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DEVELOPMENT OF REAL-TIME SYSTEMS TO DETECT AND TRACK ON-DUTY INJURED FIREFIGHTERS USING MACHINE LEARNING AND ADVANCED SIGNAL PROCESSING TECHNIQUES

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LIST OF PUBLICATIONS

1. Pham Van Thanh, Tuan Khai Nguyen, Duc Anh Nguyen, Nhu Dinh Dang, Huu Tue Huynh, Duc-Tan Tran*, ***Adaptive Step Length Estimation Support Indoor Positioning System using Low-Cost Inertial Measurement Units,*** 2020 IEEE Eighth International Conference on Communications and Electronics, pp.271-275, 13-15 Jan.2021.

2. Pham Van Thanh, Le Quang Bon, Nguyen Duc Anh, Dang Nhu Dinh, Huynh Huu Tue, Tran Duc Tan, ***Multi-Sensor Data Fusion in A Real-Time Support System for On-Duty Firefighters***, Sensors 2019 (ISSN: 1424-8220 **SCIE, IF=3.275**).

3. Van Thanh Pham, Duc Anh Nguyen, Nhu Dinh Dang, Hong Hai Pham, Van An Tran, Kumbesan Sandrasegaran and Duc-Tan Tran, ***Highly Accurate Step Counting at Various Walking Speeds Using Low-Cost Inertial Measurement Unit Support Indoor Positioning System,*** *Sensors*. 2018; 18(10):3186. (ISSN: 1424-8220 - **SCIE, IF=3.275).**

4. Pham Van Thanh, Duc-Tan Tran, Dinh-Chinh Nguyen, Nguyen Duc Anh, Dang Nhu Dinh, S. El-Rabaie and Kumbesan Sandrasegaran, ***Development of a Real-time, Simple and High-Accurate Fall Detection System for Elderly Using 3-DOF Accelerometers***, *Arabian Journal for Science and Engineering.* 2018 (ISSN: 2191-4281 **– SCIE, IF=1.711**).

5. Pham Van Thanh, Anh-Dao Nguyen Thi, Quynh Tran Thi Thuy, Dung Chu Thi Phuong, Viet Ho Mau and Duc-Tan Tran, ***A Novel Step Counter Supporting For Indoor Positioning Based On Inertial Measurement*** Unit", 7th international conference on Integrated Circuit, Design, and Verification (ICDV), IEEE, pp. 69-74, 5-6 Oct. 2017.

6. Nguyen Van Duong, **Pham Van Thanh**, Tran Van An, Nguyen Tuan Khai, Duong Thi Thuy Hang, Hoang The Hop and Tran Duc Tan,

Elevator Motion States Recognition Using Barometer Support Indoor Positioning System, The 7th International Conference in Vietnam on the Development of Biomedical Engineering, IFMBE Proceedings, Springer, pp.581-587, 27-29 Jun.2018.

7. The Hop Hoang, **Van Thanh Pham**, Thuy Quynh Tran Thi, Huu An Nguyen, Tuan Khai Nguyen and Tan Tran-Duc, ***Xây dựng hệ thống xác định độ cao bên trong nhà và công trình sử dụng đa cảm biến áp suất,*** Hội nghị Quốc gia lần thứ XXI về Điện tử, Truyền thông và Công nghệ Thông tin (The 21st National Conference on Electronics, Communications and Information Technology), 2018, pp. 193-197.

PREFACE

1. Introduction

There was 68,085 US firefighter injuries and US 64 firefighters died on-duty in 2015 [1], [2], and the fire ground injuries accounted the largest percentage in all causes of injuries with about 29,130 occurrences (~43%).

In Vietnam, there are thousands of burning that occurs each year; for example, there were 2357 and 2792 fire in 2014 and 2015, respectively [3,4]. The on-duty firefighters are facing with dangerous while firefighting and rescue because of the lack of suitable supporting systems to protect their's life. Therefore, the research to propose a suitable and high accuracy supporting systems that can help to protect the firefighter's life while they are firefighting and rescue.

There are several injuries detection systems, such as fall detection system, personal alert safety system (PASS) [5]. Nevertheless, the proposed fall systems still show the limitations when applying to detect on-duty firefighter's injuries because most all fall detection systems are only intended for the elderly or patients who have slow movement. The PASS system was developed by Homeland Security to detect lack of movement in a specific of time. It will activate a 95-decibel alarm in the case of lack of movement was detected. However, in the fire condition, there are variety of noises, such as the human voices, the operation of fire detection and extinguishing systems…therefore, the audible alarm is not effective enough in support on-duty firefighters in a large scale. Hence, although US firefighters were equipted the PASS system but there were six and nine on-duty firefighters.

2. The goal of research

The thesis focus on research and develop a method to detect and track on-duty injured firefighters based on four problems need to solve as below:

+ The most related literature review

+Choosing the sensors, designing the proposed system, calibrating sensors, sensors fusion and map processing.

+ Activities classification and injured firefighter detection.

+ Track and locate the indoor position of firefighter.

3. Object and Scope of the Thesis

The injured detection and indoor positioning tracking mainly focus on the specific object that is firefighter under fire condition in a building or construction. Furthermore, the proposed method studies on indoor positioning system without using the pre-installed system like access points, transmitters, etc.

4. Content of the Thesis

Studying on the causes of injury in firefighters and the published methods for injured detection and fall detection as well as.

Studying about the most related published methods on indoor positioning.

Studying the methods to calibrate sensors, process the recorded signal from sensors.

Studying about the signal processing and machine learning techniques in fall detection in the most related works.

Studying to find out the efficient method to count the number of steps, estimate the step length; and detect the time and the turning direction.

Proposed the algorithm to fuse sensor data to enhance the accuracy of injured detection and indoor positioning system.

Evaluate the proposed algorithms on the recorded data and multiple public datasets.

