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Efficient Survey Database Construction Using Location Fingerprinting Interpolation

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***Abstract*—A critical problem with location fingerprinting is the considerable time and effort spent measuring received signal strengths at all location candidates to create the survey database. To reduce this cost, existing methods use a signal path loss model to interpolate part of the survey database from data actually measured at location candidates. However, the positioning accuracy can become degraded, especially in an indoor area delimited by walls. In this paper, we confirm the degradation in accuracy of the existing method through a preliminary experiment, and propose an accurate interpolation method for survey databases. In the proposed method, part of the survey data is interpolated using a path loss model containing wall attenuation. Furthermore, to confirm the effectiveness of the proposed method, we evaluate the location estimation performance with the interpolated survey database and also verify the interpolated data. The proposed method improves the positioning accuracy by 25% over that of the existing method.**

***Keywords*-Location fingerprinting, survey database, interpolatation method, and wall penetration loss.**

I. Introduction

The spread of wireless LAN in indoor and outdoor environments is continually improving the connectivity of broadband wireless networks. Consequently, the access to network services on mobile platforms becomes more convenient and familiar, and location-based services emerge as a promising mobile network service. Such location-based services require positioning capabilities to estimate the current location of their users. The global positioning system (GPS) is the most popular positioning device, and is mounted on almost all smartphones and tablet PCs. However, GPS cannot be used in an indoor environment. This has motivated many studies on indoor positioning systems, such as wireless LAN-, radio-frequency identification (RFID)-, and ultrasound-based positioning systems.

Wireless LAN-based positioning systems have recently attracted considerable attention for use in practical location-based services. In a wireless LAN-based positioning system, location fingerprinting is widely used to estimate the current location of a mobile device by measuring the received signal strength indicators (RSSIs) from surrounding (or observable) access points (APs). A set of RSSIs from observable APs is called a fingerprint, and is location-dependent. The positioning process in location fingerprinting can be divided into two phases: a survey phase and an estimation phase. During the survey phase, a set of fingerprints is collected at all of the predetermined location candidates and stored in a survey database. In the estimation phase, the mobile device measures the fingerprint at the current location. The current location can then be estimated from the current fingerprint and the previously collected fingerprints stored in the survey database. A critical problem with location fingerprinting is the considerable time and effort required to build the survey database, which depends on the number of location candidates and the size of a given positioning area. Furthermore, if the radio propagation characteristics in the positioning area change, e.g., obstacles are inserted/removed or the layout of the APs is rearranged, the survey database needs to be reconstructed.

To address this problem, several approaches for interpolating the survey database have been proposed [1], [2], [3], [4]. In these studies, location candidates are classified into observation points and interpolation points. Fingerprints for the interpolation points can be estimated using a radio propagation path loss model from the actual fingerprints measured at the observation points. Although these methods can reduce the time and effort needed to construct the survey database, the positioning accuracy is degraded, especially in indoor areas delimited by walls. In this paper, we first examine the accuracy degradation in the existing method through a preliminary experiment in a realistic environment, and then propose an accurate interpolation method for building a complete survey database. In the proposed method, part of the survey database is interpolated using a path loss model that considers wall attenuation. Furthermore, to confirm the effectiveness of the proposed method, we examine the performance of the location estimation with the interpolated survey database, and verify the interpolated fingerprints. As a result, the proposed method can improve the positioning accuracy

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by 25%, as compared with the existing method, while reducing the cost of building the survey database.

This paper is organized as follows: Section II describes some related research. In Section III, we explain the preliminary experiment to show the degradation of an existing method's positioning accuracy in an indoor area delimited by several walls. In Section IV, we propose an interpolation method to mitigate this degradation. In Section V, we evaluate our method, and in Section VI, we present our conclusions.

II. Related Work

In this section, we introduce several existing methods for reducing the cost of building a survey database.

Although the RSSI values are closely correlated to the distance between the mobile device and the AP, the value fluctuates significantly, even when the distance is fixed, which can lead to significant degradation in the estimation accuracy. In location fingerprinting in particular, the RSSI variation is caused by the time lag between the survey and estimation phases. To address this problem, we need to prepare the survey database for each estimation period. In [9], an adaptation method for the survey database was proposed. This method adapts the survey database to the current RSSI variation observed at deployed reference points. Through several experiments, it was shown that the method could achieve high positioning accuracy during the day and at night.

