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Enabling Guardian Angels: Designing and Constructing a Wireless Nurse Call System with IMU-Based Fall Detection for Enhanced Patient Safety

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A B S T R A C T

Falling poses a significant health concern across all age groups, with particular severity among the elderly. Hospitalized patients, in particular, are vulnerable to injuries and even death due to falls. While patient supervision is essential for fall prevention, constant proximity between patients and healthcare staff is not always feasible. To tackle this challenge, this study aimed to develop a solution that enables immediate assistance for patients who are distant from the nurse call button when a fall occurs. The study employed the IMU sensor, which combines an accelerometer and a gyroscope. This sensor served as a transmitter to detect gravity acceleration and magnitude when a fall event takes place. The data obtained from the IMU sensor were further processed using an Arduino Uno microcontroller. The sensor was integrated into a belt worn around the waist of the participants, who performed various movements such as falling facing down, falling up, falling to the right, falling to the left, standing then sitting, and sitting then standing. The experimental tests yielded compelling results, with all trials achieving an accuracy rate of 81.7%. The accuracy was determined by analyzing the confusion matrix, which enabled accurate calculations. The utilization of this innovative tool significantly reduces the risk of patients experiencing detrimental outcomes following falls by promptly notifying medical personnel, even when they are distant from the nurse call button. Moreover, the implementation of this tool enhances overall safety for hospitalized patients, especially those at a high risk of falling. Future research can explore the integration of additional sensors or the development of more sophisticated algorithms to further enhance the accuracy and efficacy of this tool.

INTRODUCTION

Nurse call systems are one of the most important devices in hospitals. The device helps medical staff to signal so that patients can get help more easily [1-3]. A nurse call system has the ability to assist nurses in caring for a patient during treatment. The wireless nurse call system is a communication technology system commonly used in hospitals and requires no cables for operation. A fall is a health accident. It is caused by a decrease in the strength and stability of one's own body.

The rapid development of technology can minimize the incidence of patient falls. Some patients need to get out of bed and engage in activities such as going to the bathroom or other activities that may predispose them to accidents such as falls. A way to minimize the incidence of falls is to categorize the daily activities of hospitalized patients [4]. Falling on a patient can be very dangerous for some patients. If the patient falls, the nurse should be called as soon as possible. There are several ways to quickly summon a nurse, one of which is a Nurse Call. In many hospitals, nurse calls are now located next to the patient's bed. Based on the above problems, a fall detection system tool using wireless nurse call accelerometers and gyroscopes was developed to prevent nurse calls from being performed when patients go about their daily lives [5-10].

A tool mechanism using an Arduino Uno microcontroller, Bluetooth HC-05, accelerometer, and gyroscope sensors contained in the Mpu6050 sensor can generate data when the patient falls. The appropriate method used in this study uses bandpass and high pass filters by calculating precision and sensitivity values. This method is suitable for use with used and low energy consumption devices. This is because the method is computationally simple and can be implemented on small devices [11-13].

One way to detect falls is to compute the x-, y-, and z-axes and combine them. Accelerometers have also been used in fall studies by researchers such as González-Cañete FJ and Casilari E. Their work is titled " Consumption analysis of smartphone-based fall detection systems with multiple external wireless sensors" [5]. This study has a small drawback. Data collection is inefficient if a used mobile phone falls into your pocket before an accident

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occurs. In my opinion, the smartphone in the other breast pocket is more likely to crash.

Graseo Granteo Putra1, and Djoko Untoro Suwarno, conducted research on human activity readers with gyro sensors. In this study, the processing of data derived from human activity is performed by gyroscopic sensors attached to the human body. Data from the gyro sensor is stored on the SD card [14-18]. The downside of pegs is the tool used on the sole of the shoe. This is because the tool may fall during data acquisition. It also gives you a little more movement when you put the tool on your leg.

This research is creating a device that can detect falls that can be used in hospitalized patients. Using accelerometer and gyroscope sensors to get acceleration and velocity due to changes in the user's angle [19,20].

