Path Loss Exponent Prediction for Outdoor Millimeter Wave Channels through Deep Learning

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***Abstract*—In this paper, we propose a new algorithm for predicting the path loss exponent of outdoor millimeter-wave band channels through deep learning method. The proposed algorithm has the advantage of requiring less inference time compared to existing deterministic channel models while concretely considering the topographical characteristics. We used three-dimensional ray tracing to generate the outdoor millimeter-wave band channel and path loss exponent. We trained a neural network with generated path loss exponent. To evaluate the performance of the proposed method, we analyzed the influence of the hyperparameters and environmental features, for example, building density and average distance from the transmitter.**

***Index Terms*—Convolutional Neural Network, Deep learning, Path loss exponent, Ray tracing**

I. Introduction

Recently, a 5G communication system using a millimeter-wave band to process massive data traffic has been receiving a great deal of attention. The millimeter-wave band has a broader bandwidth than the 6 GHz band used in conventional communication systems, and it is easy to allocate continuous frequency resources, which can increase the capacity of the communication system. However, the millimeter-wave band is known to be strongly influenced by obstacles, atmospheric conditions, and rainfall due to propagation loss [1], [2]. Therefore, it has different propagation characteristics than the sub-6 GHz band, and high path loss occurs at the same distance. Thus, more accurate channel information is required for base station placement and cell planning.

Propagation phenomena in mobile communication environment are very complicated due to reflection, transmission, diffraction, and dispersion, and expressing them using analytical tools (e.g., mathematical modeling) has limitations. Propagation phenomena vary depending on the carrier frequency, bandwidth, propagation environment (indoor/outdoor, urban/residential area, terrain, building material structure, etc.). Existing channel models use the stochastic or deterministic model to represent radio wave propagation phenomena. The former uses model parameters that are statistically represented through repeated measurements in each radio environment, and the latter uses a method like a ray tracing algorithm that expresses the propagation environment by ray paths.

The statistical method is expressed as a probability function of the parameters that can represent the propagation environment. The stochastic model has the benefit that it can estimate the propagation characteristics quickly even over a large area because the amount of computation required is small. However, it has low accuracy because it does not consider environmental characteristics.

On the other hand, the ray tracing method has much higher accuracy than the stochastic model because it considers the environmental characteristics of a specific area. However, the ray tracing method has very high computational complexity because each ray used for propagation prediction must be tracked.

In the existing 3G and 4G communication systems, the computational complexity, inference time, and accuracy of the channel models were not the biggest issue because there was little need for an accurate and rapid prediction of the optimum location of the base station. However, with the arrival of 5G communication and the need for smaller coverage and moving base stations like drone-base stations, the task of finding the optimal location of the base station is common and must be done in a very short time.

[3]–[5] used machine learning methods (feedforward net, random forest) to predict the path-loss exponent. However, because the training was only based on experimental results, the generality of neural networks is insufficient. In addition, latitude, longitude, and altitude are used as input parameters, so the specificity of the environment is ambiguously represented in the neural network. [6] uses various data obtained by ray tracing to predict time series of the received signal strength, but it does not predict the path loss exponent in a specific environment.

In this paper, to combine the advantages of deterministic and stochastic modeling, we propose an algorithm that uses deep learning method which can maintain both the advantages of the accuracy of the ray tracing model and short inference

The research was supported by Samsung Electronics.

978-1-5386-7646-2/19/$31.00 ©2019 IEEE

time of the stochastic model. We analyzed the performance changes caused by selecting the hyperparameters used for training. Moreover, to analyze whether the prediction of the trained neural network is affected by the environment, we investigated the performance difference for changes in the number of buildings and average distance from the transmitter.

II. Processing Training Data

For the neural network to recognize the characteristic of the building and the terrain of the map, the input data must represent the environment properly.

In this section, we describe input data used in neural networks and the process of obtaining output data, i.e., the path loss exponent. The process of transforming the map around the area of interest into an image for the input of the neural network is also described. The generated input and output data are used for training and testing the neural network.

A. Map transformation process

In this paper, the map around the area of interest is converted into an image for the neural network and used as input data. The map of the area of interest consists of the terrain data of the area, as well as the shape and height of the building. An example of a three-dimensional map is shown in Fig. 1.

