Data-driven simulation of wireless communication signal strength in indoor environments

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***Abstract*—Prediction of the Received Signal Strength Indicator (RSSI) distribution is a very important task. However, most of the current research is on methods that complement the RSSI distribution for beacons that actually collect data. The most common method for fully online simulation without beacons is based on physical Ray-Tracing. However, the Ray-Tracing model requires the determination of the attenuation rate of the wall. This makes it difficult for ordinary people to perform the simulation. Also, without measuring the actual RSSI, it is impossible to know whether the simulation results are appropriate for the actual environment or not. To address these issues, we propose a data-driven RSSI simulation method. RSSI can be collected by various devices, and it is easy for the general public to obtain RSSI for each location. The simulation is based on the actual RSSI data, so that the simulation can be performed in a realistic environment. In this paper, we have realized a data-driven simulation that matches the environment by learning the attenuation of RSSI derived from the environment and actual data using Generative Adversarial Network(GAN). In order to conduct experiments in a real environment, the simulation model is trained in an office environment, and its accuracy is evaluated using actual RSSI values. As a result, the average absolute error of RSSI values was improved by 8% and the average positioning error of indoor localization was improved by 19% compared with the simulation using the radio propagation formula.**

***Index Terms*—Frameworks for indoor positioning and navigation, Machine learning.**

I. Introduction

In recent years, many communication technologies have been used in our daily lives, including Internet of Things (IoT). Therefore, research on Received Signal Strength Indicator (RSSI), which indicates the strength of radio waves, has been very active. Indoor localization [8]–[10] using RSSI has attracted much attention due to its ease of implementation and higher accuracy in indoor environments compared to GPS, and various studies have been conducted to prepare an environment suitable for IoT by optimizing beacon placement based on the prediction of RSSI distribution. [11], [12] In particular RSSI simulation, which predicts the distribution of RSSI when beacons are placed, is a very important research.

Currently, Ray-Tracing models [13], [14] are commonly used as simulation models for RSSI prediction. These models calculate the ray path from the beacon to the prediction point, taking into account reflections and transmissions by walls, etc., and then simulate the attenuation of RSSI due to reflections and transmissions by walls. The simulation is based on the attenuation of RSSI in the reflection and transmission of walls.

On the other hand, in the past few years, the use of Generative Adversarial Networks (GAN) in RSSI research has been increasing, and the usefulness of these models in RSSI has been recognized. Research has been published on the detection of abnormal changes in RSSI using Discriminator [15], and on the extension of RSSI distribution data used in learning indoor positioning using Generator [16], as well as on the completion of RSSI from a part of RSSI to the whole RSSI. [17] However, it has not yet been possible to simulate RSSI.

Therefore, we propose a data-driven RSSI simulation method based on real data using GAN. Specifically, the proposed method learns the difference between the predicted RSSI value based on the general RSSI propagation formula using the distance from the beacon and the actual value, and understands the environmental characteristics without the need for environmental surveys. This makes RSSI simulation easy for general users in the actual environment.

The contributions of this study are as follows

- The difference between the prediction by the radio propagation formula using the distance from the beacon and the actual value is learned, and the environmental characteristics are understood without the need for an environmental survey.
- We will compare the usefulness of the simulation method with the existing method by using actual RSSI data.

The structure of this paper is as follows: section 3 describes the problem setup for the RSSI simulation in this study. In section 4-7, we explain how the RSSI simulation is realized in this study. In section 8, we actually collect RSSI data and conduct an evaluation experiment of the proposed method, and in section 9, we summarize our conclusions.

II. Related work

A. Physics-based RSSI simulation

The Ray-Tracing model is the most common method used in RSSI simulations today. This model calculates the ray path from the beacon to the measurement location, taking into account walls and obstacles. The attenuation of the RSSI when it moves along the ray path due to wall reflections and transmissions is set up based on an actual environmental survey.

