

Two-step path loss prediction by artificial neural network for wireless service area planning

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Abstract: In recent years, wireless network systems are utilized in various industry fields and the wireless service area planning became one of the important tasks to realize efficient and high-quality wireless communication service. The machine learning technology attracts the interests of researchers to improve the efficiency of the area planning task because the radio propagation loss in unknown locations can be predicted by the training data without explicit algorithms. Our previous work showed that the path loss (PL) characteristics become complicated in the high PL region, and it can degrade the entire prediction accuracy. In this paper, we propose the two-step PL prediction method by the artificial neural network (ANN) to solve the issue. Firstly, the area is classified into several zones according to the PL range. And then the PL is predicted by ANNs that were trained for respective zones. Our proposal was evaluated by the ray-tracing simulation data, and the result showed that it improved the root mean square error (RMSE) of PL prediction from 7.9 dB to 4.1 dB. The method is expected to be utilized for the wireless service area planning in various environments.

Keywords: cell planning, indoor propagation, machine learning, neural network, path loss prediction, wireless area planning

Classification: Antennas and Propagation

References

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1 Introduction

In recent years, wireless network systems are utilized in various industry fields owing to the widespread of the Internet of Things (IoT) services. Therefore, the wireless service area planning became one of the urgent issues to realize efficient and high-quality wireless communication service. In the area planning, the base stations should be placed so as to provide sufficient signal strength within the entire service area while minimizing the interference outside the area. For the purpose, many radio propagation measurements and simulations such as the ray-tracing and the finite difference time domain methods were conducted. However, those tasks require the cost and a lot of efforts of the system planner because it requires the similar measurements and simulations repeatedly whenever the area plan changes.

The machine learning technology has a great potential to improve the efficiency of such area planning tasks. In the machine learning technology, the radio propagation characteristics, which are the results of the complex interactions between the radio wave and the surrounding environment, can be obtained from the training data without explicit algorithms. In [1, 2], the path loss (PL) predictions in urban areas were investigated by the artificial neural networks (ANN). Those works showed the potential of the machine learning technique that can predict the PL at the unknown locations by the training data. However, the prediction error was quite large in some conditions, and further prediction accuracy improvement is still needed.

The radio wave suffered from reflection, scattering, and diffraction by many interactive objects in the environment during the propagation process. And, the complexity of the PL characteristics tends to increase as the number of those interactions increases. In our previous research [3], it is found that the PL prediction error was significant in the high PL region and the entire effectiveness of training also degrades if those data are mixed in the training data. Furthermore, it is necessary to consider that the objectives of PL prediction are different in each PL region. In the low PL region, the accurate PL prediction is needed for the evaluation of service area quality and radio interference level to other service areas. Meanwhile, in the region outside the service area, to grasp the boundary of the service area is more essential than predicting the individual PLs. Therefore, this paper proposes the two-step PL prediction method by ANN to solve the issue. In our proposal, firstly, the area was classified into the service zone (S-zone), the interference zone (I-zone), and the negligible zone (N-zone). Next, the PL was predicted by ANNs that were trained with the data in respective zones. The proposed method was evaluated by the ray-tracing simulation data. The prediction

error was found to decreased from 7.9 dB to 4.1 dB by our proposal. It is also expected that our proposal makes the area planning task more flexible by combining the zone classification and the PL prediction.

2 Two-step PL prediction method by artificial neural network

The overview of the proposed two-step PL prediction method is shown in Fig. 1. The input data of the estimator is $\mathbf{x} = \{x_{Tx}, y_{Tx}, x_{Rx}, y_{Rx}\}$. Here, (x_{Tx}, y_{Tx}) is the position of the transmitter (Tx), and (x_{Rx}, y_{Rx}) is the position of the receiver (Rx). The zones are defined by the range of PL P , and they consist of S-zone ($P < P_S$), I-zone ($P_S \leq P < P_I$), and N-zone ($P_I \leq P$). Here P_S and P_I are the parameters that should be determined by the network planner. Firstly, the data are classified into those three zones by the ANN classifier. Next, the PL \hat{P} is predicted by the ANN regressors that were trained with the data in respective zones.

