Design of automatic fall detector for elderly based on triaxial accelerometer

Jiewen Zheng, Guang Zhang, Taihu Wu*
Institute of Medical Equipment
Academy of Military Medical Science
Tianjin, China
jaroncheng@yahoo.cn

Abstract—**Falls in elderly people have been recognized as a major health problem in aging population. This paper describes the development of an accurate, accelerometer based fall detector capable of locating the wearer and sending alarm short messages (SMS). The device worn on the waist uses a two-stage fall detection algorithm, which senses rapid impact and body orientation of the wearer. To evaluate the device and the algorithm, an experiment on 5 subjects was conducted. The device is especially adapted to safely and accurately monitor elderly people without influencing their privacy and comfort. It is hoped that such a device will promote an integrated approach to the management of falls of elderly in the community.**

Keywords-fall detecion; two-stage; triaxial accelerometer; gpsOne

I. INTRODUCTION

Health-threatening falls amongst elderly people are serious social problem in a growing segment of aging population. It often cause many physiological and psychological problems, such as restricted activity, injury, fear of falling, worry about living independent, or death [1-5]. The elderly person suffered a fall could remain there undetected for a long period, which will bring many possible consequences. Automatic fall detection and alarm would help to minimize this possibility by reducing the time between the occurrence of event and the arrival of medical attention. Thus, there are significant needs in the development of fall detector to monitor elderly people in an accurate, convenient, unobtrusive, and socially acceptable method.

Currently, a number of different fall detection approaches have appeared. These approaches can be basically classified in three types[6]: (a) video analysis-based, where real-time movement of the subject is monitored through video; (b) acoustic frequency analysis-based, where falls are detected by analyzing the frequency components of vibration caused by the impact; (c) worn sensor-based, where falls are picked up by the sensors attached in the subject. The sensor-based, in particular accelerometer-based method has been thought of the most important and popular technologies in fall detection for its advantages of low-cost, convenience, and high accuracy. Many related works have been published in recent years. Reference [4] describes the design of a commercially available Tunstall fall detector that used a patented two-step algorithm. The fist step is to detect a collision with an impact sensor. The second step determines if the orientation of the device before and after the impact has changed significantly. But the paper does not tell what types of sensors are used in the detector. Reference [7] presents a fall detector worn on a wrist watch that uses a multi-stage fall detection algorithm. Firstly, the watch detects a high velocity towards the ground. Next another impact must be detected in 3 seconds. After that, if at least 40 seconds of inactivity are observed within 60 seconds, a fall event is detected. But results are not optimal as the diversity of activity when sensor is integrated in the wrist, which makes the signal analysis become very difficult. Reference [8] tells a fall detection algorithm based on a resultant signal with 3-Axis accelerometer. The author acquires the threshold from the 240 simulated falls. Then to determine the extent of misdetection of simulated ADL as fall events. Although good results are received, limited simulated fall models could hardly prove its reliability.

This paper describes an automatic fall detector composed of 3-axis accelerometer and CDMA/gpsOne module. The detector worn on the waist performs real-time fall detection with a two-stage algorithm. If a dangerous fall is detected, the device could rapidly get the location of the wearer, and then an alarm SMS will be sent to his/her guardian. To evaluate the device and the algorithm, an experiment on 5 volunteers will be conducted.

II. FALL SENSOR DESIGN

A. Fall Detecion System

In order to assess daily physical activity, accelerometers must be able to measure accelerations up to ±6g when attached at waist level (near the centre of mass of the subject) [9]. To meet this requirement, a 3-Axis accelerometer, Freesclae MMA7260 with a range of ±6g was used to detect the human fall in our device. An 8-Bit MCU C8051F920 with a 10-Bit ADC was chosen as the control unit for its ultra low supply voltage (0.9 to 1.8V). One 3.7v Li-Ion cell power the device for it is more powerful with relatively small size. The gpsOne is an advanced positioning solution that utilizes assisted GPS alone or in combination with wireless network measurements to get reliable and accurate location whether indoors or outdoors. The device uses a CDMA/gpsOne module FD820 to perform locating and sending alarm SMS. The device fits inside a plastic box measuring 80mm×45mm×20mm with the cell enclosed (Fig. 1). The device can be worn on the arm, wrist, waist, or other parts of the body, but previous works had

