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Evaluation of Three-Axial Wireless-based Accelerometer for Fall Detection Analysis

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Abstract: Injuries from falling can be a serious problem for the elderly people and nowadays, a variety of research has been done on the topic of fall detection. Health professionals often refer to a person's ability to perform Activities of Daily Life (ADL) as a measurement of their functional status. In this research, a wearable wireless-based three-axial accelerometer sensor from Shimmer has been evaluated using a falling detection algorithm from Lindemann et al. and expanded by Chia-Chi Wang et al. which is according to two parameters of sum-vector of all axes (S_a) and sum-vector of horizontal plane (S_h). These parameters are used to determine significant points of time in the falling process, and identify lying condition. For this purpose, a walking activity has been used to analyse between the fall and the ADL. According to the analysis of falls and walks through the ADL of walking activity on ten and three healthy subjects, respectively, the method is 100 percent capable to classify between the fall and the walk.

Keywords: Shimmer three-axial accelerometer, falling detection, Activities of Daily Life (ADL)

1. Introduction

There are causal processes involved in falls and they are not simply random events [1]. There are many factors lead to a fall including environmental factors, failure of body functions, visual impairment, failure of muscle strength, and balancing disorder. A fall is generally be defined as inadvertently coming to the ground, floor or other lower level, excluding intentional change in position to rest in furniture, wall or other objects [1,2]. A fall is a single incident that happens instantaneously, which separates it from walking or exercising which has the characteristic of frequent repetitiveness [3].

Falls can cause problems for an elderly person physiologically, such as a serious physical injury, such as fracture or internal bleeding and subsequently develop fear of falling which has a negative impact on mental health [1,4]. When emergency treatments are not applied on time, it may results in permanent disability or even death [1,2]. Instead of assigning nurse to monitor the elderly people daily life activities, detection of falls is an important aspect. Nowadays, the wide range of assistive technologies to monitor elderly people provides plenty of choices for users. One of the ways to help person with health disease is to give doctors an opportunity to monitor remotely their patient's daily life [1].

According to previous studies, there are several developments in fall detection system that commonly used single or multiple sensing units attached to different parts of human body. These sensing units are used to collect data and transfer them through communication unit to a nearby processing unit for an automatic fall detection where the system can call for help when the user falls [5,6,7,8,9]. The accelerometer, gyroscope, camera and combinational of them are the most frequently used sensors, while Bluetooth, Wireless Fidelity (Wi-Fi) and server technologies are usually used for communication purposes with microcontrollers, desktops or laptops are usually used for processing the information received from the sensors' outputs via the communication units. However, the automatic fall detection system is a relatively new technology that needs several improvements to overcome some challenges regarding detection of falls which is inherently prone to high levels of false fall detection as what appears to be a fall might not be a true fall. These challenges include issues related to sensing performance, accuracy of a fall detection algorithm, usability and user acceptance [4,10].

In this research, an evaluation of a three-axial wireless-based accelerometer based on a recent fall detection algorithm has been done in analyzing falls through walking activities in order to look over the performance of the method for the fall detection. In this research, a Shimmer wearable three-axial accelerometer sensor has been evaluated through acceleration signals measurements in walking activities in order to classify between the falls and walks using a falling detection algorithm from Lindemann et al. [11] with a measurement method expanded by Chia-Chi Wang et al. [12]. The findings from this research are then can be

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implement for further refine solutions in developing a fall detection system potentially used in remote monitoring system of elderly people.

2. Methodology

2.1 Hardware and software requirements

Figure 1 shows the process block diagram for the fall detection analysis. The acceleration signals are received from a Shimmer three-axis accelerometer and collected by the ShimmerConnect software via the Bluetooth. The data received are then saved in CSV file format and the collected data are then analyzed using the algorithm by Lindemann et al. [11] in MATLAB software.

