Abstract— In this paper, an indoor positioning system of pedestrian dead reckoning (PDR), with WiFi fingerprint and map-matching techniques, is proposed on a smartphone. Based on five different holding styles, which are classified by using decision tree method, the proposed system supports the user in a more freedom of holding style while walking but still be able to track the location of the user accurately. To compensate the accumulating error of the PDR system, WiFi fingerprint and map-matching techniques are applied. The proposed method aims to enhance the tracking performance of the whole system with the WiFi fingerprint technique as well as can reduce the building cost of the radio map with fewer number of reference positions compared to conventional systems. In addition, the methods to detect turning behaviour and collisions based on a given map information are suggested to correct the position from the PDR system. From numerous experiments, the performance of the whole system is demonstrated.

Keywords— pedestrian dead reckoning; WiFi fingerprint; map-matching; holding styles; smartphone

I. INTRODUCTION

For the past 20 years until now, smartphones have become popular dramatically in our daily life. Many applications have been developed to support the users in different ways of their life such as entertainment, work, and so on. As an example, in the area of healthcare management, smartphone can play a role as the main device to collect personal health records (PHRs) such as the activities of the user in a day, then gives the user the feedback to help him/her manage a healthier life. Recently, many researchers have attempted to build better indoor localization systems to support many location-based services for various indoor environments where the Global Navigation Satellite Systems (GNSS) cannot work well. There are several commercial indoor positioning systems on the market that use different techniques such as Radio Frequency Identification (RFID) positioning, ultra-wideband, camera positioning, etc.

As a promising indoor positioning method, the pedestrian dead reckoning (PDR) is one of the relative techniques that is more relevant in indoor localization. Based on the characteristics of human walking, the current position can be updated from the previous position with an incremental locomotion, i.e. one step length in heading direction. The implementation of the PDR technique with handheld devices such as smartphone or tablet is being concentrated on because the increased number of sensors is installed in those devices and non-additional infrastructure. However, the PDR technique suffers from cumulative errors, which are easily caused by the errors of estimating for step length and heading direction.

The WiFi fingerprint technique has also been used for indoor positioning for several years. This technique utilizes the existing the wireless local area network (WLAN) infrastructures which currently are very popular. The typical WiFi fingerprint matching algorithm generally consists of two components: a radio map and an estimation method. The radio map which includes the fingerprint of the reference positions was built in the offline phase (training phase). Then, in online phase, the current fingerprint (scanned received signal strength indicator (RSSI) values) will be compared with the reference positions in the database, so the location can be determined. Nowadays most indoor environments have WLAN system so it does not cost much for implementation but the instability of RSSI limits the tracking performance.

A map of the given indoor environment should be required for almost applications generally. Moreover, it could be used to estimate the current location of a user. For example, if a system detects that user is going up or down on a stairway, then it can be used to correct the current location of the user with the location of the stairway. In this study, these clues are called landmarks. The landmarks can be defined as a sort of reference positions where the system can know the exact location.

In recent studies, many researchers try to find a better positioning system which can handle more natural situations such as various ways of holding a smartphone while a user walks. In previous works, the holding style (or installation site of sensors on the body) was fixed and assumed that the system knows in-priori for estimating the heading direction of the pedestrian. Currently, there are methods to handle the holding style recognition.

In this paper, based on five holding styles, the PDR, WiFi fingerprint and map-matching techniques will cooperate tightly to enhance the performance of determining the location of the user in the indoor environments in a real-time way. The influence of WiFi fingerprint and map-matching techniques in enhancing the performance of PDR is focused. A comparison among the proposed system and other PDR-based fusion
approaches are set up to show the improved performance of the proposed system.

The rest of the paper is structured as follows. Section II mentions related works. Section III describes the proposed system in detail. The performance evaluations and analyses are presented in Section IV. Finally, Section V concludes the paper.

II. RELATED WORK

Until now there have been developed wireless indoor positioning systems such as Microsoft RADAR [1], Horus [2] or Ekahau [3]. Liu et al. [4] made a survey to compare among some well-known systems and came to a conclusion. Each system has its own pros and cons and is used in different schemes and purposes. Generally, wireless fingerprinting scheme is better for open areas while Active RFID is suitable for dense environments. In terms of scalability and availability, indoor positioning systems have their own important characteristics when applied in real environments. The choice of technique and technology significantly affects the granularity and accuracy of the location information.

