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

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Abstract

This paper proposes to develop of a low cost fall detection system to precisely detect an event where an elderly person accidentally falls. The fall detection algorithm compares the acceleration with Lower fall Threshold (LFT) and Upper Fall Threshold (UFT) 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 in our proposed method to enhance the performance and accuracy of it. In case of a fall, our device will transmit the location information to the contacts instantly via SMS and voice call. The smartphone application will ensure that the notification is delivered to the elderly person's relatives so medical attention can be provided with minimal delay. The system was tested with volunteers and achieved 100% sensitivity and accuracy. This was confirmed by testing with public data and it also achieved the same percentage in sensitivity and accuracy as in our recorded data.

Keywords: Lower fall Threshold (LFT), Upper Fall Threshold (UFT), post-fall, SMS, VIP contacts.

1. Introduction

Population aging is the trend in modern society [1] and the elderly are more likely to fall because of age, mental and physical diseases such as stress, high/low blood pressures, heart disease, knee pain, and falling stairs ~~up/down falling~~. The Fig.1 is an example of fall event in elderly, it will lead to many dangerous issues, even death if they do not receive immediate attention.

Based on the above statistical information, the authors proposed to develop an effective fall detection system to support the elderly, especially for ones living alone. There are a lot of published methods about fall detection in recent years such as image processing [5]-[8], [12]-[16], location sensors [17], smartphones [18]~~[18]~~, accelerometers [19]~~[19]~~ or wristband and smartwatches. However, these methods have certain limitations such as the systems are inconvenient, expensive and unsuitable in modern society.

Firstly, for the image processing approach [5]-[8], [12]-[16], the authors used different types of cameras to distinguish between Activities of Daily Living (ADLs activities) and fall risk detection in home environments such as depth Kinect camera of Microsoft, monitoring cameras. However it showed many drawbacks in the outdoor environments: the resolution of cameras, distance between camera and objects, target occlusion and privacy of users as well as when elderly person is outside of the camera's view. These limitations are the same in location sensor [17] method because it combined four tags on the body to detect locations via radio sensors and recognize the user's activity. It is a complex system, expensive and was not commercially successful.

The systems detect a fall through the built-in accelerometer in smartphones [18], [20]-[22] that can be used for both indoor and outdoor environments. However, the smartphones used different types of

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accelerometers. Hence, the algorithm's performance and accuracy of the systems are not the same in each type of smartphones [31]. Besides, fall detection will also be affected by incoming and outgoing calls, messaging and the mounted position. This method makes it difficult to integrate additional sensors such as heart rate, blood pressure etc.

Wristband and smart watches [38] [39] are more popular in recent researches because people can wear in hands which is one of the most comfortable positions. Nevertheless, it is a big challenge in fall detection because hands can move anytime and anywhere around the end-user. Then, 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)...to classify between fall events and daily activities is becoming popular in recently. It can detect most of the fall events [29] with high sensitivity and accuracy. But these methods are more sophisticated and it is hard to implement on MCU due to the amount of computations and data requirements making it the main cause of the high system cost [5] [6].

Another common method is using the low cost accelerometer available in the market, but the precision in fall detection is weak [19], [23]. These studies used 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 [24], [25]. In [19], the authors used at least three accelerometers to wear on three positions of the body, thus, this system is inconvenient and uncomfortable to the user. In [23], 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 in [24]. The publication [6] also used LFT, UFT and t_{FE} thresholds and theta angle, vertical velocity to estimate the fall with the high sensitivity and accuracy. However, this system cannot be considered as the completed system since the fall events were not sent out to a responsible person, or monitoring system.

To overcome above limitations, this paper mainly focuses on the development of an effective fall detection system. Our proposed fall detection system addresses two main contributions: the posture recognition module and software application to enhance the accuracy of the system and improve efficiency of seniors care. Compare with the related works, we propose the following approaches. Firstly, the hardware device will detect falling events automatically using fall detection module and post-fall recognition module. If a fall is confirmed, it will be checked by the post-fall posture after 2 seconds in two consecutive times to enhance the accuracy of the proposed device. Secondly, the communication model which is used to send appearance of a fall event to the monitoring system is designed. 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 hospital, nurse and relatives for emergency supporting, then the device tries to make phone calls to relatives in priority until answered or rejected to avoid missing the fall events. Third, we design a mobile software App, which is allowed to create alert messages on mobile phones even in cases where the phones 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.

2. System Design

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

2.1. System Architecture

The Fig. 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 sampling rate of 50Hz because elderly motion is quite slow with simple ADLs. Furthermore, the analyzed results in [31] showed that sampling at 100 Hz is not better than 50 Hz and the performance and accuracy of the device depends directly on the detection algorithms. Hence, a sampling frequency of 50 Hz was chosen to save energy.

In this design, two rechargeable batteries (3.7V and 3000mAh) 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 equation (1).

