Fast Generation of Wi-Fi Positioning Fingerprint Database Using Reference Location Information Acquired Based on 1D-PDR

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Abstract

Wi-Fi signal-based fingerprinting technique is widely used as an indoor positioning method due to its advantage that positioning is possible at a relatively low cost without the construction of separate equipment and infrastructure. For fingerprinting positioning, a database that stores signal patterns in the service space must first be constructed. The conventional fingerprint databased generation systems use wireless signal information that can be obtained from reference points divided at regular intervals in the entire service area. This typically requires several minutes of data acquisition for each reference point to account for variability in signal patterns. However, since the collection process must be performed at all reference points, there is a limitation in that too much time and cost is required for database construction. To overcome this disadvantages, we propose a reference location acquisition method using 1D-Pedestrian Dead Reckoning (PDR) and the Wi-Fi fingerprint database construction method based on it. In this method, a person walks with a collection device along predetermined waypoints within a service area. The Wi-Fi signal data is corrected by the smartphone's collection application itself, and the signal acquisition location along the movement path is calculated based on 1D-PDR. Finally, a fingerprint database is constructed using the collected data together with spatial interpolation. The efficiency of the proposed method is verified experimentally.

Keywords

Indoor Positioning, Wi-Fi, Fingerprint Database, 1D-PDR

1. Introduction

In accordance with the recent increase in demand for smart devices, the rapid development of internet of things technology, and expansion of its application fields, research on indoor positioning technology based on wireless signals is being actively conducted [1]. The global navigation satellite system is the most widely used system for outdoor positioning. However, as is well known, indoor positioning based on satellite signals is impossible or provides position information with a very large error. Therefore, positioning using wireless communication signals is widely used indoors [2]. To expand the service coverage to indoor areas, various wireless communication technologies such as Wi-Fi [3], Bluetooth Low Energy (BLE) [4], Ultra-Wide Band (UWB) [5], infrared [6], ultrasound [7], ZigBee [8], and Radio Frequency Identification (RFID) [9] have been used. Among these technologies, BLE, UWB, infrared, ultrasound, ZigBee, and RFID require support from specific hardware or installation of multiple beacons. On the other hand, Wi-Fi does not require additional devices because most smart devices already have a built-in Wi-Fi chipset. Additionally, with the increasing demand for Wi-Fi and the ubiquitous presence of Wi-Fi signals in everyday life, it is possible to provide low-cost indoor positioning based on this signal [10].

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Various positioning technologies based on Wi-Fi signals are used to provide indoor location information. Typically, a user's location can be estimated using various measurements such as Angle of Arrival (AoA), Time of Arrival (ToA), Time Difference of Arrival (TDOA), and Received Signal Strength Indicator (RSSI) [11, 12, 13]. Positioning systems based on AoA, ToA, and TDoA have limitations in terms of vulnerability in non-LOS environments and high cost [14]. Positioning systems based on RSSI can be classified into two categories: range-based and fingerprinting-based methods [15, 16]. The range-based positioning method constructs a signal propagation model between the user and the Access Point (AP) based on the distance between them. Therefore, if the distance to multiple APs is calculated, the user's location can be estimated. The attenuation of each AP signal is determined not only by the distance between transmitter and receiver, but also by several environmental factors such as people, walls, and furniture. In fact, in complex indoor environments, the propagation of wireless signals is interfered with by multipath effects, including reflection and refraction [17]. As a result, it is not easy to construct an accurate propagation model, which can lead to unsatisfactory positioning performance.

The Wi-Fi fingerprinting is one of the widely used methods for indoor positioning [18]. Generally, the fingerprinting approach consists of two stages: the offline stage of constructing a database, and the online stage of conducting positioning. Therefore, in the online stage, the RSSI values measured by the user's terminal device are used to calculate the similarity between the RSSI information in the database constructed the offline stage, and the coordinates of the reference point for position estimation are selected.

The Wi-Fi fingerprinting-based indoor positioning method is robust to multipath environments because it uses actual RSSI values that reflect the characteristics of the surrounding environment and is not affected by non-LOS conditions [19]. Moreover, it does not require the location information of APs, and can provide positioning information without the need for distance or angle measurements.

However, the fingerprinting method has the problem of requiring a significant amount of time and cost to construct the database. Typically, the fingerprint database divides the service area into regular intervals and is constructed of a combination of APs and RSSI patterns acquiring at each location. To do this, the RSSI pattern must be directly acquired by being located at the reference point before database generation. In addition, data must be collected for a certain period of time at all points. Consequently, providing fingerprint database in broad areas is usually unaffordable to service providers unless limited to a small scale.

To deal with the inefficiency, in this paper, 1D-PDR is used to obtain reference location information and generate the Wi-Fi fingerprint database based on this information. The proposed system first acquires raw data necessary for 1D-PDR calculation using the 3-axis accelerometer sensor built into the smartphone. Thereafter, the system estimates the user's moving distance using a step detection and stride length estimation algorithm. While moving along a pre-determined routes, it simultaneously collects the pedestrian's step data and the RSSI pattern. The RSSI pattern is collected through a smartphone signal collection application, and the position of the collector, which is synchronized with the scanning period of the Wi-Fi signals, is calculated based on the 1D-PDR algorithm. Finally, the Wi-Fi fingerprint database is constructed using the collected location-based RSSI measurements and spatial interpolation together.