In a PDR system, three main characteristics could be focused. The first one is how to detect a new walking step using the inertial sensors such as accelerometer and/or gyroscope. Some researchers used the smartphone that was mounted in different parts of user body ([5], [6], [7]) and based on that they attempted to count the walking steps. Pratama et al. [8] presented methods for step detection that use peak detection and zero-crossing. The second one is how to estimate the step/strike length. Even for one pedestrian, but up to the mood, personal characteristics and environments, the step length is not a constant value, respectively. Based on the cadence and variance of the accelerometer, the step length is estimated in [9], [10]. Weinberg [11] suggested an adaptive method to calculate the step length by using the acceleration magnitude, vertically. In the survey of Harle [12], he summarized a lot of methods to detect accurately number of walking steps. The last one is how to measure the heading direction while walking. Especially, the small error of the heading could make a big position error. To handle the heading estimation errors, El-Diasty [13] proposed an heading estimation procedure based on the integration of gyroscope and magnetometer measurements. Roy et al. [14] developed a stable technique to estimate the heading direction within a few steps by estimated and canceled magnetic interference from the compass data.

For motion classification, using Finite State Machine (FSM), Tian et al. [15] classified among three main holding styles, i.e. holding, swing and pocket. Then based on these styles, they improved their PDR system. Moreover, using machine learning is one of the most common method for motion classification. In [16], Zhang et al. proposed a navigation system which addressed different device poses then different step modes while walking. The device poses were classified by using Multilayer Perceptron (MLP) and Support Vector Machine (SVM). More recent, Shin et al. [17] used Artificial Neural Network (ANN) to recognize the six motions such as swing, talking, pocket, etc.

Currently, hybrid systems with the combination of the classical PDR and other techniques such as Bluetooth, Infrared, WiFi, etc. were suggested in order to improve the accuracy of the whole positioning system. Pei [18] presented an indoor pedestrian navigation solution relying on motion recognition in an office environment utilizing the existing WLAN infrastructure. He et al. [19] introduced an indoor localization system with the cooperation of information from PDR and wireless fingerprints, then calibrate the system. Lee et al. [20] proposed a hybrid indoor location tracking method that used the smartphone with dead reckoning and WiFi fingerprint techniques and tried to reduce the cost of building a radio map for WiFi fingerprint technique.

Moreover, with the valuable map information, there are systems which used this information to enhance the performance of PDR. By using the Kalman filter, Chen et al. [21] and Deng et al. [22] introduced a sensor based indoor positioning system which combines the PDR, WiFi and floor plan information simultaneously. A landmark-aided PDR which includes the information from WiFi and map landmarks to correct the accumulated errors of PDR was proposed by Wang et al. [23]. Recently, Wang et al. [24] used the particle filter model to fuse information of above techniques to determine the user’s location.

III. PROPOSED SYSTEM

A. Overview

Fig. 1 shows the block diagram of the proposed indoor positioning system, which composes PDR technique and two techniques to improve the performance of PDR: WiFi fingerprint and map-matching.

In the PDR component, by using a set of sensor signals in a smartphone, the smartphone holding style of the user is determined. The sampling rate for the sensors is 30Hz. The holding style recognition is required to calibrate the heading direction based on the relative orientation information between

![Fig. 1. Block diagram of the overall proposed system.](image-url)
the device and the user. By using the decision tree method, five main smartphone holding styles are classified. Then the system tries to detect and count the number of walking step of the user based on the holding styles. For each current walking step detected, the step length is also estimated by using the cadence and physical characteristics of the user. The heading direction is estimated with the combination of three sensors: accelerometer, magnetometer and gyroscope based on the recognized holding style. This means the system can estimate the heading direction of the pedestrian by knowing the relative orientation difference between the device and the user’s body.

The system also includes two components named WiFi fingerprint and map-matching. These components attempt to correct the position of the user if some conditions are met. The typical WiFi fingerprint technique is used. The component can estimate the initial and final positions when the user does not move. Even during walking, the proposed system also attempts to find a reference position from the database. If one reference position can satisfy a set of conditions then the location error caused by the PDR component is corrected. The WiFi fingerprint component is implemented with the effort to reduce the number of the reference points in the radio map. The map-matching component includes two subparts: the corner/door detection and the wall detection. Those methods are implemented based on the map information.

