Using an inertial motion unit to find the optimal location to continuously monitor for near falls

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Abstract:
The world population is ageing and a key hazard to healthy ageing is falls. The consequences of falls can be costly to health and social care systems. Falls can be prevented by continuously monitoring of older people for near falls, as they are a major risk factor for falls. This preliminary study's aim was to find the optimal placement of a monitoring device to detect falls, as this is the first step towards understanding how to detect a near fall. This study involved one participant wearing four commercially available motion trackers simultaneously. The participant performed five controlled sideways falls onto a crash mat. The motion trackers were controlled using the associ-ated software that also logged the data. The results presented display the ac-celerometer and gyroscope data for falls at the four locations (wrist, waist, ankle, and thigh). The data shows monitoring at the thigh gives the most consistent pattern per fall for both the accelerometer and gyroscope data.

Keywords:
Fall Detection, Near Fall Detection, Wearables, IoT.

1 Introduction

Today people are living longer and the world population is ageing [1], with the world population of over 65s expected to increase from 9.3 % in 2020 to 16.0 % by 2050 [1]. Therefore, the concept of healthy ageing has become increasingly important. The World Health Organization (WHO) defines healthy ageing as 'the process of developing and maintaining the functional ability that enables wellbeing in older age' [2]. Healthy ageing is about quality of life rather than just physical health and wellbeing.

A major risk factor to the quality of life of the ageing population is falling. The impact of a fall can cause physical injury ranging from minor (such as bruises) to serious (such as a hip fracture) [3], decline in mental wellbeing [4], or in the worst cases mortality [5]. The cost of falls to health and social care systems is large and increasing globally, for example the average cost to health care systems in Australia is US$ 1049 per fall [6]. The quicker a fall is detected, the lower the likelihood of serious complications and damage to mental health, which could prevent further falls [7]. Importantly quicker detection will result in a faster delivery of medical treatment, which is important for good clinical outcomes in the case of a serious fall. Therefore, the ability to remotely monitor falls would reduce pressure on health and social care systems and would allow for the ageing population to live comfortably at home for longer, however, this will not prevent the risk of falls. The definition of a near fall is a slip, trip, or imbalance that is corrected to prevent a fall [8]. Near falls are more likely to occur than falls, and near falls are a risk factor for a fall [8]. Consequently, continuous monitoring for frequent near falls can be used to prevent falls.

Wearable technology is often used for continuous monitoring of health and well-being [9], and wearables have been implemented for fall detection in the form of watches [10, 11] and pendants [12, 13]. It is unclear how these products detect the fall, but the Apple Watch does state that it uses the accelerometer and gyroscope inside of the watch to detect a hard fall [14].

The position of the sensor will be important, and the prevalence of wrist mounted, or pendant based devices is likely due to ease of implementation. There have been studies to find the optimal placement of the sensor for fall detection [15] and activities of daily living (ADLs) [16] exploring placing sensors on the waist, ankles, wrist, chest, arm and knee, however these studies have been inconclusive. In the literature, the sensors are often placed in several different locations for fall and near fall detection, without any clear reasoning provided.

The first step towards understanding how to detect a near fall is to ensure that a fall can be accurately detected. This study aims to find the optimal placement of a sensor to detect falls. This preliminary work only covers fall data taken at four locations.

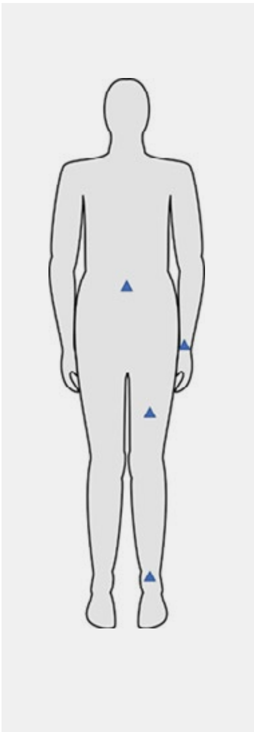

Fig. 1. Image of outline of the human body taken from [17] and edited to include the sensor locations of the wrist, waist, ankle and thigh. his image is licensed under a CC0 1.0 Universal Public Domain Dedication License.

2 Methods and Materials

This preliminary study was completed using one healthy volunteer (female, age 31, 170 cm, 61 kg) that was asked to perform five controlled sideways falls onto a crash mat (244cm x 122cm x 20cm). The experiment took 34 seconds to complete. Ethical approval was obtained from Nottingham Trent University Ethics committee. The participants provided their written informed consent prior to testing.

For monitoring the falls, the MbientLab MetaTracker (MbientLab, San Francisco, CA, USA) was used, which is capable of monitoring acceleration and orientation in real-time. In this preliminary study data is presented from four location (see Figure 1); left wrist, waist, left thigh, and left ankle. These are commonly used monitoring locations in the literature for fall [7], near fall [8] and activity detection [16]. Data presented in this work was taken as part of a larger study including five participants, where additional activities and monitoring locations were explored.

