Efficient Indoor Localization Model Construction by Sequential Recommendation of Data Gathering Position Based on Bayesian Optimization

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Abstract

In recent years, with the spread of smartphones and IoT devices, the demand for indoor localization is increasing. GPS is not suitable for indoor localization, so radio signal strength indicator (RSSI) such as Wi-Fi or BLE is frequently used. On the other hand, indoor localization based on RSSI requires data gathering in advance and it is quite costly. We insist that data gathering costs should be reduced in terms of the number of data needed, walking distance, and required time during data gathering. However, to the best of our knowledge, none of the previous work could simultaneously reduce the cost in all aspects above. To reduce the cost in all three aspects, we propose Effective Sequential Recommendation of Neighborhood Data Gathering Position, which is based on Bayesian Optimization and streamlined data gathering. Experiments show that our method could reduce not only the number of data gathered, but walking distance and required time during data gathering compared with other methods.

Keywords

indoor localization, data gathering, Bayesian Optimization

1. Introduction

In recent years, with the spread of smartphones and IoT devices, various services such as material management in factories based on their location information indoors and entry/exit management of people in offices have been developed. In the future, it can be expected to be applied to route guidance in subway stations and advertisements based on the user's current position in the building. Demand for indoor localization is increasing as the basic technology for such indoor location information services [1]. GPS is commonly used for outdoor localization, but GPS may not be available indoors or sufficient accuracy may not be obtained, so it is necessary to perform localization using an alternative information source. There is indoor localization by PDR using IMU and indoor localization using illuminance sensor, but in particular, indoor localization using wireless radio signal strength indicators (RSSI) such as Wi-Fi and BLE are attracting attention due to its high penetration rate and accuracy.

For indoor localization using radio signal strength, a fingerprint consisting of RSSI received from multiple access points is used as the information source of localization. In addition, an indoor localization method based on triangulation using radio signal strength has also been

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proposed; however, this framework cannot obtain sufficient localization accuracy because of the effects of radio signal reflection and diffraction in the indoor environment. Indoor localization using fingerprint can be defined as estimating the target mesh from the meshes set on the target area using fingerprint.

The model that estimates the acquired position of the fingerprint is called the localization model. In this localization model, the parameters must be optimized for all sections of the localization target environment. Therefore, it is necessary to acquire fingerprint data evenly in the entire localization target environment prior to localization. The high cost of gathering data required to construct an indoor localization model has been regarded as a problem.

Therefore, many studies have been working on the reduction of data gathering costs. For example, a method that utilizes a small amount of labeled data and a large amount of unlabeled data using semi-supervised learning [2, 3, 4, 5] and distribute the effort of gathering data per person by crowdsourcing [6, 7, 8, 9, 10] are proposed. In addition, a method to reduce costs by gathering data while walking has also been proposed. [11, 12, 13, 14]. This method aims to significantly reduce the data gathering time by combining data gathering and movement. These methods efficiently gather a large amount of data and do not reduce the amount of data itself.

On the other hand, a method that reduces the amount of data gathered by constructing an indoor localization model with a small amount of data has the same accuracy as when learning with a large amount of data has also been studied. This method fundamentally reduces the data gathering cost. As a typical example, a method of maximizing the improvement of localization accuracy by gathering each data using Bayesian optimization has been proposed [15]. This method has succeeded in constructing a highly accurate localization model with a small amount of data by gathering data at a position that maximizes the possible accuracy improvement of the localization model by each scan according to Bayesian optimization. On the other hand, since this method maximizes the immediate reward focusing only on the accuracy improvement range of the localization model, the distance to be moved during continuous data gathering tends to become long, and most of it is redundant.

Considering the burden on the data collector when gathering data in an actual situation, we should reduce the number of data collected, the walking distance and the required time during data gathering. The method of gathering a large amount of data has not been sufficiently reduced by the method of Shimosaka et al. [15], which aims to reduce only the number of data gathered, but the walking distance during data gathering is costly. Since this problem was not taken into consideration, the ratio of redundant walking was larger than that of the conventional method.

Therefore, we propose a method named Effective Sequential Recommendation of Neighborhood Data Gathering Position. Our method achieves the target gathering accuracy by reducing redundant data gathering and movement. The Effective Sequential Recommendation of Neighborhood Data Gathering Position is a method that can simultaneously reduce the number of data collected, the walking distance during data gathering, and the data gathering time. Specifically, our algorithm recommends data gathering position sequentially with using Bayesian Optimization to reduce not only the number of data but also walking distance during data gathering for constructing enough accurate indoor localization model.

