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Radial Reference Map-Based Location Fingerprinting Technique

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Abstract

In this paper, we propose a radial reference map-based location fingerprinting technique with constant spacing from an access point (AP) to all reference points by considering the minimum dynamic range of the received signal strength indicator (RSSI) obtained through an experiment conducted in an indoor environment. Because the minimum dynamic range, 12 dBm, of the RSSI appeared every 20 cm during the training stage, a cell spacing of 80 cm was applied. Furthermore, by considering the minimum dynamic range of an RSSI in the location estimation stage, when an RSSI exceeding the cumulative average by ±6 dBm was received, a previously estimated location was provided. We also compared the location estimation accuracy of the proposed method with that of a conventional fingerprinting technique that uses a grid reference map, and found that the average location estimation accuracy of the conventional method was 21.8%, whereas that of the proposed technique was 90.9%.

Index Terms: Fingerprinting, Indoor location, Location estimation, Radial reference map, RSSI

I. INTRODUCTION

A location-based service estimates the location of a moving object and accordingly provides an appropriate service. Recently, studies have been conducted to diversify the fields of application of location-based services, with indoor location-based services transcending the global positioning system (GPS), which is typically an outdoor location-based service [1].

GPS is a typical location-based service that is unsuitable for use in indoor environments since its signal strength weakens indoors and in shaded areas because of the poor penetrability of satellite signals [2]. Although indoor location estimation technologies using the ultra-wide band (UBW) [3], ultrasonic waves [4, 5], or radio-frequency identification (RFID) technology [6] can provide location information with high precision in an indoor environment, they have the disadvantages of complex infrastructure construction, high costs, and deterioration of network life [7]. To prevent such problems from occurring when using the aforementioned location estimation technologies, various location estimation technologies based on Wi-Fi installed inside buildings have been proposed. Synchronous methods, such as time of arrival (TOA) and time differences of arrival (TDOA), as

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well as asynchronous methods, such as angle of arrival (AOA) and fingerprinting techniques, have been applied to location estimation techniques using Wi-Fi [1].

The fingerprinting technique is based on empirical data. It estimates the location of an mobile station (MS) through a comparison of the received signal strength indicator (RSSI) during the position determination stage, by dividing the area where the position is to be determined in terms of cells, and stores the RSSI of each cell. The fingerprinting technique is widely used due to its suitability for indoor location positioning because no additional hardware is required and its implementation is simple [8, 9].

When a fingerprinting technique is used, a reference map, i.e., an RSSI database (DB) for position estimation, is one of the important factors determining the accuracy of location estimation. The precision usually increases with a decrease in the cell spacing. However, the RSSI shows changing values due to the surrounding environment. When a narrow cell spacing is selected, errors of location estimation occur because of the changes in the RSSI [9]. Furthermore, when constructing a reference map, many studies have set up grid-type cells of constant spacing. However, in the case of a reference point located diagonally across from an access point (AP), an identical distance between them in the horizontal and vertical directions cannot be ensured.

Therefore, in this paper, we propose a fingerprinting technique that estimates location by periodically selecting spacing that shows the minimum dynamic range of the RSSI in an indoor environment, and by constructing a radial reference map with an identical distance between the AP and every reference point. The remainder of this paper is organized as follows: in Section II, we describe the location estimation procedure for the conventional fingerprinting technique. The proposed fingerprinting method is introduced in Section III, and the experiment to test this method as well as its results is discussed in Section IV. The concluding remarks are presented in Section V.

II. CONVENTIONAL FINGERPRINTING TECHNIQUE

Fingerprinting techniques have recently attracted research interest as indoor wireless positioning technologies are based on the early stage of the RADAR system proposed by Bahl and Padmanabhan [10]. The RADAR system estimates location by using a radio wave model of a wireless signal and the nearest neighbor technique, which selects the location closest to a calculated point.

