Arabian Journal for Science and Engineering (2019) 44:3329–3342
https://doi.org/10.1007/s13369-018-3496-4

RESEARCH ARTICLE - COMPUTER ENGINEERING AND COMPUTER SCIENCE

Development of a Real-Time, Simple and High-Accuracy Fall Detection System for Elderly Using 3-DOF Accelerometers

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Received: 4 October 2017 / Accepted: 1 August 2018 / Published online: 14 August 2018

Abstract

Falls represent a major problem for the elderly people aged 60 or above. There are many monitoring systems which are currently available to detect the fall. However, there is a great need to propose a system which is of optimal effectiveness. In this paper, we propose to develop a low-cost fall detection system to precisely detect an event when an elderly person accidentally falls. The fall detection algorithm compares the acceleration with lower fall threshold and upper fall threshold values to accurately detect a fall event. The post-fall recognition module is the combination of posture recognition and vertical velocity estimation that has been added to our proposed method to enhance the performance and accuracy. In case of a fall, our device will transmit the location information to the contacts instantly via SMS and voice call. A smartphone application will ensure that the notifications are delivered to the elderly person's relatives so that medical attention can be provided with minimal delay. The system was tested by volunteers and achieved 100% sensitivity and accuracy. This was confirmed by testing with public datasets and it also achieved the same percentage in sensitivity and accuracy as in our recorded datasets.

Keywords Lower fall threshold (LFT) · Upper fall threshold (UFT) · Post-fall recognition · Vertical velocity · SMS · VIP contacts

1 Introduction

Population aging is the trend in modern society [1] and the number of the elderly's falls because of old age, mental and physical diseases such as stress, high/low blood pressure, heart diseases, knee pains is on the increase. Figure 1 shows an example of fall event with the elderly which will lead to many dangerous problems, even death if they do not receive immediate attention.

In order to solve the problem, the authors proposed to develop an effective fall detection system to support the elderly, especially for those living alone. There have been a lot of published methods about fall detection in recent years such as image processing [3–11], location sensors [12], smartphones [13], accelerometers [14] or wristband and smartwatches. However, these methods have certain limitations, for instance, the systems are inconvenient, costly and inaesthetic.

Firstly, for the image processing approach [3–11,15], the authors employed different types of cameras to distinguish between activities of daily living (ADLs activities) and fall risk detection in home environments such as depth Kinect

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Fig. 1 Example of fall in older adults [2]

camera of Microsoft, monitoring cameras. However, it shows several drawbacks in the outdoor environments: the resolution of the cameras, distance between camera and objects, target occlusion and privacy of users as well as a situation when an elderly person is out of the camera's view. These limitations are the same as with the location sensor [12] method because it combines four tags on the body to detect locations via radio sensors and recognize the user's activities. This system is complex and expensive.

The systems detect a fall through the built-in accelerometer in smartphones [13,16–18] that can be used for both indoor and outdoor environments. However, various types of accelerometers are incorporated in smartphones. Hence, the algorithm's performance and accuracy of the systems are not the same in each type of smartphones [19]. Besides, fall detection will also be affected by incoming and outgoing calls, messages and the mounted position. This method makes it difficult to integrate additional sensors such as heart rate, blood pressure.

Wristband and smartwatches [20,21] are becoming more popular in recent researches because people can wear them round their wrists which are one of the most comfortable positions. Nevertheless, there is a big challenge in fall detection because end-users can move their hands anytime and anywhere. Hence, this system is hard to distinguish between Activities of Daily Living (ADLs activities) and fall events.

Using machine learning, such as support vector machine (SVM), neural network (NN), the dynamic Bayesian network (DBN) model [22], etc., to classify fall events and daily activities has been becoming popular recently. It can detect most of the fall events [23] with high sensitivity and accuracy. Nevertheless, these methods are more sophisticated, and it is hard to implement on microcontroller unit (MCU) due to the huge number of computations and data requirements which result in the system's high cost [3,4].

Another common method is using the low-cost accelerometer available in the market, but the precision in fall detection is low [14,24]. These studies utilized posture recognition and fall detection algorithms by applying thresholds to accelerations from accelerometer or angular velocities from gyroscope worn on the waist/chest/thigh in order to detect a potential fall [25,26]. In [14], the authors used at least three accelerometers to wear on three positions of the body; thus, this system is inconvenient and uncomfortable for the user. In [24], the authors used ZigBee transceiver to communicate with the center to save energy, but it prevents the elderly from outside activities. This limitation is the same as in [25]. The publication [4] also used LFT, UFT and t_{FE} thresholds and theta angle, vertical velocity to estimate the fall with high sensitivity and accuracy. However, this system cannot be considered as the completed system since the fall events are not sent out to a responsible person, or monitoring system.

To overcome above limitations, this research focuses on the development of an effective fall detection system to support the elderly, especially for ones living or staying at home alone. Our proposed fall detection system addresses two main contributions: the posture recognition module to enhance the accuracy of the system, and a software application to improve efficiency of senior care. Comparing with the related works, we propose the following approaches. Firstly, the hardware device will detect falling events automatically in elderly using fall detection module. Secondly, if a fall is confirmed, after 2 s it will be checked by the post-fall posture with two consecutive times to enhance the accuracy of the proposed device. When the final decision is confirmed as a fall event, the device will get the current position of the falling event. A message that has the fall position attached will be sent to a hospital, a nurse and relatives for emergency support, and then the device attempts to make phone calls to relatives in priority until answered or rejected to avoid missing the incident. Thirdly, we designed a mobile software application which allows smartphones to switch to normal mode in case they are in silent mode. When calls from the fall-monitoring device are received, the software will put the mobiles into the emergency mode to ensure the relatives are informed about the fall event.

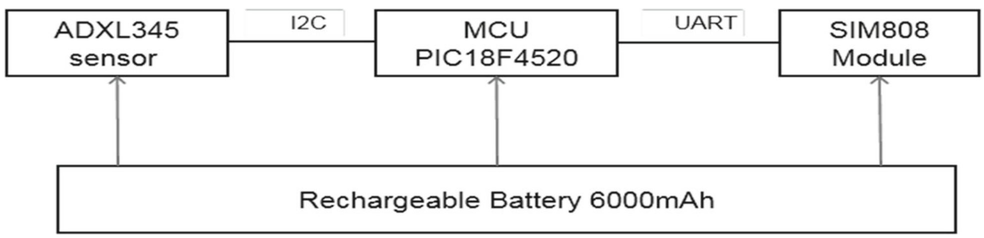


Fig. 2 Block diagram of the fall detection device

Table 1 Power consumption of our proposed device

Components	Voltage (V)	Current (mA)	Power consumption (mW)
MCU (PIC18F4520)	3.7	2	7.4
ADXL345	3.7	23×10^{-3}	8.51×10^{-2}
SIM808	3.7	24	88.8
Total of power consumption			96.2851

The paper is organized as follows: In Sect. 1, we present the related works, problem definition and the contributions of our proposed system. The system designed to monitor and detect the fall event is introduced in Sect. 2. The experimental results and discussion of relevant issues are reported in Sect. 3. Finally, conclusions and the future works of the paper are given in Sect. 4.

2 System Design

In this section, the system architecture and the hardware components are described in detail.

2.1 System Architecture

Figure 2 shows the block diagram of the proposed fall detection system, the accelerometer used in this paper is ADXL345 (3-DOF accelerometer) from analog devices. The proposed system uses I^2C (inter-integrated circuit) interface in the connection between ADXL345 and MCU (Pic18F4520 from microchip) in sensing along the Ax-, Ay-, and Az-axes with a sampling rate of 50 Hz because the elderly's motion is quite slow with simple ADLs. Furthermore, the analyzed results in [19] showed that sampling at 100 Hz is not better than 50 Hz and the performance and accuracy of the device depend directly on the detection algorithms. Hence, a sampling frequency of 50 Hz was chosen to save energy.

