# Implementation of a Real-Time Human Movement Classifier Using a Triaxial Accelerometer for Ambulatory Monitoring

Dean M. Karantonis, *Student Member, IEEE*, Michael R. Narayanan, Merryn Mathie, Nigel H. Lovell, *Senior Member, IEEE*, and Branko G. Celler, *Member, IEEE*

***Abstract*—The real-time monitoring of human movement can provide valuable information regarding an individual's degree of functional ability and general level of activity. This paper presents the implementation of a real-time classification system for the types of human movement associated with the data acquired from a single, waist-mounted triaxial accelerometer unit. The major advance proposed by the system is to perform the vast majority of signal processing onboard the wearable unit using embedded intelligence. In this way, the system distinguishes between periods of activity and rest, recognizes the postural orientation of the wearer, detects events such as walking and falls, and provides an estimation of metabolic energy expenditure. A laboratory-based trial involving six subjects was undertaken, with results indicating an overall accuracy of 90.8% across a series of 12 tasks (283 tests) involving a variety of movements related to normal daily activities. Distinction between activity and rest was performed without error; recognition of postural orientation was carried out with 94.1% accuracy, classification of walking was achieved with less certainty (83.3% accuracy), and detection of possible falls was made with 95.6% accuracy. Results demonstrate the feasibility of implementing an accelerometry-based, real-time movement classifier using embedded intelligence.**

***Index Terms*—Accelerometer, ambulatory monitoring, home telecare, movement classification.**

## I. Introduction

MORE RECENT progress in information communication technologies and sensor miniaturization have provided the foundation for the development of systems concerned with the remote supervision of home-based physiological monitoring. Limited funding for public health care services and an aging population are driving factors for reducing the reliance on institutionalized health care and moving toward the adoption of a home telecare paradigm.

The ability to record and classify the movements of an individual is essential when attempting to determine his or her degree of functional ability and general level of activity. Furthermore, the real-time monitoring of human movement can provide an automated system of supervising functional status over extended time periods. Accelerometry has been employed to facilitate such long-term monitoring using wearable sensor units [1], [2]. Previous studies have also demonstrated using similar units to recognize activities of daily living [3]–[5], in acquiring indirect measures of metabolic energy expenditure [1], [6]–[8], and in smart personal alarm systems to detect falls [7], [9]. Many of these systems [10]–[12] employ multiple accelerometer units placed at various bodily sites to assist in their detection of activities such as walking, ascending stairs, descending stairs, and cycling. The complexity of the algorithmic technique employed to perform movement classification also exhibits diversity, with researchers having investigated fixed-threshold methods [10], [11], [13], [14]; pattern recognition strategies [12]; conventional or fuzzy logic [15]; and artificial neural networks [9], [16].

This paper presents an implementation of a real-time classification system for the types of human movement associated with the data acquired from a single triaxial accelerometer (TA) unit worn at the hip. Our system distinguishes between periods of activity and rest, recognizes the postural orientation of the wearer, and detects events such as walking and falls to a reasonable degree of accuracy, as well as provides an estimation of metabolic energy expenditure. The algorithm developed was based on the classification framework presented by Mathie *et al.* [17], which involves a hierarchical binary structure where broad classifications are made in the top levels of the decision tree, and more detailed subclassifications are made at lower levels. Such a structure allowed the required classification decisions to be modularized and the associated algorithms to be tested independently.

Previous studies into ambulatory monitoring of human motion have involved the processing and analysis of raw accelerometer signals after transmission to a local computer [1], [2], [5]. Data processing was often performed offline, after a recording had been completed [1], [9]. The major advance proposed by the system under consideration is to perform the vast majority of such signal processing onboard the wearable unit using embedded intelligence. As such, the movement classification algorithm developed was strictly constrained by the limited memory and processing resources found in low-power microcontrollers. The benefits of such resource limitation, however, were to promote the longevity of battery life and to simplify the processing required on the receiver end, therefore enhancing the system's usability in a real-life

Manuscript received January 20, 2005; revised April 26, 2005.

D. M. Karantonis, M. R. Narayanan, M. Mathie, and N. H. Lovell are with the Graduate School of Biomedical Engineering, University of New South Wales, Sydney 2052, Australia (e-mail: z2272629@student.unsw.edu.au; z2275423@student.unsw.edu.au; merryn.horrocks@silverbrookresearch.com; N.Lovell@unsw.edu.au).

B. G. Celler is with the School of Electrical Engineering and Telecommunications, University of New South Wales, Sydney 2052, Australia (e-mail: B.Celler@unsw.edu.au).

Digital Object Identifier 10.1109/TITB.2005.856864

context. To further satisfy the usability requirements for a long-term monitoring environment, a single, waist-mounted wireless TA unit was employed, thus providing a practical prototype rather than simply a theoretical research tool. Now, although this study employed a local computer for data collection, the wearable unit is primarily designed for home telecare application in which the patient's daily activities are remotely monitored.

## II. Methods

### A. System Requirements

The guiding principle in the design of our system is to achieve real-time classification of movement signals in a small, wireless, low-power-consuming device. Processing of the TA output is to be performed by the microcontroller embedded onto the portable unit and information regarding the movement of the user transmitted to a local receiver unit before being forwarded to a local computer for display and evaluation.

With the knowledge that the memory and processing capabilities of the embedded microcontroller are greatly limited as compared with a PC, the range of movements that may be classified will face a similar limitation. Thus, in specifying the system requirements, caution was taken so any classifications involving computationally intensive tasks could be appropriately simplified during the development process without having to sacrifice the aim of onboard processing.

Nonetheless, a range of movements requiring classification by the system were identified as fundamental in providing for an adequate assessment of the activities performed by the user. Of critical importance to the system is the ability to detect fall events. In this way, our device acts as an automated personal alarm service, with the capability of alerting the appropriate monitoring staff when assistance may be required. Furthermore, it is desired that any signs of recovery following the fall be indicated by the presence of user activity together with their subsequent postural orientation. The rationale here is that the level of activity and posture of the user following a fall provide important information on the severity of the fall and the user's state of well-being. For this reason, the system is required to distinguish between periods of activity and rest, upright and lying postures, and lying subpostures—if the user is lying on his or her right or left side, on his or her back, or face down. In addition to fall detection, the system is required to recognize other types of activity, such as sitting and standing, and depending on hardware limitations, walking as well. A measure of metabolic energy expenditure will also be provided. Such information will provide valuable insight into the user's level of physical activity and general health status.

Low power consumption is a major feature to be incorporated into the system design. This requirement will enhance the system's usability by ensuring the longevity of battery life in the portable unit and relieving the user from the task of regularly recharging or replacing the battery. Performing the movement classification onboard means that the accelerometer output signal need not be transmitted, but rather only the classification information, which is of considerably less magnitude, requires transfer. As such, the duration of data transmission, and hence the power consumed by the transmitter module, are significantly reduced.

