Embedded Fall Detection System using Accelerometer & Threshold-based Algorithm

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Abstract

Most of the current commercialized fall detection systems are primarily wearable technologies, with the device located on the wrist, which can result in false positives due to wrist movement. This journal proposes a fall detection system that is both reliable and cost-effective, allowing people nearby to be alerted for assistance in case of an emergency. Our proposed fall detection system is made up of an accelerometer and a gyroscope, which compute acceleration, orientation, and other motion features. Overall, this journal proposed a fall detection system with a sensitivity of 90%, specificity of 85%, and accuracy of 87.5%.

1 Introduction

1.1 Problem

Due to the birth rate live independently are at risk of a fall, which can cause psychological, physiological, and physical damage, leading that people who are above the age of 50 will be doubled as excepted by 2050 or increase to around 20 billion by 2050 from 900 million in 2015, which accounts for 22% of the world's population (Brunier & Lindmeier, 2015). With the increasing number of elderly, the demand for health care services increases to meet the requirement of care. The World Health Organization (WHO) states that "28 to 35% of elderly people aged 65 and above" (Kalache, et al., 2007) will experience any type of fall each year. Following this, increase to "32 to 42%" (Kalache, et al., 2007) for elderly people who are aged above 70.

The elderly who lives independently are at risk of a fall, which can cause psychological, physiological, and physical damage, leading to injuries or death if the patient cannot receive immediate medical assistance. To reduce the time of seeking medical attention from a fall, a fall detection system is required to fill in this void, alongside the fall detection system should be reliable and detect a fall and able to contact staff to assist the elderly patent that had fallen, following from this the fall detection should be user friendly and must not interfere with other daily activities such as walking, squatting and other daily activities.

1.2 Introduction of Embedded Systems

Embedded systems are microprocessor computer hardware that can be programmed with software that is designing a specific function or task, for example, a calculator and a desktop computer, both systems can calculate functions such as basic addition functions, however, due to the size comparison between both systems are significantly the same, however, the power requirements for these two are significant such as a modern desktop requires 240+ volts to power it while a calculator requires a button cell battery, overall manufacturing enable mass production of embedded systems such as calculators.

Embedded systems are made up of two key components, hardware, and software. The software side is used to program the embedded systems and that runs Real-Time Operating Systems (RTOS) which supervise the software and provides a mechanism that allows the processors to run instructions ana d schedules example of a Real-Time Operating system is the Central Processing Unit (CPU) on a Raspberry Pi and Arduinos, however, not only these two applications but more importantly Embedded Systems are continued to be developed on the Internet of Things sector and the Artificial Intelligence field.

1.3 Introduction of The Internet of Things

The Internet of Things, commonly shortened to IoT, is currently experiencing rapid development of smart wearable devices that enhance the lifestyle of humans. With the data that has been collected by Internet of Things devices, it has a possibility of obtaining new information, and yet sometimes there is a possibility of a positive impact on society, an example of this soil moisture sensor, which is suitable for smart farming and irrigation controllers or general agricultural projects which includes a soil moisture sensor which is cost-efficient to produce sensors, to develop and most importantly cost-efficient to maintain equipment. Internet of Things had made a rapid push in the development of IoT devices within the medical/ health care industry such as blood oxygen monitoring systems, heart rate monitoring, and many components that can be used in the medical/ health care industry. An example that could improve is the fall detection system that uses IoT devices to detect a fall, with reasonable cost to produce and maintain IoT devices.

2 Literature Review

2.1 Introduction of Fall Detection Systems

Fall Detection Systems combined with the Internet of Things can relieve the burden of the lack of healthcare staff available to monitor the elderly and due to elderly people living more independently followed by post-impact if the patient is not treated quickly, with this IoT and Embedded systems become more affordable.

Two main approaches when it comes to fall detection, are physical and physiological methods. Both methods can be used to detect if a fall had occurred, for example, the physical method could use an accelerometer that detects any change from acceleration that can be caused by falling or general movement and can be sub-categorized as body motion. The physiological methods can detect blood pressure changes such as a temporary spike in blood pressure due to adrenaline. The physical approach is the most common method to detect a fall due to the body acceleration of a fall's initial impact. The impact can be monitored and measured to determine if a fall occurred. This literature review reviews the current literature surrounding wearable fall detection devices which use a physical approach.

2.2 Type of Fall Detection Systems

Three types of methods to detect physical signals: Vision, Ambient and Wearable, according to Mozaffari, et al. (2019). For example, vision detection uses a video stream that relies on Close-Circuit-Television (CCTV) or Raspberry Pi camera which uses visual machine learning techniques to detect a fall. An ambient method based on environmental changes, for example, sound and/or vibration detect sound caused by falling, and voice detection if the patient asks for help verbally. Finally, Wearable devices that use small microprocessors to detect a fall such as Electrocardiogram (ECG) detect pressure changes in the blood and it is a classified as a wearable devices, however, the form of detecting a fall is through wearable devices reliable of wearable devices compared to Visual and Ambient. Methods.

2.3 Wearable Device

Wearable technology had recently become popular and affordable, this includes wearable IoT glasses, bracelets, and other devices that can provide functionality and collection of user's data example, calculating steps walked today, heart rate monitoring, GPS location, and many more. Not only user data but environmental data such as sound, light intensity, and gas monitoring. The advantages of wearable devices are that the device can fit naturally on a human body such as a GPS controller for patients who suffer from Alzheimer's and could attach a GPS controller to a watch or bracelet. Another example of wearable device sensors by Hsieh, et al., (2014) used tri-axis sensors that detect body acceleration in X, Y, and Z coordinates which are used to collect and determine if a fall had occurred.

