Real-time energy-efficient fall detection based on SSR energy efficiency strategy

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Abstract: Falling of the elderly has become a growing concern of the community due to the increase of the ageing population and the serious consequences caused by falling. Devising a fall detection system that is not only highly accurate and reliable, but energy efficient and durable is a challenge. In this paper, we proposed an energy efficient fall detection algorithm based on segmented sampling rates. Most of the time, the algorithm uses a low sampling rate to minimise the energy consumption, but a higher sampling rate when a possible fall is sensed. This unique design helps to increase the fall detection accuracy, while reducing the total energy consumption. Results of comprehensive performance evaluation show that the accuracy rate of the proposed fall detection algorithm is 98.33%, meanwhile, the system can save energy by 9.13% comparing to other algorithms running with a high sampling rate without an energy efficient strategy.

Keywords: fall detection; energy efficient; segmented sampling rate; accuracy; real-time.

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1 Introduction

Worldwide the elderly people make up the fastest-growing age population, due to the longer life expectancy as well as the declining birth rate. This trend is expected to continue for the next several decades (Ageing, see http://www.who.int/topics/ageing/en/)(Ageing in the Twenty-First Century, https://www.unfpa.org/public/home/publications/pid/11584). Japan is purported to have the highest proportion of the elderly population. It is reported that a quarter of the population will be over 65 years old by 2013 (Japan's ageing population could actually be good news, see http://www.newscientist.com/article/dn24822-japans-ageing-population-could-actually-be-good-news.html#.Ux_N8WJUr5M). According to the latest figures from the National institute of Population and Social Security Research, the population aged 65 years old or over will increase to nearly a third due to Japan's ageing by 2060 (Data: 1920–2010: National Census, pushing total population, see http://www.ipss.go.jp/site-ad/TopPageData/Pyramid_a.html). The same phenomenon is occurring in Canada. The 2011 Census counted nearly 500 million elderly people aged 65 or over in Canada, with an increase of up to 14.1% between 2006 and 2011 (The Canadian Population in 2011: Age and Sex, see http://www12.statcan.ca/census-recensement/2011/as-sa/98-311-x/98-311-x2011001-eng.cfm). Among the elderly people, falling is one of the leading causes for both fatal and nonfatal injuries, and it is also a key risk affecting living independency of the elderly people. Statistics show that about one in every three elderly people aged 65 or over suffers falling each year. The possibility of falling will rise with the increasing age. It is estimated that the elderly people aged 75 or over fall four to five times more than people aged 65–74 (Stevens and Dellinger, 2002). The consequences of falling are always serious, for example, it may cause direct external trauma, various body part fractures, head injuries, and in the worst scenario, it results in fatal damages. Furthermore, it also causes great social and financial burden, including high medical or healthcare costs. As falling imposes huge risks to the aged population, it becomes more and more critical to develop a practical, real-time and highly accurate fall detection system.

Despite its importance being widely recognised, fall detection research of the elderly people is limited. Power consumption, which is a key design factor for developing a practical product, is largely ignored in the research. Products are often useless for elderly people if they require frequent battery replacement or charging. Fall detection researches for the elderly should not only focus on high accuracy, but also on high energy efficiency to prolong the usage time of the device for continuous monitoring (Hu et al., 2008). Currently, typical server side computing based fall detection systems, such as a distributed multiple intelligent biomedical sensors-based fall detection system (Estudillo-Valderrama et al., 2009), a distributed cameras-based fall events detection system (Huang et al., 2009), and a distributed intelligent fall detection architecture research based on a four-axis accelerometer (Prado et al., 2002), mainly contribute on how to improve fall detection accuracy without considering the energy efficiency issue. In these design, large amounts of activity data collected by sensors are all sent to the server end via wireless transmission for advanced determination (Xiao et al., 2011), which consumes most of the power energy of sensors (Ling-Dong et al., 2011). Consequently, fall detection systems based on server side computing have big drawbacks on power consumption despite high accuracy. Since sensor nodes usually use battery as a power source, the continuous wireless transmission significantly reduces the performance of the entire system in terms of the battery life. On the other hand, portable and real time in-hardware processing fall detection solutions collect activity data, analyse and make a determination directly at the sensor nodes; therefore, power consumption can be reduced via less wireless transmission. However, such local in-hardware solutions also consume certain energy (Hu et al., 2011), which is not studied in their research. Compared with the server side computing based algorithms, Soaz et al. (2012), Brown (2005), Chen et al. (2005) and Purwar et al. (2007) investigate accelerations of three orientations by a tri-accelerometer, combining with various parameters such as angle, time interval or others to identify the fall at the sensor node, and they only transmit a fall alarm when the fall is detected. Such local computing based algorithms consume less power by reducing wireless transmission. However, these algorithms require the sensors to actively process and analyse the data most of time to achieve the accuracy at the cost of high power consumption. Consistent with (de la Guia Solaz et al., 2010), the more frequently the sensor collects and processes the data, the more detailed data of the fall can be collected, which in turn will increase the fall detection accuracy, but accordingly, it also brings high energy cost accordingly. On the contrary, low processing frequency consumes less energy, but may be more likely to miss the critical data, and results in unacceptable large fall missing or false alarm situations.

