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HUMAN BEHAVIOUR RECOGNITION USING MOBILE PHONES

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Abstract: An emerging research field that is based on Human-centered computing aims to understand human activity and integrate users and their social context with computer systems. One of the most recent and unique and challenging applications in this framework consists in recognizing human body motion using smartphones to gather context information about people actions. In this context, we have described in this work with the help of Activity Recognition database, created from the recordings of many subjects doing Activities of Daily Living (ADL) while carrying a waist attached smartphone with mounted inertial sensors, which is released to public domain on a well-known on-line repository. Results, obtained on the dataset by using a multiclass Support Vector Machine (SVM), are also honored.

I. INTRODUCTION

The actions carried out by a person given a set of observations of him/her and the surrounding environment is recognized by Human Activity Recognition (HAR) which aims to identify Recognition and that can be accomplished by using the information extracted from various resources such as environmental or body attached sensors . Some approaches have adapted particular motion sensors in different body parts such as the waist, wrist, chest and legs or thighs leading to good classification performance. These sensors are usually not very comfortable for common people and do not provide a long way solution for activity sensing (e.g. sensor repositioning after dressing).

Mobile phones nowadays are bringing up better research opportunities for human centered apps where the person is a good source of information and the phone is the first in hand sensing tool. Today devices are with inbuilt sensors such as microphones, dual cameras, accelerometers, gyroscopes, etc. The use of smartphones with inertial sensors is an alternative solution for Human Act Recognition. These popular devices provide a flexible, affordable and efficient solution for automated and without any obstruction recognize Activities of Daily Living while also providing telephonic services. Frequently, in past years, some works aim to know human behavior using phones have come up: for instance in , the first approach is to exploit an Android smartphone for Human Act Recognition employing its mounted triaxial accelerometers; additional results have also been presented in . Improvements

No.	Static	Time (sec)	No.	Dynamic	Time (sec)
0	Start (Standing Pos)	0	7	Walk (1)	15
1	Stand (1)	15	8	Walk (2)	15
2	Sit (1)	15	9	Walk Downstairs (1)	12
3	Stand (2)	15	10	Walk Upstairs (2)	12
4	Lay Down (1)	15	11	Walk Downstairs (1)	12
5	Sit (2)	15	12	Walk Upstairs (2)	12
6	Lay Down (2)	15	13	Walk Downstairs (3)	12
			14	Walk Upstairs (3)	12
			15	Stop	0
				Total	**192**

Table 1: Protocol of activities for the HAR Experiment.

are still presented in topics such as in multi-sensor fusion for better Human Act Recognition classification, which standardizes performance measures , and provides public data for inspection.
In the HAR research framework, some datasets have been released to the public do- main: the one of the Opportunity Project is one of the example which has collected a set of Activities of Daily Life in a sensor efficient environment using many environmental and body mounted sensors. Similarly, other works have given public data. Many available datasets provide a free source of data across different discipline and researchers in that field. For this reason, we presented a new dataset that has been created using inertial data from smartphone accelerometers and gyroscopes, targeting the observation of six various human activities. Some results given by using a multi class Support Vector Machine classifier, are presented as well.

II. METHODOLOGY

A set of experiments were carried out to obtain the Human Activity Recognition dataset. A group of 30 volunteers with ages ranging from 19 to 48 years were selected for this task. Each person was instructed to follow a protocol of activities while wearing a waist-mounted Sam- sung Galaxy S II smartphone. The six selected Activities of Daily Life were *standing, sitting, laying down, walking and walking downstairs and upstairs*. Each subject performed the protocol twice: on the first trial the smartphone was fixed on the left side of the belt and on the second it was placed by the user himself as preferred. There is also a separation of five seconds before the next task where people are told to rest, this facilitated repeatability (each behavior is at least tried twice) and ground trough generation through the visual interface. The tasks were performed in laboratory conditions but volunteers were asked to perform freely the sequence of activities for a more naturalistic dataset. Table 1 shows experiment protocol details.

2.1 Signal Processing

We have obtained triaxial linear acceleration as well as angular velocity signals via the mobile phone accelerometer and gyroscope at a sampling rate of 50Hz. These are Pre- processed signals done for noise reduction with a median filter and a 3rd order low-pass Butter

Name	Time	Freq.
Body Acc	1	1
Gravity Acc	1	0
Body Acc Jerk	1	1
Body Angular Speed	1	1
Body Angular Acc	1	0
Body Acc Magnitude	1	1
Gravity Acc Mag	1	0
Body Acc Jerk Mag	1	1
Body Angular Speed Mag	1	1
Body Angular Acc Mag	1	1

Table 2: Time and frequency domain signals obtained from the smartphone sensors.

body motion since 99% of its energy is contained below 15Hz . The acceleration worth filter with a 20 Hz cutoff frequency. The given rate is sufficient for capturing human signal, which has gravitational as well as body motion components, was separated using different Butterworth low-pass filter in body acceleration and gravity. The gravitational force is assumed to have only low frequency components, therefore we have found from the experiments that 0.3 Hz was an optimal corner frequency for the gievn constant gravity signal. Additional time signals were obtained by calculating from the triaxial signals the euclidean magnitude as well as time derivatives (jerk *da/dt* as well as angular acceleration *dw/dt*). The time signals were then sampled in a fixed-width sliding windows of 2.56 sec as well as fifty percent overlap found between them, since:The cadence of an average person walking is within [90, 130] steps/min , i.e. a minimum of 1.5 steps/sec; At least a full walking cycle (two steps) is preferred on each window sample; this method. We assumed the minimum speed equal to fifty percent of average human People with slower cadence such as elderly as well as disabled should also be benefitted from cadence; form (FFT), optimized for power of two vectors (2.56sec × 50Hz = 128cycles). • Signals are also mapped in the frequency domain through a Fast Fourier Trans- Therefore , a total of seventeen signals were obtained with this method, which are listed in Table 2.

