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Statistical Indoor Location Estimation for the NLoS Environment Using Radial Extreme Value Weibull Distribution

Kosuke Okusa and Toshinari Kamakura

Abstract—**In this study, we investigate the possibility of analyzing indoor location estimation under the NLoS environment by radial extreme value distribution model. In this study, we assume that the observed distance between the transmitter and receiver is a statistical radial extreme value distribution. The proposed method is based on the marginal likelihoods of radial extreme value distribution generated by positive distribution among several transmitter radio sites placed in a room. To demonstrate the effectiveness of the proposed method, we carried out a simulation study and conducted two sets of experiments to assess the accuracy of the location estimation for the static case and dynamic case. In the static experiment, the subject was stationary in some places within the chamber. In this experiment, we were able to demonstrate the precise performance of the proposed method. In the dynamic experiment, the subject was moved around within the chamber. In this experiment, we were able to determine the suitability of the proposed method for practical use. Results indicate that high accuracy was achieved when the method was implemented for indoor spatial location estimation.**

Index Terms—**Indoor Location Estimation, Radial Distribution, Extreme Value Distribution, Weibull Distribution**

I. Introduction

In this study, we investigated the possibility of analyzing indoor spatial location estimation under the NLoS environment by radial extreme value distribution model. In recent times, the global positioning systems (GPS) are used daily to obtain locations for car navigation. These systems are very convenient, but sometimes we also require location estimation in indoor environments, for instance, to obtain nursing care information in hospitals. Indoor location estimation based on the GPS is very difficult because it is difficult to receive GPS signals.

A study on indoor spatial location estimation is very important in the fields of marketing science and design for public space. For instance, indoor spatial location estimation is an important tool for space planning based on the evacuation model and shop layout planning [13], [12], [7], [6], [11] .

Recently, indoor spatial location estimation is mostly based on the received signal strength (RSS) method [8], [26], [21] , angle of arrival (AoA) method [15], [23], and time of arrival (ToA) method [22], [5], [25].

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The RSS is a cost-effective method that uses general radio signals (e.g., Wi-Fi networks). However, the signal strength is affected by signal reflections and attenuation, and hence, it is not robust. Therefore, location estimation accuracy using the RSS method is very low. The AoA is a highly accurate method that uses signal arrival directions and estimated distances. However, this method is very expensive because array signal receivers are required. The ToA method only makes use of the distance between the transmitter and the receiver. The accuracy of this method is higher than that of the RSS method and its cost is also lower than that of the AoA method. For this reason, it has been suggested that the ToA method is the most suitable method for practical indoor location estimation system [19].

In this study, we made use of the ToA data-based measurement system. The location estimation algorithm implemented in previous studies were mostly based on the least-squares method. However, using the least-squares method to process the outlier value is difficult, and such data is frequently encountered in the ToA method .

To address this problem, we propose a method based on the marginal likelihoods of radial extreme value distribution generated by positive distribution among several transmitter radio sites placed within a room. A comparison of the proposed statistical method with other previously implemented methods was carried out to demonstrate its potential for practical use.

To demonstrate the effectiveness of our method, we carried out a simulation study and conducted two sets of experiments to assess the accuracy of the location estimation for the static case and dynamic case. In the static experiment, the subject was stationary in some places within the chamber. In this experiment, we were able to demonstrate the precise performance of the proposed method. In the dynamic experiment, the subject was moved around within the chamber. In this experiment, we were able to determine the suitability of the proposed method for practical use. The results indicate that high accuracy was achieved when the proposed method was implemented for indoor spatial location estimation.

The rest of this paper is organized as follows. In Section II, the features and problems of ToA signals are discussed. In Section III, we will present models for indoor location estimation under the NLoS environment based on the radial extreme value distribution. In Section IV, we will present some performance results from two experiments to demonstrate the effectiveness of our model. We will conclude with a summary in Section V.

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II. Time of Arrival (ToA) data

ToA is one of the methods used to estimate the distance between the transmitter and receiver. This method is computed from the travel time of radio signals between the transmitter and receiver. When the transmitter ' time and the receiver's time have been completely synchronized, the distance d between the transmitter and receiver is calculated as follows:

$$d = C(r_r - r_t), \tag{1}$$

where r_t and r_r are transmitted and received time, respectively. C is the speed of light. In an ideal circumstance, d provides accurate distance between the transmitter and receiver called the Line-of-Sight. In this case, the location of the subject is easily estimated by trilateration (Figure 1).