Another issue related to the RSSI variation is the difference between wireless LAN devices. To achieve high positioning accuracy, it is necessary to build a specialized survey database for each wireless LAN device. To address this problem, an adaptation approach has been proposed that converts the fingerprint from a wireless LAN device to one from a reference wireless LAN device using the linear correlation of RSSI values among such devices [10]. Experimental results have shown that the adaptation method can achieve higher accuracy than location estimation with a survey database developed using all devices.

Several interpolation methods for survey databases have been proposed in [1], [3]. The procedure for these methods mainly consists of three steps: determination of the observation points, measurement of RSSI values, and calculation of RSSI values for the interpolation points. In the following, we show the specific steps in the interpolation method proposed by [1]:

1) Configure information about the wall layout from an image file or CAD file of a sketch map from the positioning area.
2) Calculate several signal propagation paths from transmitter to receiver, and then calculate the number of walls and the number of reflections for each path.
3) Calculate the signal strength loss from passing through and being reflected by the walls.
4) Estimate the fingerprint using the calculated values.

However, this method requires some computational time to calculate the signal propagation paths, signal strength attenuations for passing through walls, and the reflections caused by the walls.

In [3], an interpolation approach based on an empirical model for indoor signal path loss was proposed. More specifically, observation data (i.e., a fingerprint) measured at an observation point is stored in the survey database DB. The observation data u is represented as a tuple of observation point (u_s), observed AP (u_{AP}), distance (u_d) between u_s and u_{AP}, and measured RSSI value (u_{RSSI}). If multiple APs can be measured during one observation, one tuple for each observed AP is stored in DB. Let $DB(AP_j)$ denote a set of observation data for AP_j in DB. The RSSI value $RSSI(t_i, AP_j)$ received from AP_j at interpolation point t_i is estimated as follows:

$$RSSI(t_i, AP_j) = \frac{1}{|DB(AP_j)|} \sum_{p \in DB(AP_j)} S(p, d(t_i, AP_j)) \quad (1)$$

$$S(p, l) = p_{RSSI} + 10\gamma \log(\frac{l}{p_d}), \quad (2)$$

where $d(t_i, AP_j)$ denotes the distance between t_i and AP_j, and γ is the attenuation coefficient. In [3], the average error in the location estimation with the interpolated survey database was compared with that when using a fully measured survey database. The experimental results gave an error of 5.9 [m] when using the interpolated survey database and 5.3 [m] when using the fully measured one. However, this evaluation was conducted in an indoor environment in which any pair of location candidate and deployed AP was delimited by the same number of walls. In most buildings, however, the number of walls will not be the same. Therefore, we evaluate this interpolation method in a more realistic environment.

III. Preliminary Experiment

In this section, we conduct an experiment to evaluate the interpolation method proposed in [3] in an indoor environment in which the location candidate and AP are delimited by a variable number of walls. We explain the experimental setup and summarize the results.

A. Experimental Setup

Figure 1 shows the experimental environment. In addition, Figure 1 shows the layout of 36 location candidates and the deployment of ten APs. The average distance between two consecutive location candidates is about 3 [m], and the distance between two adjacent APs is about 15 [m]. In this environment, we measure the RSSI values several times at each location candidate. The top-4 APs, with respect to signal strength, are used as our observation data. We use an Apple iPod Touch as the wireless devices and PicoCELA PCWL-0100 as the APs. In this environment, we estimate the location of the wireless device using location fingerprinting with the survey database interpolated by the method proposed in [3].

The steps in this experiment are as follows:

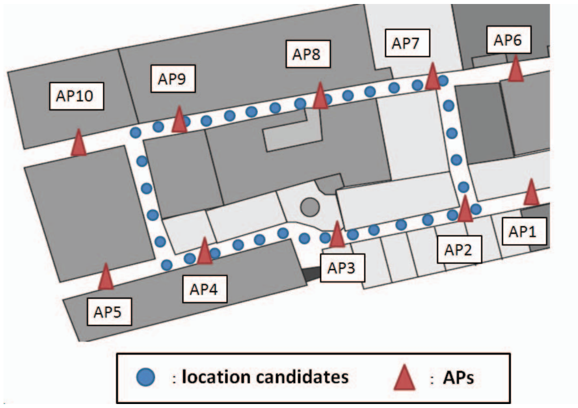

Figure 1. Experimental environment.

