Indoor Path Loss Modeling for 5G Communications in Smart Factory Scenarios Based on Meta-Learning

Pei Wang
Department of Computer Engineering
Kwangwoon University
Seoul, South Korea
wangpei@kw.ac.kr

Hyukjoon Lee
Department of Computer Engineering
Kwangwoon University
Seoul, South Korea
hlee@kw.ac.kr

***Abstract*—Millimeter waves (mmWaves) of the 28 GHz frequency bands have been selected for the 5G communications with special usage scenarios such as smart factories. Indoor path loss prediction plays an important role in configuring a base station to be able to utilize the full capacity of the new technology. Although machine learning has attracted much attention recently in path loss modeling thanks to its ability to make accurate predictions, its performance can be limited by the size of available measurement data set used for training. In this paper, we propose a new training strategy to train path loss models based on convolutional neural network (CNN). The proposed strategy is based on meta-learning which performs well in few-shot learning scenarios with multiple tasks comprising a meta-task. It is shown that the indoor path loss model based on a CNN configured as a meta-task of multiple beams can outperform the CNN models by a conventional training algorithm as well as empirical models.**

Keywords—millimeter wave, smart factory, path loss modeling, meta-learning, deep learning, 5G

I. Introduction

Millimeter waves (mmWaves) in 28 GHz frequency bands have been selected for the fifth-generation (5G) communications in South Korea, US, and Japan [1] with special usage scenarios such as smart manufacturing, C-ITS for autonomous driving, and sports game broadcasting within stadiums. Path loss modeling has received a great deal of attention as one of the important elements for the optimal planning and configuration of base stations due to precarious channel characteristics of millimeter waves.

There are three types of path loss models: empirical model, deterministic model, and machine learning-based model. Empirical models such as close-in (CI) free space reference distance model, floating-intercept (FI) model, and alpha–beta–gamma (ABG) model are some of the examples used for indoor prediction [2-4]. These models define the amount of path loss as a function of the strength and environment parameters using multiple equations with a few parameters including the distance between transmitter (Tx) and receiver (Rx), the frequency of Tx, and so on. Since they do not take building interior layouts into account, they cannot model the path loss closely enough in practice.

Deterministic methods, such as ray tracing, have been proposed that can achieve good performance in some scenarios [5]. However, ray tracing requires detailed building layout information and dielectric properties of materials [6-7].

Machine learning has gained popularity as an alternative approach to build path loss models thanks to its ability to make accurate predictions based on training data even when detailed information about a particular propagation environment is not available. It allows learning of the underlying functions between input and output variables based on training data set [8].

Machine learning approaches can be used to build accurate path loss models for both indoor and outdoor scenarios. It has been reported that in many scenarios the prediction accuracy and computational efficiency of machine learning models are higher than those of empirical models and deterministic models, respectively [9-17]. One of the fundamental limitations of machine learning models is that they require a sufficient amount of training data which are often not available in practice. A smart factory is a good example where the interior space is crowded with manufacturing devices and machines. With the manufacturing machines operating often 24/7, collecting measurement data for training is usually difficult if not impossible. Furthermore, there may exist only a few places to set up the base station within the smart factory for measurements. These unfriendly measurement conditions lead to the insufficient number of training data for machine learning models.

Meta-learning builds a machine learning model from the models of previous tasks and quickly adjusts the model with few samples from a new task. The main goal of meta-learning is to learn to learn and has been proposed as a framework to address the challenges of few-shot learning. Reptile is one of the most popular meta-learning algorithms derived from Model-Agnostic Meta-Learning (MAML) and it can provide good parameter initialization in the model given various learning tasks [18-19].

One important feature of meta-learning is that it is a task-based method, i.e., the training process is based on tasks. This lends itself well to indoor path loss modeling for mmWave communications which are based on multiple beams transmitted simultaneously. To our best knowledge, there exist no previous works in mmWave path loss modeling based on meta-learning.

The contributions of our work can be summarized as follows:

1) We present a new indoor path loss modeling method for mmWaves based on meta-learning.

2) We compare our proposed model with FI model and CNN model and highlight the strengths of our proposed model.

The paper is organized as follows: Section II presents some path loss models. Section III describes our proposed path loss model. The experiments and results are included in section IV. The conclusion and future work are discussed in section V.

