Journal of Advanced Research in Applied Sciences and Engineering Technology 52, Issue 1 (2025) 151-162

SEMARAK ILMU PUBLISHING

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage: https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

Monitoring and Analysis of Human Activities Using Heterogeneous Sensors in the Gas Room of a Hospital

Plengpin Nupan[1], Apidet Booranawong [1], Dujdow Buranapanichkit[1,*]

[1] Department of Electrical and Biomedical Engineering, Faculty of Engineering, Prince of Songkhla University, Hat-Yai, Songkhla, 90110, Thailand

ARTICLE INFO

Article history:
Received 2 February 2024
Received in revised form 28 August 2024
Accepted 29 August 2024
Available online 1 October 2024

Keywords:
Monitoring system; accelerometer sensor; gas sensors; fall detection

ABSTRACT

Every hospital relies on the gas pipeline system. There is common three types of gases are used: oxygen, nitrogen, and nitrous oxide. Each type of gas is critical in many departments, including the operating room and intensive care unit. Gas room administrators, such as engineers or hospital personnel, are just as important as gas rooms. If something happens to engineers or personnel, an unattended gas room may malfunction and cause trouble in the hospital. Therefore, we proposed a monitoring system with a human activity surveillance project using accelerometer sensors, video images, and gas sensors. This system can collect all the signals used for the analysis of the posture or activities of the personnel who examine the gas in the gas room. We also developed surveillance in the event of an unexpected event in the gas room.

1. Introduction

The medical gas pipeline system is the heart of every hospital therefore there is a gas control room in the hospital. Taking care of the gas room requires an expert caregiver. These are engineers or personnel inside the hospital. They normally check the gas in the gas chamber every day. Inside the gas room is quite dangerous because it is a cramped space with moderately warm temperatures. Technically, the current permissible limit for harmful gases such as nitric oxide (NO) and carbon monoxide (CO) is 25 and 50 ppm during an 8-hour time period. If a toxic gas's concentration is more than 200 ppm, it is hazardous. There also may be dangers from congenital diseases of the personnel or engineers themselves. Therefore, for safety and timely assistance to engineers or hospital personnel, a system for tracking the walking posture of engineers or personnel while working in the gas chamber is very significant.

A fall detection system was introduced by Irwan *et al.,* [1]. The idea of develop a wearable device with an accelerometer and gyroscope sensor [2] that can detect falling. The device is placed in the position of the waist. It describes the nature of the three falling accidents such as falling forward, to the right, and to the left. The system chose to use all sensors and transmit data via Bluetooth wireless communication [3] to a computer. By comparing the results, the falling threshold values can be

[*] *Corresponding author.*
E-mail address: dujdow.b@psu.ac.th

https://doi.org/10.37934/araset.52.1.151162

obtained. The system can detect the fall with a simple design. This research [4] realizes the problems and importance of caring and monitoring for the health of the elderly. Accelerometer sensors embedded in smartphones [5, 6] provide information about user activity, which is widely used in fall detection. We have studied and analyzed the limitations of currently available applications, including their limitations. It develops new efficient algorithms to be a model for monitoring the healthcare of the elderly [3, 7, 8]. From the trend of daily activities that occur from wearable devices [1, 9, 10, 11, 12] or smart devices. Model presentation simulates the behavior of each elderly person differently from daily physical activity data to develop further into innovations in the form of applications. It can serve the elderly who need care and monitoring Including warning of dangers to caregivers of the elderly so that they can save lives in time.

We proposed the human activity detection using heterogeneous sensors for a gas room in hospital. Many sensor types are more effective and flexible with less deployment cost, and coverage communication. This is a dominant system for people working in high-risk areas. The signal detected by the engineer or personnel entering the gas chamber has been read the vibration values and sent a signal to the receiver, thus allowing us to monitor and help personnel promptly. The method has been described in next section. Section 3 and 4 show the experimental results and conclusion respectively.

2. Methodology

In general, a medical gas pipeline system is the key of every hospital, therefore it is necessary to have a gas room. The inside of the gas room is hazardous as it is closed and noisy. Moreover, the gas chamber has a hot and humid climate. It may cause bad symptoms to the gas room inspector. Hazards may arise from congenital diseases of engineers or hospital personnel. The objective of the system is to measure the activity signals of authorities who maintain the gas in the gas chamber. We can count gas leaks and make a video recording. The system analyzes the obtained signals to be used to notify in the event of an unexpected accident.

2.1 System Equipment

Figure 1 shows the system architecture.