5. The Research Method

To be able to implement the topic successfully, this thesis combine theoretical research, simulation, testing experiment and consult of experts. Firstly, I focus on study and master the theory of machine learning as well as signal processing techniques. Secondly, it is necessary to understand the fire conditions in a building and psychological state of the firefighter as well as.

6. Scientific significance and Contributions of the Thesis

Most of the published studies mainly focus on activity classification and fall detection for patients, elderly and children. Nevertheless, the activities of firefighter on the fire are different with humans under normal conditions. Hence, these publication methods are not suitable to apply in injured detection for firefighters. Besides, the collection of firefighters's activities data for research in the world is not much. Therefore, the study of firefighter activities and injured detection, tracking and locating firefighters under fire conditions are new contributions with high practical and scientific significance.

Contributions

Firstly, the data fusion of three-axis accelerometer, three-axis gyroscope, and three-axis magnetometer has been proposed for fall detection in firefighters. Several publications have integrated these sensors for fall detection, but these methods mainly focus on detecting fall events for the elderly who do not perform any complex and strenuous activities and the thresholds within which to detect the fall events in firefighters are also different from those with the elderly. Furthermore, most of the datasets in previous publications were recorded from students, elders, or other volunteers other than firefighters. As a result, they are not really effective in detecting the fall events in the firefighters who perform complex and strenuous activities in fire environments. (Publication No. 2 and 4).

Secondly, the proposed system has an integrated barometer to detect loss of physical performance and support to estimate the state and vertical position of firefighters because the using of 3-DOF accelerometer, 3-DOF gyroscope, and 3-DOF magnetometer to detect loss of physical performance, estimate the state and vertical position of firefighters as well as are not strong enough. It will cause false warnings while the elevator is in use. Furthermore, long-time verification may cause death or permanent health damage in firefighters. (Publication No. 2, 6 and 7).

Thirdly, CO gas or the so-called “silent killer” gas is one of the most dangerous gases emitted from combustion. This gas can be seriously detrimental to firefighters’ health. Hence, the MQ7 sensor has been integrated into our proposed supporting system to optimize the use of self-contained breathing apparatuses (SCBA). (Publication No. 2).

Fourthly, based on the different experiments on types of data and users, we suggest that enhancing the adaptively of this approach can be made by adaptively changing parameters while training K to gain the best result. This can be done by periodic state update and utilizing the relation of height to K training. (Publication No. 1).

Finally, we proposed to develop a highly accurate step counting method by proposing four features: Minimal peak distance, minimal peak prominence, dynamic thresholding, and vibration elimination, and these features are adaptive with the user’s states. Specially, minimal peak prominence is a powerful technique that is used to remove the false peak by measuring the intrinsic height of the current peak, together with other peaks, by using a horizontal line from the current peak. The horizontal line will extend both to the left and right of the peak until it satisfied either of the following conditions:

+ Crosses the higher peak

+ Reaches the left or right of the signal in a window

Furthermore, the proposed features are combined with periodicity and similarity features to solve false walking problem. (Publication No. 2 and 5).

7. Thesis structure

Beside the introduction and conclusion, the thesis is divided into 5 chapters as the following:

Chapter 1: Overview of Research

Chapter 2: System Design, Sensor Calibration and Map Processing

Chapter 3: Development of a Method to Detect Injured Firefighters

Chapter 4: Development of a Method to Track On-Duty Injured Firefighters

Chapter 5: Indoor Firefighter Positioning and Tracking Using Multi-Sensor Data Fusion and Map Matching Algorithm.

CHAPTER 1. OVERVIEW OF RESEARCH

1.1. Literature review

1.2. The Researches on Injured Detection

There are a lot of published methods about fall detection in recent years such as image processing [88-99], location sensors [100], smartphones [101], accelerometers [102] or wristband and smart watches. However, these methods have certain limitations such as the systems are inconvenient, expensive and unsuitable in modern society.

1.3. The Researches on Indoor Positioning

The Global Positioning System (GPS) is unreliable for indoor localization applications. Therefore, an indoor positioning system is essential and attractive for both researchers and companies since it is employed in widespread practical applications; thus, several techniques have been proposed for it. Firstly, indoor positioning is based on pre-installed sensors/devices with a high accuracy of such as camera, wireless sensor network, wireless network, UWB (Ultra-wideband), and Doppler radar [28], but limitations of these techniques are that it is expensive and only applicable on pre-installed environments. Other methods use an accelerometer or IMU (Inertial Measurement Unit) that do not require a pre-installed support system, so it is suitable for unknown environments. However, it is shown that accuracy is not high. Hence, highly accurate step counting is an essential part to enhance the accuracy of an indoor positioning system in the case of using IMU.

1.4. The challenges in study on injured detection and indoor positioning

Basing on the above literature reviews and the limitations of these publications as well as. We can ensure that the big challenges related to injured detection that we need to estimate the kind of injuries that the firefighters will meet during the task and kind of on-duty activities as well as. Then, the proposing the algorithm to detect the injured with high accuracy for this object is also a big challenge. Secondly, the indoor positioning based on IMU and other sensors without using the pre-installed system may achieve low accuracy because of drift, random and cumulative errors of sensors.

1.5. Summary

In this chapter, the thesis has been analyzed the most related on injured detection and indoor positioning methods and showed the limitations of these studies. Furthermore, the thesis also presented the goal of it and the challenges which can meet durning the doing this thesis.

CHAPTER 2. SYSTEM DESIGN, SENSOR ERRORS ELIMINATION AND MAP PROCESSING

2.1. System Architecture

Figure 2-1 shows the block diagram of the proposed system. The accelerometer used in this thesis is ADXL345 (3-DOF accelerometer) from Analog Devices. The proposed system uses I2C (Inter-integrated Circuit) interface in the connection between ADXL345 and MCU.

