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Article *in* Medical & Biological Engineering & Computing · June 2003

Impact Factor: 1.73 · DOI: 10.1007/BF02348434 · Source: PubMed

Detection of daily physical activities using a triaxial accelerometer

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Abstract—*Triaxial accelerometers have been employed to monitor human movements in a variety of circumstances. The study considered the use of data from a single waist-mounted triaxial accelerometer to distinguish between activity states and rest. A method using acceleration magnitude was applied to data collected from 26 normal subjects performing sit-to-stand and stand-to-sit transitions and walking. The effects of three parameters were investigated: the length n of a smoothing median filter, the width w of the averaging window used to process the signal and the value of the acceleration magnitude threshold th. These were found to be inter-related, and sets of parameters that resulted in accurate discrimination were determined by the relationship between th and the product of w and n, and by the relationship between n and w. The subjects were randomly divided into control (N= 13) and test (N= 13) groups. Optimum parameter sets were determined using the control group. Eleven sets of parameters yielded the same optimum results of a sensitivity of 1.0 and a specificity of 0.96 in the control group. Upon application to the test group, using these parameters, the system successfully distinguished between activity and rest, giving sensitivities greater than 0.98 and specificities between 0.88 and 0.94.*

Keywords—*Triaxial accelerometer, Energy, Activity detection, Movement*

Med. Biol. Eng. Comput., 2003, **41**, 296–301

1 Introduction

THE ASSESSMENT of activity in subjects living in the community is an important means of monitoring health status and quality of life. Accelerometers have been shown to be an objective and reliable tool for the assessment of physical activity levels (BOUTEN *et al.*, 1997). Accelerometers allow the assessment of physical activity in large populations over periods that are long enough to be representative of normal daily life and with minimum discomfort for the subjects (WESTERTERP, 1999; MATHIE *et al.*, 2001).

When assessing health status and functional ability, it is also useful to be able to identify the activities on which the energy has been spent. Systems in which accelerometers are placed at a number of locations on the body, typically including the waist and thigh, as well as at other locations, have been used to resolve resting states, such as sitting, standing and lying, and activities including walking, climbing up and down stairs and cycling (UITERWAAL *et al.*, 1998; VELTINK *et al.*, 1995; FAHRENBERG *et al.*, 1997; FOERSTER and FAHRENBERG, 2000). Accelerometry, in combination with a global positioning system (GPS), (MURAKAMI and MAKIKAWA, 1997) has also been used for this purpose. Additionally, single waist-mounted units have been used to study gait patterns (SEKINE *et al.*, 2000; EVANS *et al.*, 1991).

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Paper received 30 May 2002 and in final form 6 January 2003

MBEC online number: 20033762

In this study, we conducted an investigation of an automatic detection system for distinguishing activity from non-activity using only a single waist-mounted triaxial accelerometer (TA). The detection system compared the time-averaged, integrated signal magnitude with a preset threshold to distinguish between rest and activity. An accurate detection of activity is needed so that the subjects' activities (such as walking, sit-to-stand transitions and stand-to-sit transitions) can be further analysed and classified. This requires a high degree of sensitivity. This was determined to be the primary requirement for this detection system.

This method was applied to data collected from 26 normal subjects to distinguish between activity and rest, and the system detection performance was evaluated. The system was defined by three parameters: filter length n, window width w and energy threshold th. The effects of these were explored for a wide range of values, and optimum ranges were determined for the subject cohort.

2 Methodology

2.1 *Triaxial accelerometer device*

The TA device consisted of two orthogonally mounted biaxial piezo-resistive accelerometers* (range: $\pm 10g$; frequency response: 0–500 Hz; noise level: $6.12 \times 10^{-3} g$ RMS). They respond to both acceleration due to movement and gravitational acceleration g. The magnitude of g is $9.81\,\mathrm{ms}^{-2}$, and, in this study, all accelerations were cited in terms of g. The accelerometers were enclosed in a small, light pager case (size: $71 \times 50 \times 18$ mm; total device weight: approximately $50g$,

*ADXL210 supplied by Analog Electrics

including the AA battery) designed to be clipped onto a waist belt. The data were anti-alias filtered, then sampled at 45 Hz (to 12-bit accuracy) and transmitted by 433 MHz wireless link using bi-phase mark encoding to a receiver unit connected to a personal computer, where the data were time-stamped and stored. This system led to a data resolution better than $25 \times 10^{-3} g$.

The wearable unit consumed 15 mA from a 1.5 V source when transmitting 0 dBm into a 50 Ω surface-mounted planar antenna. At this level of power consumption, the telemetry system functioned reliably over a range of up to 50 m.

