A Robust Room-level Localization Method Based on Transition Probability for Indoor Environments

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Abstract— **Several scene analysis methods** [1, 2] **such as location fingerprinting have been proposed to execute room-level localization with high accuracy. However, these methods estimate locations wrongly when received signal strength (RSS) observed at a target user's current position is similar to RSS in another place. By utilizing the heuristic of passing through a passable boundary point (for example, an entrance door) when moving between rooms, we introduce a technique for evaluating the distance between the current position of the target user and the boundary point by comparing RSS around the boundary point with RSS at the user in order to reduce the number of erroneous judgments. Experiments conducted in office environments confirmed that our proposed technique achieved an accuracy rate of 97.1% in localizing the target user.**

Keywords- room-level localization; RSS of wireless LAN; transition probability; distance to boundary point; scene analysis

I. INTRODUCTION

Expectations for location-awareness are increasing along with the popularization of smartphones in many countries. In fact, some location-based services (LBSs) are already provided. Apple Inc., for example, provides a location-based reminder service with its iCloud. It automatically sends a to-do list reminder to an iPhone's user when he or she arrives at a preconfigured location. In recent years, LBSs have been provided for the outdoor environments where GPS can be used. LBSs are expected to become available in indoor environments as well. For that to happen, the localization methods must achieve practical accuracy of measurement without the costly arrangements of positioning infrastructure.

An indoor positioning system faces a trade-off between the cost of building positioning infrastructure and the accuracy of localization measurement. That is, utilizing a high- accuracy positioning system offers the possibility of a fine-tuned LBS, but an over-engineered positioning system where accuracy is higher than necessary might increase costs. Although an ultra wide band (UWB) positioning system [3], for instance, can measure target position with high accuracy to within about 10 centimeters, many UWB transmitters must be expensively arranged at intervals of a few meters throughout the coverage region. That leaves the following question: What is a reasonable positioning system for an indoor LBS? For examples of indoor LBSs, we consider the following situations [4]. In a hospital, a necessary electronic health record (EHR) is automatically downloaded from an EHR server to a mobile terminal when a nurse enters a patient's bedroom with the terminal. In an office building, conference materials for a presentation are automatically copied to a mobile terminal when an office worker enters a meeting room and automatically deleted from the terminal when the worker leaves the room. In these cases, knowing in what room the user resides, i.e., room-level localization [5], is sufficient for LBS, and a more precise positioning system is not necessary. Room-level localization is thus possible for many kinds of indoor LBS. We therefore aimed to achieve robust and cost-effective room-level localization. In this paper, we propose a new room-level localization method for indoor environments.

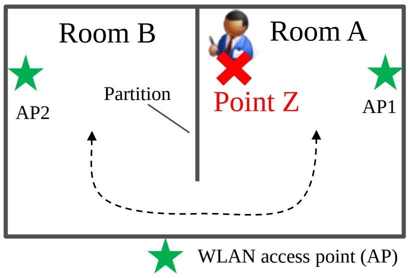
II. RELATED WORK

Hui et al. [1] categorized positioning methods into three types on the basis of their calculation principle: 1) triangulation, 2) proximity, and 3) scene analysis. 1) Triangulation is a positioning method that determines the target's position by using the geometric properties of triangles. However, its measurement accuracy easily decreases under the influence of fading, and it is not suitable for usage in narrow spaces. 2) Proximity is a positioning method relying upon a grid of antennas, each having a cell. When the mobile target detects a single antenna, it is considered to be within a cell region. If high-resolution positioning is necessary, the proximity method requires an increased density of antennas. 3) Scene analysis is a positioning method using location fingerprints. This method first collects features (fingerprints) from a scene and then estimates the target's location by matching online measurements with the closest prior location fingerprints. RSS-based location fingerprinting [6] is commonly used in scene analysis. Location fingerprinting-based positioning methods utilize pattern recognition techniques such as probabilistic methods, k-nearest-neighbor and support vector machines (SVM) [7-10]. Additionally, position estimation based on statistical techniques such as Bayesian filters have been proposed [11].

