A Description of an Accelerometer-Based Mobility Monitoring Technique

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Technical note

A description of an accelerometer-based mobility monitoring technique

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Abstract

Accurate monitoring of the mobility status of older adults, over the long-term, is important in rehabilitation medicine, as regular physical activity is central to maintaining both physical and mental health, as well as evaluating quality of life.

This technical note describes an accelerometer-based mobility monitoring technique, which can distinguish between static and dynamic activities and can detect the basic postures of sitting, standing and lying. The technique allows thresholds for these postures to be set and two different posture threshold methods are described: mid-point and "best estimate". Preliminary results from using these methods are presented. This preliminary evaluation of the technique was carried out over the long-term (>29 h) in an uncontrolled environment and the method used to carry out the evaluation is described in detail.

The two different posture thresholding methods were tested on long-term mobility data from one older adult subject. The subject did not have to follow a specific activity protocol during the recording period (4 days) and was shadowed by an observer in order to evaluate the accuracy of this technique. The monitoring hardware consisted of two accelerometer devices, one on the trunk and the other on the thigh and a pocket-sized ambulatory data-logger. Applying 'best estimate' thresholding, as opposed to mid-point thresholding, improved sitting detection accuracy by 18%, to 93% and lying detection accuracy by 5%, to 84%. Thus, based on these preliminary data, an accurate mobility monitoring system for older adults is described and it was observed that the actual posture threshold limits applied have a high impact on the mobility monitoring system's accuracy and are particularly important for accurately detecting postures when used over the long-term, in an uncontrolled environment.

Keywords: Mobility monitoring; Threshold method; Posture; Accelerometer; Older adults

1. Introduction

The ability to accurately monitor the amount of daily physical activity is important in older adults as regular physical activity is associated with both physical and mental health [1–5] and is a primary determinant of quality of life. The use of accelerometers to objectively measure body movement is recorded as early as the 1970s [6]. Veltink et al. [7,23] investigated the feasibility of detecting postures and movements using accelerometers, and five healthy subjects followed a strict and supervised activity protocol of sitting, standing, lying and walking at various speeds. Veltink concluded that using a minimum of two accelerometers, one mounted on the trunk and another mounted on the upper leg, was sufficient to distinguish postures from movements and to discriminate between the postures of sitting, standing and lying. Veltink used posture thresholds to identify which posture a person had but did not describe the posture threshold method or the values used. Following Veltink's work, other researchers developed similar accelerometer-based mobility monitoring systems [8–20].

Like Veltink, Busser et al. [9], Uiterwaal et al. [19] and Aminian et al. [8] also used predetermined fixed threshold levels to define each activity classification. These monitors used trunk accelerometers and a single thigh accelerometer and activities were classified based on an analysis of the mean and deviation of the acceleration signal. However, in these

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cases also, the posture threshold method or values used were not described in detail.

As far as we are aware, information on the actual posture threshold limits set to distinguish between different postures has not been published by any of the investigators who used a fixed-threshold method.

This technical note describes an accelerometer-based mobility monitoring technique, which can distinguish between static and dynamic activities and detect the basic postures of sitting, standing and lying. The technique allows thresholds for these postures to be set and two different posture threshold methods are described: mid-point and “best estimate”. Preliminary results from using these methods are presented. This preliminary evaluation of the technique was carried out over the long-term (>29 h) in an uncontrolled environment and the method used to carry out the evaluation is described in detail.

2. Technique

A custom-designed analysis program was implemented in MATLAB®.[1] The program control flow is as follows:

(1) The recorded accelerometer signals are input from an ASCII representation of the recorded data.
(2) The program calibrates the signals by calculating and removing any offset in the recorded signal.
(3) The signals are then low-pass filtered and a 1 s window is moved over the signal and the mean and standard deviation corresponding to each window is calculated.
(4) Static and dynamic activities are distinguished using standard deviation thresholding, where a threshold value of the standard deviation of the accelerometer signal is applied.
(5) Static activities are divided into sitting, standing and lying by applying minimum and maximum threshold angles for both the trunk and thigh, for each activity.
(6) A per-second computer-generated summary of the detected activities is created.
(7) By analysing the per-second activity summary, a per-minute summary of the detected activities is generated.
(8) The computer-generated, per-minute activity summary is compared minute-by-minute with the manual activity summary created by the observer.
(9) A hit/miss ratio for the activity record is compiled.

