A Preliminary Study on Using Smartphones to Detect Falling Accidents

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***Abstract*—In order to improve the disadvantages of current smartphone-based fall detection systems, this paper analyzes the characteristics of triaxial accelerometer values to identify thresholds of the non-falls and falls, and proposes an improved threshold-based fall detection method, which is not only able to quickly filter out most of daily activities (including walking running, sitting down, and so on) but also to detect the direction of four types of falling events. Moreover, as soon as a falling accident is detected, the user's position could be immediately sent to the rescue center so as to get medical help.**

Keywords—fall detection; smartphones; triaxial accelerometers.

I. INTRODUCTION

In order to solve the fall crisis that the elderly will be faced with in daily life, there are many research scholars devoted to the research field of fall detection [1]. The fall detection methods could be mainly divided into environmental detection type and wearable detection type. Environmental detection type is mainly to place sensors in the detective areas of daily life. Shieh and Huang [2] collected the monitored images from different areas by placing numerous surveillance cameras and proposed using a pattern recognition approach to detect the elder's falling event. However, the disadvantage of this approach is that fall detection is limited to the monitored environment. Also, the privacy issue of users is a problem. In order to overcome the disadvantages of this type, many research scholars come up with a wearable detection method, in which the user wears sensors so as to provide human activity data for fall detection. Cheng and Jhan [3] used tri-axis acceleration sensor with the proposed cascade-AdaBoost-support vector machine (SVM) classifier. The algorithm could automatically determine whether to replace the AdaBoost classifier by SVM. The results are compared to those of the neural network, SVM, and the cascade-AdaBoost classifier. The experimental results show that the triaxial accelerometers around the chest and waist produce optimal results, and our proposed method has the highest accuracy rate and detection rate as well as the lowest false alarm rate.

Tong *et al.* [4] proposed a hidden Markov model (HMM)-based method to detect and predict falls using triaxial accelerations of a human body. The acceleration time series extracted from human motion processes are used to describe human motion features and train HMM so as to build a random process mathematical model. Thus, the outputs of HMM could be used to evaluate the risks to fall. The experiment results showed that fall events can be predicted 200-400 ms ahead of the occurrence of collisions, and distinguished from other daily life activities with an accuracy of 100%.

With the popularization of smartphones, the mobile phone has become an indispensable product in our daily life. Therefore, in recent years, many researchers integrate the smartphone into fall detection study. In [5], the authors demonstrated techniques to detect a fall and also automatically classify the type. Four different types of falls, left and right lateral, forward and backward falls are discussed and five machine learning classifiers are applied to a large time-series feature set to detect falls. The results showed that SVM and regularized logistic regression were able to identify a fall with 98% accuracy and classify the type of fall with 99% accuracy. In [6], the angles acquired by the electronic compass and the waveform sequence of the triaxial accelerometer on the smartphone are used to generate an ordered feature sequence and then examined in a sequential manner by their proposed cascade classifier for fall detection. The experimental results show that a fall accident detection accuracy up to 92% on the sensitivity and 99.75% on the specificity could be obtained.

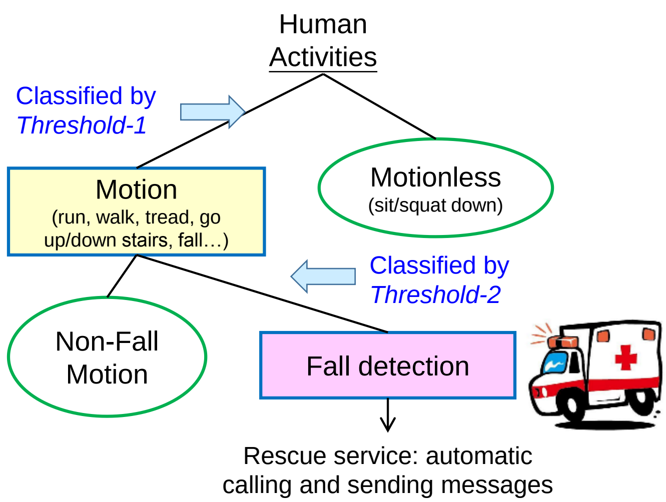

Figure 1. Proposed threshold-based fall detection scheme.

