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Fall Algorithm Development Using Kinematic Parameters Measured from Simulated Falls performed in a Quasi-realistic Environment Using Accelerometry

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Abstract **This study aims to determine the optimal temporal, angular and acceleration parameters and thresholds for an accelerometer based, chest-worn, fall detection algorithm. In total, 10 healthy male subjects performed 14 different fall types, 3 times by each. The falls were performed onto in a quasi-realistic environment consisting of mats of a minimum thickness.**

Optimum parameters for; $t_{falling}$: time-to-fall, θ_{max}: max-angle, $t_{\theta max}$: max-angle-time, $t_{RTStanding}$: Return-to-standing-time and t_{lying} : lying-time were determined using a data set consisting of a total of 420 falls.

I. Introduction

THE percentage of people in the world over 65 years is set to increase by 98.5% by the year 2050, resulting in 29% of people being considered elderly [1]. Injuries as a result of falls are a primary health risk for this population, both in a home environment, hospitals and residential care homes.

With the improvement of IMEMS sensor technology, research into the monitoring of human movement and the automatic detection of fall, the number of systems to promote safer independent living amount the elderly, has increased dramatically in the last 20 years.

The automatic detection of falls facilitates early medical intervention, reduces the consequences of the "long-lie" [2] thus promoting more independent living [3].

A number of fall detection systems do currently exist which employ temporal parameter detection, posture, body segment angle detection and impact detection to distinguish falls from normal activities.

The system developed by Doughty et al. [4], which was later developed by Tunstall[1] into a popular commercial system, employs a 2-stage detection process detecting impact at the waist followed by monitoring of the users posture. An alarm is raised within 20s if the subject remains lying.

An algorithm developed by Boissy et al. [5] also performs a 2-stage detection process. Detecting impact using fuzzy logic and a change in trunk angle in two, 1s windows, 1.5s before and after the peak acceleration. A total of 450 falls were distinguished from 300 non-falls with a sensitivity of 93% but with a high false-positive rate of 29%.

Recently Kangas et al. [6],[7],[8] assessed a number of low-complexity fall detection algorithms, consisting of different combinations identified aspects of a fall, namely; beginning of the fall, velocity, peak impact, and post-fall posture. Results show detection of a fall-impact followed by, post-fall posture, produced high sensitivity (97–98%) and specificity (100%) for a head or waist-worn system. The start of the fall was detected if the root-sum-of-squares (RSS) signal was lower than 0.6g and an impact peak was detected within 1s. A lying posture was detected if 2s post-impact, the average acceleration in a 0.4s window, was 0.5g or lower.

Chao et al. [9] also used impact detection and post-fall posture (PP) for fall detection. PP was defined as a lying posture, if the trunk posture averaged more than 45° (0.707g) in a temporal window of 1.8s to 2.2s after a suspected fall. A total of 7 young male subjects performed 56 falls and 119 ADL. A combination of acceleration cross-product and PP produced a sensitivity of 100% and >98% specificity for the chest or waist.

Thus many studies on fall detection algorithms have monitored certain kinematic and temporal aspects of falls to enhance the fall detection accuracy by using postural detection following a fall or a postural change from before and after the fall-impact. To date however, little or no detail as to how the parameters employed in these algorithms, were derived. In this study we aim to examine a data-set of 420 simulated falls, which were performed under quasi-realistic falling and landing conditions onto a surface of minimum thickness, performed with realistic falling technique. We thus propose to analytically derive temporal angular and vertical acceleration parameters for a chest-worn accelerometer-based fall-detection algorithm.

II. Materials and Method

Longitudinal, anterior/posterior and medial-lateral tri-axial accelerometer readings were recorded from the chest during simulated falls performed in a quasi-realistic

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[1] Tunstall Ltd, Whitley lodge, Yorkshire, England.

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environment, using a custom designed wearable wireless tri-axial accelerometer-based sensor, Fig. 1.

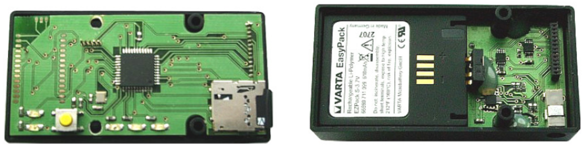

Fig. 1 - Tri-axial accelerometer based sensor (size 78x40x20 mm, weight 30g). The sensor consists of; a single liPo battery capacity 610mAh, a LIS3LV02 tri-axial accelerometer from ST Microelectronics Inc. and dsPIC (Microchip Technology Inc.) microcontroller. The Accelerometer data was downloaded via the Bluetooth link using a custom designed PC-based data logging software written in LabVIEW[2]. Calibration of the tri-axial accelerometer signals was performed using the method outlined by Ferraris *et al.* [10]. Signals were recorded at a frequency of 120Hz.