In this design, two rechargeable batteries (3.7 V and 3000 mAh) are used to supply power for the hardware device. Based on the energy consumption in each component in the integrated device as in Table 1, we can calculate the active time of the device using Eq. (1). The specification of the Lithium battery is 3.7 V–6000 mAh and the battery power is 3.7 V × 6000 mAh = 22,200 mWh. Therefore, the battery lifetime of the device in working mode equals to the total power consumption of components from $i = 1{:}N$ including MCU, ADXL345 and SIM808:

$$\frac{22{,}200 \text{ mWh}}{96.2851 \text{ mW}} = 230\,\text{h} = 9.6\,\text{days} \tag{1}$$

Hence, the proposed device can work constantly for more than 9 days without being recharged.

2.2 The 3-DOF Acceleration Sensor

The accelerometer is the heart of the proposed device, and it is calibrated carefully through the measurement process in each axis. It will have accelerations in both positive (a^+) and negative (a^-) of Ax-, Ay-, and Az-axes. Then the K value can be estimated in each axis by using Eq. (2):

$$K = \frac{2}{(a^+ - a^-)} \tag{2}$$

K may be positive or negative depending on the real value of a^+ and a^- measured in each axes. Then, $a'^+ = K.a^+$ and $a'^- = K.a^-$. Based on a'^+ and a'^- to calculate the Offset values using Eq. (3):

$$\text{Offset} = \frac{a'^+ + a'^-}{2} \tag{3}$$

Based on Offset values, acceleration in each axes can be estimated using Eq. (4):

$$\begin{aligned} A^+ &= a^+ - \text{Offset} \\ A^- &= a^- - \text{Offset} \end{aligned} \tag{4}$$

After calibration, due to measurement error and sensor error, a simple Kalman filter was applied with $A = 1$, $P = 1$, $u = 0$ and $Q = 0$ (very small process variance) into MCU to predict and estimate data due to the low processing speed of the microprocessor.

The time update:

$$\begin{aligned} \hat{x}_k^- &= \hat{x}_{k-1} \\ P_k^- &= P_{k-1} \end{aligned} \tag{5}$$

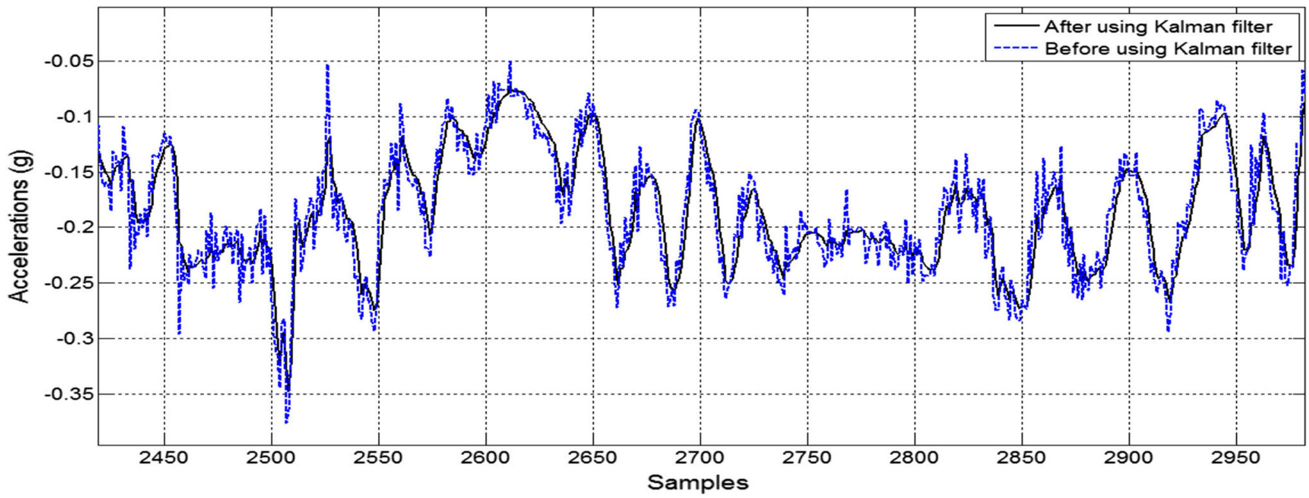


Fig. 3 Recorded data before and after using Kalman filter

and the measurement updates:

$$K_k = \frac{P_k^-}{P_k^- + R}$$
$$\hat{x}_k = \hat{x}_k^- + K_k \left(z_k - \hat{x}_k^- \right)$$
$$P_k = (I - K_k) P_k^- \tag{6}$$

where K_k is the Kalman gain, $\hat{x}_k$ is the estimate of the signal on current state, $\hat{x}_k^-$ is the estimate of the signal on the previous state, P_k is the posteriori error covariance, P_k^- is the priori error covariance, z_k is the measured value, R is noise in the environment. The recorded signal is smoother when using a simple Kalman filter (see Fig. 3). However, it still keeps the shape and characteristic of the signal.

The hardware device was mounted on the waist so that Ay-axis is parallel to the Earth's gravity as shown in Fig. 4. The ADXL345 is small, thin with low power, three-axis accelerometer with high-resolution (13-bit) measurement up to ± 16g. Digital output data are accessible through the I^2C digital interface. The data received from the accelerometer is in the form of three-valued vectors of individual accelerations in the Ax, Ay, and Az axes. The expected reading of the accelerometer in standing state would be [0, 1, 0] g (with $g = 9.81\ \mathrm{m/s^2}$). Next, the preprocessing step was applied to filter noises before taking it into the attribute extraction module to compute the mean, orientation, and standard deviation.

2.3 Fall Detection Module

Phase 1 in Fig. 9 shows the flowchart of the fall detection algorithm. Data are recorded in three dimensions Ax, Ay and Az and then root-mean-square (RMS) of the recorded signal (Acc) is computed using Equation (7):

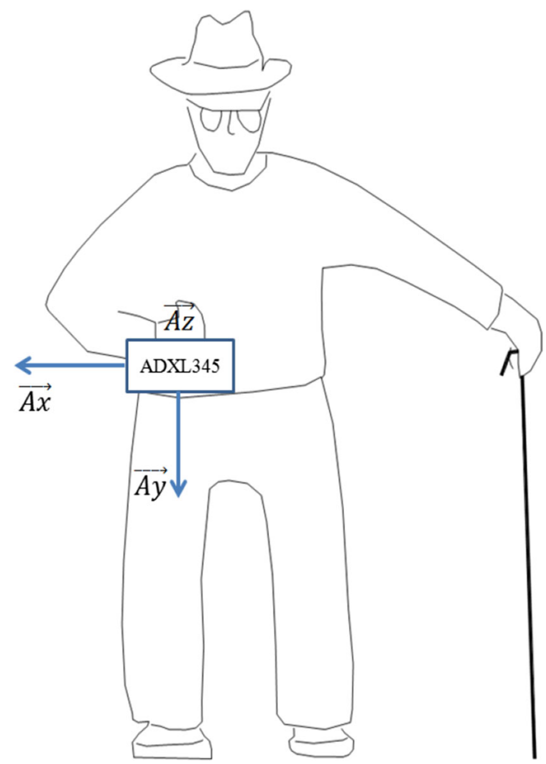


Fig. 4 Position of the 3-DOF accelerometer around the waist

$$\mathrm{Acc} = \sqrt{(Ax)^2 + (Ay)^2 + (Az)^2} \tag{7}$$

Next, the values of Acc will be compared with LFT (lower fall threshold) and UFT (upper fall threshold) to detect a fall. If Acc value is below LFT and above UFT with t_{FE} is greater than $t_{\mathrm{threshold}}$, it will be confirmed as a fall event [27]