II. Related Work

A. Empirical Path Loss Models

Empirical path loss models rely on the measurement data obtained from a specific propagation environment in order to determine the statistical relationships between path loss related parameters (T-R separation, working frequency, etc.). CI model and FI model are two examples of empirical models frequently used in indoor path loss prediction [2][4][20]. Several path loss related parameters including frequency (f) and distance (d), are considered in CI model which uses measurement data to estimate the path loss exponent (n) and standard deviation (σ) as given by:

$$\mathrm{PL}^{\mathrm{CI}}(f,d)[\mathrm{dB}] = \mathrm{FSPL}(f,d_0) + 10n\log(d) + \chi_\sigma^{\mathrm{CI}}, \quad (1)$$

where $\mathrm{FSPL}(f,d_0)$ is the free-space path loss at the close-in reference distance. The FI model is given as:

$$\mathrm{PL}^{\mathrm{FI}}(d)[\mathrm{dB}] = \alpha + 10\beta\log(d) + \chi_\sigma^{\mathrm{FI}}, \quad (2)$$

where d is the distance between Tx and Rx, α is the path loss offset which is determined by measurement data, and β is path loss exponent like n in CI model. These two models include χ, a zero-mean Gaussian random variable with standard deviation σ, as the shadow fading term. FI model is recommended by 3GPP [21] and WINNER II [22].

Despite their simplicity and computational efficiency, the performance of these models in terms of prediction accuracy is limited since they do not take detailed indoor propagation effects such as wall penetration, reflection, scattering, diffraction, and NLOS loss factor of walls into account.

B. Deterministic Path Loss Models

Ray tracing is one of the most popular deterministic models which can simulate signal propagation and provide realistic light and shadow effects. This method applies radio wave propagation mechanisms and numerical analysis techniques [8]. It shows the simulated rays emitted from Tx to Rx and obtains the data like received power, path gain, path loss, etc. Before starting the simulation, user needs to set up the propagation environment, place the Tx and Rx, and enter some parameter values in the ray tracing software. Its predictions instead of relying on measurement data depend on the reflection, diffraction, etc. of signal propagation process. The prediction accuracies of the ray tracing model depend on some values, such as the number of reflections, the precision of reflections loss parameter. The more rays generated, the finer the details of the rendering, but obviously the greater the amount of calculation. With the continuous reflection of rays, you can imagine the huge amount of calculation [23].

In comparison with empirical models, ray tracing includes more factors and simulates all paths of rays, from which the composition of the path loss of each Rx can be derived. However, ray tracing lacks computational efficiency, and time-consuming calculation process must start from the beginning again once a new Rx is added.

C. Machine learning-Based Path Loss Models

Machine learning path loss models are different from aforementioned methods. The important part for most machine learning-based path loss models is training. The quality of training directly determines the accuracy of the predictions. Supervised machine learning algorithms like random forest, artificial neural network and convolutional neural network are capable of performing regression after training the model. Machine learning-based models are also with high computation in the training stage. Whereas once the model is trained, we can load the trained model multiple times and use it directly without retraining.

Exploring the application of machine learning algorithms in modeling path loss has been generalized in urban and suburban environments, but none of the existing works is at 28 GHz in a smart factory.

III. Path Loss Modeling Based on Meta-Learning

A. CNN Models with Meta-Learning

Meta-learning has the ability to learn fast a new task with a small amount of data based on existing knowledge. One important feature of meta-learning is that it is a task-based method, i.e., the training process is based on tasks.

Reptile is a meta-learning method that finds a common initialization across meta-training tasks and uses it to quickly adapt to new tasks [24]. Reptile is the application of the shortest descent algorithm in meta-learning [25]. It has lower computational compared with MAML which includes second-order derivation. It can learn an initialization for the parameters of a neural network model so that it is fast to optimize these parameters at test time, that is, the model generalizes from a small number of samples from the test task. Compared with other meta-learning methods, Reptile is easy to apply that does not need a training-test split for each task. The Reptile algorithm is as follows:

Algorithm 1 Reptile Training Procedure

Initialize ϕ
for iteration =1,2, ..., **do**
    Tasks $\tau_1, \tau_2, \dots, \tau_n$
    for $i = 1,2,\dots,n$ **do**
        for $j = 1,2,\dots,k$ **do**
            Compute parameters: $P = \mathrm{Optimizer}(L_{\tau_i}, \sigma)$
        end for
        Save $W_i = P$
    end for
    Update parameters: $\phi \leftarrow \phi + \frac{\epsilon}{n}\sum_{i=1}^{n}(W_i - \phi)$
end for
Fine-tune ϕ on the test task

where ϕ denotes a vector of parameters of the model, L_t is loss, k is the step size of optimizer, and σ and ϵ are the learning rate.

