Human Daily Activity and Fall Recognition Using a Smartphone's Acceleration Sensor

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Abstract. As one of the fastest spreading technologies and due to their rich sensing features, smartphones have become popular elements of modern human activity recognition systems. Besides activity recognition, smartphones have also been employed with success in fall detection/recognition systems, although a combined approach has not been evaluated yet. This article presents the results of a comprehensive evaluation of using a smartphone's acceleration sensor for human activity and fall recognition, including 12 different types of activities of daily living (ADLs) and 4 different types of falls, recorded from 66 subjects in the context of creating "MobiAct", a publicly available dataset for benchmarking and
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developing human activity and fall recognition systems. An optimized feature selection and classification scheme is proposed for each, a basic, i.e. recognition of 6 common ADLs only (99.9% accuracy), and a more complex human activity recognition task that includes all 12 ADLs and 4 falls (96.8% accuracy).

Keywords: Human activity recognition · Activities of daily living · Falls · Smartphone · Accelerometer · Dataset

1 Introduction

Human activity recognition (HAR) 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 for their recognition through automated means use vision sensors, inertial sensors or a

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combination of both. Exploiting the increasing tendency of smartphone users, latest published studies introduce systems which use smartphone sensors to recognize human activities [1–5]. Besides the aforementioned normal daily activities, occasionally abnormal activities may also occur. Falls can be categorized as abnormal and sudden activities of a person's physical activity routine. Thus, the detection and recognition of falls is crucial in an activity recognition system especially when this is applied for the monitoring of elders [6]. Several approaches have been published using both threshold based and machine learning techniques, with the second one outperforming in terms of recognition accuracy [7].

The aim of this work is to present an optimized system in terms of feature selection and classification for the recognition of ADLs and falls based on smartphone's triaxial accelerometer data. To this end, the open, benchmark dataset "MobiAct" [1] was further extended in the context of this study. The introduced extended version of the MobiAct dataset contains records of the accelerometer, gyroscope and orientation sensors of a smartphone from sixty six subjects in total performing twelve different types of ADLs, four different types of falls and a scenario of daily living. In order to achieve an optimized recognition system for activity and fall recognition, special emphasis was placed on the selection of the most effective features from feature sets already validated in previous published studies [1, 7, 8]. A comparison study was performed to evaluate a proposed version of a feature set optimized for basic activity recognition tasks with the MobiAct dataset, as well as with an additional dataset, with results showing higher classification accuracies than previous reported studies. Furthermore, a second feature set was elaborated and tested in a more complex activity and fall recognition task, utilizing the full capabilities provided by the diversity and richness of the MobiAct dataset.

2 Related Work

2.1 Activity Recognition

A smartphone-based recognition system is proposed in [9], 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 s with 50% overlap was used for feature extraction.

Anjum and Ilyas [10] 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 s 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. [7] 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 fast ICA 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 [11] 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 s 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 et al. [12] 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 [13], accelerometer data from a smartphone were recorded with a sampling frequency of 40 Hz 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 s 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 [14] 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 s with 50% overlap were used. The placement of the smartphone, in terms of position and orientation, was left at each user's will. Although 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 s.

Saputri et al. [15] 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 s, 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.

Another activity recognition system based on smartphone sensors is proposed by Hung et al. [16] using an open dataset [17, 18], which includes six activities (standing, walking, running, upstairs, downstairs, laying) performed by thirty volunteers with the smartphone positioned at the waist. In the referred dataset, data was collected with a sampling rate of 50 Hz and pre-processing included a sliding window of 2.56 s in duration with 50% overlap. Forty-five features were extracted and three different classifies were tested, namely, Decision Tree (J48), Support Vector Machine and Logistic Regression, with the last one outperforming the others with an overall accuracy of 96%.

A comparative study exploiting the accelerometer and gyroscope sensors of a smartphone for human activity recognition was reported by Wang et al. in [19]. Using an open dataset [18] the authors introduced a feature selection method that takes advantages of filter and wrapper methods in order to conclude to a set of discriminant features. The best results, 87.8% classification accuracy, reported with the use of kNN classifier and a subset of 66 features.