The way the device works is a belt that the patient wears inside the IMU sensor and reads the data when they fall. The IMU data is then sent by her Bluetooth, and the data sent by the IMU can later be detected when the patient falls right, left, down, and up. Send the data received from the patient who has collapsed to Firebase for storage, and display the data stored in Firebase on a website to inform the nurse that the patient has collapsed.

METHOD

The manufactured fall detection system consists of several key components, such as microcontrollers, sensors, and Wi-Fi Modul. Figure 1 will provide a detailed description of the system layers, including their sensor and module components. The activation process of the system is depicted in Figure 2.

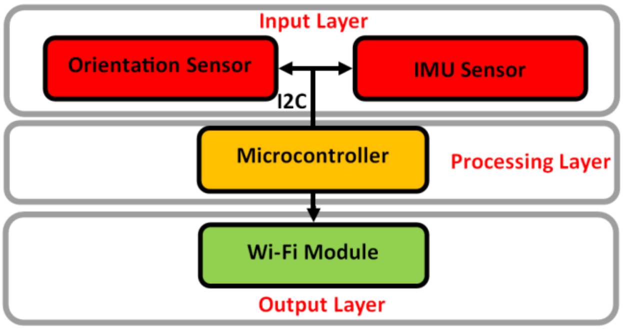

Figure 1. System design

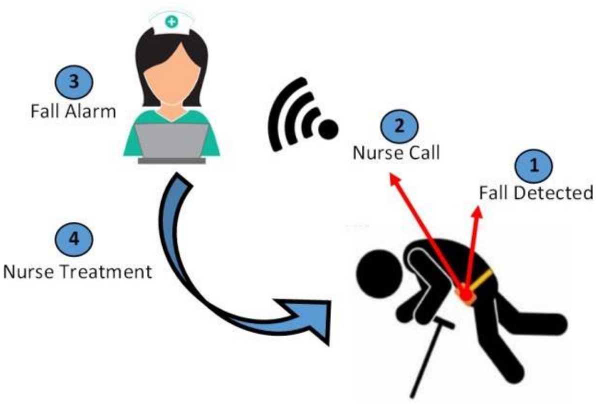

Figure 2. Activation process system

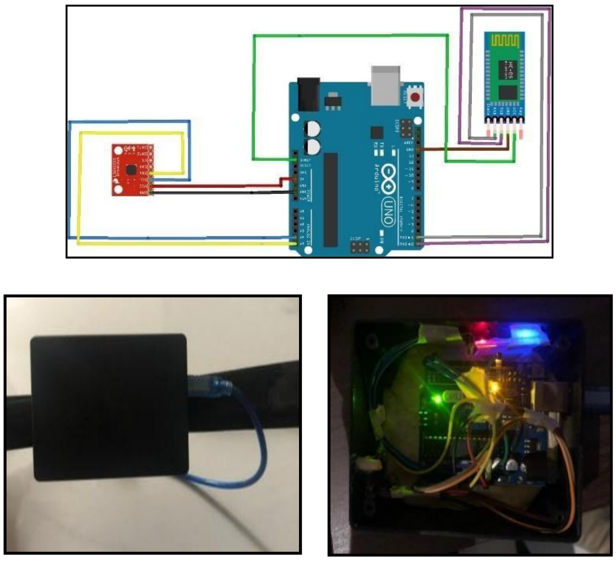

Figure 3. The device consisting components included in the fall detection device and belt packaged device.

The system design in Figure 1 and 3 shows how wireless nurse call works with IMU-based fall detection. Instrument Measurement Unit (IMU) as a falling motion detector. A wireless nurse call tool system with IMU-based fall detection consists of a belt containing multiple components such as an Arduino Uno, a Mpu6050 sensor, and a Bluetooth Hc-05. The working system of this tool is straightforward, starting with an Arduino Uno as a data processor, connected to a Mpu6050 sensor used to collect fall data, and the fall data generated by the Mpu6050 sent to a serial monitor via Bluetooth. It will be sent. HC-05. Data captured by the serial monitor is then sent to Firebase for storage. Your website displays sensor data stored in Firebase. The Mpu6050 sensor can detect static and dynamic movement changes. This sensor can detect motion based on the acceleration and orientation that occurs when an object is in motion. All these components are packaged into a belt that the object uses to detect motion.