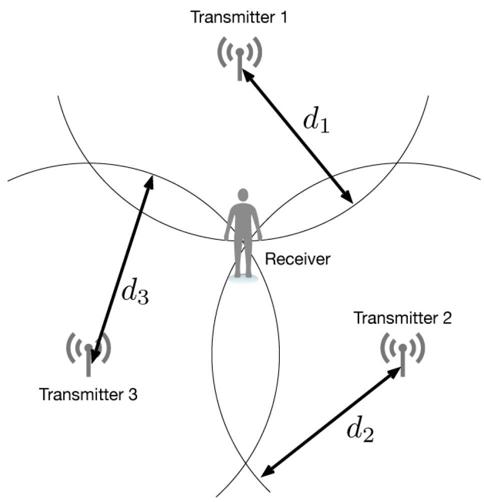

Fig. 1. Location estimation by trilateration (ideal case)

However, in many cases, the distance d includes error components called Non Line-of-Sight (NLoS) [3], [24] (Figure 2).

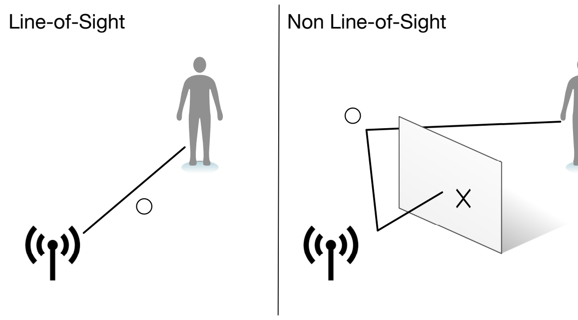

Fig. 2. LoS, NLoS illustration

NLoS conditions are mainly due to obstacles between the transmitter and receiver, i.e., signal reflections. In this case, the observed distance d will be longer than the true distance. Fujita *et. al.* [4] reported that the observed distance of LoS and NLoS are defined as follows:

$$d_{k,LoS} = \sqrt{(x - c_{k1})^2 + (y - c_{k2})^2} + e_k \tag{2}$$
$$d_{k,NLoS} = \sqrt{(x - c_{k1})^2 + (y - c_{k2})^2} + e_k + b_k \tag{3}$$

In the LoS case, the observed value is distributed from the true distance with error term $e_k \sim N(0, \sigma_k^2)$, where $N(\cdot)$ is the normal distribution. However, in the NLoS case, the observed value contains an additional bias term $b_k \sim U(0, B_{\max})$, where $U(\cdot)$ is the uniform distribution. $B_{\max}$ is the possible maximum bias value of the observed value.

Figure 3 shows an example of the error density between the true distance and observed distance. Here, solid line represents the LoS case density, and dashed line represents the NLoS case density. Figure 3 indicates that for the NLoS case, the estimated distance is not distributed in true distance.

To address this, some studies implemented the model-based MLE approach[10], [18], [14]; however, these methods were modelized by 1-D distribution. ToA signals indicate only the distance, and not the angle. We can assume that the observed signal is a 2-D distribution and we propose the statistical radial distribution.

From the viewpoint of 2-D distribution, Kamakura & Okusa [9] proposed the radial distribution-based location estimation. However, this method did not consider the NLoS situation. For the NLoS case, Okusa & Kamakura [16], [17] proposed the NLoS bias correction approach, but this method requires iteration calculation. Therefore, it is not suitable for real-time location estimation.

In this study, we assumed that the minimum value of the observed signal is the true distance between the transmitter and receiver (Figure 5). We modeled the distribution of the minimum value (extreme value distribution) for indoor location estimation.