2.4 Review of the Type of Sensors for Fall Detection

There are many different types of sensors for wearable devices, there are two categories for wearable devices: Body Motion and Physiological Signs (Mozaffari, et al., 2019). Body motion sensors can be used to detect movements from the body, while physiological can detect brain reactions such as blood pressure increase due to the heart rate increase, here are the sensors for body motion:

Accelerometer	Gyroscope	Magnetometer
EMG	Pedometer	GPS
Inclinometer	Altimeter	Ultrasonic / RFID Tags

Table 1: Body Motion Sensors

List of physiological sensors that can be used in wearable devices to detect a fall:

Temperature Sensor	Humidity Sensor	ECG
Blood Pressure Sensor	Blood Oxygen Sensor	EEG

Table 2: Physiological Sensors

2.5 Review on Tri-Axis Based Fall Detection

Wu, F. et al., (2015) used an ADXL345 accelerometer which measures 13 bits ± 16g with maximum precision of 4mg MCU. Wu, F. et al., (2015) experiment had different participants conducting different activities such as walking, jumping, and other daily activities, and repeated 20 times. In one experiment, Wu, F. et al., (2015) state that ADXL345 did "*not rotate 90 degrees when the peak values were quite high, so the fall alarm has not been triggered"* (Wu, F. et al., 2015, p. 9). This suggests that the algorithm is reliable to detect differences between a fall and activity of daily living, in conclusion, the algorithm reported at 97.1% and the specificity at 98.3%, and in the testing phase, it was reported that sensitivity was at 91.6% and specificity at 88.7%.

Rihana & Mondalak (2016) developed a device that used ADXL345 with identical components as to Wu, F. et al., (2015), however, Rihana, S. & Mondalak, J. (2016) concluded with sensitivity is 90%, specificity of 85% and accuracy 87%.

Kumar, et al., (2018) created a device that used EPS8266 and MPU 6050 (Accelerometer), Kumar, et al., (2018) concluded that it produced 99% accuracy, however, data analysis suggests that backward falls are difficult to detect, and overall accuracy for backward fall were 66%, while forward falls at 80% accuracy. On another note, Kumar, et al., (2018) added a reset button which is used to reset if a false positive was flagged by the device.

Guo, et al., (2015) developed wearable clothing that used MPU 6500 which captures 8 types of simulated falls and 6 different activities of daily living. And the placement of fall detection is placed on the left side of the breast and the algorithm used a threshold-based algorithm which has three conditions to be met. The experiment simulated different simulated falls such as backward fall, forward fall, and knee flexion, as the activities of daily living example sitting down, standing up on a chair, laying down, and getting up from a bed. In conclusion, limited participants, and the age range were 30 to 39 years old require optimization, however, the device can perform and detect a fall and ADLs with the specificity of 100% under test conditions.

2.6 Review of Fall Detection Algorithm

Algorithms can be used to determine if a fall occurred, for example, by detecting the velocity change. By defining a set of rules to determine if a fall had occurred the micro-controllers can decide if a fall had occurred using calculations to detect if a fall had occurred. Alongside converting raw data to meaningful data from the sensors. An example of an algorithm, using Hidden-Markov-Model (HMM) which is used for machine learning can be used in the decision if a fall had occurred or not, another algorithm is threshold-based which can use a 3-Dimensional vector using X, Y, and Z-axis with this method of detecting a fall requires body acceleration which can be achieved in this formula that detects the magnitude of the acceleration of three values a_x, a_y and a_z values.

Equation 1: Equation of 3-Dimension Vector (OpenStax, n.d.):

$$a = \sqrt{a_x^2 + a_y^2 + a_z^2} \quad (1)$$

Machine Learning (ML) can improve the overall performance of the fall detection system, example of an ML model is the Hidden-Markov-Model (HMM), Tong, et al., (2013) used HMM, and concluded it was a reliable system that can predict a fall within 200 to 400ms (millisecond) range. Overall concluded with 100% sensitivity and specificity while during the testing phase, received 81% for accuracy and sensitivity.

Guo, et al., (2015) used a threshold-based without ML techniques, it requires a set of rules such as FT1 will trigger if lower acceleration was detected, FT2 upper acceleration will trigger, and FT3, if lower angular acceleration is detected will flag up. If one of three conditions were met, then it will trigger the fall detection system. Guo, et al., (2015) concluded 100% specificity, however, the threshold-based is not accurate compared to ML but can produce reliable results.

Waheed, S.A. and Khader, P.S.A. (2017) conducted research that use Camera Technology that used Motion History Images that provides information on the movement of the human body. The technique used Fore-ground splitting, which creates the background into black and the outline of a human to be white which creates an Adaptive Gaussian Mixture model to the value of the intensity matching varying backgrounds. However false positives were made if the participants lay on the ground, however, it did detect motions that are greater than the threshold values, but it detected the 'fall' however it was a false positive

2.7 Review of Sensor Placement

There are many different positions in that a fall detection device can be placed and the position can affect the performance example wrist placement Tong, et al., (2013) experiment, "*the arm, wrist, hip, and leg are not the suitable positions for the accelerometer, based devices due to their high movement frequency and complexity, although they may be the more comfortable place to wear*" (Tong, et al., 2013, p. 1850), however Özdemir, (2016) performed a different machine learning algorithm, which Özdemir, (2016) study has achieved accuracy above 95% example between the crown and nape of the head had produced a result of 96.61%, chest at 96.50%, the waist at 98.42%, wrist at 94.92%, thighs 97.89% and final the ankles at 97.00%, however from Özdemir's method of setting up the sensors use specialized steps that housing the sensors as shown by Özdemir, (2016) work in Figure 1.

Figure 1: Sensor Placement Locations (Özdemir, 2016, p. 7)

In conclusion, this research will use the Tri-Axis based which falls under the wearable category, due to the cost-efficiency and energy effect device, which is calculated using the threshold-base algorithm instead of machine learning due to the power constraint of the device, the threshold-base algorithm is suited to meet the needs. The tri-axis will be placed on the chest due to less body motion compared to the rest of the body and to reduce false positives and gain more desirable results. Three objectives have been formed:

- Investigate methods of what are fall detection systems and their key components through a literature review.
- Produce an embedded system for fall detection.
- Gain data from the fall detection system and analyze it to see if it's reliable (accuracy is above 85%).

