ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2012, i6doc.com publ., ISBN 978-2-87419-049-0. Available from http://www.i6doc.com/en/livre/?GCOI=28001100967420.

Supervised and unsupervised classification approaches for human activity recognition using body-mounted sensors

D. Trabelsi[1], S. Mohammed[1] , F. Chamroukhi[2] , L. Oukhellou[3] and Y. Amirat[1]

1−University Paris-Est Créteil (UPEC), LISSI,
120-122 rue Paul Armangot, 94400, Vitry-Sur-Seine, France

2−University Sud Toulon-Var, LSIS,
Batiment R BP 132 - 83957 La Garde Cedex, France

3−University Paris-Est, IFSTTAR, GRETTIA,
F-93166 Noisy-le-Grand, France

Abstract. In this paper, the activity recognition problem from 3-d acceleration data measured with body-worn accelerometers is formulated as a problem of multidimensional time series segmentation and classification. More specifically, the proposed approach uses a statistical model based on Multiple Hidden Markov Model Regression (MHMMR) to automatically analyze the human activity. The method takes into account the sequential appearance and temporal evolution of the data to easily detect activities and transitions. Classification results obtained by the proposed approach and compared to those of the standard supervised classification approaches as well as the standard hidden Markov model show that the proposed approach is promising.

1 Introduction

The wearable and ubiquitous technologies are becoming a powerful solution to provide assistive services to humans, such as health monitoring, well being, security, etc. Within the activity monitoring, one can notice the importance of the physical human activities recognition [1]. Several techniques have been used to quantify these activities such as video-based motion capture systems, on-body wearable sensors, etc. Among the inertial sensors used for posture classification, the accelerometers are the most commonly used thanks to the rapid evolution of the microelectromechanical (MEMS) technology [2].

Human activity classification has been studied using many machine learning approaches such as k-Nearest Neighbor (k-NN) [3], multi-class support vector machines (SVM) [4], artificial neural networks (ANN) [5] and systems based on the Hidden Markov Models (HMM) [6]. In this study, we propose an approach based on HMM in a regression context. Each activity is represented by a regression model and the switching from one activity to another over time is governed by a hidden Markov chain. This paper is organized as follows: Section 2 presents the experimental protocol for human activity recognition. Section 3 presents the proposed model and its unsupervised parameter estimation technique. Finally, in section 4, the performance of the proposed Multiple Hidden

ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2012, i6doc.com publ., ISBN 978-2-87419-049-0. Available from http://www.i6doc.com/en/livre/?GCOI=28001100967420.

Markov Model Regression approach is evaluated and compared to well-known alternative approaches for human activity recognition.

2 Experimental Setup

In this study, human activities are classified using three sensors placed at the chest, the right thigh and the left ankle (see Fig.1). The sensor's placements are chosen to represent the human body motion while guaranteeing less constraint and better comfort for the wearer as well as its security. These sensors consist of three MTx 3-DOF inertial trackers developed by Xsens Technologies [7].

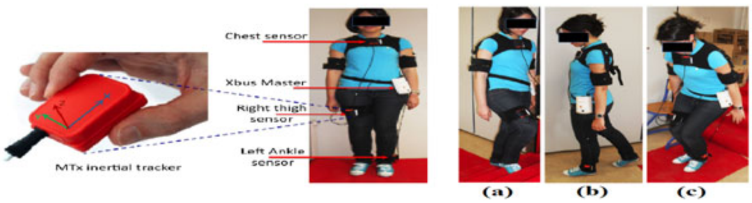

Fig. 1: MTx-Xbus inertial tracker, sensors placement and examples of some considered activities: a) Stairs Up , b) Walking , c) Standing Up

The activities were performed by six different healthy subjects of different ages. The activities to be recognized are as follows: Stairs down A_1, Standing A_2, Sitting down A_3, Sitting A_4, From sitting to sitting on the ground A_5, Sitting on the ground A_6, Lying down A_7, Lying A_8, From lying to sitting on the ground A_9, Standing up A_{10}, Walking A_{11}, stairs up A_{12} (see Fig.1). Each sensor has tri-axial accelerometer, a total of nine accelerations are therefore measured and recorded overtime for each activity. In the following section, an unsupervised approach dedicated to sequential data segmentation and classification is presented.