The rest of this paper is organized as follows: Section 2 introduces the overall overview of the proposed system, followed by a detailed description of the algorithm for acquiring the reference location based on 1D-PDR and the generation method of the Wi-Fi fingerprint database in Section 3. Section 4 presents and evaluates the experimental results of the proposed system. Finally, Section 5 summarizes and concludes this paper.

2. System overview

This section provides an overall overview of the proposed system with the problem definition. The fingerprinting technique is a pattern-matching localization method and consists of two

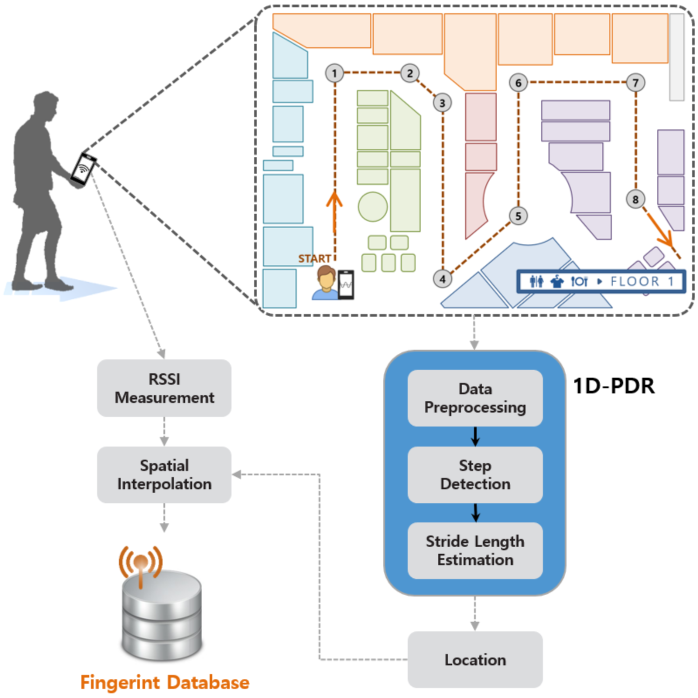


Figure 1: Fingerprint database generation system exploiting 1D-PDR

phases [20]. In the first phase, the fingerprint database that stores the signal patterns of the service area is constructed through the collection process of RSSI measurements. In the second phase, the point with the most similar signal pattern is estimated as the user's location by comparing the user's RSSI measurements with the pre-constructed fingerprint database.

The patterns of signals received from multiple APs are acquired differently depending on the acquisition location. In addition, the information of the identified AP also has a different combination for each location. The conventional fingerprint database generation system collects measurements with the signal collection device fixed in place [21]. At first, the service area is divided into a grid and multiple reference points are selected. Then, the signal collection device is used to collect the RSSI measurement sets for all reference points and average the signal patterns. The averaged RSSI values are stored in the database together with the coordinates of the corresponding reference points. To deal with the variability of RSSI according to the service environment and noise, sufficient sets of measurements are required. Therefore, the RSSI value must be measured for a certain period of time at each reference point, and it may take up to several minutes. For these reasons, it takes a lot of time and cost to generate the fingerprint database, and if the coverage of the service is wide, it is impossible to collect measurements.

To improve this problem, we propose the fingerprint database generation system utilizing the 1D-PDR algorithm. Figure 1 shows the overall overview of the proposed system. First, a collection path for signal acquisition in the service area is explored in advance. Then, while moving along the determined routes, the RSSI measurements are acquired. The RSSI is measured through a Wi-Fi signal collection application on the smartphone, and the raw data required for 1D-PDR is acquired using the built-in accelerometer sensor on the smartphone. Therefore, both accelerometer data and RSSI measurements for fingerprint database construction can be collected based on a smartphone.

The 1D-PDR is a method that estimates only the moving distance, so it does not calculate heading information. Therefore, turning points where the direction changes along the pre-determined routes are marked, and the absolute coordinates of those points, as well as the angles for the heading direction, are measured in advance. Afterwards, when arriving at the turning point while moving along the collection path, the pre-measured heading angle is input. Additionally, the absolute position of that point is used to initialize the starting point. Therefore, by utilizing the pre-measured heading information, it becomes possible to resolve the issue of direction changes, and through the initialization of the starting point, the accumulated error in the moving distance can also be compensated for.

The fingerprint database generation system calculates the patterns of signals that represent unique characteristics for each reference point using the collected RSSI measurements. Especially indoors, there can be significant variations in RSSI measurements due to environmental changes related to surrounding movements and the noise characteristics of wireless signals. Therefore, to calculate the representative RSSI patterns, all the collected RSSI measurements from the reference points are averaged to smooth out the signal variations. However, in the proposed system, data is not collected from fixed reference points. Instead, the location synchronized with the RSSI acquisition time is calculated based on 1D-PDR. In other words, the estimated location through the 1D-PDR algorithm is stored as the reference location. Therefore, the variability of RSSI is continuously collected by moving back-and-forth through the collection route several times, and the RSSI value is estimated using the measurements and spatial interpolation together. As a result, the RSSI representative pattern at the point to be estimated is calculated using the location-based RSSI measurements collected within a certain interval.