The MetaTrackers were controlled using the MetaHub from MbientLab and data was recorded from the various locations simultaneously with a 25 Hz sample rate, allowing for a direct comparison between locations. The MetaTracker has an embedded 6-axis inertial motion unit (IMU) (BMI160, Bosch Sensortec, GmbH, Gerhard-Kindler-Strasse 9, 72770 Reutlingen, Germany) which is comprised of a 3-axis accelerometer and 3-axis gyroscope. Acceleration was measured in g acceleration due to gravity (g) and the gyroscope data was measured in degree per second (deg/s). The data was processed using Microsoft Excel to create a pivot table that averaged three points logged at each time interval. The MetaTrackers where attached to the body using fabric (95% polyester and 5% spandex) cut up into strips and tied tightly onto the body.

3 Results and Discussion

3.1. Wrist

Figure 2 shows the accelerometer (Fig. 2a) and gyroscope (Fig. 2b) data taken at the wrist for the five controlled falls.

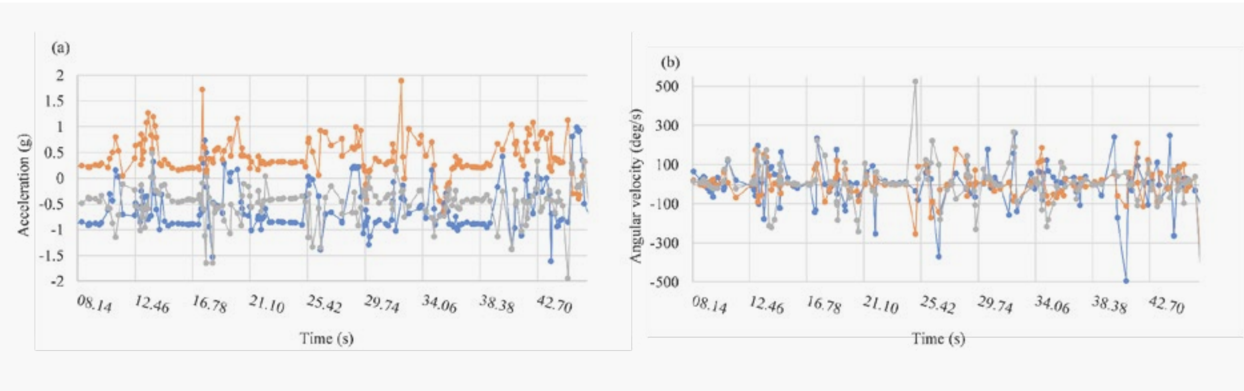

Fig. 2. (a) Accelerometer and (b) gyroscope data as a function of time taken at the wrist for the five controlled falls in the x-axis, y-axis and z-axis.

From Figure 2, the graphs show that the accelerometer data during each fall is not consistent. The only clear features are when the participant is standing still prior to the fall. The gyroscope data does not have any visible pattern. This is likely due the participant moving their wrist differently during each fall. Together the two graphs do not appear to provide valuable information for identifying a fall.

3.2. Ankle

Figure 3 shows the accelerometer (Fig. 3a) and gyroscope (Fig. 3b) data at the ankle of the five controlled falls.

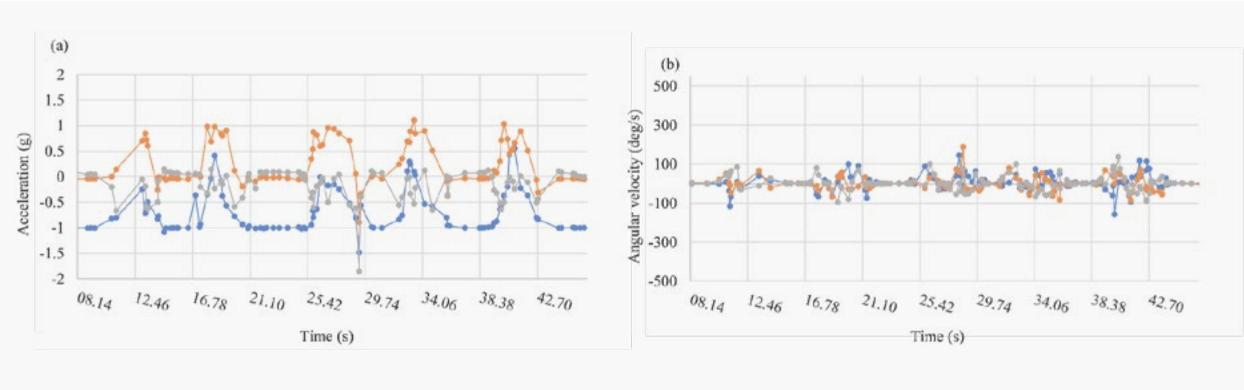

Fig. 3. (a) Accelerometer and (b) gyroscope data as a function of time taken at the ankle for the five controlled falls in the x-axis, y-axis and z-axis .

Fig. 3a shows the acceleration at the ankle as a function of time. It is clear from the data when the participant is standing prior to the fall. During the fall there is a consistent 1 g increase in the z-axis acceleration, and a 1 g increase in the x-axis acceleration. For the gyroscope data alone, it can be seen that there are five points of movement that correspond to the falls, but the pattern of motion is not consistent each time the fall occurs.