In general, the following log-distance path-loss model is taken into consideration for wireless signals [11]:

$$L(d) = L_0 + 10n\log(d), \quad (1)$$

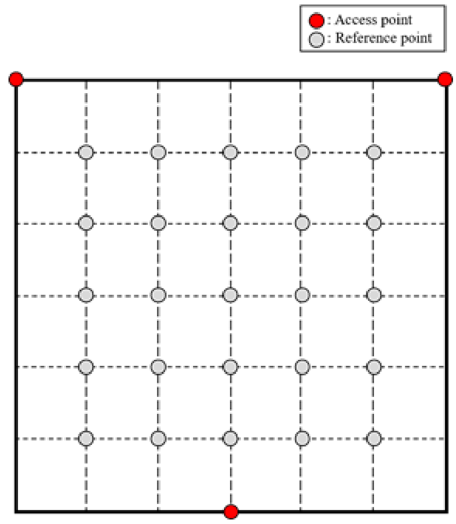

Fig. 1. Fingerprinting reference map.

where L_0(dB) denotes the loss on the basis of a 1-m distance, n indicates the path loss exponent, and $d(m)$ represents the distance. However, the fingerprinting technique has an advantage that there is no need to find a wireless signal loss factor. This is because the effect of obstacles is already reflected, since the RSSI vectors are collected from the location where the AP is installed.

The fingerprinting technique is divided into a training stage and a location positioning stage. During the training stage, by considering the area where the location is to be determined as a two-dimensional (2D) plane, shown in Fig. 1, the pertinent plane is divided into grid-type cells, and the task of storing an RSSI vector of each cell is carried out. A point where an RSSI vector is collected is called a reference point. When the spacing has been set up with L points along the x- and y-axes, there are $L \times L = L^2$ reference points in the pertinent space [11]. For the RSSI of each reference point, multiple RSSIs are repetitively collected from a reference point to build a fingerprinting DB table.

During the location positioning stage, a mobile device sends RSSI vectors received from different APs to a server, which estimates the location of the mobile device by using an algorithm. The typically used algorithms include the k-nearest neighbor (K-NN) algorithm and a location estimation algorithm that employs the Euclidean distance, which is a similarity function [1, 2, 8, 10].

The K-NN algorithm finds k points closest to a given point by comparing the RSSI vectors being measured at any given time against the RSSI vectors of the reference map constructed in the DB. The algorithm obtains the average values of these distances and estimates the location of the mobile device.

The location estimation algorithm using the Euclidean distance calculates the distance between an RSSI vector measured from a mobile device and an RSSI vector of a reference map constructed in the DB, as shown in Eq. (2):

$$Z = \left\lfloor \sum_{i=1}^{N} (\rho_i - r_i)^2 \right\rfloor \quad (2)$$

where ρ denotes the RSSI of the reference map constructed in the DB and r indicates the RSSI measured from the mobile device. When a calculation is conducted using all RSSI vectors of the reference map by utilizing Eq. (2), the location of the mobile device is estimated using the coordinates of the nearest value.

III. PROPOSED FINGERPRINTING TECHNIQUE

This section describes the rationale for considering the minimum dynamic range of an RSSI, the training stage in constructing a radial reference map of the proposed fingerprinting technique, and the location estimation stage that considers the minimum dynamic range.

A. Training Stage

1) Extraction of the minimum dynamic range of an RSSI having periodicity in an indoor environment

In an indoor environment, an RSSI has a dynamic range due to reflections, shadows, and fading, which occur due to obstacles such as walls, furniture, and other equipment [11]. When the cell spacing is selected such that an RSSI has a large dynamic range, a problem can occur in the accuracy of the location estimation because the probability of the RSSI being collected at an adjacent reference point with the same value increases. Furthermore, when the cell spacing of the reference map is narrow in order to estimate the accurate location, the location estimation error can increase because similar RSSI values are measured at various reference points. Therefore, as a prerequisite to setting the spacing of the reference map, a spacing where the RSSI periodically has a minimum dynamic range in an actual environment was obtained.

In consideration of the actual environment in the context of our experiment to test our method, a classroom with all its furniture was chosen, and the experiment was conducted in an environment where people could move freely. At a 1-cm spacing from a position 1 m in a straight line from the AP, the RSSI was collected for the 1-m distance. The RSSI was measured 100 times for each spacing, and a range of ±10 dBm was set for the RSSI with the maximum frequency. Fig. 2 shows a graph of the dynamic range of RSSI measured at a spacing of 1 cm.