Unlike the method of collecting signals from all reference points, the proposed method autonomously collects RSSI measurements while walking along a pre-determined route. Therefore, the proposed system has the advantage of significantly reducing the unnecessary time spent in the process of collecting RSSI measurements. A detailed explanation of the methods for generating reference locations and constructing the fingerprint database will be presented in Section 3.

3. Fingerprint database generation system utilizing 1D-PDR-based reference location information

In this section, we provide a detailed explanation of the system we propose. First, an algorithm is described that estimates the reference location information based on 1D-PDR to calculate the acquisition location of RSSI measurements. And then, we describe how to construct the fingerprint database by utilizing the collected RSSI measurements and reference locations that are synchronized with the scanning period of the Wi-Fi signal.

3.1. A reference location acquisition based on 1D-PDR

The PDR algorithm is ideal for realizing seamless navigation as it can continuously provide location information in both indoor and outdoor environments [22]. PDR can achieve accurate localization within a short period of time, but it suffers from the accumulated errors of the Inertial Measurement Unit (IMU). IMUs are generally easy to be mounted to the foot of a pedestrian [23]. And also, PDR can be achieved through the built-in inertial sensors in a smartphone. In this paper, in order to estimate the reference location where the Wi-Fi signal is acquired, the smartphone-based 1D-PDR was adopted. The pedestrian's smartphone-carrying mode is the hand-held type, where the pedestrian tightly grips the smartphone and walks while monitoring the screen. In this case, the smartphone is kept almost stationary.

The 1D-PDR algorithm is a method that estimates the moving distance based on walking information. To calculate the location of the pedestrian, the step detection and stride length estimation phases are combined. Step detection is a crucial process in 1D-PDR as it is used to estimate stride length. If there are missed or false detections of steps, it can cause substantial errors in total stride length estimation. Therefore, it is necessary to accurately detect the step cycle that occurs during walking situations. We use the 3-axis accelerometer sensor built into the smartphone and detect the step cycle through the magnitude of the output data as follows:

$$a_{M,t} = \sqrt{a_{x,t}^2 + a_{y,t}^2 + a_{z,t}^2} - g \tag{1}$$

where $a_{M,t}$ is the magnitude of the acceleration, $a_{i,t}$ is the accelerometer output values of the i-axis acquired at time t, respectively, and g is the gravity component.

The raw acceleration data may contain interference and noise signals due to the continuous shaking of the human body. This becomes the factor that degrades the performance in detecting steps after recognizing walking patterns. Therefore, data filtering is applied to mitigate the effects of interference and noise. A low pass filter is a filtering method that attempts to pass a low-frequency signal through the filter as it is while reducing the amplitude of a signal whose frequency is higher than the cutoff frequency. We applied a 3rd-order Butterworth digital low pass filter, with a cutoff frequency of 2 Hz to filter the high-frequency components of $a_{M,t}$. Filtering can help to remove some noise and smooth the curves of the signal, but it can cause a delay of the signal on the time axis. This can result in a delay error occurring at the point of synchronization with the wireless signal acquisition time, which is equal to the lag caused by the filtering process. To solve this problem, as shown in Figure 2, a zero-phase filter that compensates for lag through time inversion of the data array is applied [24]. In this method, the same Infinite Impulse Response (IIR) filter is used twice, and the time reversal process represents the left-right reversal of a time-domain sequence. When the raw data $x(n)$ is filtered, the frequency component with the original phase α is delayed by ϕ. The time reversal process negates the phase of the input and additionally delays the frequency components by θ. The phase delay caused by the initial IIR filtering process is compensated for by the subsequent IIR filtering process, and the phase output through the final time reversal process matches the phase of the input. The effects of IIR filtering and zero-phase IIR filtering for the magnitude of acceleration are shown in Figure 3. The IIR-filtered result smooths out the curves of the signal but causes a lag on the time axis. On the other hand, the zero-phase filtered result shows that the amplitude of the signal is additionally attenuated due to the two filtering processes. However, no time delay occurs, and the original temporal relationship of the signal is preserved. Therefore, in order to compensate for the synchronization error with wireless signal scanning time caused by the lag issue, the zero-phase filter technique is crucial in the filtering process.

In the data preprocessing stage, the filtered acceleration takes the shape of a sin (or cos) wave pattern according to the gait cycle. We use the sign inversion of the slope to detect peaks corresponding to the gait cycle in order to extract the walking information of pedestrians. As a result, we can identify the ascending and descending sections of the acceleration data and detect peak values that correspond to the gait cycle.

