Pseudo Ray-Tracing: Deep Leaning Assisted Outdoor mm-Wave Path Loss Prediction

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Pseudo Ray-Tracing: Deep Leaning Assisted Outdoor mm-Wave Path Loss Prediction

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***Abstract*—In this letter we present our results on how deep learning can be leveraged for outdoor path loss prediction in the 30GHz band. In particular, we exploit deep learning to boost the performance of outdoor path loss prediction in an end-to-end manner. In contrast to existing 3D ray tracing approaches that use geometrical information to model physical radio propagation phenomena, the proposed deep learning-based approach predicts outdoor path loss in the urban 5G scenario directly. To achieve this, a deep learning model is first trained offline using the data generated from simulations utilizing a 3D ray tracing approach. Our simulation results have revealed that the deep learning based approach can deliver outdoor path loss prediction in the 5G scenario with a performance comparable to a state-of-the-art 3D ray tracing simulator. Furthermore, the deep learning-based approach is 30 times faster than the ray tracing approach.**

***Index Terms*—Ray tracing, radio propagation, deep learning, covolutional neural network, 5G.**

I. Introduction

WIRELESS network planning entails conducting multiple simulations to identify signal coverage and signal strength, such that the best location for the base station can be found while minimizing deployment resources. The tools employed to accomplish this task typically build on either empirical or deterministic propagation models. Empirical propagation models leverage observations and measurements to estimate the path loss in particular environments and were favored owing to their speed, despite their lack of accuracy [1]. On the other hand, deterministic propagation models can be more accurate, but they require detailed site-specific information of each propagation environment. Three dimensional (3D) ray tracing, which is based on the geometrical optics approximation, is one of the state-of-the-art deterministic path loss modeling methods [2]. At the high frequency limit, Maxwell's equation can be transformed into an eikonal and a transport equation. Then, the propagating fields can be approximated as rays or ray-tubes, whose phase and amplitude are estimated through the eikonal and the transport equation, respectively [3]. Ray tracing simulations can provide high-accuracy estimates of the wireless channel characteristics, however, they require significantly larger computational resources.

More recently, the use of artificial neural networks (ANNs) in radio propagation modeling has become popular [4], [5]. Such models can acquire and generalize knowledge through experience, and they have been considered for the prediction of the received signal strength or the path loss in outdoor environments. By using layered network structures and raw data, one can automate feature engineering, however, the performance of adaptive models such as ANNs is limited by the features used. Hence, the utilization of deep learning in wireless communication has been documented by several authors [6]–[10]. In 2019, Imai et al. [8] proposed a convolutional neural network (CNN)-based radio propagation modeling method, which focused primarily on short range environmental factors, i.e., those within 128 meters of the transmitter. The proposed model yielded a modest root-mean-square error of 10 decibels (dB). In [9] Levie et al. introduced RadioUNet as a method for estimating path loss, considering only the Dominant Path Model and a limited number of reflections, ignoring other paths with relatively small energies. Ozyegen et al. [10] also explored use of the U-Net architectures with inception modules for fast radio propagation prediction. However, due to the localized receptive field of U-Net like architectures, long distance dependence between transmitter and receiver are ignored.

In this paper, a path loss-Prediction-Net (PPNet) is proposed along with a unique post-processing method for fast and reliable urban path loss prediction. Motivated by Zhang et al. [11], we utilized a 3D ray tracing simulator to generate a path loss data set in urban scenarios. The major contributions of this paper can be summarized as follows.

1. A novel map pre-processing method is introduced, in which information regarding the city layout and the distance between the receiver and the transmitter is conveyed through the input tensor. In addition, the location of the transmitter is represented using a Gaussian kernel which boosts training efficiency and benefits accuracy of prediction.

2. We introduced a deep learning-based propagation model that can accurately estimate the path loss for varying outdoor environments and various location of the serving base station. The data set used for training is collected from simulation inspired by [11] and it poses a difficult path loss prediction task, requiring a methodology that can yield accurate predictions in

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previously unacquainted environments.

3. Building on the efficiency and the robustness of the SegNet architecture [12], PPNet guarantees rapid and reliable path loss prediction. In particular, it employs a modified pooling method that memorizes the initial location of pixels in high-level feature maps, and consequently exploits these maps during the up-sample phase to achieve a higher edge resolution in the prediction.

