Development of an Enhanced Threshold-Based Fall Detection System Using Smartphones With Built-In Accelerometers

Jin-Shyan Lee, *Senior Member, IEEE*, and Hsuan-Han Tseng

***Abstract*— Falls are a primary accident for elderly people living independently. Obviously, timely and accurate fall detection is critical to reduce the injuries and avoid the loss of life. In order to improve existing smartphone-based fall detection systems, this paper investigates the features of triaxial acceleration values acquired from built-in accelerometers of a smartphone, identifies crucial thresholds of the falls and non-falls, and then proposes an enhanced threshold-based fall detection approach, which could not only distinguish fall events from the most of daily activities (including walking, running, and sitting down), but also support four directions (forward, backward, left lateral, and right lateral) of the falls. In addition, once a falling accident is identified, the user position would be instantaneously transmitted to an emergency center in order to have timely medical assistance. As a consequence, experimental results show the feasibility of our enhanced approach with accuracy and detection rates of 99.38% and 96%, respectively, while a set of 650 test activities including 11 different kinds of daily activities are performed.**

***Index Terms*— Fall detection, smartphones, threshold-based approaches, triaxial accelerometers.**

I. Introduction

OVER the past decades, life expectancies in most industrialized countries have increased rapidly and are expected to continue growing. This aging population has motivated the development of various healthcare research and technologies. In the current society, elderly persons may live alone and the risk caused by fall events is a critical issue. In order to reduce the injuries and avoid the loss of life resulting from fall accidents, several scholars devoted to the research field of fall detection [1], [2]. According to the location of deployed sensors, the fall detection could be generally classified into two types: the environmental [3], [4] and wearable [5], [6] detection schemes. In the environmental detection scheme, the sensors such as cameras are deployed in the regions of interest so as to measure or capture the actions of users.

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For elderly people, Zigel *et al.* [7] presented an automatic fall detection system on the basis of floor vibration and sound sensors, and utilized signal processing and pattern recognition methods to determine the fall events from other activities of daily living (ADLs) by both temporal and spectral features. Their proposed approach could detect falls with a sensitivity of 97.5% and specificity of 98.6%, respectively. By placing numerous surveillance cameras, Shieh and Huang [8] presented a human-shape-based falling detection algorithm in a multiple-camera video surveillance scheme. Multiple cameras were adopted to capture the images from a variety of regions and then a falling-pattern recognition formula was developed to determine whether a falling event has happened. Also, Stone and Skubic [9] investigated an unobtrusive approach to the fall detection by environmentally deploying Microsoft Kinect, which is a depth imaging sensor. However, the disadvantage of the environmental type is that fall detection is limited to the monitored regions. Moreover, the privacy issue of users is a problem. In order to overcome the disadvantages of this type, several researchers have presented a wearable detection scheme, in which the user wears sensors so as to provide human activity information for fall detection.

On the basis of a pair of instrumented and wearable shoes, Montanini *et al.* [10] proposed a threshold-based approach to fall detection with low complexity. A 97.1% accuracy has been demonstrated by performing experiments on a developed prototype. In [11], Bianchi *et al.* presented the augmentation of fall detection systems with a barometric pressure sensor, as a surrogate measure of altitude, to assist in discriminating real fall events from normal ADLs. The acceleration and air pressure data were recorded using a wearable device and analyzed offline. A heuristically trained decision-tree classifier was used to label suspected falls, leading to the accuracy, sensitivity, and specificity of 96.9%, 97.5%, and 96.5%, respectively. Moreover, Cheng *et al.* [12] proposed a framework for activity awareness and fall detection using surface electromyography and accelerometer signals. A continuous daily activity monitoring and fall detection scheme was performed with the recognition accuracy over 98%.

Cheng and Jhan [13] applied triaxial acceleration sensors with the proposed cascade-AdaBoost support vector machine (SVM) classifier to fall detection. Their approach could automatically identify the situation to change the AdaBoost to the SVM classifier. As compared with the basic neural network, SVM, and the cascade-AdaBoost classifier, the proposed approach resulted in the highest rates in accuracy and detection as well as the lowest rate in the false alarm. On the other hand, Tong *et al.* [14] presented a hidden Markov model (HMM)-based approach to detect and predict fall events by using triaxial accelerations of a human body. The acceleration time series extracted from human motion processes were 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 experimental results showed that fall events could be predicted 200-400 ms in advance of the occurrence of collisions, and distinguished from other daily life activities with an accuracy of 100%. Furthermore, Er and Tan [25] proposed a fuzzy logic-based fall detection algorithm by using the sensor fusion from an accelerometer and a sound sensor. According to the experiment results, their false fall detection rate could be reduced from 20% to 2.5% as compared with the algorithm using the accelerometer only.

