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A threshold-based fall-detection algorithm using a bi-axial gyroscope sensor

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Abstract

A threshold-based algorithm, to distinguish between Activities of Daily Living (ADL) and falls is described. A gyroscope based fall-detection sensor array is used. Using simulated-falls performed by young volunteers under supervised conditions onto crash mats and ADL performed by elderly subjects, the ability to discriminate between falls and ADL was achieved using a bi-axial gyroscope sensor mounted on the trunk, measuring pitch and roll angular velocities, and a threshold-based algorithm. Data analysis was performed using MATLAB® to determine the angular accelerations, angular velocities and changes in trunk angle recorded, during eight different fall and ADL types. Three thresholds were identified so that a fall could be distinguished from an ADL: if the resultant angular velocity is greater than 3.1 rads/s (Fall Threshold 1), the resultant angular acceleration is greater than 0.05 rads/s^2 (Fall Threshold 2), and the resultant change in trunk-angle is greater than 0.59 rad (Fall Threshold 3), a fall is detected. Results show that falls can be distinguished from ADL with 100% accuracy, for a total data set of 480 movements.

Keywords: Falls in the elderly; Fall detection; Gyroscope; Activities of Daily Living; Threshold

1. Introduction

Falls in the elderly are a major problem for today's society. Approximately one in every three adults 65 years old or older, falls each year [1,2]. Falls are the leading cause of injury deaths and accounted for 83% of all fatal falls in 2005 in Ireland [3] and are the leading cause injury-related hospitalisation among people 65 years and older in society [4]. Injuries sustained from falls include broken bones, superficial cuts and abrasions to the skin as well as connective and soft tissue damage [1,2,5]. Fall related admissions of older adults are a significant financial burden to the health services world wide and is estimated to have an annual cost of €10.8 m alone for just one Irish hospital [6].

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 [7]. The 'long-lie' is a common occurrence and it has been shown that many elderly people lack that ability to stand up, even from non-injurious falls, and as a result remain on the ground for even longer than an hour [8]. It has also been found that half of those elderly who experience a 'long-lie' die within 6 months, even if no direct injury from the fall has occurred [7], indicating a deterioration in general health. Thus, if an elderly person experiences a fall followed by a 'long-lie' while living alone, the consequences can be quite serious and potentially fatal.

Detection of a fall, either through automatic fall detection or through a Personal Emergency Response System (PERS), would help to minimize the occurrence and ramifications of the 'long-lie', by reducing the time between the fall and the arrival of medical attention [9]. However, the most common existing PERS, the push-button pendant, is not always a satisfactory fall-detection method, as during a loss of consciousness or a faint the pendant will not be activated [10]. Also, even when elderly people have fallen and injured themselves, they still did not activate their PERS, even though they had the opportunity to do so [11].

A number of different approaches for the automatic detection of falls, using subject worn sensors have appeared in

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recent years [12–16]. These fall-detection devices use either the near horizontal orientation of the faller, following the fall, and/or the impact of the body with the ground to identify a fall, the typical sensors used for this are accelerometers.

Currently work is underway by several groups to attempt to detect falls prior to impact. Patents detailing inflatable hip protectors to cushion the fall prior to impact exist, although these systems do not describe how they pre-empt falls, and are essentially anticipating technological advances in this area [17–19]. Pre-impact detection of falls has been shown, by Wu [20], using motion analysis techniques. Wu showed that falls can be distinguished from ADL 300 to 400 ms before impact, by thresholding of the horizontal and vertical velocity profiles of the trunk. For this to be accomplished using a wearable sensor, both 3-D accelerometer and 3-D gyroscope sensors must be employed to obtain the velocity profiles used by Wu with 3-D video motion analysis.