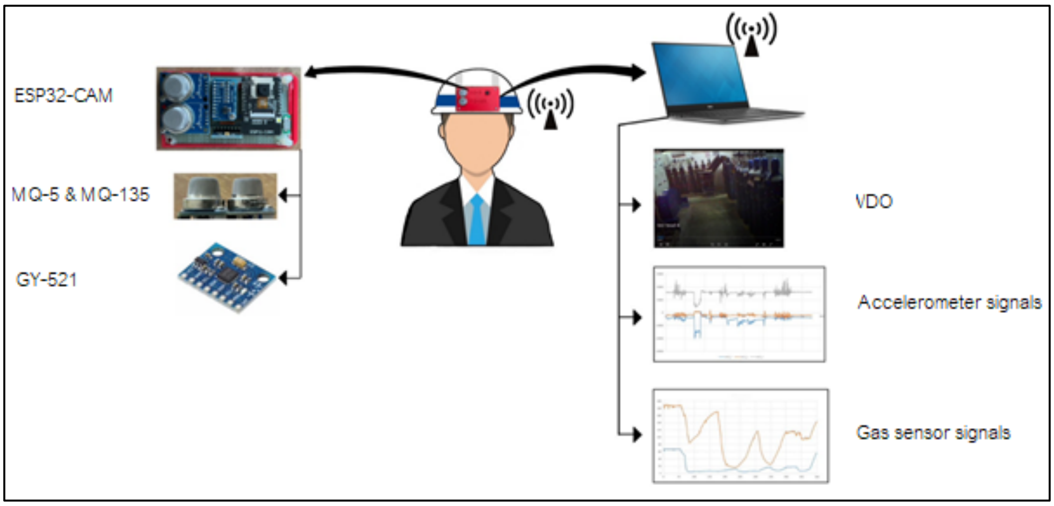


Fig. 1. Overview of the system architecture

2.1.1 Input section

Our system consists of the three-axis Accelerometer/Gyro Module using MPU6050 (GY-521) with acceleration ranges of ±2, ±4, ±8, and ±16 g. The accelerometer module measures three axes x, y, z. When we tilt the module with the angular rate measured by the accelerometer and the angular velocity measured by the gyroscope. It is used to measure signals, postures, and activities of engineers and personnel in gas chambers. The ESP32-CAM module is an ESP32 Wi-Fi module with a built-in miniature video camera. It supports Wi-Fi image upload with a transfer rate of 15 to 60 fps. This can assist with new features like surveillance or the ability to capture any video while a person is away and transfer it to any device for recording and monitoring. This system uses the ESP32-CAM module as a video transmitter and recorder. Additionally, there are two gas sensors. MQ-5, is used to measure gas, LPG, natural gas, alcohol, and various smokes. While, MQ-135 is used to measure NH_3, NO_x, alcohol, various fumes, carbon dioxide, and various types of flammable gas.

2.1.2 Output section

We connect various devices to the same circuit board and then put them in a box for the convenience of attaching the device to a helmet that has a power bank with a capacity of 5000 mAh/25WH as the power source. The expected battery life is approximately 4-6 hours. We can use the power bank's own power indicator to check whether the power level is low. There are three outputs: a video image, a signal from the accelerometer, and a signal from the gas sensor. When personnel or engineers start any activities inside the gas room, the accelerometer measures walking posture and various activities, while the camera from ESP32-CAM captures a video when walking and gas sensors detect gas leaks.

2.2 Test Scenario

Our scenario has proposed three test cases for studying this system. The study is a collection of signal data generated from the activities of engineers working from the moment they enter the gas chamber until they walk out of the room. The test case I is gesture detection for test activities that engineers or personnel within the hospital do regularly. It starts from the steps below.

I. A: Held still and then walked toward position two as seen in Figure 2(a) with eleven steps.
B: Bent down to check the belt. After that, walk straight to number three eight steps.
C: Move the cart used to carry the gas tank, push it back four steps and forward another four steps, then turn around and walk back to the starting point, which is point four as seen in Figure 2(a).

Next is test case II. The objective of this test is to detect the signs of falls. It begins with the procedures below.

II. A: Stand still, and walk to number three as seen in Figure 2(b) with eleven steps.
B: Fall as seen at number two in Figure 2(b).
C: Sit up, then stand up as demonstrated at number three in Figure 2(b), and then walk ten steps back to position four or the starting point.

The final test case III is testing the case of walking upstairs using a ladder. It starts with the following steps.

III. A: Stand still and then walk twelve-foot steps towards number two as seen in Figure 2(c).
B: Walk up two steps with a ladder to position number three as seen in Figure 2(d).
C: Turn your body to the right and then check the valve. After that, walk down the stairs and walk ten steps to number one as seen in Figure 2(c) or the starting point.

