HIERARCHICAL DYNAMIC MODEL FOR HUMAN DAILY ACTIVITY RECOGNITION

Blanca Florentino-Liaño, Niamh O'Mahony and Antonio Artés-Rodríguez
Department of Signal and Communications Theory, Universidad Carlos III de Madrid, Madrid, Spain

Keywords: Activity recognition, Inertial sensors, Ambulatory monitoring.

Abstract: This work deals with the task of human daily activity recognition using miniature inertial sensors. The proposed method is based on the development of a hierarchical dynamic model, incorporating both inter-activity and intra-activity dynamics, thereby exploiting the inherently dynamic nature of the problem to aid the classification task. The method uses raw acceleration and angular velocity signals, directly recorded by inertial sensors, bypassing commonly used feature extraction and selection techniques and, thus, keeping all information regarding the dynamics of the signals. Classification results show a competitive performance compared to state-of-the-art methods.

1 INTRODUCTION

The task of human activity recognition using wearable inertial sensors is becoming popular in applications which require context-aware monitoring, such as ambulatory monitoring of elderly patients and home-based rehabilitation. In such applications, knowledge of the activity being carried out by the patient is vital for providing the context within which the patient is being monitored and this context-awareness can help to overcome the limitations associated with the use of self reporting in medical assessment. One of the major advantages of such systems is that they can reduce the frequency of patients' visits to medical centers, improving their quality of life and reducing medical costs.

There are two main methods for human activity recognition: vision-based, e.g. (Moeslund et al., 2006), and inertial sensor-based, e.g. (Sabatini et al., 2005). The main disadvantages of vision-based systems are that they can only be used in a confined space, they interfere with the privacy of the individual and they produce an excessive amount of information that must be processed. On the other hand, due to recent advances in sensor technologies, inertial sensor devices have become compact and portable enough to be unobtrusively attached to the human body. For this reason, wearable miniature inertial sensors, incorporating accelerometers and gyroscopes, have became the ideal platform for human movement monitoring (Sabatini et al., 2005), falls detection (Wu and Xue, 2008), medical diagnosis and treatment (Powell et al., 2007), and tele-rehabilitation (Winters and Wang, 2003).

Nowadays, the main challenge in activity recognition is the development of a system for real-life monitoring applications using wearable sensors. Long term recording capabilities and unobtrusiveness are the primary requirements of such systems. The main constraint for the long term recording capabilities requirement is the battery life of the sensor devices. This drawback is even more important in real-time applications, such as fall detection systems. The processing of the data in real time can either be done by the sensor, if it has an on-board processor, or by transmitting the data wirelessly from the sensor to an external processor. Both cases result in high battery consumption and the latter case also requires the patient to be confined within the range of the wireless communication system. In order to make the system as unobtrusive as possible, the number of sensors placed on the body should be kept to a the minimum despite the fact that the larger the number of sensors, the more activities the system can recognize (Bao and Intille, 2004). Thus, choosing the number of sensors is a trade off between performance and usability.

Further to simply identifying which activities a subject is carrying out, this work proposes to also provide information regarding of the dynamics of the activity itself. There are two benefits to this approach: (1) the intra-activity dynamics can aid the classification task and (2) additional contextual information

Florentino-Liaño B., O'Mahony N. and Artés-Rodríguez A..
HIERARCHICAL DYNAMIC MODEL FOR HUMAN DAILY ACTIVITY RECOGNITION.
DOI: 10.5220/0003781900610068
In *Proceedings of the International Conference on Bio-inspired Systems and Signal Processing* (BIOSIGNALS-2012), pages 61-68
ISBN: 978-989-8425-89-8

could be gained from characteristics of the dynamic behaviour. With this in mind, we propose a hierarchical dynamical model which takes into account two levels of dynamics: inter-activity and intra-activity. The model aims to represent the activities as intuitively as possible in terms of the patterns present in the raw data from the sensors. Thus, not only are different activities recognized, but the "events" within a given activity are also distinguished, for example, the steps in the case of walking. Three different dynamic models are described, each one pertaining to a particular type of activity: the first is for stationary activities like standing, sitting and lying; the second, for active movements like walking and running, whilst the third deals with short-time motions like jumping and falling.

