Classification of basic daily movements using a triaxial accelerometer

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Abstract—*A generic framework for the automated classification of human movements using an accelerometry monitoring system is introduced. The framework was structured around a binary decision tree in which movements were divided into classes and subclasses at different hierarchical levels. General distinctions between movements were applied in the top levels, and successively more detailed subclassifications were made in the lower levels of the tree. The structure was modular and flexible: parts of the tree could be reordered, pruned or extended, without the remainder of the tree being affected. This framework was used to develop a classifier to identify basic movements from the signals obtained from a single, waist-mounted triaxial accelerometer. The movements were first divided into activity and rest. The activities were classified as falls, walking, transition between postural orientations, or other movement. The postural orientations during rest were classified as sitting, standing or lying. In controlled laboratory studies in which 26 normal, healthy subjects carried out a set of basic movements, the sensitivity of every classification exceeded 87%, and the specificity exceeded 94%; the overall accuracy of the system, measured as the number of correct classifications across all levels of the hierarchy, was a sensitivity of 97.7% and a specificity of 98.7% over a data set of 1309 movements.*

Keywords—*Accelerometer, Ambulatory monitoring, Human movement classification*

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1 Introduction

ADVANCES IN miniature sensor and wireless technologies have resulted in interest in the development of systems for monitoring subjects over long periods of time using wearable monitoring units (BOUTEN *et al.*, 1997; ASADA *et al.*, 2003; PARK and JAYARAMAN, 2003; JOVANOV *et al.*, 2003; KORHONEN *et al.*, 2003). Within this, there is a trend towards wearable systems that go beyond traditional physiological monitoring to include measures of environmental health, functional performance and activities related to daily living (WINTERS *et al.*, 2003; MATHIE *et al.*, 2002).

Wireless accelerometry systems have been used to measure parameters of environmental health (MATHIE *et al.*, 2004*a*). They have been used as a means of indirectly assessing metabolic energy expenditure (BOUTEN *et al.*, 1996; NG and KENT-BRAUN, 1997; STEELE *et al.*, 2000); to measure various parameters of movement, such as step rate and postural sway (CURRIE *et al.*, 1992; EVANS *et al.*, 1991; MAYAGOITIA *et al.*, 2002; KAMEN *et al.*, 1998); and in smart personal alarm systems to detect falls (PETELENZ *et al.*, 2002; LEHRMAN *et al.*, 2002).

Accelerometers are useful because they are very small, low-cost instruments that provide quantitative measurements. The accelerometers that are most widely used in these applications respond to both acceleration due to gravity and acceleration due to body movement. This makes them suitable for measuring postural orientations as well as body movements.

With the exception of metabolic energy expenditure calculations, the applications described above require knowledge of the movements that are being performed. In a free-living context, the movements are generally not known and thus need to be identified from the accelerometer signals. Monitoring systems using multiple body-worn accelerometers have been used to classify postures and activities, including standing, sitting, lying, walking, stair climbing and cycling, with a high degree of accuracy (AMINIAN *et al.*, 1999; FAHRENBERG *et al.*, 1997; FOERSTER and FAHRENBERG, 2000; UITERWAAL *et al.*, 1998; VELTINK *et al.*, 1996).

Researchers have proposed different approaches to classification, including fixed-threshold classification (TAMURA *et al.*, 1997; AMINIAN *et al.*, 1999; FAHRENBERG *et al.*, 1997;

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FOERSTER and FAHRENBERG, 2000), reference-pattern-based classification (VELTINK *et al.*, 1996; MAKIKAWA and MURAKAMI, 1996), pattern recognition strategies that use statistical algorithms (VELTINK *et al.*, 1996), conventional or fuzzy logic (WINTERS *et al.*, 2003) or artificial neural networks (AMINIAN *et al.*, 1995; KIANI *et al.*, 1997).

These studies have provided support for the viability of classifying movements using the signals from accelerometers. However, each group has developed its own algorithms and methods to discriminate between a specific set of movements using a custom-designed monitoring system. The highly specific systems and methodologies make it difficult to make direct comparisons between the approaches of the different investigators. The other difficulty is that the algorithms tend to have been specifically designed to deal with a particular domain of activities, and it is not easy to adapt the methods that have been presented to work in a different environment or with a different set of movements.

KIANI *et al.* (1997) presented a more systematic approach to classification, based on a formal, hierarchical, decision tree. Each node of the tree had multiple branches leading to all of the movements of interest at the next level of the hierarchy. The decision at each node was obtained by the measurement of parameters such as average, norm and standard deviation and then classification on the basis of these parameters. At each node, all the possible subclassifications were considered, and the most likely candidate was selected. Although this structure allowed a logical flow of decisions, it still had the drawback that a movement branch could not be added to, nor removed from, a node without affecting the algorithm by which all the other movements from that node were classified.