Fig. 1 shows the different ways to update the parameter vector. Fast weight update method is the regular way to update the vector. Slow weight update method (Reptile way) can fast adjust model to fit different tasks. After training process, a small number of samples from test data will be randomly selected to fine-tune. Fine-tuning is an important step to adjust model parameters based on new task samples.

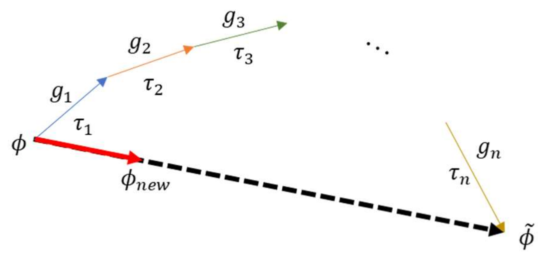


Fig. 1. The method to update model parameter vector. The ϕ_{new} is calculated by slow (Reptile) weight update method and $\tilde{\phi}$ is updated through the fast weight update method.

In this paper, path loss modeling of mmWave communications based on multiple beams is regarded as a meta-learning problem with multiple meta-training tasks. We used Reptile algorithm [26] as the main training algorithm for CNN. Convolutional neural networks, which are specifically designed to deal with the variability of 2D shapes, are shown to outperform other techniques [27]. CNN can be trained to extract features automatically to make predictions based on previously unseen input data.

Our CNN model includes three convolutional layers and a single fully-connected (FC) layer. Each convolution is followed by batch normalization and ReLU activation function. Leaky ReLU is used as the activation function in both convolution and FC layers. The filter size and stride size of each convolutional layer are (5, 5) and 2, respectively. The number of neurons in the FC layers is 1281 and 1. The input data of the CNN is the local area multi-scanning (LAMS) image described below. T-R separation is also used as an input to the FC layer. The output is the predicted path loss value. Fig. 2 provides an illustration of the CNN architecture used in our work.

B. Image Generalization

Local area multi-scanning (LAMS) includes the region of interest between Tx and Rx shown in Fig. 3. Given the Tx point and an Rx point with coordinate, we can locate these two points in the floor plan. Next, we make a line segment l_{TR} which connects Tx and Rx, and find the line segment l_T and l_R which pass Tx and Rx respectively and are perpendicular and bisect by l_{TR}. The lengths of l_T and l_R are decided in advance. Then, it is clear where we are interested. In this area, we select the specified number of pixels at equal intervals and save them. Finally, we need to resize the image into a square of the fixed size [28].

IV. Experiments and Results

A. Path Loss Environment

The path loss environment we use in our experiment is a smart factory of size 86.8 m x 28.7 m x 4 m as shown in Fig. 4. A base station operating as the Tx (shown by a green square surrounded in black) was set up at (12.9, 8.1) and RSS measurements were taken at 537 locations in total. The circles in Fig. 4 represent Rx locations with the filled colors indicating path loss values. The parameters related to the Tx and Rxs are listed in Table I. The Tx transmits 16 beams simultaneously in slightly different directions and the Rx stores the maximum of the 16 receiver signal strength (RSS) values and the beam ID at each measurement location. The resulting number of data collected in this way for each beam is listed in Table II. Since we had a small training dataset with multiple disjoint subsets, we adopted meta-learning to train the CNN. Specifically, the measurement data of beam 1 to beam 8 were used for meta-training tasks and beam 9 to beam 16 were used for meta-test. These two groups of data were mostly collected in the bottom half and the top half of the factory floor, respectively.