This data flow is summarised in Fig. 1.

2.1. Calibration

The sensors were calibrated by measuring the accelerometer signal under controlled inclination conditions, i.e., by rotating the sensor to provide a signal output corresponding to +1 g, 0 g and −1 g. The analysis program then reads in the raw acceleration signals from each of the accelerometers when attached to the body while in a standing position and corrects for any offset.

2.2. Low-pass filtering

The accelerometer signals are low-pass filtered using a second-order, low-pass, forward-backward, digital, Butterworth filter with a cut-off frequency of 3 Hz.

2.3. Distinguishing static and dynamic activities

Using a 1-s window, which is moved over the signal, both the mean and standard deviation, for that second, of each signal was computed. The standard deviation indicates the variability of the thigh accelerometer signal for each 1-s window of recorded data. (High variability would be expected during dynamic activities and low variability would be expected during static activities.) A static/dynamic threshold is then applied to the standard deviation signals. If the signals are above the standard deviation threshold for that second the activity is considered dynamic and if it is below the threshold, the activity is deemed static (Fig. 2).

2.4. Posture detection

When the activity of a 1-s window is deemed a static activity, the mean accelerations over this 1 s are converted to a corresponding inclination angle (θ in degrees) using the arccos transformation of Eq. (1), where ‘a’ is the accelerometer output and ‘g’ is equal to 9.81 m s^{-2}, θ corresponds to the angles of α, β, γ and δ of Figs. 3–5.

$$\theta_{\text{degrees}} = \frac{180}{\pi}\cos^{-1}\left(\frac{a}{g}\right) \qquad (1)$$

Specific trunk and thigh inclination ranges are set for sitting, standing and lying and the algorithm tests which range is met by the trunk and thigh inclinations determining which static activity is occurring. In selecting the upper and lower limits of trunk and thigh inclination, for the three static activities, two different methods were investigated. The first posture threshold method used a mid-point threshold value of 45°, as was used by Dunne et al. [16] on evaluation of this system on a healthy, young subject using a standardised protocol. In that trial, detection accuracies of 98% and greater were achieved for each of the activities of sitting, standing, lying and moving. The second method employed ‘best estimate’ thresholds for each activity. ‘Best estimate’ threshold values were thresholds proposed by the authors to more accurately reflect real-life trunk and thigh ranges for each of the activities and were based on the authors observations of these static postures which depended on the presence and position

[1] The Mathworks Inc., 24 Prime Way, Natick, MA, USA.

