Research article

A Bed-Fall Notification System Using Pressure and Ultrasonic Sensors

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Abstract

Keywords

android mobile device;

fall;

finite state machine;

internet of things;

pressure and ultrasonic sensor

Falls are a major cause of unintentional injury and mortality in the senior population. Therefore, early fall notification can prevent any undesirable damage. This paper aims to present a mobile electronic device-based bed-fall notification using the combination of six thin-film pressure sensors and six ultrasonic sensors. The proposed system monitors movements, detects a bed-fall, and sends an alarm to caregivers. The Finite State Machine (FSM) is used to classify 3 states of movement patterns: the lying, sitting, and falling states. The Internet of Things (IoT) system is adopted to transmit the movement status to the application on an android mobile device. The proposed bed-fall classification system yielded promising results for accuracy, sensitivity, and specificity: 86.67%, 73.33%, and 100%, respectively. In future work, the proposed system can be improved by increasing the number of thin-film pressure sensors, modifying circuit, and applying machine learning models. Accreditation of the system is expected to benefit young and elderly patients in nursing homes, hospitals, and residential areas.

1. Introduction

The concept of the aging society already features strongly in global awareness, and the number of senior people is expected to increase by 16 percent in 2050 [1, 2]. The number of caregivers is insufficient to take care of the elderly who needs intensive care for both day and night [3]. Bed-fall is an acute injury that can cause disability and death amongst the elderly at a rate three times higher than in other age groups [2]. Falls can cause serious injuries such as bruises, fractures of the hip and

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head bones, and so on [4], which tend to be more severe in the elderly because of their pre-existing diseases and lower bone densities [5]. Bed-fall, which can occur due to poor sleep posture and sleep apnea, occurs in people sleeping in the supine position twice as often as it does in people sleeping in the lateral position [6, 7]. In addition, bedridden patients, especially bedridden diabetic patients who need to change their sleep posture every two hours [8, 9], are at higher risk of bed-fall accidents. Therefore, in order to prevent injuries which is a cause leading to disability and death, early bed-fall detection is important [10].

Several studies have proposed automatic bed-fall detection approaches. Depth cameras, infrared cameras, or ultrasonic sensors were earlier introduced in previous research to capture and monitor the movement patterns of patients while sleeping [3, 11-13]. However, the use of cameras involved sleeper privacy violations, and the accuracy of detection was reduced due to coverage of the patient by bedding. Accelerometer sensors were later applied attached to the bodies of patients; however, these interfered with patient comfort [14-16]. A recent system employed pressure sensors that were installed beneath patient mattresses [3, 17]. These showed promise; they had better accuracy and gave patients better levels of sleep satisfaction.

As aforementioned reviews, this study aims to develop an automatic bed-fall notification system based on an integration of thin-film pressure and ultrasonic sensors in order to enhance the efficiency of caring for elderly patients through an android mobile device application. The pressure sensors are installed on a rubber topper placed under the bedsheet, while the ultrasonic sensors are installed on the headboard and the four legs of the bed. The Finite State Machine (FSM), which is a mathematical model for classifying states that change from one state to another in response to particular inputs, is also employed. The change from one state to another is called a transition. The FSM is used to monitor the 3 movement patterns: lying, sitting, and falling. This system transmits the data via Wi-Fi to the Firebase database and the application on the android mobile device.

2. Materials and Methods

2.1 Participants

We recruited ten volunteers who were healthy and have no injuries, aged between 22-23 years. Five female volunteers had a mean (SD) age = 22.4 (0.55) years, mean (SD) weight = 63.2 (15.34) kg, and mean (SD) height = 163.6 (2.07) cm. Five male volunteers had a mean (SD) age = 22.6 (0.55) years, mean (SD) weight = 80.8 (13.88) kg, and mean (SD) height = 172.2 (3.11) cm. The participant profiles are tabulated in Table 1.

The study has an accredited certificate of ethics number SWUEC 274/2563, issued by the research ethics committee, Srinakharinwirot University, Thailand. The participants were fully informed about the research aims, processes, data recordings, potential risks, and relevant compensation. All procedures were carried out with the written consent of the participants before participating in the experiment.

