Radio Propagation Prediction Model Using Convolutional Neural Networks by Deep Learning

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***Abstract*—Recently, advancement of artificial intelligence has been remarkable, and many applied researches are attracting attention now. Most of them are based on deep learning. Here, we have proposed radio propagation prediction model using convolutional neural networks (CNN) by deep learning. This paper explains our proposed model in detail, and clarifies its performance by evaluating behaviors for map-parameters input to CNN.**

***Index Terms*—deep learning, convolutional neural network, machine learning, radio propagation prediction.**

I. Introduction

Recently, Advancement in artificial intelligence has been remarkable, and a lot of applied researches have been reported. Here, they are mainly based on deep learning. The deep learning is one of the methods of Machine-learning for neural networks with many layers (or DNN: deep neural networks). Deep learning has succeeded the dramatic performance improvement of image recognition, natural language processing etc., while utilizing of abundant computer resources and big data. The main reason for its success is that the deep learning can automatically extract features of contents.

On the other hand, in mobile communication, accurate prediction of radio propagation characteristics is needed for optimum cell design, various prediction models have been proposed so far [1]. These are categorized into two approaches. One is deterministic approach which is based on electromagnetic theory, and another is statistical approach which is based on measurement data. Here, when the target characteristic is only propagation loss, the statistical approach is preferred because its calculation time is shorter than deterministic approach. In the statistical approach, multi-regression analysis is applied to analyze the characteristics in general [2]. The multi-regression analysis is a very powerful tool, but we have to manually determine input parameters (especially environmental parameters related to building, street, etc.) and functional form beforehand. This is very difficult because there are a lot of candidates. So, the prediction models with neural networks (NN) have been proposed in [3, 4]. By using these models, functional form is automatically generated, and it is reported that prediction accuracy for propagation loss is improved. However, the models are based on conventional Fully Connected NN (FNN), so optimal input parameters have to be investigated, manually.

As mentioned above, the deep learning can automatically extract features of contents. Especially, convolutional neural networks (CNN) are very useful to extract features form image. This means that optimal parameters for propagation loss prediction can be automatically obtained from map-data. So, we have proposed the model with CNN by deep learning in [5]. Note that although our proposed model is for propagation loss prediction in urban macro cell scenario, the paper [6] has applied our model to urban micro cell scenario.

In this paper, we explain our proposed model, and moreover proposed new techniques to improve the prediction accuracy. And then clarify its performance by evaluating behaviors for map-parameters input to CNN.

II. Proposed Model

A. DNN Configulation

DNN of our proposed model is constructed by two parts:

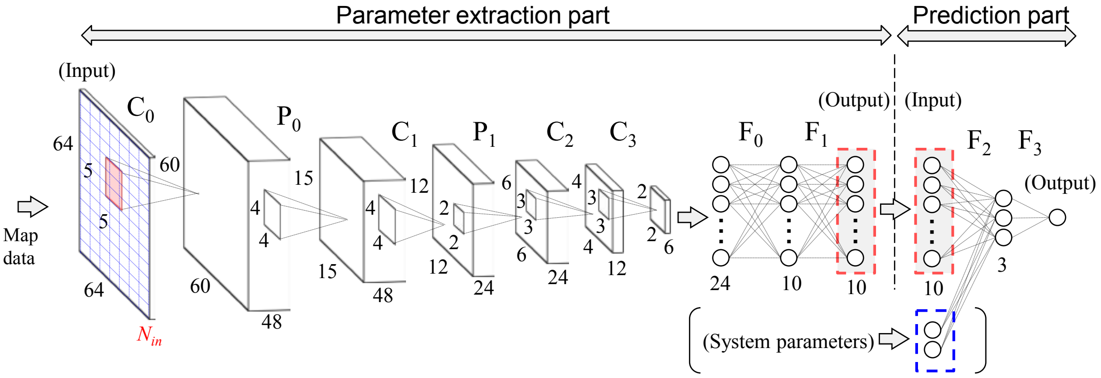


Fig. 1 DNN configulation of the proposed model

parameter extraction part and prediction part, as show in the figure 1.