B. PDR system

Firstly, the system tries to classify five basic holding styles of the pedestrian which can be considered as the installation position of the smartphone on the body of the user: holding the phone on hand vertically (HA-V) and horizontally (HA-H), holding the phone parallel with ears while calling (CA), swinging the phone while walking (SW), and putting the phone into a front pocket of pants (PO) as shown in Fig. 2.

![Fig. 2. Smartphone holding styles.](image)

Decision tree is one of the most popular machine learning methods by its ease of implementing and fast prediction. In this work, the J48 classifier was chosen to recognize the holding styles. There consists the training and testing phases. In the training phase, the feature will be extracted from the training samples by using the sliding window approach. In this paper, the window length is 1 second with the overlap of 50%. The 30 features are extracted in the time domain from three axes of accelerometer and gyroscope sensor. The feature include: mean, standard deviation, variance, maximum, and minimum. For each holding style, the scheme was trained with the data of 10 minutes.

Next, different holding styles could affect to the performance of the step detection method. For holding styles (HA) and (CA), linear acceleration values are used to detect new waking step. On the contrary, the gyroscopic values are used to detect the step for holding styles (SW) and (PO). During a gait cycle, there are always stance and swing phases. The step detection method includes two features: the absolute value between the maximum and minimum peaks and the duration between two peaks in swing phase. The threshold method is used to detect a new step if it can satisfy the conditions of two features.

![Fig. 3. Heading calibration.](image)

Moreover, the proposed scheme estimates the step length by using the features of the cadence and the strength of acceleration (for styles (HA) and (CA)) or gyroscope (for styles (SW) and (PO)) as in our previous work [25].

Lastly, the system tries to estimate the heading direction by processing acceleration, magnetic, and gyroscope values. The accelerations and magnetic values are used to calibrate the value of the gyroscope by applying the complementary filter. After that, by adding/subtracting the recent calculated heading angles with constant values by using the relative direction difference based on the recognized holding styles. Some heuristic methods such as quantization, alignment of missing true North, and hysteresis methods are also applied to compute the final heading direction. A more detailed explanation can be referred to our previous work [26]. Fig. 3 shows the estimated heading direction after applying a set of methods when a user walks in a straight path with one direction while he/she changes holding styles freely.

C. WiFi fingerprint

The proposed WiFi fingerprint method was designed to use a database which has a few reference points (called landmarks) in compared to the conventional system. The landmarks are chosen at the special places where the user visits frequently, i.e., working seat in an office, a restroom, stairs, gates and so on. Each user can choose the landmarks based on his/her right when entering the building. The WiFi component provides mainly the initial and final positions when the user does not move and corrects the current position while walking. Because
the strength of wireless signal can be greatly and easily affected by various sources surrounding environment, it could be challenging to handle this problem in WiFi fingerprint technique.

In the proposed scheme, three access points in the order of strongest RSSI are chosen as a fingerprint at a certain position. That means the fingerprint of a position is a vector including three components. For building a radio map (database) for a landmark, a set of signals were collected in different environmental conditions such as using different devices, different directions of phone, different time zones, and different scanning intervals. The radio map was implemented on the smartphone locally, i.e. using a local database on a device.

The PDR component can only provide incremental changes in position of the user. Therefore, the estimation of the initial position plays an important role in the accuracy of the entire positioning system. In order to estimate the initial position among the landmarks, the WiFi component computes the matching error $e_2$ between the current position and all the potential landmarks after the user starts the program and does not move in 10 seconds. The final position estimation uses the same method with the initial position estimation. The PDR component does not work in case of initial and final position estimation.

After the initial position is determined, the WiFi component tries to determine whether the user is in the area of a landmark or not during he/she walks after every scanning time with the interval of 3 seconds. To do this, two features were chosen. The first one is the minimum value $e_2$ of the matching error values as described above. The second feature is the geometric distance between the current position of the pedestrian and the closest landmark on the two-dimensional (2D) map. If the component finds that the first feature is less than a threshold, then the system could correct the current position with the given position of the landmark. However, this does not guarantee that the user is really in the landmark area because the actual distance between the current position and the center position of the landmark could be affected by the threshold value and/or the quality of the scanned RSSI signals as shown in Fig. 6. In order to reduce this error, the second feature was introduced. The component calculates the geometric distance between the current position and the given center of the close landmark. In this work it was assumed that the representative shape of the user and the landmark is a circle shape with the radius of 1.5 meters. So the component can determine whether the collision of these two circles occurs or not in 2D plane as:

$$\left| (x - x_a)^2 + (y - y_a)^2 - (r_1 + r_2)^2 \right| \leq \epsilon_2$$

where the $(x_a, y_a)$ is the location coordinate of the current position of the user and the $(x_l, y_l)$ is that of the landmark, $r_1$ and $r_2$ are the radii of two circles.