Figure 4. The device is worn on the waist

The tool's system is a device worn on the user's waist that uses the device as a belt to detect situations in the event of a fall shown in Figure 4. During the test phase, the fall condition is performed by acquiring acceleration data from an IMU (Inertial Measurement Unit) sensor used by the subject. The subject's first step is to demonstrate a standing position and then fall in short.

Fall forward, fall back, fall right, fall left. The data obtained is in the form of a font indicating whether the camber is up, down, right, or left. The data were collected in each experiment in 10 replicates. The fall position is shown in Figure 5.

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Figure 5. Fall position

Data acquisition is performed using a serial monitor made by the author. A serial monitor can act as a data receiver or sensor data reader. The data received by the serial monitor points up, down, left, and right. Once we have the data from the four sections, the next step is to find the mean and difference of the blended readable data from each of those sections. From the results obtained, comparisons are made from the characteristic differences between standing, inverted, forward, backward, right and left postures.

System Process

The manufactured fall detection system consists of several key components, such as microcontrollers, sensors, and Bluetooth. The system also connects to websites by sending Bluetooth data to the serial monitor. The laptop's serial monitor sends the data received from the serial monitor to Firebase for storage. Data stored in Firebase is displayed on a website, as shown in the system blueprint in Figure 1, the system circuit in Figure 2, and the manufactured device in Figure 3. Some of the components of the microcontroller system used in this study are the Arduino Uno as the controller of the system. The fall detection sensor module used in this study uses MPU-6050, and this sensor is used as a fall detector to get the acceleration and angular velocity values. The Bluetooth module used in this study uses the HC-05 Bluetooth module. This Bluetooth module is used to connect the device system to the laptop's serial monitor.

Device Test Design

In this study, the authors used two tests. The first test tested the distance from Bluetooth, tested the movement of falling and normal activities, or not using the confusion matrix. They determine the success rate of the system made. To calculate the sensitivity parameter, use equation (1). Equation (2) is used when calculating the accuracy parameter.

$$Sensitivity = \frac{TP}{TP+FN} \quad (1)$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (2)$$

This study uses a confusion matrix to calculate precision and sensitivity values. A confusion matrix is a special table that allows you to visualize the performance of your algorithm. This method has four frameworks for fall detection systems as measurements [21]. Among them are true positives (TP). This will fall if the demonstration is true and will be recognized as a fall by the system. True Negative (TN) if the display has not been dropped and is recognized by the system as having not been dropped. False Positive (FP): If the demonstration ethics are correct, the demonstration will fail, but the system will recognize it as not a failure. False negative (FN) if the display did not fall and was detected as a fall by the system.

This test creates several activity scenarios to test the system, separated into falling and normal activities. Activity tests are shown in Table 1.

RESULTS AND DISCUSSION

Based on the connection range between the Bluetooth HC-05 and the laptop, the covered range is quite large. The results of the Bluetooth HC-05 connection test are shown in Table 2.

Table 2. Wireless communication range testing

Condition	Distance	Status
	1 meter	Connect
	5 meter	Connect
	8 meter	Connect
	14 meter	Connect
	20 meter	Connect
No Barriers	23 meter	Connect
	27 meter	Connect
	33 meter	Connect
	37 meter	Connect
	40 meter	Connect
	42 meter	Not Connect
	1 meter	Connect
	5 meter	Connect
	8 meter	Connect
With Barrier	14 meter	Connect
	20 meter	Connect
	23 meter	Connect
	27 meter	Connect
	33 meter	Not Connect

Figure 5-10 shows that the pitch, roll, and yaw behavior values for several activities match the system test, based on test results for several falling activity behaviors and normal or non-falling activities.