A dynamic range of RSSI from a minimum of 9 dBm to a maximum of 18 dBm was observed. Table 1 presents a summary of the minimum dynamic range and the maximum dynamic range at a spacing of 10 cm.

From the results of Table 1, it is difficult to calculate the periodicity for a minimum dynamic range of 9 dBm. However, in Table 2, which summarizes the data for a 20-cm spacing from the initial 108 cm, a dynamic range of 12 dBm was periodically found, which did not reach the minimum dynamic range of 9 dBm.

Because the obstacles in each experimental environment were different, it is impossible to generalize the pertinent results for every environment.

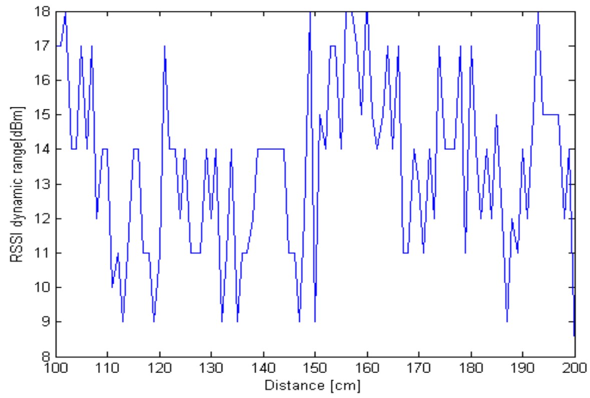

Fig. 2. Dynamic range of RSSI for each centimeter.

Table 1. Minimum and maximum dynamic ranges of an RSSI in a 10-cm range

Range (cm)	Min. dynamic range (dBm)	Max. dynamic range (dBm)	Min. distance (cm)
100–109	12	18	108
110–119	9	14	113, 119
120–129	11	17	120, 126, 127, 128
130–139	9	14	132, 135
140–149	9	18	147
150–159	9	18	150
160–169	11	18	167, 168
170–179	11	17	171, 179
180–189	9	17	187
190–199	12	18	191, 198

Table 2. Minimum dynamic range of an RSSI at a spacing of 20 cm for a 108-cm distance

Distance (cm)	Min. dynamic range (dBm)
108	12
128	11
148	12
168	11
188	12

Therefore, to consider the minimum dynamic range of the proposed RSSI, the range should be re-obtained according to the environment. In this study, we selected a cell spacing of 160 cm, a multiple of 20 cm, on the basis of the relevant experimental results.

2) Construction of the radial reference map

In the case of a reference map for a conventional fingerprinting technique, the reference points are set by dividing the positioning space into grids with constant spacing. However, because the reference points located diagonally across from the AP have different values of the spacing from the reference points in the horizontal and vertical directions, the minimum dynamic range of the RSSI proposed in this paper cannot be taken into account. Therefore, we constructed a radial reference map with equal spacing among all APs.

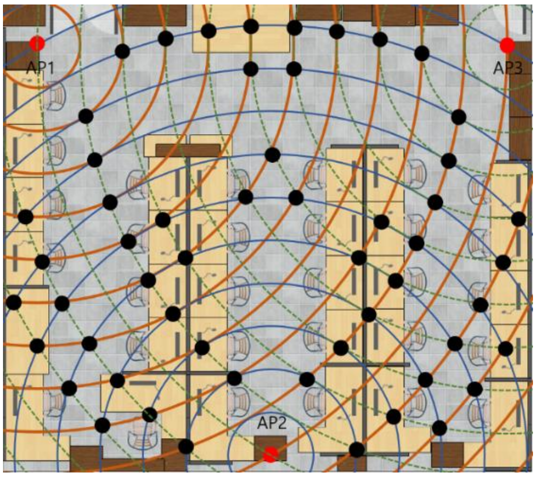

Fig. 3. Initial reference map.