The method for compensating while walking is suggested: For each new step, if the system can find a potential landmark with a minimum of $e_2$ value, and the collision condition as (1) is satisfied, then the component would update the current position with the landmark position.

### D. Map constraints

#### 1) Corner/Door detection

When a user walks at a corner or a door to go into a room, he often turns his walking heading. Therefore, based on the turning behaviors, the corner or the area in front of a door can be considered as a new landmark. In this paper, the turning behaviors include U-turn (for example, the user turns around) and normal-turn (for example, the user changes his heading to walk into a room) as mentioned in [27]. Two features are used to detect the turn. The first one is the average of magnitude of tri-axes gyroscope sensor in 2 seconds (60 samples)

$$\bar{\omega} = (\omega_x, \omega_y, \omega_z)$$

This feature can reflect the changing of the user’s body while walking.

The second feature is the absolute difference between four heading values got from four consecutive walking steps ($d_h$). The heading value is measured from the walking heading of PDR system. Algorithm 1 describes the detection.

#### Algorithm 1: Corner/Door Detection Algorithm

**input :** $\omega_{wo}$, heading $h_i$

**output :** Corner/Door detection

1. **if** (new step detected) **then** // from PDR system
   1. **if** ($\omega_{wo} > \text{Th}_1$) **then**
   2. **if** ($d_h \leq \text{Th}_2$) **then**
       3. WALKING_STRAIGHT
   **else if** ($\text{Th}_2 < d_h \leq \text{Th}_3$) **then**
       5. NORMAL_TURN
   **else if** (U_TURN) **then**
   **end if**
   14. **end if**
15. **end if**

The thresholds from 1 to 3 in this paper are determined empirically as 0.5 rad/s, 20 degree, and 70 degree.

Then the compensation of the turning phase is executed as described in WiFi fingerprint with the collision between two circles, the user, and the turning area.

#### 2) Wall detection

When a user walks in a building, clearly that he/she cannot walk through physical obstacles/barriers such as the walls, furniture, etc. The proposed system uses a method to detect the walls and compensate the position of the user in the 2D map. Let assume that the user’s representative on the 2D map is a circle and the walls are the rectangles. Then the system attempts to detect the collision/intersection between the circle and the rectangle.

Assume that $x_c$, $y_c$, and $r_c$ are two coordinates of the circle in 2D map and the radius of the circle, respectively. $rec_l$, $rec_r$, $rec_t$, and $rec_b$ are the left, top, right, and bottom coordinates of the rectangle as shown in Fig. 4. At the first step, the method determines the point $P$ $(x_P, y_P)$ on the rectangle which is closest to the center of the circle. The coordinate of point $P$ is

$$P = \left( x_c + \frac{r_c - rec_l}{2}, y_c + \frac{r_c - rec_t}{2} \right)$$
as below:

\[ x_p = \max \{ \text{rec}_c, \min[x_c, \text{rec}_t + \text{rec}_b] \} \quad (2.1) \]
\[ y_p = \max \{ \text{rec}_c, \min[y_c, \text{rec}_t + \text{rec}_b] \} \quad (2.2) \]

The collision between the circle and the rectangle is determined if point P is in the circle. Assume \( x_0 = x_c - x_p \) and \( y_0 = y_c - y_p \), then the collision is determined when \((x_p)^2 + (y_p)^2 \leq (r)^2\).

When the collision between the user and the wall is detected on 2D map, there are four directions that the circle can intersect the rectangles: left, right, top, and bottom. Assume \( C = (x_c, y_c) \) is the coordinate of the user when the collision is detected, then the position of the circle is compensated as following: If (collision at the left side) then \( C = (x_c - I_{\text{prev}}, y_c) \); If (collision at the right side) then \( C = (x_c + I_{\text{prev}}, y_c) \); If (collision at the top side) then \( C = (x_c, y_c - I_{\text{prev}}) \); If (collision at the bottom side) then \( C = (x_c, y_c + I_{\text{prev}}) \). \( I_{\text{prev}} \) value is calculated from PDR system.

