fall, which could help in the location of joint weakness or post-fall fracture. This work uses a waist-worn sensor, encompassing a 3D accelerometer and a barometric pressure sensor, for reliable fall detection and the determination of the direction of a fall. Also assessed is an efficient analysis framework suitable for on-node implementation using a low-power micro-controller that involves both feature extraction and fall detection. A detailed laboratory analysis is presented validating the practical application of the system.**

I. INTRODUCTION

Falls are the leading cause of injury and death among elderly [1]. In the WHO report of 2002, fall-related mortality rate was at 6 % [2] just slightly under the injury mortality rates in wars. Globally, 4 out of 10 falls are fatal in persons over 70 [2]. Fortunately, not all falls result in death - but post-fall injuries can often be very severe and lead to increased disability and an extended period of rehabilitation. 20-30% of those who fall suffer from moderate to severe injuries such as lacerations, hip fractures, or head traumata. These injuries usually trigger a rapid decline in health [3] and increase the risk of early death [4]. Women are more likely than men to be injured in a fall, leading to twice the rate of hip fractures [5]. One of the most serious dangers of a fall is the potential for a long period spent on the ground after a fall, often caused by a delayed discovery of the fallen person. Half of those who experienced an extended time lying on the ground died within 6 months of the fall [6].

There are several risk factors that could lead to falls. These include changes in the cognitive, visual, musculoskeletal, sensory or cardiovascular systems due to ageing, as well as extrinsic factors normally related to the environment such as trip hazards and poor lighting [7]. In many cases, falls are a combination of these factors [8]. When a fall occurs, a rapid response by trained staff is essential. However, this is not always possible if the elderly lives alone or in remote areas that are not easily accessible. Thus, there has been much research interest in fall-alerting systems. Existing commercial systems include the neck-worn pendant systems requiring the elderly to push a button after a fall. Sometimes, the fall victim suffers from a loss of consciousness rendering such systems ineffective [9].

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TABLE I
PREVIOUS APPROACHES IN FALL DETECTION

Sensors Used	Location	References
Triaxial Accelerometer	Waist Worn	[12][15]
Triaxial Accelerometer	Behind the Ear	[16]
Triaxial Accelerometer	Waist, Wrist and Head	[17]
Triaxial Accelerometer and Gyroscope	Chest and Leg	[18]
Gyroscope	Trunk	[13]
Triaxial Accelerometer	Carried Mobile Phone	[19]
Triaxial Accelerometer and Air Pressure Sensor	Waist Worn, Wrist Worn	[20], [21], [14]

Recently, a number of automatic methods for fall detection have also been proposed. Automatic systems for fall detection can be based on vision [10], sound [11] or wearable sensing. Wearable sensors for fall-detection generally use accelerometers [12], gyroscopes [13] or a combination of several sensing modalities and devices [14]. The miniaturisation in electronics combined with on-node processing and their ease of use has made them the method of choice for effective and cost-efficient fall detection techniques. Although the use of a group of sensors on different body parts could lead to higher detection rates, it could impair wearability and patient compliance, thus limiting its practical use. It is therefore desirable to use one single wearable device that is simple and easy to use. Within the research community, fall detection has been a well-researched area and Table I highlights some of the recent techniques used for fall detection using wearable sensors.

Clinically, in addition to detecting the occurrence of falls, it is very important to recognise the direction of a fall, which could further indicate the weakness in particular joints and fractures. A sideways collapse, for instance, may result in a femoral neck fracture, which can put great strain on the elderly due to its long rehabilitation and possible constraints on the quality of living. Directional information can shed light on possible causes of the falls and help decrease reaction time. In this study, our primary aim was to detect, as well as recognise the direction of falls. This was achieved by using a waist-worn sensing device encompassing a 3D accelerometer and a barometric pressure sensor.

