PL-GAN: Path Loss Prediction Using Generative Adversarial Networks

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ABSTRACT Accurate prediction of path loss is essential for the design and optimization of wireless communication networks. Existing path loss prediction methods typically suffer from the trade-off between accuracy and computational efficiency. In this paper, we present a deep learning based approach with clear advantages over the existing ones. The proposed method is based on the Generative Adversarial Network (GAN) technique to predict path loss map of a target area from the satellite image or the height map of the area. The proposed method produces the path loss map of the entire target area in a single inference, with accuracy close to the one produced by ray tracing simulations. The method is tested at 900MHz transmission frequency; the trained model and source codes are publicly available on a Github page.

INDEX TERMS Deep learning, height maps, satellite images, GANS, channel parameter estimation, wireless network, regression, excess path loss, air-to-ground communication system.

I. INTRODUCTION
Path loss, which refers to the signal power reduction between transmitter and receiver antennas, is a critical component in the design and optimization of wireless communication networks. Path loss is affected by many factors, including the reflection, refraction and absorption of electromagnetic waves, terrain, vegetation, and weather conditions. Simple analytical models, such as the free-space model and the two-ray ground reflection model, are insufficient for urban environments and irregular terrains. There are empirical models (e.g., Okumura-Hata [1], [2] and COST Hata [3]) that are aimed for urban environments; these models require a characterization of the environment as, for example, “suburban”, “urban” and “metropolitan” [4]; however, such a general classification may not reflect the actual characteristics of a specific area or a specific transmitter-receiver path. Various models have been developed to incorporate the local features along the transmitter-receiver path. For instance, Walisch–Ikegami model [3] includes parameters, such as average building heights, average road widths and road orientation between transmitter and receiver. There are also alternative parametric models, such as the alpha-beta-gamma and the close-in models [5], which do not define the parameter values based on specific building characteristics but require the optimization of parameters from measurement data.

Compared to analytical and empirical models, ray tracing simulations result in more accurate predictions in urban environments when there is a 3D model of the region [6], [7], [8]. The downside of ray tracing simulations is the high computational cost, making it impractical for network planning applications.

Machine learning based approaches have also been utilized for path loss prediction. Traditional machine learning methods use hand-crafted features (e.g., building density, average building height and average street width) to train a model [9], [10]. The training data may be obtained from ray tracing simulations or field measurements.

The need for choosing the right features is a major issue in traditional machine learning methods; deep learning methods overcome this issue by learning the features as well during the training process. In recent years, deep learning based path loss prediction methods have been proposed. In [11],
the satellite image of a target area is input to a convolutional neural network (CNN) to produce path loss model parameters. The path loss model is the log-distance path model; the network predicts the path loss exponent and shadowing factor of the model. In [12], the path loss distribution of an area, instead of specific model parameters, is predicted again from satellite images. The path loss distribution does not tell the path loss value at a specific point, but it can be used to determine critical regional values, such as the coverage area. In [13], the building profile between transmitter and receiver is input to a deep fully connected neural network to predict the path loss value at the receiver. The main disadvantage of such point-to-point path loss modeling is the need to run the network for each receiver point. There are also methods that combine features extracted from satellite images with some additional features (e.g. transmitter height, receiver height, transmitter-receiver distance and frequency), and then input to a neural network for path loss regression [14], [15].

In this paper, we present a deep learning based approach to predict path loss at every point in a target region (in a single inference) directly from the satellite image or the height map of the region. This is a clear advantage over the point-to-point prediction models, which require a separate inference for each point, and over the parametric prediction models, which fit a global model for the entire region and do not predict path loss at every receiver point.

Our approach is based on the Generator Adversarial Network (GAN) technique. GANs are typically used in computer vision for style transfer applications [16]. We are able to adopt the GAN technique by treating path loss values of the target region as an image. The proposed network, which we call PL-GAN, is trained with data obtained from extensive ray tracing simulations. The trained network produces path loss values almost instantly, with accuracy close to ray tracing simulations. The trained model and source codes are publicly available on a Github page1.