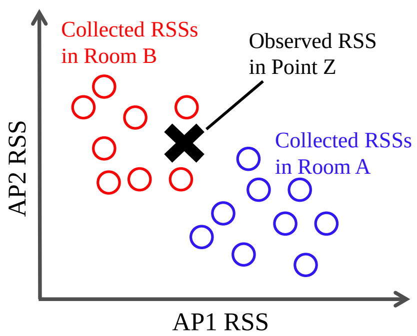
Among the three methods described above, scene analysis is considered the most robust position estimation method [1] and room-level localization methods based on scene analysis have been proposed [2]. Using observable WLAN RSS, this method estimates the room where the target user most likely is on the basis of a priori location fingerprints. Its drawback is that it may estimate the wrong room when the user is near the edge of a room. Fig. 1 helps to explain how such mistakes happen.

The target user is at Point Z located near the edge of the room (Fig. 1 (a)). In this case, the RSS obtained at Point Z is similar to the RSS obtained from Room B, i.e., the location fingerprint of Room B. Fig. 1 (b) illustrates the feature space of RSS distribution. Because the RSS observed at Point Z is located within the class of Room B, the user's location is estimated as Room B, even though the user is actually in Room A. To solve this problem, Chiu et al. [12] and Krumm et al. [13] introduced a path-restriction into the localization algorithm. The key idea is as follows. When estimated location at time *t* differs from the previous estimation at time *t-1*, the algorithm checks whether the user can actually move from the previous position to the current estimated position based on path-restriction derived from the building layout. If the algorithm detects an impossible movement, it first eliminates the mistaken estimation and then makes another attempt to estimate the likely location of the user. This technique works well only when the path-restriction is effective. To our knowledge, no localization method has been proposed that can deal with a situation like that in Fig. 1 (a), i.e., when no path restriction exists between Rooms A and B.

We therefore propose a new localization method that can handle the case depicted in Fig. 1 (a). The remainder of this paper is organized as follows. Section 3 describes the proposed localization method in detail. Section 4 confirms the effectiveness of the proposed technique through the results of experiments. Section 5 summarizes this paper.



(a) Problematic situation.



(b) The feature space of WLAN RSS distribution situation.

Figure 1. Problem of room-level localization based on scene analysis.

III. PROPOSED LOCALIZATION TECHNIQUE

Our proposed localization method is to be used in indoor environments such as office buildings and hospitals. These buildings consist of various rooms such as offices, hallways, conference rooms, and corridors. The goal to be achieved in this work is to estimate in which room the target user is, i.e., to achieve room-level location with high-accuracy.

Our room-level localization method adopts a technique to reduce the rate of erroneous estimation. The concept of the technique is based on the heuristic of passing through a boundary point (for example, an entrance door, an entry, a front of elevator, and so on) when moving from one room to another. To determine whether the target user is near the boundary point, the similarity of two RSS vectors is observed. One is obtained around the boundary point beforehand, and the other is observed at the user's current position. If the user is determined not to be near the boundary point, the current location of the user is estimated under the assumption that the probability the user has moved from one room to the other is low. In this paper, we focus on a doorway as a boundary point since we conducted experiments in our office environment.

Fig. 2 shows the flow chart of the proposed localization method. Room-level localization is executed in three steps. The first step is to calculate the user's existence probability in each room on the basis of a pattern recognition technique (SVM) using WLAN RSS for observation values. The second step is to evaluate the distance from the user's current position to each doorway by using observed WLAN RSS and then to calculate the transition probability that the user moved from one room to another. The third step is to estimate the room in which the user exists on the basis of a probabilistic method by using the resulting existence probability and the transition probability. In the following section, we describe the details of these steps.

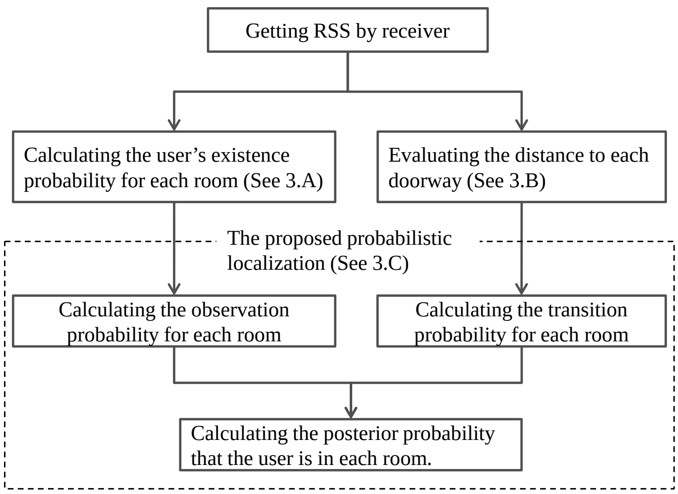


Figure 2. The flowchart of proposed method.