The specification of the Lithium battery is 3.7V–6000mAh and the battery power is 3.7V×6000mAh = 22200mWh. Therefore, the battery lifetime of device in running mode equals the total of power consumption of components from i=1:N, that includes MCU, ADXL345 and SIM808:

$$\frac{22200\text{mWh}}{96.2851\text{mW}} = 230 \text{ hours} = 9.6 \text{ days} \tag{1}$$

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

2.2. The 3-DOF Acceleration Sensor

The accelerometer is at the heart of the proposed device, and it was calibrated carefully through the measurement process in each axi~~e~~s, 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 equation (2):

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

K may be positive or negative depending on real value of a^+ and a^- measured in each axes. Then, $a'^+=K.a^+$ and $a'^-=K.a^-$. Based on a'^+ and a'^- to the Offset value can be found using E~~e~~quation (3):

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

Based on Offset value, acceleration in each axes can be estimated using equation (4):

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

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:

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

and the measurement updates:

$$\begin{aligned} K_k &= \frac{P_k^-}{P_k^- + R} \\ \hat{x}_k &= \hat{x}_k^- + K_k(z_k - \hat{x}_k^-) \\ P_k &= (I - K_k)P_k^- \end{aligned} \tag{6}$$

where K_k is the Kalman gain, $\hat{x}_k$ is the estimate of the signal, $\hat{x}_k^-$ is the signal of the previous time step, P_k is the posteriori estimate error covariance, P_k^- is the priori estimate 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 than without using it (see Fig. 3), however it is still keeping 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 a small, thin, low power, 3-axis accelerometer with high-resolution (13-bit) measurement up to ±16g. Digital output data is 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. Under normal conditions, the expected reading of the accelerometer would be [0, 1, 0] g (with g=9.81 m/s^2). Next, the preprocessing step was applied to the filtered data before taking it into the attribute extraction module to compute the mean, orientation, and standard deviation.

2.3. Fall Detection Module

The Phase 1 in Fig. 9 shows the flow chart of the fall detection algorithm. Data is recorded in three dimensions Ax, Ay and Az, then Root Mean Square (RMS) of the recorded signal (Acc) is computed using the E~~e~~quation (7):

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

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 $t_{threshold}$, it will be confirmed as a fall event [26].

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

For the different type of falls such as downstairs-lying, forward-lying, backward-lying, sideward-lying, back-sitting-lying; the fall to be 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 1g (g=9.81 m/s^2) when the body initially reaches to ground.

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

Besides using Acc value to detect the fall, vertical velocity is also added in our proposed algorithm to enhance the accuracy of the system. In period “flight of fall”, the vertical velocity will increase and it reaches a~~to~~ maximum vertical velocity when the body initially reaches to ground. Hence, ~~formula~~Equation (9) was used to check the suddenly chang~~inge~~ in vertical velocity. If the vertical velocity is greater than $v_{threshold}$, the algorithm will confirm the fall.

$$\mathrm{V} = \int_a^b \left(\sqrt{\mathrm{A_x^2(t)} + \mathrm{A_y^2(t)} + \mathrm{A_z^2}(t)} - 9.81\right) dt \tag{9}$$

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

After falling, the body will change to rest state (post-fall period). In the post-fall period, the body gets to the rest state, the recorded values of Acc oscillate approximately the expected reading of [0, 1, 0] g and vertical velocity will fluctuate around 0 m/s.

2.4. Post-fall Recognition Module

The post-fall recognition module is a combination of posture recognition module and vertical velocity estimation after fall detection module detected fall event 2s. The post-fall is checked after 2s, because after falling, the body will be changed to rest state and 2s delay is used to avoid any fluctuation after the body reached to the ground. Our proposed algorithms will check the posture and vertical velocity in two consecutive times after 0.5s because most elderly people walk slowly without any complex activities and the time for each step cycle is around 1 second as shown in Fig. 6. Hence, a time interval of 0.5s is used to avoid two times of checking on peaks. A fall even is confirmed if both checking times result in a fall event. Others situation will be auto eliminated (see the Table 2 for more details).

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^o, it changes when the wearing person is in walking or others active states. The postures of elderly are detected using the scalar product of the reference gravity vector $\vec{A}_0$ and the vector at time (t) to determine the θ angle [6]:

$$\theta = \cos^{-1}\left(\frac{A_y}{\sqrt{A_x^2(t)+A_y^2(t)+A_z^2(t)}}\right)\frac{180}{\pi} \text{ (degree)} \tag{10}$$

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

2.4.2. Vertical Velocity Estimation

As discussion above, after falling the body will change to rest state. Hence, vertical velocity estimation is essential to distinguish between rest and active states. After remove the gravity, the vertical velocity at the rest states should fluctuate around 0 m/s. The following formula is a condition to check the state of user:

$$V < v_{threshold\_1} \tag{11}$$

where, $v_{threshold\ 1}$ is the threshold to distinguish between rest and active states. If the fomula 11 is satisfy, the algorithm will confirm the state of user is the rest state, others are active states.

2.5. The Software App Algorithm

The proposed algorithm in smartphone is shown in Fig. 8. When this software is installed on smartphone, it will be checking the callers and states of phone. If the calling from emergency contacts list and status of the phone is silent mode, this software app will be change the phone to normal mode (the mode is including ringing and vibrating) to avoid the missing phone calls from elderly falling device because fall can occur at anytime, anywhere while the relatives may turn phone to silent mode in important meeting or before sleeping. In Vietnam, there are a large number falls of elderly when going to toilet at mid-night [40]~~[40]~~ while young generation has habit to change phone to silent mode and put it away to avoid the disturbing from others. Hence, this is incredibly meaningful application which is not included in any published researches.

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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 P~~p~~hase 3 is the so~~l~~ftware app algorithm. Firstly, in Phase 1, the accelerometer senses in three dimensions based on the change of accelerations when falling 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 wearing. The final fall decision is confirmed by both fall detection module and post-fall recognition module. If a fall event is occurred, the GSM/GPS modem will get the fall position and attach to massages with content "Serious fall has occurred at link + fall position" to send to relatives, nurses and/or hospitals. Then, the device tries to send phone calls to relatives in priority until they are answered or rejected it. The details of the final decision are shown in Fig. 9.