The paper is organized as follows. In Section II, we describe how the training/testing dataset is generated. We present the proposed network architecture in Section III. We explain the training method in Section IV. We present the results in Section V and conclude the paper in Section VI.2

II. DATASET GENERATION

The dataset is generated following the process described in [11] and [12] with some changes necessary for the proposed architecture. We have the satellite images and corresponding 3D models of some urban/suburban regions, each with size 1.8km × 1.8km [11]. The PlaceMaker3 extension for Google SketchUp4 is used to obtain the 3D models along with the satellite images. The 3D models are imported and merged with a flat terrain in Wireless InSite5 ray tracing simulation environment. The terrain is set as dry earth and the building material is set as concrete. In each model, the transmitter is placed at the center of a region at a height of 40m above ground. The receivers are placed at 1.5m above ground on a 110 × 110 grid. The transmitter power is set to 60 dBm, the transmission frequency is set to 900 MHz, and the antenna type is set as an omni-directional antenna. Using the ray tracing simulations, excess path loss values at the receivers are calculated. (Receivers that are placed inside the buildings are known since the 3D models are available. The path loss values corresponding to these locations are not reliable, and they are excluded from the final performance evaluation, as we will explain later.)

The size of each satellite image is 256 × 256; to match this size, the path loss values on the 110 × 110 grid is resized to 256 × 256 with bilinear interpolation.

As an alternative to satellite images, we want to investigate the use of 3D models to predict path loss values. 3D models are converted to height map images using orthographic projection; a pixel value in a height map represents the height of that point in the 3D model. The height maps are also resized to 256 × 256 to match the sizes of satellite images and path loss images.

A block diagram of the dataset generation process is presented in Figure 1. The satellite image, height map image, and path loss image of a sample region is given in Figure 2.

![Figure 1. Block diagram of dataset generation. The satellite image, height map image and path loss image of each target region is added to the dataset.](https://example.com/dataset.png)

III. NETWORK ARCHITECTURE

We treat path loss values on a grid of receivers as an image; this allows us to utilize image synthesis methods in the path loss prediction. Generative Adversarial Network (GAN) is a recently developed deep learning based image synthesis approach; it has been successfully used in style transfer, inpainting, super resolution and image-to-image translation. GAN training includes two networks: a generator network to generate new examples, and a discriminator network to classify examples as real or fake [16].

Our idea is to use GAN to produce path loss image (that is, path loss values on a grid of receivers in the entire target region) from a satellite or a height map image. The proposed generator and discriminator architectures are presented in Figures 3 and 4, respectively. The generator is essentially a U-Net structure with skip connections, which is known to allow deeper architectures. We use 15 convolutional blocks

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1 https://github.com/ahmarey/PLGAN
2 https://www.remcom.com/wireless-insite-em-propagation-software
3 https://www.sketchup.com
4 https://www.suplacemaker.com
5 https://www.sketchup.com
increase the size while reducing the depth until the original image dimensions are reached. (The generator architecture is given in Figure 3.)

For the discriminator, we use a patch discriminator [17] that decides on each patch of the generator output as true or fake. The advantage of patch discriminator is that it has fewer parameters, can be applied to arbitrarily large images, and has been shown to produce high quality results [18]. We use stride of two at the initial layers to reduce the number of parameters to be estimated while preferring stride of one later in order not to lose the image details. The discriminator has the concatenation of generated image and true image as its input; and it consists of eight convolutional blocks, producing an output of size $5 \times 5 \times 1$ for each patch. (The discriminator architecture is given in Figure 4.)

The loss functions and the training process are described in the next section. Regarding the architectures, we tried some other variations as well. Using a small sized output for the discriminator and having enough depth turned out to be crucial for the current success.

### IV. TRAINING THE NETWORKS

We train two separate networks, one for satellite image as the input and one for height map as the input. At the end, we will compare their performances. The training process is very similar for both cases, except for some minor changes. Training a GAN network is not straightforward; in this section, we explain our training process in detail. The final goal of GAN training is such that the generator is able to deceive a well-trained discriminator.

The loss function for the generator training has two components, as illustrated in Figure 5. One loss component measures how well the discriminator is deceived. An input image, which is either a satellite image or a height map, is passed to the generator. The generated path loss image is input to the discriminator, which decides patch-by-patch whether the generator output is true. The discriminator output is compared against an array of ones, each corresponding to patch; and binary cross entropy is used as the cost function. In the perfect case, the discriminator is totally deceived and produces an output of one for each patch. The other loss component is the L1 loss between the true path loss image and the generated path loss image. Finally, a weighted sum of the binary cross-entropy loss and L1 loss is taken, where the weight of the L1 loss is 100 times the other weight, as suggested in [18].