3 Segmentation with Multiple Hidden Markov Model Regression for Human Activity Recognition - MHMMR

In this framework, each observation, denoted by y_i, represents the ith acceleration measurement and the corresponding hidden state, denoted by z_i, represents its corresponding activity.

3.1 General description of the Multiple Hidden Markov Model Regression

In Hidden Markov Model Regression (HMMR), each time series is represented as a sequence of observed univariate variables $(y_1, y_2, \ldots, y_n)$, where the observation y_i at time t_i is assumed to be generated by the following regression model [8, 9, 10]:

$$\boldsymbol{y}_i = \boldsymbol{\beta}_{z_i}^T \boldsymbol{t}_i + \sigma_{z_i}\epsilon_i \quad ; \quad \epsilon_i \sim N(0,1), \quad (i = 1, \ldots, n) \tag{1}$$

ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2012, i6doc.com publ., ISBN 978-2-87419-049-0. Available from http://www.i6doc.com/en/livre/?GCOI=28001100967420.

where z_i is a hidden discrete-valued variable taking its values in the set $\{1, \ldots, K\}$. In our application, K corresponds to the number of considered activities. The vector $\boldsymbol{\beta}_{z_i} = (\beta_{z_i 0}, \ldots, \beta_{z_i p})^T$ is the one of regression coefficients of the p-order polynomial regression model z_i and σ_{z_i} represents the corresponding standard deviation, $\boldsymbol{t}_i = (1, t_i, t_i^2 \ldots, t_i^p)^T$ is a $p + 1$ dimensional covariate vector and the ϵ_i's are standard Gaussian variables representing an additive noise.
For the multiple regression case, the model is formulated as follows:

$$\boldsymbol{y}_i^{(j)} \quad = \quad \boldsymbol{\beta}_{z_i}^{(j)T} \boldsymbol{t}_i + \sigma_{z_i}^{(d)} \epsilon_i, \quad (j = 1, \ldots, d) \tag{2}$$

where $z = (z_1, \ldots, z_n)$ is a homogeneous Markov chain of first order parametrized by the initial state distribution π and the transition matrix A, which A governs simultaneously all the univariate time series components and d represents the dimension of the time series. The model (2) can be rewritten in a matrix form as:

$$\boldsymbol{y}_i = \boldsymbol{B}_{z_i}^T \boldsymbol{t}_i + e_i \quad ; \quad e_i \sim N(0, \Sigma_{z_i}), \quad (i = 1, \ldots, n) \tag{3}$$

where $y_i = (y_i^{(1)}, \ldots, y_i^{(d)})^T$ is the ith observation of the time series in R^d, $B_k = \left[\beta_k^{(1)}, \ldots, \beta_k^{(d)}\right]$ is a $(p+1) \times d$ dimensional matrix of the multiple regression model parameters associated with the regime (class) $z_i = k$ and Σ_{z_i} its corresponding covariance matrix.
The MHMMR model is therefore fully parametrized by the parameter vector $\theta = (\pi, A, B_1, \ldots, B_K, \Sigma_1, \ldots, \Sigma_K)$.

3.2 Parameter estimation

The parameter vector θ is estimated by the maximum likelihood method. The log-likelihood to be maximized in this case is written as follows:

$$\begin{aligned} L(\theta) &= \log p(y_1, \ldots, y_n; \theta) \\ &= \log \sum_{z_1, \ldots, z_n} p(z_1; \pi) \prod_{i=2}^{n} p(z_i | z_{i-1}; A) \prod_{i=1}^{n} \mathcal{N}(y_i; B_{z_i}^T t_i, \Sigma_{z_i}). \end{aligned} \tag{4}$$

Since this log-likelihood cannot be maximized directly, this is done by the EM algorithm [11, 12], which is known as the Baum-Welch algorithm in the context of HMMs [12]. From the estimated model, the optimal state sequence; i.e activity sequence is then determined by using the Viterbi decoding algorithm [13].
In the next section, the performances of MHMMR approach is evaluated and compared to those of standard supervised and unsupervised classification techniques.