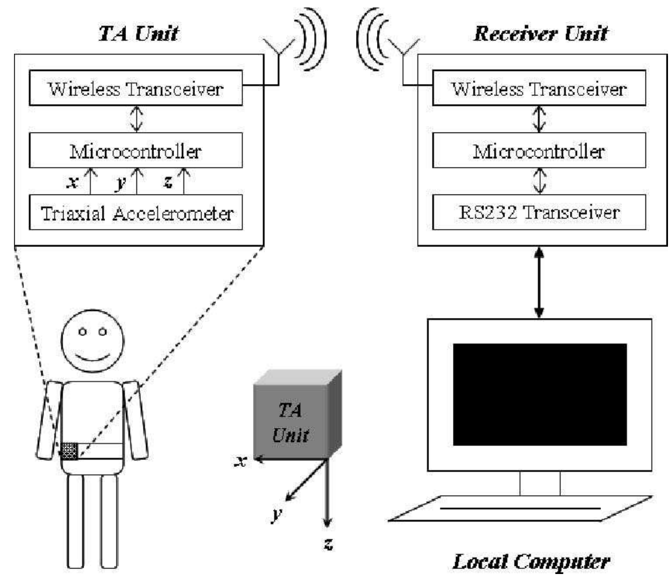


Fig. 1. Schematic diagram of the system. Processing of the triaxial accelerometer output is to be performed by the microcontroller embedded onto the portable TA unit and information regarding the movement of the user transmitted to a local receiver unit before being forwarded to a local computer for display and evaluation. The orientation of the x-, y-, and z-axes in relation to the TA unit in its upright position is also illustrated.

### B. Instrumentation

Measurements of human movement are performed using a small wireless TA unit of dimension $22 \times 50 \times 50$ mm (excluding the antenna) and weight 51 g. At the heart of the unit are two orthogonally mounted dual axis accelerometers (MXR7210GL, MEMSIC, Inc., North Andover, MA) with a range of $\pm 10\ g$, a noise level of 5.06 m$g$ rms and a selected bandwidth of approximately 100 Hz. This device was chosen for its suitability in acquiring accelerations due to both bodily motion and gravity.

Of similar importance is the microcontroller (MSP430F149, Texas Instruments, Dallas, TX) whose ultralow power consumption and versatile interfacing capabilities ensure a minimal consumption of current, while providing effective control over the system's components. The clock signal of the processor is limited to a maximum of approximately 6 MHz (when active), and the onchip RAM provides 2 KB of data memory—factors that impose various constraints on the system's capabilities. Output signals from the accelerometers are sampled by the microcontroller via its ADC at a rate of 45 Hz. These digitized data are then subject to the classification algorithm (discussed later in this article) embedded in the flash memory of the microcontroller. The relevant data are then wirelessly transmitted from the TA unit to a local receiver unit and forwarded to a PC for the recording and display of classified events (Fig. 1).

Wireless communication in our system is facilitated by ZigBee-compliant transceiver modules (CC2420EM, Chipcon, Oslo, Norway). The emergence of ZigBee (specified in the IEEE 802.15.4 standard) and its associated hardware has provided a low data rate and a low-power-consuming alternative to other wireless protocols. In particular, the CC2420 is designed for low-power and low-voltage wireless applications operating in the 2.4-GHz ISM band with an effective data rate of 250 kb/s. With a sleep mode power consumption of approximately 1 uA, the use of ZigBee devices will serve to maximize battery life. Furthermore, data transfer between transceivers has a practical range of 20 to 75 m (depending on obstacles such as walls), which suffices for most home-based environments.

### *C. Real-Time Constraints*

To develop a movement classifier for an onboard real-time application, various considerations need to be made to satisfy the following constraints

1) There is no knowledge of future events.
2) The amount of data that may be buffered is limited (1 s worth of data samples in our system).
3) The amount of processing time available is limited—it must keep up with the rate of data acquisition.

The first constraint implies that methods of movement classification that involve examining future states of motion cannot be performed. For example, classification of a sit-to-stand transition relies on knowledge of both the preceding sitting state, as well as the following standing state, to ensure an accurate decision has been made. As such, the embedded algorithm is inherently limited in its ability to recognize movements in which subsequent motion states are essential for accurate classification.

In our application, limited memory space (2 KB of RAM on the MSP430F149) has meant that only 1 s worth of data samples will be buffered. This hardware constraint affects the system's ability to detect movements whose recognition requires longer sets of data to be processed. For example, the detection of cyclic upright activity characteristic of walking requires a fast fourier transform (FFT) to be applied to at least 3 s of data to obtain a magnitude spectrum of the signal. Because more than 3 s worth of data cannot be buffered, we will not be able to verify (on the TA unit) if an activity is actually walking.

With regard to the third constraint, we have attempted to avoid any types of processing that consume significant amounts of time. For example, to avoid the division required for the calculation of mean values that are subsequently compared with some threshold, we have instead multiplied the thresholds by the appropriate number and used the sum of the values (as opposed to their mean) for the comparison. The calculation of an FFT for the determination of cyclic activity (as mentioned previously) was also considered an exorbitant cost and was moved to the local computer for execution, necessitating the transmission of z-axis output to the receiver in the case, where upright activity is detected. Determining the various types of transition movements (e.g., sit to stand or lying to sit) has in previous studies involved employing either a neural network [9] or a rule-based expert system [18], which requires significant processing demands and prior acquisition of training data.

### *D. Classification Algorithm*

*1) Preliminary Processing on the TA Unit:* Due to the limited buffering capacity of the onboard microcontroller, a *second-by-second* classification scheme was adopted, whereby movement is classified based on the data collected over a 1 s interval. An evaluation of the most suitable size for such a classification window was presented in [18], where it was determined that a window of around 1 s (0.8–1.4 s) was optimal.

Because essentially all measured body movements are contained within frequency components below 20 Hz (indeed, even in gait, 99% of the energy is contained below 15 Hz [19]), each axis of the onboard accelerometers is sampled at 45 Hz. As such, a timer interrupt routine is called at intervals corresponding to the sampling rate, during which accelerometer data are sampled via the analog-to-digital converter (ADC), and an update of the variables required for motion classification is performed. The major processing that must be performed on the raw data after each sample is acquired includes two steps. The first step is *median filtering*, whereby a median filter with $n = 3$ is applied to the raw digitized signal to remove any abnormal noise spikes produced by the accelerometers. The output of this filter is used in the calculations of all decisions. The second step is *low pass filtering* (LPF),where custom third-order elliptical infinite impulse response (IIR) filter with cut-off frequency at 0.25 Hz (0.01 dB passband ripple; stopband at $-100$ dB) is employed to separate the acceleration components due to gravity (GA) and bodily motion (BA) from the median-filtered $(n = 3)$ signal. These two components are linearly combined in the TA signal, and because they overlap both in time and in frequency, they cannot be easily separated. However, LPF allows approximations to the two components to be made. The GA component is taken directly from the result of applying the LPF to the median-filtered signal, whereas the BA component is taken as the difference between the original signal and the GA component. The BA component is used when distinguishing activity from rest because in this case, we are not interested in the effects of gravity. The GA component provides information on the tilt angle of the TA device, which can be used to make inferences about the postural orientation of a subject.

When 1 s has elapsed, the updated variables are used in the classification of the TA signal. A classification keyword is assigned to each second of time, according to the algorithm shown in Fig. 2. This keyword, together with information regarding metabolic energy expenditure, is transmitted to the local computer for analysis and display.

