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Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm

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We dedicate this paper to the memory of our late colleague and co-author, Jacinta O'Brien, who died suddenly on February 3, 2004: "Ar dheis Dé go raibh a hanam dílis".

Abstract

Using simulated falls performed under supervised conditions and activities of daily living (ADL) performed by elderly subjects, the ability to discriminate between falls and ADL was investigated using tri-axial accelerometer sensors, mounted on the trunk and thigh. Data analysis was performed using MATLAB to determine the peak accelerations recorded during eight different types of falls. These included; forward falls, backward falls and lateral falls left and right, performed with legs straight and flexed. Falls detection algorithms were devised using thresholding techniques. Falls could be distinguished from ADL for a total data set from 480 movements. This was accomplished using a single threshold determined by the fall-event data-set, applied to the resultant-magnitude acceleration signal from a tri-axial accelerometer located at the trunk.

Keywords: Falls in the elderly; Fall detection; Accelerometer; ADL; Resultant-magnitude signal

1. Introduction

Falls affect over one in every three elderly people [1,2]. They are the leading cause of injury deaths [3] and of injury-related hospitalisation [4] among the elderly population. Injuries sustained from falls can include broken or fractured bones, superficial cuts and abrasions as well as soft tissue damage [2,5]. A serious consequence of sustaining a fall is also the 'long-lie', which is identified as involuntarily remaining on the ground for an hour or more following a fall [6]. The 'long-lie' occurs in more than 20% of elderly people admitted to hospital as a result of a fall [7]. Half of elderly people who experience a 'long-lie' die within 6 months, even if no direct injury from the fall has occurred [8].

Detection of a fall, either through automatic fall detection or through a personal emergency response system (PERS) might reduce the occurrence of the 'long-lie', by minimizing the time between the fall and the arrival of medical attention [9]. The most common existing PERS, the push-button pendant, is not always satisfactory because during a loss of consciousness or a faint the pendant might not be activated [10]. Moreover, some elderly people do not activate their PERS, even when they have the ability to do so [11].

A number of different approaches for the automatic detection of falls have appeared in recent years [12]. Some detect the impact of the body with the ground or the near horizontal orientation of the faller following a fall [12]. Most fall-detection systems detect the shock received by the body upon impact using accelerometers [12–15]. For example, Diaz et al. [13] developed a primary fall-detection system which consisted of a small adhesive sensor patch that could be attached to the sacrum. Its fall detection accuracy was 100% (100% sensitivity) and only 7.5% of activities of daily living (ADL) were misdetected as falls. Hwang et al. [14] used a tri-axial accelerometer and gyroscope, both placed at

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the chest, to successfully distinguish between falls and ADL. This system had a sensitivity of 95.5% and specificity of 100%. However, ADL testing of the system was only for three young adults who performed sitting and a daily life activity.

To date fall-detection systems have used young subjects to test the extent of misdetection of ADL as falls. Elderly people often move differently than younger people as they typically have less control over the speed of their body movements due to reduced muscle strength with old age. As a result elderly people may ‘‘fall’’ into a chair when sitting down instead of sitting in a controlled manner and thus would be expected to produce higher peak accelerations when performing certain ADL. Thus, it was considered appropriate by the authors of this paper that the ADL-based measurements be performed using elderly subjects to increase the robustness of the test methodology.

This paper describes the development and testing of a threshold-based algorithm capable of automatically discriminating between a fall-event and an ADL, using tri-axial accelerometers. The accelerometer signals were acquired from simulated falls performed by healthy young subjects and from activities of daily living performed by elderly adults in their own homes. When a person falls and contacts the ground the forces to the body exceed those experienced during normal daily activities. We predicted that trunk and thigh tri-axial accelerometer signals would have peak values during a fall, which would be distinct from the signals produced during the performance of normal ADL.

2. Materials and method

Trunk and thigh longitudinal, anterior/posterior and medial–lateral accelerometer readings were recorded during simulated falls and ADL tasks. As it was not appropriate to subject elderly people to simulated falls, the first study involved young subjects performing simulated falls, in a safe controlled environment, under the supervision of a physical education professional. The second study involved elderly subjects performing ADL tasks in their own homes. Both studies were completed with people wearing the same tri-axial accelerometers, on the trunk and thigh.