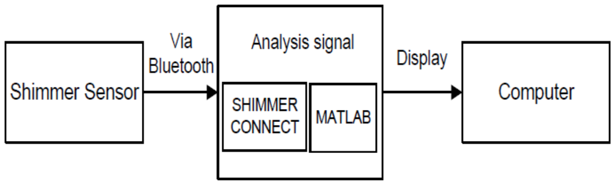


Fig. 1 Block diagram of the fall detection analysis.

The Shimmer three-axis accelerometer as shown in Figure 2 is a small wireless sensor platform that suited for wearable applications with a large storage, and low power standards based communication capabilities that allow a standalone application in a robust motion capture devices for people and equipment [13]. It is also capable of streaming data to more-capable device. According to Figure 2, positive *x*-axis of the sensor device is directed towards the bottom along the vertical axis, the positive *y*-axis is directed to the front outward along the sagittal plane while the *z*-axis is directed to the right outward along the coronal plane.

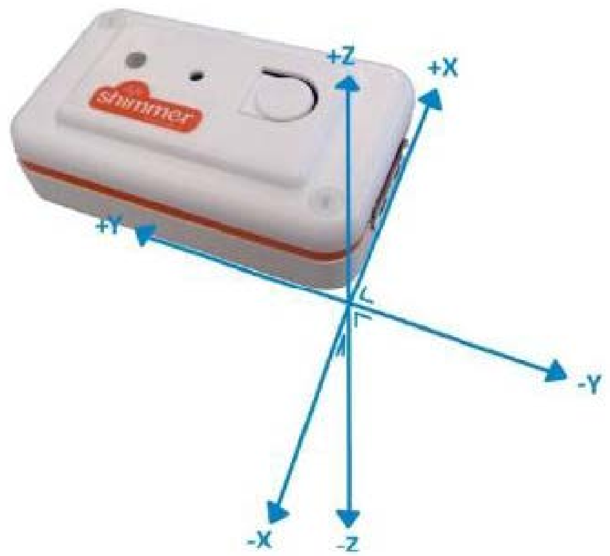


Fig. 2 Shimmer three-axial wireless-based accelerometer.

2.2 Activities of Daily Life (ADL) and a fall

Activities of Daily Life (ADL) is a term used in healthcare to refer to people's daily self-care activities. ADL is defined as the things people normally do such as bathing, dressing, walking, work, homemaking, and leisure. Health professionals often use a person's ability or inability to perform ADL as a measurement of their physical functional status.

Meanwhile, a fall is any abnormal movement with respect to ADL in which a discrimination process between falls and ADL is commonly conducted for the detection of fall using motion sensing inputs with a specific detection algorithm. Through this research, three-axial acceleration signals are used as the main input to discriminate between falls and ADL based on a walking activity.

2.3 Fall detection algorithm

For this project, a fall detection algorithm that has been used is based on the algorithm developed by Lindemann et al. [11] which is based on two parameters; a sum-vector of horizontal plane, S_h and a sum-vector of all axes, S_a in order to identify falls. These parameters are used to determine significant points of time in the falling process and identify lying condition whether a fall or ADL.

The equation of sum-vector of horizontal plane, S_h (*x-z* plane) is shown in Equation (1). An acceleration change of the horizontal plane is recognized as the body reaches the largest tilt angle while falling to the ground. Moreover, it is a point that gives the exact timing of body's initial contact to the ground. Meanwhile, S_a is used to describe the spatial variation of acceleration during the falling interval and Equation (2) is used to compute the value of S_a. The derived equation is basically followed the Newton's second Law. In order to distinguish between falls and ordinary activities of daily life based on the S_h and S_a, falls can be recognized at the moment when the S_h exceed the threshold value of two times gravity, 2g (19.61m/s^2) and the S_a exceed the threshold value of the upper fall threshold (UFT) of 2.8 g (27.46 m/s^2) and fall below the lower fall threshold (LFT) of 0.65 g (6.37 m/s^2).

$$S_h = \sqrt{A_x^{\,2} + A_z^{\,2}} \qquad (1)$$

$$S_a = \sqrt{A_x^{\,2} + A_y^{\,2} + A_z^{\,2}} \qquad (2)$$

Where, A_x, A_y and A_z is the acceleration signal from *x*-, *y*- and *z*-axis, respectively.