Due to the popularization of mobile computing, the smartphone has become a necessary device in our daily life. Hence, several scholars recently have applied the smartphone to fall detection studies. In [15], the authors presented a method to detect a fall and then determine the fall types automatically. In their proposed scheme, four different types of falls (the left and right lateral, forward, and backward) were considered and five machine learning classifiers were used with a large time-series feature set. Their experimental results demonstrated that SVM and regularized logistic regression were able to determine a fall accident with 98% accuracy and identify the fall type with 99% accuracy. By utilizing the accelerometers in smartphones and modeling the fall activities as a finite state machine, Hsieh *et al.* [16] proposed a fall detection approach. Their experimental results showed that the proposed method could effectively detect actual falls and would not misidentify the normal activities as falls.

Also, Bai *et al.* [17] utilized the accelerometer of a smartphone to design a fall monitor with GPS function and supported six typical ADLs, including standing up, sitting down, going upstairs, going downstairs, running, and jumping. By using smartphones for fall detection, Medrano *et al.* [18] applied supervised machine learning algorithms which rely only on true ADL. In this way, a fall would be any abnormal movement with respect to ADL. Their results showed that in most situations, a generic SVM outperformed an adapted nearest neighbor-based technique (NN). Furthermore, Kau and Chen [19] adopted the angles acquired by the electronic compass and the waveform sequence of the triaxial accelerometer on the smartphone to produce an ordered feature sequence and then examined in a sequential manner by their presented cascade classifier for fall detection. The experimental results revealed that a fall accident detection accuracy up to 92% on the sensitivity and 99.75% on the specificity could be obtained.

In this paper, by means of analyzing the features of triaxial accelerometer values experimentally, an enhanced

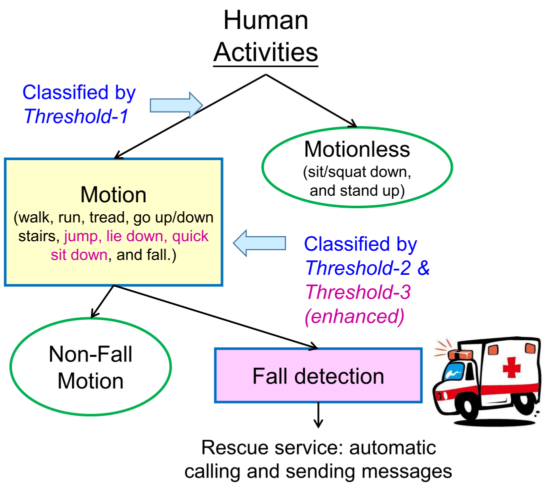

Fig. 1. Enhanced threshold-based fall detection scheme based on [20].

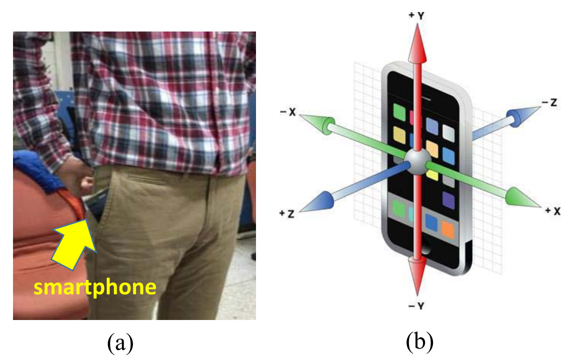

Fig. 2. (a) Smartphone position in a front pants pocket. (b) Orientation axes of a smartphone.

threshold-based fall detection mechanism has been proposed. An earlier version of this paper was presented at the Int. Conf. Systems and Networks Communications and was published in its proceedings [20]. This paper expands the previous work by

1) adding the literature review in Section I,
2) enhancing the approach to support more ADLs in Section II, and
3) enriching the comparison with more related approaches in Section III.

As shown in Fig. 1, the human activities are initially categorized into motion or motionless class by the *Threshold-1*. Three motionless actions, including sitting down, squatting down, and standing up, are considered in our work. Then, in the motion category, including the actions of walking, running, treading, going up and down stairs, as well as falling, the *Threshold-2* is adopted to identify the fall events. It is noted that both the *Threshold-1* and *Threshold-2* have been presented and determined in our previous work [20]. However, through our experimental analysis, the fall events could not be distinguished from the ADLs of jumping, lying down, and quickly sitting down as using only these two thresholds. In this paper, one more threshold *Threshold-3* has been newly added so as to enhance our previous threshold-based fall detection scheme with more ADLs supported. Furthermore, once a falling event is detected, an emergency service would

