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Development of Falling Notification System for Elderly Using MPU6050 Sensor and Short Message Service

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ABSTRACT
Falls in the elderly are quite common because their motor skills have begun to decline. The elderly who live alone are often late in getting first aid after a fall, as a result of which intensive care is needed. This paper describes the design of falling detection and notification system for the elderly in the form of short messages sent to mobile phones and stored in the system database. The proposed prototype is designed using the MPU6050 sensor to detect falling movements and a continuous notification system in the form of three different messages immediately sent after falling. The tools used to test the research results are the confusion matrix method. The experimental results of this study show that the recall value is 90%, the precision is approximately 82%, the specificity is about 94%, and the accuracy equals 93% respectively.

Keywords: *confusion matrix, elderly, falling notification system, MPU6050 sensor.*

1. INTRODUCTION

Along with increasing age, the aging process will experience a physiological degenerative body that affects the health level of the elderly. Diseases that are often suffered by the elderly, such as gout, osteoporosis, and even strokes, will limit daily activities for the elderly. These diseases can trigger falls in the elderly. Falls in the elderly is quite dangerous and can cause a high risk if it is not handled quickly. It is recorded that in Indonesia, the prevalence of falling injury to people over the age of 55 reaches 49.4%, while those over 65 years are approximately 67.1% [1].

The incidence of falls is reported to occur in about 28-35% of the elderly aged 65 years and over who live in the home (community), half of which experience repeated falls [2]. The elderly who fall at home experience a fall of around 50% and nearly 10-25% require treatment in hospital. Of all the elderly falls, 20% of the elderly was on the ground for longer than an hour and 50% of these elderly die within six months of the fall, even when they do not suffer any physical injuries, the psychological effects can be so dangerous since it leads to death [3]. To minimize the bad effects of other diseases that can arise due to falls, they must be treated quickly.

However, for the elderly who live alone at home or have families who do not live with them, when they fall, they will not get immediate treatment. To solve this problem, a tool is essential to detect falls in the elderly so that the relevant parties can find out the information. The device is made to be attached to the elderly body so that when they fall, and a notification can be sent at any time to the mobile phone. Thus, the fall position can be identified and suitable treatment can be conducted faster.

This paper describes the design of a falling detection and notification system for the elderly. A fall detector is attached to the body of the elderly as belts. The proposed system utilizes angle detection using the MPU6050 sensor and its data acquisition that infers fall conditions from the elderly. The MPU6050 sensor is an electronic module that can read the tilt angle based on data from the accelerometer and gyroscope sensors embedded in it. This sensor is also equipped with a temperature sensor that can be used to measure the ambient temperature. With this capability, the MPU6050 sensor is widely used in applications that require angle information. Rifajar & Fadlil in [4] employed such a sensor to render a yaw angle in the dancing robot. Atoir *et al* in [5] used the MPU6050 sensor to capture angles that move according to hand movements in virtual reality games. Zhang *et al* in [6] included MPU6050 sensors to detect the tilt of the transmission tower to be monitored in real-time. Meanwhile, Mohd Ismail *et al* in [7] exploited such a sensor to get the actual vibration in water pipeline leakage detection.

Previous works which also used the MPU6050 sensor in a fall detection system were reported in [3], [8], [9]. In [3], Krooneman developed a device based on MPU6560 sensor which capable of detecting the fall of the elderly

and passively alerting caregivers or family members. Xu *et al* in [8] proposed the falling posture identifying scheme with wearable sensors including MPU6050 and flexible graphene/rubber. Meanwhile, Jefiza *et al* in [9] employed the MPU6050 sensor to support the back propagation-based fall detection for the elderly.

This paper is in line with those previous works in terms of using the MPU6560 sensor to detect falling conditions. The data in this work were obtained from the sensor and processed using the Arduino microcontroller. Then, it is sent via short message to the mobile phone in which the phone number is registered in the system. Furthermore, these short messages can be processed using social media applications such as WhatsApp, Telegram, and others.

