Reliable Fall Detection System Using an 3-DOF Accelerometer and Cascade Posture Recognitions

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Abstract—**An unintentional fall can make injure to elderly. This paper aims to develop a portable and efficient device to monitor the falls in the elderly population by integrating a micro controller, a 3-DOF acceleration sensor, a GSM/GPRS modem and corresponding embedded fall detection algorithms. This system can work well in both indoor and outdoor environments. The human activities can be sensed by the low-cost and low power 3-DOF accelerometer. The acceleration signals are brought to the micro controller to monitor and alert the fall events. The cascade posture recognitions are proposed to enhance the fall detection accuracy by determining if the posture is a result of a fall. If the people fall, an alert message would be sent to their relative or a health center via the GSM/GPRS modem. The experiment device has been tested carefully and it can be applied to real applications for the elderly health.**

Keywords- fall detection; 3-DOF accelerometer; GSM/GPRS; cascade posture recognitions.

I. INTRODUCTION

Every year in the world, approximately 28-35% of people aged of 65 and over experience falls. Experiencing a fall unobserved can be dangerous, highly probability of get serious injury consequence or due to death if treatment is not providence in time [1]. By the research, the falls mortality rates account for 40% all of injury and the cost of fall injury in older person reached for hundreds of millions of dollars. Many elderly living alone either department, nursing home or a smaller house after their children grown up and left home or go out to work, in case of older people who taking a long - term to treatment in hospital without nurse around [2][3]. Usually, elderly people can not get up by themselves after falls. Therefore, we have built an automatic fall detect system device to send help to other people like their relative or nurse to help them in time.

There are many methods that used to design a system to detect falls such as image processing [4], using location sensors [5] or accelerometers [6]. However, each of these methods has certain limitations. Firstly, in the image processing approach, the disadvantage is limited functioning in the outdoor environment and limited of resolution in camera or target occlusion. One more the biggest issue is concerning to user privacy. Secondly, in using of location sensors approach, the problem is that the price of location sensor is higher many times than accelerometer. Similar to image processing, location sensors approach is also limited in outdoor environment. Another common way of formulating posture recognition and fall detection is using accelerometer with lower cost and more commercially available in the market but still keep high precision in detecting fall [6][7]. Most studies uses posture recognition and fall detection algorithm by applying thresholds to accelerations derived from accelerometers, or angular velocities from gyroscopes worn on the waist/chest/thigh in order to detect a potential fall [8][9]. In order to design a cheap device, only one 3-DOF accelerometer is concerned [10].

In [6], authors have to use at least three accelerometers to wear in the body, and it prevents this device from practical applications due to its inconvenient. In [7], author used ZigBee transceiver to communicate with the center, thus, it prevent the elderly from outside activities. Similarly, the system in [8] can only work in the indoor environment. In [9], the system implemented on mobile phones would meet difficulties to extend the ability to measure of the elderly such as heart rate, blood pressure.

To overcome these limitations, this paper proposed to design and develop a low-cost, automatic fall detection system for elderly using a 3-DOF accelerometer. This system can work well in both indoor and outdoor environments. Our system works with two main functions: The first is automatic detect a truly fall in elderly when they live home alone or in the nurse house, etc. The second function is automatically send a SMS to their relative contact to help to avoid from the bad situation happing. We proposed to use a final decision algorithm based on cascade posture recognitions to enhance the sensitivity and accuracy of the system. We also built a database of falls of Vietnamese people in this study.

II. SYSTEM DESIGN

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

A. System Architecture

Figure 1 shows the block diagram of the proposed fall detection system. The sensor used in this project is a 3-DOF accelerometer ADXL345 from Analog Devices. Our accelerometer was positioned in the waist body so that y-axis must parallel with Earth's gravity (see Fig. 2). By using I2C interface between MCU (Pic18F4520 from Microchip), sampling rate of 10 Hz, and processing within buffer 10 data samples, accelerations along the x, y and z-axes can be sensed, and processed. By applying two thresholds, posture recognition module will declare whenever the person is standing, walking, lying or in Null state. The function of fall detection module is detecting the fall events base on the third threshold. If the system detects the falling event, concurrent posture recognition and a 7-second delayed one would be combined to determine if there is a true fall. If the fall events happen, the system automatically sends an SMS message through GSM/GPRS modem SIM900 to the responsive contact to provide help in time.