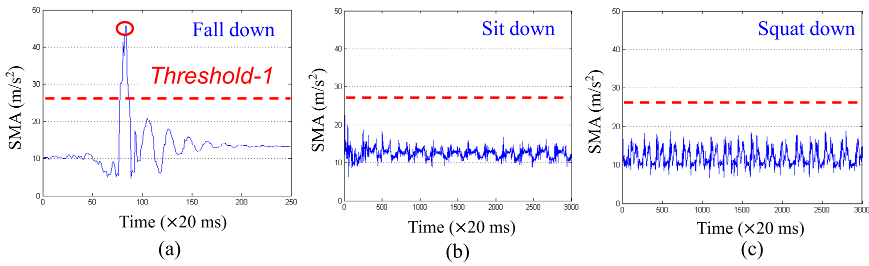

Fig. 3. SMA values of three human activities: (a) fall down, (b) sit down, and (c) squat down [20].

TABLE I
SMA VALUES OF NINE HUMAN ACTIVITIES

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

+ means more.
- means less.
Threshold = 27 (determined via experimental observations)

Fig. 4. (a) Forward, (b) backward, (c) left lateral, and (d) right lateral falls [20].

be performed by immediately calling and sending messages to the rescue center so as to have timely medical assistance.

The rest of this paper is organized as follows. Section II describes the proposed and enhanced fall detection scheme. Next, realistic experiments with results and comparisons are conducted in Section III. In the end, Section IV concludes this paper.

II. Proposed and Enhanced Approaches

In this section, both the proposed approach presented in [20] and the newly enhanced one would be illustrated. As shown in Fig. 2 (a), this work utilized a smartphone with Android system for the implementation of the fall detection approach. Also, the phone is assumed to be placed in a front pants pocket. Furthermore, to continuously acquire data from the built-in triaxial accelerometer in a smartphone, a sampling rate of 50 Hz is employed. Also, the accelerometer is oriented according to the X, Y, and Z axes in Fig. 2 (b).

A. Distinguish Motion Activities by Threshold-1

Through observing triaxial accelerometer's values, it could be found that the acceleration changes significantly when a fall occurs. Hence, the variation of acceleration intensity value could be employed to identify if a fall occurs. In this paper, the signal magnitude area (SMA) value at the sampling time n, formulated as (1), is adopted to distinguish the motion and motionless activities.

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

where $x[i]$, $y[i]$, and $z[i]$ are respectively the acceleration values of the three axes at the sampling time i, and N is the number of samples.

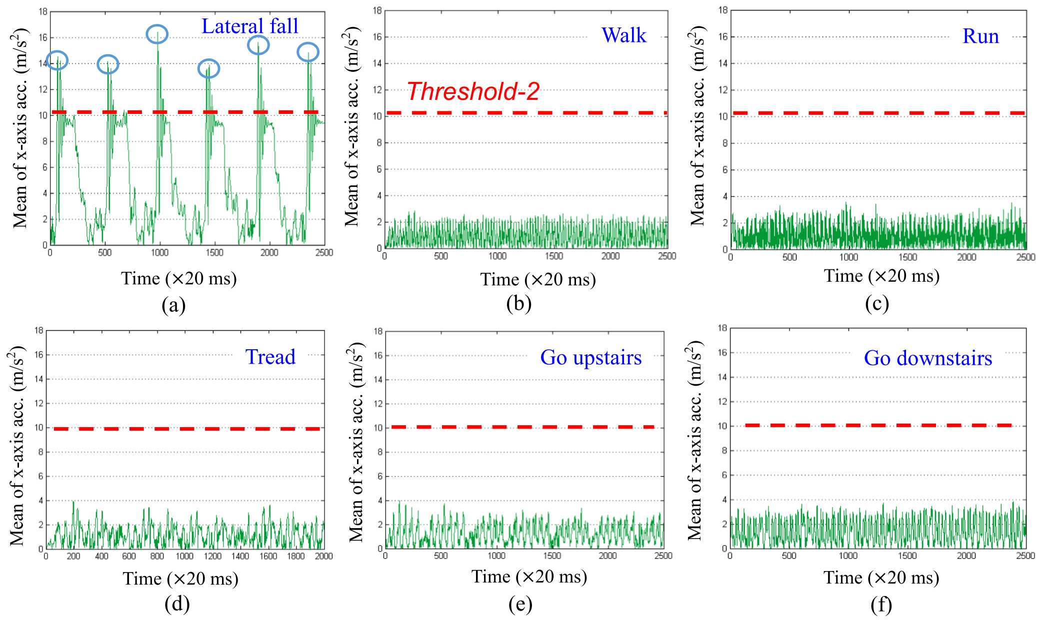

Fig. 5. The mean of x-axis acceleration values of human activities: (a) lateral fall, (b) walk, (c) run, (d) tread, (e) go upstairs, and (f) go downstairs.

