

A baseline walking dataset exploiting accelerometer and gyroscope for fall prediction and prevention systems

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ABSTRACT

Fall datasets usually record normal activities and transitions from one posture to another one with falls. Many fall detection datasets based on different sensors are adopted by researchers to improve their systems. Although fall avoidance are dramatically increasing, a public fall prediction and prevention dataset based on an accelerometer and gyroscope is absent. So, this study creates a dataset based on the state-of-the-art techniques in simulating a fall. Different techniques are evaluated to find the best fall simulation. Since accelerometer and gyroscope sensors embedded in a smartphone are recognized to be suited for fall avoidance systems, in this study, they are used to obtain data from users. At the end, some statistical analysis of the observed data are presented and a nonlinear regression model is proposed.

1. INTRODUCTION

Fall prediction and prevention systems usually have some steps in common: firstly, data are collected from sensors, then data are analyzed to compute the appropriate feature set. Finally, the risk of a possible fall is evaluated through some classification algorithms. Fall prediction systems only recognize the probability of a fall occurrence while fall prevention systems provide a solution for preventing it. This study considers the fall prediction step. Fall prediction and prevention studies are able to predict two types of falls: future and real-time falls. Future fall solutions evaluate the user to estimate the user fall risk in the future: if the user fall risk is high, there is a probable future fall which can be prevented through some exercises [1]. Real-time fall solutions predict a fall in real-time and avoid the fall through alerting the user [2, 3, 4, 5] or using an external aid such as walker or robot [6, 7]. This study covers both real-time and future fall prediction.

A fall dataset can facilitate evaluating and comparing different fall avoidance systems in a homogeneous environment. Although algorithms are slightly sensitive to the sampling frequency, the number of training samples in a dataset have an influence on the performance. Actually, a higher number of samples in a dataset makes it more valuable. Several datasets have been made publicly available to evaluate fall detection systems [8, 9, 10, 11, 12]. Although one

of the most promising approaches of fall avoidance system is fall prediction and prevention, to the best of our knowledge, there is not a challenging baseline dataset for predicting and preventing a fall. Firstly, this paper investigates different abnormal walk simulation techniques in order to find the best one. Then, a preliminary test was taken to find the best simulation of an abnormal walk. Then, a dataset of different tests for fall prediction and prevention systems was created and published¹. Since movement sensors are usually used to investigate the extrinsic parameters of a fall, this study exploits the accelerometer and gyroscope to create a dataset.

The remainder of the paper is organized as follows. In Section 2, parameters of a dataset are presented and several fall detection dataset have been reviewed. Sections 3 describes fall factors and experiments of future fall. Then, Section 4 describes real-time evaluation techniques. Section 5 describes the experiments. Section 6 presents primary analysis on the dataset. The proposed dataset is published, and researchers might have access to develop services which are specialized for fall prediction and prevention.

2. RELATED WORK

In order to evaluate a fall avoidance method, preparing a dataset with realistic parameters is essential. Datasets strive to record a scenario which resembles an actual fall incident as closely as possible. To reduce the gap between fall simulation dataset and real-life, several parameters have to be considered.

Realistic setup is one of the most important parameters. Datasets record the real life activity in comparison with fall incident or abnormal walk simulation. They attempt to cover the majority of daily activities such as normal walking, sitting, changing clothes, fall, etc., [13].

Different fall factors require *different sensors*. For example, some datasets use camera but, since visual sensors disturb users privacy, exploiting movement sensors is more preferable [13, 8].

The *number of samples* is a parameter that directly affects the performance of a fall avoidance system. In case of few samples more probably the classification algorithm faces either underfitting or overfitting. An algorithm underfits or overfits when the model is not able to classify properly the case under analysis. In other words, the model is not predictive (underfit) or only works with the presented training data (overfit).

Chronological and physiological parameters such as age, weight, and height are recorded in most of the datasets [9, 10, 11].

Table 1 shows different datasets and their parameters. The following notation is used: Accelerometer (Acc), Gyroscope (Gyr), Daily Activity (DA), Walking (W), Standing (S), Ascending (A) and Descending (D) stairs, Lie down (L), Sit down, Stand up (SS),

Dataset	DA	Sensor	NS	Age	Weight (kg)	Height (cm)
[8]	W, S, A, D, JO, JU	Accl/Gyr	57	20-47	55-120	161-193
[9]	W, S, A, D, JO, JU, SS	Accl/Gyr	11	22-36	50-102	160-189
[10]	W, L, SS	Accl/Gyr	NA	NA	NA	NA
[11]	S, W, L, SS	Accl/Gyr	42	18-30	50-82	162-177

Table 1: Comparison among online fall datasets.

Jumping (JU), and Jogging (JO).

