A Simple and Real-Time Support System for Firefighters Using Low-Cost 3-DOF Accelerometer and CO Sensor

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Abstract—During the operations, firefighters can be injured or killed because of the smoke and heat emission from the fire area, broken structure elements such as floors, walls, or boiling liquid ejection and gas explosion. Therefore, this paper aims to develop an efficient and portable system to monitor falls and high CO level through integrating a three degrees of freedom accelerometer and an MQ7 sensor to recorded acceleration and measured CO concentration with the embedded fall and high CO level detection algorithms. The embedded fall detection algorithm can detect fall events with high accuracy without mistakenly identifying normal activities such as walking, standing, jogging, and jumping as fall events. The posture recognition and cascade posture recognition after three seconds are proposed in this paper to gain the accuracy of our proposed fall detection system. If a firefighter falls and is unable to stand up, the alert message will be sent to their commander at the outside through the GSM/GPRS module. The embedded high CO detection algorithm used to alert the dangerous CO level to recommend using self-contained breathing apparatuses (SCBA) and saving fresh air with acceptable CO level. We carefully investigated the proposed thresholds and window size before embedding them into the microcontroller. The sensitivity and accuracy achieved were around 96.5% and 93% respectively in our recorded data. Furthermore, the proposed fall detection algorithm also achieved higher geometric mean in comparison with Support Vector Machine classifier (SVM) and a nearest neighbor rule (NN) in the public datasets with the achieved around 99.44%, 98.41% and 95.76% respectively.

Keywords—firefighters, fall detection, posture recognition, cascade posture recognition after 3s

1 Introduction

Fires and explosions can occur at any time and they can be started by a number of causes such as electrical impact, children messing, fire spark, gas leaks, etc. [1], [2]. In Vietnam, thousands of fires are reported annually; for example, there were 2357, 2792 and 5354 reported fires in 2014, 2015 and 2020, respectively, resulting in a large number of deaths and injuries [1], [3]-[4].

In US, there were 1,291,500 fires [5], leaving 60,825 on-duty firefighters injured in 2019. The figure increased by 4% compared to that of 2018 [6]. Firefighter injuries are caused in various ways: overexertion, strain, fall, jump, slip, trip; exposure to fire products; contact with the object; exposure to chemicals or radiation, and so forth, as shown in Figure 1. It indicates that firefighters continuously face a variety of dangers during their duty performance. Several studies focus on developing the support systems for firefighters in the line of duty, such as the fall detection systems and PASS (Personal alert safety system) system [7]. Nevertheless, most fall detection systems available on the market were only used for the elderly with mobility deficits [8]-[14], thus being unsuitable for firefighters working in the fire environment conditions or inapplicable to work in fire conditions. For example, the study [10] proposed to use Kinect sensor of Microsoft for fall detection which revealed limitations when being applied in fire conditions. Smoke generated by the fire can create invisible environment; thus, applying camera in these conditions is ineffective. The publication [11] recommended the combination of location sensors and accelerometer. After being recorded, the data is preprocessed and used for activity classification and fall detection. Nevertheless, this method proposed to mount sensors at multiple positions on the wearer's body, namely chest, waist, and ankle. This may create inconvenience for firefighters during performing their tasks.

The use of smartphone built-in sensors for fall detection has also been widely suggested in recent studies [15]-[17] due to the popularity of smartphones. Instead of developing a new fall detection system, we only need to focus on building fall detection software programs for operating system of smartphones such as Android, iOS, etc. However, the accuracy of the proposed algorithms may decrease when these softwares are applied on different kinds of built-in accelerometers in smartphones [18]. Furthermore, the incoming and outgoing calls may also affect the performance of fall detection algorithm in these smartphones while the injury detection system for on-duty firefighters requires high accuracy and stability.

Wristbands and smartwatches [19] have been widely employed for fall detection in recent studies because of the convenience. People can wear these devices on their wrists, which is one of the most comfortable positions. However, frequent hand movements in users can create wrong decision since it is difficult to distinguish between normal activities and fall events [20].

Homeland Security developed the PASS system; it can sense the lack of motion. If the lack of motion exceeds a specific period of time, this device will activate a 95-decibel alarm. Nevertheless, there are various noises in fire areas like a person's voice, the siren and bell from fire alarm systems, fire truck siren and fire pump running, etc. making the PASS system ineffective in case of a big fire. One typical example is that six and nine firefighters were killed because of the fires in the Worcester cold storage and warehouse Co. at 266 Franklin street Worcester, Massachusetts, and in the Charleston Sofa Super Store in Charleston, South Carolina although they have been equipped the PASS system [21]-[22].

The Proetex project [23] proposed to develop a system which integrates multi-sensors to monitor users' health state including heart rate, breathing rate, body temperature and blood oxygen saturation and environment parameters, such as environment temperature and toxic gases. However, the proposed prototype is still at early state and simple without any specific application scenario [24].

The publication [25] focused on developing a wearable system to monitor physiological states of firefighters through using of accelerometers, which measured respiratory cycle and heart rate in order to monitor wearer's health conditions instead of detecting on-duty firefighters' injuries. Furthermore, this system has been evaluated on both women and men, and it seems inappropriate in case of applying for on-duty firefighters who work in fire conditions. It is more suitable to monitor firefighters' health during training or drilling.