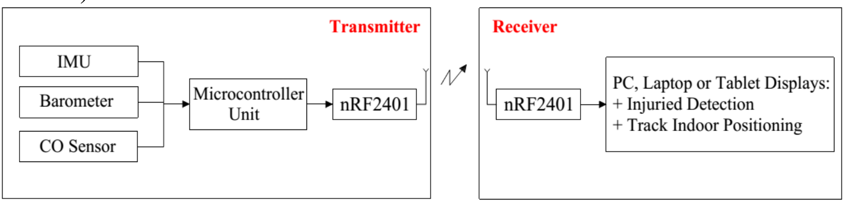

Figure 2-1. Block diagram of the proposed system.

2.2. Sensors Errors Elimination

Sensors are existing two main kind of errors, including systematic error and random error. In order to eliminate the systematic error and random error, we applied the calibration process and the Kalman filter respectively.

2.2.1. The 3-DOF Accelerometer

2.2.2. The Magnetic Sensor

2.2.3. The Barometer

2.2.4. The CO Detection

2.3. Map Processing

2.3.1. Map Preprocessing

The Map will be converted from color image or grey image to a binary image based on the threshold. Based on the experimental result, this thesis proposed the threshold equals 0.5412. If a pixel in color space image or grey image is greater than the proposed threshold, it will be assigned 1 in binary image and 0 when it is smaller than the proposed threshold value.

2.3.2. Map Simplification

The proposed algorithm only keep important and fixed objects like wall and stairs. In order to solve this problem, this thesis used two basic operations in mathematical morphology include Dilation and Erosion.

2.3.3. Map Scale

The map scale refers to ratio between distance on a map and distance on the ground. In this reseach, map scale is the relationship between image pixels and the real size (cm) of building or constructions.

2.4. Summary

In this chapter, the thesis has been proposed the algorithm to calibate sensors include 3-DOF accelerometer, 3-DOF magnetometer, barometer and MQ7 sensor. Based on the achieved results after calibration process can bee seen that the abnormal parts of signal are eliminated. Furthermore, the drift errors of these sensors are also solved in this chapter. Besides, the map processing to remove unimportant objects, keep the main structure such as the walls, stairs,…and estimate map scale have been done in this chapter.

CHAPTER 3. DEVELOPMENT OF A METHOD TO DETECT INJURED FIREFIGHTERS

3.1. Fall Detection Method

3.1.1. Fall Detection Module

Data is recorded in three dimensions Ax, Ay and Az, then Root Mean Square (RMS) of the recorded signal (Acc) is computed using the equation (3-1):

$$\mathrm{Acc} = \sqrt{(\mathrm{Ax})^2 + (\mathrm{Ay})^2 + (\mathrm{Az})^2} \tag{3-1}$$

Next, the values of Acc will be compared with LFT (Lower Fall Threshold) and UFT (Upper Fall Threshold) to detect a fall. If Acc value is below LFT and above UFT with t_{FE} is greater than $t_{threshold}$, it will be confirmed as a fall event.

$$t_{FE} = \frac{\text{count}}{\text{frequency sampling}} \tag{3-2}$$

3.1.2. Post-fall Recognition Module

The post-fall recognition module is a combination of posture recognition module and vertical velocity estimation after fall detection module detected fall event 2s. The post-fall is checked after 2s, because after falling, the body will be changed to rest state and 2s delay is used to avoid any fluctuation after the body reached to the ground.

3.1.3. Posture Recognition Module

The post-fall posture recognition used to detect the angle θ between Ay and gravity. The accelerometer is positioned around the waist; Ay is parallel with gravity acceleration in standing state. Hence, the θ angle in standing state is around 0^{o}, it changes when the wearing person is in walking or others active states. The postures are detected using the scalar product of the reference gravity vector $\vec{A}_0$ and the vector at time (t) to determine the θ angle [89]:

$$\theta(t) = cos^{-1}\left(\frac{\vec{A}_{cc}(t)\bullet\vec{A}_0}{|\vec{A}_{cc}(t)|.|\vec{A}_0|}\right)\frac{180}{\pi} \text{ (degree)} \tag{3-3}$$

3.1.4. Vertical Velocity Estimation

Vertical velocity (v) estimation is a key to distinguish between rest and active states, if we remove the gravity, the vertical velocity at the rest states should be equal to zero as the following formula:

$$\mathrm{v} = \int \left(\sqrt{\mathrm{A}_\mathrm{x}^2(\mathrm{t}) + \mathrm{A}_\mathrm{y}^2(\mathrm{t}) + \mathrm{A}_\mathrm{z}^2(t)} - 9.81\right)\mathrm{dt} \tag{3-4}$$

where, $a = \frac{m}{Fs}$, b = $\frac{m+1}{Fs}$ with m = 0: $number\ of\ data\ samples$

$$V < v_{threshold} \tag{3-5}$$

where, $v_{threshold}$ is the threshold to distinguish between rest and active states. If the Equation 3-5 is satisfying, the algorithm will confirm the state of the user is the rest state, others are active states.

3.2. Detect On-Duty Injured Firefighters

The fall detection module consists of three features: Upper threshold, post-fall, and posture recognition. The loss of physical performance detection includes two main features: Altitude threshold and loss of physical performance threshold. The key condition for fall detection that is $Acc_{(j)} > U_{th}$ when RMS of acceleration exceeds the U_{th} threshold value. In contrast, the loss of physical performance algorithm will work when $L_{u\_mov} > \left(Acc_j\colon Acc_{j+4*Fs}\right) > L_{l\_mov}$.

3.2.1. The Proposed Fall Detection Algorithm for Firefighter

The algorithm combines the use of three kinds of sensors: 3-DOF accelerometer, 3-DOF gyroscope, and 3-DOF magnetometer. The data fusion of these sensors has proved effective through our proposed algorithms.

+ Upper Threshold. After the volunteer's loss of contact with the ground, their body will drop to "flight of fall" period. Due to the effect of gravity force, when the body initially contacts the ground or other objects, it will create a sudden change in acceleration data. Hence, using the upper threshold to detect the sudden increase in acceleration data has essential meaning.

$$Acc_{(j)} - U_{th} > 0 \tag{3-6}$$

where, $Acc_{(j)}$is the acceleration data at the sample of j; U_{th} is the threshold to check the acceleration excess.

