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Development of Wearable Sensor-Based Fall Detection System for Elderly using IoT

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Abstract: Recently, there are many elderly living independently might be more dangerous in the house. This is because people who are 65 and above have a high risk of physical health problems such as musculoskeletal disorders, dizziness and imbalance. Falls among the elderly are a growing serious problem. This is because falling has many effects on the elderly and even mortality. People who live alone may not be able to seek help after falling down. In this project, an IoT system that integrates a wearable fall detector was invented to minimise elderly fall injury at home. The system consists of sensors, hardware devices, a cloud server, and the internet. The proposed system is designed with a notification, which can be sent automatically through email and the android smartphone phone of the user if detected any falling condition occurred based on the data received from the wearable device. The fall detector is also designed for indoor use with Wi-Fi conditions. If the elderly is outdoors, elderly can open a hotspot of a smartphone as Wi-Fi. The fall detector will detect the fall signal and the alert system will send a fall notification via email and push notification of the Blynk application to alert family members or caregivers without touching the wearable fall detector button. The system was developed successfully into a wearable form that can be worn at the centre of the chest and detect the fall movements and activities of daily living (ADL).

Keywords: Fall Detection System, Elderly, Blynk IoT, Wearable Fall Detector, Alert notification, Falling Activities, ADL

1. Introduction

According to a survey from the American Association of Retired Persons (AARP), there are approximately 90 % of seniors want to stay in their current homes for the next five to ten years [1]. Most seniors want to stay in their own homes as they age. This is because moving to a new home may cause physical and emotional stress. Many seniors are reluctant to leave their own home that is full of memories and their beloved neighbours. However, the truth is that for many seniors living at home alone without any assistance can be unhealthy and even more dangerous [2]. The National Safety Council reveals that about 24,000 older people age 65 and above die from accidental injuries each year. The common injuries among elderly people are falls, burns, poisoning, and automobile accidents [3].

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A global report by the World Health Organization (WHO) states that 25 – 35 % of older people aged 65 and above experience falls each year, and it is increasing to 32 – 42 % for those 70 years and above [4]. From a WHO global report, 56 % of falls occurred outside the home, such as in the yard, on the street or in a public place. Falls that occur inside the home happen most frequently in bedrooms, kitchens, and dining rooms. Relatively few falls occur in the bathroom, which is 3 %, 6 % on the stairs and 3% from ladders as well as step stools [5].

Currently, the commercialised fall detector response system is in the form of a pendant, necklace, or wristband like a watch. The system consists of a base unit that looks like a speakerphone with a portable button. This system works with a portable push button that requires it to be pushed during an emergency whether it is about a medical issue, a fall or a fire. However, elderly people might be unable to activate it because they become unconscious after falling down [6]. Another current fall detector system is used and implemented as a home camera-based fall detection system such as CCTV to monitor the elderly. Normally, the device is hung onto walls or ceilings. Thus, he/she can directly observe and monitor their family members at home, especially the elderly. When a fall is detected, an alarm message is sent to the caregiver along with a picture. However, this type of system might cause false alarms because it is sensitive to body movement [7].

An IoT system that integrates a wearable fall detector was developed and invented in this project, hence can potentially minimise elderly fall injury at home. The developed system was designed with a notification that can be sent automatically through email and an android smartphone phone if detected, any falling condition occurred based on the data received from the wearable device. The fall detector will detect the fall signal and the alert system will send a fall notification instantly via email and push notification of the Blynk application to alert a family member or a caregiver without touching the wearable fall detector button (as applied in the current wearable device). Hence, medical treatment can be provided immediately if the elderly fall down at home.

2. Methodology

2.1 Overview of the system

An overview of the architecture for the fall detection and alert system is shown in Figure 1. The system is categorized into three parts: the wearable sensor; the smart IoT gateway, and the user terminal. A wearable device is connected to a NodeMCU microcontroller, ESP8266 Wi-Fi module, and a triaxial accelerometer and triaxial gyroscope of the MPU6050 sensor. If the acceleration and angular velocity meet the threshold values, a signal will be sent to the Blynk server via Wi-Fi to send a notification to the family members or caregivers ESP8266 Wi-Fi module is connected to the IoT gateway for better communication between the sensors and the cloud server. The main role of the cloud server is to process, store and analyse data and send the encoded data to the user terminal.