2.2 Hardware design

The proposed bed-fall notification system consists of the hardware components, processing unit, and the android application, as shown in Figure 1. The hardware assembly design is composed of the thin-film pressure and ultrasonic sensors, and can be explained as follows. The six thin-film pressure sensors were installed on a rubber topper and placed under the bed-sheet of a single bed having a standard width of 90 cm and length of 200 cm [18]. The pressure sensors measure forces ranging between 20g - 10kg, according to the change in resistance [19].

Table 1. Profile of the participants

Participant	Sex	Age(years)	Weight(kg)	Height(cm)
S-1	male	22	60	168
S-2	male	23	74	170
S-3	male	23	92	173
S-4	male	22	93	175
S-5	male	23	85	175
S-6	female	22	57	163
S-7	female	22	51	164
S-8	female	23	65	162
S-9	female	22	54	167
S-10	female	23	89	162
Mean		22.5	72	167.9
SD.		0.53	16.62	5.17

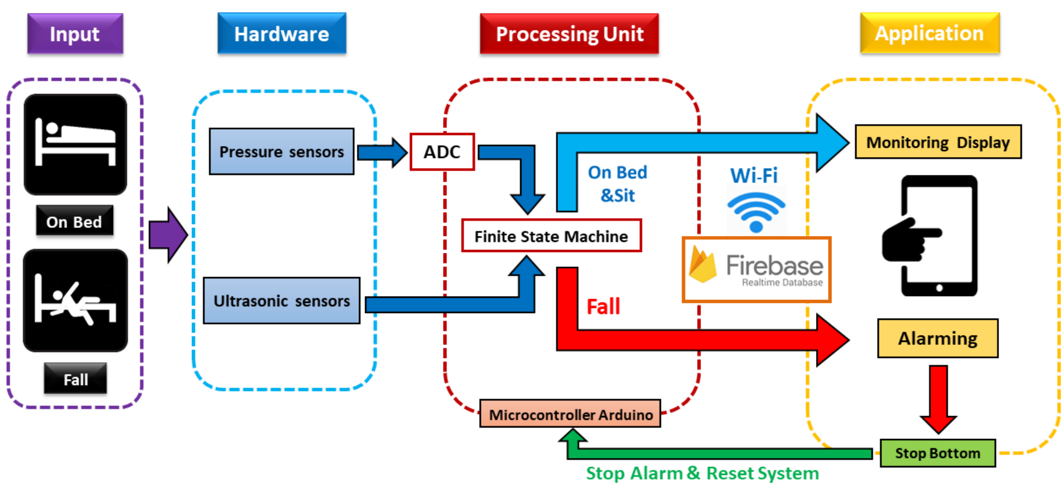


Figure 1. A block diagram of bed-fall notification system

The six ultrasonic sensors were installed on the two sites of the headboard and the four bed legs at an angle of five degrees from the bed. These sensors were used to obtain the distance between the sensor and the obstacle with a detection distance ranging between 2 - 400 cm. The sensors were placed on the bed and mattress as shown in Figures 2-4.

The microcontroller Arduino Nano 33 IoT was used to integrate all sensors in the system. The pressure sensors were connected to an Analog to Digital Converter port for converting analog to 10-bit digital values (0 - 1023) and the ultrasonic sensors were connected to the digital port. The microcontroller transmitted data via Wi-Fi to the cloud system for connecting to the other platforms.