MobiFall is an activity dataset for fall detection based on inertial sensor of a smartphone [8]. The dataset contains signals recorded from the accelerometer and gyroscope sensors. Moreover, a software-based orientation data which is derived from the accelerometer and the geomagnetic sensors are also recorded in the dataset.

Mobiact is a publicly available dataset which includes data from a smartphone with different types of activities and a range of falls [9]. It is based on the MobiFall dataset which was initially created with fall detection in mind.

Another dataset records falls and activities of daily life exploiting mobile phone integrated accelerometer and gyroscope sensor data [10]. It uses five different mobile phones to prepare the dataset. Dataset records the data of five martial artists in parallel.

The last dataset simulates four types of falls (forward, backward, lateral left and right) and daily activity [11]. In this study, forty-two volunteers are participated.

Actually, all presented datasets are used to evaluate fall detection systems, which only notify an acquaintance of the user in case of fall occurrence. The dataset proposed in this study can be used for fall prediction and prevention, which is one of the most promising approaches in fall avoidance systems.

3. FUTURE FALL

The relation between falls and lower muscle strength is studied in many contexts [14, 15, 16]. Decreased muscle strength of lower limbs is an important risk factor for falls in elderly people [17]. Because it reduced capacity to deal with a balance disturbance. There are various standard tests to estimate a future fall risk. In the Sit-To-Stand test (STS), firstly, a user sits in the middle of a chair, and he/she places his/her hands on the opposite shoulder crossed at the wrists. Then, he/she keeps feet flat on the floor. Afterwards, he/she rises to a full standing position and then he/she sits back down again. Eventually, this test counts the number of full stands that is completed in 30 seconds. Since slowing of postural movements can be an indicator of the weak lower limb, a low number of full stands shows a high risk of a fall. The statistical parameters of the postural transition duration in each step of the STS test is an indicator of the fall risk. Since the trunk tilt has an important role in the maintenance of the posture, it can be measured during the sit to stand phase to assess risk of a fall. Acceleration and angular rotation of the chest are used to extract the mentioned measures of the STS test. The first step to calculate the measurements is the signal segmentation according to the postural transition, either standing up or sitting down. Segmentation can be performed based on the repetitive patterns produced by the signals, which vary in line with the movement. An application exploits the mentioned features to automatically count and evaluate the user [18]. The output of the accelerometer and gyroscope sensors of the STS test are recorded in dataset.

The maintenance of posture and the mobility depend on orientation and balance. So, keeping balance is important to avoid a fall during the movement. The One Leg Stand (OLS) test is used in fall

prediction and prevention system to evaluate the user's balance. A user stands with feet together and arms down. Then, he/she raises one leg, either leg, with the foot approximately six inches off the ground, keeping raised foot up for 30 seconds. He/she can sway side-to-side or back-and-forth while maintaining the one-leg stand position. If a user puts his/her foot down some times during the 30-second period, then he/she will fail the test. The OLS test measures the Center Of Mass (COM) displacement and speed of COM displacement. Displacement can be computed by the acceleration of the COM to evaluate balance.

4. REAL-TIME FALL

The best way to predict and prevent a fall in real-time is identifying abnormal and normal walks. A fall may happen due to the weakness, balance deficit, gait deficit, visual deficit and mobility limitation. The most frequently method which can lead to a fall are:

- Walking with straightened knee [2, 4, 3]
- Walking with leg length discrepancy [2, 4, 3]
- Walking on rough surface [19]
- Walking through obstacles [20].

In order to evaluate the different methods, accuracy and ROC area criteria are used as explained in the following. In all the presented formulas, P and N represent the total number of positive and negative instances while True Positive (TP) and True Negative (TN) are defined as correct identification of a true classification of positive and negative instance, respectively. False Positive (FP) and False Negative (FN) present misidentifying a positive and negative instances, respectively.

- Accuracy
The accuracy of an algorithm demonstrates the number of samples correctly classified:

$$Accuracy = \frac{\#TP + \#TN}{\#P + \#N}. \quad (1)$$

- Specificity
The specificity or True Negative Rate (TNR) measures the rate of negative instances that are correctly identified as negative. Moreover, generality is computed as 1 - specificity.

$$Specificity = \frac{\#TN}{\#TN + \#FP}. \quad (2)$$

- Sensitivity
The sensitivity or True Positive Rate (TPR) measures the rate of positive instances that are correctly identified as positive:

$$Sensitivity = \frac{\#TP}{\#TP + \#FN}. \quad (3)$$

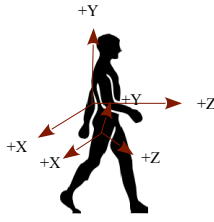


Figure 1: Sensors axes and positions.

