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IoT-based Architecture for Automatic Detection of Fall Incident using Accelerometer Data

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ABSTRACT

Fall incident is an unexpected event that can happen to anyone, anywhere, and anytime. For the elderly, the chance of fall incident occurs is higher because of their decreasing physical abilities. Fall incident might bring fatal effect for the elderly if there is no immediate help after the incident occurs. Therefore, there is a need for a device that can immediately sent an alarm or notification when fall incident occurred. In this article, we propose an IoT based device to detect whether a fall incident happened to the user wearing the device. User activities are recorded by the accelerometer sensor embedded in the device. If the value of accelerometer exceeds the threshold limit, an alarm or notification is sent to the caregiver smartphone. The developed device has a sensitivity and specificity level of 98% and 96% respectively in recognizing fall events.

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1. INTRODUCTION

In our daily life, we do several and various activities. From these activities, most of them are the activities that we do consciously. However, there are also some activity or incident that happened without being conscious or unintentionally. Fall is one of the conditions where we go down or slide down quickly due to gravity [1]. Fall incident is a sudden and unintentional event resulting the subject suddenly lying or sitting on the floor [2]. Fall incident is more likely to occur for those infant and the elderly. For the elderly, fall incident is more likely to be occurred due to the decreasing in their physical conditions such as loss of balance, vision, and hearing ability. Some of the consequences after a fall incident can vary among people. Beginning with minor injuries, disabilities, and even can increase the risk of death [3]. The limited physical abilities of the elderly such as the inability to stand up independently when falling and limitation of first aid access, makes the elderly need a special treatment to monitor their daily activities. Serious injuries are triggered by the long delay between fall incident and getting helped [4]. Therefore, monitoring through early detection of falling incidents will help minimizing the risk of death caused by falling by shortening the time gap between the incident and first aid or getting the help.

The advancement in technology have made possible to monitor falls incident remotely. Electronic components such as accelerometer and gyroscopes are often used in several studies related to the automatic detection of falls incident. Rakhman et al. [5] using accelerometer, gyroscope, and magnetometer sensors on smartphone for detecting falls incident for the elderly. The research was carried out by placing the smartphone in the shirt pocket in order to monitor subject activities. The developed system was able to detect falls with the best accuracy rate of 96.7% using thresholding methods. Such a system is not very economical and ergonomic, considering that a smartphone was placed in the shirt pocket, so there is a high possibility of being thrown off and damaged. Similar approach conducted by Hardijanto et al. [6] using accelerometer sensor on smartphone. The smartphone was attached to the user's waist in order to monitor falls incident. The system yielded the best accuracy rate of 95% for detecting fall incident. A different approach was taken by Norhabibah et al. [7] in their research, using the data from accelerometer and gyroscope sensors embedded in Arduino devices, they could process user activity data recorded by the sensor. The use of Arduino as an alternative for smartphones for data processing is considered quite effective and efficient given the lower price with an equivalent computing capability. In the study, if the system detects a fall incident, the system will notify to the smartphones that are connected via Bluetooth wireless connections. This system was able to detect falls incidents with an average accuracy of 89%. However, sending notifications via a Bluetooth wireless connection is considered less effective, considering the range of this protocol is no more than 10 meters. Another different approach using machine learning techniques in detecting falls were done by Hussain et al. [8] by using the Support Vector Machine (SVM) technique. By using a public dataset, the developed algorithm could distinguish between ordinary activities and fall incidents with the best accuracy rate of 99.98%. Furthermore, the use of the k-Nearest Neighbor technique applied by Vallabh et al. [9] were able to distinguish ordinary activities and fall incidents with an average accuracy rate of 87.5% based on the MobiFall dataset.

Based on several related studies that have been mentioned before, the use of machine learning techniques has a good potential for recognizing falling incidents automatically. In this article, we try to explore the application of machine learning techniques, specifically Recurrent Neural Network (RNN) algorithm in order to develop fall detection model based on public dataset. Furthermore, we also developed an IoT-based device using thresholding techniques for detecting fall incidents. The use of the Internet of Things (IoT) architecture is expected to facilitate remote monitoring of fall incidents by developing an IoT-based hardware prototypes for recording the activities of subject using Wemos and accelerometer sensor.