The parameter extraction part is for extraction of key parameters for propagation loss prediction, and it is constructed by CNN which has four convolutional layers: C_0-C_3, two pooling layers: P_0, P_1, and two fully connected layers: F_0, F_1. First, N_{in} Maps (the size of each map: 64-by-64) are input. In C_0 layer, convolutional processing with 48 filters (the size of each filter: 5-by-5) is done and then the 48 maps (the size of each map: 60-by-60) are obtained. In next P_0 layer, average pooling processing is done for 48 maps. Here, pooling size is 4-by-4, so the size of output map is reduced to 15-by-15. After the similar convolutional and pooling processing are repeated, 6 maps (the size of each map: 2-by-2) are output from C_3 layer. Here, the number of samples is 24 (=2×2×6) and these are input to F_0 layer. After processing of F_1 layer, 10 parameter values are output finally. This means that 10 types of key parameters are extracted from map data.

On the other hand, prediction part is constructed by FNN with two fully connected layers: F_2, F_3. In F_2 layer, System parameters are input in addition to output from the parameter extraction part. After the processing in F_2 and F_3, path loss is predicted as output. Here, system parameters are that cannot be expressed by map, such as frequency, distance from BS to MS, BS antenna height, MS antenna height, etc. However, in this paper, we do not consider system parameters in order to simplify the evaluation of behaviors for map-parameters input to CNN. Note that we show that the distance from BS to MS, BS antenna height and MS antenna height are not necessary if selecting map parameters appropriately, in this paper.

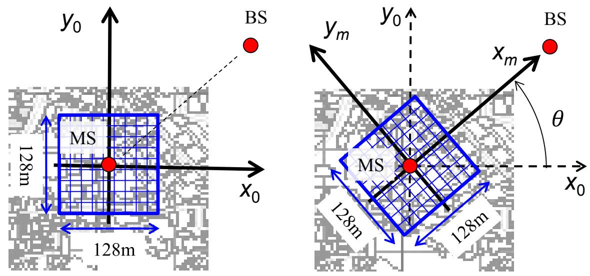
B. *Input Map Parameters*

In our model, the spatial information of rectangular area centered on MS position is input to CNN as map data. The size of rectangular is 128m-by-128m, and also area is sampled with 2m mesh, so, the sample size is 64-by-64. The clipping method of spatial information and considered map parameters are as follows.

1) *Clipping of spatial information*

When clipping the rectangular spatial information from electronic housing map, global coordinate system (x_0-y_0 coordinate) as shown in the figure 2(a) was used in [5]. Here, the clipped spatial information is independent of BS position. By DNN learning the clipped spatial information, spatial statistical value surrounding MS such as average building height may be extracted. However, detailed information considering BS direction cannot be obtained.

In this paper, we propose the method with local coordinate system (x_m-y_m coordinate) as shown in the figure 2(b). The local coordinate system is defined that BS exists on the x_m axis (here, x_m >0). Therefore, the spatial information about "BS direction" are indirectly considered for DNN learning, even if the BS position are not directly



(a) Global coordinate (b) Local coordinate
Fig. 2 Clipping of spatial information

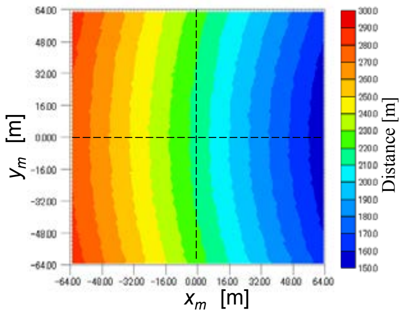


Fig. 3 BS distance map

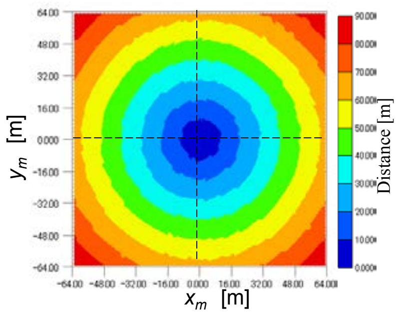


Fig. 4 MS distance map

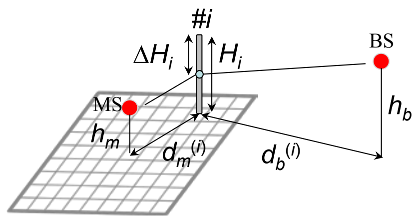


Fig. 5 Definition of Frenel basis building height

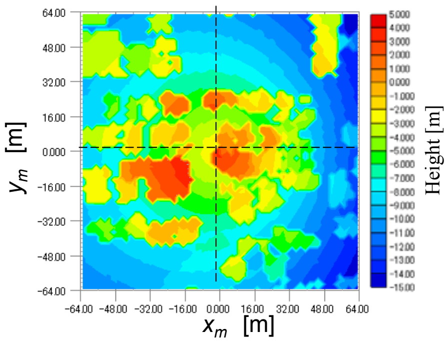


Fig. 6 Building map

input to the DNN as parameter, and then the we can expect that prediction accuracy is improved.

