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# Advanced classification of ambulatory activities using spectral density distances and heart rate

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ABSTRACT

As motion sensors are getting light-weighted and low-priced, there is a growing appetite for the accelerometer-based approaches for efficiently monitoring human activities. This paper proposes an original feature selection approach based on the spectral distances between a given signal and an activity model. This new technique is evaluated and compared to existing techniques in literature. This study also investigates the improvement of classification performances brought by the heart rate (HR) data in addition to the accelerometer data. The experimental dataset is composed of both acceleration and HR recordings from eight volunteers performing five ambulation activities. Four wearable sensor units, including an ECG node are employed. The response of the system to three widely used classifiers, the K-nearest neighbors K-NN, the Naïve Bayes NB and the decision Tree C4.5 is reported along with the classification rates. The results reached up to 99% of overall recognition accuracy and higher than 98% using a single-sensor acceleration data and the HR data. These results demonstrate that the spectral distances approach can be adopted to accurately classify activities and that the joint processing of acceleration signals together with the HR signals can increase the classification accuracy compared to the case when processing the acceleration signals alone.



## 1. Introduction

Physical activity recognition (PAR) is a topic extensively researched nowadays in the biomedical domain. As a health status indicator, PAR is capable of providing feedback about the individual behavior, and is thus used in the treatment of adult overweight and obesity as well as the supervision of the balance and the locomotion of the elders and the disabled in order to avoid the physical risks they might be subjected to, falling for example [1,2]. Furthermore, physical activity (PA) information is also the key to home-based rehabilitation and physical therapies for some pathology [3,4]. Hence, monitoring the daily life activities and identifying them automatically become the research focus in these fields. From the application point of view, it is essential to pair the recognition precision with the basic demands like patient confidentiality, accessibility, user-friendliness and affordability [4].

The present study has a two folded contributions. Firstly, it proposes a novel method for activity classification using the spectral density distance measures from acceleration data. Secondly, it studies the influence of combining the spectral density distance and HR information in the enhancement of the classification performances. The paper is organized as follows: Section 2 analyzes the state of the art in PAR, Section 3 presents the system architecture and the experimental protocol for data collection. Section 4 explains the interest of the distance measure using spectral density and Section 5 gives methodological details on the AR spectral model training and the inclusion of HR for activity classification. Section 6 compares the proposed method with the reference feature selection method in the literature [12] and outlines the most important contributions. Finally, Section 7 summarizes our study.

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## 2. Related work

The traditional monitoring techniques were either based on physical observations: surveys, questionnaires and self-reports or on pedometers and actimeters. Thanks to the revolution of sensor technologies, advances in miniaturizing the size, the weight and the cost of commercially available inertial sensors, accelerometers become the most popular choice for PAR [5]. The raw output of accelerometers is processed and transformed into pertinent information: the PA type, as well as its intensity, frequency and duration.

The general procedure of PAR includes feature extraction phase then classification phase based on selected feature vector [6]. The model should be trained and finally tested by assessing its performance in predicting the activity.

Signal processing researchers were tempted by this field to investigate techniques applied in PAR covering features selection, features dimension reduction and learning techniques, as it is the case in many data mining issues [7]. Although in the literature, there exist many algorithms to accurately classify activities based on acceleration data; few are dedicated to the efficiency in terms of the relevance of the selected features. In fact, fetching and incorporating a large number of features in the classification process lead to the following issues: (1) the redundancy or irrelevance of some features that may not add significant information to the classification performance; and (2) the complexity and the additional computational time required for calculating the features and training the model based on the big features set [8–12].

Another important methodological question that remains challengeable in the research literature is the issue of "extending the measurement session from laboratory to real-life conditions" [6,13]. The procedure conducted by the majority of researchers is based on 'controlled' activities involving a treadmill to study running and walking patterns or an exercise bike for cycling [9,12,14]. However, a previous study [15] conducted to identify nine different ambulation activities has shown a decrease of around 30% of precision in activity identification when shifting the data collection from a controlled protocol to out-of-lab protocol. As discussed in [6], it is crucial to gather a representative dataset of daily life activities outside the laboratory to fortify the flexibility of the recognition system.