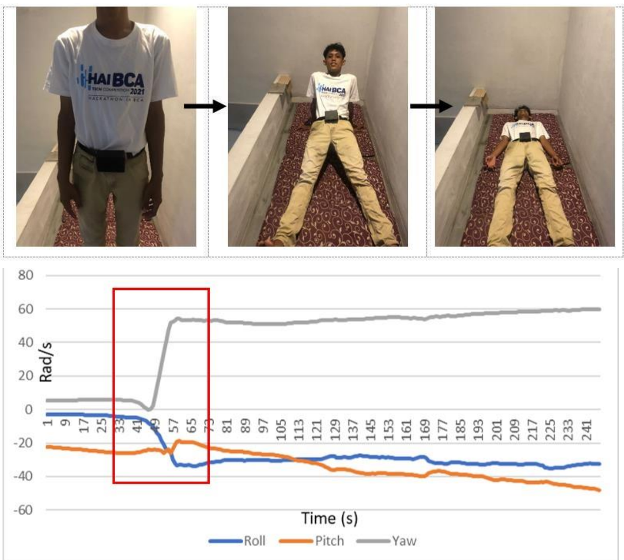

Figure 6. Graph of upward pitch roll and yaw fall motion

The data in Figure 6 shows the yaw data clearly changes in the positive direction. The yaw data moves significantly due to the falling motion of the yaw axis. Although the consecutive pitch and roll data did not change significantly. This proves that there is fall motion with the strap carrier raised.

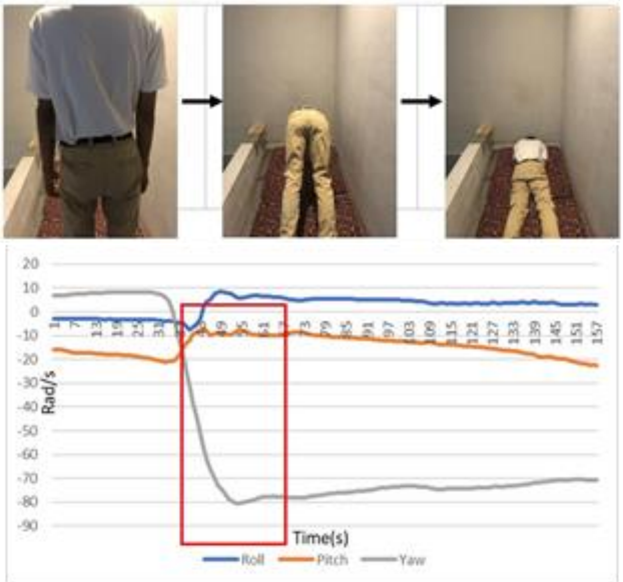

Figure 7. Graph of downward pitch roll and yaw fall motion

As shown in figure 7, the yaw data changes significantly in the negative direction. The yaw data moves significantly due to the falling motion of the yaw axis. Although the consecutive pitch and roll data did not change significantly. This proves that there is a falling motion with the strap carrier facing down.

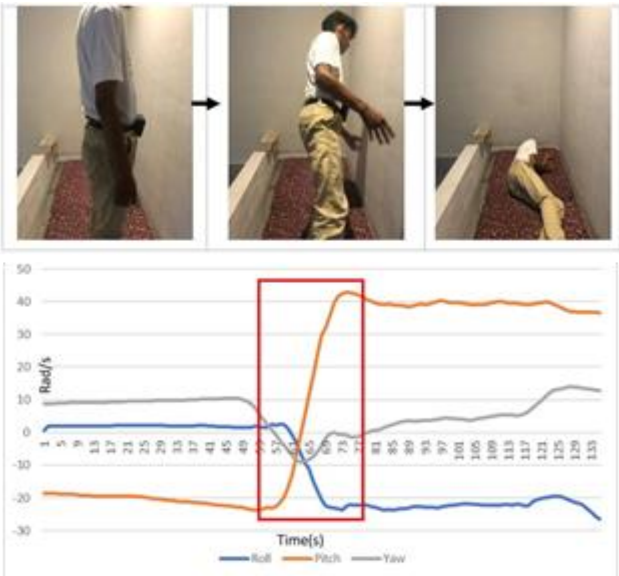

Figure 8. Graphs of pitch roll and yaw results for left fall motion.