$$t_{\mathrm{FE}} = \frac{\text{count}}{\text{frequency sampling}} \tag{8}$$

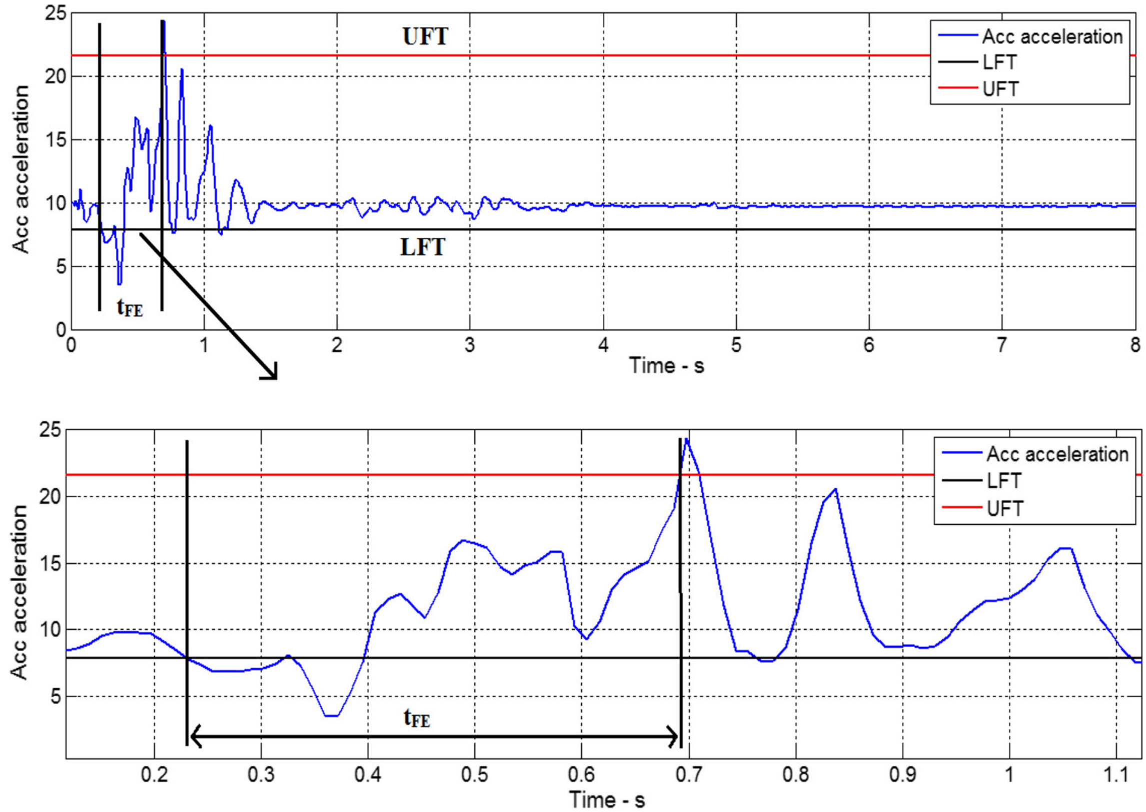


Fig. 5 A real fall event with UFT, LFT and t_{FE} threshold

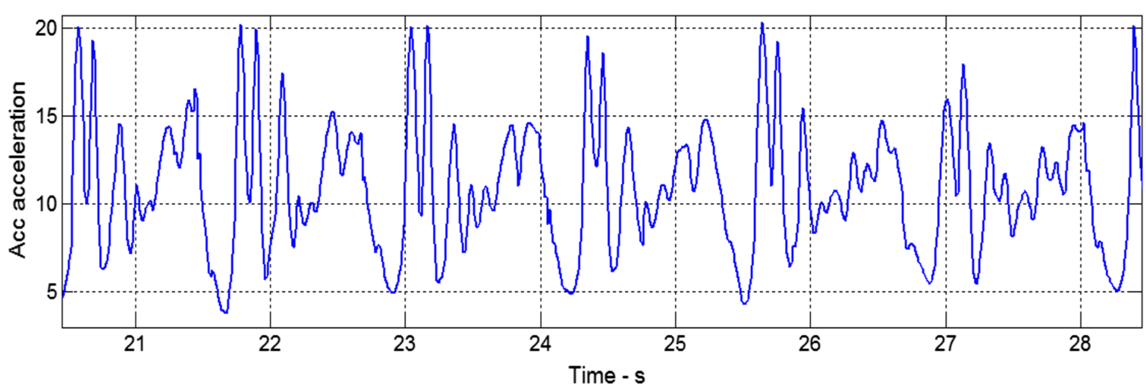


Fig. 6 Time cycle of six walking steps of an elderly

For the different types of falls such as downstairs-lying, forward-lying, backward-lying, sideward-lying, back-sitting-lying; the fall is divided into three periods: pre-fall, flight of fall, and post-fall. In period "flight of fall," Acc signal will decrease, and it will return to 1 g ($g = 9.81\ \text{m/s}^2$) when the body initially reaches the ground.

Figure 5 shows an example of a real fall event to illustrate a fall and threshold values of LFT, UFT, and t_{FE}. It can be clearly seen that when a fall event occurs, the recorded value of Acc is reduced below LFT threshold, then it will exceed UFT threshold with t_{FE} value is about 340 ms. After falling, the body gets into the rest state—the state of post-fall phase, the values of Acc is around $9.81\ \text{m/s}^2$.

2.4 Post-fall Recognition Module

The post-fall recognition module is a combination of posture recognition module and vertical velocity estimation, which are used to enhance the accuracy of our proposed system by checking twice with an interval of 0.5 s because the time cycle for each step execution in walking state is around 1s as shown in Fig. 6. The post-fall recognition module is checked

Table 2 Final decision of post-fall algorithms

Posture recognition module		Vertical velocity estimation		Final decision
1st time	2nd time	1st time	2nd time	
Fall occurred	Fall occurred	Fall occurred	Fall occurred	Fall occurred
One/some or all of them is/are No fall occurred				No fall occurred