Table I
SUCCESS RATIO AND AVERAGE ERROR FOR THE EXISTING METHOD WITH VARIOUS NUMBERS OF INTERPOLATION POINTS.

Interpolation points	Average error[m]	Success ratio[%]
9 points	4.1	25.4
18 points	4.4	18.5
22 points	4.5	21.9
24 points	4.5	24.3

1) Select interpolation points from location candidates.
2) Measure RSSI values at each observation point.
3) Interpolate the RSSI value for each AP at each interpolation point using eq. (1), and store the top-4 APs with respect to RSSI strength for each interpolation point in the survey database.
4) Estimate the current position at location candidates using the interpolated survey data. Location fingerprinting uses a Bayesian technique [11] to estimate the current position from the survey database.
5) Calculate the success ratio and average error. The success ratio is defined as the ratio of the number of correct position estimates to total trials. The average error represents the average distance between the correct and estimated positions.

The above steps are repeated while the number of interpolation points is varied.

B. Results

Table I shows the success ratio and average error from this experiment. The success ratio for the fully measured survey database was 30.6% and the average error was 3.7 [m]. From the table, we can confirm that the success ratio and average error using the interpolated survey database are significantly degraded relative to those using the fully measured survey database. This is because the number of walls between each location candidate and AP is not the same in the experimental environment, i.e., the interpolation method proposed in [3] does not consider such an environment, and therefore it cannot achieve a good interpolation performance.

IV. PROPOSED INTERPOLATION METHOD

In this section, we propose an accurate interpolation method for the survey data used in location fingerprinting. The proposed interpolation method considers wall attenuation in its indoor path loss model. First, we give an overview of the proposed method, and then describe the process in detail.

A. Overview

The proposed method considers wall penetration loss, as well as distance power loss, in the total signal path loss. More specifically, it separately estimates the wall penetration loss and distance power loss, and then interpolates the RSSI value based on these obtained values.

The procedure for the proposed method is as follows:

1) Obtain data measured at observation points.
2) Set RSSI threshold.
   We set a threshold for the RSSI values. If the RSSI value from an AP is below the threshold, we exclude the AP from the observation data.
3) Configure the number of walls.
   For each location candidate, we obtain the number of walls that cross the path from the location candidate to each AP from the layout of the positioning area.
4) Estimate distance power loss.
   We estimate the distance power loss using only observation data that are not affected by wall attenuation, i.e., there is no wall on the propagation path from the location candidate to the AP.
5) Estimate wall penetration loss.
   We estimate the penetration loss per wall using only observation data that are affected by wall attenuation.
6) Interpolate RSSI values for interpolation points.
   We interpolate RSSI values at the interpolation points using the losses estimated by an interpolation equation, and then construct fingerprints from the interpolated RSSI values.

We now explain the signal path loss model used in the proposed interpolation. In [5], [6], [7], [8], radio attenuation models of RSSI values have been proposed. In [5] and [6], the signal propagation loss models recommended by ITU-R for indoor and outdoor environments are introduced. In [8], two signal attenuation models for wireless-LAN based on IEEE802.11b have been proposed; one is a one-slope model that assumes a linear dependence between the path loss and the logarithm of the distance, and the other is a multi-wall model that includes the loss caused by walls and floors between transmitter and receiver. In the proposed method, we use the following simplified model proposed in [5].

$$RSSI(t_i, AP_j) = C_j + \gamma_j \log(d(t_i, AP_j)) + w(t_i, AP_j)N, \quad (3)$$

where C_j denotes environmental variables of AP_j, γ_j is the distance attenuation, and N denotes the attenuation

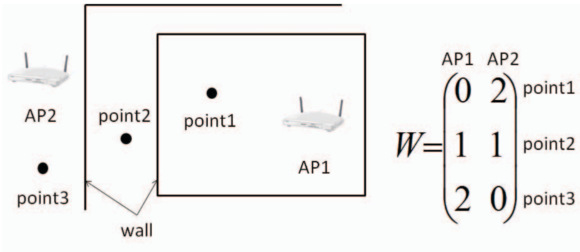

Figure 2. Configuration example for the wall matrix.