II. Data Collection and Data Post-Processing

A. Data Collection

Our fixed-region data set contains 50,000 samples, each representing a radio propagation scenario in a 1140 m by 1140 m area with a resolution of 5 meters in both directions. To train our model, we simulated the path loss for multiple outdoor environments, an example of which is shown in Fig. 1, generated by 3D-ray-tracing software (Ranplan Professional). The grid size for each sample is $W \times H = 228 \times 228$ pixels, and the color density of each pixel represents the path loss, i.e., the difference between the transmitting signal strength and the actual received signal strength measured in dB in a 5×5 m^2 area. To augment our data set, we randomly rotate each input and target image by 90°, 180° or 270°, hence effectively increasing the size of our training data set the by a factor of 3.

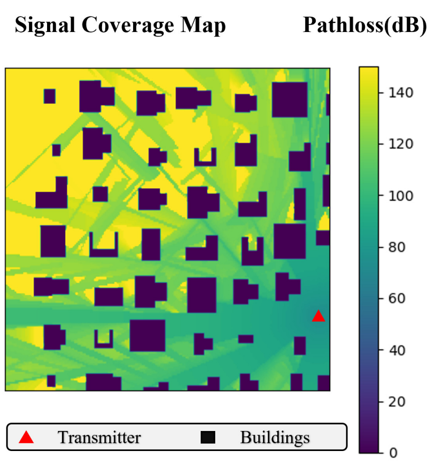

Fig. 1. Sample of signal coverage map.

B. Data Post-Processing

We then processed each sample to yield two equal-sized 2D images, one with three layers and one with a single layer. The single-layer image is used as the target output tensor of our model and it comprises the values of the path loss for each city layout, simulated via a 3D ray-tracer. The three-layer image conveys information related to the geometry of the problem and it is used as our model's input. An example of the input image is shown in Fig. 2. The first layer (blue channel) depicts the city layout, where the height of each building is encoded via the blue color pixel intensity. The second layer indicates the location of the transmitter, representing it as a green dot, enlarged through to the use of a 2D Gaussian kernel:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x_d^2 + y_d^2}{2\sigma^2}} \tag{1}$$

where x_d and y_d are the distance from the transmitter in the horizontal and vertical dimension, respectively, and σ is the standard deviation of the Gaussian distribution. After fine-tuning, σ was selected to be equal to 3. Through (1), we can fuse to the input tensor a surface whose contours are concentric circles with a Gaussian distribution from the center of transmitter, and thus better highlight the transmitter location information, avoiding the use of a sparse matrix in this layer.

The third layer is the positional encoding layer, where the distance from the transmitter is represented by the intensity of the red color. This layer helps our model to have a better understanding regarding the impact of distance on signal attenuation. The three-layer image is used as the input for the model training phase.

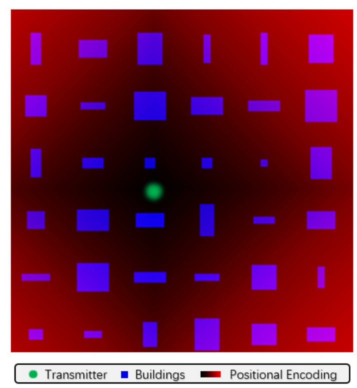

Fig. 2. Example of the three-channel input tensor.

Our goal is to transform the three-layer input image into a radio coverage map at the form shown in Fig. 1. As mentioned, the path loss within the simulated grid is calculated through a ray tracing simulator which is used to train our model at the first stage. This task is similar to semantic segmentation with one major difference. In semantic segmentation the predicted per pixel values are discrete and they represent a certain classification class, while in our case, they are real numbers representing continuous path loss values. To address this problem, in our work we divided the path loss value into 150 classes from 0 dB to 150 dB, where each class represents a range of path loss values within 1 dB. We have found that such treatment enables a faster optimization of the loss function and more accurate path loss predictions, since our model is called to choose between a limited number of discrete values, instead of performing a regression over continuous path loss values. We note that the fine granularity, i.e., 1 dB of the simulated path loss prediction values has a negligible impact on the wireless network design decisions. For all the simulations we use omnidirectional antennas for transmission and reception, and the transmitting frequency is 30 GHz. The base station transmitting power and height of the antenna are 30 dBm and 25 m, respectively. The receive antenna is at the height of 1.5 m above the ground level.

III. Model Selection and Training

In order to predict path loss in outdoor environments, we employed two CNNs: (i) U-Net, which is used in some previous works [10], [12] and (ii) the PPNet which builds on the SegNet architecture. Both SegNet and U-Net are fully convolutional encoder-decoders, designed to perform a pixel-by-pixel transformation of input image to a target output image through supervised learning. By removing all fully connected layers in both network architectures, the number of trainable parameters is significantly reduced, resulting in improved computational efficiency. Also, fully convolutional networks (FCN)-based architecture enables the model to work with scenarios of a non-fixed size that helps generalization to a non-fixed size region data set.