+ Post-Fall. After the "flight of fall" period, the body will fluctuate in a short time before changing to the rest state. Postfall thresholds include upper and lower thresholds. Based on the experimental testing results, the rest state will be checked after the signal exceeds the upper threshold value by 3s and the upper and lower thresholds of the post fall feature equal 1.25 and 0.75g, respectively in this research. When RMS acceleration is greater and smaller than L_{pt} and U_{pt} thresholds within 2 s, respectively. The post-fall will confirm that a fall event has occurred.

$$\begin{gathered}\mathrm{Pos}_{fall} = (\mathrm{U}_{pt} > \left(Acc_{j+3*Fs}\colon Acc_{j+5*Fs}\right) \\ \&\&\mathrm{L}_{pt} < (Acc_{j+3*Fs}\colon Acc_{j+5*Fs}))\end{gathered} \tag{3-7}$$

+ Posture Recognition. After falling, the posture of the body will change. Hence, the roll, pitch, and yaw angles will change in comparison with the reference frame. The roll and pitch angles are used to estimate the posture of the firefighter after falling.

- Condition 1: The angle T between Az and gravity estimation:

The accelerometer is positioned in the front trouser pocket. Thus, the T angle in the standing state is around 0°, and it changes when the device carrier is standing. The postures of the firefighter are detected using Equation (3-3) to determine the difference between T angle and the gravitational acceleration.

$$T = \cos^{-1}\left(\frac{A_z(t)}{\sqrt{A_x^2(t)+A_y^2(t)+A_z^2(t)}}\right)\frac{180}{\pi} \text{ (degree)} \tag{3-8}$$

- Condition 2: The orientation estimation:

This thesis will apply Madgwick orientation filter in eliminating noise for inertial measurement unit (IMU). The Euler angles represents the difference between the reference frame and the sensor frame defined by the following equations [67]:

$$Y = Atan2(2q_2q_3 - 2q_1q_4, 2q_1^2 + 2q_2^2 - 1) \tag{3-9}$$

$$P = -sin^{-1}(2q_2q_4 + 2q_1q_3) \tag{3-10}$$

$$\mathrm{R}= Atan2(2q_3q_4 - 2q_1q_2, 2q_1^2 + 2q_4^2 - 1) \tag{3-11}$$

where, Y, P, and R are the yaw, pitch, and roll of the Euler angles that rotate around the Az, Ay, and Ax axes of the reference frame, respectively.

Combination of Condition 1 and Condition 2:

The theta angle, pitch angle, and roll angle are combined to enhance the sensitivity and accuracy of our proposed algorithm. Furthermore, the double check with an interval of 0.5 s also proposed in this thesis to improve the accuracy of our proposed system.

3.2.2. The Proposed Loss of Physical Performance Detection Algorithm for Firefighter

There are several kinds of fall events such as crawling then falling or being stuck in narrow paths and spaces. The application of the previous algorithms to detect the accelerations that exceed the threshold are not applicable to these situations.

To solve these limitations, this thesis has proposed the loss of physical performance algorithm. The loss of physical performance algorithm is an essential part of our proposed algorithm to detect accident events of firefighters. The data fusion between barometric and 3-DoF acceleration will help solve the existing limitations.

$$\mathrm{L}_{loss\ of\ physical\ performance} = (L_{u_{mov}} > \left(Acc_j : Acc_{j+4*Fs}\right) \&\& L_{l\_mov} < (Acc_j : Acc_{j+4*Fs})) \tag{3-12}$$

$$\Delta_{Altitude} = H_{(j+4*Fs)} - H_{(j)} \tag{3-13}$$

Based on the predicted result by fusion the data of both barometer and 3-DOF accelerometer, the loss of physical performance event will be confirmed when Equation (3-17) is satisfied.

$$Predict(l) = \tag{3-14}$$

$$Acc < L_m\ within\ T\ \&\Delta_{Altitude} > A_{th} => l = moving\ up \tag{3-15}$$

$$Acc < L_m\ within\ T\ \&\Delta_{Altitude} < A_{th} => l = moving\ down \tag{3-16}$$

$$Acc < L_m\ within\ T\ \&A_{th1} < \Delta_{Altitude} < A_{th2} => l = loss\_of\_physical\_performance \tag{3-17}$$

3.2.3. CO Detection Algorithm for Firefighter

After recorded, the raw data will be preprocessed to eliminate abnormal parts in the signals. The simple Kalman filter also used to detect the CO level in our proposed CO detection algorithm, as shown in Figure 3-10.

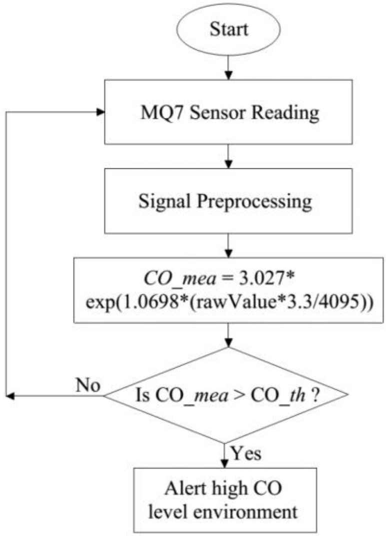

Figure 3-10. The high CO level alerting algorithm.

3.3. Result and Discussion

3.3.1. The Experimental Results

The volunteers were randomly selected from many firefighters in The University of Fire Prevention and Fighting (UFPF)—Vietnam. The details of volunteer information are described in Table 3-3.

Table 3-3. The volunteer characteristics.