Because propagation characteristics vary with the building, terrain, and transmitter height and location in the area, it is essential to adequately represent a parameter in the two-dimensional image. Since we always set the position of the transmitter to the center (0,0) of the area of interest, only the height of the building, the terrain, and the height of the transmitter are represented in the input image. In this paper, the color corresponding to each pixel of the two-dimensional image was used to convert the three-dimensional map data into two-dimensional. Each pixel of color image data has a value corresponding to red, green, and blue. In this study, the value corresponding to the height of the building is represented in red as follows:

$$R = \frac{H_B}{40} \times 255 \tag{1}$$

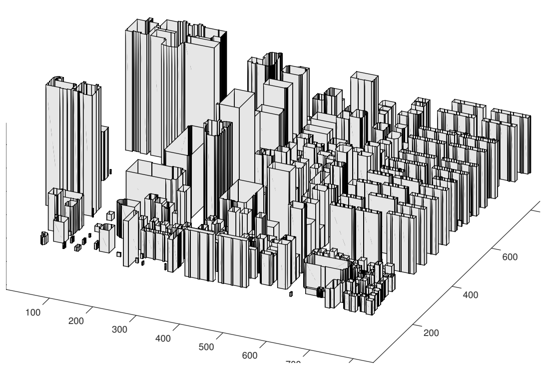


Fig. 1. Three-dimensional building map example.

where R is the color value of red and H_B is the height (m) of the building. Since the value corresponding to each color should have a number between 0 and 255, the maximum value of the calculated value is normalized to be 255. Also, since almost all buildings in Seoul used as the training and test data in this study have a height of less than 40 m, normalization was performed by dividing the height of all buildings by 40 m. An example of such a red colored map is shown in Fig. 2(a).

In this study, we mixed the height of the transmitter and the terrain data of the building adequately and represented this value in green. Instead of defining the height of the transmitter and the terrain data of the building in color separately, there are two reasons for mixing the height of the transmitter and the terrain data of the building. One reason is that we fixed the position of the transmitter at (0, 0) in this study. The convolutional neural network (CNN) technique, which is a deep learning method used in this study, observes multiple pixels at the same time and extracts characteristics from the images instead of observing the individual pixels of the image. Neural networks cannot correctly infer properties if only the color changes at a fixed position (0, 0). Therefore, to represent the height of the transmitter and terrain data simultaneously, we defined new a parameter that combines the height of the transmitter with the terrain data of the building so that the neural network can recognize it properly. Another reason is that the height of the transmitter and the terrain data of the building affect the propagation characteristic of the radio in combination. The higher height of the transmitter and the lower height of the building terrain yields the greater height difference between them. Since the high relative height of the transmitter increases the probability of line of sight, it is reflected in green so that the image can predict the propagation characteristics well. Transmitter height and terrain data are indicated in green as follows:

$$G = \frac{H_{T0} - H_{G0}}{40} \times 255 \tag{2}$$

where G is the color value of green, H_{T0} is the height of the transmitter from sea level, and H_{G0} is the height of the ground from sea level. An example of a map reflecting the green color is shown in Fig. 2(b). The maps reflecting the red and green colors are combined as a color image as shown in Fig. 2(c). We used this color image as input data for the neural network.

B. Generating path loss exponent for output data

This section describes how to generate the path loss exponent, which will be used as the output data of the neural network. When the map of the area of interest is entered into the neural network, the average path loss exponent should be generated as the output. The path loss exponent can be obtained based on the received signal strength (RSS) at each receiving point in the area. Ideally, it is best to use experiment-based measurement data for all maps used in training, validation, and testing and then use this as output data. However,

(a)

(b)

(c)

Fig. 2. Examples of image sets used as learning data. Transmitter height, ground height, and building height are represented in each color map.

it is impossible to obtain millimeter-wave band channel data for a substantial number of areas. Therefore, in this paper, we used the ray tracing simulator which applies the vertical plane launch (VPL) method, one of the ray tracing techniques, to obtain RSS values in various regions. The VPL method was first proposed in 1998 by Liang and Bertoni to simulate three-dimensional radio propagation channels efficiently [7]. The ray tracing method, which predicts propagation characteristics using building shape, terrain data, and transceiver characteristics, has the advantage of higher accuracy than the existing stochastic model. [8]–[10] confirmed that the RSS obtained through the VPL technique is very similar to the actual measurement results.

The ray tracing simulator used in this study traces the ray path by dividing the space into vertical and horizontal planes. The simulator first emits rays in the horizontal direction, as in the case of the two-dimensional pincushion method, as shown in Fig. 3. This ray represents a vertical plane containing all elevation angles originating from the transmitter. The vertical plane is divided into a plane that passes through the wall when facing it or a plane that diffracts or reflects in the direction of the specular reflection. After considering the propagation of the vertical plane in the horizontal area, the path between the transmitter and the receiver is calculated.

A ray is considered to reach the receiver when it crosses a capture circle at the reception location. When the ray reaches the receiver, the path and all reflection and diffraction coefficients are calculated. Because the simulator emits rays at all azimuth and elevation angles, the computation time exponentially increases with map area, angular resolution, and so on.