In this paper, we present a framework for the classification of movement of free-living subjects using the signals obtained from an accelerometry monitoring system. The purpose of the framework is to allow hierarchical classification of an arbitrary set of movements in such a way that new movements can easily be added to the classification, the accuracy of each individual classification decision can easily be evaluated, and new methods for classifying particular movements can be introduced without the need to redesign other parts of the classifier.

The framework was then employed to develop a classifier for identifying basic movements performed in the home environment using a single waist-mounted triaxial accelerometer (TA) unit.

2 Framework for movement classification

The purpose of the framework is to classify activities and postural orientations of subjects using the signals obtained from an accelerometry-based monitoring system. Once an activity or posture has been identified, then relevant parameters can be extracted from the movement.

Our classification framework is based on a hierarchical, binary tree. The structure of the classifier is illustrated in Fig. 1. Broad classifications are made in the top levels of the tree, and more detailed subclassifications are made in the lower levels of the tree. Movements are subclassified until either the required level of detail or the limit of what can be achieved using the monitoring system is reached.

The decisions made higher up the tree are more certain than the decisions made further down the tree, as any classification uncertainty from the higher branches is transferred to the lower branches.

Categories at the same hierarchical level must be independent, and each set of categories must encompass every possible case of the parent category. This requires the presence of a fallback case that is accepted if all the other classification possibilities are rejected. The existence of a fallback case is built into the framework and can be easily identified from the flowchart structure. It can be a generic case, such as the category of 'other movement', or an explicit case, as is the category 'sub-movement 2' of Fig. 1. Subcategories from the same parent node that are at the same hierarchical level are tested sequentially, until either a category is selected or the fallback case is reached.

Use of a binary decision tree provides the classifier with a modular, flexible structure. Movement categories can be added

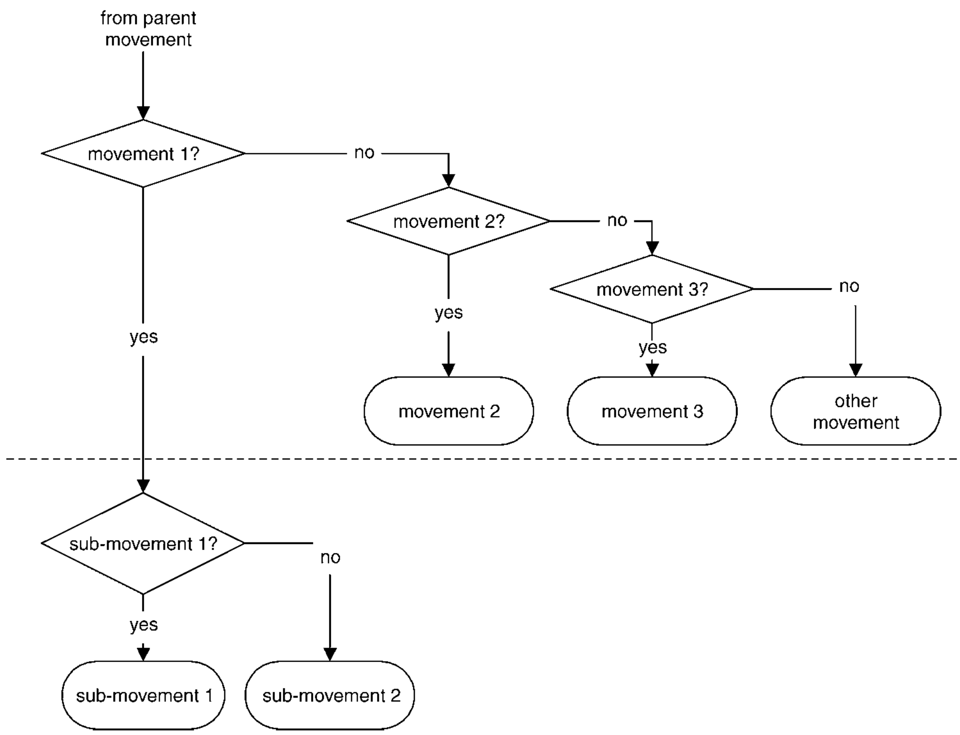

Fig. 1 *Illustration of classification framework, which is structured as binary tree. Dotted lines show different levels within hierarchy. Broad classifications are made at top of tree, and more detailed classifications are made at lower levels*

and removed without affecting other parts of the tree. Individual algorithms can also be changed without the need to alter the other algorithms, and, conversely, other valid logical flows can be used to create different decision classifiers from the existing algorithms.