*2) Activity and Rest:* To distinguish between periods of user activity and rest, a measure that includes the effect of signal variations in all three axes is required. A suitable measure, which is discussed in several previous studies [1], [18], is the normalized signal magnitude area (SMA). Defined in (1), the SMA was used as the basis for identifying periods of activity:

$$\mathrm{SMA} = \frac{1}{t}\left(\int_0^t |x(t)|dt + \int_0^t |y(t)|dt + \int_0^t |z(t)|dt\right) \quad (1)$$

where $x(t), y(t)$, and $z(t)$ refer to the body components of the x-, y-, and z-axis samples, respectively. Calculation of this parameter is performed by summing each sampled value progressively (i.e., following the digitization of each accelerometer sample) over a 1-s interval. An appropriate threshold value (*th* in Fig. 2) was determined via testing-for an SMA value above

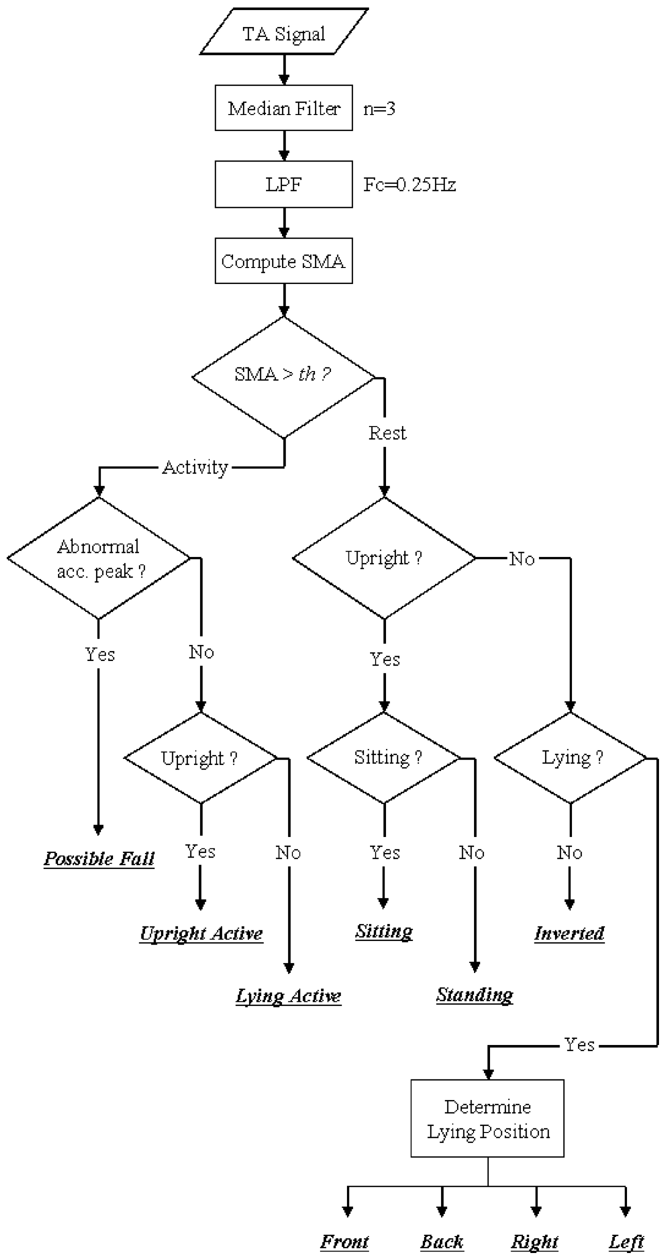


Fig. 2. Real-time movement classification algorithm. This flowchart displays the major components of the algorithm embedded onto the TA unit's microcontroller. Each second, a suitable classification keyword (underlined) is chosen to describe the type of movement associated with this time period. Signal magnitude area (SMA) is defined in (1).

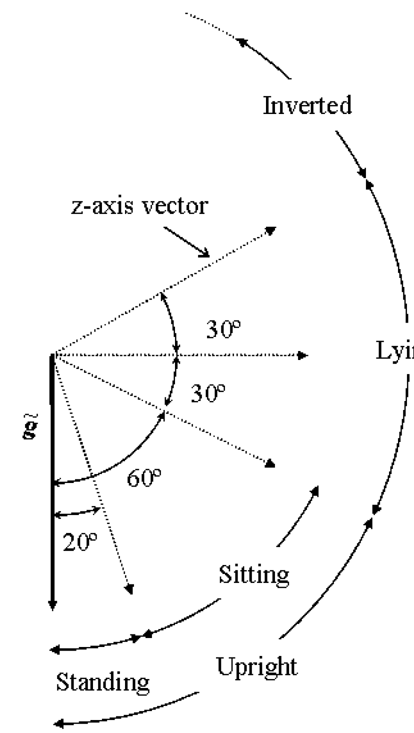


Fig. 3. Method for determining the postural orientation of the user. The tilt angle ($\Phi$) is the angle between the z-axis vector and the gravitational vector $\boldsymbol{g}$ and is calculated when considering only the gravitational component of the triaxial accelerometer output signal.

the threshold, activity was deemed to have occurred, and values below the threshold mean the user is in a resting state.

*3) Postural Orientation:* Postural orientation refers to the relative tilt of the body in space. In our application, we have aimed to provide a distinction between the upright postures of sitting and standing, as well as the various subpostures associated with lying. When determining postural orientation, only the gravitational component of the TA signal is used because we are dealing with static accelerations where tilt is measured.

The basic technique employed to perform such classifications relies on evaluating the user's tilt angle ($\Phi$), defined as the angle between the positive z-axis and the gravitational vector $g$ by the relation:

$$\Phi = \arccos(z). \tag{2}$$

An overview of how the tilt angle relates to the various postural orientations is illustrated in Fig. 3. If the patient's tilt angle is 0 to 60 °, it is classified as *upright*, whereas values of 60 to 120 ° indicate a *lying* posture; any greater a tilt angle and the user is classified as *inverted*. Because we employ fixed thresholds to determine postural orientation, we need not calculate the exact tilt angle value in degrees, but rather we only need to perform comparisons of the z-axis data with equivalent thresholds of the same units.

The technique used to distinguish sitting and standing is a highly simplified version compared with other studies that have used neural networks, rule-based classifiers, and/or knowledge of future events. However, because such methods are infeasible due to the system constraints for the TA unit, we have been forced to use this simpler technique based on tilt angle differences. Mathie [18] determined that a tilt angle between 20 and 60 ° is definitely sitting, and angles of 0 to 20 ° may be either sitting or standing, depending on various other parameters. Thus, in our scheme, sitting and standing may sometimes be incorrectly classified.

When the patient is lying down, their orientation is divided into the categories of right side (*right*), left side (*left*), lying face down (*front*), or lying on their back (*back*), as shown in Fig. 4. The x- and y-axis labels indicate the direction of positive

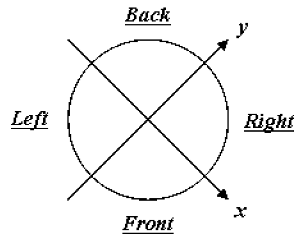


Fig. 4. Classification of lying postures. The x- and y-axis labels indicate the direction of positive acceleration relative to the wearer, given that they are facing the *back* label. The TA unit is mounted at the right anterior iliac crest of the pelvis at an angle of 45 ° to the frontal plane.

acceleration relative to the patient, given that they are facing the back label. It should be noted here that the TA unit is mounted at the right anterior iliac crest of the pelvis at an angle of 45 ° to the frontal plane.

*4) Falls:* Falls are said to have occurred if at least two consecutive peaks in the signal magnitude vector (SVM) above a defined threshold are recorded. SVM [defined in (3)] essentially provides a measure of the degree of movement intensity, as derived from the TA output signal. This fall detection technique and the associated threshold are described in [18]. The threshold was determined by considering accelerations in SVM and in the x-, y-, and z-axes, whereas falls and stumbles were simulated. A review of these test results identified the most suitable parameter to be SVM at a threshold of 1.8 g, and this value was justified through formal patient studies. When such a fall event occurs, a classification of *possible fall* is assigned to the current time period, and the system operator will be notified of a potential safety threat. The operator will receive the fall event data together with the complete signal for 60 s following the event, via transmission to the receiver unit. In this way, the system operator can more precisely determine if the wearer has actually fallen and whether he or she has recovered. Movement classifications are performed as per usual in this period:

$$\mathrm{SVM} = \sqrt{x_i^2 + y_i^2 + z_i^2} \tag{3}$$

where $\boldsymbol{x_i}$ is the $i$th sample of the x-axis signal (similarly for $\boldsymbol{y_i}$ and $\boldsymbol{z_i}$).