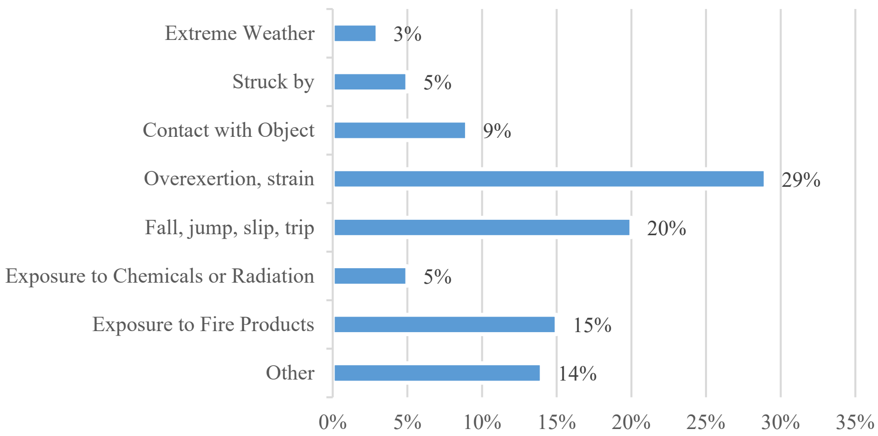


Fig. 1. The cause of US Firefighter injuries in 2019 [6]

Based on above literature review it can be seen that although a myriad of studies have been conducted to develop systems to detect fall events in the elderly and monitor physical health of firefighters, these algorithms are inapplicable to detection of injured on-duty firefighters. To solve these limitations, we propose developing a system that embeds our proposed algorithms to support firefighters while conducting their tasks. The proposed system is simple, yet it works well in both normal and fire environments with high accuracy. The proposed algorithm combines the fall detection module and posture recognition module without depending on a pre-install structure like transmitters or access points. Suppose a fall event satisfies both fall detection and posture recognition conditions. In that case, the cascade posture recognition will be used after 3 seconds to re-check the fall event to confirm whether it is a fall. Then, the CO detection module is used to measure CO levels in the fire environment. If the CO concentration is higher than the predetermined threshold, the system will send an alert signal to firefighters to recommend using the self-contained breathing apparatus (SCBA). Otherwise, our proposed support system will give a safety signal to recommend saving the fresh air in SCBA for other urgent situations.

2 Methods

2.1 The proposed system

We use the ADXL345 accelerometer from Analog Devices in this research and I^2C interface (Inter-integrated Circuit) to connect the accelerometer and MQ7 sensor with the Microcontroller Unit (MCU). The MCU used in this research is Pic18F4520 from Microchip. Furthermore, as the firefighter's activities are quicker and more substantial than the elder, we proposed that the sampling frequency of accelerometer equals 100 Hz along the A_x, A_y, and A_z axes. The sampling frequency of the MQ7 sensor equals 10 Hz to measure CO concentration. The chosen sampling frequency of 10 Hz in measuring CO concentration will save energy because the step frequency of people in all walking states (fast walking, normal walking and slow walking) is usually lower than 3Hz [26]. Hence, this chosen sampling frequency can work in real-time to measure CO concentration to support on-duty firefighters. The UART (Universal Asynchronous Receiver/Transmitter) is applied to send data from MCU to the computer for analysis. Furthermore, when a firefighter falls without standing up by himself, an alert message will be sent to their commander outside through the SIM900 module. The details of the proposed system is shown in the Figure 2:

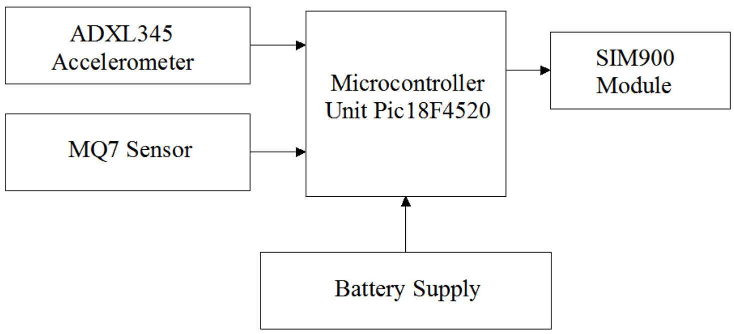


Fig. 2. The block diagram of our proposed system

In comparison with those proposed by other publications in the literature review, our system has several advantages as it uses a specific accelerometer with suitable proposed calibration methods and embedded algorithms. Hence, it works more stably than other methods such as the ones which use smartphones, wristbands or smartwatches. Furthermore, the system is not affected by incoming and outgoing calls as in smartphones or hand movements as in wristbands and smartwatches.

2.2 CO detection module

As it is known that CO is one of the most dangerous toxic gases that directly affect people's lives. Hence, the integrated CO sensor in our proposed system with the embedded algorithm to detect the high CO level in the fire environment is very essential.

In this research, the MQ7 sensor was chosen to be integrated into our proposed system because it gives high reliability and accuracy with low energy consumption and cost. The MQ7 sensor is located at the outside of the mask as shown in the Figure 3. The CO concentration estimation and high CO detection algorithm can support firefighters in using the SCBA device because it has limited working duration of about 30, 45, or 60 minutes [27], depending on the device's capacity. The working time of firefighters is unpredictable as it varies according to the fire. Therefore, the CO detection module will detect the CO concentration in the environment. The CO proposed threshold was chosen based on the experimental testing and the previous publications as shown in Table 4. If the CO level exceeds the proposed threshold, an alarm signal will be sent to alert firefighters. Based on the alarm signal, the firefighters will decide to use air supporting device. Inversely, the firefighters can decide to remove the breathing apparatus to save fresh air in the cylinder for the dangerous situations.