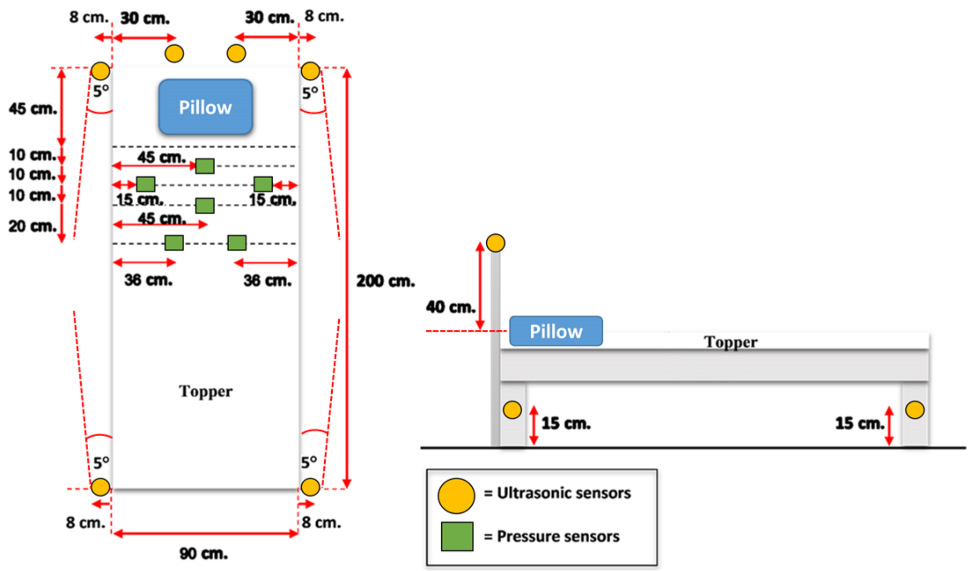


Figure 2. The installation of the ● ultrasonic and ■ pressure sensors

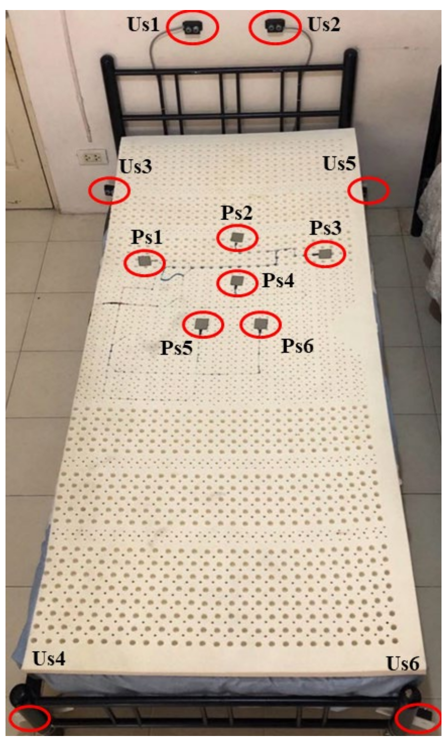


Figure 3. Prototype of the proposed bed-fall notification system

(Ps: Pressure sensor and Us: Ultrasonic sensor)

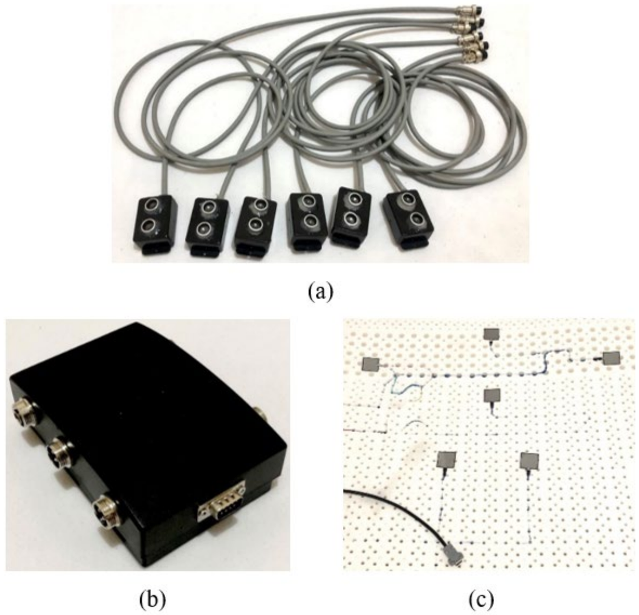


Figure 4. The hardware component is composed of (a) ultrasonic sensors, (b) central processing unit, and (c) pressure sensors

The Universal Testing Machine (UTM) was the reference device used to analyze the error and device performance testing for the pressure and the ultrasonic sensors. The pressure sensors were tested at the dynamic force magnitude ranging from 0 to 1000 N, and the ultrasonic sensors were tested at a distance ranging from 0 to 50 cm, respectively. The calibration error was computed using the root mean square error (RMSE). The repeatability test was performed to evaluate the device performance by testing the device with a sampling frequency of 100 Hz for 4 times. Root Mean Square Error can be calculated by using the equation (1) [20].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(F_{ref}(i\Delta T) - F(i\Delta T)\right)^2} \tag{1}$$

Where F_{ref} and F are the force or the distance data measured by the reference device and our device, respectively. The i, ΔT, and N are the number of data, the sampling time of the device, and the total amount of sample data, respectively.