2.7. The proposed fall detection system

The Fig. 10 shows the actual model of our proposed system. The hardware device runs independently after embedded the best threshold values into MCU. The working principle as the ADXL345 sensor was assembled in a fixed bag and held on the waist to collect data in Ax, Ay, Az axes which ~~, then~~ data is sent to the microcontroller for processing to detect and confirm the fall. If it is a true fall, the alert message that attached falling position will be sent to relative/ nurses/hospitals via GSM/GPS modem.

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

3. Results and discussions

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 – 1.75 m, weight: 46-65 kg who were randomly selected from various students in Vietnam National University Hanoi and 2 elderly aged between 65 and 72, height: 1.4 m and 1.46 m, weight: 38 kg and 42 kg to get 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 elderly, and most of data were recorded from the students who were equipped the devices and followed the elderly motions and try to execute various kinds of falls and ADLs to avoid elderly’s injuries. Furthermore, this device was investigated with many single ADLs or combined ADLs, the data will be brought to computers to analysis and take suitable thresholds.

3.2. Calibration and Testing

3.2.1. Calibration and testing on our recorded and public datasets

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

In order to protect the lives of the elderly, 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 data. The Table 3 is the features of the public data [35], available online [accessed 05.02.16]. Public data is an important part to self-evaluation the current proposed algorithms with variety of fall events and ADLs activities. Based on the features in Table 3 can be seen that the sampling the public data were recorded at 100Hz with the minimum range (2g).

To evaluate the proposed hardware device, we used four of the following factors: True positive (TP) factor to determine if a fall occurred and the device can detect it, False Positive (FP) factor to determine if a normal activity can be declared as a fall; True Negative (TN) factor to determine if a fall-like event is declared correctly as a normal activity, and False Negative (FN) factor to determine if a fall occurs, but the device cannot detect it [28].

Next, the sensitivity, specificity and the accuracy of the device can be evaluated by the following equations:

$$sensitivity = \frac{TP}{TP + FN} \tag{12}$$

$$specificity = \frac{TN}{FP + TN} \tag{13}$$

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{14}$$

where, $sensitivity$ used for checking the algorithm in detect correctly falls, $specificity$ used for checking the alogirthm in detect correctly non-fall (ADLs activities) and $accuracy$ used for checking the algorithm in detect correctly falls and non-falls in data. Based on the public data, it can be seen that there are some types of ADLs that are not applicable to the elderly because elderly do not perform any complex and high activities such as jumping, jogging. This paper mainly focus on developing the supporting system for elderly who are living or staying at home alone. Hence, we have discarded jumping, jogging activities in public data for testing our proposed algorithms.

The experiment testing results are given in Table 5 by using the F~~f~~ormula 12, 13, 14~~-~~. Firstly, as in Table 5 can be seen that, when we used only fall detection module, it can detect very well the fall events with sensitivity and accuracy of 100% in both our recorded datasets and public datasets. Nevertheless, some of ADLs activities in both our recorded datasets and public datasets are declared as fall events such as sitting chair when we used fall detection module only or combined fall detection module with posture recognition or vertical velocity with 98.6%, 99.5%, 99.5% and 99.6%, 100%, 99.6% respectively in our recorded datasets and public datasets.

Our proposed method combined fall detection module, posture recognition module and vertical velocity estimation (the threshold of these parameters as in Table 4)detect correctly 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 ~~in~~ both in our recorded data and public data when using our proposed method.

The Fig. 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 and Fig. 13b, A_n acceleration and vertical velocity changed suddenly when a fall event occurred, these values exceeded the LFT, UFT, t_{FE} and $V_{threshold}$ 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 zero with small fluctuation and the theta angle also changed to about 85^o (see Fig. 13c).

In order to improve the performance and accuracy of our proposed hardware device, we proposed to check two consecutive times with 0.5s intervals in post-fall recognition module.

