Low-Power Fall Detection in Home-based Environments

Lingmei Ren[1], Quan Zhang[1] and Weisong Shi[1 2]

[1]School of Electronics and Information Engineering
Tongji University
Shanghai, P.R. China
rlingmei@gmail.com, dante.zq@gmail.com

[2]Department of Computer Science
Wayne State University
Detroit, MI, USA
Weisong@wayne.edu

ABSTRACT
Fall detection of the elderly becomes more critical in an aging society. However, how to put forward fall detection with reliability and high accuracy while maintaining real-time and energy-efficiency is an important issue. To this end, we design and implement an energy-efficient prototype called Asgard, in which a fall detection algorithm and a hybrid energy-efficient strategy are proposed. The algorithm, which can flexibly track the body change by recovery angle detection, helps to reduce the false positive phenomenon as well as detection time (DT). Results of comprehensive evaluations show the accuracy rate of 96.25%, which is higher than AMD (Advanced Magnitude Detection). More notably, the prototype still has low DT with the aforementioned accuracy. More precisely, with the proposed hybrid energy-efficient algorithm, Asgard functions well for approximately one month using only two AA batteries (1500mAH each).

Categories and Subject Descriptors
J.3[**Computer Applications**]: Life and Medical Sciences-Health, Medical information systems

General Terms
Algorithms, Experimentation, Performance, Reliability, Design

Keywords
Fall Detection, Accelerometer, Energy-efficient, Detection Time, Hybrid Strategy

1. INTRODUCTION
In almost every country, the aging issue becomes more serious and outstanding. Large amounts of data show that elderly people aged over 65 will soon comprise a much larger ratio to the total population. The aging population, over 629 million worldwide, accounts for 10% of the total population [1]. There exit many dangers and accidents when the elderly live alone. Falling is one of the most common and dangerous accidents, as falls always bring not only physical hurt, but also psychological effects. According to statistics, more than 30% of elderly people aged 65 or over fall at least once every year [2], and the risk of falling rises with increasing age. About 50%-80% of the elderly aged over 80 risk falling. Furthermore, it is reported that each year, nearly 1 million deaths in the United State are a result of a fall. To respond to the challenges of the aging issue, it is important to propose a high accuracy fall detection method.

A great number of different fall detection approaches have appeared in recent years. Most of them are threshold-based solutions, which achieve detection by receiving parameters using accelerometers. For example, some studies utilize the impact of the body to detect fall [3].Others detect fall by combining the large impact with the angle of the body [3], [4], [5]. However, in this type of fall detection, threshold determination is important for the accuracy of the fall detection, which may bring many false positives and false negatives, as it is mostly determined by empirical data. Moreover, many studies consider fall with limited fall tasks, limited fall actions and limited volunteers while against to a specific fall scenario for evaluation, which always brings out many phenomena of false alarms or alarm omission. In addition, some of the previous studies use various sensor arrays such as vibration [6] and acoustic [7], as well as different processing technologies such as image processing [8] and pattern recognition [9] to detect fall, but all of these methods have high cost, high power consumption and large computation. Furthermore, few systems refer to the energy-efficiency issue, which affects the usage of the system. Therefore, we propose a novel fall detection algorithm which provides long-term, real-time, and energy-efficient detection by leveraging the parameters of the Vector Sum of three Axes (VSA), Body Tilt Angle (BTA), and recovery angle measured by a triaxial accelerometer to draw an efficient and immediate alarm solution in an emergency situation. Additionally, a hybrid energy-efficient strategy is proposed to solve the power saving issue.

In our paper, we proposed a single triaxial accelerometer-based, wearable, real-time fall detection system, including our customized hardware prototype with the features of low cost and low power, called an Accelerometer Sensor Generic Board (Asgard), and a novel fall detection algorithm. One distinguishing key advantage of our system over others is that we emphasize energy-efficient detection. In detail, our fall detection framework contributes the following: First, a novel fall detection algorithm is proposed to improve the detection accuracy. Second, a hybrid hardware/software energy-efficient strategy for a low-power fall sensor design is proposed to reduce power consumption.