The rest of the paper is structured as follows. Section 2 describes the literature review used in this paper, which includes the elderly concept according to WHO, factors that cause the elderly to fall, and previous works related to fall detection and fail prevention for the elderly. Section 3 presents a complete description of the proposed system and how to apply a confusion matrix to measure the effectiveness of the proposed system. Then, hardware realization, experimental results, and determination of performance metrics are discussed in Section 4. Finally, Section 5 concludes the paper and presents a direction for future research.

2. LITERATURE REVIEW

The Elderly is someone who has reached the age of 65 years and over as stated by The United Nations. Falling in the elderly is a condition that occurs quite often for some people, almost 50 percent of people who are around 80 years old have experienced falls [10]. This is due to the physical limitations possessed by the elderly along with the aging process. The high potential for falling can also be caused by disease factors such as osteoporosis, blurred vision, loss of ability to balance the body, and also stroke [11].

In addition to the physical limitations possessed by the elderly, other factors are external, outside of the physical characteristics of the elderly. These external factors are often referred to as home hazards or dangerous conditions in the house. Falls due to external factors can occur because the floor is slippery. This condition can be caused by puddles of water or other types of floor materials or materials on the floor such as carpets and doormats. In addition, falls in the elderly due to external factors can be caused by the elderly stumbling. This can happen because the placement of goods in the house is not good. Another cause is the height of the stairs which are often too steep for the elderly. Follow-up medical care is needed to overcome the fatal injuries suffered by the elderly. These injuries can result in trauma, fractures, more severe strokes, bleeding in the head, injuries to internal organs, even more severe, namely death. World Health Organization (WHO) states that falls are the second largest contributor to mortality in the world with a total of 684,000 incidents per year [12].

Fall detection and fall prevention are two important strategies for dealing with falls in the elderly and have been studied for the past two decades. The fall detection method has been explored in depth by researchers. The system uses various types of sensors to collect important signals for further processing and analysis, while various analysis algorithms are used to process the collected data [2]. Anam & Rastono in [13] developed The Elderly Health Monitor system named ELMOS to provide a framework for maintaining health awareness for the elderly. He *et al* in [14] realized a smart device-enabled system for fall detection and alert using a motion sensor, smartphone, and Bluetooth communication. Meanwhile, Kalinga *et al* in [15] discussed a non-obtrusive vision-based fall detection system using a service robot with a Kinect sensor attached and an automatic fall notification system based on Q-Learning. Vetsandonphong in [16] implemented a fall detection and its alert system using Arduino microcontroller.

3. RESEARCH METHODS

In this work, a fall detector for the elderly was designed using the MPU6050 sensor and a notification system in the form of a short message to inform that the user falls or gets up from the fall. A schematic diagram of the proposed system is depicted in Figure 1.

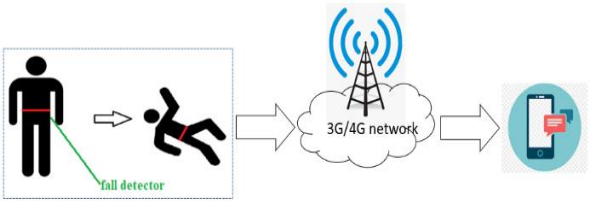

Figure 1 A schematic diagram of a fall notification system for the elderly.

The MPU 6050 sensor can identify the relative position of the user and is used to detect the type of movement experienced by the user. These movements are divided into three types, namely light movements, heavy movements, and falling movements. Light movements consist of small movements, getting up, or sitting, while heavy movements consist of walking and jogging. Each user's movement can be classified based on the angle data generated by the gyroscope embedded in the MPU6050 sensor. Angle data was recorded for 0.1 s to infer the type of user movement. The prototype of the fall detector is placed on a belt with a distance of about 88.5 cm from the floor and the height of the chair used for sitting movement is about 44.5 cm. The movement that has been detected by the sensor will produce output in the form of a blinking of the LED and a short message notification. If the sensor detects light movements then the LED stays on and a short message notification is not

sent. Meanwhile, if the user makes heavy movements then the LED flashes every 0.5 seconds, and a short message is not sent. If the user is detected falling then the LED flashes once every 0.1 seconds and a short message will be sent.