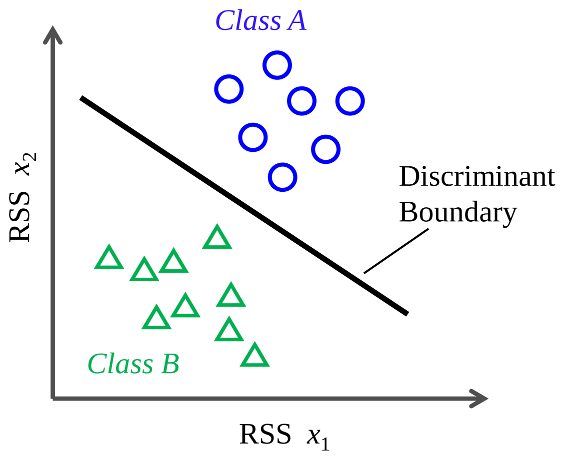


Figure 3. A simple case of classification in sensor space.

A. User's existence probability in each area

In this section, we describe how to calculate the user's existence probability in each area using the scene analysis method.

Now we consider an indoor environment where the number of WLAN access points (APs) installed is M. Let $\mathbf{x}=\{x_1, \dots, x_M\}$ be the observed RSS vector at the current position of the target user. The principle of a scene analysis algorithm [1, 2] utilizes the fact that an area has a unique location fingerprint, i.e., observable BSSID and RSS characteristics depending on location [1]. Here, an area is represented as a class in the M-dimensional vector space where each spatial axis is RSS from each WLAN AP, as shown in Fig. 3. Fig. 3 depicts the case of M=2.

If we can define the boundary plane (line) to distinguish each class in M-dimensional vector space, we can correctly estimate the user's location corresponding to the observation value $\mathbf{x}$. This can be done by utilizing a pattern recognition technique. Pattern recognition using a machine learning technique is performed in three steps: (1) preparing a training data set, (2) training a classifier using a learning algorithm, and (3) identifying the class to which the observation value belongs by using the classifier.

WLAN RSS is collected beforehand in each area as a training data set. This is described in detail in section 4.B. We adopted a support vector machine (SVM), a two-class classifier, to train a discriminator. Fig. 3 illustrates a simple case in which SVM determines the boundary between two classes from an input data set. In multi-dimensional space, this boundary is represented as a hyperplane. We adopted SVM because it discriminates better than other machine learning techniques such as neural networks and k-nearest neighbor [14].

Location fingerprints are generally difficult to separate by linear discriminant function because the distribution of RSS in multidimensional space is complex depending on deployment of APs [15]. To solve this problem, we adopted nonlinear SVM with Gauss kernel [14], which can discriminate between two clusters by a nonlinear boundary.

We defined the minimum distance between the observed point and the discriminant boundary in the RSS vector space as the user's existence probability. Chang and Lin describe how to calculate the probability [16]. The existence probability is calculated for each area, and the area with the highest probability is regarded as the current user's location.

When M WLAN APs are used for localization, the RSS vector space becomes M-dimensional. This means that the number of dimensions of observation RSS vectors must be M, because SVM cannot process pattern matching if the dimensional number of the observation vectors differs from the dimensional number of the learning data space. In actual use, one faces the problem that Wi-Fi receivers often fail to obtain RSSs from all WLAN APs, so the dimensional number of actually observed RSS vectors becomes smaller than M.

This RSS observation loss occurs when the line of sight between the WLAN receiver and an AP is impeded by another person, for example. Thus, we decided to compensate for lost RSS observation with the lowest sensitivity of the WLAN receiver (-95dBm).

B. The distance between the user and the doorway

In this section, we introduce a parameter representing the distance between the current position of the target user and the entrance door.

The situation is shown in simplified terms in Fig. 4, where only one WLAN AP is fixed near the doorway. We set the point P near the entrance door and point Q_i (i=0,...,4) as observation points.