Both ANNs were defined by the seven-layer network model. They consist of four neurons in the input layer, and three neuron outputs \hat{C} for the classification and one neuron output \hat{P} for the regression in the output layer. The numbers of neurons in the hidden layers are shown in the figure. All the adjacent layers are fully connected. The output of n -th ($1 \leq n \leq N$) neuron in the l -th layer $z_{n,l}$ is calculated as follows.

$$z_{n,l} = f\left(\sum_{n'=1}^{N'} w_{n,n',l-1} z_{n',l-1} + b_{n,l}\right). \quad (1)$$

Here, $w_{n,n',l-1}$ is the connection weight from the n' -th ($1 \leq n' \leq N'$) neuron in the $(l-1)$ -th layer to the n -th neuron in the l -th layer, $b_{n,l}$ is the bias of the neuron, and $f(\bullet)$ is the activation function. The initial weight values were decided by Glorot Uniform Initialization method, and the rectified linear unit (ReLU) function was used for the activation functions in the hidden layers. In the output layer, the Softmax function was used for the classifier, and the ReLU was used for the regressor. As the cost function L_c , the cross entropy was used for the classifier.

$$L_c = \frac{1}{M} \sum_{m=1}^M \sum_{k=1}^3 t_{k,m} \log(C_{k,m}) \quad (2)$$

Here, M is the size of training data, $t_{k,m}$ is the training datum, and $t_{1,m} = 1$ if the data is of the S-zone, $t_{2,m} = 1$ if the data is of the I-zone, $t_{3,m} = 1$ if the data is of the N-zone, and otherwise $t_{k,m} = 0$. The classification result $C_{k,m}$ corresponds to the probability that data is classified to k -th zone. The root mean squared error (RMSE) was used as the cost function for the regressor. In either model, the backpropagation algorithm was used for the supervised learning [4].

3 Evaluation by ray-tracing simulation data

The proposed two-step PL prediction method was evaluated by the ray-tracing simulation data. The simulation environment and parameters are shown in Fig. 2. The environment was the indoor area including an entrance hall, meeting spaces, and connecting corridors in a research building. The environment model was created from the floor layout information, and the training data were generated

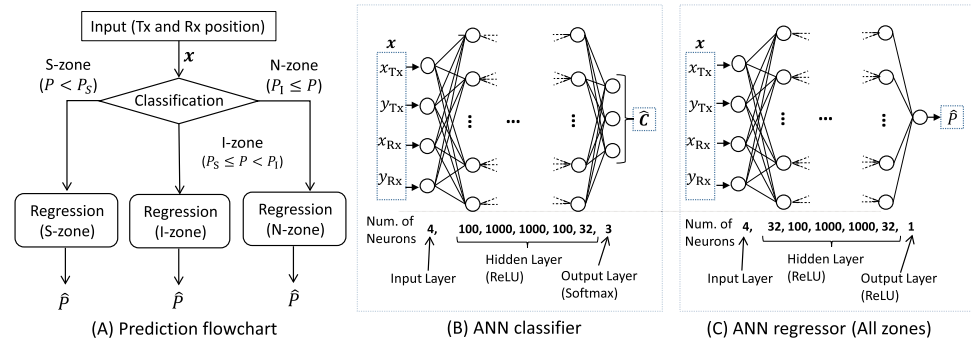


Fig. 1. Proposed two-step path loss prediction method.

by the ray-tracing simulation. In the simulation, the 2 m size grid was set in the area for the Tx and the Rx positions. 218 positions were randomly selected for the Tx, and 233 Rx positions were selected for each Tx setting. The carrier frequency was 5.2 GHz by assuming the 5 GHz band wireless LAN system and the omnidirectional antennas were used on both the Tx and the Rx side. The maximum numbers of reflection and diffraction were 2 and 1, respectively.

In the training phase, 80% of data sets were randomly selected from the ray-tracing simulation result. For comparison, the simple regression method and the proposed two-step prediction method were applied. In the simple regression method, all the training data were directly inputted to the ANN regressor that was explained in Fig. 1(C) without classification. In the two-step prediction method, the P_S and P_I were 100 and 150 dB respectively, by considering the typical dynamic range of the system. The iteration number of training was 100 for both methods. For the validation, the PL prediction errors were evaluated by using the remaining 20% of data sets. By using the training result of the proposed method, the PL was predicted in the new test scenario which is shown in Fig. 2(B). The locational characteristics of prediction error were investigated concretely in the test scenario.