This work was supported by "863" Project.
*Corresponding Author: Taihu Wu, Professor
E-mail: wutaihu@vip.sina.com

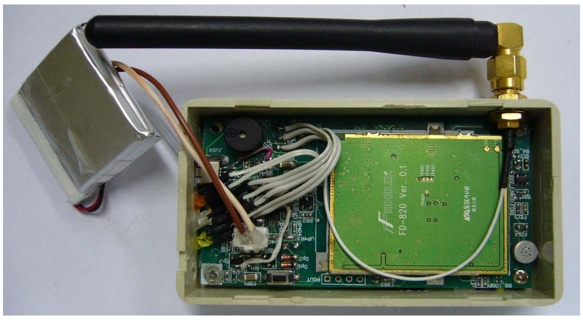

Figure 1. The prototype of the fall detector

acquired more success when sensors placed on the waist [4,8]. For our work, we put the device on the waist with an elastic belt.

III. Methodology of Fall Detecion

Before introducing the fall detection algorithm, some pretreatment for acceleration signals must be implemented. According to [9], in order to detect daily activities in real time, the sampling rate should be at least 40Hz. So 10-Bit ADC in MCU converts 3-Axis signals to an integer in the range [0,1023] with a sampling rate of 40Hz, corresponding to a measured voltage of [0,3.3v]. The major energy band for human daily activities is 0.3-3.5Hz. So a high pass finite impulse response (FIR) filter with a cut-off frequency at 0.25Hz was applied to each axis's signal for the purpose of removing noise. This paper elaborates a two-stage fall detection algorithm, which can detect an impact and subsequent orientation of the wearer. The flowchart in Fig. 2 summarizes the two-stage fall detection algorithm.

A. Detecting Impact

In general, human falls can be classified as linear fall (LF) or non-linear fall (NLF) [10]. A LF occurs when a fall results without significant movement or external force being applied just liking a free fall, such as falling through a hole or a fall in a faint. A NLF means that a significant rotation of body follows the fall or a fall is accompanied by external force, such as an individual is knocked down by a speeding car or falling down the stairs. Many works had showed that the methods of detecting the impact base on accelerometer could be classified as using peaks of acceleration and using trends of acceleration. As for the former one, it has been proved to be unstable for that some types of activities are often confused with a fall when using peak acceleration as detecting thresholds, such as sit, jump, etc. In this paper, we will use the latter method to detect the impact. As expected, when a fall occurs, three axes of measurements or a resultant signal of those will trend to go into a certain range. Reference [10] tells that a LF occurs when each axis of measurement are each within a specified value range for a specified duration of time and a NLF occurs when a resultant signal (S_A) is within a specified value range for a specified duration of time. The S_A is defined with following formula:

$$S_A = \sqrt{X^2 + Y^2 + Z^2} \tag{1}$$

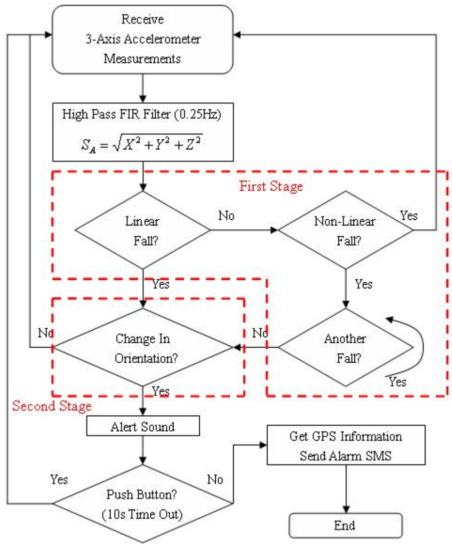

Figure 2. The flow chart of two-stage fall detection algorithm

In order to determine the detecting thresholds of LF and NLF, many tests were carried out with a manikin. The results show that the value range of LF and the duration of time are $\pm$ 4% of zero g and 50ms respectively, while those of NLF are 3% to 10% of zero g and 100ms respectively. First, if the measurements of x, y, and z are within the $\pm$4% of zero g for at least 50ms, it indicates that a LF occurs. If the fall is not a LF, the next step is to determine if it is a NLF. If S_A is within 3% to 10% of zero g for at least 100ms, a NLF is detected. After that, it is indispensable to determine whether another NLF has occurred within 2 second or not. The algorithm would not go to the next stage to detect the orientation of the wearer until the last NLF finished.