3 Methodology and Experiment

3.1 Fall Detection Algorithm

To determine if a fall had occurred for the threshold-base algorithm, firstly measure the current magnitude of acceleration, if condition one is true then, acceleration is great than the threshold which is 40gs then if true it will check if the orientation has changed within 500 milliseconds, if this is true then the buzzer will trigger until the user press the reset button, if not it will continue till it reset, if any conditions are false then it will loop back to magnitude of acceleration measurement. Overall basic algorithm design can be found in figure 2.

The equation for the 3-Dimension Vector can be translated from Equation 1 to programming language by:

```
Float [NAME] = power(power(X-Axis,2) +power(Y-Axis,2) +power(Z Axis,2));
```

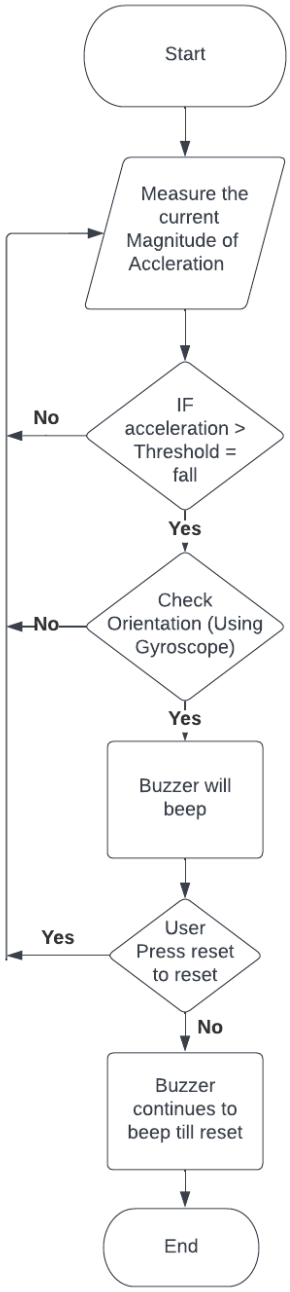

Figure 2: Threshold-Base Algorithm Design

3.2 Hardware

In this research, MPU 6050 will be used due to six-axis motion tracking with six degrees of freedom, due to 6 outputs from 3 accelerometers and 3 gyroscope outputs. The processing unit is an Arduino Nano, which is used to collect data from the sensors and process the algorithm, alongside buzzer will be attached to the device which allows notification that a fall had occurred, and a reset button will be placed if a false positive occurred. Figure 3 shows the schematics of fall detection, and Figure 4 shows the physical components of the fall detection system.