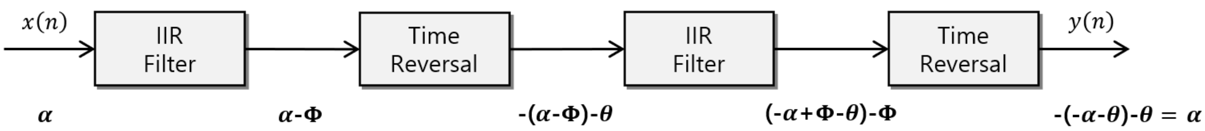


Figure 2: The process of zero-phase IIR filtering

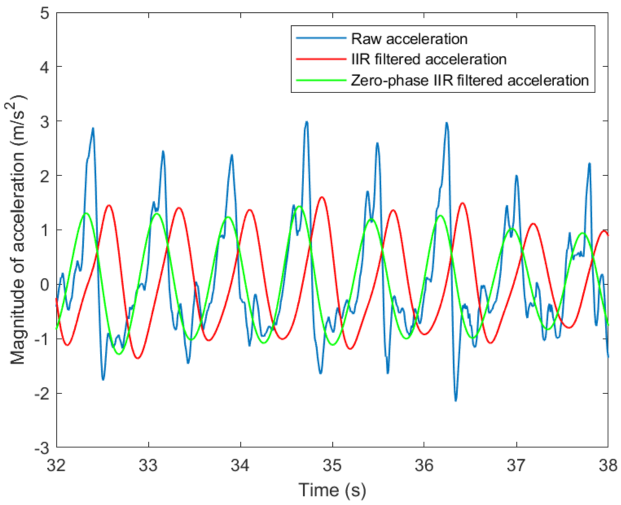


Figure 3: Comparison of IIR filtered acceleration and zero-phase IIR filtered acceleration

The stride length represents the distance between steps. In other words, by accumulating stride lengths, the total moving distance can be calculated. Inertial Navigation Systems (INS) typically calculate distance by double integrating the output of an accelerometer. However, this method is not suitable for smartphone-based PDR systems. Therefore, in order to calculate stride length in smartphone-based systems, the relationship between step cycle and variance that can be determined by the accelerometer output is utilized. The stride length is estimated using a linear combination of step frequency and acceleration variance as follows [25]:

$$SL_k = \alpha \cdot f_k + \beta \cdot v_k + \gamma \tag{2}$$

where α, β, and γ are model parameters that should be calibrated based experiments, and f_k and v_k represent the pedestrian's step frequency and the variance of acceleration signals, respectively, which can be calculated as follows:

$$f_k = \frac{1}{t_k - t_{k-1}} \tag{3}$$

$$v_k = \frac{1}{N_k} \sum_{t=t_{k-1}}^{t_k} (a_t - \overline{a_k})^2 \tag{4}$$

where t_k, t_{k-1} is the starting and ending timestamps of step k, a_k is the acceleration at time t, $\overline{a_k}$ is the average acceleration of step k, and N_k represents the number of samples during step k.

The model parameters vary depending on the pedestrian and step patterns, and each step pattern corresponds to a set of model parameters. The model parameters for each step pattern can be calculated using the least squares method. In fact, when using L as the stride length, the sum of squared errors is as follows:

$$E = \sum_{i=1}^{n} \left(L_i - (\alpha \cdot f_i + \beta \cdot v_i + \gamma) \right)^2 \tag{5}$$

Equation (5) can be written in matrix form as follows:

$$E = (Z - HX)^T (Z - HX) \tag{6}$$

where

$$H = \begin{bmatrix} f_1 & v_1 & 1 \\ \vdots & \vdots & \vdots \\ f_n & v_n & 1 \end{bmatrix}$$

$$Z = \begin{bmatrix} L_1 \\ \vdots \\ L_n \end{bmatrix}, \quad X = \begin{bmatrix} \alpha \\ \beta \\ \gamma \end{bmatrix}$$

The step parameters of matrix X can be calculated using the least squares method by minimizing Equation (6), as follows:

$$X = (X^T X)^{-1} X^T Z \tag{7}$$

The 1D-PDR algorithm estimates the moving distance by assuming that it is possible to walk stably along the pre-determined route for RSSI collection. Since the pre-defined collection path is followed during walking, it is possible to calculate the location of the pedestrian based only by moving distance without relying on heading information. Furthermore, as described in Section 2, the positions and heading information of turning points that exist in the collection route have been previously surveyed. Therefore, when the pedestrian reaches a point where the heading changes, both the accumulated error in the moving distance is compensated for, and the heading angle is adjusted.

3.2. Wi-Fi fingerprint database construction

Due to environmental factors such as furniture and walls, not all points in the service area of an indoor space can be accessed. Therefore, as shown in Figure 4 (a), a collection route is pre-generated based on the starting and ending points. After determining the collection route, RSSI measurements are acquired while walking along the route. The acquisition locations of the collected RSSI are estimated by the 1D-PDR algorithm described in Section 3.1.

By using the collected RSSI measurements, the fingerprint database is generated to be utilized in pattern matching based positioning phase. To adapt positioning algorithms such as k-Nearest Neighbor (kNN) to the database regardless of the collection method, the 1D-PDR-based fingerprint database is designed to have the same elements as the conventional fingerprint database, which divides the service area into grid points.

