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Optimum gravity vector and vertical acceleration estimation using a tri-axial accelerometer for falls and normal activities

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Abstract— **This study aims to determine an optimum estimate for the gravitational vector and vertical acceleration profiles using a body-worn tri-axial accelerometer during falls and normal activities of daily living (ADL), validated using a camera based motion analysis system.**

Five young healthy subjects performed a number of simulated falls and normal ADL while trunk kinematics were measured by both an optical motion analysis system and a tri-axial accelerometer.

Through low-pass filtering of the trunk tri-axial accelerometer signal between 1Hz and 2.7Hz using a 1st order or higher, Butterworth IIR filter, accurate gravity vector profile can be obtained using the method described here.

Results: a high mean correlation (≥0.83: Coefficient of Multiple Correlations) and low mean percentage error (≤2.06m/s^2) were found between the vertical acceleration profile generated from the tri-axial accelerometer based sensor to those from the optical motion capture system.

This proposed system enables optimum gravity vector and vertical acceleration profiles to be measured from the trunk during falls and normal ADL.

I. Introduction

With the percentage of the global population of people ages 65 or over, set to increase dramatically over the next 40 years [1], a severe burden will be put on national health services [2, 3]. Recent advances in wireless telecommunication technology combined with sensor miniaturization and an overall reduction in technology cost has facilitated the development of more affordable and wearable health-monitoring systems. In order to reduce this projected economic burden on state and private health care services, greater emphasis will be put on technology to monitor the health of older people when it begins to deteriorate, thus enabling and promoting independent living in their own homes for longer.

The monitoring of human movement using strap-down kinematic sensors is now a major area of research and is quickly becoming a part of people's everyday lives [4]. The development of algorithms for the classification of; the intensity and type of activity [5] and the detection of falls [6], using body-worn tri-axial accelerometers (TA) has thus increased dramatically in the last 20 years. Within these algorithms the measurement or estimation of kinematic quantities such as horizontal and vertical, acceleration, velocity and displacement as well as body segment angle and rotation measurement, have been made using exclusively accelerometer.

The total acceleration measured by an accelerometer during human movement can be described as the sum of the acceleration vector due to linear and rotational movement of the attached body or body segment and the acceleration vector due to gravity [7]. For the kinematic quantities mentioned, it is thus desirable to determine an accurate gravitational vector component from the TA signal vector, with respect to the local geographic frame.

Within the accelerometer signal, the frequency spectra of the gravitational component overlaps with that of the linear and rotational acceleration component [8].

Previously a number of researchers have estimated that filtering of the TA signal would provide an accurate estimate or separation of the gravitational component during human movement monitoring applications.

Bouten et al. [9], who located a TA at the lower back, high pass filtered (0.11 Hz, 5.6 dB/octave (1st order)) the TA signal at 0.11 Hz, to attenuate the DC-response of the accelerometer. The filter was implemented in hardware.

Fahrenberg et al. [10] and Foerster et al. [11] extracted the DC component of the accelerometer signal by digitally low-pass filtering the signal at 0.5Hz using a 1st order Butterworth filter. This filtering technique was applied to accelerometers at the trunk, sternum, wrist, both thighs and lower leg. However, it was not explicitly stated how the filter cut-off and filter order was chosen.

Mathie et al. [8] chose to custom FIR low-pass filter with an 8th order cut-off frequency of 0.25Hz with an attenuation of 50DB/octave. The cut-off frequency of 0.25Hz was selected as it was a compromise between 0.11Hz selected by Bouten et al. [9] and 0.5 selected by Fahrenberg et al. [10] and Foerster et al. [11].

Recently, Karantonis et al. [12] developed a waist mounted tri-axial accelerometer based long-term monitoring system for normal activities and falls. Separation of the acceleration caused by body motion, from that due to gravity was achieved by low-pass filtering, with a third-order elliptical IIR filter with cut-off frequency at 0.25 Hz (0.01 dB passband ripple; stopband at −100 dB). The extracted gravitational acceleration component was used to provide

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information on the device tilt-angle and thus postural orientation of the subject.

All of these studies presented methods of separation, through filtering, between acceleration cause by gravity and acceleration caused by body movement which exists in the signal from a subject worn TA. Mathie [13] has proposed that the TA signal consists of a body acceleration (BA) component, a gravitational acceleration (GA) component and noise. The gravitational component provides information on the tilt angle of the body-worn TA device, which can be used to make inferences about the postural orientation of a subject. The body acceleration component provides information on the movement of the subject. These two components are linearly combined in the TA signal and they overlap both in time and in frequency and cannot be easily separated, although approximations to the two components can be made [13].