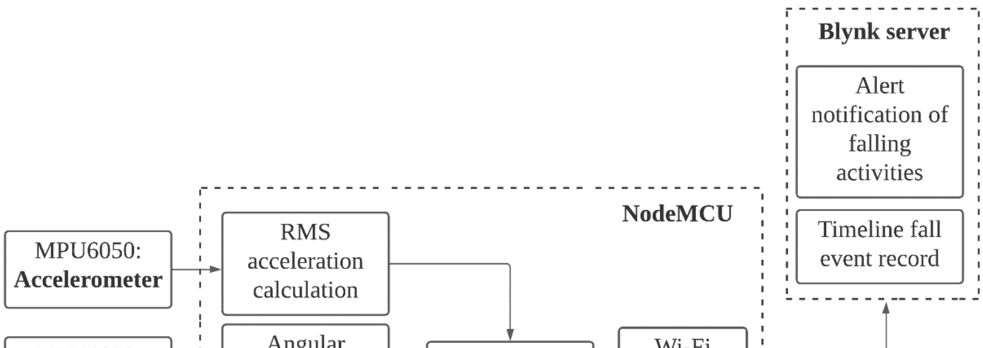


Figure 1: Block diagram of fall detection system

2.2 Fall Detection System

Figure 2 shows the flowchart of the fall detection system. First, the system can be located at the chest of the elderly. Once, the power of the system is turned on, the NodeMCU microcontroller will connect to the Blynk IoT cloud via a network. The MPU6050 sensor is used to sense elderly movements by detecting and measuring the acceleration and angular velocity of the elderly. If acceleration and angular velocity exceed threshold values in the system, then, a fall is detected. Blynk IoT cloud will automatically send notifications in real-time to Gmail and Blynk Android application to notify family members or caregivers instantly.

