

Machine Learning-Based Estimation of 28 GHz Radio Propagation Changes Due to Scatterers

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This paper presents a method for estimating changes in electromagnetic wave propagation in the 28 GHz band due to scatterers using machine learning. In 28 GHz and mmWave band communications, it is necessary to understand the effects of moving scatterers on electromagnetic wave propagation to dynamically control the radio wave environment. In this research, a convolutional neural network (CNN) is used to quickly understand radio propagation considering scatterers. The analytical model and results of the ray tracing method are used as explanatory and objective variables for training data. The estimation of radio propagation by the CNN is found to be in good agreement with the results of the ray tracing method, with a coefficient of determination of 0.84. Furthermore, it is found that radio propagation with a modified radiation pattern of the transmitting antenna can be estimated with less training data through transfer learning.

Index Terms—Convolutional neural networks, Radio propagation, Millimeter wave propagation, Ray trace method.

I. INTRODUCTION

FIFTH generation mobile communications use electromagnetic waves in the 28 GHz and mmWave bands, such as the 39 GHz band [1]. In communications using mmWaves, the radio environment is dynamically controlled using metasurface reflectors [2] and beamforming to ensure a wide communication area. It is necessary to quickly obtain radio wave propagation data because mmWaves are affected by moving scatterers such as people and robots [3]. Radio propagation is typically obtained through electromagnetic field simulation and electric field sensors. However, electromagnetic field simulation requires a long analysis time, and electric field sensors are expensive for sensing large areas. In this study, the 28 GHz band radio propagation is obtained using a convolutional neural network (CNN).

CNNs have been used to predict radio propagation in tunnels [4] and to estimate radio propagation and loss using building maps [5]–[6]. In this study, we use a CNN to estimate the change in radio propagation in the 28 GHz band due to moving scatterers with height information. The analytical model and results of the ray tracing method [7] are used as explanatory and objective variables for the training data of the CNN.

II. CNN OF RADIO PROPAGATION

A. Training Data

CNN requires a large amount of training data consisting of explanatory and objective variables. The simulation model and results of the ray tracing method are employed as explanatory and objective variables in this research. Figure 1 shows an example of an explanatory variable. It is a 224 x 224 pixel image of the top view of simulation model. The explanatory variable is a randomly sized scatterer in an 18 m x 16 m wide room surrounded by 3 m high plasterboard. The various characteristics of the randomly generated scatterers are shown in Table 1. The height of the scatterer is represented by the RGB

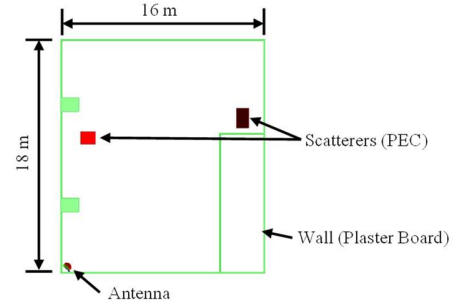


Fig. 1 Example of explanatory variable. It is 224 x 224 pixel image of analytical model. PEC Scatterers are in a room 18 m deep, 16 m wide, and 3 m high. Floors and ceilings are PEC.

TABLE 1 VARIOUS CHARACTERISTICS OF SCATTERERS

Characteristic	Value
Number of Scatterers	1 - 10
Width	0.1 - 2.5 m
Depth	0.1 - 2.5 m
Height	0.1 - 2.5 m

color. The objective variable is the electric field values at 323 points in a room with randomly placed scatterers, as shown in Fig. 1, obtained using the ray tracing method.

The horizontal beamwidth of the antenna shown in Fig. 1 is 90 degrees, and the vertical beamwidths are 90 and 60 degrees. For an antenna with a vertical beamwidth of 90 degrees, the training data and the test data are set to 1500 and 100, respectively. Transfer learning is performed with 100 training and test data when the antenna has a vertical beamwidth of 60 degrees.

B. CNN

In this study, the CNN is composed of three convolution layers as shown in Table 2. The input data is the 224 x 224 pixel color image shown in Fig. 1, and the output data is the text data of 323 electric fields. Transfer learning is applied only to the final and pre-final linear, ReLU, and Dropout layers shown in Table 2.

