Path Loss Prediction in Urban Areas: A Machine Learning Approach

Irfan Farhan Mohamad Rafie, *Student Member, IEEE*, Soo Yong Lim, *Senior Member, IEEE*, and Michael Jenn Hwan Chung

***Abstract*—Propagation prediction is important in that it contributes toward optimal base station planning and placement. This is especially relevant for 5G and other future generations of cellular networks. In this work, we propose a machine learning-based method to rapidly predict path loss in an urban area using data extracted from online sources, such as OpenStreetMap and other geographical information systems to aid in cellular coverage estimation in an area. The outcome of this work is useful for an urban environment that sees rapid development and changes to its landscape. In such a scenario, the location of the existing base station will benefit from adjustment for optimal coverage provision.**

***Index Terms*—Convolutional neural network (CNN), outdoor radio propagation, path loss prediction, ray tracing.**

I. Introduction

RADIO propagation modeling in urban areas has been a hot topic for research due to the increasing number of mobile devices that require high bandwidth. Maintaining constant connectivity is crucial especially in fields where time-critical information is transmitted, such as the Internet of Things (IoT) [1]. With the new generation of fifth generation (5G) and the proposed future generations of cellular connectivity, higher frequencies are being used and they are more affected by the loss of line of sight (LoS). This makes accurate path loss prediction important because it contributes toward optimal base station planning. Furthermore, rapid environmental changes due to urban development may reduce the accuracy of currently deployed base stations. This in turn requires changes in base station placement either by adding new nodes to increase coverage or adjusting the placement of current base stations. Using machine learning and open-source data, it is possible to rapidly predict path loss in an urban area using data extracted from OpenStreetMap or other 3-D sourced building information to aid in adjusting cellular coverage in an area.

In general, radio propagation in urban areas is predicted using one of the following three models: 1) empirical, 2) theoretical, and 3) deterministic models. These models' pros and cons are shown in Table I.

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TABLE I
PATH LOSS PREDICTION MODELS

Path Loss Model	Speed	Accuracy	Complexity
Empirical	Fastest	Lowest	Lowest
Theoretical	Medium	Medium	Medium
Deterministic	Slow	Highest	Highest

Although deterministic models have the highest accuracy, they have a tradeoff in that computing complexity increases as the number of propagation paths and buildings increase. This limits the accuracy of ray-tracing models above certain distances which is limited by either software or hardware. MATLAB ray-tracing method for example is only limited to ten ray reflections and this may cause inaccuracy issues in high density areas even for short distances. And yet, for accurate propagation prediction, it is crucial to identify the particular propagation mechanisms for each urban environment, such as direct rays, reflected and transmitted rays, and diffracted rays. Past research shows that in a narrow structure, which could imply urban canyon or narrow street, reflection phenomenon becomes a very complex solution in the non-line-of-sight (NLoS) section of the structure as far as ray-tracing is concerned [2]. In such scenarios, a deterministic method may not be a good choice. (For records, the world's narrowest street is located in the old town of Reutlingen in Germany. This street is only 31 cm wide at its narrowest point and on average it is 40 cm wide).

On the other hand, machine learning looks set to boast a positive outlook in path loss prediction [3]. In [3], the frequency considered is on the lower end of the frequency spectrum, whereby the attenuation caused by the loss of LoS is marginally less compared to higher frequencies. In [4], similar work was done but less reflections were considered due to the complexity of performing prediction in a dense urban area. The common point is, machine learning was utilized and the reported improved performance compared to traditional methods is encouraging. Along this line of interest, in this work we have further explored machine learning methods to conduct propagation modeling and prediction in urban areas, as they contribute greatly toward modern cellular network planning and optimization, especially for 5G communication, or beyond. As research progresses, the key goal for machine learning is to provide accurate path loss prediction results similar to ray-tracing with the prediction speed closer to empirical methods for a similarly sized area. Public map

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data are extracted from OpenStreetMap across a wide range of frequencies, from 897 MHz to 60 GHz, for propagation prediction with convolutional neural networks (CNN). Promising results are obtained with reasonable accuracy recorded.