In this paper, we proposed a segmented sampling rate energy efficient strategy which is denoted as SSR energy efficient strategy for the portable fall detection sensor design.

The proposed strategy balances the energy cost and fall detection accuracy by segmenting activity stages with different sampling rates. We also build a SSR based fall detection prototype combining with impact, impact rate and angular state to verify the proposed design. The key advantage of the SSR energy efficient strategy is to reduce the energy cost of the fall detection system, while ensuring high fall detection accuracy. Besides, the proposed novel energy efficient strategy can also be used in other threshold-based fall detection methods or other real-time detection to reduce the energy consumption of the sensor node.

The remaining sections of this paper are organised as follows. More details about the deficiency of existing fall detection algorithms and the reasons for proposing a novel energy-efficient fall detection algorithm are presented in Section 2. We give an overview of the hardware structure and the parameter preliminaries of the proposed fall detection algorithm in Section 3. Section 4 states the assumption and presents the proposed SSR energy-efficient strategy as well as the novel fall detection algorithm. The details on the evaluation of the proposed SSR energy-efficient strategy and fall detection algorithm are revealed in Section 5. Finally, we draw conclusions and directions for the future in Section 6.

2 Research background

The research of fall detection systems was intrigued by the observation that falls occur more frequently and cause more serious impact as elderly people getting older. In recent years, numerous research groups have studied real-time fall detection at sensor end employing body motion sensing with accelerometer-based wearable devices. Typically, an accelerometer is embedded with a microcontroller recording the body motion impact and detecting a fall event with the recoded data, locally. Once a fall is detected, a fall alarm is sent through a wireless link to a designed receiver end.

Bourke et al. (2007) monitored 10 healthy young males performing 240 falls and 10 healthy elderly people performing 240 normal activities of daily lives (ADLs), while they collected tri-axial accelerometer data of the trunk and thigh at a sampling rate of 1 KHz. The proposed fall detection algorithm based on the threshold of the trunk root sum of squares of the upper peak values achieves high fall detection accuracy up to 100%.

Boissy et al. (2007) proposed an algorithm based on fuzzy-logic, which incorporated threshold in impact and posture change. During evaluation, 10 young volunteers were monitored with a tri-axial accelerometer-based device worn on the front and the side of the trunk. The accelerometer was sampled at 100 Hz. The result shows 93% fall detection accuracy.

Recently, Ren et al. (2012) recorded the tri-axial acceleration data with the accelerometer fixed at the volunteers waist. The sensor platform continually collected data with a sampling rate of 62.5 Hz. A total of 10 volunteers, including 7 males and 3 females participated in the experiments, while 13 different activities were done 6 times. The threshold of the vector sum of the three axes acceleration value combining with more parameters such as the body angle tracking and the final body angle state have been used, however, many fall missing situations still occur.

Both algorithms proposed in Boissy et al. (2007) and Ren et al. (2012) achieved lower than 100% fall detection accuracy. However, the algorithm proposed by Bouke can completely distinguish falls from normal daily activities with 100% fall detection accuracy. A sampling frequency of 1KHz which is higher than that commonly used in fall detection research is used in this paper to capture the higher frequency collisions associated with falls (de la Guia Solaz et al., 2010). However, such high sampling frequency will result in high energy cost due to high frequency running of the system. Therefore, the system with high sampling frequency achieves high detection accuracy at the cost of energy efficiency. We propose the SSR energy-efficient strategy based fall detection algorithm to properly balance the accuracy with energy consumption.

3 Design of system architecture

The main objective of our system design is to achieve high fall detection accuracy with minimal power energy. A smart sensor platform is used to achieve and verify the proposed energy efficient strategy based fall detection algorithm. The platform has sensing function to collect the body change, processing capability to achieve fall detection algorithm, as well as wireless transmission to send out fall alert information.

