Human Actigraphy's Analysis Through an Inertial Sensor

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Abstract

The evolution of wearable technology has provided an expansion in physiological monitoring allowing a greater comfort and proximity to the user in the medical field, personal monitorization and sports performance. Human actigraphy is a non-invasive method of monitoring various activities. This project presents the development of an automatic system based on human action analysis to recognize a set of predefined activities.

The data acquisition was done by two wearable devices which combine wearable technology and biomedical engineering: VitalJacket®, a certified medical device, and VitalSticker, which consists of a new prototype. The sustainable development in the MATLAB language is based on the signal of a triaxial accelerometer. The main activities considered for recognition are divided in four classes: lying down, standing/sitting, walking and running. Two sessions were implemented: a training session, with different isolated instances within the motion classes mentioned, and a test session for testing the various classes of motion occurring in sequence in the same signal.

For the signals' analysis, a 5 seconds windowing analysis was implemented and considered eight independent features in the time domain. This allows a discrimination of the most relevant accelerometer's axis (x, y or z) for the distinction between the various classes and the feature that presents the greatest separability between activities. The obtained results consist of the recognition performed by the algorithm for the two devices. Presenting an accuracy of 95% for VitalSticker and 74% for VitalJacket®, using a single characteristic and considering a single axis signal of a single triaxial accelerometer.

1. Motivation

Wearable devices allow to monitor physiological indicators, obtained by the Electrocardiogram (ECG), Electromyogram (EMG) or blood pressure measurement, among others, in a comfortable, non-invasive way while the users perform their daily activities. Joining in actigraphy provides the possibility of obtaining additional information and conducting long-term exams without causing any kind of inconvenience to the patient. Despite the presence of accelerometers in several devices or composite sensors, this project was intended to contribute to the implementation of human actigraphy analysis in specific wearable devices that were already available for development: the VitalJacket® and the VitalSticker.

The evaluation of human body movements can be successfully used in medical rehabilitation or posture evaluation, among other applications. By providing an analysis of the human activity and rest cycles, this project aims to be a support system for the information gathering process of a health-care professional in a real environment (non-hospital), rehabilitation or individual follow-ups in physiotherapy treatments.

2. Introduction

Actigraphy is a non-invasive method that, by monitoring movement, allows to analyse activities such as rest cycles or estimate the type of activity that was performed by a human being in his daily life. This information may be a complement to other exams such, as vital signs analysis, for building enhanced clinical frameworks and decision support system for healthcare [1]. Medicine evolution tends to follow technological evolutions, emphasizing the measurement instruments that allow to monitor the health status of the patient, helping the health professionals' decisions [2,3]. A simple form of physiological monitoring consists in using inertial sensors, since those will not be affected by surroundings, that are usually combinations of sensors such as accelerometers, gyroscopes and even a magnetometers [4]. These sensors are characterized by their low energy consumption, low cost and its size, which has been successively reduced. A triaxial accelerometer is a sensor that returns an estimate of the actual acceleration evaluated along the x, y and z axes, as a variation of motion, from which velocity and displacement can be estimated [5]. These sensors find applications in many areas, from the medical field to a sports context. Specifically concerning wearable technology, we can find inertial sensors on devices such as the VitalPatch [6] or the BioHarness [7], that allow the registration of various vital signals, or even the VitalJacket® [8], a certified medical device that is to be evolved into the VitalSticker.

As related work in recent years, it is possible to define many approaches for human daily activity recognition using inertial sensors [4,5]. Such studies to determine action and movement using neural networks to classify the basic activities [9], rule-based activity classification system for tracking the flexion angles of the human body [10] or study gait-related movement patterns [3].

This project aims to develop an automatic system for the analysis of human actigraphy that can recognize the activities performed in an examination acquired by a triaxial accelerometer. The recognition system focus consists in four classes: lying down, standing/sitting, walking and running. For system development, a training session and a test session were implemented. The obtained results are presented in a visual graph returning and distinguishing the activities performed in a certain time interval. Tests were made with two wearable devices: VitalJacket® and the VitalSticker, that allowed to compare its analysis of the actigraphy.