In this paper, through experimentally analyzing the characteristics of triaxial accelerometer values, a threshold-based fall detection approach has been proposed. As shown in Figure 1, the human activities are first classified into motion or motionless category by the *Threshold-1*. Then, in the motion class, including the actions of running, walking, tread, going up/down stairs, as well as falling, the *Threshold-2* is employed to recognize the fall events. After detecting a falling accident, a rescue service will be carried out by automatic calling and sending messages to the emergency center so as to immediately get medical help.

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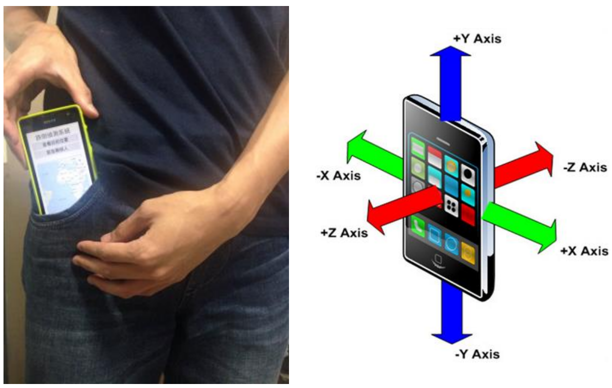
The rest of this paper is organized as follows. Section II briefly introduces the proposed scheme. Next, preliminary experiments are described in Section III. Finally, Section IV concludes this paper.

II. PROPOSED METHODS

As shown in Figure 2, this paper adopts an Android-based smartphone, which is assumed to be carried in a front pants pocket, as the development platform for fall detection. Moreover, a sampling rate of 50 Hz is used to collect sensing data from the build-in triaxial accelerometer in a smartphone.



(a) (b)

Figure 2. (a) Smartphone position in a front pants pocket. (b) Three axes of a smartphone.

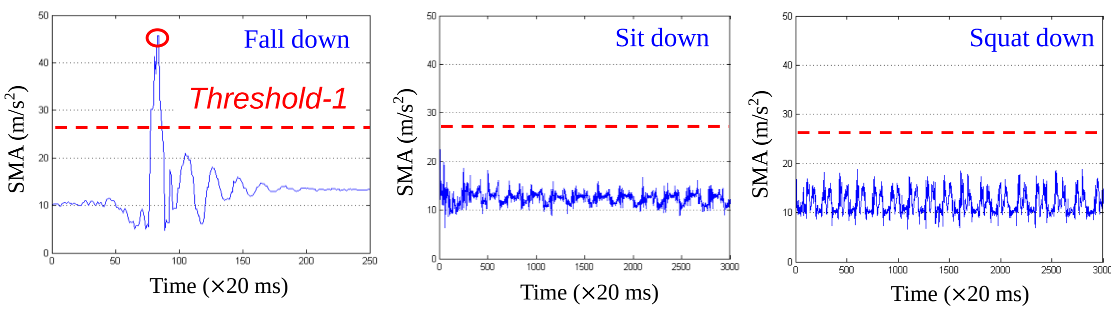
A. *Motion Activities Recognition*

Through observing triaxial accelerometer's values, it could be found that the acceleration changes significantly when a fall occurs. Therefore, the change of acceleration intensity value can be used to determine whether a fall occurs. In this paper, the signal magnitude area (SMA) value, defined as (1), is used to determine the motion and motionless activities.

$$\mathrm{SMA}[n] = \frac{1}{N}\left(\sum_{i=n-N+1}^{n}|x[i]| + \sum_{i=n-N+1}^{n}|y[i]| + \sum_{i=n-N+1}^{n}|z[i]|\right) \tag{1}$$

where $x[n]$, $y[n]$, and $z[n]$ are the acceleration values of the three axes, respectively, at the sampling time n.

Through several practical experiments, we found as the user is engaged in a motion activity, the SMA value is much higher than that in motionless ones, such as sitting and squatting down. Figure 3 shows the SMA values for human activities, including falling down, sitting down, and squatting down. Table I shows the nine types of human activities and its corresponding SMA values (the signs + means more and – means less, respectively). Hence, the *Threshold-1* is determined as 27 $\mathrm{m/s^2}$ via experimental observations. It is noted that even though this parameter is not theoretically proved, the feasibility would be later verified via experimental results.



(a) (b) (c)

Figure 3. SMA values for human activities: (a) fall down, (b) sit down, and (c) squat down.