Electromagnetic diffraction has been the subject of research by many people. [18] Among them, Yun et al. [19] have developed a method for ray-tracing in radio waves, and their RSSI simulations have been used in many papers. In contrast to Yun et al., Nicolas Amiot et al. [13] proposed py-layers, a simulation method for RSSI that takes into account all paths between the wall and the point to be simulated and uses the attenuation rate due to the wall.

On the other hand, however, there are many problems with the Ray-Tracing model. The first problem is the high computational cost. It is well known that the more obstacles there are and the larger the target area, the more ray paths from the beacon to the predicted point increase, requiring a large amount of computational memory. This is a major problem in RSSI simulations that need to be implemented in various environments. There have been attempts to reduce the computational cost for a long time, such as the method proposed by Mudhafar et al. [20] in 2002, in which all walls are processed in the same way. Therefore, there are some papers that present the multi-wall model as a comparative method, which greatly reduces the computational cost and considers only the walls between the beacon and the predicted location as a simpler model. [14], [21], [22]

Naturally, without collecting actual RSSI data, it is impossible to know whether the values are in line with the actual environment or not. In fact, in the experiment of beacon placement optimization conducted by Yang Zhen et al. [12], although the RSSI simulation is clearly necessary to determine where to place beacons and how much radio waves are received, the data completion method using Gaussian Process Regression (GPR) with sequential data collection was used, and the Ray-tracing method was not accurate enough. The results show that the accuracy of the Ray-tracing method alone is not sufficient.

B. Machine Learning-Based RSSI Approach

In recent years, various forms of machine learning have been used in the field of RSSI research. Abbas et al. [10] aimed to improve the accuracy of indoor positioning by removing noise from the RSSI distribution using the Encoder-Decoder model. Suroso et al. [23] used Variational Autoencoder (VAE) to learn the latent distribution of RSSI distribution. Hamada Rizk et al. [24] learned a latent distribution of RSSI independent of the device from which RSSI is acquired using VAE and proposed a model to transform the RSSI distribution of other devices.

Among the various models proposed, the compatibility between GAN and RSSI has attracted particular attention. Haojun Ai et al. [15] proposed the use of the discriminator in GAN to detect abnormalities in RSSI caused by environmental changes such as wall movement. This allows us to determine whether or not we need to take actions such as re-collection of data in response to changes in the environment. Ran Guan et al. [17] proposed the use of GAN to complement the RSSI distribution. Furthermore the model is able to respond to different locations by inputting a map.

It has been found that the GAN approach is a very good match for learning features for RSSI, and RSSI simulations are performed using this approach.

III. Problem setting and existing methods for RSSI simulation

A. RSSI simulation problem setting

We use Bluetooth RSSI as the simulation target The target area is divided into a grid of $w \times h$, and the length of each grid is assumed to be the same in both w and h directions. One RSSI is obtained for each beacon. Let x_i be the location information of beacon B_k.$(k \in D_{test})$ Let $r_{k,i,j}$ be the RSSI value obtained for beacon B_k at the location of grid (i,j).$(i \in \{1,2,...,w\}, j \in \{1,2,...,h\})$ In the case of a physical simulation, the environmental information obtained from the environmental survey is used. In the proposed method, we use the data B_k,$r_{k',i,j}$,x_k of the training beacon as the training data.$(k' \in D_{train})$ The problem of this study is to simulate $r_{k,i,j}$ using these data.

B. Physical Simulation in RSSI

The most common approach in physical simulation is the Ray-Tracing model. Using information on the location and material of the wall and the calculation of the ray path, the reflection and transmission of the RSSI from the beacon to the destination point are calculated, and the RSSI at the destination point is predicted based on the attenuation rate of each.

The simulation of RSSI using the Ray-Tracing model requires the correct setting of the wall information, which makes it difficult for ordinary people to perform the simulation. Also, since the actual RSSI values are not used, there is always a deviation from the actual RSSI values, no matter how correctly the environmental information is set. These problems still exist in physical simulations.

C. Advantages of Data-Driven RSSI Simulation

In this paper, we propose a data-driven RSSI simulation to solve the problem of RSSI simulation models. In the data-driven simulation, instead of acquiring environmental information by off-line investigation of walls, etc., the data-driven simulation aims to collect RSSI data and to learn environmental information from the data. This allows us to perform more realistic simulations with a simpler method of RSSI data collection.