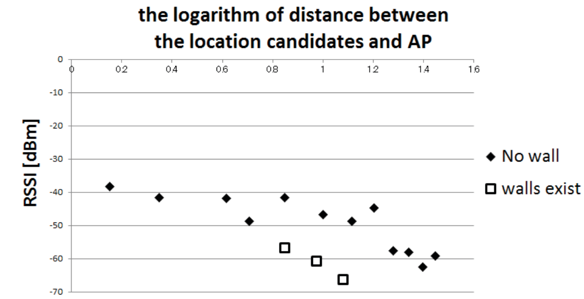

Figure 3. Comparison of RSSI values for the cases of walls and no walls.

per wall [dBm]. In addition, the number of walls between the interpolation point t_i and AP_j is represented as $w(t_i, AP_j)$.

B. Set Number of Walls

To consider wall penetration loss in total signal path loss as well as distance power loss, first we set the number of walls for each location candidate. More specifically, the number of walls W is formally defined in a matrix form, as shown in eq. (4);

$$W = \begin{pmatrix} w_{11} & w_{12} & \dots & w_{1m} \\ w_{21} & w_{22} & \dots & w_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \dots & w_{nm} \end{pmatrix}, \tag{4}$$

where n denotes the number of interpolation points and m denotes the number of APs. We set the number of walls for all location candidates, i.e., both observation points and interpolation points. For example, we show how the number of walls is set in Figure 2. In this figure, there is no wall between AP1 and point1, one wall between AP1 and point2, and two walls between AP1 and point3. Thus, as shown on the right side of Figure 2, we can set the number of walls in each element of the wall matrix. Similarly, we set the number of walls for AP2 in W.

C. Distance Power Loss

To estimate the distance power loss model for AP_j, we calculate the two parameters C_j and γ_j in eq. (3) using observation data. From the path loss model, we know that there is a linear relationship between the path loss and the logarithm of the distance. Thus, we calculate C_j and γ_j by a least-squares method using a set of observation data pertaining to AP_j. It is difficult to extract only the distance power loss from the observation data, because these data contain results with wall penetration, as shown in Figure 3. Therefore, we use only observation data that are not affected by wall attenuation, i.e., there is no wall on the propagation path from the location candidate to AP_j.

D. Wall Penetration Loss

It is possible to estimate the RSSI value from the estimated distance power loss, as described in Section IV-C. The estimated RSSI value is represented as $RSSI_{nw}(t_i, AP_j)$. It is calculated from the distance between t_i and AP_j based on eq. (3), except for the attenuation term:

$$RSSI_{nw}(t_i, AP_j) = C_j + \gamma_j \log(d(t_i, AP_j)). \tag{5}$$

Using eq. (6), we can calculate the penetration loss per wall N;

$$N = \frac{1}{|DB_w|} \sum_{p \in DB_w} \frac{p_{rssi} - RSSI_{nw}(p_s, p_{AP})}{w(p_s, p_{AP})}, \tag{6}$$

where DB_w denotes a set of observation data that are affected by wall penetration loss. We obtain the penetration loss per wall by subtracting the distance power loss from the observed RSSI (p_{rssi}) and then dividing by the number of walls.

E. RSSI Threshold

Because the total path loss is proportional to the logarithm of the distance between a transmitter and a receiver, the attenuation decreases as the distance becomes greater. Figure 4 shows the relationship between the RSSI value and the distance. From this figure, we can confirm that the decrement in RSSI is small as the distance increases. In particular, the RSSI value does not decrease in the range circled in Figure 4, despite the increase in distance of about 10 [m]. Therefore, such observation data would not be helpful for interpolation. The proposed method uses a threshold for the RSSI value to exclude such observation data.

V. Evaluation

In this section, we conduct several experiments to evaluate the effectiveness of the proposed interpolation method and compare it to the existing method described in [3].

A. Experimental Environment

To evaluate the performance of the proposed method, we use the experimental environment described in Section III. To confirm the effectiveness of our method for multiple wireless devices, the following three mobile devices are tested:

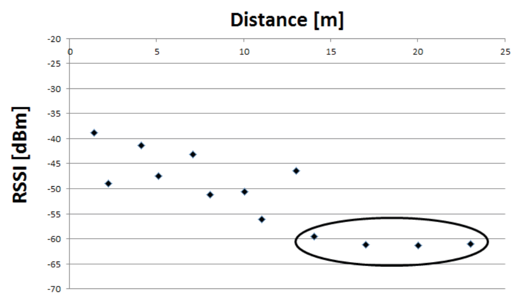

Figure 4. Relationship between distance and RSSI.