The method of acquiring signals from fixed locations simplifies the calculation of signal patterns because the collection points are the same with the grid points in the database. Therefore, the representative signal pattern can be easily calculated by taking the average of the RSSI measurements obtained at the collection points. On the other hand, the method utilizing the results obtained through 1D-PDR as the reference locations for signal acquisition does not match the location divided by the grid because the collection point is dispersed. However, despite the collection points dispersed, the variation of RSSI is insignificant within small range. Thus, if the distance between grid points is not too large, interpolation can be used to estimate the representative signal pattern. Using the RSSI measurements synchronized with the 1D-PDR position, the signal pattern of grid points is estimated through kNN-based Inverse Distance Weighting (IDW) technique, as shown in Figure 4 (b). This technique calculates the signal pattern through a weighted average of the collected measurements in the vicinity of the target estimation point, as follows [26, 27]:

$$\hat{X}(x_R, y_R) = \sum_{i=1}^{n} \lambda_i X(x_i, y_i) \tag{8}$$

where $\hat{X}(x_R, y_R)$ is the estimated signal pattern at the grid point (x_R, y_R), $X(x_i, y_i)$ is the measurement collected at the point near the grid point (x_i, y_i), and n is the number of measurements. Additionally, λ_i represents the distance-based weight of $X(x_i, y_i)$ and has the characteristic that the sum of all weights is '1'. Therefore, the weight λ_i can be calculated by inversely converting the distance information between the point to be estimated and the location of the nearby measurements, as follows:

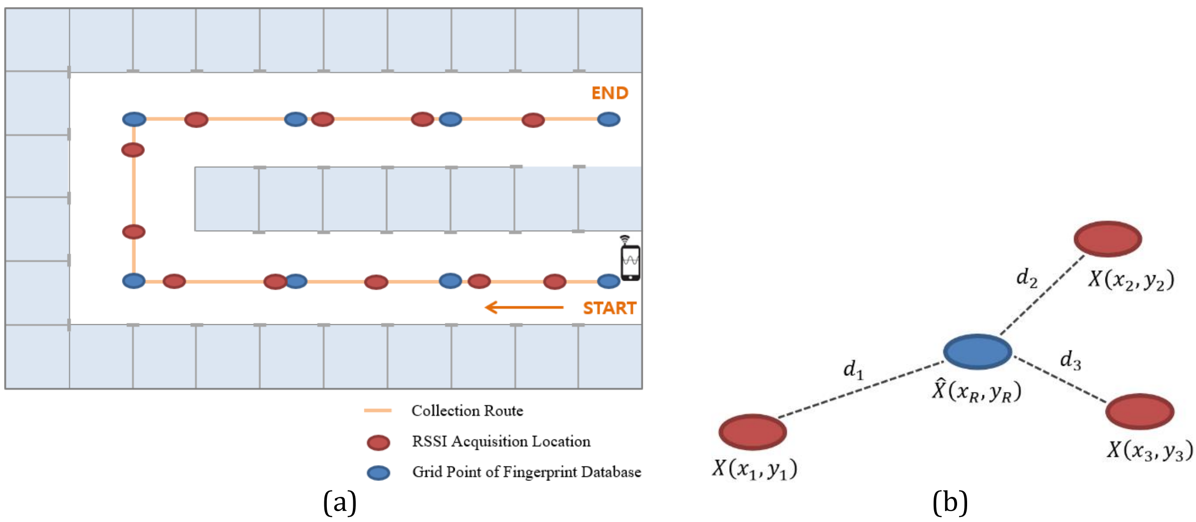


Figure 4: The fingerprint database generation method (a) grid points and acquisition location of RSSI measurements (b) IDW algorithm

$$\lambda_i = d_i^{-1} \Big/ \sum_{j=1}^{n} d_j^{-1} \tag{9}$$

where d_i represents the distance between the desired estimation point (x_R, y_R) and the location of the nearby measurement (x_i, y_i).

4. Experimental results

In this section, we compare and analyze the performance of the fingerprint database generated using the conventional fixed point collection method with the fingerprint database generated exploiting the proposed 1D-PDR. Firstly, we analyze the performance of step detection and stride estimation in the 1D-PDR algorithm. Then, we compare the consumed time for the two collection methods. Finally, we evaluate the performance of the fingerprint database generated based on both methods using a positioning algorithm.

4.1. Experimental setup

The proposed method was evaluated through a series of experiments conducted in the 1st Engineering Building of Kyungil University, Korea. The indoor area was directly measured, and a floor plan was created and depicted in Figure 5. In Figure 5, accessible points within the service area were pre-explored to determine the collection route for signal acquisition. Then, the coordinates and heading angles of the turning points, where the direction changes, were pre-investigated. The indoor space was divided into two segments: the A and B segments, which followed a straight route, and the H segment, which contained multiple turning points.

The collection route was defined from the starting point, moving to the B segment, and returning back to the starting point. The database point is a grid point that divides the indoor area at regular intervals and is used for pattern matching in the later positioning process. For the experimental data, the raw output values were acquired using the acceleration sensor built into the smartphone (Samsung Galaxy S21), and the RSSI measurements of Wi-Fi were acquired using a signal collection application capable of simultaneous collection and storage. During the data collection process, the participant walked while holding the smartphone in hand and monitored the screen.