Fig. 3. The CO sensor position on the mask

2.3 The proposed fall detection system

The firefighters are physically healthy; thus, their falls are frequently associated with causes such as toxic gases, gas explosion, boiling liquid ejection, or damage of floors and constructional elements, etc. Figure 4 shows the embedded algorithm. Firstly, the accelerometer will record the signal along the A_x, A_y, and A_z axes. Then, the recorded accelerations will be used in both fall detection and posture recognition algorithms. The final decision will use cascade posture recognition after 3s to confirm a fall event. Using cascade posture recognition after 3s improves significantly the performance of the proposed fall detection system as it can reduce and prevent false alarm in case the firefighters can self-recover after falling.

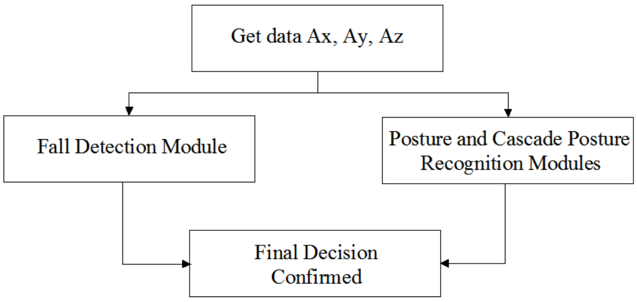


Fig. 4. The block diagram of our proposed fall detection system

The posture recognition algorithm. The posture recognition algorithm will determine firefighters' states comprising walking, standing, lying, and Null state (Null state defines as the state of non-movement). In Figure 5, A_n is the L2 norm of three acceleration axes, as shown in formula 1 below:

$$A_n = \sqrt{A_x^2 + A_y^2 + A_z^2} \quad (1)$$

The sliding window size is formulated as:

$$W_m = [A_n \quad A_{n-1} \; \dots \; A_{n-34}], \quad (2)$$

where, m is the number of samples. The following formula will compute the zero-crossing rate (ZCR):

$$ZRC_n = \sum_{i=0}^{m-2} (A_{n-i} - DC < \delta)(A_{n-i-1} - DC > \delta), \quad (3)$$

$$DC = \sum_{i=0}^{m-1} \frac{A_{n-i}}{m}, \quad (4)$$

where DC is the averaged value of m samples of the A_n and δ is the threshold to compute the zero-crossing rate.

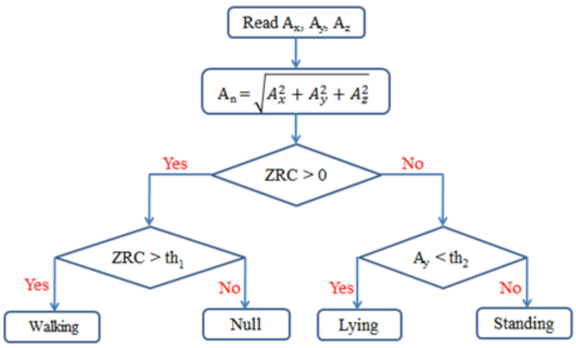


Fig. 5. Flow chart of posture recognition

By comparing ZRC with the proposed thresholds th_1 and th_2, we can recognize four postures: walking, lying, standing, and Null states. Then, these identified states will be assigned by the values shown in Table 1, with the 2nd column being used for illustrating; the 3rd column being used for determining the fall events with the value 0 in the 3rd column means no fall event occurred, and value 1 indicates the fall event has occurred.

Table 1. The assigned values for different postures

The States	Values for illustration	Decision values
Walking	2	0
Standing	4	0
Lying	10	1
Null	15	1

The proposed fall detection algorithm. The proposed fall detection algorithm based on the difference between the maximum peak and minimum valley in the proposed window size as below:

$$D_n = A_n - A_{n-1} \tag{5}$$

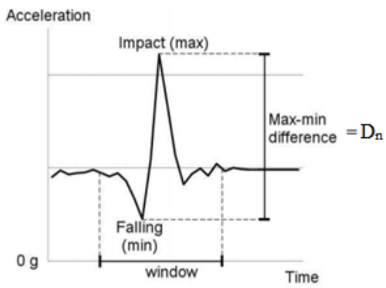


Fig. 6. The difference between the maximum peak and minimum valley in the proposed window size

If the peak A_n is more significant than a threshold, the difference between the maximum peak and minimum valley in the proposed window size will be computed to find the value of D_n. The calculated value D_n as in formula 5 will be compared with the proposed threshold th_3 to determine if the fall event happened or not. Hence, the experimental testing to find out the most suitable value of th_3 is extremely important. If the predetermined threshold of th_3 is too large, the fall may be ignored, but the small threshold may cause false detection. The experimental testing has been executed for selecting th_3. The details of our proposed fall detection algorithm is illustrated in Figure 7.

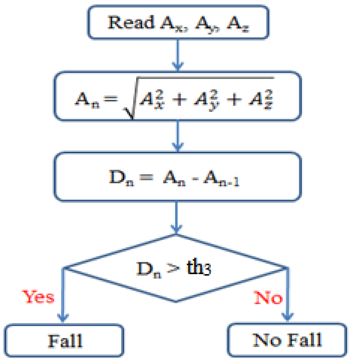


Fig. 7. The proposed fall detection algorithm

Final fall decision. Both the fall detection and posture recognition algorithms are used to confirm a fall event. The cascade posture recognition after 3s is used to verify the fall event. Suppose that an event satisfies all three proposed conditions comprising fall detection algorithm, posture recognition, and cascade posture recognition after 3s. In that case, it will be confirmed as a fall in the final decision, as shown in Figure 8. If one of the three proposed conditions is not satisfied, the event will be determined as a regular activity.