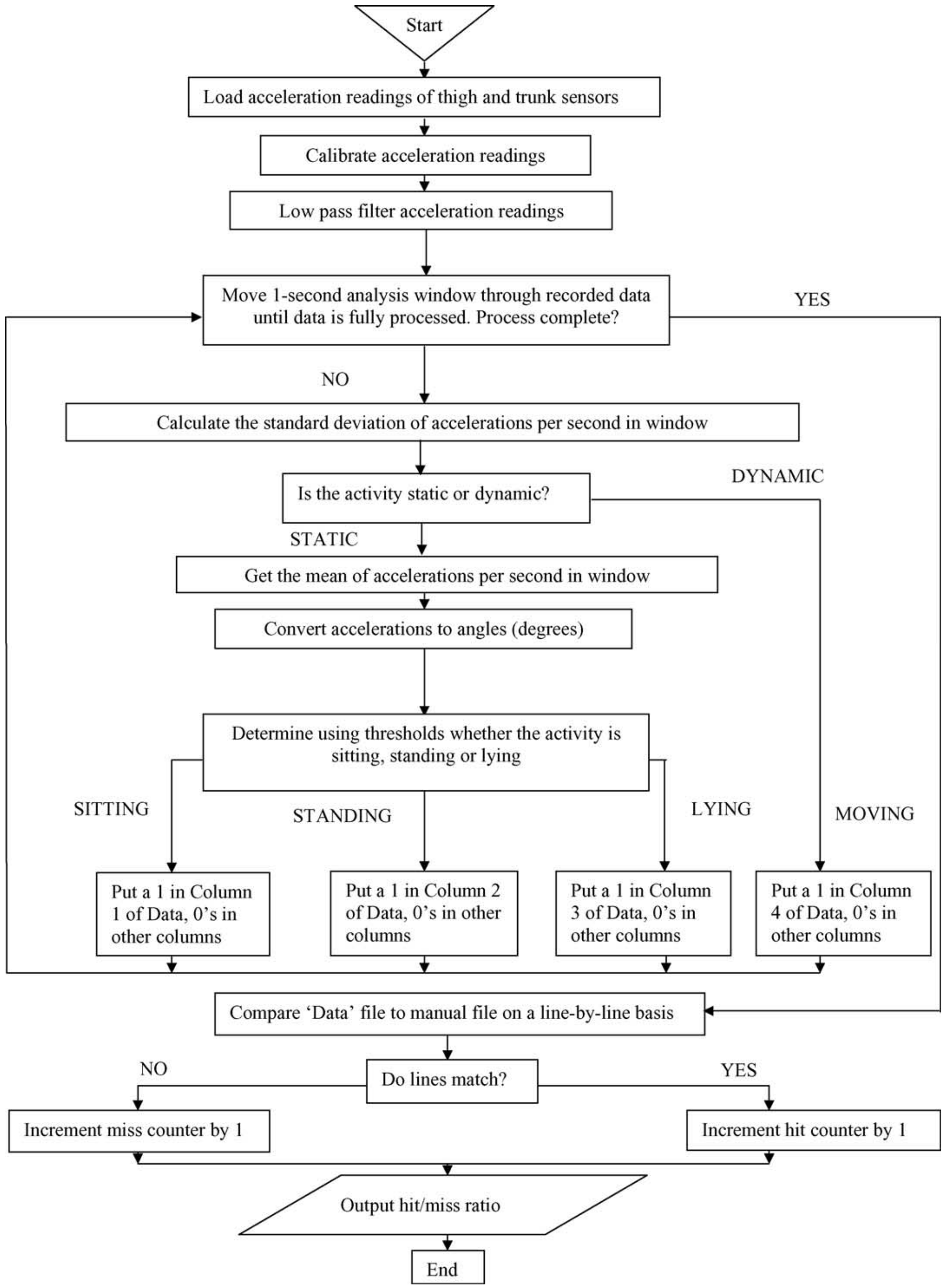

Fig. 1. Flowchart of MATLAB® analysis program.

of supporting surfaces. The upper and lower threshold values applied for the thigh and trunk angles for each posture using both threshold approaches are outlined in Figs. 3–5. Thus, with the mid-point threshold approach if the thigh inclination is between 45° and 135° and the trunk inclination is 50°, the activity is deemed to be lying and with 'best estimate' thresholding the activity is deemed to be sitting comfortably.

2.5. Activity summary generation

The per-second activity summary is generated in a text file format with four columns corresponding to the four activities of interest and entries are input in rows corresponding to each second of recording. A '1' at a column position indicates that the corresponding activity occurred at that second; a '0' indicates that the corresponding activity did not occur.

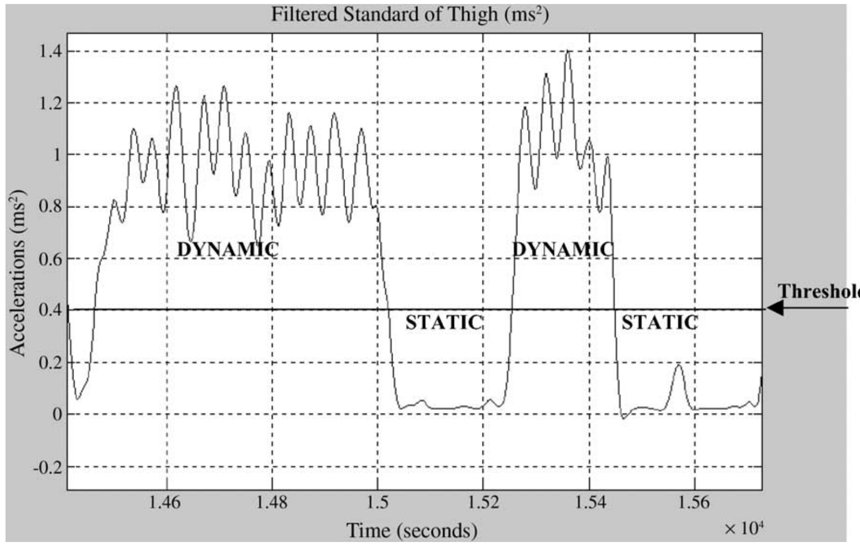

Fig. 2. Plot of the standard deviation of the thigh acceleration signal.

