IEICE Communications Express, Vol.13, No.6, 181–184

ComEX

Special Cluster in Antennas and Propagation Technologies 2023

LETTER

Proposal on rain attenuation prediction method using convolutional neural network

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Abstract Recently, the practical application of HAPS (High Altitude Platform Station) as the next-generation communication platform is studied actively. HAPS employs adaptive rain attenuation countermeasure techniques such as site diversity methods, therefore it is ideal to predict rain attenuation on the path in real time. We proposed real-time rain attenuation prediction method by convolutional neural network that inputs image of rainfall rate and path distance. Result showed that prediction accuracy of our proposed method is better than a method using conventional formulas.
Keywords: rain attenuation, convolutional neural network, deep learning
Classification: Antennas and propagation

1. Introduction

Recently, the practical application of HAPS as the next-generation communication platform is studied actively [1]. In Japan, the frequency band of 38-39 GHz is allocated to the HAPS feeder link [2], and then the quality degradation of communication due to rain attenuation is a problem.

ATPC (Automatic Transmit Power Control), AMC (Adaptive Modulation and Coding), and site diversity are being considered for HAPS systems to counter rain attenuation [1]. It should be controlled in real-time because these countermeasure methods are adaptive.

Rain attenuation estimation methods for non-terrestrial network systems such as satellite communications and HAPS have been standardized as ITU-R Recommendation P.618 [3]. However, the ITU-R Recommendation P.618 is designed to derive statistics for instance the attenuation to be exceeded for p[%] of a year, and is not intended for real-time rain attenuation prediction.

Real-time rainfall rate information is required for real-time rain attenuation prediction. In Japan, "High-resolution Precipitation Nowcasts [4]" (hereinafter referred to as "Nowcasts") which is distributed every 5 minutes by the Japan Meteorological Agency are available. Nowcasts provide current status of rainfall rate and short time range rainfall rate forecast with a spatial resolution of 250 m square. In other words, the nowcast can be regarded as two-dimensional rainfall rate data with a temporal resolution of 5 minutes and a spatial resolution of 250 m.

Nowadays, in order to predict radio propagation loss with high accuracy, a method using convolutional neural network (CNN) has been proposed in mobile communication environments. In the method, map data with building height and path distance information are used as inputs [5, 6]. Here is, since map data on rainfall rate along the path, are available from Nowcasts, we thought it would be effective to follow the CNN-based propagation loss prediction method in proposing a rain attenuation prediction method. And also no such study existed as far as I could find.

In this paper, we propose a rain attenuation prediction method using a CNN with map data with rainfall rate and path distance information as input, and validate effectiveness of the method.

2. Conventional method

Rain attenuation per unit distance γ is indicated as ITU-R Recommendation P.838 [7], called specific rain attenuation, as calculated by

$$\gamma = kR^{\alpha} \, [\mathrm{dB/km}], \tag{1}$$

where R is rainfall rate[mm/h], k and α are determined as function of frequency. Equation (1) has originally intended to derive rain attenuation statistics such as those ITU-R Recommendation P.618, although in this paper, we use this equation and Nowcasts to perform real-time prediction for comparison with our proposed method.

The way to real-time rain attenuation prediction using Equation (1) is as follows.

Let the distance between the transmitting (Tx) and receiving points (Rx) be D[m] and the elevation angle from Rx to Tx is θ[deg]. First, the path is divided per 1 m, and the rainfall rate on the Nowcast for each of the segmented points is R_i ($i = 0, 1, \cdots, D, i = 0$: Tx, $i = D$: Rx). Rain attenuation at point i, A_i is calculated by

$$A_i = \frac{1}{1000} \frac{1}{\cos\theta} k R_i^{\alpha} [\mathrm{dB/m}]. \tag{2}$$

In consequence the rain attenuation value A[dB] for the entire propagation path is given by

$$A_i = \frac{1}{1000} \frac{1}{\cos\theta} k \sum_{i=0}^{D} R_i^{\alpha} [\mathrm{dB}]. \tag{3}$$

Hereinafter this prediction method called "ITU model".

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DOI: 10.23919/comex.2024SPL0015
Received January 12, 2024
Accepted February 21, 2024
Publicized March 12, 2024
Copyedited June 1, 2024

3. Proposed method

3.1 Input data

3 maps data shown below are input to prediction model we proposed.