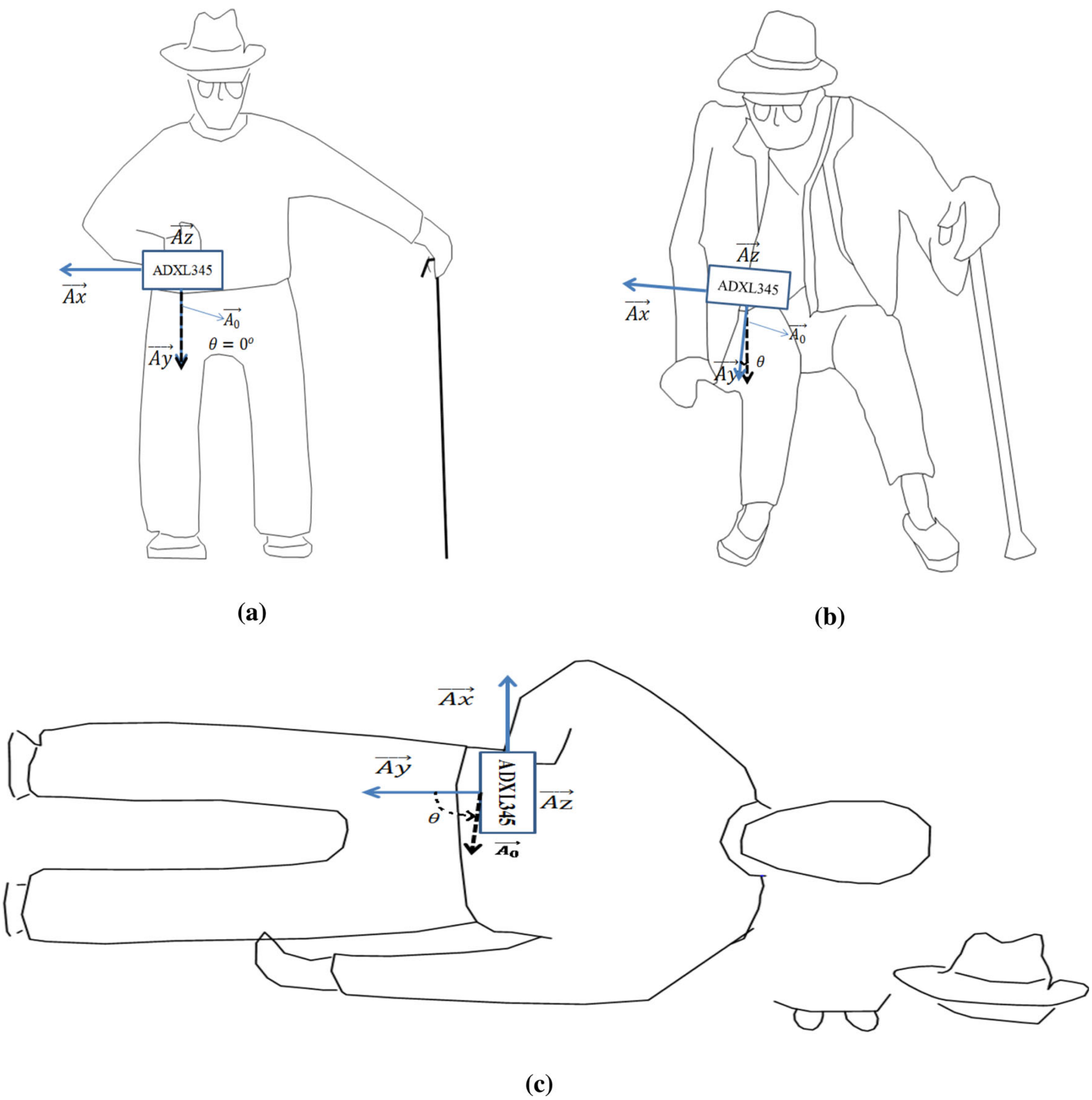


Fig. 7 Angle θ in standing (**a**), sitting (**b**) and lying (**c**) states

after fall detection module confirmed a fall event 2 s to ensure the body gets stable at the rest state after initially contacts with the ground.

A fall event is confirmed when it detected in both checking times. Others will be eliminated automatically, the details are shown in Table 2:

2.4.1 Posture Recognition Module

The post-fall posture recognition plays an essential role in our fall detection system. It is used to detect the angle θ between Ay and gravity. The accelerometer is positioned around the waist; Ay is parallel with gravity acceleration in standing state as in Fig. 7a. Hence, the θ angle in standing state is around 0°, it changes when the person carrying the device is in walking or other active states. The postures of the elderly are detected using Eq. (9) to determine the θ angle:

$$\theta = \cos^{-1}\left(\frac{A_y}{\sqrt{A_x^2(t) + A_y^2(t) + A_z^2(t)}}\right)\frac{180}{\pi}\ \text{(degree)} \tag{9}$$

In sitting state, the angle θ between A_y and the gravity vectors is changed, but the value is smaller than that in lying state as in Fig. 7b, c.

2.4.2 Vertical Velocity Estimation

Besides using Acc value to detect the fall, the vertical velocity is also added to our proposed algorithm to enhance the accuracy of the system. In period "flight of fall," the vertical velocity will increase and it reaches a maximum vertical velocity when the body initially reaches the ground. After falling, the body will change to rest state (post-fall period) and vertical velocity will fluctuate around 0 m/s. Hence, the estimation of vertical velocity is essential to distinguish between rest and active states. After the gravity is removed, the vertical velocity at the rest states should fluctuate around 0 m/s. Equation (10) is a condition to check the state of the user:

$$V = \int_a^b \left(\sqrt{A_x^2(t) + A_y^2(t) + A_z^2(t)} - 9.81\right)\mathrm{d}t \tag{10}$$

where, $a = \frac{m}{Fs}$, $b = \frac{m+1}{Fs}$ with $m = 0$: *number of data samples*

$$V < v_{\text{threshold}} \tag{11}$$

where, $v_{\text{threshold}}$ is the threshold to distinguish between rest and active states. If Eq. 11 is satisfying, the algorithm will confirm the state of the user is the rest state, others are active states.

2.5 The Software Application Algorithm

The proposed algorithm in smartphones is shown in Fig. 8. When this software is installed on smartphones, it will be checking the callers and states of the phones. If the call is from the emergency contacts list and the status of the phone is silent mode, this software application will automatically switch the phone to normal mode (i.e., including ringing and vibrating) to avoid missing phone calls from the elderly's falling device since a fall can occur at anytime, anywhere while the relatives may turn the phone to silent mode in important meetings or before sleeping. In Vietnam, there are a large number of fall cases for the elderly when going to toilet at midnight [28] while the young have a habit to switch the phone to silent mode and puts it away to avoid being disturbed. Hence, this is an incredibly meaningful application which has not been included in any published research.