2.4 Subjects

Intentional falls are performed with ten healthy volunteer: five female (23 years and 24 years) and five males (23 years and 24 years). Falls are performed towards a mattress with thickness 20 cm. Each subject performed a forward fall with legs straight. Meantime, ADL samples are collected from three subjects: one female (24 years) and two male (23 years) through walking. Besides, the main reason of choosing young subjects in this research is to test the extent detection of ADL as falls since elderly people would be expected to produce higher peak acceleration during the falls [14].

2.5 Measurement setup

The measurement setup in this project is based on the method that had been introduced by Chia-Chi Wang et al. [12] which set the position of the sensor at the waist. The accelerometer is placed at the front waist which is near the center of body mass as in Figure 3. The site of signal detection prefers waist because this placement has several advantages compared with wrist, knee, head and neck which are near the center of body mass and capable to provide more reliable information on body movements since it is less affected by sudden limb motion artifacts. Furthermore, the use of a belt at a waist is generally perceived by elderly persons as non-invasive.

Fig. 3 Accelerometer sensor worn on the subject's waist

3. Results and Discussion

3.1 Falls evaluation

Figure 4 shows the graphical representation of sample data from the three-axial accelerometer: for a fall activity obtained from the subject 1. While, Figure 5 shows the graphical representation for fall detection analysis from the subject 1 of the sum of all the three-axial acceleration components, S_a and the sum-vector of horizontal plane (*x-z* plane), S_h. The data of S_h and S_a are calculated from the Equation (1) and (2), respectively. The red lines in Figure 5 represent the threshold value for the upper fall threshold (UFT) of 2.8 g (27.46 m/s^2) and the lower fall threshold (LFT) of 0.65 g (6.37 m/s^2)for the S_a ,and the threshold value of 2g (19.61m/s^2) for the S_h.

From Figure 5, point at the time of 0 msec to 80 msec shows the pre-fall phase which is a period before the subject 1 entering a critical phase of the fall event. While, at the time of 80 msec to 105 msec, the subject experiences a sudden movement towards the ground and is in a temporary period of flight during which the downward vertical velocity increases. Then, the subject sinks into the mat and experiences a deceleration. The maximum deceleration occurs at the time around 110 msec as the body sinks further into the mat and maximum deformation of the body movement occurs which causes fluctuations in the waveform. When the body initially contacts the ground, the dynamic acceleration is approaching zero as the body is no longer accelerating. After that, the body enters the post-fall phase, where the body eventually settles to rest at the time of 200 msec.

According to Figure 5, the moment around 100 to 110 msec it is predicted as a fall, which is when the S_a exceeds the threshold value of the upper fall threshold (UFT) of 27.46 m/s^2 and falls below the lower fall threshold (LFT) of 6.37 m/s^2, and the S_h exceeds the threshold value of 19.61m/s^2. The compilation of the graphical representations of S_a and S_h from the Subject 2 to Subject 10 is shown in Figure 6 which all are also detected as falls since there is a moment of the S_a exceed 27.46 m/s^2 and falls below 6.37 m/s^2, and the S_h exceeds 19.61m/s^2 in each of the waveforms in Figure 6.

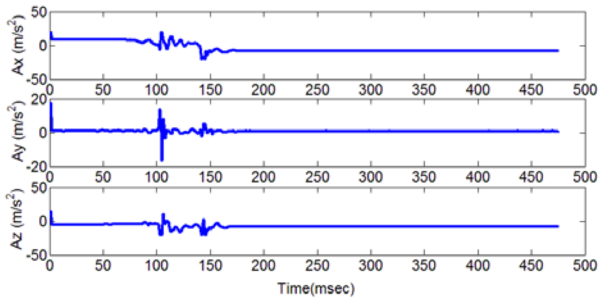


Fig. 4 Graphical representation of three-axial acceleration signals (A_x, A_y, A_z) in falls evaluation (Subject 1).

