Minimizing the Set Up for ADL Monitoring through DTW Hierarchical Classification on Accelerometer Data

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Abstract: - Systems for remote monitoring of motor activities in the elderly are becoming very popular in developed countries. In this context, recognition and classification of Activities of Daily Living (ADL) is a very important step that can open intriguing scenarios, especially if real-time techniques become available. The present work proposes a hierarchical classifier based on the Dynamic Time Warping (DTW) technique, applied on data recorded from a tri-axial accelerometer placed on the shin, to classify among different motor activities. The classifier was applied to the recognition of walking, climbing and descending stairs of five different subjects. After the calibration phase needed to extract the templates, the technique makes it possible to recognize activities by determining the distance between the signal input and a set of the previously defined templates. Signals coming from the three different channels are used in a hierarchical way, with three layers. The hierarchy has been set based on sorting channels by signal to noise ratio in descending order. The results show a classification with overall percentage of error less than 5%.

Key-Words: - Wearable sensors, Accelerometer, ADL , Dynamic Time Warping, Template, Classification

1 Introduction

Accelerometers have been extensively used in rehabilitation engineering to gather information on the physical status of patients. With this idea in mind, different techniques applied to accelerometer signals have been devised to either monitor the activity of patients, estimate the amount of metabolic consumption and energy expenditure [1-2] during different activities, or detect falls in the elderly [3].

If long term monitoring of motor activities is to be pursued, a couple of issues need to be addressed: on the technological side, having a compact set up to minimize intrusiveness to the patient, and on the processing side, having a robust way to classify among different motor activities, which are generally associated with different amounts of energy expenditure. To perform the task of classifying activities, a number of studies have been presented in the past, which usually rely on the use of different ensembles accelerometers (typically either bi-axial or tri-axial), placed on the subject's body surface in correspondence of the body segments.

The redundancy offered by the presence of multiple axis accelerometers and different sets usually lets one improve classification performance, using different approaches to classification [4-6]. If instead, a single sensor is used [7], more refined techniques of classification are generally needed.

The majority of the classification techniques are generally hierarchical, i.e. they first try to recognize body posture based on first order moments extracted from accelerometer data (typically the mean value of the signal components, with respect to gravity [8])), whereas discrimination among different activities corresponding to the same body posture is generally achieved by using differences in higher order moments, reflecting changes in terms of energy or amplitude. If it is possible to include information on the sequence between different activities and transitions, more sophisticated techniques are usually based on Hidden Markov Model [9], whereas joint time-frequency domain [10], or shape matching [11] are other methods which have been proven as effective in this sense.

One of the often underestimated issues related with classification of motor activities resides in the ability of a system to discriminate between different activities, some of which are generally performed in a repetitive fashion (such as walking on level surfaces and up or down stairs, rising from a chair and sitting down), some can be performed simultaneously (such as reaching for an object while

walking) and at different speed depending on a number of unpredictable variables.
Limiting to the velocity dependence, when the tasks are performed with significantly different speeds, the way the motor activity patterns, as captured by accelerometer data, vary cannot be modelled 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. This is one of the reasons why performance in classification rates generally decrease when people are requested to perform tasks at varying speeds.
To overcome these limitations, Dynamic Time Warping (DTW) has been proposed as a flexible solution for pattern matching techniques, because it takes into account shape modifications of template patterns [12-14]. It has been recently been proven as a reliable classifier based on a single sensor [15].
DTW will be used in this work in the framework of a hierarchical classifier based on acceleration data coming from a single tri-axial accelerometer. The hierarchical approach has been chosen in this work with the idea in mind of minimizing the computational burden, and using the information coming from ancillary signals only when it will help in the classification, and thus minimizing the computational burden.

2 Materials and Methods

2.1 Participants and Procedure

Five young healthy participants (age 25-33) were asked to take part to the study. They were requested to perform a sequence of three different activities, randomly interleaved: level walking (WW), stair ascending (SU), and stair descending (SD). Stair ascending and descending was performed on a stairway with steps 11 cm high and 30 cm long.