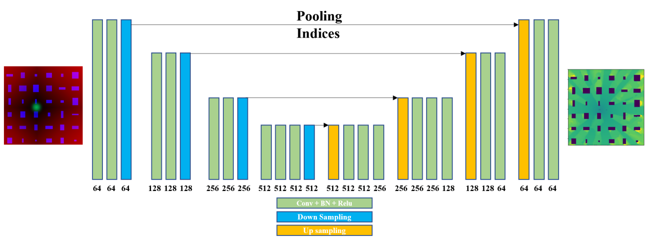

Fig. 3. An illustration of the SegNet [12] architecture used to implement the PPNet.

The SegNet architecture shown in Fig. 3 passes the pooling indices from the compression path to the expansion path, enabling less memory to be used while keeping location information during up-sampling. Also, in our specific task, pooling indices help the model capture the information related to the geographical location. From now on we will refer to the deep learning-based propagation model that leverages SegNet and applies the data post-processing outlined at Section II.B as PPNet. The difference between the pooling layers of PPNet and other conventional fully convolutional networks, such as U-Net, is shown in Fig. 4. The max-pooling layer in conventional FCN, such as U-Net, only passes the largest values to the next layer, therefore, the precise locations of the path loss values are missing during the decoding phase. However, in PPNet the pooling layers keep the locations of the largest value and use them in the decoding phase. This allows our deep learning-based propagation model to benefit from the geometrical information and consequently outperformed U-Net based approaches. We note that the U-Net architecture, shown in Fig. 5, transfers feature maps with different resolution from the encoding to the decoding path. This helps the model to capture correlations of the input image at different scales but at the cost of losing geographical information.

To evaluate the performance ouf model we use the mean average error (MAE) and the root-mean-squared error (RMSE) the defined as:

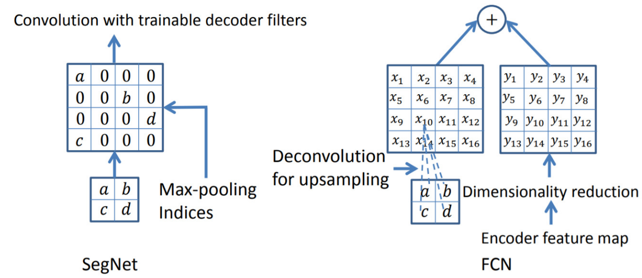

Fig. 4. Max-pooling indices (first introduced in SegNet).

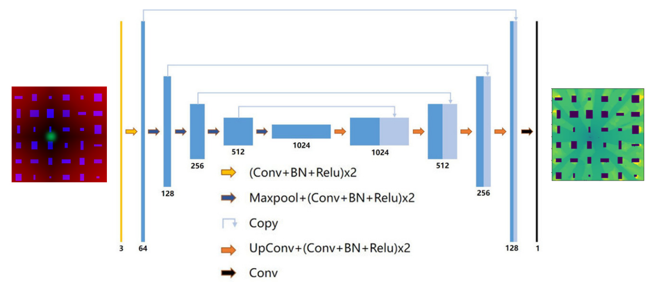

Fig. 5. An illustration of the U-Net architecture.

$$MAE = \frac{1}{NWH}\sum_{n=1}^{N}\sum_{i=1}^{W}\sum_{j=1}^{H}\left|y_{o,(n)}(i,j) - \hat{y}_{o,(n)}(i,j)\right| \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N}\sum_{i=1}^{W}\sum_{j=1}^{H}\left(y_{o,(n)}(i,j) - \hat{y}_{o,(n)}(i,j)\right)^2}{NWH}} \quad (2)$$

Our model is trained with 50,000 samples, and the resolution of input and output images is the same. The data set is divided into a training set and a validation set according to the ratio of 7:3. All the models are trained on an NVIDIA RTX3090 24GB GPU with a batch size of 8. The loss function to be optimized is the cross-entropy, and we use the Adam optimization algorithm with initial learning rate equal to 0.001, and the exponential decay rates set to 0.9 and 0.999, respectively [13].

IV. Results and Analysis

The simulated and predicted coverage maps for nine test set samples are shown in Fig 6, which shows the ground truth, prediction and the absolute error between the ground truth and the predicted path loss, for both known and unknown geometries. As can be observed, the widely adopted U-Net model gives acceptable prediction results in open areas while the prediction accuracy is poor close to the building edges and in dense areas. Also, as the distance between transmitter and receiver increases, the quality of prediction generated by U-Net deteriorates significantly due to its limited receptive field.