4 Results and discussion

Series of experiments were conducted on a real dataset to evaluate the performance of the proposed approach based on MHMMR. The data contain recordings of six healthy volunteers performing the twelve activities described in section 2.

ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2012, i6doc.com publ., ISBN 978-2-87419-049-0. Available from http://www.i6doc.com/en/livre/?GCOI=28001100967420.

Each person performed the following sequence of activities: A_2 - A_1 - A_2 - A_3 - A_4 - A_5 - A_6 - A_7 - A_8 - A_9 - A_6 - A_{10} - A_2 - A_{11} - A_2 - A_{12} - A_2 in his own style and he was not restricted on how and how long the activities should be performed but only with the sequential activities order. In addition, the duration of each activity is not restricted to be the same from one subject to another, as it may vary (120 sec $\pm$12 sec). The experiments include also comparisons of the proposed unsupervised approach to well-known classification approaches such as Naive Bayes, MultiLayer Perceptron (MLP), k-NN ($k = 1$), Support Vector Machines (SVM), Random Forest and the standard HMM.

4.1 Classification performance of the proposed approach - MHMMR

The following experiments aim to qualitatively assess the performances of the proposed approach in terms of automatic segmentation of human activities on the basis of acceleration signals. From the sequence of nine observed variables $y_i = (y_i^{(1)}, \ldots, y_i^{(9)})$ at each time step i for $i = 1, \ldots, n$ corresponding to the 3-axis accelerations measured by the three sensors, the MHMMR is used to identify the latent sequence $z = (z_1, \ldots, z_n)$ corresponding to the twelve activities. The number of classes K is fixed to twelve. The model parameters are estimated from the data using the EM algorithm. Note that the labels were not used to train unsupervised models; they were only used afterwards for the evaluation of classification errors.
Figure 2 shows the performance of the proposed method to segment a particular sequence as it represents the evolution of acceleration data and the corresponding posterior probabilities compared to true labels. Note that the posterior probability is the probability that a sample i will be generated by the regression model k given the whole sequence of observations $(\boldsymbol{y}_1, \ldots, \boldsymbol{y}_n)$.
This example highlights the potential benefit of the proposed approach in terms

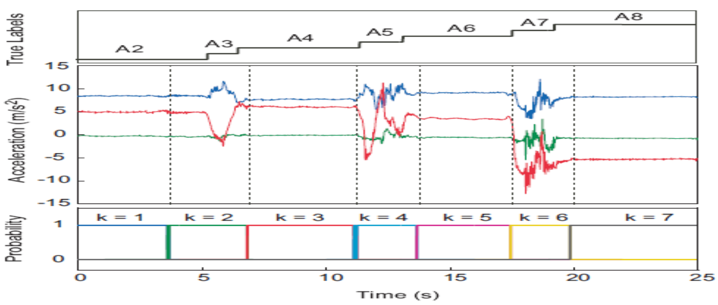

Fig. 2: MHMMR segmentation for the sequence (Standing A_2 - Sitting down A_3 - Sitting A_4 - From sitting to sitting on the ground A_5 - Sitting on the ground A_6 - Lying down A_7 - Lying A_8) for the seven classes k=(1,. . . , 7) .

of automatic segmentation of human activities. Both transitions and stationary activities are well-segmented. Next, in order to highlight the efficiency ratio of

ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2012, i6doc.com publ., ISBN 978-2-87419-049-0. Available from http://www.i6doc.com/en/livre/?GCOI=28001100967420.

the three sensors used for activity recognition, the MHMMR algorithm has been evaluated using data from only two sensors. The classification results, given in Table 1, show as expected, that the percentage of correctly classified instances decreases with the number of data sources. The worst result is obtained when the sensor placed at the thigh is not taken into account.

Sensors	Percentage of correct classification
Chest, thigh, ankle	91.4%
Chest, ankle	83.9%
Chest, thigh	86.2%
Thigh, ankle	84.0%

Table 1: Effects of reducing the number of sensors on the classification results using the MHMMR

In the following, classification results obtained with standard supervised classification approaches and the standard HMM are given and compared to those of the proposed approach.