- Device A : KOHJINSHA SC3KP06GA
- Device B : Logitec Corp. LAN-WAG/U2
- Device C : Apple iPod Touch

In this experiment, we evaluate the success ratio and average error of the location estimation by varying the number of interpolation points. We then change the layout of the observation points, while fixing their number, to examine the impact of the observation point selection. Furthermore, we evaluate the impact of the RSSI threshold on the interpolation performance.

B. Success Ratios and Average Errors

Table II shows the success ratios and average errors in the location estimation. In this table, use of the fully measured survey database is denoted by "No interpolation." From the results, the success ratio and average error obtained by the proposed method show an improvement over those from the existing method for all devices.

In particular, the average error across all three devices is reduced by 25% relative to the existing method, and furthermore it is improved by 31 for device C when 18 interpolation points are used. This is because the proposed method considers not only distance power loss but also wall penetration loss in the path loss model, and thus it can accurately interpolate fingerprints in the wall-delimited experimental environment. Moreover, as the number of interpolation points increases, both methods see their success ratio and average error degrade. However, compared with the existing method, the proposed method mitigates this performance degradation, e.g., the success ratio for device A decreases by 31.6% (61.0 - 29.4) for the existing method and 27.7% for the proposed method.

Although the proposed method can improve the location estimation performance relative to the existing method, its performance for devices A and B is worse than that with no interpolation. In particular, the performance becomes worse for device A as the number of interpolation points increases. Thus, there is room for improvement in the proposed method. On the other hand, in some cases, the performance with interpolation is better than that without interpolation, especially for device C. The reason why device C has the worst performance is that there would be considerable noisy observation data, which does not follow the radio path loss model, in the survey database for this device. By interpolating the survey database, such observation data are replaced with correct ones. However, an interpolation between two noisy data points will still give an incorrect fingerprint.

Table II
RESULTS OF AVERAGE ERROR AND SUCCESS RATIO.

(a) Device A

Number of interpolation points	Average error [m]		Success ratio [%]	
	Existing	Proposed	Existing	Proposed
9 points	2.7	2.1	55.9	61.9
18 points	3.5	3.0	43.0	46.9
22 points	4.0	3.8	25.9	36.1
24 points	4.1	3.7	29.4	33.3
No interpolation	1.8		61.0	

(b) Device B

Number of interpolation points	Average error [m]		Success ratio [%]	
	Existing	Proposed	Existing	Proposed
9 points	3.1	2.5	39.8	39.4
18 points	3.6	2.7	32.9	37.8
22 points	4.0	2.7	25.9	38.1
24 points	3.9	3.2	30.9	31.7
No interpolation	2.8		39.0	

(c) Device C

Number of interpolation points	Average error [m]		Success ratio [%]	
	Existing	Proposed	Existing	Proposed
9 points	4.1	3.5	25.4	30.4
18 points	4.4	3.1	18.5	35.0
22 points	4.5	3.2	21.9	33.4
24 points	4.5	3.4	24.3	28.5
No interpolation	3.6		30.6	

Next, we investigate the quality of the interpolated RSSI values to confirm the above result in more detail. In this experiment, we evaluate the difference between measured and interpolated RSSI values. The results are shown in Table III. This table also shows results for cases where walls are and are not present. From the results, the overall interpolation accuracy of the proposed method is higher than that of the existing method. In particular, when walls are present, the accuracy is significantly improved, e.g., by 15% when walls are present and 10% when walls are not present. Hence, from these results, we can confirm the effectiveness of the proposed interpolation method.

C. Impact of the RSSI threshold

Next, we examine the impact of the RSSI threshold on the location estimation performance. In this experiment, we measure the average error and success ratio for device C while varying the RSSI threshold. Table IV shows the results. From this table, we can confirm that the performance is improved when a threshold is applied. Compared with no threshold, the accuracy is improved by 8% when the threshold is -60 [dBm], by 14% when it is -65 [dBm], and by 6% when it is -70 [dBm]. In this experimental environment, the proposed method achieves its best performance at a threshold of -65 [dBm]. However, the optimum threshold would be different in each positioning environment. If the RSSI threshold is too tight, some APs that are necessary for distinguishing locations would be excluded. On the contrary, if the RSSI threshold is too loose, many unnecessary APs would be included in the survey database.