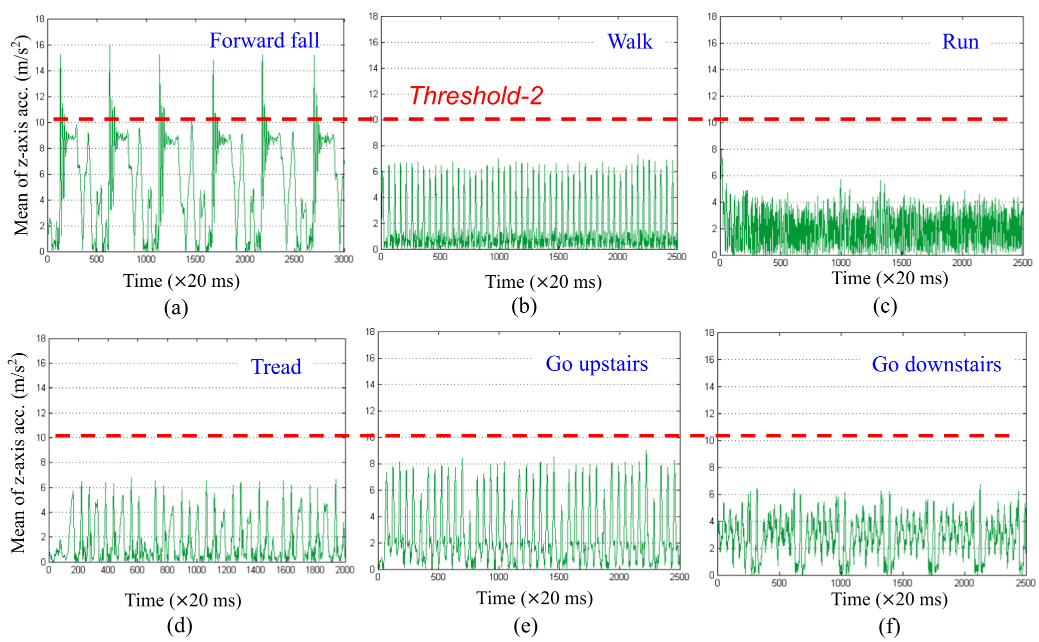

Fig. 6. The mean of z-axis acceleration values of human activities: (a) forward fall, (b) walk, (c) run, (d) tread, (e) go upstairs, and (f) go downstairs.

Through conducting several realistic experiments, we found when the user is performing a motion activity (such as walking, running, or going upstairs), the SMA value is much higher than that in motionless one (such as sitting down, standing up, or squatting down). The SMA values for human activities, including falling down, sitting down, and squatting down are displayed in Fig. 3. Nine types of human activities (including the fall down) and its corresponding SMA values are revealed in Table I, wherein the signs + means more and – means less, respectively Therefore, the *Threshold-1* is designed as 27 m/s^2 through experimental observations. It is noted that despite the fact that this parameter is not theoretically verified, the practicability would be later confirmed through realistic experiments.

B. Recognize Lateral Falls by Threshold-2

For the purpose of fall detection, the mean values of acceleration of a single axis would be utilized. As revealed in Fig. 4, four directions of falls (containing the forward, backward, left lateral, and right lateral falls) are studied in the presented scheme. Since the smartphone is assumed to be located in the front pants pocket, the mean of x-axis

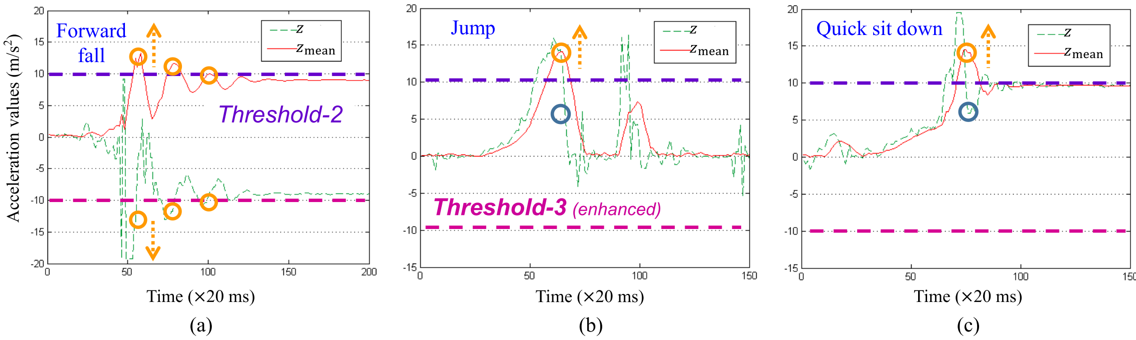

Fig. 7. Acceleration values of human activities: (a) forward fall, (b) jump, and (c) quick sit down.