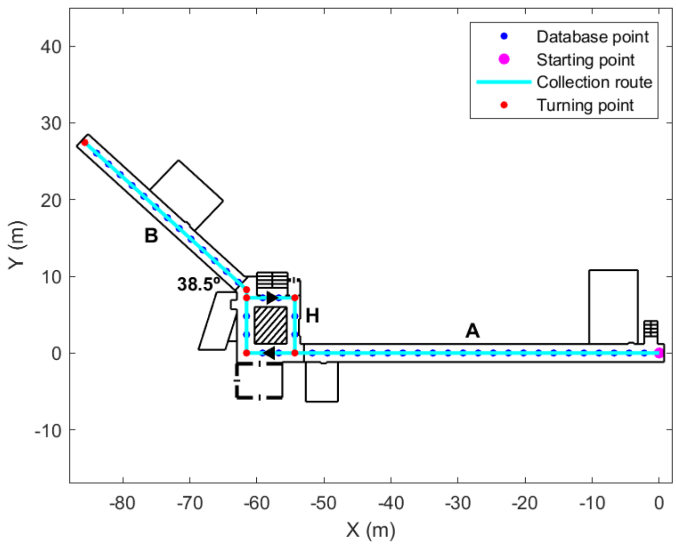


Figure 5: The indoor layout experiment site and data collection route

4.2. 1D-PDR

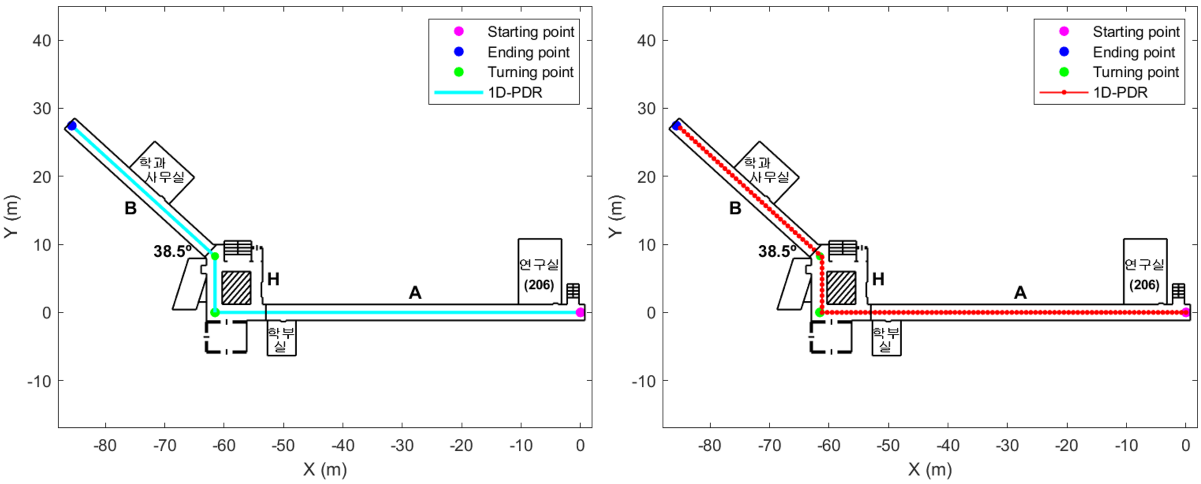
To evaluation the performance of 1D-PDR, the results of step detection and total stride length estimation were analyzed. The objective of 1D-PDR is to estimate the reference locations of acquired wireless signals for fingerprint database generation, so the experiments were conducted based on the collector's walking patterns. Figure 6 (a) shows the reference trajectory used for the experiments. Figure 6 (b) shows the estimated trajectory based on 1D-PDR, where the red dots represent the estimation result of the cumulative stride length calculated at each detected step. The collector walked a total of 122 steps along the experimental trajectory, and as seen in Figure 7, it can be observed that peaks are well detected for each step.

A total of 5 experiments were conducted. The results of step detection and stride length estimation based on 1D-PDR are presented in Table 1 and Table 2, respectively. Table 1 shows that the counting number of steps based on peak detection is the same as the actual number of steps in all 5 experiments.

The estimated stride length is obtained by accumulating each step length. The following formula is used to calculate the error of the estimated stride length.

$$Error = |L_S - L_T| \tag{10}$$

where L_S is the estimated stride length and L_T is the actual stride length.



(a) (b)

Figure 6: The results of 1D-PDR (a) experimental trajectory (b) estimated location based on 1D-PDR