A further advantage of the proposed system is that it uses raw signals directly from the sensor, thus avoiding computationally expensive techniques such as feature extraction and selection. Because the system is designed to capture directly the dynamics of the signals, activity recognition is achieved with high accuracy whilst eliminating costly processing techniques.

The paper is organized as follows: in Section 2 the activity recognition literature is reviewed. Section 3 describes the proposed hierarchical dynamic model. The test procedure is outlined in Section 4, whilst in Section 5 the results obtained with our model are presented. Section 6 provides a discussion of the operation of the proposed method. Finally, in Section 7, conclusions and future lines of work are discussed.

2 BACKGROUND AND RELATED WORK

2.1 Sensors and Feature Extraction

The previously published literature in the area of human activity recognition using inertial sensors is quite extensive. Most of the published work follows a similar approach of data collection and processing, as outlined in this section.

Perhaps the first consideration in any activity recognition system, is the selection of the type and the number of sensors, as well as the positions on the human body where they will be worn. The simplest sensor used in the recent literature is a triaxial accelerometer (Han et al., 2010; Krishnan et al., 2008; He and Jin, 2008; Khan et al., 2010). In (Frank et al., 2010; Altun and Barshan, 2010; Zhu and Sheng, 2010), inertial measurement units (IMU), combining triaxial accelerometers and triaxial gyroscopes, are used to provide measurements of specific force and angular rate, respectively. As has been previously mentioned, the larger the number of sensors used, the more activities the system can recognize. Similarly, the choice of sensor positions on the body is crucial. In the case of a single sensor, the most popular place is the waist, on the belt or in the pocket of the trousers (Frank et al., 2010; Han et al., 2010; He and Jin, 2008). In this work, a single IMU placed on either the left or right hip is considered for testing purposes, although the model is not limited to this configuration.

The first processing step is, typically, focused on the construction of a feature vector derived from the raw signals of the sensor. In the literature, a large number of different features have been reported as being suitable for the classification task considered in this work; (Preece et al., 2009) provides a comparison of the most popular features. A common approach is to extract many features (for example in (Krishnan et al., 2008) thirty-nine features are extracted); then, dimensionality reduction techniques such as Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) are used to reduce the size of the feature vector before classification.

In addition to the processing required for feature extraction and selection, another disadvantage of this approach is that a predefined window length must be determined to compute the features. Furthermore, an overlap is often used between consecutive windows. The selection of such parameters is somewhat arbitrary and there is a lack of agreement on the best choice; in the literature, the window length varies widely (e.g. from 16 msec (Han et al., 2010) to 6 sec (Bao and Intille, 2004)), whilst a 50% overlap is common.

Once the feature vector has been computed from the windowed signals, the next step is the development of a model that is able to discriminate among activities. The most popular methods that have been used to solve this sequential supervised learning problem are batch supervised learning algorithms and Dynamic Bayesian Networks (DBN).

In (Altun and Barshan, 2010), a comparison of classification results using various batch supervised learning algorithms, including Bayesian Decision Making (DBM), Least-Squares Method (LSM), *k*-Nearest Neighbor (*k*-NN), Support Vector Machines (SVM) and Artificial Neural Networks (ANN) can be found. Batch supervised learning algorithms, which ignore the dynamics of the signals, are not considered in this work. One reason for this is to bypass the feature extraction step and, furthermore, it will be seen that consideration the dynamics of the signals can give useful information about the type of activity that is being performed.

In the case of DBN, Hidden Markov Models (HMM) are the most frequently used. The model proposed in this work is based on HMMs and, so, the next section will describe, briefly, the theory governing HMMs and discuss, in detail, their use in the task of daily human activity recognition.