To generate the per-minute activity summary, the mean of each 60-s segment of the per-second activity summary was calculated and stored in a separate text file. The columns of this text file correspond to the activities detected. However, each row now contains the mean value of each activity over 1 min.

The dominant activity for each minute is now determined by finding the column with the highest mean value. Entering a ‘1’ in the row (for this minute) and in the column (for this activity) in a new text file and placing ‘0’s in the other three columns for this minute generated a per minute activity summary.

2.6. Comparing observed data to recorded data

Reference data for the mobility status of the subjects were obtained by an investigator shadowing the subject and manually logging their activity each minute in specially prepared

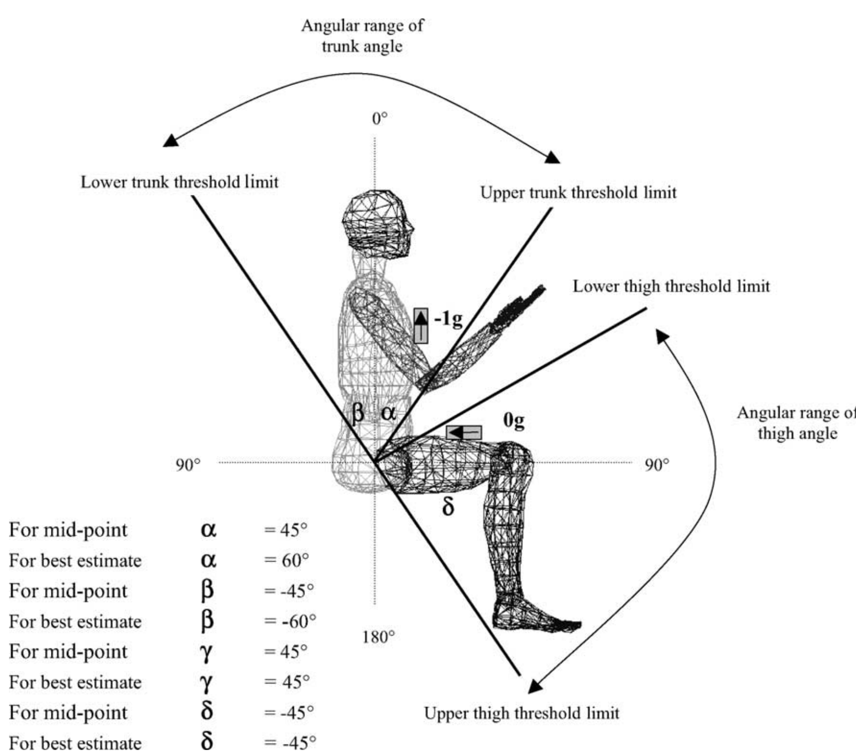

Fig. 3. The inclination threshold arrangement for sitting with the acceleration values corresponding to the accelerometer output in the sitting position. If the thigh and trunk angles met the criteria of this figure, the subject was deemed to be sitting.