Repeatability can be calculated by using the equation (2) [21].

$$Repeatability = \frac{1}{N+1}\sum_{i=0}^{N}\left(\frac{\left|F(i\Delta T) - \overline{F(\imath\Delta T)}\right|}{Fa(iTs)}\right) \times 100 \tag{2}$$

Where N is the number of repetitions. $\overline{F(\imath\Delta T)}$ is the average of the measured data. The experimental repeatability results are shown in Figures 5, 6 and Table 2.

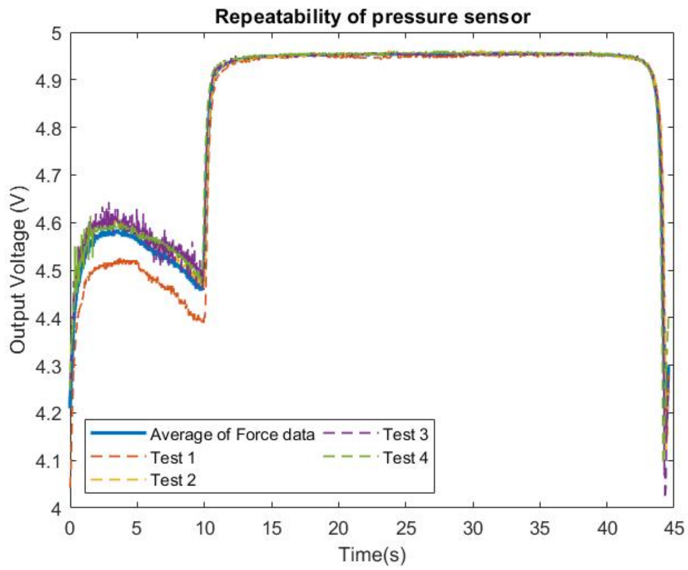


Figure 5. The experimental repeatability calibration of the pressure sensor

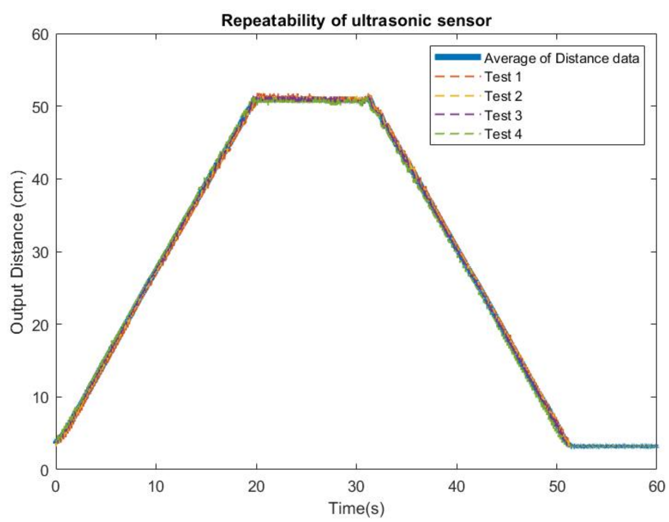


Figure 6. The experimental repeatability calibration of the ultrasonic sensor

Table 2. Characteristics of measurement device

Type of sensor	Repeatability Error (%)	Root Mean Squared Error (%)
Pressure sensor	0.27	23.98
Ultrasonic sensor	1.78	0.23

2.3 Experimental procedure

Each subject put on the protective gear on the head, arms and legs to prevent injury and lay on the standard single bed. An extra mattress was placed beside the bed to support the subject falling off the bed. The volunteers were instructed to adopt 6 postures, accounted as 3 states: (1) the lying state which included the supine, left lateral, and right lateral sleeping positions, (2) the sitting state, and (3) the falling state which included left and right falls. The volunteers stayed in each posture for at least a minute to allow data recording.