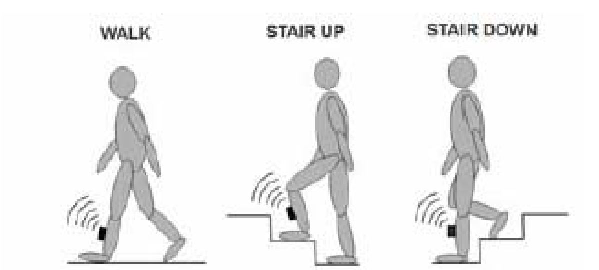

Fig. 1. Monitored activities, and sensor placement

To obtain a balanced number of samples for every motor activity and to avoid biased execution of the movement, the participants were first asked to familiarize with the set up, and then perform a number of motor activities in the most natural way. A portion of the obtained signals was then used for the calibration phase (approximately 20 s), whereas the remaining part 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 tri-axial accelerometer sensor (based on coupling two Analog Devices ADXL202 bi-axial accelerometers) was placed on the medial portion of the right shin thus recording activity along radial, longitudinal, and lateral direction, respectively.
The accelerometer signals were band-pass filtered between 0.2 and 15 Hz and fed at 2000 samples/s to a 12-bit A/D converter. This fairly high sampling rate was chosen to reduce the effect of quantization [16].

2.3 Calibration

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

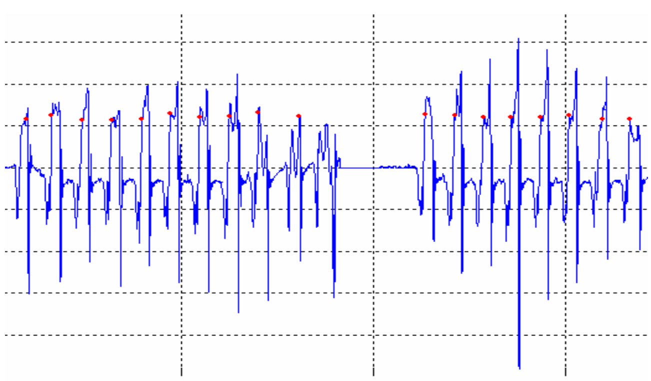

Fig. 2. Segmentation procedure. Small circles identify the segmented activities.

Signals have been portioned into epochs by calculating the integral and comparing it with a threshold value (see Figure 2) based on the statistical properties of the signal. The segmentation of the signal into epochs was associated to the detected motor activities. The template was chosen as the one that presented the minimum distance, in DTW terms, from all the others. The flow diagram corresponding to the calibration phase is presented in Figure 3.
Templates associated to motor activities were respectively called as TW_j, TSD_j, TSU_j, where j ={1,2,3} represents the channel (1 for the longitudinal direction, 2 for the radial direction, and 3 for the lateral direction, respectively). The total number of templates is thus 45 (5 people x 3 directions x 3 activities).
A graphical user interface, designed with the MatLab GUI Layout editor under Matlab© R2007A (The Mathworks™, inc.), was specifically created to see the different activities in different channels, and to set the threshold and the first guess.

