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Abstract: The use of smartphones for human activity recognition has become popular due to the wide adoption of smartphones and their rich sensing features. This article introduces a benchmark dataset, the *MobiAct* dataset, for smartphone-based human activity recognition. It comprises data recorded from the accelerometer, gyroscope and orientation sensors of a smartphone for fifty subjects performing nine different types of Activities of Daily Living (ADLs) and fifty-four subjects simulating four different types of falls. This dataset is used to elaborate an optimized feature selection and classification scheme for the recognition of ADLs, using the accelerometer recordings. Special emphasis was placed on the selection of the most effective features from feature sets already validated in previously published studies. An important qualitative part of this investigation is the implementation of a comparative study for evaluating the proposed optimal feature set using both the *MobiAct* dataset and another popular dataset in the domain. The results obtained show a higher classification accuracy than previous reported studies, which exceeds 99% for the involved ADLs.

1 INTRODUCTION

Human activity recognition is the process of identifying and recognizing the activities and goals of one or more humans from an observed series of actions. In recent years, human activity recognition has evoked notable scientific interest due to its frequent use in surveillance, home health monitoring, human-computer interaction, ubiquitous health care, as well as in proactive computing. Human activities can be further decomposed as a set of basic and complex activities, namely activities of daily living (ADLs) and instrumental activities of daily living (IADLs). Typical approaches use vision sensors, inertial sensors and a combination of both. Exploiting the increasing tendency of smartphone users, latest reports introduce systems which use smartphone sensors to recognize human activities (Kwapisz, Weiss & Moore 2011; Siirtola & Röning 2012; Khan et al. 2010; Lee & Cho 2011).

The aim of this work is to introduce a benchmark dataset and to present an optimized system in terms of feature selection and classification for recognition of ADLs based on smartphone's triaxial accelerometer data. The "*MobiAct*" dataset contains records of the accelerometer, gyroscope and orientation sensors of a smartphone from fifty subjects performing nine different types of ADLs and fifty-four subjects performing four different types of falls. In order to achieve an optimized recognition system, special emphasis was placed on the selection of the most effective features from feature sets already validated in published studies. Furthermore, a comparison study was performed to evaluate the proposed optimal feature set with the MobiAct dataset, as well as with an additional dataset. The results show higher classification accuracy than previous reported studies.

2 RELATED WORK

As already said, human activity recognition has evoked notable scientific interest in recent years. A recent study (Bayat, Pomplun & Tran 2014) proposes a smartphone-based recognition system, in which the application of a low-pass filter and a combination of Multilayer Perceptron, LogitBoost and Support Vector Machine (SVM) classifiers reached an overall accuracy of 91.15% when the smartphone was held in the hand of the user. Samples were recorded from four volunteers while performing six activities: slow and fast running, walking, aerobic dance, ascending stairs (“stairs up”) and descending stairs (“stairs down”). The sampling rate was set at 100 Hz while a window of 1.28 seconds with 50% overlap was used for feature extraction.

Anjum and Ilyas (2013) introduced a similar approach with ten users performing seven different activities which included walking, running, stairs up, stairs down, cycling, driving and remaining inactive, by carrying the smartphone in various positions. A sampling rate of 15 Hz and matching time windows of 5 seconds were used. Based on the ranking of the information gain, nine features were selected from the auto correlation function. For the classification process Naïve Bayes, C4.5 Decision Tree, K-Nearest Neighbor and SVM classifiers were tested. The C4.5 Decision Tree performed better than the other classifiers with an accuracy of 95.2%.

Zheng et al. (2014) proposed a two-phase method to achieve recognition of four different types of activities (sitting, standing, walking and running) using tri-axial acceleration data from a Samsung galaxy SIII smartphone. Five subjects performed the activities with the phone placed loosely in a pocket. Records of two minutes were used for the training phase while for the testing phase data from continuous records of several days were used. A sampling rate of 100 Hz was used. In order to achieve noise reduction, the authors deployed Independent Components Analysis, specifically the fastICA algorithm, in combination with the wavelet transform for feature extraction. For the classification, a Support Vector Machine was employed using the WEKA toolkit. A maximum accuracy of 98.78% was reported for a leave-one-out validation.

