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A Public Domain Dataset for Human Activity Recognition Using Smartphones

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Abstract.
Human-centered computing is an emerging research field that aims to understand human behavior and integrate users and their social context with computer systems. One of the most recent, challenging and appealing applications in this framework consists in sensing human body motion using smartphones to gather context information about people actions. In this context, we describe in this work an Activity Recognition database, built from the recordings of 30 subjects doing Activities of Daily Living (ADL) while carrying a waist-mounted smartphone with embedded inertial sensors, which is released to public domain on a well-known on-line repository. Results, obtained on the dataset by exploiting a multiclass Support Vector Machine (SVM), are also acknowledged.

1 Introduction

Human Activity Recognition (HAR) aims to identify the actions carried out by a person given a set of observations of him/herself and the surrounding environment. Recognition can be accomplished by exploiting the information retrieved from various sources such as environmental [1] or body-worn sensors [2, 3]. Some approaches have adapted dedicated motion sensors in different body parts such as the waist, wrist, chest and thighs achieving good classification performance [4]. These sensors are usually uncomfortable for the common user and do not provide a long-term solution for activity monitoring (e.g. sensor repositioning after dressing [5]).

Smartphones are bringing up new research opportunities for human-centered applications where the user is a rich source of context information and the phone is the firsthand sensing tool. Latest devices come with embedded built-in sensors such as microphones, dual cameras, accelerometers, gyroscopes, etc. The use of smartphones with inertial sensors is an alternative solution for HAR. These mass-marketed devices provide a flexible, affordable and self-contained solution to automatically and unobtrusively monitor Activities of Daily Living (ADL) while also providing telephony services. Consequently, in the last few years, some works aiming to understand human behavior using smartphones have been proposed: for instance in [6], one of the first approaches to exploit an Android smartphone for HAR employing its embedded triaxial accelerometers; additional results have also been presented in [7, 8]. Improvements

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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 expected in topics such as in multi-sensor fusion for better HAR classification, standardizing performance evaluation metrics [9], and providing public data for evaluation.

In the HAR research framework, some datasets have been released to the public domain: the one of the Opportunity Project [10] is an example which has recorded a set of ADL in a sensor rich environment using 72 environmental and body sensors. Similarly, other works have provided public data, such as [11] and [12]. Publicly available datasets provide a freely available source of data across different disciplines and researchers in the field. For this reason, we present a new dataset that has been created using inertial data from smartphone accelerometers and gyroscopes, targeting the recognition of six different human activities. Some results, obtained by exploiting a multi class Support Vector Machine (SVM) classifier [13], are shown as well.

2 Methodology

A set of experiments were carried out to obtain the HAR 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 Samsung Galaxy S II smartphone. The six selected ADL were *standing, sitting, laying down, walking, 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 5 seconds between each task where individuals are told to rest, this facilitated repeatability (every activity 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 collected triaxial linear acceleration and angular velocity signals using the phone accelerometer and gyroscope at a sampling rate of 50Hz. These signals were preprocessed for noise reduction with a median filter and a 3rd order low-pass Butter-

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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.

worth filter with a 20 Hz cutoff frequency. This rate is sufficient for capturing human body motion since 99% of its energy is contained below 15Hz [3]. The acceleration signal, which has gravitational and body motion components, was separated using another Butterworth low-pass filter into body acceleration and gravity. The gravitational force is assumed to have only low frequency components, therefore we found from the experiments that 0.3 Hz was an optimal corner frequency for a constant gravity signal.

Additional time signals were obtained by calculating from the triaxial signals the euclidean magnitude and time derivatives (jerk da/dt and angular acceleration dw/dt). The time signals were then sampled in fixed-width sliding windows of 2.56 sec and 50% overlap between them, since:

- The cadence of an average person walking is within $[90, 130]$ steps/min [14], i.e. a minimum of 1.5 steps/sec;
- At least a full walking cycle (two steps) is preferred on each window sample;
- People with slower cadence such as elderly and disabled should also benefit from this method. We supposed a minimum speed equal to 50% of average human cadence;
- Signals are also mapped in the frequency domain through a Fast Fourier Transform (FFT), optimized for power of two vectors $(2.56\text{sec} \times 50\text{Hz} = 128\text{cycles})$.

Thus, a total of 17 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. Standard measures previously used in HAR literature [15] such as the mean, correlation, signal magnitude area (SMA) and autoregression coefficients [16] 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 skewness, 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

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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 remaining 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 vectors for each pattern. It has been submitted as the *Human Activity Recognition using Smartphones* dataset in the UCI Machine Learning Repository [17] 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`

3 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.

The classification results using the multiclass SVM (MC-SVM) for the 6 ADL are presented in Table 4. They show an overall accuracy of 96% for the test data composed of 2947 patterns. Similar work on HAR using special purpose sensors have shown comparable performance (90%-96%), such as in [3] 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 similarly in [18] where a chest-mounted accelerometer was used for classifying 5 ADL obtained a recognition performance of 93.9%. This allows to argue that the use of smartphones, in addition to be more unobtrusive and less invasive than other special purpose solutions (e.g. wearable sensors), is a feasible way to walk for effectively performing HAR. It is also worth

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	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 multiclass SVM. Rows represent the actual class and columns the predicted class. Activity names on top are abbreviated.

underlining that the MC-SVM model outperforms by 7% the classifier learned on our previous dataset described in [19], where only acceleration data from the smartphone were taken into account for the recognition: this suggests that the new features, introduced in the publicly available dataset as depicted in Section 2.2, allow to ease the learning process.

The classification performance for each class is also shown in terms of recall and precision measures, with the *sitting* activity having lowest recall equal to 88%. In particular, there is a noticeable misclassification overlap between this activity and *standing* attributed 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).

4 Conclusions

In this paper we introduced a new publicly available dataset for HAR using smartphones and acknowledged some results using a multiclass Support Vector Machine approach. 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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