3. Results and Discussion

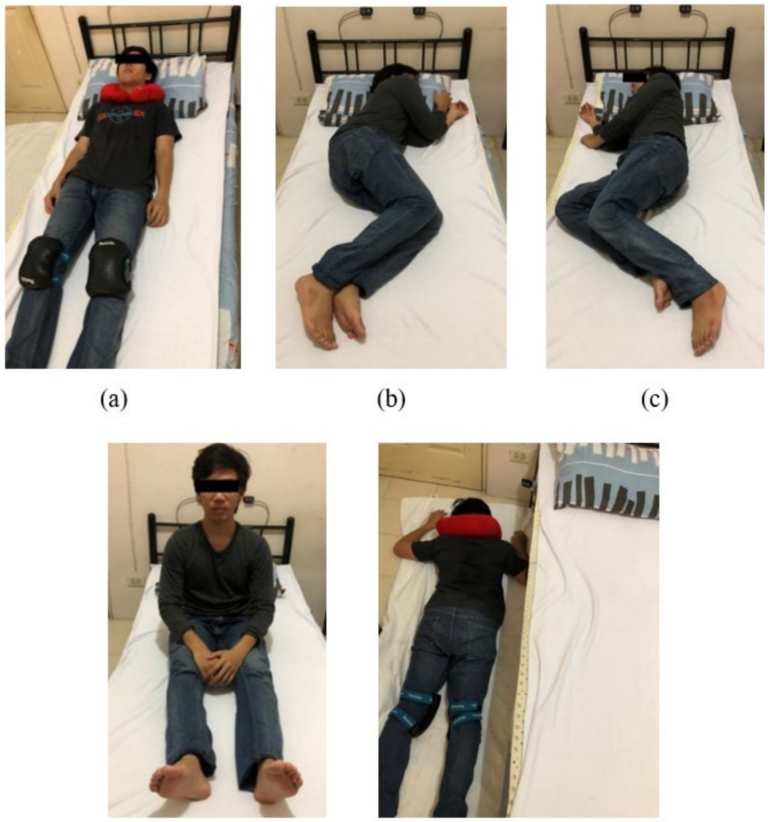
State classification was determined by a threshold, which was analyzed from the changes in all sensor data in the system. The subjects lay on the bed and performed 6 movement postures. Each posture was recorded 3 times. The data from sensors obtained from all subjects are shown in Table3.

Table 3. The mean and SD of the six pressure and ultrasonic sensors for the six movement patterns

			Lying state			**Sitting state**	**Falling state**	
			supine	left lateral	right lateral	sitting	left	right
Pressure sensor (10 bit)	PS1	Mean (SD)	105.8 (91.4)	4.6 (5.9)	874.7 (32.0)	2.0 (1.4)	1.7 (1.5)	1.6 (1.4)
	PS2	Mean (SD)	972 (7.8)	653.4 (438.5)	635.1 (454.4)	1.8 (1.4)	1.6 (1.4)	1.5 (1.4)
	PS3	Mean (SD)	104.5 (83.6)	871.2 (36.2)	3.3 (2.2)	1.9 (1.2)	1.8 (1.6)	1.6 (1.5)
	PS4	Mean (SD)	980.3 (14.5)	721.6 (410.1)	716.7 (416.2)	1.8 (1.4)	2.0 (1.4)	1.7 (1.5)
	PS5	Mean (SD)	979.7 (15.3)	3.3 (3.5)	953.0 (29.1)	981.3 (67.6)	1.6 (1.3)	1.6 (1.4)
	PS6	Mean (SD)	971.3 (40.1)	953.1 (29.2)	2.2 (2.8)	976.3 (66.0)	1.7 (1.3)	1.7 (1.2)
Ultrasonic sensors(cm.)	Us1	Mean (SD)	348.4 (0.5)	348.2 (0.4)	348.7 (0.5)	85.3 (1.7)	348.5 (0.5)	348.5 (0.5)
	Us2	Mean (SD)	338.6 (0.5)	340.1 (9.1)	338.5 (0.5)	85.4 (1.6)	338.5 (0.5)	338.5 (0.5)
	Us3	Mean (SD)	197.8 (1.5)	197.5 (1.6)	197.0 (1.6)	197.3 (1.4)	197.0 (1.6)	74.0 (14.3)
	Us4	Mean (SD)	196.8 (1.6)	197.1 (1.4)	196.7 (1.6)	197.8 (1.9)	197.6 (1.9)	92.6 (19.4)
	Us5	Mean (SD)	197.2 (1.9)	197.1 (1.6)	191.6 (32.5)	197.5 (1.8)	70.6 (16.9)	197.6 (1.8)
	Us6	Mean (SD)	197.0 (1.5)	197.7 (2.0)	197.7 (1.6)	197.3 (1.9)	87.8 (21.1)	197.8 (1.5)