IV. Data-driven RSSI simulation in indoor environments

A. The idea of RSSI simulation with GAN

We aimed to perform RSSI simulations using GAN. In recent years, many GAN have been studied in the field of image processing, especially in the area of pix2pix [25], which solves the task of restoring the original image using semantic data and segmentation data as input. We use these ideas in our RSSI simulation. As the input semantic data, we use data that only depends on the location of the beacon, ignoring environmental information. Then, a model that learns the environmental information is added to the data and attenuates the data according to the real environment to realize a data-driven RSSI simulation.

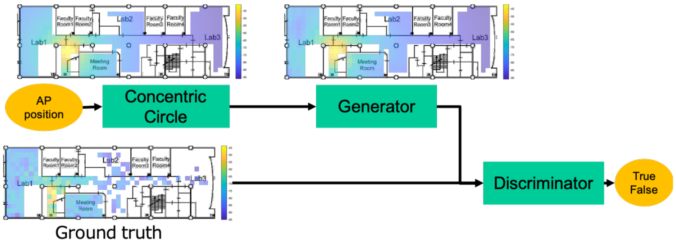

Fig. 1. RSSI Simulation Overview

The full description of the proposed GAN simulation is Figure1.

B. Input data generation

The goal of this study is to learn environmental information using GAN. Therefore, the input data should have the average RSSI distribution when it is not affected by walls and so on. In general, the propagation equation of RSSI is expressed as follows [8].

$$\mathrm{RSSI} = \alpha + \beta \log \frac{L}{L_0} + \psi \tag{1}$$

In this case, L refers to the distance between the measurement position and the beacon position. L_0 is the reference distance that can be determined and is considered as 1(m) in this case. ψ is noise and follows a normal distribution. Since the target value in the simulation is the mean value, the noise is ignored. By determining the remaining values α and β, we can determine the RSSI based on the distance from the beacon.

C. Determination of coefficients in the propagation equation

In this paper, the least-squares method is used to determine the propagation equations α, β. The least-squares method is one of the common regression analysis methods. In this case, for the beacon B'_k $(k' \in D_{train})$ used in the training data, the RSSI value $r_{k',i,j}$ obtained at the position of grid (i, j) and the distance $L_{k',i,j}$ from the beacon are obtained. The least-squares method requires minimizing the following equation

$$\mathrm{LS}(\alpha, \beta) = \sum_{k'}^{D_{train}} \sum_{i}^{1,2,..,w} \sum_{j}^{1,2,..,h} (r_{k',i,j} - (\alpha + \beta \log L_{k',i,j}))^2 \tag{2}$$

Minimize the sum of the squared error between the predicted and measured values ignoring noise according to the propagation equation. Solve the following equation

$$\frac{\partial LS(\alpha, \beta)}{\partial \alpha} = 0 \tag{3}$$

$$\frac{\partial LS(\alpha, \beta)}{\partial \beta} = 0 \tag{4}$$

Solving this yields the following equation using the mean r' of $r_{k',i,j}$ and the mean l' of $L_{k',i,j}$.

$$\alpha = \frac{\sum_{k'}^{D_{train}} \sum_{i}^{1,2,..,w} \sum_{j}^{1,2,..,h} (r_{k',i,j} - r')(\log L_{k',i,j} - l')}{\sum_{k'}^{D_{train}} \sum_{i}^{1,2,..,w} \sum_{j}^{1,2,..,h} (\log L_{k',i,j} - l')^2} \tag{5}$$

$$\beta = r' - \alpha l' \tag{6}$$

The input data are generated from the predicted values using the determined α, β. The actual input data are normalized from this generated data.

V. Learning environmental information using GAN

The input data generated by the propagation equation is considered as semantic data, and the goal is to create generated data to which wall information is added by the Generator.

