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Assessment of Waist-worn Tri-axial Accelerometer Based Fall-detection Algorithms using Continuous Unsupervised Activities

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Abstract— **This study aims to evaluate a variety of existing and novel fall detection algorithms, for a waist mounted accelerometer based system. Algorithms were tested against a comprehensive data-set recorded from 10 young healthy subjects performing 240 falls and 120 activities of daily living and 10 elderly healthy subjects performing 240 scripted and 52.4 hours of continuous unscripted normal activities.**

Results show that using a simple algorithm employing Velocity+Impact+Posture can achieve a low false-positive rate of less than 1 FP/day* (0.94FPs/day*) with a sensitivity of 94.6% and a specificity of 100%.

The algorithms were tested using unsupervised continuous activities performed by elderly subjects living in the community, which is the target environment for a fall detection device.

I. Introduction

The proportion of people in the world aged 65 or over is set to double to more than 1 in 5, by the year 2050, with those aged 80 or over set to almost treble [1]. Falls and related injuries are not only life-threatening [2], they also herald an inability for older people to live independently [3]. Conversely, the automatic detection of falls facilitates early medical intervention, reduces the consequences of the "long-lie" [4] and promotes independent living [5].

In recent years the number of proposed fall-detection systems and algorithms developed has increased dramatically [2]. Most of these use accelerometer based sensors attached directly to the body to measure the kinematic quantities of interest. The waist has been viewed as one of the most popular locations for a fall detection system [6-10], due to its proximity to the person's centre-of-mass, thus providing a reliable indication of full-body movement and its ease of acceptance to the user [9], allowing its attachment directly to an existing waist-band with minimal interference [7].

Recently Kangas *et al.* [8] evaluated different low-complexity fall detection algorithms, using triaxial accelerometers attached at the waist, wrist, and head. High sensitivities (97%-98%) and specificities (100%) were achieved. However, only 3 subjects (38-48 years), performing 59 falls and a small selection of scripted Activities of Daily Living (ADL) were used.

Kangas *et al.* [9] continued the evaluation of this algorithm set on data recorded from 20 middle-aged (40–65 years) volunteers performing 240 falls and scripted (ADL), these same scripted ADL were also recorded from 21 older people (aged 58–98 years) from a residential care unit, 164 ADL recorded in total. They showed that a simple algorithm of impact detection and posture measurement can discriminate various types of falls from ADL with a sensitivity of 97.5% and a specificity of 100%.

Chao *et al.* [10] recruited 7 young male subjects (25±1.5 years old), a total of 56 falls and 119 ADL were recorded overall. They used 4 different combinations of impact detection and post-fall posture on sensors located at the chest and waist to determine an optimum algorithm. They found that a combination of acceleration cross-product and post-fall posture produced a sensitivity of 100% and >98% specificity for the chest or waist.

In the studies by both Chao *et al.* [10] and Kangas *et al.* [8, 9] varying degrees of scripted fall and ADL were used to assess fall detection algorithm accuracy. However no extended continuous unsupervised activities were used for testing, which is the ultimate operating environment for a fall detection system and algorithm.

The aim of this study is to evaluate a number of the existing and novel fall-detection algorithms of varying complexity, on a comprehensive data-set of recorded falls and ADL. The data-set contains both simulated falls and normal ADL performed by young subjects as well as scripted ADL and continuous unscripted ADL performed by both urban and rural based elderly subjects. It is envisaged that this evaluation will uncover a more appropriate and accurate fall-detection algorithm, using a waist worn device, for both independent community-dwelling elderly and those in residential care facilities and hospitals.

II. Materials and Methods

Longitudinal, anterior/posterior and medial-lateral

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accelerometer readings were recorded from the waist during the simulated falls and ADL tasks, using a custom designed wearable wireless tri-axial accelerometer-based sensor [11], Fig. 1. Participants were fitted with the sensor located at the right anterior iliac crest of the pelvis. Data processing and analysis was performed using MATLAB[1]. Written informed consent was given by each subject and the University of Limerick Research Ethics Committee (ULREC) approved the trial protocols.