The ROC curve is a graphical plot that illustrates the performance of a classifier [22]. The curve is drawn by sensitivity and generality. The generality and sensitivity are plotted on the x and y axes of the ROC plot, respectively. The best classifier is located at the top left corner of the ROC graph, which represents 100% sensitivity and 100% specificity. Moreover, A higher ROC area i.e, the area under the ROC curve indicates a better accuracy.

Since people with increased fall risk tend to walk slower, the actual fall risk can be quantified according to the gait speed [21]. In the act of motion, the acceleration varies according due to the body movements, it can be an indicator of the pre-fall state [20]. Moreover, when a user tilts in a direction more than normal, it shows an abnormal posture which can be led to a fall. So, the user tilt can be a factor to assess the risk of fall. User tilt is estimated with the combination of a gyroscope and accelerometer [3, 4, 2].

5. EXPERIMENT

There are many studies proving that sensors (accelerometer and gyroscope) present in a smartphone are precise enough to be used in fall avoidance systems [23, 21, 18]. Therefore, a smartphone is adopted in the experiments. Most of the developed applications exploit two main approaches to obtain and analyze the sensors signals: low-level programming and general-purpose middleware [24]. In this study, MATLAB R2015b is used as a middleware to obtain and analyze the data. Before creating the main dataset an experiment is done to find the best method in simulating an abnormal walk. Data is collected through an Iphone 4S which is equipped with the STMicro STM33DH 3-axis accelerometer and the STIMicro AGDI 3-axis gyroscope.

WEKA tool version 3.6.13, a powerful data mining toolkit, is used to classify the obtained data. Decision Tree (DT) and Support Vector Machine (SVM), two commonly used classification algorithm in fall prediction and prevention system, are used in WEKA to classify the input. In order to see the impact of the position of the sensor on the performance, the smartphone is used once on back trunk and once on the pocket of the participants. The directions of x , y , and z -axis of the accelerometer and yaw, pitch and roll of the gyroscope, and the body of the participant in both positions are illustrated in Fig. 1. In order to eliminate the initial condition, the participants walk from a standing start.

Table 2 shows the result of the experiment with different permutations of normal and abnormal walks. N-A is the abbreviation of the Normal versus Abnormal (with different kind of abnormal technique), N-O is the abbreviation of Normal versus walking through Obstacles, N-S means Normal versus walking with Straightened knee and N-L means Normal versus walking with Leg length discrepancy. As can be seen, in both position, Normal waking versus walking through obstacles with DT classification has the highest ROC area and accuracy. So, in the main experiments of the dataset, the participants walk through obstacles to simulate an abnormal walk. Moreover, as the result shows, back position is more appro-

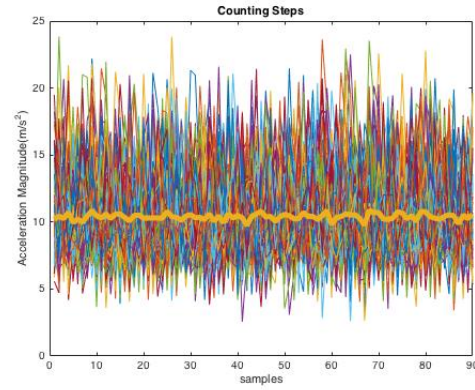


Figure 2: Normal walk.

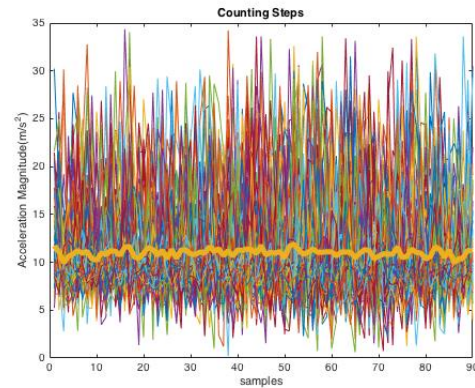


Figure 3: Abnormal walk.

priate for the sensor location in the body.

The main experiments are designed according to the tests for future fall (STS and OLS) and real-time fall (normal and abnormal walks). 25 participants with age 18-35, weight 80 ± 10 kg and height 160-185 cm are involved in the experiments. In order to do the STS and OLS tests, a smartphone is located on the chest of the participants to record the acceleration and gyroscope data. Since the experiments showed the back trunk position has higher accuracy in fall prediction and prevention system, a smartphone is located on the lower back trunk of the participants in real-time fall test. Participants are asked to walk normally, and also walk through the obstacles for 10 seconds. Finally, the collected data, three axes of accelerometer and gyroscope of each user, are stored in the dataset.