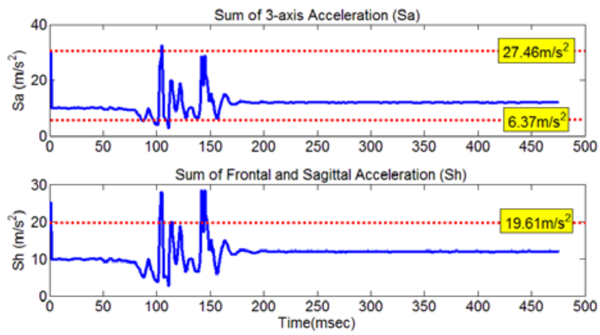
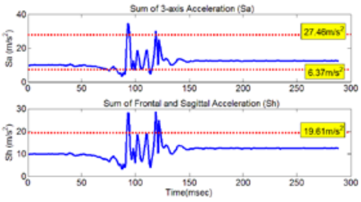
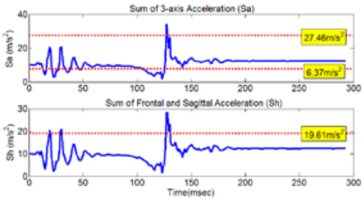


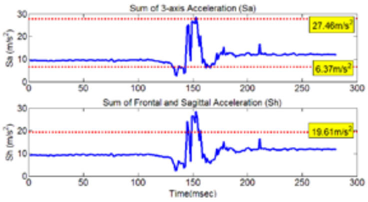
Fig. 5 Graphical representation of S_a and S_h in falls evaluation (Subject 1).



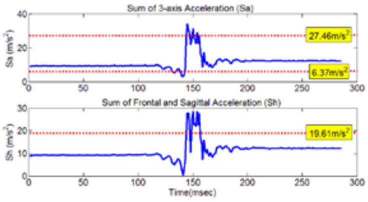
(a) Subject 2



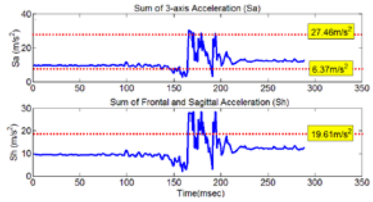
(b) Subject 3



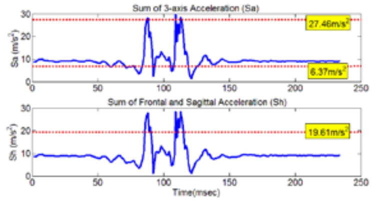
(c) Subject 4



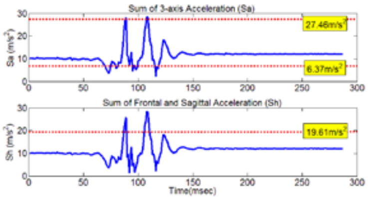
(d) Subject 5



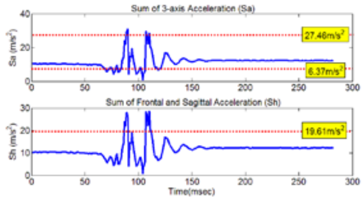
(e) Subject 6



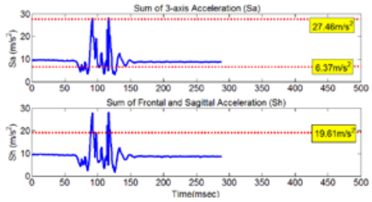
(f) Subject 7



(g) Subject 8



(h) Subject 9



(i) Subject 10

Fig. 6 The compilation of the graphical representations of S_a and S_h in falls evaluation from the Subject 2 to Subject 10 in (a) to (i).

3.2 Walks evaluation

Figure 7 (a) to (c) show the waveform obtained from the subject 1 that contain data from the three-axial accelerometer for walking activities. According to Figure 7 (a) to (c), A_x, A_y and A_z are the vector components of the acceleration data. Meantime, Figure 8 (a) to (c) show the waveforms of the sum of all the three-axial acceleration components, S_a and the sum-vector of horizontal plane (*x-z* plane), S_h, where the red lines represent the threshold value for the S_a and S_h. Figure 8 (a) to (c) are derived from the analysis of data in Figure 7 (a) to (c).