Furthermore, few researchers were motivated to study physiological, environmental and location signals in addition to the acceleration signals, in the aim of improving the recognition accuracy and identification precision [16–18]. In this paper, we propose a formal methodology to improve the activity recognition and study the impact of integrating other physiological signals, the heart rate as in [16,17].

## 3. Materials

### 3.1. Data collection

The dataset comprised recordings from eight volunteers. The participants were recruited from University of Rennes 1 and from the Ecole Normale Supérieure (ENS) – Rennes, France, from both sexes, aged between 18 and 30 years, healthy with different levels of physical fitness (Table 1). The data were collected at the Ker Lann stadium, Bruz.

Each subject was asked to perform five ambulatory activities in a random order: running, walking, cycling, car riding (as a passenger) and resting. Three activity intensity levels are considered, ranging from light (resting), moderate (walking) to vigorous (running). Subjects chose freely the speed of their movement. The duration of each activity was at least three minutes. An observer accompanied the subjects during the experiments to annotate each tested activity.

**Table 1**
Participant characteristics.

| Characteristics | Mean (SD) |
|---|---|
| N | 8 |
| Female/Male | 4/4 |
| Age, year | 26.3 (4.7) |
| Height, cm | 172.1 (12) |
| Weight, kg | 65.9 (12.1) |

### 3.2. Experimental procedure

During the performance of all the activities, four triaxial accelerometers were attached to the chest, the wrist, the hip and the ankle of the subjects as shown in (Fig. 1). The units were wrapped and secured to the subject's body with straps. Thus, subjects could execute the vigorous activities without any limitations on their movement or risk to harm the electronics. In the literature, the accelerometers were mostly placed on positions such as ankle, wrist, waist and/or trousers' pocket. It was shown that the types of the activities under study played an influential role in determining the choice of each placement [19,20]. For this reason, we are also interested in finding the best and optimal placement of the accelerometers to achieve the best accuracy for the ambulatory activities, as will be demonstrated in the next sections. The accelerometers are manufactured by SHIMMER Company (Shimmer Research, Dublin, Ireland) (Fig. 1) [21]. These devices can accurately record in three directions in the dynamic range of $\pm 16$ g at different sampling frequencies. Each unit was calibrated to store acceleration data on their compact internal memory at 90 Hz, which is more than adequate when compared to the 20 Hz frequency needed to monitor daily PA. Since Shimmer units record the raw acceleration signals without timestamps, a smart watch was used to mark the beginning and the ending of each activity giving it timestamps manually. The ECG dedicated Shimmer units were calibrated to record ECG signals with a frequency of 512 Hz through 6 lead electrodes placed on the appropriate positions on the chest. In this study, only the HR is extracted from ECG signals to contribute in the classification of the ambulatory activities.

## 4. Interest of the spectral density distance measures

### 4.1. Limitation of classical approaches

It is difficult to recognize the pattern for each PA using the raw acceleration signals due to the fact that they are by nature noisy and containing repetitive variations. In general, typical procedures of a PAR system start by extracting basic statistical features from the signals in the time and frequency domain, then reduce these feature dimensions in order to choose the most relevant features to discriminate PA, and finally recognize the PA pattern using a classification tool [11,12].

However, in these methods, features are mostly designed arbitrarily to contain first, second and third order statistics truncated to a certain dimension in the first place, some may hold meaningless or loose important information with respect to the PA recognition task. Furthermore the selection results vary from one training database to another which in turn proves that the selected features without an appropriate model might not be representative of the PA of interest. For example, in [12] time- and frequency- domain features were computed from 1st, 2nd and 3rd order statistics, before reducing their number to a vector composed of 30 features. In order to prove our hypothesis, we reproduced the work in [12] in our dataset and sorted the features based on their pertinence in discriminating the activities.