IV. EXPERIMENTAL RESULTS

A. Holding style recognition

To evaluate the performance of holding style recognition by using J48, two subjects held their smartphones while walking in five holding styles serially changing. For each second, the classifier attempt to determine which holding style the subject is using. The total times of each holding style is 250 times. By using the confusion matrix as in Table I, the performance of the proposed method is evaluated. The rows present the ground truth of actual activity, while the columns present the activity predicted from the classifier. The measures include F-score, the positive predictive value (P\(_s\)), the sensitivity, and the specificity. The proposed methods performed with high global sensitivity (99.12%) and specificity (99.84%). The bold number indicates the percentage of successful classifications.

B. Initial position estimation

This experiment tests the performance of recognizing one

<table>
<thead>
<tr>
<th>Classified as</th>
<th>HA-V</th>
<th>HA-H</th>
<th>CA</th>
<th>SW</th>
<th>PO</th>
</tr>
</thead>
<tbody>
<tr>
<td>HA-V</td>
<td>99.6</td>
<td>0</td>
<td>0.08</td>
<td>0.08</td>
<td>0</td>
</tr>
<tr>
<td>HA-H</td>
<td>0</td>
<td>100</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>CA</td>
<td>0.08</td>
<td>0</td>
<td>99.84</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>SW</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>99.92</td>
<td>0.16</td>
</tr>
<tr>
<td>PO</td>
<td>0.32</td>
<td>0</td>
<td>0.08</td>
<td>0</td>
<td>99.84</td>
</tr>
</tbody>
</table>

F-score | 0.986 | 0.992 | 0.987 | 0.992 |

P\(_s\) | 98.02 | 99.2 | 99.49 | 99.2 |
Sensitivity (%) | 99.2 | 100 | 99.2 | 98 | 99.2 |
Specificity (%) | 99.6 | 100 | 99.84 | 99.92 | 99.84 |

in six landmarks as the initial position of the pedestrian. Six WiFi landmarks are shown in Fig. 5. For each landmark, the system scans for RSSIs in four directions: North, East, South, and West and five times for each direction. All the experiments are executed in Engineering building, Hallym University.

The result is shown in Table II with the confusion matrix. From Table II, it can be seen that the method to recognize the initial position is simple but works quite efficiently. The bold number indicates the successful estimations. The lowest error rate can reach to 0% meanwhile the highest error rate is 10%. The mean error rate is 4.29%. The reason for the errors is mostly because of the direction when the smartphone scans at one landmark. The body of the user is also one factor that affects to the RSSI signal. The average distance between two landmarks of approximate 12 meters can also support to the accuracy of this method.

C. Landmark recognition during walking

This experiment examines the performance of recognizing the location when the user is walking. For each landmark, the user walks 2 rounds from the farthest point (about 50 meters), crosses the landmark and goes far away from that landmark again. It is expected that when the user crosses the landmark, the \( e_2 \) value at that point will be the smallest value then the system would compensate for the current location. The distance is considered based on the number of walking steps. Fig. 6 shows a trajectory of the matching error value of the current position and the landmark. The red line presents the relative signal difference for this landmark and the blue line is the truth value when the user truly crosses the landmark (1.5 meters before and 1.5 meters after crossing). Based on this figure, the moment when the user crosses the landmarks and the estimated moment is not far. The same results happened for other landmarks. The average difference between the true and
TABLE II. RESULT FOR INITIAL POSITION ESTIMATION.

<table>
<thead>
<tr>
<th>Landmarks</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>Unk</th>
<th>Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recognized</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>20</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>20</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>0</td>
<td>20</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>18</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>18</td>
<td>1</td>
<td>1</td>
<td>10</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>18</td>
<td>0</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>Unk</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Fig. 6. Estimation of landmark crossing while walking.

estimated landmark by number of walking steps is about 3 steps, with the standard deviation is 1.29.

Moreover, it can be shown that for each time the user crosses the landmark area, he needs about 6-8 steps at a normal speed. Another experiment to figure out the performance of landmark recognition was executed. The user was asked to walk in the same scenario with previous experiment with three different speeds: slow, normal, and fast. The ground truth is marked 1.5 meters before and 1.5 meters after crossing the landmark. For three different speeds, the average steps for each speed to cross the landmark area is 7.5, 7.2, and 6.1 steps, meanwhile the standard deviation for each speed is 1.91, 0.98, and 1.51. These results can prove that choosing 3 seconds for interval scanning time of the AP is enough to compensate for the pedestrian position while walking.