According to all the waveforms of S_a and S_h in Figure 8, none of the subjects are being detected in involvement in fall activity since the S_a are closely within the upper fall threshold (UFT) and the lower fall threshold (LFT) and the S_h is below the threshold.

(a)

(b)

(c)

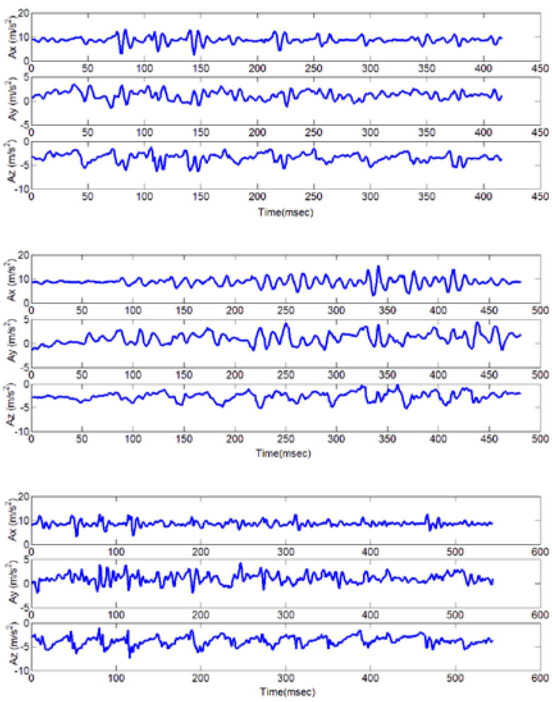


Fig. 7 Waveforms of three-axial acceleration signals (A_x, A_y, A_z) in walks evaluation. (a) Subject 1, (b) Subject 2 and (c) Subject 3.

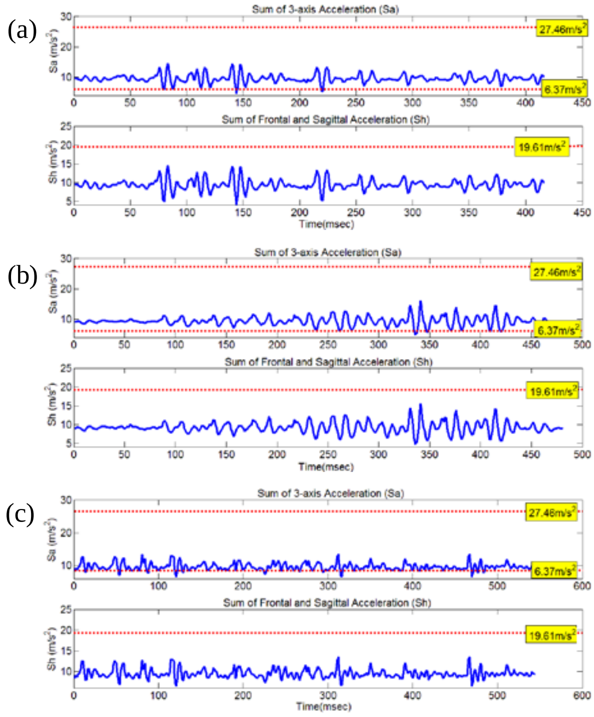


Fig. 8 Waveforms of S_a and S_h in walks evaluation. (a) Subject 1, (b) Subject 2 and (c) Subject 3.

4. Summary

Results of fall detection analysis on the evaluation of the Shimmer three-axial wireless-based accelerometer based on the fall detection algorithm introduced by Lindemann et al. [13] have been reported in detail. Based on the 13 measurement data on walking activities, it is found that the measurement using the Shimmer three-axial wireless-based accelerometer based on the fall detection algorithm introduced by Lindemann et al. is 100 percent capable of discriminating the falls and the ADL. Therefore, this method of detecting falls can be further implemented in realizing the fall detection remote monitoring system of elderly people.

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