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Classification of Motor Activities through Derivative Dynamic Time Warping applied on Accelerometer Data

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Abstract— **In the context of tele-monitoring, great interest is presently devoted to physical activity, mainly of elderly or people with disabilities. In this context, many researchers studied the recognition of activities of daily living by using accelerometers. The present work proposes a novel algorithm for activity recognition that considers the variability in movement speed, by using dynamic programming. This objective is realized by means of a matching and recognition technique that determines the distance between the signal input and a set of previously defined templates. Two different approaches are here presented, one based on Dynamic Time Warping (DTW) and the other based on the Derivative Dynamic Time Warping (DDTW). The algorithm was applied to the recognition of gait, climbing and descending stairs, using a biaxial accelerometer placed on the shin. The results on DDTW, obtained by using only one sensor channel on the shin showed an average recognition score of 95%, higher than the values obtained with DTW (around 85%). Both DTW and DDTW consistently show higher classification rate than classical Linear Time Warping (LTW).**

I. INTRODUCTION

WEARABLE sensors are an established means to monitor motor activities, both at home and in the community [1, 2]. The reliability of those systems is needed to overcome limitations associated with the use of self-reports, which suffer from bias and discrepancies between judges [3].

Even if the pedometer has been extensively used in this context to roughly estimate energy expenditure on the basis of the number of steps [4-6], and the reliability in the estimation of energy expenditure from pedometer data has been quantified providing good results [7], these systems showed poorer results than other instruments in terms of both reliability and validity [8]. Among the alternatives, positioning a single accelerometer on the body segment mostly involved in the relevant motor activity represents a suitable choice [9]. Following this perspective, several researchers used accelerometers for diverse applications in clinical and rehabilitation contexts: monitoring tremor in Parkinson disease [10], and classifying motor activities in chronic obstructive pulmonary disease [11].

When activities are made on the field, though, one crucial element for their analysis consists in the ability of a system to discriminate between different activities, some of which are generally performed sequentially (walking on level surfaces and up or down stairs, rising from a chair and sitting down), and some can be performed simultaneously (making movements with the upper limbs while walking).

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) [12], 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 e.g. on Hidden Markov Model and quadratic discriminant analysis [13], or shape matching [14].

To improve the classification performance, both in terms of misclassification reduction, and in terms of accuracy in timing detection, the redundancy offered by adding two or more accelerometers is generally exploited [15, 16], whose counter effect is though apparent in terms of set-up.

No matter which kind of classification is employed, a non trivial problem resides in the inherent variability of the waveforms, associated with the variability in performing a task during activities of daily living. If the speed significantly affects accelerometers output in walking [17], the way the motor activity patterns associated with different conditions (age, speed, subjectivity) vary cannot be simply modelled as a linear warping, so that it is necessary to take into account nonlinearities coming from the stretching and shrinking of the different phases of each activity.

To this end, this work proposes a method based on Dynamic Time Warping (DTW), which takes these nonlinearities into account. DTW has been successfully used in different fields of biosignal processing, e.g. the alignment of event related potentials [18], or of ECG leads [19], but to the authors' knowledge, no application of DTW to the alignment and recognition of accelerometers data has been published yet.

The approach to the DTW in this work is based on a variation of the Derivative Dynamic Time Warping (DDTW) presented from other researchers [20]. This idea was born considering that accelerometer signals can remarkably differ in amplitude among subjects, yet maintaining similar shape.

It is possible that, by modelling nonlinearities in the variation of the accelerometer data patterns, one great advantage would reveal: i.e. avoiding the subject calibration phase, generally needed to create the set of template patterns to be used for the shape matching by using a non subject specific set.

II. Materials and Methods

A. Participants and Procedure

Three healthy consenting participants were recruited for the tests. Tests were divided into 2 sessions: Walk Session (WS) and Stair Session (SS). WS signals were recorded while the participants were walking straight on plain along a 10 m long unmarked path. For SS signals participants used a common 16-steps stairway with steps 6 cm high and 30 cm long. Participants were invited to stop walking at the end of the path or at the end of the stairway, before turning back and start walking again. The recording sessions were designed to obtain a balanced number of samples for every motor activity and to avoid biased execution of the movement by asking the participants to walk for a fixed number of gait cycles.

Fig. 1. The experimental set up.

Recognition performance was evaluated by dividing data into three classes associated to the analysed motor activities: Walk Level (WL), Stair Up (SU) and Stair Down (SD).

B. Data acquisition

A biaxial accelerometer sensor (based on Analog Devices ADXL202) was placed on the medial portion of the right shin with axes disposed on the sagittal plane along radial and longitudinal directions. The position and orientation of the accelerometers was chosen according to the literature [12, 21]. All accelerometer signals were band-pass filtered between 0.2 and 15 Hz.