Also, we conducted an experiment to confirm the performance of the proposed method in an office environment of $450\ \mathrm{m}^2$. As a result, our method beats baseline and comparison methods in all the number of data, walking distance, and required time.

The contributions of this research are as follows:

- We propose a brand new data gathering framework for constructing an indoor localization model, reducing the amount of data required to achieve the target localization accuracy by using Bayesian optimization and the walking distance required throughout the data gathering. Specifically, instead of improving the usage of the acquisition function and recommending the data gathering position that takes the maximum value, in our method, the data gathering position is recommended based on the estimation of the current position and the acquisition function after data gathering.
- We confirm the performance of our method from the viewpoint of the actual gathering accuracy to the target accuracy, the required amount, walking path length, and needed time by an experiment using actual Wi-Fi fingerprint data. We show that our method collects the data necessary for achieving target localization accuracy in a significantly shorter walking distance.

The structure of this paper is as follows. Chapter 1 summarizes the position of this research based on related work, and Chapter 2 describes the premise of setting indoor gathering problems. Regarding the contribution of this research, Chapter 3 describes a sequential recommendation algorithm for data gathering positions considering walking distance based on Bayesian optimization. In Chapter 4, an evaluation experiment of the proposed method is conducted, and the conclusions are summarized in Chapter 5.

1.1. Related Work

Indoor Localization with Wi-Fi RSSI Bahl et al. [16] proposed indoor localization based on radio signal strength indicator. In particular, the method using RSSI of Wi-Fi has attracted attention for its high penetration rate of Wi-Fi and its high localization accuracy and has been actively researched [17, 18, 19, 20]. In addition, many localization methods based on deep learning using Wi-Fi RSSI have been proposed[21, 22]. And not only Wi-Fi RSSI, but also channel state information [23, 24, 25, 26, 27], phase difference for each antenna[28, 29], AP-to-user propagation time of RSSI [30, 31, 32] has also been used for indoor localization. While these methods have improved the localization accuracy, they require a high cost for data gathering.

1.1.1. Methods for collecting a large amount of data efficiently

Semi-supervised learning A method has been proposed to reduce the number of labeled data collected by using a large amount of unlabeled data by a method using semi-supervised learning[2, 3, 4, 5]. This is to utilize unlabeled data in consideration of the cost of collecting labeled data in general. However, it is hard to say that the data gathering cost is reduced from the viewpoint of the amount of data collected because not only at least one labeled data is required for each localization target point but also a large amount of unlabeled data is required.

Crowdsourcing A method to reduce the burden of data collection per person by using crowdsourcing has been proposed[6, 7, 8, 9, 10]. This is to disperse the data gathering cost by asking the public to collect data, but the data collected by the public is unreliable, and the total number of gathered data is not reduced.

Data gathering while walking A method to reduce the data collection cost by collecting data while walking has been proposed[11, 12, 13, 14]. Although it is possible to significantly reduce the data collection time by collecting data while walking, it has been pointed out that there is a problem of deterioration of localization accuracy due to inaccuracies in labeling. A method for improving the labeling accuracy by making the walking route known has also been proposed. On the other hand, there are problems such as it needs to specify the walking route before collecting data, but the efficiency of data collection is not taken into consideration when specifying the walking route.

1.1.2. Methods for collecting a short amount of data with high collection efficiency

Bayesian Optimization While the method in the previous section is a method for efficiently collecting a large amount of data, a method for fundamentally reducing the data collection cost by reducing the amount of data collected itself has been proposed. Bayesian optimization[33, 34, 35] is an efficient sampling algorithm for collecting training data. An example of using Bayesian optimization is controlled parameter adjustment in the field of robot control[36, 37, 38, 39]. A method has been proposed in which a reduction in the number of data collections is applied to indoor localization data collection using Bayesian optimization[15]. This method aims to achieve the maximum localization accuracy with the minimum amount of data by sequentially recommending the most effective data collection points for improving the localization accuracy by Bayesian optimization. However, unlike sampling in the context of robot control parameter adjustment, data collection in the context of indoor localization model construction requires movement to the data collection position for each scan. This movement is one of the main factors included in the data collection cost, but the method of Shimosaka et al. tends to increase the walking distance required during data collection, which was a problem from practicality. In this study, based on the reduction of the number of data collected using Bayesian optimization, by improving the utilization of the acquisition function, the number of data collected and the walking distance during data collection is reduced to achieve the target accuracy. We propose a sequential recommendation algorithm for possible data gathering positions.