Let m be the mean value of RSS observations at P, and x_i the RSS observation at Q_i. Here, we define d_i as the following formula.

$$d_i \equiv | x_i - m | \tag{1}$$

We will show the physical sense of d_i through the results of experiment. We measured RSS 100 times at point Q_i. The mean value and standard deviation of d_i are plotted in Fig. 5. Here, we noted that Q_0 coincides with P. As seen in Fig. 5, d_i tends to decrease as the distance from the doorway increases. This corresponds to the fact that WLAN signal strength decreases exponentially in accordance with the distance from the access point. Looking at the results for Q_0, Q_1, Q_2, and Q_3 in Fig. 5, d_i appears to be a good parameter for representing the distance between the observation point and the doorway, but it is actually insufficient. In spite of the short distance between Q_4 and the doorway, d_4 has a relatively high value. This is because RSS decreases depending not only on the distance between AP and receiver but also on the influence of walls that shield RF waves.

To evaluate d_i consistently whether shielding obstacles exist or not, we used the following method. We set the point P_{in} inside the room, and P_{out} outside the room. Let m_{in} be the mean value of RSS at P_{in} and m_{out} the mean value of RSS at P_{out}. Using these parameters, we redefine d_i as follows.

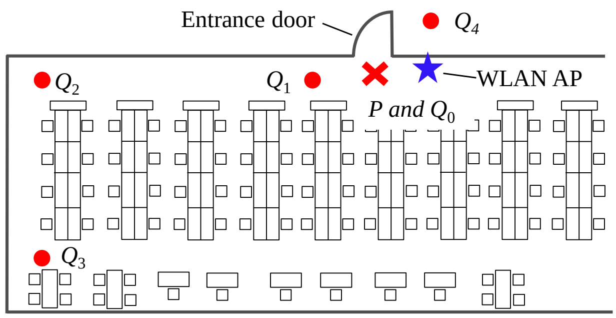


Figure 4. A preliminary experiment to evaluate the distance between the entrance door and observation points.

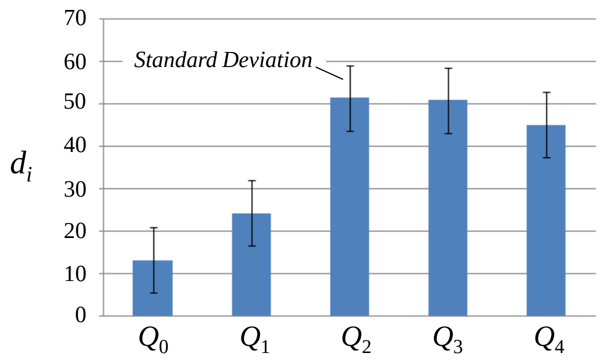


Figure 5. Results of experiment.

$$d_i = \min\left(|\, x_i - m_{\text{in}} \,|, |\, x_i - m_{\text{out}} \,|\right) \qquad (2)$$

Thus, d_i can represent the distance between the observation point and the doorway regardless of the existence of obstacles. Ordinarily, multiple APs are installed in the environment, so we generalized equation (2) to the multiple AP case as follows.

$$d_i = \min\left(\|\, \mathbf{x}_i - \mathbf{m}_{\text{in}} \,\|, \|\, \mathbf{x}_i - \mathbf{m}_{\text{out}} \,\|\right) \qquad (3)$$

where ||.|| denotes Euclidean distance, and $\mathbf{x}_i$, $\mathbf{m}_{\text{in}}$, and $\mathbf{m}_{\text{out}}$ the RSS vectors of multiple APs.

To handle situations where multiple doorways exist in a room, minimum d_i is selected as follows.

$$d_i = \min_j\left(d_{i,1}, \cdots, d_{i,j}, \cdots, d_{i,J}\right) \qquad (4)$$

where j denotes the index of the doorway and J the number of doorways.

Next, we discuss how to arrange WLAN access points in an environment. As mentioned above, RSS from AP decreases exponentially as distance increases. If the target user is far from the AP, the RSS value is severely influenced by noise because the value is quite low, causing loss of RSS observation. The less RSS observation is lost, the more stably our proposed method operates. Thus, an AP should be set near the doorway.

C. *Room-level localization using probabilistic method*

In this section, we describe a room-level localization using a probabilistic method. Our localization method uses the user's existence probability discussed in section 3.A and the distance d_i introduced in section 3.B.

In our method, the probability of the user's location is updated sequentially when RSS observation is obtained. In the following, we explain basic ideas of our method to calculate the posterior probability after obtaining RSS observations.