The sensors were concealed in rigid plastic cases and securely located at the anterior aspect of the trunk, at the sternum, using a chest-strap made from elastic material and Velcro. Data processing and analysis was performed using MATLAB[3]. The University of Limerick Research Ethics Committee (ULREC) approved the trial protocol and written informed consent was given by each subject before the trial.

A. *The quasi-realistic simulated falls*

In total 10 young healthy male volunteers performed simulated falls onto minimum thickness mats while being monitored using the accelerometer based sensor, Fig 1. Each subject performed 14 functional movements which involved a fall, 3 times each (420 falls). The subjects ranged in age from 19-28 years (24.3±3.16 years), body mass from 57 to 96 kg (78.9±11.34 kg), and height from 1.7 to 1.85m (1.77±0.05 m). Volunteers fell onto mats that were selected to be of minimum thickness (80mm, unless stated, an additional mat of 150mm thickness was placed over the 80mm mat in cases where the fall involved a highly concentrated impact which may cause injury) so as to simulate falling on a stiff surface, but without sustaining an injury. Subjects were instructed to fall as naturally as possible at a self selected speed. Following the fall, subjects were requested to return to a standing position, at a normal comfortable speed but not to spring-up unnaturally.

The falls performed include the following:

1) Faint fall forward with knee flexion.
2) Step down off a platform and fall forward, thick (150mm) soft mat on floor.
3) Walking and self-trip, thick (150mm) soft mat on floor.
4) Faint fall backwards with a round back and knee flexion
5) Backward sitting-on-empty on the floor, no use arms or taking a step back, thick (150mm) soft mat on floor.
6) Backward fall at the base of wall, thick (150mm) soft mat on wall.
7) Faint fall left with knee flexion
8) Fall backwards and turn to the left side
9) Side fall to the left landing at the base of a padded wall, thick (150mm) soft mat on wall
10) Faint fall left with knee flexion
11) Fall backwards and turn to the right side
12) Side fall to the right landing at the base of a padded wall, thick (150mm) soft mat on wall
13) Falling off a chair, sit on the edge and slipping off.
14) Unrestricted ADL with an unscripted fall at the end, walking-lying-walking-sitting-walking-fall-standing.

B. *Posture measurement*

Trunk posture-angle is determined through taking the dot-product of the reference acceleration vector, $\vec{g}$, and the current acceleration vector at time t, $\vec{a}(t)$, Fig. 2. This signal was then low-pass filtered at 5Hz using a 2nd order Butterworth digital filter, Fig. 7. The reference acceleration vector is the average of the three accelerometer signals recorded when the sensor is attached, with the subject standing still for 5 seconds at the start of each recording session. This provides the location of the gravity vector within the sensor coordinate frame. The angle that the body tilts away from the vector is used as the posture angle of the chest (1), Fig. 2.

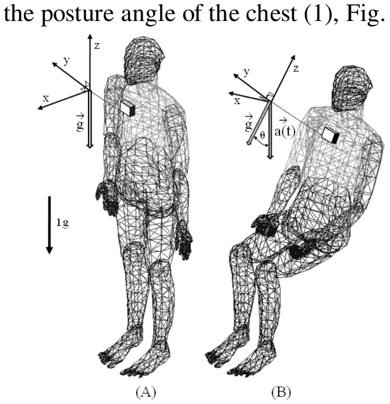

Fig. 2 - Graphical operation of the dot-product angle during (A) Standing where the vector g is obtained and (B) sitting.

$$\theta(t) = \cos^{-1}\left(\frac{\vec{a}(t)\bullet\vec{g}}{|\vec{a}(t)|.|\vec{g}|}\right)*\frac{180}{\pi} \quad \text{(degrees)} \qquad (1)$$

$\vec{a}(t)$ The 3D accelerometer signal at sample point t. ($a_x(t)$, $a_y(t)$, $a_z(t)$)

$\vec{g}$ The reference gravity vector values. (g_x, g_y, g_z)

A standing posture was detected if the posture was between 0^o and 20^o ($TH_{standing}$) [11],[12]. In the studies by Culhane and Lyons, a lying posture is determined when the posture angle exceeds either 60^o ($TH_{lying\text{-}60^o}$) or 45^o [11],[12]. With the threshold angle of 60^o suggested as the optimum for activity classification. Both thresholds are tested here with the recorded data set of falls and normal activities.

C. *Vertical acceleration profile*

A vertical acceleration profile estimate (a_v) is obtained by taking the dot-product between the tri-axial accelerometer signal and a low-pass filtered delayed

[2] National Instruments Corporation, 11500 N MoPac Expwy, Austin, TX, USA.
[3] The MathWorks Inc., 3 Apple Hill Drive, Natick, MA, USA.

version of the TA signal, using a 2nd order IIR Butterworth filter with a cut-off of 2.05Hz. The filter delay introduced by low-pass filtering was removed it is dependent on the cut-off frequency (fc) and filter order (Oc) [13]. The maximum vertical acceleration ($a_{v,MAX}$) is recorded.