Thus, it is expected that the future overall sensor arrangement for pre-impact fall detection will consist of both a 3-D accelerometer and a 3-D gyroscope. A question then arises about the fault tolerance of such a system. If one of these components fails, pre-impact detection of a fall cannot be obtained. However, if under these circumstances a fall on impact could be detected, this would be desirable as non-detection of a fall either prior to, or at impact could have very serious consequences. Previously, it has been shown that detection of falls, upon impact is possible, using just a 3-D accelerometer on the trunk [12]. However, in the event that the 3-D accelerometer sensor fails in the pre-impact fall sensor, fall detection on impact using the 3-D gyroscope is required if sensor fault tolerance is to be accomplished. This paper describes the development and testing of an algorithm for the detection of falls at impact using a 2-D gyroscope.

Najafi et al. [21] used gyroscope sensors to evaluate fall-risk in elderly people through the measurement of stand-sit and sit-stand transitions, however this work used gyroscope instrumentation as a screening device to determine if an elderly person was at an elevated risk of falling and did not attempt to detect falls in real time. Pre-impact fall detection using gyroscope sensors has been attempted by Nyan et al. [22] who attached gyroscope sensors at three different locations: the sternum, front of the waist and under the arm. With this system, Nyan achieved 100% sensitivity; however, 16% of ADL events tested were misdetected as falls.

Several Fall-detection systems have used young subjects to test the extent of misdetection of ADL as falls by their systems [13–15]. Elderly persons 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 persons 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 and angular velocities 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. As it was not appropriate to request elderly subjects to perform simulated-falls, elderly subjects were asked to perform ADL and young subjects performed the simulated falls.

This paper thus describes the development of a threshold-based algorithm, capable of automatically discriminating between falls and ADL, using a bi-axial gyroscope sensor. The gyroscope signals were acquired from simulated-falls performed by healthy young subjects and from ADL performed by elderly persons in their own homes.

When a person falls and hits the ground it is expected that the changes in angular acceleration, angular velocity and body angle would be different from those experienced during normal daily activities. We hypothesised that: trunk bi-axial angular acceleration, angular velocity and body angle signals will have peak values, during a fall, which will be distinct from those produced during normal ADL.

2. Materials and methods

To establish our hypothesis, trunk pitch and roll gyroscope readings Fig. 1, were recorded, during separate simulated-fall and ADL studies, and their results compared. As it was not appropriate to request elderly subjects to perform simulated-falls, different groups of subjects were used for the two studies. 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 Activities of Daily Living (ADL) tasks in their own homes. Both studies were completed with subjects wearing the same sensor arrangement, namely a bi-axial gyroscope sensor, on the trunk.

2.1. The simulated-fall study

The simulated-fall study involved 10 young healthy male subjects performing simulated-falls onto large crash mats,

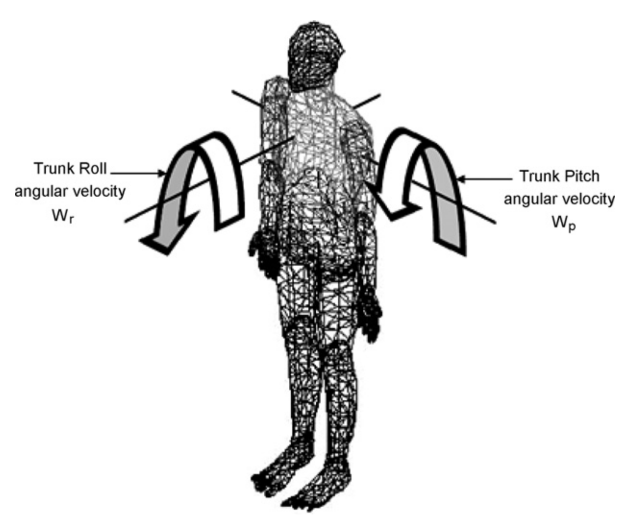

Fig. 1. Trunk pitch and roll angular velocity measurement system.

from a specially constructed platform, under the supervision of a physical education professional. Bi-axial gyroscope signals were recorded during each simulated-fall. Each subject performed eight different fall types and each fall-type was repeated three times, thus each subject performed 24 falls.