The magnitude and frequency ranges of $\pm 10\,g$, and 0–500 Hz, respectively, and the sampling rate of 45 Hz were chosen based on the work of BOUTEN *et al.* (1997), who concluded that body-fixed accelerometers placed at waist level must be able to register frequencies up to 20 Hz over an amplitude range of $\pm 6g$.

The sensors were calibrated by the sensor being placed with each one of its six sides on a flat, horizontal surface. This provided a signal output corresponding to $+1g$ and $-1g$, when the sensitive axis was parallel to the gravitational field, and $0g$ when the sensitive axis and the gravitational field were perpendicular.

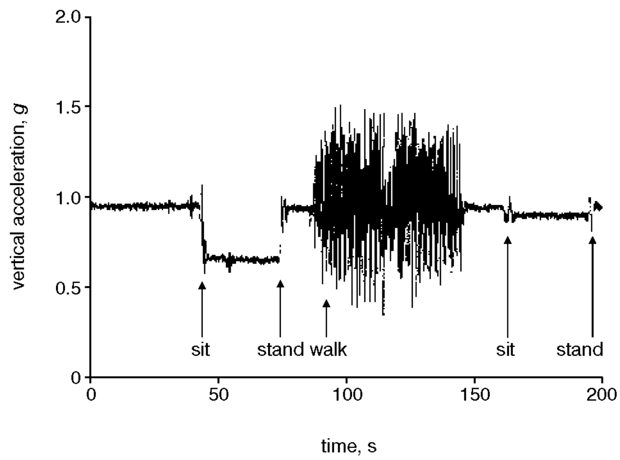

Fig. 1 *Typical sample of data collected in study showing vertical axis acceleration ($g = 9.81\,ms^{-2}$) from subject performing part of test sequence. Activity segments were timed by investigator and correlated with time stamp of signal. Different activities are indicated*

2.2 *Experimental procedure*

An experiment was conducted in which 26 healthy volunteers with no mobility limitations (seven female, 19 male; age: 30.5 years ± 6.3 years standard deviation) performed a sequence of normal daily movements in a controlled laboratory setting while wearing the TA. The testing procedure was the same for all subjects. The subject was told to attach the TA at the waist, above the right anterior superior iliac spine, as this was identified as the preferred site by the subjects (MATHIE *et al.*, 2001).

Each subject carried out 11 distinct activities, being sit-to-stand transitions, stand-to-sit transitions and walking. These were interspersed by 12 distinct rest periods of either standing or sitting.

The sequence was: (i) stand (30 s); (ii) sit down in a lounge chair; (iii) remain sitting (30 s); (iv) stand up; (v) remain standing (10 s); (vi) walk along a flat, straight corridor; (vii) remain standing (10 s); (viii) sit down on an office chair; (ix) remain sitting (30 s); (x) stand up; (xi) remain standing (10 s); (xii) walk up and down a flight of stairs; (xiii) remain standing (10 s); (xiv) sit down on an office chair; (xv) remain sitting (30 s); (xvi) stand up; (xvii) remain standing (10 s); (xviii) walk along a flat, straight corridor; (xix) remain standing (10 s); (xx) sit down in a lounge chair; (xxi) remain sitting (30 s); (xxii) stand up; (xxiii) remain standing (10 s). The protocol took 8 min to complete.

The subject was directed through the procedure by an investigator who identified the time of onset and offset of each segment using a stopwatch. The investigator indicated to the subject what movement to make and when to carry it out. Every data sample was time stamped by the data acquisition system, so that each activity could be identified on the resultant signal trace, using the independent timing data obtained by the investigator. Fig. 1 shows a typical sample of data.

Thirteen of the subjects were randomly selected as a control group, and the other 13 were allocated to a test group (control group: four female, nine male; age: 30.9 years ± 9.0 years standard deviation; test group: three female, ten male; age: 30.5 years ± 6.4 years standard deviation). The TA signals from the control group were used to identify optimum sets of parameters for the detection system, which was then applied to the test group, and its performance was evaluated.

2.3 *Data analysis*

Activity acceleration amplitude and duration are highly variable, between different activities, between subjects and even for the same subject and activity. For example, a sit-to-stand transition can take from 1 s to more than 3 s, in healthy subjects (KERR *et al.*, 1997), and even longer in unhealthy or disabled subjects (MUNRO *et al.*, 1998). If, for example, a subject sits rapidly on a chair, we see a large signal magnitude over a short duration, in contrast to a slow movement, in which we observe a smaller signal magnitude over a longer period, as shown in Fig. 2. Thus, to identify activity, both the magnitude and duration of the signal need to be taken into account.