2. Formulation of Indoor Localization

2.1. Information source for Indoor Localization

Wi-Fi RSSI is used as an information source for indoor localization. One RSSI is obtained for each AP (Access Point). Here, the RSSI corresponding to AP_i is expressed as x_i. The APs used for localization are specified in advance, and the total number is N_a. The RSSI from N_a APs obtained by one scan is expressed as a vector $\boldsymbol{x} \in \mathbb{R}^{N_a}$, which is the fingerprint at the data collection point. In addition, the data collection points are set by dividing the localization target environment into a mesh and setting one for each divided section. This partition r is also a unit of localization. Assign a label to each partition and define it as the position label $r \in \mathcal{R}$. Here, $\mathcal{R}$ is a set of localization target sections. Based on them, indoor localization using Wi-Fi signal strength becomes a multi-class classification problem that estimates the collection position r by inputting the collected RSSI vector $\boldsymbol{x}$ of the fingerprint. RSSI x takes real numbers from -100 to 0. The unit is dBm, and the larger the value, the stronger the signal strength. Also, RSSI x_i for unobserved AP$_i$ is complemented as -100.

2.2. Indoor Localization based on Fingerprint

Fingerprint $\boldsymbol{x}$ is featured and used for training and localization. Each section r has corresponding parameter $\boldsymbol{w}_r$ of the same dimension as the featured fingerprint $\boldsymbol{\phi}(\boldsymbol{x})$. This parameter is learned with training data $\mathcal{D}_l = \{\boldsymbol{x}_i, r_i\}_{i \in (1,\cdots,N_l)}$, and $N_l = |\mathcal{D}_l|$. The parameters are learned to minimize the localization error. Let r be the ground truth data gathered position and $\hat{r}$ be the estimated position as data gathered, localization error l_r is defined by $l_r = d(r, \hat{r})$. Here, $d(\cdot,\cdot)$ is Euclidean distance between sections.

When estimating the collection position of a certain fingerprint, estimated gathered position $\hat{r}$ is calculated by (1), using $\boldsymbol{W} = \{\boldsymbol{w}_1, \cdots, \boldsymbol{w}_{|\mathcal{R}|}\}$.

$$\hat{r} = \operatorname*{argmax}_{r \in \mathcal{R}} \boldsymbol{w}_r{}^{\mathsf{T}} \boldsymbol{\phi}(\boldsymbol{x}). \tag{1}$$

2.3. Learning method of Indoor Localization model with a small amount of data

When constructing a localization model as a multi-class classification problem, it is necessary to learn the parameter $\boldsymbol{W}$ corresponding to all sections. The simplest solution to this problem is to collect data in all sections contained in $\mathcal{R}$, but this method requires data gathering at least once in each area, $|\mathcal{R}|$ times in total. Therefore, we introduce multitasking regularization. Multitasking regularization is a parameter learning method that considers the proximity between classes, which enables learning with a small amount of data less than $|\mathcal{R}|$. Here, in the context of indoor localization, classes correspond to sections, so the proximity between classes is defined by the Euclidean distance between the coordinates of the representative points of the areas. In other words, the closer the distance on the floor map, the higher the proximity of the corresponding classes between the plots.

2.3.1. Streamlining data gathering to reduce the number of data

In this study, we adopt an experimental design method using Bayesian optimization. The function that models the accuracy improvement range of the target model is called the acquisition function. Let that the acquisition function be A_Q, and the coordinate space of the data be $\mathcal{Y}$, the coordinates $\hat{\boldsymbol{y}}$ of the next observed data are determined by (2).

$$\hat{\boldsymbol{y}} = \operatorname*{argmax}_{\boldsymbol{y} \in \mathcal{Y}} A_Q(\boldsymbol{y}) \tag{2}$$

In the context of indoor localization, we model the localization error that decreases by observing the fingerprint in each section and recommend the most efficient data collection position.

In the context of indoor localization, the coordinate space of the data is $\mathcal{R}$, and the accuracy improvement range of the target model can be obtained from the localization error l_r in each section $r \in \mathcal{R}$. Since the acquisition function is modeled depending on the set of collected data $\mathcal{X}$, it can be expressed as $A_Q(r; \mathcal{X})$. This $A_Q(r; \mathcal{X})$ can be obtained by the following procedure.

First, we construct a localization error data set $\mathcal{L}$ using $\mathcal{X}$. Though the localization error of the localization model is originally calculated using data different from the data used for model training as an evaluation metric of the constructed localization model, at the data collection stage for constructing the indoor localization model, since it is impossible to use data other than the data currently being collected, the data used for training is same as for estimating the localization error. Parameters $\{\boldsymbol{w}_r\}_{r \in \mathcal{R}}$ corresponding to each section $r \in \mathcal{R}$ contained in $\mathcal{R}$ are trained using the gathered data $\mathcal{X}$. Here, the training method is not limited to a specific method, and any method may be used as long as a fingerprint is regarded as an input vector, and multi-class classification is performed.

