A Method with Triaxial Acceleration Sensor for Fall Detection of the Elderly in Daily Activities

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Abstract. Falls are one of the major risks which the elderly people face. Recently, due to the demands for guardianship of physical functions, the device to detect falls automatically is urgently needed. This study was focused on the method of fall detection and the wireless device based on a triaxial acceleration sensor. To evaluate the performance, experiments were conducted on fall, squat, stand up and walk. The device was also set in three body positions (head, shoulder and belly) to get fall signals compared. It is considered that the difference between valley and peak of the acceleration on *z* axis can be used to detect falls as an obvious feature. If it's higher than 0.5V, it can be concluded that the person has a fall occurrence. The device is expected to be useful to detect falls of the elderly as healthcare equipment.

Keywords: Fall Detection, 3D Acceleration Sensor, Wireless Detection Device, Different Body Positions, the Elderly.

1 Introduction

In most countries, the elderly people are becoming an important segment of the population, and there is a trend that more and more elderly people are living alone. This fragile group needs much more health care both physically and mentally. One of the major risks they face is fall. It is estimated that over a third of adults aged 65 years and older fall each year [1], making it the leading cause of nonfatal injury for that age group. Among older persons, 55 percent of fall injuries occur inside the home. An additional 23 percent occur outside, but near the home [2]. There are many factors, which can result in falls [3]. Meanwhile, there are also many methods to prevent falls in advance. From inside, the elderly can have more exercises to improve the physical balance and increase the bone density. From outside, we can use many facilities to help the elderly people concerned to detect falls and take measures to get help once a fall occurs.

Since the variety of daily activities that the elderly perform, a device with a high precision is needed to detect the fall. The kinds of fall detection methods have been

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classified into three categories: wearable device, camera-based and ambience device [4]. Among many researches, the use of 3D acceleration sensor has the most influential impact on solving this issue [5-6]. However, the research concerning the 3D acceleration sensor is often lacking of detail explanation about where to put the sensors and how the whole detection process works.

In this paper, a research about how to detect falls using 3D acceleration sensors will be discussed in detail. First, the wireless device will be shown, and then the signal got will be processed by eliminating noise. The results of falls and other daily activities will be followed. Detail discussion about the fall progress and different body position placement will be explained in the last section explicitly.

2 Materials and Methods

2.1 Wireless Device

The hardware setup developed for the fall detection prototype includes a 3D acceleration sensor, a wireless communication unit and a data processing unit.

MMA7260 is a kind of specialized 3D acceleration chip, which is adopted to sample the instant human body's posture in our posture experiments [7-9]. MMA7260 can notice the change of acceleration in three perpendicular axes at the same time and output the acceleration change with the form of voltage at the three output pins. The microcontroller gets the sampled data through an A/D conversion ship, then does simple analyses or transports the data directly to the PC.

Fig. 1 shows the real module used in our experiment which is designed and made by our team. We fixed a helix antenna in each senor node instead of a patch antenna to enhance the strength of wireless signal.

In general, the module of fall detection is portable and wearable [10], so wireless communication is adopted to transmit the data sampled from the fall detection sensor node. At first, a wireless communication program without any specialized protocol was written. In an obstacle-free room, the quality of wireless transmission was stable. But when the sensor node carried by human body was placed in a cluttered room, the quality of wireless transmission declined evidently. After a series of comparisons and experiments, a kit of ZigBee2006 protocol was given to guarantee a lower error rate of wireless transmission [11]. CC2430 is designed by Texas Instruments specialized for organizing ZigBee networks, it contains a multiple A/D conversion module which can meet the characteristics of MMA7260 to exchange acceleration change in three axes at the same time.

GSM Modem is accepted in this project and a mobile card (SIM) is utilized to work with GSM Modem to connect into the mobile phone's network. When the fall detect module notices a specified event which maybe in a dangerous situation, it sends a warning message to the PC. We developed a VC++ application program to drive the GSM Modem to ring up the elderly person. If the elderly person is safe and sound, then he rings back to the GSM Modem, the application program will know that there is no accident happened and cancels the warning. Otherwise the application program will ring up to notify the person who is responsible for the elderly person and then call for the ambulance.