The subjects, for the simulated-fall study, were young (<30 years) healthy male subjects. A total of 10 subjects were recruited for the study, the subjects ranged in age from 21 to 29 years (23.7 ± 2.2 years), body mass from 67.6 to 85.3 kg (75.9 ± 5.1 kg), and height from 1.68 to 1.85 m (1.78 ± 0.06 m). The University of Limerick Research Ethics Committee approved the protocol and all subjects gave written informed consent.

The fall types used during testing were selected to best simulate the type of fall that occurs most commonly with, and causes injury to, elderly people. A study by Lord et al. [2], found that 82% of falls occurred from standing height. Thus, in order to obtain an accurate fall-detection algorithm standing height falls should be performed.

Several studies into the circumstances surrounding falls in elderly populations have shown that a forward fall is the most common type of fall [23,24]. O'Neill et al. [23] observed that 60% of falls in older adults, were in the forward direction. This higher percentage of forward direction falls is likely due to the falls mainly occurring during walking and is supported in findings by Smeesters et al. [25]. These findings were challenged by Hsiao and Robinovitch [26] who argued if a random distribution of perturbations arose during daily activities, backward falls, and their related injuries would be the most common [26].

Laterally directed falls also pose a major threat to the elderly population since, a laterally directed fall producing lateral impact on the greater trochanter has the potential to fracture an elderly hip every time it happens [27] with very serious consequences for the person.

Thus, falls from standing height in all directions should be examined during the test phase of a fall-detection device. Attempts should also be made to mimic realistic falls (i.e. with knee flexion), similar to those observed in previous studies [25,26,28]. The simulated-falls thus 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 of two studies performed, involved elderly subjects performing Activities of Daily Living, in their own homes, while fitted with the same sensor configuration as the simulated-fall study. For the ADL study, 10 community-dwelling elderly subjects, three female and seven male, were monitored while performing a set of prescribed Activities of Daily Living. The subjects ranged in age from 70 to 83 years (77.2 ± 4.3 years). All subjects gave written informed consent and the ULREC approved the measurement protocol.

Each subject performed each ADL three times and each subject both commenced and finished each ADL in a standing position. The ADL chosen were those that may have produced impacts or abrupt changes in a person's movement (and thus possibly results in false triggering of a threshold-based fall-detection algorithm) and would be activities carried out during the normal course of an elderly person's daily life. Thus, the activities performed were:

- Sitting down and standing up from an armchair (height, 42.6 ± 1.1 cm).
- Sitting down and standing up from a kitchen chair (height, 46.2 ± 1.0 cm).
- Sitting down and standing up from a toilet seat (height, 43 ± 0.8 cm).
- Sitting down and standing up from a low stool (height, 39.2 ± 1.5 cm).
- Getting in and out of a car seat (height, 52 ± 1.7 cm).
- Sitting down on and standing up from a bed (height, 53.5 ± 1.8 cm).
- Lying down and standing up from a bed (height, 53.5 ± 1.8 cm).
- 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 sensor signals were recorded at a frequency of 1 kHz and resolution of 12 bits.

The bi-axial gyroscope was constructed using two, uni-axial Analog Devices ADXRS300[2] iMEMS gyroscopes, mounted orthogonally to each other thus achieving a bi-axial gyroscope sensor.

The ADXRS300 produces representative analogue angular velocity voltages at its RATEOUT output. The placement of the sensors at the trunk was chosen as Wu [20] had shown that this location was suitable for pre-impact detection of falls and would be the proposed site for a pre-impact fall sensor.

2.4. Sensor location

All 20 participants were fitted with the bi-axial gyroscope sensors located at the anterior aspect of the trunk, at the sternum. The sensors were concealed in rigid plastic cases and securely held in place on the subjects' body using a harness made from elastic straps and Velcro. The sensors were worn over the subject's clothes (Fig. 2).