2.2 Hidden Markov Models

2.2.1 Background

A HMM (Rabiner, 1990) is a probabilistic model that represents the joint distribution of the observations and the unobserved (hidden) variable. In this work the observations are continuous signals of acceleration and angular velocity. The unobserved variable must be discrete and its possible values are called states. The proposed hierarchical model in this work, defines two different unobserved variables: the activities (e.g. walking, running, etc.) and the events within each activity. This will be explained in more detail in the Section 3.

A first order HMM is characterized by the following:

- N, the number of states in the model. The individual states are denoted as $S = \{S_1, S_2, \ldots, S_N\}$, and the state at time t as q_t.
- The state transition probability distribution matrix, $A = \{a_{ij}\}$. This is an $N \times N$ matrix where the element, a_{ij}, is the probability of making a transition from state S_i to state S_j:
$$a_{ij} = P(q_{t+1} = S_j | q_t = S_i). \qquad (1)$$
- The emission distribution vector, $B = \{b_j(\mathbf{O})\}$, where, for state j:
$$b_j(\mathbf{O}) = \sum_{m=1}^{M} c_{jm} \mathfrak{N}(\mathbf{O}, \boldsymbol{\mu}_{jm}, \mathbf{U}_{jm}), \qquad (2)$$
where $\mathbf{O}$ is the vector to be modeled, M is the number of mixtures, c_{jm} is the mixture coefficient for the mth mixture in state j and $\mathfrak{N}$ is any log-concave or elliptically symetric density (in our case we have selected a Gaussian density) with mean vector $\boldsymbol{\mu}_{jm}$ and covariance matrix $\mathbf{U}_{jm}$ for the mth mixture component in state j.
- The initial state distribution $\pi = \{\pi_i\}$ where
$$\pi_i = P(q_0 = S_i) \qquad (3)$$

Thus, the HMM is defined by $\lambda = (A, B, \pi)$.

For HMMs, the problem of learning the model parameters is solved by the Baum-Welch algorithm (Rabiner and Juang, 1993). The Viterbi algorithm (Viterbi, 1967) is used to compute the most likely sequence of states, $Q = q_0\, q_1 \ldots q_T$, from time $t = 0$ to $t = T$ and its probability, given the model and an observation sequence, $O = O_0\, O_1 \ldots\, O_T$.

2.2.2 HMMs and Activity Recognition

In the literature, there are two main approaches to solving the activity recognition task using HMMs. In the first approach (Zhu and Sheng, 2010), only the temporal dependency among activities is modeled and there is just one HMM, whose number of states is equal to the number of activities. This model is very simple and is usually combined with batch supervised learning algorithms. Modeling the temporal dependencies among the activities allows the system to model human behavior by forbidding impossible transitions like, for example, a direct transition from running to lying down. An example of this approach can be found in (Zhu and Sheng, 2010) where the classification is done in two steps; first, two ANNs are used for determining whether or not the feature vector corresponds to a dynamic activity and whether the movement is vertical or horizontal; then, the fusion of these two outputs becomes the input to a HMM where the states are the activities.

In the second approach (Han et al., 2010), one HMM per activity is modeled. The number of states of each HMM is a design parameter. The inference step consists of computing the likelihood of a test sequence with each of the HMMs. The activity corresponding to the HMM with the highest likelihood is the chosen activity. The main drawback of this approach is that it is necessary to define a sequence size in order to learn the models and to infer the test sequence. Well-defined sub-units do not exist in the recorded IMU signals, since human activities are continuous and any given activity can have a highly variable duration. The sequence size is often selected taking into account the time interval during which only one activity exists. In (Han et al., 2010), this is set to 2 seconds. Some disadvantages of this approach are the requirement to define the sequence size, that the temporal dependency among activities is not modeled and that the HMM of each activity does not represent the activity itself but a sequence of, for example, 2 seconds of the activity. Thus, dynamic information is lost by truncating movement patterns and rhythmic movements.