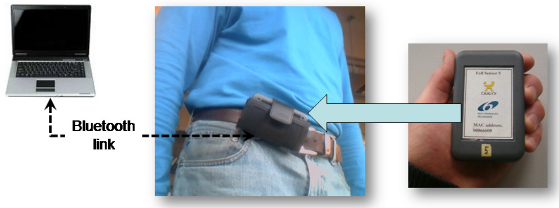

Fig. 1 Recording set-up using the waist mounted accelerometer-base sensor [11] (weight 106g; size 10.4 by 6.5 by 1.9cm). The sensor is held in place at the subjects' waist using a standard waist belt and modified commercial mobile-phone carry-case (Nokia cp-153). Signals were recorded at a frequency of 200Hz at a resolution of 12 bits, each signal was low-pass filtered using an onboard first-order low-pass Butterworth analogue filter, with a cut-off frequency of 100 Hz. Calibration of the tri-axial accelerometer signals was performed using the method outlined by Ferraris *et al.* [12]. Accelerometer data can be downloaded via the Bluetooth link using a custom designed PC-based message handler. The Accelerometer data was also stored on the micro SD card, which is suitable for long-term unrestricted recording.

A. *The simulated fall and ADL study with Young subjects*

In total, 10 healthy male subjects fell from a specially constructed platform onto a large foam crash mat (both 0.76m thickness). Each subject performed 8 fall types and 4 different ADL types, 3 times each (240 falls and 120 ADL). The subjects ranged in age from 24-35 years (27.2±3.6 years), body mass from 68 to 111 kg (84.2±14.4 kg), and height from 1.65 to 1.96m (1.81±0.1 m). The simulated falls performed were: forward falls, backward falls, lateral falls left and right all performed with both legs straight and with knees relaxed to allow flexion, similar to those in the study by Bourke *et al.* [13] . The ADL performed were; walk-turn-walk (10m), stand-sit-stand from a kitchen chair (height 43cm), stand-sit-stand from a bench with a sloped back (height 44.5cm), stand-lie-stand on a bed (height 40cm).

B. *The ADL study with elderly subjects*

A total of 10 older healthy volunteers (65 years and older) were recruited through advertisement in two community-based General Practices. A total of 5 urban (2 women and 3 men) and 5 rural (2 women and 3 men) volunteers were recruited. The subjects ranged in age from 73 to 90 years (78.8±5.1 years). The volunteers performed a series of scripted ADL and continuous unscripted and unsupervised ADL. The study took place in the volunteer's own home.

1) *The Scripted ADL study*

Subjects performed a set of 8 activities, each performed 3 times by each volunteer (240 ADL). The following ADL were recorded: Stand-sit-stand from an armchair, kitchen chair, toilet seat, car seat and bed, Stand-lie-stand from a bed, Stand-sit-stand from a bed, Walk up and down stairs and Walk-turn-walk (10m).

2) *The Unscripted ADL study*

Subjects continued to wear the sensor for a maximum of eight daylight hours and were free to withdraw from the study at any time. During this time the subjects carried out their normal daily activities which included: sitting, lying on a bed, walking, using the bathroom, travelling on a bus, using the stairs, cycling, driving a car and dining. A total of 52.4 hours of activity were recorded. The recording times ranged from 3.03hours to 7hours (5.24±1.24 hours).

C. *Fall Impact detection*

Previous research has shown that by thresholding of the upper peak of the root-sum-of-square (RSS) of the tri-axial accelerometer signals, that falls can be distinguised from normal scripted ADL with a high degree of accuracy [8-10, 13]. This technique emulates the detection of the impact that occuring when the body contacts the ground following a fall.

The threshold for fall-impact detection was selected by using the maximum upper peak values recorded, during all the fall activities [13]. These values were used to select the Upper Fall Threshold (UFT), as shown in Fig. 2.

D. *Velocity estimate (Vertical velocity)*

Studies have indicated that thresholding of the vertical velocity is also as positive indication of a fall [8, 14, 15]. An estimate of vertical velocity is obtained through numerical integration of the resultant vector signal after the magnitude of static acceleration (gravity) is subtracted [16], Equation 1. The resultant vector signal was down sampled to 50Hz.

$$v_{ve} = \int (RSS - 1g).dt \tag{1}$$

The minimum peak value for all the falls performed was used to determine the threshold for the V_{ve}, Fig. 2.

