Mobile phone-based fall detectors: ready for real-world scenarios?

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Abstract. Falls are a major health problem among the elderly. The consequences of a fall can be minimized by an early detection. In this sense, there is an emerging trend towards the development of agent systems based on mobile phones for fall detection. But when a mobile phone-based fall detector is used in a real-world scenario, the specific features of the phone can affect the performance of the system. This study aims to clarify the impact of two features: the accelerometer sampling frequency and the way the mobile phone is carried. In this experimental study, 5 participants have simulated different falls and activities of daily living. Using these data, the study shows that the sampling frequency affects the performance of the detection. In the same way, when a fall detector intended to be attached at the body is carried in an external accessory, the performance of the system decreases.

Keywords: Fall detection, mobile phones, real-world scenarios

1 Introduction

Falls in the elderly are a common cause of mortality, morbidity, reduced functioning, and premature nursing home admissions [1]. Among many other factors, the severity of a fall depends on the amount of time the elder remains lying on the floor after falling [2]. Therefore, a quick detection and assistance is needed.

The evolution of mobile phones to integrated systems with computing power, communication resources and embedded sensors opens the door to new innovative research in fields such as ambient intelligence [3]. Modern mobile phones have the potential to act as intelligent agents [4]. In particular, the design of agent systems based on mobile phones for automatic fall detection is an emerging research area. The first system appeared in 2009: Sposaro et al. [5] presented a detector for the Android operating system that is available for download from the Google Play store. Since then, the number of mobile phone-based detectors has increased dramatically, each time with more features and enhanced algorithms. The system of Dai et al. [6] can be considered the first relevant work in this field. Following this trend, Lee et al. [7] compared the motion signals acquired by the built-in accelerometer of the phone to those recorded by an independent body-mounted accelerometer, showing better results in the latter. Albert et al. [8] propose a system not only to detect a fall but also to automatically classify the type. In this sense, Martin et al. [9][10] describe a multi-agent system capable of detecting falls through the sensors embedded in a mobile phone. Other authors have also worked in this direction [11,12].

In all of these studies, the signals from the built-in accelerometer of the phones are used for fall detection. However, it should be noted that there is high variability within mobile phone models. When mobile phone-based fall detectors are used in real-world scenarios, there is a risk that the performance is affected by the specific device features. This risk is greater for sensor-dependent applications such as fall detectors. In this experimental study, we aim not only to identify some of these features but also to quantify them.

The rest of this paper is structured as follows: Section 2 examines the contributions of this work, section 3 describes the methodology used in the experiments, section 4 introduces the detection algorithm, section 5 explains the influence of the accelerometer sampling frequency, section 6 explores the idea of wearing the phones in handbags, and section 7 draws some initial conclusions and outlines areas that can be researched further.

2 Contributions

This study aims to clarify the impact on mobile phone-based fall detection of some factors that can compromise its performance in a real-world scenario. We put the focus on two:

- Accelerometer sampling frequency: The built-in accelerometer of the phones samples at different frequencies depending on the model in question. This study examines the degradation of the detection as the sampling frequency decreases. This is an important aspect when selecting the suitable smart phone for a real-world application.
- The way the mobile phone is carried: All previous research placed the mobile phone in a standardized position of the subject's body (waist, thigh, trunk, back, wrist, etc.). However, users may wish to carry the mobile phones in external accessories like handbags. To the best of our knowledge, this is the first study that examines the effect on fall detection of wearing the phone externally.

3 Subjects and methods

Mobile phone-based fall detectors use the acceleration signals from the built-in accelerometers of the phones. Then, these signals can be classified as falls or activities of daily living (ADL). Therefore, to measure the performance of a detector, it is necessary to acquire acceleration data from both falls and ADL.

Since this is an experimental study, these data have been collected from 5 young volunteers (mean age 27.6, SD 8.5, 3 males, 2 females). All participants performed 4 different simulated falls: forward, backward, lateral left and lateral right. Fall types were selected to fit into the broader categories of typical fall events of older people [13,14]. They were completed on a soft mattress. The methodology of the simulations was the following: firstly, researchers gave oral information on the experiment including the preventive measures that should be adopted to avoid any risk, secondly a written consent was obtained from each participant; thirdly researches performed a practical demonstration of each fall type, fourthly subjects were required to be as natural as possible, using, if desired, common strategies to minimize the fall impact such as flexing their knees or putting their hands. Each fall type was repeated 4 times.