II. Data Preparation

Data from several cities were extracted from OpenStreetMap and ray-tracing simulation was performed using MATLAB with a maximum range of 1000 m. The cities considered include Munich, Paris, and Singapore. The input for training was images that only contain information in a bounded box surrounding the transmitter–receiver pair. The bounding box size was set to be 44.4 m away from the transmitter and receiver to ensure that possible reflection paths are included without including too much unnecessary building information. The position of the transmitter was marked by the darkest spot in the contour image. Several functions were applied to this data to generate five distinct transmitter–receiver paired files which are as follows.

1) *Side View*: This indicates the number of intersecting objects between transmitter and receiver.
2) *Contour*: This indicates the distance between the transmitter and receiver, where brightness increases as distance increases.
3) *Top View Cluster*: This indicates the position of building layout, where their height is marked by color.
4) *Top View Negative*: This indicates possible paths for the LoS path at similar transmitter–receiver pair height.
5) Companion CSV tabular file that contains:
   a) carrier frequency;
   b) distance between transmitter–receiver pair;
   c) free-space path loss value derived from the Friis equation

$$\mathrm{FSPL} = \left(\frac{4\pi d}{\lambda}\right)^2 \tag{1}$$

   d) visible objects seen in the top view cluster;
   e) the number of objects intersecting a straight-line path between transmitter and receiver;
   f) maximum building height seen in top-view cluster;
   g) minimum building height seen in top-view cluster;
   h) the height difference between transmitter and receiver.

Fig. 1 shows the input image for the tensor, where the top-left image is the side view, top right is the contour, bottom left is the top-view cluster and bottom right is the top-view negative. The red line shown in Fig. 1(a) and (b) is to indicate the straight-line path between transmitter and receiver. This provides angle information in the side view [Fig. 1(a)], as well as distance information in the top-view contour [Fig. 1(b)].

Our metric for model accuracy is the root mean square error (RMSE), which is the industry standard as

$$\mathrm{RMSE} = \left(\frac{\sum_{i=1}^{N}\left(z_1 - z_0\right)^2}{N}\right)^{1/2} \tag{2}$$

where

$N =$ sample size;
$Z_1 =$ predicted value;
$Z_0 =$ ground truth value.

III. Model Training

This image data were then passed through a CNN and concatenated with our multilayer perceptron (MLP) as tensor objects.

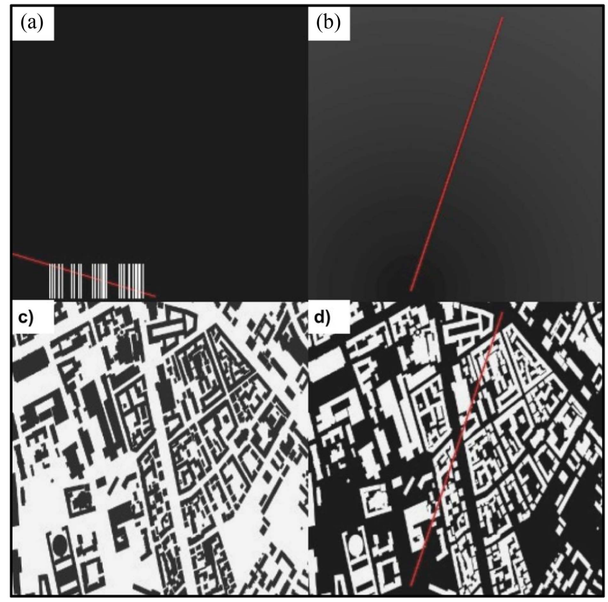

Fig. 1. Illustration of the input images. (a) Side view. (b) Contour. (c) Top-view cluster. (d) Top-view negative.

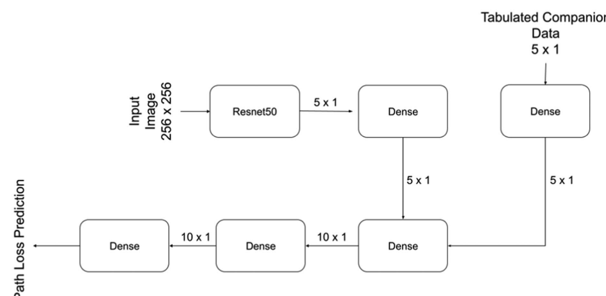

Fig. 2. Model illustration.