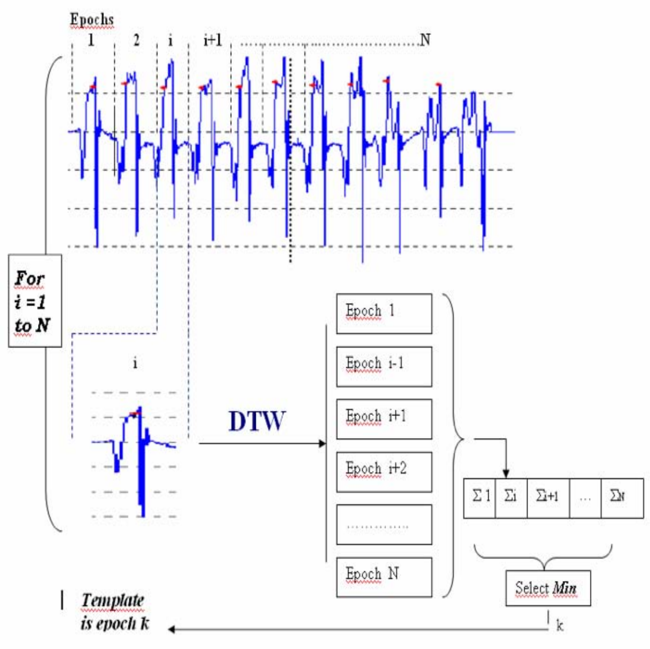

Fig. 3. Flowchart of the calibration process

2.4 Activity detection and data preparation

The first phase of accelerometer data processing regards detecting single motor activities from the accelerometer data. For this, a statistical approach was used, which was based on calculating the integral over a predefined window, and then comparing it against a threshold value chosen on the statistical properties of the accelerometer data (the same for each channel). Each epoch may be of different length for the different speed with which each activity is completed. All those epochs are then 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. This was considered as the testing set for the classification procedure that will be described in the following.

2.5 Classification through DTW

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

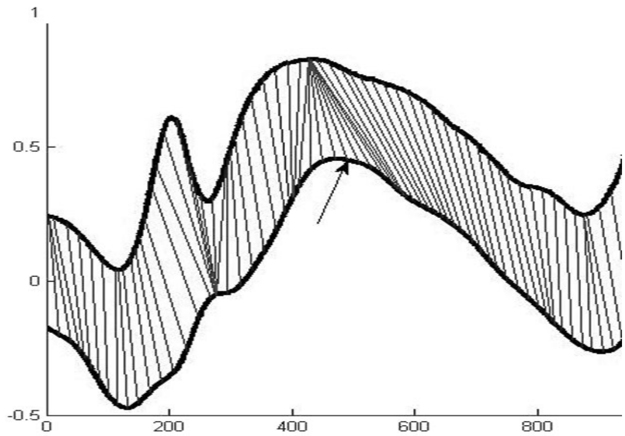

Fig. 4. Dynamic Time Warping (DTW) sample

The input signal is considered as a sequence of n samples $X=[x_1,x_2,\ldots,x_n]$, and the template is a sequence of m samples $Y=[y_1,y_2,\ldots,y_m]$.
DTW builds a matrix D [*n* x *m*] in which each element represents the distance between the i-th element of X and the j-th element of Y.
The matrix D is then used to obtain a matrix Θ, in which every element is the sum between the local distance $d_{i,j}$ and the minimum of the total distances of the neighbour-most elements according to the equation:

$$\theta_{i,j} = d_{i,j} + \min\{\theta_{-1i,j-1}, \theta_{i,j-1}, \theta_{i-1,j}\} \qquad (1)$$

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:

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

The warping path is generally calculated under a set of specifications: among them, the requirement to start and finish in diagonally opposite corner cells of the matrix, restriction to the number of allowable steps to adjacent cells, and monotonic behaviour over time. $\theta_{i,j}$ allows the alignment between X and Y. At the same time, $\theta_{n,m}$ represents the whole distance between X and Y.

2.6 Hierarchy determination

The next phase targets the issue of including the DTW technique into a hierarchical framework for classification. To accomplish this aim, DTW was used for each channel separately to determine the hierarchy among the different channels, based on the goodness in terms of classification percentage.

TABLE 1
Overall performance on single axis DTW.

PATH	Channel 1	Channel 2	Channel 3
Path 1	95%	93%	79%
Path 2	98%	93%	77%
Path 3	90%	90%	78%
Path 4	95%	95%	79%
Mean	**94,5%**	**92,75%**	**78,25%**

Table 1 present the results for the classification percentage: channel 1, which corresponds to the component in the longitudinal direction of the acceleration, provides the best results. The radial component (channel 2) provides results almost as good as the ones coming from the longitudinal component, whereas the results coming from channel 3, which gives information on the lateral component of the acceleration vector, are not as good as the other two, thus reflecting the relative low signal to noise ratio in this component for the monitored activities.