Based on tri-axial accelerometer data of a smartphone, Buber and Guvensan (2014) developed a recognition system for the following activities: walking, jogging, jumping, stairs up, stairs down, sitting, standing and biking. Five volunteers performed those activities with the smartphone placed in the front pocket of their trousers. The sampling rate was set at 20 Hz and a 10 second moving window was used for feature extraction. The evaluation was performed with two feature selection algorithms (OneRAttributeEval and ReliefF AttributeEval) and six classification algorithms (J48, K-Star, Bayes Net, Naïve Bayes, Random Forest, and k-NN) using 10-fold cross-validation. The authors resulted in a combination of 15 features with k-NN to perform best at a recognition rate of 94%.

Fan Z. Wang and H. Wang (2013) studied three different decision tree models based on a) the activity performed by the user and the position of the smartphone (vector), b) only the position and c) only the activity. Fifteen users performed five kinds of activities: stationary, walking, running, stairs up and stairs down with the smartphone placed into a carrying bag, a trouser pocket or in the hand. Ten-second samples of accelerometer data were recorded for each different kind of activity and position of smartphone. The authors concluded that the model based only on the activity outperformed the other two with an accuracy of 88.32%.

In another study (Siirtola & Roning 2013), accelerometer data from a smartphone were recorded with a sampling frequency of 40Hz while seven volunteers were performing five different activities: walking, running, cycling, driving a car, and sitting/standing. In each recording, four smartphones were placed in various positions, namely, trousers’ front pocket, jacket’s pocket, at backpack, at brachium and one was held at the ear only when it was physically allowed. For feature extraction a sliding window of 7.5 seconds with 25% overlap in an online (on device) application and one with 50% overlap in an offline application, were used. Classification was achieved using five classifiers based on quadratic discriminant analysis arranged in a three stage decision tree topology. Average recognition rate of almost 98.9% was reported in the offline and 90% in the online system.

Exploiting the accelerometer sensor of a smartphone (Dernbach et al. 2012) developed a system for recognizing simple (biking, stairs up, driving, lying, running, sitting, standing and walking) and complex (cooking, cleaning etc.) activities performed by ten participants. The sampling frequency was set at 80 Hz maximum although variations in the sampling rate were reported. Multiple windows sizes of 1, 2, 4, 8 and 16 seconds with 50% overlap were used. The placement of the smartphone, in terms of position and orientation, was left at each user’s will. Although

Table 1: Overview of the methodology and results followed by the related studies.

Study	No of subjects	Activities[1]	Sampling Frequency	Window size/overlap	No of Features	Smartphone position	Algorithms[2]	Performance
(Bayat et al. 2014)	4	RUN, SWL FWL, ADN, STU, STN	100Hz	1.28s/50%	18	hand of the user	J48, K-Star, BN, NB, RF, kNN	MLP & LB &SVM: 91,15% Accuracy
(Anjum and Ilyas 2013)	10	RUN, STN, STU, BIK, STC, DRI, INA	15Hz	5s	9*	various positions	NB, C4.5, KNN, SVM	C4.5: 95.2%.
(Zheng et al. 2014)	5	SIT, STD, WAL, RUN	100Hz	-	ICA + Wavelet	freely in pocket	SVM	98.78%
(Buber and Guvensan 2014)	5	WAL, JOG, STN, STU, SIT, JUM, BIK	20Hz	10s	15	front pocket	J48, K-Star, BN, NB, RF, kNN	k-NN: 94%
(Fan et al. 2013)	15	STC, WAL, RUN, STU,STN	-	10s	10*	bag, trouser pocket & hands	ID3 DC	80.29%
(Siirtola and Roning 2013)	7	WAL, RUN, BIK, DRI, SIT/STD	40Hz	7.5s/25% online app 7.5s/50% offline app	76	5 smartphones : various position	DC & QDA	90% online 98.9% offline
(Dernbach et al. 2012)	10	BIK, STU, DRI, LAY, RUN, SIT, STD WAL.	80Hz	1,2,4,8,16/50 %	6	user's choice (position & orientation)	MLP, NB, BN, DT, B-FT, K-star	MLP: 93% 2s window
(Saputri et al. 2014)	27	WAL, RUN, STN,STU, HOP	50Hz	2s	21	front pocket	ANN	93%

[1] WAL: Walking, JOG: Jogging, STN: Stairs down, STU: Stairs up, SIT: Sitting, STD: Standing, RUN: Running, BIK: Biking, LAY: Laying down, STC: Static, ADN: Aerobic dancing, HOP: Hopping, DRI: Driving, INA: Inactivity.