2.2 Fall Detection and Recognition

Techniques to detect and automatically classify a fall, using acceleration data from a smartphone, were demonstrated in [21]. Ten second episodes with the falls and "fall-like" (uncontrolled) events positioned in the center of the episodes were created and linearly interpolated to a sampling frequency of 20 Hz. Five different classifiers were tested: SVM, Regularized Logistic Regression (RLR), Naïve Bayes, k-NN, and Decision Trees. In the testing process, 10-fold cross-validation and subject-wise cross-validation were performed.

A smartphone-based fall detection system called "FallAlarm" was introduced by Zhao et al. [22]. The investigated activities were: stationary, walking and running while the falls were: forward fall, backward fall, left fall and right fall. In their method, the acceleration signals were evaluated via a decision tree model, which performed better in comparison to Naïve Bayes and SVM classifiers. A4 s window with 50% overlap was applied.

Kansiz et al. [23] developed a fall detection system using a smartphone's accelerometer data. The activities of daily living included walking, jogging, jumping, sitting, standing, stairs up and stairs down, while the tested falls were forward fall, backward fall, side fall, hard fall and soft fall. The sampling rate was set at 20 Hz. For feature extraction a time window of 3 s in duration was applied. For the classification process, K-Star, Decision Tree and Naive Bayes classifiers were chosen. The authors report that K-star outperformed the others in a 10-fold cross-validation.

Figueiredo et al. [24] proposed a simple threshold based technique for the detection of falls. The results indicated 100% sensitivity and 93% specificity using the accelerometer data of two participants performing falls and six participants performing ADLs. Furthermore an SVM classifier was deployed and resulted on 96.16% accuracy using 3 features and 2-fold cross-validation as an evaluation method.

2.3 Summarizing Findings of Related Work

The above non-exhaustive review on activity and fall 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 con-
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ducting objective comparisons between different implementations, because of the

Table 1. Overview of the methodologies and their results followed by the related studies for activity recognition. Partially reproduced from [1].

Study	No of subjects	Activities[a]	Sampling Frequency	Window size/overlap	No of Features	Smartphone position	Algorithms[b]	Performance
[9]	4	ADN, STN, STU, SWL FWL, RUN	100 Hz	1.28 s/50%	18	hand of the user	BN, k-Star, kNN, NB, RF, J48	MLP & LB &SVM: 91.15% Accuracy
[10]	10	BIK, DRI, INA, STC, STN, STU, RUN	15 Hz	5 s	9[c]	various positions	C4.5, kNN, SVM, NB	C4.5: 95.2%.
[20]	5	RUN, STD, WAL, SIT	100 Hz	–	ICA + Wavelet	freely in pocket	SVM	98.78%
[11]	5	BIK, JOG, JUM, SIT, STN, STU, WAL	20 Hz	10 s	15	front pocket	BN, J48, K-Star, kNN, NB, RF	k-NN: 94%
[12]	15	RUN, STU, WAL, STC, STN	–	10 s	10[c]	bag, trouser pocket & hands	ID3 DC	80.29%
[13]	7	BIK, DRI, RUN, SIT, STD, WAL	40 Hz	7.5 s/25% online app 7.5 s/50% offline app	76	5 smartphones: various position	DC & QDA	90% online 98.9% offline
[14]	10	BIK, DRI, LYI, RUN, SIT, STD, STU, WAL	80 Hz	1,2,4,8,16/50%	6	user's choice (position & orientation)	B-FT, BN, DT, K-star, MLP, NB	MLP: 93% 2 s window
[15]	27	HOP, RUN, STN, STU, WAL	50 Hz	2 s	21	front pocket	ANN	93%
[16]	30	LYI, RUN, STD, STN, STU, WAL	50 Hz	2.56 s/50%	45	Waist	J48, LR, SVM	LR 96%
[19]	30 from [18]	LYI, SIT, STN, STU, STD, WAL	50 Hz	2.56 s/50%	74: NB, 66:kNN	Waist	kNN, NB	NB 90,1%, kNN 97,8%

[a]ADN Aerobic dancing, BIK Biking, DRI Driving, HOP Hopping, INA Inactivity, JOG Jogging, JUM Jumping, LYI Laying, RUN Running, SIT Sitting, STC Static, STD Standing, STN Stairs down, STU Stairs up, SWL slow WAL, FWL fast WAL, WALWalking.