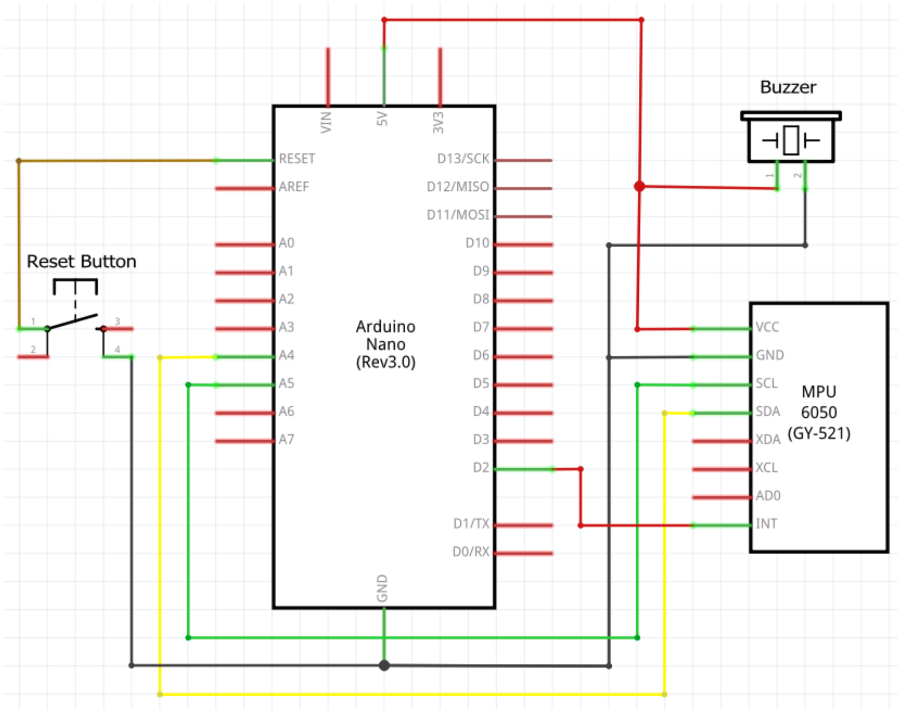

Figure 3: Schematic View

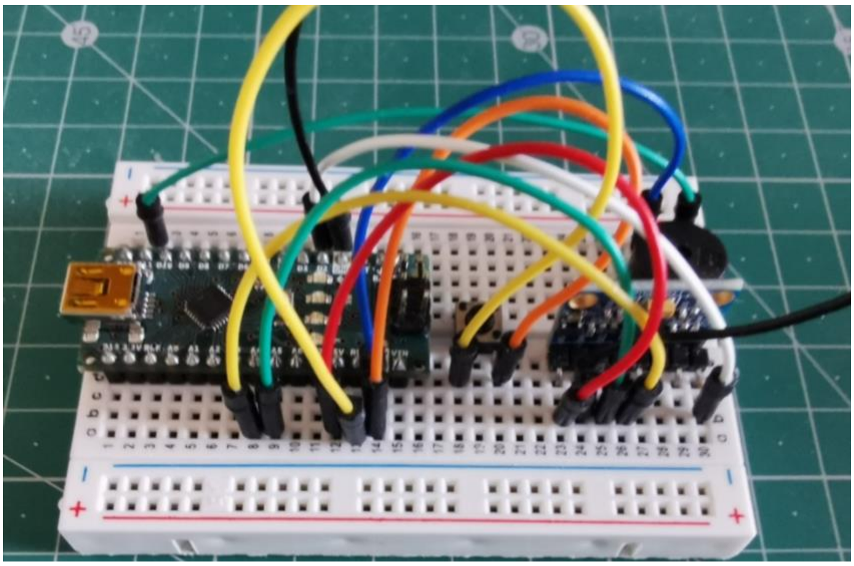

Figure 4: Physical Device

Figure 3 shows what components are connected between Arduino Board and the MPU6050 IMU to create the fall detection system, however, this shows similar on how the fall detection device looks due to the limitation of the software to create similar results in Figure 4. Figure 4 shows the physical connection between devices and the final prototype for the fall detection system.

3.3 Software

Arduino IDE will be used to work efficiently and implement the algorithm which can convert the raw data from the MPU 6050 to readable data which generates signals if the accelerometer exceeds the threshold value and allow to view real-time graphics and values which can be viewed on Serial Monitor (Figure 5) and Serial Plotter (Figure 6).

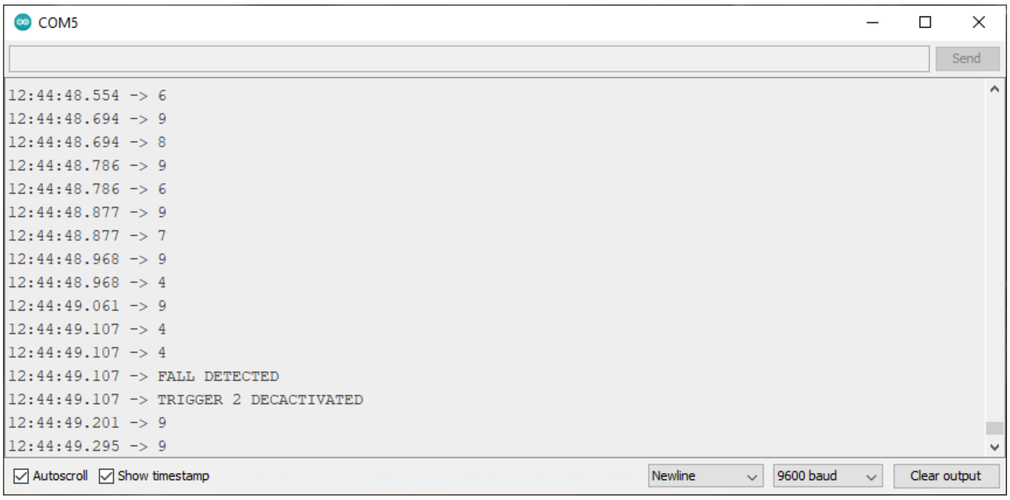

Figure 5: Serial Monitor

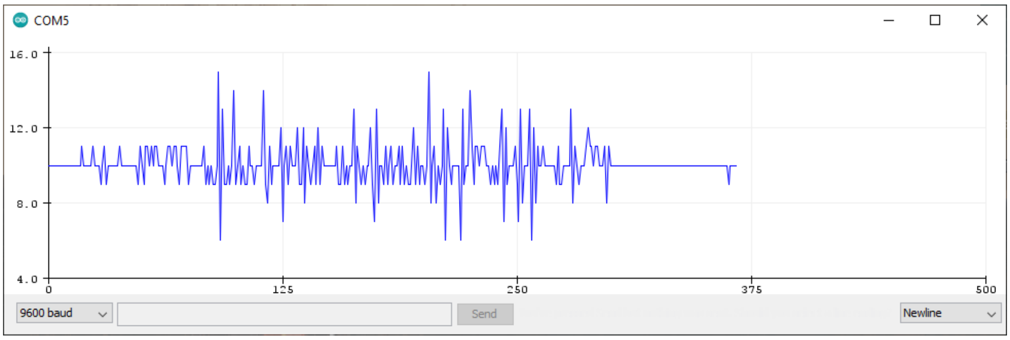

Figure 6: Serial Plotter

The IDE contains open-source libraries that will be used to convert raw data into meaningful data from Electronics Cats Version 0.5.0. this allows us to read raw data and convert them into meaningful data from MPU 6050 examples in Figures 5 and 6.

3.4 Fall Detection Placement Location

The device will be placed on the frontal chest, due to Tong, et al., (2013) suggesting that there is less movement in the chest compared to other parts of the body.

3.5 Data Collection

Data will be collected from participants' movement from the MPU 6050 and visualized in the IDE Serial Monitor and Plotter. The participants will conduct four simulated falls and four activities of daily living which can be split into two categories:

- Falls:
  - Forward falls (Fall exp. 1), backward falls (Fall exp. 2), sideway falls (Falling onto the arm) (Fall exp. 3), mixed between backward and sideways falls (Fall exp. 4).
- Activities of Daily Living:
  - Walking (ADL exp. 1), squatting (ADL exp. 2), standing, and sitting on a chair (ADL exp. 3), opening, and closing doors (ADL exp. 4).

Forward Fall (Fall 1), landing chest-first, fall 2 backward falls onto the mattress where the back spine will contact. Sideway falls are where the arms will contact first, and the final fall will be in between backward and sideways fall. Overall, 20 falls and 20 ADLs in a total of 40 experiments in total, to confirm if a fall had occurred a buzzer will be triggered to notify if a fall had been detected by the algorithm. Each participant will do two categories and each activity will be done once.