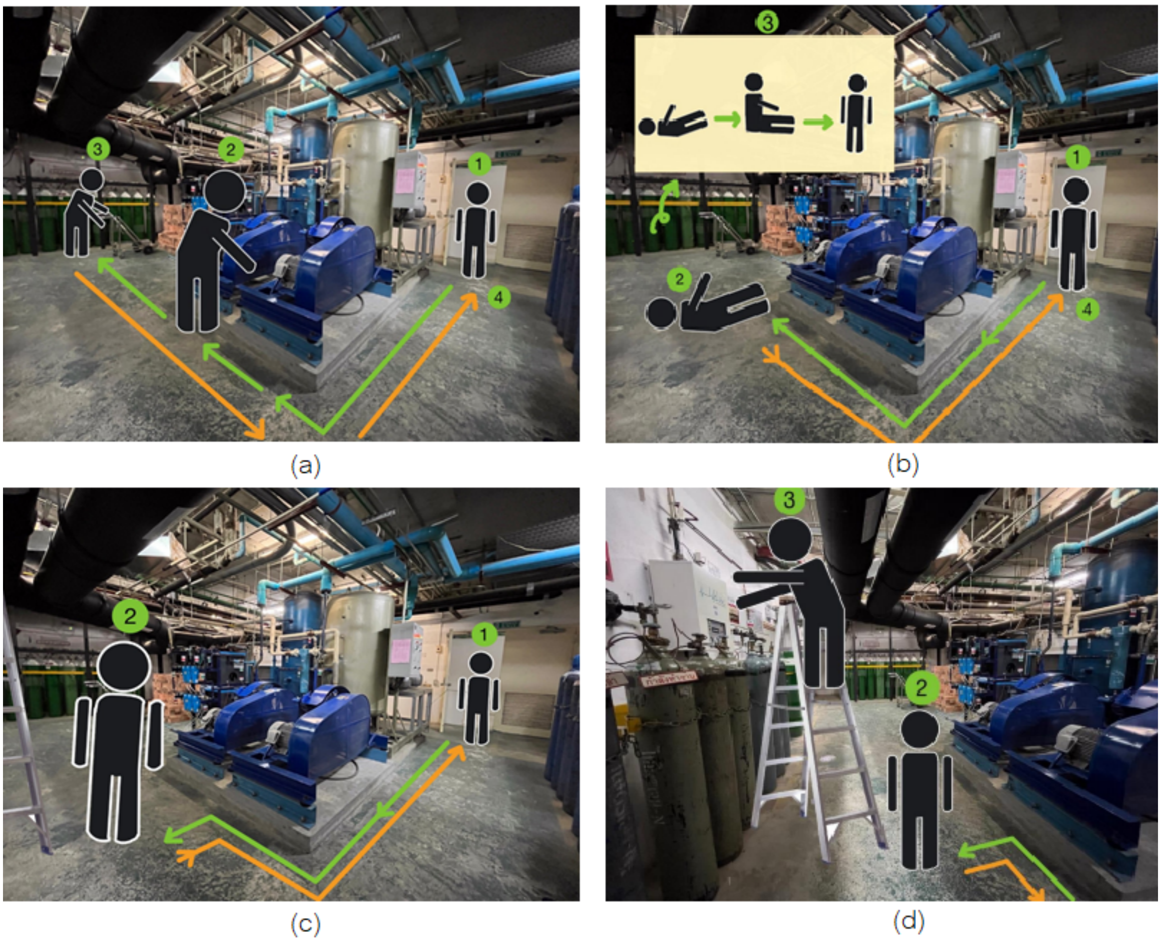


Fig. 2. Pattern of activities (a) test case I (b) test case II (c and d) test case III

2.2 System Equation

The output will be an accelerometer signal with 3 axes: the x-axis, the y-axis, and the z-axis. Then, the system takes the X-axis, Y-axis, and Z-axis signals to find the net force or signal vector magnitude using Eq. (1) as follows.