The estimated localization error data set $\mathcal{L}$ is initialized with an empty set and then constructed by the following procedure: For each data $(\boldsymbol{x}_i, r_i)$ contained in $\mathcal{X}$, find the estimated collection position $\hat{r_i}$ according to (1). Then, the Euclidean distance $d(r_i, \hat{r_i})$ between the ground truth data collection position r_i and the estimated collection position $\hat{r_i}$ is regarded as the estimated localization error. Tuple $(d(r_i, \hat{r_i}), r_i)$ is inserted into $\mathcal{L}$.

The accuracy improvement range of the localization model must be estimated for all sections of $\mathcal{R}$, but the data contained in $\mathcal{L}$ is insufficient. Therefore, the predicted distribution of localization error is obtained using Gaussian process regression. The predicted distribution estimated by Gaussian process regression is the Gaussian distribution, and the predicted distribution of the estimated localization error in r can be obtained in the form of $\mathcal{N}(\mu_r, \sigma_r^2)$. As a modeling method for improving the accuracy of the localization model using them, it is possible to use only the average of the predicted distributions of the estimated localization errors, but that alone is not sufficient. Since the variance of the predicted distribution obtained from Gaussian process regression increases as the number of observed data decreases, the variance information is also important in the context of data collection position recommendation for indoor localization models. Therefore, the metric GPUCB (Gaussian Process Upper Confidence Bound) [40] is used, which can consider both the mean and variance of the predicted distribution. Here, the GP-UCB score s_r at r is obtained by (3) using the mean μ_r and variance σ_r^2 of the predicted distribution. Here, β is a parameter that adjusts the degree of influence of μ_r and σ_r on s_r.

$$s_r = \mu_r + \beta\sigma_r \tag{3}$$

Using this s_r, we get the acquisition function as $A_Q(r; \mathcal{X}) = s_r$.

However, the number of data collected $N = |\mathcal{X}|$ is reduced when Bayesian optimization is used. In the context of indoor localization, data collection requires user movement. In particular, in the method of Shimosaka et al., The next data collection position is obtained according to (2), and since only the number of data collections is considered, the data collection route becomes rather redundant and the number of data collections is reduced. On the other hand, the burden on the user has been increased from the viewpoint of the walking route length and the required time.

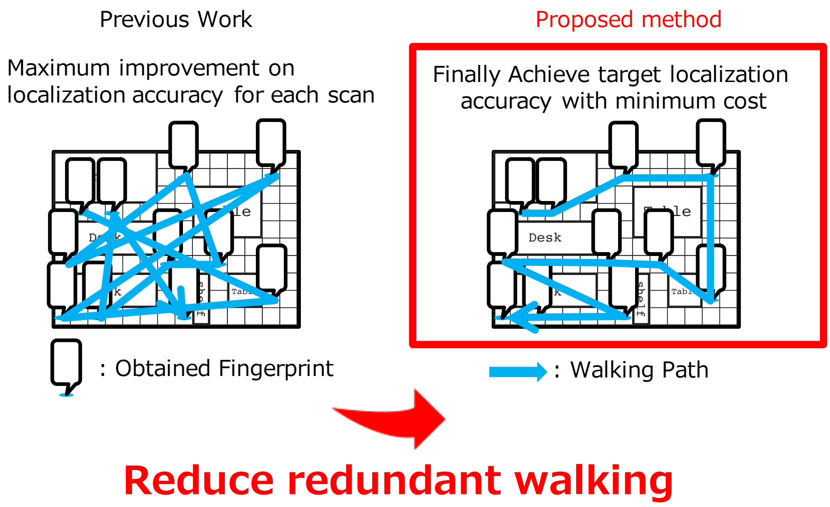


Figure 1: Change of route length by considering order of data gathering

3. Effective Sequential Recommendation of Neighborhood Data Gathering Position

3.1. Sequential Recommendation of data gathering position considering both localization accuracy and walking cost

This study aims not only to reduce the number of data collections by using Bayesian optimization but also to reduce further the data collection cost required to build an indoor localization model by reducing the distance traveled during data collection. Shimosaka et al.[15] set the section with the highest GPUCB value of the estimated localization error using the acquired data as the next data collection position, but it caused redundant walking. Therefore, we propose a new method to recommend the next data collection position sequentially named Effective Sequential Recommendation of Neighborhood Data Gathering Position that considers the GPUCB value of the estimated localization error and the relationship with the current location is taken into consideration.