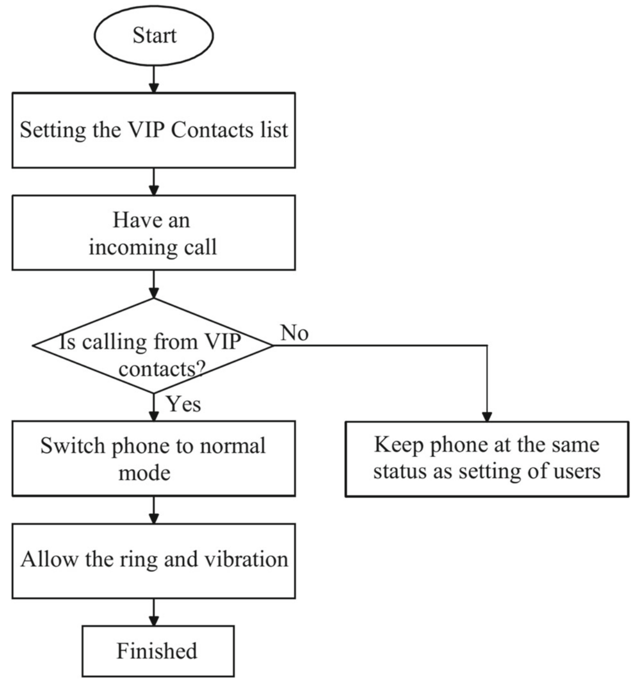


Fig. 8 Software application algorithm

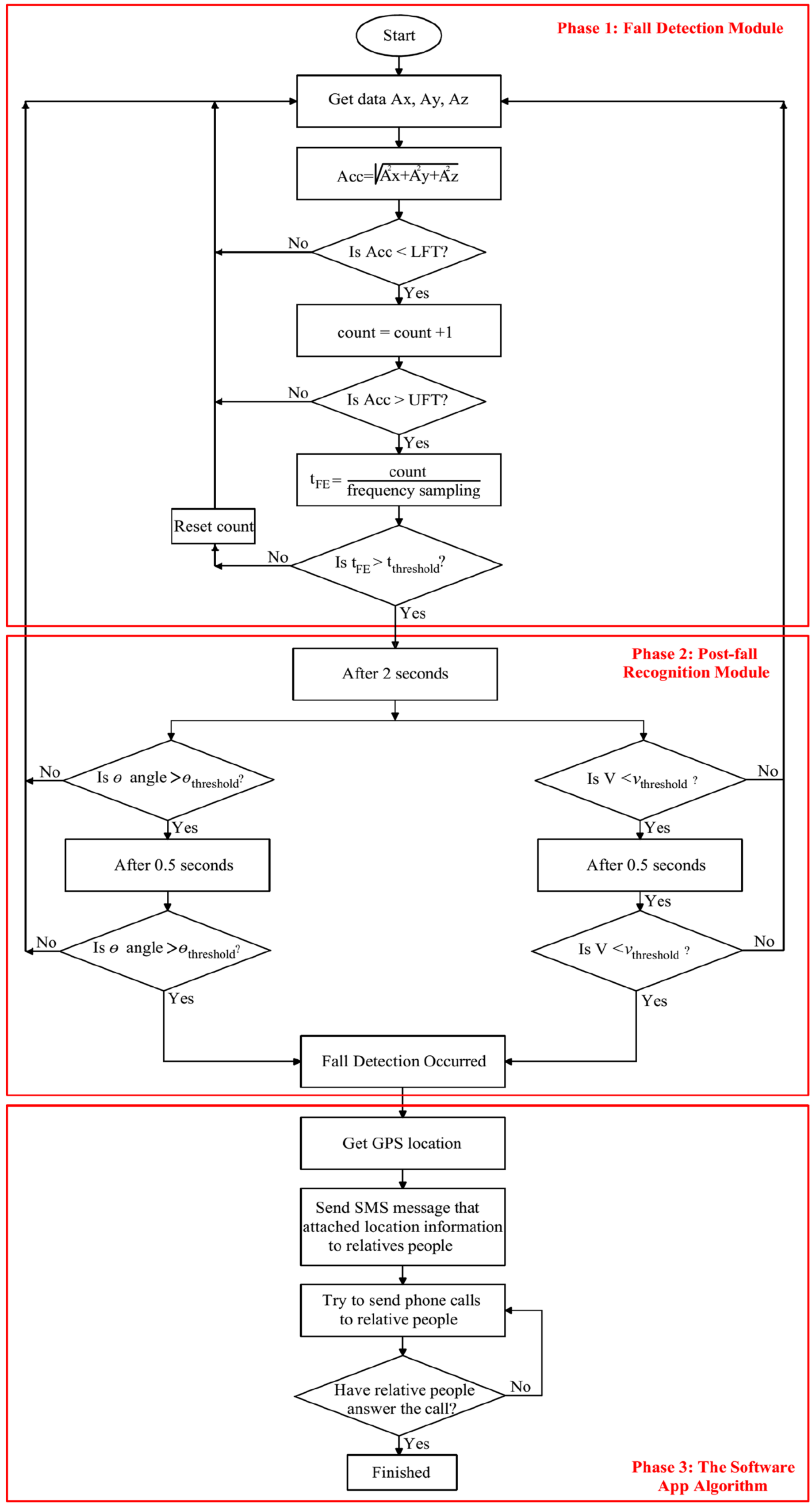
2.6 Final Decision

The proposed algorithm of our system includes three phases as shown in Fig. 9: Phase 1 is fall detection module, Phase 2 is post-fall recognition module and Phase 3 is the software application algorithm. Firstly, in Phase 1, the accelerometer senses acceleration in three dimensions based on the falling features in accelerations for fall detection. If an event satisfies the conditions in Phase 1, the algorithm will turn to Phase 2, the post-fall algorithms are used to recognize the states of the users carrying the device. The final fall decision is confirmed by both fall detection module and post-fall recognition module. If a fall event occurs, the GSM/GPS modem will get the fall position and attach it to messages with content "Serious fall has occurred at link + fall position" to send to relatives, nurses and/or hospitals. Then, the device attempts to send phone calls to relatives in priority until they answer or reject it. The details of the final decision are shown in Fig. 9.

2.7 The proposed fall detection system

Figure 10 shows the actual model of our proposed system. The hardware device runs independently after being embedded the best threshold values into MCU. Our device is assembled in a fixed bag and held on the waist to collect data in Ax, Ay, and Az axes which is sent to MCU for pro-

Fig. 9 Proposed algorithm flowchart



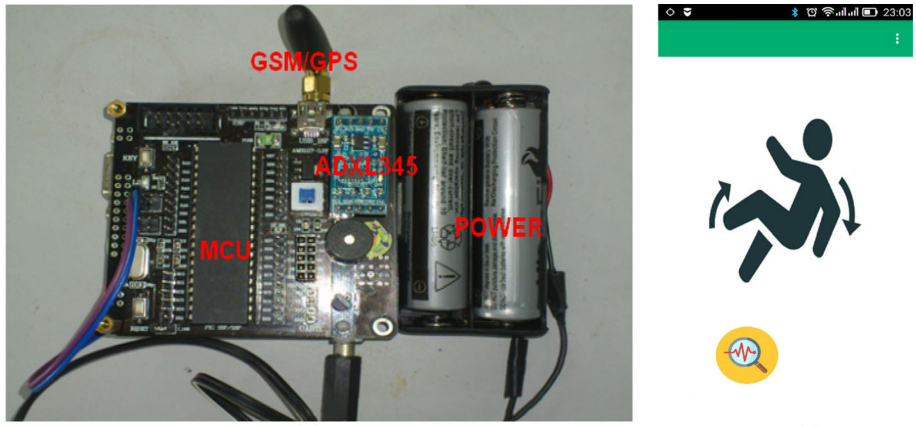


Fig. 10 Our proposed fall detection system **a** hardware device, **b** software application

Fig. 11 A volunteer is wearing the fall detection device

cessing to detect and confirm the fall. If it is a true fall, the alert message attached with falling position will be sent to relatives/ nurses/hospitals via GSM/GPS modem.

The software application has an interface as in Fig. 10b, after clicking "start button," the application will check the incoming calls. If the incoming calls are from an emergency contact list and the state of the phone is silent, our proposed software will switch the phone to normal mode to avoid missing the calls about falling events. This is an important feature of the application because it ensures the fall event being notified to the relatives.

3 Results and Discussion

3.1 Experimental Setup

For the experimental testing, we tested on 110 sets and 14 students (7 males and 7 females), ages: 18–22, height: 1.56–

Table 3 Features of our recorded data and the public datasets

	Public datasets (MobiFall datasets [29])	Our recorded datasets
Experiments		
No. Volunteers	11	16 (14 students and 2 elders)
Recorded from	Samsung Galaxy S3	3-DOF (ADXL345)
Position	Pocket	Waist
Types of falls	Forward-lying, front-knees-lying, sideward-lying and back-sitting-lying	Downstairs-lying, forward-lying, backward-lying, sideward-lying, back-sitting-lying
Types of ADLs	Standing, walking, jogging, jumping, stairs up, stairs down, sitting chair, car-step in, car-step out	Standing, walking, downstairs, upstairs, sitting chair
No. ADLs	486	240
Samples		
No. falls	288	210
Transition between the activities	Not specific	42 (standing–walking–sitting–walking–lying)
Sampling frequency	100 Hz	50 Hz
Acc. range	2 g	2 g

Table 4 Threshold values and units of the different parameters used for fall detection

Thresholds	Value	95% Confidence interval in falls (CI)	Unit
UFT	2.2	2.40–2.67	g
LFT	0.80	0.40–0.66	g
t_{FE}	200	389.02–600.77	ms
$\theta_{threshold}$	60°	74.23–88.02	degree
$v_{threshold}$	0.2	0.019–0.107	m/s

Table 5 Algorithms in Validated with Our Recorded and Other Public Datasets

Datasets	The testing results		
	Sensitivity	Specificity	Accuracy
Our recorded datasets			
Falls datasets	100%		100%
ADLs datasets		100%	100%
MobiFall datasets			
Falls datasets	100%		100%
ADLs datasets		100%	100%

1.75 m, weight: 46-65 kg who were randomly selected from a large number of students in Vietnam National University, Hanoi and 2 elderly people aged between 65 and 72, height: 1.4 m and 1.46 m, weight: 38 kg and 42 kg to obtain actual daily activities data. The volunteers wore the devices around the waist, which was the most comfortable position (see Fig. 11). A part of ADLs data were recorded from the elderly, and most of data were recorded from the students who were equipped with the devices and followed the elderly motions and try to execute various kinds of falls and ADLs to prevent injuries. Furthermore, this device was investigated with many single ADLs or combined ADLs, the data will be brought to computers for analyzing and extracting suitable thresholds.