[b]ANN Artificial neural network, B-FT Best-First Tree, BN Bayes Net, C4 5 Decision Tree, DC Decision Tree, DT Decision Table, ID3 Decision Tree, J48 Weka implementation of C4.5 DC, K-star, kNN k-Nearest Neighbors, LR Logistic Regression, MLP Multilayer Perceptron, NB Naïve Bayes, QDA Quadratic discriminant analysis, RF Random Forest, SVM Support Vector Machines.

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

Table 2. Overview of the methodology and results, followed by the related studies for fall detection and recognition.

Study	No of subjects	Activities	Sampling Frequency	Window size/overlap	No of Features	Smartphone position	Algorithms[2]	Performance
[21]	15	Fall like events, 4 ADLs	20 Hz	10 s	178	Belt: Set position& orientation	C 4.5, k-NN, NB, RLR, SVM	RLR: Detection: 98% Classification: 99.6%
[22]	10	4 falls, 3 ADLs	32 Hz	4 s/50%	5	Waist	C 4.5, NB, SVM	C 4.5 100% Precision, 75,8% Recall
[23]	8	4 falls, 6 ADLs	20 Hz	3 s	5 to 43	Pocket	J48, k-Star, NB	K-StarAverage recall 0.88
[24]	2 falls, 6 ADLs	10 falls, 17 ADLs	50 Hz, 100 Hz	–	3	Trouser pocket, Belt	SVM, threshold algorithms	SVM 96.19%

Ưu điểm của MobiAct dataset

heterogeneity of the acquired raw data, as shown in Tables 1 and 2. The issue of differentiation in smartphone positions, sampling frequency and kinds of activities and falls, along with the relatively small number of subject recordings is addressed with the use of the publicly available MobiAct dataset. Moreover, there is no constancy in the computational methodology applied for both fall detection/recognition and activity recognition, thay vào đó rather each task is handled separately. In this work, the proposed computational methodology (see Sect. 4.3) has been tested and evaluated in order to handle the recognition of falls and activities as a unified system.

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 recorded from a smartphone's inertial sensor while participants were performing different types of activities and a range of falls. It is based on the previously released MobiFall dataset [7], 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. The latest version of MobiAct has been used in the context of this study.

The MobiAct dataset includes 4 different types of falls and 12 different ADLs from a total of 66 subjects with more than 3200 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 (thường bất động ở cuối) 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 (mục tiêu cuối cùng) has been to extend our original work towards recognition of not only falls, but also complex everyday activities and, eventually, behaviour patterns. Moreover, the fact that such activities are included is an advantage concerning human activity recognition in general. The latest addition to the MobiAct dataset includes two extra types of ADLs ("chair up" and "sitting"), and five different continuous sequences of daily living, which include all the different types of the separate ADLs mentioned above. These sequences of the activities are based on a scenario of daily living where a person leaves her/his home, takes her/his car to get to her/his working place (although real driving was not recorded), reaches her/his office, sits on the chair and starts working. Once she/he gets off his work, she/he takes her/his car and goes in an open area to perform physical exercise. At the end of the day she/he gets into the car and returns back home. The initial scenario was split into five sub-scenarios (continuous sequences), which are connected with idle ADLs ("standing" and "sitting"), in order to avoid recording issues that would lead to several repetitions and the frustration of the participants. The main purpose for the construction of scenarios is to investigate how the recognition of different activities with natural transitions between them in continuous recordings, will affect the performance of the system, since in a real life scenario there is no clear separation from one activity to another. This investigation is part of our ongoing work. As a result, MobiAct is suitable for investigating both fall detection/recognition and human activity recognition tasks. Tables 3 and 4 summarize all recorded activities (and activity codes), their present trial counts, durations and a short description.

Table 3. Falls recorded in the MobiAct dataset.