TABLE I. Tx and Rx Information

Parameter	Value
Frequency (GHz)	28
Transmission Power (dBm)	32.5
Tx Height (m)	2.45
Rx Height (m)	1.5

TABLE II. The Number of Data for Each Beam

Beam ID	No. of data	Beam ID	No. of data
1	24	**9**	82
2	25	**10**	33
3	49	**11**	8
4	43	**12**	12
5	57	**13**	10
6	63	**14**	14
7	62	**15**	6
8	31	**16**	18
Total	354	**Total**	183

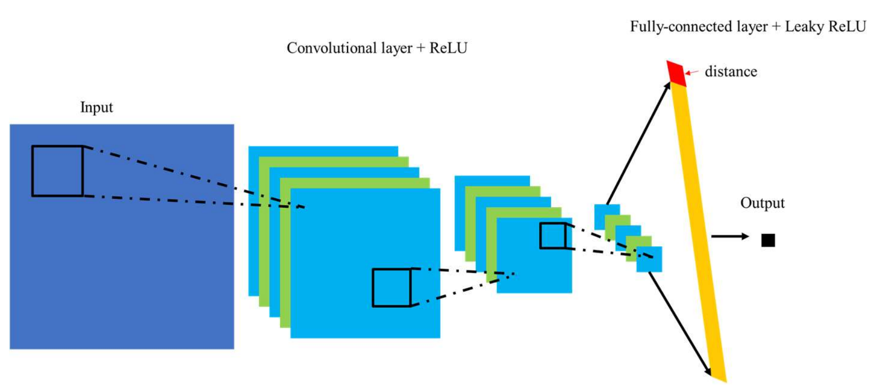


Fig. 2. The structure of CNN.

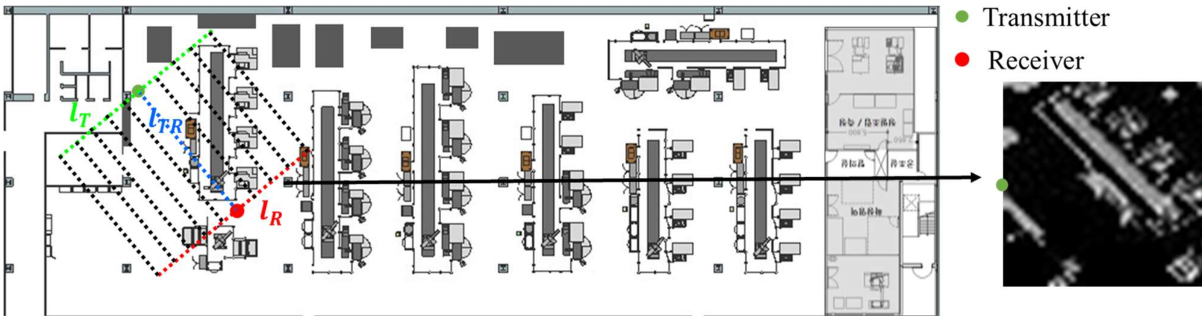


Fig. 3. Illustration of local area multi-scanning image generation.

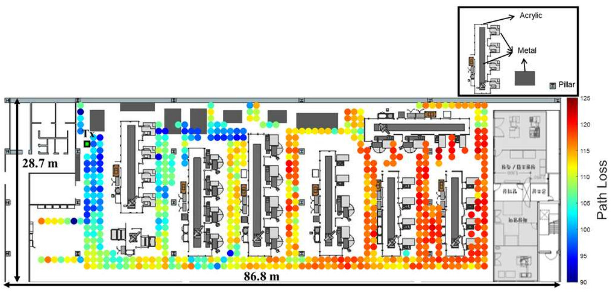


Fig. 4. Experiment environment: a smart factory.

B. Comparison Models

In order to compare the performance of the proposed method, i.e., the CNN trained by meta-learning in terms of prediction accuracy against that of conventional methods, a vanilla CNN model and FI model were selected. Most previous works path loss modeling based on machine learning use vanilla CNNs with different types of input image [29-30]. The hyperparameters were specified with the same values as those used for the CNNs for meta-training. The path loss values of FI model were calculated by using equation (2) with the model parameter values specified as shown Table III.