2.7 The classification framework

From the results obtained in the previous section it was possible to identify a hierarchy among the different channels.

a) Three-layer hierarchy

The hierarchical scheme makes use of the longitudinal channel first. The current activity is then compared with the templates of the different activities for this channel only. If the difference, in DTW terms, between the two most similar activities is below a certain threshold, the second channel (i.e. the radial one) is taken into account, and the DTW calculation is repeated for the templates corresponding to the two chosen activities. The DTW distances over the two channels are then added up. If the difference between them is lower than a certain threshold, the last channel is then taken into account, the process is repeated, and the activity is estimated as the one with the minimum sum of DTW distances. The flow diagram of the overall process for the three layer hierarchy is presented in Figure 5.

Table 2 reports the results of the recognition percentage and the utilization percentage of the third axis channel.

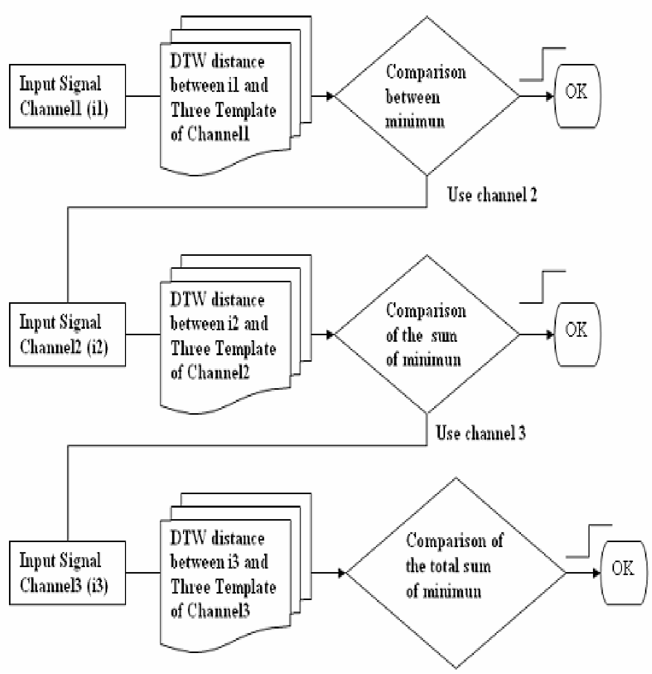

Fig. 5 : Flowchart for the three-layer hierarchical classifier

b) Two-layer hierarchy

Since the lateral channel resulted as the noisiest, and its utilization percentage is fairly low, it has been chosen to compare the results of the three-layer hierarchy, with a two-layer hierarchy applied on the radial and longitudinal channels only. Thus, if the distance between the first-guess activity and the

second/nearest activity falls below a certain threshold, the second channel comes into play.
The flowchart of an instance of two-layer hierarchical classifier is expanded in Figure 6.

TABLE 2
Overall performance for the three-layer hierarchy

PATH	Classification performance	Third layer use
Path 1	94%	14%
Path 2	95%	10%
Path 3	97%	13%
Path 4	98%	16%
Mean	**96%**	**13.25%**