Subjects were also requested to simulate the most common types of ADL (table 1). Each ADL was repeated 3 times.

During the experiments, participants wore a mobile phone in both their pockets (left and right) and in two handbags. Thus a total of 64 fall records and 180 ADL records were collected from each participant. Half of them were acquired from the pockets and the other half from the handbags. After each simulation, the acceleration data were downloaded wirelessly from the mobile phones to a PC. The sampling frequency was 50 Hz. Each record contained a 6 second width time window around the highest peak of the acceleration magnitude.

Table 1. List of common ADL performed by the 5 volunteers

Most common types of Activities of Daily Living	
Sitting down on a soft chair	Getting up from a soft chair
Sitting down on a hard chair	Taking the lift (two floors, up)
Picking up something from the floor	Squatting and tying shoelaces
Lying down on a bed	Getting out of bed
Jogging	Walking
Walking downstairs	Walking upstairs
Getting into the car	Getting out of the car
Jump to pick something	

4 Fall detection algorithm

A low-complexity algorithm has been selected for fall detection. This algorithm has been tested with the data from the falls and ADL (section 3). It considers both an upper and a lower threshold. If the maximum value of the acceleration within a checking time window of 1 second around the peak, is higher than the upper threshold, the pattern recognition is triggered to check the minimum value. If this value is less than the lower threshold, a fall detection is reported [5].

This algorithm has been used to measure the impact on its performance of the two mentioned factors: the acceleration sampling frequency (section 5) and the way users carry the phones (section 6).

5 Frequency-dependent detection

The present section quantifies the effect on performance of the reduction of the accelerometer sampling frequency. The fall and ADL records from the pockets, initially sampled at 50 Hz, have been resampled to lower frequencies (50/4 Hz, 50/8 Hz, 50/16 Hz, 50/25 Hz). A total of 5 datasets have been obtained, one set for each frequency.

The performance of the detector is measured using ROC curve. A ROC curve plots the true-positive rate of detection, TPR, against the corresponding false-positive rate of error, FPR [15]. The formulae to calculate both rates are the following:

$$TPR = \frac{TP}{TP+FN} \tag{1}$$

$$FPR = \frac{FP}{FP+TN} \tag{2}$$

where TP is the number of falls labelled as falls, FN is the number of falls labelled as ADL, FP is the number of ADL labelled as falls and TN is the number of ADL labelled as ADL.

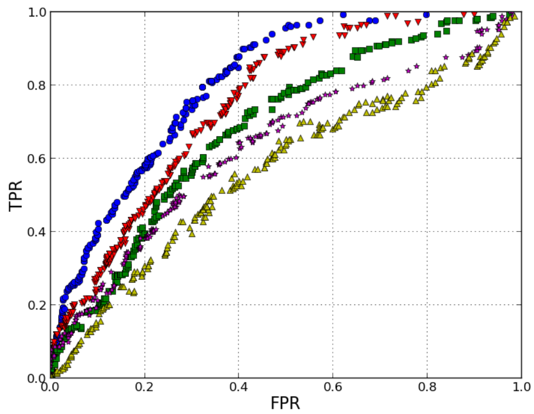

Fig. 1. Representation of ROC curves corresponding to the threshold based algorithm using different data sets: 50 Hz (blue circles), 50/4 Hz (red triangles down), 50/8 Hz (green squares), 50/16 Hz (magenta stars), 50/25 Hz (yellow triangles up)

A ROC curve of the algorithm of section 4 has been obtained for each one of the 5 datasets. Each set has been randomly divided in two equal parts: one for training and the other for testing. For each one of the 5 datasets, we have selected a set of threshold pairs from its training set in the following way. One of the thresholds is kept fixed while varying the other. In this way a ROC curve can be plotted. For several values of the fixed threshold, several ROC curves are obtained, whose envelope is taken as the final ROC. In other words, for a given FPR, the thresholds are adjusted to get the maximum TPR. Using these optimal thresholds, the ROC curve of each dataset (50, 50/4, 50/8, 50/16, 50/25) has been obtained with its testing set. The 5 curves are represented in figure 1.