2) Map parameters

By considering physical meaning, three map parameters; “BS distance map”, “MS distance map” and “building map” are investigated in this paper.

BS and MS distance maps are constructed by two-dimensional distance from each mesh to BS and MS, respectively. Figure 3 shows the example of BS distance map. Rectangular area is clipped based on above mentioned local coordinate system, so BS exists on x_m axis (here, x_m >0). And the values change in an arc shape. Figure 4 shows the example MS distance map. In this map, the values changes in a circular shape. And also this map is same even if the BS and MS positions change.

Next, the building map is described. In general, building height is normalized by MS antenna height. Now, let the height of i^{th} mesh and MS antenna height H_i and h_m, respectively. Here, the both are above sea level, and H_i includes building height on the i^{th} mesh. In this case, normalized relative antenna height ΔH_i is given by

$$\Delta H_i = H_i - h_m \tag{1}$$

This definition is very simple, but do not have radio propagation sense because the influence of building appears as scattering (including diffraction and reflection). Therefore, we propose that the building height is defined as the height normalized by the height of Fresnel-zone center when assuming one time scattering. Specific definition is as follows.

Let the distance to i^{th} mesh from BS and MS $d_b^{(i)}$and $d_m^{(i)}$, respectively, as shown in the figure 5. And let BS antenna height above sea level h_b. When assuming one scattering time, the height of Fresnel-zone center is given by

$$H_F^{(i)} = h_m + \frac{(h_b - h_m)d_m^{(i)}}{d_b^{(i)} + d_m^{(i)}}, \tag{2}$$

and then normalized relative building height ΔH_i is given by

$$\Delta H_i = H_i - H_F^{(i)}. \tag{3}$$

The figure 6 shows the example of building map which is obtained by Eq. (3). From the definition, when ΔH_i is positive value, scattering occurs on the mesh. The advantage of Fresnel base building map is that BS antenna height and MS antenna height are indirectly considered as input parameters. So, it may not be necessary to consider the both antenna heights as input system parameters.

III. Evaluation Method

A. Ray-Tracing Simulation

In order to evaluate our proposed model for propagation loss, we performed the ray-tracing [7]. Figure 7 shows calculation area. As shown this figure, the number of BS is five. Calculation conditions are shown in table I.

B. Training Data and Validation Data

Ray-tracing results are used for DNN learning. Here, in order to simplify the discussion, the samples are that satisfy the conditions of "NLOS" and "Distance between BS and MS being 50 m or more". The number of samples is 2658. However, we randomly extract 266 samples (10 % of the all samples) and use that for validation. Remaining 2392 samples are for training. These samples are shown in the figure 8. Here horizontal axis represents distance between BS and MS, *D*.

AS a reference, we performed single regression analysis for the training data. The obtained result is

$$\mathit{Loss}\ [\mathrm{dB}] = 20.631 + 38.984 \log D. \tag{4}$$

When predicting the validation data by using the equation (4), RMS error is 13.25 dB and correlation coefficient with ray-tracing results is 0.34.

Table I Ray-tracing conditions

Parameters		Values
Frequency		2 GHz
BS	Antenna	Isotropic antenna
	Antenna height	40 m
MS	Antenna	Isotropic antenna
	Antenna heigh	1.5 m