Number of Volunteers	The Trial Times	Gender	Age	Height	Weight
5	3	Male	18–35	1.68–1.75	62–75 kg

3.3.2. Fall Detection Results

3.3.3. Loss of Physical Performance Detection

Figure 3-13 below illustrates the difference between the loss of physical performance because of being stuck or facing an accident and moving up in an elevator. As shown in Figure 3-13, both of the recorded datasets from the accelerometer and barometer are constant or show little change when a firefighter passes through a narrow path and they get stuck or have an accident. Similarly, Figure 3-14 shows the loss of physical performance because of moving up in an elevator.

3.3.4. High CO Level Alerting Algorithm

In experimental tests, the real-time CO measurement in smoke-filled room is shown in ppm (parts per millions). In the clean air (without a fire burning), this value only varied around 7 ppm, but it escalated rapidly when we moved the MQ7 sensor closer to the fire and the value varied from 33 to 45 ppm

Based on the empirical test at the UPFP (Vietnam) and comparison to signs/symptoms listed in [63], we can confirm that when carbon monoxide concentration is around 35 ppm, headache and dizziness happen within 6 to 8 h of constant exposure. Hence, the authors propose using th5 = 33 ppm for alerting. If the CO level in a fire is lower than th5 threshold, firefighters can remove the breathing apparatus to save compressed air in a SCBA in case of a more serious situation ahead.

3.4. Comparison

In the comparison, we considered algorithms including:

- Algorithm 1: Our full algorithm with the features shown in Table. 3-5.
- Algorithm 2: The reduced version of algorithm 1 (without checking theta, pitch, and roll angles at the second stage).
- Algorithm 3: The reduced version of algorithm 2 (without condition 1).
- Algorithm 4: The reduced version of algorithm 2 (without condition 2).
- Our previous fall detection algorithm.
- Paola Pierleoni et al. algorithm.

3.4.1. The Comparison on Our Experimental Data

Table 3-5. 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, Crawling on the floor; Walking stairs up, Walking stairs down; Running stairs up, Running stairs down; Crawling stairs up, Crawling stairs down; Jumping, Taking the elevator up/down
Pos.	Pocket
Freq.	100 Hz
No. Vols	6

To evaluate the accuracy, specificity, and sensitivity of our currently proposed algorithms, our previous publication and Paola Pierleoni et al., we used the following equations (Equations (3-18)–(3-20):

$$Sen = \frac{TP}{TP + FN} \tag{3-18}$$

$$Spec = \frac{TN}{TN + FP} \tag{3-19}$$

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{3-20}$$

Table 3-6. The testing performance of our current proposed algorithms (fall detection and loss of physical performance detection), our previous fall detection algorithm, and Paola Pierleoni et al. algorithm on our experimental datasets.

The Algorithms Comparison	**Sen**	**Spec**	**Acc**
Algorithm 1	100%	100%	100%
Algorithm 2	100%	94.44%	95.83%
Algorithm 3	100%	90.74%	93.05%
Algorithm 4	100%	91.67%	93.75%
Our previous fall detection algorithm [18]	88.9%	94.45%	91.67%
Paola Pierleoni et al. algorithm [17]	66.7%	100%	83.33%

3.4.2. The Comparison on Public Datasets

Based on the testing performance in Table 3-8, it can be seen that our proposed algorithm (Algorithm 1) achieves better performance in terms of specificity and accuracy on public datasets. It can detect 762/762 non-fall actions and 724/755 fall actions equaling 100% and 97.96% in Table 3-8, respectively. Nevertheless, some kinds of fall such as the fall events in 920 syncope-wall, from standing falling down slowly slipping on a wall in folders 107, 109, and 110 were declared as normal activities.

Table 3-8. The testing performance of our current proposed algorithms (fall detection and loss of physical performance detection), our previous fall detection algorithm, and Paola Pierleoni et al. algorithm on public datasets.

The Algorithms Comparison	**Sen**	**Spec**	**Acc**
Algorithm 1	95.89%	100%	97.96%
Algorithm 2	96.15%	98.42%	97.3%
Algorithm 3	97.75%	94.48%	96.11%
Algorithm 4	96.68%	93.43%	95.05%

Our previous fall detection algorithm	93.33%	91.67%	92.5%
Paola Pierleoni et al. algorithm	36.95%	97.76%	67.5%

3.5. Summary

We proposed the complete fall detection and loss of physical performance detection algorithms. These algorithms are fusing the data of 3-DoF accelerometer, 3-DoF gyroscope, 3-DoF magnetometer, and barometer. We have proposed the supporting system for a new subject which has not been focused on in previous publications that is the on-duty firefighter. This is the first time the loss of physical performance algorithm has been introduced to significantly enhance the accuracy of our supporting system. Furthermore, the thesis also proposes using the suitable threshold value of CO in the fire to protect firefighter lives. The combination of five sensors and data fusion algorithms enable us to achieve noticeable results on a new subject as firefighter with high sensitivity, specificity of 100% and accuracy of 100% in our experimental datasets, and accuracy of 97.96% in public datasets. The research also shows the main kind of activities by firefighters in fire scenarios and proposes the suitable algorithms and threshold values through the use of five sensors and recording of data fusion of these sensors. For further research, we will integrate more toxic gas sensors to detect aldehyde, fine particles, CO_2, and HCN to give a more precise decision on whether to use SCBA; and optimize our algorithms and thresholds in real-environments at the fire scene to save the life of firefighters.

CHAPTER 4. DEVELOPMENT OF A METHOD TO TRACK ON-DUTY INJURED FIREFIGHTERS

The chapter 4 will present the details of our proposed method to tract and locate the indoor positioning of on-duty firefighters through the proposed algorithm to fuse the recorded data from the integrated sensors.. The proposed method based on the recorded data from sensors. Then, these datasets will be transferred to base station for processing. The proposed indoor positioning method does not depend on the pre-infrastructure. Hence, it is suitable to track and locate the indoor positioning of firefighters in fire conditions. The process of tracking and locating include 4 steps in sequence as the following:

+ *Detect and count the number of steps.*

+ *Step Length Estimation.*

+ *Turning Time and Direction Estimation.*

+ *Vertical Position Estimation.*

4.1. The Step Counting Method

The method combined peak detection with suitable minimal peak distance, minimal peak prominence, dynamic thresholding, and vibration elimination to compute the amplitude of acceleration to eliminate all peaks that fluctuated around gravity acceleration (g = 9.81 m/s^2)) in step counting.

