A Theoretic Algorithm for Fall and Motionless Detection

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Abstract: A robust method of fall and motionless detection is presented. The approach is able to detect falls and motionless periods (standing, sitting, and lying) using only one belt-worn kinematic sensor. The fall detection algorithm analyses the phase changes of vertical acceleration in relation to gravity and impact force using kinematic variables. A phase angle value was used as a threshold to distinguish between falls and normal motion activity. There are two advantages with this approach in comparison with existing approaches: (1) it is computationally efficient and theoretic (2) it is based on a single threshold value which was determined from a kinematic analysis for the falling processes. To evaluate the system, ten subjects were studied each of which performed different types of falls and motionless activities during a period of monitoring activity. These included: normal walking, standing, sitting, lying, a front bend of 90 degrees, tilt over 70 degrees and four kinds of falls (forward, backward, tilt left and right). The results show that 100% of heavy falling, 97% of all falls and 100% of motionless activity were correctly detected in a laboratory environment and the beginning and ends of these events were determined.

Key words: Acceleration; Fall detection; Threshold; Phase angle; Motionless.

I. INTRODUCTION

Chronic diseases, such as heart disease, stroke, cancer, diabetes, renal failure and chronic pain are the leading cause of death and disability [1]. In addition, they represent an economic burden for the government and its health and social care provision. Today heart disease and stroke are the top 2 causes of death [2]. In addition, chronic pain is a common and frequently disabling problem in older adults [3].

Walking is an important way to perform physical exercise for people with chronic conditions or elderly people. Nevertheless, those who suffer from a chronic disease are at a high risk of experiencing falls during normal walking activities [4]. More specifically, people with CHF (chronic heart failure), stroke and CP (chronic pain) may suffer a form of abnormal heart rate or abnormal balance and gait disorders. These symptoms lead to the increased risk of falling during completion of daily activities. In addition, 32% of people over 75, have experienced a fall at least once a year with 24% encountering serious injuries [5][6]. Moreover, persons experiencing frequent falls may experience a change in self-confidence and motivation, affecting their ability to self-manage their own condition [5]. In instances of falls, reliable and immediate detection of the fall itself is important to ensure that the person may receive assistance as necessary. Approximately 3% of all persons who experience a fall will remain on the ground for more than 20 minutes prior to receiving assistance [7].

To reduce the impact of falling it is important to distinguish between falling and daily activities. The provision of real-time alarm message delivery will be beneficial for people with chronic conditions and those wishing to live independently. This research aims to develop a walking monitoring system for patients suffering from chronic diseases (CHF, stroke and CP) who are empowered by home based self-management. The ability to categorize activities of daily living (ADL) from sensor data is an important goal. In this study we embark upon this goal by developing a robust algorithm to distinguish falls and periods of inactivity from other activities. Initially we study a group of healthy volunteers using a belt worn sensor.

II. RELATED WORK

Automatically monitoring abnormal ambulatory activities of people with chronic conditions and the elderly using small and lightweight sensors is an important issue for self-management applications [8]. In the case of older people living independently, there is a particular need for monitoring their daily activities, along with instances of a fall and/or motionless (standing, sitting and lying down, etc.). The early detection of abnormal walking and gait patterns coupled with the delivery of real-time alarm messages can help to obtain timely assistance and promote self confidence in undertaking these important activities.

Accurate fall detection with real-time alarm delivery has been the main challenge for walking based monitoring systems. Many studies have been undertaken which have addressed fall detection using different technologies. These technologies can be broadly classified into three main categories: ① video recording and image analysis via one or several cameras based on the identification of some image features [9]; ②acoustic frequency analysis via the analysis of audio signals [10]; ③ data analysis based on the features extracted from the wearable sensors. For the video-based activity monitoring system, the main disadvantages are the need to install cameras in each room of the house and in fixed locations. Such surveillance may be viewed as being too intrusive and given their fixed nature are not suitable once the person leaves their own home environment. Methods based on audio signal analysis have been reported to offer lower accuracy for fall detection and may be viewed as a subordinate approach in comparison with the other methods [11]. The wearable sensor approach is one of the most attractive methods. It is low-cost and can be worn with ease allowing a subject to be monitored both within and

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outside of their home environment. In addition, it can be easily embedded into existing community based alarm and emergency systems [12].