3.2. Effective Sequential Recommendation of Neighborhood Data Gathering Position

The Effective Sequential Recommendation of Neighborhood Data Gathering Position uses the collected data to calculate the estimated localization error and the estimated localization error in the entire indoor environment, similar to Shimosaka et al.[15], calculate GP-UCB of localization error prior to the recommendation of the next data collection position. These procedures are similar to those described in 2.3.1, and only the next data collection position recommendation method after calculating the GPUCB value of the estimated localization error for the entire $\mathcal{R}$ is different. The flow of the entire algorithm of Effective Sequential Recommendation of

Algorithm 1 Effective Sequential Recommendation of Neighborhood Data Gathering Position

$r_{\text{current}} \leftarrow$ current position
$\mathcal{R} \leftarrow$ set of localization target positions
$\mathcal{X} \leftarrow \text{scan}(r_{\text{current}})$
$\mathcal{R}_1 \leftarrow \{r | r \in \mathcal{R} \wedge \text{ GPUCBScore}(\mathcal{L}, r) \geq s_t\}$
while $\mathcal{R}_1 \neq \emptyset$ **do**
    $\mathcal{R}_2 \leftarrow \{r | r \in \mathcal{R}_1 \wedge \text{ GPUCBScoreOnRouteLower}(\mathcal{X}, r_{\text{current}}, r)\}$
    $\mathcal{R}_3 \leftarrow \{r | r \in \mathcal{R}_2 \wedge \text{ NearestInAdjacent}(\mathcal{R}_2, r, r_{\text{current}})\}$
    $r_{\text{current}} \leftarrow \text{argmin}_{r \in \mathcal{R}_3} d'(r_{\text{current}}, r)$
    $\mathcal{X} \leftarrow \mathcal{X} \cup \text{ scan}(r_{\text{current}})$
    $\mathcal{L} \leftarrow \text{PredictedLocalizationErrorDataset}(\mathcal{X}, \mathcal{R})$
    $\mathcal{R}_1 \leftarrow \{r | r \in \mathcal{R} \wedge \text{ GPUCBScore}(\mathcal{L}, r) \geq s_t\}$
end while

Neighborhood Data Gathering Position is shown in Algorithm 1, and the state of selecting the next destination is shown in Fig. 2. The detailed flow of the algorithm is as follows:

The initial position of the user who collects data is r_{current}, and the set of the entire localization target section is $\mathcal{R}$. Define $\text{scan}(r)$ as a function that collects fingerprints in section r and returns their values, and $\text{scan}(r_{\text{current}})$ is added to the data set $\mathcal{X}$. Let $\mathcal{R}_1$ be the set of compartments $r \in \mathcal{R}$ whose estimated localization error GP-UCB value exceeds the threshold s_t. Of the section r contained in $\mathcal{R}_1$, the set of sections that satisfy $\text{GPUCBScoreOnRouteLower}(\mathcal{X}, r_{\text{current}}, r)$ constitutes $\mathcal{R}_2$. The details of the procedure for $\text{GPUCBScoreOnRouteLower}(\mathcal{X}, r_{\text{current}}, r)$ will be described later in Algorithm 2. $\mathcal{R}_2$ still contains many sections, which is not enough to narrow down the section candidates for the next data collection position. Therefore, we focus on the fact that $\mathcal{R}_2$ tends to include adjacent sections. Divide $\mathcal{R}_2$ into a set of adjacent compartments, select one compartment from each set, and use it as an element of $\mathcal{R}_3$. Here, when selecting one block from the block group, the section with the shortest required travel distance $d'(r_{\text{current}}, r)$ from the current location r_{current} is selected. Select the next data collection position from $\mathcal{R}_3$ constructed in this way. If there are multiple sections included in $\mathcal{R}_3$, select the section with the shortest required travel distance from the current location r_{current} $d'(r_{\text{current}}, r)$. The user moves to the next destination selected in this way.

By repeating the above procedure, the algorithm stops when the GP-UCB value in the entire localization target environment becomes less than the threshold s_t, that is, when $\mathcal{R}_1$ becomes an empty set.

3.3. Next data gathering position selection based on predicted localization error on route

Here, The calculation method of $\text{GPUCBScoreOnRouteLower}(\mathcal{X}, r_{\text{current}}, r_{\text{destination}})$ is described. The flow of the algorithm is summarized in Algorithm 2.