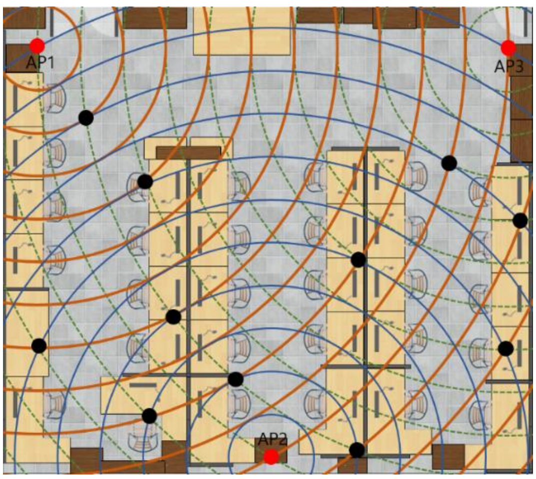

Fig. 4. Final radial reference map.

Centering on an AP, the initial circle had a radius of 108 cm according to the experimental results, and subsequent circles became larger at a spacing of 160 cm, a multiple of 20 cm. The APs were placed in a triangle by selecting an intersection point of the circles drawn with each AP as the center. Furthermore, with respect to the reference points, the intersection points were selected where all circles drawn from each AP intersected. Fig. 3 shows the initial radial reference map created according to the relevant rules.

With respect to a reference point located at the same distance from all APs, a case exists where the RSSI vector receives the same value from each AP. Moreover, several intersection points with the same distance can be created on a single circle. This can lead to the problem of selecting a different reference point when determining the location of a device through a similarity function during the positioning stage. Therefore, for the final reference points, intersection points with a different radius from each AP were selected. Fig. 4 shows the final reference map wherein the reference points were selected according to the pertinent rules.

Having determined the final reference points, we collected the RSSI from each reference point to construct a reference map DB table. When constructing the DB table, the minimum dynamic range of the RSSI, 12 dBm, was taken into account. Based on the RSSI vector that showed the maximum frequency of the RSSI collected from each reference point, only RSSI vectors corresponding to the range of ±6 dBm were selected, and the final reference map DB table was built using the average of the selected RSSI vectors.

B. Location Estimation Stage

1) Location estimation using a similarity function

The location estimation stage uses the nearest neighbor technique, which finds the highest vector by calculating the similarity of the RSSI received from an actual smartphone as well as all the RSSI vectors of the reference map constructed during the training stage. The similarity functions used in the nearest neighbor technique include the Manhattan distance [11], the Euclidian distance [12], and the Tanimoto coefficient [13]. In this study, the Tanimoto coefficient was selected as the similarity function to estimate locations.

The Tanimoto coefficient is also called the Jaccard coefficient and is defined as the ratio of the intersection of two given sets to their union. In the estimation stage of the RSSI vector and the location on the reference map, the similarity with the received RSSI vector can be described as follows:

$$T = \frac{\sum_{j=1}^{k} rssi_j \times rssi'_j}{\left(\sum_{j=1}^{k} rssi_j^2 + \sum_{j=1}^{k} rssi'^2_j - \sum_{j=1}^{k} rssi_j \times rssi'_j \right)}. \quad (3)$$

In Eq. (3), k indicates the number of APs and $rssi_i$ and $rssi'_i$ represent the signal strength value scanned by a user and the signal strength value stored in the DB table, respectively, for the AP j. The Tanimoto coefficient T has a value in the range of 0.0–1.0, and the RSSI vector showing the result closest to 1.0 has the highest similarity. Having compared the similarities of all the reference points, the reference point with the highest value of T is determined to be the location of the user.

2) Final estimated location considering the minimum dynamic range

For the RSSI received during the location estimation stage, cases involving a received RSSI with a large range of ±20 dBm, as compared to an average RSSI value, also occur owing to environmental changes and signal reduction, among other reasons. This can become a factor of error when estimating location by using a similarity function. Therefore, prior to estimating location, an RSSI that is significantly different from the average RSSI value is regarded as the error, and a new RSSI vector is received to reduce the estimation error. Considering the minimum dynamic range of an RSSI, i.e., 12 dBm, obtained from experiments, we determined a range of ±6 dBm on the basis of the average received RSSI as an acceptable range of the RSSI value. Fig. 5 shows a flowchart to determine such an RSSI vector.

