Free context smartphone based application for motor activity levels recognition

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***Abstract*—Despite being considered as simple everyday objects, smartphones have the most innovative sensors and electronics technology built in. These features make them powerful, non-intrusive tools for monitoring the user's physical and cognitive performance. This study aims at exploiting smartphone-based physical activity identification, implementing a classification algorithm that makes use of data extracted from in-built smartphone's accelerometer and gyroscope. Data were gathered from three subjects carrying a standard smartphone equipped with a devoted application able to acquire data from the smartphone' sensors and send them to a remote server. We implemented a specific software that uses K-Nearest Neighbours (KNN) and Support Vector Machines (SVM) classifiers to recognize the type of activity performed with 1.5 seconds granularity. We evaluated the performances of the two classifiers in the cases of 3 (low/medium/high intensity activity) and 4 (rest/walk/stairs/run) activity levels classification. The 3 levels classification showed accuracy and F-1 scores always >90% for both classifiers, whereas the 4 levels classification was not effective in distinguishing between walk and climbing stairs. A reliable classification among low, medium, and high intensity activity demonstrates to be a meaningful achievement for overall monitoring of physical activity level, giving a precise and fairly accurate estimation of type and duration of the activity.**

I. Introduction

Nowadays, smart devices like smartphones and smart watches are essential part of our lives, accompanying us in all our daily activities, from work to entertainment. As such, we are offered with the possibility of gathering highly accurate data related to user activity, without altering the user's natural behaviour. Our interest is to exploit this potential in the medical field: smart devices can help recording continuous data describing physical activities, keeping track of any improvements, worsening, or sudden changes of the user's motor behaviour. This technology is part of the user's routine and therefore offers the unique opportunity to obtain detailed person-specific lifestyle information in an ecologic and unobtrusive way. Despite the assessed validity of the results of phone-based measurement of physical activity, smartphone use is a relatively new field of study in this research area [1]. We want to exploit smartphone-based activity monitoring adopting a longitudinal approach able to build a person-specific profile using data generated performing normal daytime activities, while being transparently sensed by smart devices. Longitudinal user monitoring may prove to be a reliable instrument to support tailored home-based motor rehabilitation. Several smartphone apps claim to be able to monitor physical activity in free environment, but none of them provide evidence of a rigorous scientific approach in design and development. Many scientific papers involving smartphones for monitoring purposes put constrains on the device usage [2][3][4][5], whereas we aim at investigating the performances of an app designed to operate in free conditions. Using the smartphone's in-built sensors data, we trained a robust classification algorithm able to detect different activities with resolution of few seconds. Among the several machine learning techniques available, we chose two methods which are widely used in the field of activity classification: K Nearest Neighbours (K-NN) [6][5][7][8] and Support Vector Machines (SVM) [4].

II. Previous Work

Mobile devices offer the advantage of unobtrusiveness in advance data capture and elaboration, with no need for further equipment. They enable for a fairly accurate estimate of daily physical activity, making them a valuable tool for monitoring and for rehabilitation purposes. Lot of research has been performed in the field of physical activity monitoring using wearable and portable sensors [1], and a wide range of experimental design choices have been proposed, in terms of: device position, type of sensors employed, classification algorithm used, extracted features, and time window for features extraction [4][9][6][7][5][10]. Several studies implemented classifiers using data from 3-axial accelerometers mounted in specific body positions [11][12]. Other works considered the combination of accelerometric and gyroscopic data from specific MEMS sensors [9]. Various studies implemented classification algorithms using data from inbuilt smartphone's sensors. Usually, studies for activity classification involving smartphones put constrains on the smartphone usage, with different types and levels of constrains: in some cases, the smartphone was used as a normal sensor unit and mounted on the subject in a specific position [3], whereas in other cases limitations were less strict (e.g. in front pocket) [4][6]. Duarte et al. obtained >90% accuracy by positioning the smartphone along the waist in the right front pocket [2]. Wu et al. acquired data from accelerometer and gyroscope using an iPod positioned in the armband or in shorts' front pocket [7]. Lee et al. used only the 3-axial smartphone accelerometer to classify different activities, having the device hand-grasped by the user [13]. Ketabdar et al. used accelerometer data to classify activities acquired from the smartphone positioned in the user's pocket [14]. Brezmes et al. proposed a subject-dependent activity recognition with Nokia N95 in different positions using only the accelerometer data [8]. Derenbach et al. evaluated the performances of Multilayer Perceptron, Naïve Bayes, Bayesian network, Decision Table, Best-First Tree, and K-star, for activity classification of simple and complex activity using a Samsung Captivate™ smartphone and data from accelerometer and gyroscope. They considered different possible smartphone orientations and obtained a >90% accuracy for simple activities classification [15].