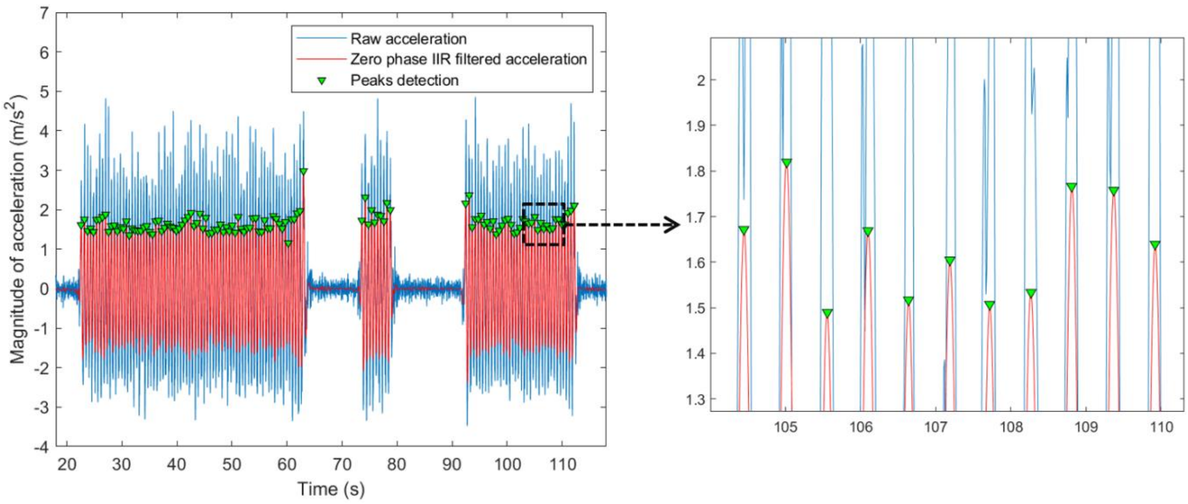


Figure 7: The results of step detection in hand-held mode

Table 1
Results of the step detection algorithm

Number of experiments	Actual step number	Detected step number
1	122	122
2	122	122
3	122	122
4	122	122
5	122	122

Table 2
Results of the estimated stride length algorithm

Number of experiments	Actual walking distance (m)	Estimated total stride length (m)	Error (m)
1	100.62	99.77	0.85
2	100.62	100.24	0.38
3	100.62	99.55	1.07
4	100.62	99.94	0.68
5	100.62	100.08	0.54

As shown in Table 2, among the 5 experiments, the lowest error is 0.38 m in the walking of the second time, while the error in the walking of the third time is highest estimated, which is 1.07 m. However, the average error of the 5 experiments is 0.70 m, indicating that the calculated total stride length error can be estimated within approximately 1m. Therefore, the reference positions estimated based on 1D-PDR for obtaining RSSI measurement locations can be calculated with a low error.

4.3. Fingerprint database performance

In this section, the performance of the Wi-Fi fingerprint database generated using the acquired RSSI measurements based on the collection route is validated. To compare it with the conventional method of collecting from fixed locations, the time consumed for both collection methods is provided. Furthermore, the positioning performance of the fingerprint database generated using the proposed technique is evaluated.

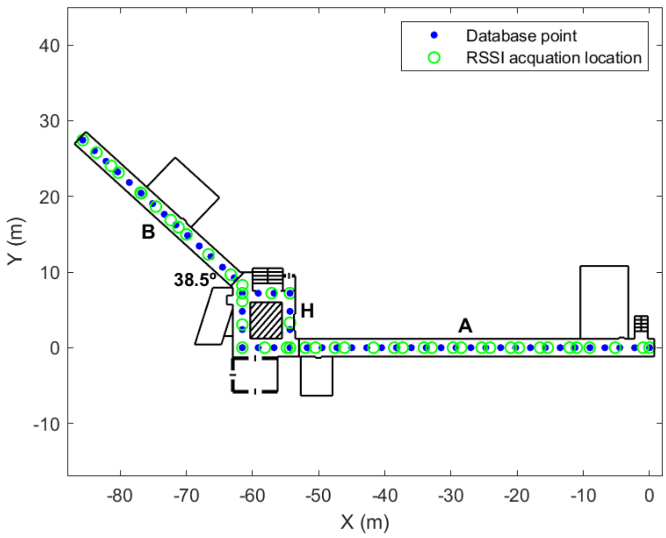


Figure 8: RSSI acquisition location synchronized with estimated reference location based on 1D-PDR

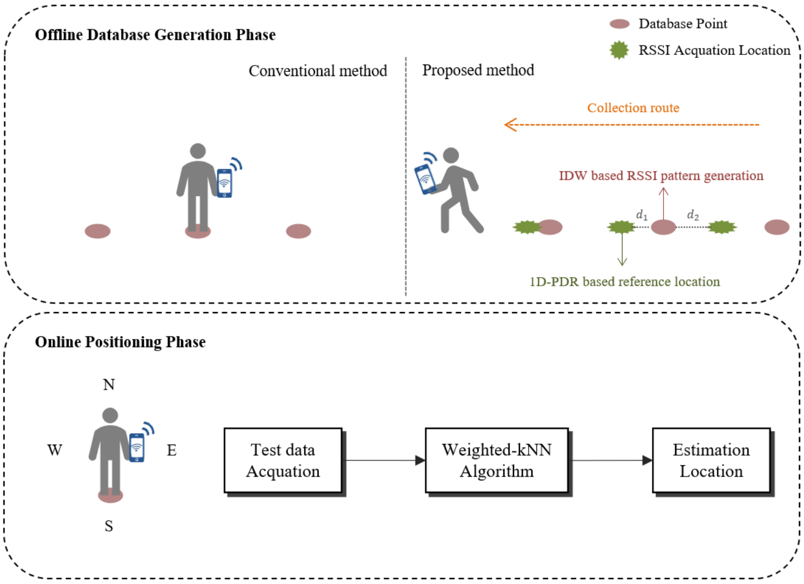


Figure 9: The positioning algorithm for comparing the performance of the generated fingerprint database by method

Figure 8 shows the acquisition positions of RSSI measurements synchronized with the reference locations estimated based on 1D-PDR in the indoor service area. The indoor space consists of 50 database points (A segment: 24, B segment: 14, H segment: 12) evenly spaced. A total of 96 RSSI measurements were acquired along the collection route. In the case of measuring with the signal collection device fixed in place, it takes approximately 1 hour and 28 minutes to collect data for all database points. However, in the case of the method of acquiring measured values while moving the collection route, collection is completed in less than about 5 minutes.