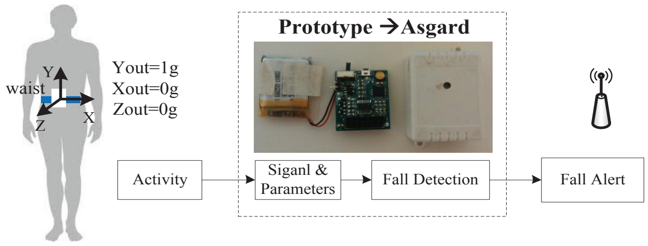
3.1 Sensor hardware platform

Bourke et al. (2005) verified the acceleration of a triaxial accelerometer is more accurate in threshold-based fall detection than a single axis accelerometer. Therefore, a triaxial accelerometer is chosen and used to measure the accelerations of each axes in three directions. An Accelerometer Sensor Generic Board (Asgard), designed to detect a fall in our former research (Ren et al., 2012), consists of a MMA7260Q triaxial accelerometer, a STMS103F microcontroller, and also a CC2520 Zigbee radio module. It is chosen as a platform for SSR energy-efficient strategy evaluation as well as fall detection algorithm achievement in our research. The Asgard can sense the users body motion impact of three directions, which can be expressed as acceleration data and useful parameters for the proposed strategy and algorithm. The core task of Asgard is fall detection implementation. It pre-processes the collected acceleration data and determines whether there is a fall or not according to the processed data. Once a fall is detected, Asgard will send a fall alert through the wireless module to an emergency rescue centre or/and related guardian for timely discovery and treatment. The prototype structure of Asgard is shown as Figure 1. The MMA7260Q triaxial accelerometer in Asgard is an analogue accelerometer sensor produced by Freescale Semiconductor. Data collected by MMA7260Q is analogue value, while STM8S103F converts the analogue output into digital value by formula (1) as follows:

$$\mathrm{Acc} = \frac{\mathrm{VDD} \times \frac{\mathrm{Samplevalue}}{1024} - \frac{\mathrm{VDD}}{2}}{\mathrm{Sensitivity}}, \tag{1}$$

where VDD is the power supply voltage of the accelerometer with mV as unit. Samplevalue is the value sensed by the accelerometer, while Sensitivity can be chosen according to the setting of the related pins. In our application, the Sensitivity is 200 mV/g. The CC2520 Zigbee module controlled by the STM8S103F is used for wireless communication between the smart fall detection sensor and remote service terminal.

Figure 1 The prototype structure of Asgard (see online version for colours)



3.2 Data parameters collection

Kangas et al. (2008) indicated that the fall detection algorithm with an accelerometer placed at the waist has higher accuracy than ones on the wrist, trunk or leg in the threshold-based fall detection systems. Moreover, inappropriate places are thought to interfere with the elderly's daily lives due to the size or weight of the sensor node. Therefore, the Asgard in our research is worn at the waist of the elderly people, as shown in Figure 1. The MMA7260Q triaxial accelerometer can sense three axes acceleration values of X, Y, Z at each sample point, which can be mapped to the spherical coordinates. When the person wearing the sensor stands still or remains in a stationary state, the accelerometer will always be 1g pointing in an upward direction as shown on the y-axis, while x-axis and z-axis orthogonal to the y-axis will be 0g.

The MMA7260Q triaxial accelerometer provides us three channels of acceleration signals: x_i, y_i and z_i, with which we can calculate the total acceleration: the vector sum of the three axes acceleration. We define the vector sum of the three axes acceleration as VSA, which can be determined by equation (2).

$$\mathrm{VSA} = \sqrt{x_i^2 + y_i^2 + z_i^2}, \tag{2}$$

where x_i is the ith sample value of the x-axis, which represents the acceleration value of the x-axis and has g as unit. It is the same for the y_i as well as z_i. Previous research has shown that VSA can be used to distinguish falls from ADLs (Perry et al., 2009) as it can be used to measure the movement intensity, which will be a small VSA for most ADLs, while there will be a large VSA when one falls to the ground. Therefore, by comparing the VSA with a VSA threshold (we define it as VSA_{th}), a fall can be distinguished from ADL.