We also tested the performance of our proposed post-processing method in a quantitive way and compared them

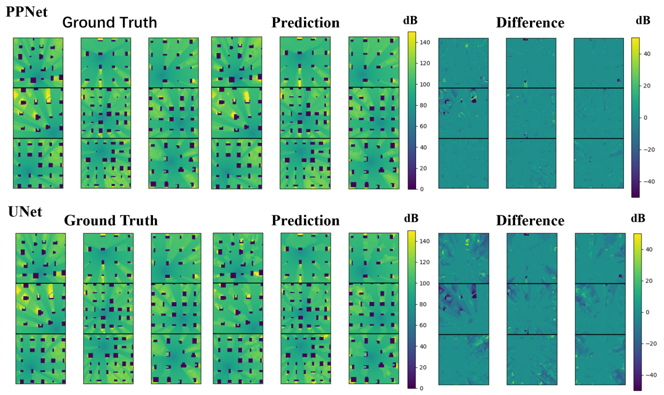

Fig. 6. Ground Truth, Prediction and Difference results (dB scale) for PPNet (top) and U-Net (bottom).

with U-Net. The performance of the models is presented in Table I. As can be seen, the PPNet with pooling indices exhibits a stronger generalization ability and it can model better the path loss. In addition, it can be seen from the result of ablation experiments, our model also benefits from the positional encoding and the Gaussian kernel assisted pre-processing.

TABLE I
PERFORMANCE OF MODELS

Model	MAE (dB)	RMSE (dB)
U-Net	3.29	8.22
PPNet w/o. Positional Encoding	1.14	6.08
PPNet w/o. Guassian Kernal	1.27	6.12
PPNet	1.08	5.78

As mentioned previously, we also calculated the accuracy of our path loss prediction for different values of the error tolerance. We consider the prediction to be accurate if the error between prediction and ground truth in one cell (5×5 m^2) is lower than the tolerance level, and define the prediction reliability to be the number of accurate cells divided by the total number of cells in one prediction. In this case, PPNet improves average prediction reliability by more than 10% compared to that of U-Net, for each tolerance level. Also, attributable to the end-to-end encoding decoding process, our proposed PPNet significantly improves the speed of prediction compared with a 3D ray tracing approach. For our tested urban scenarios, our proposed method takes 1.5 s to complete, while the 3D ray tracing method takes 49.6 s. Thus, the prediction speed is improved by a factor in excess of 30.

V. CONCLUSIONS

In this letter, the SegNet architecture, which enhances the operation of pooling layers through max-pooling indices, is leveraged to create a deep learning-based propagation model that can be used for fast and reliable urban scale path loss prediction. We demonstrate that the SegNet architecture, which was originally used for semantic segmentation, can be also exploited in the field of radio propagation modeling, outperforming other state-of-the-art architectures used in previous

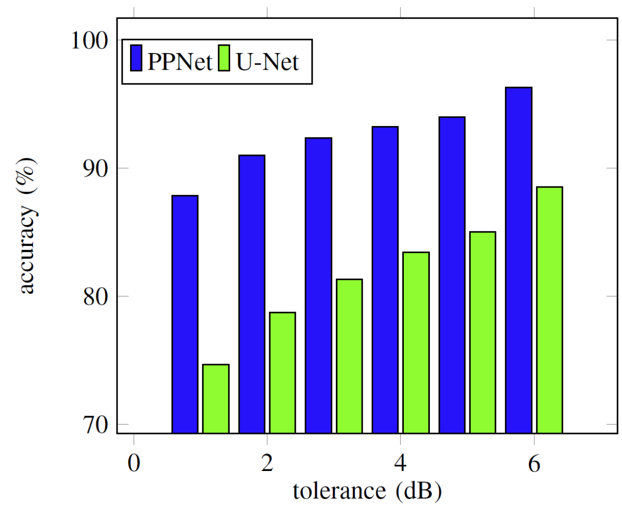

Fig. 7. Pathloss prediction accuracy with different error tolerance of PPNet and UNet

work. The performance of our model is augmented via the positional encoding and the Gaussian kernel layer used during the data pre-processing phase. That helps our model generalize better and improves the accuracy of its prediction. Experimental results show that our method significantly improves the accuracy compared with other U-Net based methods and also provides a rapid path loss prediction compared with the 3D-ray-tracer.

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