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Classification of Physical Activities using a Smartphone: evaluation study using multiple users

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Abstract

Nowadays, smartphones play an ubiquitous role in accessing and processing information, most of them having a myriad of integrated sensors that makes them capable of generating information with high accuracy and precision. The monitoring of physical exercises presents itself as one of the new trends, made possible by the use of devices like smartphones. Motion sensors such as the accelerometer enable live motion measurement. This paper intends to study this issue and develop an application for the Android operating system, which takes advantage of sensors embedded in smartphones and web technologies, with the goal to classify multiple physical activities. The developed solution is based on client-server architecture. The client application performs data acquisition, visualization and recording of the signal obtained by the smartphone's accelerometer and the server application receives the information acquired by the client, processes it and classifies it. In order for the application to be able to classify multiple movements throughout the activity performed by the user, an extensive analysis of the acquired signals was carried out to understand their most distinctive features. We used a supervised approach with the goal of reviewing the best techniques that should be useful for achieving the classification with the lowest error. For the signals acquisition the smartphone was positioned along the waist, inside the right front pocket in an attempt to simulate conditions as naturally as possible. The study explored features extracted in both the time and frequency domain, and parametric and non-parametric classifiers. Preliminary results demonstrate that the classification of activities can be done with remarkable accuracy (> 95%).

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Keywords: Accelerometer, Android, Smartphone, Feature extraction, Activity classification, Quantified Self

1. Introduction

Physical inactivity is a serious concern that affects the population especially in developed countries. Cardiovascular diseases, depression and obesity are just some of the consequences of this practice [1]. However, the consciousness and consequent prevention of this problem is increasing, in part due to the growth of tools that enable the measurement of physical activity.

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In a society that increasingly perceives the benefits of physical exercise for health, this study aims to contribute actively to combat sedentary habits, motivating and monitoring physical activity through the use of accelerometer sensor.

Since the beginning of the commercialization of mobile devices, dated from the late twentieth century, they have reached a technological level that does not go unnoticed by the common citizen. According to several studies, the level of computing, size and design, has made these devices indispensable in everyday life of its users, regardless of their age.

The smartphones have an important role in the ubiquitous access and information processing. Most of them have a myriad of integrated sensors (light, proximity, acceleration, gyro, compass, GPS) that make them capable of generating information with high accuracy and precision. This set of factors, both technological and subjective nature, is the cause of a recent trend of market-oriented development of platforms and applications.

This article is an ongoing study, based on a previous one [2], where we developed an application for Android operation system, which takes advantage of sensors embedded in smartphones and web technologies in order to perform the automatic classification of physical activities.

To be able to classify activities we have carried out an extensive analysis of the acquired sensorial data, to understand what the most distinctive features are. A supervised approach was adopted, with the goal to review the best techniques useful for achieving the classification with the smallest error. For the acquisition, the smartphone was positioned along the waist inside the right front pocket in an attempt to simulate natural conditions.

The application was created with a new framework for developing applications for Android [3], which simultaneously utilizes Web technologies and enables a rapid application development. The developments made at the client side, were especially targeted to acquire data from the accelerometer, record and send those data to the server.

We believe that the monitoring of activities is currently a big trend. In recent years the commercial offer of applications based on the monitoring of activities has greatly increased. That increase is based on a new concept called "Quantified-Self". This concept consists of auto-monitoring daily activities daily activities with the goal of self-awareness and self-improvement.

This study helps to understand the best method for the classification of activities. The accelerometer is presented in this study as a solution for monitoring and motivating physical activity to promote a more productive lifestyle. By knowing the most relevant features to classify activities and which algorithm to use, it can be very helpful to do an efficient activity classification. Most of the currently commercial applications for activity monitoring are based on GPS sensor and in most cases it is required that the user first select on the device the activity that he will perform.

With an efficient method to classify activities it is possible to catalogue automatically all the activities performed in one day and give that feedback to the user in a way that he will become more self-aware of the intensity of his physical activity.

The novelty of this work is the following aspects: the study of the proposed activities, most representative for an efficient classification; the study of the best algorithms used to classify the activities; the development of an application to capture the signal from the accelerometer sensor on the smartphone and send it to the server.