TABLE II

FALL DETECTION PROTOCOL

	Activity	Fall/Non Fall
1	Forward collapse (fall on knees)	F
2	Forward collapse (lie down)	F
3	Forward collapse with attempted getting up	F
4	Backward collapse (end up in sitting position)	F
5	Backward collapse (end up lying down)	F
6	Backward collapse with attempted getting up	F
7	Sideways collapse (right)	F
8	Sideways collapse (left)	F
9	Fall from chair (slide)	F
10	Fall with recovery (then walking)	F
11	Fall with recovery (then standing)	F
12	Collapsing into a bed	F
13	Fall from bed (trying to get up, then fall)	F
14	Sitting down on a chair	N
15	Standing up from a chair	N
16	Collapsing into a chair	N
17	Resting against a wall, then sliding down	N
18	Lying down on a bed	N
19	Getting up from a bed	N
20	Jumping	N
21	Pick up something from the floor	N
22	Bend forward and tie shoe laces	N
23	Take the lift down	N
24	Take the lift up	N
25	Walk down stairs (6 steps)	N

II. METHODOLOGY

A. Experimental Setup

The sensor used in the study was a 6cm long and 2cm wide waist-worn sensor composed of a triaxial accelerometer ADXL330 with a full-scale range of $\pm$ 3g and a barometric pressure sensor (VTI SCP 1000-D01) with a resolution of 1.5 Pa in high-resolution measurement, integrated with a BSN (Body Sensor Networks) wireless sensor node [22]. 12 healthy subjects (8 male and 4 female, average age of 26.25) wore the sensor and performed the activities shown in the protocol of Table II with informed consent. The protocol is classified into a group of falls and a list of activities of daily living, which in some cases could be mistaken for falls. The subjects simulated falls on a 20cm thick mattress on the floor. We asked the subjects to remain on the mattress for 15-25 seconds after the fall to simulate the lying down period experienced by some elderly fallers. Certain activities include stage where one attempts to get up from the fall, and even the successful recovery from the fall. This is to ensure a realistic scenario in which an elderly person is struggling to get up again. The sampling rates for the sensors were 10 Hz both for the accelerometer and for the pressure sensor.

B. Feature Extraction

The accelerometer data required preprocessing by subtracting the zero-g-bias level on each axis. The zero-g-bias describes the output voltage under solely gravitational forces (with g=9.81 m/s^2). It can be calculated by subtracting the output in one direction from the output rotated by 180°. The accelerometer is then correctly calibrated.

The processing required for fall detection is designed in such a way that it is amenable to on-node processing by the BSN low-power on-board micro-controller. As shown in Fig. 1, the detection method consists of two processing stages with an empirically determined threshold. Hence the different types of falls may vary in impact, tilt angle and direction, different methods of detection have to be combined to encompass the different characteristics of falls. For the calculation of ratios, a time window is set for all features which looks at 50 samples at a time and uses 80% thereof as "previous values" and 20% as the "most recent ones".

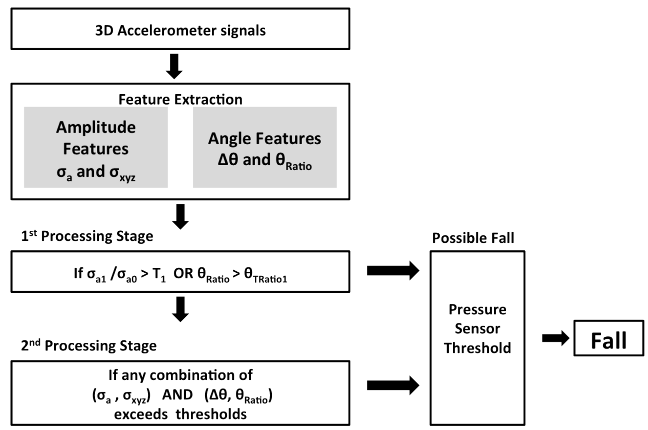


Fig. 1. Fall detection algorithm.

The first threshold stage is designed to detect falls which stand out by either a sudden change in orientation but not necessarily a hard collision, or falls lacking a tilt angle but with a strong impact which would indicate a fall. Nonetheless, most falls can be characterised by a combination of a tilt angle and impact or acceleration peaks for which the second stage has been designed. The features selected for this work are:

- The magnitude of a moving-window standard deviation per axis: $|\sigma_{xyz}| = \sqrt{\sigma_x^2 + \sigma_y^2 + \sigma_z^2}$ This feature is sensitive for rotations even without a change of acceleration magnitude, allowing the detection of sudden tilt change. The ratio of σ_{xyz} is calculated per window (containing both previous and current values) and compared with a selected threshold.