Note: Us1-2 is an ultrasonic sensor on the headboard, Us3-4 is an ultrasonic sensor on the left side of the bed and Us5-6 is an ultrasonic sensor on the right side of the bed, as shown in Figure 3.

The lying state meant that the subject was lying on the bed in supine, left lateral and right lateral sleeping positions, as shown in Figure 7(a)-(c). In this state, it was found that only the pressure sensor changed, while the ultrasonic sensors did not detect any object.



(a) (b) (c)

(d) (e)

Figure 7. Examples of bed postures and falling (a) supine, (b) left lateral sleeping position, (c) right lateral sleeping position, (d) sitting, and (e) falling off the bed

The sitting state meant that the subject sat on the bed, as shown in Figure 7(d). In this state, it was found that the pressure sensors Ps5 and Ps6 and the ultrasonic sensors Us1 and Us2 were changed simultaneously.

The falling state meant that the subject lay on the bed and then fell to either side of the bed (Figure 7(e)). In this state, it was found that only the ultrasonic sensors on the falling side were altered, while all pressure sensors on the bed showed no force applied to the sensors.

Therefore, we set the threshold for each sensor as follows. If the pressure sensor indicates 500 of 10-bit ADC value or more, it means that the sensor detects the sleeper. If the ultrasonic sensor indicating distance less than 100 cm (the half bed length), it means that the sleeper is detected.

3.1 Finite state machine

The sensors detection system, as shown in Figure 8, was composed of the headboard ultrasonic sensors, bedside ultrasonic sensors, and pressure sensors. The symbols denote the states as follows: O is the same state, X is both detected and not detected, U denotes the ultrasonic sensor when a subject stays within a detection range, P denotes the pressure value within the pressure measuring range and N denotes that there is no object detected either from ultrasonic or pressure sensors.

In the experiment, in order to see the changes from the sensors in the system in each state, the state and posture were roughly classified by our defined threshold. The working process of the system follows the concept of FSM as defined by the states and transitions. In this experiment, we considered three states and four transitions, which are explained as follows:

(1) The lying state: If the ultrasonic sensors (Us1 or Us2) and the pressure sensors detected the subject, the system was notified as the sitting state.

(2) The sitting state: If the ultrasonic sensors (Us1 and Us2) did not detect the subject, the system was changed to the lying state.

(3) The caregiver standing beside the bed: If the caregiver entered the detection range of the bedside ultrasonic sensor (Us3-6) while the sleeper was still lying on the bed, the system must not send an alarm.

(4) The falling state: If all pressure sensors (Ps1-Ps6) did not receive the pressure from the subject but either the right-sided ultrasonic sensors (Us3 and Us4) or the left-sided ultrasonic sensors (Us5 and Us6) detected the subject, the alarm system was activated as falling.

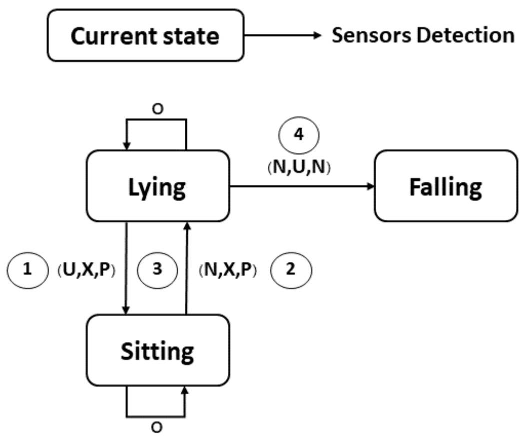


Figure 8. Finite State Machine

3.2 Application

After receiving the data from the sensors, the data was analyzed by the microcontroller Arduino Nano 33 IoT. The result was subsequently transmitted via Wi-Fi to be stored in the Firebase database and forwarded to the application on the android mobile device.