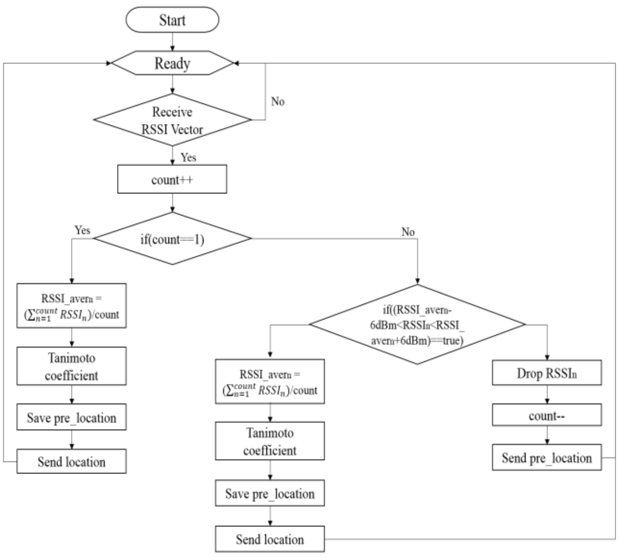

Fig. 5. Flowchart for determining a valid RSSI vector.

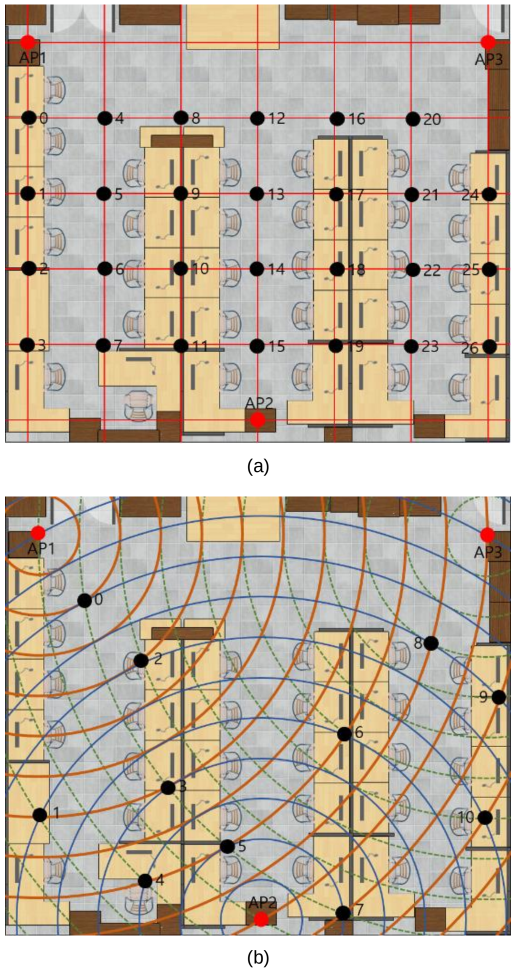

Fig. 6. Reference points. (a) Conventional method, (b) proposed method.

For the first RSSI vector received, the location of the device is estimated using the results of the Tanimoto coefficient. The estimated location is stored in a variable showing the previous location, and each RSSI vector received in the second round and subsequently is checked to determine whether it falls within the range of 6 dBm of the cumulative average. If a received RSSI vector belongs to this range, the estimated location is transmitted; if it exceeds this range, the pertinent RSSI vector is eliminated. The eliminated RSSI vector is not included in the count, and the value of the previous location is transmitted for the relevant round.

IV. EXPERIMENTAL RESULTS

The proposed method was implemented in a laboratory with an area of 8.8 m × 10 m. To consider the actual environment, the laboratory equipment was not removed. The APs were located 1.1 m from the ground, and the smartphone was arranged 0.8 m above it. The smartphone was placed near the reference points of the radial reference map, and a cell spacing of 80 cm was set. Furthermore, the location estimation results of a conventional fingerprinting technique and the proposed fingerprinting technique were compared. The reference points of each map are shown in Fig. 6. The estimated location was a reference point with the highest RSSI vector similarity obtained when using the Tanimoto coefficient as a similarity function.