An attempt was made at automating the detection of a recovery by the wearer following the possible fall. Typically, a fall event involves a sequence of classifications such as *possible fall*, *lying active*, *lying active*, *front*, *front*, and *front*. If the wearer has injured themselves as a result and remains motionless for the following minute, then third-party assistance may be urgently required. As such, if the system recognizes that no activity has occurred during this 60 s postfall interval (ignoring the first 5 s due to potential residual movement relating to the fall), then the alert is upgraded to a *fall*, and further measures taken to ensure the operator is made aware of the situation. If, however, there is activity detected in the postfall period, then the event is left marked as a *possible fall*.

*5) Walking:* As mentioned earlier, the task of performing signal processing for the recognition of walking was deemed infeasible for the TA unit. As a solution to this problem, when a situation is reached where there is *activity* in which the patient is *upright*, the z-axis signal data will be transmitted to the receiver unit. In this way, an opportunity exists to apply various signal processing techniques to the raw accelerometer output that will clarify whether the activity is indeed *walking* or some other type of activity.

In the current system, signal data acquired by the receiver that is classified as *upright active* are buffered. If less than four consecutive such classifications are received, then no further processing is performed on the data. This decision was made in accordance with the walking algorithm presented by Mathie [18]. If a longer sequence of upright activity presents itself, then the z-axis data associated with this movement event are buffered and subsequently subject to a highpass filter (HPF) to obtain the body component of the signal. Even though the body component is derived on the TA unit, better results were obtained when applying an HPF on the local computer because a filter of much higher order could be implemented. The HPF employed was a seventh-order IIR elliptic filter with cut-off frequency of 0.25 Hz (0.01 dB ripple in passband; $-100$ dB in the stopband). Following application of the HPF, an FFT of the z-axis data is employed to obtain its magnitude spectrum and to determine whether there is a frequency peak in the expected range of walking frequencies (0.7–3.0 Hz) [18]. This method is used to determine if the motion is cyclic, and if a suitable frequency peak is found, this is identified as the step rate, and the motion is reclassified from *upright active* to *walking*.

*6) Metabolic Energy Expenditure:* A typical model used for the estimation of metabolic energy expenditure (EE) in accelerometry systems is its linear relationship with the SMA of the body component accelerations. This relationship has been demonstrated with triaxial accelerometers in several studies [1], [8]. Furthermore, in comparing 11 estimators of EE, Bouten *et al.* [20] found that the SMA in the anteroposterior direction was the best estimator during walking, whereas the SMA of the combined triaxial accelerations proved most accurate for a range of daily activities. However, the accuracy of such SMA-based estimations is greatly variable under free-living conditions, primarily due to the inability of a waist-mounted TA unit to detect the energy costs associated with movement of the upper limbs. In studies of EE estimation during daily activities, Bouten *et al.* [1] reported a correlation coefficient of 0.89 for 13 subjects, whereas Hendelman *et al.* [21] reported correlations of only 0.59 to 0.62.

In addition to movement classification, our system also utilizes the SMA-based EE estimation model to provide an indirect measure of user EE. The SMA calculated in the TA unit is a triaxial SMA [as in (1)], and it is this value that is transmitted along with the classification keyword to the receiver each second. There is, however, no attempt made at developing and implementing a regression model to ascertain the actual EE (in Joules) from the related SMA variable. We have simply provided the SMA parameter (in units of $g$) so an approximate comparison of the energy consumed in successive events can be made.

*7) Data Transmission:* As mentioned, classification of the TA output is performed once per second, based on the parameters calculated during the preceding 1-s interval, the result of which is a classification keyword (as shown in Fig. 2) and a value of EE estimation (the SMA value). With the exception of intervals in which the *upright active* or *possible fall* keywords are assigned, a data packet composed of the keyword (1 byte) and the SMA value (4 bytes) is sent to the receiver immediately after the classification algorithm has completed its execution. When the interval is classified as *upright active*, the transmitted data packet is composed of the keyword, the SMA value, and the median-filtered z-axis data samples (90 bytes). In this case, further processing is performed on the local computer as discussed in Section V. After a *possible fall* is detected for an interval, every data packet sent to the receiver for the next 60 s is composed of the keyword, the SMA value, and the median-filtered x-, y-, and z-axis data samples (90 bytes per axis). Additional processing is then performed on the local computer as discussed in Section II-D4.

Depending on the desired application and level of classification detail required, one could run the system such that only the classification keyword and SMA value are ever transmitted, and no further processing is completed by the local computer. Such a scenario would mean that a purely onboard real-time algorithm would be fulfilled, with power consumption kept to a minimum. Of course, this approach would mean that walking could no longer be definitively classified, and detecting recovery from a fall would be performed manually by the system operator.

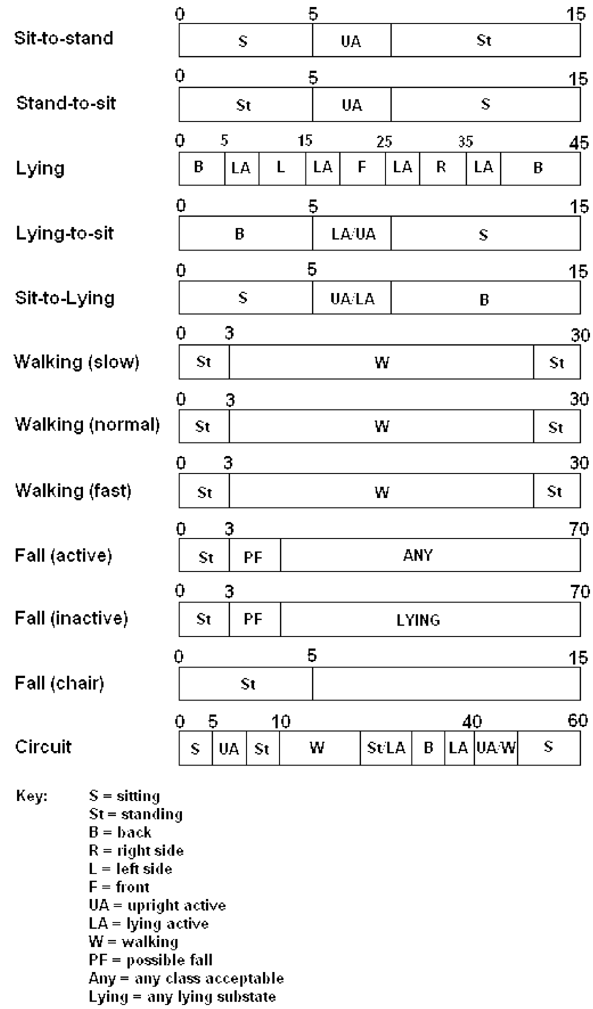


Fig. 5. Expected sequence of movement classifications obtained for each experimental task. The timing of each expected change in classification is indicated in seconds above each timing bar. Many instances allow for two or more classification keywords to be assigned in the same time period.