Therefore, we use GANs for the task of generating images by coloring segmentation data such as line drawings and semantic data. pix2pix proposed by Phillip et al. [25] is a suitable model for these tasks.

A. Generator

U-net proposed by Ronneberger et al. [26] is used as the Generator. U-net uses the Encoder-Decoder model instead of a simple Convolutional Neural Network (CNN) [27]. The Encoder-Decoder model first computes the input using the Encoder to compress the dimensionality and then expands it to the original dimensionality using the Decoder. In this case, we use a CNN for the Encoder and a Deconvolution Neural Network (DCNN) for the Decoder in order to convolve the two-dimensional data. structure that can upsample the data size by performing the convolution and inverse computation of a CNN. In general, it is assumed that the number of dimensions is symmetrical between the Encoder and Decoder.

By ignoring the layers in between and passing the input image information directly to the Decoder, which would otherwise be excessively lost due to Encoder compression, U-net produces output that is closer to the input image. Although the Generator usually includes noise to allow various types of generation, since our goal is to reproduce the RSSI distribution, the inclusion of noise leads to a loss of accuracy. Therefore, dropout [28] is used to avoid overlearning. By setting the output of the layer to 0.0 with a certain probability, overlearning is avoided by partially generating missing data.

B. Discriminator

The Discriminator does not simply input the data output by the Generator and the real data, but also simultaneously inputs the semantic data, the data generated by the propagation equation input to the Generator. This allows us to make inferences based on whether the Generator is able to simulate the input data.

C. loss function

The loss function using these methods is explained.

Let P_k be the input data generated by the propagation formula for beacon B_k, A_k be the real data, $\mathrm{G}(P_k)$ be the output by the Generator, and $\mathrm{D}(P_k : A_k)$ be the output by the Discriminator. Let $px{\times}py$ be the output size of the discriminator. First, as in general GAN, the Generator needs to fool the Discriminator, so the following adversary loss L_{GA} is used.

$$L_{GA} = \sum_{k}^{k \in D_{train}} \mathrm{BCE}(ones, \mathrm{D}(P_k : \mathrm{G}(P_k))) \tag{7}$$

$$\mathrm{BCE}(p, q) = \mathbb{E}\{-p_i \log q_i - (1 - p_i)\log(1 - q_i)\} \tag{8}$$

$$(p_i \in p, q_i \in q) \tag{9}$$

BCE means binary cross entropy. $ones$ is a matrix of size $px{\times}py$ and value 1. The data generated by the Generator is trained so that the Discriminator guesses it to be true, i.e., 1. At the same time, the real purpose of the Generator is to generate real data A_k. Therefore, we consider the following reconstruction loss L_{GR} between the distribution simulated by the Generator and the actual RSSI.

$$L_{GR} = \sum_{k}^{k \in D_{train}} \mathbb{E}|A_k - \mathrm{G}(P_k))| \tag{10}$$

These loss functions give the Generator loss function L_G as follows

$$L_G = \lambda_{GA} L_{GA} + \lambda_{GR} L_{GR} \tag{11}$$

where $\lambda_{GA}, \lambda_{GR}$ is a coefficient determined to adjust the ratio of adversary loss to reconstructed loss.This paper use $\lambda_{GA} = 1, \lambda_{GR} = 100$.

Also, the Discriminator needs to guess 0 for false if the data are generated by the Generator, and 1 for true if the data are real. Therefore, the following loss function L_D is computed

$$L_D = \mathrm{BCE} \sum_{k}^{k \in D_{train}} \{\mathrm{BCE}(zeros, \mathrm{D}(P_k : \mathrm{G}(P_k))) \tag{12}$$

$$+ \mathrm{BCE}(ones, \mathrm{D}(A_k))\} \tag{13}$$

where $zeros$ is a matrix of size $px{\times}py$ and value 0 as well as $ones$.

The GAN is learned by alternately learning L_D, L_G.

VI. RSSI Simulation in virtual Beacons

Determine where to place the virtual beacon, propagation formula determined by the aforementioned method generates the input data for the virtual beacon. By inputting this data to the Generator, you can simulate the virtual beacon.