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

3.2 Dataset Acquisition Details

All activities related to the design of the acquisition protocol and the production of the MobiAct dataset itself were performed at the Technological Educational Institute of Crete. Data was 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 lấy được 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 from the acceleration, the angular velocity and orientation [25]. In order to achieve the

Table 4. Activities of Daily Living Recorded in the MobiAct Dataset.

Code	Activity	Trials	Duration	Description
STD	Standing	1	5 min	Standing with subtle movements
WAL	Walking	1	5 min	Normal walking
JOG	Jogging	3	30 s	Jogging
JUM	Jumping	3	30 s	Continuous jumping
STU	Stairs up	6	10 s	Stairs up (10 stairs)
STN	Stairs down	6	10 s	Stairs down (10 stairs)
SCH	Stand to sit (sit on chair)	6	6 s	Transition from standing to sitting
SIT	Sitting on chair	1	1 min	Sitting on a chair with subtle movements
CHU	Sit to stand (chair up)	6	6 s	Transition from sitting to standing
CSI	Car step in	6	6 s	Step in a car
CSO	Car step out	6	6 s	Step out of a car
LYI	Lying	12	–	Activity taken from the lying period after a fall

highest sampling rate possible the parameter "SENSOR_DELAY FASTEST" was enabled. Finally, each sample was stored along with its timestamp in nanoseconds.

The techniques that have been applied in the majority of published studies, as presented in Sect. 2, which focus on smartphone-based activity recognition and fall detection/recognition, require the smartphone to be rigidly (cố định) placed on the human body and with a specific orientation (hướng cụ thể). 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 [7].

3.3 Dataset Participants

The MobiAct dataset currently includes records from 66 participants, 51 men and 15 women. In particular, 66 subjects performed the falls described in Table 3, 59 subjects performed nine of the eleven ADLs described in Table 4, while 19 performed all the ADLs, and finally 19 subjects performed the five sequences representing the scenario of daily living described in Sect. 3.1. The subjects' age spanned between 20 and 47 years, the height ranged from 160 cm to 193 cm, and the weight varied from 50 kg to 120 kg. The average profile of the subject that occurs based on the described characteristics is 26 years old, 176 cm of height and 76 kg weight. All participants had different physical status, ranging from completely untrained to athletes (minimum of cases). The challenge of the generalization [26] is addressed due to the high number of participants, the range of ages and the range of physical status included in the MobiAct dataset.

4 Methods

4.1 Datasets for Comparison and Evaluation

Our intention in 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 [2]. 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 was left up to each subject to freely select the orientation of the smartphone into their pocket.

Other freely available datasets, such as the DALIAC dataset [27] and the UCI dataset [17] could not be used for comparison, since they differ significantly in terms of the recorded ADLs and the data acquisition conditions. Specifically, the DALIAC dataset uses multiple accelerometer nodes statically placed on the human body. It does not use the smartphone-based inertial sensors and therefore it is not suitable for the study at hand. The UCI data, on the other hand, was recorded with a specific position for the smartphone (waist mounted) and 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 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 from Kwapisz et al. [2] was selected, which uses the WISDM dataset. Our hypothesis is that, if the results of our 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. [7]. For this comparison a subset of MobiAct was used. Specifically, the scenario recordings were excluded, since the WISDM does not include comparable data.

In order to extract features from the two selected datasets a common file format and sampling rate for both had to be achieved. Following MobiAct's file format, the WISDM 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 20 Hz sampling frequency which is what is used for the production of the WISDM dataset. 20 Hz as a sampling frequency is also reported by Shoaib et al. [28] as being suitable for the recognition of ADLs from inertial sensors. In MobiAct, the duration of some types of activities was smaller than 10 s, which is the time window for feature extraction that the WISDM study uses [2]. To achieve a minimum of 10 s trial duration especially in trials of stairs up, stairs down and sitting the last sample of each file in question was padded.

The results of our effort to reproduce the WISDM study are presented in Table 5. 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.

4.3 Feature Extraction and Feature Sets

In attempting to estimate the parameters for an optimized computational and analysis pipeline, it is obvious that the selection of a respective optimized feature set is of paramount importance. To construct this feature set, a combination of the features used in the study employing the precursor of MobiAct [7] and the WISDM study [2] were used.