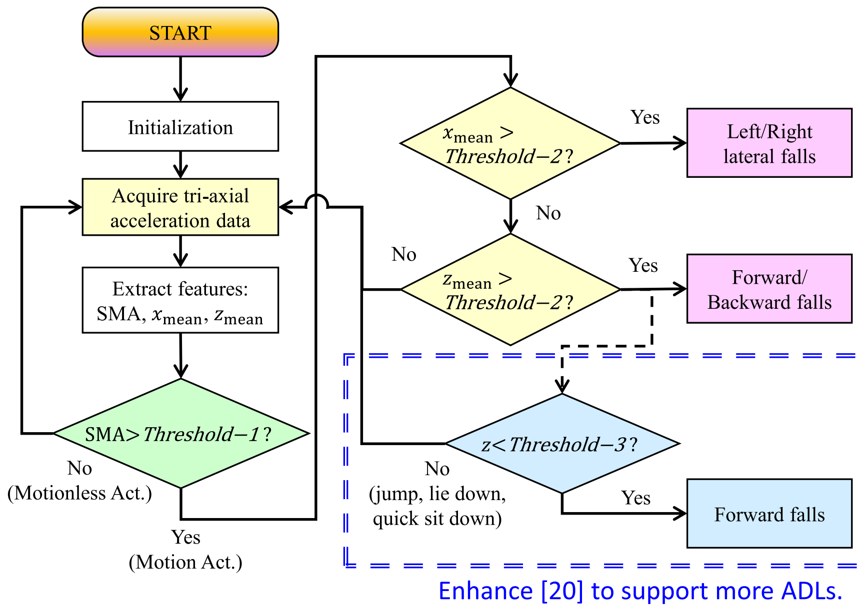

Fig. 8. Enhanced threshold-based fall detection approach based on [20].

acceleration values could be adopted to detect lateral falls towards the right and left directions. At the same time, the mean of z-axis acceleration values would be employed to forward and backward fall detections. For the lateral fall detection, the mean of x-axis acceleration values is formulated as (2).

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

The threshold value would be obtained by intensive experiments. Fig. 5 displays the mean of x-axis acceleration values for human activities, including the lateral fall, walk, run, tread, going upstairs, and going downstairs. For the purpose of inspection, it is noted that six lateral falls occur one after the other. Therefore, the *Threshold-2* is selected as 10.05 m/s^2 through experimental observations. Similarly, in spite of the fact that this parameter is not theoretically verified, the feasibility would be proved later through realistic experiments.

C. Recognize Forward and Backward Falls

Since the smartphone is assumed to be located in the front pants pocket, the mean of z-axis acceleration values could be employed to detect forward and backward falls. Similarly, the mean of z-axis acceleration values is formulated as (3). It is obvious that the $z_{\text{mean}}[n]$ is always positive, while the $z[i]$ could be either positive or negative. Fig. 6 reveals the mean of z-axis acceleration values for human activities, containing the forward fall, walk, run, tread, going upstairs, and going downstairs. Also, six falls occur in succession for the purpose of examination. In a similar manner, the *Threshold-2* is also identified as 10.05 m/s^2, which is the same as the lateral fall recognition has, for simple and easy implementation. Subsequently, the practicality of the threshold value would be validated through realistic experiments.

$$z_{\text{mean}}[n] = \frac{1}{N}\left(\sum_{i=n-N+1}^{n} |z[i]|\right) \quad (3)$$

D. Enhance [20] to Support More ADLs by Threshold-3

As mentioned above, the fall events could not be distinguished from the actions of jumping, lying down, and quickly sitting down by the threshold-based fall detection scheme presented in [20]. As shown in Fig. 7, it is clear that the *Threshold-2* (for the mean of z-axis acceleration values) would

TABLE II
SUMMARY OF THE THRESHOLDS USED IN THE ENHANCED APPROACH

Thresholds	Features	Values (m/s^2)	Description
Threshold-1	SMA	27	Check if SMA$[n]>$*Threshold−1*
Threshold-2	x_{mean} z_{mean}	10.05	Check if $x_{mean}[n]>$*Threshold−2* Check if $z_{mean}[n]>$*Threshold−2*
Threshold-3	z	-10	Check if $z[n]<$*Threshold−3*

TABLE III
FUNCTIONAL COMPARISON OF THRESHOLD-BASED FALL DETECTION APPROACHES USING SMARTPHONES

Approaches/Indices	Sensors	Supported ADLs	Supported fall types
[13] Cheng & Jhan	• Tri-axial accelerometers	–	–
[16] Hsieh *et al.*	• Tri-axial accelerometers	5	3
[19] Kau & Chen	• Tri-axial accelerometers • Electronic compass	8	4
[20] Our previous work	• Tri-axial accelerometers	8	4
This extended work	• Tri-axial accelerometers	11	4