3.2.2. The testing results on Android smartphone

After setting VIP contacts (the contacts include emergency numbers) as shown in Fig. 14. If the caller is existing in the VIP contacts, the application software on smartphone will be allowed to change the phone from silent mode to normal mode with ringing and vibrating. This condition is important because elderly may live or stay at home alone, the relatives may change the phone to silent during their activities and they might miss the emergency calls in case of a fall event. 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);
```

The Fig. 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 in 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 micro controller, a GSM/GPS module and the corresponding embedded algorithms complete with a smartphone application. In this system, post-fall posture recognition has been built in to dramatically improve 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 elderly in Vietnam by allowing it to request medical attention urgently in case of a fall. The tested results, which were conducted carefully 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 system works in ~~realtime~~real-time. Nevertheless, the axes of accelerometer need to fix on the waist as shown in Fig. 4. Moreover, most of our recorded data performed by young volunteers and they try to execute various kinds of falls and ADLs as elderly. However, the simulated falls and ADLs are difference with real conditions. Hence, the performance of the proposed algorithm may be different~~reduce~~ in real conditions.

In the near future, more sensors such as pressure sensor, heart rate sensor ~~are~~will be integrated into our proposed system for blood pressure and heart rate measurement to monitor and better predict fall events.

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

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

TABLE 3. THE FEATURES OF OUR RECORDED DATA AND THE PUBLIC DATA

		Public data (MobiFall data [35]~~[35]~~)	**Our recorded data**
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	2g	2g

TABLE 4. THRESHOLD VALUES AND UNITS OF THE DIFFERENT PARAMETERS USED FOR FALL DETECTION

Threshold	Value	Unit
UFT	2.2	G
LFT	0.80	g
t_{FE}	200	ms

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$\theta_{\text{threshold}}$	60^o	degree
$v_{\text{threshold}}$	1.4	m/s
$v_{\text{threshold\_1}}$	0.2	m/s

TABLE 5.THE ALGORITHMS IN VALIDATED WITH OUR RECORDED AND OTHER PUBLIC DATASETS

Datasets		**Algorithms**	**The testing results**		
			Sensitivity	**Specificility**	**Accuracy**
Our recorded datasets	Falls datasets	Fall detection module	100%		100%
		Fall detection module + Posture Recognition Module ($\theta_{\text{threshold}}$)	100%		100%
		Fall detection module + Vertical velocity estimation ($v_{\text{threshold\_1}}$)	100%		100%