[2] J48: Weka implementation of C4.5 Decision Tree, LR: Logistic Regression, MLP: Multilayer Perceptron, kNN: k-Nearest Neighbors, SMO: Sequential Minimal Optimization, NB: Naïve Bayes, SVM: Support Vector Machines, RF: Random Forest, DT: Decision Table, B-FT: Best-First Tree

[*] Feature set includes that number of features but is not limited to.

complex activities were classified with an accuracy of 50%, simple activities were classified with 93% accuracy with a Multilayer Perceptron and a window size of 2 seconds.

Saputri, Khan, and Lee (2014) proposed a system for activity recognition in which twenty-seven subjects performed six types of activities, namely, walking, jogging, running, stairs up, stairs down and hopping. The smartphone was placed in the front trouser pocket using a sampling rate of 50 Hz. In the feature extraction process, the window size was set at 2 seconds, while feature selection was performed using a self-devised three-staged genetic algorithm. The use of an Artificial Neural Network produced 93% accuracy in the activity recognition.

The above non-exhaustive review on ADLs recognition systems using smartphone embedded inertial sensors reveals that several research studies have already been published, reporting acceptable results while employing various different data processing and analysis approaches. However, there is an inherent weakness of conducting objective comparisons between different implementations, because of the heterogeneity of the acquired raw data, as shown in Table 1. The issue of differentiation in smartphone positions, sampling frequency and the kinds of activities addressed, along with the relatively small number of subject recordings is addressed in the following work with the use of the developed MobiAct dataset.

3 THE MOBIACT DATASET

3.1 Dataset Description

MobiAct is a publicly available dataset (available for download from www.bmi.teicrete.gr) which includes data from a smartphone when participants are performing different types of activities and a range of falls. It is based on the previously released MobiFall dataset (Vavoulas et al. 2014), which was initially created with fall detection in mind. The fact that MobiFall included various activities of daily living made it also suitable for research in human activity recognition. In its current version, and with a more generic name, MobiAct is introduced for the first time in the context of this study.

It encompasses four different types of falls and nine different ADLs from a total of 57 subjects with more than 2500 trials, all captured with a smartphone. The activities of daily living were selected based on the following criteria: a) Activities which are fall-like were firstly included. These include sequences where the subject usually stays motionless at the end, in different positions, such as sitting on a chair or stepping in and out of a car; b) Activities which are sudden or rapid and are similar to falls, like jumping and jogging; c) The most common everyday activities like walking, standing, ascending and descending stairs (“stairs up” and “stairs down”). These activities were included from the start of the effort, since our ultimate objective has been to extend our work towards recognition of not only falls, but also complex everyday activities and, eventually, behaviours. Moreover, the fact that such activities are included is an advantage concerning human activity recognition (HAR) in general. As a result, MobiAct is suitable investigating both fall detection and HAR. Table 2 and Table 3 summarize all captured activities (and activity codes), their present trial counts, durations and a short description for each activity.

3.2 Dataset Acquisition Details

All activities related to the design of the acquisition protocol and the acquisition of the MobiAct dataset itself were performed at the Technological Educational Institute of Crete. Data were recorded from the accelerometer, gyroscope and orientation sensors of a Samsung Galaxy S3 smartphone with the LSM330DLC inertial module (3D accelerometer and gyroscope). The orientation sensor is software-based and derives its data from the accelerometer and the geomagnetic field sensor. The gyroscope was calibrated prior to the recordings using the device’s integrated tool. For the data acquisition, an Android application has been developed for the recording of raw data for the acceleration, the angular velocity and orientation (Vavoulas et al. 2013). In order to achieve the highest sampling rate possible the parameter “SENSOR_DELAY FASTEST” was enabled. Finally, each sample was stored along with its timestamp in nanoseconds.

The techniques applied in the majority of published studies focusing on smartphone-based activity recognition, require the smartphone to be rigidly placed on the human body and with a specific orientation. For this purpose a strap is frequently used. In contrast to this and in an attempt to simulate every-day usage of mobile phones, our device was located in a trousers’ pocket freely chosen by the subject in any random orientation. For the falls, the subjects used the pocket on the opposite side of the direction of the fall to protect the device from damage. For the simulation of falls a relatively hard mattress of 5 cm in thickness was employed to dampen the fall (Vavoulas et al. 2014).

Table 2: Falls recorded in the MobiAct dataset.