This paper is organized as follows. The deficiency of the existing fall detection system and the reason for proposing a novel algorithm are presented in section 2. Section 3 gives an overview

MobileHealth'12, June 11, 2012, Hilton Head, South Carolina, USA.

of our detection system and describes related hardware models. We proposed a novel, fall detection algorithm and a hybrid energy-efficient strategy in section 4. In section 5, details on evaluation of the proposed algorithm and the efficiency of low power are revealed. Moreover, section 6 draws conclusions and directions for the future.

2. BACKGROUND and REQUIREMENTS

Large demands for public healthcare service of the fall detection technique promote the progress of research work. In recent years, a great number of fall detection solutions have been proposed. Some fall detection methods use sensors to detect fall. We know that there is an angle change of the body from upright to lying that occurs after a large impact, which manifests a fall using an accelerometer [3] or multi-sensors [10], so large impact and angle change of the body are combined to detect a fall. C Dinh et al. [11] used the paradigm of a knowledge-based method with one accelerometer to detect a fall, and Tong Zhang et al. [9] proposed a fall detection method based on pattern recognition with only one sensor. Furthermore, by installing a camera in the living room to track the user, a fall can be detected through image processing. Bin Huang et al. [8] achieved camera-based fall detection while using an extraction technology. Furthermore, information acquired from an ambience environment can also detect a fall. Alwan et al. [12] distinguish a fall from ADL by measuring vibration information on the floor.

Currently, fall detection has become a hot research point. Threshold-based fall detection is the most common one among existing research. However, most of those solutions have the limitation of a specific fall assumption or scenario, e.g., [10], [3] consider a fall as being horizontal with the ground, which evidences alarm failure when one falls on an object. The Advanced Magnitude Detection (AMD) proposed in [3] is proposed to reduce a false positive when one falls but tries to grasp an object and ends up slumping next to the object. However, fall detection solutions of this type work badly in other fall situations. Furthermore, a false positive frequently occurs in detection when determining the angle of the body at a specified time, e.g., Jay Chen et al. [4] calculate angle 2 seconds after the last impact to determine one fall or no fall. Amit Purwar et al. [5] detect the angle after 1s following an impact that is above or below the threshold. In addition, AMD analyzes the user's orientation after a short time interval of 12 seconds, and further detection is implemented within another time interval of 16 seconds. Evidently, there will be a false alarm when successful recovery occurs or a missed alarm if the recovery situation is considered at a fixed time in existing studies. An ideal fall detection system also has many other requirements, e.g., being easy and convenient to wear, as the elderly prefer to use one device rather than many devices to detect a fall. Continuous and long-term usage is also an important factor, not considered in most studies while high accuracy and quick response time are two other necessary requirements.

The insufficiencies and requirements mentioned above drive us to design a novel fall detection that uses a continuous and energy-efficient fall detection algorithm, improving detection accuracy and Detection Time (DT) by following tracks of recovery action after a fall is implemented in an Asgard prototype. A comprehensive evaluation of our algorithm is achieved by comparing it with AMD. Moreover, energy-efficiency is considered as an essential point, which is achieved by proposing a hybrid energy-efficient detection strategy.

3. DESIGN of SYSTEM ARCHITECTURE

The high-level overview of our system is shown in Figure 1. The whole system can be divided into two parts including a family healthcare network and CloudPIS, which we researched in previous work. The family healthcare network consisting of Fallsensor and Homeserver, responds to collection of alarm information and transmits those data to CloudPIS. CloudPIS is an information-sharing platform for patients and caregivers [13]. Then, a remote monitoring center or caregivers can obtain related data from CloudPIS, so that one can be helped in time once an emergency occurs. The most important part of the family healthcare network is Fallsensor, which accomplishes the main work of fall detection. It is constructed using the Asgard, which consists of an accelerometer, a microcontroller, and a wireless communication module. The accelerometer measures physical change information, and is converted to acceleration by the A/D of the microcontroller. The acceleration transformed is used to detect a fall and distinguish a fall from ADL through processing in the microcontroller. Once a fall is detected, alarm information will be sent to Homeserver via ZigBee, and this can reduce risk to the elderly.