Feature Set A(FSA)
This feature set consists of 68 features based on the reported work in [7]. 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:

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

- 4 features from: Mean, standard deviation, skew and kurtosis of the tilt angle TA_i between the gravitational vector and the y-axis (since 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:

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

  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.

Feature Set B (FSB)
A total of 43 features were generated in accordance to the WISDM study reported by Kwapisz et al. [2] 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 (× 10 bins) were calculated in addition to the average resultant acceleration as a single feature.

First Optimized Feature Set (OFS1)

Following elaborate experimentation (totally 70 different experimental setting) on the subset of 6 activities covered by both the WISDM and MobiAct datasets in which (a) various combinations of window size (10, 5, 2 s) 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 (kNN), J48, Logistic regression and Multilayer Perceptron (from the WEKA's algorithm set), a first optimized feature set 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 s 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 as shown in Table 6. A total number of 64 features were thus retained to form the first optimized feature set. The features excluded from FSA were the kurtosis for the x, y and z axes and the spectral centroid.

Table 5. Classification results (% accuracy) in comparison to the WISDM published results (10 s window size, no overlap). Reproduced from [1].

Activity	Published results (WISDM study, FSB)			Reproduced results (FSB)			Results using the first optimized feature set (OFS1)		
	J48	LR	MLP	J48	LR	MLP	J48	LR	MLP
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
Stairs up	59.3	27.5	61.5	65.5	53.2	79.3	85.2	79.5	92.5
Stairs down	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**

The features excluded from FSB were: Time between peaks, binned distribution and average absolute difference. Finally, the features from OFS1 were also calculated by using a 10 s window and no overlap as defined in the WISDM study for a final comparison to their results, as shown in Table 5.

Second Optimized Feature Set (OFS2)

The first optimized feature set was further optimized for activity recognition based on the 6 common activities included in both the WISDM and the MobiAct dataset. Since

Table 6. Classification results using the first optimized feature set (5 s window size, 80% overlap). Reproduced from [1].

Dataset/Classifier:	MobiAct/IBk		MobiAct/J48		WISDM/IBk		WISDM/J48	
Activity	TP Rate	FP Rate	TP Rate	FP Rate	TP Rate	FP Rate	TP Rate	FP Rate
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
Stairs up	0.993	0.001	0.930	0.004	0.992	0.001	0.939	0.006
Stairs down	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%**	

MobiAct includes more ADLs it is important to move forward towards a recognition system including all. Some of these, such as the transition from sitting to standing, are less than 2 s in duration, a fact that has to be considered when selecting the window size for feature extraction. The importance of recognizing transition activities, which are short duration activities taking place in a sequence of normal activities, is highlighted as an open issue in the study of Reyes-Ortiz et al. [29]. In addition to this, we, also, strived to further reduce the number of features of OFS1 by removing the majority of absolute value features. The tests, briefly described in [8] were performed with three different window sizes (2, 1.5, 1 s) and four subsets of OFS1. The finally selected feature set (OFS2) consists of the following 39 features taken with a window size of 1 s and an overlap of 80%:

- 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 (1).
- 4 features from: Mean, standard deviation, skew and kurtosis of the tilt angle TAi (2).
- 10 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 roll off, zero crossing rate and spectral flux from the magnitude of the acceleration vector.
- 3 features from: The kurtosis of the absolute of the acceleration in each axis (x, y, z).

Using this feature set and the two best performing classifiers (IBk and J48) we performed a generalized evaluation with the total of 16 activities (falls included) from the MobiAct dataset, as opposed to the limited number of activities commonly used in the literature (cf. Sect. 2). A 10-fold cross-validation was used on both the complete MobiAct dataset, as well as on a subset that did not include the consecutive activities recorded for the daily living scenario. The intention for this was to perform a preliminary examination of the impact of using consecutive sequences of activities. The results are shown in Tables 7, 8, 9 and 10.

Table 7. Classification results using the J48 decision tree without the activities from the scenarios. Values below 0.80 are highlighted in italic.