One way of including both effects is to calculate the signal magnitude area (magnitude × time) and compare it with a preset threshold. Other researchers have demonstrated that a similar measure, the sum of the integrals of the signal magnitudes, provides a useful measure of metabolic energy expenditure (BOUTEN *et al.*, 1997; CHEN *et al.*, 1997). BOUTEN *et al.* (1997) found that, after the gravitational components of the

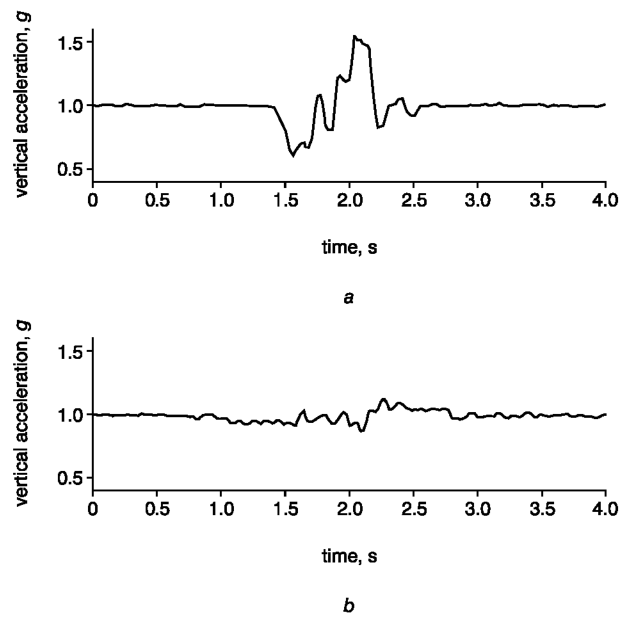

Fig. 2 *Comparison between data for two stand-to-sit transitions, showing vertical axis acceleration ($g = 9.81\,ms^{-2}$) against time. (a) Typical rapid transition, in order of 1 s in duration. (b) Typical slower transition in order of 2.5 s in duration. Note that magnitude of acceleration in rapid transition is approximately 5 times larger than that in slow transition*

signals have been removed by high-pass filtering of the signals, the sum of the integrals of the signal magnitudes from a TA is proportional to metabolic energy expenditure in the activities of daily living, with correlation coefficient $r = 0.89$. We defined a parameter A, the signal magnitude area, to be the sum of the areas under the moduli of the integrals, normalised to the length of the signal

$$A = \frac{1}{t} \times \left(\int_t |a_1(t)| dt + \int_t |a_2(t)| dt + \int_t |a_3(t)| dt \right) \qquad (1)$$

where a_1, a_2 and a_3 are the acceleration signals from each of the accelerometers with respect to time t. A has units of ms^{-2}. We used A as the basis for identifying periods of activity in this study.

The signals obtained from the TA were processed in the following way. Each of the three orthogonal signals from the TA was passed through a high-pass filter (finite impulse response filter with cutoff frequency at 0.25 Hz) to remove the gravitational acceleration component from the signal. A cutoff frequency of 0.25 Hz was chosen as it is consistent with the frequencies used by other researchers (for example, BOUTEN *et al.* (1997) used 0.1 Hz, and FORSTER and FAHRENBERG (2000) and FAHRENBERG *et al.* (1997) chose to use 0.5 Hz). A cutoff frequency of 0.25 Hz represents a compromise between a filter that is realisable and a cutoff frequency that is as low as possible.

Each signal was then passed through a median (non-linear, low-pass) filter of length n samples to remove high-frequency noise spikes. A non-overlapping averaging moving window, of width w s, was applied to the signal, and A was calculated for each window. A was then compared with a fixed preset threshold th, to determine the presence or absence of activity in the signal at a given time. th was a measure of the signal magnitude area, having units of ms^{-2} and, like A, was independent of the window width. The threshold comparison $A > th$ was used to identify activity in the signal.

Contiguous windows containing activity were joined together to form blocks of activity interspersed by blocks of rest. These blocks of classified activity were compared with the blocks of actual activity in the following way. If the timing of the classified activity overlapped the timing of the actual activity, then this was recorded as a true positive. In this process, we were not looking for a definitive recording of the start and endpoints of the activity, but were rather establishing that an activity had been detected within a block of time. If the timing of the classified activity did not overlap the timing of an actual activity, then this was recorded as a false positive. Negatives were defined similarly.

The effects of three parameters affecting the system's function were investigated. These were

(*a*) the length of the median filter n
(*b*) the width of the window w
(*c*) the threshold value th.

Each parameter was varied from its minimum value to a value above which discrimination between rest and activity did not occur.