Using binary decisions ensures that only one (simple) decision is made at each node. This can speed up the processing and allows the reliability of each decision to be measured easily. It also means that all decision nodes have exactly two branches, which makes the tree easy to read and helps to ensure that no valid logic paths have been inadvertently omitted.

3 Utilising the framework

A classifier can be developed for a particular situation, using the classification framework, by following a six-step process. These steps are described in the following Sections.

3.1 *Step 1: define requirements*

The purpose for which the classifier is required should be clearly defined. The reasons why continuous, unsupervised monitoring and processing are necessary should be identified. The movements and classes of movements to be detected by the system need to be determined.

3.2 *Step 2: select instrumentation*

The choice of instrumentation dictates the movements that can be detected. For instance, an accelerometer attached at the waist can provide monitoring of whole-body movements, but cannot provide information on movements of the wrist. The monitoring instrumentation needs to be selected so that identification of all of the important movements can be consistently and reliably achieved.

3.3 *Step 3: arrange movements within tree*

For the movements to be placed inside a binary classification tree, they need to be ordered hierarchically from the most general through to the most specific. This is achieved by identifying any parent–child relationships between categories and structuring these into the tree. Independent movements stemming from the same parent node are placed at the same hierarchical level.

The ordering of movements at the same hierarchical level is important, as careful ordering can lead to improved processing efficiency. The choice of ordering depends on the context of the classification. For example, movements can be ordered from the most to the least likely, to minimise the overall amount of processing required, or they can be ordered such that the classifier tests for critical movements first.

3.4 *Step 4: develop algorithms*

Once the structure has been established, an algorithm needs to be developed for each of the binary decision nodes. The algorithms depend on the choice of instrumentation, which affects the signals that are received.

To develop an algorithm to detect a particular movement, it is necessary to develop a signal signature for that movement. This can be done explicitly by identifying particular characteristics of the signal, such as the value of the signal, that can then be compared with a threshold, or by developing a template pattern and comparing the signal with this. It can also, be carried out implicitly using a neural network or a fuzzy template classifier.

3.5 *Step 5: evaluate the classifier*

Once the classifier has been developed, its performance needs to be evaluated. There are two stages to the evaluation: evaluation of individual algorithms and evaluation of the complete classifier. It is also important to check that the classification tree actually encompasses the full scope of the movements intended for monitoring.

The modular structure means that the performance of every algorithm can be assessed independently, and its accuracy can be determined. In the context of the complete classifier, algorithms that occur lower down the tree or later on at the same level can have no effect on algorithms that occur earlier or higher in the tree. However, changing algorithms higher up the tree, or earlier on at the same level, can change the movements that are passed to a later node for classification and, hence, change the overall effective classification rate. For example, if a classification tree has been designed to identify activities of walking, jumping and falling from the set of all movements, and walking is the first activity that is tested for, then the walking-detection algorithm will be presented with instances of jumping and falling as well as other movements. If, however, the system tests for walking after testing for falling and jumping, then the walking detection algorithm should never be presented with instances of falling or jumping, and this can change the effective classification accuracy.

Therefore, in addition to assessment of the performance of each individual algorithm, the complete classifier should be evaluated. This evaluation should occur in the environment and with the types of subject for which the classifier has been designed, and the overall limits of accuracy of the classification tree should also be established.

3.6 *Step 6: refine the classifier*

The signal-based classification system can be refined by the addition of an overlay to introduce memory, so that individual movements are not classified in isolation. There are many different approaches that can be employed. For instance, a rule-based system can be applied that checks sequences of movements determined by the classifier and detects and corrects impossible sequences. A more sophisticated approach could involve the development of a movement template for the subject in which the likelihood of sequences of movements is determined, and the set of possible movements following a given movement sequence is determined. This can be achieved using methods such as Markov modelling. This system could then be used dynamically to prune branches that represent options that are not possible (and even those that are highly improbable) for each decision. Branches could also be dynamically reordered so that more likely classifications are tested first.

Steps 3–6 form an iterative process in which development of a later step can prompt changes to an earlier step, in which case, all the subsequent steps need to be reworked. This process needs to be repeated until a classification system has been designed that is fit for purpose.

In the following Sections, we demonstrate the application of this framework for monitoring basic daily movements using a single, waist-mounted triaxial accelerometer.

4 Classification of movements using a waist-mounted triaxial accelerometer

4.1 *Monitoring requirements*

Our long-term aim in developing an accelerometry monitoring system was to develop a practical system that could be used to monitor and assess movements in free-living subjects.