III. Neural Network Structure

This section describes the structure of CNN, which is a neural network used in the proposed technique. The neural network is a machine learning method that can learn the characteristic of data through hierarchical abstraction at various levels using a computational model composed of several layers of nonlinear modules. Unlike the feature extraction step in the existing data-based diagnostic method, it is possible to learn the optimal hierarchical features directly from the data. Also, the neural network shows high performance in various fields

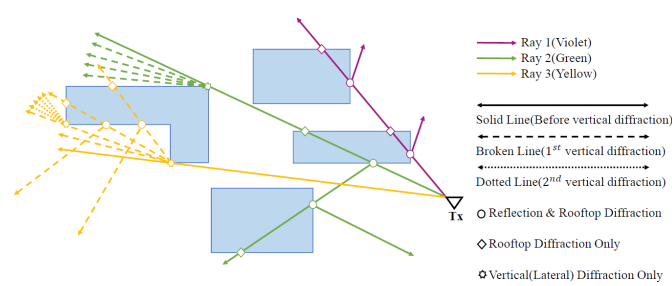


Fig. 3. Computation of three-dimensional ray tracing in horizontal space.

such as object recognition. CNN is a deep learning technique that improves performance in computer vision and image recognition. As shown in Fig. 4, it consists of a convolutional layer, a pooling layer, a nonlinear activation function, and a fully-connected layer. The CNN model is characterized by local connectivity and weight sharing, and it is a neural network model that significantly reduces the number of weights compared to the fully-connected neural network model. In this study, we used a converted two dimensional image for input of CNN. The map of 1 km by 1 km used for input is converted into an image of 300 × 300 pixels by the method described in Section II. The output is the path loss exponent obtained from ray tracing simulation.

IV. Numericl Result Analysis

A. Simulation parameters

We obtained Geographic Information System (GIS) data from the National Geographic Information Institute, a subordinate organization of the Ministry of Land, Infrastructure, and Transport, South Korea to simulate the propagation channels in various environments. We divided the obtained maps of Seoul into 1 km by 1 km units and used them as input data. A total of 644 maps were generated. The process of dividing the map is shown in Fig. 5. We transformed individual maps to the two dimensional image according to the transmitter's height (5, 10, 15, 20, 25 m). Therefore, the number of total maps became 3220. Also, each map was copied and rotated from 0 to 180 degrees by 1 degree to increase the generality of the neural network. Thus, we used a total of 576,720 images for training and testing neural networks. Propagation channel prediction was carried out in the 28 GHz millimeter-wave band. The simulation parameters and ray tracing modeling parameters are shown in Table I. For the training of neural networks, we classified the data into training, validation, and test set. Each set used 70%, 15%, and 15% of the total data, respectively.

B. Optimal hyperparameter selection

In this study, we analyzed how the prediction performance changed according to the hyperparameter change. The relative root mean square error (RMSE) for each hyperparameter is shown in Table II. Table II shows the prediction performance according to the learning rate and layer number change.

If the learning rate is not properly selected, the validation loss increases. Therefore, the learning rate was chosen as an appropriate value so that the validation loss does not diverge. As a result of testing several hyperparameters, number of layers and learning rates with optimal performance are 6 and 5×10^{-4}, respectively.

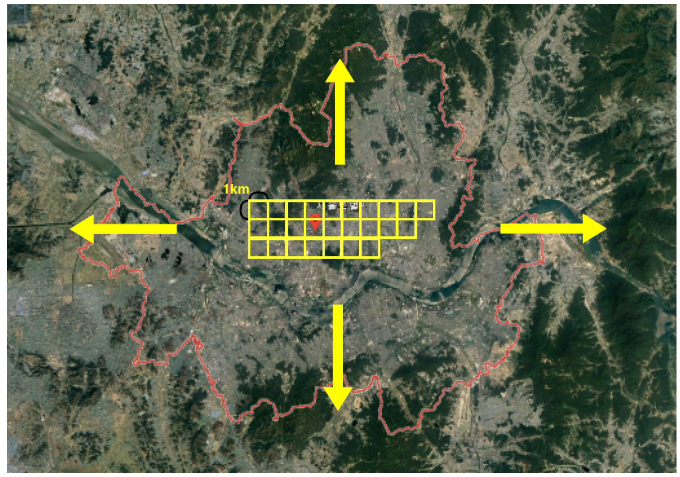


Fig. 5. The process of dividing Seoul into square shaped tiles. A total of 644 tiles are created.