We began by investigating the effect of the parameters n, w and th on the detection system, using the TA signals from all 26 subjects. As a second task, 13 of the subjects were randomly selected as a control group, as outlined above. The rates of true and false positives were measured using each combination of these three parameters. The sets of parameters were ranked in descending order of true positive rate (sensitivity) and, within this ordering, in increasing order of false positive rate (1-specificity). This allowed the optimum set of parameters to be determined.

As discussed earlier, given the criterion that a high sensitivity was more important than a high specificity, acceptable parameter sets were predefined as those that gave specificities above 0.9 and sensitivities as high as possible, but not below 0.9.

The system, using the optimum parameters as determined for the control group, was tested on the remaining 13 test group subjects, and the effectiveness of the system was evaluated for the test group in terms of sensitivity and specificity.

3 Results

Filter lengths $n = 3, 5, 7, \ldots, 89$ samples, window widths $w = 0.2, 0.4, 0.6, \ldots, 4.0$ s and thresholds $th = 0, 22.5 \times 10^{-3}g$, $45.0 \times 10^{-3}g, \ldots, 900 \times 10^{-3}g$ were tested. We began by investigating the effect of the parameters n, w and th on the detection system, using data from all 26 subjects. Each of the three parameters was found to affect the specificity and the sensitivity of the system.

The sensitivity of the system was found to be controlled by a relationship between the product of n and w and threshold th and by a subsequent relationship between n and w. Fig. 3 shows the relationship between $n \cdot w$ and th and the effect on the discrimination ability of the system for all 26 subjects. Sets of parameters that achieved both sensitivity and specificity greater than 0.9 are shown. The relationship between n, w and the discrimination ability of the system is illustrated in Fig. 4 for the instance where $th = 157.5 \times 10^{-3}g$. Curves of best fit (third and first degreee polynomials, respectively) through the upper and lower limits are shown in both Figures.

The effect of the filter length n on the windowed signal magnitude area A was found to have two components. The first component acted on the measurement for the individual subject and is illustrated in Fig. 5*a*. As n was increased, the difference between A for activity and rest for any one subject was reduced, making discrimination more difficult. The second component acted across subjects and is shown in Fig. 5*b*. As n was increased, the differences between subjects decreased, making detection easier until the first effect became too significant.

In the second task, optimum parameters were found for the control group and then applied to the test group to determine their effectiveness. Fig. 6*a* shows a receiver operating characteristic (ROC) curve (true positive rate against false positive rate) for all of the parameters tested on the subject control group. Fig. 6*b* shows the ROC curve with the parameters that, in the

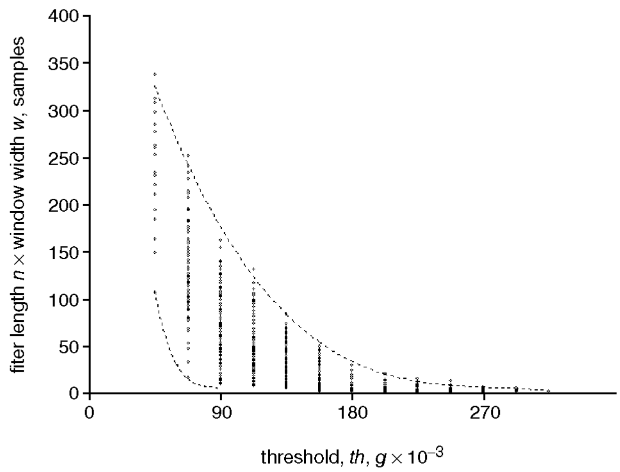

Fig. 3 *Filter length $n \times$ window width w against threshold* th, *plotted for all sets of parameters giving both sensitivity and specificity greater than 0.9, across all 26 subjects. Note that, for these parameter sets, $n \cdot w$ is bounded by smoothly decreasing functions of th*