4.1.1. The Results

4.1.1.1. The Experimental Setup

The process of recording data was gathered from the experiment that was executed on eight male volunteers with the age: 18–28, height: 1.65–1.78 m, and weight: 58–76 kg who were selected from The University of Fire Fighting and Prevention (UFFP). The volunteers carried our system in trouser pockets and five types of data were recorded: normal walking, fast walking, slow walking, free walking, and false walking. Each type of data was recorded three times for the testing process. Then, six volunteers carried our device in their trousers' pocket to record data for comparison with step counting based on periodicity, similarity, continuity method, and step counting based on peak detection method; two other volunteers carried our device and three comparison phones (which were installed with three popular applications: Health app on IPhone 5s, S-Health on Galaxy S5, and Pedometer and Weight Loss Coach installed on Lenovo P780) in the trouser pockets and performed 500 steps five times in free walking with the same conditions. For free walking, the volunteers walked with normal speed on the floor and up and down stairs. Figure 4-10 is our proposed indoor positioning system and data is being recorded with a firefighter in the free walking state.

4.1.1.2. The Testing Process

The proposed method has been tested with various kinds of walking states comprising normal walking, fast walking, slow walking, and false walking. The results showed that the proposed method detected the number of steps with an ultra-high accuracy: 227/227 steps detected in normal walking, 500/500 steps in slow and intermittent walking, 187/188 steps in fast walking, and 500/500 steps in free walking.

4.1.2. Discussion

4.1.2.1. Comparison with Other Methods

The following formula to estimate the error of the proposed method [32]:

$$\text{Error} = \frac{|\text{E-T}|}{\text{T}} \times 100\%, \qquad (4\text{-}9)$$

where E is the estimated number of steps by our method and T is the number of true steps.

The results in Table 4-7 shows that our proposed method has ultra-high improvement in comparison with step counting based periodicity, similarity, continuity method, and peak detection based method in all states.

Table 4-7. The average errors among our proposed method and two methods presented in Reference [32].

The States	**Our Propose Method**	**Step counting Based Periodicity, Similarity and Continuity [32]**	**Step Counting Based Peak Detection Method [32]**
Free walking	0.58%	11.18%	37.35%
Fast walking	1.06%	4.26%	26.73%
Slow walking	2.42%	14.92%	96.77%
False walking	3.53%	15.90%	52.70%

4.1.2.2. Comparison with Other Commercial Applications

From the results shown in Table 4-8, it can be seen that the Pedometer and Weight Loss Coach installed on Lenovo P780 has the worst performance. Our proposed method and S-Health have approximately the same average error results of 0.16% and 0.32%, respectively. (see Table 4-8).

Table 4-8. Comparisons between our proposed system and different commercial applications on 500 steps of free walking.

Times	**1**	**2**	**3**	**4**	**5**	**Average Number of Steps**	**Average Error**
True steps	500	500	500	500	500	500	0
Our proposed system	500	498	499	500	499	499.2	0.16%
Health App on IPhone 5s (iOS 10.3.3) [46]	499	507	489	477	482	490.8	2.40%

S-Health on Galaxy S5 (Android 6.01) [45]	500	502	498	503	499	500.4	0.32%
Pedometer & Weight Loss Coach installed on Lenovo P780 [47]	461	448	376	483	472	448	10.40 %

4.1.2.3. Testing with Public Datasets

We tested our proposed algorithm on public datasets [72], the data of the public datasets were collected by Samsung S6 in different positions: Hand, frontpocket, backpocket, neck pouch, bag, and armband. The public datasets [72] are available at: https://github.com/Oxford-step-counter/DataSet/tree/master/validation (Accessed on 30 August 2018). The proposed algorithm also achieved very good results of 97.04% for the average of accuracy.

4.2. Step Length Estimation

The process begins with the input of height and state recognition. After the state is confirmed, a step check will be taken place and K is chosen accordingly. With maximum acceleration A_{max} and minimum acceleration A_{min} of the step, the length is calculated and the distance is the sum of all length of steps that happen during the moving period.

Height Range	State	Calculation of K
≥1.75m	Walking	$0.738 - 0.37\times v_{step} + 0.15\times v_{step}^2$
	Running	$1.162 - 0.37\times v_{step} + 0.15\times v_{step}^2$
1.65m<&<1.75m	Walking	$0.724 - 0.37\times v_{step} + 0.15\times v_{step}^2$
	Running	$1.099 - 0.37\times v_{step} + 0.15\times v_{step}^2$
1.55m≤&≤1.65	Walking	$0.692 - 0.37\times v_{step} + 0.15\times v_{step}^2$
	Running	$1.034 - 0.37\times v_{step} + 0.15\times v_{step}^2$

4.3. Turning Time and Direction Estimation

4.3.1. Turning Time Estimation

Using the magnetic sensor in IMU 9250 to record the earth's magnetic in $Mx, My,$ *and* Mz axes are essential. The sampling frequency (Fs) of the Magnetometer equals 50Hz.

To illustrate clearly the changing of magnetic signal when rotating, we proposed to calculate the mean value of $MaxMin\_X(i)$ and $MaxMin\_Z(i)$ by the following formula:

$$M(i) = \frac{MaxMin\_x(i) + MaxMin\_z(i)}{2} \quad (4\text{-}16)$$

The combination of the signal in Mx and Mz can solve the limitations in each axis. Based on this combination can be detected the rotation changing during the moving of volunteers by using a proposed threshold as shown in the following formula:

$$\text{thresh} = \frac{\max(M) - \min(M)}{2} \quad (4\text{-}17)$$

After normalization, the signal presents clearly turning position, the value of 1 and 0 represent rotating and non-rotating respectively

4.3.2. Turning Direction Estimation

The turning directions depend on the signal changing of Mx and Mz. Hence, we proposed to use the threshold include $threshold\_x$ and $threshold\_z$ to detect the signal changing in Mx and Mz axes. If the signal value is greater or smaller than the proposed threshold, it will be normalized to 1 or 0 respectively as the following figure.