2.1. The simulated fall study

The simulated fall study involved 10 young healthy young subjects performing simulated falls onto large crash mats. They fell from a specially constructed platform under the supervision of a physical education professional. Tri-axial accelerometer signals were recorded from the trunk and thigh during each simulated fall-event. Each subject performed eight different fall types and each fall-type was repeated three times. Thus, each young adult performed 24 falls. These subjects ranged in age from 21 to 29 years (23.7 $\pm$ 2.2 years), body mass from 67.6 to 85.3 kg (75.9 $\pm$ 5.1 kg) and height from 1.68 to 1.85 m (1.78 $\pm$ 0.06 m). All gave written informed consent and the University of Limerick Research Ethics Committee (ULREC) approved the protocol.

The fall types used during testing for the current study were selected to simulate common fall types in elderly people. A study by Lord et al. [1], found that 82% of falls occurred when people were in upright stance. The most common causes of falls were trips, slips and loss of balance. Elderly people also most often fall forward [16–18]. O’Neill et al. [16] observed that 60% of falls in older adults were in the forward direction. Laterally directed falls also pose a major threat since, a laterally directed fall that produces impact on the greater trochanter has the potential to fracture every time it happens [19]. Thus, falls from standing height in all directions should be examined when validating fall detection devices. Attempts should also be made to mimic realistic falls (i.e. with knee flexion), as has been reported in previous studies [20–22]. Thus the simulated falls performed were: forward falls, backward falls, lateral falls left and right all performed with both legs straight and with knee flexion.

2.2. The ADL study

The second study involved elderly subjects performing ADL, in their own homes, while fitted with the same sensor configuration. Ten community-dwelling elderly subjects, three females and seven males, were monitored. They ranged in age from 70 to 83 years (77.2 $\pm$ 4.3 years). All subjects gave written informed consent and the ULREC approved the measurement protocol.

Each ADL was performed three times by every older person. The ADL were tasks that could produce impacts or abrupt changes in a person’s movement and result in false triggering of a threshold-based fall detection algorithm. They were:

- sitting down and standing up from an armchair;
- sitting down and standing up from a kitchen chair;
- sitting down and standing up from a toilet seat;
- sitting down and standing up from a low stool;
- getting in and out of a car seat;
- sitting down on and standing up from a bed;
- lying down and standing up from a bed;
- walking 10 m.

2.3. Data acquisition set-up

A portable battery-powered data-logger (Biomedical Monitoring BM42[1]) was used for data acquisition. The

[1] Biomedical Monitoring Ltd., Glasgow, Scotland.

sensor signals were recorded at a frequency of 1 kHz and resolution of 12 bits.

The tri-axial accelerometer was constructed using two, bi-axial Analog Devices ADXL210, mounted orthogonally to each other thus achieving a tri-axial accelerometer sensor. The ADXL210 produces representative analogue acceleration voltages at the X_{FILT} and Y_{FILT} outputs. The placement of the sensors at the trunk and thigh was chosen as a uni-axial version of this sensor arrangement (vertical accelerometer on trunk and thigh) has been shown to provide subject mobility data (amount of time spent sitting, standing, lying and walking) [23]. Thus, it was envisioned that this sensor arrangement would measure both mobility and detect falls.

2.4. Sensor location

The 20 participants were fitted with the tri-axial accelerometer sensors located at the anterior aspect of the trunk, at the sternum and, at the anterior of the thigh at the midpoint of the femur. The sensors were concealed in rigid plastic cases and securely held in place on the subjects' body segments using harnesses made from elastic straps and Velcro.