Of particular importance is the detection of fall events, so that the system can be used to provide an automated, intelligent personal alarm service. In addition, we wanted to know whether the subject was able to rise again after the fall; whether there was any movement by the subject after the fall; and the postural orientation of the subject after the fall: lying face up, face down or on the side. This was because the posture and activities of the subject following a fall provide important information on the severity of the fall and on the state of the subject. This required the system to be able to distinguish between upright and lying postures, and between subpostures of lying.

Secondly, we wanted to be able longitudinally to monitor parameters of movement that are sensitive to changes in health status and increasing risk of falling. This required the automatic identification of basic movements fundamental to independent living, including various postural orientations, walking and transitions between postures, particularly rising from, and sitting down into, a chair.

4.2 *Instrumentation*

A single, waist-mounted triaxial accelerometer (TA) was chosen to perform the measurements. This instrumentation was designed for ease of use, comfort and convenience of the wearer. The unit was composed of two orthogonally mounted biaxial accelerometers*(range $\pm 10\,g$; frequency response: 0–500 Hz; noise level: $6.12 \times 10^{-3}\,g$ rms), a push button, a 1.5 V AA battery and a wireless transmitter contained in a small, light pager case that measured $71 \times 50 \times 18$ mm and weighed 50 g. The unit was designed to be clipped onto a belt or clothing at the waist. The TA unit sampled accelerations due to gravity and body movements, at 45 Hz, and then transmitted the data to a receiver unit and thence to a personal computer, where the data were processed and stored (MATHIE *et al.*, 2003; CELLER *et al.*, 2000).

This instrument was designed for research purposes, and data were transmitted continuously rather than being buffered or processed on board the wearable unit. However, the unit consumed only 15 mA from a 1.5 V source when transmitting 0 dBm into a 50 Ω surface-mounted planar antenna, which meant that one 1.5 V alkaline battery provided 80 h of continuous transmission before needing to be replaced.

4.3 *Arrangement of movements*

The movements were first grouped into two mutually exclusive classes of activity and rest. In each class, the relationships between the movements were determined. Each pair of movements was identified as either two independent movements, or as two movements in a parent–child relationship. In this system, no overlap between movements was permitted, unless the movements were in a parent–child relationship. Child movements were drawn below parent movements. Independent movements were drawn side-by-side with other movements having the same number of ancestor movements. This resulted in a hierarchical structure of increasingly detailed submovements, which is shown in Fig. 2*a*. In this Figure, the arrows indicate parent–child dependencies, and the dotted lines represent the borders between different levels in the hierarchy. This hierarchical diagram was used to guide the development of the flowchart.

Activities of falling, walking and postural transitions were determined to be at the same level in the hierarchy. As these three activities did not represent the complete domain of activities, a fourth category of 'other' was added. The 'other' category included movements such as bending down or reaching up. These four categories now covered the complete domain of activities. Similarly, postural orientations of upright and lying were set at the same level in the hierarchy, and an additional posture, 'inverted', was added so that the classification covered the complete domain of postural orientations. An inverted orientation would indicate that the person's head was below the feet. This situation would be expected to occur rarely, but could, for example, happen if a person were to fall down a flight of stairs.

Of these activities, falls were placed on the left, so as to be the first activity tested, as this was the most critical activity and should be detected the most rapidly and without any possibility of the movement being misclassified as another activity. Walking was placed next, for reasons of processing efficiency, because the algorithm that was used to detect periods of walking was simpler and faster than the algorithm that was used to detect transitions. Once the activities at the same level had been ordered, the flowchart for this part of the tree could be constructed.

Fig. 2*b* shows the final structure that was developed for classification of the movements. The dotted lines on the flowchart show the hierarchical levels that were developed and are shown in Fig. 2*a*.

4.4 *Development of algorithms*

An algorithm was developed for each decision node. The algorithms were developed and tested using data collected from 26 normal, healthy subjects (seven female, 19 male; mean age 30.5 years $\pm$ 6.3 years standard deviation) in a controlled laboratory environment. The movements were performed in a set sequence: stand; lie supine; lie left side; lie face down; lie right side; stand; sit; stand; walk along a level corridor; stand; sit; stand; walk up a flight of stairs; walk down a flight of stairs; stand; sit; stand; walk along a level corridor; and stand. Each of the resting postures was held for 30 s, with the exception of the later periods of quiet standing between activities, which were held for 10 s. Subjects wore the TA unit at the waist, above the right superior anterior iliac spine, while performing the movements.

An investigator supervised performance of the routine. Each movement was timed using a stopwatch. All acceleration data were time stamped and stored in the personal computer for retrospective analysis.