2.5. Signal conditioning

Each pitch (ω_p) and roll (ω_r) angular velocity signal was low-pass filtered using a second-order low-pass Butterworth 2-pass digital filter, with a cut-off frequency of 100 Hz. The

[1] Biomedical Monitoring Ltd., Glasgow, Scotland.
[2] Analog Devices, BV, Limerick, Ireland.

Fig. 2. Subject wearing gyroscope based sensor with backing cardboard.

resultant vector for the angular velocity signal (ω_{res}) was derived by taking the root-sum-of-squares of the pitch (ω_p) and roll (ω_r) angular velocities, this would thus provide a combined measure of the angular velocity in the sagittal and frontal planes.

2.6. The fall-detection algorithm

Fall detection by applying a threshold to the peak values from the resultant angular velocity signals (ω_{res}) recorded from fall and ADL data will result in one of two scenarios:

(1) The peak values from recorded ADL will not overlap with the recorded fall peak values, Fig. 3(A), in which case a single threshold may be used to distinguish falls from ADL, where the threshold level would be placed at the lowest fall peak value.
(2) The peak values from recorded ADL will overlap with recorded fall values, Fig. 3(B). In this case applying one threshold is insufficient to distinguish falls from ADL and thus further investigation into additional aspects of the signals is required.

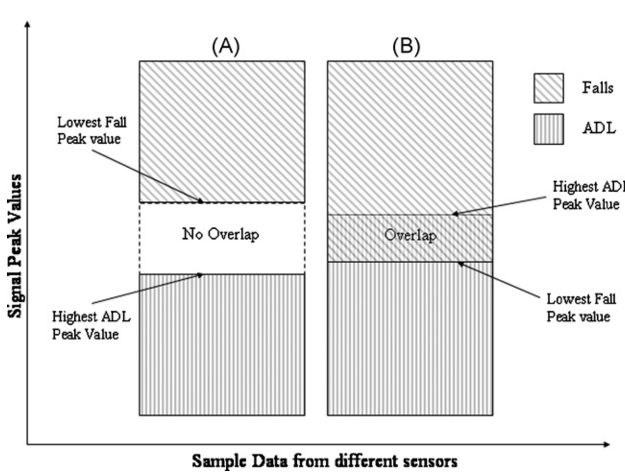

Fig. 3. Overlapping and non-overlapping sample Fall and ADL data.

From preliminary investigation into the angular velocity peaks from simulated falls and ADL recordings, it transpires that overlap between the resultant angular velocity (ω_{res}) peak values for the recorded falls and ADL occurred. A number of the resultant angular velocity peak values from ADL were greater than those from falls.

By setting a threshold at the lowest recorded resultant angular velocity (ω_{res}) fall peak value, we will ensure that 100% of falls are correctly identified but consequently some ADL are misdetected as falls, this threshold is referred to as Fall Threshold 1 (FT1). Through investigation of the resultant angular acceleration (α_{res}) and the resultant change in trunk angle (θ_{res}) signals, it is anticipated the remaining ADL may be distinguished from the falls.

Thresholding of the resultant angular acceleration (α_{res}) will indicate the occurrence of a sudden change in the subjects' trunk rotation. The threshold for this signal (FT2) is set