TABLE IV
SPECIFICATIONS OF THE SMARTPHONE [21]

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

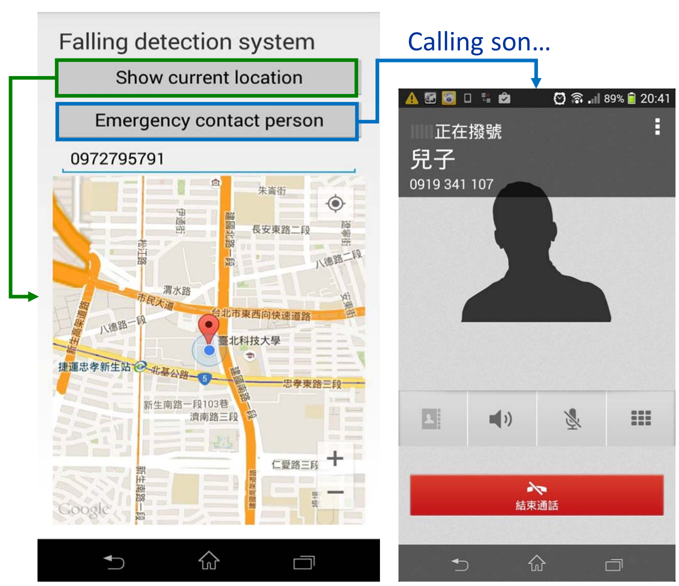

Fig. 9. The designed user interface of the fall detection APP.

not only be activated by the forward fall, but also by the jump and quick sit down. Thus, a false alarm would occur under these situations.

In this paper, one more threshold *Threshold-3* has been newly added so as to enhance the threshold-based fall detection scheme. As shown in Fig. 7, the acceleration values of the z-axis between the forward fall and jump (or quick sit down) are extremely different. The fall mainly produces large negative peak values while the jump (or quick sit down) primarily generates positive ones. Therefore, the *Threshold-3* is decided as a negative value $-10\ m/s^2$, which is also from experimental observations. In Fig. 7 (a), when the mean of z-axis acceleration values exceeds the *Threshold-2*, the z-axis acceleration is also lower than *Threshold-3*. Thus, it could be concluded that if both thresholds could be reached simultaneously, the corresponding activity is inferred as a fall event. On the other side, in Fig. 7 (b) and (c), it is clear that only *Threshold-2* could be crossed. It is noted that the difference between the forward fall and jump (or quick sit down) is not held for backward falls. As shown in Fig. 8, the backward fall detection is based on the approach presented in our previous work [20]. Through adding the *Threshold-3* criterion, our previous work would be enhanced to support three more ADLs (that is the jump, lie down, and quick sit-down).

As shown in Fig. 8, after acquiring triaxial acceleration data from the built-in accelerometers in a smartphone, three features would be extracted. Then, after checking the three thresholds one after the other, the fall event could be identified. It is noted that the *Threshold-3* is an enhancement of [20] so as to support ADLs of the jump, lie down, and quick sit-down.

Moreover, the employed thresholds with descriptions in our approach are summarized in Table II. Despite the fact that these parameters are not theoretically verified, the practicability would be validated later through realistic experiments.