The aim of the current study is to determine an appropriate method for extracting an estimate of the gravitational vector and vertical acceleration profile, from a TA signal, for both falls and normal ADL and identify the optimum filter cut-off frequency and filter order.

In order to determine the optimum gravitational vector the accuracy of the vertical acceleration profiles were compared during a number of simulated falls and normal ADL, while the subjects movements were recorded using both the TA and captured using an optical motion analysis system, Fig. 1. The vertical acceleration profiles were obtained from a mathematical transformation of the signals from the TA and were then compared by amplitude and closeness in shape to the vertical acceleration profiles from the optical motion analysis system[1] (MA).

II. Materials and Methods

A. Sensor Design and Calibration

Longitudinal, anterior/posterior and medial-lateral accelerometer readings were recorded from the sternum during simulated falls and ADL tasks, using a custom designed wearable wireless TA-based sensor, Fig. 1.

Calibration of the TA was performed using the method outlined by Ferraris, et al. [14]. In addition, to ensure accurate calibration, the technique outlined by Lötters et al. [15] was used to update the calibration offset values.

III. Evaluation: The Experiment

The MA tracks reflective markers that are placed at anatomical points of interest. Three-dimensional tracking of the marker coordinates was performed using the Evart 4.4 software. A marker was placed on, or vertically above, the TA sensor. Tracking of this marker provided the vertical acceleration of the trunk where the TA sensor was located. The TA sensor signals were recorded at a sampling frequency of f_s=50Hz. Tracking of the marker set was simultaneously recorded at 200Hz with both the marker locations and the sensor signal recorded to the same system.

A total of 5 young (<30 years) healthy male subjects were recruited through informal discussion for the study, the subjects ranged in age from 23 to 28 years (25.6±1.9years), body mass from 72kg to 98kg (81.4±10.7kg), and height from 1.75m to 1.93m (1.81±0.08m).

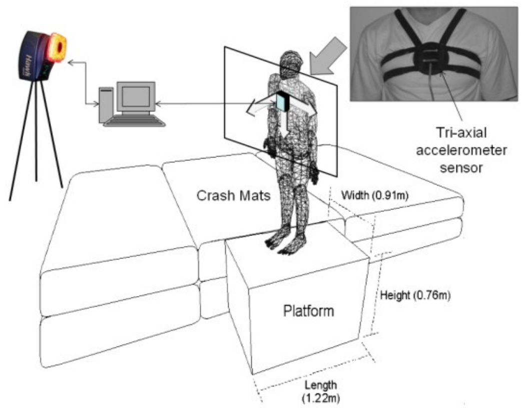

Fig. 1. The tri-axial accelerometer sensor is attached to a subject using the harness shown. The harness is made from Velcro straps and elastic material and the sensor is attached securely to a circular plastic. The inertial sensor consists of a tri-axial accelerometer sensor, consisting of two bi-axial Analog Devices ADXL210E accelerometers. The ADLX210E measures both static and dynamic acceleration with a full-scale range of ±10 g.

Also shown are the crash mats (height 0.76m) and recording set-up for the simulated fall and ADL trial. The inertial sensor signals were recorded through the analogue inputs of the optical MA system.

Four different types of fall were completed: forward falls with legs straight, forward and backward falls with knee flexion and right side-falls with knee-flexion. Each fall was repeated three times. The subject initiated the fall with a slight movement of the body in the direction of their fall.

The ADL activities performed included: sitting on a chair (height 46cm), kneeling on the ground, bending to pick an object from the ground, lying on a mat (37cm thick), walking (5m) and practiced coughing.

Each fall was performed with subjects initially in a standing position. Following the fall, subjects were asked to remain lying until recording had finished. Subjects fell from a support platform onto crash mats, Fig. 1. For the ADL activities, subjects returned to a standing position to complete the activity and were advised to perform activities as naturally as possible within the guidelines provided.

All the fall and ADL were performed in the Biomechanics Laboratory at the University of Limerick. The University of Limerick Research Ethics Committee approved the protocol for this study and the subjects gave written informed consent prior to participation in the study.

A. Data Analysis

Off-line data processing and analysis was performed using MATLAB[2]. The acceleration profiles from the optical motion analysis system (MA) were filtered using a 3-point

[1] Motion Analysis Corporation, 3617 Westwind Blvd., Santa Rosa, CA, 95403, USA.