B. Detecting Orientation

After an impact has been detected, the next step is to determine if the orientation of body has significant change before the first impact and after the last impact. According to experimental data, it is evident that the orientation of the device could be easily recognized when it is stationary or moving slowly. The accelerometer has been widely used to measure tilt of a static object. In the absence of actual acceleration with respect to the ground, the acceleration of gravity could be detected [11]. It was observed that averaging over one second window of data worked well for estimating the angle, even when the device was slowly moving [12]. When a fall occurs, the device would undergo a large change in position from before the fall to after. The simplest example would be from standing upright to lying flat with an orientation change of about 90 degrees. The actual change may be more or less different with that depending on the initial and final position of the wearer. In our device, the X axis of MMA7260 was in the direct of the gravity, while Y axis and Z axis are orthogonal to that. If two axes of the three, both X and Y or both X and Z, have changes of angle more than 30 degrees simultaneously, it indicates that a significant orientation change of wearer has occurred. This threshold of degree change was set arbitrarily based on empirical data.

Once the two stages are met, a dangerous fall would be considered to be detected. The device will raise an audio indication of detection of a fall. If the wearer doesn't react within 10 seconds, the device will soon get location of the wearer and send an emergency SMS for summoning of help. Moreover, the wearer could manually active the button for acquiring rapid external help.

C. Detecting Nom-Movement

Considering a longtime inactivity may have potential danger to the wearer, a simple algorithm for identifying extended non-movement was added to the device. We also utilize two thresholds to detect inactivity, similar to those used in the detection of impact. The S_A provides an instantaneous data of the net acceleration experienced by the accelerometer. The non-movement detection requires information about the change in acceleration. Therefore, the difference of SA is calculated from the last data.

$$\Delta S_A = \left| S_{ACurrent} - S_{ALast} \right| \tag{2}$$

Finally, we would calculate the average of $\triangle S_A$ with a window of 1 second chosen for that it can clearly reflect the amplitude of an activity.

$$AVG\_\Delta S_A = \frac{1}{SPS}\sum_{i=1}^{SPS} \Delta S_{Ai} \tag{3}$$

Where SPS is the sample frequency, in our case SPS is 40.

If the AVG_△SA less than a threshold for a duration of time, then a extended non-movement is detected. The threshold has been set to half one g in our device. The duration of time will have to be individually calibrated for every wearer according to their professions because of extreme variations in activity levels of the wearer. As for elderly people, the value could be set to 40 minutes.

IV. EXPERIMENT AND RESULTS

A. Experiment

TABLE I. THE RESULT OF SIMULATED AVTIVITIES IN EACH SUBJECT

Subject	Simulated Activity Categories															
	1		*2*		*3*		*4*		*5*		*6*		*7*		*8*	
	TP	*NF*	*TP*	*NF*	*TP*	*NF*	*TP*	*NF*	*TP*	*NF*	*TP*	*NF*	*TP*	*NF*	*TN*	*FP*
1	10	0	6	4	10	0	6	4	10	0	3	7	1	3	1	0
2	10	0	7	3	10	0	7	3	10	0	4	6	2	2	1	0
3	10	0	6	4	10	0	6	4	10	0	5	5	3	1	1	0
4	10	0	7	3	10	0	5	5	10	0	5	5	2	2	1	0
5	10	0	5	5	10	0	4	6	10	0	4	6	1	3	1	0
Total	50	0	31	19	50	0	28	22	50	0	21	29	9	11	5	0
	Success = 325, Fail = 81; Se = 74.7%, Sp = 100%, Acc = 75.1%															

Note: TP is true positive, FN is false negative, TN is true negative, and FP is false positive.