TABLE I
SMA VALUES FOR HUMAN ACTIVITIES

Activities	Fall down	Run	Walk	Tread	Go downstairs	Go upstairs	Sit down	Squat	Stand
SMA ($\mathrm{m/s^2}$)	30 +	30 +	30 +	30 +	30 +	30 +	25 -	25 -	25 -

Threshold = 27 (determined via experimental observations)

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B. Falling Accidents Detection

In the proposed scheme, four types of falls are considered, including the forward, backward, left lateral, and right lateral falls, as shown in Figure 4.

In order to detect falling accidents, the mean values of acceleration of single axis would be employed. Since the smartphone is assumed to be placed in the front pants pocket, the mean values of x-axis acceleration could be used to detect lateral falls towards the right and left direction. On the other hand, the mean values of z-axis acceleration would be used to forward and backward fall detection. As an example, the mean values x-axis acceleration is defined as (2).

$$x_{\text{mean}}[n] = \frac{1}{N}\left(\sum_{i=n-N+1}^{n} |x[i]|\right) \tag{2}$$

Figure 5 shows the mean values of x-axis acceleration values for human activities, including the lateral fall, run, walk, go upstairs, and go downstairs. Hence, the *Threshold-2* is determined as 10.05 $\mathrm{m/s^2}$ via experimental observations. It is noted that even though this parameter is not theoretically proved, the feasibility would be later verified via experimental results.

(a) (b) (c) (d)

Figure 4. (a) Forward, (b) backward, (c) left lateral, and (d) right lateral falls.

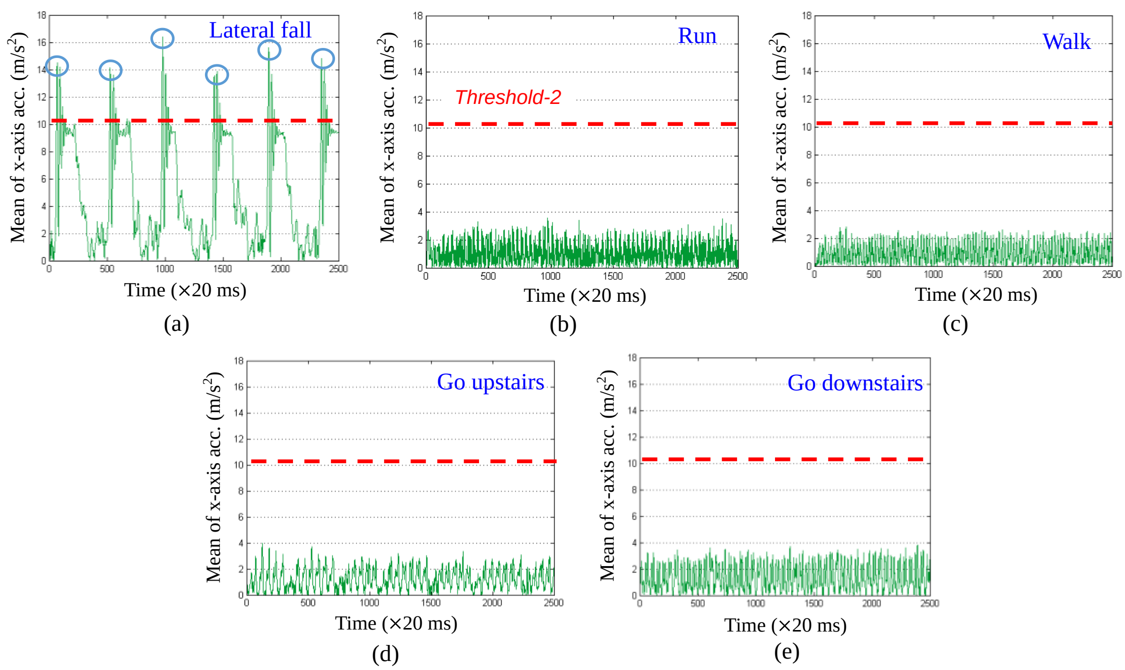

Figure 5. Mean of x-axis acceleration values for human activities: (a) lateral fall, (b) run, (c) walk, (d) go upstairs, and (e) go downstairs.