A small number of additional, unspecified actions were performed by the subjects during the sequence, such as taking a step during quiet standing or adjusting their seating position. These activities were also included in the analysis.

The periods of quiet standing were included to separate the individual movement, to ensure that there was no overlap in the signals from the different movements. The use of periods of quiet standing between movements also meant that the movement signals were not affected by the order in which the movements were performed.

Additionally, a preliminary data set of 'simulated' falls and stumbles was collected from four consenting subjects. Each subject performed four falls onto a carpeted floor from positions of quiet standing and while walking across the room.

Some of the recorded signals were randomly selected for use in developing the algorithms. The remainder were set aside as a test set for use in evaluation.

The different movements were distinguished in time using the activity detection classifier (MATHIE *et al.*, 2003*b*). This algorithm identified periods of activity and periods of rest in the signal. Each of these periods of activity and rest was then classified as a particular movement using the classification framework. The time period of each classified movement was compared with the movement or movements that actually occurred during that period. If the classified movement actually occurred during that period (even if it started or stopped outside that period), then it was deemed to be correctly classified. If the

*ADXL210, Analog Electronics

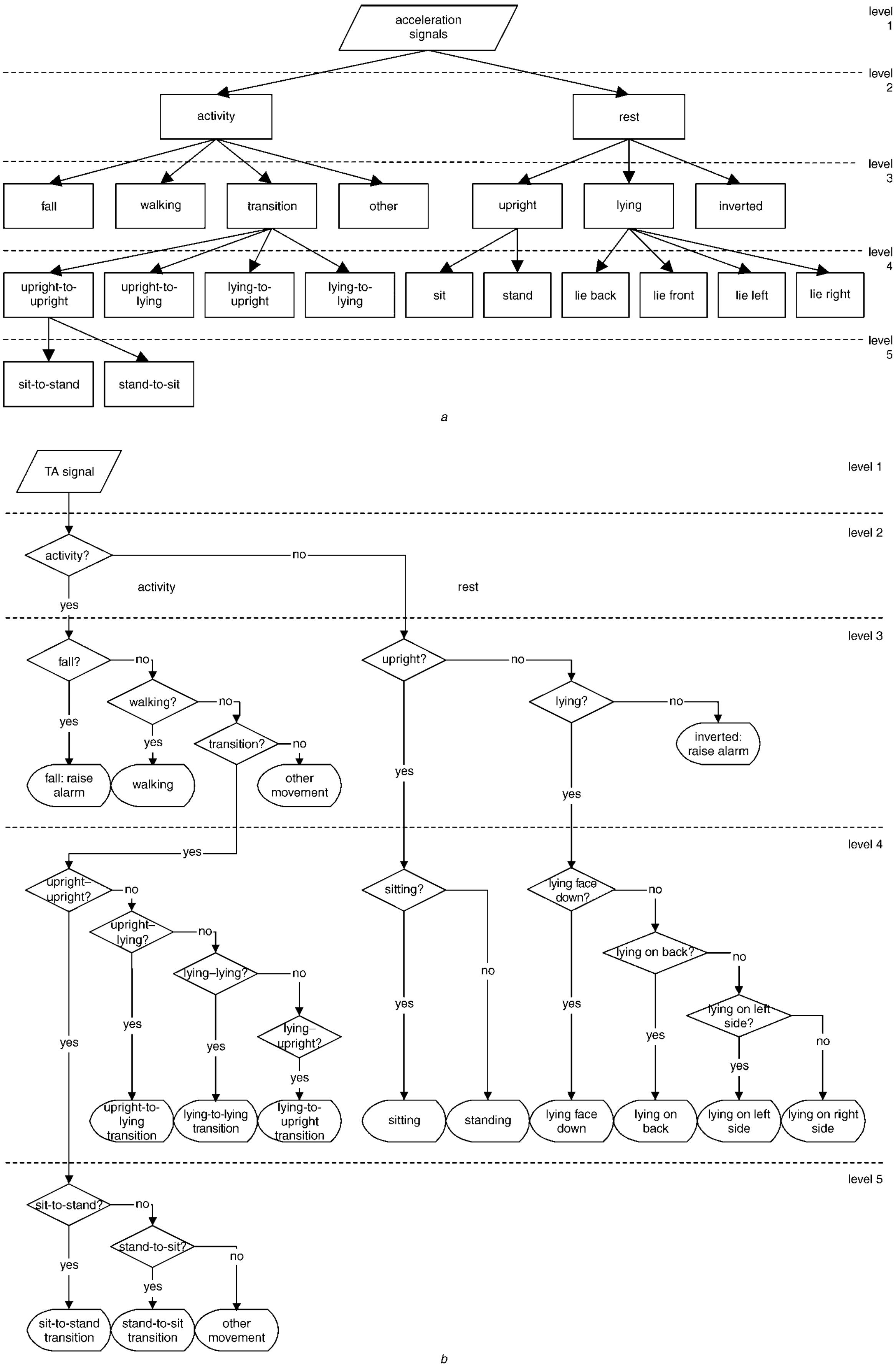

Fig. 2 *(a) Hierarchical structure showing relationships between different movements of interest. (b) Binary tree flowchart diagram showing process for classification of movement signals from triaxial accelerometer. Dotted lines indicate different levels in hierarchical structure*