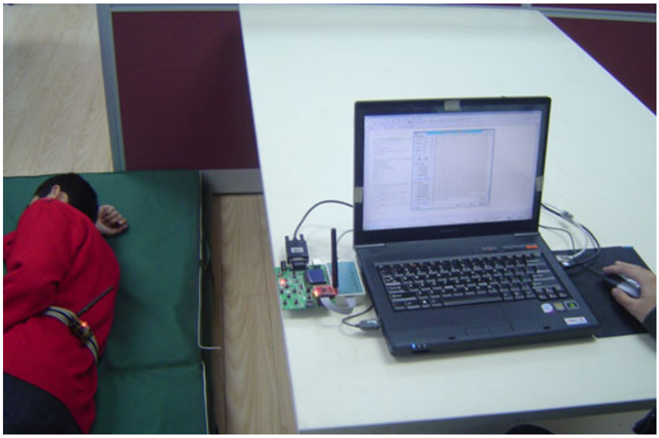


Fig. 1. Fall detection module

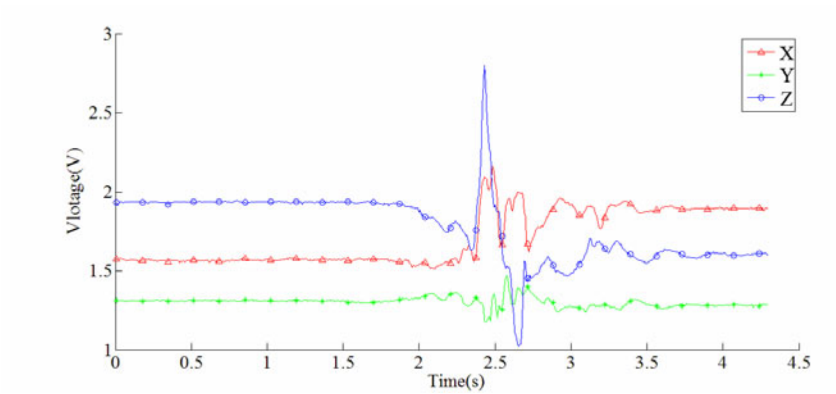
2.2 Denoising

In order to eliminate the noise in the sampled data, Discrete Wavelet Transform (DWT) is used in this step. DWT is a very useful tool for signal multi-resolution analysis. It has two complementary filters, the low-pass filter *g* and the high-pass filter *h*, which saves the approximation part and the detail part of the signal respectively. The signal $s(n)$ is split into two parts through the first level transform-approximation coefficients V_1 and detail coefficients W_1. These two coefficients can be split into the second level approximation coefficients V_2 and detail coefficients W_2. The coefficient *g*, the low-pass filter, associates with the scaling function φ and the coefficients *h*, the high-pass filter, associates with the wavelet function ψ. The functions are defined as

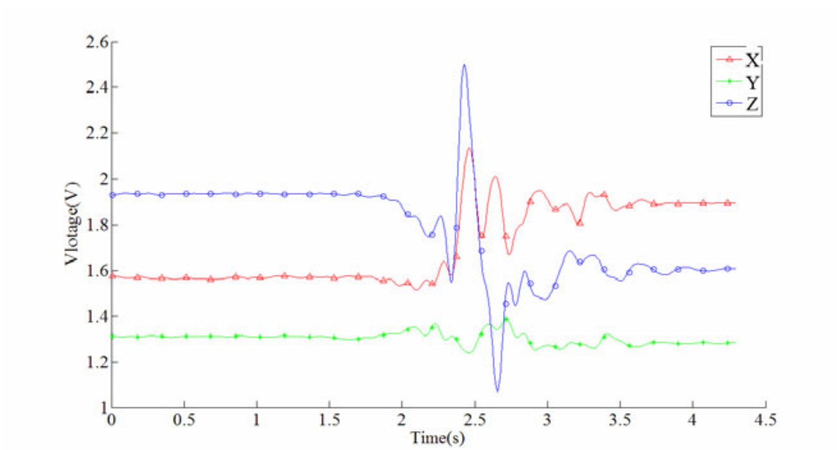
$$\phi_{j,m}(n) = 2^{-\frac{j}{2}}\phi(2^{-j}n - m) \tag{1}$$

$$\psi_{j,m}(n) = 2^{-\frac{j}{2}}\psi(2^{-j}n - m) \tag{2}$$

These coefficients can also be used to reconstruct the signal again. Also compared to Fourier Transform, DWT has temporal resolution: it captures both frequency and time information. There are many mother wavelets we can choose to use. In this paper, a Symlets mother wavelet (sym2) was used in decomposition and reconstruction and 2 levels of transforms was applied (results are shown in Fig. 2) due to its better performance than others by testing. It is clear that the signal after using DWT has the least error estimation and is suitable to be further processed.



a) Before DWT



b) After DWT

Fig. 2. The waveform before and after DWT

3 Results

An experiment was conducted on falls and another 3 kinds of actions (squat, stand up and walk). Besides, the device was also placed in three different positions (head, shoulder and belly) to get falling signals compared. The results are as follows after using DWT:

3.1 Device Set on Head

Head is a perfect place to set the sensor, but due to the neck's effect, it's very flexible and may not in the same plane as the body when fall happens. This could lead to wrong judgment.