## *E. Trial Experiment Protocol*

A set of experiments were designed to test the accuracy of the real-time movement classification algorithm, ensuring all paths of the classifier flowchart (Fig. 2) were adequately evaluated. The laboratory-based tests were performed with six healthy subjects (five of ages 22 to 23 and one of age 60), with each performing a set of 12 different directed tasks as described in Table I. The fall and circuit tasks were repeated three times, whereas all other tasks were performed five times per subject. The TA unit is mounted at the right anterior iliac crest of the pelvis at an angle of 45$^\circ$ to the frontal plane and worn on the subjects' belt. During these trials, all the median-filtered TA output (together with the usual classification keyword and EE estimate) was transmitted to the local computer for storage and display and to aid in the process of data analysis.

For the walking tasks, the subject was asked to count the number of steps taken so an assessment of accuracy could be made for the computed step rate. It should be noted here that the chair used for certain tasks possessed four legs with a solid metal frame and limited cushioning. The mattress used for falls and for lying was approximately 25 cm thick with little spring and was placed directly onto the floor.

Each task described in Table I is composed of a number of separate movements. As such, we were able to specify the expected sequence of movement classifications received for each task (Fig. 5) and use this as a template with which to judge the experimental result. The overall accuracy of each task is calculated as the percentage of correct classifications made ($\pm$ standard deviation), taken across the six subjects. Total accuracy for all tasks is determined similarly, with the standard deviation calculated from the total accuracies (i.e., including all tasks) of each subject.

# III. RESULTS

## *A. Algorithm Performance*

An evaluation of the test results involved comparing the subject's actual movements with the movements classified by the system. If the classified movement actually occurred during the appropriate time interval (as indicated in Fig. 5), then this outcome was recorded as a correct classification; if a particular movement produced an unexpected classification, then this outcome was considered an incorrect classification. In this way, the accuracy of the system in correctly classifying the movements of the tests was measured (see Table II).

Viewing the results as a whole, the distinction between activity and rest was correctly made in all tests $(n = 283)$.

TABLE I
DESCRIPTION OF ACTIVITIES PERFORMED BY EACH SUBJECT DURING TRIALS OF REAL-TIME MOVEMENT CLASSIFICATION SYSTEM

| **Task** | **Description** | **Duration (s)** |
|---|---|---|
| *Sit-to-stand* | From an initially seated position, the subject stands up and remains standing. | 15 |
| *Stand-to-sit* | From an initially standing position, the subject sits down and remains seated. | 15 |
| *Lying* | The subject lies down on a mattress initially on their back. After 5s, they proceed to turn onto their left side, front and right side in succession at 10s intervals. | 45 |
| *Lying-to-sit* | Initially lying on their back on the mattress, the subject sits up and remains in this position. | 15 |
| *Sit-to-lying* | Initially sitting up on the mattress, the subject lies down on their back and remains in this position. | 15 |
| *Walking (slow)* | The subject walks for 15m at a pace reasonably slower than their normal. | 30 |
| *Walking (normal)* | The subject walks for 15m at their normal pace. | 30 |
| *Walking (fast)* | The subject walks for 15m at a pace reasonably faster than their normal. | 30 |
| *Fall (active)* | Initially standing, the subject falls onto the mattress in an unspecified manner. They simulate a recovery from the fall by performing some activity within the 60s following the fall. | 70 |
| *Fall (inactive)* | Initially standing, the subject falls onto the mattress in an unspecified manner. They remain inactive for the 60s following the fall and for the remainder of the test. | 70 |
| *Fall (chair)* | Initially standing, the subject sits down into a chair by falling into it. | 15 |
| *Circuit* | Initially seated, the subject stands after 5s, begins a 10m walk at 10s before lying down on their back. At 40s the subject rises, walks 3m to a chair and remains seated. | 60 |

TABLE II
RESULTS OF TRIAL EXPERIMENTS

| **Movement Class** | **Task** | **No. Tests** | **Overall Correct** | **Overall Incorrect** | **Accuracy (%)** |
|---|---|---|---|---|---|
| *Postural Orientation* | *Sit-to-stand* | 30 | 29 | 1 | 96.7±8.2 |
| | *Stand-to-sit* | 29 | 29 | 0 | 100±0.0 |
| | *Lying* | 27 | 20 | 7 | 74.1±39.3 |
| | *Lying-to-sit* | 25 | 25 | 0 | 100±0.0 |
| | *Sit-to-lying* | 24 | 24 | 0 | 100±0.0 |
| *Walking* | *Walking (slow)* | 30 | 19 | 11 | 63.3±44.6 |
| | *Walking (normal)* | 30 | 27 | 3 | 90.0±24.5 |
| | *Walking (fast)* | 30 | 29 | 1 | 96.7±8.2 |
| *Falls* | *Fall (active)* | 15 | 15 | 0 | 100±0.0 |
| | *Fall (inactive)* | 15 | 15 | 0 | 100±0.0 |
| | *Fall (chair)* | 15 | 13 | 2 | 86.7±18.3 |
| | *Circuit* | 13 | 12 | 1 | 92.3±14.9 |
| | ***Total*** | 283 | 257 | 26 | 90.8±6.4 |