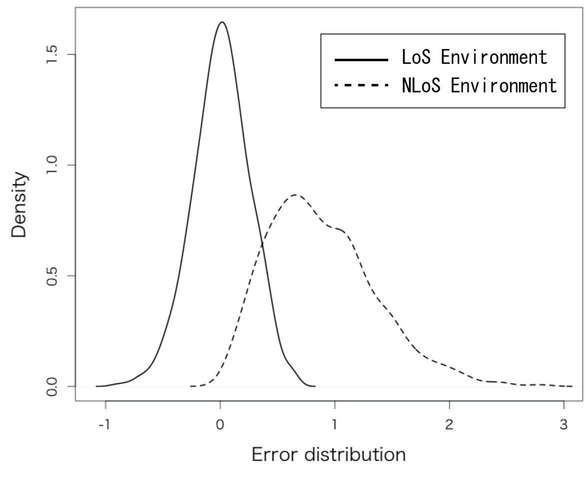

Fig. 3. Error density between true distance and observed distance

III. Indoor Location Estimation Algorithm

In this section, the indoor location estimation algorithm is presented. The proposed method is based on the marginal likelihoods of radial distribution generated by positive distribution.

Considering that the obtained distances were all positive, we propose the following circular distribution based on the 3-parameter Weibull distribution:

$$f(r, \theta) = \frac{1}{2\pi}\Big(\frac{m}{\eta}\Big)\Big(\frac{r - g}{\eta}\Big)^{m-1} \exp\Big\{ -\Big(\frac{r - g}{\eta}\Big)^{m}\Big\}$$
$$(r, g, \eta, m > 0,\ 0 \le \theta < 2\pi). \tag{4}$$

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Here, g is the location parameter, η and m are the shape and scale parameters of the Weibull distribution, respectively.

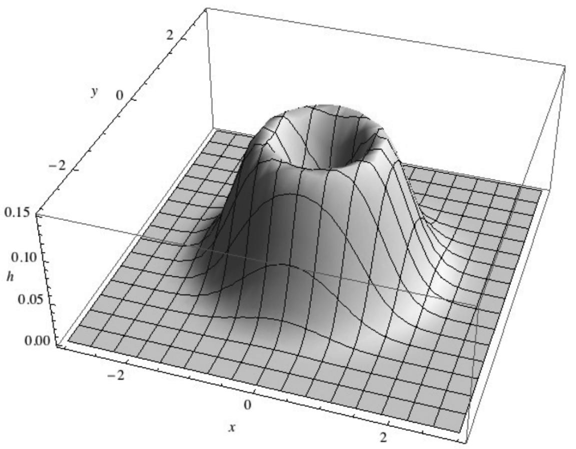

Fig. 4. Radial Weibull Distribution ($m = 3, \lambda = 0.5, g = 0$)

From Eq.4, we can convert from Polar to Cartesian coordinates:

$$g(x, y) = \frac{\lambda m}{2\pi}(\sqrt{x^2+y^2} - g)^{m-2} \exp\Big\{ -\lambda(\sqrt{x^2+y^2} - g)^m \Big\}$$
$$(x, y, g, \lambda, m > 0). \quad (5)$$

Here, $\lambda = 1/\eta^m$ (Figure 4).

Assuming that each transmitter station observes independent measurements, the likelihood based on the data set is calculated as follows:

$$L(\lambda_1, m_1, g_1, ..., \lambda_K, m_K, g_K) = \prod_{i=1}^{K}\prod_{j=1}^{n_i} \frac{\lambda_i m_i}{2\pi}(\sqrt{(x_{ij}-c_{i1})^2 + (y_{ij}-c_{i2})^2} - g_i)^{m-2}$$
$$\exp\Big[-\lambda_i\{\sqrt{(x_{ij}-c_{i1})^2 + (y_{ij}-c_{i2})^2} - g_i\}^m \Big]. \quad (6)$$

Here, K is the number of stations and for each station i, the sample size is n_i. The observed data set for station i is (x_{ij}, y_{ij}). The coordinates (c_{i1}, c_{i2}) are given transmitter station positions (Figure 1).