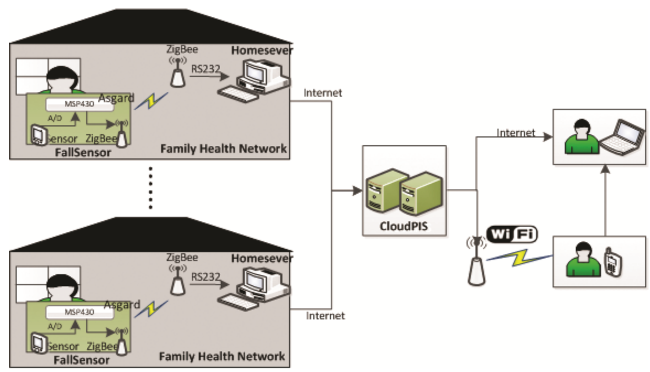

Figure 1. The high-level overview of fall detection system

3.1 System Hardware Description

The Asgard, implemented to detect a fall, consists of the MMA7260Q triaxial accelerometer, STM8S103F microcontroller, and CC2520 radio model. The Asgard is used as a platform for acquiring acceleration data, achieving data processing, and radio communication. The prototype of the Asgard board is constructed as the one on the right of Figure 2.

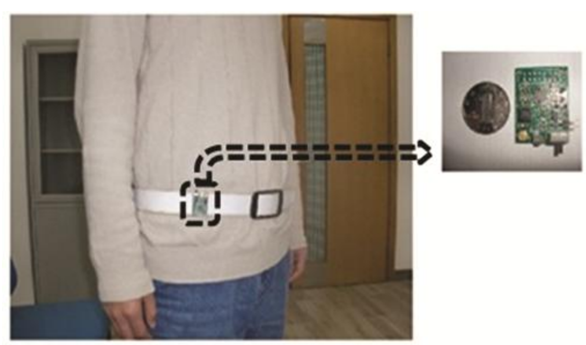

Figure 2. A prototype implementation of Asgard

In the Asgard, MMA7260 is connected to a 10 bit A/D of the microcontroller, which converts analog output into digital output ranging from [0, 1023]. The range of digital output corresponds to a measured voltage of [0, VDD3.3]. Those digital values were again converted into voltage signal and then actual acceleration was calculated by subtracting the reference voltage and dividing the sensitivity of MMA7260. The formula for calculating acceleration (Acc) is given as:

$$\mathrm{Acc} = \frac{\mathrm{VDD3.3} * \mathrm{SampleValue}/1024 - \mathrm{VDD3.3}/2}{\mathrm{sensitivity}} \qquad (1)$$

Where VDD3.3 is the supply voltage of the accelerometer with mV as unit, SampleValue is the value acquired from the accelerometer. Sensitivity is different according to different applications, and the final calculated result of Acc is in g unit.

The STM8S103 microcontroller, which has features of low cost, low power, high performance, and high reliability, meets all the functional module interfaces of our system, so it is chosen as the core of Asgard. In addition, wireless transmission is used to achieve real-time fall detection for the elderly in a home environment. As the collected accelerometer data in our system is a small amount. CC2520 radio Zigbee module, with features of low-power and low data rate, is chosen as the wireless communication media between the FallSensor and Homeserver. It is a good choice to replace Bluetooth or other protocols, which face issues of high power, high cost, and high system complexity.

3.2 Fall Detection

Current studies of fall detection have many false positives and false negative cases, as most of them focus on simple fall actions or specific fall circumstances that cannot be detected. For example, detection action is assumed to be parallel with the ground after a fall. However, there always exit complex states after a fall. In the case of a fall, the user may try to grasp a wall, chair, or other objects and end up slumping next to the object. In another instance, the person may fall slightly and try to recover after that. Each scenario evidences deficiency. Therefore, we proposed a novel algorithm to catch these falls and others. Differing with other studies, a large VSA and BTA are used in our algorithm while recovery angle is another parameter employed to track the status after human falls. The algorithm starts from a large impact, with subsequent continuous monitoring to detect whether the person recovers to stand up or not at every fixed time interval. The maximum angle change of the body is utilized to determine the recovery status of the human body. Until there is no maximum angle change that exceeds the fixed threshold, the body posture will be analyzed and determined.

3.3 Hybrid Energy-efficient Design

The idea to achieve a hybrid energy-efficient strategy is to combine software energy saving measures with hardware energy saving measures. Power consumption of wireless communication is larger than other modules in the Asgard, the idea that the radio module does not work in the course of fall detection until the fall has been detected can achieve energy efficiency. However, CC2520 consumes energy even when STM8S103 is in stand-by or sleep mode. Therefore, the hardware approach is also needed to achieve further energy-efficiency. Besides, software deployment of a microprocessor can be used to reduce power consumption, such as low-power mode, low clock frequency, and so on.