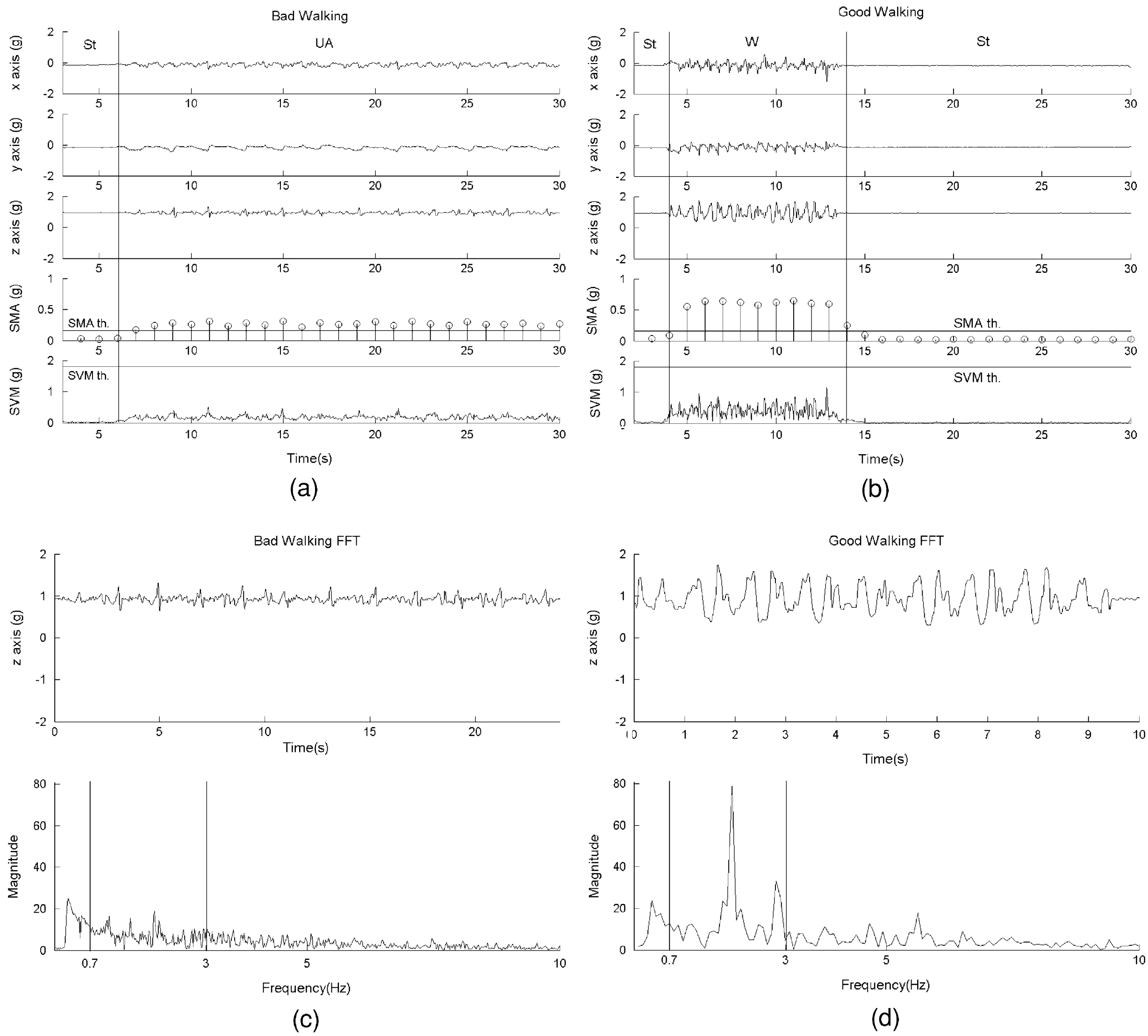


Fig. 6. Comparison of slow- and normal-paced walking. The magnitude of z-axis oscillations was significantly smaller in (a) slow walking output as compared with (b) ambulation at normal speed. Because relatively little pressure is placed on the feet during slow walking, the acceleration peaks present in the z-axis output are not recognized as steps. The corresponding magnitude spectrum of slow walking (c) was thus unable to produce a frequency peak of sufficient size, such that the movement could be classified as walking. The spectrum for normal walking is given in (d), in which the frequency peak is clearly visible at around 1.3 Hz. (a) and (b) are segmented according to the classifications that were made, with abbreviations for the classification keywords given as in Fig. 5. The SMA threshold (*SMA th.*) indicated separates rest periods from activity, whereas the SVM threshold (*SVM th.*) indicates a fall event if exceeded for two consecutive samples. Note also the frequency band of 0.7 to 3.0 Hz indicated in (c) and (d), which corresponds to the expected range of walking frequencies.

Both the *sit-to-stand* and *stand-to-sit* tasks were classified with only one error between them, which involved the problem of the tilt angle fluctuating between the sitting and the standing threshold. The *lying* task was classified with $74.1(\pm 39.3)\%$ accuracy. Inconsistencies with this test were due to the TA unit slipping along the belt to which it was attached, changing its position from $45^\circ$ relative to the frontal plane, to perpendicular with the frontal plane. A number of subjects also turned quite vigorously between lying postures, causing a *possible fall* to be registered on several occasions. Transitions between lying and sitting were classified without error. Overall, the set of tasks associated with postural orientation were carried out with $94.1(\pm 4.9)\%$ accuracy.

Of the walking tests, normal and fast-paced walking were classified with at least 90% accuracy; however, there were problems with the recognition of slow-paced walking. As illustrated in Fig. 6, the magnitude of z-axis oscillations were significantly smaller in slow walking output as compared with ambulation at normal speed. Because relatively little pressure is placed on the feet during slow walking, the acceleration peaks present in the z-axis output are not recognized as steps. The corresponding magnitude spectrum was thus unable to produce a frequency peak of sufficient size such that the movement could be classified as walking. As a group, the walking tasks were classified with $83.3(\pm 23.8)\%$ accuracy. Of the tests in which walking was correctly classified, all but two recorded an accurate step rate.

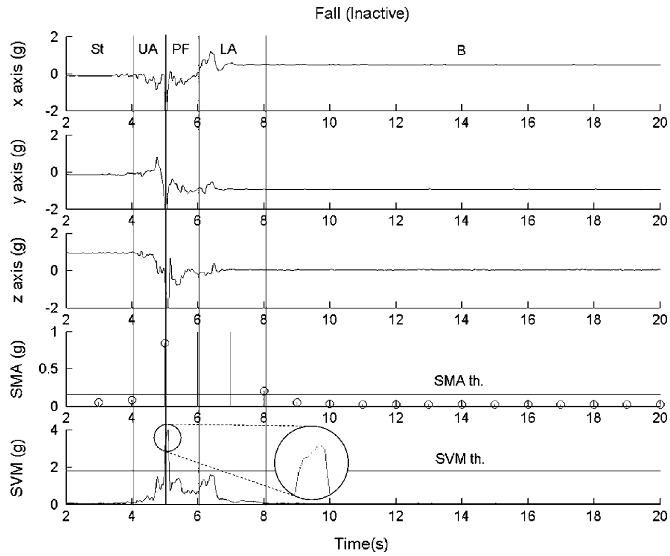


Fig. 7. Example output of a simulated fall in which the subject remained inactive following the fall event. The figure is segmented according to the classifications that were made, with abbreviations for the classification keywords given as in Fig. 5. The SMA threshold (*SMA th.*) indicated separates rest periods from activity, whereas the SVM threshold (*SVM th.*) indicates a fall event if exceeded for two consecutive samples. At the point where several samples exceed the SVM threshold, an enlargement of the plot area circled is shown for clarification.

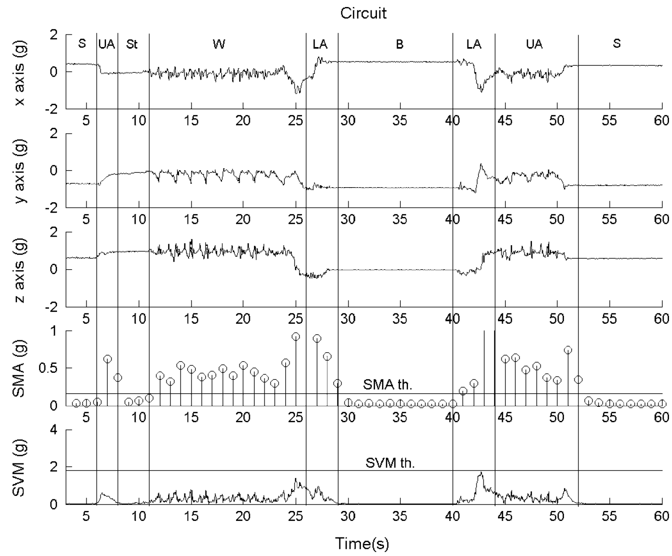


Fig. 8. Example TA output of the circuit task, in which a series of regular daily activities was performed. The figure is segmented according to the classifications that were made, with abbreviations for the classification keywords given as in Fig. 5. The SMA threshold (*SMA th.*) indicated separates rest periods from activity, whereas the SVM threshold (*SVM th.*) indicates a fall event if exceeded for two consecutive samples.

All falls onto the mattress were correctly detected as *possible falls*. Those falls in which the subject remained inactive following the fall event (as shown in Fig. 7) were correctly identified as events where further assistance was required, and they subsequently had their classification upgraded to a *fall*. When a recovery was attempted by the subject, in which he or she either moved around while lying or actually stood up and walked to a nearby seat, the event remained classified as a *possible fall* without emergency assistance deemed as necessary.

With regard to the task of falling into a chair, only two such tests were not classified as a *possible fall*. This scenario raises some obvious questions regarding the distinction between falls in which harm may be incurred and others in which the user has simply sat heavily into his or her chair or fallen into bed. When falling into the chair, the system detects a *possible fall* event followed by a series of inactive sitting states, and thus indicates that emergency assistance is required. However, the output of these different types of falls is essentially indistinguishable, and because the system cannot sense the subject's level of pain, it must assume the detected fall has potentially harmed the user. Overall, the fall tasks were classified with $95.6(\pm 6.1)\%$ accuracy.