3.6 Participants

Due to ethical issues due to the recruitment of elderly participants and the potential hazards and high possibility of injuries, this experiment will not include elderly participants, however, in this research, 5 participants were involved in this experiment, and the general average characteristics of the participants were:

- Average Age: 21.2 years.
- Average Height (cm) 178.4cm
- Average Weight (kg): 68.4kg.

4 Results, Findings, Analysis, Discussion, and Conclusion

The experiment was conducted using MPU6050 IMU as data input from participants which is processed by Arduino Nano. Which allows the collection of acceleration and orientation data, when conducting ADL and Fall scenarios. The results have been split into two sections, the first section will review the Activities of Daily Living (ADL) and the second part will review the Fall Events when the participants conduct a fall and can be displayed on a time graph that shows Acceleration vs Time.

4.1 Activity of Daily Living (ADL)

Activities of Daily Living (ADL) was conducted using MPU 6050 to collect the acceleration and orientation that was conducted during the experiment phase for Activities of Daily Living.

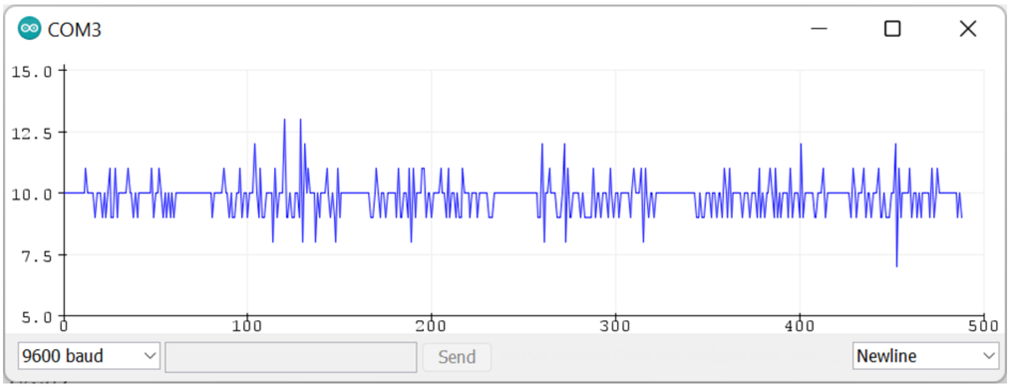

Figure 7: Acceleration Graph for Walking (ADL 1)

Experiment	Maximum Peak Acceleration (g)	Magnetometer
1	13.00	7.0
2	13.00	7.0
3	16.00	4.0
4	15.00	5.0
5	14.00	6.0

Table 3: Results Table for Waling (ADL 1)

Table 3 average maximum peak acceleration is 14.2g and the minimum peak acceleration is 7.4g, and the fall detection system did not trigger.

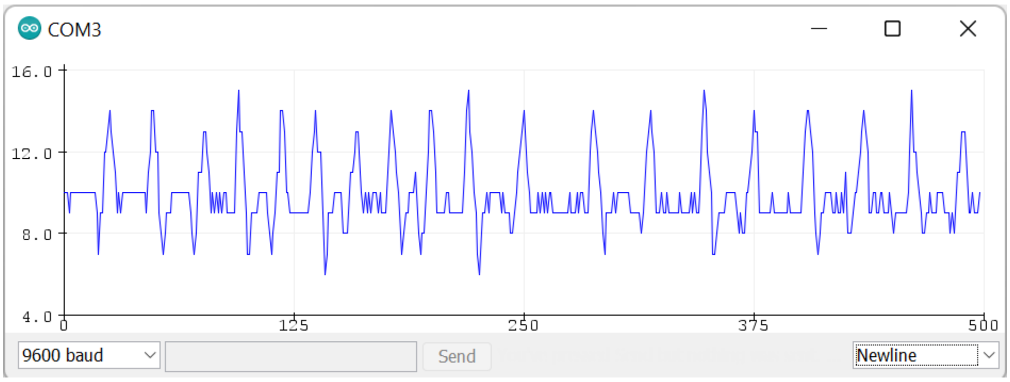

Figure 8: Acceleration Graph for Sitting and Standing (ADL 2)

Experiment	Maximum Peak Acceleration (g)	Magnetometer
1	15.00	6.0
2	15.00	7.5
3	45.00	7.5
4	50.00	7.5
5	16.50	4.0

Table 4: Results Table for Sitting and Standing (ADL 2)

Experiments 3 and 4 for ADL 2, had peak acceleration above 40g, and the buzzer had triggered to indicate that a fall had occurred. Table 4 average maximum peak is 28.3g and the minimum peak average is 6.9g.

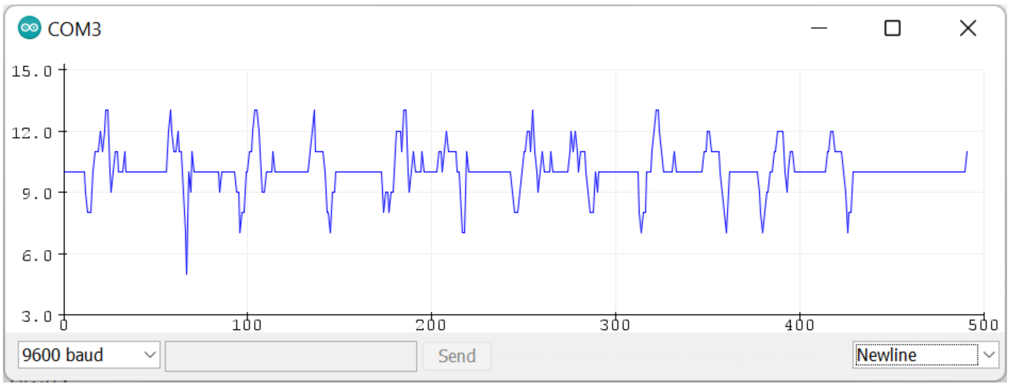

Figure 9: Acceleration Graph for Squatting and Standing (ADL 3)

Experiment	Maximum Peak Acceleration (g)	Magnetometer
1	13.50	5.5
2	15.00	5.0
3	20.00	5.0
4	45.00	5.0
5	20.00	4.0

Table 5: Results Table for Sitting and Standing (ADL 3)

Table 5 shows the maximum peak value of 45.00g which triggered the buzzer to activate due to the algorithm detecting a fall from experiment 4. The maximum peak average is 22.7g and the minimum peak average is 4.9g.