3.2 Calibration and Testing

3.2.1 Calibration and Testing on Our Recorded and Public Datasets

We recorded data from 16 volunteers and they tested each type of falls, ADLs and transition between the activities three trial times in each. For the elderly volunteers, fall data were not recorded to avoid the accidents. The details about our features of recorded data are in Table 3.

In order to protect the elderly's lives, we have tested our proposed algorithms with publicly available data to compare the performance of the proposed algorithms on both our recorded data and the public datasets. Table 3 shows the features of the public datasets [29], available online [accessed 05.02.16]. Public datasets are an important part of self-evaluation the current proposed algorithms with a variety of fall events and ADLs activities. Based on the features in Table 3, the sampling of the public datasets were recorded at 100 Hz with the minimum range (2 g).

To evaluate the proposed method, we used four of the following factors: True positive (TP) factor to determine whether a fall occurred and the device can detect it, false-positive (FP) factor to determine whether a normal activity can be declared as a fall; true- negative (TN) factor to determine whether a fall-like event is declared correctly as a normal activity, and false-negative (FN) factor to determine whether a fall occurs, but the device cannot detect it [30]. Next, the sensitivity, specificity, and the accuracy of the method can be evaluated by the following equations:

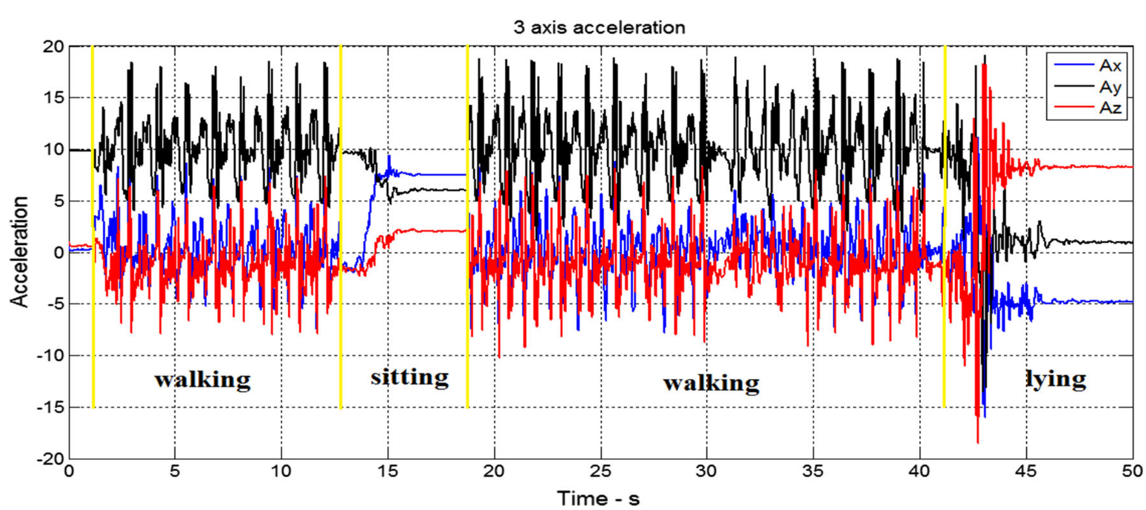
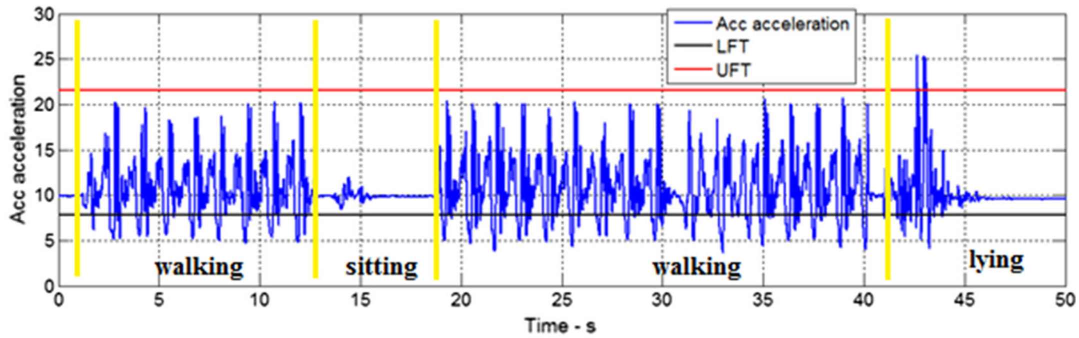
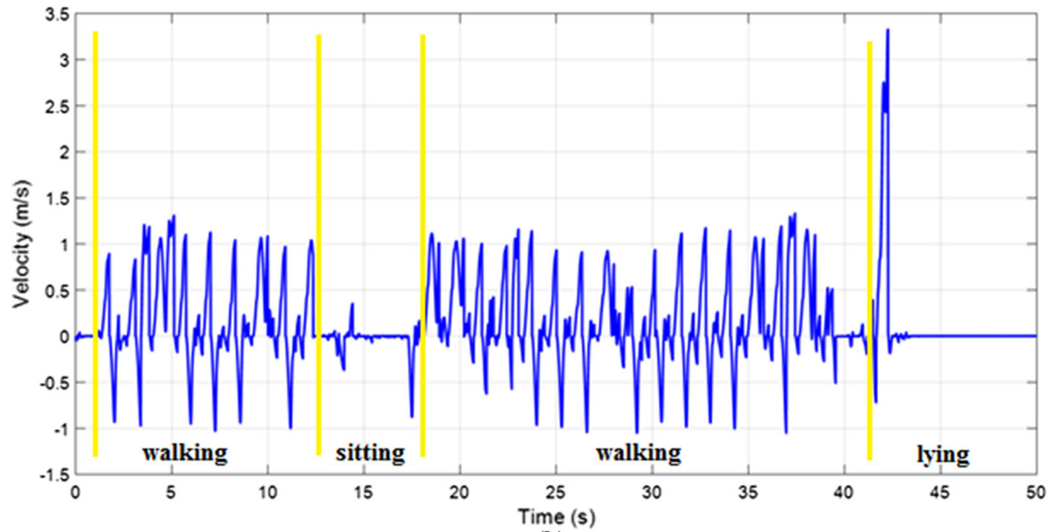