E. *Posture detection (z-axis)*

A fall is often followed by a period of lying. Posture is determined through thresholding of the angle that the z-axis $\vec{g}_{SEG,Z}(t)$ (vertical accelerometer) axis is inclined the gravity vector, Equation 2. This angle is used as the posture angle of the waist segment.

$$\Phi_{z-axis} = \cos^{-1}\left(\vec{g}_{SEG,Z}(t)\right) * \frac{180}{\pi} \tag{2}$$

A lying posture is detected if the average of the waist posture signal $\Phi_{z\text{-axis}}$ from $t+1s$ to $t+3s$, after the impact peak or velocity peak has occurred, is greater than the lying threshold for more than 75% of that time. The threshold selected was 60^o from vertical, which is consistent with previous studies [6, 8].

F. *Fall Detection Algorithm Parameters*

In this study we examined three different parameters associated with a fall, namely: velocity, impact and

[1] The MathWorks Inc., 3 Apple Hill Drive, Natick, MA, USA.

posture detection. Different combinations of these parameters were tested on both the scripted falls, normal activites and on the continuous unscripted activities recorded. The different algorithm combinations are shown in Table 1.

III. Results

Through examining the maximum and minimum recorded values for the signals and parameters: RSS and v_{ve},Fig. 2, the thresholds that would ensure 100% sensitivity were selected, Table 2. Thus all falls would be detected.

Table 1

Algorithm	*Parameter combinations*
Algorithm 1	Impact
Algorithm 2	Impact + Posture
Algorithm 3	Velocity + Impact + Posture
Algorithm 4	Velocity + Posture
Algorithm 5	Velocity + Impact

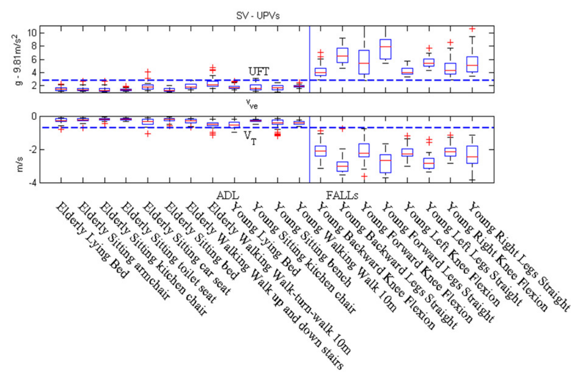

Fig. 2 Boxplots and thresholds for the *UPV*s and Vertical velocity estimate.

Table 2

Threshold	value	units
UFT	2.8	g - 9.81m/s^2
V_{ve}	-0.7	m/s
Θ (z-axis)	60	° (degrees)

Table 1 presents all the different algorithms tested against the overall data set. A selection of the signals used and the thresholds selected can be seen in Fig. 3.

A. Sensitivity and specificity analysis

The sensitivity was calculated for each of the different algorithms with scripted activities, Table 3. The fall detection sensitivity varied from 94.6% to 100%. A 100% sensitivity for falls was achieved using algorithms; Algorithm 1 (Impact) and Algorithm 5 (Velocity + Impact).

Table 3

Sensitivity (%) and specificity (%) for the fall-detection algorithms.

	n	Algorithm 1	2	3	4	5
sensitivity	240	100	94.6	94.6	94.6	100
specificity	360	97.2	100	100	97.8	98.9

The specificity was calculated for each of the different algorithms, Table 3. The specificity varied from 97.8% to 100%. The ADL that were miss-detected as falls most consistently performed by the elderly subjects were: getting in and out of a car and lying on a bed. For young subjects these were: lying on a bed and sit-stand from a kitchen chair.

Overall, sensitivites greater than 94.6% and specificities greater than 97.2% were achieved. However no algorithms achieved 100% accuracy with the scripted data set.

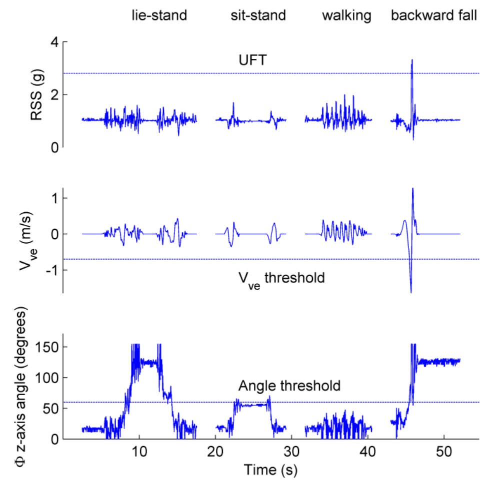

Fig. 3 Sample signal and thresholds for the RSS, *Vve* and $\Phi_{z\text{-axis}}$ angle.