However, many studies have concluded that fall detection algorithms distinguishing a fall from ADL only using VSA have low accuracy (Bagalà et al., 2012). Nevertheless, ADLs or falls always accompany body angle change. It will change significantly when the body falls on the ground, but will change slightly when performing daily activities. Therefore, the final angle of the body can be chosen as one parameter for further fall detection. To keep consistent with Ren et al. (2012) and Ren and Shi (2016), the final angle of the body is defined as Body Tilt Angle (denoted as BTA), as shown in formula (3):

$$\mathrm{BTA} = \arccos \frac{y_i}{\mathrm{VSA}}, \tag{3}$$

where y_i is the sample value of the y-axis. VSA is the total acceleration of the current sample point, while BTA refers to the tilt of the body in space. Previous researches studied BTA after a fixed time such as 20s when a large VSA is detected to distinguish falls from ADLs (Brown, 2005). However, if the person falls slightly, he or she may struggle to stand up slowly after falling down. The attempt to recover to stand up will last a long time, which may be beyond the set fixed time, as the activities of most elderly persons are slow, while the recovery time lasts different for different person under different situations. The method seems not to work for this situation. On the other hand, if the person falls down seriously and cannot move anymore or completely loses consciousness, it takes a bit longer time to wait for the setting time for fall detection. Acceleration rate (AR) is introduced to confront these situations, which can be calculated by VSA within a time window. AR is defined as equation (4):

$$\mathrm{AR} = \mathrm{VSA}_{t_2} - \mathrm{VSA}_{t_1}, \quad \text{with} \quad t_2 - t_1 = 0.5 \text{ s}, \tag{4}$$

where AR refers to the acceleration rate of the body, t_1 and t_2 are two time points, with a time interval between them set to 0.5 s to detect AR, while VSA_{t_1} and VSA_{t_2} are the two acceleration values on time t_1 and t_2. With this parameter, we can track the body changing, which is the basic idea to improve the fall detection accuracy.

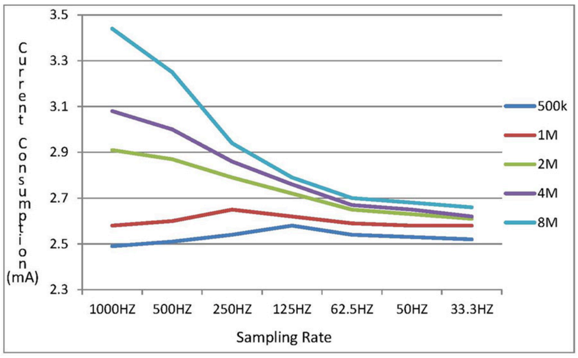
4 Implementation of energy-efficient fall detection

This paper mainly focuses on developing an energy-efficient fall detection system. A durable and reliable fall detection system can extend the battery life and avoid the inconvenience of frequently recharging or replacing batteries, while maintaining high fall detection accuracy. In our survey of 20 elderly people, up to 95% volunteers consider long battery life of fall detection system as an important decision factor to use a fall detector. Most of them consider it troublesome to frequently recharge or replace batteries, and they want a long-time device. Certainly, all of the volunteers consider the accuracy most important. The survey result clearly shows that fall detection accuracy is a critical success factor for adopting a fall detection system. On the other hand, energy consumption is also an important decision factor. The SSR based fall detection algorithm proposed in this paper tackles both problems at a time to increase fall detection accuracy while reducing its energy cost. Our approach uses a threshold to divide two sampling rate segmentations, by which a low sampling rate is used for normal activity detection while it increases to a higher one when an abnormal activity such as dramatic impact is detected. In the remainder of this section, we describe and discuss SSR energy efficient strategy as well as the proposed fall detection algorithm.

4.1 Relationship between sampling rate and energy cost

During our research, the energy consumption of Asgard under different sampling rates and CPU frequency is measured as represented in Figure 2. From the figure, it is discovered that the energy cost is higher with a continuously increasing sampling rate for the system running with a CPU frequency larger than 2M. However, the trend is different for the system with a CPU frequency lower than 2M, the energy cost increases firstly, and then it reduces a bit with the sampling rate increasing. According to our measurement and analysis, we find Asgard cannot finish the entire fall detection procedure when Asgard runs with a low CPU frequency but high sampling rate. It periodically handles part of fall detection algorithm, which will cost less energy. This can be seen in the lower left corner of Figure 2. According to Figure 2, a CPU frequency larger than 2M will be a proper range for our fall detection system design. Furthermore, it is obvious that the higher the CPU frequency, the more energy will be consumed. For example, under the same sampling rate of 250 Hz, it consumes 2.5 mA current with 500K CPU frequency, while Asgard of 8M CPU frequency has a current up to 3.1mA. As a total, Asgard of 8M CPU frequency consumes more energy, nearly 16% to finish the same task than the system running with 500K CPU frequency. Therefore, low CPU frequency is a good choice for the portable device from the energy efficiency perspective. Finally, 2M CPU frequency is chosen based on the analysis above. With the CPU frequency of 2M, the higher sampling rate, the more energy will be consumed. But that does not mean the lower sampling rate is the optimal choice for our fall detection research.