The turning direction is estimated based on the standardization signal of both $\boldsymbol{Mx\_normal}$ and $\boldsymbol{Mz\_normal}$. When the values of $\boldsymbol{Mx\_normal}$ and $\boldsymbol{Mz\_normal}$ equal 1, it means that the standardization signal belongs to high (H) and 0 means low (L).

The increase in the value of the standardization signal from 0 to 1 is called signal increase (↑) and the inverse is called signal attenuation (↓). Hence, the signal variation of both $\boldsymbol{Mx\_normal}$ and $\boldsymbol{Mz\_normal}$ is used to estimate the turning directions.

Table 4-11. The turning directions estimation based on the fusion of $\boldsymbol{Mx\_normal}$ and $\boldsymbol{Mz\_normal}$

The turning / Signal	Turn right				Turn left			
Mx_normal	H	L	↑	↓	H	L	↓	↑
Mz_normal	↓	↑	H	L	↑	↓	H	L

The turning directions estimation will be saved in turn [] array with value 1 is related to turn right and 0 is turn left.

4.4. Vertical Position Estimation

The barometer use to estimate the vertical position of the volunteers in the building. Based on the measured pressure values to estimate the altitude based on the following formula:

$$H = 44330 * \left(1 - \left(\frac{p}{p_0}\right)^{\frac{1}{5.255}}\right) \tag{4-18}$$

where $p0$ is the pressure at sea level (p_0= 1013,25 hPa) and p is the measured pressure by the barometer.

Based on the estimated altitude values and map information to estimate the vertical position of volunteers.

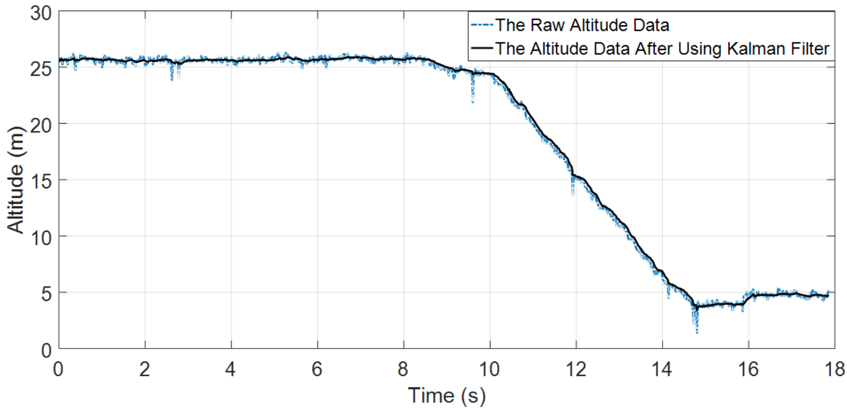

Figure 4-25. The data before and after using the simple Kalman filter

The volunteers executed two scenarios; it includes elevator up and elevator down movements.

Based on the Figure 4-25 above can be seen that when elevator moves down from floor 7 to floor 2, the pressure data will increase. Based on the formula 4-18, we calculated the altitude changing from around 21m to 5m.

4.5. The Proposed of Indoor Positioning Model

Besides the directions estimated based on the accelerometer and magnetometer, we had estimated the vertical position based on the barometer. The algorithm of vertical position estimation has been proposed in our previous publication [84]. Furthermore, the turning algorithm was combined with step counting [18] to detect the indoor position of the user. The sensors fusion method is proposed as the following Figure:

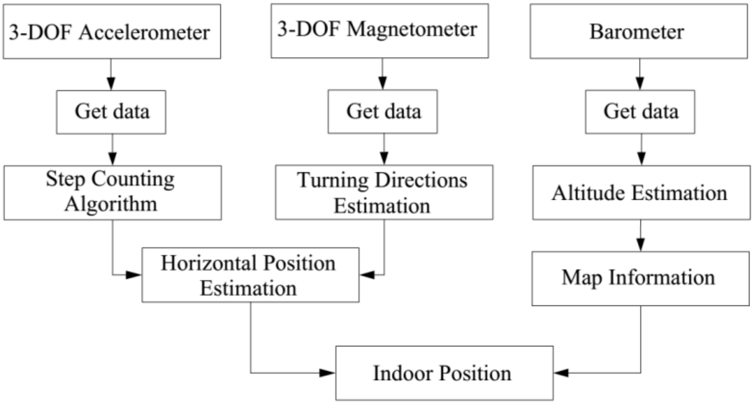

Figure 4-27. The flowchart of the indoor positioning system based on sensors fusion

4.6. Summary

In this chapter, we have successfully developed a highly accurate step counting with real-time response using a low-cost 3-DoF accelerometer for various walking states. We have successfully solved the over-counting, under-counting, and false walking problems by proposing four features: Minimal peak distance, minimal peak prominence, dynamic threshold, and vibration elimination in combination with peak detection and periodicity and similarity features. Minimal peak prominence and dynamic thresholding are novel and powerful techniques in false peak elimination in step counting. In the future, we will expand to detect steps in a crawling state to support indoor positioning systems to predict the positions of on-duty firefighters.

This chapter is also presents the method to estimate the step length, step direction and vertical position. The proposed step length estimation method is adaptive with the height and the state of user. Hence, it can achieve a very high accuracy. Besides, the signal changing of magnetometer along Mx and Mz axes and barometer used to estimate the turning directions and altitude respectively with high accuracy.

