A hierarchical classifier to monitor ADL through dynamic programming on dual-axis accelerometer data

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Abstract: - T The new focus on active ageing in developed countries renders more urgent the development of remote monitoring for motor activities in the elderly. Recognition and classification of Activities of Daily Living in this context open intriguing scenarios especially if real- time techniques are available. The present work proposes a hierarchical classifier for activity recognition that used only a dual axis accelerometer placed on the shin, and the DTW algorithm. The classifier was applied to the recognition of walking, climbing and descending stairs of five different subjects. The first part is a calibration phase, to obtain the template signals, and the second part recognizes activities by determining the distance between the signal input and a set of previously defined templates. The signals of the two channels will be used in a hierarchical way. The results show a classification with overall percentage of error less than 5%.

Key-Words: - **Wearable sensors, Accelerometry, Classification**

1 Introduction

The classification of daily living activities by way of accelerometers has been proposed in the literature by placing a single sensor on the relevant body segments [1]. To improve the classification performance, some authors combined multiple axis accelerometers, or other types of sensors, together with different combinations of classifying techniques [2-4] .
In emergency contexts, accelerometers have been also used to detect falls [5], whereas in physical activities monitoring, techniques have been devised to estimate the metabolic consumption and energy expenditure (EE) from accelerometer data, even if these techniques are highly dependent on sensor positioning procedure [6-7].
Most of the techniques for activity detection and classification are performed on a hierarchical basis, i.e. first by estimating body posture through first order moments extracted from accelerometry data (typically the mean value of the signal components) [8], whereas higher order moments are generally used to discriminate between different activities corresponding to the same body posture, based on differences in terms of energy or amplitude. More sophisticated techniques are based on hidden markov model [9], joint time-frequency domain [10], or shape matching [11].
In the context of motor monitoring, one critical aspect resides in the ability of a system to discriminate between different activities, some of which are generally performed sequentially (such as walking on level surfaces and up or down stairs, rising from a chair and sitting down), and some can be performed simultaneously (such as reaching for an object while walking) and at different speed.
When the speed significantly affects accelerometers signals in movements, the way the motor activity patterns vary cannot be modeled as a linear warping, so that it is necessary to take into account nonlinearities coming from the possible stretching and shrinking of the different phases of each activity.
To this end, an algorithm based on Dynamic Time Warping (DTW), which takes these nonlinearities into account has been recently proposed [12-14], and it has been proven as a reliable classifier based on a single sensor.
In this work, the objective is to realize a hierarchical classifier by combining DTW on data obtained by a dual axis accelerometer.

2 Materials and Methods

2.1 Participants and Procedure

Five young healthy participants (age 25-33) were recruited for the tests. Three different activities were selected: level walking (WW), stair ascending (SU) , and stair descending (SD). The stairway had steps 15 cm high and 30 cm long.

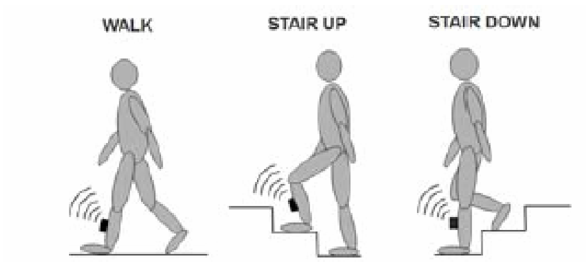


Figure 1. Monitored activities, and sensor placement

To obtain a balanced number of samples for every motor activity and to avoid stereotyped execution of the movement we ask the participants to execute a number of motor activities in the most natural way. A portion of the obtained signals were then used for the calibration phase (approximately 20 seconds), whereas the remaining was used to test the classifier, by generating four different activity paths:

- P1: 11 walking steps, 8 stair ascending steps, 11 walking steps, 8 stair descending steps;
- P2: 8 stair ascending steps, 11 walking steps, 8 stair ascending steps, 2 walking steps, 8 stair descending steps;
- P3: 8 stair descending steps, 11 walking steps, 8 stair descending steps, 2 walking steps, 8 stair ascending steps.
- P4: 11 walking steps, 8 stair descending steps, 11 walking steps, 8 stair ascending steps.