4. IMPLEMENT OF LOW-POWER FALL DETECTION

4.1 Low-power Fall Detection Algorithm

We proposed a novel fall detection algorithm in our system. It can alarm once the trigger conditions are met. In addition, the whole prototype system was developed in C language, which is easily extended to other uses.

4.1.1 Pre-process of acceleration

To make sure the collected value from the accelerometer is effective, calibration of the accelerometer is essential. MMA7260 exports three axes acceleration values of X, Y, Z at each sample point, which can be mapped to the spherical coordinates. According to spherical values computed from the acceleration data, the actual change of the user body can be tracked in real time with respect to a real world perspective. In a regular scenario, when a subject stands still, it would be affected only by Gravity, so one axis value of the accelerometer will be 1g or -1g, while the other two are 0g when the Asgard is placed still, i.e., the vector sum of the three-axes acceleration is 1g, which is directed toward the center of the earth. According to this phenomenon, we adjust the direction prototype board continuously and keep it horizontal, then adjust the parameters of the equation of the Acc according to accelerations of two opposite directions. In the premise of the smallest error, we achieve calibration of the accelerometer. In the Asgard, three axes acceleration is collected with a sampling frequency of 1KHz while the VSA of the MMA7260 is sampled at 62.5HZ, which means that the VSA is updated every 16ms. However, the sampled data of three axes acceleration is always affected by unwanted artifacts like noise or peaks, median filter is applied with n = 16 to reduce data amount and remove noise before further processing and analysis.

4.1.2 Parameters of fall detection algorithm

The Asgard is worn on the waist of the body as seen in Figure 2, because Kangas et al. [14] indicates fall detection with an accelerometer placed at the waist to have higher accuracy than ones placed on the wrist, trunk or tag in a threshold-based fall detection algorithm. In our system, the Asgard was placed as in Figure 2 with the Y-axis toward the direction of the earth, while x- and z-axes were orthogonal to the Y-axis. The total acceleration will change along with movement intensity, which is around 1g in a general situation. Evidently, regardless of whether one falls on the ground or hits some object, there will be a large impact, which can be reflected by the vector sum of the three axes acceleration data, which is defined as VSA. As expected, comparison of the VSA with the VSA threshold (VSA_th) can distinguish a fall from ADL, as the VSA caused by a fall is larger than that of movements in daily life. VSA is defined in equation 2:

$$\mathrm{VSA} = \sqrt{x_i^2 + y_i^2 + z_i^2} \qquad (2)$$

where x_i is the i-th sample value of the x-axis, and is the same for $y_i$andz_i. However, previous research has found and verified that those methods using VSA only can distinguish a fall from ADL with low accuracy.

Various activities always accompany an angle change of the body. The angle between the body and ground will change significantly when the body falls while performing small tasks in daily life. As many experimental data have proved, the orientation of the device could be easily acquired when it keeps stationary or moves slowly. Therefore, the final angle change of the body is selected as another parameter for further improvement of the fall detection accuracy. We define Body Tilt Angle (BTA) to represent angle shown in formula 3:

$$\mathrm{BTA} = \arccos(y/\mathrm{VSA}) \qquad (3)$$

where y is the sample value of the y-axis. BTA refers to the tilt of the body in space.

The parameters of VSA and BTA in many studies can distinguish a simple fall and ADL, but if the person falls slightly and then tries to recover, those methods do not appear to work. Detecting recovery action allows us to track the real-time status of the human after a fall, so recovery angle is cited as another parameter of our algorithm to provide better detection.

4.1.3 A novel fall detection algorithm

Complex fall situations show deficiencies regarding the existing systems. Therefore, we proposed a novel algorithm illustrated in Figure 3 as shown below.

In the flowchart of our algorithm, the basic algorithm design for carrying this out proceeds as follows:

1) Look for a large VSA, which exceeds the preset VSA threshold (VSA_th). The method of determining VSA_th will be explained in section 5.

2) Wait until a large VSA dissipates and obtain the current BTA of the body. This situation is the moment that the person has an impact with the ground or an object.

3) Analyze the max recovery of the body tilt angle, which we called BTA_MR every period of 0.5s.