III. Methodology

A. Data collection

Data collection was performed on three 26-year-old subjects, one male and two females. Acquisition was not limited to a specific smartphone brand and model, the only requirement being that the device had to have accelerometer and gyroscope sensors. Each subject installed an ad-hoc application designed to send the data collected to a remote server. Subjects had to select the activity to be performed before the recording session. In this preliminary phase, we selected 5 main categories of activities which, at our knowledge, represent the main subset of activities naturally performed using a smartphone, and namely: resting, typing, walking, running, and climbing stairs. By furthering differentiating the acquisition by the position of the device (holding the smartphone in the hand, keeping it in the pocket - with tight and non-tight pocket for walk and climbing stairs - or in a bag), the overall number of activities scales up to twelve. Each recording session was set to last one minute, as a good compromise between physical demand of the task and wideness of the data set. Indeed, longer acquisition time would generate more data, but it would affect the uniformity of the performance and would make the tasks more physically demanding (in particular, thinking about applications in pathological conditions). On the other hand, a shorter acquisition time would have generated a reduced data set that would have not been large enough for future features extraction in the frequency domain. The subjects were asked to perform the one-minute acquisition for each activity, for at least 6 times, and were free to perform each task at any time within their daily routine, without any additional constrain on smartphone position and orientation. All the data from the accelerometer and gyroscope were sent from the application to a remote server, from which they were downloaded and processed by a devoted Java software for elaboration and classification. Data were sampled at 10Hz and, for the accelerometer data, the gravity component was filtered using a digital high pass filter with 0.25Hz cut-off frequency [11][12][3]. The 10Hz sampling frequency allows to obtain low computational load and, at the same time, it preserves the main frequency content of the signal [16].

B. Feature extraction

We extracted temporal features onto 3-second time-windows with 50% overlap. To improve computational speed, we chose only temporal features. For each time-window, both for accelerometer and gyroscope, we extracted the mean and standard deviation of the signal amplitude which is computed as: $amplitude = \sqrt{x^2 + y^2 + z^2}$ [9][10][12][3][14]. Prior to classification, all features were normalized [4][12].

TABLE I
Table of all the feature computed and the correspondent number

feature name	feature number
accelerometer amplitude mean	(1)
accelerometer amplitude standard deviation	(2)
gyroscope amplitude mean	(3)
gyroscope amplitude standard deviation	(4)

C. Classification

We implemented two classification algorithms: a K-NN (K=5) and a SVM. For each subject, we built a training set using at least 3 one-minute acquisitions for each of the 12 activities previously defined, for a resulting total of about 40 minutes of recording. The test set was built accordingly, using a different set of one-minute acquisitions. For each subject, the training set was used to train the algorithms, whereas the test set was used to evaluate the performances of the classification. The ad-hoc mobile phone application requires the subject to annotate the performed activity. This means that, together with the accelerometer and gyroscope data used for features extraction, we also save an identifier of the activity, which is used, in the training phase, for the algorithm training, and, in the test phase, as the reference to quantify the classification performance. An example of amplitude and class value extraction from row data acquired during different activities is shown in Fig.1.

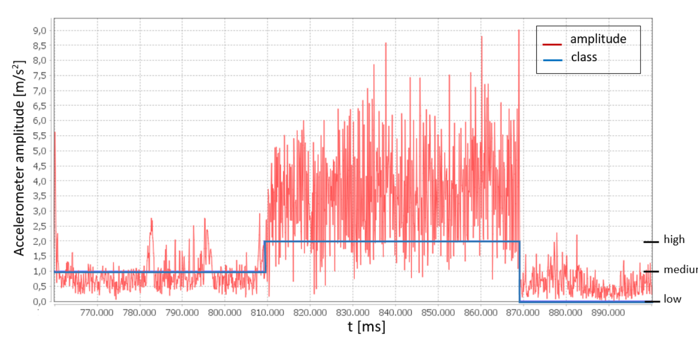

Fig. 1. Amplitude (red line) and class value (blue line) extraction on few seconds acquisition.

IV. Results

In order to evaluate the classification performances of the two algorithms, we extracted the confusion matrix and computed classification accuracy and F-1 score:

$$accuracy = \frac{TP + TN}{total}$$

$$\text{F-1} = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

where:

TP: true positive
FP: false positive
TN: true negative
FN: false negative

$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$

Figure 2 shows the results obtained with the 3-level classification experimental design, deployed in order to correctly classify low, medium, and high activity using only feature(1). For low activity, we considered the person still, holding the mobile phone or typing (standing or sitting). Medium activity included walking and climbing stairs, while for high activity we considered only running: for both medium and high activity, the mobile phone could have been placed in all possible positions.