2. RESEARCH METHOD

In order to record subject activities, accelerometer and gyroscope sensors were used. The following is an explanation of the component and hardware design of fall detection device.

2.1. Hardware Component

An accelerometer is a sensor component that record the acceleration of an objects. Acceleration is the change of speed over time. Measuring physical activity using an accelerometer is often used because the acceleration can reflect the intensity and frequency of object movements. Information about the object's movement can be measured from the data recorded by the accelerometer over the time. One of the accelerometer sensors that is common on the market is the MPU6050. This component is an integrated motion sensor consisting of accelerometer and gyroscope sensors. The object's acceleration is measured in three-dimensional space. So, they often called this sensor a tri-axial accelerometer. The sensor is accurate, with an internal ADC (analog-to-digital) in 16-bit resolution. Figure 1 shows the physical form of the MPU6050 sensor.

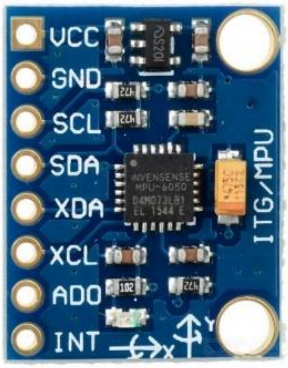

Figure 1. An MPU6050 sensor

We also use Wemos D1-R2 board for processing the data recorded by MPU6050. Wemos is a kind of Arduino board specifically designed for IoT architecture. Wemos is integrated with ESP8266 WiFi chip. Wemos has a compatibility with the Arduino library. Such compatibility made the development process can be done easily because of Arduino library support from a large community. Just like the Arduino board, Wemos is also a kind control board. One advantage using Wemos board compared to an ordinary Arduino board is, there is no need for additional WiFi modules to be attached on the board. In addition, Wemos also has a similar pin-out configuration with Arduino Uno. Figure 2 shows the physical form of the Wemos control board.

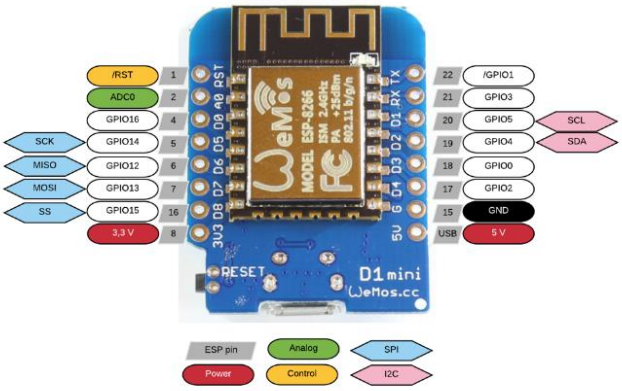

Figure 2. Wemos D1-R2 and its pin configuration

2.2. Hardware Design

We use electronic components such as Wemos D1-R2, MPU6050, buck converter, 9V battery and pin cable to design our hardware device. We use a buck converter in order to reduce the DC voltage from a 9V battery energy source into 3.3V. The hardware design can be seen in Figure 3.

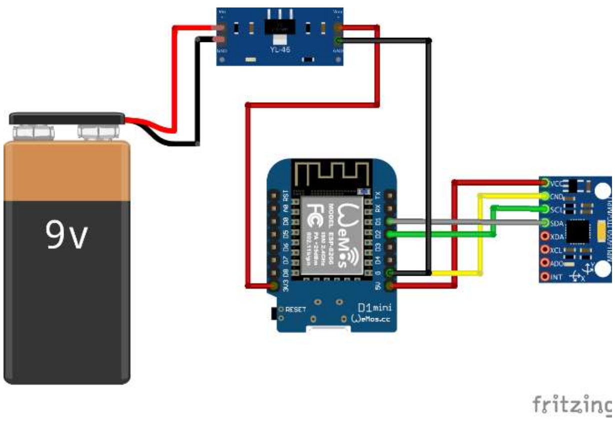

Figure 3. Hardware schematic diagram using Fritzing[1]

