A Smartphone Based Fall Detector with Online Location Support

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ABSTRACT

Falls are identified as a major health risk not only for the elderly but also for people with neurodegenerative diseases, such as epilepsy, and are considered as a major obstacle to independent living. Fast detection of falls would not only decrease the health risks by enabling quick medical response; but also make independent living a safe option for the elderly. In this paper, we propose a fall detector that uses the accelerometers available in smartphones and incorporates different algorithms for robust fall detection such as thresholding and wavelet transforms. We implemented our fall detector on a smart phone running the Android 2 operating system. We performed an extensive set of experiments for evaluating the performance of the implemented fall detector. To the best of our knowledge, although using smartphones for fall detection have been recently studied, evaluating the performance of robust algorithms, rather than thresholding, has not been explored before. Our experimental results show that compared to a simple thresholding algorithm, using wavelet transforms achieve better true positive performance while decreasing the rate of false positives drastically. Besides the fall detection capability, our implementation also provides location information using Google Maps about the person experienced the fall, using the available GPS interface on the smartphone and a warning about the fall and the location information are transmitted to the users, such as the caregivers, via SMS, email and Twitter messages.

1. INTRODUCTION

Falls are risky, especially for the elderly people living independently and people with neurodegenerative diseases. Studies show that, more than one third of the adult population over the age of 65 falls at least once a year in the USA [1]. And up to 30% of these falls result in medium to severe injuries that can lead to the death of the elderly [2]. Besides elderly, patients with neuromotor dysfunction attacks, such as the epilepsy patients, suffer from falls during a seizure due to loss of consciousness. We currently work on a research project together with Istanbul Capa Medical School on monitoring epilepsy patients outdoors and aim to detect seizures that result with a fall event. Quick medical response is desired in fall situations, but the injuries may cause the person to be immobile to the extent that they could not even be able to reach a phone to call for help. One proposed solution to this problem is to use emergency buttons installed throughout the house or on the elderly people themselves so that they can press them in case of a fall related injury. However, if the person ends up in an unconscious state, he/she may not be able to press the button to call for help. Hence, it is important to develop an "automatic fall detection system" that requires no human intervention.

World Health Organization (WHO) defines a fall as an event which results in a person coming to rest inadvertently on the ground or floor or other lower level [3]. Since these events involve motion and change of pose, observing certain characteristics of these may provide us with the necessary information to detect falls. Many types of sensors can be used to observe motion and pose of the elderly and determine if a fall has occurred or not. Current work on automatic fall detection methods can be classified into three main categories in terms of the sensors they use: video-based methods, acoustics-based methods and wearable sensor-based methods [4]. Video-based methods use images provided by cameras installed in the environment and they analyze changes in designated features to detect falls (e.g. orientation and aspect ratio of a bounding ellipse [5]). Acoustics-based methods try to detect falls by detecting vibrations caused by the impact to the ground. For instance, in [6] Zigel et al. propose a method that uses a vibration sensor and a microphone to detect vibrations and noise generated by the impact. Wearable sensor-based methods involve a sensor worn on the subject. For automatic fall detection, methods based on wearable sensors are more attractive since video based methods raise privacy concerns and acoustics based methods are very susceptible to ambient noise. Moreover, video-based and acoustic-based methods require wiring and pre-installation, while wearable sensor based methods will be able to operate as long as the person wears the sensors, even when the user is outdoors.

With the improvements in mobile technology, the cost of smartphones decreased reasonably while their computational capabilities increased. With the decline in the prices, many people currently use smartphones. Many of these smartphones have integrated accelerometers that are used mainly for user interaction and orientation detection. In most of these platforms, it is also possible to access acceleration signals provided by the integrated accelerometer. Such platforms are ideal for developing an application that can automatically detect falls and provide a warning mechanism.