There are many types of wearable sensor based systems which can detect falls. Most of the systems used specially designed sensors such as a fall sensor, or have used accelerometers to detect the elderly person falling. Tamura et al. [13] used a photo-interrupter as the fall sensor attached to the left waist region to detect and record the fall time. Their experiments were performed both during daily routine with the 'dummy' fall for one healthy young person and during rehabilitation training for 14 hemiplegic patients. The results showed that normally the fall sensor worked well, however it produced false positives when the subject tilt more than 60° or went to bed. Bourke et al. [14] proposed a threshold-based algorithm to detect eight different types of falls. The fall-event data was investigated using two tri-axial accelerometer sensors, mounted on the trunk and thigh. Their results showed that 67-100% of activities of daily living tasks were correctly classified, and the upper fall thresholds (UFT) for each signal gave higher specificity than the lower fall thresholds (LFT) value. Their results also showed that the upper peak value of the acceleration signal for each different activity was different. A study by Luo et al. [15], introduced a dynamic motion pattern analysis approach for fall detection using a waist-mounted accelerometer. Within this approach two thresholds (acceleration amplitude and acceleration direction angle) were used to detect the instances of falls. Lindemann et al. [16] described a simulated fall detection system using two accelerometers placed orthogonally at the head behind the ear. This system combined three thresholds (acceleration in the xy-plane and all spatial axes, as well as velocity in all axes) to distinguish human daily activities from seven kinds of falls. Hwang et al. [17] combined accelerometer, gyroscope and tilt sensor signals transmitted through Bluetooth modules and used an algorithm of three thresholds to distinguish fall patterns from daily activities such as sit, stand, supine, and tilt over 70°. The accuracy of fall detection within this work was 96.7%.

In this work, we have used a reliable algorithm to distinguish and automatically mark instances of falls and motionless (standing, sitting or laying), using a belt-worn sensor. In the remainder of the paper, we describe the details of our work. Section 3 presents the system design and the algorithm in detail. Experimental results are shown in Section 4. Finally, discussion and conclusion will be presented in Section 5.

III. METHODOLOGY

A. System Architecture and Data Preprocessing

In order to decrease the possible discomfort which may occur due to sensors being attached on two or more places on the body, our system was designed to use one belt-worn sensor on the waist. The system configuration is shown in Fig.1. This system includes four independent components: data sensing, wireless communication (Bluetooth), data analysis algorithm (Fig. 2), and alarm message delivery.

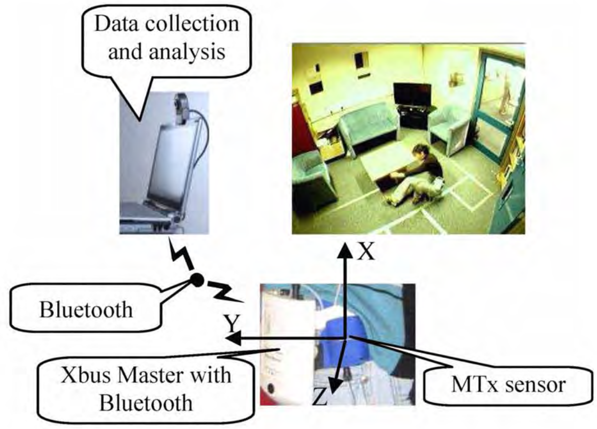

Figure 1 System configuration

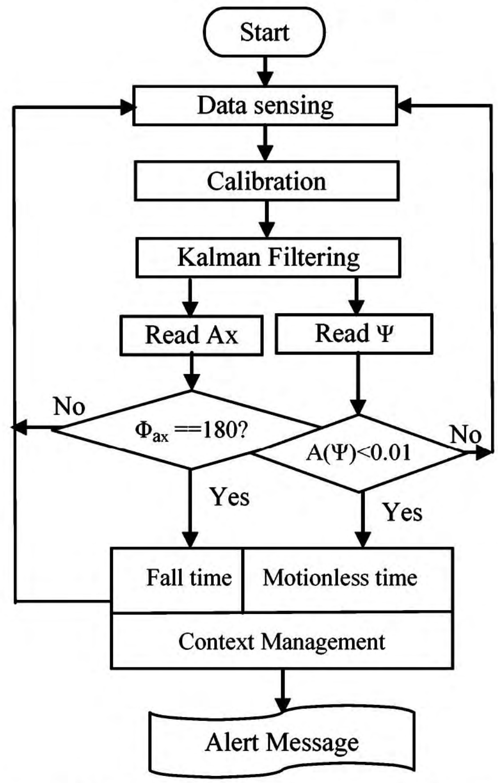

Figure 2 Algorithm flow chart. Φ_{ax}: phase angle of vertical acceleration. Ψ: angular velocity around Z. A (Ψ): amplitude of Ψ.