6. DATA ANALYSIS

To analyze a dataset a function model should be defined for data behaviour. Finding a suitable model to present the data is called curve fitting. The model can be linear, polynomial, nonlinear, etc.. Firstly, an average signal of all abnormal walks is computed. Then, a simple nonlinear regression model is developed according to the average signal. Fig. 2 and 3 show the normal and abnormal acceleration signal magnitude of the users. The average signals are plotted with thicker line. The average signal is a sinusoidal function so, firstly, a model function is defined as follows:

$$F(x, [a, b]) = a \sin(x) + \cos(x) + b \quad (4)$$

	Back				Pocket			
	N-A	N-O	N-S	N-L	N-A	N-O	N-S	N-L
ROC Area	0.905	0.953	0.925	0.825	0.850	0.930	0.735	0.900
Accuracy	85%	97.5%	92.5%	82.5%	88.7%	95%	77.5%	92.5%
Classification	DT	DT	SVM	SVM	DT	DT	DT	DT

Table 2: Result of the experiment on different abnormal walks.

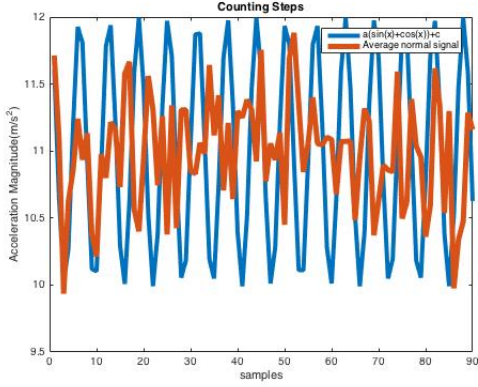


Figure 4: Comparison between normal walks and adopted model.

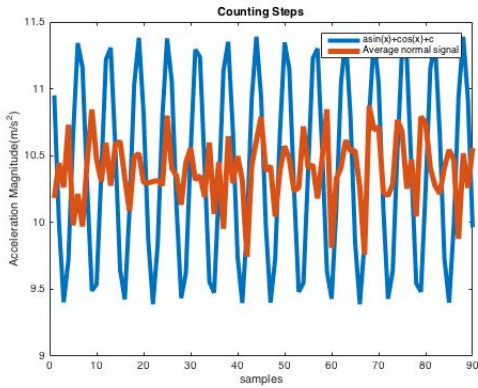


Figure 5: Comparison between abnormal walks and adopted model.

The important point is finding the best coefficients of the model function to be more representative as the dataset behaviour. There are different techniques which can solve the problem but in this study least-squares is exploited. Least-square strives to minimize the sum of squared difference between a value and the fitted value provided by a model. In other words, the main problem is solving the following optimization problem:

$$S = \min \sum_{i=1}^n (F(x, [a, b]) - \bar{y}_i)^2 \quad (5)$$

where n presents number of data, and \bar{y} is the given observed data. The goal is to find the best $F(x, [a, b])$ to reduce the error. Fig. 4 and 5 show the function model in comparison with normal and abnormal walk. This function model is appropriate for an abnor-

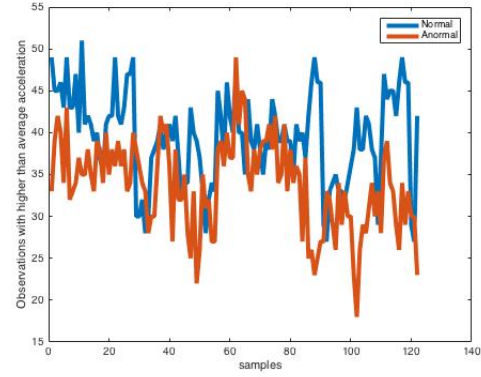


Figure 6: Average signal of abnormal and normal walks.

mal walk. The coefficients in the presented functions are [0.0259, 10.3892] for abnormal and [0.0926, 10.9925] for normal walk. Another statistical analysis on the dataset is measuring the number of observations with value higher than average acceleration. As Fig. 6 shows, the number of observations in normal walk is much higher than in abnormal walk. Observations support the idea that high acceleration is not a feature of abnormal walk, since walking with lower speed may increase the risk of fall [21].

7. CONCLUSION

Evaluating a fall avoidance system requires a coherent dataset with realistic parameters. Actually, most of the existing dataset are used in fall detection systems. Since fall prediction and prevention systems are one of the most promising approaches to avoid a fall, this study evaluates different parameters to create a dataset based on the state-of-the-art fall prediction and prevention studies. 25 users participated in four different tests. One-Leg Stand and Sit-to-Stand tests were used to evaluate the risk of a fall in the future. Moreover, walking through obstacles has been proposed to simulate an abnormal walk and to evaluate the real-time fall risk. Furthermore, acceleration and gyroscope embedded in a smartphone were used to collect the data. All the recorded data are published to facilitate the access to the dataset.

8. ACKNOWLEDGMENT

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