In this paper, we propose a fall detection application which is developed on a Nexus One smartphone running the Android 2.0 operating system. The proposed application uses discrete wavelet transform as a feature extraction method and uses the differences of falls and normal actions in the frequency domain to distinguish them from each other. We evaluate the performance of our fall detection application using 5 different subjects and with a scenario which includes actions that cannot be easily distinguished from a fall, such as jumping or lying on a bed. The following are some of the key contributions and findings of our work:

- To the best of our knowledge, although using smartphones for fall detection have been recently studied [7, 8], evaluating the performance of robust algorithms, rather than thresholding, has not been explored before. We show that, compared to a simple thresholding algorithm, using wavelet transforms achieve better true positive performance while decreasing the rate of false positives drastically.
- We conducted an extensive set of experiments on 5 different users (with different age, height and gender) carrying a smartphone and showed that wavelet transforms achieve 37% better true positive performance.
- Besides automatic fall detection, our application provides location information of the subject using the integrated GPS module and also sends a warning about the fall and the location information to interested users, such as the caregivers, the doctor or ambulance service providers, via SMS, email and Twitter messages.

The rest of the paper is organized as follows: In Section 2, we give a brief overview of the related work. In Section 3, we present details of the proposed application. In Section 4, we explain the experimental setup and present our results. Section 5 draws the conclusions.

2. RELATED WORK

There have been various studies on fall detection using wearable sensors. In [12], Nyan, et al. propose a pre-impact fall detector which uses two sets of sensors, one with an accelerometer and a gyroscope and the other with only an accelerometer. They use the angular data calculated using the sensors to detect falls before the impact to the ground occurs. Although the system yields good lead-time, it is vulnerable to normal activities that cause angular movement on their sensors. Moreover, the need to use two sets of sensors may be uncomfortable for the elderly.

In [13], Chen, et al. propose a fall detector based on a wearable accelerometer. In this work, they assume that a large acceleration impulse will occur upon impact to the ground. When such an impulse is observed on the acceleration signal, they then calculate the orientation of the sensor before and after the impact, and check if there has been a change in the orientation. If both conditions are satisfied, they detect a fall.

Another similar approach described in [11], focuses on acceleration change characteristics during the process of a human body falling. They assume that there are four critical characteristics of a falling event: the *initial status* which is still a non-fall state, *weightlessness* at the start of a fall, *impact* when the human body makes contact with the ground, *motionlessness* since human body cannot rise immediately.

A major criticism to wearable sensor-based approaches is that, the user may forget to charge or wear the sensor, therefore leaving the system in a non-functioning state. With the integration of accelerometers on smartphones, it has become possible to develop fall detector applications that can run on the smartphones. Since people are more likely to carry their phones with themselves, rather than an additional sensor, smartphones with integrated accelerometers can easily be used for pervasive fall detection.

Similar to our work, iFall [7] is an Android application designed for fall detection. However it only uses a basic thresholding method for identifying falls. The algorithm uses two thresholds on the root-sum-of-squares of the accelerometer's three axes. The lower threshold, which is set to 1g, is for identifying the free fall effect and the second threshold, which is set to 3g, is used for capturing the spike occurring when the free fall ends with an impact. This method generates a large number of false alarms; therefore some extra processing is needed. The authors suggest using the orientation of the phone, before and after the impact, in order to validate the fall decisions. Nonetheless, this method still suffers from the similarities in the acceleration signals generated by different actions. PerFallID [8] is another application developed for Android mobile phones. Again, it uses the thresholding mechanism, yet its threshold is adjusted using data collected from real users. However, PerFallID does not have localization support as well as it is lacking warning mechanisms. Therefore in case of a fall, it is unable to inform caregivers or the medical personnel about the fall event and its whereabouts.

Our proposed application is designed to directly address some of these issues and yield better detection result. It uses wavelet decomposition as a feature extraction method, in order to better distinguish falls from non-fall actions. In case of a detected fall, our application can inform predefined caregivers about the event and the location of the event. With the addition of the panic button in the application, the application enables the user to inform caregivers about events that cannot be detected by the application.

3. FALL DETECTOR

Gathering accelerometer signals with different scenarios and with varying system parameters – (including different people doing activities that could potentially be confused with falling, i.e. walking, jumping sitting, lying on the bed) and analyzing these activities in the frequency domain, we realized that the falling activity has very distinctive frequency components that could be useful to distinguish it from the rest of the activities. However, for accelerometer signals whose frequency content varies with time, a simple 1-D Fourier frequency transformation is not sufficient. Although Fourier transform gives what frequency components exist in the signal, it cannot locate the frequencies in the time domain. Short Time Fourier Transform (STFT) is a variation of Fourier Transform, which tries to overcome this problem. In STFT, the signal is divided into windows which can be non-overlapping or sliding and the Fourier transform is applied to these windows. Therefore STFT can localize the frequency components to these windows, but its time-frequency resolution is limited.