We used a tri-axial MTx (Xsens, Enschede, the Netherlands) sensor with an Xbus Master to collect the digitized motion signals at a sampling rate of 100 Hz. The device has the ability to calculate absolute orientation and acceleration in a three-dimensional space from miniature sensors (accelerometers, gyroscopes and magnetometers). The device was attached to the person's belt with a vertical orientation. The Xbus Master is a lightweight, portable device that provides power to and samples digital data from the MTx. It can be connected to any peripheral device for the data processing via a serial cable or Bluetooth wireless connection. The wireless connection enables ambulatory measurement of human motion.

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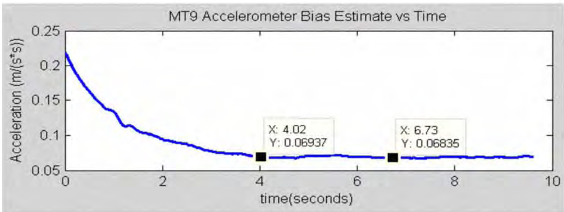

Figure 3 Estimation of the MTx bias

The sensor-fixed coordinate system is defined as x-axis=vertical, y-axis=sagittal, z-axis=frontal (Fig.1). The output is a calibrated 3D linear acceleration which includes the acceleration due to gravity. From factory calibration, the calibrated data is only assigned a unique gain matrix and a bias vector to relate the sampled digital voltages from the sensors. There is no additional filtering applied to the data. In order to reduce the influence of sensitive sensor bias, measurement noise and process noise, we used a Kalman Filter to pre-processing the data. The Kalman filter is an effective tool to estimate the states of a linear system or nonlinear systems [18][19]. As the filter accurately estimates process variables it can minimize the variance of the estimation error. It has been applied in embedded control systems such as vehicle navigation systems (airplane, spacecraft, satellite, etc.).

We model the estimated acceleration a and measurement vector z using a Kalman Filter as presented in Equation (1) and (2):

$$a(t+1) = Aa(t) - b(t) + w(t) \qquad (1)$$

$$z(t) = Ha(t) + v(t) \qquad (2)$$

Equation (1) is the system model and equation (2) is the measurement model where A and H are called the gain matrices. In our model, the gain is used with a constant value 1. The $b(t)$ term describes the sensor bias, and the Kalman filter removes it from any measured acceleration. In order to estimate the sensor bias, we placed the sensor sitting still on a table for ten seconds, and estimated the nonzero output from the motionless sensor. After about four seconds, the MTx sensor bias signal becomes a stable value of 0.07 m/s2 as shown in Fig. 3. In addition, $w(t)$ is the random, time-varying process noise and $v(t)$ represents measurement noise. The noise model considered here is referred to as white and with normal probability distributions as shown in equation (3) and (4).

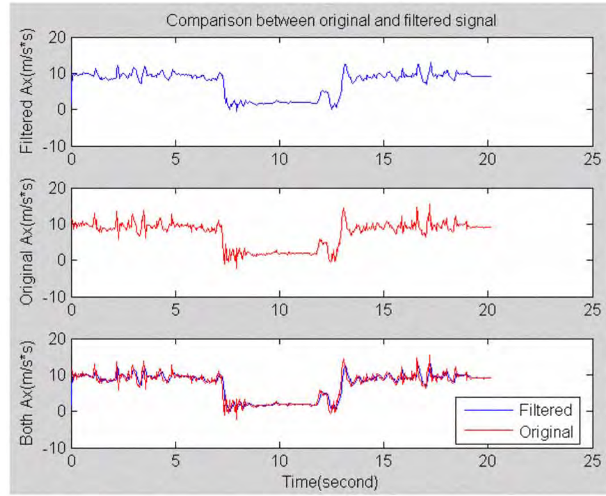

Figure 4 Comparison of original and filtered signals

$$P(w) \sim N(0, Q) \qquad (3)$$

$$P(v) \sim N(0, R) \qquad (4)$$

Where P is the covariance of the prediction error, Q is process noise covariance and R is the measurement noise covariance. The comparison between the original and the filtered data signal is shown in Fig. 4. As can be seen, the filtered signal is smooth and has removed most noise sources. This could improve the accuracy of data analysis.