The results of the *circuit* task, in which a more natural sequence of common movements was tested, were quite promising [$92.3(\pm 14.9)\%$ accuracy]. An example of the output from this task is given in Fig. 8. Only one such test was deemed to contain an incorrect classification, and this was due to the detection of a possible fall while a subject was in the process of lying down on the mattress. Of particular importance was that the first period of walking in the circuit was detected in all test cases.

TABLE III
INTERRUPT SERVICING DURATION FOR VARIOUS STATES OF TA UNIT

| ***State of TA unit*** | ***Interrupt Servicing Time (ms)*** |
|---|---|
| 1. Sampling ADC + update of variables | 4.56 |
| 2. Transmitting data (classification + EE estimation) | 10.0 |
| 3. Transmitting data (classification + EE estimation + z-axis accelerometer output) | 18.8 |
| 4. Transmitting data (classification + EE estimation + all accelerometer output) | 40.8 |

## *B. Instrumentation Performance*

When developing the code for execution on the MSP430, careful consideration was given to the setting of the microcontroller and CC2420 chip into low power modes. As described earlier, the microcontroller is active—consuming about 420 uA—only when servicing the interrupt routine and is in low power mode 3 (LPM3)—consuming about 1.6 uA—at all other times. The timing information for the interrupt servicing routine is given in Table III. When the onboard code is executing, the clock frequency was selected via software to be 4.3 MHz. Taking an average value for the typical code execution sequences, the millions of instructions per second (MIPS) rate was estimated at 1.034.

As the time between interrupt service routine calls is 22.2 ms (the sampling rate is 45 Hz), it is clear that the MSP430 is in LPM3 for the vast majority of time, and thus is a relatively minor consumer of power in our system. Concerning the CC2420 chip on the TA unit, it remains in shutdown mode, consuming only 1 $\mu$A of current, unless transmitting a data packet. Worthy of note here is the current consumption of the accelerometers, which is typically 4.0 mA. Because the accelerometers

TABLE IV
CURRENT CONSUMPTION FOR VARIOUS STATES OF TA UNIT

| ***State of TA unit*** | ***Current Consumption (mA)*** |
|---|---|
| 1. Idle state | 7.91 |
| 2. Sampling ADC + update of variables | 8.31 |
| 3. Transmitting data | 29.8 |

are always operational (even in the idle state) and continuously supplied with this current, they are the major source of power consumption. Measurements of current consumption in the various states of operation were made and are given in Table IV. Given these values, and the fact that the TA unit was powered by 3 AAA batteries of approximately 1100-mAh capacity each, the battery life of the TA unit is estimated to be 407.3 h or 17 days.

The wireless communications functioned correctly up to a distance of roughly 35 m, which should suffice for most home environments. The presence of noise in data transmission was of small significance, occurring in only a few experimental tests; when present, however, the classification was unaffected.

## IV. DISCUSSION

Testing of the system revealed its ability to distinguish between activity and rest and to recognize sitting, standing, and lying postures with a high degree of accuracy. The ability to detect slow-paced walking was somewhat constrained but still produced acceptable results. Overall, however, the real-time classification algorithm employed was able to provide a reasonably detailed illustration of the movement performed by the wearer.

Despite the inherent limitations of the system, the experimental results achieved suggest that the implementation of a real-time movement classifier is indeed feasible. At the time of development, the chosen microcontroller (MSP430F149) possessed the most memory (2 K of RAM) and fastest processor speeds (up to 6 MHz) in the ultralow power range of these devices. Despite this, the size of memory constrained our ability to enhance or add functionality onboard the TA unit. The LPF implemented to separate the gravitational and body components of the accelerometer signals was constrained to a third-order elliptic IIR filter with a relatively slow roll-off in its frequency response; even though a cut-off frequency of 0.25 Hz was specified, the response did not decline to $-50$ dB until 2.8 Hz. Although these filtering constraints did not affect the correct detection of activity and rest, a higher-order filter with improved frequency response would clearly be desirable.

Classification of walking was another area clearly limited by memory availability, requiring the associated FFT calculation to be executed on the local computer. Transmission of the accelerometer data to the receiver in this scenario not only required extra processing time and battery power, but it also acted against the guiding rule of performing all classifications onboard the TA unit. A greater memory capacity would allow the FFT to be computed on the TA unit, reducing the need for surplus transmissions and lowering power consumption.

Power consumption could also undergo a major reduction if the system incorporated accelerometers based on optical technology. Such accelerometers possess a supply current that is a fraction of those employed in the present system; whereas the MEMSIC accelerometers consume 4 mA, optical-based accelerometers from analog devices, for instance, typically consume only 0.4 mA. Thus, the estimate of battery life for the TA unit may increase from 17 days to several months. Unfortunately, their limited availability prevented their use in the instrumentation developed for this study.

Processor speed did not prove to be a constraint in our system development; however, this was simply because the memory constraint imposed itself first. If we consider the scenario where memory was sufficiently large, then it would be possible to implement a higher-order LPF and to complete the task of classifying walking on the TA unit. Processor speed would, however, become an issue if more elaborate processing techniques were employed to achieve more accurate and/or detailed classifications, such as using a neural network to classify fall events or stand-to-sit transitions. New microcontrollers (e.g., MSP430F1611) coming onto the market in the near future will possess larger memory capacities (10 K RAM for the MSP430F1611) and may allow these functionality enhancements to be implemented.

The laboratory studies conducted involved healthy participants, as opposed to the elderly and chronically ill individuals for whom this system is designed to aid. As such, further experimentation is required to evaluate the performance of the movement classification algorithm on this target group. However, in terms of verifying the feasibility of the system from a technical viewpoint, the study performed is sufficient.

An issue requiring further examination is in developing appropriate methods to deal with possible fall events and detection of recoveries from these events. Although attempts were made at automating recovery detection, testing of simulated fall events revealed a weakness in these attempts. Whether the subject performed a fall onto a mattress or into a chair and then remained inactive, the output was essentially indistinguishable. In either case, the user may have injured him- or herself, may have simply retired to bed or the couch, or the TA unit may have fallen off. A method of resolving this problem would clearly be of great value. One proposal might be to have user input into the system, whereby if a possible fall is detected, the patient is notified (perhaps via sound), and if they fail to indicate that this is a false alarm (perhaps by pressing a button), then third-party assistance is required. As such, this system would act as a reliable personal alarm.

In the current system, the local computer receives one classification keyword per second from the TA unit. Further analysis of this sequence of keywords is limited to automatic fall recovery detection and the recognition of walking; however, the system could be improved by extending such analysis. For example, if the sequence: *sitting* ... *sitting*, *upright active* ... *upright active*, *standing* ... *standing*, was received, then the *upright active* event in the middle might be reclassified in greater detail as a *sit-to-stand transition*. Furthermore, sequences that would seem impossible in normal daily activity might be detected and reclassified appropriately. In this case, Mathie *et al.* [17] suggest the use of an overlay for validation of classification sequences, which could be implemented using rule-based heuristics, fuzzy logic, or statistical behavioral modeling, such as Markov chaining.

## V. Conclusion

A human movement classification system based on the data acquired from a single, waist-mounted triaxial accelerometer was developed for use in a real-time environment. The classification algorithm employed was designed specifically to perform the required signal processing using embedded intelligence. Despite the inherent limitations in implementing such a system, our experimental results demonstrate the technical feasibility of our approach in performing the task of long-term ambulatory monitoring in the home as a method of determining an individual's functional status.

## References


[1] 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, no. 3, pp. 136–147, Mar. 1997.

[2] M. J. Mathie, A. C. F. Coster, N. H. Lovell, and B. G. Celler, "A pilot study of long term monitoring of human movements in the home using accelerometry," *J. Telemed. Telecare*, vol. 10, pp. 144–151, 2004.