B. False-positive rate

All algorithms were then applied to the continuous unscripted ADL data-set recorded from the elderly subjects. No falls occurred. The amount of false-positives (Fp) for each subject were recorded, Table 4 and the false-positive quantity and false-positive rate were calculated. The false-positive quantities ranged from 3 FPs to 144 FPs with the false-positive rate ranging from 0.94FPs/day* to 45.34FPs/day*. The Algorithms with the lowest false-positive rate was Algorithm 3 (Velocity + Impact + Posture) with a rate of just 0.94 FPs/day* produced. In 52.4 hours of recording just 3 FPs were recorded, these occurred when subject 5 was cycling a bicycle and subject 7 lay down quickly on a bed. Algorithms 2, 4 and 5 also showed good performance.

IV. Discussion and Conclusion

This study was aimed at evaluating the performance of a number of existing and novel fall-detection algorithms of varying complexity, on a comprehensive data-set of recorded falls and ADL. Falls performed by young subjects were used to determine the thresholds for a number of fall detection algorithms. The Algorithms were then tested against recorded scripted ADL performed by young and elderly subjects and recorded continuous unsupervised unscripted activities by both urban and rural based elderly volunteers in their own homes. Algorithm 5 (Velocity + Impact) was the only algorithm to produce a 100% sensitivity along with a high specificity (98.9%) but

* A "day" in this case refers to the number of waking hours. An elderly person on average sleeps 7.5 hours per day [17] C. R. Baumann, "Sleep: Approaching the Fundamental Questions," *Current Biology*, vol. 18, pp. R665-R667, 2008., thus a day of waking hours is defined here as 16.5h.

with a high FP rate (4.72/day*). The algorithm that produced the lowest FP rate was algorithm 3 (Velocity + Impact + Posture) which achieved a FP rate of less than 1 false-positive per day (0.94 FPs/day*), it also achieved a specificity of 100%, however a sensitivity of 94.6% was achieved. Thus some fall went undetected by this algorithm, due directly to the posture detection.

Previous studies by Kangas *et al.* [8, 9] have found that fall detection using a waist-worn tri-axial accelerometer is reliable with quite simple detection algorithms such as Impact + Posture (z-axis) which agrees with our findings. However a variation of this algorithm produced a false positive rate of 4.41 FPs/day* during the unsupervised testing, which was not the best seen here.

Table 4

False-positive (FP) quantities, false positive rate (FPs/hour) and false positives per day (FPs/day*) for the different fall detection algorithms.

Subject	Time	Algorithm				
	(hrs)	1	2	3	4	5
1	5.6	27	2	0	2	0
2	6.0	5	1	0	3	0
3	6.0	15	6	0	1	0
4	6.0	10	2	0	4	0
5	4.8	42	3	2	1	12
6	7.0	5	0	0	1	0
7	3.0	25	0	1	0	0
8	6.0	11	0	0	0	3
9	4.0	2	0	0	1	0
10	4.0	2	0	0	0	0
Total	52.4	144	14	3	13	15
(FPs/hour)		2.75	0.27	0.06	0.25	0.29
(FPs/day*)		45.34	4.41	0.94	4.09	4.72

This study uses simulated falls performed by young subjects onto crash mats, as opposed to real-life hard surfaces. Thus the impact values recorded here would be expected to be lower than would occur in real conditions.

Previous studies have used ADL recorded from older adults [6, 8] and elderly subjects [9] to test their waist mounted fall-detection algorithms. However, none so far have tested these algorithms against continuous unsupervised activities, performed by both urban and rural based elderly subject, in their own home environment. This is however the eventual target audience and operating environment for an autonomous fall-detection system.

V. Conclusion

We have tested a variety of fall-detection algorithms of varying degrees of complexity. Fall detection using IMPACT+POSTURE+VELOCITY can achieve a low false-positive rate of less than 1 FP/day* (0.94FPs/day*) however a sensitivty of less than 100% was achieved (94.6%). Thus further research into more reliable and adaptive posture detection method is required to improve this alogorithm. We have thus tested a set of novel and existing fall detection algorithms, in the most realistic operating environment to date.

VI. Acknowledgments

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