Figure 2 Current consumption of Asgard under different sampling rates and CPU frequency (see online version for colours)



Based on the case study analysed in the section research background, we make an assumption that the sampling rate will also impact the fall detection accuracy. More specifically, with a higher sampling rate the system can collect more acceleration data so as to have a higher probability of capturing the high frequency collisions associated with fall events. With those high frequency data, the likelihood of missing a detection event will be reduced, while the detection accuracy can be increased. And vice versa, a system with a lower sampling rate will cause fall missing and also reduce the accuracy of fall detection. The assumption will be verified in the evaluation section.

4.2 SSR energy efficient strategy

SSR energy efficient strategy is concerned with segmenting the fall detection procedure with different sampling rates to reduce the total energy consumption and improve fall detection accuracy. In an actual fall detection application, the elderly people will do ADLs for the most time, while fall occurring has very low probability. According to the analysis and assumption made above, if we use low sampling rate during most of the time to reduce the energy consumption, but a high sampling rate when there is a possible fall to increase the fall detection accuracy, we can achieve our target of improving fall detection accuracy with less power energy.

Now, we are in the position to present how to achieve the SSR energy efficient strategy. The basic idea is that the fall detection algorithm runs with segmented sampling rates according to the setting threshold to distinguish normal or abnormal activities. Segmented sampling rate is denoted as SR. During normal activities, the sampling rate will be set to a low sampling rate (denoted as SR_{low}). Once an abnormal activity is detected, a high sampling rate (denoted as SR_{high}) will substitute SR_{low} for advanced fall detection. SR can be calculated as formula (5):

$$SR = t \times SR_{\text{low}} + (1 - t) \times SR_{\text{high}} \tag{5}$$

$$t = \begin{cases} 0 & VSA < TH, \\ 1 & VSA > TH. \end{cases},$$

where t is one coefficient for choosing the sampling rate between SR_{low} and SR_{high}, which is equal to 0 or 1 according to the values of the current VSA compared with the setting threshold. The choice of SR_{low} and SR_{high} are described in the evaluation section. VSA is the current collected acceleration, while TH is the setting threshold to distinguish between normal activity and abnormal activity. The proposed SSR energy efficient strategy is illustrated in Figure 3.

Figure 3 describes how the SSR energy efficient strategy works to achieve energy efficiency:

1 For the initial stage, the algorithm runs at a low sampling rate of SR_{low}, to collect VSA data, continuously. For actual fall detection application, most of the initial situations or activities are common actions, such as ADLs, and there will not be a fall-like activity. So it is considered as normal activity.

2 Continuously monitoring VSA and finding VSA exceeds the preset threshold (TH). In our paper, the threshold value of TH is set to 3g, lower than the

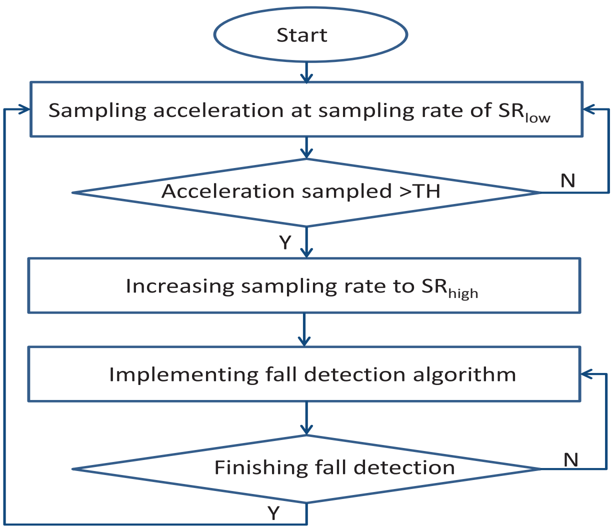
threshold used for the fall detection algorithm, both of which are calculated by confidence interval of statistics knowledge and verified in our former research (Ren et al., 2012).

3 If a large VSA is detected, the sampling rate will increase to SR_{high} to ensure fall detection accuracy.

4 The fall detection algorithm described in the next subsection will be performed. Once fall detection is performed and finished, it will continuously run at a lower sampling rate as step 1).