After falling, firefighters can stand up by themselves in some cases. Choosing to check the posture after 3s also can help to prevent unnecessary alerting. Furthermore, after falling, the body will reach the ground with vibration before changing to a stable state. Hence, checking the posture after 3s can ignore false alerting and enhance our proposed fall detection system's performance.

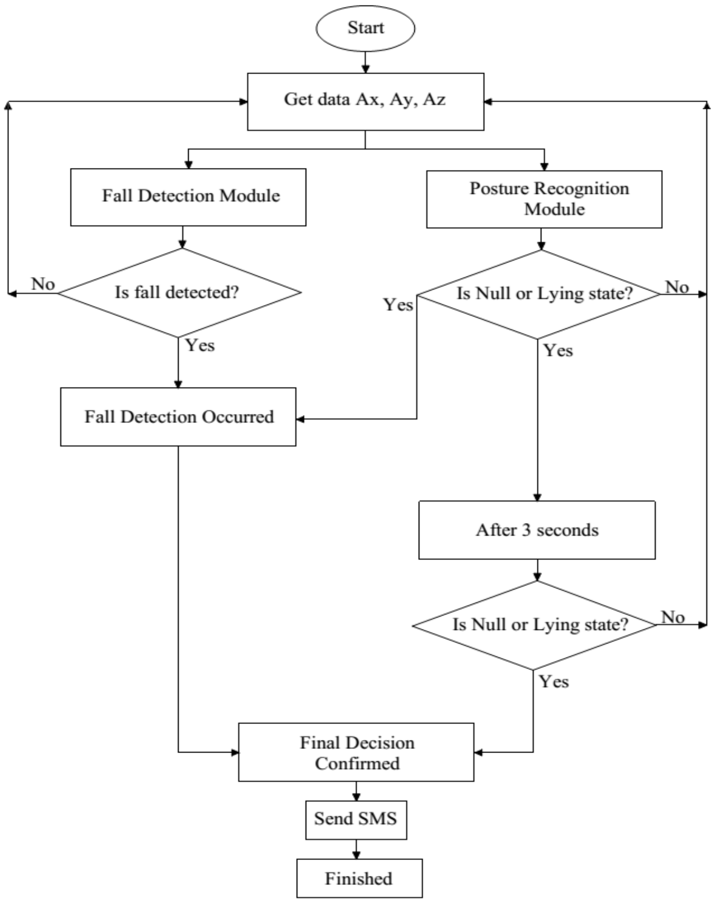


Fig. 8. The flow chart of our proposed fall detection algorithm

Based on the Table 2, it can be seen clearly that, the first decision in fall detection is the combination of fall detection and posture recognition algorithms, the fall event in the first decision will be confirmed when both of these conditions are satisfied. The fall detection algorithm's final decision in this research is the result of AND logic with three inputs: fall detection algorithm, posture recognition algorithm, and cascade posture recognition after 3s of fall. When the results of all three proposed conditions represent a fall, the final decision will determine whether the fall event is real; otherwise, it will be confirmed as a non-fall event (no fall occurred) (see Table 2).

Table 2. Final fall decision based on fall detection, posture recognition, and cascade posture recognition after 3s algorithms

Fall detection algorithm	Posture recognition	First Decision	Cascade posture recognition after 3s of fall	Final Fall Decision
Fall	Standing	No fall occurred	Do not check	No fall occurred
Fall	Walking	No fall occurred	Do not check	No fall occurred
Standing or Walking	Lying	No fall occurred	Do not check	No fall occurred
Fall	Lying	Fall occurred	Standing or Walking	No fall occurred
			Lying or Null	Fall occurred
Fall	Null	Fall occurred	Standing or Walking	No fall occurred
			Lying or Null	Fall occurred

3 Results and discussions

3.1 The experimental setup

Our experiment tested eight firefighters were aged 18-35, with the height of 1.68 – 1.75 m and weight of 62-75 kg. These volunteers were selected at the University of Fire Prevention and Fighting (UFPF). The device was mounted/positioned in their trouser pocket or on their waist. Figure 9 illustrates the demo position on the waist on the outside of fire resistant clothing in order to be readily observed. However, in a real situation, the device is mounted at under the fire resistant clothing to avoid the effect of high temperature and flame from the fire. The details of the experimental datasets were as the following:

Table 3. The features of our experimental datasets

	Our Experimental Datasets
Falls	Forward fall, Backward fall, Lateral left fall, Lateral right fall
OADs	Walking on the floor, Running on the floor, Walking stairs up, Walking stairs down; Running stairs up, Running stairs down
Pos.	Trouser pocket or waist
Freq.	100 Hz
No. Vols	8

Fig. 9. Volunteers are wearing our proposed system to record data

3.2 High CO level detection

In this research, the threshold of CO concentration was chosen carefully based on wood-burning testing at UFPF (the University of Fire Prevention and Fighting, Hanoi, Vietnam). Wood material used for measuring CO concentration in this research because this kind of material is one of the most popular fuels in a fire in Vietnam.