CHAPTER 5. INDOOR FIREFIGHTER POSITIONING AND TRACKING USING MULTI-SENSOR DATA FUSION AND MAP MATCHING ALGORITHM

The chapter 5 presents the experimental results of the proposed indoor positioning method using multi-sensor data fusion and map matching algorithm. There are 6 scenarios from simple to complex that has been tested in the experimental testing.

5.1. Data Fusion

The method of injured detection, step counting, step length estimation, turning direction estimation, time of turning and vertical position estimation have been proposed in Chapter 3 and chapter 4 of this thesis.

The method of these parts will not present in this chapter. In this chapter, the thesis mainly focus on propose the suitable algorithm to fuse the information of these part to estimate the injured and the positions of fire firefighters at the inside of a building.

5.2. Data Fusion and Map Matching to Detect Indoor Position

5.2.1. Experiment Setup

The process of recording data was gathered from the experiment that was executed on eight male volunteers with age: 18-28, height: 1.65 – 1.78 m, weight: 58 – 76 kg who were selected from The University of Fire Fighting and Prevention (UFFP).

This thesis used $times[]$ and $turn[]$ arrays to save turning times and turning directions respectively to combine with step counting and step length estimations for indoor positioning and tracking.

The turning estimation based on the signal is recorded from a magnetometer; step counting and step length estimation based on the signal recorded from an accelerometer. The magnetometer and accelerometer have the same sampling frequency as Fs = 50Hz. Hence, the thesis fused data from these sensors to support indoor positioning and tracking.

5.2.2. The Scenarios Testing

Scenario 1: The step counting with three turning times of free walking state.

Scenario 2: The step counting with two turning times of a free walking state from the beginning of the hallway (start point) to the end of the hallway (endpoint).

Scenario 3: The step counting with three turning times of a free walking state from the outside of the building and walk around the hallway.

Scenario 4: Free walking from inside of a room to the end of the hallway

Scenario 5: Free walking from the beginning of the hallway (start point) to a room then walking from the room to the end of the hallway (endpoint) with seven turning times and walking inverse.

Scenario 6: Go straight 30 steps then turn left – go straight 3 steps then turn right – go straight 48 steps then turn right – go straight 8 steps then turn right – go straight 10 steps then turn left – go straight 2 steps then turn right – go straight 4 steps then turn right – go straight 3 steps then turn right – go straight 14 steps then turn left – go straight steps then turn right – go straight 35 steps then stop.

Based on the step counting and turning times in the Figure below can be seen clearly that the proposed algorithm detected exactly the number of steps and the number of turning directions. The experimental result in Figure…illustrates the indoor position of the volunteer with ultra-high performance and accuracy.

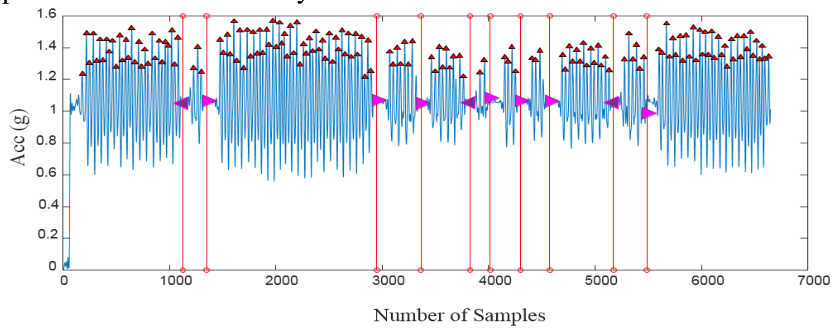

Figure 5-10. The experiment result of step counting and turning directions of free walking of scenario 6

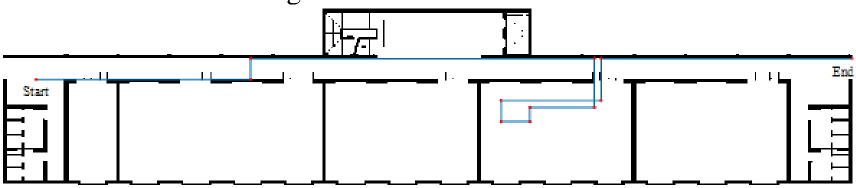

Figure 5-11. The indoor positioning of scenario 6 on the map

The below table is the summary results of the 5 scenarios above.

Table 5-1. The experimental results on step counting of our proposed algorithm

Sce.	**True steps**	**Steps detected by our proposed algorithm**	**No. of steps Error**
1	16	16	0
2	122	122	0
3	248	248	0
4	112	112	0
5	148	148	0
6	163	163	0

Table 5-2. The experimental results on turning times and turning directions of our proposed algorithm

Sce.	**True turning directions**	**Turning times detected by our proposed algorithm**	**No. of turning times and turning directions Error**	**Dist. Error (m)**
1	Turn right 3 times	Turn right 3 times	0	N/A
2	Turn left 2 times	Turn left 2 times	0	0
3	Turn right 1 time and turn left 2 times	Turn right 1 time and turn left 2 times	0	1.3
4	Turn right 2 times and turn left 3 times	Turn right 2 times and turn left 3 times	0	0
5	Turn right 3 times and turn left 4 times	Turn right 3 times and turn left 4 times	0	1.1
6	Turn right 7 times and turn left 3 times	Turn right 7 times and turn left 3 times	0	1.6

Based on the summary results in the table 5-1 and table 5-2 above can be seen that our proposed algorithm detected exactly the number of steps, turning times and turning directions. The accuracy of step counting, turning times and turning directions in indoor positioning and tracking system is 100%. The highest error in distance between true position and the estimated position is only 1.6m and the positions on the map display exactly the rooms that the volunteers were entered.

5.3. SUMMARY

This chapter has been evaluated the proposed method about indoor positioning with multiple scenarios from simple to complex. Based on the testing results in Table 5-1 and 5-2 can be seen that the proposed method detected the number of steps, the number of turns, the time of turning, the turning directions with very high accuracy. Furthermore, the indoor positions displayed correctly on the map with the acceptable errors.