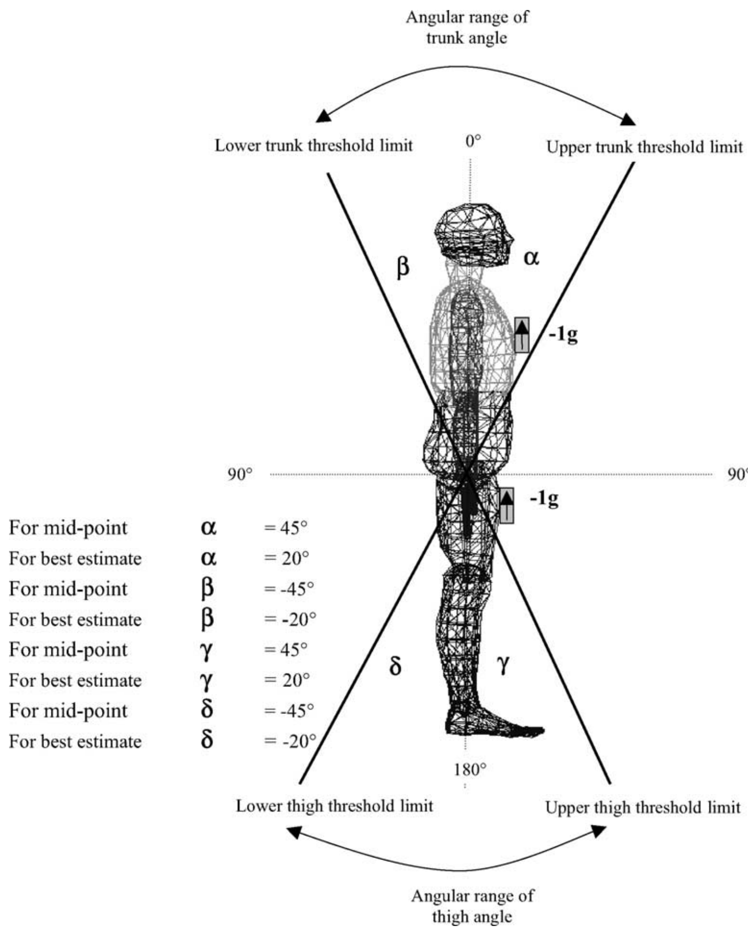

Fig. 4. The inclination threshold arrangement for standing with the acceleration values corresponding to the accelerometer output in the standing position. If the thigh and trunk angles met the criteria of this figure, the subject was deemed to be standing.

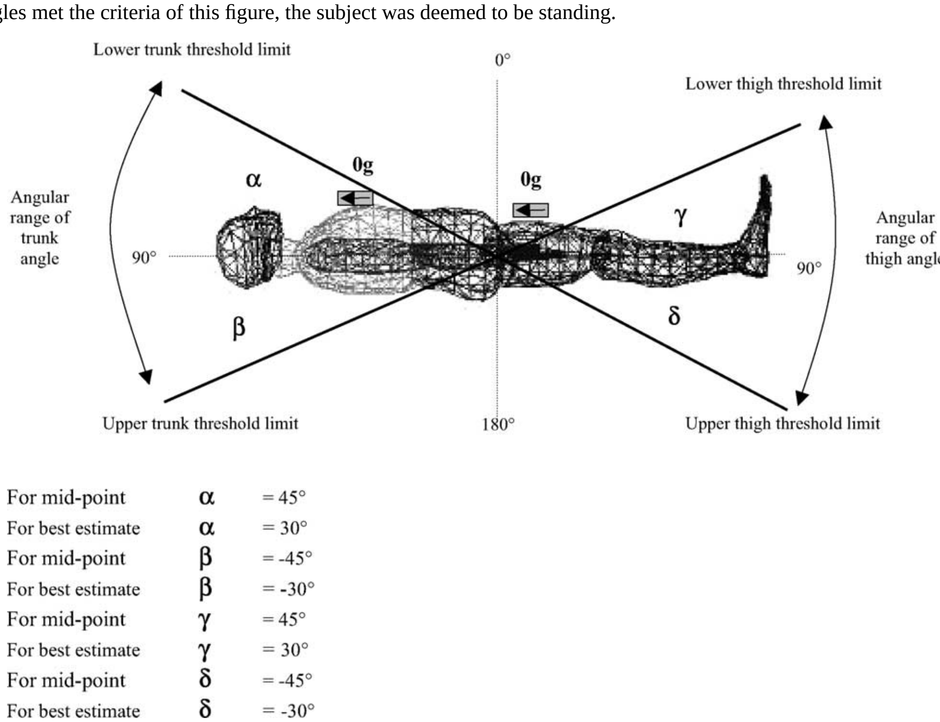

Fig. 5. The inclination threshold arrangement for lying with the acceleration values corresponding to the accelerometer output in the lying position. If the thigh and trunk angles met with the criteria of this figure, the subject was deemed to be lying.