VII. Experiment

A. Experiment overview

The model was tested on the 4th floor of the West 8E building at Tokyo Institute of Technology using actual data. This floor measures 15.3m × 45.2m. Forty beacons were placed in Figure 3, and 321 data points were used for RSSI collection, as shown in Figure 2 with blue dots. These measurement points are basically set 1 m apart. The beacon used is a Bluetooth 5.0 beacon with a txPower of 0 (dBm).

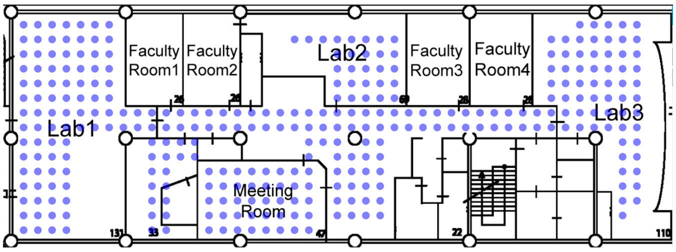

Fig. 2. Locations where data was collected

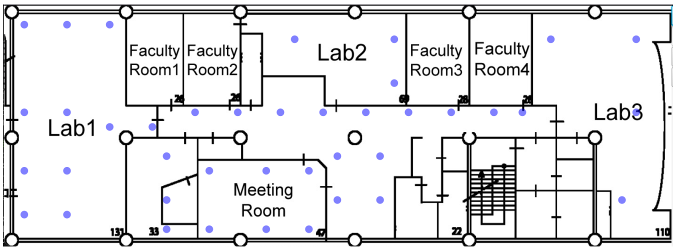

Fig. 3. Point where the beacon was placed

Data was collected using a MacBook Pro. Data was measured three times at each location, and the average of the obtained values was used as the measured value at that beacon. Experiments are conducted using 20 beacons as training data and 20 beacons as test data.

The number of filters and kernels used in the Generator and Discriminator are shown in I and II. Because of the use of U-net, the number of filters for the Generator's DCNN is twice as many as the output before one input.

For comparison, a prediction model using a simple distance-based radio propagation equation and a multi-wall model that

TABLE I
Generator structure

Layer	model	input-filter	output-filter	kernel
1	CNN	1	16	3
2	CNN	16	16	3
3	CNN	16	32	3
4	DCNN	32	16	3
5	DCNN	16 × 2	16	3
6	DCNN	16 × 2	1	3

TABLE II
Discriminator structure

Layer	model	input-filter	output-filter	kernel
1	CNN	1	6	3
2	CNN	6	12	3
3	CNN	12	24	3
4	CNN	24	12	3
5	CNN	12	6	3
6	CNN	6	1	2

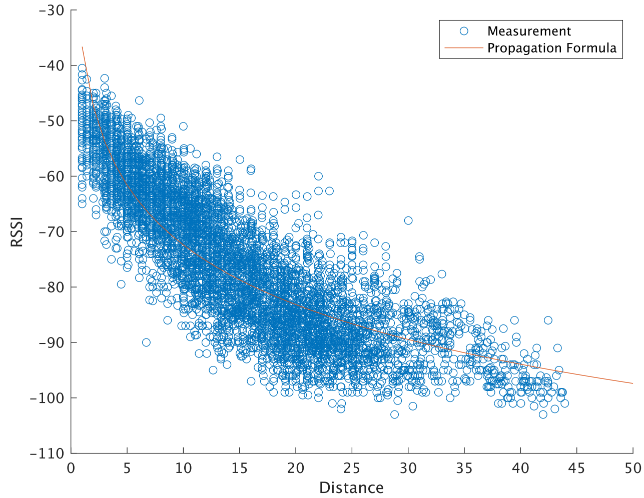

Fig. 4. Approximate curve by propagation formula

takes into account walls between the beacon and the predicted location in addition to the distance are provided.

The multi-wall method was created in reference to [21]. In the paper, the wall was divided into two types with a constant minute thickness, and the damping ratio was set for each. In this experiment, since a glass wall is present, the attenuation rate is set separately for the normal wall and the glass wall. The least-squares method was used as the damping rate setting method.