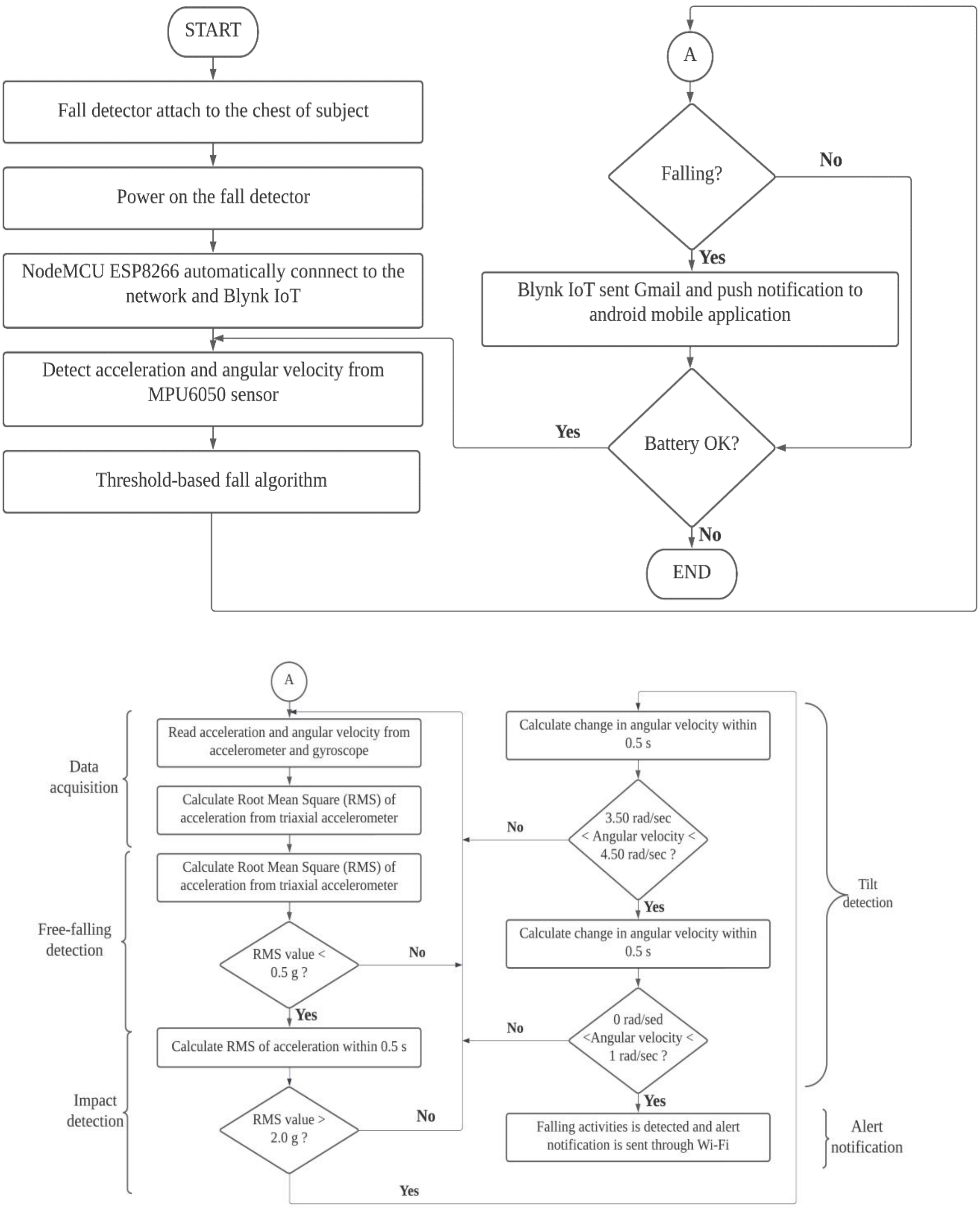


Figure 2: Flowchart of the fall detection system

The system will be worn at the chest, so the sensing axes of the accelerometer and gyroscope are as shown in Figure 3.

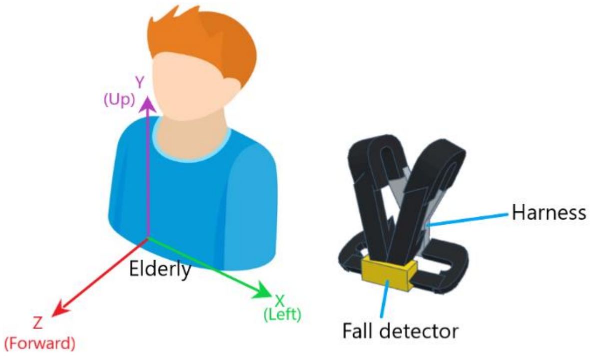


Figure 3: Sensing axes of MPU6050 on the chest and prototype design of system

Threshold-based method (TBM) was used in this project to develop the fall detection system due to it can classify fall detection regularly. Fall detection methods based on thresholds are very common, due to the expected physical impact related to falls [8]. Fall detection methods based on thresholds are very common, due to the expected physical impact related to falls [8]. The threshold-based method of acceleration is based on the equation of Root Mean Square (RMS) acceleration [9]. The RMS acceleration, Acc which is representing the measured triaxial acceleration of the user and calculated by using Equation (1) [9].

$$Acc = \sqrt{(A_x)^2 + (A_y)^2 + (A_z)^2} \quad Eq.1$$

where A_x, A_y and A_z are the accelerations in the X-axis, Y-axis and Z-axis directions, respectively in the accelerometer sensor. If the RMS acceleration value is exceeding the threshold acceleration, it means that there is a falling movement. There are two levels of threshold-based method (TBM) that will be set in the system which are lower fall threshold (LFT) and upper fall threshold (UFT) for acceleration. Lower fall threshold (LFT) of acceleration, LFT_{acc} is the minimum value that refer to lower peak value of RMS Acceleration [9]. For the upper fall threshold (UFT) of acceleration, UFT_{acc} is the maximum value that is referred to the higher peak value of RMS acceleration. When people fall, there will be a free-fall and impact condition. The free fall condition will obtain a lower peak of RMS acceleration while a higher peak of RMS acceleration occurs when elderly reach on the ground (impact condition). The unit of RMS acceleration is a meter per second squared (ms^{-2}). When the acceleration is static or stationary, the RMS acceleration is approximately 9.81 ms^{-2} (1 g) where g measurement of acceleration due to gravity [10]. The three axes of angular velocity in X-axis, Y-axis and Z-axis directions are calculated using Equation (2) [9].

