The MobiFall Dataset: An Initial Evaluation of Fall Detection Algorithms Using Smartphones

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***Abstract*—Fall detection receives significant attention in the field of preventive medicine, wellness provision and assisted living, especially for the elderly. As a result, numerous commercial fall detection systems exist to date and most of them use accelerometers and/ or gyroscopes attached on a person's body as primary signal sources. These systems use either discrete sensors as part of a product designed specifically for this task or sensors that are embedded in mobile devices such as smartphones. The latter approach has the advantage of offering well tested and widely available communication services, e.g. for calling emergency if necessary, when someone has fallen. Apparently, automatic fall detection will continue to evolve in the following years.**

The aim of this work is to introduce a human activity dataset that will be helpful in testing new methods, as well as performing objective comparisons between different algorithms for fall detection and activity recognition, based on inertial-sensor data from smartphones. The dataset contains signals recorded from the accelerometer and gyroscope sensors of a latest technology smartphone for four different falls and nine different activities of daily living. Using this dataset, the results of an initial evaluation of three fall detection algorithms are finally presented.

I. INTRODUCTION

A fall is defined as a sudden, uncontrolled and unintentional downward displacement of the body to the ground. Automatic fall detection systems rely on a set of threshold values for predetermined parameters, as well as classification rules, in order to continuously process motion data, obtained from an accelerometer and/or a gyroscope, or other sensors, and to determine if a fall event has occurred. It is evident that falls affect millions of people (especially the elderly) and may result in significant injuries [1]. Moreover, injury is a leading cause of death among elderly people [2].

In the literature many fall detection systems are described today, allowing users to obtain assistance on demand or automatically. Automatic fall detection is one of the hottest topics in the field of preventive health care since the last decade. Numerous papers report approaches to automatic fall detection based on the analysis of images, video, audio, as well as inertial sensor data from sensors that are either discrete (stand-alone) or integrated inside a mobile phone [3]–[11].

The engagement of mobile phones or smartphones for pervasive health care provides a cost-effective and powerful solution to the well-known issue of increasing health-care needs and costs due to the growing population of elderly. Various such fall detection systems already exit [8]–[11] and each one of these uses a specific phone with specific and different embedded sensors. Moreover each method is evaluated within its own testing environment and with its own data. Thus it very difficult, if not impossible, to compare different existing approaches on their validity and effectiveness.

The aim of this article is to introduce a dataset that will be helpful in testing new methods, as well as performing objective comparisons between different algorithms for fall detection and activity recognition, based on inertial-sensor data from smartphones. It incorporates signals recorded from the accelerometer and gyroscope sensors for four different falls and nine different activities of daily living (ADLs). The dataset, called "MobiFall" can be downloaded from the website of the Biomedical Informatics and eHealth Laboratory at the Technological Educational Institute of Crete[1]. Using this dataset, an initial evaluation of three fall detection algorithms has been performed and the results are presented herein.

The remaining of this article is structured as follows. Section II presents the dataset and the conditions under which it was produced. Section III describes three of the most popular algorithms that serve as an evaluation basis, while Section IV presents the respective results. Finally a brief discussion and critical assessment of the dataset and algorithms is given in Section V.

II. THE MOBIFALL DATASET

Data from the accelerometer and gyroscope sensors (plus orientation data; the orientation sensor is software-based and derives its data from the accelerometer and the geomagnetic field sensor) of a smartphone were recorded. Specifically, a Samsung Galaxy S3 device with the LSM330DLC inertial module (3D accelerometer and gyroscope) was used to

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capture the motion data. The gyroscope was calibrated prior to the recordings using the device's integrated tool. For the purpose of data capture an Android application was developed that records raw data for acceleration, angular velocity and orientation with the enabled parameter "SENSOR_DELAY_FASTEST." This provides the highest possible sampling rate. The signals can be subsampled at any time if lower sampling rates are desired. Each sample is stored along with its timestamp in ns. This allows for any convenient subsampling, e.g. in order to achieve a more constant sampling rate, although the standard deviation of the sampling period is ~7.6 ms at 87 Hz mean sampling frequency for the accelerometer, and ~0.3 ms at 200 Hz mean sampling rate for the gyroscope and the orientation data. The developed application uses a SQLite database in order to store activities and the subject's data. The user of the application has the ability to insert, edit or delete activities and participants. An automatic timer stops the data capture after the end of each trial. Three .txt-files are stored for each trial, one for the accelerometer, one for the gyroscope and one for the orientation data. In the header section of every file there is information about the recording, subject and activity code.