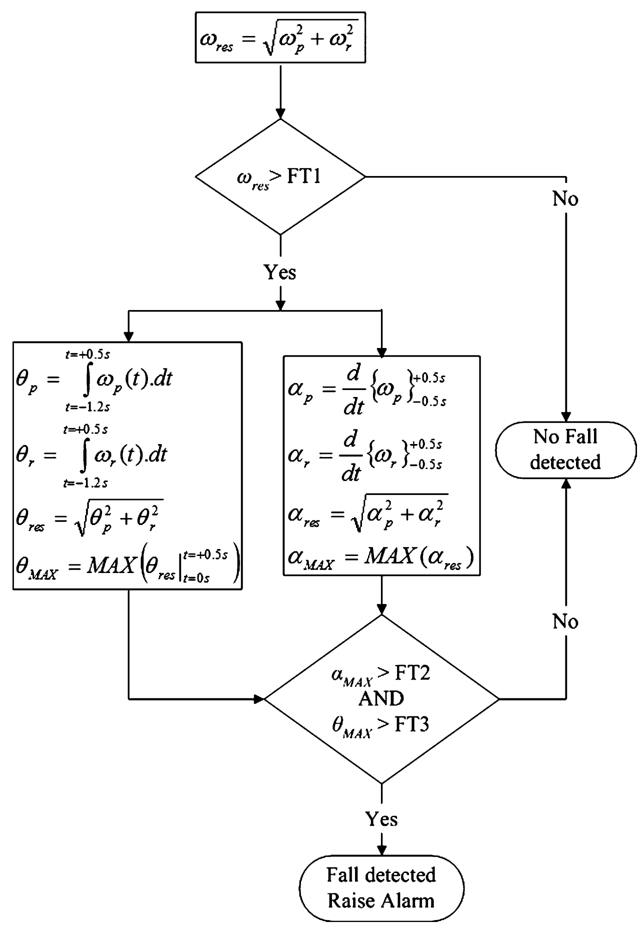

Fig. 4. Bi-axial gyroscope fall-detection algorithm flow chart, the time $t = 0$ ms corresponds to the exact time that FT1 was exceeded, ω refers to angular velocity of the trunk, θ refers to trunk angle, α refers to the angular acceleration of the trunk, the subscripts p, r and res refer to pitch, roll and resultant signals, respectively, and MAX refers to the maximum peak value of the signal segment under examination.

just below the lowest recorded α_{res} fall peak value, recorded in a 1 s window centred at t_0. The time $t = 0$ ms (t_0) refers to the exact time when FT1 is exceeded by the resultant angular velocity signal (ω_{res}). This 1 s window width, centred at t_0, was chosen to capture the abrupt change in trunk rotation associated with the impact from a fall.

Thresholding of the resultant change in trunk angle signal (θ_{res}) indicates through what angle the trunk has swept through in the time just prior to impact. By firstly integrating and subsequently taking the root-sum-of-squares of the pitch and roll angular velocity signals from 1.2 s prior to t_0, to 0.5 s subsequent to t_0, the resultant change in trunk angle signal (θ_{res}) associated with a fall will be obtained. The threshold is only applied to the portion of the θ_{res} signal from t_0 to 0.5 s subsequent to t_0 as this will indicate what angle the trunk has moved through at impact, and subsequent to, impact. The threshold value (FT3) is set just below the lowest recorded θ_{res} fall peak value. The value of 1.2 s was obtained as Hsiao and Robinovitch [26] observed that pelvis impact occurs 715 ms ± 160 (S.D.) after the initial perturbation during unexpected falls from standing height. The value of 1.2 s (715 ms + 3 × 160 ms) was thus chosen as it will include 99.7% of all falling times during unexpected falls from standing height [26].

Our hypothesis was that setting the threshold value of FT1, FT2 and FT3 just below the lowest recorded fall peak values