D. *Temporal and kinematic parameters of falls*

The following parameters were examined:

$t_{falling}$ – time-to-fall, this is the time between when the standing threshold is exceeded and the maximum upper peak value (UPV), indicating the impact, is detected.

θ_{max} – max-angle, this is the maximum recorded angle in a 3 second window centered at the recorded acceleration UPV.

$t_{\theta max}$ – max-angle-time, this is the time when the maximum angle occurs in relation to the maximum acceleration UPV.

$t_{RTStanding}$ – Return-to-standing-time, this is the time taken for the subjects to return to a standing position.

t_{lying} – lying-time, total time when the lying threshold, TH_{lying}, is exceeded in the immediate time around a fall.

$a_{v,MAX}$ - the maximum recorded vertical acceleration peak, which can be used for impact detection.

III. Results

The previously detailed temporal and kinematic parameters were examined and the results are displayed in Table I. From Fig. 4 and Table I we see that the maximum amount of time taken to fall ($t_{falling}$) from the recorded data set, is 2.58s, however 99.05% of $t_{falling}$ were less than 1.6s. The longer times observed for this fall activity occur, as to initiate this fall type subjects first sat-down and then performed an exaggerated lean to one side before finally falling off the chair.

TABLE I

	max	min
$t_{falling}$	2.581s*	0.001s
θ_{impact}	164.8°	41.35°
$t_{\theta max}$	1.489s	-0.588s
$t_{RTStanding}$	10.33s	3.02s
t_{lying}	2.797s	0s
$a_{v,MAX}$	66.7m/s^2	10.66m/s^2

* 99.05% of $t_{falling}$ were less than 1.6s

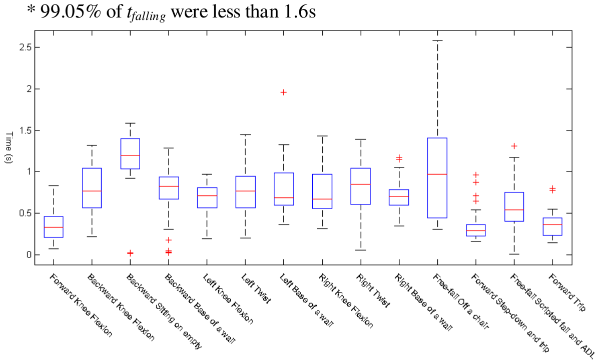

Fig. 3 – This plot represents the time between when the standing threshold is exceeded to when the maximum UPV is reached, $t_{falling}$.

From Fig. 4 (B) we can see the maximum peak values for the trunk angle during a fall. The minimum recorded trunk angle, θ_{max}, was 41.35°, Table I. Unsurprisingly the fall types that consistently produced the lowest trunk angles were falls where the subject landed at the base of a wall.

From Fig. 4 (A) we see that the time, $t_{\theta max}$, when the maximum trunk angle occurs, θ_{max}, is between -0.59 seconds to +1.49 seconds after the peak UPV. With the 99.3% of maximum trunk angles occurring within a 1.06s window from -0.463s to +0.604s.

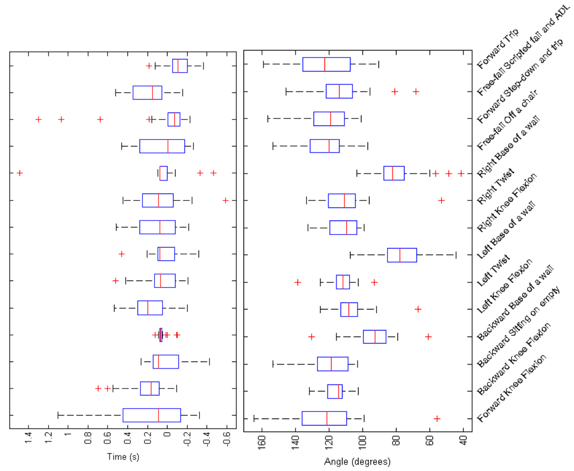

Fig. 4 – (A) This plot displays the time when the maximum angle occurs in a 3 second window centred at the maximum UPVs for each recorded fall. A negative time indicates that the maximum angle occurred before the maximum UPV. (B) This plot displays the maximum angle measured in a 3 second window centered on the Maximum UPV for each recorded fall.

In Fig. 5.the times for a subject to return back to standing again after a fall are displayed. The minimum time recorded here, represents the quickest time that a person returned back to standing after a fall at a self-selected speed. A minimum time for, $t_{RTStanding}$, 3.02s was recorded.