Figure 10 presents the proposed algorithm in measuring the CO concentration in environment. After being recorded, the data is preprocessed to eliminate abnormal parts in the signal. Then, the cleaned data will be used to estimating the CO concentration in the environment. Finally, the estimated CO level will be compared with the proposed threshold (th_4) to detect high CO level concentration.

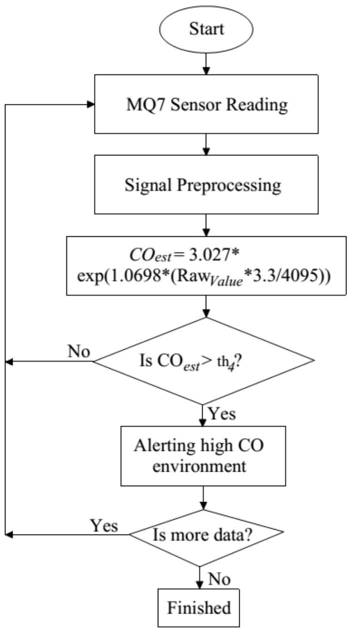


Fig. 10. The proposed algorithm to measure CO concentration (ppm) in environment

Figure 11 shows the experimental testing in clean and fire environments. The CO concentration in the clean environment is around 7 ppm (parts per million). This parameter significantly increased in the fire environment with the values fluctuate from 34 ppm to 46 ppm as in this Figure.

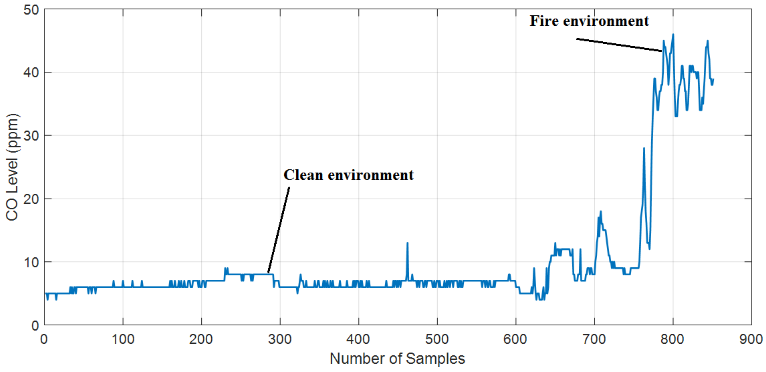


Fig. 11. The measured CO level (ppm) in clean and fire environments

Based on the experimental testing results, the signs and symptoms related to CO level that had been researched and published in [28], the CO level for working in the hazardous environment provided by the U.S. Occupational Safety and Health Administration Code of Federal Regulations (US OSHA CFR) [29] as well. We decided to propose the CO threshold value of 35 ppm (th_4=35 ppm) to recommend for firefighter using SCBA. Nevertheless, apart from the CO toxic gas, various toxic gases may also be present in the burning area. Hence, in the future of research, we will integrate more kinds of sensors with suitable threshold values to detect and alert other toxic gases such as NO, NO_2, H_2S to protect firefighter's life during their task performance.

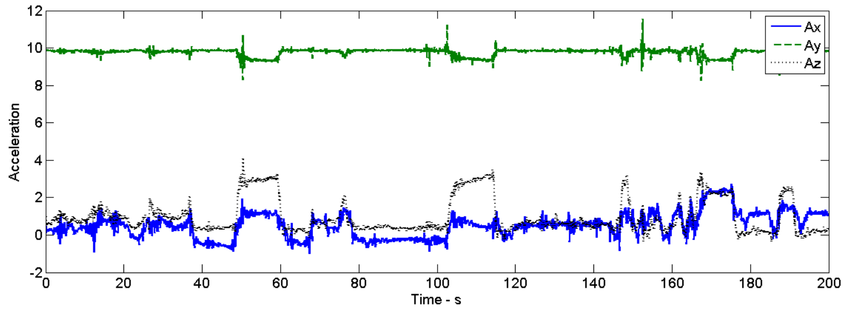
Table 4. The CO Concentrations and Associated Symptoms [28]

Carbon Monoxide Concentration	Signs and Symptoms
35 ppm	Headache and dizziness within 6h to 8h of constant exposure
100 ppm	Slight headache in 2h to 3h
200 ppm	Slight headache within 2h to 3h; loss of judgment
400 ppm	Frontal headache within 1h to 2h
800 ppm	Dizziness, nausea, and convulsions within 45 min; insensible within 2h
1600 ppm	Headache, tachycardia, dizziness, and nausea within 20 min; death in less than 2h
3200 ppm	Headache, dizziness, and nausea in 5 min to 10 min; death within 30 min
6400 ppm	Headache and dizziness in 1 to 2 min; convulsions, respiratory arrest, and death in less than 20 min
12800 ppm	Death in less than 3 min

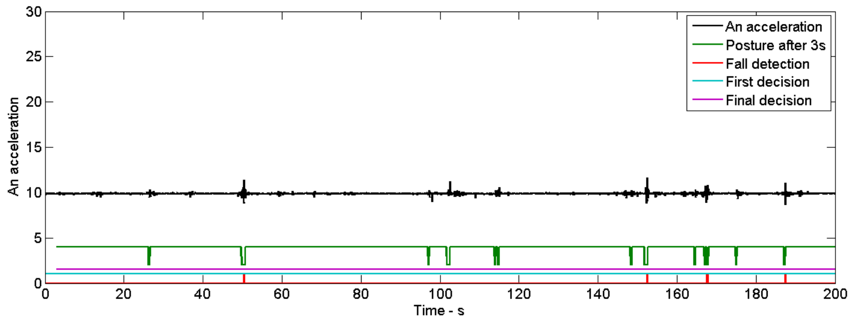
3.3 Fall detection testing

We tested and evaluated on many single and combined activities recorded data; then, the data was entered into computers to be processed and calculate suitable thresholds. After careful testing and calibration, the system works well with our proposed thresholds and window size. The results are shown in the following figures:

Figure 12a illustrates Ax, Ay, Az in standing state (without any motion): Ax and Az are around 0m/s^2, Ay stays constant around 9.81m/s^2, and Figure 12b is the final decision for standing state, the value of posture recognition is 4m/s^2. It can be clearly seen that the applied fall detection algorithm only still detected the false of fall events in the standing state. After combining the fall detection algorithm and posture recognition in first decision, no fall events were detected in this algorithm. The final decision also yielded the same result as the first decision algorithm.



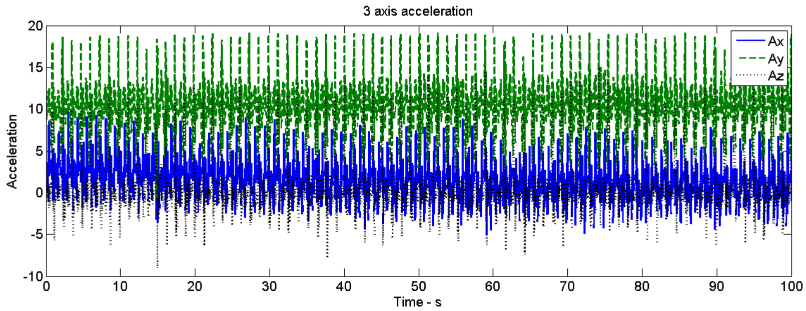
a) Ax, Ay, Az in standing status



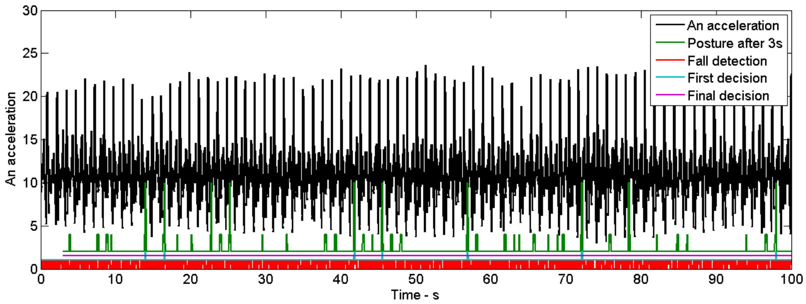
b) The final decision for standing state

Fig. 12. Ax, Ay, Az in a standing status and the final decision for standing state

Figure 13a is Ax, Ay, Az in a walking state, which shows that Ay moves continuously around 9.81m/s^2. Figure 13b indicates clearly that the fall detection algorithm only detected a lot of fall events in the walking state. After combining the fall detection algorithm and posture recognition in first decision, the false detection of fall events are reduced but the false detection is still remained. The final decision is the combination of fall detection algorithm, posture recognition and cascade posture recognition after 3s are detected no fall events in walking state (see Figure 13b).



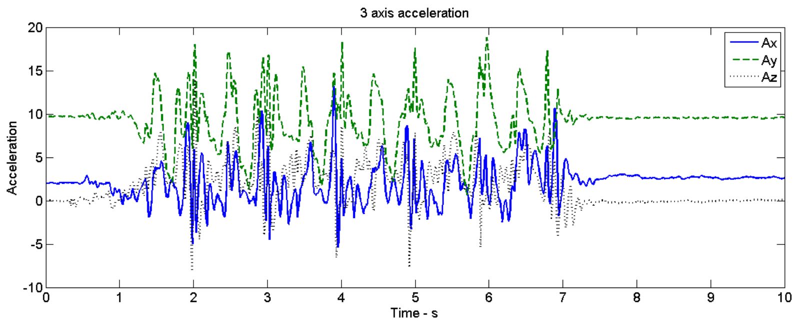
a) Ax, Ay, Az in a walking status



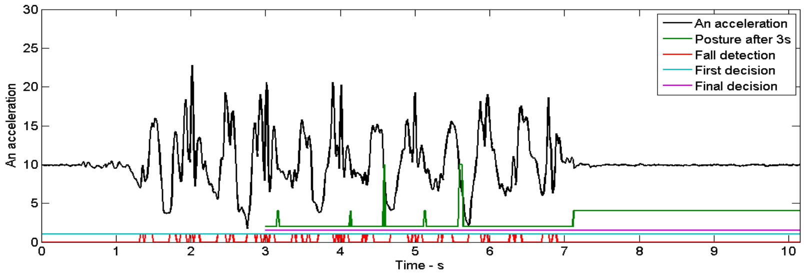
b) The final decision for walking state

Fig. 13. Ax, Ay, Az in a walking states and the final decision for walking state

Furthermore, in Figure 14 and Figure 15, we also tested with activities of walking up and down stairs because the firefighters can go up, or go down stairs during the rescue process. When only fall detection module is used, many wrong decisions can be created in these figures. However, the combination of fall detection, posture recognition and Cascade posture recognition after 3s of fall significantly improved the performance of our proposed method. Based on the final decision of results in both climbing up and down stairs, the system worked correctly with no fall detection.