III. Implementation and Experiments

A. System Implementation

The proposed fall detection approach has been implemented as an APP with the user interface as shown in Figure 6. In addition, the message flows among the user, fall detection APP, and emergency center are shown in Figure 7. Moreover, an Android-based smartphone with the specification shown in Table II [7] is applied to conduct the experiments.

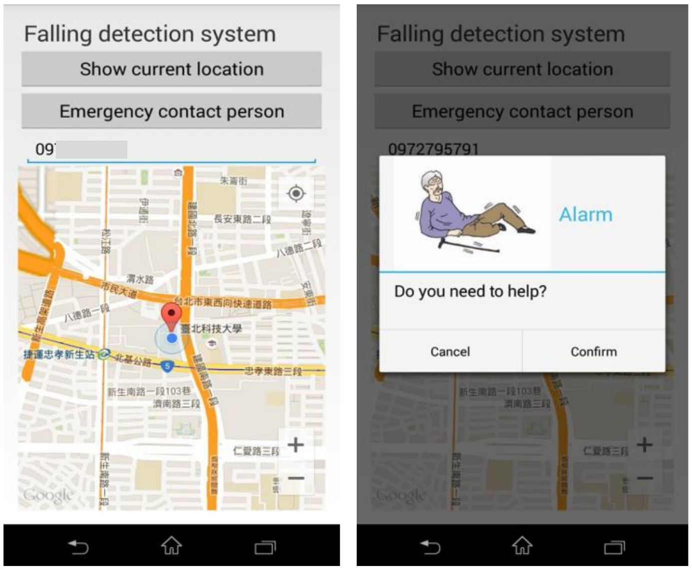

Figure 6. The developed user interface of the fall detection system.

TABLE II
SPECIFICATIONS OF THE SMARTPHONE [7]

Type	Sony Xperia TX
OS	Android 4.3
Size	4.6 inch
Resolution	1280 x 720 pixels
CPU	Qualcomm S4 MSM8260A - 1.5GHz
RAM	1GB
ROM	16GB
Communication	3G、GPS、Bluetooth、Wi-Fi
Sensor	Tri-axial accelerometer (± 20 G)

B. Experimental Results

To conduct the evaluation process, nine different kinds of activities including a fall down event, running, walking, sitting down, going upstairs, going downstairs, tread, standing up, and squatting have been evaluated, each with 50 tests. In order to assess the testing effect, accuracy rate (AR), detection rate (DR), and false alarm rate (FAR) are expressed as (3), (4), and (5), respectively.

$$\mathrm{AR} = (\mathrm{TP} + \mathrm{TN})/(p + q) \tag{3}$$

$$\mathrm{DR} = \mathrm{TP}/p \tag{4}$$

$$\mathrm{FAR} = \mathrm{FP}/q \tag{5}$$

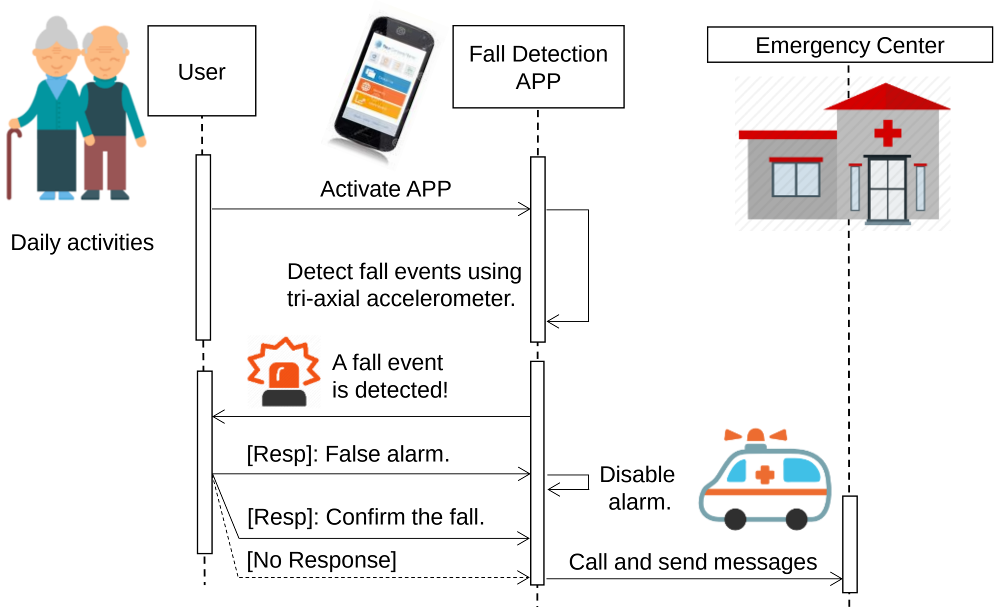

Figure 7. Message flow among the user, fall detection APP, and emergency center.