First, let V be vertex set composed of elements of $\mathcal{R}$ and E be edge set composed of undirected

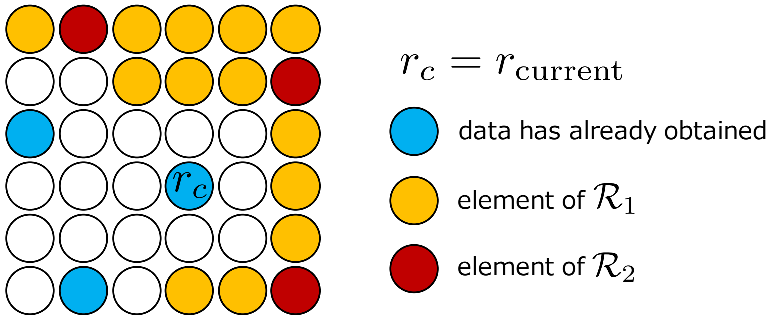


Figure 2: Example of $\mathcal{R}_1$ and $\mathcal{R}_2$: Each circle corresponds to section and is placed geographically. Element of $\mathcal{R}_1$(orange) is far from visited section (light blue), and some of them becomes element of $\mathcal{R}_2$ (red).

Algorithm 2 GPUCBScoreOnRouteLower

Require: $r_{\text{current}}, r_{\text{destination}}$

$V \leftarrow \mathcal{R}$
$E \leftarrow \forall_{r_i \in V, r_j \in V \setminus r_i}(r_i, r_j, 1)$
$G \leftarrow (V, E)$
$\mathcal{L} \leftarrow \text{PredictedLocalizationErrorDataset}(\mathcal{X}, \mathcal{R})$
$\mathcal{L}' \leftarrow \mathcal{L} \cup \{0, r_{\text{destination}}\}$
$\boldsymbol{r} \leftarrow \text{route}(G, r_{\text{current}}, r_{\text{destination}})$
for $r \in \mathcal{R}$ **do**
  $s \leftarrow \text{GPUCBScore}(\mathcal{L}', r)$
  if $s > s_t$ **then**
    return false
  end if
end for
return true

edge with a uniform weight between adjacent sections included in V. Let G be a graph composed of edge set E and vertex set V. Function route$(G, r_{\text{current}}, r_{\text{destination}})$ find the shortest path from r_{current} to $r_{\text{destination}}$. Here, the function route can be easily obtained by using breadth-first search because the edge weight is uniform. Let $\boldsymbol{r}$ be the path from r_{current} to $r_{\text{destination}}$, calculated by this function. Here, the estimated localization error to be obtained is the value when data is collected at $r_{\text{destination}}$. However, the data collected in $r_{\text{destination}}$ cannot be used at the stage of estimating the utility of data collection in $r_{\text{destination}}$. Therefore, assuming that the localization of the data collected at $r_{\text{destination}}$ is correct, that is, the localization error was 0 m. We construct $\mathcal{L}'$ by adding dummy data $(0, r_{\text{destination}})$ to $\mathcal{L}$. For all sections r contained in $\boldsymbol{r}$, calculate GP-UCB score of estimated localization error. If the GP-UCB value of the estimated localization error is less than or equal to the threshold s_t for all sections on $\boldsymbol{r}$, $r_{\text{destination}}$ is added to $\mathcal{R}_2$.

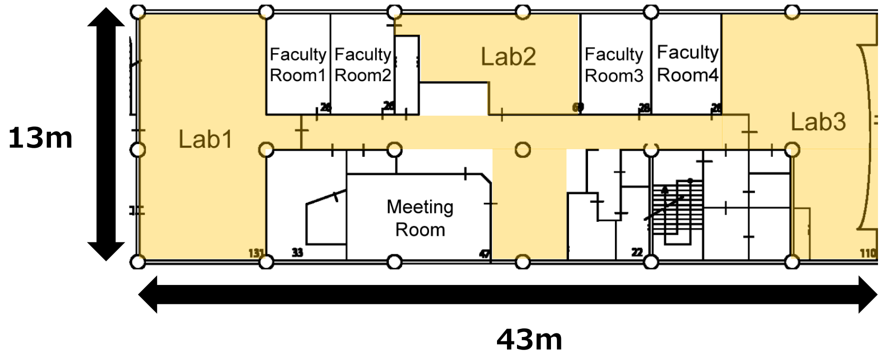


Figure 3: Floor map of indoor environment. Yellow parts are target of localization.

4. Experiments

4.1. Purpose

The purpose of this experiment is to show that the proposed method can construct a highly accurate localization model while keeping the amount of data collected small and the walking distance during data collection short in comparison with other methods.