To overcome this problem, (Oliver et al., 2002) develop a Layered Hidden Markov Model (LHMM), in which each layer of the architecture is connected to the next layer via its inferential results. This representation segments the problem into distinct layers that operate at different temporal granularities. But, again, the parameters of the HMMs do not give any intuitive information about how the person is performing the activity and it is necessary to arbitrarily define these temporal granularities.

As has been shown in this section, there is no consensus on the most discriminative features for use in an activity recognition system. For this reason, it is usual to extract a large number of features and, then, use a dimensionality reduction technique. The major drawback of this approach is the computational cost. Moreover, it has been mentioned that the window length used to compute the features is another design parameter that varies widely among previous studies. With this in mind, this work aims to bypass the feature extraction step and work directly with the raw data produced by the sensor.

3 PROPOSED METHOD

The method proposed in this work consists of a hierarchical dynamical model based on HMMs whose inputs are the raw signals given directly by the sensor. This model takes into account the temporal dependencies among activities and models each activity in terms of acceleration and angular velocity signals. The hierarchical scheme concept has been mentioned before in the activity recognition literature (Khan et al., 2010). In their work, the term hierarchical is used because the learning process is done in two steps. First, the type of the activity (static, dynamic or transition) is recognized, using an ANN, and, then, the activity itself is determined.

3.1 Hierarchical Dynamical Model

The final result of our hierarchical dynamical model is a single HMM ($\lambda^F = (A^F, B^F, \pi^F)$). This final HMM is built up of "sub"-HMMs, one for each activity, which are joined to yield the final HMM. The learning process is performed in two stages. In the first stage the intra-activity dynamics are taken into account, modeling each activity separately with a unique "sub"-HMM and learning its parameters, as described in Section 3.1.1. The second stage concatenates these HMMs, modeling inter-activity dynamics, as outlined in Section 3.1.2.

3.1.1 Intra-activity Dynamics

At this level, the hidden variable represents the significant events occurring during the activity. These events are the internal states of the sub-HMMs of each activity. The individual events, or states, of activity, Z, are denoted by $E^Z = \{E_1^Z, \cdots, E_{K^Z}^Z\}$ where K^Z is the number of states of activity, Z, and the state at time t is denoted by e_t.

In this first stage of the learning process, the joint probability distribution of the observations, $\boldsymbol{O}$, and the events, e, given the activity, Z, ($p(e, \boldsymbol{O}|Z)$) are modeled:

$$p(e, \boldsymbol{O}|Z) = \prod^{t} p(\boldsymbol{O_t}|e_t, Z)p(e_t|e_{t-1}, Z). \quad (4)$$

Each activity can have a different number of events and a different topology, as detailed in the following.

We propose three different topologies, depending on the type of the activity. All of them have in common that they have two transient states (the first and the last), that describe the transition from one activity to another. Each activity must begin in the first state, and once this state is left it cannot be returned to from within the activity. The only possible transition from the last state is to itself. This is achieved by forcing the values of the model parameters to be:

- The transition matrix A^Z of the activity Z:

$$A^Z = \begin{pmatrix} a_{11}^Z & a_{12}^Z & 0 & \cdots & 0 \\ 0 & a_{22}^Z & a_{23}^Z & \cdots & a_{2K^Z}^Z \\ 0 & 0 & a_{33}^Z & \cdots & a_{3K^Z}^Z \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix} \quad (5)$$

- The initial state distribution vector:

$$\pi^Z = \begin{bmatrix} 1 & 0 & \cdots & 0 \end{bmatrix} \quad (6)$$

For stationary activities like standing, sitting and lying, a left-right model with three states is proposed (Figure 1). The first and the last states are the transient states and the state in the middle models the permanent state of being seated, for example.

The second model is designed for active movements like walking and running (Figure 2). In this case there are two intermediate states which represent the pattern of stepping. These two states are fully inter-connected in order to model the periodicity of walking or running.

The last topology models short-time motions like jumping and falling. This model is made up only of transient states since there is neither a permanent action nor a rhythmic movement (Figure 3).