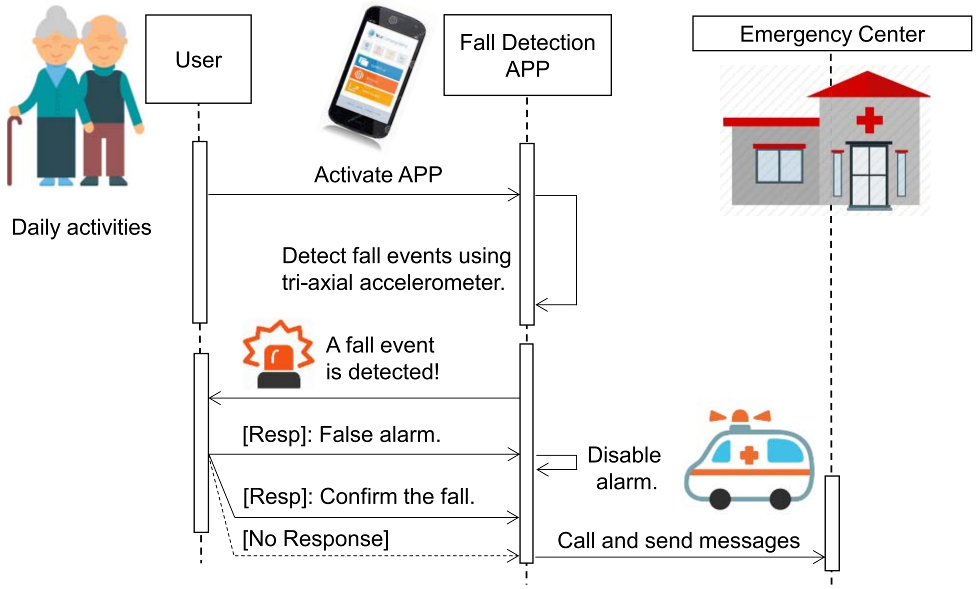

Fig. 10. Message flows among the user, fall detection APP, and emergency center [20].

Furthermore, Table III shows the comparison of threshold-based fall detection schemes using smartphones. Obviously, the extended work in this paper supports the most ADLs as eleven.

III. Implementation and Experiments

A. System Implementation

In this paper, a smartphone which has an Android platform is utilized to perform the experiments. The specification is displayed in Table IV [21]. The phone supports the sensing functions of triaxial acceleration, GPS, and Wi-Fi communications with a 1.5 GHz CPU.

On the basis of the Android platform, the proposed fall detection approach has been realized as an APP, of which the user interface is shown in Fig. 9. The user could show his or her current location via the built-in GPS receiver in smartphones. Also, phone numbers of emergency contact persons could be set up through the interface. Moreover, the message flows among the user, fall detection APP, and emergency center are represented in Fig. 10. In the beginning, the user has to activate the APP which would continuously detect fall events using the proposed approach with built-in triaxial accelerometers. As soon as a fall is happened and detected, the APP will pop out an alert window for user confirmation so as to avoid false alarms. If the user responses the APP with a false alarm message, the APP will disable the alarm. On the other hand, as the user confirms the fall or has no responses (maybe due to the injuries), the APP will call and send messages to the emergency contact person (or medical center) immediately.

B. Experimental Configuration

For the reason of safety and efficiency, four young healthy volunteers are employed to perform the experiments on falls and ADLs. All are male with an average age of 24. To perform the experimental process, eleven different kinds of ADLs, including sitting down, squatting down, standing up, walking, running, treading, going upstairs, going downstairs, jumping, lying down, and quickly sitting down, have been evaluated. Each ADL has been carried out at least 50 tests, while the fall down event has been executed over 100 tests.

In order to evaluate the enhanced approach, the accuracy rate (AR), detection rate (DR), and false alarm rate (FAR) formulated as (4), (5), and (6), respectively, are utilized for assessment.

$$\mathrm{AR} = (\mathrm{TP} + \mathrm{TN})/(p + q) \tag{4}$$

$$\mathrm{DR} = \mathrm{TP}/p \tag{5}$$

$$\mathrm{FAR} = \mathrm{FP}/q \tag{6}$$

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

C. Experimental Results and Comparison

In this paper, the conducted experiments are according to human daily activities, which are occurred most frequently, as well as the falls. Table V shows the experimental results of our previous work on detecting fall events [20]. Results of the AR, DR, and FAR are 99%, 96%, and 0.25%, respectively, when a set of 500 test activities including eight different kinds of ADLs are performed. Moreover, the computation time is 17.8 ms.

On the other hand, the experimental results of the enhanced fall detection approach are shown in Table VI. The AR, DR, and FAR are 99.38%, 96%, and 0%, respectively, while a set of 650 test activities including eleven different kinds of ADLs are performed. Moreover, the computation time is 25.33 ms.

TABLE V
EXPERIMENTAL RESULTS OF OUR PREVIOUS WORK ON DETECTING FALL EVENTS [20]

Our previous work [20]	Walk	Run	Tread	Go upstairs	Go downstairs	Sit down	Squat down	Stand up	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	0	0	0	1	0	0	N/A
TN	50	50	50	50	50	49	50	50	N/A
Accuracy rate	99%								
Detection rate	96%								
False alarm rate	0.25%								
Computation time	17.8 ms								

TABLE VI
EXPERIMENTAL RESULTS OF THE ENHANCED FALL DETECTION APPROACH

This extended work	Walk	Run	Tread	Go upstairs	Go downstairs	Sit down	Squat down	Stand up	Jump	Lie down	Quick sit down	Fall down (4 types)
Test samples	50	50	50	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	N/A	N/A	N/A	96
FP	0	0	0	0	0	0	0	0	0	0	0	N/A
TN	50	50	50	50	50	50	50	50	50	50	50	N/A
Accuracy rate	99.38%											
Detection rate	96%											
False alarm rate	0%											
Computation time	25.33 ms											