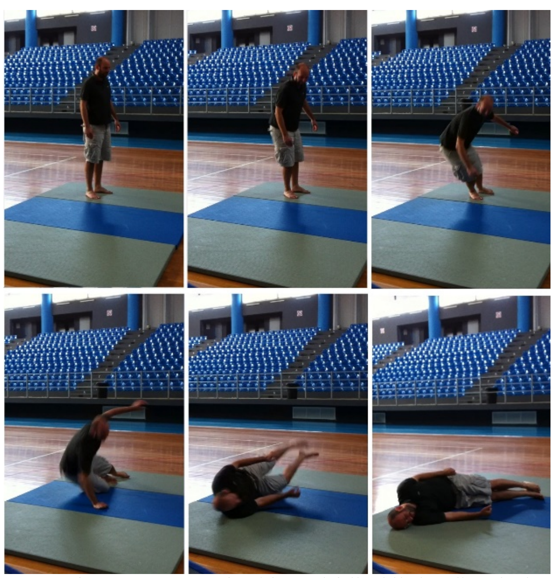

Figure 1. A frame sequence of a sideward fall while bending the legs

At its present state, the MobiFall dataset contains data from 11 volunteers: six males (age: 22-32 years, height: 1.69-1.89 m, weight: 64-102 kg) and five females (age: 22-36 years, height: 1.60-1.72 m, weight: 50-90 kg). Nine participants performed falls and ADLs as shown in Tables I and II, while two performed only the falls. The ADLs were chosen based on their commonness and on their similarity to actual falls, which may produce false positives.

The majority of inertial sensor-based fall detection techniques require the sensor to be rigidly placed on the human body with a specific orientation [5]–[11]. Usually a strap is used for this purpose. In contrast to this and in an attempt to simulate every-day usage of mobile phones, the device was located in a trouser pocket freely chosen by the subject in any random orientation. For the falls, the subjects used the pocket on the opposite side of the falling direction. For the fall simulation a relative hard mattress of 5 cm in thickness (as used in martial arts) was utilized to dampen the fall. Figure 1 shows a frame sequence of sideward fall while bending the legs. All the falls were performed under the strict instructions of the authors to be sure that the subjects perform the right fall in a realistic way.

TABLE I

FALLS RECORDED IN THE MOBIFALL 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 sidewards from standing, bending legs
BSC	Back-sitting-chair	3	10s	Fall backward while trying to sit on a chair

TABLE II

ACTIVITIES OF DAILY LIVING RECORDED IN THE MOBIFALL 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 a car

III. ALGORITHMS UNDER EVALUATION

Fall detection with inertial sensor data has been thoroughly studied with various algorithms [5]–[11]. The algorithms use the accelerometer and/or orientation data to detect separate phases of a fall ordered in time. If all phases in the given sequence are detected, then a fall is confirmed. Depending on each algorithm, this sequence of phases may include: start of fall (SOF), velocity (VEL), impact detection (IMP), change in orientation (ORI) and posture monitoring (POS). Although all related algorithms can be applied on data recorded by smartphone sensors, this article evaluates three algorithms that have been reported in connection to fall detection based on mobile phone or smartphone devices only.

The first algorithm is reported by Sposaro and Tyson [8]. It uses the magnitude M_i of the acceleration vector at each ith sample:

$$M_i = \sqrt{{x_i}^2 + {y_i}^2 + {z_i}^2} \tag{1}$$

where x, y and z are the accelerations in the respective axes. A fall is suspected if a lower ($TH1_a$) and an upper ($TH1_b$) threshold are crossed in a given short duration of time ($W1_a$).

According to the authors, these thresholds are adjusted based on user age, weight, height and level of activity. After this phase, the algorithm checks if the orientation[2] changed ($TH1_c$) with respect to the last orientation, recorded while the phone was resting at $M = 1\ g$ for a long period of time ($W1_b$), before the threshold crossing. Finally, if the changed position remains constant ($TH1_d$) for another given time window ($W1_c$), in order to account for the fact that the person may stand up again, then a fall is detected. This results in the following phase sequence: SOF, IMP, ORI, POS.

Another algorithm applied in mobile phone-based fall detection is presented by Dai et al. [9]. The authors use the acceleration magnitude M_i as defined in (1), as well as the magnitude MV_i of the acceleration in the absolute vertical direction, which is calculated as shown in (2), given the yaw, pitch and roll from the orientation sensor, denoted as α, β and γ respectively.

$$MV_i = x_i \sin\gamma_i + y_i \sin\beta_i - z_i \cos\beta_i \cos\gamma_i \qquad (2)$$

The fall detection algorithm is based on the difference between the maximum and the minimum value of M_i within a given time window ($W2_a$). If it exceeds a certain threshold ($TH2_a$), then the same difference is observed within a second adjacent time window ($W2_b$). If a second threshold ($TH2_b$) is not exceeded this time, then a fall is suspected. The same rule applies to MV_i (with respective parameters $W2_c$, $TH2_c$, $W2_d$ and $TH2_d$) and if both conditions are satisfied, then a fall is being reported. The authors also augmented the method with a magnetic accessory that can be sensed by the mobile phone's magnetic sensor, in order to infer a relative position of e.g. the legs to the phone.