4) If a person is recovering to stand, i.e., the BTA_MR is large and exceeds the threshold of the recovery angle within 6s, continue the next recovery determining up to 6s, until 5) appears.

5) If no recover activity occurs within 6s, go to 6). The elderly is considered as having a fall too serious or non-fall or the body has recovered to static.

6) Obtain the current angle, which we define as a final body tilt angle (BTA_FIN). If it is designated as deviating from uprightness, classify it as a fall.

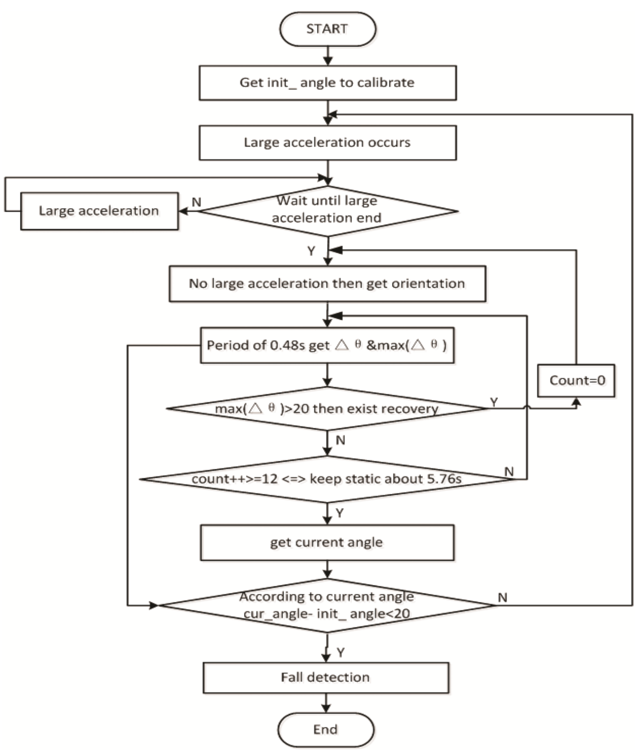

Figure 3. Flowchart of the novel fall detection.

4.2 Hybrid Energy-efficient Strategy

Development of an energy-efficient fall detection method is also within our scope. A durable fall detector can extend the usage period of portable devices, and avoid the trouble of replacing batteries or frequently recharging. In the Asgard, we proposed a variety of energy-saving strategies to achieve this goal, which consists of software energy saving measures and hardware energy saving measures.

Section 5 indicates that the wireless transmission has the highest energy cost. So reducing the times of wireless transmission can achieve energy-efficiency. In the proposed algorithm, the amount of data is small and the algorithm is simple, so locally processing can reduce the frequency of wireless transmission, as the wireless transmission does not work in the course of fall detection until a fall is detected and the fall information needs to be sent out. However, CC2520 will consume power whether the wireless function is used or not. To power on a radio module in certain circumstances, a switching circuit module is added between the power parts of STM8S103 and CC2520 as a switch circuit module can control the power supply of the module. When the switch circuit receives a high-level voltage signal, the switch circuit module will connect the STM8S103 with the CC2520. Similarly, it cuts off the power when the receiving signal is at a low voltage level. Therefore, the radio module can be turned off in a timely manner, which can reduce the power consumption of the system. In our algorithm, the wireless module is powered on only when a fall occurs, and then alert information is sent out four times circularly to reduce the loss of the wireless link. In the Asgard, the transmission procedure lasts for 100ms, and a total time of 100ms * 4=1.2s when the transmission is achieved, which means that system is a low-power operation most of the time and power consumption is low.

In the Asgard, if the sampling frequency of the microprocessor is too high, data processing will have a high speed, but large power consumption, correspondingly. As is known, all measured body movements are within frequency components below 20HZ [15]. A sampling frequency of 62.5Hz, which is verified effective, was chosen in our algorithm. In addition, other measures are also used to achieve an hybrid energy-efficient detection method, including selection of low-power hardware, working in low-power mode, turning off those unused peripherals and theirs clocks, setting all unused pins to be low, preventing an AD Schmitt trigger, and so forth.