3. Methods and Results

During system training an adapted supervised learning approach has been used where the training data is known (activities and time instants previously defined in a fixed procedure) which allowed to perform its labelling. Therefore, focusing on the signal analysis, it is done a best feature study through class separability, using a single triaxial accelerometer. For the algorithm development a two parts pipeline was followed, as depicted in figure 1. The first part, training session, which allows the extraction of the distinction parameters to differentiate each activity and the second part, test session, to examine the signal and to determinate the activity occurring in each time interval. The algorithm can work in near real time conditions if we consider a 5 seconds delay. During the training session an extraction of eight features in the time domain is performed for the definition of the distinction parameters. These are picked by a selection method of the best feature for class separability on the most relevant axis of the accelerometer. This axis is determined by being the most affected by the movements in study, which means it is the vertical accelerometer axis when the person is standing up.

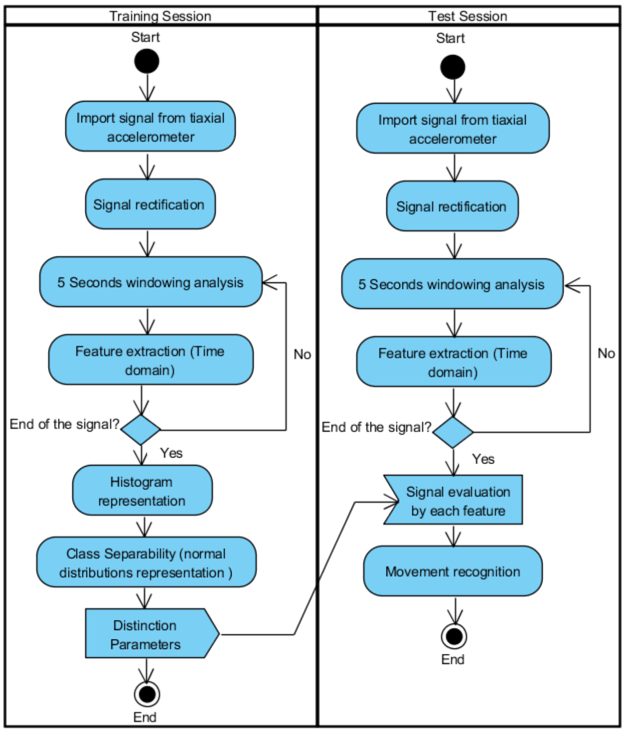

Figure 1. *Flowchart of the human actigraphy algorithm*

3.1. Database acquisition and organization

The acquisition of data was performed simultaneously using two different devices, both using a 10Hz sampling frequency: the VitalJacket® where the accelerometer is placed on the t-shirt's pocket on the hip area and the VitalSticker, placed directly to the skin on the chest area. The signals consisted in the acceleration value on each axis (x, y, z) along with the respective time stamp. The effect of gravity is important and so it is not cancelled.

As a support to the development and subsequent testing, the recording sessions followed a pre-defined procedure, common to all subjects, divided in two parts: the first one for training, with the different isolated activities within the motion classes and the second one for testing, with several classes of movement occurring in sequence.

3.2. Signal processing and analysis

Before the feature extraction process, the signals are initially rectified for a simpler analysis of their data considering the features in study. Due to the signals' behaviour, their oscillation around the base value (0), the extracted characteristics would be compromised to non-conclusive extraction values for comparisons.

After importing and rectifying the signal, it is necessary to analyse the entire signal for the activities sequence delimitation. This analysis is performed by the features extraction. Thus, the signal is analysed by 5 second sliding windows, for an evaluation of small intervals suitable for the various selected features extraction and the time intervals spent in each activity performance. This duration gave the best results on a 3s to 7s evaluation range.

3.3. Signal's feature extraction and study

The feature selection for the recognition of human activity, as the acquisition sequence study, is the most important step for a recognition algorithm. This study focuses on possible features for time domain analysis, where the testing signal is evaluated for the window size decided. Based on a bibliographic research, these 8 features were selected for testing, to conclude the best one for an accurate distinction between classes/activities. The features extracted were: Average, Median, Standard Deviation, Maximum, Minimum, Range, Root Mean Square and Energy.

3.4. Class Separability and Distinction Parameters

The feature extraction allows an organization of eight new sets of signals, a set consisting of the three signals corresponding to x, y, z for each feature. Each set consists of the values obtained by extracting each feature of the rectified signal from the selected window size. Thus, it was imperative to develop a method of comparison between the three main classes, corresponding to states of rest (lying down or siting/standing), walking and running.