TABLE III. PARAMETERS OF FI MODEL

Models	FI model	
Parameters	α	87.15
	β	1.67
	σ	2.47

C. Results

The performance of each model was evaluated in terms of Root Mean Square Error (RMSE). RMSE is defined by:

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}, \qquad (3)$$

where n is the number of data points, y_i is the i-th measurement, and $\hat{y}_i$ is its corresponding prediction.

Table IV shows the RMSE of each model for each beam. It can be clearly noticed the proposed model outperforms FI model and CNN model. The proposed model has RMSE values less than 2 dB for all beams. CNN model performs better than FI model but worse than the proposed model. The average RMSEs of FI model, CNN model and CNN model

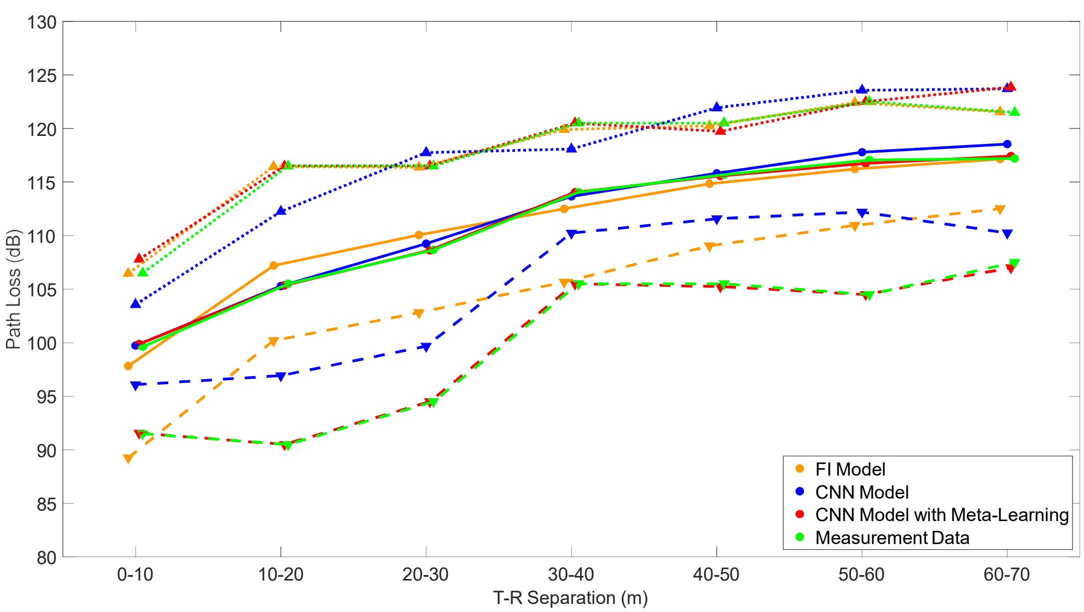


Fig. 5. The average, maximum and minimum values of the measurement data in the range are compared with the three models.

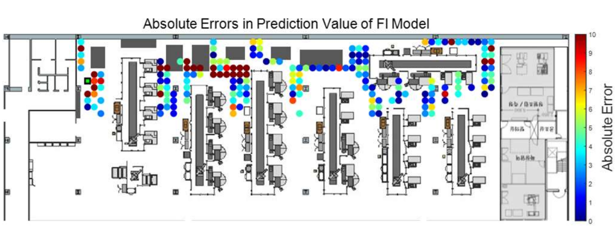
with meta-learning are 3.59 dB, 2.38 dB and 1.08 dB, respectively. The maximum and minimum RMSE of 6.42 dB and 0.41 dB were obtained by the FI model and the proposed model, respectively.

Fig. 5 shows the average, maximum, minimum prediction of three models compared with the measurement data against T-R separation of 10 m ranges in the increasing order. We use visualization of this style since the measurement data are not only distributed unevenly in the values of T-R separation, but the path loss value also varies largely within the same range. This is mainly due to the existence of multiple measurements at a similar distance but in different locations. It can be observed the difference between the range of predicted values and that of the measurement data is smaller for the proposed model than the vanilla CNN model and FI model whereas the difference between the average predicted values and the average measurements is very small. This implies that the prediction accuracy of the proposed model is higher than that of the other models not just on average but in individual measurements as well.