Most of the previous published work on activities classification doesnt usually use the accelerometer from an Android smartphone. When it does, its goal is not to understand which are the best features and algorithms to classify the activities. In our study we attempt to understand the most relevant features for the classification of activities and their distinction, trying out several classifiers and comparing the results obtained.

2. Methodology

A high-level functional diagram of the proposed system is shown in figure 1 and follows the steps of a classical pattern recognition system: signal acquisition, features extraction and classification . In this study we follow a supervised learning approach [4,5], using data acquired during a training phase to estimate the classifiers to be used while running the application. To demonstrate the approach feasibility, we have identified six different activities, grouped into the main classes: a) inactivity; b) outdoor activity; c) indoor activity; figure 2.

In the first module, the signal is acquired during the activity using the smartphones accelerometer sensor. In the second module, feature extraction, some features are extracted, both in time and frequency domain, and then analysed

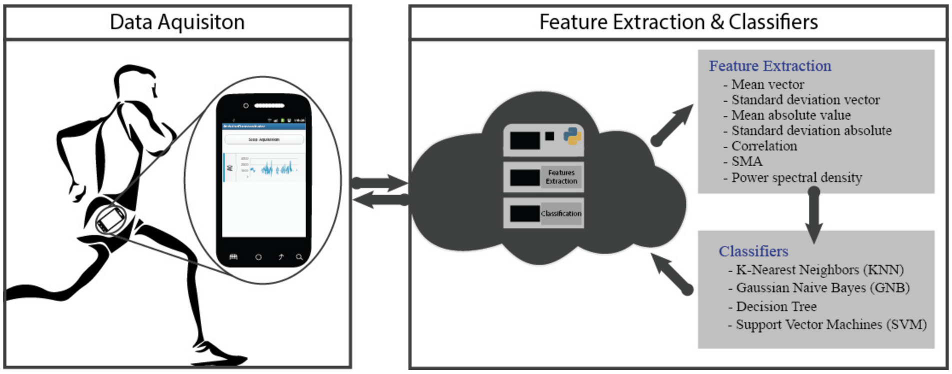


Fig. 1: Proposed system: The signal is acquired with the accelerometer of a smartphone Android and the data is send to the server for feature extraction and classification.

to allow identifying those features that are more suitable to achieve an efficient classification. In the last module, we use various classifiers to understand which one is able to provide a more accurate classification.

2.1. Data Acquisition

The application was made with the goal of running on Android smartphones and for that reason it should take into account the battery life of the devices. The use of more than one sensor (GPS, gyroscope and accelerometer) will contribute to a faster reduction of battery drain. The reason for choosing the accelerometer sensor was because it can be applied to both indoor and outdoor activities and it's possible to get more information about each activity, such as the amount of steps taken and the level of intensity employed.

Data acquisition is performed by the embedded accelerometer on the smartphone. This sensor has the characteristics of being ultra small and low consumption, especially targeted to low-power devices like smartphone and tablets. It is an electromechanical device that will measure acceleration forces. These forces may be static, like the constant force of gravity, or they could be dynamic caused by moving or vibrating the accelerometer. By measuring the amount of dynamic acceleration it is possible to analyse the way the device is moving and hence determining the type of activity performed.

In the study we take into consideration six activities, as shown in figure 2. In the indoor environment: cycling, rowing and running; in the outdoor environment: walking and cycling; and the inactivity, which was considered the sixth activity in this study. We chose these activities because we think that they are the most commonly performed, and also the easiest to provide information.

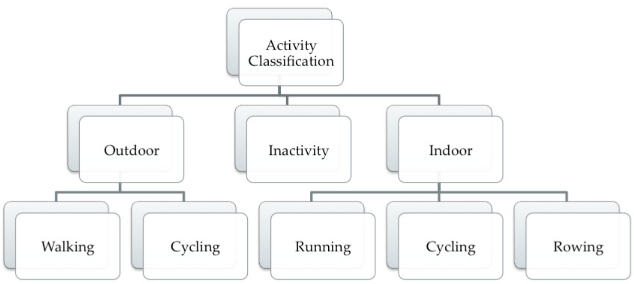


Fig. 2: Activities considered for the study

2.2. Feature extraction

The feature extraction from smartphone accelerometer is crucial for the efficient activity classification.