The generator training is modified slightly for the height map network. When the input image is satellite image, the L1 loss between the generated and true images is calculated for all pixels. When the input image height map, we know whether a pixel corresponds to an indoor location or an outdoor location. Therefore, the L1 loss is calculated for only the outdoor pixels, forcing the network to minimize the error on the outdoor path loss estimation and disregard the error for the indoor locations.

For the discriminator, the goal is to train a network that distinguishes between true and fake path loss images.
FIGURE 3. The generator architecture. BLOCK1, which consists of 2D convolution with filter size $4 \times 4$ and stride 2, batch normalization and Leaky ReLU layers, is repeated eight times. These layers are followed by upsampling layers. The upsampling layers include repeated application of BLOCK2, which consists of transpose convolution with filter size $4 \times 4$ and stride 2, batch normalization and Leaky ReLU layers. The number of filters is indicated above each block.

FIGURE 4. The discriminator architecture. BLOCK1, which consists of 2D convolution with filter size $4 \times 4$ and stride 2, batch normalization and Leaky ReLU layers, is repeated three times. These layers are followed by repeated application of BLOCK2, which consists of 2D convolution with filter size $4 \times 4$ and stride 1, batch normalization and Leaky ReLU layers. The number of filters is indicated above each block.

FIGURE 5. The loss function for the generator training.

The discriminator takes two inputs, one is the true path loss image and the other is either the generated path loss image or the true path loss image. When the inputs are true path loss image and the generated path loss image, the discriminator should classify each patch as fake (i.e. return “0”); therefore, the loss function is binary cross-entropy loss.

FIGURE 6. The loss function for the discriminator training when true and generated images are input.
between the discriminator output and a matrix of zeros, as illustrated in Figure 6. When both input images are real path loss images, binary cross-entropy between the discriminator outputs and a matrix of ones is calculated.

The dataset, which consists of 997 image pairs, is split into training (902) and testing (95) sets. The training images are augmented, using rotations (90 and 180 degrees) and flipping (horizontal and vertical), to increase the training set size eight times.
folds to 7216. We used Adam optimizer for training both the generator and discriminator with learning rate 0.0001 and batch size of 32. We trained the network on Tensorflow 2.0 on Nvidia RTX 2060 GPU where the training goes for about 12 hours for 500 epochs. (The trained model is available on the Github link, as mentioned before.)

V. EVALUATION
To evaluate the performance of the proposed approach, we use two quantitative measures. The first one is the root mean squared error (RMSE) between true path loss values and predicted path loss values, averaged over the entire test set. The second one is the mean squared error (MSE) between the true path loss distribution and the distribution obtained from the predicted path loss image, averaged over the entire test set.

The results are given in Table 1. The average RMSEs for satellite image and height map as input are similar. The average MSE between the distributions for satellite image as input is lower than that for height map image as input. In the table, we also included a result from [12] (the closest experiment to our scenario with satellite image as input, 900Mhz frequency, 80m altitude, eight bin representation of distribution), as a rough comparison. The average MSE results are about two folds better than the ones in [12]. The average RMSE results are about 44dB, which is satisfactory considering the fact that the dynamic range of excess path loss in the experiments is more than 270dB. In addition, the visual results indicate that path loss values including shadowing due to buildings are predicted well.

In Figure 7, we provide results for three sample regions. In the figure, the first row shows the satellite images and the second row shows the height map images. The colorbar next to the height map images indicates heights in meters. The third row shows the true excess path loss values. The color bar next to the images are the path loss values in dB. The fourth and fifth rows show the predicted excess path loss images for the network that takes satellite images as input and the network that takes height map images as input, respectively.

In these images, we note that shadowing due to buildings are captured well with both methods, while height map images can result in sharper shadowing boundaries.

In Figure 8, we show the path loss distributions for the regions given Figure 7. These results also indicate that the overall shape of the distribution can be predicted well.

VI. CONCLUSION
In this work, we present a deep learning based approach to predict the point-wise path loss values of an entire region from either height map images or satellite images. Treating path loss values of a region as an image, we use a GAN model for the supervised estimation problem. The networks can produce real-time inference and prove to be viable alternative to ray tracing simulations, which have high computational complexity.

Comparing height map images and satellite images as input, we found that height images can lead to better results. This is mainly due to the fact that definite height structure is more informative about the shadowing effects compared to satellite images.

By increasing the dataset size, it is possible to achieve better results. We leave this as a future work because other than the dataset that we have there are no public datasets that have path loss images as well as corresponding satellite images and height maps. We hope that this work will initiate further research and innovations in this area.

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