In addition to the previously conducted cost-effectiveness validation, we also evaluate the positioning performance of the generated fingerprint database. Figure 9 presents the positioning algorithm used to compare the performance of the fingerprint database generated by the two methods. For positioning, we use test data consisting of RSSI measurements collected for approximately 1 minute at each database point. During this time, the collection direction is changed by about 90 degrees every 15 seconds. We collect about 60 sets of data for each database point, resulting in a total of 3000 sets of test data for all database points. The performance of the fingerprint database is evaluated using the Weighted-kNN method, which estimates the location based on signal similarity. The similarity is calculated using the Euclidean distance, as follows:

$$D_i = \frac{1}{n}\sqrt{\sum_{j=1}^{n}\left(RSSI_j - RSSI_{ij}\right)^2} \qquad i = 1,2,\cdots,m \tag{11}$$

were $RSSI_j$ is the received signal strength of the j-th AP among the values measured for positioning, $RSSI_{ij}$ is the received signal strength of the j-th AP at the i-th reference point stored in the database, and m and n represent the number of received APs and reference points, respectively. To assign higher weights to reference points with greater signal similarity and lower weights to reference points with lower signal similarity, a weighting calculation method is employed. The method for calculating the weights is as follows:

$$\omega_i = \frac{N}{D_i + \alpha} \tag{12}$$

were, ω_i is the weight calculated at the i-th reference point, D_i is similarity of the signal at the i-th reference poin, N is the number of matched APs, and α is a constant constant value to prevent the problem that the denominator becomes zero due to the same signal value. The method of

Table 3
Consumed time and generated fingerprint database positioning error according to the measurement collection method

Method	Mean (m)	Standard deviation (m)	Consumed time
Fixed correction	1.7555	2.0785	1:27:58
1D-PDR (1 cycle)	2.4719	2.1737	0:04:24
1D-PDR (2 cycle)	2.0856	1.8896	0:08:37
1D-PDR (3 cycle)	1.9913	1.8210	0:12:58
1D-PDR (4 cycle)	1.9799	1.8043	0:17:11
1D-PDR (5 cycle)	1.9307	1.7759	0:21:32

estimating the location using the weight calculated in the above equation and the K candidate reference points can be expressed as follows:

$$(\hat{x}, \hat{y}) = \sum_{i=1}^{K} \omega_i (x_i, y_i) \Big/ \sum_{i=1}^{K} \omega_i \tag{13}$$

For the evaluation of the fingerprint database performance, the value of K, representing the number of candidate reference points, was set to 1. Table 3 shows the consumed time for each collection method and the positioning error of the generated fingerprint database. In this case, the positioning results of the generated database are compared by additionally acquiring measurement data through multiple walks using the proposed collection method. It can be confirmed that the average positioning error is lowered because the number of measurement values acquired and the diversity of patterns according to signal variations increase as the number of walking along collection route increases. Furthermore, the proposed fingerprint database generation method demonstrates a significant reduction in the consumed time for collection. Therefore, the proposed collection method offers the advantage of constructing a fingerprint database with significantly lower collection costs, without a significant difference in database performance compared to the conventional collection method. Additionally, as the service area of indoor spaces becomes increasingly extensive, it is expected that the improvement rate will be even greater.

5. Conclusions

In this paper, we proposed a method of rapidly generating a Wi-Fi fingerprint database through the RSSI collection method that acquires a reference location based on 1D-PDR while moving along a pre-determined route. The proposed method autonomously collects the RSSI pattern by the collection application of the smart phone, and the RSSI acquisition location is calculated based on the 1D-PDR. When the data collection is completed, the acquisition location for the collected RSSI measurements on the moving route is displayed. Therefore, the RSSI pattern of the divided grid points for database generation is estimated by using the location-based RSSI measurements and the IDW algorithm together. This technique is a non-modeling-based estimation method and is limited to measurements that exist within grid point intervals. Therefore, the signal information estimated for the database point is stored in the Wi-Fi fingerprint database along with the location information. The validity of the proposed technique was verified through experimental results based on real data collected from indoor buildings. It was confirmed that the total time required to collect the RSSI pattern was greatly reduced from about 1 hour and 30 minutes to within 5 minutes. In addition, considering the variability of the RSSI pattern, the generated fingerprint database positioning performance after moving the collection route 5 cycles was evaluated with an overall average error of about 1.9307 m, and it was confirmed that there was no significant difference from the performance of the database generated by the existing method. Through this validation, it has been confirmed that the proposed method for generating a Wi-Fi fingerprint database greatly improves the efficiency of data collection time without compromising performance.

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