We perform the features extraction for both time and frequency domain, in order to understand which is the most important to do the classification. In the time domain the features were based on the following studies [6,7] and we extract the following features: mean vector, standard deviation vector, euclidean norm of mean vector, euclidean norm of the standard deviation and correlation values. The features in the frequency domain were based in [8,9] and was extracted the power spectral density thought the fast fourier transform.

This work followed the procedure already adopted in our preliminary study [2], supported by the approach proposed in [6].

In this paper were performed the following features extraction:

2.2.1. Feature extraction in the time domain

- **Mean Vector**: The mean vector among three axes can be expressed as:

$$\overline{a}_i = \frac{1}{N}\sum_{t=1}^{N} a_i(t), \tag{1}$$

where i represents the axes ($i = x, y, z$).

- **Standard deviation vector**: The standard deviation module of each component is calculated as follows:

$$\sigma_i = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}[a_i(t) - \overline{a}_i]^2} \tag{2}$$

- **Euclidean norm of mean vector**: The module of mean vector can be written as:

$$||\overline{a}|| = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{3}$$

- **Euclidean norm of the standard deviation**: The calculation of standard deviation module of each component is calculated as follows:

$$||\sigma^i|| = \sqrt{(\sigma_x^i)^2 + (\sigma_y^i)^2 + (\sigma_z^i)^2} \tag{4}$$

- **Correlation**: The correlation helps to establish the relationship between the axes and understand in which direction the signal presented a higher variation.
  The correlation matrix is obtained as follows:

$$\rho_{ij} = \frac{1}{N-1}\sum_{t=1}^{N}\frac{[a_i(t) - \overline{a}_i]}{\sigma_i}\frac{[a_j(t) - \overline{a}_j]}{\sigma_j} \tag{5}$$

- **Signal magnitude Area**: The signal magnitude area can be expressed as follows:

$$SMA = \sum_{t=1}^{N} |a_x(t)| + |a_y(t)| + |a_z(t)| \tag{6}$$

2.2.2. Feature extraction in the frequency domain

- **FFT**: A Fast Fourier Transform (FFT) is an algorithm to compute the discrete Fourier transform (DFT) and its inverse. A Fourier transformconverts time (or space) to frequency and vice versa; an FFT rapidly computes such transformations.
  The calculation of the Fast Fourier Transform, that refers to a way the discrete Fourier Transform (DFT) can be calculated efficiently, by using symmetries in the calculated terms. The symmetry is highest when ‘n‘ is a power of 2, and the transform is therefore most efficient for these sizes.

$$X_k = \sum_{n=0}^{N-1} x_n e^{-j\frac{2\pi}{N}kn} \tag{7}$$

- **Power spectral density**: The spectrum of the accelerometer signal decomposes the content of a stochastic process into different frequencies, and helps identify periodicities. Our analysis is focused on frequency bands of 1Hz, represented as f_i. The power of each band is given by:

$$P(f_i) = \sum_{k \in f_i} |X_k|^2 \tag{8}$$

The entropy of each band is given by

$$S(f_i) = \frac{-\sum_{f_i=0}^{f_n} P(f_i)\log(P(f_i))}{\log(N[(f_{i-1}) - f_i])} \tag{9}$$

After extraction, the features were organized and normalized in a suitable manner for the subsequent classification process.

To build the training and test dataset, was eliminated the beginning and the end of each activity and divided into samples of 1 minute of each activity.

2.3. Classification

A machine learning supervised approach [4,5] was used for the classification step.

This study explores the use of parametric classifiers using algorithms such as Gaussian Naive Bayes and non-parametric classifiers such as K-Nearest Neighbor, Decision Trees and Support Vector Machines (SVM). From the first class we have used, Gaussian Naive Bayes with the standard deviation and the mean estimated using maximum likelihood; whereas from the second class we have used K-Nearest Neighbors, with 1 and 3 neighbours, where all points in each neighbourhood with equal weights; Decision Trees in which the goal is to create a model that predicts the value of a target variable, learning simple decision rules inferred from the characteristics of the data collected; and Linear Support Vector Classification using the L1 norm regularization with which induces dispersion.