Understanding that each set of activities: rest, walking, running, can be considered a class, this step consists of a separation between classes. Signal representations by histograms were created relative to each axis for each feature. This allows an analysis of the distribution of the values obtained of each feature along the signal. Thereby, it would be expected to observe three concentrations regions in which it was possible to visually distinguish each activity class.

The study proceeds only with data from the most relevant accelerometer axis of each device, X (VitalJacket®) and Y (VitalSticker). Each represents the most affected axis by the movements oscillation (vertical axis when the person is standing) and that would to provide an ideal model approximation of separability by normal distributions in the order: Rest-Walk-Run, as can be observed in Figure 2, where each class can be fully distinguish from the other separately. Moreover, the classes' representations that would not present that order of classes were discarded.

Through Gaussian analysis and confidence intervals, Figure 3, the separability degrees between classes were calculated for each feature. The one with bigger distance between the average points of the 3 distributions was selected, since for this case it represented a sufficient separation between classes. The intersections between each pair of histograms represent the activity recognition boundaries between classes. These distinction parameters are saved and used in the test session in which they represent the limits for decision and distinction between the recognized activity.

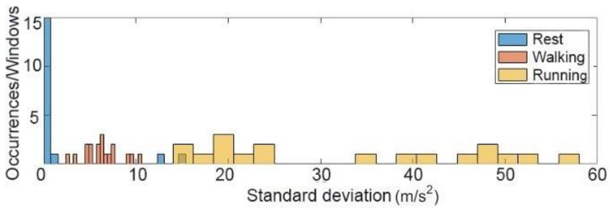

Figure 2. *Class representation through histograms*

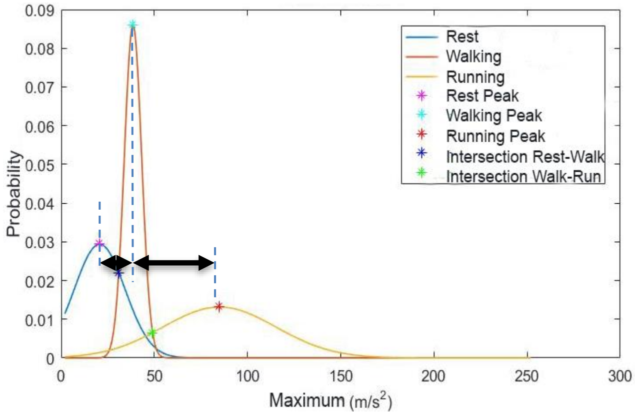

Figure 3. *Class separability and distinction parameters (asterisks)*

3.5. Test Session

For the actigraphy analysis it is essential that, after the training session, the distinction parameters are imported for the test session. The signals imported into the test session consist of a sequence of activities. These signals are also processed and analysed through feature extraction. A comparison has been made between the values extracted in each feature and the distinction parameters related to the corresponding feature. Depending on the assessed value and threshold, it is determined which class it belongs to. Concerning the Rest class, there was still the possibility to distinguish between two sub-classes: Lying down or Standing/Sitting, evaluated by the rotation of the accelerometer axes of the acquisition device.

As results for the recognition visualization, a stipulated value was assigned for each activity, to be represented in a new graph. In this case, each class corresponds to a certain level between 0 to 3, Table 1. This configuration allows an intuitive visualization for a simple and direct evaluation/recognition.

0	1	2	3
Lying down	Standing/ Sitting	Walking	Running

Table 1. *Representative values for each activity*

3.6. Wearable devices comparison

Since the acquisition process was done simultaneously in the two devices, previously mentioned, it was possible to organize a database for the subject for each device and therefore implement the algorithm for both. The main differences to be pointed out are essentially, the device position relative to the body and how it is coupled to the user. As result for a certain sequence of activities it was traced the recognition level graph with the procedure of this examination, Figure 4. Thus, it is shown the comparison between the activity detected by each device and the activity truly performed.

For a final evaluation of the performance of the developed algorithm, two tables were elaborated, one respective to each acquisition device, for calculation of its accuracy. By adapting the Confusion Matrix to determine classifiers for a greater number of classes, Table 2, it is done an evaluation for each activity and device.