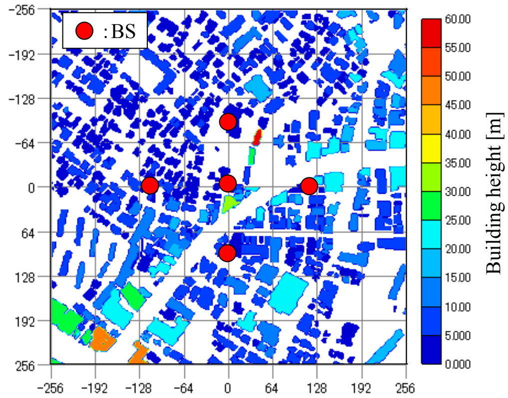


図 7　Ray-tracing area

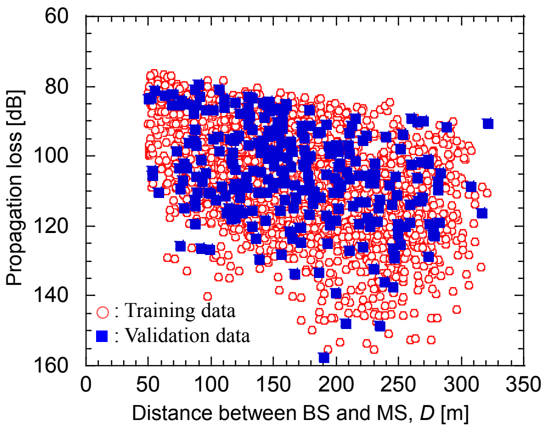


Fig. 8 Training and validation data

IV. Evaluation Results

A. *Effect of BS Distance Map*

First, we confirm the behavior of the proposed model when only BS distance map is inputted to CNN. Figure 9(a) shows the RMS error on the training and validation data as learning progress. Here, horizontal axis represents the number of epochs, *M*. The epoch is the indicator of iteration number when Stochastic Gradient Descent (SGD) is used for optimization of weight. The definition of the number of epoch is how many times all samples of the training data were considered. Note that we used Minibatch Stochastic Gradient Descent (MSGD) with batch size of 100 samples in this paper.

From the figure 9(a), we find that when the number of epochs, *M* exceeds 20, RMS error of both training data and validation data converses to approximately 13dB. This mean that it is not shift to over-learning state even if the number of iteration increases. The prediction results for the validation data in the last DNN state (*M*=418) are shown in the figure 9(b). The predicted results are almost same as the results with Eq. (4). Here, the correlation coefficient with the original validation data is approximately 0.35, it is same as the value in the case of Eq. (4). Therefore, we can say that the proposed model behaves as predicting the distance characteristics of propagation loss, in the case to input only the BS distance map to CNN.

B. *Effect of MS Distance Map*

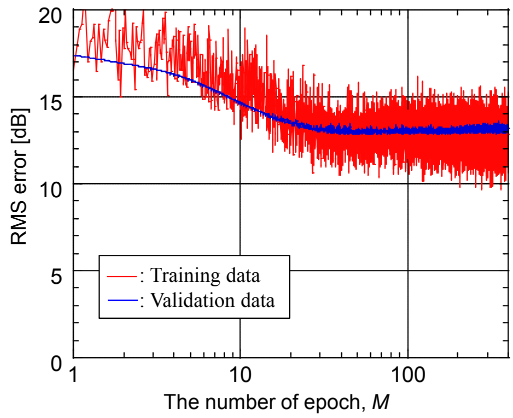
Next, we confirm the behavior of the proposed model when only MS distance map is inputted to CNN. In this case, there are no information about the distance between BS and MS. This means that the model has not potential to predict the distance characteristic of propagation loss. Therefore, we evaluate the influence of MS distance map by predicting the excess loss which is propagation loss normalized by free space loss.

Learning progress is almost same as the figure 9(a), so we show the prediction results for the validation data in the last DNN state (*M*=418) are shown in the figure 10. The predicted results are identical to the average of the original validation data. Therefore, we can say that inputting only MS distance map does not contribute the improving the prediction accuracy.

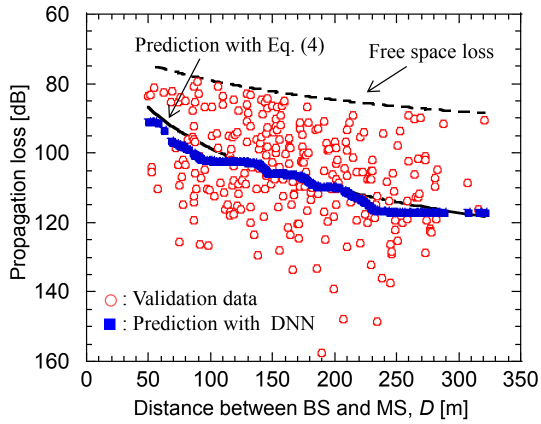
C. *Effect of Building Map*

The figure 11 shows the evaluation results when only building map is inputted to CNN. Here, the prediction target is the excess loss, similar to the evaluation of the MS distance map. From the figure 11(a), we find that as progressing the learning, RMS error of the training data approaches 0dB. On the other hand, RMS error of the validation data becomes to minimum at *M* being 142.1. Its value is 9.94dB. The figure 11(b) shows the prediction results for the validation data in the DNN state at *M* of 142.1. The correlation coefficient with the original validation data is approximately 0.65. Note that correlation coefficient is 0.70 when it is calculated while adding free space loss.