$$\text{Accelorometer} = \sqrt{Ax^2 + Ay^2 + Az^2} \tag{1}$$

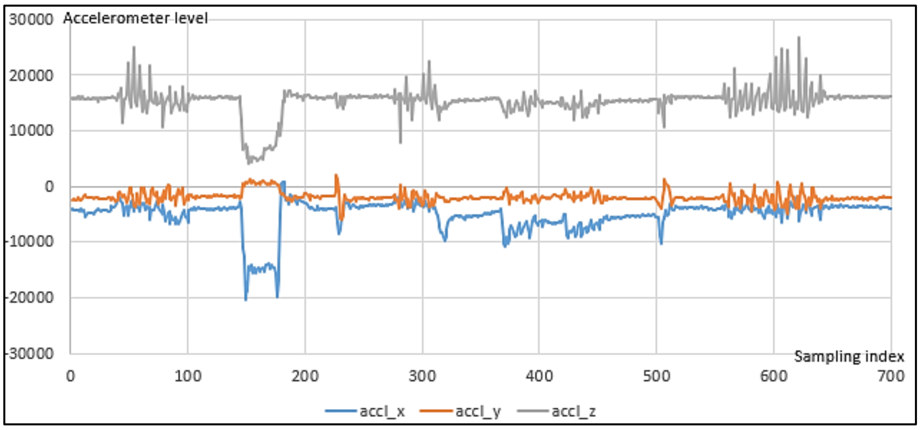
3. Results
3.1 Accelerometer

The gadget will be tested while the experimenter is wearing a helmet. An accelerometer signal with three axes, the X-axis, the Y-axis, and the Z-axis will be produced for three test cases, as illustrated in Figures 3(a) to 5(a) for each test scenario. The accelerometer level displays the unit of gravity, g. One g is approximately 9.8 m/s^2. While the sample data has been taken in every 250 milliseconds. The X-axis, Y-axis, and Z-axis signal can be calculated as the net force as in Eq. (1). The finding results have been demonstrated in Figure 3(b) to 5(b) for each test case. We measure the activity signals of officials who enter to inspect the gas chamber and store them as a database for use in signal classification. We can analyze and notify an alert timely If there is an accident in this room.

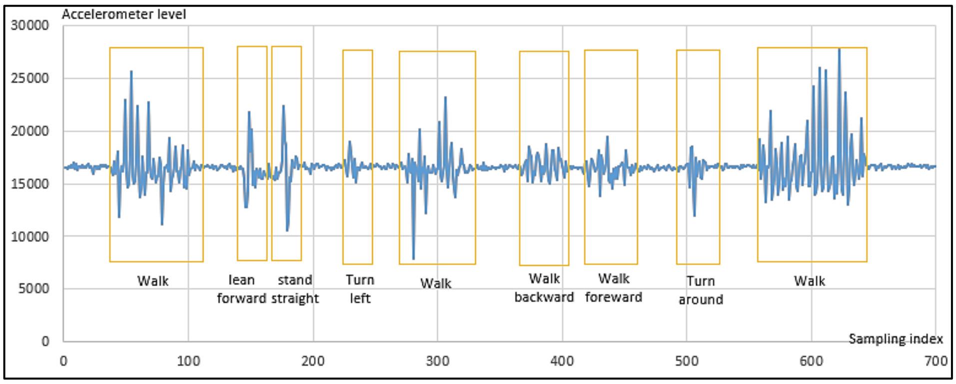
3.1.1 Test case I

The configuration for this experiment is shown in Figure 2(a). The test case is a gesture detection test, which engineers or healthcare staff members do frequently. The gas chamber inspector's regular activities include the inspection of belts and the transportation of gas tanks. It begins with the processes from number one to four in Figure 2(a).

In this test case, it can be seen that the received signal will be in accordance with the activities that the experimenter has done. For example, when walking eleven steps, the amplitude of the signal will oscillate eleven times as seen in Figure 3(b). An example of a recorded video during the experiment for this test case as seen in Figure 3(f), however, it will be recorded at the same time as collecting the signal to monitor the activities.



(a)



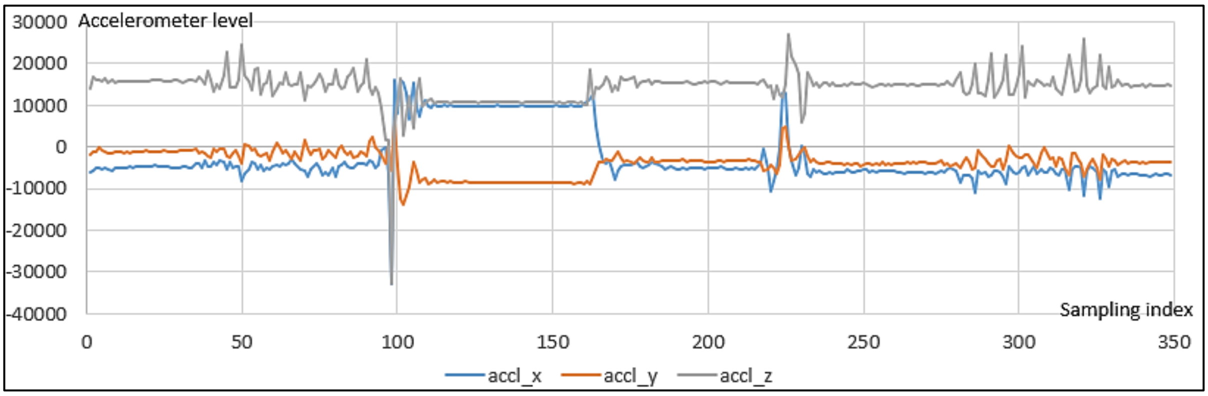
(b)