Code	Activity	Trials	Duration	Description
FOL	Forward-lying	3	10s	Fall Forward from standing, use of hands to dampen fall
FKL	Front-knees-lying	3	10s	Fall forward from standing, first impact on knees
SDL	Sideward-lying	3	10s	Fall sideward from standing, bending legs
BSC	Back-sitting-chair	3	10s	Fall backward while trying to sit on a chair

Table 3: Activities of Daily Living recorded in the MobiAct dataset.

Code	Activity	Trials	Duration	Description
STD	Standing	1	5m	Standing with subtle movements
WAL	Walking	1	5m	Normal walking
JOG	Jogging	3	30s	Jogging
JUM	Jumping	3	30s	Continuous jumping
STU	Stairs up	6	10s	Stairs up (10 stairs)
STN	Stairs down	6	10s	Stairs down (10 stairs)
SCH	Sit chair	6	6s	Sitting on a chair
CSI	Car step in	6	6s	Step in a car
CSO	Car step out	6	6s	Step out of a car

3.3 Dataset Participants

For the generation of the MobiAct dataset 57 subjects (42 men and 15 women) were recorded while performing the predefined activities. The subjects' age spanned between 20 and 47 years (average: 26), the height ranged from 160 cm to 189 cm (average: 175), and the weight varied from 50 kg to 120 kg (average: 76). 50 subjects completed successfully all ADLs and 54 subjects completed all falls. In total 10 trials had to be removed from the dataset due to errors in acquisition.

4 METHODS

4.1 Datasets for Comparison and Evaluation

Our intention for generating MobiAct was to enable testing and benchmarking between various methods for human activity recognition with smartphones. As a result a comparison to other existing and publically available datasets is of significant value. The most suitable such public dataset is the WISDM dataset (Kwapisz, Weiss & Moore 2011). Both WISDM and MobiAct datasets include a large set of the same ADLs, namely walking, jogging, stairs up, stairs down, sitting and standing, in a common file format. Moreover, the position of the mobile device is equally treated in both datasets since it is up to each subject to freely select the orientation it will be placed into the pocket.

Other freely available datasets, such as the DALIAC dataset (Leutheuser, Schuldhaus & Eskofier 2013) and the UCI dataset (Anguita et al. 2012) could not be used for comparison since they differ significantly in terms of the recorded ADLs and the data acquisition conditions, which should be overlapping as much as possible among all the datasets under consideration. For example, the DALIAC dataset uses multiple accelerometer nodes statically placed on the human body. It does not use smartphone-based inertial sensors and therefore it is not suitable for the study at hand. The UCI data were recorded with a specific position for the smartphone (waist mounted). In addition, the UCI dataset does not include the jogging activity, which is part of both MobiAct and WISDM datasets, but instead includes the lying down activity, which is not part of MobiAct and WISDM. Apart from these differences, significant differences in the data format prevented the utilization of the UCI dataset.

4.2 Pre-processing

In order to extract features from the two selected datasets a common file format and sampling rate for both must be achieved. Following MobiAct's file format, the WISDIM raw data file was split into smaller files based on the subject's ID and activity. Linear interpolation and subsampling was applied on the MobiAct data in order to achieve a 20Hz sampling frequency which is what is used for the production of the WISDM dataset. 20Hz as a sampling frequency is also reported by Shoaib et al. (2015) as being suitable for the recognition of ADLs from inertial sensors. In MobiAct, the duration of some types of activities was smaller than 10 sec, which is the time window for feature extraction that the WISDM study uses (Kwapisz, Weiss & Moore 2011). To achieve a minimum of 10 sec trial duration especially in trials of stairs up, stairs down and sitting on chair the last sample of each file in question was padded.

4.3 Reproduction of the WISDM Study

An important qualitative part of this investigation is the validation of the feature extraction techniques through the reproduction of a published computational pipeline and the comparison of the results. For this purpose the reported study (Kwapisz, Weiss & Moore 2011) was selected, which uses the WISDM dataset. Our hypothesis is that, if the results of the reproduction of the WISDM study are approximately the same as the published results, then the feature set defined could be used for a comparison to other feature sets, such as the one reported by Vavoulas et al. (2014).

The results from the reproduction of the WISDM study are presented in Table 4. In general the reproduced and the reported results have the same behaviour in both studies. Some minor deviations may be due to slight differences in the windowing and feature extraction methodology, since, as previously mentioned, we had to split the WISDM data into smaller files.

