A mobile monitoring tool for the automatic activity recognition and its application for Parkinson's disease rehabilitation

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Abstract— **In order to perform a continuous monitoring of patients in their daily lives, it is the need to contextualize the collected data coming from the patients. In this sense, the identification of the Activities of the Daily Life (ADL) carried out by the subjects is essential to understand and to put in context other data linked to the monitoring disease itself. This work was aimed at using the accelerometers integrated in most of the current available smartphones to build an automatic activity recognizer based on the signal coming from this sort of sensors. The validation carried out showed the impact of the frequency sampling in the classifier performance as well as the impact in the battery usage. Finally, it suggested that the use of one second as sampling period is a fair trade-off between accuracy in the classification and power saving.**

Keywords— **Accelerometer, ADL, Machine Learning.**

I. INTRODUCTION

Over the past decades various technologies, methodologies and systems have been proposed for the monitoring and the identification of the Activities for Daily Living (ADL). The approach followed in most of the cases is a non-linear analysis of the signal coming from wearable systems. Generally, sensors are incorporated into a set of wearable devices which synchronize their recording procedures and transfer the recorded data for signal processing and storage.

The most extended approach is the use of the signals coming from tri-axial accelerometers. The low cost of this sort of sensors makes them really appealing for the development of wearable systems for the real-time monitoring. Analyzing accelerometers outcomes it is possible to cover with a good accuracy most of the ADL. Usually, the wearable systems used for the ADL monitoring are not enough unobtrusive to reach a complete consensus from the users involved in the trials.

Smartphones devices are becoming extremely important in the monitoring applications considering their technological features and their social impact in the society. In fact, using the smartphone as wearable device for the ADL monitoring permits to integrate the technological aspect needed for the analysis (i.e.: embedded accelerometer, powerful process capacity, storage and internet connection) and the social acceptance of the device. Moreover, using an Android-based smartphone, give the possibility to select and use commercial available device with a reduced cost.

II. APPLICATION ON PARKINSON'S DISEASE

Parkinson's disease (PD) is the second most common neurodegenerative disorder and it is expected to impose an increasing social and economic burden on societies on the coming decades. The prevalence of PD in industrialized countries is generally estimated at 0.3% of the entire population and about 1% in people over 60 years of age (1). The major motor disturbances in PD are bradykinesia (i.e. slowness at movement), hypokinesia (decreased amplitude movements), resting tremor, rigidity, and postural instability (2). Furthermore, gait performance is usually seriously affected in PD patients. These disturbances may be divided into two types (3,4): 1) continuous and 2) episodic (5,6). The episodic gait disturbances occur occasionally and intermittently and appearing randomly. The episodic gait disturbances include festination, start hesitation, and freezing of gait (7–9). The continuous changes refer to alterations in the walking pattern. The most relevant changes (temporal and spatial) affected by PD are apparent only when gait is evaluated quantitatively with gait analysis systems. Another gait feature in PD patients seems to be the inability to generate a consistent and steady gait rhythm, resulting in an increase in higher stride-to-stride variability (10–12). Several studies pointed out that repeated gait exercises lead to significant results in gait rehabilitation (13,14). Furthermore, several works have being using external cueing techniques as recurrent tool to help the PD patients to improve their gait parameters (15–18).

The gait performance in PD, as well as the automatic assessment of the motor symptoms is a topic that has been largely studied (19–21), nevertheless, in most cases this evaluation was done in supervised environments. Other works included the automatic activity recognition in order to identify and segment the daily activities of the patients (22), and to run the algorithms for the motor assessment in specific moments of the day, e.g. assessment of the gait performance and bradykinesia severity when the patient is walking. Within this work, it was intended to optimize the

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activity recognition problem by using exclusively one accelerometer and also, by identifying an optimal frequency sampling which allows the continuous monitoring of the patient along the day and at the same time minimizing the battery usage of the monitoring application. To achieve that, different classifiers were trained and tested using a range of sampling periods from 50ms to 5000ms.

III. METHODS AND MATERIAL

In order to collect data, two healthy subjects wore the smartphone in their front pocket while performing a predefined set of activities i.e. walking, resting (sitting, standing and lying), walking upstairs and walking downstairs. The smartphone used to collect the data was a BQ Aquaris E5 running Android 4.3. The application used to collect the accelerometer data in the smartphone was designed specifically for this task. It started the data collection 5 seconds after the user pressed the start button and it stored the raw signal in the SD card of the smartphone.

As it was already stated, this works is aimed at developing a mobile tool able to identify different Activities of Daily Life (ADL) using the accelerometer integrated within a smartphone.