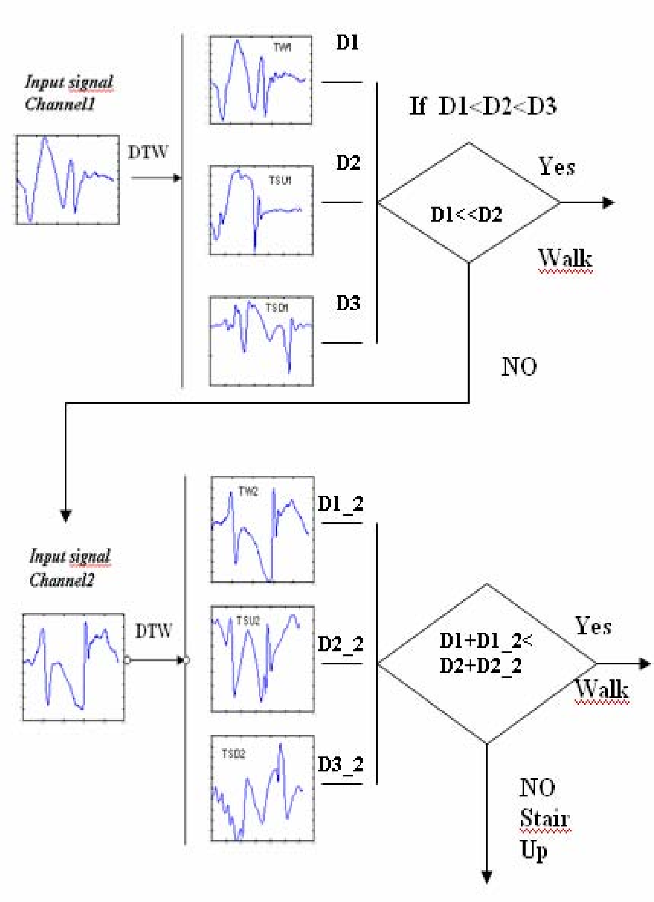

Fig. 6. An instance of the flowchart of ADL detection by distance between each epoch and each template.

The presence of the second layer, 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.
Table 3 reports the classification performance together with the utilization percentage of the second layer.

TABLE 3
Overall performance for the two-layer hierarchy

PATH	Classification performance	Second layer use
Path 1	100%	26%
Path 2	98%	28%
Path 3	90%	30%
Path 4	97%	26%
Mean	**96.25%**	**27.50%**

3 Results and Discussion

By the designed graphical interface, it is possible to view the results in a bar graph, which encodes the different classified activities with different bar levels and colour codes the use of the second layer. In particular, with the blue colour the use of the second layer is represented, whereas the different activities are coded such as: Walk -1; Stair Up- 2; Stair Down -3 (Figure 7):

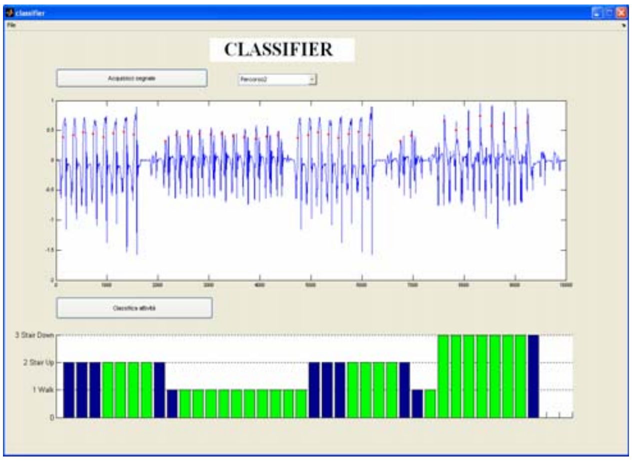

Fig. 7. GUI for activity classification. Green colour corresponds to single axis classification, blue depicts epochs classified making use of the second layer.

From the obtained results it is clear that the lateral component of the acceleration data appears unnecessary for the discrimination among the monitored activities, thus setting the basis for a two-layer procedure for the classification. As a matter of fact, the third channel actually decreases, even if not in a relevant way, the performance of the classifier. By acquiring data only from the longitudinal and radial components of the acceleration vector, and then processing the radial component only when the classification is not clear cut, it is possible to both minimize the set up for activity classification, and optimize resources in terms of computational burden.

In regards to this latter issue, the overall scheme for the classification procedure runs in approximately 5 seconds for paths lasting 1 minute over a Pentium IV 30Ghz, 512M RAM: this burden time is consistent with the hypothesis of working in real time applications.

4 Conclusion

This paper describes a hierarchical classifier for dynamic activities while standing: level walking, stair ascending, and stair descending. By using a trial 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 two-layer hierarchy for classification shows a clear 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 remote assistance in real time.

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