Fig. 2 visualizes the model adopted in this letter, where our CNN input begins at $256 \times 256 \times 3$ (width, height, and depth). The input image resolution was chosen to maximize information density whilst minimizing memory size. An investigation into the resolution indicates that the amount of extractable performance from increased resolution plateaus at this resolution. When designing the input image (Fig. 1), we have included the transmission angle, azimuth, building density, LoS information, and building height information in a small package, which is relatively less complex compared to 3-D file information used in ray-tracing technique. This simplifies the model needed in order to perform rapid path loss predictions. The input image also contains simplified information in order to train the model to recognize diffraction, transmission, and certain reflection properties from the presence of the building edges in Fig. 1(a) and (d) regardless of vertical or horizontal diffraction along the propagation path [5].

Resnet50 is selected as it performed the best compared to VGG and other Resnet variations considering model complexity and speed [6]. We observed that nonresidual models tend to perform worse compared to residual models in our use case. In Fig. 2, the CNN is fully connected to a five-node layer that is concatenated with our tabulated data that has five data inputs

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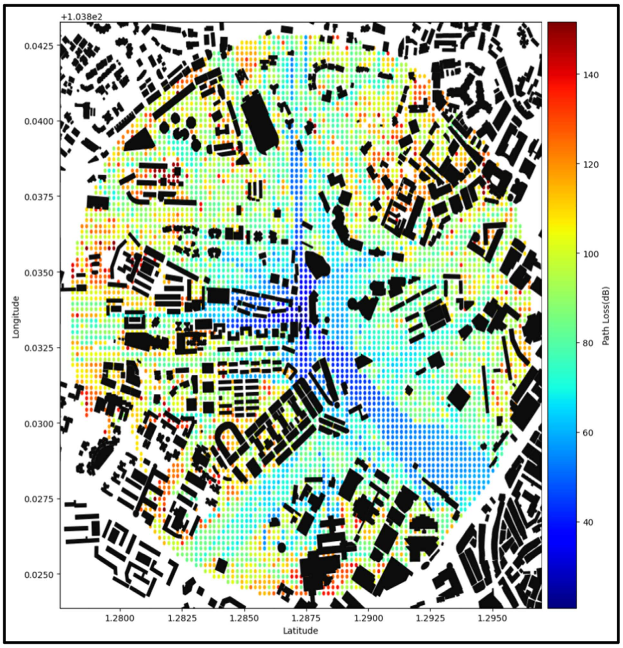

Fig. 3. Ray-tracing simulated path loss.

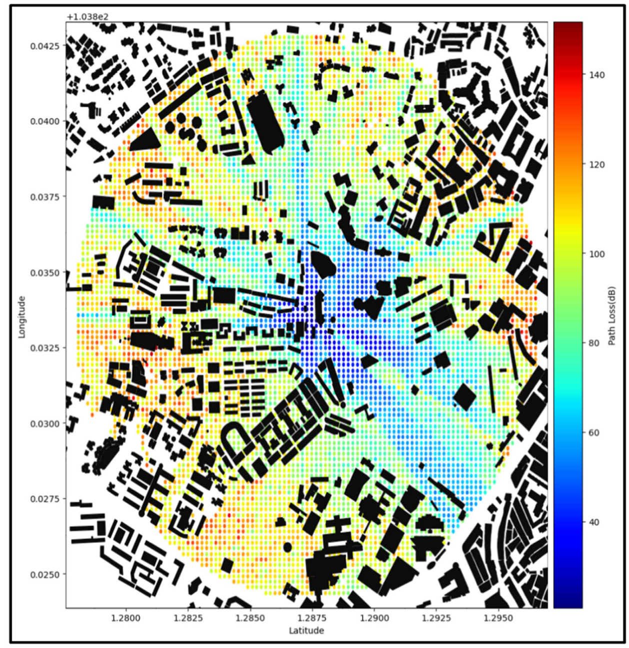

Fig. 4. Machine learning predicted path loss.

resulting in a ten-node layer. This provides weight balance between these two inputs to prevent overfitting as well as providing an extra layer of dimension to the CNN output. An investigation into this aspect demonstrated that a ratio of 1:1 when performing concatenation resulted in the best model when tested with our dataset. Two layers was chosen in our model as more dense layers tend to result in overfit models and less layers lack the depth needed to fit our data resulting in underfit models.