- Rainfall rate[mm/h]
- Distance from Tx[km]
- Distance from Rx[km]

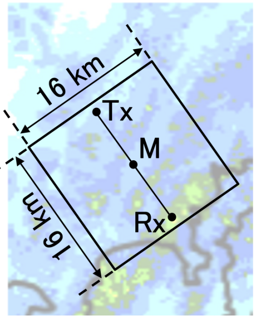
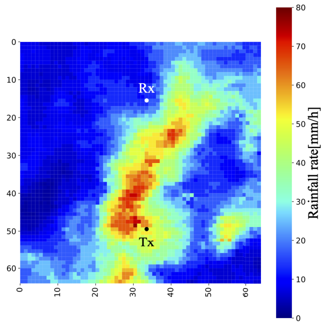
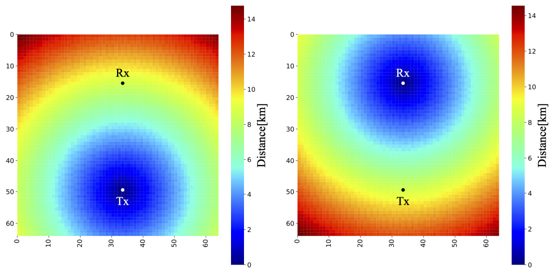


Fig. 1 Input data area



(a) Rainfall rate



(b) Distance from Tx (c) Distance from Rx

Fig. 2 Input data to prediction model we proposed

Table I Condition of Tx/Rx points

	Name	Path distance[km]	Elevation angle[deg]
Tx	Tokyo sky tree	-	-
Rx1	Ryogoku	1.350	16.34
Rx2	Akihabara	2.862	7.38
Rx3	Minamigyotoku	9.363	2.37

For rainfall rate, we use the Nowcasts data described above.

As shown in Fig. 1, Input data to the model is 16 km square around the midpoint (M) of Tx and Rx. Moreover as we can find in Fig. 1, the input data is always defined so that Tx and Rx are in a straight line and all Rx are in the same direction as seen from M. The input size is 64×64 since spatial resolution of Nowcasts is 250 m. Figure 2 shows an example of input data to the model. The actual input data are numerical matrix data without color, though they are plotted here in color for illustrate.

3.2 Rain attenuation value

In this study, measured rain attenuation data from [8] is used for evaluation. Data were measured every 1 second, although these measured data were converted to the median value for every 5 minutes in this paper. This is because to remove instantaneous fluctuations and also to correspond to Nowcasts time resolution. Tx and Rx were set as shown in Table I. In addition, the frequency of radio wave used the measurement is 39.75 GHz, and the polarization is vertical.

3.3 Model structure

The structure of the proposed rain attenuation prediction model in this study is shown in Fig. 3. This configuration is based on the CNN model known as VGG16 [9] with reduced parameters. Specifically, the model consists of a convolutional layer (C01 to C13 in Fig. 3) with 1/4 the number of filters of VGG16, five Max pooling layers (P01 to P05 in Fig. 3), and two fully-connected layers (D01 and D02 in Fig. 3) with the number of units changed from 4096 to 512. The ReLU function (Rectified Linear Unit) is used as the activation function for the convolutional and fully-connected layers of the model in this study. The output is an identity function.

4. Evaluation method

4.1 Learn proposed model

Supervised learning is performed with 200 epochs, using the “input data” as input and the measured rain attenuation values corresponding to the input data as teacher data. And also, in this study, mini-batch learning which batch-size is 256 is adopted.

Training data are from 2021-08-08 00:00 to 2021-09-18 23:55 except 2021-08-15, and from 2021-10-14 00:00 to 2021-10-28 23:55. Data from 2021-08-15 (heavy rain),