The explanation of the diagram in Figure 4 is following: The `VCC` pin on the MPU6050 sensor is connected to the `5V` pin of Wemos. The ground pin (`GND`) on the MPU6050 sensor is connected to the ground pin (`G`) on Wemos. The serial data (`SDA`) pin on the sensor is connected to the digital pin-1 Wemos (`D1`). The serial clock (`SCL`) pin on the sensor is connected to digital pin-2 (`D2`) on Wemos. The positive terminal of the battery is connected to the `Vin` pin on the buck converter. The negative battery terminal is connected to the ground-in pin on the buck converter. The ground-out pin on the buck converter is connected to the ground pin (`G`) on Wemos. The `Vout` pin on the buck converter is connected to pin 3.3V on Wemos.

2.3. System Architecture

We use IoT architecture to automatically detect falls incident. The system uses accelerometer sensor to get activity data from users. The sensor is embedded in the Wemos board and it is connected to the Internet for further processing. The developed system framework consists of three main components, including: the **user**, **server,** and **client** components. The **user** component is a device attached on the waist of the user. The main sensor in the user component is the MPU6050 sensor as described before. Real-time user activity data recorded from the accelerometer sensor is then sent to the server via the Internet network. The accelerometer sensor generates three different signals at once i.e., the object's acceleration in x, y, and z coordinates for each time measurement period. After the data received by the PC / **server**, then the server analyzed the signal by applying our proposed fall detection method. If a fall incident is detected by the server, it will send a message notification or an alarm to the **client** component (smartphone) that has been registered to monitor fall incident.

[1] https://fritzing.org/

The notification tells the client that fall incident has been detected while monitoring the user activity. Figure 4 shows the proposed system framework.

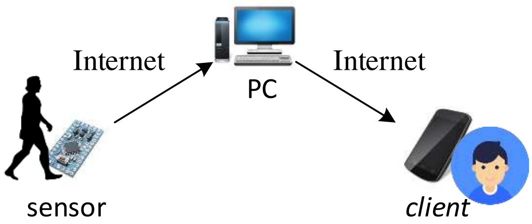

Figure 4. Overall system framework

2.3. Fall Detection Method

From the data recorded by the sensor, the next process is to determine whether fall incident happened. We use a simple thresholding technique to automatically detect fall incident. There are several steps to be done to successfully detecting fall incident. We use similar approach from [7] for detecting fall incident. The difference is that we only use tri-axial accelerometer data for detecting fall incident instead of including tri-axial gyroscope data. First step is the calibration of accelerometer data. The next process is to determine total acceleration of the object from x (A_x), y (A_y), and z-axis (A_z) data over time. We use similar approach for computing total acceleration (A_T) from [10] by using equation (1):

$$A_T = \sqrt[2]{A_x^2 + A_y^2 + A_z^2} \tag{1}$$

Then, this total acceleration (A_T) is compared to some threshold value $\boldsymbol{T}$. If the computed total acceleration is above this value, then the system assumed fall incident happened. In order to determine the value of $\boldsymbol{T}$, we use a simple observation based on all the sample data we have been gathered in this study (will be explained in chapter 3). We observed the change of total acceleration of the signal over time representing the user activity recorded by accelerometer sensor. Figure 5 illustrated a sample of user activity data from the accelerometer sensor.