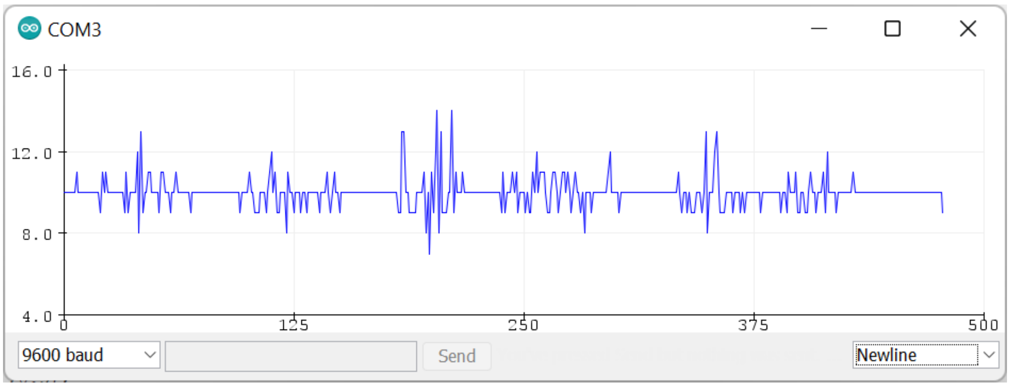

Figure 10: Acceleration Graph for Opening, closing, and walking through doors (ADL 4).

Experiment	Maximum Peak Acceleration (g)	Magnetometer
1	14.00	57.5
2	13.00	6.0
3	15.00	8.0
4	14.50	8.5
5	17.00	8.0

Table 6: Results Table for Opening, closing, and walking through doors (ADL 4)

Table 6 produced no false negatives produced as expected, the maximum average peak was 14.7g, and the minimum peak average was 7.6g. And the fall detection system did not falsely detect a fall during this experiment.

Participants	ADL Exp. 1	ADL Exp. 2	ADL Exp. 3	ADL Exp. 4
1	0	0	0	0
2	0	0	0	0
3	0	1	0	0
4	0	1	1	0
5	0	0	0	0

Table 7: Binary Table for ADL Experiments.

Overall, there were three false negatives that three activities of daily living were triggered by the algorithm, mainly due to the maximum acceleration being above 40g therefore they were triggered, however, seventeen were not triggered by the algorithm. All the graphs from the experiments are in the appendix section under Test graph data and a binary table in table 7.

4.2 Fall Detection Event

For every category fall, the participants will be asked once, however, they will not repeat the same category, alongside there were 2 false negatives that did not detect by the algorithm, as you can see in Figures 11 and 12, where both did not trigger fall detection due to acceleration did not calculate or some other fault, however, overall, 18 out of 20 falls were detected.

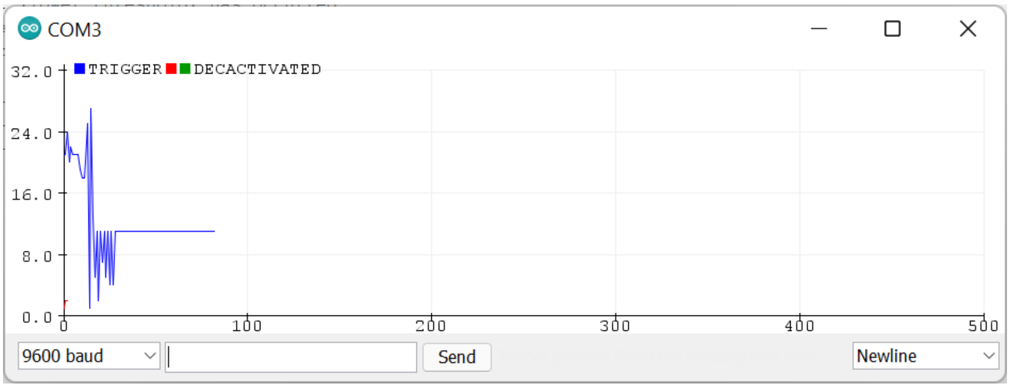

Figure 11: Fall 1 False Negative Detected.

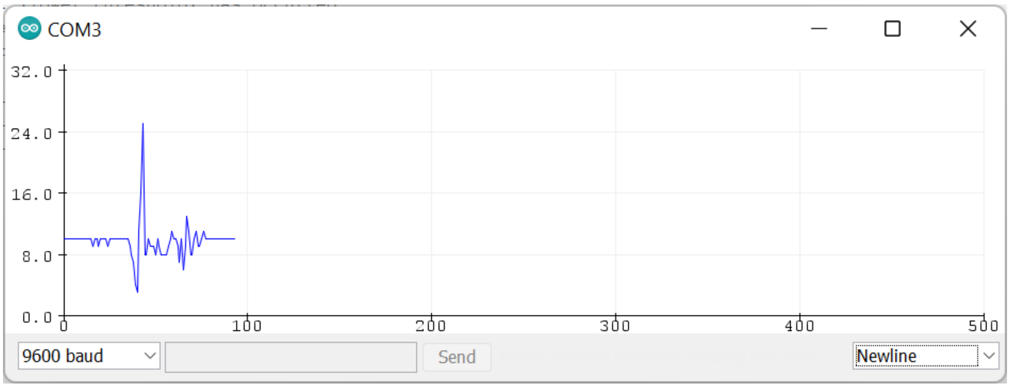

Figure 12: Fall 2 False Positive Detected.