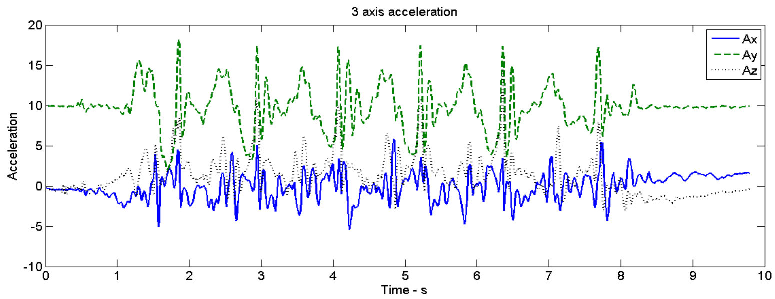


a) Ax, Ay, Az in stairs down status

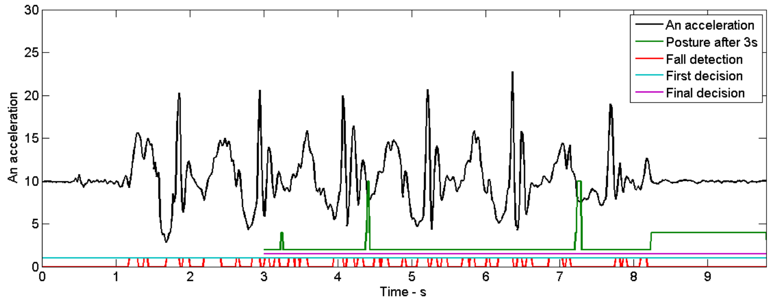


b) The final decision for stairs down status

Fig. 14. Ax, Ay, Az, and the final decision for the status of climbing downstairs



a) Ax, Ay, Az in stairs up status



b) The final decision for stairs up status.

Fig. 15. Ax, Ay, Az and the final decision for stairs up status

The accuracy of the device depends not only on the thresholds but also on the window size. Figure 16 shows the result with a window size equals 30 samples. Based on the final decision result in this figure it can be seen that two fall events were detected while there was only one actual fall event. Hence, this window size is inapplicable to our proposed fall detection algorithm. By increasing the window size to 35 samples, we could achieve relatively correct result because only one fall event was detected, which equals the number of actual fall event, as shown in Figure 17. While Figure 18 can not declare the actual fall event, this window size can ignore the fall events.

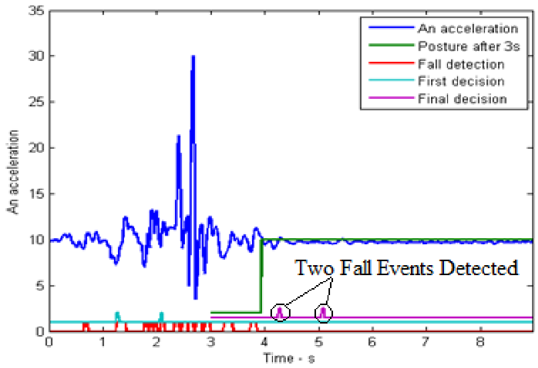


Fig. 16. The achieved fall detection result with the window size of 30 samples and threshold $th_3 = 1.4\ m/s^2$

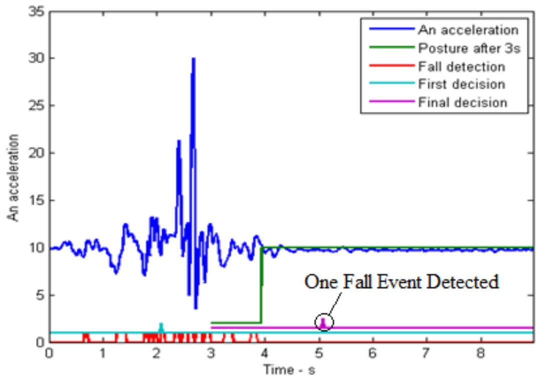


Fig. 17. The achieved fall detection result with the window size of 35 samples and threshold $th_3 = 1.4\ m/s^2$

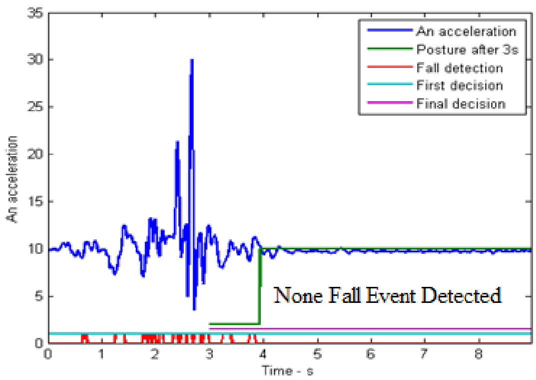


Fig. 18. The achievement fall detection result with the window size of 40 samples and threshold $th_3 = 1.4\ m/s^2$

To evaluate the proposed system, we used the four following factors [30]:

$$Sen = \frac{TP}{TP+FN} \tag{6}$$

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

Where, True positive (TP): A fall has occurred, and the system can detect it; False positive (FP): A normal activity can be declared as a fall; True negative (TN): A fall-like event is declared correctly as a normal activity; False negative (FN): A fall has occurred, but the system cannot detect it.