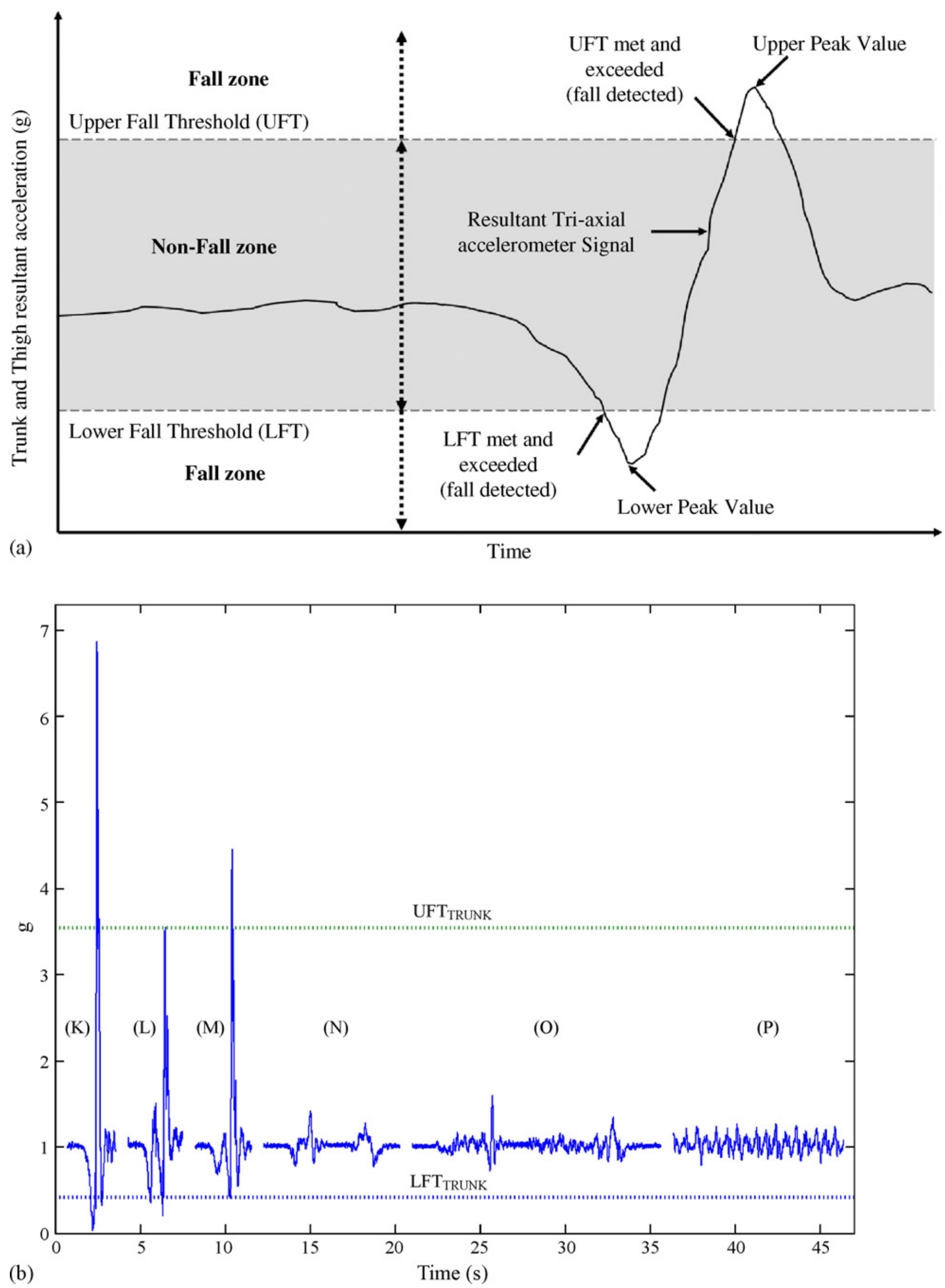

Fig. 1. Fall detection algorithm operation example for upper and lower thresholds, using an artificial example signal (a). Trunk resultant vector signals (b) for a typical fall (K), the fall that produced the smallest magnitude UPV (L), the fall that produced the smallest magnitude LPV (M), a typical sitting on an armchair activity (N), a getting in and out of a car seat activity (O) and walking (P).

2.5. Signal conditioning

Each signal was low-pass filtered using a second-order low-pass Butterworth two-pass digital filter, with a cut-off frequency of 250 Hz.

2.6. Fall detection algorithm

The resultant signal from both the tri-axial accelerometer sensors at the trunk and the thigh was derived by taking the root-sum-of-squares of the three signals from each tri-axial accelerometer recording. When stationary, the root-sum-of-squares signal from the tri-axial accelerometers is a constant +1 g.