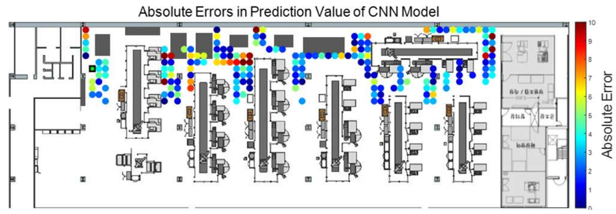
The absolute errors of each model are provided in Fig. 6. where it is shown the absolute errors of the proposed model are lower than 5 dB which are close to blue color in Fig. 6 (c). It can be easily noticed both meta-learned CNN and vanilla CNN models outperform the FI model as expected thanks to their ability to learn to extract features of path loss environments such that the underlying path loss function can be approximated based on the training data. Path loss prediction results of the three models are summarized in Fig. 7.

TABLE IV. COMPARISON OF PATH LOSS PREDICTION USING FI MODEL, CNN MODEL, AND PROPOSED MODEL

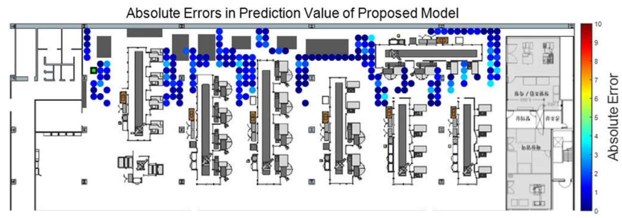
Beam ID	RMSE (dB)		
	FI Model	***CNN Model***	***Proposed Model***
9	6.42	3.22	1.60
10	3.60	3.05	1.40
11	3.36	2.16	1.16
12	3.60	3.25	1.01
13	3.61	1.33	0.50
14	2.78	2.41	0.96
15	1.82	1.42	1.63
16	3.58	2.26	0.41
Average	**3.59**	**2.38**	**1.08**



(a)

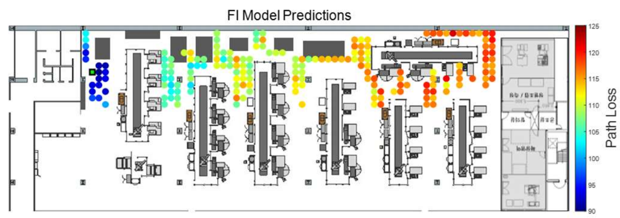


(b)

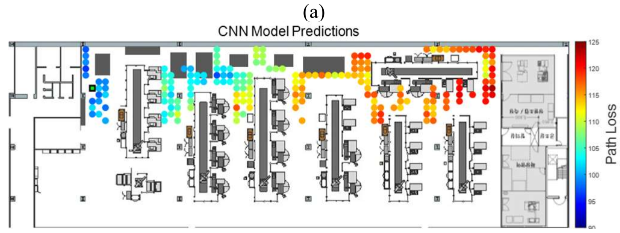


(c)

Fig. 6. Path loss absolute error comparison of three models: (a) absolute errors in prediction value of FI model, (b) absolute errors in prediction value of CNN model, (c) absolute errors in prediction value of the proposed model.



(a)



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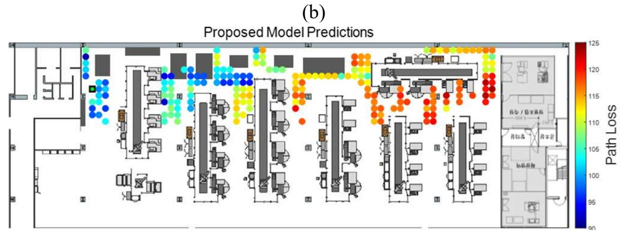

(c)

Fig. 7. Path loss prediction results of the three models: (a) FI model predictions, (b) CNN model predictions, (c) proposed model predictions.

V. CONCLUSION AND FUTURE WORK

In this paper, we develop a new path loss prediction model called CNN model with meta-learning and compare it with FI model and CNN model. Our proposed model realizes path loss prediction in a smart factory and figures out the few-shot data problem.

The presented work is only applied at 28 GHz and in smart factory. We can apply our model to other different scenarios and try to combine meta-learning with other machine learning methods. In the future, we also can consider different frequencies or different environments as different tasks.

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