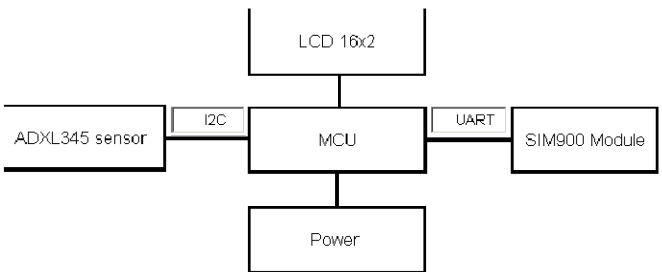

Figure 1. Block diagram of the fall detection system

There are two level power sources in this scheme, one for the MCU and the accelerometer ADXL345, and other for module SIM900. With module SIM900, it only works when the current is larger than 2A. Consequently, we used an adapter 12V, 3A with LM2576 to get +5V, 2A. The photo of integrated system is shown in Fig. 2.

B. *The 3-DOF Acceleration Sensor*

Accelerometer is the heart of the system. ADXL345 is a 3-DOF accelerometers that can sense the acceleration on three dimensions. The ADXL345 is a small, thin, low power, 3-axis accelerometer with high-resolution (13-bit) measurement at up to ±16g. Digital output data is formatted as 16-bit twos complement and is accessible through either a SPI or I2C digital interface. Thus, this sensor is suitable for fall detection applications. The accelerometer is positioned in waist body region and is sampled at the rate of 10 samples per second. The data received from the accelerometer is in the form of a three-valued vector of floating point numbers that represented the individual accelerations of sensor in the x, y, z-axes subtracted by the gravity vector *G*. Thus, the expected reading of the accelerometer would be approximately [0, 9.81, 0] m/s^2 (see Fig. 3). We then need to apply a pre-processing step before taking data into the attribute extraction module to formulate the mean, orientation, and standard deviation. The last step is data mining the body posture recognition and fall detection. Two modules offer the real time posture of body and fall event, respectively.

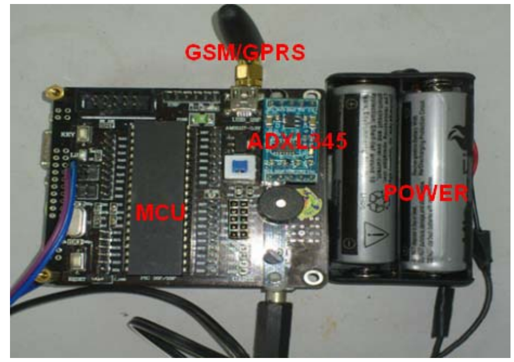

Figure 2. Photo of the integrated system

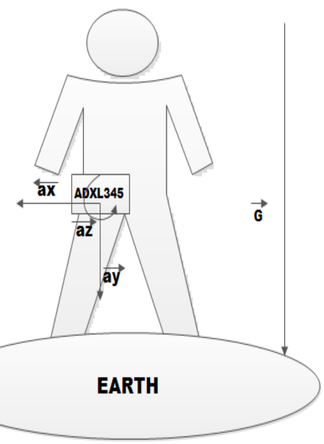

Figure 3. Position of the 3-DOF accelerometer in waist body

III. THE FALL DETECTION ALGORITHMS

The posture recognition and fall detection process describe in this project is divided to several phases such as show in Figure 4.

The final decision on event of a fall is based on both output of fall detection, and cascade posture recognitions. When a fall is detected, decision from posture recognition module in this time and seven second after that will determine whether it is a true fall event. The reason we consider posture recognition after time 7 second because some people can stand up by themselves after fall or the first posture recognition is failure, thus, we need to re-check to confirm a fall event or not.

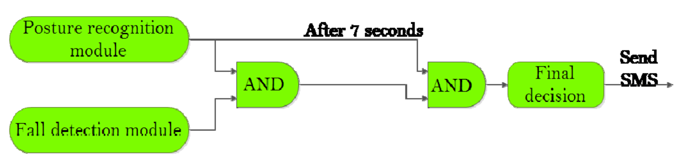

Figure 4. Final decision of fall

A. Posture recognition module

Ten acceleration samples are averaged and stored in a buffer of the microcontroller. It means that this buffer (a sliding window) refers to one second tracking. After each 0.1 second, an updated window is processed and a final decision has been made. Figure 5 shows the posture recognition module that processes each sliding window [6]. This module can classify into four fundamental postures: lying, standing, walking, and other postures which is denoted by Null. The target of this paper is fall detection, thus, we do not try to explore various kind of postures. In this diagram, A_n is L_2 norm of three accelerations:

$$A_n = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

where n denote the discrete time. Note that the n^{th} sliding window is formulated as:

$$W_n = [A_n \quad A_{n-1} \quad \dots \quad A_{n-9}] \tag{2}$$

After that, the zero cross rate (ZCR) is determined by:

$$ZRC_n = \sum_{i=0}^{8} (A_{n-i} - DC < 0)(A_{n-i-1} - DC > 0) \tag{3}$$

where DC is the DC component of the A_n. If ZCR equals to zero, it means that the person is in steady states (i.e. lying or standing). Also in Fig. 6, two thresholds th_1, th_2 are determined by empirical data obtained from sensor ADXL345. It can be seen that the values of th_1 and th_2 depends on the length of the sliding window.

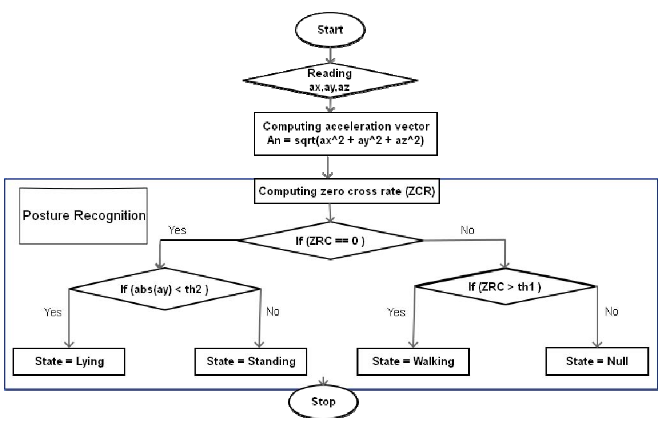

Figure 5. Posture recognition module

Figure 6 illustrates the roles of two thresholds, th_1 and th_2 with a real experiment data. In the case of the person is moving (i.e. walking or Null), the threshold th_1 is used to confirm that the person is walking [11]. Otherwise, th_2 is used to confirm standing or lying postures. It is obviously that if the person is standing, the *ay* (vertical acceleration) would show large enough amplitude.

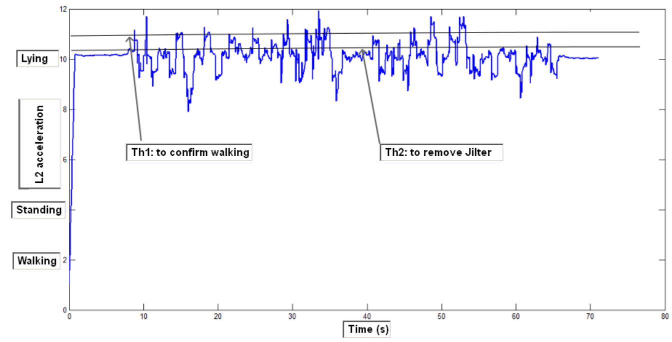

Figure 6. Illustration of two threshold th_1 and th_2

By using ZRC, L_1 norm of a_y acceleration, th_1 and th_2, four postures can be identified and assigned by corresponding values as shown in Table 1. The Boolean values in the third column would be used for the final decision (see Fig. 4). Note that, these values in the second column have illustrating meaning only (see Fig. 7). This figure shows the result of our posture recognition of a human in a period of 95 seconds with several phased of postures such as standing - walking - standing - lying - standing. All estimated postures are matched to experimented postures.

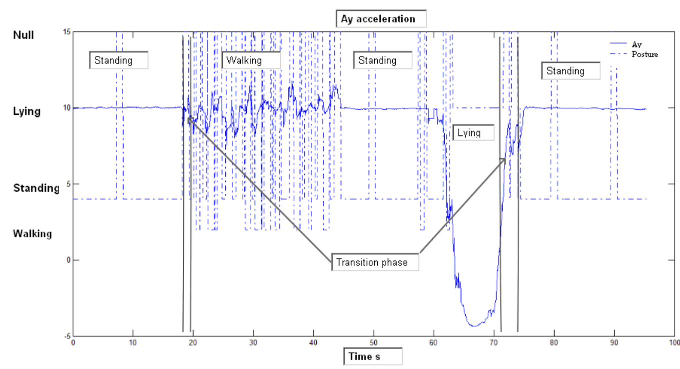

Figure 7. Ay acceleration vs. posture cognitions

TABLE I. ASSIGNED VALUES FOR DIFFERENT POSTURES [4]