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

moving average to remove any large noise spikes. To compare the acceleration profiles acquired from both sources, both the TA data and the MA were low-pass filtered at 20Hz, using a second-order Butterworth filter to remove noise (delay = 0.01125s), subsequently the MA system acceleration profiles were down-sampled to 50 Hz to make them directly comparable. The Root-Mean-Square (RMS) difference [16] was used to compare the closeness in amplitude of the vertical acceleration (a_v) signals from both systems and the similarity of the profiles was assessed by determining the Coefficient of Multiple Correlation (CMC) [16]. The MA system signals were used as the reference.

B. The vertical acceleration profile

The vertical acceleration profile estimate ($a_{v,TA}$) was obtained by taking the dot-product between the tri-axial accelerometer signal and a low-pass filter and delayed version of the same signal, using an IIR Butterworth filter. As a result of filtering the TA signal an inherent delay is introduced. This delay has been characterized in a study by Manal et al., [17] and is dependent on the Butterworth cut-off frequency (fc) and filter order (Oc). The associated filter delay (in seconds) was removed from both the gravity vector estimate GA and the filtered TA and MA signals using the algorithm from Manal et al., [17] and modeled as in (1).

$$Delay = \frac{(0.1002 \cdot Order) + 0.0246}{fc} \qquad (1)$$

The vertical acceleration estimate was then obtained by taking a projection, using the dot-product, of the filtered TA signal and the normalized gravitational vector, Fig. 2.

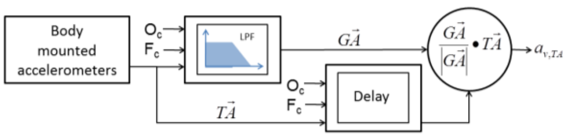

Fig. 2. Method for estimating vertical acceleration using the TA signal.

In order to obtain the most appropriate filter cut-off frequency and order, the RMS and CMC values between the vertical acceleration signal from the optical MA system ($a_{v,MA}$) and those produced using the method described with the TA signal ($a_{v,TA}$) were calculated for cut-off frequencies (fc) from 0.1Hz to 5Hz with a 0.05Hz interval and filter order (Oc) from 1 to 6. The combination of frequency (fc) and order (Oc) that gave the smallest RMS and a CMC closest to 1, provided the optimal low-pass filter parameters.

IV. RESULTS

A comparison between the vertical acceleration profiles from the TA sensor and the MA system was made using RMS error and CMC values; these are presented in Table I and II, respectively, a summary is presented in Table III.

From the minimum recorded RMS error values from orders 1 to 6, the optimum filter cut-off frequencies ranged from 0.85Hz to 1.45Hz for ADL only, 1.85Hz to 1Hz for Falls only and from 1.85Hz to 1Hz for all activities which includes both falls and ADLs. The Lowest RMS error for ADL only was produced using an fc from 1.1Hz to 1.45Hz for Oc values from 2 to 6 (1.237m/s^2). The Lowest RMS error for Falls only as well as all activities was produced using an fc of 1Hz for an Oc of 6 (2.961m/s^2) with the longest signal delay (0.615s), low RMS error values of <2.969 m/s^2 and <2.007m/s^2 were also produced however with an fc of 1.6Hz and Oc from 3 to 5, Table I.

TABLE I

ADL only						
Oc	1	2	3	4	5	6
fc (Hz)	0.85	1.1	1.2	1.3	1.35	1.45
RMS (m/s/s)	1.238	1.237	1.237	1.237	1.237	1.237
delay (s)	0.147	0.205	0.265	0.320	0.381	0.424
Falls only						
Oc	1	2	3	4	5	6
fc (Hz)	1.85	1.75	1.6	1.6	1.6	1
RMS (m/s/s)	2.997	2.984	2.969	2.965	2.964	2.961
delay (s)	0.067	0.129	0.199	0.260	0.322	0.615
All activities						
Oc	1	2	3	4	5	6
fc (Hz)	1.85	1.75	1.6	1.6	1.6	1
RMS (m/s/s)	2.020	2.014	2.007	2.005	2.005	2.004
delay (s)	0.067	0.129	0.199	0.260	0.322	0.615

Table 1: Filter cut-off frequencies (fc) and signal delays for the minimum RMS values for; ADL only, Falls only and All activities.

From the maximum recorded CMC values from orders 1 to 6, the optimum filter cut-off frequencies ranged from 1.6Hz to 2.5Hz for ADL only (CMC ≥0.791), 2.05Hz to 2.75Hz for Falls only (CMC ≥0.908) and from 2.05Hz to 2.7Hz for all activities (CMC ≥0.843), Table II.