Convolution, batch normalization, and rectified linear (reLU) activation functions were performed within each encoded layer, as described in [6]. Ray-tracing data that were generated via MATLAB was first sanitized by removing invalid values that are generated. This was afterward used to generate our input images, such as that shown in Fig. 1. Training was performed using 120 000 distinct data points from a city and was validated on 20 000 data points collected from a different area of the city with varying frequencies from 897 MHz to 60 GHz. The loss function used for this model is root mean squared logarithmic error (RMSLE) as it provides the best performance for this model and it punishes underpredicted values significantly more compared to overpredicted values, which is a feature that does not harm base station placement due to the overlapping coverage. Our maximum training epoch was set to 200, but early stopping was enabled if the model is unable to learn further from the supplied data.

IV. Results Comparison with Ray-Tracing Data

Figs. 3 and 4 show the ray-tracing and predicted path loss, respectively, while Table II records the results for the predicted cities in the following metrics RMSE, mean absolute error (MAE), and RMSLE.

In addition to Table II, in Fig. 5 we present the path loss results for Munich City. It is worth highlighting that our model is capable of predicting path loss in areas where ray-tracing is unable to simulate due to the maximum reflection count constraints. This can be seen in Fig. 5(a), where the ray-tracing model plot has null values in certain areas.

TABLE II
Other Cities Metrics

City	RMSE	MAE	RMSLE
Munich	21.60	17.07	0.2173
Paris	22.07	19.94	0.2735
Singapore	20.17	15.59	0.4859

Although we recorded higher RMSE values, which are above 7 dB, the radiation pattern and the accuracy at shorter ranges and LoS paths are remarkably accurate. We postulated that our RMSE values increase as the number of rays' reflection increases, and this is consistent with the observation reported in [7]. In addition, based on our observations, calibration is required in order to better fit both ray-racing and machine learning models to real-world measurements. As seen in Fig. 5(a), by applying a similar dB gain to both ray-tracing and machine learning models, a better fit is achieved, resulting in an RMSE of 12.87 after calibration compared to an RMSE of 32.93 prior for the METRO200 dataset. Fundamentally, a model may have different RMSE values at different frequencies due to the effects of reflection, refraction, absorption, and diffraction. Optimistically, our results at lower frequencies, such as 897 MHz and 2.4 GHz have similar RMSE values that are very much comparable to the ray-tracing results.

Fig. 5(b) and (c) shows the comparison between real-world measurements and our model, alongside other classic models. Our model is slightly skewed in the x-axis due to the additional receiver points being added in between turning points on the path. Adjusting for this skewness, we can see that the path loss pattern is very similar. In this comparison to real-world measurements from [8], we noticed that the predicted signals are more susceptible to path loss due to the loss of LoS compared

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Fig. 5. Comparison between the real-world measurements and our model. (a) Comparison between ray tracing and machine learning. (b) Comparison between real world and various models. (c) Path loss versus distance.

to real-world measurements. This result is expected due to the reduced effect of NLoS scenarios in the real world compared to ray-tracing simulations. To rectify this, in future works, a mixture of data from real-world measurements, empirical models are recommended to be used at all frequencies to align ray-tracing performance closer to real-world values. It was also observed that the prediction speed for the model is significantly faster at an average of 1.7 ms per transmitter receiver pair (using an Intel i7-9700k and RTX 3070). To predict the same number of points that were generated by ray-tracing, our model only took 47 s, whereas MATLAB took over 40 min. However, it is noted that our model is run on TensorFlow using a GPU, whereas MATLAB simulation is not capable of running on GPU.

V. Conclusion

In this letter, we have presented a machine learning-based method to rapidly predict path loss using top-view images and building footprint data from online sources, such as OpenStreetMap and other GIS. Specifically, we have trained our model using data in Munich and validated it in Paris and Singapore and achieved good accuracy in both. For mm-wave and other high-frequency backhaul systems that require LoS or a maximum of two reflections, our proposed model will come in handy. For future work, diversification of training input sources is recommended for further fine-tuning of the model.

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