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Segmentation and classification of dynamic activities from accelerometer signals

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Abstract *This article describes a system for automatically segmenting and classifying accelerometer signals. The algorithm identifies three dynamic activities (biking, walking and running) from data recorded on the shin and a second system dedicated to walking periods detects changes in speed and in incline. The methods are tested on a 24-subject corpus with data acquired in controlled conditions.*

1 Introduction

Physical activity (PA) level has a strong impact on the risk of development of several diseases such as cardio-vascular diseases, Type 2 diabetes and several types of cancer. It also plays a important part in elderly's loss of physical autonomy and in the development of obesity. Assessing and quantifying PA is therefore crucial for prevention of such diseases but also for the monitoring and the treatment of patients. Even if there exist some reliable methods to evaluate the level of physical activity (such as oxygen uptake measurement or doubly labelled water), those are often expensive and intrusive and then do not suit for daily use. An alternative approach for the assessment of PA involves the use of unconstrained wearable systems such as accelerometers. The problem of PA and energy expenditure (EE) estimation from accelerometer signals has received much attention for the latter years. Since the posture and the nature of the movements involved in different types of PA strongly affect the EE [1], quantitative information (raw accelerometer data) is not sufficient to efficiently assess EE and some additional and qualitative labelling is often needed.

The final aim of this study is to identify a subject's PA behaviour (namely, the postures and activities performed throughout the day) in order to precisely estimate the EE related to the PA. The process can therefore be summarized as a segmentation/classification task, where each sample or frame is to be labelled with one posture or activity label. Several classification methods have been used in this context: some reviews or comparisons between these methods can be found in [2, 3, 4, 5]. Most of these works aim at detecting both static and dynamic activities and thus often use sensors located on the waist or on the lower back, which provide useful information on the postural orientation of the subject. In this article, we only focus on 3 dynamic activities (`Biking`, `Walking` and `Running`) by using data recorded at the shin of the subject.

Section 2 presents the context of this study. Section 3 presents the clinical protocol and the data acquisition details. Section 4 describes the methods and algorithms used for processing the data and for segmentation and classification. Results are then presented and discussed in Section 5.

2 Context

The algorithms presented in this paper were developped as part of the SVELTE project which was composed of several academic, clinical and industrial partners. The objectives of the SVELTE project are to develop a device, highly wearable and non-invasive, which has the capacity to capture the actimetry of one's subject in the day-to-day conditions. To do so, the device has to remain small and easy to use (to be switched on or turned off, battery life, ...). An emphasis has been put during the project on the effective validation of the data treatment chain and its applicability in the real-life conditions. To do so, a number of databases and experiments were conceived and implemented in laboratory conditions to reach the design of a tool, with a high confidence in the analysed data [6]. In this framework, the Centre de Recherche en Nutrition Humaine (CRNH) organised, coordinated and validated the databases necessary for the project development, while the CEA-LETI designed and implemented the main data treatment chain.

This article describes some preliminary results obtained during the SVELTE project for the classification and segmentation of dynamic activities. While the objective of the SVELTE project is to keep the analysis based on one sensor, worn at the waist, in an arbitrarily orientation, and to deliver a physical activity analysis very robust for daily-life conditions, the present work explores the potential of an alternative data treatment chain, with the aim to focus on a different sensor and a specific subtask.

3 Data acquisition

Twenty-four healthy and consenting subjects were asked to perform a series of activities for 4 hours such as lying, standing, walking, etc... The description of the subjects' characteristics is presented on Table 1. Note that among the 24 subjects, 8 are overweight (Body Mass Index (BMI) greater than 25 and strictly lower than 30) and 4 are obese (BMI greater than 30). During the whole experiment, they wore several triaxial accelerometers (MotionPod^{TM}by MOVEA). In our study, we only used the data output by the waist and shin sensors. The data acquisition was performed by the Centre de Recherche en Nutrition Humaine (Rhône-Alpes) and CEA-LETI. Raw signals were sampled at a sampling rate of 100 Hz. The speeds and intensities of the different activities were adjusted according to the physical capacities of the subject so as to make sure the experiment is safe for the subject: in order to standardize the activities according to the physical capacity of the subjects, a simplified exercise tolerance test (step-test) was performed within 1 week of the series of laboratory activities. Results of these preliminary studies were used to adapt for example the speed of the treadmill and the resistance of the cycle ergometer.