The location estimation results obtained from the reference map were verified using every 10 RSSI vectors received near the reference point on the radial reference map. The location was considered to have been correctly estimated if the estimated location showed an error in the radial distance of 160 cm or less, and was assumed to have contained an error if the error in the radial distance was greater than 160 cm. Based on the location estimation, the accuracy of the average location estimation was 21.8% for the conventional grid reference map, and 75.4% for the proposed radial reference map. Based on 10 location estimations near each reference point, the location estimation technique proposed in this paper was, on average, more accurate than the conventional method, as shown in Fig. 7.

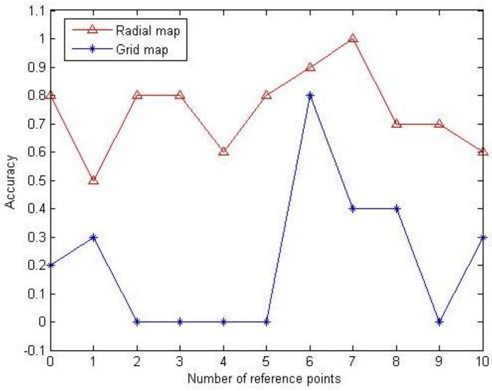

Fig. 7. Location estimation accuracy for each reference map.

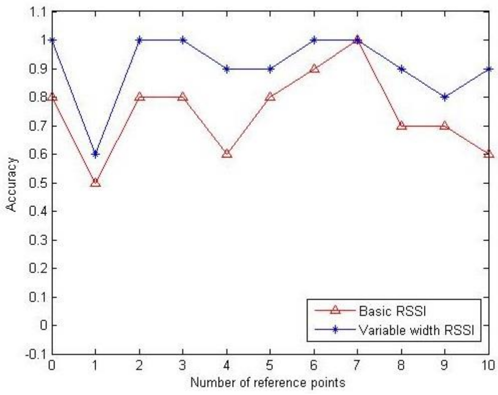

Fig. 8. Location estimation accuracy when the dynamic range of an RSSI is considered.

Table 3. Location estimation results considering the dynamic range of the RSSI at reference point no. 4

RSSI vector			Basic RSSI vector estimation	Variable-width RSSI vector estimation
−56	−56	−53	4	4
−59	−53	−59	4	4
−56	−56	−50	1	1
−56	−56	−59	4	4
−50	−53	−59	1	4
−56	−47	−59	9	4
−56	−53	−59	4	4
−50	−44	−56	3	4
−56	−44	−59	7	4
−59	−56	−56	4	4

Furthermore, location estimation results considering the dynamic range of the RSSI at reference point no. 4 are presented in Table 3. We found that a location correction effect occurred when providing the location estimated in the preceding round with respect to the estimated locations of four RSSI vectors exceeding the ±6 dBm range from the cumulative average of the received RSSI.

At all reference points of the radial reference map, the location estimation accuracies of the method, when considering the dynamic range and ignoring it, are shown in Fig. 8. Compared to the average location accuracy of 74.5% obtained when using only the radial reference map, the accuracy improved by 16.4% to 90.9% when the dynamic range was considered.

V. CONCLUSION

In this study, we experimentally obtained a spacing where an RSSI periodically recorded the minimum dynamic range, and developed a fingerprinting technique to estimate location by constructing a radial reference map such that the distances from all APs to a reference point were identical. Furthermore, by considering the minimum dynamic range of an RSSI in the location estimation stage, when an RSSI vector exceeded the ±6 dBm range with respect to the cumulative average RSSI value, we determined the value to be invalid and provided the previous estimated location. By comparing a conventional grid reference map and the proposed radial reference map in an experimental environment, we observed that the conventional and proposed methods exhibited an average location estimation accuracy value of 21.8% and 74.5%, respectively. Moreover, by estimating the locations on the proposed radial reference map when considering the dynamic range of an RSSI, we confirmed that the average location estimation accuracy improved by 16.4% over the situation where the dynamic range was not considered.

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