Participants	Fall Exp. 1	Fall Exp. 2	Fall Exp. 3	Fall Exp. 4
1	1	1	1	1
2	0	1	1	1
3	1	0	1	1
4	1	1	1	1
5	1	1	1	1

Table 8: Binary Table for Fall Detection Event.

The binary table (Table 8) shows all the fall experiments carried out and presented in a binary way to show two conditions, 0 (zero) shows that the fall detection did not detect, and 1 (one) shows that the algorithm triggered and detected a fall. Overall, 90% of this data was successfully detected by the algorithm. Sample time graph data can be found below and more in the appendix.

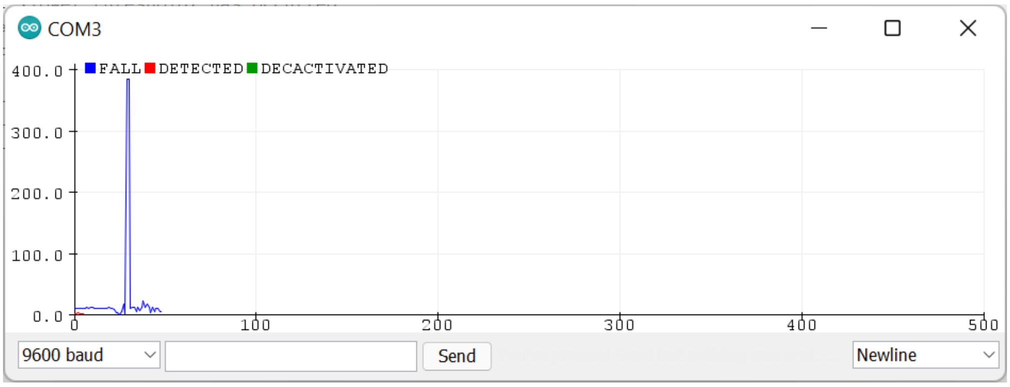

Figure 13: Acceleration Graph for forwarding Fall (Fall 1).

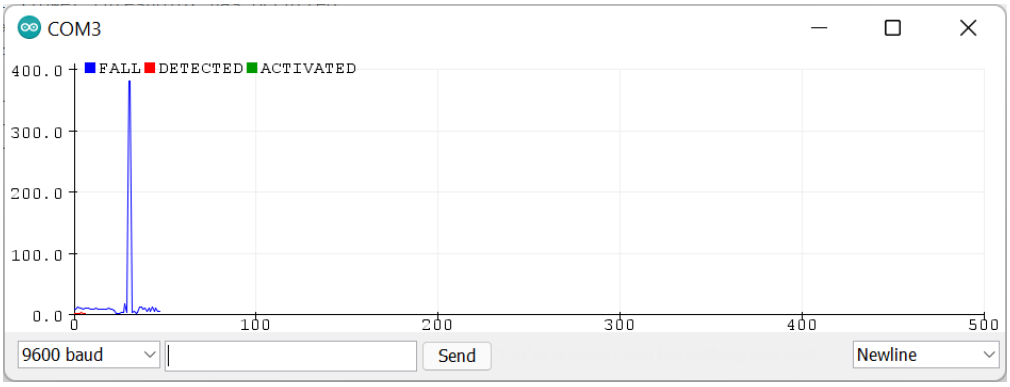

Figure 14: Acceleration Graph for Backward Fall (Fall 2).

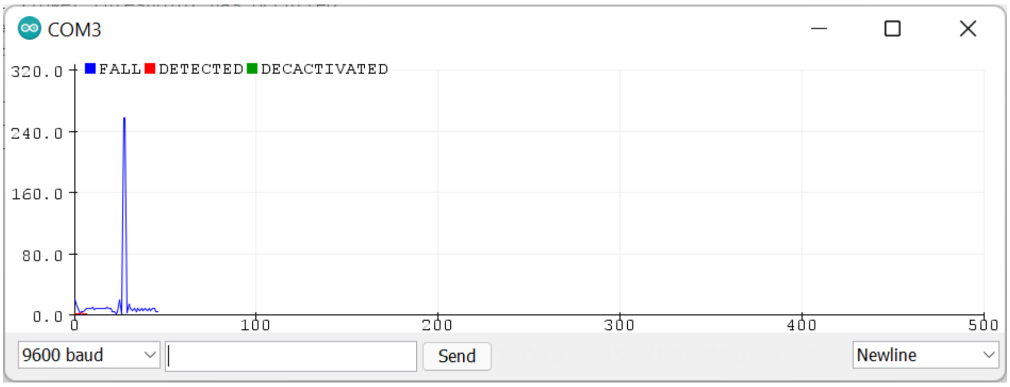

Figure 15: Acceleration Graph for Sideways Fall (Fall 3)

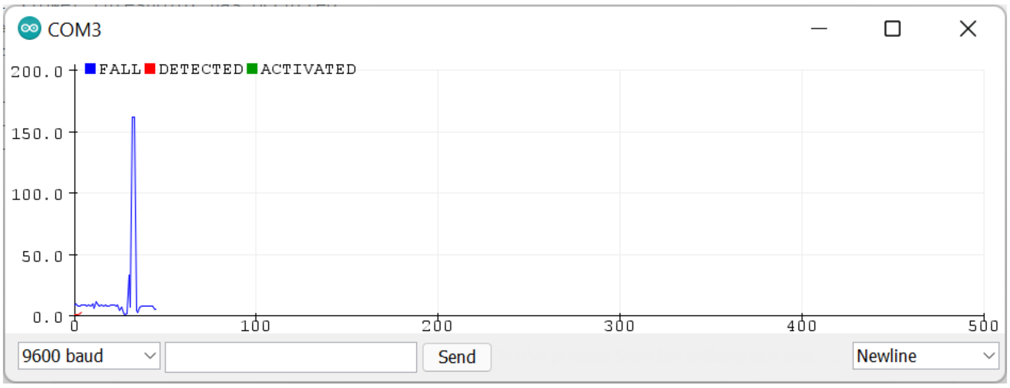

Figure 16: Acceleration Graph for Mixed between backward and Sideway Falls (Fall 4)

4.3 Binary Table Overall Experiment

Participants ID	Fall Exp. 1	Fall Exp. 2	Fall Exp. 3	Fall Exp. 4	ADL Exp. 1	ADL Exp. 2	ADL Exp. 3	ADL Exp
1	1	1	1	1	0	0	0	0
2	0	1	1	1	0	0	0	0
3	1	0	1	1	0	1	0	0
4	1	1	1	1	0	1	1	0
5	1	1	1	1	0	0	0	0

Table 9: Binary Table for Findings.