The whole experiment consists of more than 30 different activities of the daily life, but the scope of this article is limited to three dynamic activities: `Biking`, `Walking` and `Running`. Some of these labels are in fact hybrid: for instance the `Walking` label is composed of 4 or 5 successive walking periods on a treadmill at different speeds and inclines, each of them with an approximate duration of 5 minutes, the `Biking` state is composed of 1 or 2 successive biking periods on an exercise bike at different intensities, each with a duration of 5 minutes, etc... We therefore developed

Table 1: Subjects' characteristics.

Parameter	**Mean $\pm$ SD**	**Range**
Sex (M/F)	15/9	
Age (yr)	38 $\pm$ 12	19-54
Weight (kg)	74 $\pm$ 15	53.1-99.7
Height (m)	1.70 $\pm$ 0.07	1.58-1.85
Body Mass Index (kg.m^{-2})	25.4 $\pm$ 4.4	19.2-33.6

Table 2: Typical sequence of treadmill walking

Activity	**Start time**	**End time**
Level walking at 3.3 km/h	10:56:00	11:01:00
Level walking at 4.4 km/h	11:01:00	11:06:00
Level walking at 5.5 km/h	11:08:00	11:13:00
Slope walking at 4.4 km/h with 5% incline	11:14:30	11:19:30
Slope walking at 4.4 km/h with 10% incline	11:19:30	11:24:30

a second specific system only dealing with `Walking` periods, which segments the data according to changes in speed and incline. Table 2 shows an example of what composed a sequence of treadmill walking. Note that all results presented in this study are limited to data recorded in controlled conditions (treadmill and exercise bike)

4 Algorithms and methods

Our aim is to segment and label the data recorded on the shin with the three labels previously described, and then to segment the walking periods.

4.1 Calibration

In order to compare and process our signals, we need to insure that the sensors have the same position and orientation for all subjects and activities. We also need the three accelerometer components to be identifiable: in our study, we assume that the x, y and z axes record respectively the medio-lateral, vertical and antero-posterior acceleration. Yet, all signals are originally provided in the sensor coordinate system (f_x, f_y, f_y): our aim is to change this coordinate system into a person coordinate system (e_x, e_y, e_z), which is common to all sensors and subjects. This coordinate system is defined as follows:

- e_z gives the direction and the norm of the gravity vector when the subject is lying
- e_y gives the direction and the norm of the gravity vector when the subject is standing
- e_x is defined as $e_x = e_y \wedge e_z$

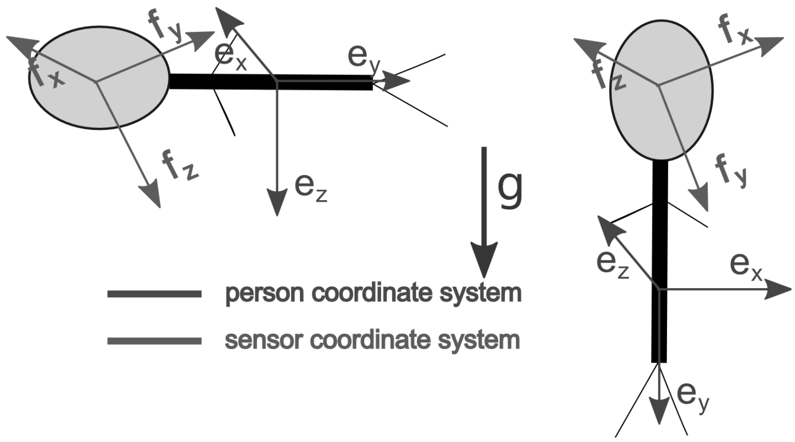

Figure 1: Calibration process: person and sensor coordinate systems.