By the way, when using building map based on MS antenna height (given by Eq. (1)) or using the clipping method with global coordinate system, learning progress is similar to that in the figure 11(a). Table II shows the minimum RMS error and correlation coefficient as item # 2



(a) Learning progress



(b) Prediction results

Fig. 9 Prediction using BS distance map

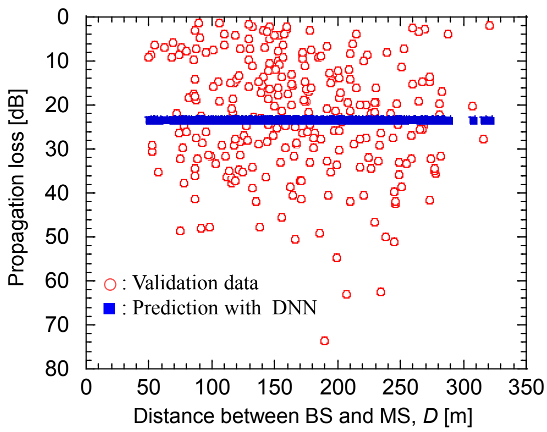


図 10 Prediction using MS distance map

and3. We understand prediction accuracy can be improved by using our proposed Fresnel based building map and the clipping method with local coordinate system.

D. Effect of Using Multiple Maps

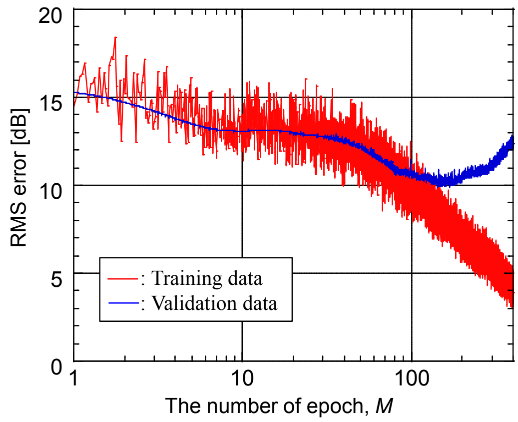
Finally, we show the evaluation results when multiple maps are inputted to CNN in the table II. The item # 4 is the case that all maps are used, and the item #5 is that two maps; BS distance map and building map are used. By comparing between the item #4 and #5, we understand that MS distance map contributes to improve the prediction accuracy by combining with other maps.

V. CONCLUSION

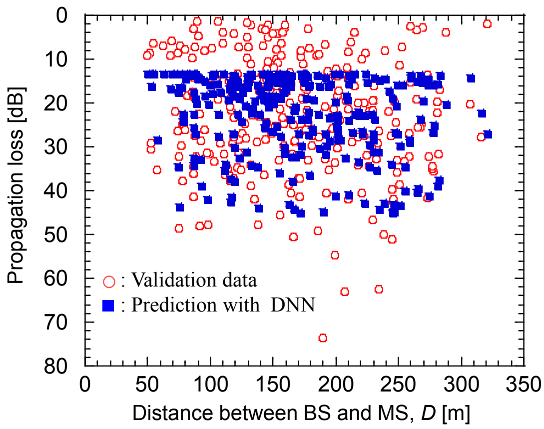
In this paper, we explained our proposed radio propagation model using CNN by deep learning in detail, and clarified its performance by evaluating behaviors for map-parameters input to CNN. The evaluated maps are BS distance map, MS distance map and building map, where each map is defined as rectangular area centered on MS position. The prediction accuracy is improved when following techniques are considered.

- When clipping the rectangular area from electronic housing map, the local coordinate system where BS exists on the x axis is applied.
- Building height is defined as that normalized by the height of Fresnel-zone center.

Optimizations of DNN configuration and parameter values in DNN are remained as future study.



(a) Learning progress



(b) Prediction results

Fig. 11 Prediction using building map

Table II Comparison results

#	Clipping method	Input map: Building	Input map: BS Dis.	Input map: MS Dis.	RMS error (dB)	Correlation
1	Local	Fresnel basis	–	–	9.94	0.65 (0.70)*
2	Global	Fresnel basis	–	–	10.48	0.60 (0.66)*
3	Local	MS Ant. basis	–	–	10.51	0.60 (0.65)*
4	Local	Fresnel basis	○	○	10.05	0.69
5	Local	Fresnel basis	○	–	10.47	0.66

* Correlation coefficient when considering free space loss

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