A. Radial Extreme Value Distribution

In the NLoS case, we can assume that the minimum value of the observed signals is the true distance between the transmitter and receiver (Figure 5). It is reasonable to assume that extreme value distribution is suitable for the NLoS data case. The extreme value distribution of the 3-parameter Weibull distribution is formulated as follows:

$$\begin{aligned} F_z(z) &= 1 - \{1 - F_x(z)\}^n \\ &= 1 - \Big[\exp\Big\{ -\Big(\frac{z-g}{\eta}\Big)^m\Big\}\Big]^n \\ &= 1 - \exp\Big\{ -\Big(\frac{z-g}{\eta/n^{\frac{1}{m}}}\Big)^m\Big\} \end{aligned} \quad (7)$$

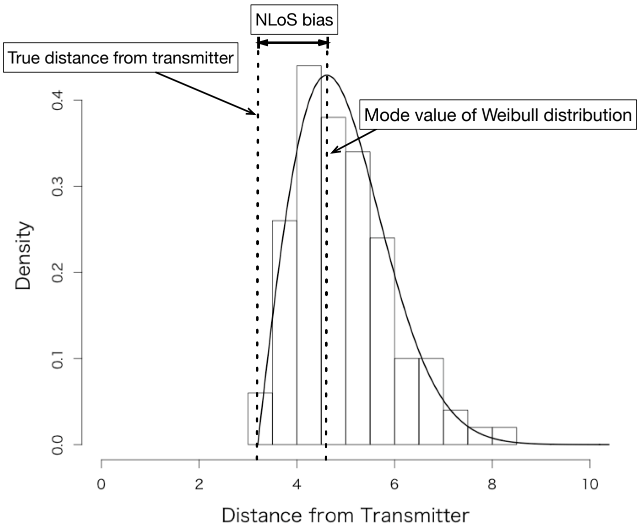

Fig. 5. ToA data NLoS bias

where $z = \min(X_1, X_2, ..., X_n)$ and g is the location parameter. The shape and scale parameters of the 3-parameter extreme value Weibull distribution are m and $\eta n^{-\frac{1}{m}}$, respectively. The shape and scale parameters are estimated from the radial Weibull distribution parameters (Eq.5). Considering the circular extreme value distribution, we can rewrite Eq.7 as follows:

$$F_z(r, \theta) = \frac{1}{2\pi}\Big[1 - \exp\Big\{ -\Big(\frac{r-g}{\eta/n^{\frac{1}{m}}}\Big)^m\Big\}\Big]$$
$$(r, g, \eta, m > 0,\ 0 \le \theta < 2\pi). \quad (8)$$

From Eq.8, we can convert from Polar to Cartesian coordinates, same as in Eq.5, as follows:

$$h(x, y) = \frac{1}{2\pi\sqrt{x^2+y^2}}\Big[1 - \exp\Big\{ -\Big(\frac{\sqrt{x^2+y^2} - g}{\eta/n^{\frac{1}{m}}}\Big)^m\Big\}\Big]$$
$$(x, y, g, \eta, m > 0). \quad (9)$$

Using a similar procedure as in Eq.6, and assuming that each transmitter station observes independent measurements, the likelihood based on the data set is calculated as follows:

$$L(\eta_1, m_1, g_1, ..., \eta_K, m_K, g_K) = \prod_{i=1}^{K}\prod_{j=1}^{n_i} \frac{1}{2\pi\sqrt{(x_{ij}-c_{i1})^2 + (y_{ij}-c_{i2})^2}}$$
$$\Big[1 - \exp\Big\{ -\Big(\frac{\sqrt{(x_{ij}-c_{i1})^2 + (y_{ij}-c_{i2})^2} - g_i}{\eta_i/n^{\frac{1}{m_i}}}\Big)^{m_i}\Big\}\Big] \quad (10)$$

It is reasonable to assume that the highest probability location $(\hat{x}, \hat{y})$ is the estimated location of the subject (Figure 6). The highest probability location from the likelihood

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function is calculated as follows:

$$
\begin{aligned}
&(\hat{x},\hat{y}) = \arg\max G(\hat{\eta}_1,\hat{m}_1,\hat{g}_1,...,\hat{\eta}_K,\hat{m}_K,\hat{g}_K)\\
&G(x,y;\eta_1,m_1,g_1,...,\eta_K,m_K,g_K) =\\
&\prod_{i=1}^{K}\frac{1}{2\pi\sqrt{(x-c_{i1})^2+(y-c_{i2})^2}}\\
&\left[1-\exp\left\{-\left(\frac{\sqrt{(x-c_{i1})^2+(y-c_{i2})^2}-g_i}{\eta_i/n^{\frac{1}{m_i}}}\right)^{m_i}\right\}\right]
\end{aligned}
\tag{11}
$$