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TABLE III
EXPERIMENT RESULTS OF DETECTING FOUR FALL DIRECTIONS

Our design	Run	Walk	Sit down	Go upstairs	Go downstairs	Tread	Stand up	Squat	Fall down (4 types)
Test samples	50	50	50	50	50	50	50	50	100
TP	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	96
FP	0	0	1	0	0	0	0	0	N/A
TN	50	50	49	50	50	50	50	50	N/A
AR (accuracy rate)	99%								
DR (detection rate)	96%								
FAR (false alarm rate)	0.25%								
Computation time	17.8ms								

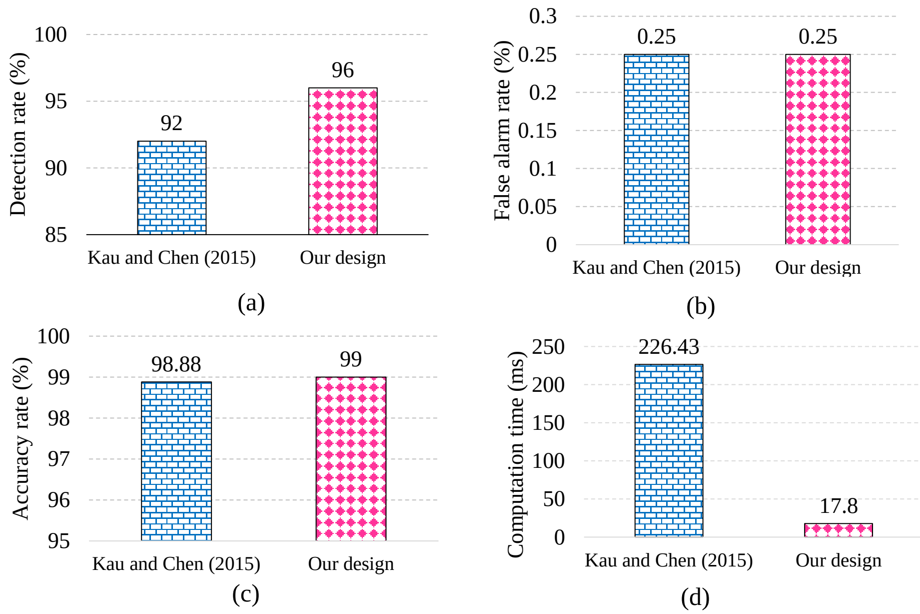

Figure 8. Comparison of (a) detection rate, (b) false alarm rate, (c) accuracy rate, and (d) computation time.

wherein p and q mean the number of collections of the positive examples (falls) and negative examples (non-falls), respectively. The true positive (TP) represents the number of falls successfully detected, true negative (TN) indicates the number of non-fall examples successfully detected, and false positive (FP) shows the number of non-fall examples detected as a fall.

The experiments conducted in this paper are based on the most frequent human daily activities, which include running, walking, sitting down, going upstairs, going downstairs, tread, standing up, and squatting, as well as the four types of falls. The experimental results of detecting four fall directions are shown in Table III. The AR, DR, and FAR are 99%, 96%, and 0.25%, respectively. Moreover, the computation time is 17.8 ms. Figure 8 compares the results of the proposed approach with [6]. It is clear that the proposed method is better in terms of AR DR, and computation time.

IV. CONCLUSION AND FUTURE WORK

This paper has proposed a fall detection system for the elderly by using smartphones placed in their pants pockets. By analyzing acceleration characteristics of three axes x, y, z values, effective threshold values to distinguish daily activities and falling accident have been determined. The results show the proposed method not only has the accuracy rate about 99% but also consumes less computation time, which greatly reduces the burden of the mobile phone operation. In the current scheme, the two thresholds are fixed. Future work will attempt to develop adjustable thresholds considering different users.

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