(c)

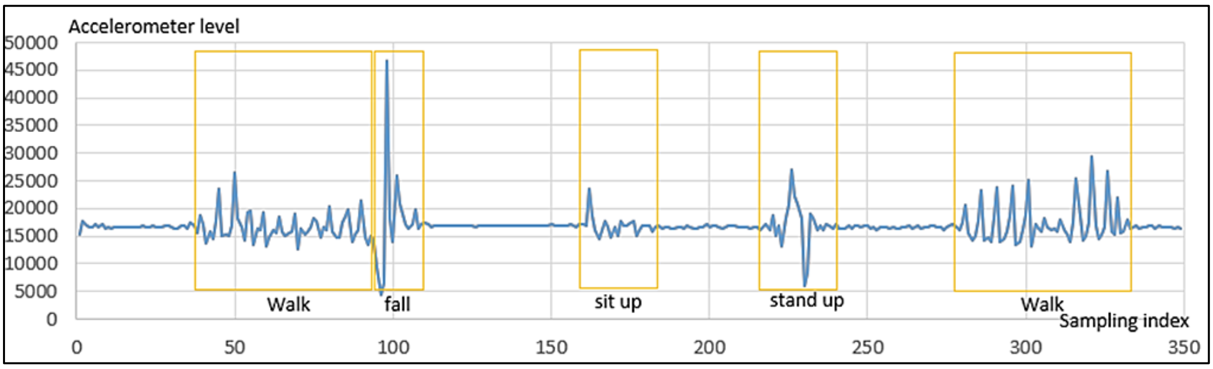
Fig. 3. Test case I (a) Displaying Ax, Ay, and Az signals (b) showing the resultant force (c) video from ESP32-CAM

3.1.2 Test case II

This test aims to observe fall warning indicators. It starts with the following steps from position one to four as shown in Figure 2(b). From Figure 4, it can be seen that the walking signal and falling signal are different significantly. There will be a swing down before the falling signal, then ascend to a very high elevation and stand stationary. Regarding walking, it would depend on how many steps the experimenter took.



(a)

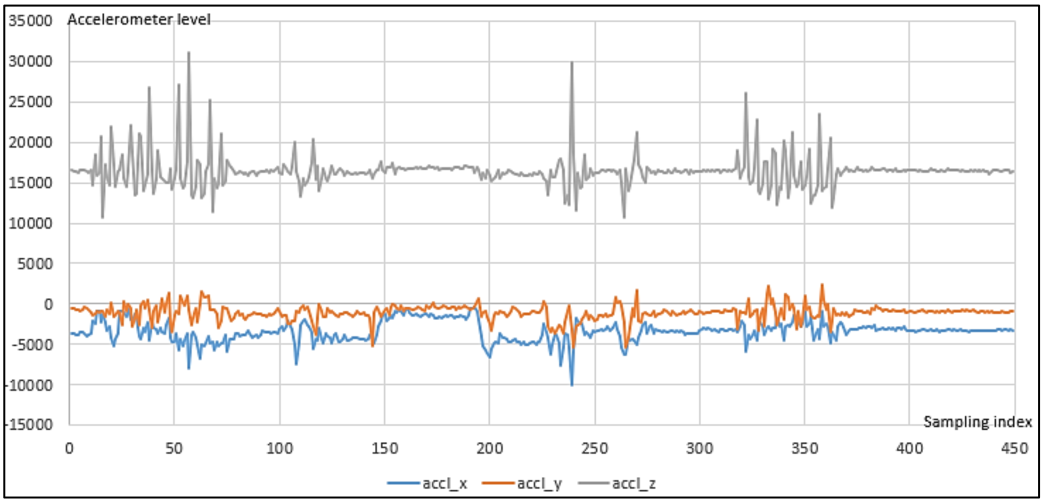


(b)

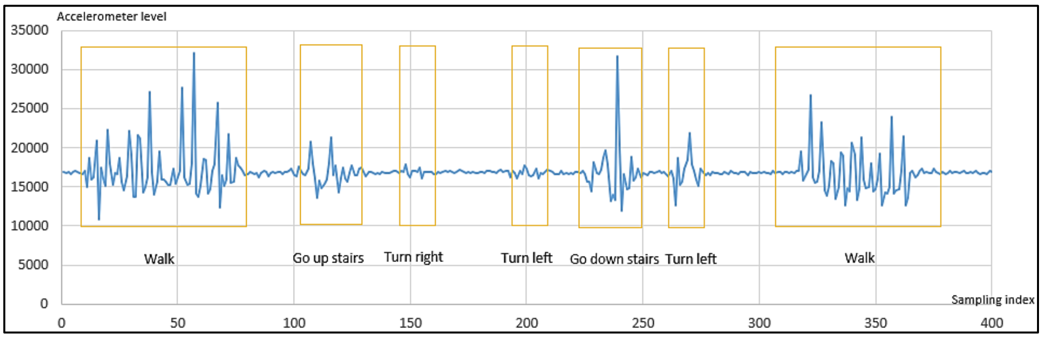
Fig. 4. The Ax, Ay, and Az signals (a) net force (b) are shown in test Case II