2.2 Data Acquisition

A dual axis accelerometer sensor (based on Analog Devices ADXL202 biaxial accelerometer) was placed on the medial portion of the right shin with axes disposed on the sagittal plane along radial and longitudinal directions.

The accelerometer signals were band-pass filtered between 0.2 and 15 Hz and sample on 2kHz.

2.3 Data Processing: Calibration

Calibration is needed to create a complete set of signal templates, one per motor activity, person, and channel. The process ids fulfilled by segmenting the signals into epochs associated to a specific single motor activity.

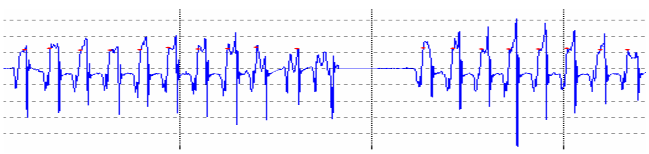


Figure 2. Segmentation procedure. Small circles identify the segmented activities.

Signals have been portioned into epochs by calculating the integral and comparing it with a statistical threshold value (see Figure 2). The segmentation of the signal into epochs was associated to the detected motor activities. The template was chosen as the one which presented the minimum distance, in DTW terms, from all the others. The flow-chart is described in Figure 3.

Templates associated to motor activities were respectively called as TW1, TSD1, TSU1, where 1 represent channel 1, longitudinal, and TW2, TSD2, TSU2, where 2 stands for channel 2, radial. The total number of templates sums to 30 (5 people x 2 directions x 3 activities).

A graphical user interface (MATLAB GUI version 7.0) was specifically created to see the different channels, set the threshold and the first guess parameters initial parameter.

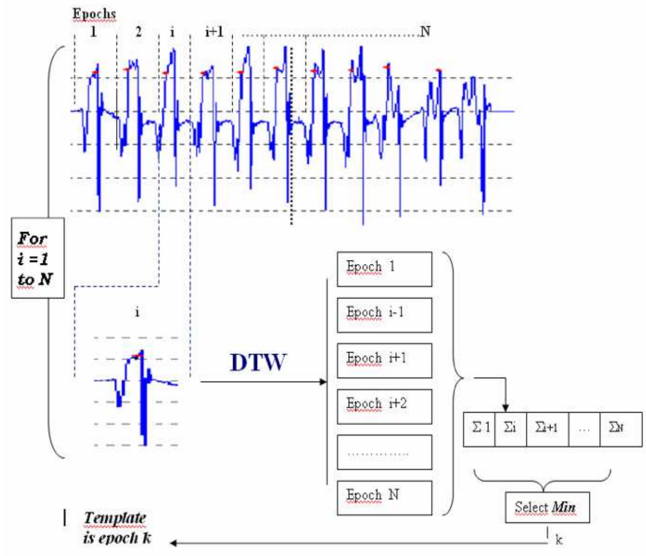


Figure 3. Flowchart of the calibration process

2.4 Activity detection

The first phase of accelerometer data processing consists of detecting single motor activities from the accelerometer data. For this, a statistical approach has been used, which is based on calculating the integral and comparing it with a statistical threshold value. (the same for each channel). Each epoch is of different length for the different speed with which each activity is completed. All those epochs are grouped into a structure for the classification procedure described in the following.

Around 70% of all the recorded signals were used to create the different paths (P1-P4) described before.

2.5 Data Processing: classification through DTW

The proposed criterion for classification is based on finding, for each pair template-current activity, the minimum distance Warp-Path, and then classifying among activities by looking for the minimum of these Warping path distances (see Figure 4).