VitalSticker recognition results		Lying down	Standing/ Sitting	Walking	Running	**Accuracy**
Gold standard	Lying down	**3186**	224	0	0	96%
	Standing/ Sitting	114	**9123**	112	1	
	Walking	55	3	**3297**	220	
	Running	2	53	0	**770**	

VitalJacket recognition results		Lying down	Standing/ Sitting	Walking	Running	**Accuracy**
Gold standard	Lying down	**1596**	493	166	0	74%
	Standing/ Sitting	1535	**7761**	439	0	
	Walking	222	987	**2640**	276	
	Running	0	165	164	**716**	

Table 2. *Four class Confusion Matrix of the recognition results*

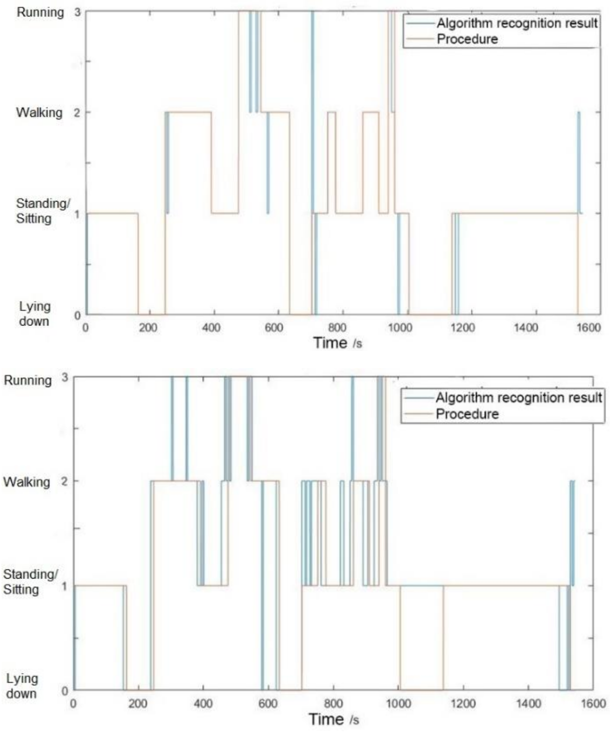

Figure 4. *Procedure (red) and algorithm recognition result (blue) comparison: VitalSticker (up), VitalJacket (down)*

4. Discussion and Conclusion

This approach to human actigraphy analysis consisted of an analysis of a triaxial accelerometer, in the time domain where all features were tested in the same way. This method allowed a definition of an optimal feature for motion recognition based on the results. Although the maximum feature permitted a better approximation of the activities recognition system to the activity performed when compared to a known sequence, the knowledge of a relevant axis in the accelerometer for each device remains an important step in the process.

However, some differences in the results obtained for each device are observable, since the VitalSticker shows a 95% accuracy while the VitalJacket® shows 76%, analysing the best axis for the maximum values. Possibly when using VitalJacket®, the lower accuracy is due to the fact that the accelerometer is located inside a loose pocket, which may be subject to a greater oscillation of the movement. On the other hand, VitalSitcker is placed directly on the skin, which can provide greater stability and monitoring of the movement of the human body.

Human monitoring is an area that is constantly evolving and is becoming increasingly important both at the medical and sporting levels. Regarding the development of this method for movement recognition, it was possible to obtain an automatic system. This system allows the recognition of movements performed in a continuous examination by determining their time intervals, through the signal of a single triaxial accelerometer in a wearable device.

After the selection of common daily activities, the recognition focused on the following situations: lying down, sitting/standing, walking or running and provided a comparison of the same signal in two devices, placed in different parts of the body. Through the acquired data, the system could determine distinction parameters between the various activities through the vertical axis analysis in the base configuration of the devices (X axis for VitalJacket® and Y axis for VitalSticker). With a 96% and 74% accuracy, this actigraphy analysis is supported from the determination of one feature from a single axis in a single triaxial accelerometer.

Since the system only requires data from a triaxial accelerometer, instead of several sensors used simultaneously, it allows a greater mobility and comfort to the user. The main novelty pf the proposed algorithm is that it consists in a very simple implementation while providing highly effective results. Using the accelerometer already incorporated in the two devices presented (VitalJacket® and VitalSticker) and a time domain implementation promotes advantages like not adding more costs or changes to the hardware used, but rather an added value, since it contributes with more information under the same examination conditions. However, a study and a system with these characteristics clearly fits into the current perspective of wearable technologies, this project presents a first approach to motion recognition, with possible evolutions, such as individual personalization or improving the classification method by combining the information from more than one of the computed temporal parameters.

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