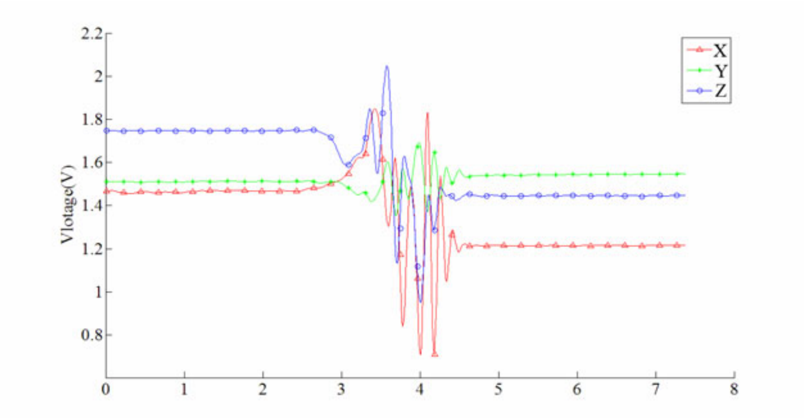


Fig. 3. Fall when the sensor is placed on head

3.2 Device Set on Shoulder

Shoulder is another place suitable for wearable sensors. But as we know, the joints around arms are also very flexible and people have the instinct to resist falling, which leads to the disaccord with the body when falling down.

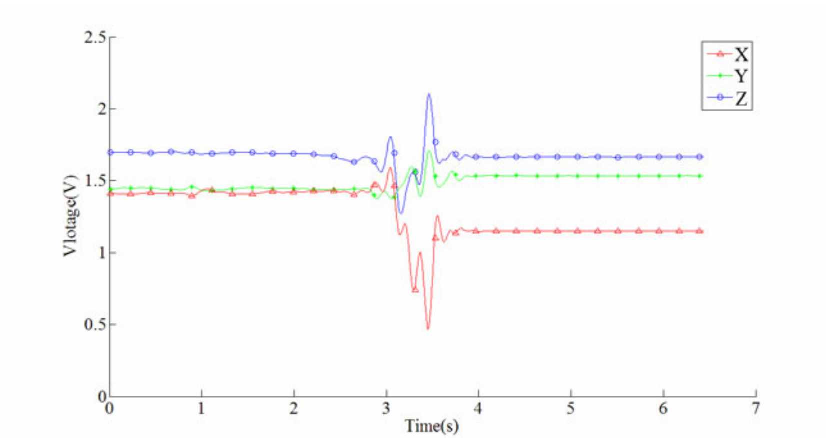


Fig. 4. Fall when the sensor is placed on shoulder

3.3 Device Set on Belly

Placing the sensor on belly can ensure its accordance with bodily direction when falling down. And it is very easy to fix because we can integrate it with a belt. Its disadvantage may be that it will be affected by respiration to some extent.

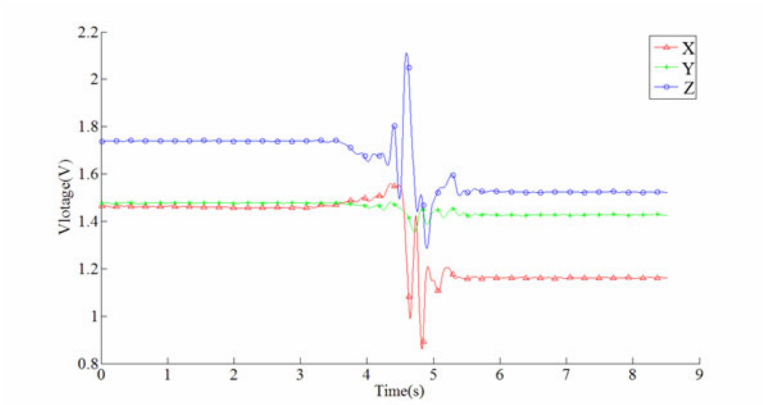
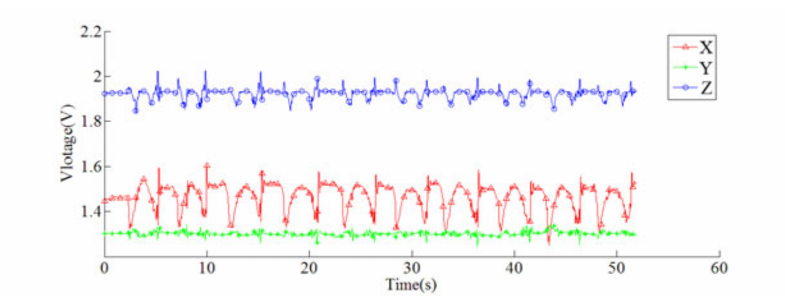