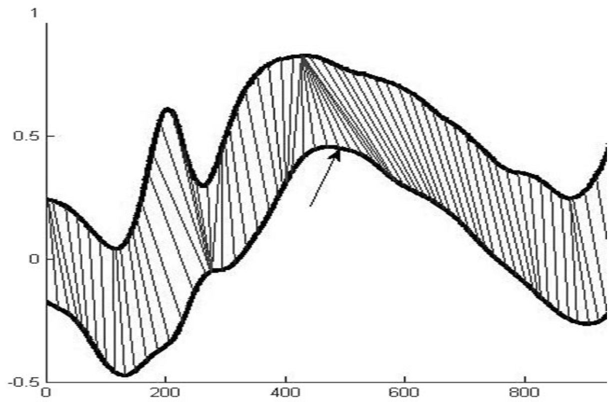


Figure 4. Dynamic Time Warping (DTW) sample

The input signals is considered as a sequence of n samples X=[x1,x2,…,xn], and the template is a sequence of m samples Y=[y1,y2,…,ym].
DTW builds a matrix D [nxm] in which each element represents the distance between the i-th element of X(i) and the j-th element of Y(j).
The matrix D is then used to obtain a matrix Θ, in which every element is the sum between the local distance di,j and the minimum of the total distances of the neighbour-most elements according to the equation:

$$\theta_{i,j} = d_{i,j} + \min\left\{\theta_{i-1,j-1}, \theta_{i,j-1}, \theta_{i-1,j}\right\} \tag{1}$$

The warping path W, is a contiguous set of matrix elements that defines a mapping between X and Y. The k-element of W is defined as wk = (i,j):

$$W = w_1, w_2, \ldots, w_k \quad \max(n,m) < k < n+m-1 \tag{2}$$

The warping path generally undergoes to several constraints: among them, the requirement for the warping path to start and finish in diagonally opposite corner cells of the matrix, restriction to the number of allowable steps in the warping path to adjacent cells, and monotonicity in time θi,j allows the alignment between X and Y;θn,m is the whole distance between X and Y.

2.6 Data Processing: hierarchical classifier

The entire flowchart of the hierarchical classifier is shown in Figure 5. The longitudinal channel has been verified as the most reliable in terms of classification performance. This has been chosen as the one for the first phase of classification, to determine the first-guess activity based on the neighbor-most one.
If the distance between the first-guess activity and the second/nearest activity falls below a certain threshold, the second channel comes into play.

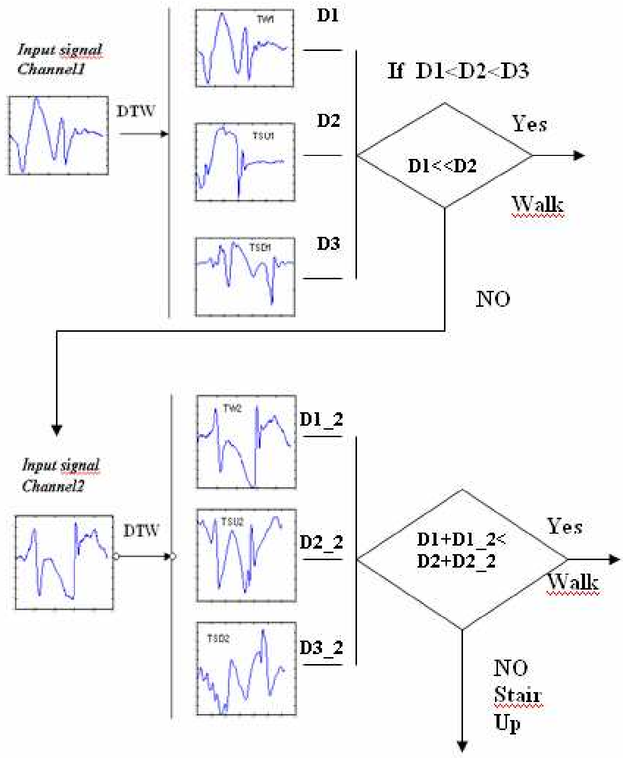


Figure 5. An instance of the flow-chart of ADL detection by distance between each epoch and each template.

The presence of the second phase, which re-applies DTW on the second direction, and then averages the distances with the value obtained with the first direction, is especially needed for those epochs corresponding to the transition phases, when the distance values are not clearly distinguished.