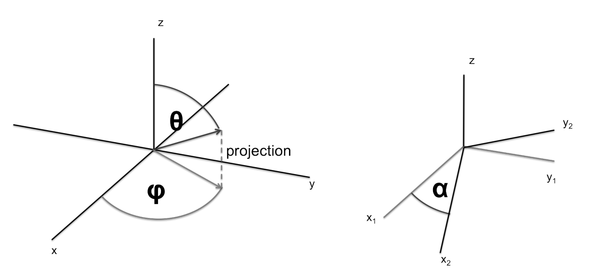


Fig. 2. The left figure shows polar angle θ and azimuth angle ϕ and the right shows the rotation of the coordinate system by the angle α around the z-axis

- The standard deviation of the vector magnitude: $\sigma_a = \sigma(\sqrt{x^2+y^2+z^2})$ This feature was selected in order to capture sudden changes in acceleration that are not necessarily combined with a change in tilt angle of the body, an example is a fall on knees. Thus, this feature detects sudden changes in signal magnitude (peaks) which could reflect an impact caused by a fall. Dividing the most recent values of σ_{xyz} by earlier values of a time frame describes the instantaneous rate of change.
- The ratio of the polar angle θ_{Ratio} calculated in consecutive windows of 20 samples. Polar angle θ (shown in Fig. 2) is calculated with $arccos(z/\sqrt{x^2+y^2+z^2})$ from pre-processed accelerometer data. This angle reflects the body-tilt and a sudden change could be indicative of a fall. The angles refer to a coordinate system associated to the sensor. In addition, the ratio of the instantaneous angle θ and its earlier values in a narrow time window reflect a sudden tilt angle change.
- The difference in the values of the polar angle in consecutive windows $\Delta\theta$ is also calculated. $\Delta\theta$ also aims to encompass large differences in tilt angle.

For all falls, the barometric pressure sensor data is checked for changes accompanying the fall. If the barometric pressure rises along with the features aforementioned, it is very likely that the person fell.

C. *Detection of Fall Direction*

To detect the direction of a fall, we assumed that the z-axis of the sensor is aligned with the vertical axis of the subject's body. The fall direction can then be calculated with the azimuth angle ϕ using $arctan2(y/x)$ (Fig. 2) on pre-processed accelerometer data. The sensor and body have separate coordinate systems caused by differences in sensor positioning. With the assumption of the z-axis as being vertical, or close to being vertically arranged, a 2D coordinate transformation suffices for the determination of a fall's direction [23]. Aligning the sensor and the body allows us then to detect the fall direction. A calibration stage was performed by tilting the sensor in a specified direction in the x-y-plane which gives us rotation angle α. Fig. 2 shows the angle α which is the rotation angle between the two coordinate systems. This rotation angle was used to conduct a 2D-cartesian coordinate transformation with rotation matrix R to align sensor and body co-ordinate systems around the z-axis in the x-y plane.

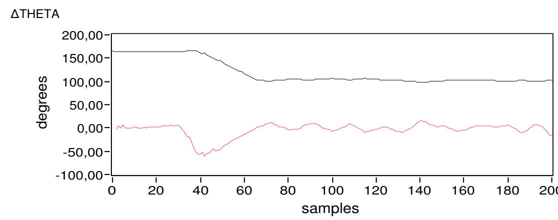
The vector $p_1 = \begin{pmatrix} x_1 & y_1 & z_1 \end{pmatrix}^T$ describes the sensor's vector direction with respect to the sensor's coordinate system before rotation (p_2 accordingly) and provided $x_1 = cos(\phi)$ and $y_1 = sin(\phi)$, an anticlockwise rotation around the z-axis with rotation angle α results in: $p_2 = Rp_1$ with $x_2 = cos(\phi+\alpha)$ and $y_2 = sin(\phi+\alpha)$.