Activity	TP Rate	FP Rate	Precision	F-Measure
Standing	0.985	0.006	0.985	0.985
Fall: Back-sitting-chair	*0.700*	*0.003*	*0.688*	*0.694*
Lying	0.985	0.001	0.983	0.984
Sitting on chair	0.957	0.002	0.952	0.954
Sit to stand	*0.466*	*0.001*	*0.481*	*0.473*
Car step in	*0.658*	*0.006*	*0.670*	*0.664*
Car step out	*0.695*	*0.006*	*0.684*	*0.689*
Fall: Front-knees-lying	*0.619*	*0.003*	*0.620*	*0.620*
Fall: Forward-lying	*0.563*	*0.003*	*0.573*	*0.568*
Jogging	0.981	0.002	0.980	0.981
Jumping	0.982	0.001	0.983	0.983
Stand to sit	*0.694*	*0.003*	*0.703*	*0.698*
Fall: Sideward-lying	*0.575*	*0.003*	*0.610*	*0.592*
Stairs down	0.876	0.005	0.874	0.875
Stairs up	0.885	0.005	0.883	0.884
Walking	1.000	0.000	1.000	1.000
Weighted Avg.	**0.954**	**0.003**	**0.953**	**0.953**
Variance	**0.032**	**0.000**	**0.030**	**0.031**

Table 8. Classification results using the IBk classifier without the activities from the scenarios. Values below 0.80 are highlighted in italic.

Activity	TP Rate	FP Rate	Precision	F-Measure
Standing	0.987	0.005	0.989	0.988
Fall: Back-sitting-chair	0.838	0.001	0.832	0.835
Lying	0.988	0.001	0.984	0.986
Sitting on chair	0.959	0.001	0.963	0.961
Sit to stand	*0.608*	*0.001*	*0.603*	*0.605*
Car step in	0.807	0.003	0.832	0.820
Car step out	0.850	0.003	0.831	0.841
Fall: Front-knees-lying	*0.747*	*0.002*	*0.766*	*0.756*
Fall: Forward-lying	*0.688*	*0.002*	*0.723*	*0.705*
Jogging	0.988	0.001	0.991	0.990
Jumping	0.992	0.000	0.996	0.994
Stand to sit	0.810	0.002	0.779	0.794
Fall: Sideward-lying	*0.721*	*0.001*	*0.803*	*0.759*
Stairs down	0.933	0.003	0.928	0.931
Stairs up	0.948	0.003	0.929	0.938
Walking	1.000	0.001	0.997	0.998
Weighted Avg.	**0.971**	**0.002**	**0.971**	**0.971**
Variance	**0.015**	**0.000**	**0.013**	**0.014**

Table 9. Classification results using the J48 decision tree with all activities, including scenarios. Values below 0.80 are highlighted in italic.

Activity	TP Rate	FP Rate	Precision	F-Measure
Standing	0.983	0.007	0.982	0.983
Fall: Back-sitting-chair	*0.704*	*0.002*	*0.707*	*0.706*
Lying	0.984	0.001	0.982	0.983
Sitting on chair	0.973	0.002	0.970	0.972
Sit to stand	*0.449*	*0.001*	*0.463*	*0.456*
Car step in	*0.640*	*0.006*	*0.651*	*0.646*
Car step out	*0.674*	*0.006*	*0.674*	*0.674*
Fall: Front-knees-lying	*0.596*	*0.002*	*0.592*	*0.594*
Fall: Forward-lying	*0.576*	*0.002*	*0.580*	*0.578*
Jogging	0.977	0.002	0.976	0.977
Jumping	0.978	0.001	0.980	0.979
Stand to sit	*0.656*	*0.003*	*0.680*	*0.668*
Fall: Sideward-lying	*0.577*	*0.002*	*0.610*	*0.593*
Stairs down	0.841	0.006	0.854	0.847
Stairs up	0.851	0.006	0.852	0.851
Walking	0.986	0.008	0.983	0.984
Weighted Avg.	**0.947**	**0.006**	**0.947**	**0.947**
Variance	**0.033**	**0.000**	**0.031**	**0.032**

Table 10. Classification results using the IBk classifier with all activities, including scenarios. Values below 0.80 are highlighted in italic.