3.1.3 Test case III

In this test case, the use of a ladder to get upstairs is hypothetically tested. As seen in Figures 2(c) and 2(d), it begins with the steps from point number one to three, then goes back to point number one. It can be seen that the signals for going up the stairs and going down the stairs are different as seen in Figure 5. The signal going down the stairs has a higher amplitude because the acceleration signal follows the earth's gravity.



(a)



(b)

Fig. 5. Test Case III (a) The Ax, Ay, and Az signals are displayed (b) The resulting force is displayed

3.2 Heterogeneous Sensor

Our system has other sensors in addition to an accelerometer. Testing of five gases: oxygen, carbon dioxide, LPG, nitrogen, and nitrous is for a gas room size of 6x4 m^2. In order to determine if there are two different sorts of gas sensors in this experiment, each type of gas will be gradually turned on. These two sensors, MQ-5 and MQ-135, are air quality sensors that can detect NH_3, NO_x, alcohol, benzene, and CO_2. There are several models, different features, and preheating periods for the MQ gas sensor series. Which one detects which type of gas? The results will be shown as follows.

It is known that the gas room comes out is around 200-300 ppm, which suggests the room may be regarded safe to be inhabited, while the findings are approximately 400-800 ppm, which indicates it is not advisable to stay in this room. From Figure 6(a), it can be seen that the sensor that can detect oxygen gas is the MQ-135 because the MQ-135 can detect flammable gas. From signal analysis, when oxygen gas is released, the amplitude of the signal will be lower. On the other hand, when the oxygen gas is turned off, the amplitude gradually returns to the normal signal. Nevertheless, both the MQ-135 and MQ-5 can detect carbon dioxide because the MQ-5 can detect various smoke gases, while the MQ-135 has the ability to detect carbon dioxide only as seen in Figure 6(b). We can see that the signal curves of both MQ-5 and MQ-135 are similar and both can detect carbon dioxide. Analyzing the graph as seen in Figure 6(c), you will find that when nitrogen gas is emitted, the amplitude of the signal becomes lower. Vice versa when turning off the gas, the amplitude of the signal will return to its original form. Moreover, it can be seen from Figure 6(d), that the signal graphs of MQ-135 and MQ-5 can both detect LPG gas because the MQ-5 can detect LPG gas specifically, while the MQ-135 has features for detecting various flammable gases. As a result, both signal graphs seem identical. It can be concluded that both the MQ-5 and MQ-135 can be used to detect LPG gas. Finally, it can be seen from Figure 6(e) that the sensor that detects nitrous gas well is the MQ-135. When analyzing the graph, it is found that as nitrous gas is released, the amplitude of the signal becomes lower and lower. In the other direction, when the gas is turned off, the signal's amplitude will revert to its initial state.