3 Results and Discussion

With a graphical interface, developed with MATLAB GUIDE ver.7.0, it is possible to visualize the results in a bar graph (Figure 6).

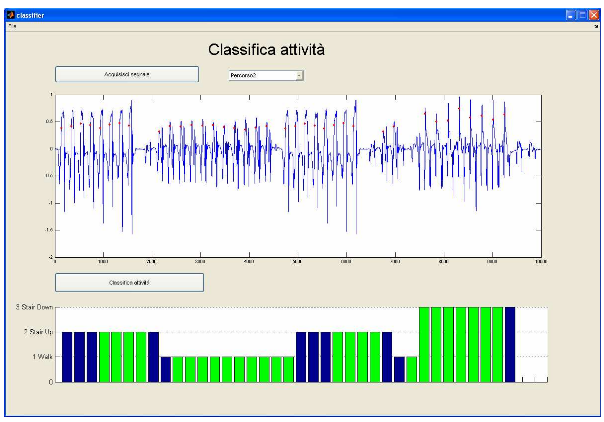


Figure 6. GUI for activity classification. Green color corresponds to single axis classification, blue depicts epochs classified through dual axis accelerometry.

With different color is represented the resort to second channel (blue) . The activities are coded like: Walk -1; Stair Up- 2; Stair Down -3:
Table 1 shows the classification performance over the four different paths for all the subjects, together with the percentage of use of the second channel.

TABLE 1

PATH	Classification performance	Dual axis use
Path 1	100%	26%
Path 2	98%	28%
Path 3	90%	30%
Path 4	97%	26%

Table 2, 3 and 4 respectively show the classification performance of single axis DTW, and dual axis.
The overall scheme for the classification procedure runs in approximately 5 seconds for paths lasting 1 minute over a Pentium IV 30Ghz, 512M RAM, Matlab ver.7.0: this burden time is consistent with the hypothesis of working in real time applications.

TABLE 2

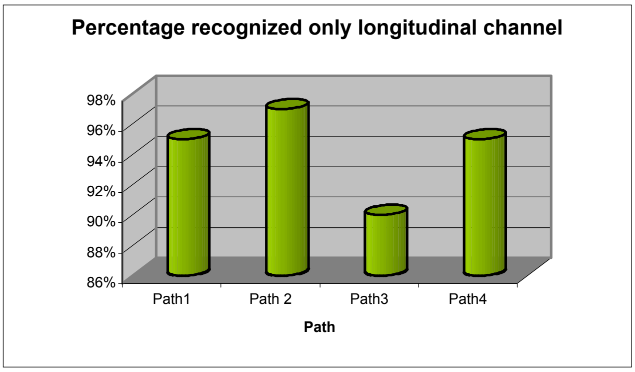


TABLE 3

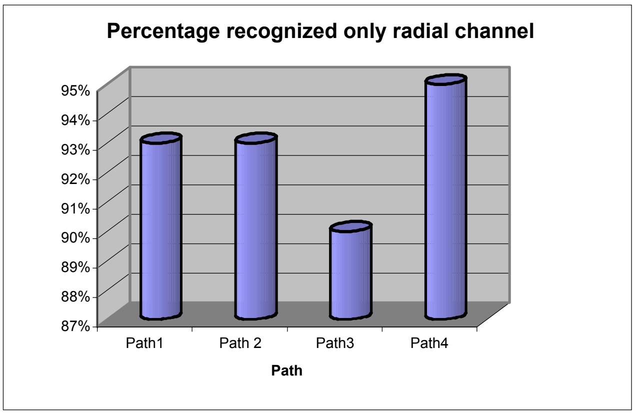
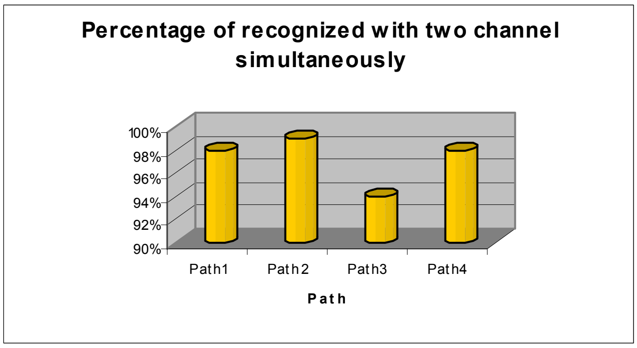