Table 1
Comparison of detection accuracy results, on a daily basis, using mid-point and 'best estimate' threshold values

Day	% Accuracy sitting		% Accuracy standing		% Accuracy lying		% Accuracy moving
	Mid-point	Best estimate	Mid-point	Best estimate	Mid-point	Best estimate	
1	71	81	90	90	79	80	97
2	79	99	94	94	86	83	95
3	71	95	100	100	65	86	97
4	79	96	94	95	86	85	98
$\bar{x}$ (σ)	75 (4.0)	93 (7.0)	94 (4.1)	95 (4.1)	79 (8.6)	84 (2.3)	97 (1.8)

log-sheets. This recording process was synchronized with the start of accelerometer recordings. The activities manually recorded were standing, sitting, lying and moving (which included walking and non-ambulatory exercise) with four columns on the log-sheet corresponding to each of these activities and each row corresponding to each minute recorded. Following recording the observed data was converted to text file form, so that the observed activity summary had the same structure as the per-minute activity summary generated by the analysis program. Both activity summaries were compared, in software, on a row-by-row basis. The number of matches (hits) and mismatches (misses) were recorded and a percentage of the overall hits/misses ratio was output indicating the level of accuracy of the system. A hit indicated that the manual and accelerometer methods matched; a miss indicated that the manual and accelerometer methods did not match.

3. Preliminary evaluation

Preliminary evaluation of the technique was carried out using mobility data from 1 older adult patient resident at the Rehabilitation Unit, St. Camillus' Hospital, Limerick, Ireland, over 4 days for an average 7 h per day (total: 29 h 28 min). Typical evaluation of mobility monitoring systems in the literature involve short-term studies with monitored periods in the order of less than 4 h [8,9,19]. The subject had recently suffered a cardiovascular accident (CVA) but was capable of independent ambulation and had daily therapy sessions. The subject did not have to follow a specific activity protocol. Informed consent was obtained from the participant and ethical approval for the study was obtained from the University of Limerick Research Ethics Committee and the Mid-Western Health Board Scientific Research Ethics Committee.

The hardware used during testing consisted of two Analog Devices ADXL202[2] accelerometer devices, a portable, compact (75 mm × 56 mm × 18 mm), battery-powered, data-logger (Biomedical Monitoring BM42[3]) and associated computer-interface hardware. The monitoring device: a combination of two accelerometers, a data-logger and associated cabling was lightweight (192 g) and easy to attach, with sufficient battery and memory capacity (32 MB) for long-term recording (>24 h).

The Analog Devices, ADXL202 accelerometer, is a dual axis, integrated accelerometer, designed for air-bag release applications in automobiles. Capable of measuring both positive and negative accelerations to a maximum level of ±2 g and outputting a voltage, whose amplitude is directly proportional to the acceleration, at the X and Y axes, at the analogue outputs of the device, the X_{FILT} and Y_{FILT} pins. The accelerometer signals were sampled at 50 Hz at a resolution of 12 bits and stored on the data-logger's memory card. At the end of each day of recording, the data-logger data were downloaded to a computer using an USB memory card reader.

The two accelerometers were attached to the subject, over clothing, using Velcro straps on the thigh and on the trunk at the sternum, oriented as proposed by Veltink et al. [7], with the active axis in the radial direction to the trunk and thigh. The orientations of the accelerometers for the various positions are shown in Figs. 3–5.

4. Results

The percentage of time spent by the subject at each of the activities of sitting, standing, lying and moving are presented in Fig. 6. As the subject was recovering from a recent CVA she was not very active with only 10% of the monitored time spent performing dynamic activities.

Accuracy results for detecting the various activities were obtained using the two separate threshold techniques, mid-point and 'best estimate' thresholds. Table 1 shows the difference in the detection accuracy (obtained using minute-by-

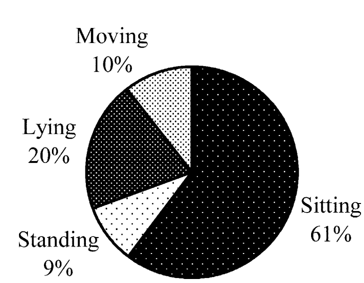

Fig. 6. The percentage of time spent by the subject in each activity.

[2] ADXL202, Analog Devices BV Ltd., Limerick, Ireland.
[3] Biomedical Monitoring Ltd., Wolfson Centre, Glasgow, G4 ONW, UK.

minute comparison) between mid-point and 'best estimate' thresholding.