- We use the user's existence probability based on RSS observation discussed in section 3.A to estimate the user's location.
- If the user is far from a doorway, we consider the user to be unlikely to have moved from the previous room to another one. That is, the probability that the user has moved from the previous room to another one becomes low.
- The large observation noise is sometimes added to RSS, which causes the unexpected location estimation. However, the user has not moved suddenly from the previous room. To prevent such error, we use the probability that the user was in room at the previous time, as the prior probability.

On the basis of those ideas, the posterior probability of the target user's location y_t at time t is calculated as (5), when obtaining a sensor observation $\mathbf{o}_t$, i.e., WLAN RSS and the previous estimated location $\hat{a}_{t-1}$.

$$p(y_t \mid \mathbf{x}_t = \mathbf{o}_t, y_{t-1} = \hat{a}_{t-1}) \propto p(y_t \mid \mathbf{x}_t = \mathbf{o}_t)\, p(y_t \mid y_{t-1} = \hat{a}_{t-1})\, p(y_t) \quad (5)$$

$\mathbf{x}_t$ is the observation variable of RSS, and $p(y_t)$ the prior probability of the user's location. We note that a prior probability at time t equals a posterior probability at previous time t-1. $p(y_t \mid \mathbf{x}_t = \mathbf{o}_t)$ denotes the probability that the user is in the location y_t when RSS observation vector $\mathbf{o}_t$ is obtained. We use the user's existence probability discussed in section 3.A as this probability. Also, $p(y_t \mid y_{t-1} = \hat{a}_{t-1})$ represents the possibility to move from the previous estimated location $\hat{a}_{t-1}$ to the current location y_t that the user is in at time t, which is called the state transition probability. Here, supposing the previous estimation result is accurate, we adopt $\hat{a}_{t-1}$ as the previous given location. Consequently, we obtain the current estimated location $\hat{a}_t$ as the user's location that has the maximum posterior probability at time t in (5).

Now, we formulate the transition probability as follows on the basis of the distance d_i in (4) discussed in section 3.B. We take the following two points into account to formulate the state transition probability. The first point is that we make the state transition probability high when the target user is near the doorway. The second point is that the probability of occurrence for the user to remain in the same room at time t does not rely on the distance from the doorway. Hence we adopted the constant value as the probability of this event. Considering these points, we formulate the state transition probability as follows.

$$p(y_t \mid y_{t-1} = \hat{a}_{t-1}) = \begin{cases} f(d_{y_t,\hat{a}_{t-1}}(\mathbf{o}_t); d_{\mathrm{th}}, k) & (if\, y_t \neq \hat{a}_{t-1}) \\ 0.5 & (if\, y_t = \hat{a}_{t-1}) \end{cases} \quad (6)$$

where $d_{y_t,\hat{a}_{t-1}}(\mathbf{o}_t)$ is represented by d_i in (4) from the current user's position to the doorway between the location y_t and the location $\hat{a}_{t-1}$ under the condition we observe RSS vector $\mathbf{o}_t$. To describe the relationship between the distance and the transition probability in general, we adopt the following logistic function.

$$f(d_{y_t,\hat{a}_{t-1}}(\mathbf{o}_t); d_{\mathrm{th}}, k) = \frac{1}{1+\exp\left[-k\left\{d_{y_t,\hat{a}_{t-1}}(\mathbf{o}_t) - d_{\mathrm{th}}\right\}\right]} \quad (7)$$

where d_{th} and k are parameters that determine the nature of the logistic function. As shown in Fig. 6, the function takes 0.5 when $d_{y_t,\hat{a}_{t-1}}(\mathbf{o}_t)$ is equal to d_{th}. This means that the probability for the user to move to another room equals to one for the user to remain the same room when the user is just at the doorway. Thus we used the average of d_i at the doorway of the room as d_{th}.

To avoid a situation in which the posterior probability almost equals zero, which would prevent updating of the posterior probability, we apply additional smoothing to the posterior probability, as follows.

$$p^*(y_t) = \frac{p(y_t \mid \mathbf{x}_t = \mathbf{o}_t, y_{t-1} = \hat{a}_{t-1}) + \gamma}{\sum_{y_t} \left\{ p(y_t \mid \mathbf{x}_t = \mathbf{o}_t, y_{t-1} = \hat{a}_{t-1}) + \gamma \right\}} \quad (8)$$

where γ is the coefficient of smoothing. We determine experimentally the value of γ in this work.