In summary, during the fall detection procedure, acceleration is sensed at a low sampling rate for the low activity, which consumes less energy. The sampling rate will be increased to a high sampling rate when a fall-like activity is detected to improve the fall detection accuracy. The choice of sampling rate is based on the current collected VSA data for fall detection.

Figure 3 Flowchart of SSR strategy (see online version for colours)



4.3 Energy-efficient fall detection algorithm

In this section, we describe the fall detection algorithm design. According to the SSR energy efficient strategy, once the sampling rate is increased, the proposed fall detection algorithm will be performed to determine whether a fall occurs or not. In this proposed algorithm design, it runs with a high sampling rate, which allows capturing the higher frequency collisions associated with falls, so as to improve fall detection accuracy. Except for the VSA, we also extract AR as a parameter to detect the body recovery status, and BTA to monitor the final body posture. The proposed fall detection algorithm is illustrated in Figure 4, which is carried out as follows:

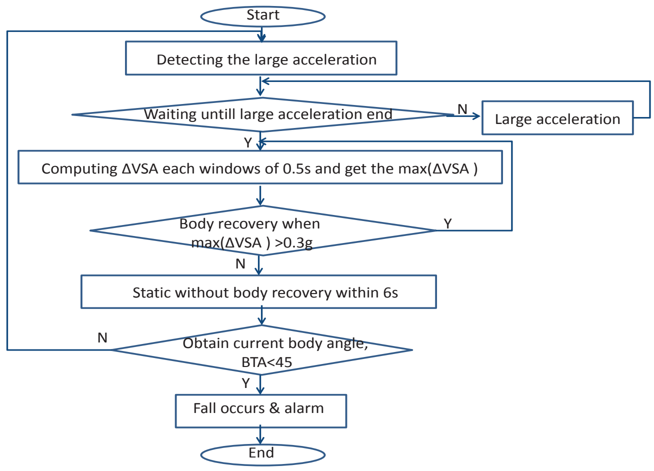
1 Looking for a large VSA acceleration, exceeding the preset VSA threshold (VSA_{th}). The large VSA happens as a dramatic impact when the person falls down on the ground or crashes on some surrounding object. VSA_{th} is preset to 4g.

2 Waiting until large VSA acceleration dissipates.

3 Analysing the body recovery status by computing the maximum AR of every window time. The window time is set to 0.5 s. If a large AR exists within a time interval, we consider the body is trying to recover to stand up, and we need to wait until there is no large AR within the time interval. The time interval is preset to 6 s.

4 Analysing the body posture by computing the BTA of the body. The BTA will be completely converse when the body falls too seriously to struggle to stand up or there is no fall appearing. Therefore, BTA is acquired for further determination. Only if BTA is smaller than 45 degrees do we classify it as a fall.

Figure 4 Flowchart of the novel fall detection algorithm (see online version for colours)



5 Evaluation

To verify the relationship between sampling rate and fall detection accuracy and study the performance of the proposed SSR based fall detection algorithm, two sets of experiments were performed. Firstly, we studied the relationship between sampling rate and fall detection accuracy. In this experiment, 7 Asgards were used together to evaluate the performance of the proposed fall detection algorithm under different sampling rates. This evaluation is important and critical for the proposed SSR-based fall detection algorithm, as it depends on this assumption. Second, we evaluated and analysed the performance of the proposed SSR-based fall detection algorithm, including fall detection accuracy as well as the energy efficiency of Asgard running the proposed fall detection algorithm. Both fall detection accuracy and energy efficiency are the main objects of our paper. During this performance evaluation, volunteers were required to wear one Asgard running the SSR-based fall detection algorithm.

5.1 Experiment setup

In this section, we describe the experiment environment and requirements of evaluation. To verify the relationship between sampling rate and fall detection accuracy, as well as evaluate the performance of the SSR-based fall detection algorithm, serial experiments were carried out by 12 volunteers, including 8 males and 4 females, respectively. All the volunteers were healthy people with average age, weight and height of 28 years old, 57.6 kg and 172.5 cm, respectively. The detail information of volunteers is shown in Table 1. Both the relationship verification and the performance evaluation have been performed in the same environment and situation, and the same types of activities were done. We considered more types of activities to draw more actual conclusions in our paper. ADLs, posture transitions and more fall scenarios were all considered, as they will bring large amounts of false alarms or fall missing for the fall detection algorithm. The experiment tasks that volunteers performed during our evaluation are described in Table 2. However, during the relationship verification, each volunteer was asked to wear seven Asgards together with an elastic belt, while only one Asgard was worn for the final performance evaluation. All the volunteers were required to carry out actions as shown in Table 2. Each activity was performed 5 times by each volunteer. Once a fall is detected by Asgard during the experiments, the label of the related algorithm will be sent out to the home server to inform which Asgard detected a fall. Worthy to note, volunteers were asked to mimic fall activities on a mattress, as fall is a dangerous action for volunteers to do directly on the ground.