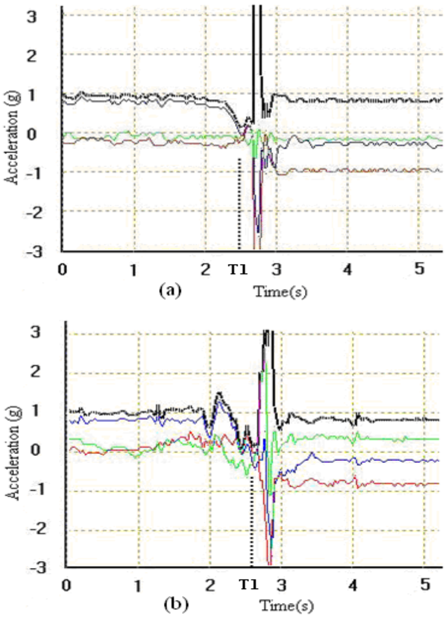

Figure 3. (a) Simulated LF wiht legs straight; (b) Simulated NLF

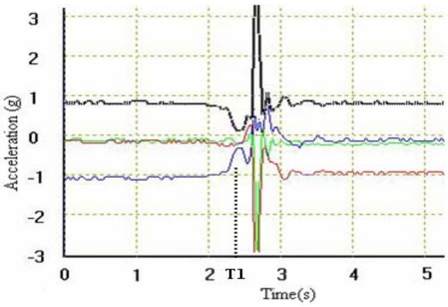

Figure 4. Simulated LF wiht legs flexion

In order to evaluate the device and the two-stage algorithm, an experiment was carried out by 5 test subjects. The subjects were young healthy males (<31 years), whose average age, height, and mass were 26years, 1.74m, and 72.4kg respectively. In order to best simulate the falls that may occurred in elderly people, each subject was told to perform 8 distinct activities inside the laboratory with the device attached to the waist. Each activity was performed on a large crash mat specially used in the gymnasium. The simulated activities categories are as follows: 1) Forward fall with legs straight; 2) Forward fall with legs flexion; 3) Backward fall with legs straight; 4) Backward fall with legs flexion; 5) Sideward fall with legs straight; 6) Sideward fall with legs flexion; 7) Forward fall with external force; 8) ADL (20 minutes). Considering the frequent occurring of LF in the elderly, six simulated LF (test 1 to 6) are designed, while only one NLF (test 7) included in the experiment because that it's difficult to simulate for the volunteers and it may be harmful to their body when acted on by external forces. Each subject was advised to perform as naturally as possible. Each simulated activity that started and ended with a standing position was repeated 10 times except for test 7 (4 times) and test 8 (1 times).

B. *Results*

Table I shows the result of the experiment. In total 325 tests, the device succeeded 244 times and failed 81 times. The accuracy (Acc), sensitivity (Se), and specificity (Sp) are 75.1%, 74.7%, and 100% respectively. Fig. 3(a) is the results while falling forwards with legs straight. As illustrated in Fig. 3(a), at time T1 x, y, and z simultaneously go into the value range of ±4% of zero g. Thus, a LF is detected when three axes signals are within the value range for more than 50ms. Fig. 3(b) is the results while falling forwards with external force. As illustrated in Fig .3(b), at time T1, S_A goes into the value range of 3% to 10% of zero g. Thus, a NLF is detected when S_A is within that value range for more than 100ms.

V. Discussion

Table I shows that 70 simulated LFs were not detected as fall events. Observing the results, it is obvious that 3 simulated LFs with legs flexion are responsible for all of those. By carefully analyzing the data, we find that when the objects simulated the LFs with legs flexion, the value range of three axes accelerations trends to be wider than ±4% of zero g . An example is shown in Fig. 4. As for this, when we simply increased the value range up to ±8%, all LFs with legs flexion could be correctly detected. But on the other hand, some ADL will be mistakenly detected as the falls such as abruptly squatting down. So, the second condition that the S_A must be more than 3.6g was added to the detection algorithm of LF because that the S_A of those ADL having the same value ranges with LF are not more than 3.6g. As a result, the improved LF detection algorithm is that only when each axis of acceleration is within the ±8% of zero g for at least 50ms, and there exists big S_A more than 3.6g after that, would the occurrence of a LF be validated. Furthermore, table I shows that more than 50% of NLFs were not correctly detected. It is because that the NLF is too difficult to simulate. An actual NLF wouldn't occur until the object was run down by a strong force, which is almost impossible in the laboratory. Thus, the test for the detecting of a NLF could be only conducted with a manikin.