The upper and lower fall thresholds for the trunk and thigh were derived as follows:

(i) *Upper fall threshold*: positive peaks for the recorded signals for each recorded activity are referred to as the signal upper peak values (UPVs). The upper fall thresholds (UFT) for each of the trunk and thigh signals was set at the level of the smallest magnitude upper fall peak (UFP) recorded for both of the trunk and thigh resultant vector signals individually. These UFT levels would thus result in 100% detection of the 240 falls recorded for each of the resultant vector signal thresholds individually. The UFT is related to the peak impact force experienced by the body segment during the impact phase of the fall.

(ii) *Lower fall threshold*: negative peaks for the resultant for each recorded activity are referred to as the signal lower peak values (LPVs). The lower fall thresholds (LFT) for the trunk and thigh signals were set at the level of the smallest magnitude lower fall peak (LFP) recorded for the trunk and thigh resultant vector signals. These levels of LFT would thus result in 100% detection of the 240 falls recorded for each of the resultant vector signal thresholds individually. The LFT is related to the acceleration of the trunk at or before the initial contact of the body segment with the ground.

Thus, four thresholds were derived: UFT_{TRUNK}, LFT_{TRUNK}, UFT_{THIGH} and LFT_{THIGH}. Exceeding any individual limit would indicate that a fall had occurred. As these thresholds would also apply to ADL, each of the four thresholds was individually tested against the recorded ADL data, to determine the extent of misdetection of ADL as falls.

A representative signal for a fall is shown in Fig. 1(a) and recorded fall and ADL signals are shown in Fig. 1(b).

3. Results

The UFT and LFT for the trunk and thigh obtained by analysing the accelerometer signals from the 240 falls are summarised in Table 1. The trunk and thigh thresholds were also applied to determine the number of ADL tasks correctly identified as non-falls. The results show that 67–100% of ADL tasks were correctly classified Table 1. The UFT for each signal gave higher specificity than the LFT value. The UFT_{THIGH} provided a specificity of 83.3%, which was better than the LFT_{THIGH} (67.1%). For the LFT_{TRUNK} 91.25% of ADL were correctly identified as non-falls. For the UFT_{TRUNK}, all ADL tasks were correctly detected as non-falls. A box plot of the trunk resultant upper peak values for both the falls and ADL is plotted in Fig. 2. This shows that the fall with the smallest trunk UPV was the laterally directed fall to the right with knee flexion, which produced a value of 3.52 g. This value was therefore chosen as the

Table 1
Specificity and largest upper and lower peak values for each ADL for each threshold

	Trunk		Thigh	
	UFT	LFT	UFT	LFT
Threshold (g)	3.52	0.41	2.74	0.60
Overall specificity (%)	100	91.25	83.33	67.08

	Trunk				Thigh			
	Specificity (%)	Largest UPV (g)	Specificity (%)	Largest LPV (g)	Specificity (%)	Largest UPV (g)	Specificity (%)	Largest LPV (g)
Sit on armchair	100	2.60	83.3	0.11	86.7	3.23	80.0	0.36
Sit on kitchen	100	3.16	86.7	0.21	90.0	3.75	90.0	0.31
Sit on toilet	100	2.41	93.3	0.30	96.7	3.76	70.0	0.30
In/out of car seat	100	3.02	86.7	0.16	60.0	7.19	36.7	0.11
Sitting on a stool	100	2.95	93.3	0.24	100	2.50	93.3	0.55
Sit on a bed	100	2.06	96.7	0.39	93.3	3.09	83.3	0.28
Lie on a bed	100	2.38	90.0	0.16	90.0	4.07	60.0	0.43
Walking	100	1.99	100	0.61	50.0	6.61	23.3	0.06

Upper and lower fall threshold values and corresponding specificity for the trunk and thigh signal thresholds, individual specificities for each ADL for each threshold and largest magnitude UPV and LPV for each ADL, The specificity percentages shown are the percentage of ADL correctly identified as non-falls, and are shown for each threshold and for each ADL activity.