B. Falling and Motionless Analysis

To detect and locate the occurrence of a fall we based our approach around the use of the vertical acceleration phase. The vertical acceleration phase will be reversed in direction when the person's hip or hands touch the ground. This change in acceleration during the stages of a person falling down and standing up are shown in Figure 5. From this Figure we know

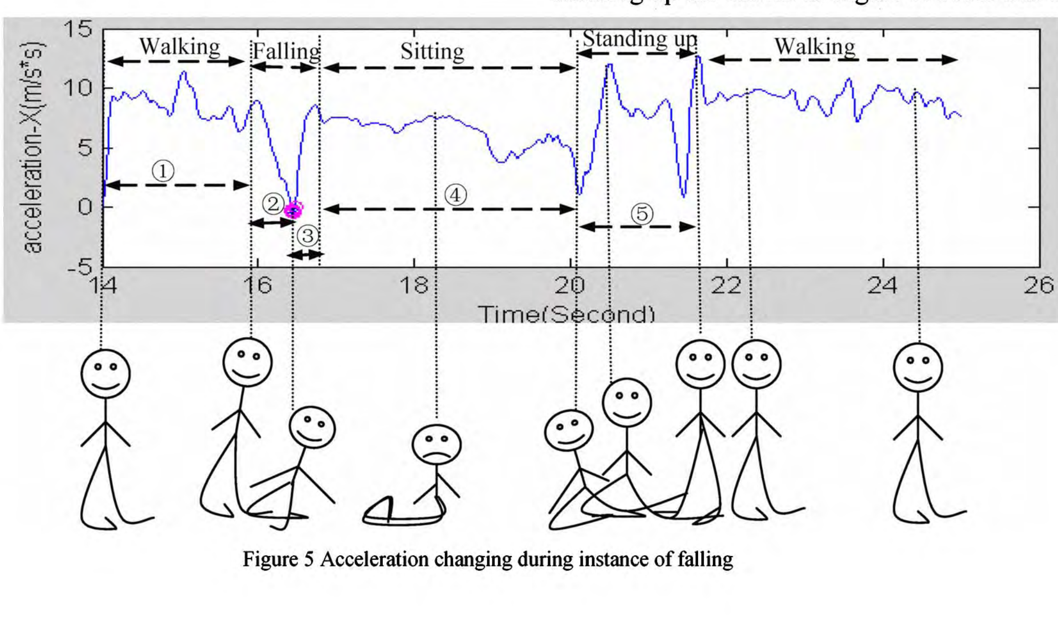

Figure 5 Acceleration changing during instance of falling

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that there are five periods varying from normal walking to falling to standing up. The five periods correspond with number ① to ⑤ in Fig.5.

1. Normal walking: the changes of vertical acceleration in this period are varied and near to the acceleration due to gravity |g|, since the output of the calibrated linear acceleration includes the acceleration due to gravity.

2. Starting to fall and prior to touching the ground: a sudden fall will cause the vertical acceleration to decrease quickly from an original value which nears |g|. In our system, the vertical axis X is positive in the upward direction, hence when the subject is falling down with the acceleration of gravity, the vertical acceleration value will reduce immediately from positive to negative.

3. Touching ground: when the subject touches the ground using their hip or hands, he or she will receive an impact force from ground. This force leads to the vertical acceleration value increasing quickly and causes the vertical acceleration direction to reverse from a falling acceleration of gravity. The impact force leads the acceleration Ax2 to be in anti-phase with the falling acceleration Ax1 of gravity. It is as shown in Fig. 6.

4. Sitting or lying on the ground: in this period, the subject is motionless, so in theory it would be expected not to witness any changes in acceleration. If the subject has some gentle motions the acceleration may be recorded as a small perturbation.