4.2 Comparison with supervised and unsupervised classification techniques

For the experiments, the correct classification rate and the classification accuracy (precision and recall) were evaluated using 10-fold cross-validation.

	Correct Classification (%)	Precision (%)	Recall (%)
Naive Bayes	80.6	80.9	80.6
MLP	83.1	82.8	83.2
SVM	88.1	87.6	88.3
k-NN	95.8	95.9	95.9
Random Forest	93.5	93.5	93.5
HMM	84.1	83.8	84.0
MHMMR	91.4	89.0	95.6

Table 2: Comparison of the performance in terms of Correct Classification, Recall and Precision of the seven classifiers

From table 2, it can be observed that the MHMMR achieves 91.4% of percentage of correct classification. Compared to standard supervised classification techniques, this result is very encouraging since the proposed approach performs in an unsupervised way and the main errors are due to the confusions located in transition segments as the obtained labels may not correspond perfectly to the expert labels in short intervals. Moreover, It can be noticed that assigning a new sample to a class using the k-NN approach requires the computation of as many distances as there are examples in the dataset, which may lead to a significant computation time. With the proposed approach, classification needs only the computation of the posterior probabilities as many as there are activities.

ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2012, i6doc.com publ., ISBN 978-2-87419-049-0. Available from http://www.i6doc.com/en/livre/?GCOI=28001100967420.

5 Conclusion and future work

In this paper, we presented a statistical approach based on hidden Markov models in a regression context for the classification and the joint segmentation of multivariate time series for human activity recognition. The main advantage of the proposed approach lies in the fact that the statistical model explicits the regime changes over time of the time series through a hidden Markov chain, each regime being interpreted as an activity. The comparison with well-known supervised classification methods shows that the proposed method is competitive even if it performs in an unsupervised framework. This work can be extended in several directions. Indeed, more complex modeling techniques for multidimensional time series could be investigated in order to better take into account the transition between activities. Finally, data fusion involving information supplied by several classifiers can be carried out in the context of activity recognition.

References

[1] K. Altun, B. Barshan, and O. Tuncel, Comparative study on classifying human activities with miniature inertial and magnetic sensors, *Pattern Recognition*, 43:3605–3620, 2010.

[2] J. Y. Yang, J. S. Wang, and Y. P. Chen, Using acceleration measurements for activity recognition: An effective learning algorithm for constructing neural classifiers, *Recognition Letters*, 29:2213–2220, 2008.

[3] C. Liu, C. Lee, and P. Lin, A fall detection system using k-nearest neighbor classifier, *Expert Systems with Applications*, 37:7174–7181, 2010.

[4] H. Qian, Y. Mao, W. Xiang, and Z. Wang, Recognition of human activities using svm multi-class classifier, *Pattern Recognition Letters*, 31:100–111, 2010.

[5] J.Y.Yang, J.S.Wang, and Y.P.Chen, Using acceleration measurements for activity recognition: An effective learning algorithm for constructing neural classifiers, *Pattern Recognition Letters*, 29:342–350, 2008.

[6] R. Wassink, C. Baten, P. Veltink, R. Veldhuis, and J. Smeding, Monitoring of human activities using a trainable system based on hidden markov modelling technology, *Gait & Posture*, 24:109–110, 2006.

[7] B. Enschede, Mti and mtx user manual and technical documentation, 2009, www.xsens.com.

[8] L. R. Rabiner, A tutorial on hidden markov models and selected applications in speech recognition, *Proceedings of the IEEE*, 77:257–286, 1989.

[9] M. Fridman, Hidden markov model regression, Technical Report, Institute of mathematics, University of Minnesota, 1993.

[10] F. Chamroukhi, A. Samé, G. Govaert, and P. Aknin, “Time series modeling by a regression approach based on a latent process,*Neural Networks*, vol. 22, no. 5-6, pp. 593–602, 2009.

[11] G. J. McLachlan and T. Krishnan, *The EM algorithm and extensions*. New York: Wiley, 1997.

[12] A. P. Dempster, N. M. Laird, and D. B. Rubin, Maximum likelihood from incomplete data via the EM algorithm, *Journal of The Royal Statistical Society, B*, 39(1):1–38, 1977.

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