TABLE II

ADL only						
Oc	1	2	3	4	5	6
fc (Hz)	1.6	1.6	1.65	1.85	2.3	2.5
CMC	0.791	0.791	0.791	0.791	0.791	0.792
delay (s)	0.078	0.141	0.193	0.225	0.224	0.246
Falls only						
Oc	1	2	3	4	5	6
fc (Hz)	2.2	2.05	2.15	2.3	2.5	2.75
CMC	0.908	0.909	0.910	0.910	0.910	0.909
delay (s)	0.057	0.110	0.148	0.181	0.206	0.224
All activities						
Oc	1	2	3	4	5	6
fc (Hz)	2.2	2.05	2.15	2.25	2.5	2.7
CMC	0.843	0.844	0.844	0.844	0.844	0.844
delay (s)	0.057	0.110	0.148	0.185	0.206	0.228

Table 1: Filter cut-off frequencies (fc) and signal delays for the maximum CMC values for; ADL only, Falls only and All activities.

Thus it is clear that a wide range of values between 0.85Hz (Oc=1) and 2.75Hz (Oc=6) can be used depending on the type of activity being measured if the technique described previously is used. A summary of the minimum CMC values and maximum RMS values for different selected ranges of fc and Oc is presented in Table III.

TABLE III

	ADL only	*Falls only*	*All activities*
Oc range	1-6	1-6	1-6
fc range	0.85-2.5Hz	1-2.75Hz	1-2.7Hz
CMC	≥0.7906	≥0.895	≥0.8373
RMS	≤1.24m/s/s	≤3.083m/s/s	≤2.058

Table 1: CMC minimum and RMS maximum values for filter cut-off frequency ranges (fc range) and filter order ranges (Oc range).

An illustration of the vertical acceleration produced from both the optical motion analysis system and that produced using the TA signal in presented in Fig. 3. The $a_{v,TA}$ was produced using an fc of 1.85Hz, which represents an average filter cut-off frequency for the ranges presented in table III. On Oc of 2 was chosen as higher orders introduce larger delays and increased computation requirements if implemented in an embedded system.

V. Discussion and Conclusion

This study aimed to determine an accurate method, including filter cut-off frequencies and order, for determining an estimate of the gravitational vector and vertical acceleration profile from a TA signal, for both falls and ADL. Using a dot-product projection between the TA signal and a low-pass filtered, delayed version of the TA signal, accurate vertical acceleration signals were obtained and validated using an optical MA system; thus producing an optimum gravitational vector estimate.

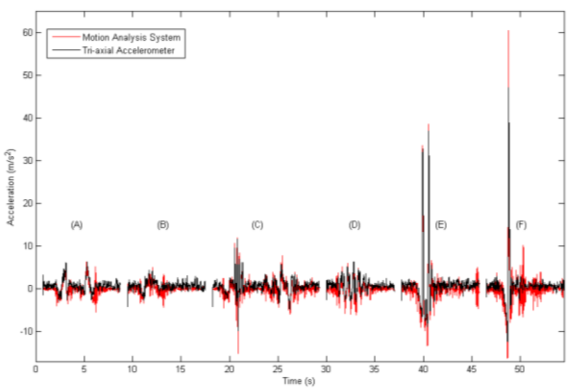

Fig. 3. Vertical acceleration profiles from both the tri-axial accelerometer sensor (black line) and motion analysis system (red line) for both falls and ADL; (A) sitting on a chair, (B) object picking, (C) lying on the floor, (D) walking, (E) forward fall with knee flexion and (F) a side-fall right with knee flexion. The gravity vector was obtained with fc=1.85Hz and Oc=2.

Measurement of the gravitational vector can be achieved with the addition of a tri-axial rate gyroscope sensor [18]. However, the aim of this study was to achieve gravitational vector estimation using only a tri-axial accelerometer as a number of human movement monitoring system only employ this sensor due to it cost and power efficiency.

An alternative to method presented, is to high-pass filter the TA signal, account for the delay, and subtract if from the original TA signal. This was also attempted however inferior results were obtained.

The filter cut-off frequencies presented here are higher than those presented in previous literature where separation of the effect of gravity from the TA signal was performed. The filter cut-off frequencies recommended in those studies were also examined here, however higher RMS error values and lower CMC values were produced.