3.1.2 Inter-activity Dynamics

Once the models of each activity have been defined, they can be concatenated by means of their transient states (Figure 4) defining the transition probabilities

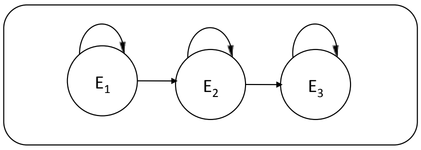

Figure 1: HMM topology for stationary activities.

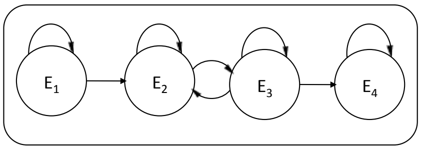

Figure 2: HMM topology for active movements.

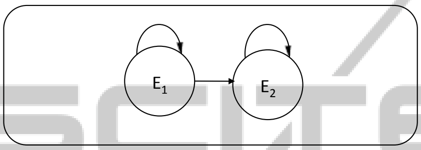

Figure 3: HMM topology for short-time motions.

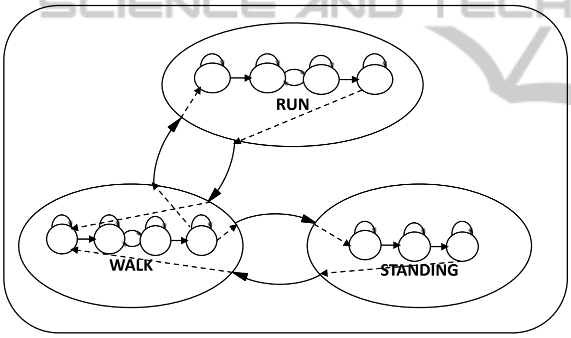

Figure 4: Concatenation of the HMMs.

among activities. These transition probabilities model human behavior; for example, the transition probability from walking to standing is higher than the transition probability from walking to running. Nevertheless, if the activity recognition system is used to monitor the elderly, the transition probability between walking and running would be lower than that in the case of monitoring children.

The result of the concatenation is a single HMM, $\lambda^F = (A^F, B^F, \pi^F)$, with twenty-one states, corresponding to all events of all activities as follows: running (states 1-4), walking (5-8), standing (9-11), sitting (12-14), lying (15-17), jumping (18-19) and falling (20-21). The state transition probability matrix of the final model, A^F, is built up following the steps below:

(i) Set the transition probability matrixes of the sub-HMMs in the diagonal transition probability matrix of the final HMM:

$$A^F = \begin{bmatrix} A^{Run} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & A^{Wlk} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & A^{Std} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & A^{Sit} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & A^{Lie} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & A^{Jmp} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & A^{Fll} \end{bmatrix}. \tag{7}$$

(ii) Connect the sub-HMMs. This step is straightforward, thanks to the definition of transient states, since all the activities must begin at the first state and end at the last state of their sub-HMM. Thus, we set:

$$\begin{aligned} a^F_{ij} &= P(e_{t+1} = S_j | e_t = S_i) \\ &= P(act_{t+1} = Z' | act_t = Z), \end{aligned} \tag{8}$$

for all $i \neq j$ which satisfy the condition that S_i is the last state of any activity, Z, and S_j is the first state of any other activity, Z'. For example, to connect the sub-HMM of running to the sub-HMM of walking, the value of the parameter $a^F_{45} = P(e_{t+1} = E^{walk}_1 | e_t = E^{run}_4)$ of the final HMM will be set to $P(act_{t+1} = walk | act_t = run)$.

(iii) Reset the self-transition probabilities corresponding to the last event of each activity, i.e. set:

$$a^F_{jj} = 1 - \sum_{m=1, m \neq j}^{21} a^F_{jm} \tag{9}$$

for each j which satisfies the condition, $S_j \in \{E^{run}_4, E^{wlk}_4, E^{Std}_3, E^{Sit}_3, E^{Lie}_3, E^{Jmp}_2, E^{Fll}_2\}$.