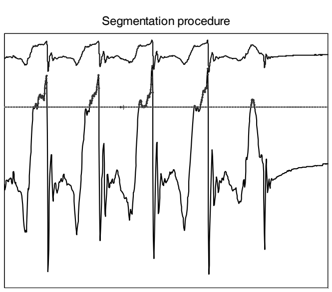

Fig. 2. Sample of accelerometer signal (above), and corresponding activity detection based on integration and threshold (below).

C. Data processing: template extraction

In this first phase, a complete set of signal templates, associated to different motor activities, was built. The set was formed by using one template per subject, per activity and per sensor channel. The calibration process allows the construction of signal templates after dividing the signals into portions associated to a specific motor activity.

The segmentation was carried on by detecting the activities on the basis of a maximum energy approach, and using a statistical threshold.

More in particular, signals have been portioned into epochs by calculating the integral and comparing it with a statistical threshold value (see Figure 2). The segmentation was then obtained by using the overall maximum among successive points above the threshold as trigger.

For each motor activity, the template was then obtained by randomly selecting and then averaging, through spline interpolation, five occurrences for each motor activity, discarding the activity cycles associated to movement initiation and termination. Templates associated to motor activities were respectively called as WT, SDT, SUT for WL, SD, and SU activities. Around 25% of all the motor activity epochs were used to create the set of templates.

D. Data Processing: activity detection

The first phase of accelerometer data processing consists of detecting single motor activities from the accelerometer data. To this end, a statistical approach has been used, which is based on the maximum energy approach described for the template extraction. Some regularity in the pace of each motor activity was taken into account to minimize false positives. Around 75% of all the detected motor activities for each subject were used to test the algorithms.

The motor activity epochs are of different length, corresponding to the variability in speed with which each activity is completed. All those epochs are grouped in a structure for the classification procedure described in the following.

E. Data Processing: DTW and DDTW

DDTW is acronym of Derivative Dynamic Time Warping. This algorithm is used in order to overcome some limitations of the classic DTW algorithm. To find the similarity between two sequences, DTW looks for the best alignment, which is generally referred to as Warp-Path, and thus "warps" the time axis of one of the series and calculates the distance between the two sequences. In some cases it can produce some misalignments, for instance when multiple points on one time series correspond to only one point in the matching time series ("*singularities*"), or when the two sequences strongly vary in the Y-axis. Figure 2 shows the limitations of DTW.

In the present case, each input signals 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 [nxm] in which each element represents the distance between the i-th element of X(i) and the j-th element of Y(j). Then, a new matrix Θ is introduced, with

$$\theta(j,i) = d(j,i) + \min\left[\theta(j-1,i-1), \theta(j,i-1), \theta(j-1,i)\right] \quad (1)$$

so that each element is the sum between the local distance d(j,i) and the minimum of the total distances of the neighbour-most elements.

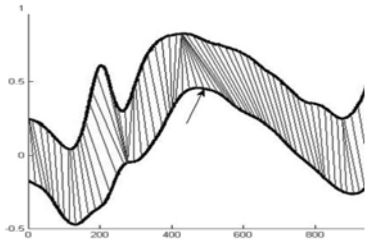

Fig. 3. Alignment produced by DTW. Alignment fails because of differences in the y axis.

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 $w_k = (i,j)_k$:

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

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.

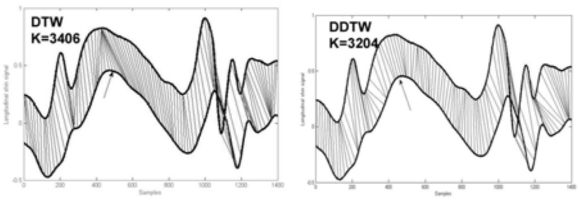

Fig. 4. The alignment product by DTW (a) compared with the alignment produced by DDTW (b). K is the number of points of the optimal path.

Among all the warping paths that satisfy the above conditions, for recognition/classification purposes the interest is in the path that minimizes the warping cost:

$$DTW(Q,C) = \min\left(\sqrt{\frac{\sum_{k=1}^{K} w_k}{K}}\right) \quad (3)$$

DDTW differs from DTW by considering the square of the difference of the estimated derivatives of X_i and Y_i instead of the original time series time series:

$$D(X) = \frac{(X_i - X_{i-1}) + (X_{i+1} - X_{i-1})/2}{2} \quad 1<i<n \quad (4)$$

This is the average of the slope between the line through the sample and its left neighbour, and the slope of the line through the left neighbour and the right neighbour.

From this point on, the procedure follows the one described for DTW. Figure 4 exemplifies the performance of the recognition for both DTW and DDTW. Both DTW and DDTW results underwent the distance calculation of each motor activity with each template. Each motor activity was classified according to the minimum distance criterion, and the performance was evaluated by considering three classes associated with WL, SU, SD. For comparison, also classical liner time warping (LTW) was performed, by linearly stretching/shrinking each epoch to match the template duration. Signals were then classified according to the maximum value of the normalized cross-correlation coefficient.