Data in Figure 8 show that there is a large negative change in the pitch data. The falling motion of the pitch axis causes the pitch data to move significantly. The sequential yaw and roll data did not change significantly. This proves that there is a falling motion facing the belt wearer's right.

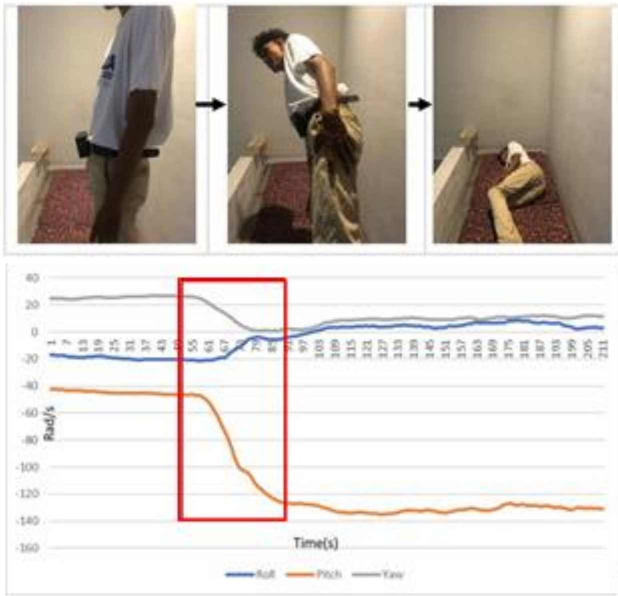

Figure 9. Graphs of pitch roll and yaw results for right fall motion.

Figure 9, the pitch data changes significantly in the positive direction. The falling motion of the pitch axis causes the pitch data to move significantly. The sequential yaw and roll data did not change significantly. This proves that there is a falling motion on the left side toward the belt wearer.

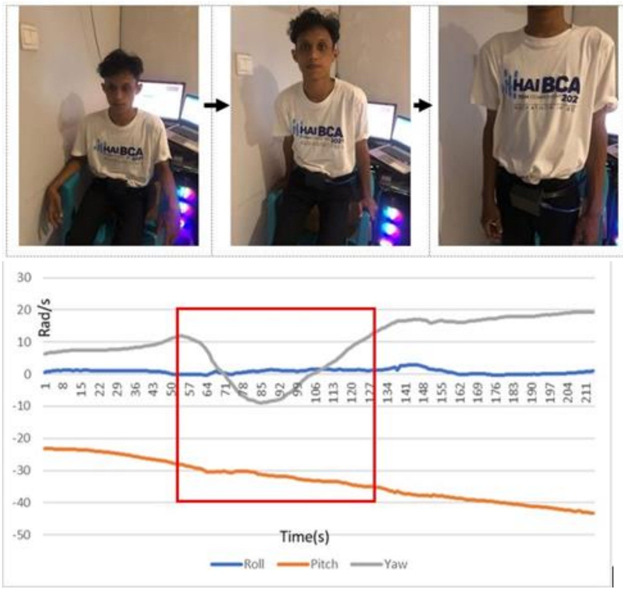

Figure 10. Graphs of pitch, roll and yaw results while sitting and standing.

Figure 10 shows the movements that occur when the harness wearer starts from a seated position and then from a standing position. In Figure 10 we can see that there is a change in the pitch data, but it is not significant. Figure 11, on the other hand, shows the movements that occur when the wearer starts in a standing position and then sits down. In Figure 11 we can see that there is a change in the pitch data, but it is not significant. From the graphs in Figures 10 and 11, we can see that the non- recumbent states, i.e. sitting and standing, have very different characteristics from her IMU data when she is crumbling. increase.