In our study, there exist some possible limitations. Firstly, only young volunteers performed the simulated activities for the reason that the experiment is dangerous to the elderly people. Considering the necessities of experiment on elderly, it will be conducted after consulting with some physicians. Secondly, all simulated activities except for ADL are performed on a large soft mat. It is doubtable that whether the detecting thresholds adapt to the actual falls on the solid ground. Thus, we will adjust the thresholds of the algorithm according to the practical test. Finally, all tests were performed in the laboratory with some fixed experimental patterns, which more or less simplified the actual circumstance. We will continuously improve the device through clinical study in the future

VI. Conclusions

In this paper, we have demonstrated the feasibility of a two-stage fall detection algorithm and built a prototype of a fall detector. A medical experiment on 5 young volunteers had been conducted. Although the initial result that the accuracy for fall detection is only 75.1% is not optimal, the device has become accurate enough to distinguish the fall from the ADL with the improved algorithm. By adding the second condition that comparing the S_A with a threshold in the detection of an impact of LF, the device could distinguish the LF with the ADL with an accuracy of 100%. Our detector worn in the waist is very easy to use and could allow real-time monitoring of the elderly people. In case of emergency, the device can locate the wearer whether he/she is indoors or outdoors with the help of gpsOne, and can also summon extern help by sending alarm SMS. In this way, the elderly people are able to walk out of their homes to any place without worrying about getting in helplessness when encountering accidental falls.

References

[1] M. J. Mathie, J. Basilakis, and B. G. Celler, "A system for monitoring posture and physical activity using accelerometers" Proc. 23rd Annu. Intl. Conf. IEEE-EMBS, vol. 4, pp. 3654-3657, 2001.

[2] M.J. Mathie, A. C. F. Coster, N. H. Lovell, and B. G. Celler, "Acceleromery: providing and integrated, practical method for long-term, ambulatory monitoring of human movement" Physiol. Meas., vol. 25, pp. R1-R20, 2004.

[3] F. G. Miskelly, "Assistive technology in elderly care" Age and Ageing, vol. 30, pp. 455-458, 2001

[4] K. Doughty, R. Lewis, and A. Mclntosh, "The design of a practical and reliable fall detector for community and instituional telecare" J. Telemed. and Telecare, vol. 6, pp. 150-154, 2000

[5] T. Zhang, J. Wang, P. Liu, and J Hou, "Fall detecion by embedding an accelerometer in cellphone and using KFD algorithm" Intnational Journal of Computer Science and Network Security, vol. 6, pp. 277-283, Oct 2006.

[6] S. H. Luo and Q. M. Hu, "A dynamic motion pattern analysis approach to fall detection" IEEE Intl. Workshop on Biomedical Circuits and Systems, pp. S2.1_5-S2.1_8, 2004.

[7] T. Degen, H. Jaeckel, M. Rufer, and S. Wyss, "SPEEDY: A fall detector in a wrist watch" Proc. 7th Intl. IEEE-ISWC, pp. 184-187, 2003.

[8] A. K. Bourke, C. N. Scanaill, K. M. Culhane, J. V. O. Brien, and G. M. Lyons, "An optimum accelerometer configuration and simple algorithm for accuracy detecion falls" Proc. 24th IASTED Intl. Multi-Conf. BME, pp. 156-160, 2006.

[9] C. V. C. Bouten, K. T. M. Koekkoek, M. Verduin, R. Kodde, and J. D. Janssen, "A triaxial accelerometer and portalbe data processing unit for the assesment of daily physical activity" IEEE Trans. Biomed. Eng., vol. 44. pp. 136-147, 1997.

[10] M. A. Clifford, R. L. Borras, and L. Comez, "System and method for human body fall detecion" US Patent, US0214806A1, 2006.

[11] "Measuring tilt with low-g accelerometers" Freesclae Semiconductor Application Note, AN3107, 2005.

[12] J. Chen, K. Kwong, D. Chang, J. Luk, and R. Bajcsy, "Wearable sensors for reliable fall detection" Proc. 27th Annu. Conf. IEEE Engineering in Medicaine and Biology, pp. 3551-3554, 2005.

[13] T. R. Burchfield and S. Venkatesan, "Accelerometer-based human abnormal movement detection in wireless sensor networks" HealthNet'07 USA, pp. 67-69, Jun 2007.