State	Values for illustration	Boolean values
Walking	2	0
Standing	4	0
Lying	10	1
Null	15	1

B. Fall detection

The second module is fall detection which is shown in Fig. 8. Firstly, the different between two consecutive L_2 accelerations is calculated by:

$$D_n = A_n - A_{n-1} \tag{4}$$

Secondly, the searching algorithm utilizing D_n is applied to find two positions (denoted by n_1 and n_2) corresponding to minimum and maximum of A_n. Thirdly, the difference between A_{n2} and A_{n1} would be compared to another empirical threshold th_3 to determine whether the fall event is happen (see Fig. 9). If th_3 is chosen large, the fall event may be ignored. If th_3 is chosen small, both positive and negative fall events would be declared. Therefore, the final decision made by combining posture recognition and fall detection would be used.

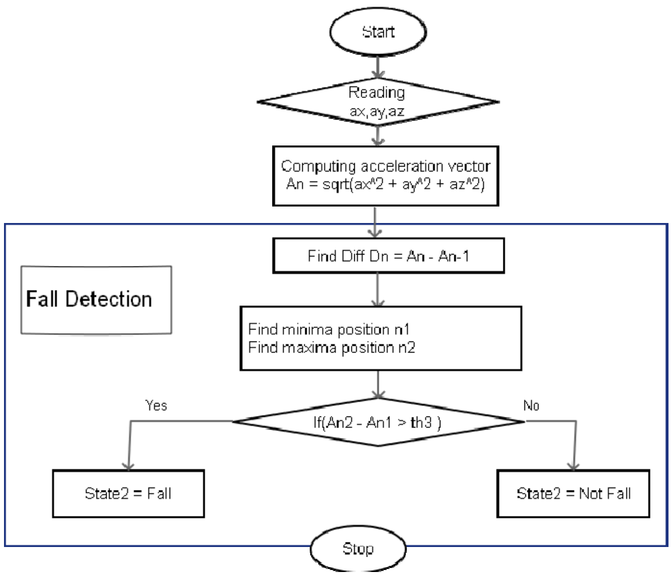

Figure 8. Fall detection module

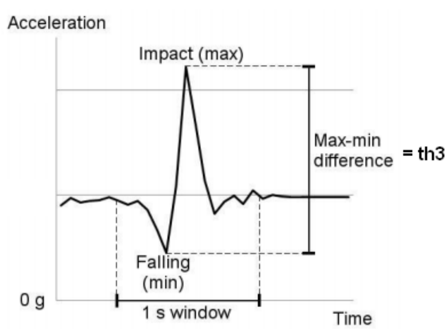

Figure 9. L_2 acceleration pattern of a fall sample

C. Final decision

The final decision on event of a fall is based on both output of posture recognition and fall detection as shown in Fig. 4. The more detail of the final decision proposed in this paper is shown in Fig. 10. When a fall is detected, the first posture recognition is executed to determine if the posture state is Lying or Null. After 7 seconds, the second posture recognition is used to confirm a true fall alarm. The reason for the need of cascade posture recognitions is that after a short time, some people can stand up by themselves. Table 2 summarizes the whole of final decision.

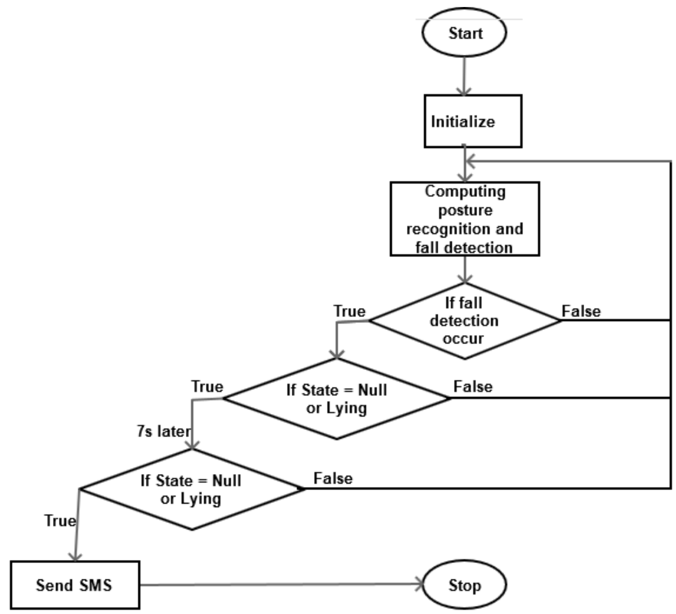

Figure 10. Fall decision using fall detection and cascade posture recognitions

TABLE II. FINAL DECISION OF FALL USING CASCADE POSTURE COGNITION

Fall Detection	Posture Recognition	Posture after 7s of Fall	Final Decision
Fall	Standing	Don't care	False
Fall	Walking	Don't care	False
Fall	Lying	Don't care	False
Fall	**Lying**	Standing or Walking	False
		Lying or Null	**True**
Fall	**Null**	Standing or Walking	False
		Lying or Null	**True**