With this definition and in the person coordinate system, the accelerometer outputs are $\begin{pmatrix} 0 \\ 0 \\ -1 \end{pmatrix}$ when the subject is lying and $\begin{pmatrix} 0 \\ -1 \\ 0 \end{pmatrix}$ when he is standing. Figure 1 displays both coordinate systems for a lying and standing subject. By recording the direction and the norm of the gravity vector in the sensor coordinate system when the subject is lying $\begin{pmatrix} g_x^l \\ g_y^l \\ g_z^l \end{pmatrix}$ and standing $\begin{pmatrix} g_x^s \\ g_y^s \\ g_z^s \end{pmatrix}$, it is possible to compute a matrix of the change-of-coordinates between (f_x, f_y, f_z) and (e_x, e_y, e_z) which allows us to assume that all signals lie in the same coordinate system:

$$\mathbf{P} = \begin{pmatrix} g_y^s g_z^l - g_z^s g_y^l & -g_x^s & -g_x^l \\ g_z^s g_x^l - g_x^s g_z^l & -g_y^s & -g_y^l \\ g_x^s g_y^l - g_y^s g_x^l & -g_z^s & -g_z^l \end{pmatrix}. \quad (1)$$

4.2 Features

The dynamic activities `Biking`, `Walking`, `Running` inherently have a periodic structure, which suggests to work in the frequency domain. Preliminary results on our database showed the most relevant component when dealing with dynamic activities on the shin sensor was the antero-posterior. This component is therefore processed in the frequency domain through a Short-Time Fourier Transform (STFT) calculated on 1024 samples (10.24 sec) with an overlap of 75% (which gives a new frame every 2.56 sec). Since the frequencies of most walking, running and biking movements are approximately ranged from 0.6 Hz to 2.5 Hz [7], we only consider the frequency bins between 0.5 Hz and 5 Hz. We are therefore considering 92 frequency bins. The spectrogram is then normalized so that every column vector sums to 1. Figure 2 presents an example of spectrogram recorded during these periodic activities.

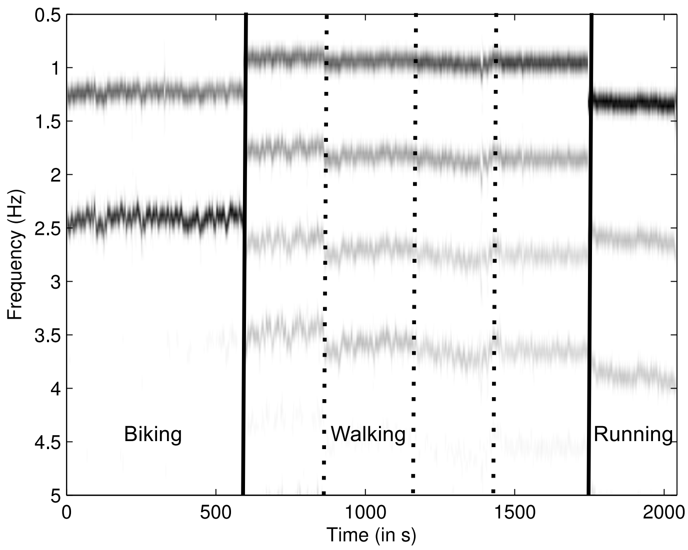

Figure 2: Example of Short-Time Fourier Transform of the antero-posterior component recorded on the shin. The three major zones respectively correspond to `Biking`, `Walking` and `Running`. The dotted lines represents the changes in incline and speed.

4.3 Classification of dynamic activities

The general workflow for our system is summarized on Figure 3. It is described in details in [8] but the major steps can be summarized as follows:

- The detection criterion for periodic activities is obtained by summing the spectrogram over the frequency range 0.5-5 Hz: it is then compared to an empirical threshold learned on the database.
- Typical frequency templates are learned for each activity with annotated data and a Nonnegative Factorization Matrix (NMF) algorithm.
- The templates are then compared to the data thanks to the Wasserstein distance, which offers the good property of being less sensitive to small frequency shifts (change in speed) than classical distances such as Euclidean distance.
- For each frame of signal, we choose the activity label whose template minimizes the distance with the data.
- A regularization algorithm is applied in order to smooth the results and take into account the time persistence.