The result of the least-squares method for the simulation with the radio propagation equation is shown below.

$$\mathrm{RSSI} = -15.53 \times \log(distance) - 36.63 \tag{14}$$

The approximate curve is shown in Figure 4 Since the log is used, the expected RSSI rises sharply for locations near the beacon. However, the actual data does not show such an increase. Therefore, it can be seen that the radio wave propagation equation used as an approximation equation can be improved.

The simulation results with the proposed method and the average absolute error between the comparison method and the real data are summarized in TableIII. The average absolute

TABLE III
THE AVERAGE ABSOLUTE ERROR

method	Proposed	Multi-wall	Formula
Training beacons average absolute error[dBm]	4.92	5.13	5.53
Test beacons average absolute error[dBm]	5.12	5.21	5.58

error was improved by 11% for the training beacon and by 8% for the test beacon. This indicates that the proposed method is able to learn not only the simple distance but also the effects of obstacles such as walls and furniture, and to improve the RSSI simulation.

In addition, 5 of the 20 beacons selected for training were in Lab1, so the accuracy was improved especially in Lab1. The average absolute error of the simulation with the radio propagation formula is 5.43[dBm] in Lab1, while the proposed method is 4.66[dBm], which is a 14% improvement. Compared to the average overall error of the entire experiment in the proposed method, only Lab1 has a 5% improvement.

This indicates that further improvement in accuracy can be expected by deploying more beacons and collecting more data.

B. Evaluation by Indoor localization

The RSSI distribution contains a lot of noise even in real data. Therefore, even if a simulation that faithfully reproduces the real data can be performed, it may not be a truly correct simulation. The ultimate simulation is to predict the mean value of RSSI distribution without the noise. In the study of RSSI distribution in general, the evaluation of RSSI distribution by indoor positioning is used as an evaluation method to confirm the consistency of RSSI distribution.

We evaluate the RSSI distribution generated by the simulation using indoor positioning with a feature called Ellipsoid proposed by Sugasaki et al. [8]

Experiments will be conducted on each of the beacons used to train the model and the test beacons. Using the indoor localization model trained on the predicted RSSI data, perform indoor localization on the actual RSSI data and evaluate the accuracy.

The average indoor positioning error is 19% better with the proposed method than with the prediction using the propagation formula.

VIII. Conclusion

In this study, a data-driven RSSI simulation method is proposed. The existing RSSI simulations are generally based on the Ray-Tracing model, which requires the determination of parameters such as the attenuation rate of walls and other objects, which requires an investigation of the real-world environment. The task of determining the attenuation rate of RSSI transmission and reflection based on the material and thickness of the wall is highly specialized and difficult for the general public. Even if such a study was actually conducted, the simulation would not necessarily be accurate to the actual environment unless it was compared with the actual RSSI.

For this reason, we have created a data-driven RSSI simulation model using only actual RSI data. The collection of RSSI itself is possible with various devices, and the task of collecting RSSI at a specific location is easy for the general public. In addition, the use of real RSSIs makes the simulation more realistic to the actual environment.

As a result, the average absolute errors of the training beacon and the test beacon were improved by 11% and 8%, respectively, compared to the simulation using the radio propagation formula. In addition, the evaluation of the simulated data by indoor positioning showed that the average absolute error in positioning was improved by 19%. These results indicate that the proposed simulation method improves on the

TABLE IV
AVERAGE ABSOLUTE ERROR IN INDOOR LOCALIZATION

$\lambda_{GA}, \lambda_{GR}$		Training Beacon Absolute Error	Test Beacon Absolute Error
Proposed	Mean	6.49	5.68
	90%	14.32	10.82
	Max	40.61	38.33
Propagation Formula	Mean	7.23	7.05
	90%	16.49	16.28
	Max	40.61	41.19
Multi-wall	Mean	7.21	5.98
	90%	19.65	11.05
	Max	35.69	34.53

propagation equation and that the model is able to learn the environmental information.

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