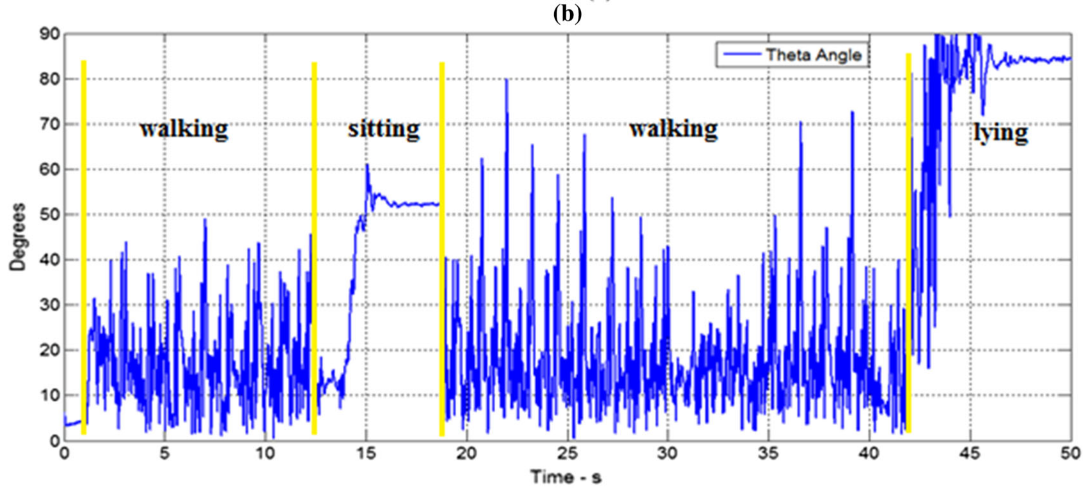
Fig. 12 Acceleration recorded along three axes Ax, Ay and Az



(a)



(b)



(c)

Fig. 13 A_n acceleration, velocity and theta angle when transiting between activities: standing–walking–sitting–walking–lying **a** Acc acceleration and UFT, LFT thresholds, **b** Velocity, **c** theta angle

$$\text{sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (12)$$

$$\text{specificity} = \frac{\text{TN}}{\text{FP} + \text{TN}} \quad (13)$$

$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (14)$$

where, sensitivity for checking the algorithm to correctly detect falls, specificity for checking the algorithm to correctly detect non-fall (ADLs activities) and accuracy for checking the algorithm to correctly detect falls and non-falls in data. Based on the public datasets, it can be seen that there are some types of ADLs that are not applicable to the elderly

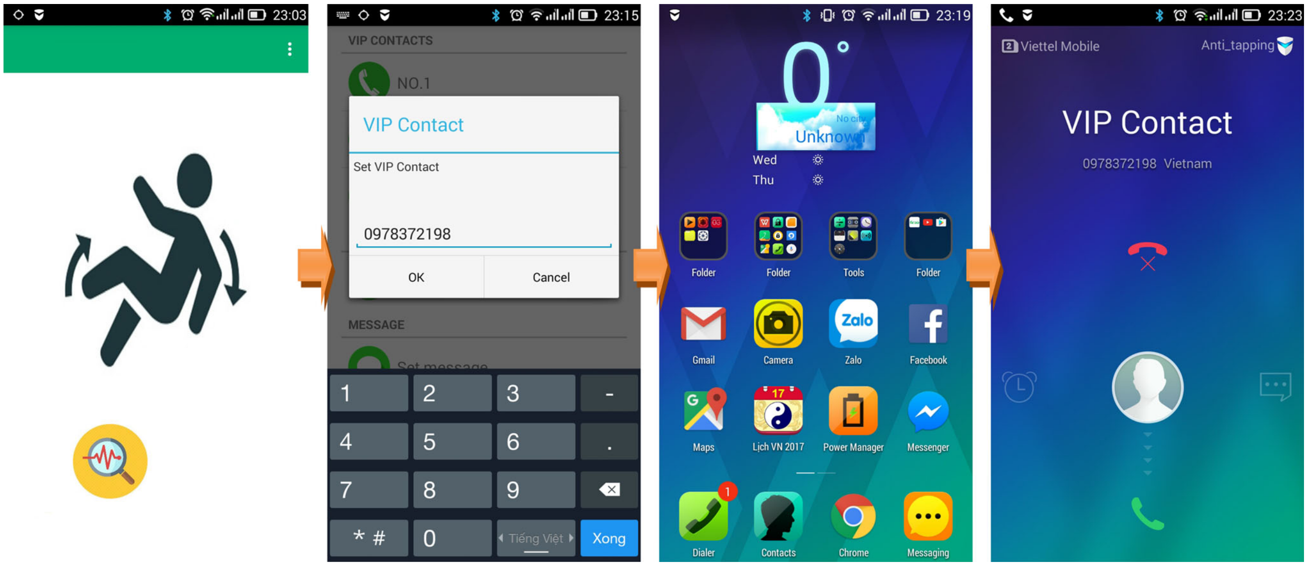


Fig. 14 Setting VIP contact in fall monitor application and changing phone status from silent to normal mode when receiving phone calls from VIP contacts

Fig. 15 Message notification and address of the fall

because the elderly do not perform any complex and strenuous activities such as jumping and jogging. This research mainly focuses on developing the supporting system for the elderly who are living or staying at home alone. Hence, we have discarded jumping and jogging activities in public datasets for testing our proposed algorithms.

The experiment results by using Eqs. (12), (13), (14) are given in Table 5. Firstly, from Table 5 can be seen that our proposed method combined fall detection module, posture recognition module and vertical velocity estimation (the threshold of these parameters as in Table 4. These thresholds are very important to determine the system performance as shown in Table 5.) correctly detects all the fall events (forward-lying, front-knees-lying, sideward-lying, back-sitting-lying, downstairs-lying and back-sitting-lying) with high sensitivity and accuracy of 100% in both our recorded datasets and public datasets. Furthermore, no ADLs activities (standing, walking, downstairs, upstairs, sit chair) were declared as fall events both in our recorded datasets and in public datasets.

Figure 12 shows acceleration recorded along three axes Ax, Ay, and Az when transiting between the following four activities: standing, walking, sitting, walking, and lying.

In Fig. 13a, b, A_n acceleration and vertical velocity changed suddenly when a fall event occurred. These values exceeded the LFT, UFT and t_{FE} thresholds. Then, the body changed to post-fall phase, the values of A_n acceleration measured around 9.81 m/s^2, the vertical velocity equals to 0 m/s with small fluctuation and the theta angle also changed to about 85° (see Fig. 13c).

3.2.2 The Testing Results on Android Smartphone

After setting VIP contacts (the contacts including emergency numbers) as shown in Fig. 14 if the caller exists in the VIP contacts, the application software on the smartphone will be allowed to switch the phone from silent mode to normal mode (i.e., including ringing and vibrating). The code below is the key string to change the phone status on android from silent to normal mode when receiving the incoming calls from VIP contacts.

```
if (!PhoneStatus.isReady()){
if(incommingNumber.equals(phone1)
||incommingNumber.equals(phone2)||
incommingNumber.equals(phone3)){
am.setRingerMode(AudioManager.RINGER
_MODE_NORMAL);
```

Figure 15 shows the received message content of the user's relatives. After receiving this message, the relatives simply click on the link to see the accident location on the map.

4 Conclusions

In this paper, we have presented the design and testing of a prototype system for fall detection using a 3-DOF accelerometer, a MCU, a GSM/GPS module, the complete algorithm embedded in MCU and a smartphone application. In this system, post-fall posture recognition module dramatically improved the accuracy of the fall detection device. Furthermore, a software application was developed to improve the efficiency and completeness of the proposed system in saving life of aged people in Vietnam by allowing it to request medical attention urgently in case of a fall. The tested results, which were conducted carefully on 110 hardware devices and mobile software app by 16 volunteers, indicated that the accuracy of our proposed system can achieve 100% in fall detection.