The applications in this research were developed by the MIT App Inventor [22]. It consists of a page showing the values from both the pressure sensors and the ultrasonic sensors. The pressure sensor page displays a digital value (10bit) measured with color gradients as follows: green (low pressure) in the range from 0 to 400, orange (medium pressure) in the range from 401 to 800, and red (high pressure) in the range of 800 and above.

Figure 9(a)-(d) shows the color gradients indicating possibility of particular movement patterns (supine, left lateral sleeping position, right lateral sleeping position, and sitting), which is planned for future development. Figure 9(e) displays the ultrasonic sensor page, showing values of detected distance. Figure 10 shows the notification on the bed: on-bed or fall. When the falling state is notified, the alarm system is activated until the stop button is pressed to reset the system.

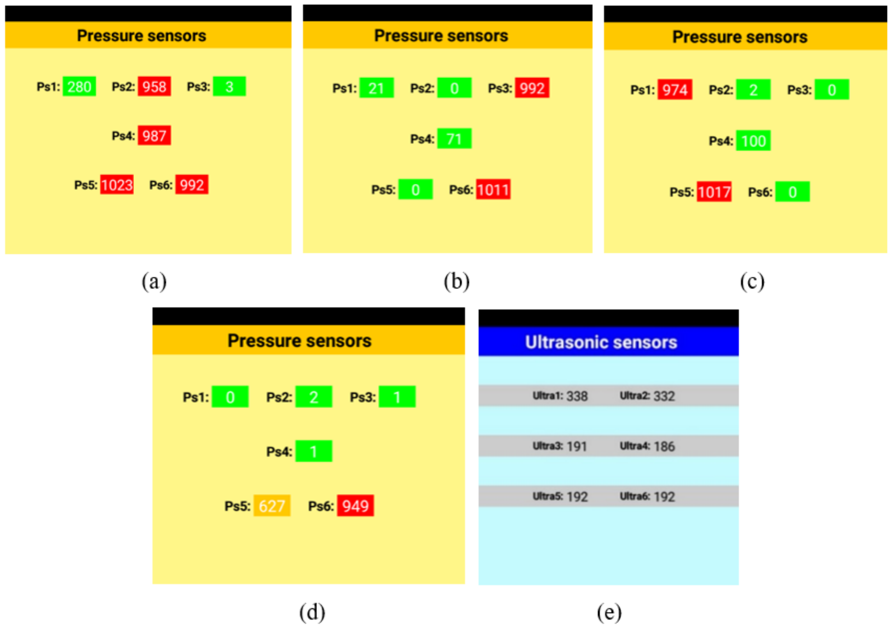


Figure 9. Examples of the application pressure sensors page (a) supine, (b) left lateral sleeping position, (c) right lateral sleeping position, (d) sitting, and (e) ultrasonic sensors page lying on the bed

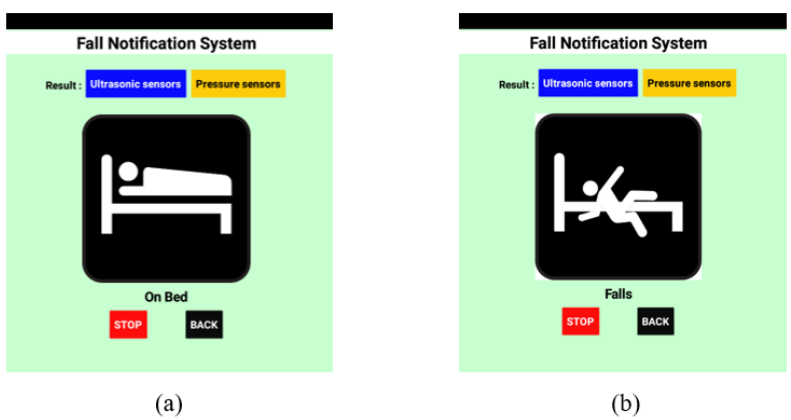


Figure 10. Examples of the application page shows (a) lying state, and (b) falling state