4 Evaluation result

The evaluation results are summarized in Fig. 3. The cumulative distribution function (CDF) of PL of the raytracing simulation, the simple regression, and the two-step prediction method are shown in (A). In this environment, 80% of the data belonged to S-Zone. Although the ratio of N-zone was quite small, it had a wide variation of PL distribution. The existing of N-zone is thought to have caused the overestimation tendency of PL by the simple regression method as described in Sec. 1. On the contrary, the PL prediction result of the two-step prediction method matched with the raytracing data more closely.

Table II, Fig. (C), and (D) summarized the prediction error results. The prediction RMSE was improved up to 4.1 dB compared to 7.9 dB RMSE of simple regression. Especially, the PL prediction RMSE was improved up to 2.4 dB in S-zone, that means the accuracy improvement of system performance evaluation in the service area. Although the RMSEs of I-zone and N-zone were relatively higher, it is not thought to be the critical defect because grasping the area of each zone is

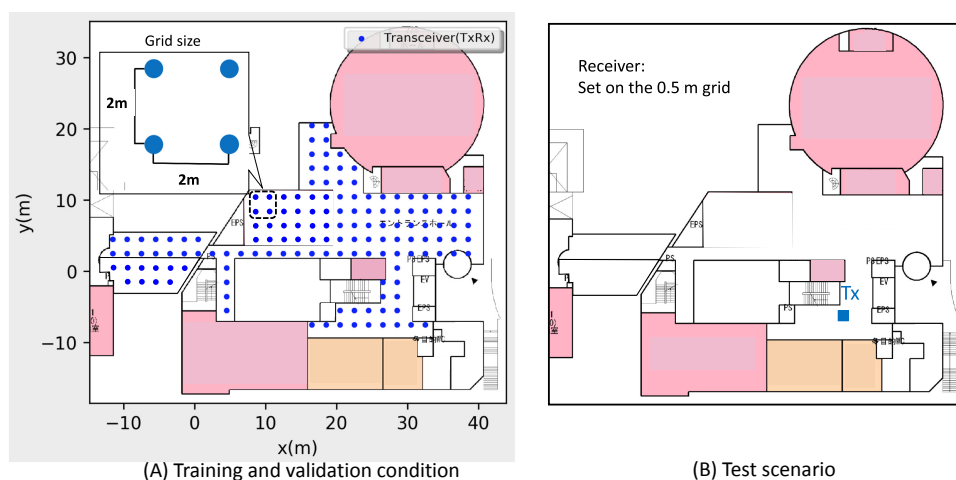


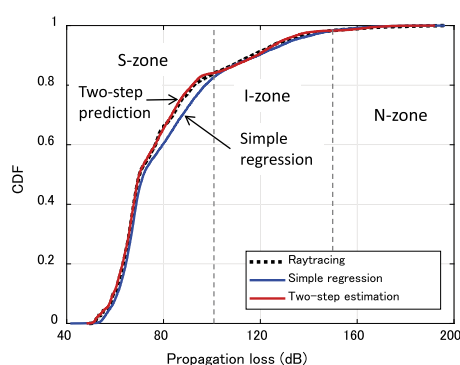
Table I. Simulation Parameters

Ray-tracing Simulation		Neural Networks	
Carrier Frequency	5.2 GHz	Number of neurons (7 layers)	Classifier: (4, 100, 1000, 1000, 100, 32, 3) Regressor: (4, 32, 100, 1000, 1000, 32, 1)
Transmission power	23 dBm	P_s	100 dB
Tx/Rx antennas	Dipole antenna (2 dBi)	P_l	150 dB
Tx/Rx point num.	Tx: 218, Rx: 233 points	Maximum epoch	100
Simulation Condition	Reflection: 2 times, Diffraction: 1 time	Learning algorithm	Back Propagation

Fig. 2. Simulation environments and parameters.

rather important than estimating individual PLs from the viewpoint of area planning. In that sense, our proposal is practical because the 89% of the N-zone was successfully predicted.