D. Full system performance

There are two scenarios to test the whole system. Fig. 5 shows two scenarios and the landmarks that are used to compensate for the PDR location. In both scenarios, firstly the smartphone starts to scan the WiFi signals to estimate the initial position, then three pedestrians walked along the path while holding the smartphone freely with the combination of five holding styles (HA–V), (HA–H), (CA), (SW), and (PO) and at the end the system compensates the final position of the users. The information of subjects is described in Table III. There are three cases for comparison: the PDR only, PDR aided WiFi fingerprint, and the proposed system. Each pedestrian executed three times for each case.

TABLE III. SUBJECTS’ INFORMATION.

<table>
<thead>
<tr>
<th>User</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years)</td>
<td>28</td>
<td>33</td>
<td>29</td>
<td>30</td>
</tr>
<tr>
<td>Height (m)</td>
<td>1.65</td>
<td>1.70</td>
<td>1.78</td>
<td>1.71</td>
</tr>
</tbody>
</table>

Fig. 7. Trajectories of three methods in Scenario 1. (a) PDR only; (b) PDR aided WiFi fingerprint; (c) Proposed method.

Fig. 8. Trajectories of three methods in Scenario 2. (a) PDR only; (b) PDR aided WiFi fingerprint; (c) Proposed method.

Fig. 7 and Fig. 8 show the results among using three methods in two scenarios. From the figures, the proposed method show the enhanced accuracy of PDR. The mean errors between the start and stop positions of each method are 5.75 m, 4.52 m, and 3.05m for scenario 1. In scenario 2, the mean errors for the proposed method is 4.62 m, while the mean errors for the PDR only and PDR–WiFi fingerprint methods are 9.91 m and 7.69 m. The more details of distance errors and standard deviations for each subject in two scenarios can be found out in Table IV.

Fig. 9 and Fig. 10 show the precision of positioning results of the system in scenario 1 and scenario 2. For scenario 1, at the 50th percentile, the positioning error of the proposed method is within 2.3 m and at the 80th percentile, it is within 4 m. For scenario 2, at the 50th percentile, the positioning error is within 3.8 m and at the 80th percentile, it is within 5.25 m.
TABLE IV. POSITION ERRORS FOR EACH SUBJECT.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>User</th>
<th>Method</th>
<th>Mean Error (m)</th>
<th>Standard Deviation (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>PDR</td>
<td>8.74</td>
<td>4.66</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PDR–WiFi</td>
<td>5.22</td>
<td>4.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Proposed method</td>
<td>2.69</td>
<td>1.16</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>PDR</td>
<td>4.84</td>
<td>2.02</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PDR–WiFi</td>
<td>1.24</td>
<td>1.18</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Proposed method</td>
<td>2.67</td>
<td>2.02</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>PDR</td>
<td>3.69</td>
<td>1.90</td>
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Fig. 9. Localization error CDF in scenario 1.

Fig. 10. Localization error CDF in scenario 2.

In compared between the proposed system errors with other existing systems, the proposed system has a bigger error than the methods in [22] and [24] (2.40 m and 2.17 m) but the authors used only one holding style as (HA). Meanwhile, the result of the study is higher than the result in [18], [19], and [28] (3.53 m, 4 m, and 5.75 m).

V. CONCLUSION

In this paper, an indoor localization system with the cooperation of PDR, WiFi fingerprint and map-matching techniques is proposed. The PDR is widely used in indoor navigation but having the cumulative errors by time because of the drift of the sensors embedded on the smartphone. By applying the WiFi fingerprint and the map-matching with the corner/door detection and the wall detection, the proposed whole system provided the better performance for the average error is 3.05 m without any assumption or limitation for holding style of smartphone. The proposed method could reduce the positioning errors by 51.02% in compared to the original PDR method and 37.18% with the PDR aided WiFi fingerprint.

As the future works, the authors would like to suggest a method to handle more various holding styles including the cases of putting a phone into various bags and/or various pockets of clothes. Moreover, the covered area would be extended to a multi-story building using other sensors in a smartphone.

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