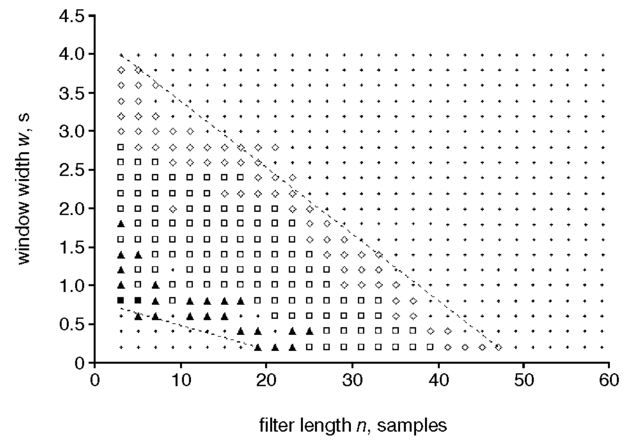

Fig. 4 *Window width w against filter length n across all 26 subjects. All sets of tested n and w where threshold th = 157.5 × 10^{-3}g are plotted. Bands of sensitivity with specificity greater than 0.9 are shown. Linear bounds on the band, specificity greater than 0.9 are indicated by dotted lines. (◇) Sensitivity ≥ 0.90 and < 0.95; specificity ≥ 0.90. (□) Sensitivity ≥ 0.95 and < 0.99; specificity ≥ 0.90. (▲) Sensitivity ≥ 0.99 and < 1.00, specificity ≥ 0.90. (■) Sensitivity = 1.00; specificity ≥ 0.90. (+) Sensitivity < 0.90 or specificity < 0.90*

control group, achieved sensitivity and specificity greater than 0.9. The sensitivity and specificity achieved when these same sets of parameters were applied to the test group are superimposed on the diagram.

Table 1 lists the proportion of parameters tested on the control group that achieved various true positive rates and a false positive rate of less than 0.1. There were 11 parameter combinations that yielded the same optimum result. These are listed in Table 2, together with their sensitivities and specificities when applied to each of the control and the test groups. When each of the 11 sets of optimum parameters from the control group were applied to the test group, the true positive rate of the system ranged from 0.98 to 0.99, and the false positive rate ranged from 0.12 to 0.06.

4 Discussion

It is important to be able to detect movements such as walking and postural transitions because they provide valuable information on the functional ability of the patient. On the other hand, it is not necessary to identify small movements, such as a slight readjustment of posture while sitting. There is always some movement when at rest (sitting, standing or lying), and the aim of this investigation was to find a robust method for consistently distinguishing between significant activity and resting states.

Sets of parameters that resulted in accurate discrimination showed a relationship between *th* and the product of *w* and *n*, and a relationship between *n* and *w*. When the data from all 26 subjects was analysed, all of the parameters with high sensitivity and specificity were contained within a band on a plot of $n \cdot w$ against *th* (Fig. 3). The band was described above and below by smoothly decreasing curves. However, not all sets of parameters inside this band yield good discrimination results. A second condition described a relationship between *n* and *w*. For each *th* and sensitivity, the range of *w* was linearly bounded above and below, as shown in Fig. 4.

The data for this study alternate periods of rest with periods of activity. When the system is working optimally, it should detect a period of rest followed by a period of activity, followed by another period of rest and so on. If the system is insufficiently sensitive, periods of activity are not detected, resulting in a rest-activity-rest sequence in the signal being classified as rest. If the system is completely insensitive, as occurs when the energy threshold *th* is set too high, the entire signal is classified as a single rest period. If the system is too sensitive, then parts of rest periods are classified as activity. In the extreme case, the entire signal is classified as a single period of activity. The result of either error (oversensitive or insensitive) is to reduce the ability of the system to discriminate between rest and activity. Thus, the energy threshold parameter *th* needs to be carefully chosen to provide a balance between sensitivity and specificity.

The median filter, which was applied to the signal to filter out noise, affects the energy contained in the signal. The longer the filter length *n*, the smoother the signal, and the more energy lost from the signal. Increasing the filter length made the signal in the activity periods become more like the signal in the rest periods for each subject, and this made the distinction between activity and rest more difficult (Fig. 5*a*). However, as *n* was increased