$$\omega = \sqrt{(\omega_x)^2 + (\omega_y)^2 + (\omega_z)^2} \quad Eq.2$$

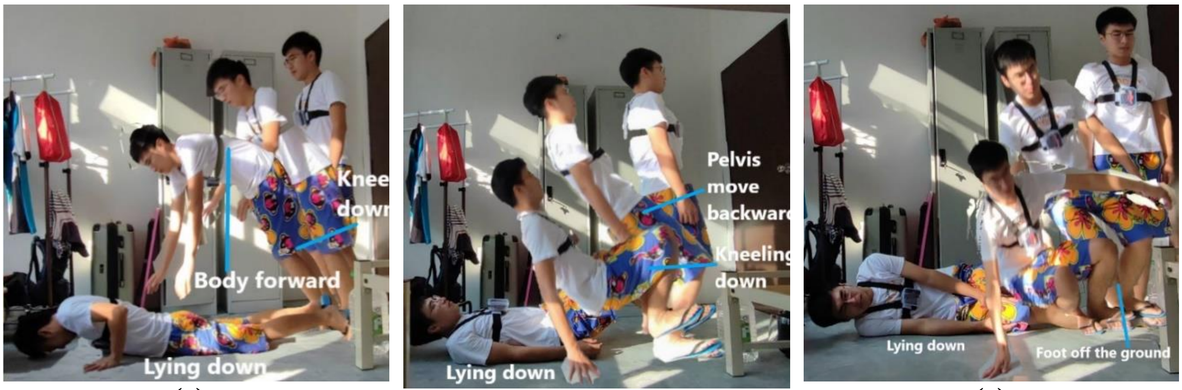
where ω_x, ω_y and ω_z are angular velocities in X-axis, Y-axis and Z-axis directions in the gyroscope. The fall thresholds of LFT_{acc}, UFT_{acc} and UFT_{gyro} are used to determine fall events. Fall event is detected when three threshold values are detected.

The fall detection system is used both LFT_{acc} and UFT_{acc} in combination with the UFT_{gyro}. In order to obtain the optimal threshold for detecting free fall, impact and angular velocity, a preliminary experiment was carried out with three volunteers with 90 falling movements, which were 10 forward falls, 10 backward falls and 10 lateral falls. The age of the volunteers is in the range from 23 kg to 24 kg, weight ranges from 160 cm to 175 cm. All the data values are observed by using line graph chart in Blynk application. Based on recorded data from three volunteers, the free fall, impact fall of RMS acceleration as well as angular velocity were used to set the threshold values for the proposed system. The lower threshold acceleration is set to 4.91 ms^{-2} (0.5 g) and the upper threshold acceleration is set to

19.62 ms^{-2} (2 g). For the angular velocity, there are two levels of algorithm in the proposed system. The lower threshold acceleration is set to 4.91 ms^{-2} (0.5 g) and the upper threshold acceleration is set to 19.62 ms^{-2}. For the angular velocity, there are two levels of algorithm in the proposed system. The first level is set for the impact condition, which is between 3.50 rad/s until 4.50 rad/s (200.55 degree/s until 257.83 degree/s) and second level is for the elderly after hitting the ground, which is set between 0 rad/s to 1 rad/s (0 degree/s until 57.30 degree/s).

2.3 Falling and ADL Experimental Test

The feature of falling movements in this proposed system is at the center of the chest. Hence, when the elderly loses balance and fall, there will occur significant changes in acceleration and angular velocity at the chest. Three volunteers with the of range age from 23 to 24, weights range from 60 kg to 80 kg and heights range from 165 cm to 175cm were asked to wear the system-implemented fall detector. There are three common falling movements which are forward fall, backward fall and lateral fall as shown in Figure 4 (a), (b) and (c) respectively. In order to test whether the proposed system would generate false alarms, six activities of daily living (ADL) movements were tested including standing, walking, standing up and sitting, lying and sitting up and, stairs climbing and down stairs. In order to improve the accuracy of data, volunteers must follow the procedure for falling movements that are listed in Table 1. This is because the triaxial acceleration and angular velocity will be inaccurate and affect the accuracy of the result.



(a) (b) (c)

Figure 4: Falling experiment (a) Forward fall (b) Backward fall (c) Lateral fall

Table 1: Procedure of falling movements

	Forward Fall	**Backward Fall**	**Lateral Fall**
Falling Movements	Kneeling down, body forward and lying down in the end	Pelvis moves backward, knee bending, lying down in the end	One of the foots off the ground and lying down in the end