Another alternative to Fourier transform, which also give temporal localization for frequency components is the wavelet transformation which has become popular in the last two decades in signal processing due to its ability to give better time-frequency resolution and existence of fast transform algorithms.

3.1 Fall Detection Algorithm

Discrete wavelet transform (DWT) basically yields a multi-scale representation of a discrete signal, formed by iteratively applying the analysis filters to the original signal. The transformation begins with a selection of a mother wavelet, Ψ, from which the analysis filters, *h* and *g*, are formed. Then the wavelet coefficients of a discrete signal *x* at the first scale are calculated as:

$$a_1[n] = \sum_{k=-\infty}^{\infty} x[k]h[n-k] = (x * h)[n]$$

$$d_1[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k] = (x * g)[n]$$

where *a* represents the approximation coefficients and *d* represents the detail coefficients. Due to the nature of the analysis filters *h* and *g*, approximation and detail coefficients contain half of the frequency components of the original signal and therefore can be subsampled by two. After the subsampling, approximation coefficients can be used to calculate the coefficients for the next scale, effectively forming a filter bank:

$$a_{s+1}[n] = \sum_{k=-\infty}^{\infty} \bar{a}_s[k]h[n-k] = (\bar{a}_s * h)[n]$$

$$d_{s+1}[n] = \sum_{k=-\infty}^{\infty} \bar{a}_s[k]g[n-k] = (\bar{a}_s * g)[n]$$

where $\bar{a}_s$ represents the subsampled approximation coefficients of scale s. The process of the wavelet transformation decomposes a signal by concentrating the signal energy in a relatively small number of coefficients [9]. It is this property of reducing a signal to a comparatively small number of components that makes wavelet-based techniques potentially powerful for signal processing algorithms. A more detailed explanation of DWT can be found in [10].

In our application, we use DWT as a feature extraction method. DWT is applied to the discrete acceleration signal provided by the integrated accelerometer, *X*, in order to extract the detail coefficients of *X* at the first scale. Then a predefined threshold, *t*, is applied to the detail coefficients. If the value of the coefficients is above the threshold, a fall is detected. Formally:

$$F(n) = \begin{cases} 1 \; if \; \overline{d_1}\left(\left\lfloor \frac{n}{2} \right\rfloor\right) > t \\ 0 \; if \; \overline{d_1}\left(\left\lfloor \frac{n}{2} \right\rfloor\right) < t \end{cases}$$

where *F(n)*, is the fall decision for the *X[n]*, and $\overline{d_1}$ is the subsampled detail coefficients at the first scale, and $\lfloor \quad \rfloor$ is the floor function.

3.2 Implementation

The fall detection application is designed for special use of the users who are susceptible to sudden falls like epilepsy patients, the elderly as well as slightly cognitively impaired people, such as the Alzheimer patients. It incorporates the sensing capabilities of the smartphones and sophisticated signal processing techniques to produce a handy application that most people may benefit. The overview of the application is depicted in Figure 1. It basically detects the unexpected fall situations and alerts the caregivers and alternatively the followers of the user in a social network, namely Twitter. The application is also location aware. The emergency messages contain the location information shown on the map. It also has a panic button for general use and an emergency alert cancellation mechanism is available for preventing false alarms.

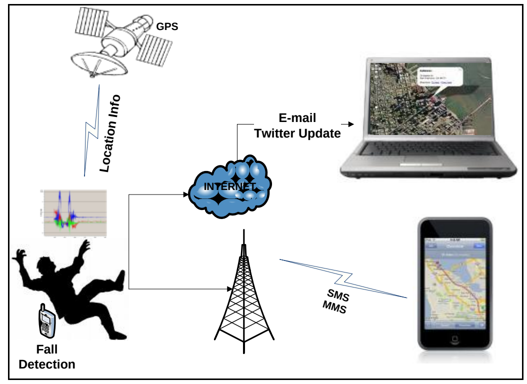

Figure 1. The overview of Fall Detection Application

We implemented our Fall Detector application on the Android 2.0 Platform. Android is an open source mobile operating system and it has a powerful Software Development Kit (SDK) based on Java Framework. It has also SQLite database management system. The core of the application is composed of five parts:

- *Fall Service*: Services are background processes. They are designed to run for long durations and they do not interrupt any other application or process that the mobile phone runs. The "Fall Service" is the most important part of the application, since it allows the fall detection mechanism to run at the background while the user is able to perform other tasks with the phone.
- *Fall Activity*: Activities are the components with which the users directly interact. Activities can be created, started, resumed, paused, stopped, and destroyed. An activity is associated with a user interface, called layout, in the Android application. "Fall Activity" is the visible part of the application and it runs on foreground as depicted in Figure 2.
- *Content Provider*: Content providers are one of the main components of Android applications. All applications can access the data by using a single Content Resolver interface. Content providers not only provide data to the applications but also enable them to share the data among themselves. We use the content provider to access the mobile phone's contact database. In this way, we can select the contacts that will be called when an emergency occurs.
- *Sensor Manager*: "Sensor Manager" allows the application to access the sensors of the mobile phone. We use Sensor Manager to read the acceleration values of the mobile phone's integrated three-axis accelerometer.
- *Location Manager*: By using the "Location Manager", the application is able to obtain the periodic updates for the mobile phone's geographical location retrieved by GPS. In this way, the location of the user is identified when an emergency situation takes place.

Figure 2. Application Screen Shots

One of the most important features of the application is its simple and efficient interface. There are four large buttons on the main screen. “Start” button starts the fall detection service to run in the background. “Stop” button stops the service. The tick and the cross icons represent the state of the service as being active or inactive. The “Panic Button” at the bottom is used for sending emergency alerts to the caregivers manually. This can be used for when a fall situation is not detected by the service or it may also indicate some other kind of emergency condition, such as a cognitively impaired person getting lost. The location of the user will be delivered to his/her caregivers. The “Settings” button leads the user to the settings screen where he/she can select the contact details of the caregivers and also the user’s account information. There are three types of alerting mechanisms.

1. The user can select the caregivers to be sent SMS message which includes the coordinates of the event. The contact information is taken from the database of the mobile phone.
2. The user can select the caregivers to be sent an e-mail which includes the Google Map link of the fall event. The information is taken from the database of the mobile phone.
3. The user may also select the Twitter update option with his/her own account. In this way, he/she is able to reach more people and one of the closest followers may offer help. Figure 3 shows an example Twitter update.

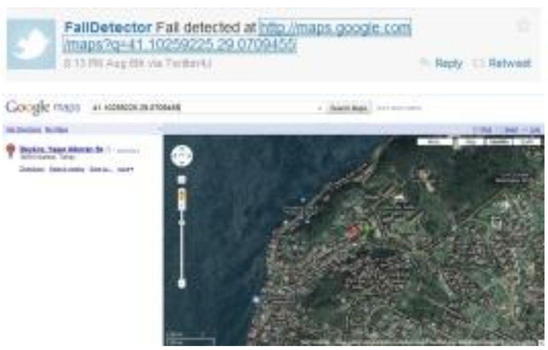

Figure 3. The Twitter update after a fall, and the Google maps page reached via the link posted in Twitter

When a fall is detected, a notification is displayed together with a sound alert (Figure 4). The users are able to cancel the request within a specific time duration which can be configured. We selected this timeout duration as 20 seconds which is a long-enough period for the people who use the phone relatively slower. If the user did not experience a real fall, he/she can simply cancel the request within the timeout duration. If a real fall has occurred, then the caregivers will be immediately alerted by SMS messages and e-mails together with the social network status update message. This property also helps to solve the problem of differentiating phone falling and user falling.

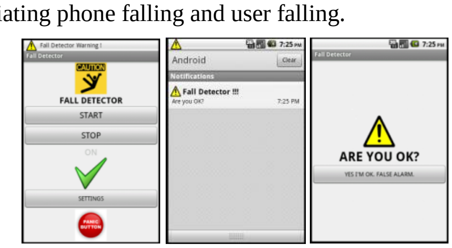

Figure 4. False Alarm Cancellation Mechanism

4. EXPERIMENTAL EVALUATION

For our experiments, we used a Nexus One phone with Android 2.0 operating system installed on it. In the tests, we asked the subjects to repeat a predefined motion scenario, which includes normal actions such as walking, sitting down and lying, and actions that may be challenging to distinguish from falls such as jumping and sitting down quickly.