Table 9 shows all experiments carried out and presented in a binary way to show two conditions, 0 (Zero) alarm did not trigger, or a 1 (one) alarm was triggered, overall, 18 out of 20 were correctly triggered when a fall was detected. While 17 out of 20 did not detect a fall during Activity of Daily Living (ADL), however, 3 out of 20 from ADL triggered.

4.4 Data Analysis

As with any other experiment, this fall detection system is reliable, it has four test outcomes to determine if the system is reliable, and a confusion matrix is used to predict results on classification problems in which the amount of positive (correct) and negative (incorrect) predictions are summarized into four possible outcomes from this reliability test:

- True Positive (TP): Correctly detected a fall correctly.
- False Positive (FP): Incorrectly detected a fall that did not happen.
- True Negative (TN): Correctly detected that a fall did not happen.
- False Negative (FN): Incorrectly detects a fall when it did not occur.

		Daily Activity (Actual)	
		Fall (True Positive)	ADL (True Negative)
Fall Detection (Predicted)	Fall (Predicted Positive)	18 (True Postive	3 (False Positive)
	ADL (Predicted Negative)	2 (False Negative)	17 (True Negative)

Figure 17: Confusion Matrix Fall Detection vs ADL.

From Figure 17 the rows (Fall Detection Predicted) correspond to what was predicted in the outcome, and the columns (Activity of Daily Living) correspond to the known truth. There are only two categories, Fall and Activity of Daily Living, in which that True Positive mean that the participants that had fallen, was correctly detected by the fall detection system, and 18 out of 20 correctly triggered a response.

The True Negative are activities of daily living, that did not detect falls, 17 out of 20 were activities of daily living, therefore out of 17, only 3 had been flagged as false positives. The False negatives are when detection did not occur in a fall which only 2 out of 18 experiments, only two had been flagged as false negatives. And finally, the false positives, are where a fall had been detected during the activity of daily living in which only 3 had detected as a fall during an activity of daily living.

Calculating two metrics, sensitivity and specificity, sensitivity gives us the value of the fall that was correctly detected which is calculated by True Positives divided by True Positives and False Negatives. Specificity tells us the value of Activity of Daily Living was incorrectly triggered. Specificity is calculated by True Negatives divided by True Negatives and False Positives; both can be defined below.

- Sensitivity: If it has the capability needs to be detected.

Equation 2: Sensitivity calculation:

$$Sensitivity = \frac{True\ Positives}{(True\ Positives + False\ Negatives)} \quad (2)$$

- Specificity: If it’s capable to detect only a fall.

Equation 3: Specificity calculation:

$$Specificity = \frac{True\ Negatives}{(True\ Negatives + False\ Positives)} \quad (3)$$

Equation 4: Accuracy calculation:

$$Accuracy = \frac{(True\ Positive + True\ Negative)}{(True\ Postive + False\ Negative + False\ Postive + True\ Negative)} \quad (4)$$

$$Sensitivity = \left(\frac{18}{18+2}\right) * 100\% \quad (2)$$

$$Sensitivity = 90\%$$

$$Specificity = \left(\frac{17}{17+3}\right) * 100\% \quad (3)$$

$$Speciicity = 85\%$$

$$Accuracy = \frac{(18+17)}{(18+17+2+3)} * 100 \quad (4)$$

$$Accuracy = 87.5\%$$

Sensitivity is 90% of falls were identified by the fall detection system, specificity gave 85% of the activity of daily living was not flagged up as a fall. This means that 90% of the time, the fall detection system will correctly detect Falls, while 85% of the time, the activity of daily living will not trigger the fall detection system. Overall, this experiment achieved above 80% for sensitivity and specificity, and the accuracy was 87.5% which had been achieved is reliable to use, another achievement is to produce the fall detection system.

4.5 Conclusion and Future Work

Due to ethical issues, this research cannot be replicated in the real world, where elders would use this, however, enable it to replicate for industries such as construction, where the likelihood to be at risk of a fall. Compared to Wu, F. et al., (2015), produced a sensitivity of 97.1% and specificity of 98.3%, while Rihana, S. & Mondalak, J. (2016) research produced 90% sensitivity and 85% specificity. However, there are flaws and limitations to this research, the primary flaw is due to the data quantity, compared to Rihana, S. & Mondalak, J. (2016) who conducted 50 simulated falls.

This research concluded that sensitivity had reached 90%, specificity at 85%, and accuracy at 87.5% respectively shows that fall detection is reliable, however, improvements can be made, such as using machine learning models to predict and detect a fall such as Hidden-Markov-Model (HMM), however, this requires high quality and quantity data. Overall, this research achieved three objectives, first, to produce a fall detection system, the second objective was to collect data and the final objective was to produce sensitivity, specificity, and accuracy above 85%, in this research has achieved all three goals, which had been achieved.

Overall, this is a foundation of this research on developing a fall detection system which had achieved three objectives, for future studies different approaches methods examples components, algorithms, and the possibility of the fall detection device talking to the internet and to the cloud to help people in need of a fall detection system.

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