TABLE 4



4 Conclusion

This paper describes a hierarchical classifier for dynamic activities while standing: level walking, stair ascending, and stair descending. By using a dual axis accelerometer placed on the shin of the volunteer, it is possible to classify in real time these three different activities with an overall classification performance higher than 96% .
The calibration process is quite rapid, and allows the user to determine the stereotypic waveform, based on DTW distances.
The hierarchical classifier ha san advantage as compared to the combined use of both channels, both in terms of computation time, and in terms of memory allocation.
This concept could be extended to a higher number of accelerometers which might be likely needed if a higher number of different activities need to be monitored: by maintaining the hierarchical structure, it is envisioned to let new sensors come into play when classification is doubtful.
For these characteristics, classifier applies to activity of tele-monitoring and tele-attendance in real time.

References:

[1] M. J. Mathie, A. C. Coster, N. H. Lovell, and B. G. Celler, "Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement," Physiol Meas, vol. 25, pp. R1-20, 2004.

[2]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, pp. 375-85, Dec 1996.

[3] Makikawa M and Iizumi H 1995 Development of an ambulatory physical activity memory device and its application for the categorization of actions in daily life Medinfo 8 (pt 1) 747–50

[4] Sekine M, Tamura T, Akay M, Fujimoto T, Togawa T and Fukui Y 2002 Discrimination of

walking patterns using wavelet-based fractal analysis IEEE Trans. Neural Syst. Rehabil. Eng188–96

[5] Williams G, Doughty K, Cameron K and Bradley D A 1998 A smart fall and activity monitor for telecare applications Proc. 20th Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society

[6]Fehling P C, Smith D L, Warner S E and Dalsky G P 1999 Comparison of accelerometers with oxygen consumption in older adults during exercise Med. Sci. Sports Exerc. 31 171–5

[7]Hendelman D, Miller K, Baggett C, Debold E and Freedson P 2000 Validity of accelerometry for the assessment of moderate intensity physical activity in the field Med. Sci. Sports Exerc. 32 S442–9

[8]Foerster F and Fahrenberg J 2000 Motion pattern and posture: correctly assessed by calibrated accelerometers Behav. Res. Methods Instrum. Comput. 32 450–7

[9]D. M. Karantonis, M. R. Narayanan, M. Mathie, N. H. Lovell, and B. G. Celler, "Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring," IEEE Trans Inf Technol Biomed, vol. 10, pp. 156-67, Jan 2006.

[10]S. G. Trost, K. L. McIver, and R. R. Pate, "Conducting accelerometer-based activity assessments in field-based research," Med Sci Sports Exerc, vol. 37, pp. S531-43, Nov 2005.

[11]Y. Schutz, S. Weinsier, P. Terrier, and D. Durrer, "A new accelerometric method to assess the daily walking practice," Int J Obes Relat Metab Disord, vol. 26, pp. 111-8, Jan 2002.

[12] Sakoe, H. & Chiba, S. (1978). Dynamic programming algorithm optimization for spoken word recognition. IEEE Trans. Acoustics, Speech, and Signal Proc., Vol. ASSP-26. pp. 43-49.

[13]S. Casarotto, A. M. Bianchi, S. Cerutti, and G. A. Chiarenza, "Dynamic time warping in the analysis of event-related potentials," IEEE Eng Med Biol Mag, vol. 24, pp. 68-77, Jan-Feb 2005.

[14] Hong Li,Michael Greenspan Multi-scale Gesture Recognition from Time-Varying Contours.Proceedings of the Tenth IEEE International Conference on Computer Vision (ICCV'05)1550-5499/05 ,2005