[3] M. Makikawa and D. Murakami, "Development of an ambulatory physical activity and behavior map monitoring system," in *18th Annual Conf. IEEE Engineering in Medicine Biology Soc.* Amsterdam, Holland, 1996.

[4] M. J. Mathie, N. H. Lovell, A. C. F. Coster, and B. G. Celler, "Determining activity using a triaxial accelerometer," in *Proc. 2nd Joint EMBS-BMES Conf.*, Houston, TX, Oct. 2002.

[5] M. Uiterwaal, E. B. Glerum, H. J. Busser, and R. C. van Lummel, "Ambulatory monitoring of physical activity in working situations, a validation study," *J. Med. Eng. Technol.*, vol. 22, pp. 168–172, 1998.

[6] C. V. Bouten, W. P. Verboeket-van de Venne, K. R. Westerterp, M. Verduin, and J. D. Janssen, "Daily physical activity assessment: Comparison between movement registration and doubly labeled water," *J. Appl. Physiol.*, vol. 81, pp. 1019–1026, 1996.

[7] A. V. Ng and J. A. Kent-Braun, "Quantitation of lower physical activity in persons with multiple sclerosis," *Med. Sci. Sports Exerc.*, vol. 29, pp. 517–523, 1997.

[8] B. G. Steele, L. Holt, B. Belza, S. M. Ferris, S. Lakshminaryan, and D. M. Buchner, "Quantitating physical activity in COPD using a triaxial accelerometer," *Chest*, vol. 117, pp. 1359–1367, 2000.

[9] K. Kiani, C. J. Snijders, and E. S. Gelsema, "Computerized analysis of daily life motor activity for ambulatory monitoring," *Technol. Health Care*, vol. 5, pp. 307–318, 1997.

[10] J. Fahrenberg, F. Foerster, M. Smeja, and W. Müller, "Assessment of posture and motion by multichannel piezoresistive accelerometer recordings," *Psychophysiol.*, vol. 34, pp. 607–612, 1997.

[11] F. Foerster and J. Fahrenberg, "Motion pattern and posture: Correctly assessed by calibrated accelerometers," *Behav. Res. Meth. Instrum. Comput.*, vol. 32, pp. 450–457, 2000.

[12] P. H. Veltink, H. B. Bussmann, W. de Vries, W. L. Martens, and R. C. van Lummel, "Detection of static and dynamic activities using uniaxial accelerometers," *IEEE Trans. Rehabil. Eng.*, vol. 4, no. 4, pp. 375–385, Dec. 1996.

[13] K. Aminian, P. Robert, E. E. Buchser, B. Rutschmann, D. Hayoz, and M. Depairon, "Physical activity monitoring based on accelerometry: Validation and comparison with video observation," *Med. Biol. Eng. Comput.*, vol. 37, pp. 304–308, 1999.

[14] T. Tamura, M. Sekine, M. Ogawa, T. Togawa, and Y. Fukui, "Classification of acceleration waveforms during walking by wavelet transform," *Meth. Inf. Med.*, vol. 36, pp. 356–369, 1997.

[15] J. M. Winters, Y. Wang, and J. M. Winters, "Wearable sensors and telerehabilitation," *IEEE Eng. Med. Biol. Mag.*, vol. 22, no. 3, pp. 56–65, May/Jun. 2003.

[16] K. Aminian, P. Robert, E. Jéquier, and Y. Schutz, "Incline, speed, and distance assessment during unconstrained walking," *Med. Sci. Sports Exerc.*, vol. 27, pp. 226–234, 1995.

[17] M. J. Mathie, A. C. F. Coster, B. G. Celler, and N. H. Lovell, "Classification of basic daily movements using a triaxial accelerometer," *Med. Biol. Eng. Comput.*, vol. 42, pp. 670–687, 2004.

[18] M. J. Mathie, "Monitoring and Interpreting Human Movement Patterns Using a Triaxial Accelerometer," Ph.D. thesis, Univ. New South Wales, Sydney, Australia, 2003.

[19] E. K. Antonsson and R. W. Mann, "The frequency content of gait," *J. Biomech.*, vol. 18, no. 1, pp. 39–47, 1985.

[20] C. V. Bouten, K. R. Westerterp, M. Verduin, and J. D. Janssen, "Assessment of energy expenditure for physical activity using a triaxial accelerometer," *Med. Sci. Sports Exerc.*, vol. 26, pp. 1516–1523, 1994.

[21] D. Hendelman, K. Miller, C. Baggett, E. Debold, and P. Freedson, "Validity of accelerometry for the assessment of moderate intensity physical activity in the field," *Med. Sci. Sports Exerc.*, vol. 32, pp. S442–S449, 2000.



**Dean M. Karantonis** (S'05) received the B.E. (Hons.) degree in computer engineering and the M.Biomed.E degree in biomedical engineering from the University of New South Wales (UNSW), Sydney, Australia, in 2005. Currently, he is pursuing the Ph.D. degree with the Graduate School of Biomedical Engineering at UNSW, in collaboration with industry partner Ventracor.

His research focuses on simulation and control of an implantable rotary blood pump.



**Michael R. Narayanan** received the B.E. (Hons) degree in computer engineering and the M.Biomed.E degree in biomedical engineering from the University of New South Wales (UNSW), Sydney, Australia, in 2005. Currently, he is pursuing the Ph.D. degree at the School of Electrical and Telecommunications Engineering at UNSW.

His research focuses on smart wireless sensor networks for patient monitoring and health status classification.



**Merryn Mathie** received the B.E. degree in electrical engineering and the Ph.D. degree, both from the University of New South Wales, Sydney, Australia, in 1997 and 2004, respectively.

Her research interest is in the field of home telecare, using home monitoring techniques to promote and maintain health by providing indicators of changing health status, and thus allowing for early intervention. In particular, her work has focused on the use of accelerometry for monitoring free-living subjects.



**Nigel H. Lovell** (SM'94) received the B.E. (Hons) and Ph.D. degrees from the University of New South Wales, Sydney, Australia.

Currently he is a faculty member of the Graduate School of Biomedical Engineering. He has authored more than 150 refereed journals, conference proceedings, book chapters, and patents. His research has covered the areas of cardiac modeling, home telecare technologies, biological signal processing, and visual prosthesis design.

Dr. Lovell is currently the IEEE Engineering in Medicine and Biology Society (EMBS) Vice President (VP) for Conferences (2004–2005) and was the VP for Member and Student Activities (2002–2003). He was awarded the IEEE Third Millennium Medal for services to the EMBS.

**Branko G. Celler** (M'88) received the B.Sc. degree in computer science and physics, the B.E. (Hons) degree in electrical engineering, and the Ph.D. degree in biomedical engineering from the University of New South Wales (UNSW), Sydney, Australia, in 1969, 1972, and 1978, respectively. From 1977 to 1980, he was a Postdoctoral Fellow working at the Johns Hopkins School of Medicine in Baltimore, MD. He returned to UNSW in 1981 as a Lecturer, where he was appointed an Associate Professor in 1991 and a Professor in January 1997. He is currently Director of the Laboratory for Health Telematics and Head of the School of Electrical Engineering and Telecommunications at UNSW.

Prof. Celler is on the Editorial Board of the *International Journal of Telemedicine and Telecare* and the IEEE TRANSACTIONS ON INFORMATION TECHNOLOGY IN MEDICINE. He is a Foundation Member of the Australian College of Medical Informatics and was the Foundation Co-Director of the Centre for Health Informatics at UNSW.