Fig. 5. Fall when the sensor is placed on belly

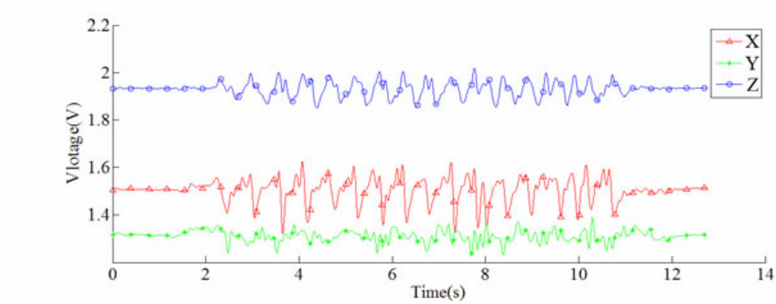
3.4 Device Set on Belly When Standing Up, Walking and Squatting

Standing up and walking are the most common activities in daily life. Squatting suddenly may be like falling down more or less, only without fierce changes in *z* axis. Here we use this action to be distinguished with falling.



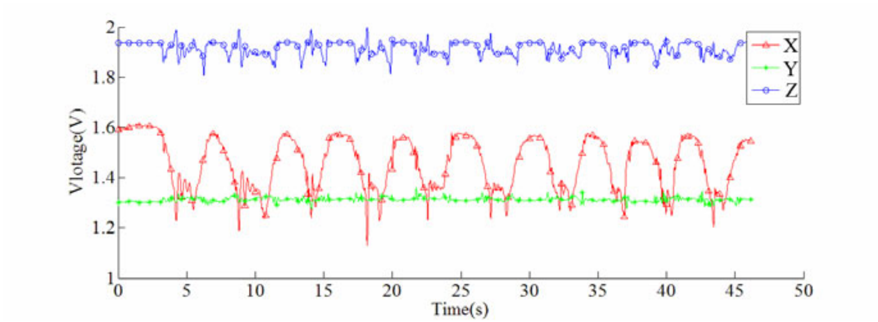
a) Standing up

Fig. 6a. Sensor placed on belly when standing up



b) Walking

Fig. 6b. Sensor placed on belly when walking



c) Squatting

Fig. 6c. Sensor placed on belly when squatting

4 Discussion

4.1 Fall Waveform Analysis

From the large amount of data we got, it shows that when people started to fall, it only took about 2 seconds for people to fall on the ground. In this period the acceleration changes to a great scale. The whole process can be divided into 5 phases. Fig. 7 shows the 5 phases:

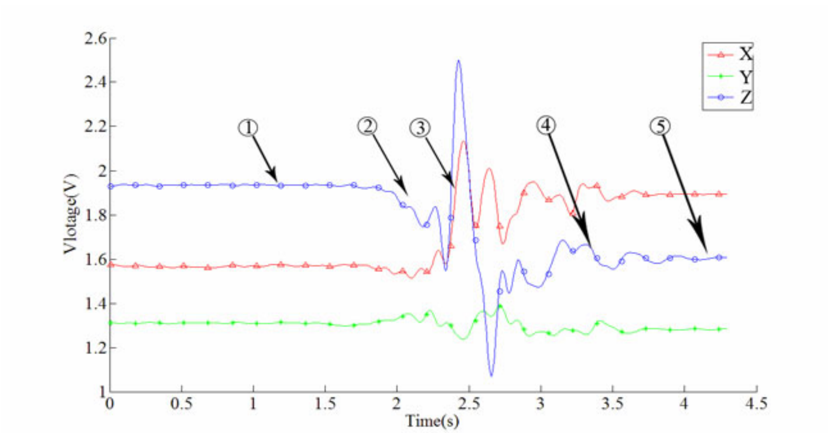


Fig. 7. The 5 phases of a fall

Phase I: At the beginning, the static status which includes the values of three axes is shown. Before a fall occurs, the values of the three axes will fluctuate slightly in the specific region but don't vary much, which indicates that the status is static.