5. Standing up: upon rising the vertical acceleration suddenly increases again.

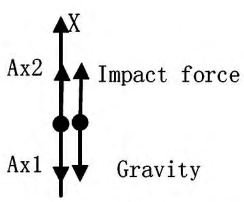

Figure.6 Impact force leads an up acceleration Ax2 to be in anti-phase with the falling acceleration Ax1 of gravity.

In order to capture changes in the vertical acceleration in accordance with the person touching the ground from a high position after falling down, we use the phase angle function. We use this feature to be a threshold value to detect falling from normal daily activities. The angle function is a logical function that extracts the angular component of a complex vector. The phase angle can be expressed in degrees from 0° to 360°, or in radians from 0 to 2π. It is defined in equation (5) and (6). If the phase difference is 180°, then the two vectors are said to be in anti-phase.

$$z = re^{i\emptyset} \qquad (5)$$
$$\emptyset = \arg(z) \qquad (6)$$

In our system, we only consider the vertical acceleration Ax. With its phase angle there are only two cases: anti-phase or in-phase and two values as shown in equation (7).

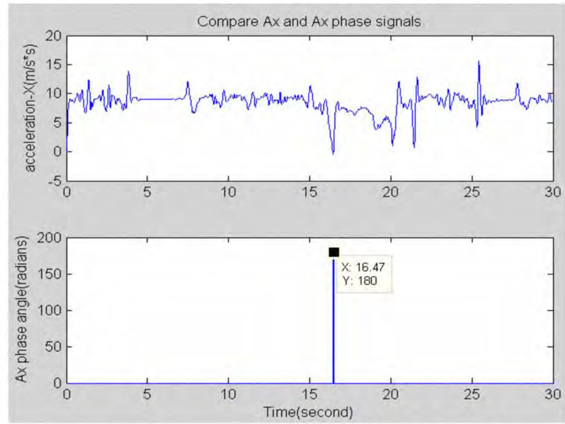

Figure 7 Comparison Ax and its phase angle signals

$$\emptyset(t) = \arg\big(ax(t)\big) = \begin{cases} 0 & (ax > 0) \\ 180 & (ax < 0) \end{cases} \qquad (7)$$

We use the value of 180° of the vertical acceleration phase angle as a threshold to quickly and accurately distinguish between falling down from other motion activity. Fig. 7 shows that the vertical acceleration Ax signal and its phase signal. We can deduce that the person falls down and touches the ground time at 16.47 seconds in this instance.

For the motionless detection, the angular velocity should be zero in theory when a person is motionless (standing, sitting, or lying). So we use an empirically derived threshold (0.01) of amplitude of angular velocity around Z axis to distinguish the motionless state from movement. It is as shown in Fig. 8. It also shows the signal of corresponding vertical acceleration, and the motionless time was marked automatically with the symbol '+'.

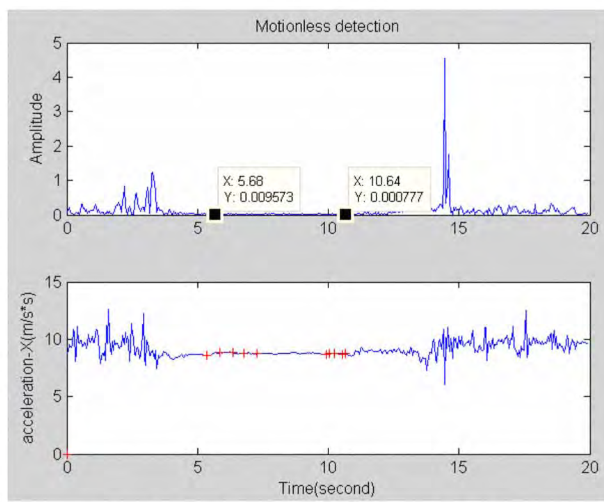

Figure 8 Amplitude of angular velocity for motionless detection

IV. EXPERIMENTS

Ten young (age range 20-40 years) healthy people (three female and seven male) were studied to verify our threshold algorithm to detect falling. The simulated activities performed were: normal walking, standing, sitting, front bend 90 degrees, lying, tilting over 70° and different types of falling down