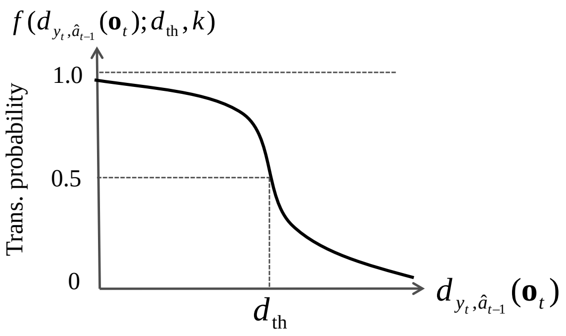


Figure 6. Transition probability based on distance to the doorway.

IV. Performance Evaluation

A. *Experimental setup*

We used a Fujitsu F-12C smartphone as the sensor for WLAN RSS data. The data sampling rate was 1.4 seconds. We used a Fujitsu FMWT-54AG WLAN access point to send BSSID as a beacon signal. In the experiment, we moved along a predetermined path and logged WLAN RSS to an SD card on the smartphone. We executed localization using our proposed method on an offline desktop PC.

B. *Experimental environment and training data set*

Fig. 7 illustrates the experimental environment. The environment is one floor in an office building, comprising three rooms connected to one hallway. Those four areas are compartmentalized by walls. The number of doorways differs with each area, with one doorway each in Area *A* and Area *B*, three doorways in Area *C*, and five doorways in Area *D*.

There are four APs, represented by blue stars in Fig. 7, within the environment. When estimating the user's area, we used RSSs from those four APs and other APs located in the office building whose RSS was observable in the environment. Consequently, the total number of available APs was 17, so the dimension number of observed vectors of RSS was M=17.

A training data set of RSS for each area had to be collected in order to implement the scene analysis method described in section 3.A. To collect the training data set of RSS, the user walked around in each area holding the smartphone in one hand. The number of training data points in each area was 200, which we determined empirically.

Also, we had to measure values of RSS near doorways for evaluating the distance to each doorway as described in section 3.B. The red crosses in Fig. 7 represent the observed points near the doorway. To collect RSSs, the user stayed still at each observed point, and 100 samples of RSS vectors were collected.

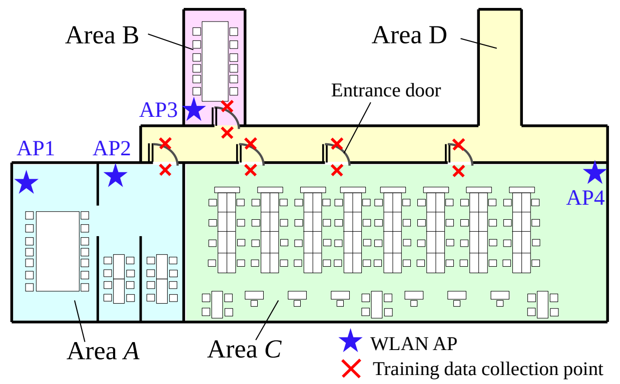


Figure 7. Experimental environment is one floor in an office building, comprising four areas, i.e., three rooms and one hallway.

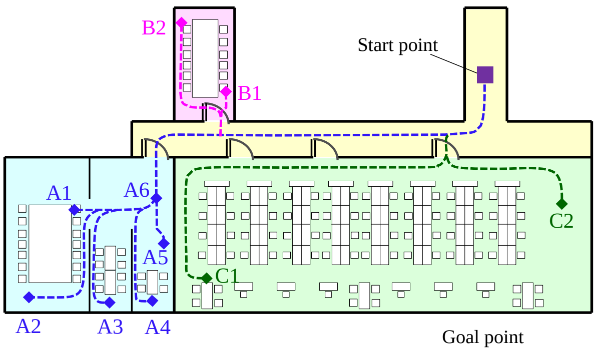


Figure 8. The pathways in experiments.

C. *Test data set*

Fig. 8 illustrates the pathways in our experiments. The purple square represents the start position, the diamond represents the goal position, and the dotted lines represent the pathway. The target user moved from one room to another, passing through the entrance doors between those rooms when following each pathway. The user remained at the goal position in each pathway for a while in order to evaluate the performance of our proposed method near walls, where erroneous judgment often occurs with the scene analysis method. Thus, we obtained test data by observing RSS vectors while passing along each pathway and staying at each goal position. The total number of pathways was 10. We collected 150–200 samples of RSS vectors in each pathway.