		Our proposed algorithm (Fall detection module + Posture Recognition Module ($\theta_{\text{threshold}}$) + Vertical velocity estimation ($v_{\text{threshold\_1}}$)**)**	**100%**		**100%**
	ADLs datasets	Fall detection module		98.6%	98.6%
		Fall detection module + Posture Recognition Module ($\theta_{\text{threshold}}$)		99.5%	99.5%
		Fall detection module + Vertical velocity estimation ($v_{\text{threshold\_1}}$)		99.5%	99.5%
		Our proposed algorithm (Fall detection module + Posture Recognition Module ($\theta_{\text{threshold}}$) + Vertical velocity estimation ($v_{\text{threshold\_1}}$)**)**		**100%**	**100%**
MobiFall datasets	Falls datasets	Fall detection module	100%		100%
		Fall detection module + Posture Recognition Module ($\theta_{\text{threshold}}$)	100%		100%
		Fall detection module + Vertical velocity estimation ($v_{\text{threshold\_1}}$)	100%		100%
		Our proposed algorithm (Fall detection module + Posture Recognition Module ($\theta_{\text{threshold}}$) + Vertical velocity estimation ($v_{\text{threshold\_1}}$)**)**	**100%**		**100%**
	ADLs datasets	Fall detection module		99.6%	99.6%
		Fall detection module + Posture Recognition Module ($\theta_{\text{threshold}}$)		100 %	100%
		Fall detection module + Vertical velocity estimation ($v_{\text{threshold\_1}}$)		99.6%	99.6%
		Our proposed algorithm (Fall detection module + Posture Recognition Module ($\theta_{\text{threshold}}$) + Vertical velocity estimation ($v_{\text{threshold\_1}}$)**)**		**100%**	**100%**

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

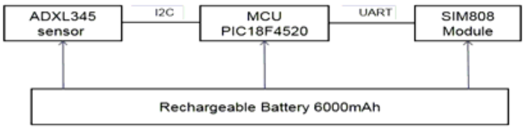


Fig. 2. Block diagram of the fall detection device

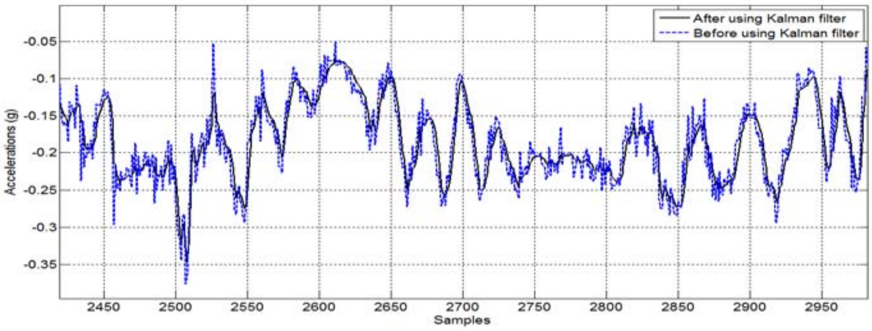


Fig. 3. The recorded data before and after using Kalman filter

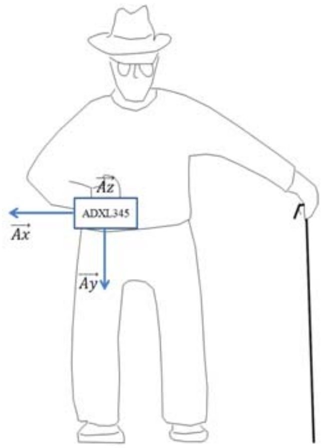


Fig. 4. Position of the 3-DOF accelerometer around the waist

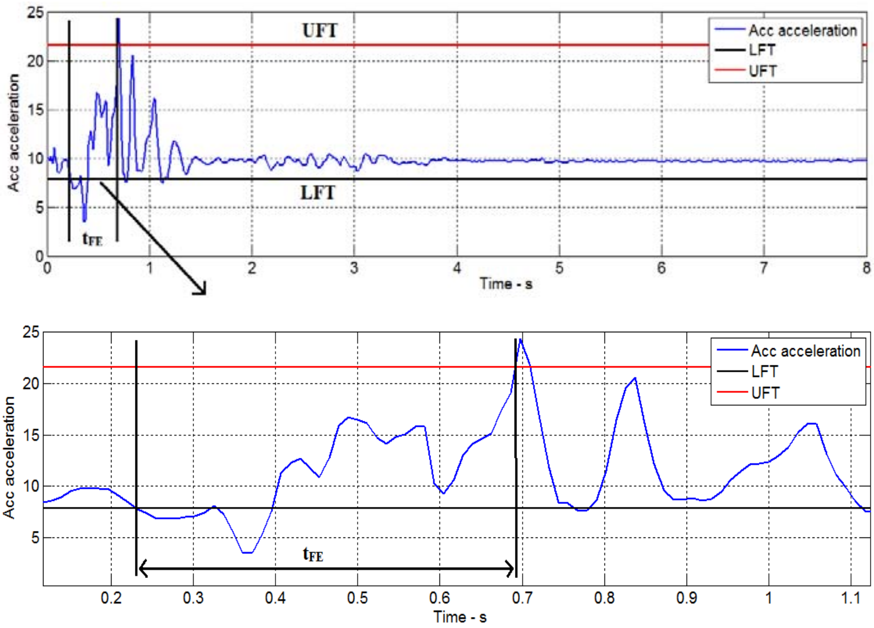


Fig. 5. A real fall event with UFT, LFT and t_{FE} threshold

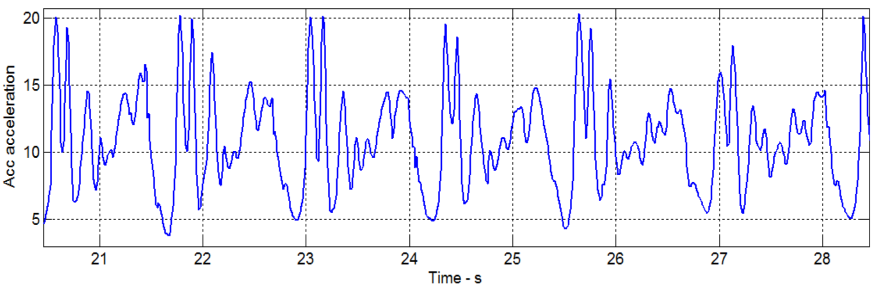


Fig. 6. Time cycle of 6 walking steps of an elderly

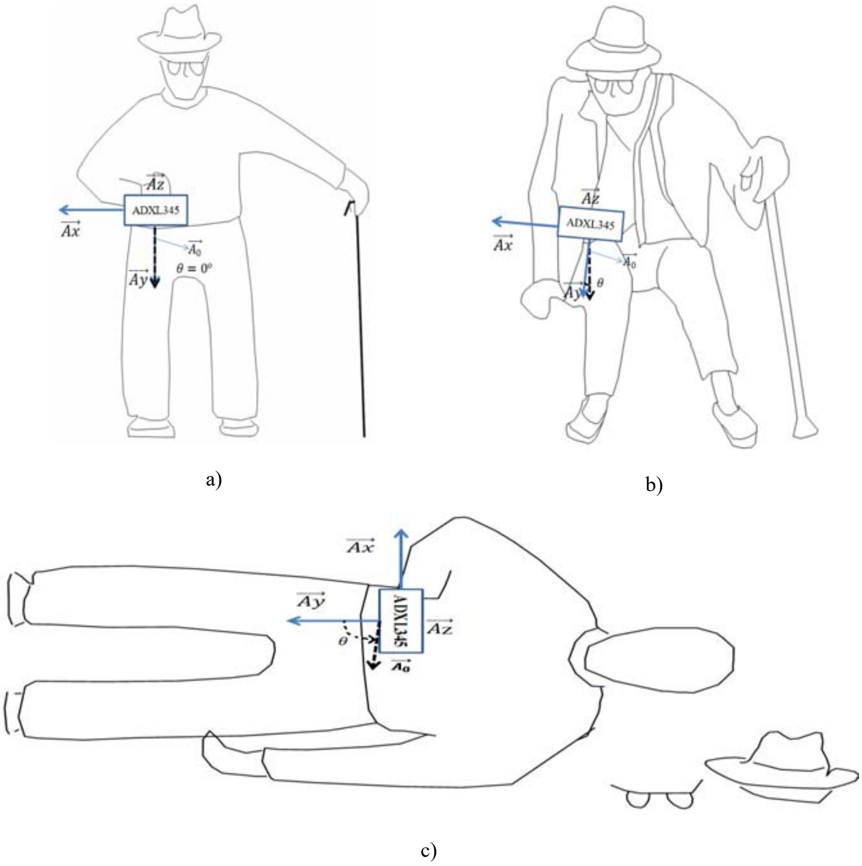


Fig. 7. The angle θ in standing (a), sitting (b) and lying (c) states

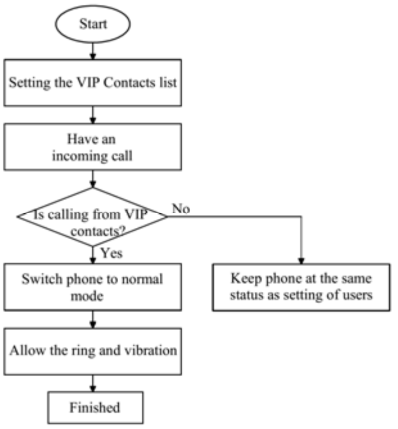


Fig. 8. The software app function

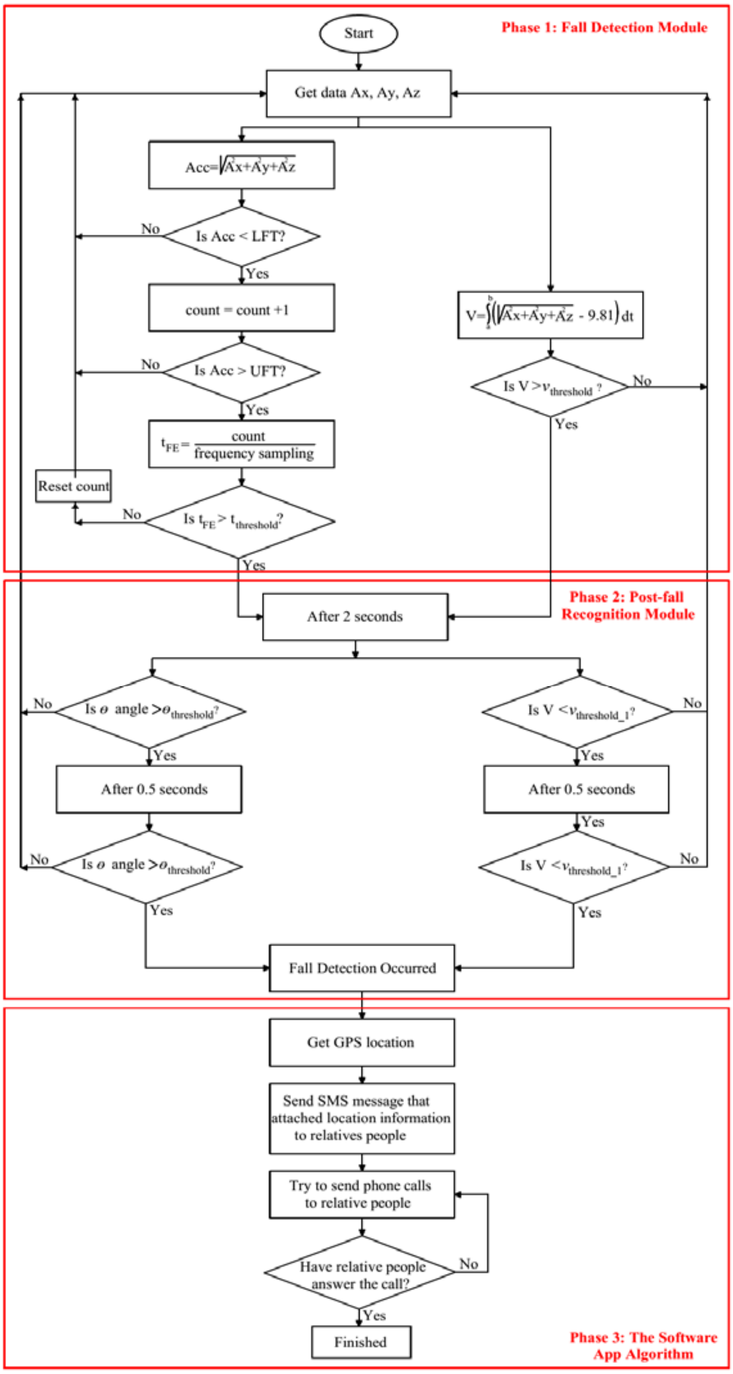
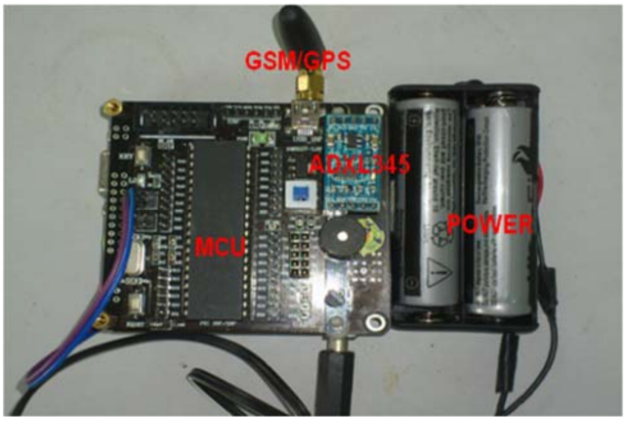


Fig. 9. The proposed algorithm on system



a) Hardware device

b) Software App

Fig. 10. Our proposed fall detection system

Fig. 11. A volunteer is wearing the fall detection device

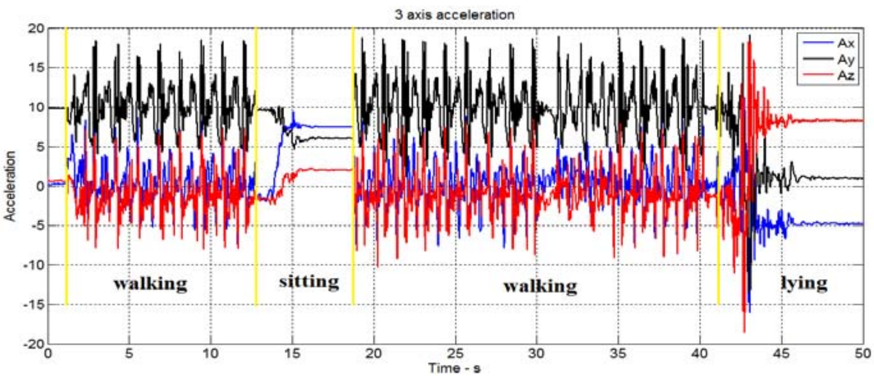
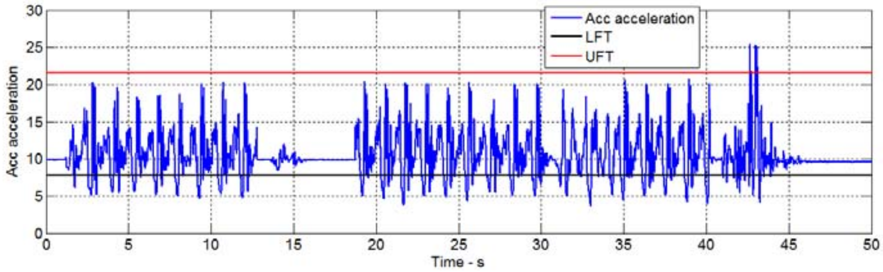
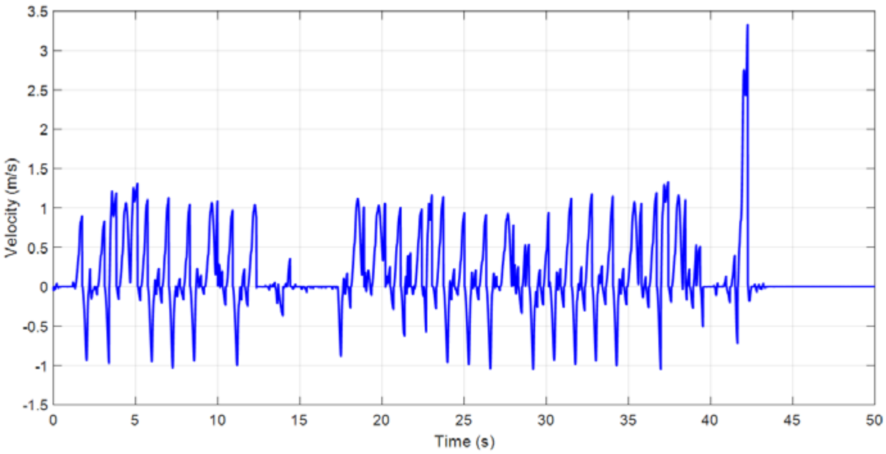


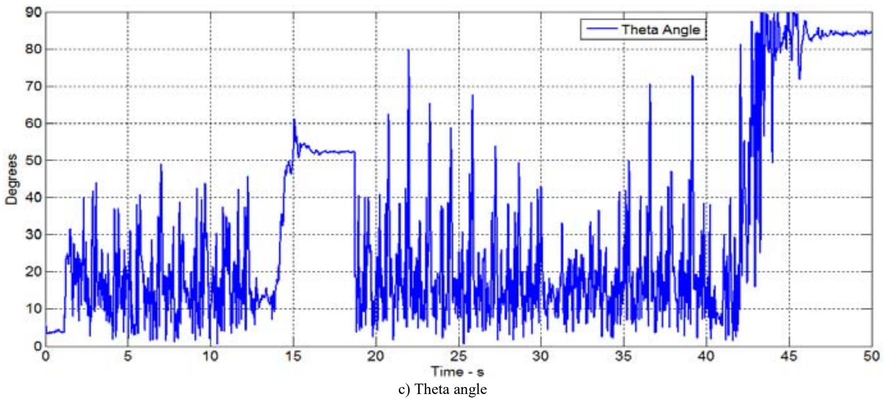
Fig. 12. The acceleration recorded along 3 axes Ax, Ay and Az



a) Acc acceleration and UFT, LFT thresholds



b) Velocity



c) Theta angle