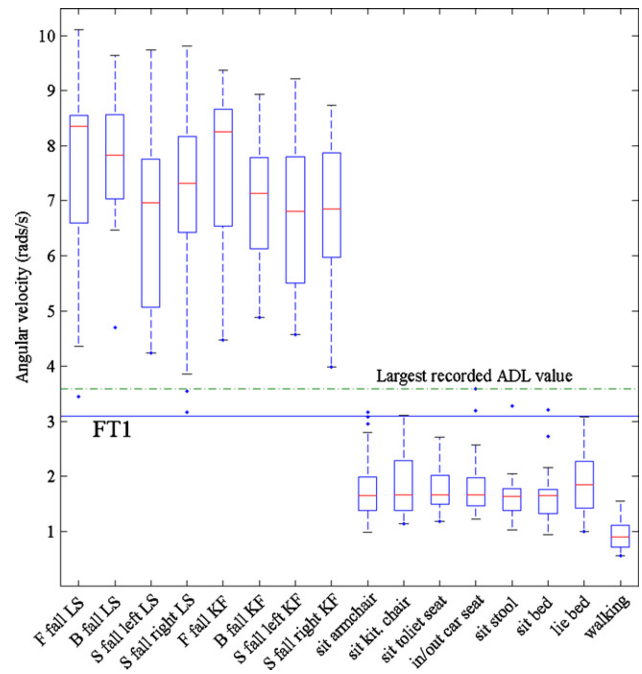

Fig. 5. Boxplot of peak values for falls and ADL. The horizontal axis crosses at 0 rad/s as this is the value from the resultant-magnitude bi-axial gyroscope signal, when the individual is static. F: forward, B: backward, S: lateral, LS: legs straight, KF: knee flexion.

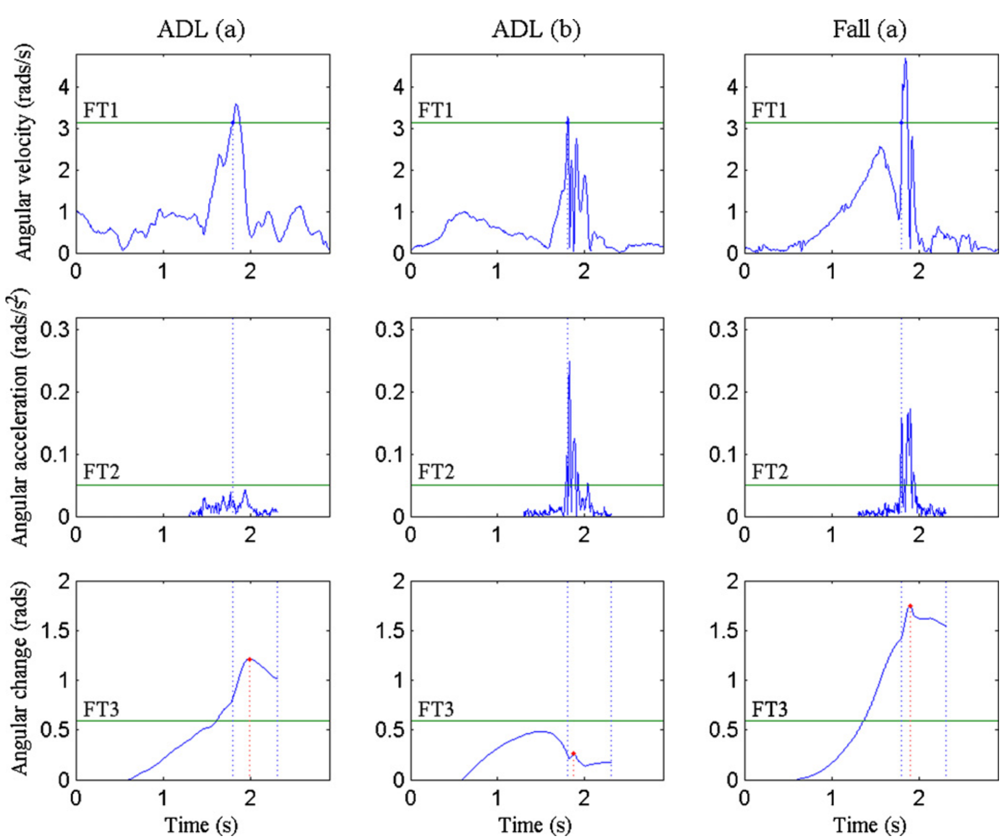

Fig. 6. The resultant angular velocity, resultant angular velocity and resultant angular change from, ADL (a), an ADL that exceeded FT1, FT3 but not FT2, ADL (b), an ADL that exceeded FT1 and FT2 but did not exceeded FT3, and, Fall (a), the signals from a typical fall, where all three thresholds are exceeded.