Finally, He et al. [10] report a fall detection method, which incorporates a user activity measure, the "signal magnitude area" SMA_i, shown in (3), with the magnitude M_i as defined in (1) and a tilt angle TA_i (4) between the gravitational vector and the y-axis, which is defined as being in parallel to the human body longitudinal axis.

$$SMA_i = \frac{1}{i}\left(\sum_{u=1}^{i}|x_u| + \sum_{u=1}^{i}|y_u| + \sum_{u=1}^{i}|z_u|\right) \qquad (3)$$

$$TA_i = \sin^{-1}\left(\frac{y_i}{\sqrt{x_i^2 + y_i^2 + z_i^2}}\right) \qquad (4)$$

He et al. [10] use the three metrics in order to detect various states such as lying, sitting etc. Only the fall detection path is considered for the evaluation at hand. At first, a median filter with n = 3 is applied to the acquired data in order to attenuate noise, such as mechanical resonance due to bouncing of the sensor against other objects and external vibration, not produced by the body. In order to detect a fall, the three metrics are sequentially thresholded. At first SMA_i has to be above a certain threshold ($TH3_a$) in order to detect user activity. Subsequently, M_i is checked to be above a second threshold ($TH3_b$) and finally if the tilt angle TA_i also crosses $TH3_c$ then a fall is being reported.

[2] The authors do not clearly state how the orientation is measured. It can be assumed that the direction of the 3D acceleration vector is used for this purpose.

IV. Results

The parameters shown in Table III were used for the evaluation of the three algorithms. Since not all parameters were given by the authors of the respective studies, they were manually specified with the aim to maximize the sensitivity (detection of a fall). For the first algorithm (Sposaro and Tyson [8]) an additional time window of 3 s was used as a delay before checking the change in orientation. This allowed for the signal to settle down after the impact. For the same algorithm $W1_b$ starts immediately with each trial.

TABLE III
Parameters for each algorithm

Method	Parameter	Value
Sposaro and Tyson [8]	$TH1_a$	5.5 m/s^2
	$TH1_b$	16 m/s^2
	$TH1_c$	80°
	$TH1_d$	± 10°
	$W1_a$	0.5 s
	$W1_b$	1 s
	$W1_c$[1]	3 s
Dai et al. [9]	$TH2_{a,c,d}$	17 m/s^2
	$TH2_b$	10 m/s^2
	$W2_{a,c}$	20 samples
	$W2_{b,d}$	200 samples
He et al. [10]	$TH3_a$	12 m/s^2
	$TH3_b$	8 m/s^2
	$TH3_c$	40°

[1]A time window of 3 s for detecting inactivity might be too short for a real application. The fact that each recorded trial ends soon after a fall, limits this value.

The results in terms of sensitivity and specificity are shown in Table IV. It has to be noted that the results are to be interpreted with respect to detecting a fall or not. Although the dataset includes various activities, no classification of the activities or falls has been attempted. Cases, where an algorithm could not utilize its full window lengths because of no sufficient data where discarded from the evaluation.

V. Discussion

This article presents a versatile dataset that will be helpful in testing new algorithms, as well as performing objective comparisons between different algorithms for fall detection and activity recognition, based on inertial-sensor data from a smartphone. This dataset was used in order to evaluate three of the most popular fall detection algorithms applied on mobile phones. It shows that each algorithm has its strengths and weaknesses with respect to different types of falls and

TABLE IV

RESULTS OF THE THREE ALGORITHMS, TESTED WITH THE MOBIFALL DATASET

Type of activity	Code	Sposaro and Tyson [8]		Dai et al. [9]		He et al [10]	
		Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity
Fall	FOL	0.48	-	0.55	-	0.73	-
	FKL	0.73	-	0.36	-	0.33	-
	SDL	0.33	-	0.42	-	0.85	-
	BSC	0.66	-	0.21	-	0.94	-
ADL	STD	-	1.00	-	1.00	-	1.00
	WAL	-	1.00	-	1.00	-	1.00
	JOG	-	-[1]	-	1.00	-	0.44
	JUM	-	1.00	-	1.00	-	0.74
	STU	-	1.00	-	1.00	-	1.00
	STN	-	1.00	-	1.00	-	1.00
	SCH	-	1.00	-	1.00	-	1.00
	CSI	-	1.00	-	0.96	-	0.63
	CSO	-	1.00	-	1.00	-	0.74
	Total:	0.55	1.00	0.39	1.00	0.71	0.84

[1]Due to the nature of the dataset, the final "inactivity" window ($W1_c$) could not be tested, since the recording ends while the subject is still jogging.

ADLs. For example, the algorithm of He et al [10] shows the best overall performance but one of the lowest sensitivities in frontal falls with knee impact (FKL), while the algorithm of Sposaro and Tyson [8] returns the highest sensitivity in FKL falls, which otherwise has a low overall performance. The performance of Dai et al. [9] seems to be rather low. A possible reason for this could be the random phone orientation in the MobiFall dataset since this algorithm is the only one that uses the orientation sensor data. Finally the overall good specificity of the algorithms suggests that the parameters (Table III) might have been set too conservatively.

Considering the dataset, one of its biggest issues is the short duration of remaining data after the end of a certain activity. As already mentioned in the previous sections, some trials, especially falls, were discarded because the "inactivity" period could not be checked. A simple solution to that is to repeatedly pad the last few seconds of each activity at the end.

For the future, the expansion of the dataset with more subjects, as well as an evaluation of fall detection and activity recognition algorithms using all three information sources is planned.

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