classified movement did not occur during that period, then it was deemed to be incorrectly classified. This allowed the accuracy of the algorithms to be quantified.

Each algorithm was developed in the following manner. Simple threshold-based classification techniques were applied wherever possible. For example, activity and rest were discriminated by integration of the area under the acceleration curves every second, to produce a measure of metabolic energy expenditure, and then comparison of the measured value with a predetermined threshold. If the measured value exceeded the preset threshold, then the subject was classified as engaged in activity. Otherwise, a classification of resting was made (MATHIE *et al.*, 2003*b*, 2002). An upright posture and lying were discriminated using the measured tilt angle of the subject. Lying substates were discriminated using the measured angle of rotation of the subject when lying.

If simple, threshold-based classification techniques did not give satisfactory results (sensitivity and specificity both greater than 95% in the control set), then more sophisticated, pattern-based techniques were developed. Standing and sitting were discriminated using a probability rule-based system that used a range of parameters, including tilt angle, duration over which the subject maintained the posture, measured metabolic energy expenditure and previous and next activities, and determined the probabilities that the subject was sitting and standing. The state with the higher probability was then selected as the actual state of the subject. Falls were also identified using a rule-based algorithm. Sit-to-stand and stand-to-sit transitions were identified by comparison of the measured signals with signal templates for the two movements.

4.5 *Laboratory evaluation of classifier*

Once algorithms had been developed that gave satisfactory performance on the development data set (described above), they were applied to the test set. Their performances were evaluated by measurement of the true and false positive classification rates. The classification accuracies for each of the algorithms were determined in the same way as was described in the preceding Section and are presented in Table 1.

Using this instrumentation, periods of activity and rest could be reliably and easily distinguished using the signals from the TA unit, as could upright and lying postures and subpostures of lying. Each of the activities in level 3 of the hierarchy (refer to Fig. 2) could be identified with a high degree of accuracy from within this fixed domain of movements. All the movements in levels 4 and 5 of the hierarchy were classified, but some of the algorithms were more involved, and the results were not as reliable as for parent classes higher in the tree. Sitting and standing postures and transitions between the two postures could be identified, but with less confidence than was achieved in the other classifications. This was owing to inherent limitations in the monitoring instrumentation that resulted in an overlap in the signal patterns for sitting and standing postures.

5 Discussion

A generic framework for the classification of movements was introduced and applied to process basic movement data from a single, waist-mounted triaxial accelerometer. The classifier that was developed gave excellent results when applied to the classification of specific movements performed in a controlled environment.

There are clear limits on what can be achieved in a free-living monitoring environment using a single, waist-mounted TA. A greater number of instruments provide more information that allows more accurate classifications at a more detailed level, but a single instrument is more practical for continuous, long-term monitoring, as the simplicity and ease-of-use of the single instrument facilitates compliance and minimises cost.

Positioning at the waist was chosen because this location provides the most useful information on subject movements, being close to the centre of the body (MATHIE *et al.*, 2004*a*). Although other approaches, such as wrist-bands and pendants, require less subject compliance as they need never be removed, they are less able to provide reliable information on whole body movements and are more susceptible to artifact (such as accelerations due to swinging or knocking against other objects). Moreover, the waist is also a location that has been found to be comfortable for, and useable by, subjects. In a recent field study, six elderly subjects (four female and two male) each wore a waist-mounted unit every day for a three month period and reported that they found the unit comfortable to wear and not inconvenient to use (MATHIE *et al.*, 2004*b*).

The single-instrument system located at the waist was able accurately to distinguish between activity and rest in the free-living environment. It could also distinguish between upright and lying postures and detect periods of walking with a high degree of accuracy. The ability to make more detailed distinctions, such as between sitting and standing, was limited in this context. Overall, the single instrument was able to generate a reasonable picture of the basic movements of the free-living subject.