5. EVLUATION

5.1 Experiment Cases

The experiment environment and requirements of evaluation are described in this section. To evaluate our algorithm, serial experiments were carried out by 10 volunteers, including 7 males and 3 females. Volunteers are healthy person with average age, weight and height of 30 years old, 58kg and173cm, respectively. All the volunteers performed experiments wearing the Asgard on their waist. Those tests were done in the same situation. Furthermore, many fall situations should be considered as fall scenarios vary. The experiment tasks that volunteers did are described in Table 1.

AMD is re-implemented in our study as a comparing algorithm. Both algorithms are implemented on the Asgard we have implemented in the same condition including sampling frequency, experimental tasks, experimental environment, participate volunteers and so on.

Table 1. Task description

Category	Task	Description
ADL	Sit down	The subject stands still at first, then sits down and remains seated.
	Lay down	From a standing position, the subject lays down and sleeps.
Transform	Walk to sit	The subject walks at normal speed for 5s and then sitson the seat or sofa.
	Run to sit	The subject runs at normal speed for 5s and then sits on the seat or sofa.
	Jump to sit	The subject jumps and sits on the seat or sofa.
	Squat and stand	Initially in a standing position, the subject then squats down.
	Fall but recovery to stand	From an initial standing position, the subject falls on the ground or sofa, but he/she tries to recover, and finally stands up.
Simple fall	Fall forward	The subject stands still and falls on the ground or sofa with face toward the ground.
	Fall backward	The subject stands still and falls on the ground or sofa with back to the ground.
	Fall lateral	The subject stands still and falls on the ground or sofa with the lateral first touching the ground.
Complex fall	Fall on sth	The subject stands still and falls down on something.
	Fall with recovery	From an initial standing position, the subject falls to ground or sofa, and he/she tries to recover, but finally, fails to stand up.
	Fall from stairs	The subject standson stairs and falls to ground.

5.2 Comprehensive Evaluation

5.2.1 Determining of threshold

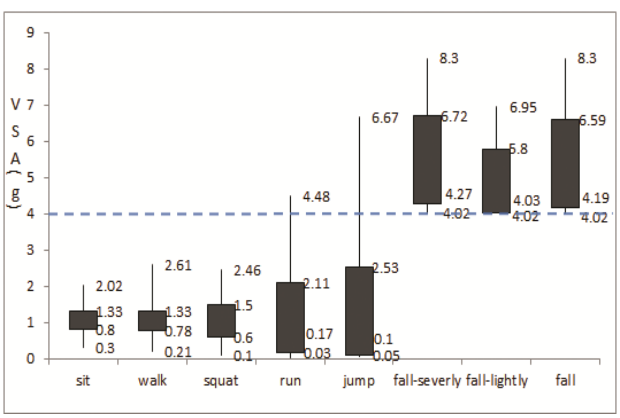

Figure 4. 95% confidence interval of VSA.

To improve accuracy of fall detection, a reasonable threshold of VSA is essential. The difficulty of determining this threshold is that lower VSA leads to the case that common ADL is wrongly judged as a fall, which we called a false positive (FP), on the contrary, higher VSA causes failure of a fall detection, which is termed a false negative (FN). Many algorithms determine the threshold empirically [3], [11]. In determination of VSA_th, we apply confidence interval of statistics to calculate the range of possible predictions within a 95% confidence level.

In our experiment determining VSA_th, we invited three volunteers to perform the specified activities mentioned in Figure 4. Each volunteer engaged in all of the actions, which lasted 5 seconds, 5 times. We chose 1000 continuous sample data, and drew a confidence interval of VSA in Figure 4 above.

The figure shows a 95% confidence interval of VSA of different activities, each activity gives maximal value, upper limit of confidence interval, lower limit of confidence interval, and minimal value in order from up to down. The dotted line in the figure is marked as selected threshold (VSA_th). As Figure 5 shows, VSA_th could distinguish most ADL from falls except for run and jump. The first three actions will not trigger detection, as maximum values of those actions are lower than VSA_th while the others will trigger the detection. Therefore, we can distinguish a fall from most of the ADL.

5.2.2 Accuracy verification of threshold determination

To verify the VSA_th determined is appropriate, we test the accuracy of the algorithm under different thresholds. In experiments, the prototype runs the proposed algorithm with a different setting of parameter values. One difference is that each activity is done 6 times. Table 2 shows the accuracy results of different thresholds.