III. Results and Discussion

Distributions of both DTW and DDTW distances for each of the three motor activities are represented in Figures 5 and 6, for radial and longitudinal shin sensor, respectively. It is worth outlining that a robust classification corresponds to well separated distance distributions between activities for each motor activity portion. For both the sensors, DDTW consistently granted better separated distributions than DTW, and, as a result, better performance in classification for all the activities recognized through the longitudinal shin sensor, and for two out of three activities, as recognized through the radial shin sensor.

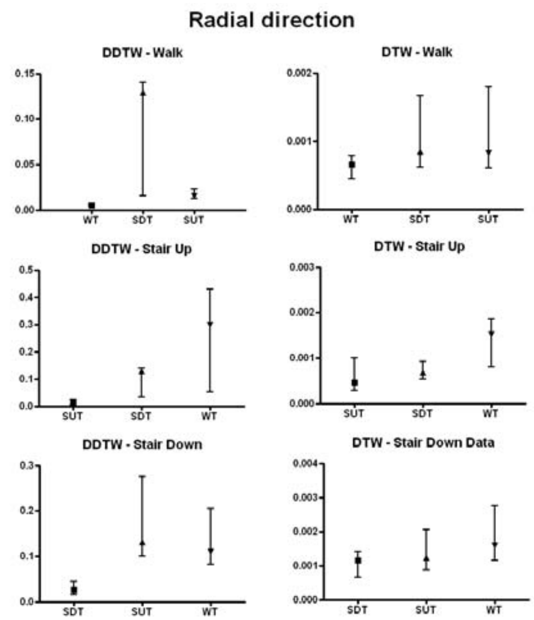

Fig. 5. DDTW and DTW distances for each activity template and each activity, radial direction sensor. Each bar represents interquartile range, whereas the symbol shows the median value.

TABLE I

RECOGNIZED ACTIVITIES (RADIAL DIRECTION)

Motor Activity	DDTW	DTW	LTW
WL	86%	84%	74%
SU	93%	93%	58%
SD	90%	78%	96%

TABLE II

RECOGNIZED ACTIVITIES (LONGITUDINAL DIRECTION)

Motor Activity	DDTW	DTW	LTW
WL	100%	82%	87%
SU	100%	91%	89%
SD	100%	81%	96%

The percentage of recognized activities is obtained by averaging the recognition performance for each subject. Classification rate is displayed in Tables I and II. As far as the sensor position is concerned, longitudinal direction shows better results than radial in DDTW, and comparable in DTW.

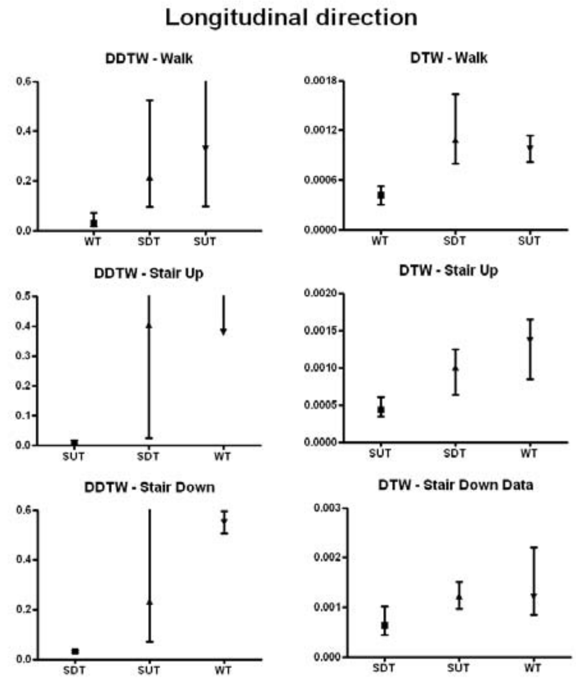

Fig. 6. DDTW and DTW distances for each activity template and each activity, longitudinal direction sensor. Each bar represents interquartile range, whereas the symbol shows the median value.

IV. CONCLUSIONS

This paper describes a new method to recognize different dynamic activities while standing: level walking, climbing and descending stairs. A set of biaxial accelerometer sensors were placed on the shin of the subjects. The results showed that both DTW and DDTW provide an effective solution to the classification of motor activities from acceleration data coming from single sensor accelerometers placed on the shin. DDTW is to be considered more effective than DTW in the classification of these activities. From a data processing point of view, it is likely that more sophisticated approaches to DDTW might enhance the performance.

Given the possibility to incorporate more than a single axis accelerometer over one device, it is envisioned that the classification rate would be enhanced by combining results coming from single sensors, and it is also likely that other activities during standing, such as turning around, or open and close doors, might be classified as well.

The flexibility offered by DDTW in capturing the variability of waveforms due to different speed execution can be used to minimize the calibration phase for template extraction, so that it wouldn't be necessary in the future to ask the subject to perform tasks in a controlled environment. This would greatly enhance the applicability of this approach in a context of self-monitoring and tele-care.

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