The threshold method used was particularly important for accurate detection of sitting in an uninhibited environment. When the mid-point value was used overall detection accuracy was only 75% but by applying 'best estimate' thresholding, it improved by 18%, to 93%. For lying, applying 'best estimate' thresholding improved the detection accuracy by 5%, to 84%.

5. Discussion

It was observed that the actual posture threshold limits applied have a high impact on the mobility monitoring system's accuracy and are particularly important for correctly detecting postures when used over the long-term, in an uncontrolled environment.

Previous findings in a controlled setting, showed that using a mid-point posture threshold approach produced excellent mobility detection accuracies in the order of 98% when monitoring a healthy subject, performing a standardised protocol, over the short-term [16].

However, in the preliminary evaluation described in this technical note, when the mid-point posture threshold method was applied, in the less restrictive environment of a rehabilitation centre, on an older person, monitored over the long-term the results were much poorer, with a sitting detection accuracy of only 75% and a lying detection accuracy of 79%. Applying 'best estimate' posture thresholding to these data improved sitting detection accuracy by 18%, to 93% and lying detection accuracy by 5%, to 84%. There was effectively no change in the standing detection accuracy with only a 1% improvement when using 'best estimate' values. Using the selected static/dynamic threshold, moving was detected with 97% accuracy. Thus, selection of an appropriate threshold approach in a mobility monitoring system is vital for accurate monitoring.

The results for our system using 'best estimate' thresholding, compare favourably with the accuracy results of other accelerometry based activity monitors, using the threshold method, published in the literature. The activity monitor of Bussmann et al. used a preset fixed threshold method for distinguishing postures and activities and produced accuracy results, when compared with video analysis, of between 81% and 93% [10,20–22]. With the activity monitors of Busser et al. [9] and Uiterwaal et al. [19], using a fixed threshold method for determining activities, accuracies of between 76% and 93% were obtained.

For the system described in this technical note, the target population is elderly subjects and the key information of interest is the amount of time spent active with details as to the actual postures adopted, during periods of inactivity. A 2-sensor set-up is sufficient for this application and this minimum sensor configuration, keeps associated sensor cables to a minimum so that the monitoring device is easy to attach and unobtrusive, characteristics that are especially important when used on an older adult in a clinical environment, means that the system does not interfere with or impede the daily activities of the patient.

In most mobility monitoring studies, the reference data were obtained using video techniques and the monitor output and video recordings were compared on a second by second basis. For this study, video recording was deemed unsuitable due to the public setting (Rehabilitation Clinic) and recording duration (>29 h) of the study. It was also important to protect the privacy of the other patients. Therefore, extended long-term mobility monitoring required a different approach to performance evaluation. The software technique outlined in this paper generates a minute-by-minute summary of activities from analysis of the second-by-second accelerometer data and then compares this to the minute-by-minute activity summary manually recorded by the observer. In the rehabilitation setting of this study, it was not of clinical interest to monitor short-lasting postures and activities. As the patients residing at this rehabilitation unit tended to be of an older age, not in perfect health and generally not as active as young people a 1-min monitoring time frame was deemed sufficient to determine the accuracy of this technique.

A sampling frequency lower than the 50 Hz used would be adequate as the bandwidth of the mobility data of interest is less than 3 Hz. Thus, a sampling frequency of 6 Hz would suffice to meet the Nyquist criterion. Use of a lower sampling frequency would reduce the size of the recorded data files, however 50 Hz sampling did not result in the daily data file recorded exceeding the data-logger's 32 MB memory and as recorded data were down-loaded to the computer on a daily basis on doffing of the equipment, recording at 50 Hz did not present a problem.

6. Conclusion

An accelerometer-based mobility monitoring technique is described, with detection accuracies in the order of 90%. It was observed for a single elderly subject resident in a rehabilitation centre that the posture threshold limits used have a large influence on the system's accuracy, where using 'best estimate' posture threshold values as opposed to mid-point values improved sitting detection accuracy by 18%, to 93% and lying detection accuracy improved by 5%, to 84%. Therefore, the actual posture threshold limits applied are particularly important for detecting postures especially when used over the long-term and in an uncontrolled environment.

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