Table 2. Accuracy of different thresholds

Threshold / Item	Non-Fall(108)	Fall (54)	Accuracy
VSA_th=3&BTA_FIN=30	101	44	89.51%
VSA_th=3&BTA_FIN=40	98	53	93.21%
VSA_th=3&BTA_FIN=50	88	49	84.57%
VSA_th=3&BTA_FIN=60	86	53	85.80%
VSA_th=4&BTA_FIN=30	106	41	90.74%
VSA_th=4&BTA_FIN=40	103	48	93.21%
VSA_th=4&BTA_FIN=45	105	51	96.30%
VSA_th=4&BTA_FIN=50	99	51	92.59%
VSA_th=5&BTA_FIN=45	102	27	79.63%

From Table 2, we can see that different thresholds will draw different accuracies of fall detection. Obviously, the accuracy of detection will go down if the threshold is too big or small, e.g., the threshold of VSA_th is set to 4, determined in our experiment as having high accuracy over a value set to 3 or 5. Many serious ADL can trigger detection when the VSA_th is equal to 3, while many slight falls fail to drive detection when VSA_th is 5. Results show our algorithm has the highest accuracy at 96.3%, better than other thresholds, when VSA_th is 4 with BTA_FIN set to 45.

5.2.3 Comparison of two algorithms

The Comparative experiments for two algorithms are done with the same experiment tasks, as shown in Table 1 above.

In Table 3 below, TP is true positive, FN is false negative, TN is true negative, FP is false positive, and DT is detection time, A is accuracy of the fall detection. Viewing Table 3 as a whole, our proposed algorithm has higher accuracy than AMD while the DT is more flexible. The accuracy of our algorithm is 96.25%, while

AMD has accuracy of 93.75%. The most important difference of those algorithms lies in the high false positive rate of AMD, as BTA_FIN is set a bit higher in AMD, which caused many fall-like activities alarms. False negatives of our algorithm are higher than AMD, as the times of the test are far lower than ADL. In fact, a false negative occurs only once in all of the experiments. In all, the accuracy of our algorithm is better than others are. Additionally, DT is another advantage of our system. The result shows that the average DT of AMD is 12s, which is nearly 6s higher than our algorithm among simple falls. In a complex situation, our algorithm has an average DT of 19.3s, which is longer than AMD, but a long time helps to reduce false positives, as some recovery actions may last long, exceeding the threshold AMD had set, which will not occur in our system.

Table 3. Accuracy and DT of two algorithms

Categories	i-Alarm Algorithm						Berkeley Algorithm					
	TP	**TN**	**FP**	**FN**	**A**	**DT**	**TP**	**TN**	**FP**	**FN**	**A**	**DT**
Simple ADL	94 %	97.86 %	2.14 %	6%	96.3%	6.1s	95 %	92.83 %	7.14%	5%	93.8%	12s
Complex ADL						19.3s						16s

5.2.4 Power consumption of the Asgard

Energy-efficiency is another issue we focus on. We proposed strategies to solve this problem. Experiments with various conditions as shown in Table 4 have been performed.

Table 4. Power Consumption of Different Conditions

Current(mA)	**Run Model**			**Low Power Model**		
Transmit data	**No wireless**	**Alarm only**	**wireless alarm**	**No wireless**	**Alarm only**	**wireless alarm**
Fall only	10.93	12.37	30.99	4.61	6.05	27.53
Whole process	29.53			26.09		

According to the results of power consumption of the Asgard, we can see that the wireless transmission has the most energy cost, the current of no wireless will be less than that of wireless to about 26.06-4.61=21.45mA in the low power model, while about 29.53-10.93=18.6mA in the run model. When the system transmits fall information and open alarm, the cost of the current reaches 27.53mA in the low power model and 30.99mA in the run model. Obviously, the low power model has a lower current than the run model. We assume two AA batteries with a capacity of 1500mAH are used, then they can be used to 1500*2/4.6=651 hour=27.1 days, as the wireless transmission has the feature of few occurrences and a short duration of about 1.2s. Karantonis et al. [4] highlights that monitoring status consumes 8.31mA, which is 3.7mA higher than ours and the same batteries can be used 15 days. In addition, the Asgard is built by a development board, which uses a regulator costing a large current of 2mA. Therefore, we will rebuild the board ourselves, which reduces the current of the regulator module to uA, i.e., our board will cost less than 3mA in ADL.