D. *Evaluation method*

We evaluated the performance of our proposed method using an accuracy rate. The accuracy rate was calculated in each pathway by dividing the number of times when the estimated room accorded with the actual room in which the user was located by the number of collected samples in each pathway. This estimation results were obtained through offline implementation of the method described in section 3.C to the test data set described in the previous section.

To validate the effectiveness of introducing our proposed transition probability (6), we identified the difference in the accuracy rate when calculated with and without the probability (6). We refer to the latter method as the “previous method,” since it has been reported as a type of scene analysis method [1]. We implemented the previous method by setting $f(d_{y_t,\hat{a}_{t-1}}(\mathbf{o}_t); d_{\text{th}}, k)$ in (6) as the value 0.5 at any time step. Additionally, the initial prior probability of each area is set as $p(y_t)$=0.25, because there are four rooms, and we assume the user is equally likely to be in each room. We determined empirically the parameters in (7) and (8) as k=-1, d_{th}=15.0, γ=0.05.

E. *Experimental results*

Fig. 9 shows the results of experiments on 10 pathways. The horizontal axis represents the index of the pathways, and the vertical axis the accuracy rate. The blue bar in the histogram denotes the previous method, and the red bar our proposed method. In the experiment, our proposed method achieved an average accuracy rate of 97.1% for localizing the target user, while the previous one achieved a rate of 81.7%. In particular, the accuracy rate of our proposed method was more than 50% higher than that of the previous method in the cases of *A4* and *A5*.

From the results of *A4*, we consider why the proposed method remarkably improves the accuracy of location estimation. We first look at the posterior probability (5) described in section 3.C. Fig. 10 (a) and (b) illustrate the time-varying posterior probabilities that the user was in the initial *Area D* and the destination *Area A*, respectively. The blue lines represent the resulting posterior by using the previous method, and the red lines the proposed method. After the user actually moved to *Area A*, the previous method made estimation errors continuously and erroneously estimated the user’s location to be in *Area D* with high probability. In contrast, after the user passed through the doorway between *Area A* and *Area D*, our method estimated the posterior probability in *Area A* to be significantly high, in accordance with the user’s actual movement. Since the proposed method performs correctly when the target user is far from doorways, the estimation accuracy was clearly improved.

We also look at the effect of the state transition probability that we originally introduced. Fig. 11 shows the time-varying distance d_i calculated by (4), and Fig. 12 shows the variation of the state transition probability calculated by (6) over time. As shown in Fig.11, the distance d_i takes minimum value at time T_0, which corresponds to the time when the user actually passed through the doorway, and increases afterward while moving. This indicates that the distance d_i reasonably represents the actual distance between the current user’s position and the doorway. Fig. 12(b) also shows that the state transition probability takes a high value just before T_0, and Fig. 12(a) shows this probability takes a low value just after T_0, corresponding to the variation of d_i. This property of the state transition probability contributes to make the location estimation robust even if the existence probability in a false room becomes high because of wrong observation.

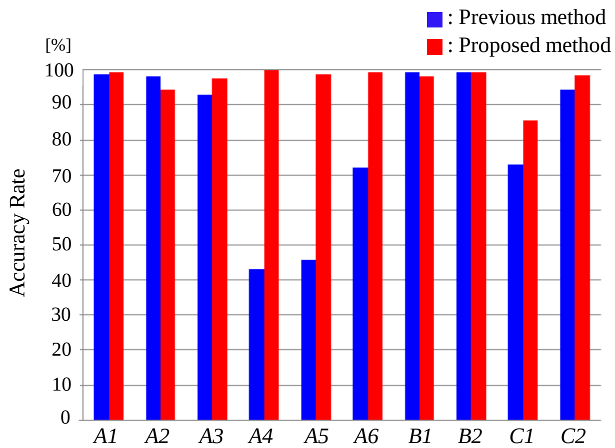
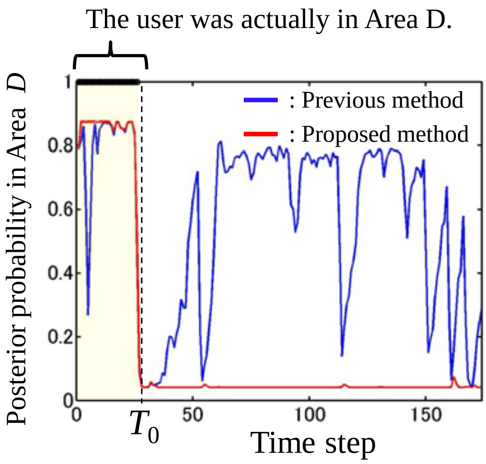
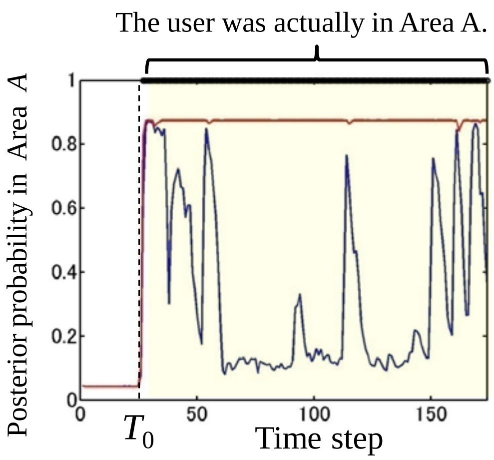