2.4 Estimation Metrics

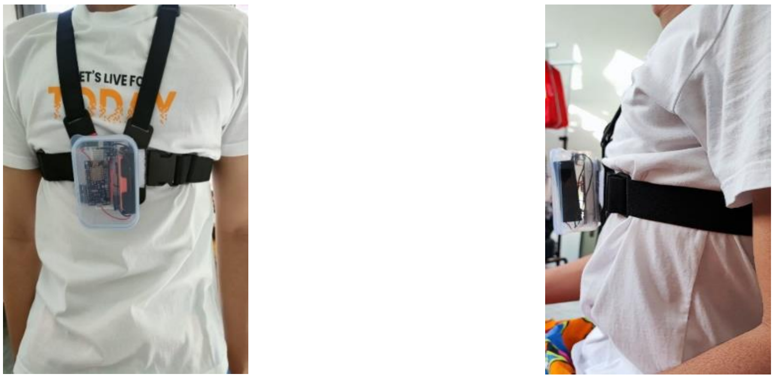
For the robustness of the proposed system, the six ADL data and three falling activities will be estimated using sensitivity, specificity and accuracy. Sensitivity refers to, detects and identifies the rate of falling movements. Specificity refers to identify the six ADL that are recognised accurately. Sensitivity and specificity are calculated as equations (3) and (4) respectively [10], where True Positive (TP) is the number of falling movements detected correctly. False Positive (FP) is the number of ADL detected as falling movements. True Negative (TN) is the number of ADL that are identified correctly, and False Negative (FN) is the number of systems that do not detect fall movement; even falls occur.

$$Sensitivity = \frac{TP}{TP + FN} \quad Eq. 3$$

$$Specificity = \frac{TN}{TN + FP} \quad Eq. 4$$

3. Results and Discussions

Figure 5 (a) shows the harness that was used with the fall detector device is sketchable, which can improve the comfortability of elderly The fall detector device with dimensions of 105 mm (L) x 7.5 mm (W) x 4.5 mm (H) and build with a harness. The total mass of the fall detector device with battery and casing was 127 g, where gram (g) is a unit of mass.



(a) (b)

Figure 5: Wearable fall detector attached at the centre of chest (a) front view (b) side view

In the forward fall test, volunteer kneeling down and body forward to the ground, causing free fall condition before the impact of the chest. In the free fall condition results in Figure 6, the RMS acceleration reached at 3.57 ms^{-2}. In the impact condition, there is a peak in the graph about 26.32 ms^{-2} of RMS acceleration, and it is caused by the volunteer being hit on the ground. Based on results in Figure 7 shows that, the angular velocity reached 3.88 rad/s after volunteer hit on the ground (during impact condition). After several milliseconds, the angular velocity maintains between 0.02 rad/s and 0.15 rad/s in the graph. Results from the forward fall test clearly show that all the characteristics of free fall, impact and falling down period are matched with threshold-based method (TBM). Hence, the fall accidents are detected and matched correctly by the developed system.

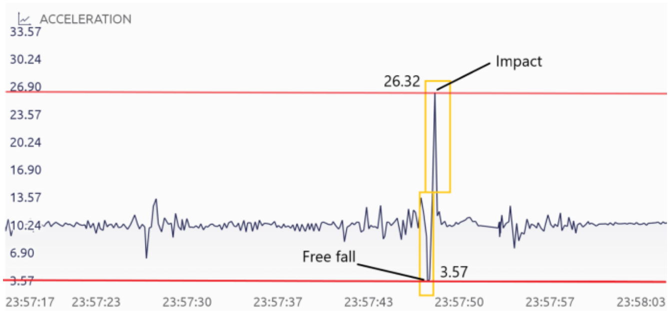


Figure 6: Forward fall RMS acceleration

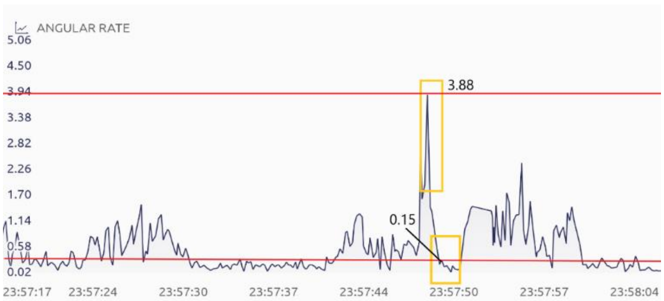


Figure 7: Forward fall angular velocity

In the backward fall test, the volunteer moves his pelvis backward and bends his knee. These movements cause free fall conditions before the impact of the chest. In the free fall condition, the RMS acceleration reached 2.57 ms^{-2} as shown in Figure 8. In the impact condition, there is a peak in the graph about 33.31 ms^{-2} of RMS acceleration, and it is caused by the volunteer being hit on the ground. Based on results in Figure 9 shows that, the angular velocity reached at 3.88 rad/s after volunteer hit on the ground (during impact condition). After several milliseconds, the angular velocity maintains to be smaller than 0.10 rad/s. It can be analysed that the RMS acceleration and angular velocity had exceeded the threshold in the proposed system. Hence, the fall accident is detected correctly.