6. CONCLUSION AND FUTURE WORK

In this paper, we presented a novel fall detection algorithm, which can achieve real-time and continuous detection while maintaining energy savings. Comprehensive evaluations were implemented by us and were conducted using the Asgard. Experiment results show detection parameters we selected can successfully track the body status as reflected with increasingly significant accuracy. Moreover, a hybrid energy-efficient strategy reduces the power consumption of the whole system. In the future, we will try to improve the accuracy by utilizing a self-adaptive threshold determination detection method. Meanwhile, due to the diversity and quantity of healthcare monitoring data, we consider reducing the power consumption by optimizing communication protocol.

7. ACKNOWLEDGMENTS

The authors would like to thank anonymous reviewers for their constructive comments, and we are also grateful to the volunteers in our evaluation experiments. This project is in part supported by Guangdong Province Introduction Innovation Team Fund, Tongji University and Wayne State University.

8. REFERENCES

[1] United Nations Releases New Statistics on Population Ageing, Note No.5713, 28 February 2002. DOI=http://www.un.org/swaa2002/note5713.doc.htm.

[2] Harold Rubin, MS, ABD, CRC, Guest Lecturer, Allan Rubin. 2010. Dizziness-Trying to Prevent Falls and Accidents Among the Elderly, Updated September 28, 2010. DOI= http://www.therubins.com/aging/DIZZI.htm.

[3] Garrett Brown. 2005. An accelerometer based fall detector: development, experimentation, and analysis. University of California, Berkeley CA, EECS/SUPERB, July, 2005.

[4] Jay Chen, Karric Kwong, Dennis Chang, Jerry Luk, and Ruzena Bajcsy. 2005. Wearable sensors for reliable fall detection. Proceedings of the 27th Annual International Conference of the IEEE EMBS. Shanghai, China: IEEE, Sept 2005, pp. 3551-3554.

[5] Amit Purwar, Do UnJeong, Wan Young Chung. 2007. Activity monitoring from real-time triaxial accelerometer data using sensor network. International Conference on Control, Automation and Systems 2007Oct. 17-20, 2007, pp. 2402-2406.

[6] Litvak Dima, Zigel Yaniv, Gannot Israel. 2008. Fall detection of elderly through floor vibrations and sound. Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE. 20-25 Aug, 2008, pp. 4632- 4635.

[7] M. Popescu, Y. Li, M. Skubic and M. Rantz. 2008. An acoustic fall detector system that uses sound height information to reduce the false alarm rate. 30th Annual International IEEE EMBS Conference, pp. 4628-4631, 2008.

[8] Bin Huang, Guohui Tian, Xiaolei Li. 2008. A method for fast fall detection. Proceeding of the 7TH World Congress on Intelligent Control and Automation, 25-27. 2008, pp. 3619-3623.

[9] Tong Zhang, Jue Wang, Liang Xu, et al. 2006. Fall Detection by Wearable Sensor and One-Class SVM Algorithm. ICIC 2006, LNCIS 345,2006, pp. 858-863.

[10] Thinh M. Le, R. Pan. 2009. Accelerometer-based Sensor Network for Fall Detection. Sensors Peterborough NH(2009), pp. 265-268.

[11] C Dinh, D Tantinger and M Struck. 2009. Automatic emergency detection using commercial accelerometers and

knowledge-based methods. Computers in Cardiology 2009, vol 36, pp. 485-488.

[12] M. Alwan, P.J. Rajecdran, S. Kell, D. Mask, S.Dalal, M. Wolfe and R. Felder. 2006. A smart and passive floor-vibration based fall detector for elderly. Information and communication technologies, ICTA'06. 2nd, pp. 1003-1007.

[13] Quan Zhang, Lingmei Ren and Weisong Shi. HONEY: A Home-based Multimodality Fall Detection and Telecare System. unpublished.

[14] Kangas M, Konttila A, Lindgren P, Winblad I, Jämsä T. 2009. Comparison of low-complexity fall detection algorithms for body attached accelerometers. Gait & Posture 28 (2009), pp. 285-291.

[15] Karantonis, D.M. Narayanan, M.R. Mathie, M. Lovell, N.H. Celler, B.G. 2006. Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. Information Technology in Biomedicine, IEEE Transactions on, vol. 10, Jan. 2006, pp. 156-167.