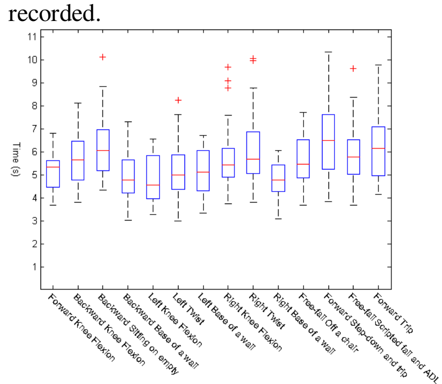

Fig. 5 – This plot displays the time when volunteers finally returned to a standing position. It represents the time between the maximum UPV and when the trunk angle is less than the standing threshold angle, $t_{RTStanding}$.

Through examining the amount of time where the subject could be considered lying in a window of between 0.6s before and 3.02 seconds after the impact, for a TH_{lying} = 45° threshold, for the t_{lying} parameter, 91.19% of times were above a 0.72s threshold and for TH_{lying} = 60°, 82.6% of times were above a 0.81s. The time thresholds t_{lying}; 0.72s and 0.81s represent the lower quartile point of all the 420 recorded falls.

From Fig. 6 we can see the minimum recorded upper peak vertical was 10.66m/s^2.

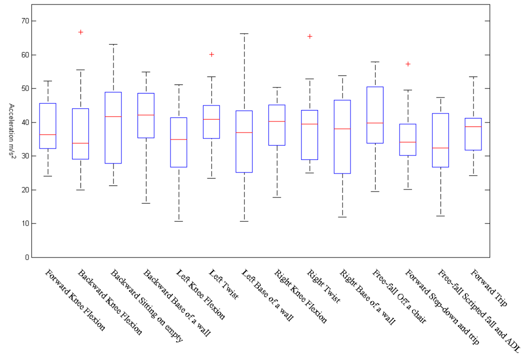

Fig. 6 – Displayed is the maximum recorded vertical accelerations

IV. Discussion

This study aimed to determine a number of optimum temporal and angular parameter thresholds associated with falls performed in a quasi-realistic setting and fall strategy.

From the 420 falls recorded we have determined that:

1) The maximum time taken for a person to go from an upright posture to impact from a fall is 2.58s, however 99.05% of $t_{falling}$ were less than 1.6s.
2) The minimum recorded trunk angle, θ_{max}, that occurred during a fall was 41.35^o
3) This peak trunk angle, θ_{max}, occurs within a time window, $t_{\theta max}$ from -0.59s to 1.49s at the occurrence of the maximum recorded acceleration UPV of the fall.
4) The quickest time a subject returned back to standing after a fall, at a self-selected speed, $t_{RTStanding}$, was 3.02s.
5) Selecting a lying threshold of TH_{lying} at 45^o as opposed to 60^o produced a greater posture detection proportion, when the threshold was set at the lower quartile point of all recorded lying times, t_{lying}.
6) Selecting a vertical acceleration threshold, $a_{v,MAX}$, at 10m/s^2 would ensure 100% detection of fall impacts.

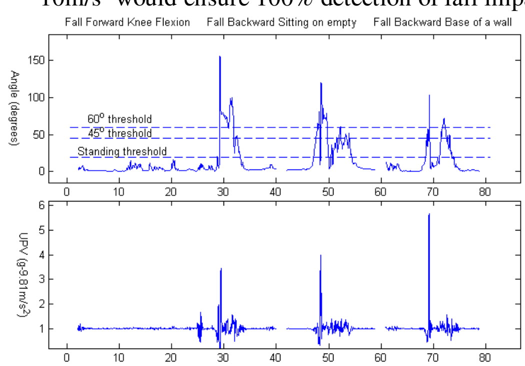

Fig. 7 – Sample trunk posture and RSS signals from 3 different falls.

From visual feedback of the posture signal, it was interesting to observe that subject first orientated their trunk in a kneeling position with their trunk in an up-right posture soon after landing from a fall. Then to return to a standing position, their trunk returned to a near horizontal state in order to perform a knee extension and to balance with their hands on the ground, before finally returning to an upright standing position. Thus the trunk angle signal was bimodal in nature following a fall, Fig. 7.

The minimum recorded time, $t_{RTStanding}$, of 3.02 seconds was the fastest time a young health male subject returns to standing after a fall. It can thus be anticipated that this time may be less than would be recorded from an elderly person following a fall. However it is unknown how psychological reactions along with physiological reactions of the body, such as a release of adrenalin caused by the shock, may affect the actual return-to-standing time.

Future work will involve testing of these parameters in a fall-detection algorithm, over extended period of recorded unscripted as well as scripted ADL.

V. Conclusion

In conclusion we have examined 420 falls, performed in quasi-realistic conditions and falls performed with a realistic technique. We have determined optimum temporal and angular parameters that will allow for more robust detection of falls using an accelerometer based chest worn system.

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