The Block diagram of the proposed fall detector is shown in Fig. 2. The MPU6050 sensor that has been activated will detect the relative position caused by the movement of the user. Angle data corresponding to the user's motion is sent at any time to the Arduino microcontroller. Furthermore, the microcontroller processes the input signal to identify the type of movement experienced by the user and then issues an output signal that will be received by the LED and SIM800L module. The LED will flash with blinking variations according to the type of movement performed by the user. If the system detects falling and rising movements shortly after the elderly wakes up, the SIM800L module will send a short message to the telephone number registered in the system.

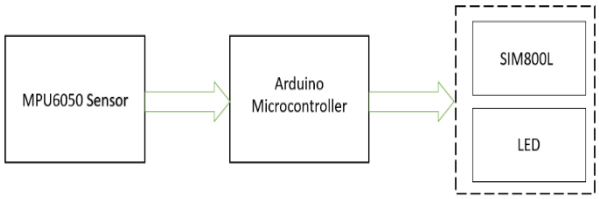

Figure 2 Block diagram of the proposed fall detector.

To test the effectiveness of the proposed system, a tool called the confusion matrix is used to assess four performance metrics, namely recall, specificity, precision, and accuracy of the system. The confusion matrix form is given in Figure 3.

Predicted Value (predicted by the test)		Actual Value (as confirmed by experiment): positives	Actual Value (as confirmed by experiment): negatives
	positives	**TP** True Positive	**FP** False Positive
	negatives	**FN** False Negative	**TN** True Negative

Figure 3 Confusion matrix (adapted from [17] and [18]).

The confusion matrix is usually used in supervised learning. The confusion matrix approach has also been carried out in image retrieval technique based on clustering [19], visualizing a configuration of classes as it is perceived by a classifier [20], land use/land cover (LULC) mapping [21], web service ranking [22], and so on. It contains the number of cases that were classified correctly as well as incorrectly classified cases. The cases that are classified correctly appear on the diagonal, because the predicted group and the actual group have the same value. Each performance metric is calculated by the following formula

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

$$precision = \frac{TP}{TP+FP} \quad (2)$$

$$specificity = \frac{TN}{TN+FP} \quad (3)$$

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

Recall is the success rate of recognizing a certain class. It is expressed in the number of entity recognition that is true, divided by the number of entities that should be recognized by the system. Meanwhile, precision is the level of accuracy of the classification results of all documents. Precision is calculated from the number of correct recognitions by the system, divided by the total number of recognitions made by the system. Specificity is a value that measures the proportion of actual negatives that are correctly identified. Specificity is also referred to as the true negative level.

4. RESULTS AND DISCUSSION

A hardware realization of the prototype is shown in Figure 4. With a length of approximately 12 cm, this fall detector can be mounted on a belt that is wrapped around the waist of the elderly. The weight of each component is light enough not to burden the elderly in wearing it.

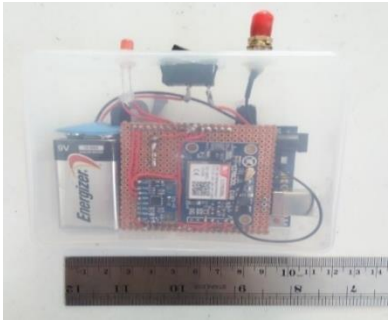

Figure 4 Hardware realization of the prototype of the fall detector.

Experimental tests are carried out to determine the ability of the system to detect each movement activity of the user. The results of the test are grouped into four general conditions according to parameters in the confusion matrix method, namely TP (true positive), TN (true negative), FP (false positive), and FN (false negative). TP is denoted whenever the actual condition falls and the system detects the fall. TN is used to mark the actual condition does not fall and the system detects not falling. FP is a state where the actual condition does not fall and the system detects a fall, while FN denotes the actual condition of falling and the system detects not falling.