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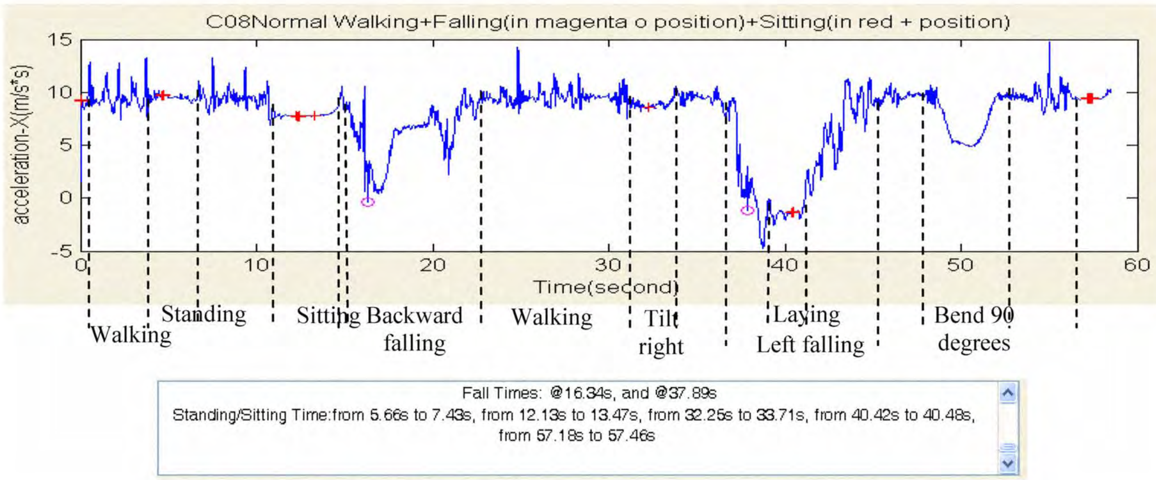

Figure 9. A subject performed 8 kinds of activities within 60 seconds, the time of falls and motionless were marked automatically using different colour symbols. The time also was printed out in a text box as shown above.

(forward falling, backward falling, tilt falling left and right). In total we collected 50 measurements from our experiments. The results indicate that 100% of heavy falling, 97% of total falling (including one lightly fall), and 100% of motionless activities were correctly detected. There was only one failure for the fall detection algorithm (Fig.13). In this case video demonstrated that the subject was slowly and lightly sitting on ground and no strong impact force was generated to influence the acceleration(in fact, this is not really falling down, it could be viewed as sitting down). Fig. 9 shows the signal of a subject who performed eight kinds of different activities within a period of 60 seconds that included walking, standing, sitting, backward falling, tilt right over 80 °, tilt falling left, laying, and bend 90 °, respectively. The falling was marked automatically by the algorithm with the symbol 'o', and motionless (standing, sitting, lying) was marked automatically with the symbol '+'. In addition, the exact times for the activities of falling and motionless were also recorded. The signals of different falls and motionless are shown in Fig.10 to Fig.13.

V. DISCUSSION AND CONCLUSION

Through the analysis of the vertical acceleration phase change during a fall we identified a falling threshold. This was tested by 10 healthy subjects and 50 recorded simulated fall