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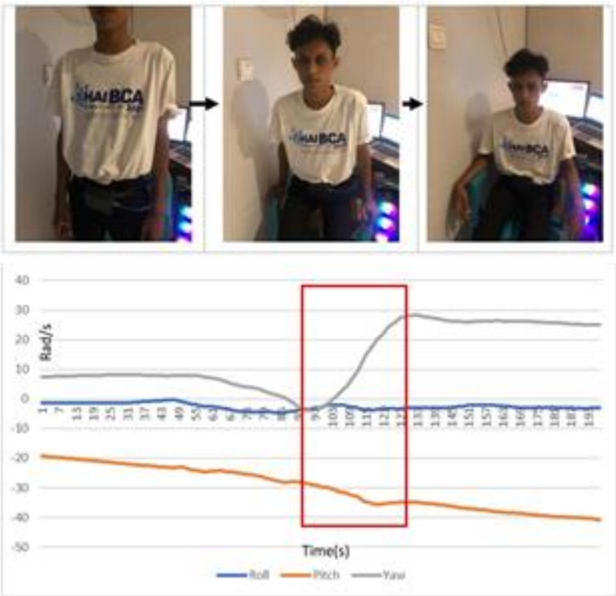

Figure 11. Graphs of pitch, roll, and yaw results while standing and sitting.

Based on the chart in Figure 6-11, there are some changes in the pitch, roll, and yaw data. This proves that the data obtained from the IMU can be used to distinguish between falls and non-falls. Then, the pattern recognition process is performed from the chart based on the patterns obtained in FIGS. The only data used in this detection process is pitch and yaw data.

Table 3. Experiment Parameter Results

Category	Experiment	(TP)	(FN)	(TP)	(FP)
Fall face up	10	8	2	0	0
Fall face down	10	7	3	0	0
Fall to the right	10	9	1	0	0
Fall to the left	10	8	2	0	0
Sit then stand	10	0	0	8	2
Stand then sit	10	0	0	9	1
Total	**60**	**32**	**8**	**17**	**3**

Table 4. Confusion Of Table

Detection Results / Actual	Fall	Not Fall
Fall	32	8
Not Fall	3	17

Table 3 uses the confusion matrix to calculate accuracy. Table 3, where all true positive, false positive, true negative and false negative values were obtained. After this value is obtained, a table is created that is a mishmash of tables from the test results shown in Table 4.

Based on Table 4 of the confusion matrix above, we can see that out of 40 fall attempts, the system was able to classify up to 32 events as falls. Additionally, the system computes a false event if up to 3 of the total non-fall events do not fall out of the 20 total non-fall events. And the remaining 17 were correctly recognized as not falling.

From the resulting confusion matrix, we can derive the following sensitivity values:

$$Sensitivity = \frac{32}{32+2} \times 100\% = 94.11\% \quad (3)$$

Then, to determine the level of accuracy of the implemented fall detection algorithm, all correct detection scores should be divided by the total number of trials performed. See the following statement for details.

$$Accuracy = \frac{31+17}{32+8+17+3} \times 100\% = 81.7\% \quad (2)$$

From the ten experimental results of each experiment, we found that the comparison of bandpass and highpass filters yielded some falling activities and some normal or non-falling activities, so the results of the measured parameters are shown in Table 3.

CONCLUSIONS

Based on the experiments conducted and the research conducted, there are systems that successfully detect normal or non-falling activity and falling activity. The accuracy with which the Mpu6050 sensor detects fall data shows that the data fall up, down, left, and right after the experimental test, with a sensitivity value of 94.11% and an accuracy value of 81.7%, which fits the above table, from several trials to. From this, it can be concluded that the successful experiment out of several experiments had up to 10 times the data fell upwards, ten times the data fell downwards, ten times the data fell to the left, and ten times the data fell. I can. In the front, ten experiments fall not standing than sitting, and ten experiments fall not sitting than standing. In doing this research, we cannot separate from various flaws and weaknesses in the hardware and software manufactured. In order for the authors to consider some suggestions and for further research, a website could be developed to display a person's position when they fall and add alarms in the form of sounds. Allows the user to perform additional checks immediately in their absence rather than in front of the application.

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