3. Android Application

The developed application follows a layered architecture, witch facilitates the future expansion of the system. We followed the Model-View-Controller (MVC) model, that isolates the ”logic” from the user interface, allowing to develop, edit and test each part separately.

The application is constructed by a set of blocks that form a functional network running on top of the Workflow Manager (WFM). This network defines application behaviour, so that each block has a task and a specific goal, such as, acquiring data from the source, signal processing, and presentation of results.

The core of the application is the WorkFlow Manager module that handles the instantiation of the system and controls its operation, described according to the structure defined in JavaScript Object Notation (JSON).

The application used in this project is based on framework MobileBIT [3], developed in Lisbon by the Institute of Telecommunications. The application was developed for the Android operation system, the most popular mobile platform in the moment [10].

The application developed to Android should be compatible with most of the devices that uses the same OS, independent of the manufacturer or brand [11].

Given that, this study focus on activity classification, we have developed the module *accelerometer* responsible for the acquisition, handling and recording the sensor data and the module *websocket* responsible for sending the sensor data to the server.

In order to better understand, in figure 3 is shown a schematic overview of the architecture of the application. That application preforms the acquisition and sends accelerometer data to the server, to do the feature extraction and then the automatic classification.

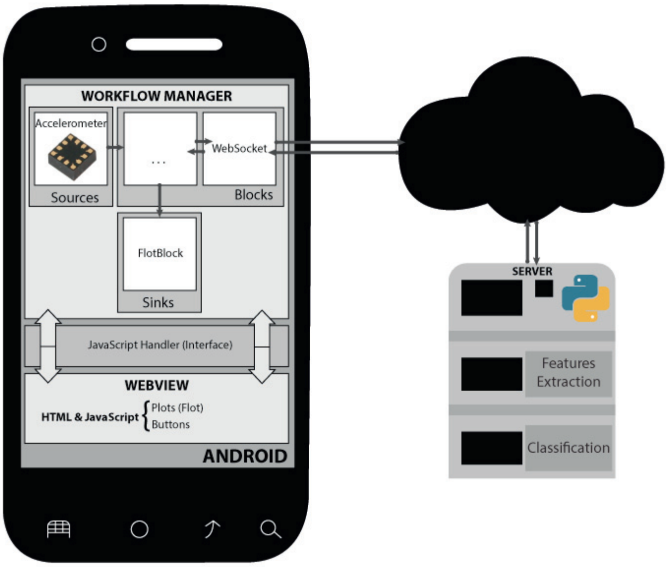


Fig. 3: Architecture of the used framework; where the signal acquired by the smartphone accelerometer is displayed in the GUI and sent to a remote server in order to have efficient processing in the activity classification; the results processing phase are returned back to the user.

4. Results

The analysis of these results is divided into three parts. The first provides details concerning the acquired signal, in the second, we study the differences between the various features extracted, in the last part, we analyse the results obtained by the various classifiers to understand which activities raised more uncertainty or confusion.

4.1. Database

Data was collected from 5 males. Subjects ranged in age from 24 to 32 (mean age: 28±4 years, mean height: 179±5.47 cm, mean weight: 71.3±5.34 kg). Prior to the acquisitions, we provided the Android applications to the subjects and a brief explanation about the objectives and procedures, in order to make the acquisition correctly.

The acquisition held by the 5 healthy subjects was done with 3 different smartphone on the right front trousers pocket (as shown on Fig. 1). The sampling frequency depends on the Android smartphone used, with an average approximately 92Hz.

The acquisitions have intra- and inter-subject variability and was acquired in different sessions and days. For this study we collected 300 samples, 50 samples of each activity, with duration of 60 seconds each.

All analyses were conducted using python 2.7 with mathematical, scientific computing, graphical and data analysis modules such as numpy, matplotlib, SciPy and scikit-learn.

4.2. Signal Aquisition

Figure 4 represents accelerometer signals acquired during the performance of the various activities under consideration. To facilitate the analysis and highlight differences in the acceleration features, each sub-figure plots only the norm of the acceleration signal (equation 3), acquired during a period of (in)activity of 60 seconds.