Activity	TP Rate	FP Rate	Precision	F-Measure
Standing	0.984	0.005	0.987	0.986
Fall: Back-sitting-chair	0.832	0.001	0.832	0.832
Lying	0.987	0.001	0.984	0.986
Sitting on chair	0.977	0.002	0.977	0.977
Sit to stand	*0.592*	*0.001*	*0.588*	*0.590*
Car step in	0.802	0.003	0.831	0.816
Car step out	0.835	0.004	0.822	0.828
Fall: Front-knees-lying	*0.756*	*0.001*	*0.764*	*0.760*
Fall: Forward-lying	*0.691*	*0.001*	*0.729*	*0.709*
Jogging	0.985	0.001	0.990	0.987
Jumping	0.990	0.000	0.996	0.993
Stand to sit	*0.788*	*0.002*	*0.773*	*0.780*
Fall: Sideward-lying	*0.721*	*0.001*	*0.795*	*0.757*
Stairs down	0.913	0.003	0.922	0.917
Stairs up	0.929	0.003	0.921	0.925
Walking	0.994	0.006	0.986	0.990
Weighted Avg.	**0.968**	**0.004**	**0.968**	**0.968**
Variance	**0.015**	**0.000**	**0.014**	**0.014**

4.4 Classifiers

The classifiers selected for the final testing of the optimized feature set were the IBk (with 1 nearest neighbor), the J48 decision tree, Logistic regression and Multilayer perceptron, included in WEKA [30] 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 their use was also reported in the specific study.

5 Results

5.1 With Respect to the First Optimized Feature Set

The first optimized feature set was produced in the context of activity recognition related to the WISDM study (6 ADLs, no scenarios and falls). The experimental results obtained using this feature set are shown in Table 6. 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 [11]. 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 and OFS1 with the WISDM dataset, for all the classifiers used, OFS1 outperforms FSB (Table 5).

5.2 With Respect to the Second Optimized Feature Set

The second optimized feature set was produced for activity recognition [8] using all ADLs included in MobiAct and was tested using both the ADLs and the falls. The results (in Tables 7, 8, 9 and 10) show that the second optimized feature set shows an overall good performance with the highest accuracy of 97.1% (cf. Table 8), while IBk shows slightly better performance results than the decision tree and less variance in the results. The performance on the ADLs is remarkably well for all cases. The detection of the short sit to stand and stand to sit activities is not ideal but would otherwise be impossible with a larger window. The confusion matrix for the case of using IBk with all activities shown in Table 11 shows that sit to stand (CHU) is most often misclassified as stand to sit (SCH) while the opposite is not as distinct. The recognition of activities which produce similar signals, such as stairs up and stairs down, does not seem to be a problem as observed in the above results using OFS1. The correct recognition of falls is more problematic. A closer look at the Table 11 reveals that most often the front-knees-lying fall (FKL) is misclassified as forward-lying (FOL) and vice versa. The same is noticeable for the sideward-lying fall (SDL) and back-sitting-chair fall (BSC).

Table 11. Confusion matrix of the results using the IBk classifier with all activities, including scenarios, expressed in terms of the percentage of total class instances. Values in light grey show misclassifications above 5% and values in dark grey show misclassifications above 10%.