Table 1 Classification results obtained during controlled laboratory studies for specific domain of movements and for free movement. Some collected data were used to develop algorithms. Remainder of data, included here, were used to evaluate algorithms. Overall accuracy measure represents number of correct decisions made by classifier. Average performance indicates mean accuracy across 9 different classification categories

			Controlled laboratory study			
Level	Classification	Method	number of subjects	number of movement	sensitivity	specificity
2	activity (activity/rest)	fixed threshold	13	143	99%	94%
3	fall	pattern matching	2	8	80.5%	100%
3	walking	expert system + pattern matching	26	156	100%	100%
3	upright (upright/lying)	fixed threshold	23	184	100%	100%
4	upright–lying transition	pattern matching	26	104	100%	100%
4	lying–lying transition	pattern matching	23	184	98.9%	100%
4	sitting (sitting/standing)	expert system	26	255	95.1%	97.7%
4	lying subpostures	fixed threshold	23	92	98.9%	100%
5	sit–stand transition (sit-to-stand/stand-to-sit)	pattern matching	26	183	93.5%	98.1%
Overall performance				1309	97.7%	98.7%
Average performance					97.0%	98.9%

sit → stand-to-sit

- If the rest state after the transition is *standing* then reclassify the *stand-to-sit* transition as a *sit-to-stand* transition.
- Else, if the rest state after the transition is *sitting* then reclassify the *stand-to-sit* transition as *other movement*.
- Else (the next rest state is *upright*, but not subclassified) classify the next rest state and then return to classify the activity.

stand → sit-to-stand

- If the rest state after the transition is *sitting* then reclassify the *sit-to-stand* transition as a *stand-to-sit* transition.
- Else if the rest state after the transition is *standing* then reclassify the *sit-to-stand* transition as *other movement*.
- Else (the next rest state is *upright*, but not subclassified) classify the next rest state and then return to classify the activity.

sit → walk

- If the duration of the *sitting* period is short and the activity before the *sitting* period is *other movement* then reclassify the *other movement* as a *sit-to-stand* transition and the *sitting* state as *standing*.
- Else assume that the *sit-to-stand* transition is contained in the same period of activity as the *walk* and was not detected separately.

upright resting state, not subclassified

- If the activity after the *upright* resting state is *walking* then classify the *upright* resting state as *standing*.
- Else, if the activity before the *upright* resting state is a *sit-to-stand* transition then classify the *upright* resting state as *standing*.
- Else, if the activity before the *upright* resting state is a *stand-to-sit* transition then classify the *upright* resting state as *sitting*.
- Else, if the activity after the *upright* resting state is a *sit-to-stand* transition and this is consistent with the next resting state then classify the *upright* resting state as *sitting*
- Else, if the activity after the *upright* resting state is a *stand-to-sit* transition and this is consistent with the next resting state then classify the *upright* resting state as *standing*.
- Else, if the activity before the *upright* resting state is a *lying-to-upright* transition then classify the *upright* resting state as *sitting*.
- Else classify the *upright* resting state as the same as the previous resting state, and reclassify the activity before the *upright* resting state as *other movement*.

upright-to-upright transition, not subclassified

- Classify the *upright-to-upright* transition based the resting states before and after the transition.
- If the resting state after the activity is *upright* but not subclassified then subclassify the resting state and then return to classify the activity.