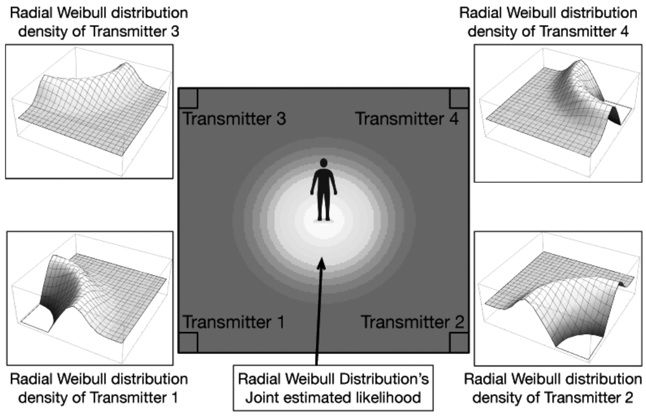

Fig. 6. Location estimation based on radial Weibull distribution

In the next section, a comparison of simulation and experimental results of the proposed method with other methods is presented.

IV. Experimental details and results

To demonstrate the effectiveness of the proposed method, we conducted two sets of experiments.

In practical experiments, we have two types of data sets: data set where the subject with the receiver continuously stops within a minute on a fixed point (static case experiment), and data set where the subject with the receiver moves on a prescribed trajectory (dynamic case experiment). The latter is, of course, extended to much difficult situations, in case the subject is randomly walking within the space. In this experiment, we compared the estimation accuracy of the least-squares method and the method by Okusa & Kamakura [16] with the proposed method. The least-squares method is a popular and simple technique for location estimation, and it can be used for the GPS location estimation system. On the other hand, the method by Okusa & Kamakura [16] is an indoor location estimation algorithm for the NLoS case, and this algorithm showed good performance for location estimation compared with other methods [9], [2], [24].

A. Static Case Experiment

In the static experiment, the subject was stationary in some places within the chamber. This experiment was conducted to demonstrate the performance of the proposed method.

Figure 7 shows the setup of the static experiment. Eight transmitters were placed in the 11 m $\times$ 5 m space. Gray squares in Figure 7 indicate the transmitters. T_x and (x, y) indicate the transmitter number and coordinates. White squares in the Figure 7 indicate the receivers, which are located at 2.5 m $\times$ 2 m intervals. At each point, we observed the distance of the subject for 3 min.

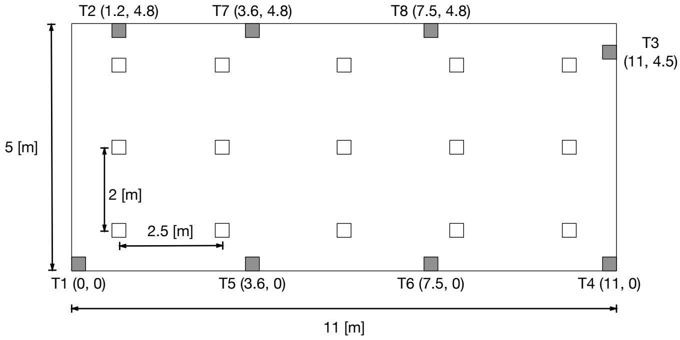

Fig. 7. Setup for Static Experiment

Figure 8 shows the error distribution between the true and estimated locations in the static case experiment. The x-axis shows the distance between the true and estimated location, and the y-axis shows the density of the error distance by kernel density estimation. Solid line indicates the proposed method's error distribution, dotted line indicates the least-squares method's error distribution, and dashed line indicates the Okusa and Kamakura [16]'s method error distribution.

