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### Chapter 10

# Clustering Algorithm for Human Behavior Recognition Based on Biosignal Analysis

**Neuza Nunes** 

PLUX - Wireless Biosignals S.A., Portugal

Rodolfo Abreu FCT-UNL, Portugal

**Diliana Rebelo** FCT-UNL, Portugal **Hugo Gamboa** FCT-UNL, Portugal

#### Ana Fred

IST-UTL, Portugal & Instituto de Telecomunicações, Portugal

#### **ABSTRACT**

Time series unsupervised clustering is accurate in various domains, and there is an increased interest in time series clustering algorithms for human behavior recognition. The authors have developed an algorithm for biosignals clustering, which captures the general morphology of a signal's cycles in one mean wave. In this chapter, they further validate and consolidate it and make a quantitative comparison with a state-of-the-art algorithm that uses distances between data's cepstral coefficients to cluster the same biosignals. They are able to successfully replicate the cepstral coefficients algorithm, and the comparison showed that the mean wave approach is more accurate for the type of signals analyzed, having a 19% higher accuracy value. They authors also test the mean wave algorithm with biosignals with three different activities in it, and achieve an accuracy of 96.9%. Finally, they perform a noise immunity test with a synthetic signal and notice that the algorithm remains stable for signal-to-noise ratios higher than 2, only decreasing its accuracy with noise of amplitude equal to the signal. The necessary validation tests performed in this study confirmed the high accuracy level of the developed clustering algorithm for biosignals that express human behavior.

DOI: 10.4018/978-1-4666-3682-8.ch010

#### INTRODUCTION

The constant chase for human well-being has led researchers to increasingly design new systems and applications for a continuous monitoring of patients through their biological signals. In the past, human activity tracking techniques focused mostly on observations of people and their behavior through a great amount of cameras. However, the use of wearable sensors has been increasingly sought because it allows continuous acquisitions in different locations, being independent from the infrastructures. The recognition of human behavior through wearable sensors has a vast applicability. In the sports field, for example, there is a need for wearable sensors to assess physiological signals and body kinematics during free exercise. Wearable sensors have also major utility in healthcare, particularly for monitoring elderly and chronically ill patients in their homes, through Ambient Assisted Living (AAL).

The human body has always been considered a complex machine in which all parts work harmoniously. Nevertheless, the endless pursuit for the optimal human performance has become an important work area of digital signal processing. Therefore, monitoring athletes is the logical way to achieve the best patterns that can be compared to pathological signals in order to contribute for patient's rehabilitation. Thereby, the continuous monitoring and evaluation of athletic performance allow the coaches to establish an optimal training program. In addition, it is useful for non-professional athletes to establish and achieve their personal goals (R. Santos et al., 2012).

The main goal of AAL is to develop technologies which enable users to live independently for a longer period of time, increasing their autonomy and confidence in accomplishing some daily tasks (known as ADL - Activities of Daily Living). However, AAL was also designed to reduce the escalating costs associated with health-care services in elderly people.

Thus, AAL's systems are used to classify a large variety of situations such as falls, physical

immobility, study of human behavior and others. These systems are developed using a Ubiquitous Computing approach (AAL4ALL Project, 2012) (where sensors and signals' processing are executed without interfering on ADL) and must monitor activities and vital signs in order to detect emergency situations or deviations from a normal medical pattern (G.N. Rodrigues et al., 2010). Ultimately, AAL solutions automate this monitoring by software capable of detecting those deviations.

Signal-processing techniques have been developed to extract relevant information from biosignals which aren't easily detected in the raw data. However, most of these techniques are integrated in tools for specific biosignals, such as electrocardiography, respiration, accelerometry, among others. Thus, a single tool to recognize the morphology of the signal without prior information, analyzing and processing it accordingly is a recurrent necessity.

The smallest change in the signal's morphology over time may contain information of the utmost importance; hence, the detection of those changes has received much attention in this field. The recognition of different patterns in the signal's morphology is usually based on clustering or classification approaches. The ultimate goal is a generic and automatic classification system that doesn't require prior information and produces an efficient analysis whichever the type of the signal used.

In the following sections we summarize the scope and results of the developed algorithm and further evaluate it by testing it in a variety of contexts and validating it with a state-of-the art approach for time-series clustering.

#### **RELATED WORK**

Nunes (2012) presented an advanced signal processing algorithm for pattern recognition and clustering purposes applied to time varying signals collected from the human body. The recognition of

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