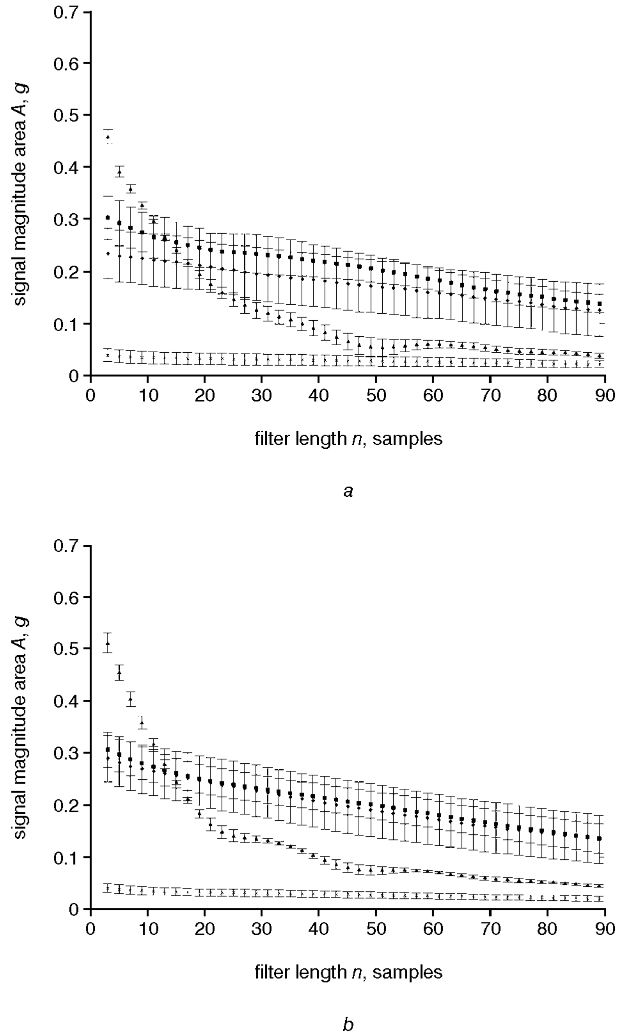

Fig. 5 *Effect of filter length n on signal magnitude area* A, *when w = 0.8 s. (a) Example of data for one subject. As n increases, activity segments more closely resemble non-activity. Points indicate mean A as function of n for each identified activity for one subject. Error bars represent standard deviation of these activities for this subject. (b) Data for all 26 subjects. As n increases, differences between subjects decrease, making overall classification better. Concurrently, however, differences between activity and non-activity are also decreasing. Points indicate mean A as function of n for each identified activity for all subjects. Error bars represent standard deviation over all subjects. (+) Sit-to-stand transition; (■) stand-to-sit transition; (▲) walking; (◇) at rest*

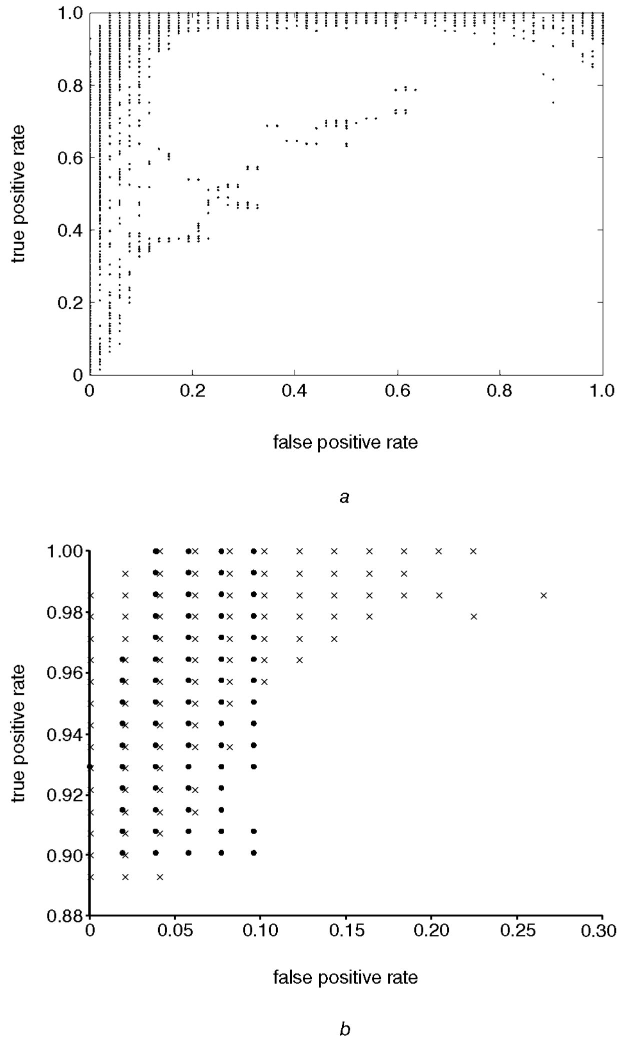

Fig. 6 *(a) ROC curve for combinations of parameters investigated, applied to subject control group (N = 13). Each point represents different combination of filter length n, window width* w *and threshold th. Note that there were multiple combinations of parameters achieving same sensitivity and specificity. Optimum parameters are those located at top left-hand corner of curve. (b) Detail of ROC curve for combinations of parameters that gave sensitivity and specificity better than 0.9 in (•) control group together with results of these same parameter sets when applied to (×) test group*

further, the accuracy of the system improved. This was owing to a second effect: the heavier smoothing made the activity periods more uniform across the different subjects, thus making it easier to distinguish between periods of activity and rest across multiple subjects (Fig. 5*b*). This effect peaked at around $n = 19$ samples. As n was increased still further, the accuracy of the system decreased as the ability to distinguish between activity and rest was lost.