Based on previous literature works and previous research works (22) the signal processing methodology followed in this work follow these steps:

a) *Epoch generation:* Raw data was split in fixed periods of time called “epochs”. This was done by using a sliding window of 10 seconds length with 50% overlapping.

b) *Feature extraction:* On each epoch a set of features were extracted. According to the literature and past experience, the features extracted were:
   - range (the difference between the smallest and the largest numbers in the epoch).
   - the root mean square (abbreviated RMS or rms), is a statistical measure of the magnitude of a varying quantity
   - the sample entropy and the approximate entropy, two alternative estimators of the entropy of a system represented by a time series. Entropy, as it relates to dynamical systems, is the rate of information production (23).
   - Autocorrelation, also known as serial correlation, is the cross-correlation of a signal with itself.

c) *Activity tag:* each epoch is labeled with a tag indicating the activity that the subject was carried out at each time.

d) *Classifier training:* the labeled epochs were used to train different Machine Learning algorithms: Support Vector Machine (SVM), J28 and Random Forest. This was done using the Graphic User Interface (GUI) of the Weka software. Weka is a collection of machine learning algorithms for data mining tasks. The algorithms can either be applied directly to a dataset or called from your own Java code. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is also well-suited for developing new machine learning schemes. Weka is open source software issued under the GNU General Public License (24).To be able to use this software, it was needed to transform the tagged epochs in a specific file format called ARFF which is a specific format for Weka. Consequently, different ARFF files, one for each sampling frequency tested, were built loaded in Weka environment to train the classifiers.

e) *Classifier validation:* To validate the accuracy performance of such algorithms in the classification process a cross-fold validation was done using the Weka tools.

IV. RESULTS

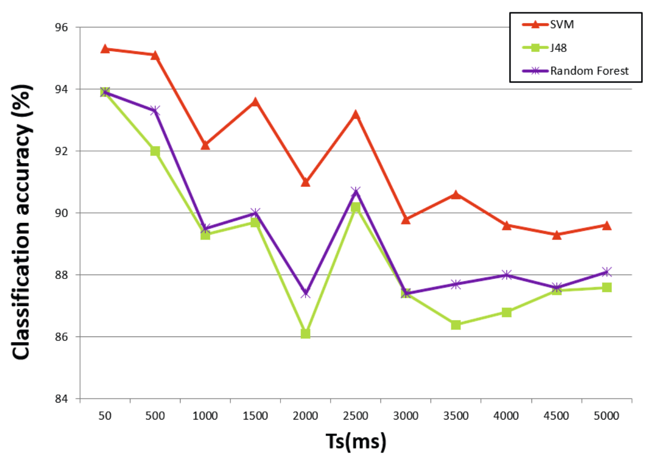

Fig. 1 Classifiers performance vs. frequency sampling

Fig. 1 shows the results of the three classifiers tested and their performance depending of the frequency of sampling used. In all the cases, the Support Vector Machine (SVM) offers a better accuracy in the activity classification. According to this results, it is evident that the higher the sampling frequency (i.e. lower T_s) the better the accuracy in the activity classification.

The second part of the research was aimed assessing the classifier performance in contrast with the battery usage in order to identify an optimal period of sampling by analyzing the battery usage.

These results are summarized in the Fig 2. This figure, shows the experimental classification error for the SVM (red square dots). Also, to understand better the trend of the error, it was also included a regression line built based on the samples of this experimental error (red line). And finally, it also includes the percentage of battery usage for each session of data collection (blue line).

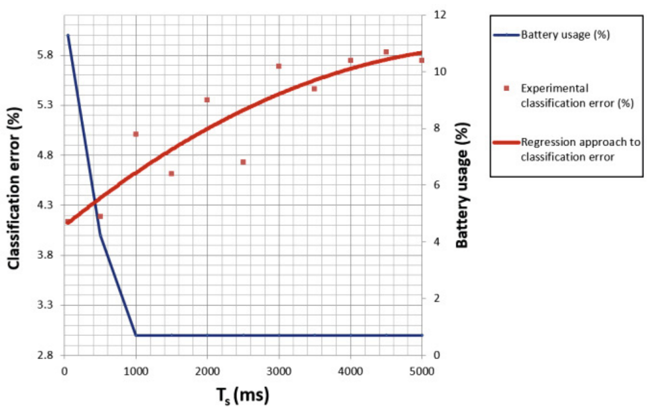

Fig. 2 SVM classification error in percentage and percentage of battery usage vs. frequency sampling

Table 1 Confusion matrix of the activity recognition by the SVM classifier (T_s = 1000ms)

	Walking	Resting	Walking	Resting
Walking	90.73%	0.47%	4.27%	1.66%
Resting	0%	100%	0%	0%
Upstairs	16.37%	0%	43.10%	40.51%
Downstairs	13.27%	0%	37.16%	49.55%

V. CONCLUSIONS

According to the results of the last chart, a fair trade-off between battery usage and classification error is to set one second length as a sampling period. Using this frequency of raw signal sampling it was achieved an experimental classification error of approximately 5% using a Support Vector Machine.

Regarding the future work and improvements, it is necessary to explore the impact of the window length in the classification accuracy as well as a more detailed study of the behavior in the region of 50ms to 1500ms. Concerning the classification performance, one of the pending challenges is the improvement of the classification accuracy to distinguish when the subject is walking upstairs and downstairs. Table 1 shows the confusion matrix of the SVM classifier for the particular case of T_s = 1000ms, this table shows that the classifier has some limitation in the identification of walking upstairs and downstairs and also, in the identification of these two activities and the normal walking. The improvement in the identification of this two actions would have a potential benefit in the global activity recognition accuracy.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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