Table 1 Characteristics information of volunteers

Type	*Numbers*
Total volunteers	12
Male/female	8/4
Average age	28 years old
Average weight (kg)	57.6
Average height (cm)	172.5
Total numbers of experiments	1020

5.2 Comprehensive evaluation

5.2.1 Relationship verification between sampling rate and accuracy

As is verified the higher sampling rate, the more energy will be consumed when the system runs with 2M CPU frequency in Section 4. However, the SSR energy efficient strategy is also based on the assumption that a higher sampling rate will help to achieve better fall detection accuracy. Therefore, to make sure the SSR energy efficient strategy is feasible, we also need to verify the relationship between the sampling rate and fall detection accuracy. During this relationship verification, all of the 12 volunteers were required to wear 7 Asgards together at the waist running only the proposed fall detection algorithm with a different sampling rate to do actions listed in Table 2. Table 3 shows fall detection accuracy results under a different sampling rate. In this table, sensitivity shows the capability to detect a fall, specificity is the capability to detect ADL, while accuracy can show the correctly detect ratio of different activities. From the table, it is obvious that fall detection accuracy will be improved with the increasing of the sampling rate, which gives strong support for the proposed SSR energy efficient strategy. Viewing Figure 2 and Table 3 as a whole, we can see the energy cost of Asgards running with a sampling rate of 62.5 Hz and 50 Hz have small variation, but there is very small difference in fall detection accuracy. Meanwhile, though the energy cost of Asgards with sampling rates of 50 Hz and 33.3 Hz have relatively small variation, fall detection accuracies have a bit of a difference. Take increasing fall detection accuracy while reducing energy cost as much as possible as the principle, sampling rate of 50 Hz is chosen as the low sampling rate (SR_{low}). Similarly, sampling rates of 1000 Hz, 500 Hz and 250 Hz also have this phenomenon, and 500 Hz is chosen as the high sampling rate (SR_{high}).

5.2.2 Performance evaluation of fall detection based on SSR energy efficient strategy

Performance evaluation of the SSR-based fall detection algorithm is a critical factor affecting its feasibility and acceptability during actual usages. In this section, we mainly study the performance of the proposed fall detection algorithm, which includes the accuracy of the SSR-based fall detection algorithm, as well as the energy cost when Asgard runs with the proposed fall detection algorithm. During performance evaluation experiments, all the volunteers were required to wear only one Asgard running with the SSR-based fall detection algorithm, which used 50 Hz as the low sampling rate and 500 Hz as the high sampling rate, to do all the actions as listed in the relationship verification part.

Table 4 shows the fall detection accuracy based on the SSR energy efficient strategy. As the data presents, the correct ratio for ADL detection is up to 100%; obviously, the algorithm can correctly detect simple ADL without any false alarms. Nearly 98.89% of transition postures can be correctly detected. Transition posture is a complex human behaviour, each person may act differently when doing such activity. However, only a small number of false alarms were detected while volunteers carried out transition postures. Furthermore, only less than about 3.6% of falls are not detected successfully when fall is mimicked for accuracy verification. It has a high correctness ratio of fall detection while false alarm takes a low ratio. During the accuracy evaluation, both running to sitting and jumping to sitting are two activities that are similar to fall and cause false alarms. As we all know, running and jumping are intense activities, the VSAs of which are easy to exceed the preset threshold compared to other activities. It means the two activities are easy to trigger the pre-fall trigger condition for the proposed fall detection algorithm. Meanwhile, there will also be a large angle if the person sits with his or her back lying on the backrest. So, the ending postures of those two