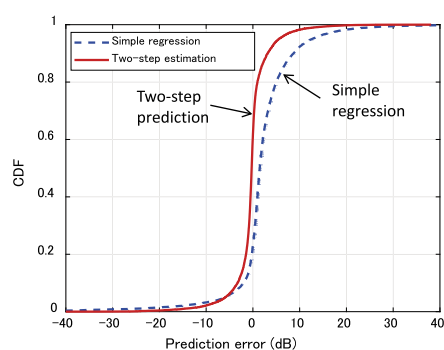
Fig. (E) and (F) show the ray-tracing simulation result and the prediction results by our proposal about the test scenario. In Fig. (F), the area was shown by categorized into three zones according to the prediction result of proposed ANN. For comparison, the area was categorized according to the actual PLs of the ray-tracing simulation result in Fig. (E). In the scenario, the left side of the area was I-zone and N-zone. The result showed that the regions of each zone and the PL distribution in S-zone were quite similar between the data and the prediction. However, it is found that the area classification error existed on the boundary of each zone, as marked (a). The further accuracy improvement by resolving the discrepancy of zone classification will be the future work.



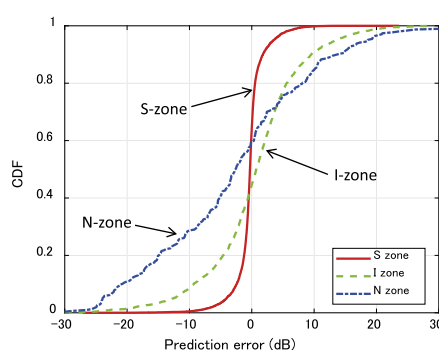
(A) PL prediction result

(B) Table II. Classification and Path loss prediction accuracy

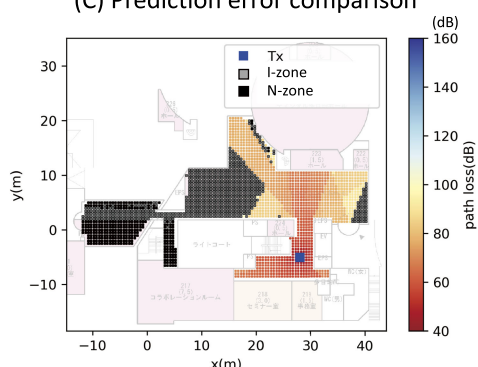
Simple regression		
	Classification success rate	PL prediction RMSE
Total		7.9 dB
Two-step prediction (proposal)		
S-zone	0.98	2.4 dB
I-zone	0.80	7.8 dB
N-zone	0.89	12.9 dB
Total	0.95	4.1 dB



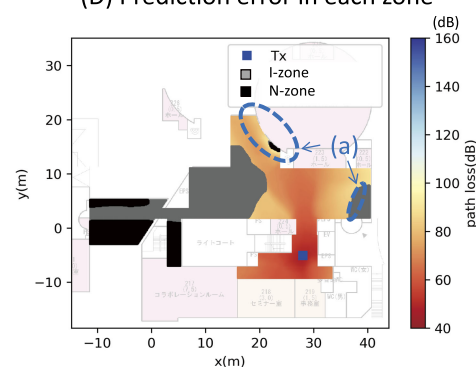
(C) Prediction error comparison



(D) Prediction error in each zone



(E) Raytracing result of test scenario



(F) Prediction result of test scenario

Fig. 3. Evaluation results.

5 Conclusion

This paper proposed the two-step PL prediction method by ANN for the wireless service area planning. The PL behavior becomes complex in the high PL region, and it can degrade the entire PL prediction accuracy by the ANN. In our proposal, we applied the area classification algorithm before the PL prediction. The proposed method improved the PL prediction accuracy in the service zone up to 2.4 dB while it also made it possible to grasp the boundary of the service area. The application of our proposal to various environments including the outdoors and the utilization for the wireless service area planning will be the future works.

Acknowledgments

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