The proposed algorithm is simple, but it is effective with high performance and accuracy. The computation is small; thus, the system works in real time. The limitations of this device are that the axes of accelerometer need to be fixed on the waist as shown in Fig. 4. Moreover, most of our recorded data were performed by young volunteers, who tried to execute various kinds of falls and ADLs like the elderly. The performance may slightly degrade with the real elderly. In the near future, more work is needed to add into our research such as the pressure and heart rate (pulse sensor) sensors will be integrated into our proposed system for blood pressure and heart rate measurement to monitor and better predict fall events. Furthermore, we will develop the software application for IOs, window phone operating systems to support the relatives who are using Apple and Microsoft products.

Acknowledgements The analysis and write-up were carried out as a part of the first author's Ph.D. studies at Faculty of Electronics and Telecommunication, VNU University of Engineering and Technology, Hanoi, Vietnam. We would like to thank two anonymous reviewers for their valuable comments.

Compliance with ethical standards

Conflict of interest The authors declare no conflict of interest.

References

1. Dobriansky, P.J.; Suzman, R.M.; Hodes, R.J.: Why Population Aging Matters—A Global Perspective. National Institute On Aging (2007)
2. Gorang, E.: Take small steps to prevent elderly falls. Literally (Sept 2014). [Online]. https://healthcare.utah.edu/healthfeed/postings/2014/09/092614_elderly.fall.php. Accessed 16 July 2016
3. Pannurat, N.; Thiemjarus, S.; Nantajeewarawat, E.: Automatic fall monitoring: A review. Sensors **14**, 12900–12936 (2014)
4. Bourke, A.K.; van de Ven, P.; Gamble, M.; O'Connor, R.; Murphy, K.; Bogan, E.; McQuade, E.; Finucane, P.; O'Laighin, G.; Nelson, J.: Evaluation of waist-mounted tri-axial accelerometer based fall-detection algorithms during scripted and continuous unscripted activities. J. Biomech. **43**, 3051–3057 (2010)
5. Lim, D.; Park, C.; Kim, N.H.; Kim, S.-H.; Yu, Y.S.: Fall-detection algorithm using 3-axis acceleration: combination with simple threshold and hidden Markov model. J. Appl. Math. **2014**, 896030 (2014). https://doi.org/10.1155/2014/896030
6. Stone, E.; Skubic, M.: Evaluation of an inexpensive depth camera for passive in-home fall risk assessment. In: Proceedings of 5th International ICST Conference on Pervasive Computing Technologies for Healthcare, pp. 71–77 (2011)
7. Mazurek, P.; Morawski, R.Z.: Application of Naïve Bayes classifier in a fall detection system based on infrared depth sensors. In: The 8th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications, vol. 2, pp. 717–722 (2015)
8. Bevilacqua, V., et al.: Fall detection in indoor environment with kinect sensor. In: Proceedings of IEEE International Symposium on Innovations in Intelligent Systems and Applications, pp. 319–324 (2014)
9. Planinc, R.; Kampel, M.: Introducing the use of depth data for fall detection. Pers. Ubiquitous Comput. **17**, 1063–1072 (2013)

10. Zhang, C.; Tian, Y.; Capezuti, E.: Privacy preserving automatic fall detection for elderly using RGBD cameras. In: Computers Helping People with Special Needs, vol. 7382, pp. 625–633 (2012)
11. Yang, S.-W.; Lin, S.-K.: Fall detection for multiple pedestrians using depth image processing technique. Comput. Mehtods Programs Biomed. **114**, 172–182 (2014)
12. Luštrek, M.; Gjoreski, H.; Kozina, S.; Cvetković, B.; Mirchevska, V.; Gams, M.: Detecting falls with location sensors and accelerometers. In: Twenty-Third IAAI Conference, pp. 1662–1667 (2011)
13. Mellone, S.; Tacconi, C.; Schwickert, L.; Klenk, J.; Becker, C.; Chiari, L.: Smartphone—based solutions for fall detection and prevention: the FARSEEING approach. Z. Gerontol. Geriatr. **45**(8), 722–727 (2012)
14. Gjoreski, H.; Luštrek, M.; Gams, M.: Accelerometer placement for posture recognition and fall detection. In: 7th International Conference on Intelligent Environments (IE), pp. 47–54. IEEE, Nottingham (2011)
15. Moussa, M.M.; Hemayed, E.E.; El Nemr, H.A.; Fayek, M.B.: Human action recognition utilizing variations in skeleton dimensions. Arab. J. Sci. Eng. (2017)
16. Abbate, S.; Avvenuti, M.; Bonatesta, F.; Cola, G.; Corsini, P.; Vecchio, A.: A smartphone—based fall detection system. Pervasive Healthc. **8**, 883–899 (2012)
17. Cao, Y.; Yang, Y.; Liu, W.H.: E-FallD: a fall detection system using android—based smartphone. In: 9th International Conference on Fuzzy Systems and Knowledge Discovery, pp. 1509 – 1513 (2012)
18. He, Y.; Li, Y.; Bao, S.-D.: Fall detection by built—in tri—accelerometer of smartphone. In: Proceedings of the IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI 2012) Hong Kong and Shenzhen, China, pp. 184 – 187 (2012)
19. Igual, R.; Medrano, C.; Plaza, I.: A comparison of public datasets for acceleration-based fall detection. Med. Eng. Phys. **37**, 870–878 (2015)
20. Gjoreski, M.; Gjoreski, H.; Gams, M.: How accurately can your wrist device recognize daily activities and detect falls? Sensors **16**, 800 (2016)
21. Park, C.; Kim, J.; Sohn, J.-C.; Choi, H.-J.: A wrist-type fall detector with statistical classifier for the elderly care. KSII Trans. Internet Inf. Syst. **5**(10), 1751–1769 (2011)
22. Liang, F.; Zhang, Z.; Li, X.; Tong, Z.: Lower limb action recognition with motion data of a human joint. Arab. J. Sci. Eng. **41**, 5111–5121 (2016)
23. Castillo, J.C.; Carneiro, D.; Serrano-Cuerda, J.; Novais, P.; Fernández-Caballero, A.; Neves, J.: A multi-modal approach for activity classification and fall detection. Int. J. Syst. Sci. **45**, 810–824 (2014)
24. Mostarac, P.; Malarić, R.; Jurčević, M.; Hegeduš, H.; AiméLay-Ekuakille, P.V.: System for monitoring and fall detection of patients using mobile 3-axis accelerometers sensors. In: IEEE International Workshop on Medical Measurements and Applications Proceedings (MeMeA), pp. 456–459 (2011)
25. Tomkun, J.; Nguyen, B.: Design of a fall detection and prevention system for the elderly. In: Electrical and Biomedical Engineering Design Project, Ontario, Canada (2010)
26. Das, S.; Green, L.; Perez, B.; Murphy, M.; Perring A.: Detecting User Activities Using the Accelerometer on Android Smartphones, Carnegie Mellon University (CMU), Pittsburgh, PA, USA. Technical Report (2010)
27. Bourke, A.K.; O'Brien, J.V.; Lyons, G.M.: Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm. Gait Posture **26**, 194–199 (2007)
28. Causes of Fall in Elderly in Vietnam. http://kienthuc.net.vn/tin-tuc/nguyen-do-nguoi-gia-hay-nga-444371.html. Accessed 16 July 2016
29. MobiFall dataset. http://www.bmi.teicrete.gr/index.php/research/mobiact. Accessed 05 Feb 2016
30. Noury, N.; Rumeau, P.; Bourke, A.; Laighin, G.; Lundy, J.: A proposal for the classification and evaluation of fall detectors. IRBM **29**, 340–349 (2008)