Table 2 Tasks description for the performance evaluation

Category	*Task*	*Task description*
ADL	Walking	Walking at a normal speed as he or she walks as usual for at least 20 s
	Sitting	Standing still first, and then sitting down on a chair and remaining sitting there.
	Running	Running at a normal speed as he or she runs as usual for at least 20 s
	Jumping	Jumping up or forward, then standing still
	Lying down	Standing there first, then the subject lays down and keeps there for 20 s at least
Posture transitions	Sitting to standing	Sitting there first, and then standing up
	Walking to sitting	Walking at a normal speed as he or she walks as usual, and then sitting on the chair or sofa
	Running to sitting	Running at a normal speed as he or she runs as usual, and then sitting on the chair or sofa
	Jumping to sitting	Jumping up or forward, and then sitting on the chair or sofa
	Squatting to standing	The subject squats down first, and then stands up
	Fall but recovery	The subject falls on the ground, but tries to recover to stand up
Fall	Fall forward	The subject falls on the ground with the face toward to the ground
	Fall backward	The subject falls on the ground with the back touching the ground first
	Fall lateral	The subject falls on the ground with the lateral body touching the ground first
	Fall on something	The subject falls down onto something
	Fall with recovery	The subject falls on the ground, and tries to recovery, but fails to stand up
	Fall from stair	The subject stands on stairs and falls to the ground

activities are also similar to the falls ending status. Therefore, during the experiments, some of the two activities are detected as falls. In total, among six transition posture false detection cases, five of them are caused by running to sitting and jumping to sitting. However, these two activities rarely happen among the elderly people. We introduced these two activities only to verify the robustness of the proposed SSR-based fall detection algorithm. In the fall mimic tests, about less than 3.6% of falls failed to alarm. Most of them are caused by the small VSAs. Some of the volunteers dared not do fall imitations in fall trials but preferred to lie down, which shows small VSAs and cannot trigger the fall detection. This is the main reason for fall missing situations.

Table 3 Fall detection accuracy under different sampling rate

Sampling rate (Hz)	1000	500	250	125	62.5	50	33.3
Sensitivity (%)	97.5	96.94	95.56	95.28	93.06	92.78	91.11
Specificity (%)	99.54	99.24	97.27	96.97	96.06	95.91	95.75
Accuracy (%)	98.82	98.43	96.67	96.37	95	94.8	94.12

Table 4 Fall detection accuracy based on SSR energy efficient strategy

Category	*Total times*	*Correct*	*Incorrect*	*Correct ratio* (%)
ADL	300	300	0	100
Transition posture	360	356	4	98.89
Fall	360	347	13	96.36
Total activities	1020	1003	17	98.33

To evaluate the energy efficiency when Asgard runs with the proposed SSR-based fall detection algorithm, the current of Asgard is tested and recorded. Table 5 illustrated the current consumption of Asgard under different running situations. From the table, we can see the current of Asgard for most of the time is lower than fall detection triggering, about $2.87 - 2.63 = 0.24$ mA, which shows us the energy will be saved up to $0.24/2.63 = 9.13\%$ compared to the fall detection triggering situation. However, most everyday activities of the elderly cannot trigger fall detection, and fall detection running and fall occurring with wireless transmission only takes very little time, which can be neglected. Therefore, the energy efficiency evaluation using the current of Asgard under daily running can be considered as the current consumption of Asgard. According to the analysis above, we can save 9.13% energy while maintaining high accuracy of fall detection, saving more overall system energy than noted in research by (de la Guia Solaz et al., 2010). If Asgard is powered by two AA batteries with a capacity of 1500 mAH, it can be continuously running for about $1500/2.63 = 1141$ h, which are 96 more hours than a fall detector running without SSR-based strategy but with the same detection accuracy. Comparing with our previous work (Ren et al., 2012), in which Asgard runs with small sampling rate, it is mainly improved on accuracy from 96.3% to 98.33%, but with small change in energy consumption. Though, the current in our previous work is 4.61 mA, while it consumes 2.63 mA in this paper, that is because a regulator of Asgard is changed in this paper to save more energy as mentioned in Ren et al. (2012).

Table 5 Current consumption under different running situations

Running situation	*Sampling rate* (Hz)	*Current* (mA)	*Asgard power* (mW)
Daily running	50	2.63	8.679
Fall detection	500	2.87	9.471
Fall occurring with wireless transmission	50	26.5	87.45

6 Conclusion and future work

In this paper, we propose an energy efficiency method called SSR energy efficient strategy, and present a novel SSR-based fall detection algorithm. The proposed fall detection algorithm can improve both energy efficiency and fall detection accuracy. Comprehensive performance evaluation is implemented, including the fall detection accuracy as well as energy efficiency of a system running with the proposed solution. Our experiment results show the proposed solution can save energy while keeping high accuracy of fall detection. For our future work, we will consider achieving energy efficiency of a system from the pre-processing hardware circuit design perspective. A new energy efficient sensor node will be developed to process the collected data with a hardware circuit directly, without MCU processing. In addition, we also plan to embark on intelligently reducing the transmitted data according to the regularity feature of the collected data to achieve energy efficiency for the server side computing based fall detection systems.

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