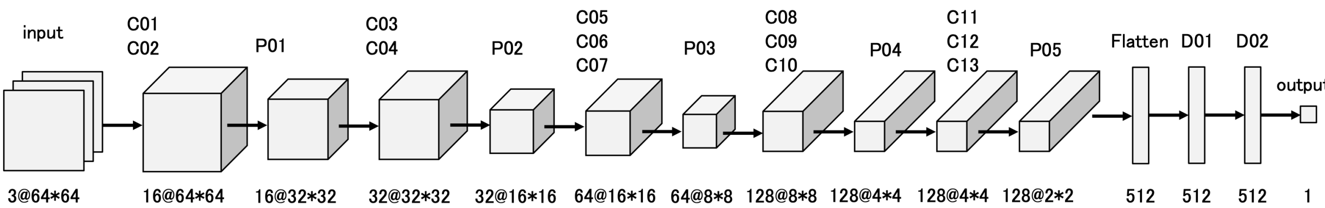


Fig. 3 Structure of proposed rain attenuation prediction model

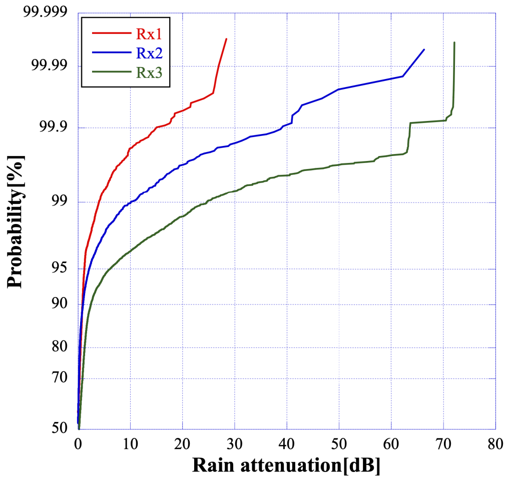


Fig. 4 Cumulative probability distribution of measured rain attenuation value used as training data

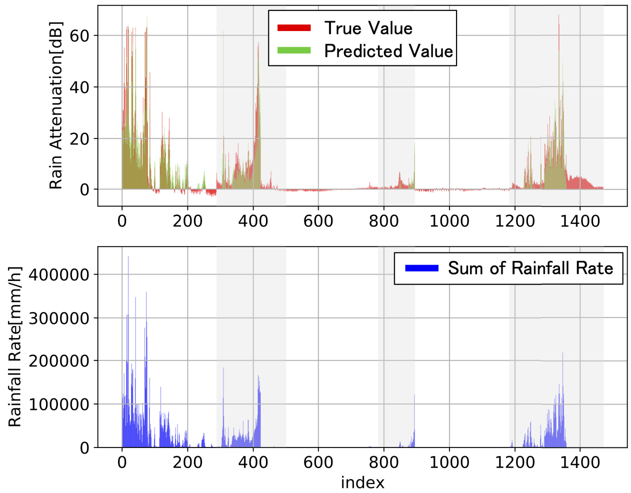


Fig. 5 Comparison result and sum of rainfall rate on the path at Rx3

2021-10-01 (heavy rain), 2021-10-07 (cloudy), 2021-10-13 (rainy), 2021-10-29 (clear), 2021-11-09 (heavy rain) [10] were used as evaluation data to evaluate the learned model. Note that, data after 2021-10-02 for Rx2 is not included in learning and evaluation. Figure 4 shows cumulative probability distribution of measured rain attenuation value used as training data at each Rx respectively with cumulative probability 50% or greater. Note that, the rain attenuation value in the training data with cumulative probability less than 50% are almost 0 (that is, not rainy).

In this study, Adam was used for the optimization algorithm, mean squared error (MSE)[dB] as the loss function between the predicted and measured values, root mean squared error (RMSE)[dB] for the evaluation function.

In this paper, in order to understand the maximum performance of the model, the learning and evaluation is performed 20 times, then we discuss the cases in which the RMSE between the model's predicted and measured values for the evaluation data is the smallest.

4.2 Comparison method with ITU model

The evaluation data mentioned in the previous section are input to the proposed model and the ITU model, while the RMSE[dB] between the predicted rain attenuation and the corresponding measured value in each model is calculated to compare the prediction accuracy of the two models.

5. Evaluation result

5.1 Comparison of prediction and measured values

For Rx3, the measured rain attenuation (red), the predicted rain attenuation by the proposed model (green), and the approximate total rainfall rate along the path at the same time as these values (blue), are shown in Fig. 5. The horizontal axis (index) in Fig. 5 is corresponds to sorted the evaluation data in ascending order by date and time. The “index” 0 to 287 is 2021-08-15, 288 to 497 is 2021-10-01, 498 to 780 is 2021-10-07, 781 to 895 is 2021-10-13, 896 to 1182 is 2021-10-29, and 1183 to 1470 is 2021-11-09. And also, in Fig. 5, the corresponding areas in 2021-10-01, 2021-10-13 and 2021-11-09 are colored light gray. Further, Table II shows the correlation between predicted by proposed model and sum of rainfall rate on the path, at each Rx.