By observing the norm of the raw acceleration data of each activity considered, figure 4, it is possible to detect some patterns and distinguish some of the activities, eg. running and walking.

The sampling frequency is not constant and depends on the smartphone used in the acquisition.

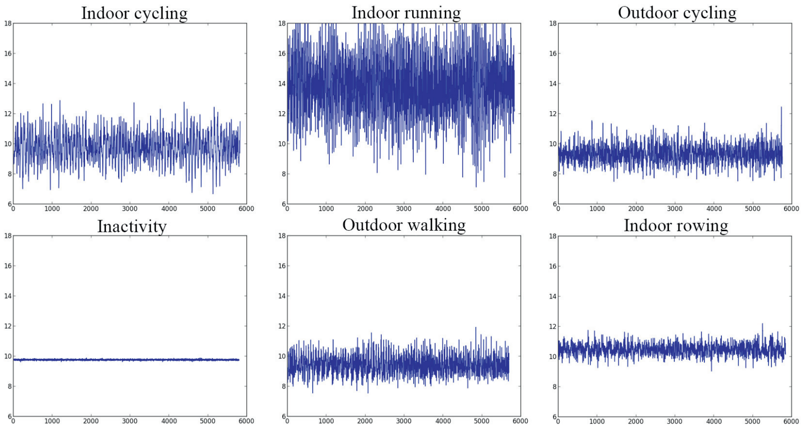


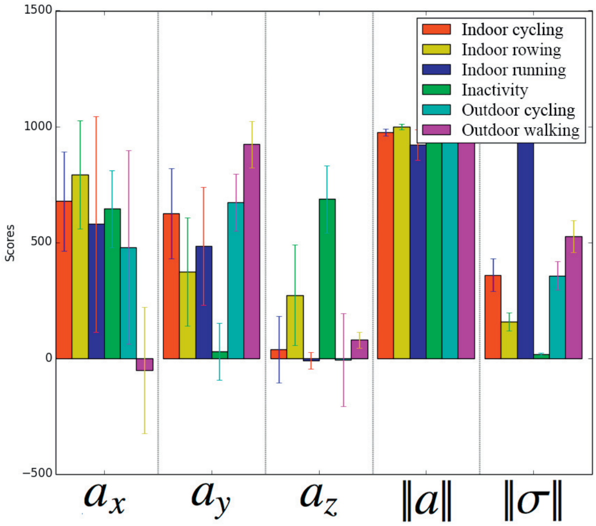
Fig. 4: Accelerometer module acquired by the smartphone into each activity.

4.3. Features Exploration

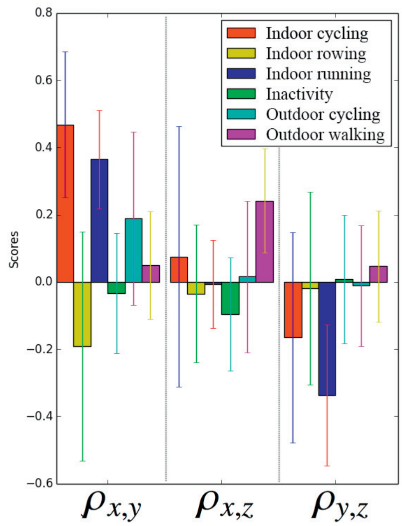
To understand better the features in time domain, and due to differences in values, we have decided to do the following separation: statistical features (a_x, a_y, a_z, $|a|$, $|\sigma|$) and correlation values($\rho_{x,y}$, $\rho_{x,z}$ and $\rho_{y,z}$).

In figures 5a and 5b each bar with a given color represents a different activity and shows the average value of that feature as well as its standard deviation, these values were obtained from the various signal acquisitions.

In figure 5b it is shown the values of the correlation matrix:



(a) Statistical features



(b) Correlation values

Fig. 5: Time Domain: Statistical features and correlation values

In order to understand some differences between the features on frequency domain it was plotted the firsts twenty bands of frequency, representing the mean of all samples of each activity. Observing figure 6 can easily distinguish some activities, such as outdoor cycling from indoor rowing or indoor running from inactivity.