Phase II: Once there is an inclination of falling, a weightlessness process occurs. The time interval of this phase is determined by the height between the sensor and ground. Also the value of z axis can't be more than $1g$. During the progress of weightlessness, the output voltage decreases because the distance in capacitance decreases relatively.

Phase III: After the weightlessness process, fierce impaction happens. The obvious phenomenon is that we will get a very high value of z axis which may be greater than $3g$ sometimes, and the values in the other two axes will also vary a lot. The reason is obvious. The plate in capacitance is in the decelerated state while the distance's becoming larger. As soon as the speed comes to zero, the accelerator and the distance get the highest value but in opposite direction, which leads to output the highest voltage. After that, the plate still vibrates until velocity comes to zero, which contributes to the lowest voltage.

Phase IV: The plate in capacitance will fluctuate in both directions until it is static. Generally, some slight vibrations come after the severe impaction. The amplitudes of the 3 axes waves will come to be constant after a short period.

Phase V: The last status, which comes back to static, can be a comparison to the first situation. We can get these statues to judge the last posture and the direction of falling.

4.2 Data Analysis

Compared with the acceleration of other actions (squat, stand up and walk), the acceleration of falls changes more severely in the 3rd phase mentioned above. Our method is based on this point to judge whether people fall by testing the difference between valley and peak of the acceleration on z axis.

We first tried three positions to place the sensor, head, shoulder and belly. The results calculated by our method are shown in Table 1.

Table 1. The difference between valley and peak of fall on z axis in different positions

	Device Set on Head	Device Set on Shoulder	Device Set on Belly
1	0.8917	1.1232	0.9379
2	1.0971	0.9887	0.8257
3	0.7877	0.6314	0.6489
4	1.3573	0.9737	0.9089

From Table 1, it can be seen that the three different positions have the similar extent when falling. Considering the advantage belly placement has discussed above, in actual experiment, we mainly focus on the data got from belly. Table 2 shows the calculated results of fall and other activities with the sensor set on belly.

Table 2. The difference between valley and peak of fall on *z* axis in different actions

	Fall	Squat	Stand Up	Walk
1	1.4179	0.1559	0.1772	0.1546
2	1.3333	0.2172	0.1713	0.1472
3	1.4318	0.1467	0.1555	0.1216
4	1.3648	0.1508	0.1527	0.1304
5	1.1753	0.1465	0.1649	0.1421
6	1.1661	0.1259	0.1623	0.1479
7	1.2577	0.1124	0.1290	0.1421
8	1.3532	0.1594	0.1078	0.1441
9	1.1158	0.1292	0.1235	0.1396
10	1.2959	0.1324	0.1054	0.1306
11	1.2565	0.2477	0.1828	0.1610
12	1.4287	0.2384	0.1805	0.1582
13	1.4729	0.2386	0.1801	0.1617
14	1.3754	0.2397	0.2703	0.1885
15	1.2427	0.1817	0.1986	0.1771
16	1.3513	0.2008	0.201	0.2042
17	1.3311	0.2212	0.1976	0.2230
18	1.4853	0.2235	0.2700	0.1746
19	1.0824	0.2141	0.2131	0.1989
20	1.3354	0.1923	0.1998	0.1818

5 Conclusions and Future Work

From Table 1 and Table 2, we can conclude that the three different positions (head, shoulder and belly) have the similar extent when falling and all differences from falls with the sensor placed in different positions are more than 0.5V, comparatively, all other actions' values are less than that value. So we can use this value as a threshold to distinguish fall and other daily activities. Once the difference value exceeds 0.5V, a primary assumption that a person has fallen can be concluded.

However, it's not enough to judge the fall occurrence alone. Many other related works, like the following steps after fall, also need careful and intensive research. What's more, the device can be designed to set many sensors in different positions in order to strengthen the detection effect and confirm the preciseness of fall direction. Meanwhile, the direction of the fall can be confirmed according to the relative position change of the three axes before and after the fall.

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