Based on the careful analysis, simulation results using MATLAB on our recorded dataset and the public datasets. We achieved the most suitable threshold values: th_1= 0.7 m/s^2, th_2 = 4.0 m/s^2, th_3 = 1.4 m/s^2, the window size = 35 samples, th_4=35ppm. After being tested, analyzed, and corrected with the most suitable proposed threshold values, our proposed fall detection algorithm can detect and distinguish most of the fall events with high sensitivity and accuracy at around 96.5% and 93%, respectively, after applying the formulas 6 and 7.

3.4 Fall detection evaluation

The proposed algorithm evaluated and compared with the proposed method in [18] on the public datasets. The details of the public datasets are showed in Table 5:

Table 5. The details of the public dataset used to evaluate [31]

Parameters	MobiFall
Falls	Forward-lying (FOL), Front-knees-lying (FKL), Back-sitting-chair (BSC), Sideward-lying (SDL)
Daily activities	Standing (STD), Walking (WAL), Jogging (JOG), Jumping (JUM), Stairs up (STU), Stairs down (STN), Sit chair (SCH), Car-step in (CSI), Car-step out (CSO).
Pos.	Pocket
Freq.	100Hz
No. Vols	24

The participant in this research is an on-duty firefighter who is working in the fire inside a building. Hence, several fall and daily activities which are recorded from female will not be considered in this study. Also, some kinds of fall and daily activities in male are not considered in this study, consisting of:

- Fall:

  - Back-sitting-chair (BSC)

- Daily activities:

  - Sit chair (SCH)
  - Car-step in (CSI)
  - Car-step out (CSO)

The reason in eliminating these fall and daily activities in performance evaluation of our proposed fall detection algorithm is that they are not similar to on-duty firefighters'. Thus, using these activities in performance evaluation may reduce the performance of the proposed fall detection algorithm. 213 and 180 fall events and daily activities respectively are used to evaluate our proposed algorithm.

Algorithm 1: Our proposed algorithm without using cascade posture recognition after 3s.

There are and two daily activities that misdeclared in public datasets, comprising:

- STN_acc_3_6.txt: The stairs down of the subject number 3 in the trial number 6.
- STU_acc_3_5.txt: The stairs up of the subject number 3 in the trial number 5.

Based on the achieved results in Table 6, it can be seen that our proposed fall detection algorithm is reliable with high accuracy in evaluation with the public datasets. Only two daily activities were mistakenly detected as falls. With careful analysis, we found that the public dataset was recorded with the Samsung Galaxy S3 in the pocket. Hence, when the legs move up/down the stairs will create a significant change in recorded acceleration. Furthermore, after stairs up/down, the data still recorded in standing state. Therefore, the fall-like event will be created in these scenarios.

Table 6. The achieved results on public dataset

The comparison	TP	FN	TN	FP	Sen (%)	Spec (%)	Acc (%)
The proposed algorithm	213	0	178	2	100	98.88	99.49
Algorithm 1	202	11	110	70	94.83	61.11	79.38

Without using cascade posture recognition after 3s, the proposed algorithm mainly ignored fall events in sideward-lying and misdeclared daily activities in stairs up/down sets as fall events. The details of the achieved results by algorithm 1 shown in Table 7 as follows:

Table 7. The details of achievement result on public dataset by algorithm 1

Type of activities		Correctly detected	Misdeclared	Total
Falls	Forward-lying	70	2	72
	Front-knees-lying	69	3	72
	Sideward-lying	63	6	69
Daily activities	Standing	9	0	9
	Walking	0	0	9
	Jogging	27	0	27
	Jumping	27	0	27
	Stairs up	23	31	54
	Stairs down	15	39	54

As can be seen from the table, while recording stairs up/down activities, the volunteers need to execute stronger physical activities. As a result, the recorded signal changed significantly and satisfied the proposed threshold (without using the cascade posture recognition after 3s).

The public dataset has been evaluated in the publication [18] based on Support Vector Machine classifier (SVM) and a nearest neighbor rule (NN). The achieved results in the publication [18] are shown in Table 8 as the following:

Table 8. The public datasets used to evaluate [18]

MobiFall	NN [19] %	SVM [19] %	The proposed algorithm %	Algorithm 1 %
	95.76	98.41	99.44	76.12

where, GM is related to the geometric mean. The GM is calculated based on the following formula [18]:

$$GM = \sqrt{Sen \times Spec} \tag{9}$$

The achieved geometric means by Support Vector Machine classifier (SVM) and a nearest neighbor rule (NN) in [18] on MobiFall dataset with 11 volunteers are 98.41% and 95.76% respectively. The MobiFall dataset has been updated with more volunteers but the kinds of falls and daily activities are still the same. Therefore, our proposed algorithm has been evaluated on 24 volunteers and achieved 99.44% in geometric mean.

4 Conclusion

We have proposed a more complete fall detection algorithms using a 3-DOF accelerometer, a microcontroller with the suitable window size and threshold values. The posture recognition and the cascade posture recognition after 3s significantly increase the fall detection algorithms' performance embedded in the microcontroller. Besides, the high CO concentration threshold in the fire is also proposed to protect firefighters' lives. The proposed system embedded with our proposed algorithm can work with stability and accuracy because it has been developed and evaluated on datasets recorded from firefighters. Furthermore, in future work, we will integrate more sensors and improve the algorithms to detect more toxic gases such as aldehyde, fine particles, CO_2, and HCN in order to give reliable decisions for firefighters in case of using SCBA. In addition, we will integrate the proposed system with indoor positioning system to track and support firefighters in the event of accidents.

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