3.3 Evaluation

The performance evaluation of the proposed system was done by measuring using accuracy, sensitivity, and specificity, with parameters explained as follows:

A true positive (TP) occurs in the system if it produces an alarm correctly when the subject falls off the bed within 10 seconds. A true negative (TN) is indicated if the system finds no fall off the bed correctly when the subject is still in bed. A false positive (FP) occurs when the system sends a false alarm while the subject is still in bed. This parameter is tested by having others walk in and out beside the bed. A false negative (FN) in the system is when the system sends no alarm when the subject falls off the bed within 10 seconds. Accuracy, sensitivity, and specificity were calculated using the following equations.

$$accuracy\% = \left(\frac{TP+TN}{TP+TN+FP+FN}\right) \times 100 \quad (3)$$

$$sensitivity\% = \left(\frac{TP}{TP+FN}\right) \times 100 \quad (4)$$

$$specificity\ \% = \left(\frac{TN}{TN+FP}\right) \times 100 \quad (5)$$

3.4 Discussion

In this study, we used repeatability tests to evaluate the device performance and used the root mean squared error for analyzing the device error with the UTM as a reference. The average repeatability errors of the pressure and ultrasonic sensors were 0.27 and 1.78%, respectively, which showed that the devices were resonably stable. The root mean square error of the ultrasonic sensor was 0.23%, which was reliable compared to the reference device. The pressure sensor had a root mean square error of up to 23.98%. This may have been due to the sensor capbability or the circuit design. In order to reduce the error of the pressure sensing part, an operational amplifier circuit can be applied to increase the sensitivity and reduce the loading effect of the circuit.

The results of the system testing, as shown in Table 4, indicate that the bed-fall notification system achieved an accuracy, sensitivity, and specificity of 86.67%, 73.33%, and 100%, respectively. In the false positive cases, the proposed system yielded a perfect outcome. For example, in the scenario where a walk-in walked toward the bedside sensors while the subject was lying on the bed, the alarm system was not activated due to the walk-in. This shows that the proposed FSM approach was effective for the false positive cases. In the false negative cases, the system alarms after 10 seconds (the proposed system is set to alarm within 10 seconds after falling). This could be due to the lack of robustness and stability of the ultrasonic sensors as well as the interference of simultaneously in-use multiple sensors, leading to longer processing time. Alternative ultrasonic sensors can be taken into consideration to reduce the delay of notification time. In addition, the machine learning approach with additional parameters (e.g., weight and height of the volunteers) will be investigated to improve the bed-fall notification system's efficiency.

Table 4. Confusion matrix of actual vs system detected states

System detected state	Actual State	
	Falling	**Lying**
Falling	22	0
Lying	8	30

In this experiment, 6 pressure sensors were employed and placed on the bed according to the highly detectable locations from human body's pressure (back, shoulders, and bottoms). However, in fact, other parts of human body (such as head, chest, arms, and legs) should also be considered for better monitoring of patient's body postures and this might involve increasing the number of thin-film pressure sensors placed on the bed. This is based on the hypothesis that an increase in number of thin-film pressure sensors can effectively receive the data from the sleeper's body in different sleeping postures.

4. Conclusions

In this study, the automatic bed-fall notification system that used a combination of thin-film pressure and ultrasonic sensors was presented. This proposed system employed the Finite State Machine to examine three states (lying, sitting, and falling) and four changing conditions. The Internet of Things system was used to notify the falls via the application on an android mobile device from which an alarm to the caregivers could be sent. The results showed the promising outcome in terms of accuracy, sensitivity, and specificity at 86.67%, 73.33%, and 100%, respectively. In future work, the automatic bed-fall notification system can be improved by adjusting the circuits, increasing the number of thin-film pressure sensors, and by applying machine learning algorithms that include participants' profiles. Accreditation of the system will be submitted for approval. The accredited system can be beneficial for both young and elderly patients who stays in nursing homes, hospitals as well as their own houses.

5. Acknowledgements

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