Table 1 Proportion of sets of parameters that gave false positive rate less than 0.1 in control group (N = 13) as function of true positive rates

True positive rate greater than, or equal to	Percentage of sets of parameters
0.90	5.58
0.95	4.04
0.99	1.56
1.00	0.80

Ideally, the window width w would be exactly matched to the width of the activity being assessed. The timescale of human movements ranges from basic reaction times of 160–190 ms to simple movements (such as sit-to-stand transitions) that take around 1–3 s (WELFORD, 1980). Extended movements, such as walking, can occur over indefinite periods.

The variability in activity duration meant that it was not possible to find a window width w that matched the width of all activities. If w was substantially longer than the length of an activity, the window area contained more signal from the adjacent resting periods than from the activity. When the energy was averaged over the whole window, the result was not distinguishable from a window containing only a resting period. Given an activity of a particular duration, long windows encompassed both this activity and some rest period. This can cause misclassifications owing to the average activity in the window not exceeding the threshold. In this case, shortening the window width increased the proportion of activity in the window. Once the window width was shorter than the duration of the activity, then we would expect that this window would be correctly classified as containing activity. However, if the window width was too short, the system became more susceptible to false positives, as brief transients in the resting signal became interpreted as movement. Using a window width that was shorter than the shortest expected activity meant that at least half of the window contained dynamic activity when the window was placed over an activity and so increased the likelihood of it being detected as activity.

The best values for the window width w were found to be around 1 s (0.8–1.4 s) for this data set. The optimum value for w found in this investigation was consistent with both the timescale of human movement and the duration of the fastest activity measured in our sequence.

The TA signals are a linear combination of the gravitational acceleration component signal and the body movement component signal. The main limitation of this method occurs in the need to separate the two. (In the case of little or no body movement, the inclination of the body can be extracted directly from the signal following low-pass filtering, without the need for separation (HANSSON *et al.*, 2001).) This is usually done using a high-pass (or a low-pass) filter, with the low-pass component being regarded as the gravitational component, and the high-pass component being regarded as the body movement component (BOUTEN *et al.*, 1997; FAHRENBERG *et al.*, 1997; VELTINK *et al.*, 1995).

However, the two component signals have a frequency overlap. The gravitational component measured by each axis of the TA changes with the postural orientation of the subject, and the body movement ranges from 0 Hz, when there is no movement whatsoever, up to several hertz. This frequency overlap means that perfect separation between the two components cannot be achieved by filtering. However, in this study, it was found that using a high-pass filter with a cutoff of 0.25 Hz to separate the gravitational and body-movement accelerations allowed periods of rest and activity to be distinguished.

The optimum values of n, w and th identified by the algorithm are influenced to some extent by the 0.25 Hz cutoff separation filter, but good discrimination results were still achieved. We would anticipate that similar, but not identical, results would be achieved using a different separation filter.

It seems likely that this method would still be effective in detecting periods of activity, that the same relationships between parameters would hold, and that similar parameter values would be appropriate, although the optimum parameters would be expected to change as a function of subject cohort and, possibly, also as a function of the separation filter. For example, frail, ill or housebound patients are likely to move more slowly and generate lower accelerations, and so a lower-valued n may

Table 2 Optimum parameters for activity identification in control set (N = 13). True and false positive rates achieved for this set of parameters on control set were optimum, being 1.00 and 0.04, respectively. False positive rate of 0.04 in control set results corresponds to 2 rest periods out of all rest periods from all control subjects being incorrectly categorised as activity. In first instance, subject was fidgeting while standing; in second instance, subject shifted in seat while sitting. These were always misclassified. Results achieved when these sets of parameters were applied to test set data are also given

			Result on control set		Results on test set	
n, samples	*w*, s	*th*, $g \times 10^{-3}$	True positive rate	False positive rate	True positive rate	False positive rate
13	0.8	157.5	1	0.04	0.99	0.06
15	0.8	157.5	1	0.04	0.99	0.06
17	0.8	157.5	1	0.04	0.98	0.08
17	1.4	135	1	0.04	0.99	0.12
19	0.8	135	1	0.04	0.99	0.08
19	1.4	135	1	0.04	0.99	0.08
21	0.8	135	1	0.04	0.98	0.12
23	0.8	135	1	0.04	0.99	0.08
25	0.8	135	1	0.04	0.99	0.10
27	0.8	135	1	0.04	0.99	0.12
29	0.8	135	1	0.04	0.99	0.08

perform more effectively on such a cohort. This will be the subject of investigation in a future study.