The first experiment was carried out to see the accuracy of the system when inferring changes from a standing position to falling. An illustration of the changes is shown in Figure 5. Table 1 shows the results of the comparison between the actual conditions and the system readings as well as the parameters in the confusion matrix

obtained from the experimental results which were carried out ten times. Y or N in Table 1 denotes a blinking of the LED and a short message notification appears or disappears during the experiment.

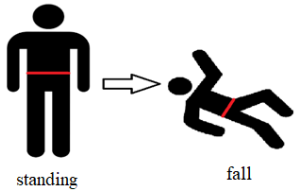

Figure 5 Change of position from standing to fall.

Table 1. Experimental results for detecting a change of position from standing to fall

Actual condition	LED blinking			Short message	Read by system	Mark
	on	0.5 s	0.1 s			
Fall	Y	N	Y	Y	Fall	TP
Fall	Y	N	Y	Y	Fall	TP
Fall	Y	N	Y	Y	Fall	TP
Fall	Y	N	Y	Y	Fall	TP
Fall	Y	N	N	N	Light movement	FN
Fall	Y	N	Y	Y	Fall	TP
Fall	Y	N	Y	Y	Fall	TP
Fall	Y	N	Y	Y	Fall	TP
Fall	Y	N	Y	Y	Fall	TP
Fall	Y	N	Y	Y	Fall	TP

Further tests were carried out for four-movement changes which included small movements, standing, sitting, walking with small steps of about 45 cm for 2.5 m, and jogging as visualized in Figure 6. Meanwhile, Table 2-5 shows the experimental results for detecting those movements. Y or N in the entire table has the same meaning as those listed in Table 1.

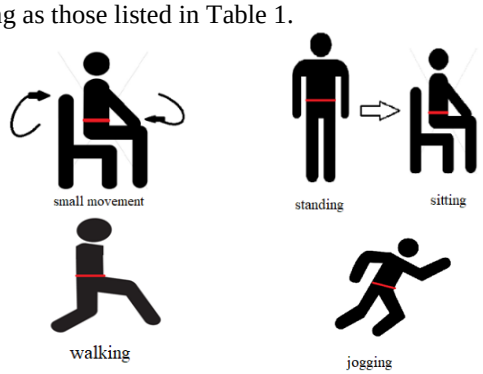

Figure 6 Visualization of movement changes during the experiments.

In the small movement test, the user was sitting on a chair, then he rotated his body 180° to the left and right for 3 rounds, while in the sitting movement test, the user stood straight and still then sat on a chair. In the gait test, the user tried walking with small steps of about 45 cm like an elderly person and walked as far as 2.5 m. Finally, in the jogging test, the user jogged with a footstep of 10 cm per step. This test was conducted to illustrate the elderly who are doing sports.

From the experimental results, it can be observed that a total of 50 tests where the results for true positive (TP) is 9 times, true negative (TN) is 31 times, false positive (FP) is 2 times, false-negative is 1 time, while testing with undefined description is 7 times. The results of the test with undefined descriptions can occur because the actual condition does not show falling motion and the system condition does not show any movements other than falling. Such results cannot be used as a reference to determine performance metrics. Based on these results, the total number of tests taken to calculate performance metrics is 43 times. The number of parameters TP, TN, FP, and FN obtained from the observations in the experiment were 9, 31, 2, and 1 respectively. By using equation (1)-(4), the performance metric of our proposed systems renders the recall value is 90%, the precision is approximately 82%, the specificity is about 94%, and the accuracy equals 93% respectively.

Table 2. Experimental results for detecting a small movement

Actual condition	LED blinking			Short message	Read by system	Mark
	on	0.5 s	0.1 s			
Small movement	Y	N	N	N	Small movement	TN
Small movement	Y	N	N	N	Small movement	TN
Small movement	Y	N	N	N	Small movement	TN
Small movement	Y	Y	N	N	Walking	-
Small movement	Y	Y	N	N	Walking	-
Small movement	Y	N	N	N	Small movement	TN
Small movement	Y	N	N	N	Small movement	TN
Small movement	Y	N	N	N	Small movement	TN
Small movement	Y	Y	N	N	Walking	-
Small movement	Y	N	N	N	Small movement	TN