Figure 9. Experimental result of room-level localization.

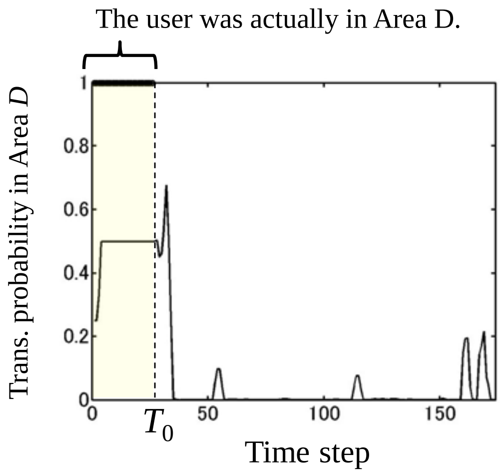


(a) Area *D*

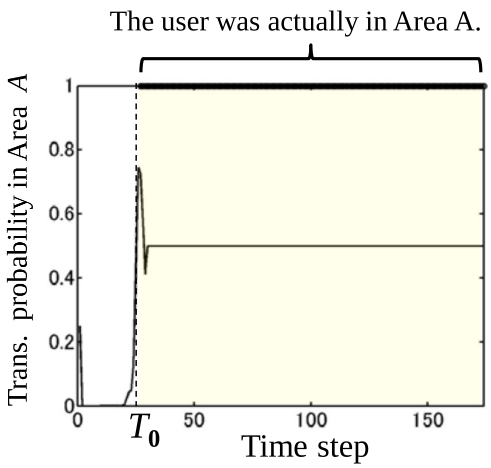


(b) Area *A*

Figure 10. The time-varying posterior probability in experiment *A4*.



(a) Area *D*



(b) Area *A*

Figure 12. The time-varying transition probability in experiment *A4*.

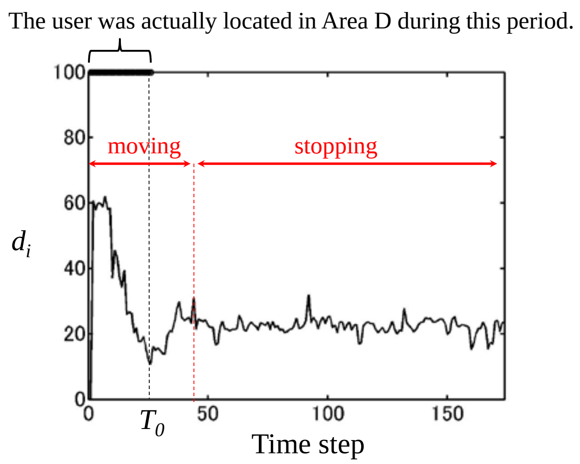


Figure 11. The time-varying distance between user's position and the entrance door no. X in experiment *A4*.

V. Conclusion

In this paper, we have proposed a highly accurate room-level localization method. In our proposed technique, we introduce a novel transition probability, evaluated by using the distance from an observed point to a passable boundary point between rooms. Experimental results show that our proposed method resolves the problem of estimation error occurring when the received signal strength (RSS) observed at a target user's position is similar to RSS observed in other areas. Applying our proposed method improved the average accuracy rate significantly, from 81.7% to 97.1%.

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