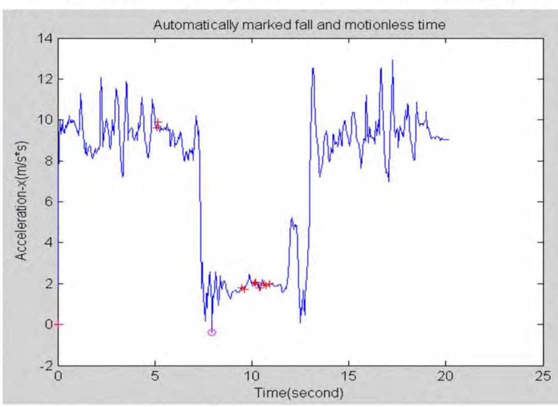

Figure 10 Tilt fall right and lying

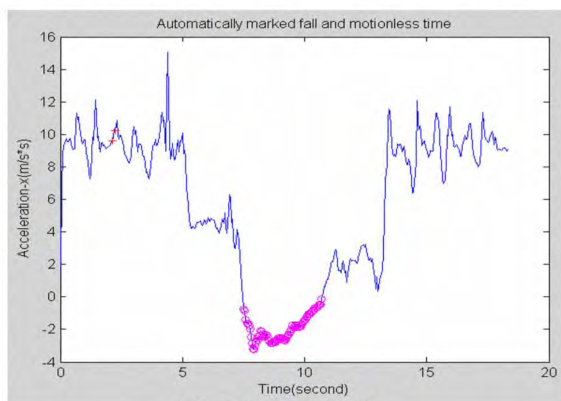

Figure 11 Forward fall

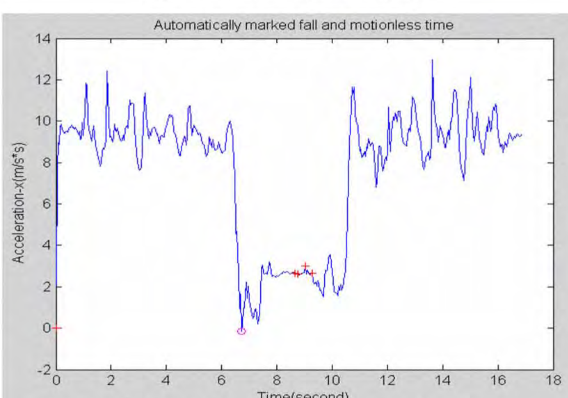

Figure 12 Backward fall and lying

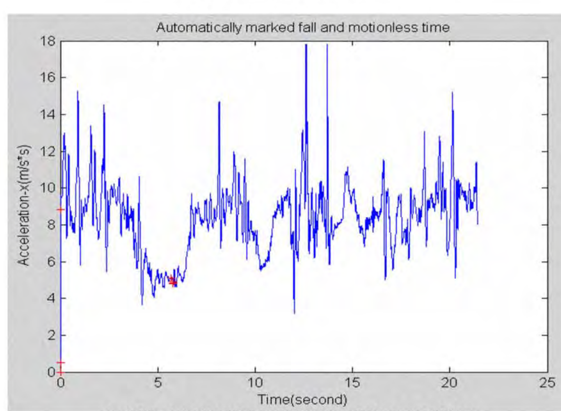

Figure 13 Slowly and lightly fall and sitting

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events. The phase threshold that could be used to correctly and quickly identify all different types of falls, with 100% accuracy was obtained for the heavy falling (dangerous-fall). There is one failure for the slowly and lightly falling (sitting down on the ground).

In this phase, the motionless activities such as standing, sitting, and lying were distinguished as the same activity i.e. motionless. Our future work will address the processing and classification of the standing, sitting and lying activities. This will require further signal processing from the signals provided by the MTx, feature identification and extraction and classification of activities. Activities of daily living may then be inferred, possibly with the assistance of other home based sensors.

Most of the current wearable sensor based fall detection systems that used one or more sensors attached on different body segments (e.g. chest, thigh, head behind the ear, waist), adopted two or more thresholds to monitor and distinguish falls [14][15]. Usually, these systems obtained their thresholds by calculating some peak values such as peaks for upper or lower acceleration along with angular acceleration and angular velocity peak values. Nevertheless, if the same person performs the same activity only in different situations (such as different speed, fall down from different height, falling into different circumstances e.g. hard ground and soft mat), the system will obtain different peak values for the acceleration or angular acceleration. So a peak value may be 100% accurate for the falling to the ground situation, but not guaranteed for the falling to a sofa situation, for example. In fact, realistic falls that may occur in various situations for elderly population in real daily life.

In conclusion, a fall detection system has been proposed and verified with 100% accuracy obtained from 10 subjects with 50 realistic measured events in a laboratory environment using healthy volunteers. The simulated falling and daily activities were recorded by a small tri-axial MTx sensor and a lightweight Xbus Master. It is low-cost and easy setting using only one belt-worn sensor. To increase accuracy and sophistication of fall detection, we used a threshold algorithm that is based on the analysis of the falling process using kinematic and mathematical knowledge. We will collect more data from elder people's daily activities for a longer period such as one week to evaluate this system and algorithms outside user's home in next step, however we should not ask the elderly volunteers to do fall intended, since the fall situation is dangerous to human body. Our algorithm is more theoretic than the data training strategy.

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