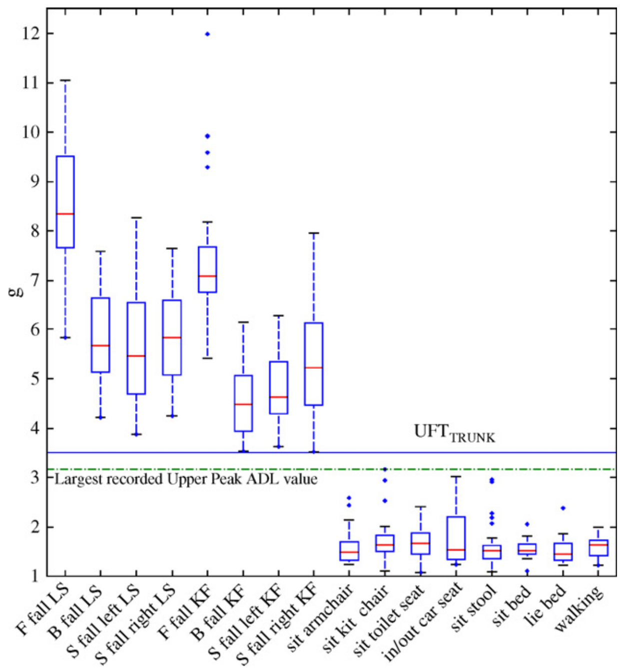

Fig. 2. Boxplot of trunk upper peak values for falls and ADL. The horizontal axis crosses at +1 g as this is value from the resultant-magnitude tri-axial accelerometer signal, when the individual is static. F: forward, B: backward, S: Lateral, LS: legs straight and KF: knee flexion.

UFT$_{TRUNK}$ as it provided 100% fall-detection accuracy. The trunk fall data had a large spread of UPVs, ranging from 3.52 to 12 g. The ADL upper peak data showed peak values concentrated between 1 and 2.5 g, with very few ADL peaks exceeding 2.5 g. Some ADL peak values came close to exceeding the 3.52 g threshold. The highest ADL value recorded was 3.16 g, but this still left a 0.36 g margin for ADL/fall distinction.

Fig. 2 also shows that the falls performed with knee flexion produced lower UPVs than the falls where the legs were straight. ''Sitting on a kitchen chair'', ''getting in and out of a car seat'' and ''sitting on a stool'' produced some of the highest ADL UPVs, although even these did not exceed the UFT$_{TRUNK}$ values.

4. Discussion and conclusion

We have investigated signals from tri-axial accelerometers placed at the trunk and thigh, to determine if their peak values could be used to discriminate between ADL and falls. Using the trunk upper fall threshold (UFT$_{TRUNK}$), all ADL tasks were correctly detected as non-falls. The closest this signal threshold came to being exceeded by one of the 240 ADL tasks was for, ''Sitting on a kitchen chair''. Even for this task a reasonable error margin of 0.36 g (14.3%) was available.

Based on our results, the trunk appears to be the optimum location for a fall sensor. This corresponds with the findings of Doughty et al. [12], Hwang et al. [14] and Noury et al. [15]. The proposed fall-detection method is quiet simple, which is appropriate where limited computational power will be available in the portable electronics worn by the person.

One of the limitations of this study was that the UFT was determined from young subjects falling under constrained conditions. To be clinically applicable in the community the device must detect falls in the elderly falling under unconstrained conditions. The young subjects falling onto crash mats were instructed to try not to break their fall, in contrast, most elderly people would naturally fully attempt to break a fall, and thus lower UPVs might be recorded in real life than those obtained with our study. It should also be noted that the simulated falls were performed onto crash mats, as opposed to real-life hard surfaces. The UPVs from the simulated falls would be expected to be much lower than would occur in real conditions. Even for cases where a person would break their fall, the UFT levels adopted could be significantly larger than the proposed levels and would thus provide a much larger margin than the 0.36 g currently available. Further research is required to establish the difference in UPVs from falls onto crash mats and those onto typical domestic surfaces using ''crash test dummy'' techniques. This involves attaching the tri-axial accelerometer sensor to an anthropometrically accurate dummy and performing a number of falls onto different real-life surfaces as well as onto the crash mats used in this study to determine the difference in peak acceleration values experienced.

To conclude, a falls detection procedure has been validated for falls and ADL events using a tri-axial accelerometer located on the trunk. A sensor of this type could be woven into a tightly fitting garment and the tri-axial accelerometer could be mounted onto a flexible PCB with a wireless connection to monitoring electronics. Future developments could incorporate this sensor arrangement into a portable unit, capable of both fall detection as well as mobility monitoring upon detection of a fall, an emergency message could be sent through a GSM modem incorporated into the unit, in the form of a short messaging service emergency message [24].

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