To produce an acceleration signal, without the influence of gravity from a TA, the gravitational vector profiles can now be accurately, delayed and subtracted from the original TA signals and the Root-sum-of-squares calculated.

VI. Conclusion

This study determined an accurate method, including filter cut-off frequencies and order, for extracting and estimating the gravitational vector and vertical acceleration profile from a TA signal from falls and normal ADL separately and in combination, validated using an optical MA system.

VII. Acknowledgments

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References

[1] UN, "Population Ageing 2009," Population Division, Department of Economic and Social Affairs, United Nations, 2009.
[2] P. E. Cotter, S. Timmons, M. O'Connor, C. Twomey, and D. O'Mahony, "The financial implications of falls in older people for an acute hospital," *Ir J Med Sci,* vol. 175, pp. 11-3, Apr-Jun 2006.
[3] *Recent demographic developments in Europe*: Council of Europe Publishing, 2004.
[4] P. Bonato, "Wearable sensors and systems. From enabling technology to clinical applications," *IEEE Eng Med Biol Mag,* vol. 29, pp. 25-36, May-Jun.
[5] A. Godfrey, R. Conway, D. Meagher, and O. L. G, "Direct measurement of human movement by accelerometry," *Med Eng Phys,* vol. 30, pp. 1364-86, Dec 2008.
[6] N. Noury, P. Rumeau, A. K. Bourke, G. ÓLaighin, and J. E. Lundy, "A proposal for the classification and evaluation of fall detectors," *IRBM,* vol. 29, pp. 340-349, Dec 2008.
[7] K. J. O'Donovan, R. Kamnik, D. T. O'Keeffe, and G. M. Lyons, "An inertial and magnetic sensor based technique for joint angle measurement," *J Biomech,* vol. 40, pp. 2604-11, 2007.
[8] M. J. Mathie, "Monitoring and interpreting human movement patterns using a triaxial accelerometer," in *Faculty of Engineering* Sydney: The University of New South Wales, 2003.
[9] C. V. Bouten, K. T. Koekkoek, M. Verduin, R. Kodde, and J. D. Janssen, "A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity," *IEEE Trans Biomed Eng,* vol. 44, pp. 136-47, Mar 1997.
[10] J. Fahrenberg, F. Foerster, M. Smeja, and W. Muller, "Assessment of posture and motion by multichannel piezoresistive accelerometer recordings," *Psychophysiology,* vol. 34, pp. 607-12, Sep 1997.
[11] F. Foerster and J. Fahrenberg, "Motion pattern and posture: correctly assessed by calibrated accelerometers," *Behav Res Methods Instrum Comput,* vol. 32, pp. 450-7, Aug 2000.
[12] D. M. Karantonis, M. R. Narayanan, M. Mathie, N. H. Lovell, and B. G. Celler, "Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring," *IEEE Trans Inf Technol Biomed,* vol. 10, pp. 156-67, Jan 2006.
[13] M. Mathie, "Monitoring and Interpreting Human Movement Patterns Using a Triaxial Accelerometer," in *Faculty of Engineering*. vol. Doctor of Philosophy Sydney: The University of New South Wales, 2003, p. 512.
[14] F. Ferraris, U. Grimaldi, and M. Parvis, "Procedure for Effortless In-Field Calibration of Three-Axis Rate gyros and Accelerometers.," *Sensors and Materials,* vol. 7, pp. 311-330, 1995.
[15] J. C. Lötters, J. Schipper, P. H. Veltink, W. Olthuis, and P. Bergveld, "Procedure for in-use calibration of triaxial accelerometers in medical applications," *Sensors and Actuators A: Physical,* vol. 68, pp. 221-228, 1998.
[16] A. K. Bourke, K. J. O'Donovan, and G. Olaighin, "The identification of vertical velocity profiles using an inertial sensor to investigate pre-impact detection of falls," *Med Eng Phys,* Jan 31 2008.
[17] K. Manal and W. Rose, "A general solution for the time delay introduced by a low-pass Butterworth digital filter: An application to musculoskeletal modeling," *J Biomech,* vol. 40, pp. 678-81, 2007.
[18] D. Titterton and J. Weston, *Strapdown inertial navigation technology*, 2nd ed., 2004.
[19] M. N. Boulos, R. C. Lou, A. Anastasiou, C. D. Nugent, J. Alexandersson, G. Zimmermann, U. Cortes, and R. Casas, "Connectivity for healthcare and well-being management: examples from six European projects.," *Int J Environ Res Public Health,* vol. 6, pp. 1947-71, 2009.