4.4 Feature Extraction & Feature Sets

In attempting to estimate with the parameters for an optimal computational and analysis pipeline, it is obvious that the selection of a respective optimal feature set is of paramount importance. To construct this feature set, a combination of features from the study using the precursor of MobiAct (Vavoulas et al. 2014) and the WISDM study (Kwapisz, Weiss & Moore 2011) were used.

4.4.1 Feature Set a (FSA)

This feature set consists of 68 features based on the reported work in (Vavoulas et al. 2014). For most of the features a value was extracted for each of the three axes (x, y, z). In detail, the following features were computed within each time window:

- 21 features in total from: Mean, median, standard deviation, skew, kurtosis, minimum and maximum of each axis (x, y, z) of the acceleration.
- 1 feature from: The slope SL defined as:

$$SL = \sqrt{(max_x - min_x)^2 + (max_y - min_y)^2 + (max_z - min_z)^2} \quad (1)$$

- 4 features from: Mean, standard deviation, skew and kurtosis of the tilt angle TA_i between the gravitational vector and the y-axis (ssince the orientation of the smartphone was not predefined it is expected that the negative y-axis will not be always pointing towards the vertical direction). The tilt angle is defined as:

$$TA_i = \sin^{-1}\left(\frac{y_i}{\sqrt{{x_i}^2 + {y_i}^2 + {z_i}^2}}\right) \quad (2)$$

  where x, y and z is the acceleration in the respective axis.
- 11 features from: Mean, standard deviation, minimum, maximum, difference between maximum and minimum, entropy of the energy in 10 equal sized blocks, short time energy, spectral centroid, spectral roll off, zero crossing rate and spectral flux from the magnitude of the acceleration vector.
- 31 additional features were calculated from the absolute signals of the accelerometer, including mean, median, standard deviation, skew, kurtosis, minimum, maximum and slope.

4.4.2 Feature Set B (FSB)

A total of 43 features were generated in accordance to the WISDM study reported by Kwapisz, Weiss and Moore (2011) as variants of six basic features. For each of the three axes, the average acceleration, standard deviation, average absolute difference, time between peaks and binned distribution (x10 bins) were calculated in addition to the average resultant acceleration as a single feature.

4.4.3 Optimal Feature Set (OFS)

Following elaborate experimentation (totally 70 different experimental setting) in which a) various combinations of window size (10, 5, 2 sec) and overlap (0%, 50%, 80%) were tested, b) features were removed or added into the feature vector based on observations of the achieved accuracy, and c) different classifiers were employed, such as IBk, J48, Logistic regression, Multilayer Perceptron and LMT (from the WEKA's algorithm set), an optimal feature set, in our view, has been produced. All experiments were conducted using 10-fold cross-validation. Specifically, the two feature sets (FSA and FSB), obtained using a time window of 5 sec and 80% overlap, were at first combined to form one new feature set. Subsequently weak features, identified through a trial-and-error approach, were taken out in an iterative process until the best overall accuracy for both datasets (MobiAct and WISDM) was obtained. A total number of 64 features were thus retained to form the optimal feature set. The features excluded from FSA were kurtosis for the x, y and z axes and spectral centroid. The features excluded from FSB were: time between peaks, binned distribution and average absolute difference. The optimal feature set was also calculated by using a 10s window and no overlap as defined in the WISDM study for a final comparison to their results, as shown in Table 4.

Table 4: Classification results (% accuracy) in comparison to the WISDM published results (10s window size, no overlap).

Activity	Published Results			Reproduced Results (FSB)			Results using the optimal feature set (OFS)		
	J48	Logistic	Multilayer Perceptron	J48	Logistic	Multilayer Perceptron	J48	Logistic	Multilayer Perceptron
Walking	89.9	93.6	91.7	90.8	93.8	95.3	99.4	98.3	99.8
Jogging	96.5	98.0	98.3	98.5	98.6	99.0	99.1	99.4	99.6
Upstairs	59.3	27.5	61.5	65.5	53.2	79.3	85.2	79.5	92.5
Downstairs	55.5	12.3	44.3	55.6	49.7	69.4	87.4	77.4	91.5
Sitting	95.7	92.2	95.0	97.0	94.1	94.6	97.0	97.5	98.0
Standing	93.3	87.0	91.9	97.0	94.6	90.4	99.4	97.0	99.4
Overall	85.1	78.1	91.7	88.3	87.5	92.4	96.7	94.9	98.2

Table 5: Classification results using the optimal feature set (5s window size, 80% overlap).