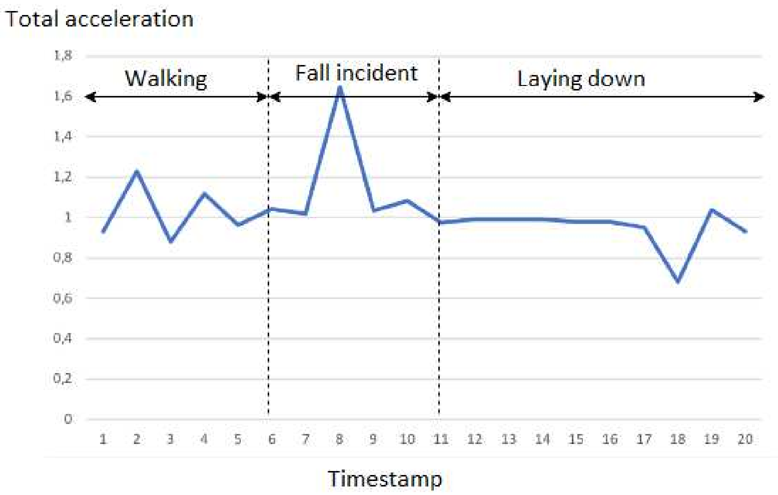

Figure 5. User activity data from the accelerometer sensor

From Figure 5, we can see a peak on the signal which determine the fall incident. When we do normal activities such as walking, the total acceleration does not drastically change. But when a fall occurs, the signal gives a significant increase in total acceleration followed by a rapid decrease in total acceleration. Based on our observation, we conclude that the threshold value $\boldsymbol{T}$ to be in the scale of **1.6** m/s^2.

2.3. Evaluation

We used sensitivity and specificity measure to evaluate system performance. Sensitivity measurement describes the system performance for accurately detecting fall incident. In other hand, specificity measurement describes the system performance for distinguishing activities of daily living with fall incident [10]. Equation (2) and (3) describe how to measure sensitivity and specificity respectively.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \tag{2}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \tag{3}$$

True Positive (TP) rate is the number of true fall incident detected by the system. False Negative (FN) rate is the number of true fall incident that the system failed to detect. True Negative (TN) is the number of normal activity (activities of daily living) successfully distinguished from fall incident. Finally, False Positive (FP) rate is the number of false alarms generated by system although there is no fall incident happened.

3. RESULTS AND ANALYSIS

Based on schematic diagram on Figure 3, we assembled all the hardware components into a prototype device that can be seen on Figure 6 below. Wemos need to be configured to connect into available WiFi Internet connection in order to works properly.

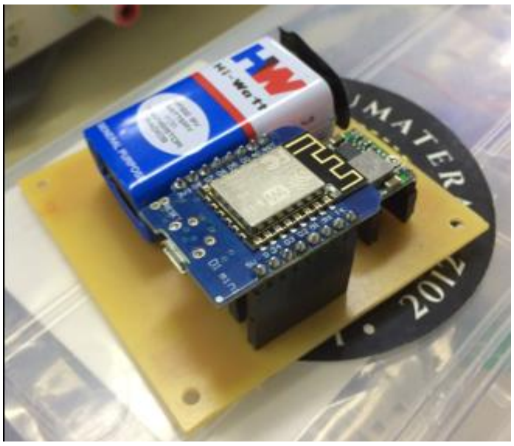

Figure 6. Hardware Implementation

In order to evaluate the proposed architecture or system, we define 2 kind of activity to be recognized by the system, i.e. activities of daily living (ADL) and fall incident (FALL). Furthermore, the daily activity consists of 7 various actions and the fall incident consists of 3 various incidents as described on Table 1. These scenario is also similar from [7] [10]. The experiments were conducted by one subject and the device was attached on the user waist. Figure 7 illustrate forward fall incident.