Table III
DIFFERENCE BETWEEN MEASURED AND INTERPOLATED RSSIS.

(a) Device A

Number of interpolation points	No wall [dBm]		Wall present [dBm]	
	Existing	Proposed	Existing	Proposed
9 points	3.0	2.3	5.4	5.1
18 points	2.7	2.3	5.2	5.0
22 points	3.3	2.3	4.8	5.0
24 points	3.1	2.6	5.6	5.2

(b) Device B

Number of interpolation points	No wall [dBm]		Wall present [dBm]	
	Existing	Proposed	Existing	Proposed
9 points	2.8	2.6	6.4	5.7
18 points	3.1	3.0	6.5	6.1
22 points	3.7	2.9	6.2	5.5
24 points	2.8	3.1	6.5	5.3

(c) Device C

Number of interpolation points	No Wall [dBm]		Wall present [dBm]	
	Existing	Proposed	Existing	Proposed
9 points	2.4	2.2	6.3	5.1
18 points	4.0	3.3	5.7	5.0
22 points	3.5	2.9	5.8	4.9
24 points	3.5	3.2	6.1	4.8

Table IV
AVERAGE ERROR [M] WHEN VARYING THE RSSI THRESHOLD.

Threshold [dbm]	Number of interpolation points			
	9	18	22	24
No threshold	4.2	3.6	3.7	3.7
-60	3.7	3.4	3.3	3.7
-65	3.5	3.1	3.2	3.4
-70	3.8	3.5	3.3	3.7

D. Impact of Observation Points

Finally, we examine the impact of different deployments of a fixed number of observation points. In this experiment, the observation points are deployed as shown in Figure 5. Note that Figure 5 represents the same environment as in Figure 1 with the omission of the background image. In this experiment, we measure the average error and success ratio using device C with six deployment layouts.

Table V shows the average error and success ratio for each layout. The location estimation performance is worse in set 3 than the other sets. This is because the layout of the selected observation points is non-uniform, i.e., the points are concentrated in the center of the area. The proposed method achieves its best performance with set 2. This is due to the uniform layout of the observation points.

The reason the performance is affected by the deployment layout is that the number of observable APs (those with no walls present on the path between observation point and AP) differs among the layout sets. Table VI shows the number of observable APs at each point. In the proposed method, if the number of observable APs is small, the estimation accuracy of the distance power loss model is degraded. To confirm the accuracy of the power loss model, we show the result of the difference between measured and interpolated RSSI values for each layout in Table VII. For set 3, only two points are observable from AP2, leading to an RSSI difference of 7.6 [dBm]. This difference is 50% worse than that of the other sets. On the other hand, for set 2, the number of points that are observable from AP10 is sufficiently large that the RSSI difference is improved by about 10% over the other sets.

Table V
SUCCESS RATIO AND AVERAGE ERROR USING THE PROPOSED METHOD FOR EACH LAYOUT IN FIGURE 5.

Layout	Success ratio [%]	Average error [m]
Set 1	23.2	3.86
Set 2	34.4	3.38
Set 3	19.4	4.81