III. Results

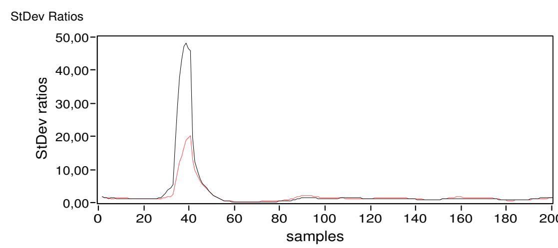
The data analysis, containing a total of 297 sequences, was performed in two steps as presented in the previous sections. The first step was the detection of those falls resulting in an accuracy of 81.48%, a specificity of 83.33% and a sensitivity of 79.08%. The barometric pressure sensor combined with the accelerometer increased the accuracy to 86.97%, specificity to 85.24% and sensitivity to 87.77%. Motions such as falling forward on the knees or jumping were difficult to classify for some subjects due to small change in pressure (height difference sometimes less than 30cm) or lacking tilt angles.

Fig. 3 shows a forward fall with attempted effort by the subject to get back up. The high peak of σ_a indicates a very strong fall impact and θ_{Ratio} shows a sudden change in vertical orientation as the ratio is higher than 1.5 at its peak.

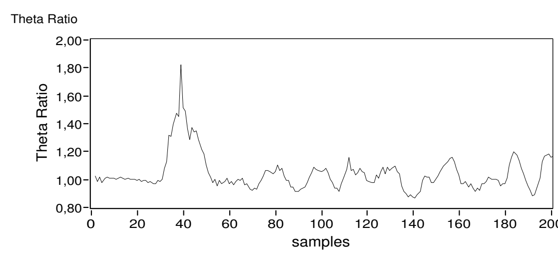
Most falls in Table II had a predetermined fall direction. The Confusion Matrix in Table IV gives the results for the prediction of fall direction. Here the predicted classes match the actual ones with 94.12% accuracy.



(a) θ (black) and $\Delta\theta$ (red)



(b) σ_{xyz} (red) and σ_a (black)



(c) θ_{Ratio}

Fig. 3. The three graphs show features $\Delta\theta$, $\sigma_{xyzRatio}$ and θ_{Ratio} for a forward fall with attempted getting up. The upper line in 3(a) shows the momentary values of θ, while the lower line shows the difference $\Delta\theta$ of the new values from the old ones. Graph 3(b) shows the two moving standard deviation ratios. Graph 3(c) shows the change in angle with θ_{Ratio}. We can clearly see the person struggling on the floor in both $\Delta\theta$ and θ_{Ratio} after the fall - without recovery as the angle θ (black) does not return to its base level in 3(a).

IV. Discussion and Conclusion

In this paper, we have proposed a system in which subjects wear a waist-worn wireless sensor for the detection of fall occurrence and orientation. The technology aims to detect

TABLE III

ACCURACY, SPECIFICITY, SENSITIVITY OF THE FALLS

	Fall- Non Fall Classification Results	
	Accelerometer	Accelerometer + Pressure Sensor
Accuracy (%)	81.48	86.97
Specificity (%)	83.33	85.24
Sensitivity (%)	79.08	87.77

TABLE IV

CONFUSION MATRIX SHOWING DETECTED DIRECTION VERSUS ACTUAL DIRECTION

		Predicted Classes		
		Forward	Backward	Left/Right
Actual Classes	Forward	41	0	2
	Backward	1	52	1
	Left/Right	1	2	19

impacts due to sudden falls as well as detect sudden changes in tilt or posture.

The complexity analysis of this algorithm resulted in a linear complexity $O(n)$ and is therefore suitable to run on a sensor if ported to a simpler implementation.

A limitation of this study, which is common in previous literature, is that falls were simulated by young subjects rather than elderly subjects. Most falls occurred on a mattress, which suggests that the impact could potentially differ from falls on harder or more unpredictable surfaces.

Even with the assumption of a vertically arranged z-axis the results for the directional fall identification are satisfactory with an accuracy of 94.12%. However, this assumption was made under the restrictions of sensor positioning. This directional information will offer valuable clues for how the person fell, e.g. after regaining consciousness and/or after experiencing possible disoriented movements shortly after the fall. The basic framework of this study can be extended to further studies in which falls may be detected regardless of the location of the sensor and the device's orientation. This would require calibration of the sensor in at least 2 different directions: standing upright position and lying down (to define the x-y-plane). This would require a 3D Cartesian coordinate transformation so that the two different coordinate systems become aligned and so that the results would be independent of the device's orientation.

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