5 Conclusions

We have shown that it is possible to distinguish between activity and resting states using a single waist-mounted triaxial accelerometer by means of a mean acceleration thresholding approach. We applied a median (low-pass) filter to the signal to remove noise spikes; we then analysed the signal on a window-by-window basis, comparing the mean acceleration contained in the windowed signal with a predetermined threshold. We found that the relationship between the product of the filter length and window width and the threshold value was most important in determining sets of parameters that would perform to the required specifications. The sets of parameters that yielded a sensitivity of 1 and a specificity greater than 0.96 when applied to data from a control group of 13 subjects were applied to data from a test group of subjects and resulted in a sensitivity greater than 0.98 and a specificity between 0.88 and 0.94. This shows the robustness of the technique for the separation of activities from rest, in the case of controlled movements. Future work will involve testing the system on data collected from frail and ill subjects in a home environment and on the classification of identified activities.

References

BOUTEN, C. V. C., KOEKKOEK, K. T. M., VERDUIN, M., KODDE, R., and JANSSEN, J. D. (1997): 'A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity', *IEEE Trans. Biomed. Eng.*, **44**, pp. 136–147

CHEN, K. Y., and SUN, M. (1997): 'Improving energy expenditure estimation by using a triaxial accelerometer', *J. Appl. Physiol.*, **83**, pp. 2112–2122

EVANS, A. L., DUNCAN, G., and GILCHRIST, W. (1991): 'Recording accelerations in body movements', *Med. Biol. Eng. Comput.*, **29**, pp. 102–104

FAHRENBERG, J., FOERSTER, F., SMEJA, M., and MÜLLER, W. (1997): 'Assessment of posture and motion by multichannel piezoresistive accelerometer recordings', *Psychophysiology*, **34**, pp. 607–612

FOERSTER, F., and FAHRENBERG, J. (2000): 'Motion pattern and posture: correctly assessed by calibrated accelerometers', *Behav. Res. Methods, Instrum. Comput.*, **32**, pp. 450–457

HANSSON, G.-Å., ASTERLAND, P., HOLMER N.-G., and SKERFVING, S. (2001): 'Validity and reliability of triaxial accelerometers for inclinometry in posture analysis', *Med. Biol. Eng. Comput.*, **39**, pp. 405–413

KERR, K. M., WHITE, J. A., BARR, D. A., and MOLLAN, R. A. B. (1997): 'Analysis of the sit-stand-sit movement cycle in normal subjects', *Clin. Biomech.*, **12**, pp. 236–245

MATHIE, M., BASILAKIS, J., and CELLER, B. G. (2001): 'A system for monitoring posture and physical activity using accelerometers'. 23rd Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society, Istanbul, Turkey.

MUNRO, B. J., STEELE, J. R., BASHFORD, G. M., RYAN, M., and BRITTEN, N. (1998): 'A kinematic and kinetic analysis of the sit-to-stand transfer using an ejector chair: implications for elderly rheumatoid arthritic patients', *J. Biomech.*, **31**, pp. 263–271

MURAKAMI, D., and MAKIKAWA, M. (1997): 'Ambulatory behavior map, physical activity and biosignal monitoring system', *Methods Inform. Med.*, **36**, pp. 360–363

SEKINE, M., TAMURA, T., TOGAWA, T., and FUKUI, Y. (2000): 'Classification of waist-acceleration signals in a continuous walking record', *Med. Eng. Phys.*, **22**, pp. 285–291

UITERWAAL, M., GLERUM, E. B. C., BUSSER, H. J., and VAN LUMMEL, R. C. (1998): 'Ambulatory monitoring of physical activity in working situations, a validation study', *J. Med Eng. Technol.*, **22**, pp. 168–172

VELTINK, P. H., BUSSMANN, H. B. J., DE VRIES, W., MARTENS, W. L. J., and VAN LUMMEL, R. C. (1996): 'Detection of static and dynamic activities using uniaxial accelerometers', *IEEE Trans. Rehabil. Eng.*, **4**, pp. 375–385

WELFORD, A. T. (1980): 'Reaction times' (Academic Press, London, New York).

WESTERTERP, K. R. (1999): *Int. J. Obesity*, **23**, pp. S45–S49

Authors' biographies

The authors are members of the Biomedical Systems Laboratory at the University of New South Wales, Australia. This laboratory is part of the School of Electrical Engineering and Telecommunications and combines expertise in biomedical engineering technologies with medical and health care experience to produce technical solutions for clinical applications. The laboratory was founded by, and is directed by Prof. B. Celler and Prof. N. Lovell. Dr A. Coster is a postdoctoral fellow, and Ms M. Mathie a doctoral student in the laboratory. One of the research interests that the laboratory has been pursuing for the last decade is home telecare with a particular focus on the aged. This research has included work on continuous ambulatory monitoring in the home using low-cost technologies.