2.2 Feature Mapping

From each sampled window described above a vector of features was obtained. Stan- dard measures previously used in HAR literature such as the mean, correlation, signal magnitude area (SMA) and autoregression coefficients were employed for the feature mapping. A new set of features was also employed in order to improve the learning performance, including energy of different frequency bands, frequency skew- ness, and angle between vectors (e.g. mean body acceleration and *y* vector). Table 3 contains the list of all the measures applied to the time and frequency domain signals.A total of 561 features were extracted to describe each activity window. In order to ease the performance assessment, the dataset has been also randomly partitioned into

Function	Description
mean	Mean value
std	Standard deviation
mad	Median absolute value
max	Largest values in array
min	Smallest value in array
sma	Signal magnitude area
energy	Average sum of the squares
iqr	Interquartile range
entropy	Signal Entropy
arCoeff	Autorregresion coefficients
correlation	Correlation coefficient
maxFreqInd	Largest frequency component
meanFreq	Frequency signal weighted average
skewness	Frequency signal Skewness
kurtosis	Frequency signal Kurtosis
energyBand	Energy of a frequency interval
angle	Angle between two vectors

Table 3: List of measures for computing feature vectors.

two independent sets, where 70% of the data were selected for training and the remain- ing 30% for testing. The Human Activity Recognition dataset has been made available for public use and it is presented as raw inertial sensors signals and also as feature vec- tors for each pattern. It has been submitted as the *Human Activity Recognition using Smartphones* dataset in the UCI Machine Learning Repository and can be accessed following this link (information concerning the licensing and usage of the data can be retrieved in the readme file included):

archive.ics.uci.edu/ml/datasets/Human+Activity+Recognition+Using+Smartphones

III. Experimental Results

We conducted some experiments on the HAR dataset to acknowledge future users with some results. For this purpose, we exploit well-known and state-of-the-art Support Vector Machine (SVM) [13] binary classifiers, which are generalized to the multiclass case through a One-Vs-All (OVA) approach: the SVM hyperparameters are selected through a 10-fold Cross Validation procedure and Gaussian kernels are used for our experiments.presented in Table 4. They show an overall accuracy of 96% for the test data composed The classification results using the multiclass SVM (MC-SVM) for the 6 ADL are of 2947 patterns. Similar work on HAR using special purpose sensors have shown comparable performance (90%-96%), where a system developed by collecting data from 6 volunteers for the classifaciton of 12 ADL using a waist-mounted triaxial accelerometer provided an accuracy of 90.8%, and performance of 93.9%. This allows to argue that the use of smartphones, in addition to chest-mounted accelerometer was used for classifying 5 ADL obtained a recognition be more unobtrusive and less invasive than other special purpose solutions (e.g. wear-able sensors), is a feasible way to walk for effectively performing HAR. It is also worth

	WK	WU	WD	ST	SD	LD	**Recall**
Walking	**492**	1	3	0	0	0	99%
W. Upstairs	18	**451**	2	0	0	0	96%
W. Downstairs	4	6	**410**	0	0	0	98%
Sitting	0	2	0	**432**	57	0	88%
Standing	0	0	0	14	**518**	0	97%
Laying Down	0	0	0	0	0	**537**	100%
Precision	96%	98%	99%	97%	90%	100%	**96%**

Table 4: Confusion Matrix of the classification results on the test data using the multi- class SVM. Rows represent the actual class and columns the predicted class. Activity names on top are abbreviated.

Observing that the MC-SVM model outperforms by seven percent the classifier learned on our previous dataset , where only acceleration data from the smartphone were considered into account for the recognition: this suggests that the new features, brought up in the publicly available dataset as depicted in Section 2.2, allow to ease the learning process. The precision measures, with the *sitting* activities having lowest recall equal to eighty eight percent. In par- The classification performance for each class is also displayed in words of point to note, there is a noticeable misclassification overlap between this activity and *standing* contributed to the physical location of the device and its difficulty to categorize them: future works will have to investigate the necessary steps in order to improve the discrimination of these non-dynamic activities (e.g. introduction of new features, for example derived by gyroscopes).

IV. Conclusion

In paper we introduced a better freely available data-set for Human Activity Recognition using mobile phones as well as acknowledged few results via multiclass Support Vector Machine method. The multiclass SVM employed for the classification of smartphone inertial data showed a recognition performance similar to previous work that have used special purpose sensors, therefore strengthening the application of these devices for HAR purposes. We also highlighted an improvement on the classification performance of the learned model using this new dataset against the previous version, which had a reduced set of features. However, rooms for improvements exist: while dynamic activities can be efficiently classified thanks to the newly introduced features in the released dataset, non-dynamic actions still present misclassification overlaps. This requires further study of available inputs and revision of the HAR process pipeline phases. Finally, computational complexity aspects such as battery life and real time processing for the application will be assessed in our forthcoming works.

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