IV. EXPERIMENT RESULTS

For the experiment testing, some students equipped with our device were involved to make various kinds of postures and falls. The elderly have not tested with fall events to prevent them from injuring. The system runs in real-time mode and the following figures are recorded for the detail explanations. According to the proposed procedure, the 3-DOF acceleration signals are sampled at the sampling cycle of 0.1 second, and then, data was processed using our proposed algorithms. At every 0.1 second, a 10-sample sliding window is processed to monitor the posture and the fall event. The empirical data provide us th_1=0.7 m/s^2, th_2=4.0 m/s^2, and th_3=1.3 m/s^{2,} respectively. In total, 110 sets of experiment were completed in our laboratory. In every experiment, volunteers placed the device on the waist because wearing a device there is the most comfortable (see Fig. 11).

Figure 12 show the L_2 acceleration, posture recognition, fall detection and final decision without cascade posture recognitions, respectively. There are two fall events have been declared at the 3rd and 120th second. The first event is not true because he was actually walking. In Fig. 13, by using the cascade posture recognitions, the posture status was confirmed as walking. Thus, this event was discarded in the final decision.

Figure 11. A volunteer wearing the fall detection device

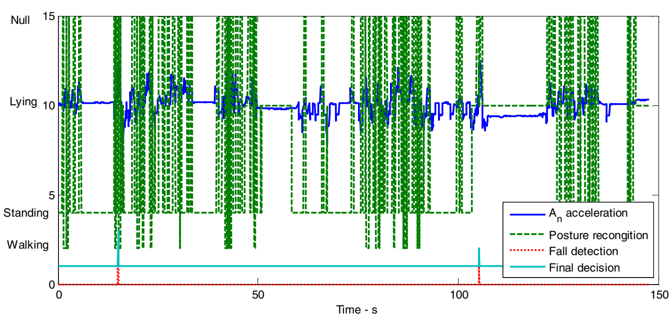

Figure 12. Fall decision without cascade posture recognitions

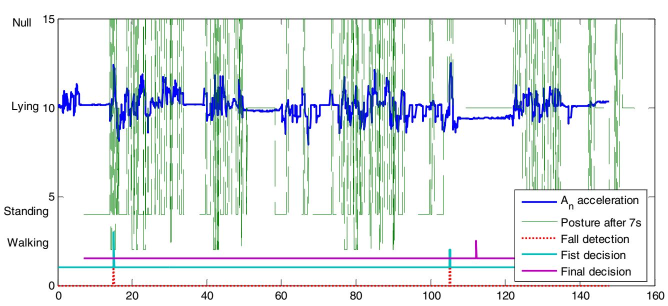

Figure 13. Fall Fdecision with cascade posture recognitions

To evaluate the proposed system, we use four following factors [12]:

- ✓ True positive (TP) factor to determine if a fall occurred and the system 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.
- ✓ False negative (FN) factor do determine if a fall occur but the system can not detect it.

After that, the sensitivity and the accuracy of the system can be evaluated by:

$$Sen = \frac{TP}{TP + FN} \tag{5}$$

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

It can be seen that our system offer a very good sensitivity of 90% and a high accuracy of 85%. It can identify most of the fall events, but there were some false judgments for the complex activities.

CONCLUSIONS

In this paper, we have proposed a completed system for fall detection using a 3-DOF accelerometer, a micro controller, a GSM/GPRS module and corresponding embedded algorithms. Posture recognition is a method to improve the fall detection. In this study, cascade posture recognitions have been introduced to drastically improve the accuracy of the detection system. The algorithms have firstly been simulated in MATLAB environment. After that, they can be re-programmed in C language which can be embedded in the micro controller. We also have built a database of postures and falls during this study. The device has been tested carefully with 110 sets of experiment. In lab experiment, the system can offer to an accuracy of 85%. Thus, it can be applied to real application after further evaluation and analyses. In future, the system can integrate a GPS receiver for outdoor activities, a pressure sensor for heart rate and blood pressure monitoring.

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