Figure 8: Backward fall RMS acceleration

Figure 9: Backward fall angular velocity

In the lateral fall test, the volunteer lifted his leg off the ground and moved his body for lateral lying on the floor. During the lying movement, this causes a free fall condition before the impact of the chest. In the free fall condition, the RMS acceleration reached at 2.28 ms^{-2} as shown in Figure 10. In the impact condition, there is a peak in the graph about 23.22 ms^{-2} of RMS acceleration, and it is caused by the volunteer being hit on the ground. Based on results in Figure 11, the angular velocity reached 4.20 rad/s after volunteer hit on the ground (during impact condition). After several milliseconds, the angular velocity maintains to be smaller than 0.58 rad/s. The volunteer is lying on the ground after falling down so the angular velocity does not exceed the threshold values. Results from the lateral fall test also showed that all fall accidents characteristics were matched with threshold-based method (TBM).

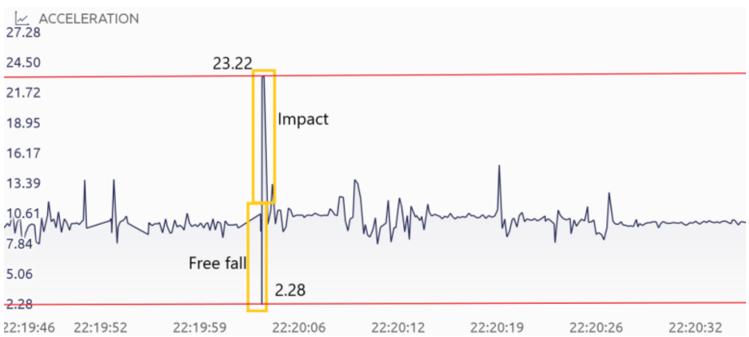


Figure 10: Lateral fall RMS acceleration

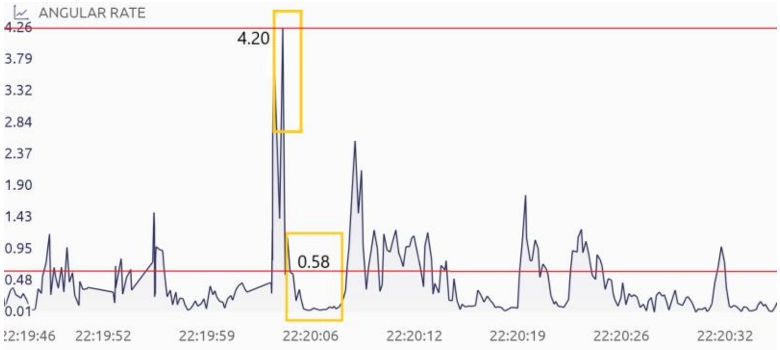


Figure 11: Lateral fall angular velocity

The sensitivity and specificity were calculated by using Equation (3) and Equation (4) for evaluating the performance of the fall detection system. The falling test experiment results are tabulated in Table 2 and ADL test experiment results in Table 3. Results in Table 2 show that the three volunteers performed 10 times for each of the fall movements. For volunteer 1, the fall detection system successfully detected a total of 9 forward fall, backward fall, and lateral fall out of 10. For volunteer 2, the fall detection system successfully detected a total of 8 in forward fall, 8 in backward fall, and 9 in lateral fall out of 10. For volunteer 3, the fall detection system successfully detected a total of 9 in forward fall, 8 in backward fall, and lateral fall out of 10. The total number of forward falls and lateral falls that were successfully detected by the fall detection system among the three volunteers was 26 out of 30. The results in Table 3 show that the ADL tests have been achieved by three volunteers. Each activity has been performed 10 times by three volunteers. In every ADL test, there were no falls detected by the system, so each volunteer achieved the total of 10 out of 10. The total of the ADL tests for three volunteers was 180 out of 180.