4.2. Experimental Environment

Fingerprint data was collected in an office environment of about 450 square meters. The size of one section, which is the unit of localization, was 1 m square, and 202 sections were used as the localization target area. We also conducted experiments in the same environment, excluding Lab2 and Lab3, to evaluate robustness. Let each be Env1 and Env2. The number of APs used for identification was 32.

4.3. Evaluation Metrics

As evaluation metrics, the accuracy of the indoor localization model learned using the collected data, the number of collected fingerprints, and the walking distance during data collection is used. We also compare the accuracy of the localization models constructed for each walking distance and collection time from the viewpoint of the efficiency of building the indoor localization model for the walking distance and collection time during data collection. The walking distance during data collection is calculated from the actual walking route by the Manhattan distance.

4.4. Proposed and Comparison Methods

4.4.1. NearestNearbyCandidate

NearestNearbyCandidate implements the Effective Sequential Recommendation of Neighborhood Data Gathering Position. The termination condition of data collection is that Effective

Sequential Recommendation of Neighborhood Data Gathering Position determines that sufficient data is obtained for learning a localization model with target accuracy.

4.4.2. Gather-all

Gather-All is a method of scanning fingerprints once in all sections in the localization target environment. The data collection order was set manually so that redundant walking would not occur as much as possible by collecting data in order from the end. The condition for terminating data collection is that the fingerprint scan is completed in all sections.

4.4.3. BayesianOptimization

We compare the method of Shimosaka et al. [15] as Bayesian Optimization. Bayesian optimization focuses only on the number of data collected and minimizes it. Specifically, using Bayesian optimization, the GPUCB value of the localization error estimated using Gaussian process regression from the data collection position recommendation model learned using the fingerprint data obtained so far takes the maximum value. Repeat the fingerprint scan in the section. The termination condition of data collection is that the model determines that sufficient data is available for learning a localization model with target accuracy.

4.5. Experimental Settings

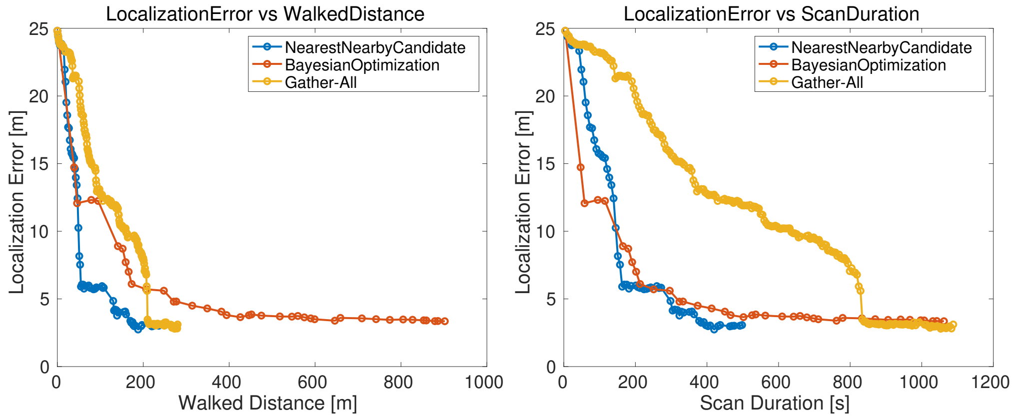
A fingerprint is featurized by Gauss features and used according to the method of Shimosaka et al. [15]. For RSSI for each AP, the Gauss feature obtained using $\mu = [-80.0, -70.0, -60.0, -50.0, -40.0, -30.0]$, $\sigma = 2.0$ is used as a vector. The feature quantity was obtained by reconnecting it for all APs. As a loss function, a cost-considered hinge loss is used according to Shimosaka et al. This makes it possible to perform learning considering not only the correctness of labels but also the distance between labels. In addition, when learning parameters, L2 norm and a quadratic norm of parameters between adjacent sections, that works as multitask learning, is used as a regularization term. FOBOS is used as an optimization method for the above loss function and a regularization term. Data collection was performed using an interactive data collection system, and the terminal used was an Apple MacBook Pro.