Dataset/Classifier:	MobiAct/IBk		MobiAct/J48		WISDM/IBk		WISDM/J48	
Activity	TPRate	FPRate	TPRate	FPRate	TPRate	FPRate	TPRate	FPRate
Walking	1.000	0.000	1.000	0.000	1.000	0.000	0.998	0.002
Jogging	1.000	0.000	1.000	0.000	0.999	0.000	0.998	0.001
Upstairs	0.993	0.001	0.930	0.004	0.992	0.001	0.939	0.006
Downstairs	0.982	0.000	0.921	0.003	0.991	0.001	0.937	0.007
Sitting	1.000	0.000	0.999	0.000	0.999	0.000	0.996	0.000
Standing	1.000	0.000	1.000	0.000	0.999	0.000	0.996	0.000
Accuracy:	99.88 %		99.30 %		99.79 %		98.63 %	

4.5 Classifiers

The classifiers selected for the final testing of the optimal feature set were the IBk (with 1 nearest neighbor), the J48 decision tree, Logistic regression and Multilayer perceptron, included in WEKA (Hall ey al. 2009) with default parameters. The first two produced the best overall results, whilst the remaining two were used for a comparison to the WISDM study since they were also reported there.

5 RESULTS

The experimental results obtained using the optimal feature set are shown in Table 5. It is worth noticing that with both classifiers the overall accuracy is close to 99% for both datasets. The best accuracy for the MobiAct dataset is obtained with the IBk classifier. IBk generally appears to have a relative better performance with 94% accuracy, a fact that has already been reported elsewhere (Buber & Guvensan 2014). Also, IBk performs better than J48 for the WISDM dataset as well. The weakness in accurately recognizing activities which produce similar signals, such as stairs up and stairs down, is noticeable with J48. Nevertheless, IBk recognizes these activities effectively. An additional noticeable point is that IBk performs slightly better in classifying the walking activity, which has been observed to be often misclassified as a stairs up or stairs down activity.

Considering the comparison of the results when using FSB (reproduced results) and OFS with the WISDM dataset, for all the classifiers used, OFS outperforms FSB (Table 4). A possible explanation to this may be the higher number of features used in OFS. This finding is in line with related published evidence. As reported by Siitrola and Roning (2013), accuracy of 98.9% achieved with the use of a large feature set (75 features).

6 CONCLUSIONS

The study's objective was to estimate an optimal computational and analysis pipeline which accurately recognizes ADLs exploiting an extensive dataset of motion data collected from a smartphone. As a result of this investigation a set of 64 features that proved to perform best with two datasets was extracted. These features were the outcome of many tests, through a trial and error process that removed weak features such as kurtosis and spectral centroid. It is noticeable that absolute values of kurtosis in all three axes improve the performance of classification and hence were included in the final optimal feature set. The spectral centroid is the key feature, which affects the results of activity recognition negatively. The stairs up and stairs down activities exhibit the worst accuracy among all those performed in the tests. This observation is also seen in other reports and may be related with the random device orientation or the dynamic and temporal resolution of the accelerometer sensor.

The best overall accuracy of 99.88% is achieved when using the IBk classification algorithm on the MobiAct dataset in combination with the optimal feature set mentioned above. This is the best reported classification result to date, when comparing with the most recent studies presented in Table 1. This result is the outcome of a 10-fold cross-validation which is a very common evaluation approach in the related studies, although we expect to decrease when using a leave-one-out cross-validation, which is a more realistic scenario. It is the intention of the authors to advance into such validation scenarios in the near future. For the above results a sampling rate of 20Hz, a window size of 5 seconds and an overlap of 80% have been used. These values are proposed as the optimal for this experimental setup. The usage of two independent datasets ensures robustness of the results, always within the limits of each dataset.

Finally, the experimental results obtained indicate that the MobiAct can be considered as a benchmark dataset since it includes a relatively large number of records and a wide range of activities in an easy to manage data format. Furthermore, since the placement of the smartphone is freely chosen by the subject in any random orientation we believe that it represents real life conditions as close as possible.

The next step towards developing a real-life application requires that a) orientation data is used in a more efficient manner and b) assessment and optimization of power consumption (battery usage) requirements for the feature extraction and classification algorithms, is thoroughly studied.

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