K-NN		PREDICTED		
		low	mid	high
ACTUAL	low	835	15	0
	mid	40	2543	0
	high	0	5	441

SVM		PREDICTED		
		low	mid	high
ACTUAL	low	882	13	0
	mid	26	2557	0
	high	0	5	441

Accuracy		
	K-NN	SVM
low	0.99	0.99
mid	0.98	0.99
high	0.99	1

F-1		
	K-NN	SVM
low	0.96	0.98
mid	0.98	0.99
high	0.99	0.99

Fig. 2. Above: confusion matrices for the two classifiers using feature(1) in the 3 classes experimental design, where “low”, “mid”, and “high” state for low, medium and high intensity activity. Below: tables for Accuracy and F-1 score for 3 classes experimental design.

We also tested the classifiers with a 4-class experimental design, considering four possible activities: resting, walking, climbing stairs, and running; the fourth class was obtained by splitting in two the middle activity group of the previous experimental design. The results are shown in Fig. 3, which shows an optimal classification performance for resting and running, whereas discrimination between walking and climbing stairs was not well identified.

K-NN		PREDICTED			
		rest	walk	stairs	run
ACTUAL	rest	880	6	8	1
	walk	26	916	440	0
	stairs	10	609	576	0
	run	0	0	5	441

SVM		PREDICTED			
		rest	walk	stairs	run
ACTUAL	rest	883	12	0	0
	walk	15	1101	287	0
	stairs	7	827	361	0
	run	0	0	5	443

Accuracy		
	K-NN	SVM
rest	0.99	0.99
walk	0.72	0.71
stairs	0.73	0.71
run	1	1

F-1		
	K-NN	SVM
rest	0.97	0.97
walk	0.63	0.66
stairs	0.52	0.39
run	0.99	0.99

Fig. 3. Above: confusion matrices for the two classifiers using feature(1) in the 4 classes experimental design. Below: tables for accuracy and F-1 score for 4 classes experimental design.

Accuracy and F-1 score slightly increase training and testing the algorithm using different subsets of features, as shown in Fig. 4.

Accuracy						
	(1)		(1) (3)		(1) (2) (3) (4)	
	K-NN	SVM	K-NN	SVM	K-NN	SVM
walk	0.72	0.71	0.78	0.74	0.8	0.78
stairs	0.73	0.71	0.79	0.74	0.8	0.78

F-1						
	(1)		(1) (3)		(1) (2) (3) (4)	
	K-NN	SVM	K-NN	SVM	K-NN	SVM
walk	0.63	0.66	0.69	0.65	0.73	0.7
stairs	0.52	0.39	0.65	0.55	0.67	0.62

Fig. 4. Accuracy and F-1 values for walk and stairs classification using different subsets of features.

V. Conclusions

Results obtained for the low/medium/high intensity activity classification show that using smartphones’ in-built sensors data to discriminate between user’s activities is feasible. Accuracy and F-1 score are always >90% for both K-NN and SVM, where SVM always performs slightly better. Using a 3-second time-window with a 50% overlap, we computed activity values every 1.5 seconds, obtaining a really high granularity, allowing for an accurate estimation of the activity’s duration. In the 3-class experimental design, walking and climbing stairs were merged in the medium activity class. In a study of Knaggs et al. on the metabolic cost of different activities for older adults in terms of Metabolic Equivalent of Task (MET) and Oxygen consumption, climbing stairs reported values similar to walking briskly [17]. According to Ainsworth et al., walking downstairs implies the same MET of walking on level ground at moderate pace, whereas walking upstairs implies greater MET level, still lower than running at medium and high intensities [18]. Having similar temporal features in terms of accelerometric and gyroscopic values, walking and climbing stairs cannot be safely distinguished, leading to a poor performance of a four-level classification with regards to these two specific activities. This problem has been detected also in previous works [3][5], and it could suggest, for future development, the need of computing other features or extracting data from other sensors (e.g. the barometer), as we are aware that walking upstairs has an important informative content in particular pathological conditions. The best result we obtained for walk/stairs classification was with K-NN using all the 4 features (mean and standard deviation for both accelerometer and gyroscope). Classification performances could be improved by widening the set of extracted features (e.g., features in the frequency domain and composite features) and performing a subset selection using a specific scoring function [3][9]. Considering that the main aim of this work was to build a software able to give an estimation of the user's overall activity for monitoring purposes, we found that the reliable recognition of low, medium, and high activity is a suitable achievement. A classification of movement capabilities, in terms of motor levels, demonstrates to be a robust index in home rehabilitation design, in order to obtain a continuous and transparent assessment of the end user's progress all along the rehabilitative path. In our opinion, the subset of activities considered in this study represents the main subset of activities performed naturally using a smartphone, but we are aware that it is not comprehensive of all the possible activities that can be performed. Improvement of this aspect is on-going, through acquisitions of additional activities (cycling, driving, etc.) and evaluation of the classification results. A limit of the smartphone-based approach is in the nature of the device itself, that does not imply continuous usage. Depending on the subject attitude and habits regarding smartphone usage, the amount of significant data could greatly vary. The results shown in this paper are extracted from data acquired on healthy subjects; the performance on pathological subjects with motor impairment is under testing.

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