Three more supported ADLs

TABLE VII
PERFORMANCE COMPARISON OF THRESHOLD-BASED FALL DETECTION APPROACHES USING SMARTPHONES

Approaches/Indices	Accuracy rate (%)	Detection rate (%)	False alarm rate (%)	Computation time (ms)
[13] Cheng and Jhan	98.23	88	1.27	–
[16] Hsieh *et al.*	98	95.5	0	–
[19] Kau & Chen	98.88	92	0.25	226.43
[20] Our previous work (8 ADLs)	99	96	0.25	17.8
Our previous approach (11 ADLs)	76.15	96	27.45	17.8
This extended work (11 ADLs)	99.38	96	0	25.33

Table VII compares performances of the enhanced approach with [13], [16], [19], and our previous work [20]. Even though other related works provide 99% accuracy, they support fewer ADLs as compared with our enhanced approach. That means when the related works consider the ADLs which are not originally supported, such as the lying down, their accuracy would decrease significantly. For example, if the previous work [20] considers three more ADLs, jumping, lying down, and quickly sitting down, the AR will decrease from 99% to 76.15%, while the FAR will increase from 0.25% to 27.45%, respectively. Furthermore, it is clear that this extended approach generally outperforms others in terms of AR, DR, and FAR. As compared with [19], the proposed approach takes less computation time and significantly reduces the smartphone burden. In addition, as compared with [20], even though this enhanced work consumes more computation time due to the *Threshold-3* check, it supports three more ADLs (jumping, lying down, and quickly sitting down), as mentioned before.

It is noted that the fall down tests conducted in the experiments are four different types of falls with normal speed. As 60 tests of slow falls are further included in the experiments of the enhanced approach (totally 160 fall tests), the DR drops from 96% to 78.13%, while the AR decreases from 99.38% to 95.07%, respectively. Even though the slow falls lower the 17.87% accuracy of DR, the enhanced approach could still achieve a high AR of 95.07%. Fig. 11 (a) and (b) shows the SMA and the mean of z-axis acceleration values of a slow fall, respectively. Obviously, this slow fall could be successfully detected since both the thresholds, *Threshold-1* and *Threshold-2*, would be exceeded at the 366th sampling time (at the time 7.32 seconds). Future work would attempt to enhance the detection of slow falls.

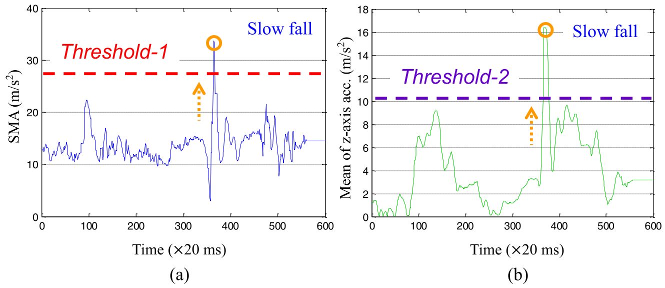

Fig. 11. Acceleration values of a slow fall.

IV. Conclusion and Future Work

Since the fall accident is an important issue among the elderly, a variety of fall detection methods have been proposed over recent years. In this paper, based on our previous work presented in [20], an enhanced fall detection approach has been proposed by using the built-in accelerometers of a smartphone which is assumed to be located in the pants pockets. By means of analyzing acceleration features of three axes, effective threshold values to recognize daily activities and falling event have been identified. In this way, the experimental results show that the enhanced approach could successfully recognize the fall events with a distinguished performance around 99.38% on the accuracy and 96% on the detection, respectively, while a set of 650 test activities including eleven different kinds of ADLs are performed.

In practical applications, the sensors from different manufacturers may record values in greatly different ranges for identical sensors, resulting in the difficulty to determine reliable values for thresholds [22]. In case that there are many different smartphones, how to define a correct and optimal threshold for each smartphone could be investigated in the future. In addition, the test subjects in the experiments are young people, but the falls of the elderly may last longer than that of the young [23]. Future work will also intend to conduct experiments for the elderly. Furthermore, the disadvantage of accelerometer sensors is prone to elevators and high-speed cars or trains [24], how to incorporate with other sensors such as the gyroscope, magnetometer, and barometer would be studied in the future.

In the current approach, the three thresholds are fixed and verified via experiments. Future work will attempt to develop adaptive and personalized thresholds with the consideration of different users. Also, the thresholds determined from theoretical analysis rather than via the experimental observations would be further investigated. Moreover, in our approach, the position of smartphones is assumed to be located in a front pants pocket. Future research considering different smartphone positions, such as in a shirt pocket, jacket pocket, or backpack, could be further studied. Also, more types of falls, such as other slow falls and in-place faints, could be investigated in the future.

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