Table 3. Experimental results for detecting a change of position from standing to sitting

Actual condition	LED blinking			Short message	Read by system	Mark
	on	0.5 s	0.1 s			
Sitting	Y	Y	N	N	Walking	-
Sitting	Y	Y	N	N	Walking	-
Sitting	Y	N	N	N	Sitting	TN
Sitting	Y	N	N	N	Sitting	TN
Sitting	Y	Y	N	N	Walking	-
Sitting	Y	N	N	N	Sitting	TN
Sitting	Y	Y	N	N	Walking	-
Sitting	Y	N	N	N	Sitting	TN
Sitting	Y	N	N	N	Sitting	TN
Sitting	Y	N	N	N	Sitting	TN

Table 4. Experimental results for detecting a walking

Actual condition	LED blinking			Short message	Read by system	Mark
	on	0.5 s	0.1 s			
Walking	Y	Y	N	N	Walking	TN
Walking	Y	Y	N	N	Walking	TN
Walking	Y	Y	N	N	Walking	TN
Walking	Y	Y	N	N	Walking	TN
Walking	Y	Y	N	N	Walking	TN
Walking	Y	Y	N	N	Walking	TN
Walking	Y	Y	N	N	Walking	TN
Walking	Y	Y	N	N	Walking	TN
Walking	Y	N	Y	Y	Fall	FP
Walking	Y	N	N	N	Walking	TN

Table 5 Experimental results for detecting when jogging

Actual condition	LED blinking			Short message	Read by system	Mark
	on	0.5 s	0.1 s			
Jogging	Y	Y	N	N	Jogging	TN
Jogging	Y	N	Y	Y	Fall	FP
Jogging	Y	Y	N	N	Jogging	TN
Jogging	Y	Y	N	N	Jogging	TN
Jogging	Y	Y	N	N	Jogging	TN
Jogging	Y	Y	N	N	Jogging	TN
Jogging	Y	Y	N	N	Jogging	TN
Jogging	Y	Y	N	N	Jogging	TN
Jogging	Y	N	Y	Y	Jogging	TN
Jogging	Y	N	N	N	Jogging	TN

Another test was to observe the ability to send short message notifications to a mobile phone in which the number is registered in the system. The movement started from standing, falling, still, then getting up. Short message notifications should be given every time a movement change occurs. The illustration of this test is depicted in Figure 7. A screenshot when notification of short messages is sent is shown in Figure 8.

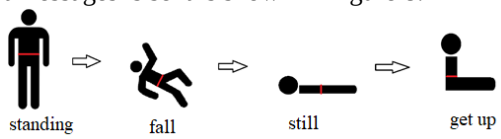

Figure 7 Change of position from standing to getting up.

Figure 8 A screenshot of notification (in Indonesian) in a mobile phone whose numbers are registered in the system.

5. CONCLUSION

The design and implementation of a fall notification system for the elderly using MPU6050 sensor and short message service have been discussed in the paper. The proposed prototype is designed using the MPU6050 sensor to detect falling movements and send a continuous notification system of three different messages immediately after falls. Data about the position of the elderly is processed at any time by the Arduino microcontroller and sent to the SIM800L module and displayed via LED. Short messages will be sent to a mobile phone which number is registered in the system. The tool used to measure the system performance are the confusion matrix method. Four parameters which are entries in each block in the confession matrix, namely TP, TN, FP, and FN are obtained from the comparison of the actual condition of the user's position with the results of the system reading. The experimental results show that the recall value is 90%, the precision is approximately 82%, the specificity is about 94%, and the accuracy equals 93% respectively.

This study is still limited to send the elderly fall condition to a certain mobile phone registered in the system. Further development can be directed to data integration with health institutions that have medical records from the elderly to realize a telehealth system. In

terms of sending messages, the use of WhatsApp or other cloud-based social media applications such as Telegram can be used to replace the communication media in the form of text in the Global System for Mobile Communication (GSM) system due to considerations of popularity and affordability. In the scale of the use of big data, the realization of the system leads to the implementation of internet-of-things.

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