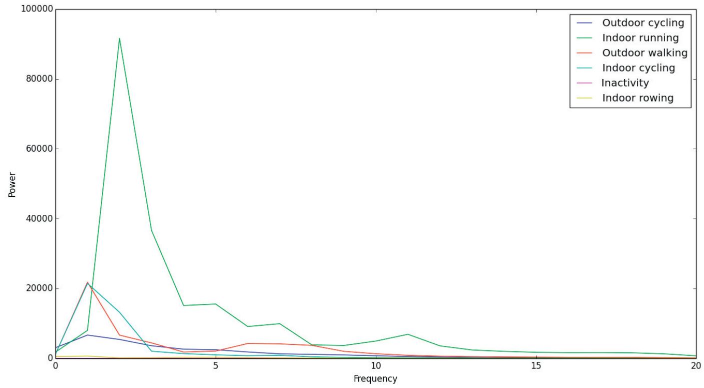


Fig. 6: Mean values of the power density bands of each activity

4.4. *Classification Results*

The implementation was done using python 2.7 based scikit learn [12]. This module is an open source library for machine learning in Python programming language.

To avoid over-fiting, we define two different data sets: the training dataset X^l, y^l, which is used to learn a prediction function and dataset test X^t, y^t, which is used to test the prediction function.

The dataset was built using data from three users and three different smartphones. The training dataset has 50 samples of each activity and the test dataset have 16 samples of each activity.

The classification results in time and frequency domains are shown below. The results based on the time domain, with the following features - the average and standard deviation of three axes, mean and standard deviation of the module, SMA and the values of the correlation matrix - are described in table 1. The results based on frequency domain, are shown on table 2.

Table 1: Time domain classification results.

Algorithm	Accuracy
1NN	0.49 (+/- 0.20)
3NN	0.48 (+/- 0.17)
Gaussian Naïve Bayes	0.17 (+/- 0.00)
Decision Tree	0.32 (+/- 0.02)
Linear SVM	0.67 (+/- 0.02)

Table 2: Frequency domain classification results.

Algorithm	Accuracy
1NN	0.98 (+/- 0.02)
3NN	0.96 (+/- 0.02)
Gaussian Naïve Bayes	0.94 (+/- 0.03)
Decision Tree	0.93 (+/- 0.04)
Linear SVM	0.94 (+/- 0.02)

The results obtained with the time domain features reveal that it's not the best method to accomplish the classification, as the GNB got the worst results with only 17% of accuracy and the Linear SVM got the best results with 67%. On the other hand, the results acquired through the frequency domain showed good results with all the algorithms, all above 93% of accuracy.

To understand which features are the most important to classify, we used a linear model with the penalty of the L1 norm, estimating the non-zero coefficient. The Support Vector Machines have the penalty parameter C, which induces the separation of data values and where chosen values from $[1^{-3}, 1^{-2}, \ldots, 1^{5}]$ in order to separate efficiently the data.

The results on time domain show that the most relevant features where $\overline{a}_z$, σ_x, $\rho_{y,z}$, $|\overline{a}|$, $|\sigma|$; on frequency domain, as shown in figure 5b, the first frequency bands are the most meaningful for the classification.

5. Conclusion

In this study we used several approaches for classifying activities. The results show that acquired accelerometer signal using an Android smartphone, positioned at right front pocket, proves to be able to classify physical activities with high precision and accuracy.

The features are extracted based on both the time domain and the frequency domain and various algorithms were tested to classify activities based on supervised learning method.

The obtained results, as listed in tables 1 and 2, suggest that the features in the frequency domain provide a more accurate classification of activities than those in the time domain. The results from frequency domain provide accuracies above 95The classifier that showed the best results was KNN.

The exploration for the most relevant features for classification are based on penalizing the L1 norm, we conclude that, in frequency domain, the first 16 frequency bands are the most significant for classification. In the time domain, the 5 features that were most important for classification were as follows: $\overline{a}_z$, σ_x, $\rho_{y,z}$, $||\overline{a}||$, $||\sigma||$.

This study aims to contribute actively to motivate and monitor the physical activity and mental health of society; drawing attention to the fundamental role of physical exercise and the benefits for health.

Acknowledgements

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