The emission probabilities of the final HMM, B^F, are the corresponding emission probabilities of each sub-HMM, defined in the first stage of the learning process.

Finally, the initial state distribution of the final HMM, π^F, is defined. In general, the value π^F_j is set to zero if S_j does not correspond to the first event of any sub-HMM. In this work, standing is always considered as the first position.

4 TEST PROCEDURE

4.1 Database Description

In order to facilitate comparison of results with state-of-the-art results, the database available in (Frank et al., 2010) has been used for testing the proposed method. This database consists of 4 hours and 30 minutes of activity data from 16 subjects (6 females and 10 males) aged between 23 and 50 years. Data were recorded in semi-naturalistic conditions. The IMU was placed on a belt, either on the right or left hip, providing 3-axis acceleration and 3-axis angular velocity signals at a sampling rate of 100 Hz.

The activities labelled in the database are running, walking, standing, sitting, lying, jumping, falling, ascending (from sitting to standing and from lying to standing), descending, accelerating (from walking to running) and decelerating (from running to walking). In the database, there are both training sequences and benchmark sequences. There are two benchmark sequences from two different subjects (Emil and Sinja). Emil has the IMU placed on his right side and Sinja, on her left side. These benchmark sequences consist of a succession of activities. More details of the data collection and labeling can be found in (Frank et al., 2010).

4.2 Training

For the purposes of learning the model for each activity, sequences corresponding to one single activity were extracted from the database, to be used as training data. Therefore, for each activity there are a different number of sequences with different lengths. Each HMM learned its parameters using the Baum-Welsh algorithm. The emission distributions were defined as mixtures of two gaussian distributions with diagonal covariance matrix.

4.3 Evaluation

The hierarchical dynamic model was tested, using the benchmark sequences, which were decimated by a factor of 4. This means that the model can be used with acceleration and angular velocity signals recorded at a sampling rate of 25 Hz, allowing the sensor device to consume less battery. In order to compute the most likely sequence of events given the observation sequence, the Viterbi algorithm was used. Using the knowledge of which set of events correspond to each activity, finally, the sequence of activities was obtained.

5 RESULTS

Figure 5 shows the sequence of events for the benchmark sequence of Emil. The blue crosses correspond to the events inferred by the Viterbi algorithm. Events 1 to 4 belong to the activity running, 5 to 8 to the activity walking and so on, as listed in Section 3.1.2. The red circles are the true, labelled activities and they are aligned in the graph with the last event of each activity. It should be remembered, here, that the model proposed in this work does not consider as activities, the “transition” activities labelled in the database (i.e. ascending, descending, accelerating and decelerating), since these events are inherently dealt with by means of the transient events in the hierarchical dynamic model. It can be seen from Figure 5 that the transition activities have, indeed, been incorporated by the proposed algorithm into the inferred intra-activity events. The figure shows good agreement between true and inferred activities.

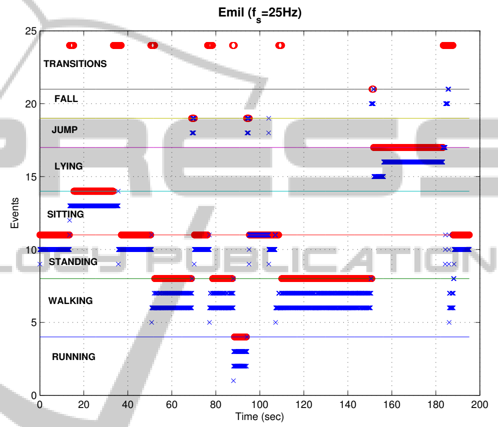

Figure 5: Sequence of events inferred for Emil’s benchmark sequence.

Tables 1 and 2 show the precision and recall values of each activity for the benchmark sequences of Emil and Sinja, respectively. The precision of activity, Z, is measured as number of samples classified correctly as activity, Z, divided by the total number of samples with inferred label equal to Z. The recall parameter is the number of samples correctly classified as activity, Z, divided by the number of samples whose true label is Z.