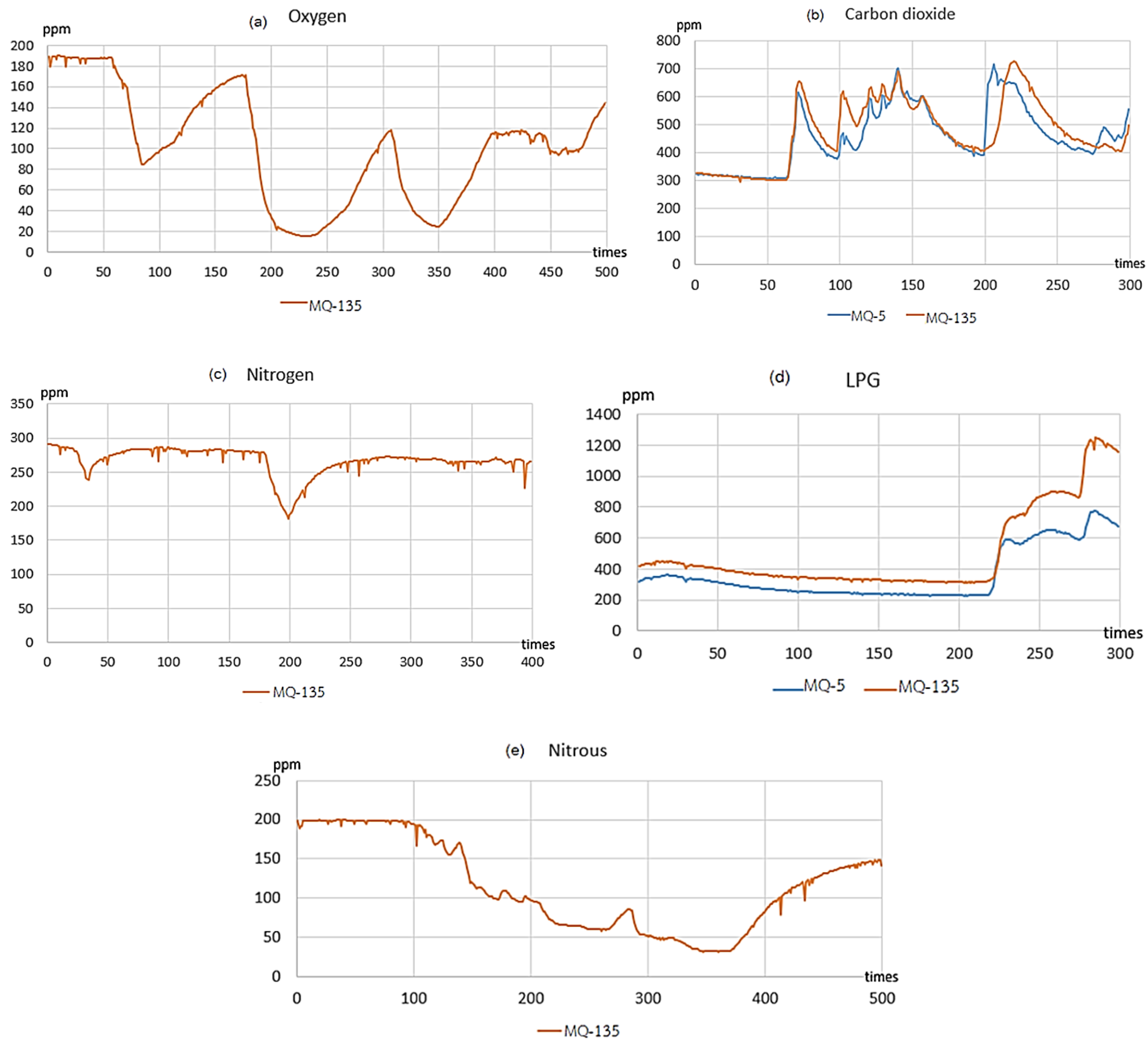


Fig. 6. Test case for gas sensors (a) Oxygen (b) Carbon dioxide (c) Nitrogen (d) LPG (e) Nitrous

3.3 Fallen People Prediction

From the experiment, our system has been done three times with the first two times being the database and the last being the test. We select the two experimental sets to be the database to find the Max, Min, and Max-Min value of the signal in each posture for example standing still, walking, falling, sitting up, and standing up, after that it has been averaged together. According to the study, the situation will be one of falling. The results from the calculation are shown in Table 1 for the Database. We also choose the third experimental result in each posture for test case II and find the values Max, Min, and Max-Min and then get the results as shown in Table 2 for the Test. Test case II consists of the signal separation and fall notification activities.

Table 1
The values of max, min, max-min of the database

Activities	Stand	Walk	Fall	Sit up	Stand up
Max	16985	29395	46681	23528	26990
Min	16352	13106	4256	14405	5893
Max-Min	623	16279	42415	9113	21086

Table 2
The values of max, min, and max-min of the test

Activities	Walk11	Fall	Stand2	Sit Up	Stand3	Stand up	Stand4	Walk10
Max	27982	42389	17240	20289	17099	28647	16814	27791
Min	9392	8438	16953	11635	1603	7535	16189	13302
Max-Min	18590	33951	287	8654	1006	21112	625	14689

It uses the equation ABS (Test(n)-Database) to find the smallest value. We formulated an equation to distinguish between various signal types and identify falls. It starts by using the max feature, and then continues with min and max-min features respectively. After we find the features of the gestures in each phase of the activity then write the conditions for classifying gestures. There will be five main conditions as follows:

i. If the value of the activity from entering the equation ABS(Test(n) - Database) has the smallest value in the field of Stand, set to 0.
ii. If the value of the activity from entering the equation ABS(Test(n) - Database) has the smallest value in the field of Sit up, set to 1.
iii. If the value of the activity from entering the equation ABS(Test(n) - Database) has the smallest value in the field of Stand up, set to 2.
iv. If the value of the activity from entering the equation ABS(Test(n) - Database) has the smallest value in the field of Walk set to 3.
v. If the value of the activity from entering the equation ABS(Test(n) - Database) has the smallest value in the field of Fall, set to 5

The designated number with an asterisk indicates that the findings still contain inaccurate predictions as seen in Table 3. There is an alternation between predicted walking to standing up, and predicted standing up to walking. As a result, the max feature's output still produces incorrect results of 37.5%. However, in other postures such as falling, standing still, and sitting up, there are accurate results.