TABLE I
AVERAGE ERROR DISTANCE AND CALCULATION TIME OF STATIC CASE EXPERIMENT

	Error Dist. [m]	Calc. Time [sec]
Proposed	0.08	1.6
Least squares	0.41	< 1
Okusa and Kamakura[16]	0.13	15.3

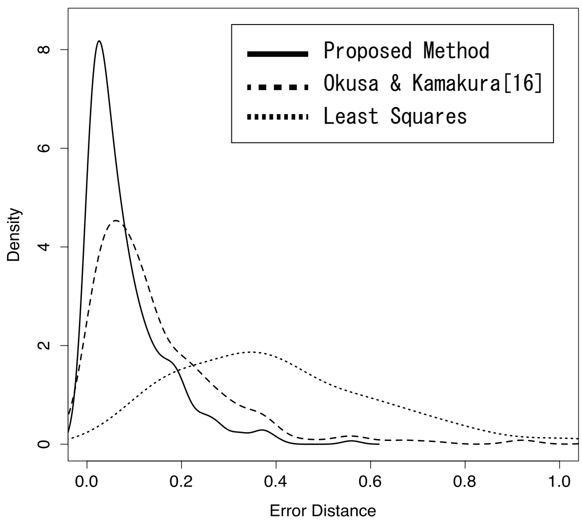

Fig. 8. Error distribution between true distance and observed distance

Table I lists the average error distance and calculation time for each method. In Table I, the proposed method performed better than other methods. The proposed method's average error distance is slightly better than that in the Okusa and Kamakura[16]'s method. However, in Figure 8, the proposed method's error variance is lower than that in the Okusa and Kamakura[16]'s method; therefore, these results indicate that the proposed method maintains precise estimation in every location.

From the viewpoint of calculation time, the least squares method is a very fast method of estimating the subject's location, but its accuracy is poor. The method from Okusa and Kamakura[16] has high precision performance, but requires high calculation time. This is because it makes use of iterative calculation . The proposed method showed good performance in terms of accuracy and calculation cost.

From Figure 8 and Table I, the accuracy of the proposed method for indoor spatial location estimation is higher than other methods in the static experiment.

Figure 9 is a circular Weibull distribution's marginal likelihood in static experiment at receiver location $(3, 4.5)$. The figure color indicates the marginal likelihood value, and light tone indicates high probability. The black circle in the light tone area is the receiver location. The figure shows that the proposed method can precisely estimate the location of the subject. In the next section, we will discuss the dynamic experiment.

B. Dynamic Case Experiment

In the dynamic experiment, the subject was asked to move around in the chamber. This experiment was conducted to evaluate applicability of the proposed method for practical use. This case is significantly more difficult than the static case. .

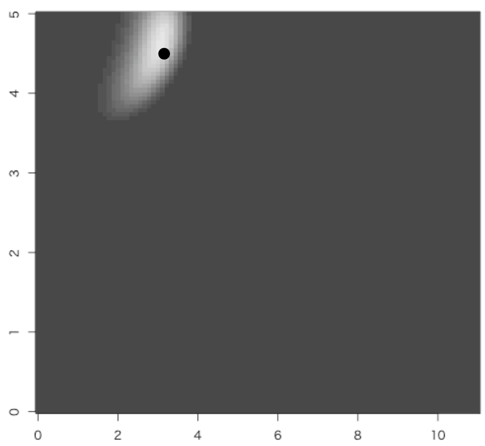

Fig. 9. Joint estimated likelihood of radial extreme value Weibull distribution

Figure 10 shows the experimental conditions for the dynamic case experiment. The number of transmitters and installation locations were same as that in static experiment. The arrows indicate the subject's movement trajectory. The subject moves along the trajectory at 0.3 [m/sec].

Figure 11, 12, 13 show the location estimation results of the least squares method (Figure 11), Okusa and Kamakura's [16] method (Figure 12), and the proposed method (Figure 13), respectively. It can be seen that proposed method produces high accuracy indoor spatial location estimations.