We conducted the tests on 5 volunteer healthy subjects; each subject repeated the scenario 20 times, yielding a total of 100 sequences which included falls. This data is then processed offline in order to evaluate the performance of the fall detection algorithm using different mother wavelets. Also in order to better evaluate the performance of our proposed method, we implemented the method proposed in [7] for comparisons

Figure 5. Images of a subject while he is falling, with the phone in his pocket

The performance metrics we use to evaluate the methods are precision and recall. These are defined as:

$$Recall = \frac{TP}{TP + FN} * 100$$

$$Precision = \frac{TP}{TP + FP} * 100$$

where TP is the number of true positives, i.e. falls that are correctly detected by the application, FN is the number of false negatives, i.e. number of falls that could not be detected; FP is the number of false positives, i.e. false alarms. Table 1 shows the recall and precision values of several different mother wavelet selections. The values in the parenthesis either represent the wavelet class, e.g. D12, or the size of the filter generated from the wavelet.

Table 1: Recall and Precision values for different wavelets

Mother Wavelet	Recall (%)	Precision (%)
Daubechies (D12)	88	59
Morlet (N=36)	89	55
Meyer (N=32)	85	95
Gaussian (N=24)	86	46
Biorthogonal (3.5)	90	50

It can be seen in Table 1 that while we get good recall results, half of the fall alarms generated by the application were false alarms in most of the cases. However, we can also see that, use of Meyer wavelet produced 85% recall while retaining 95% precision. The main reason behind these results can be identified in the frequency domain. Figure 6 shows the frequency components of a fall event and the frequency components of a non-fall event (sitting down). As it can be seen from the figure, the acceleration signals generated during a fall have high amplitudes in certain frequencies, while other actions do not. Further analysis show that Meyer wavelet with 32 sample points acts as a band-pass filter for the frequencies at which falls have high amplitudes. Therefore Meyer wavelet can distinguish falls from non-fall actions.

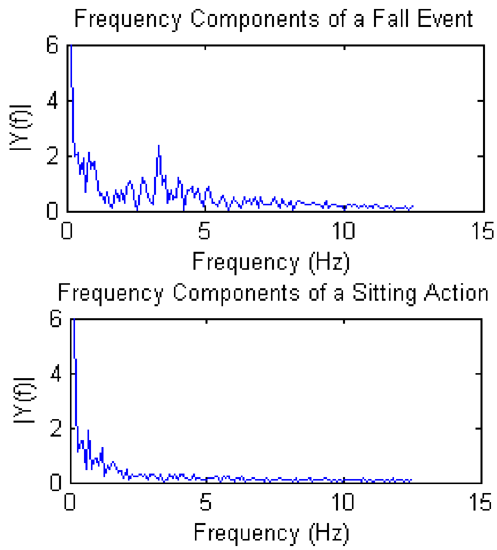

Figure 6. Top: Frequency components of a fall event. Bottom: Frequency components of a sitting action

We also applied the thresholding algorithm proposed by Sposaro, et al. in [7], to the data we have collected. Although we have used their selection of thresholds as a guide, our final threshold selection was made empirically from the data in order to get the best case results. Even in this case, the thresholding method yielded 62% recall and 33% precision. This means that our proposed method performs 37% better than the thresholding method in recall and also has three times more resolution. This also shows that although the underlying assumptions of the thresholding method about the characteristics of a fall event seems reasonable, it suffers from the fact that non-fall events can result in similar acceleration amplitudes. On the other hand, focusing on the frequency components of the acceleration, rather than its amplitude, provides better distinguishing power.

It should be noted here that our scenario includes actions that are less likely to be performed by elderly or the people with neurodegenerative diseases, such as jumping. Therefore, these results can be seen as pessimistic results.

5. CONCLUSIONS

In this paper, we presented a fall detector using the integrated accelerometers on the smartphones, in which we use the discrete wavelet transform as a feature extraction method. As demonstrated by the experimental results, using wavelet transforms yielded significantly better performance, both increasing the true positives by 37% and decreasing the false negatives drastically. Our application not only detects falls, but also provides a location-aware notification service to caregivers and all other interested parties (doctors, ambulance, etc.) through several communication channels, such as GSM, e-mail and Twitter.

In future, we are planning to explore ways of incorporating information from various scales of wavelet transform in order to improve detection performance. We are also planning to conduct experiments in which people are also actually using the phones instead of just carrying the phones on themselves, in order to see the robustness of the application under normal use.

6. ACKNOWLEDGMENTS

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