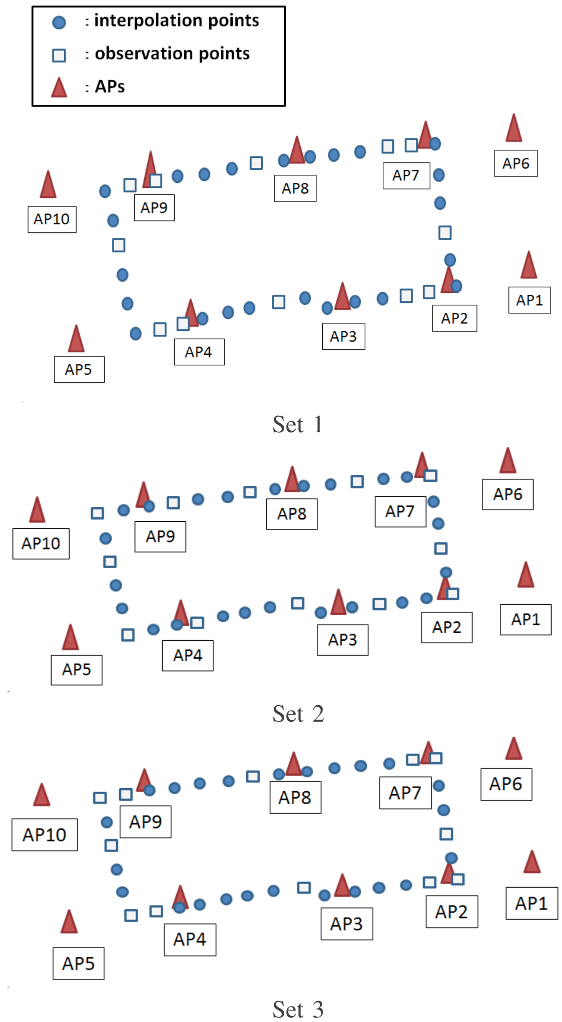

Figure 5. Observation point deployment layouts.

E. Building Cost

In this section, we discuss the cost required to construct the survey database. The cost of building the survey database is given by the following equation:

Table VI
NUMBER OF OBSERVABLE LOCATIONS IN EACH LAYOUT.

AP	Number of observed points		
	Set 1	Set 2	Set 3
AP1	2	3	3
AP2	4	3	2
AP3	4	4	4
AP4	4	4	3
AP5	3	3	3
AP6	5	5	5
AP7	3	3	2
AP8	5	5	5
AP9	4	3	4
AP10	3	4	3

Table VII
DIFFERENCE BETWEEN RSSI VALUES FOR EACH LAYOUT.

AP	RSSI difference [dBm]		
	Set 1	Set 2	Set 3
AP1	8.8	3.1	2.8
AP2	4.8	4.0	7.6
AP3	7.6	4.4	4.9
AP4	4.2	3.5	6.8
AP5	5.1	3.0	4.3
AP6	3.5	2.7	3.1
AP7	7.6	5.5	7.9
AP8	2.0	2.2	2.0
AP9	2.4	2.8	3.0
AP10	3.4	2.3	2.8

$$C = t_{pos}(n_{all} - n_{est}) + t_w * n_{all}, \tag{7}$$

where n_{all} denotes the number of location candidates and n_{est} denotes the number of interpolation points. In addition, t_{pos} denotes the observation time required per observation point and t_w denotes the time required for configuring the number of walls per location candidate.

Although the proposed method can improve the accuracy of location estimation, the cost of obtaining the survey data is greater than that for the existing method, because it is necessary to configure the number of walls. However, we need only configure the number of walls once, because it is not easy to change the layout of the building. On the other hand, it is necessary to measure RSSI values many times, and then re-measure these values when the characteristics of the radio propagation change. Thus, to build the survey database, the cost required for measuring RSSI values is greater than that for configuring the number of walls.

In this evaluation, we took eight hours to measure RSSI values at all location candidates, and an hour to configure the number of walls. In this experiment, we could reduce up to two-third observation points and reduce the cost required to measure RSSI values by five hours(= 8 × 2/3). Threfore, we estimate that the building cost in the existing method will take three hours for the observation, while the cost in the proposed method takes four hours including the observation and the wall configuration to construct the survey database. However, the proposed method can improve the average error by about 25% compared with the existing method. Furthermore, as mentioned above, the number of walls can be configured only once.

Thus, the proposed method is effective because it can reduce the cost required for measuring RSSI values, although it increases the cost required to configure the number of walls.

VI. CONCLUSION

In this paper, we have proposed an interpolation method for a location fingerprinting survey database. A critical problem with location fingerprinting is the considerable time and effort required to build the survey database. In the existing method proposed in [3], the survey database is constructed by measuring RSSI values at a subset of location candidates and then interpolating the RSSIs at the remaining locations. However, the positioning accuracy is degraded in an indoor area delimited by walls. We confirmed this degradation through a preliminary experiment. The proposed method considers wall penetration loss, as well as distance power loss, in the interpolation. More specifically, it estimates the wall penetration loss and distance power loss separately, and then interpolates the RSSI value based on these loss models. Furthermore, to confirm the effectiveness of the proposed method, we conducted several experiments in a real environment. From the results, we found that the average error of the proposed method was about 25% less than that with the existing method. The cost of building the survey database is also reduced by the proposed method, as fewer RSSI values are required.

Our future work will be as follows: first, we will establish an appropriate mechanism for selecting the observation points. Next, we will propose a dynamic decision method for the RSSI threshold, and finally we will focus on which APs are important for distinguishing locations, and propose an interpolation method using only these APs.

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