Table 1. Activity to be recognized by the proposed system

Actions	Category	Description
Walking	ADL	Normal walk
Brisk walk	ADL	Fast paced walk
Sitting	ADL	From standing position, then sitting on the chair
Laying down	ADL	Beginning from sitting position, then laying down on the bed
Bend down	ADL	From standing position, then bend down
Going upstairs	ADL	Normal walk, going upstairs
Going downstairs	ADL	Normal walk, going downstairs
Forward fall	FALL	From standing position, then falling, final position facing downward
Backward fall	FALL	From standing position, then falling, final position facing upward
Falling sideways (right)	FALL	From standing position, then falling to the right
Falling sideways (left)	FALL	From standing position, then falling to the left

Figure 7. Illustration of forward fall incident (action) with device attached on the waist of subject

Each falling incident (action) consists of 10 trials. So, there are 40 trials in total for falling incident scenario. From the experiment, we have concluded that proposed system can detect almost all type of fall incident trial with average accuracy of 97.5%. After the system detected fall incident, the system sent notification message to the client by using Telegram application. The detailed results are shown in Table 2.

Table 2. Detection result for fall incident

Actions	Notified	Not Notified	Percentage
Forward fall	10	0	100
Backward fall	9	1	90
Falling sideways (right)	10	0	100
Falling sideways (left)	10	0	100
Average accuracy			97.5%

In order to distinguish ADL with fall incident, we also carried out experiment in order to validate whether the system did not trigger the notification system if the user perform ADL instead of fall incident. As we discussed before, 7 ADL scenarios were designed to test this notification system. We did 20 trials for each ADL scenario. Table 3 shows the result of distinguishing ADL with fall incident by not sending false alarm/notification to the smartphone.

Table 3. Detection result for distinguishing ADL with fall incident

Actions	False Alarm	No Alarm
Walking	0	20
Brisk walk	0	20
Sitting	0	20
Laying down	0	20
Bend down	0	20
Going upstairs	0	20
Going downstairs	5	15

Based on Table 3, the system can almost distinguish all designed ADL scenario with fall incident. The system did not trigger the notification system if the user performs ADL scenario. The false alarm occurred while the user performed down the stairs action. This condition occurred due to a significant total acceleration change (object movement + gravity) which is similar to fall incident. The notification system sent 5 false alarms out of 20 trials. We then measured the sensitivity and specificity measurement based on our experiment as follows:

$$\text{Sensitivity} = \frac{49}{49+1} = 0.98$$

$$\text{Specificity} = \frac{135}{135+5} = 0.96$$

In addition to develop IoT-based device for detecting fall incident, we also tried to explore the potential of RNN techniques in order to distinguish ADL with fall incident using a public dataset. We used RNN based model to exploit its advantage in analyzing sequence data such as the activity data recorded by accelerometer. In our previous article, we already explored that RNN have a potential for distinguishing ADL with fall incident. The best classification performance was achieved by using the data form x-axis accelerometer data [11]. We employed LSTM network model over the plain RNN model because we try to avoid the vanishing gradient problem in plain RNN. So, in this article we tried to show the classification performance of RNN for tri-axial accelerometer data using UMA Fall dataset. The UMA Fall dataset is a public dataset with a focus for developing the algorithm to distinguish fall with daily activity [12]. We use the same training data and testing data as we did in [11]. We do the experiment on all tri-axial accelerometer data (x, y, and z-axis acceleration) combined. The best performance of classification is presented on Table 4. The RNN model again achieved a good performance using the combined tri-axial accelerometer data. This experiment shows that the potential of RNN in order to distinguish fall incident from ADL.

Table 4. Classification performance of RNN model based on combined tri-axial accelerometer data

	ADL (classified)	FALL (classified)
ADL (ground truth)	84	1
FALL (ground truth)	0	38

4. CONCLUSION

From the experiment, we can conclude that our proposed system could distinguish between fall incident and normal daily activities with sensitivity and specificity rate of 98% and 96% respectively. The false alarm occurred only when the subject did the “going downstairs” action. This could be happened because of the user’s total acceleration exceeded the threshold value when doing the action and due to the impact of gravity. Future challenge to be considered is the device power usage issue. Further analysis of device power usage is needed in the future. Power consumption is an important aspect for an IoT based device. A good IoT device needs an efficient power usage because the device expected to operate all day long. Furthermore, based on our study, machine learning based algorithm using Recurrent Neural Network model also has a good potential in distinguishing fall incident from normal daily activities.

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