Actual:	Classified as:															
	STD	BSC	LYI	SIT	CHU	CSI	CSO	FKL	FOL	JOG	JUM	WAL	STU	SCH	SDL	STN
STD	98.43	0.04	0.01	0.01	0.06	0.17	0.30	0.05	0.10	0.03	0.02	0.26	0.22	0.05	0.05	0.21
BSC	1.86	83.16	4.33	0.00	0.00	0.19	0.04	1.90	1.94	0.00	0.00	0.00	0.91	0.00	5.21	0.46
LYI	0.02	0.36	98.70	0.01	0.00	0.01	0.00	0.30	0.26	0.00	0.00	0.00	0.01	0.00	0.31	0.02
SIT	0.05	0.00	0.01	97.71	0.15	0.84	0.48	0.00	0.00	0.00	0.00	0.00	0.00	0.77	0.00	0.00
CHU	5.81	0.00	0.00	4.05	59.15	1.85	3.35	0.00	0.00	0.09	0.00	2.64	0.18	22.80	0.00	0.09
CSI	2.16	0.01	0.00	3.13	0.56	80.19	9.45	0.00	0.01	0.07	0.01	1.68	0.19	2.47	0.00	0.07
CSO	3.18	0.01	0.00	1.62	0.73	7.30	83.48	0.03	0.00	0.03	0.00	1.36	0.17	2.02	0.01	0.07
FKL	2.62	2.02	3.17	0.00	0.00	0.09	0.05	75.57	8.95	0.00	0.00	0.00	1.65	0.00	2.80	3.08
FOL	5.56	3.88	4.08	0.00	0.00	0.05	0.00	10.66	69.10	0.00	0.00	0.00	1.43	0.00	3.62	1.63
JOG	0.12	0.00	0.00	0.00	0.01	0.05	0.03	0.00	0.00	98.50	0.28	0.78	0.10	0.01	0.00	0.11
JUM	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.69	98.97	0.16	0.05	0.00	0.00	0.05
WAL	0.13	0.00	0.00	0.00	0.01	0.05	0.05	0.00	0.00	0.04	0.00	99.37	0.17	0.03	0.00	0.14
STU	1.15	0.04	0.01	0.00	0.01	0.04	0.02	0.02	0.06	0.02	0.00	2.53	92.95	0.02	0.04	3.10
SCH	1.75	0.00	0.00	5.12	6.56	2.67	2.98	0.00	0.00	0.03	0.03	1.77	0.26	78.81	0.00	0.03
SDL	2.83	7.92	4.18	0.00	0.00	0.22	0.09	3.87	3.05	0.00	0.00	0.00	2.79	0.00	72.14	2.92
STN	1.28	0.02	0.03	0.00	0.01	0.02	0.01	0.13	0.06	0.03	0.01	2.98	4.03	0.00	0.13	91.25

6 Conclusions

The study's objective was to estimate an optimal computational and analysis pipeline which accurately recognizes ADLs and falls exploiting an extensive dataset of motion data collected from a smartphone. As a result of this investigation two optimized sets of features were extracted, the first (OFS1) showing best results in human activity recognition with two independent datasets, and the second one (OFS2) performing remarkably well in the complex task of human activity and fall recognition. These feature sets were the outcome of many tests, through a trial and error process that removed weak features.

For the first optimized feature set the kurtosis of each axis of the acceleration was removed but it has been observed that the kurtosis features of the absolute values of the acceleration in all three axes improve the performance of classification and hence were included in the first optimized feature sets. The spectral centroid is the key feature, which negatively affects the results of activity recognition. The stairs up and stairs down activities exhibit the worst accuracy among all activities. 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 in 6-class human activity recognition of 99.88% is achieved when using the IBk classification algorithm on the MobiAct dataset in combination with OFS1. 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 a decrease when using a leave-one-out cross-validation, which is a more realistic scenario. It is our intention to advance into such validation scenarios in the near future. For the above results a sampling rate of 20 Hz, a window size of 5 s 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.

For the second optimized feature set the challenge was to correctly classify a set of 16 activities, including falls, with the limitation of the very short duration (<2 s) of some of them, like "stand to sit" and "sit to stand". This resulted into the necessity of reducing the window size for feature extraction with respect to the one used in OFS1. The number of features was reduced as well, striving for a simpler, computationally less demanding, pipeline. The evaluation of this feature set was performed on a subset of MobiAct, not including the activities of the continuous sequences, as well as on the complete dataset. The outcome is encouraging, showing remarkable results on activity recognition and good results in fall recognition. A slight misclassification between the falls was observed. Since it is mainly between the falls, accurate fall detection would be possible with a logical "OR" expression on the classification outcome of the four fall classes. Similar to the evaluation with OFS1, IBk performed better than the J48 decision tree, while the inclusion of scenario-based recorded activities showed practically no deterioration of the average performance of both classifiers based on the F-Measure.

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 and falls in an easy to manage data format. The latest addition to the dataset, namely the continuous activity sequences expands the suitability of the dataset towards investigating more complex HAR problems including very short activities and uncluttered transitions between activities. 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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