For comparison, Table 3 shows the performance reported in (Frank et al., 2010), relative to which the performance of the proposed algorithm is seen to be competitive.

6 DISCUSSION

The results obtained for Sinja (table 2) are lower than those for Emil (table 1) because our model does not deal specifically with the location of the sensor. The number of training sequences recorded with the sensor placed on the right side was greater than those recorded on the left side, so the model has learned,

Table 1: Recall and precision for Emil's benchmark sequence (IMU placed on the right side).

Activity	Recall (%)	Precision (%)
Running	100	95
Walking	99	97
Standing	96	99
Sitting	100	100
Lying	99	100
Jump	72	96
Fall	100	60

Table 2: Recall and precision for Sinja's benchmark sequence (IMU placed on the left side).

Activity	Recall (%)	Precision (%)
Running	100	89
Walking	99	88
Standing	92	100
Sitting	100	100
Lying	100	96
Jump	34	100
Fall	59	82

Table 3: Recall and precision results reported by (Frank et al., 2010).

Activity	Recall (%)	Precision (%)
Running	93	100
Walking	100	98
Standing	98	100
Sitting	100	97
Lying	98	96
Jump	93	93
Fall	100	80

more accurately, the models for a sensor on the right. In the case of Sinja, the sensor was on the left side. Nevertheless, the results achieved are considered acceptable.

This model also gives interesting information in terms of intra-activity dynamics. Figure 6 shows the acceleration signals in the x-, y- and z-axes (acc_x, acc_y and acc_z, respectively) and the events inferred during the activity of walking. The rhythmic transitions between events, E_2^{Wlk} and E_3^{Wlk}, are seen to correspond with the stepping pattern in the acceleration signals. So, not only has the definition of the hierarchical dynamic model proposed in this work allowed accurate classification of activities without preprocessing of the raw sensor signals, but the information regarding the dynamics within the activity itself could also be used to further characterise the subject's motion pat-

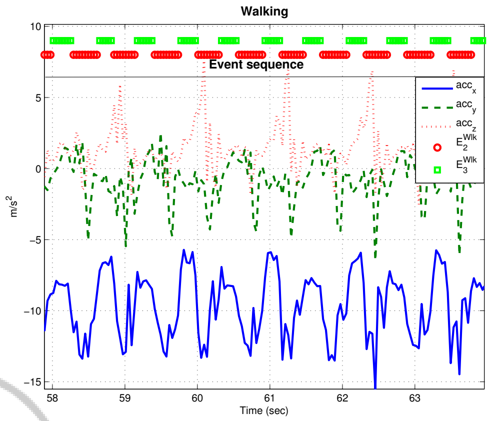

Figure 6: Events inferred for walking and acceleration signals.

terns and provide useful contextual awareness for the monitoring system.

Parameterisation of the intra-activity dynamics, inferred for a particular subject, might have potential applications in areas such as gait analysis for rehabilitation science. However, to be truly useful in this type of application, it would likely be necessary to improve the level of detail, by implementing, for example, a model with a variable number of intermediate states.

7 CONCLUSIONS AND FUTURE WORK

This work has proposed a new approach to the task of human daily activity recognition using wearable inertial sensors. The method presented has two dynamic levels, augmenting the information provided by activity classification alone, through the provision of supplementary information regarding the dynamics within the activity.

Additionally, our method bypasses the typically used feature extraction process, which is a computational bottleneck in current activity recognition methods. Working directly with the raw signals from the IMU sampled at a low sampling rate, the inherent dynamic nature of human motion is exploited. With this novel method, results with high precision and recall rates have been obtained.

Future research plans include developing more sophisticated models to take into account variations in sensor placement as well as implementing the algorithm in real-time. Moreover, a system to extract features and parameters from the intra-activity dynamics, provided among the outputs of the new algorithm, will be developed, to facilitate a detailed analysis of human behaviour in context-aware monitoring systems.