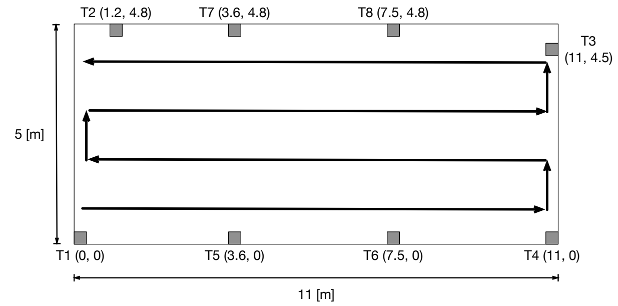

Fig. 10. Dynamic Experiment Circumstance

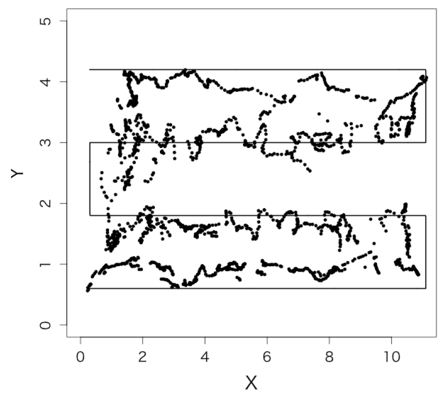

Fig. 11. Estimated trajectories (least squares method)

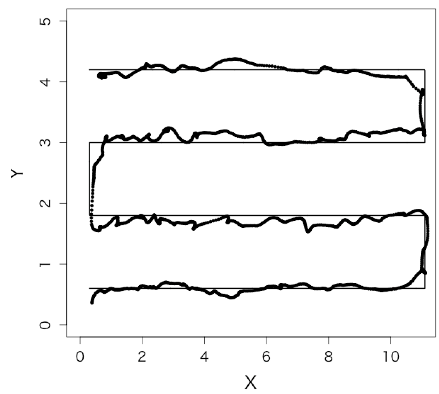

Fig. 12. Estimated trajectories (Okusa and Kamakura [16])

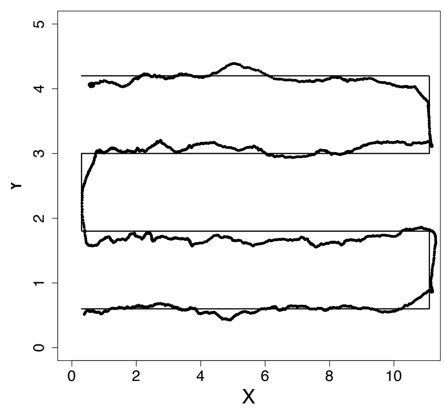

Fig. 13. Estimated trajectories (proposed method)

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Table II shows the average error distance and the calculation time required for each method. As can be seen in Table II, the proposed method and the method proposed by Okusa and Kamakura [16] show high location estimation accuracy.

From a computational cost standpoint, the proposed method exhibits good performance for location estimation; however, Okusa and Kamakura [16] method's calculation cost worsens. In the dynamic case experiment, the sample size of the dataset for the parameter estimation is small. We conjecture that the iteration calculation of Okusa and Kamakura [16] method's does not converge easily, which results in increasing computational cost. This result indicates that the proposed method has robust performance for location estimation in the dynamic case.

From Figure 13 and Table II, we can conjecture that proposed method performs better than other methods, similar to the static case experiment.

TABLE II
AVERAGE ERROR DISTANCE AND CALCULATION TIME FOR THE DYNAMIC CASE EXPERIMENT

	Error Dist. [m]	Calc. Time [sec]
Proposed	0.27	2.9
Least squares	0.82	≤ 1
Okusa and Kamakura	0.34	31.3

Based on the experimental results for both the static case and the dynamic case, we can conclude that the proposed method exhibits good performance for the indoor location estimation. This result indicates that the radial extreme value Weibull distribution based approach can be applied for indoor location estimation.

V. CONCLUSIONS

In this article, we proposed an indoor location estimation model based on the radial Weibull distribution. The experimental results suggest that our model can accurately estimate the subject's spatial locations.

In next phase, we will compare our methods with other state-of-the-are indoor location estimation methods, and evaluate its performance. The computational cost of our method is lower than that of Okusa and Kamakura ' s method [16]; however, its applicability for practical use is limited. Therefore, to address this limitation, we intend to review the location estimation process, especially $(\hat{x}, \hat{y})$ estimation from marginal likelihood of radial extreme value obtained from the Weibull distribution. In addition, we intend to implement the indoor location estimation system based on the proposed method and demonstrate its applicability.

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