3.3. Waist

Figure 4 shows the controlled fall data for the accelerometer (Fig. 4a) and gyroscope (Fig. 4b) at the waist.

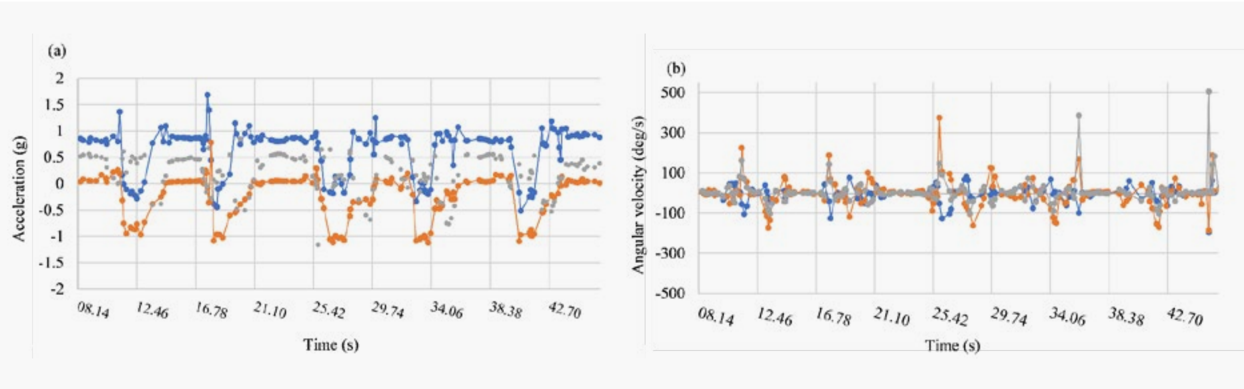

Fig. 4 (a) Accelerometer and (b) gyroscope data as a function of time taken at the waist for the five controlled falls in the x-axis, y-axis and z-axis.

From figure 4 it can be seen that there is a consistent pattern for the fall in both the accelerometer and gyroscope data. It is visible when the participant is standing before the fall. There is a decrease of 1 g in the acceleration in the x-axis and z-axis. In the y-axis for acceleration there is a smaller decrease in acceleration of 0.5 g. The pattern for the gyroscope is slightly more variable for each fall.

3.4. Thigh

Figure 5 displays the controlled fall data taken at the thigh for the accelerometer (Fig. 5a) and the gyroscope (Fig. 5b).

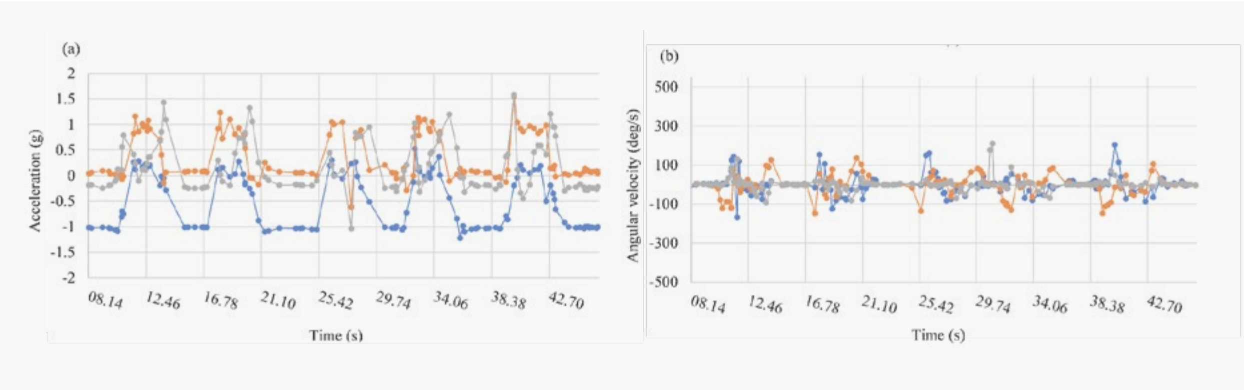

Fig. 5. (a) Accelerometer and (b) gyroscope data as a function of time taken at the thigh for the five controlled falls in the x-axis, y-axis and z-axis.

The graphs in figure 5 illustrate a clear pattern for both the accelerometer data and the gyroscope data. The graphs clearly illustrate when the participant is standing. The acceleration in the x-axis, y-axis and z-axis increase by 1 g. The gyroscope data shows an increase in angular velocity in the x-axis and y-axis and a decrease in the z-axis as the fall occurs.

4 Conclusions and future work

From the data presented it can be seen that the fall data at the thigh provides the most consistent and clear pattern and is very similar for each of the falls. The wrist data appears to be the least consistent per fall, which is most likely due to random arm movement. However, further analysis is required on the rest of the data collected at each location on the body for various activities of daily living to determine the optimal location. This may change dependent on which location can best differentiate between the various activities and a fall.

Further work will investigate monitoring different actives, such as a stumbling or tripping to mimic near falls. Additionally, extra participants of varying heights, weights, and ages will be required.

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