Fig. 13. The An acceleration, Velocity and Theta angle when transiting between activities: standing – walking – sitting – walking – lying

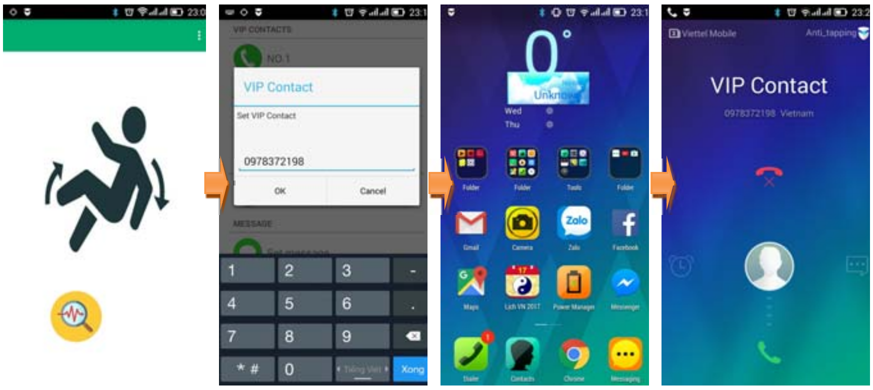


Fig. 14. The setting VIP contact in fall monitor application and changing phone status from silent to normal mode when receiving phone calls from VIP contacts

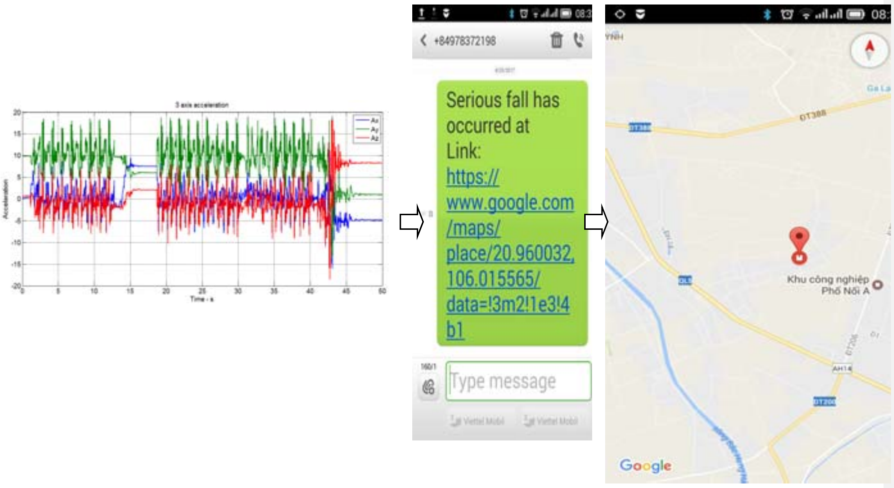


Fig. 15. Message notification and address of the fall

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

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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 (LFT) and Upper Fall Threshold (UFT) 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. Fig.1 is an example of fall event with the elderly which will lead to many dangerous problems, even death if they do not receive immediate attention.

Figure 1 to be inserted here

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 [5]-[8], [12]-[16], location sensors [17], smartphones [18], accelerometers [19] 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 [5]-[8], [12]-[16], 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 camera of Microsoft, monitoring cameras. However, it shows several drawbacks in the outdoor environments: the resolution of the cameras, distance between camera

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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 [17] 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 [18], [20]-[22] 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 [31]. 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 etc.

Wristband and smartwatches [38] [39] 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), etc. to classify fall events and daily activities has been becoming popular recently. It can detect most of the fall events [29] 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 [5] [6].

Another common method is using the low cost accelerometer available in the market, but the precision in fall detection is low [19], [23]. 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 [24], [25]. In [19], 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 [23], 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 [24]. The publication [6] 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 seconds 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 App 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.

The paper is organised 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 50Hz because the elderly's motion is quite slow with simple ADLs. Furthermore, the analyzed results in [31] 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.

Figure 2 to be inserted here

In this design, two rechargeable batteries (3.7V and 3000mAh) 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 Equation (1). The specification of the Lithium battery is 3.7V–6000mAh and the battery power is 3.7V×6000mAh = 22200mWh. 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:

Table 1 to be inserted here

$$\frac{22200\text{mWh}}{96.2851\text{mW}} = 230 \text{ hours} = 9.6 \text{ days} \tag{1}$$

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 Equation (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 Equation (3):

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

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

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

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:

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

and the measurement updates:

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

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.

Figure 3 to be inserted here

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, 3-axis accelerometer with high-resolution (13-bit) measurement up to ±16g. Digital output data is 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 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.

Figure 4 to be inserted here

2.3. Fall Detection Module

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

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

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 $t_{threshold}$, it will be confirmed as a fall event [26]

$$\mathrm{t_{FE}} = \frac{\mathrm{count}}{\mathrm{frequency\ sampling}} \quad (8)$$

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 1g (g=9.81 m/s^2) when the body initially reaches the ground.

Figure 5 is 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 occurrs, the recorded value of Acc is reduced below LFT threshold, then it will exceed UFT threshold with t_{FE} value is about 340ms. After falling, the body gets into the rest state – the state of post-fall phase, the values of Acc is around 9.81 m/s^2.

Figure 5 to be inserted here

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 0.5s 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 after fall detection module confirmed a fall event 2s to ensure the body gets stable at the rest state after initially contacts with the ground.

Figure 6 to be inserted here

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

Table 2 to be inserted here

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^o, it changes when the person carrying the device is in walking or other active states. The postures of the elderly are detected using the Equation (9) to determine the θ angle:

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

Figure 7 to be inserted here

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

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. The Equation (10) is a condition to check the state of the user:

$$\mathrm{V} = \int_a^b \left(\sqrt{\mathrm{A}_x^2(\mathrm{t}) + \mathrm{A}_y^2(\mathrm{t}) + \mathrm{A}_z^2(t)} - 9.81\right) dt \tag{10}$$