ACKNOWLEDGEMENTS

This work has been partly supported by Ministerio de Educación of Spain (projects 'DEIPRO', id. TEC2009-14504-C02-01, and 'COMONSENS', id. CSD2008-00010).

REFERENCES

Altun, K. and Barshan, B. (2010). Human activity recognition using inertial/magnetic sensor units. In *Proceedings of the First International Conference on Human Behavior Understanding*, HBU'10, pages 38–51, Berlin, Heidelberg. Springer-Verlag.

Bao, L. and Intille, S. S. (2004). Activity Recognition from User-Annotated Acceleration Data. *Pervasive Computing*, pages 1–17.

Frank, K., Nadales, M. J. V., Robertson, P., and Angermann, M. (2010). Reliable real-time recognition of motion related human activities using MEMS inertial sensors. In *ION GNSS 2010*.

Han, C. W., Kang, S. J., and Kim, N. S. (2010). Implementation of HMM-based human activity recognition using single triaxial accelerometers. *IEICE Transactions*, 93-A:1379–1383.

He, Z. Y. and Jin, L. W. (2008). Activity recognition from acceleration data using AR model representation and SVM. *Machine Learning and Cybernetics*.

Khan, A. M., Lee, Y.-K., Lee, S. Y., and Kim, T.-S. (2010). A triaxial accelerometer-based physical-activity recognition via augmented-signal features and a hierarchical recognizer. *IEEE Transactions on Information Technology in Biomedicine*, 14:1166–1172.

Krishnan, N. C., Colbry, D., Juillard, C., and Panchanathan, S. (2008). Real time human activity recognition using tri-axial accelerometers. In *Sensors Signals and Information Processing Workshop (SENSIP)*.

Moeslund, T. B., Hilton, A., and Krüger, V. (2006). A survey of advances in vision-based human motion capture and analysis. *Computer Vision and Image Understanding*, 104:90–126.

Oliver, N., Horvitz, E., and Garg, A. (2002). Layered representations for human activity recognition. In *Proceedings of the 4th IEEE International Conference on Multimodal Interfaces*, ICMI '02, pages 3–, Washington, DC, USA. IEEE Computer Society.

Powell, H., Hanson, M., and Lach, J. (2007). A wearable inertial sensing technology for clinical assessment of tremor. In *IEEE Biomedical Circuits and Systems Conference, BIOCAS 2007.*, pages 9 –12.

Preece, S. J., Goulermas, J. Y., Kenney, L. P. J., and Howard, D. (2009). A comparison of feature extraction methods for the classification of dynamic activities from accelerometer data. *IEEE Transactions on Biomedical Engineering*, 56(3):871–879.

Rabiner, L. and Juang, B.-H. (1993). *Fundamentals of Speech Recognition*. Prentice Hall, united states ed edition.

Rabiner, L. R. (1990). Readings in speech recognition. In Waibel, A. and Lee, K.-F., editors, *Readings in speech recognition*, chapter A tutorial on hidden Markov models and selected applications in speech recognition, pages 267–296. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA.

Sabatini, A., Martelloni, C., Scapellato, S., and Cavallo, F. (2005). Assessment of walking features from foot inertial sensing. *IEEE Transactions on Biomedical Engineering*, 52(3):486 –494.

Viterbi, A. (1967). Error bounds for convolutional codes and an asymptotically optimum decoding algorithm. *IEEE Transactions on Information Theory*, 13(2):260 – 269.

Winters, J. and Wang, Y. (2003). Wearable sensors and telerehabilitation. *IEEE Engineering in Medicine and Biology Magazine*, 22(3):56 –65.

Wu, G. and Xue, S. (2008). Portable preimpact fall detector with inertial sensors. *IEEE Transactions on Neural Systems and Rehabilitation Engineering [see also IEEE Trans. on Rehabilitation Engineering]*, 16(2):178–183.

Zhu, C. and Sheng, W. (2010). Recognizing human daily activity using a single inertial sensor. In *Proceedings of the 8th World Congress on Intelligent Control and Automation (WCICA)*, pages 282 –287.