Table 1
Fall-detection threshold values

Threshold	FT1	FT2	FT3
Symbol	ω_{res}	α_{res}	θ_{res}
Signal	Angular velocity	Angular acceleration	Trunk angle change
Threshold value	3.1 rads/s	0.05 rads/s^2	0.59 rad

for ω_{res}, α_{res} and θ_{res}, respectively, would ensure 100% of the falls recorded in this study will be correctly identified as falls, by cascading these thresholds, and that no ADL events would be misdetected as falls.

Exceeding of these limits would indicate that a fall had occurred. As these thresholds would also apply during ADL, to determine the extent of misdetection of ADL as falls, the threshold was tested against the recorded ADL data. Fig. 4 shows the flow for the proposed algorithm.

3. Results

Through analysis of the 240 recorded simulated falls, the three fall thresholds that could be used to correctly identify 100% of falls were obtained (Table 1).

By testing the ADL data using the algorithm and thresholds, the percentage of ADL events correctly identified as non-falls was determined, also known as specificity [22]. Since FT1, FT2 and FT3 were set as the lowest recorded upper peak values for each of their respective signals from the 240 falls recorded, 100% fall detection (100% sensitivity) was thus insured for these three thresholds (see Fig. 6 Fall (a)). The threshold FT1 individually correctly identified 97.5% of ADL as non-falls (97.5% specificity), the ADL that exceeded this threshold were "sitting on an armchair", "getting in and out of a car seat", "sitting on a low stool" and sitting on a bed Fig. 5. By combining FT1 and FT2 a specificity of 99.2% was obtained, Fig. 6 ADL (a), just leaving two ADL, "sitting on a low stool" and "sitting on a kitchen chair" being misdetected. By finally combining FT1, FT2 and FT3 100% specificity was obtained, Fig. 6 ADL (b). Thus, the combination of FT1, FT2 and FT3 obtained 100% fall-detection accuracy (100% sensitivity) and 0% of ADL were misdetected (100% specificity).

4. Discussion and conclusion

We have investigated signals from bi-axial gyroscopes placed at the trunk, to determine if their peak values could be used to discriminate between ADL and falls. Results show that by thresholding of the resultant angular velocity, angular acceleration and change in trunk angle signals, a 100% specificity was be obtained.

It could be considered a limitation of the study that the peak values were determined from falls in young subjects falling under constrained conditions whereas to be useful in the community the device must detect falls in the elderly falling under unconstrained conditions. The young subjects falling onto crash mats were instructed not to try and break their fall. It is reasonable to expect that some elderly people falling would naturally, attempt to break the fall and thus that lower peak values might be recorded than those obtained with our study. It should be noted however that as the simulated-falls were performed onto crash mats, as opposed to real-world hard surface conditions, the peak values from the simulated-falls would be expected to be much lower than would occur in real fall conditions. Thus, it is envisaged that even for cases where a person would break their fall; the fall threshold levels adopted could be significantly larger than the proposed levels, providing a greater margin for successful detection of falls, with no misdetection of ADL. Thus, the use of a single threshold set at the lowest recorded resultant angular velocity peak value obtained from crash dummy falls onto hard surfaces may be sufficient as a detection strategy, as in this study using FT1 alone resulted in 100% fall-detection accuracy with only 2.5% of ADL misdetected as falls (97.5% specificity). Thus, if falls performed onto a hard surface were measured the threshold value of FT1 would increase thus reducing the amount of misdetected ADL.

In conclusion, a fall-detection strategy has been proposed and verified with 100% specificity obtained over a total of 240 ADL events recorded. This was accomplished using a bi-axial gyroscope located on the trunk. A sensor of this type could thus be incorporated into a pre-impact fall-detection system based on work by Wu [20] which applies thresholds to velocity profiles of the trunk in order to detect falls prior to impact. The fall-detection sensor for this system may consist of a 3-D accelerometer and 3-D gyroscope which could be woven into a tightly fitting vest or garment, in the event that the accelerometer sensor fails in this configuration, fall detection upon-impact could still be achieved using the gyroscope sensor and the proposed algorithm described here, thus built-in redundancy in the sensor arrangement is achieved.

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