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

$$V < v_{threshold} \quad (11)$$

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

2.5. The Software App 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 app 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 [40] 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.

Figure 8 to be inserted here

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 app 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.

Figure 9 to be inserted here

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, Az axes which is sent to MCU for processing 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.

Figure 10 to be inserted here

The software app 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 discussions

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 – 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.

Figure 11 to be inserted here

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 3 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 is the features of the public datasets [35], 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 100Hz with the minimum range (2g).

Table 3 to be inserted here

To evaluate the proposed method, we used four of the following factors: True positive (TP) factor to determine if a fall occurred and the device can detect it, False Positive (FP) factor to determine if a normal activity can be declared as a fall; True Negative (TN) factor to determine if a fall-like event is declared correctly as a normal activity, and False Negative (FN) factor to determine if a fall occurs, but the device cannot detect it [28]. Next, the sensitivity, specificity and the accuracy of the method can be evaluated by the following equations:

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

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

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

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 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, jogging activities in public datasets for testing our proposed algorithms.

The experiment results by using the Equations (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.

Table 4 to be inserted here

Table 5 to be inserted here

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

Figure 12 to be inserted here

In Fig. 13a and Fig. 13b, 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^o (see Fig. 13c).

Figure 13 to be inserted here

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 14 to be inserted here

The Fig. 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.

Figure 15 to be inserted here

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.

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Disclosure statement

The authors declare no conflict of interest.

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