Table 2: Falling test experimental results

Volunteer	Forward Fall	Backward Fall	Lateral Fall	Total
1	9/10	9/10	9/10	27/30
2	8/10	8/10	9/10	25/30
3	9/10	8/10	8/10	25/30
Total	26/30	25/30	26/30	77/90

Table 3: ADL test experimental results

Volunteer	Standing	Walking	Stand up and Sitting Down	Lying and sitting up	Stairs climbing	Down Stairs	Total
1	10/10	10/10	10/10	10/10	10/10	10/10	60/60
2	10/10	10/10	10/10	10/10	10/10	10/10	60/60
3	10/10	10/10	10/10	10/10	10/10	10/10	60/60
Total	30/30	30/30	30/30	30/30	30/30	30/30	180/180

The sensitivity and specificity also calculated by using Equation (3) and (4) respectively by using the recorded data.

$$Sensitivity = \frac{TP}{TP + FN} \, x \, 100\%$$
$$= \frac{77}{77 + 13} \, x \, 100\%$$
$$= 85.56\%$$

$$
\begin{aligned}
Specificity \quad &= \frac{TN}{TN + FP}\ x\ 100\% \\
&= \frac{180}{180 + 0}\ x\ 100\% \\
&= 100\%
\end{aligned}
$$

The fall detection system has 85.56 % of sensitivity in fall detection and 100 % of specificity in ADL detection as shown in Figure 15. There is a 14.44 % of misdetection rate and zero percent of false alarm rate. These result shows that the fall detection system can be used for detecting the fall activities of elderly in real life.

Figure 12 shows the notification is received in Gmail after a fall is detected. Figure 13 shows the push notification of the Blynk application on a smartphone after fall is detected.

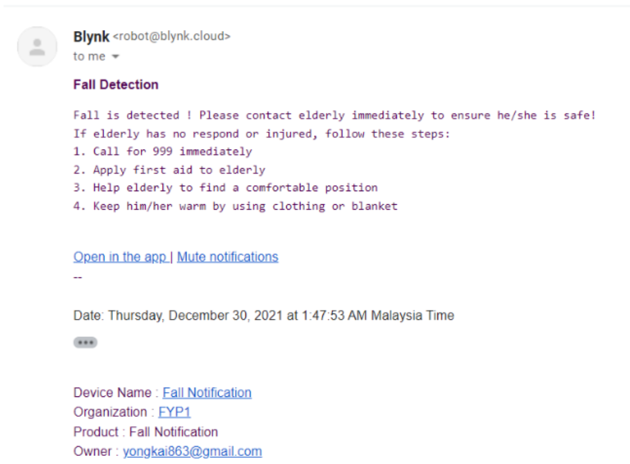


Figure 12: Notification received in Gmail

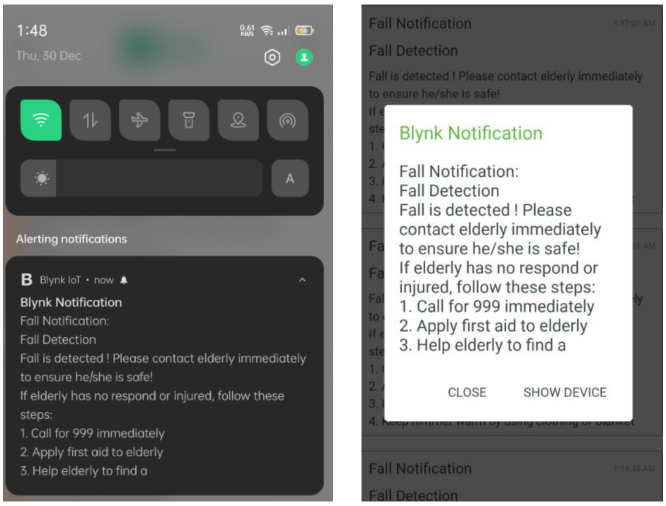


Figure 13: Push notification of Blynk application in android smartphone

4. Conclusion

The idea to implement a fall detection system into a wearable device was successfully implemented in this project. All the objectives are achieved by obtaining reliable results in experimental tests. There are a total of 90 fall tests and 180 ADL tests that are tested by three volunteers. The evaluation performance of the fall detection system reached 85.56 % sensitivity and 100 % specificity. Hence, the fall detector functions well that can recognise the falling accident in different axes of directions of elderly on daily basis. The proposed system is still in its early stages of concept for fall detection. Hence, more research needs to be carried out to focus on the range of falling movements in the future. More subject data is needed to access more realistic falling movements as well as ADL of the elderly.

Acknowledgement

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