Table II Correlation between predicted and sum of rainfall rate on the path

Path	Correlation
Tx-Rx1	0.89
Tx-Rx2	0.94
Tx-Rx3	0.93

Table III RMSE between predicted and measured at each receive point and all evaluation data

Rx	RMSE[dB]	
	Proposed	ITU-R
Rx1	1.20	1.21
Rx2	4.62	4.91
Rx3	4.00	5.14
all	3.19	3.83

Figure 5 shows the overall prediction is in line with theory, such as the attenuation become large when it was heavy rain, while they become small when it was sunny. And also, from Fig. 5 and Table II, it can be seen that there is strong correlation between predicted value by proposed model and sum of rainfall rate on the path. These results indicates when a CNN model is constructed and trained with rainfall rate as input, the model can be regarded as outputting rain attenuation values by selecting rainfall rate values that fall primarily on the propagation path of the input data. It means prediction is based on physical phenomenon of occurring rain attenuation, and therefore the learning is reasonable.

5.2 Comparison of proposed model and ITU model

For each Rx and all evaluate data, RMSE[dB] between predicted and measured value for the proposed model and the ITU model respectively, are shown in Table III. The prediction accuracy of the proposed model is better than that of the ITU model in all cases.

In addition, The rate of improvement of the RMSE in the proposed model at each Rx from that of the ITU model was confirmed to be Rx3, Rx2, and Rx1, in that order, and the

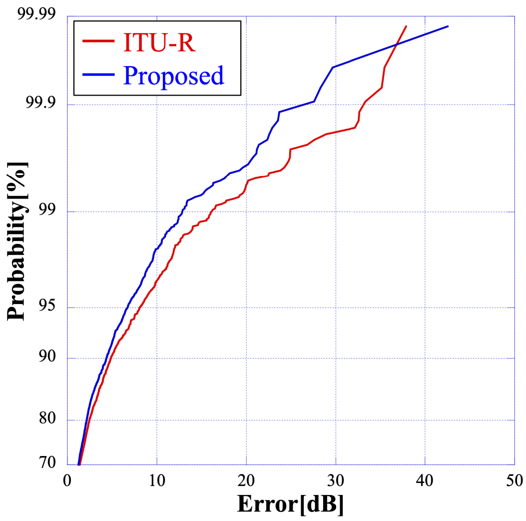


Fig. 6 Cumulative probability distribution of absolute value of prediction error with the proposed model and ITU model

difference was observed depending on the Rx.

This should be mainly due to the learning characteristics of CNNs. When the prediction model is trained by supervised learning with CNN, the prediction model will eventually be such that the value of the loss function (in this study, it is the mean squared error (MSE), which is practically equivalent to the RMSE) for the error in the entire training data will be small. In this study, the prediction model was fitted to dataset with larger rainfall attenuation values in order to reduce the MSE for the entire training data during the learning process. Here, the "dataset with larger rainfall attenuation values" mainly corresponds to the Rx3 data (refer to Fig. 4) with the longest path distance. In other words, the weights of the prediction model were adjusted to reduce the MSE of the entire training data during the training process of the CNN, resulting in a prediction model that fits the Rx3 data better.

Therefore, it can be considered that the RMSE of the proposed model for Rx3 is significantly improved from the ITU model. For the Rx1 and Rx2 data, the path distance of Rx2 is closer to that of Rx3, so the prediction was performed with the prediction model that fits the Rx3 data, and the RMSE improvement from the ITU model was higher in Rx2 than in Rx1.

Figure 6 shows that cumulative probability distribution of the absolute value of the error between predicted and measured value with cumulative probability 70% or greater for the proposed model and the ITU model respectively. We find that the absolute value of the error of the proposed model with respect to the probability value is consistently better than that of the ITU model from 70% to 99.95% cumulative probability.

From the results, we conclude that the advantage of the proposed model over the ITU model in terms of prediction accuracy.

6. Conclusion

In this paper, we proposed a rain attenuation prediction method using a convolutional neural network with map data with rainfall rate and path distance information as input, and validated effectiveness of the method. The main results are as follows:

- The correlation between predicted rain attenuation and rainfall rate on the path was higher than 0.9,
- the RMSE of the predictions was less than 3.19 dB.

These show that our proposed method reflects well physical phenomenon and is effective for rain attenuation prediction.

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