TABLE 2 LAYER OF CNN

Layer	Activation Shape
Input Image	(224, 224, 3)
Conv2d, ReLU	(222, 222, 6)
MaxPool	(111, 111, 6)
Conv2d, ReLU	(109, 109, 12)
MaxPool	(54, 54, 12)
Conv2d, ReLU	(52, 52, 24)
MaxPool	(26, 26, 24)
Linear, ReLU, Dropout	(16224, 2500, 1)
Linear, ReLU, Dropout	(2500, 1000, 1)
Linear, ReLU, Dropout	(1000, 323, 1)
Output	(323, 1)

III. RESULTS

Prediction of 28 GHz band radio propagation using CNN is evaluated by 100 test data. The evaluation results are shown in Table 3. Coefficient of determination R^2 is

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (1)$$

where y_i is electric field obtained by ray tracing method, $\bar{y}$ is average of y_i , and $\hat{y}_i$ is electric field estimated by CNN. Max

TABLE 3 COEFFICIENT OF DETERMINATION R^2

	Value	
	90 deg	60 deg
Max	0.96	0.94
Min	0.61	0.60
Total R^2	0.86	0.84

and Min in Table 3 show the best and worst estimates among the 100 test data samples. Total R^2 represents the coefficient of determination for the entire test data set. It can be seen from Table 3 that the proposed method for estimating radio propagation using CNN agrees well with the results of the ray tracing method.

The analytical model, best estimation result, and result obtained by the ray tracing method when the vertical beamwidth of the transmitting antenna is 90 degrees are shown in Fig. 2 (a), (b), and (c). Figure 3 shows the worst estimation result when the vertical beamwidth of the transmitting antenna is 90 degrees. It can be seen from Fig. 2 that the estimation of radio propagation by the proposed CNN shows good agreement when the number of scatterers is small. Good agreement is also observed when the scatterer is placed only behind a wall with a small electric field. Figure 3 shows that when the number of scatterers is large, the trend of the electric field is consistent but the R^2 is worse. A similar trend is obtained for a vertical beamwidth of 60 degrees, which is learned with less training data through transfer learning.

IV. CONCLUSION

In this research, changes in 28 GHz radio propagation due to multiple scatterers with different heights are estimated using a CNN. The proposed method is trained using the analytical model and results of the ray tracing method, achieving an accuracy of $R^2 = 0.86$. Furthermore, when the antenna is changed, good estimation can be achieved with less training data by using transfer learning.

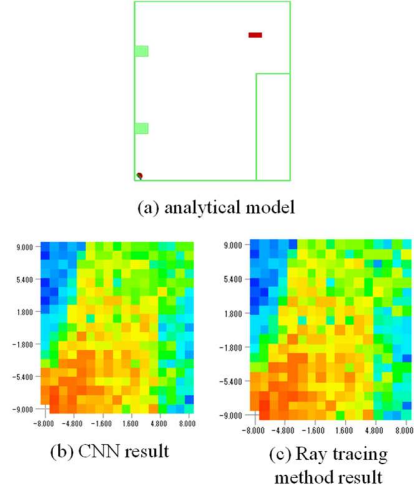


Fig. 2 Best estimation result when the vertical beamwidth of the transmitting antenna is 90 deg.

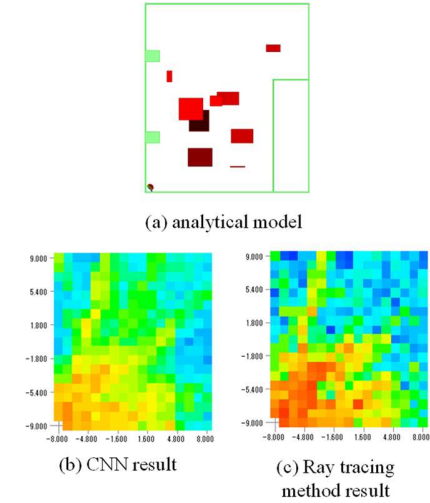


Fig. 3 Worst estimation result when the vertical beamwidth of the transmitting antenna is 90 deg.

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