4.6. Experimental Result

4.6.1. Comparison of data gathering cost

Table 1
Required costs to achieve localization error of 3.5 m at Env1

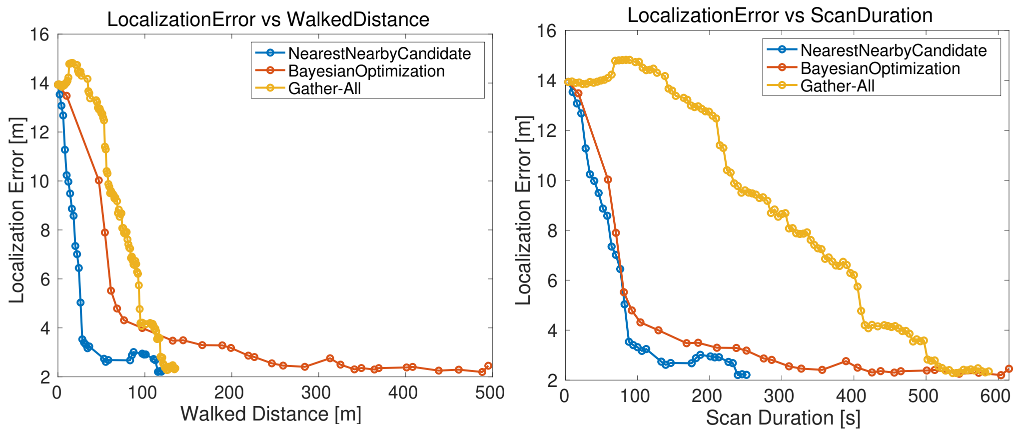
Method	Gather-All	BayesOptim	NearestNC
Data size	156	**33**	52
Walking dist. [m]	210	774	**170**
Required time [s]	834	906	**378**



(a) Averaged localization error for walking distance while data gathering

(b) Averaged localization error for required time while data gathering

Figure 4: Experimental Results at Env1



(a) Averaged localization error for walking distance while data gathering

(b) Averaged localization error for required time while data gathering

Figure 5: Experimental Results at Env2

Comparison of required walking distance for each method for achieved localization accuracy is shown in Fig. 4a, Fig. 5a, comparison of required collection time is shown in Fig. 4b, Fig. 5b. When the localization error of 3.5 m or less is achieved, the required walking distance at the end of data gathering, the required collection time and the actual values of the localization error are summarized in Table 1,Table 2, respectively. The required collection time is calculated by weighting 4.0 s per 1 data collection and 1.0 s per 1 m walk from the record when the data was actually collected. However, when comparing all the collected data, the values of the required walking distance and required collection time of Bayesian Optimization are overwhelmingly large compared to other methods, so in consideration of readability, only the result of 40 point

Table 2
Required costs to achieve localization error of 3.5 m at Env2

Method	Gather-All	BayesOptim	NearestNC
Data size	96	**10**	16
Walking dist. [m]	118	144	**30**
Required time [s]	502	184	**94**

is shown at the beginning in the graph.

Comparing the changes in the average localization error for the walking distance from Fig. 4a, the accuracy of Gather-All and NearestNearbyCandidate converges when walking about 200 m, compared with Bayesian Optimization. It can be seen that a highly accurate localization model can be constructed with a short walking distance. This can also be confirmed from Table 1.

From Fig. 4b, comparing the changes in the average localization error for the required time, Bayesian Optimization and NearestNearbyCandidate have a similar tendency, and the localization error decreases, and NearestNearbyCandidate converges first. On the other hand, it can be seen that Gather-All takes a longer time to converge the accuracy than the other two methods.

Fig. 5a and Fig. 5b show the same tendency as Fig. 4a and Fig. 4b, and it can be seen that NNC can reduce the data collection cost from the viewpoint of the number of data collected, walking distance, and required time even if the environment changes.

From Table 1 and Table 2, comparing the number of data collected when the average localization error of 3.5 m is achieved, Nearest Nearby Candidate is 33 % of Gather-All. The target accuracy was achieved with the following number of collections, and the increase in the number of collections was suppressed by about 50 % compared to Bayesian Optimization.

We confirmed from the above results that NearestNearbyCandidate could construct a highly accurate localization model with the same walking distance as Gather-All, the same required time as Bayesian Optimization, and the number of data collected. As a result, it can be said that the cost was reduced by considering all of the target numbers of data collections, walking distance, and required time.

5. Conclusion

In this research, we propose the necessity of reducing the cost of data collection for indoor localization from the viewpoint of the number of data collected, walking distance, and required time. We proposed Effective Sequential Recommendation of Neighborhood Data Gathering Position, which is effective for cost reduction from all viewpoints. Experiments have confirmed that Effective Sequential Recommendation of Neighborhood Data Gathering Position can reduce these costs simultaneously, unlike the existing method. Future tasks include constructing a localization model without using the floor map information known in this study and selecting the data collection order with proof of optimality.

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