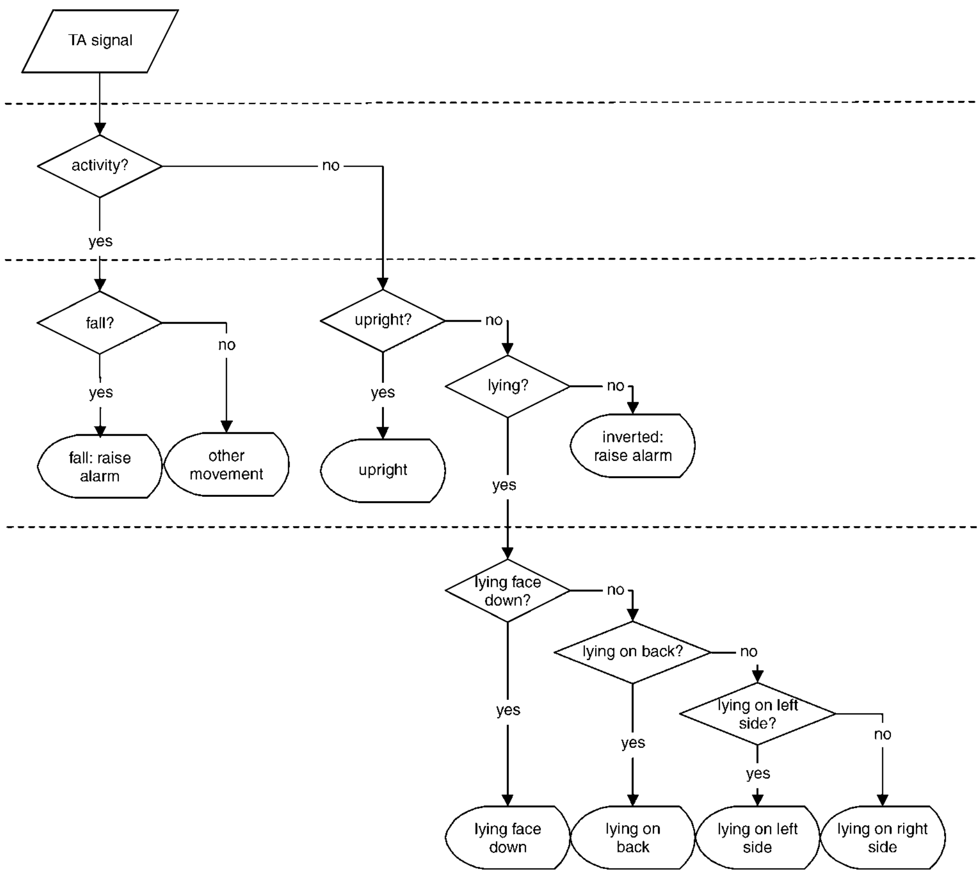

Fig. 3 *Reduction of classification tree for detection of falls only. Left-hand branch is for detection of falls. Right-hand branch has been left in tree because posture of subject immediately following fall can provide important information on severity of fall*

The fact that this classification framework is hierarchical and uses only binary decisions allows modularisation of the decision logic. Once a tree classifier has been designed, it is not fixed. The framework provides a flexibility that allows the classifier to be adapted and modified according to need. The tree can be pruned, extended or reordered, and individual algorithms can be changed. For example, if the single waist-mounted TA system was to be used in a situation where the only requirement was for the detection of falls, then the tree could be pruned down to the instance shown in Fig. 3. Note that we have left the branch identifying the lying posture, as this provides important information immediately after a fall. Alternatively, the reduced tree of Fig. 3 could be expanded to the more comprehensive tree of Fig. 2 without the need to change the existing tree or structure.

An additional advantage of the modular structure of the framework is that algorithms can be replaced without affecting any other part of the tree, as better or more appropriate algorithms are developed.

Preliminary testing of the system on free-living subjects has indicated that classification of basic movements can be achieved using this system, although the added complexity of the unlimited domain of activities in the free-living environment caused a significant reduction in classification accuracy at the most detailed level of classification when compared with the results obtained in the laboratory. This was particularly evident in discrimination between sitting and standing and transitions between these two states.

However, the system could be enhanced for use in a free-living context by the addition of an overlay to test the validity of the sequence of classified movements. For example, an error in classification could lead to a classified sequence of movements of *sitting* $\rightarrow$ *sit-to-stand transition* $\rightarrow$ *sitting* $\rightarrow$ *walking*. Such a sequence is clearly impossible, and this could be detected by a sequence-testing overlay. There are many different approaches that could be applied to generate such an overlay, including rule-based heuristics, fuzzy logic or statistical behavioural modelling, such as Markov chaining. Using these latter methods, a template of daily behaviours could be developed for the patient, similar to those that have been proposed for unobtrusive monitoring (CELLER *et al.*, 1995).

The next stage of evaluation will be assessment of the classifier technique in a free-living context. Although the free-living context is far more complex, with an unlimited range of possible movements, it is expected that the basic postures of upright or lying and distinct movements such as walking or falling will still be able to be reliably detected using the system developed in this study, although the accuracy of classification of movements lower down the hierarchical tree, such as the distinction between sitting and standing, would be expected to be lower than in this controlled study.

6 Conclusion

A generic framework was developed for automatic movement classification in unsupervised settings using accelerometric monitoring. The framework consists of a hierarchical binary tree in which general distinctions between movements are applied first, and then successively more detailed subclassifications are made in the lower levels of the tree. The structure is modular and flexible: parts of the tree can be reordered, pruned or extended at will, even during use, without the remainder of the tree being affected. Each binary decision node has associated with it an algorithm to perform the classification. The modular design allows individual algorithms to be modified or extracted for use in other systems.

Using this framework, a classifier for the identification of basic movements, based on a monitoring system consisting of a single, waist-mounted triaxial accelerometer, was developed. In laboratory studies in which 26 subjects performed a specific routine of movements, the system obtained an overall sensitivity of 97.7% and specificity of 98.7% over a data set of 1309 movements.

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