From Table 4, it can be observed that the results still have incorrect predictions with a star (*) symbol. In particular, falling is predicted to be standing up, which affects the use of the results in warning of people falling. It can be concluded that the results from using the Min feature have many errors and inaccuracies.

Table 3
Max feature for activity classification

Test	Database					Prediction result
	Stand (0)	Walk (3)	Fall (5)	Sit up (1)	Stand up (2)	
Walk11	10997	1413	18699	4454	*992*	2*
Fall	25404	12994	*4292*	18861	15399	5
Stand2	255	12155	29441	6288	9750	0
Sit Up	3304	9106	26392	3239	6701	1
Stand3	114	12296	29582	6429	9891	0
Stand Up	11662	748	18034	5119	1657	3*
Stand4	171	12581	29867	6714	10176	0
Walk10	11006	1404	18690	4463	1001	2*

Table 4
Min feature for activity classification

Test	Database					Prediction result
	Stand (0)	Walk (3)	Fall (5)	Sit up (1)	Stand up (2)	
Walk11	6960	3714	5135	5013	*3498*	2*
Fall	7914	4668	4182	5967	*2545*	2*
Stand2	*601*	3847	12697	2548	11060	0
Sit Up	4717	*1471*	7379	2770	5742	3*
Stand3	*259*	2987	11837	1688	10200	0
Stand Up	8817	5571	3279	6870	*1642*	2
Stand4	*168*	3083	11933	1784	10296	0
Walk10	3050	*196*	9046	1103	7409	3

There are no inconsistencies between the results as seen in Table 5. The outcomes of each pose's forecast are exactly as expected and correct. Therefore, it can be concluded that using the Max minus Min feature is suitable for use in gesture classification. In the case of an accident, it can describe the nature of the activity that can be employed to prevent falls. However, uncertainty in the data might be obtained if the sensors are not functioning properly or not correctly attached to their position. In addition, multiple falling tests may cause the sensor damage and variations in the data measurement.

Table 5
Max-min feature for activity classification

Test	Database					Prediction result
	Stand (0)	Walk (3)	Fall (5)	Sit up (1)	Stand up (2)	
Walk11	17967	*2311*	23825	9477	2496	3
Fall	33328	17672	*8464*	24838	12865	5
Stand2	*336*	15992	42128	8826	20799	0
Sit Up	8031	7625	33761	*459*	12432	1
Stand3	*383*	15273	41409	8107	20080	0
Stand Up	20489	4833	21303	11999	*26*	2
Stand4	*2*	15654	41790	8488	20461	0
Walk10	14066	*1590*	27726	5576	6397	3

Results from signal analysis for gesture classification of nature activities and notification of a fall use a k-nearest neighbors algorithm to find the nearest neighbors. The experiment was performed three times with the first two times being the trained data (Database) and the last being the validated data (Test). The case used in the analysis will be falling because the purpose is to warn of falling in the event of an accident. We can describe the nature of the activity and classify gestures. The results from using each feature are as follows.

i. Using the max feature, the results are still inaccurate. It alternates outcomes between the expected results of standing up and walking. Nevertheless, the predictions were correct for other positions. The accuracy is just 62.5%.
ii. Because the min function predicts that the user would fall to standing, the results are incredibly wrong. This has an impact on the usage of the results of falls and accident warnings. While the precision is only 62.5% same as using the max feature.
iii. Using the max-min feature, the results come out without any errors or discrepancies. max minus min feature can predict posture accurately 100% and describe the nature of the activity according to our goal of fall detection.

To sum up, it is a suitable feature for creating fall notifications. Describing the nature of the activity and the pose classification is the max-min feature because this feature has accurate prediction and the least error. This is also a simple method for activity classification. We believe that in order for the results to be closer to reality, there should be a large number of experimenters. It would improve the system to ensure accuracy in the future.

4. Conclusions

Different activities are detected by heterogeneous sensors such as gas sensors, video cameras, and accelerometers. Results from the signal obtained from all sensors, which were used to identify gas leaks, as well as the workers in the gas chamber walking normally, falling, and moving upstairs, were evident. It is possible to utilize this to keep a database for signal categorization. It can be operated to send out alerts in a timely manner using the max-min feature which has 100% accurate prediction for this system in the case of an accident.

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