Figure 1 clearly illustrates that the higher the sampling frequency the better the detection. Table 2 shows the area under the ROC curve for each dataset.

Table 2. Area under the ROC curve for each sampling frequency

	50 Hz	50/4 Hz	50/8 Hz	50/16 Hz	50/25 Hz
Area under the ROC curve	0.8363	0.7908	0.7129	0.6590	0.6086

According to the results of table 2, we can quantify the degradation in performance that occurs as the sampling frequency is varied. When the sampling frequency diminishes to 50/25 Hz, the area is decreased by 27% compared to the performance at 50 Hz. This decrease is higher when the frequency is less than 12.5 Hz.

6 External handbag

Subjects may wish to carry the mobile phone not only in some parts of their bodies (waist, thigh, back, etc) [16-17], but also in external handbags. This study aims to quantify the loss in performance when a detector initially intended to be worn on the body is placed in a handbag.

For this purpose, we have used the data from both pockets and handbags, obtained as described in section 3, and the low-complexity algorithm introduced in section 4. This algorithm has been trained with half of the data from the pockets (thigh), simulating a body-worn detector. Then, it has been tested using either the other half of the data from the pockets or the data from the handbags. Figure 2 illustrates the ROC curve for each set of data.

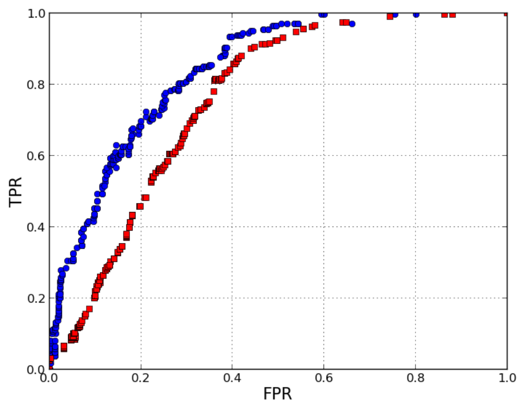

Fig. 2. ROC curves of the algorithm trained with the data from the pockets and tested with two different datasets: the rest of the data from the pockets (blue circles), the data from the handbags (red squares)

The performance of the algorithm is clearly worse when tested on the handbag data set compared to the performance on the pocket data set, the kind of data for which the detector was originally trained. Table 3 quantifies the difference by measuring the area under the ROC curves. It reaches 10%.

Table 3. Area under the ROC curve for both, the pocket-tested and the handbag-tested system

	Detector tested with data from the pockets	**Detector tested with data from the handbags**
Area under the ROC curve	0.8363	0.7559

7 Discussion and conclusions

This study has proven that the acceleration sampling frequency influences the performance of a fall detector. The level of dependence is in part conditioned by the fall detection algorithm. As an example, a low-complexity algorithm has been used in this study. Other algorithms could have strengthened or weakened this dependence. This is not a minor problem in mobile phone-based fall detection. This implies that the same application can behave differently depending on the particular phone model in which it is run. Researches in this field must be very cautious when selecting the sampling frequency. Also, the features of the built-in accelerometers must be examined to ensure they can sample at the proper frequency.

Unlike dedicated fall detectors, mobile phone-based systems not only detect falls but also perform many other tasks, for example, making calls, sending SMS, running other applications, etc. In a real-world scenario, subjects may wish to use these functions as well as to carry the mobile phones in different places. In this way, handbags are proper accessories to keep these devices. This study investigates for the first time the effect of carrying the mobile phones in them. Results show that the performance of the system decreases when a traditional fall detector intended to be worn on the thigh is carried in a handbag. Therefore, studies in this field should consider using the phones as true "phones". Otherwise, their performance may decrease in a real-world scenario, leading probably to their rejection. To be accepted by their potential users, fall detectors should meet their needs and this inevitably includes usability aspects.

This study has still some limitations. For the analysis, we have considered a simple threshold-based fall detection algorithm. Further research should incoporate more sophisticated algorithms based on machine learning and investigate their performance when faced to real-world conditions.

In conclusion, future studies in mobile phone-based fall detection should also consider the specific features of phones since they could compromise the performance in a real-world scenario. In this study, we have shown the impact of two factors: the sampling frequency and the way the device is carried.

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