4.4 Segmentation of walking periods

We here propose to divide a continuous treadmill walking record into segments where the speed and the incline are constant, by using some multiple change-points detection methods. The number of desired change points is supposed to be unknown. Mathematical details of the segmentation method are given in [9] but the process can be summarized as follows:

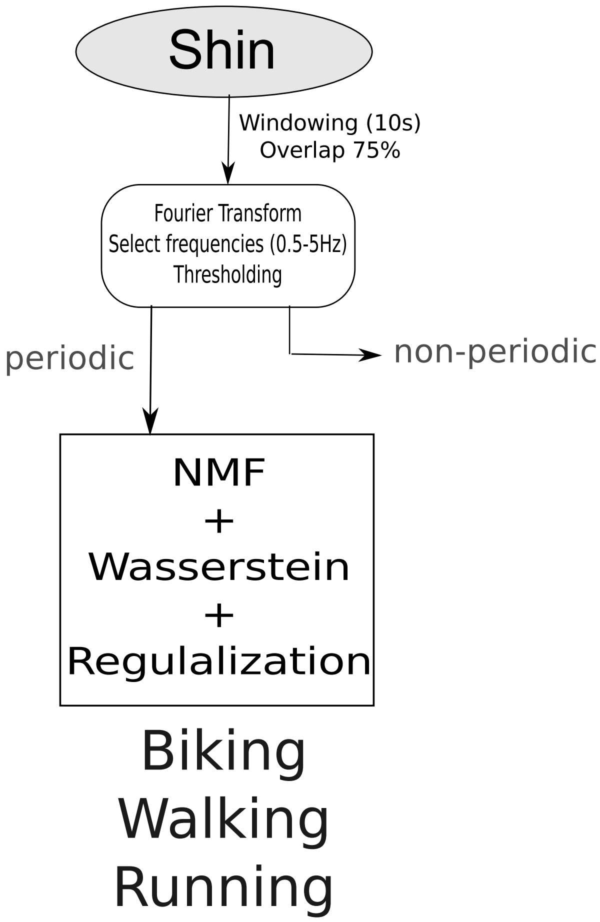

Figure 3: Workflow of the classification system

- Since the STFT calculated on walking periods tends to show a strong harmonic structure (see Figure 2), each spectrogram frame can be modelled by peaks located at each integer-multiple of a fundamental frequency bin f_0. For each frame, we therefore first estimate this fundamental frequency, along with the relative amplitudes of its harmonics (only in the range 0.5-5 Hz).
- These parameters are used to synthesize a theoretical spectrogram frame, which will serve as input for a classical change point detection algorithm. In a sense, instead of detecting changes in the spectrogram, we are detecting changes in the fundamental frequency (which is linked with the speed) and in the harmonic profile (which can be associated with incline or gait).

5 Results

5.1 Classification

The confusion matrix obtained for the classification system on our 24-subject corpus is presented on Table 3. For each subject and each step involving training, the models are learned on the 23 remaining subjects so as to prevent overfitting.

Table 3: Confusion matrix for the dynamic activities classification.

		Detected			
		Non-periodic	**Walking**	**Biking**	**Running**
Annotated	**Non-periodic**	**94.4**	5.5	0.1	0
	Walking	0	**100**	0	0
	Biking	6.8	0	**93.2**	0
	Running	0.2	2.9	0	**96.9**

The results obtained on the shin sensor for dynamic activities are satisfactory. Most of the confusions are due to the periodic/non-periodic detection. By examining the confusions we found out that they only occurred for 1 subject which suffered obesity and was therefore not able to bike with a sufficient speed.

5.2 Segmentation

As far as segmentation is concerned, we use as input only the frames belonging to the `Walking` state. Since annotations sometimes have a limited precision (e.g. : a delay may occur between two walking periods), we allow the detection to lie in an acceptable time window ($\pm$ 10 s). On our 24 subjects database, the segmentation method obtains a precision of 0.49 and a recall of 0.79. It means that in average, the algorithm detects twice the real number of change points but is able to locate 79% of the changes. These performances are interesting since even though the study only concerns treadmill walking, some changes are not trivially visible in the signals (in particular when the changes in speed are moderate, which was often the case for obese subjects.)

6 Conclusion and future work

We introduced a system for the segmentation and classification of dynamic activities based on accelerometer data recorded at the shin. The preliminary results obtained on a 24-subject corpus in controlled conditions are encouraging and the simplicity of the algorithms make it possible to implement them in simulators. Some of these methods, as well as other technologies are currently in trial with more subjects, more activities and in real-life conditions as part of the SVELTE project.

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