TABLE I
System Parameters

Parameter	Value
Center frequency	28 GHz
Transmitter height	5, 10, 15, 20, 25 m
Maximum number of reflection	4
Maximum number of vertical diffraction	1
Maximum number of horizontal diffraction	4
Relative permittivity of building wall	6
Ray shooting angle resolution	0.1°
Learning rate drop factor	0.1
Learning rate drop period	20
Filter size for each layer	3×3
Number of filters for each layer	15
Pooling method	Average pooling

TABLE II
Hyperparameter vs Prediction error (%)

Learning rate	2 Layers	4 Layers	6 Layers
10^{-6}	48.1	38.6	19.7
10^{-5}	29.1	18.4	15.4
5×10^{-5}	17.9	15.1	11.9
10^{-4}	15.9	14.7	11.8
2×10^{-4}	17.1	12.7	10.1
5×10^{-4}	11.1	12.9	9.71
10^{-3}	Inf	5.95×10^{7}	10.2

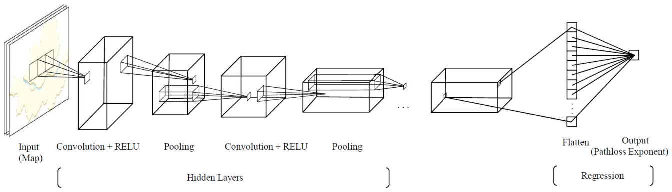
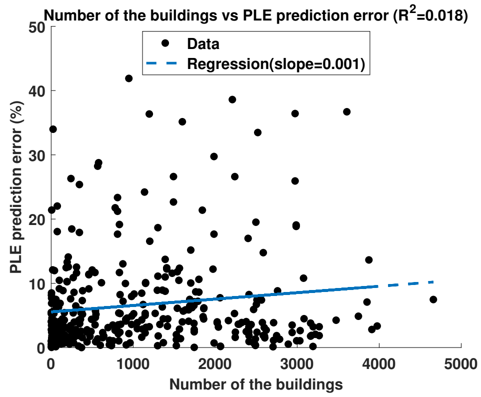


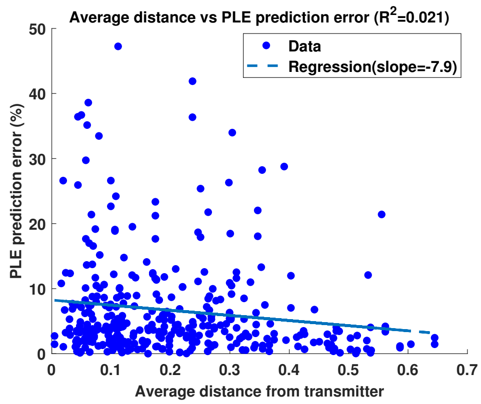
Fig. 4. Structure of a convolutional neural network. Map data is used as input, and path loss exponent is used as output.

C. Relationship between environment and prediction accuracy

In this study, we analyzed whether the relative error of the path loss exponent prediction changes according to the target environment. We examined whether the relative prediction errors change as the number of buildings around the area



(a)



(b)

Fig. 6. Analysis of path loss exponent (PLE) prediction performance change according to environment. Even if the environment changes, the prediction performance is almost unchanged.

of interest and the average distance of buildings from the transmitter change. Fig. 6(a) shows the relationship between the number of buildings and the relative prediction error of the path loss exponent. Even though the number of buildings increases, the prediction error of the path loss exponent does not increase, and the correlation between the two variables is also shallow. Therefore, we conclude that even if the number of buildings is changed, the proposed algorithm does not show a difference in prediction performance. In Fig. 6(b), we analyzed whether the average distance of buildings from the transmitter is correlated with the prediction error of the path loss exponent. It can be seen that the prediction error of the path loss exponent does not increase even if the distance from the transmitter increases and the correlation between the two parameters is low. Therefore, we conclude that the average distance between the transmitter and the building as well as the number of buildings does not affect the prediction error. In short, we conclude that the prediction error does not undergo serious changes depending on the environments.

V. Conclusion

In this paper, we proposed a new algorithm to predict the path loss exponent of outdoor millimeter-wave band channel through deep learning. A three-dimensional radio ray tracing tool was used to generate the wireless channel data to train the path loss exponent on the neural network. After training the neural network with the channel data obtained from various environments, we evaluated the prediction performance of the neural network for the test data set. We obtained the optimal hyperparameter for the prediction of the path loss exponent. Also, we showed that the prediction performance does not show a significant difference with the number of buildings in the environment or the average distance of buildings from the transmitter. If we use the results presented in this study for path loss exponent or wireless coverage prediction, we will be able to obtain path loss exponent and wireless coverage in a short time for various areas.

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