Generative Adversarial Network for Predicting Measured RF Signal Strength

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Abstract— **Accurate real-time Radio Frequency (RF) signal strength prediction is essential for optimizing wireless communication systems, enabling efficient network deployment, and supporting emerging technologies. In this paper, we propose a Generative Adversarial Network (GAN)-based approach for real-time prediction of real (or measured) RF signal strengths. In particular, we train a GAN model using both simulation and a limited number of real-world measurement data. Then, we use the GAN to predict the measured signal strength anywhere on the provided urban map. The proposed GAN model is applied to real-world urban environments and its performance is evaluated against actual measurement data. The results validate the effectiveness of the GAN-based approach in accurately predicting RF signal strength, demonstrating its potential for improving wireless network planning and optimization.**

I. Introduction

In recent years, wireless communication systems operating in the Radio Frequency (RF) range have advanced significantly, particularly in cellular technology, to enable faster and more efficient data transmission. Accurate prediction of RF signal power is crucial for optimizing network performance. Traditional empirical models, such as the free-space propagation model, are commonly used to estimate path loss. However, this model is inadequate for urban environments, where obstacles like buildings, trees, and vehicles disrupt signal transmission, making it unsuitable for urban channel modeling [1]. Alternatively, ray-tracing techniques offer precise signal strength estimation but come at the cost of high computational complexity and long simulation times [2]. Given these challenges, there is a pressing need for a channel model that can accurately predict received signal strength while maintaining computational efficiency. Furthermore, directly measuring received power at every location is impractical, underscoring the importance of developing a model that effectively replicates real-world propagation conditions with improved accuracy.

Deep learning methods have been widely applied to enhance the accuracy of RF signal power prediction. Zhang et al. [3] introduced RayProNet, an innovative approach to radio propagation modeling based on neural point fields. Ahmad Fauzi et al. [4] compared various supervised learning methods and found that the Ensembles of Trees (ET) model, utilizing the Random Forest algorithm, is the most practical for real-world signal prediction. Additionally, Hong Cheng [5] proposed a convolutional neural network (CNN) architecture with four subnetworks, incorporating feature sharing between convolution layers, which demonstrated superior accuracy and computational efficiency compared to empirical and deterministic models.

In this work, we aim to predict received signal strength and coverage area for RF transmissions in the Ultra High Frequency (UHF) band up to 6 GHz, considering a base station in an urban environment. To achieve this, we propose using a Generative Adversarial Network (GAN) trained on simulation data from Wireless InSite, a radio propagation simulation software, along with a limited set of real-world measurements to generate a more realistic received power map. By leveraging GANs' ability to learn underlying data distributions, we enhance the accuracy of power predictions while reducing reliance on extensive measurement campaigns. Compared to conventional models like U-Net, GANs require fewer training samples, making them well-suited for scenarios where generating large-scale simulation data is computationally expensive and time-consuming [6]. In this paper, we employ the Pix2Pix GAN to develop a deep learning model for accurate received signal strength prediction in urban environments. Experimental validation confirms the feasibility and effectiveness of our approach for urban channel modeling.

II. Methodology

The flow chart of GAN-based framework is provided in Fig.1. During the training process, the input to the generator is the simulation data, then the discriminator will try to distinguish the output of the generator from ground truth, which is generated by replacing the received power values in the simulation data with the real measurement data and interpolate the rest of the received power values accordingly. The interpolated measured data map is generated using a separate multilayer perceptron (MLP) trained only with the measured data. The simulation data from Wireless-Insite, together with the real measured data, will go through the trained MLP to get the interpolated measured data. Measurement locations of the real measurement data are represented by yellow dots on the map. The discriminator takes both generated images and ground truth as inputs, and try to distinguish the generated images from the ground truth.

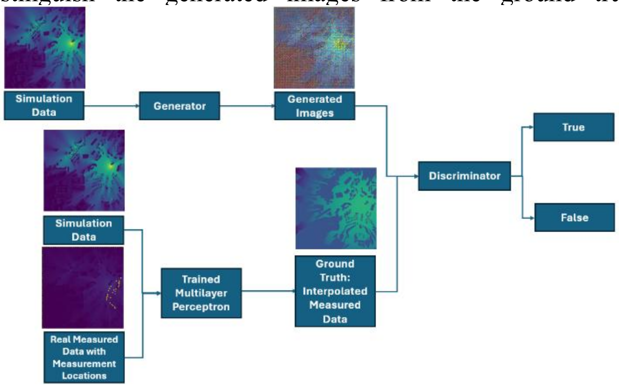
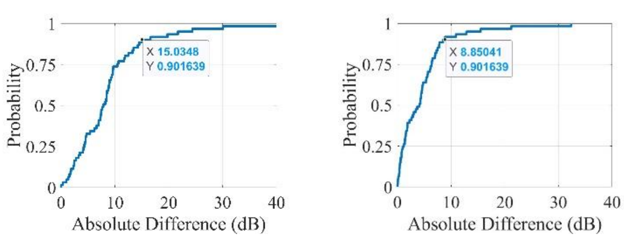


Figure 1. Flow chart of the GAN-based framework

We will use a timestamp-based approach to replace measurement data, as the transmitter's position changes over time. At each timestamp, all receivers capture the RF signal from the same transmitter location. As data collection requires large amount of time and manpower, we have 538 images in our dataset. 100 images are randomly selected from the dataset as testing dataset to test the trained GAN model. The rest of the images are used to train the GAN.

III. Results

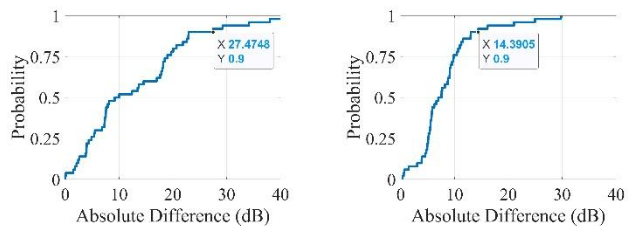
Fig.2 compares simulation, measurement, and GAN results at low-frequency range from 200MHz to 800MHz. In particular, the x-axis of both figures is the absolute difference between simulation/predicted data and real measurement data, while y-axis is the percentage of samples in dataset. In Fig.2(a), the simulation results are compared with measurement results and it was observed that 90-percentile value of the differences is within 15.0dB. This means that there exists a large difference between simulation and real measurement data. On the other hand, Fig.2(b) compares the absolute difference between GAN predictions and real measurement data. The 90-percentile value of the differences is within 8.85dB, which is 6.15dB smaller compared to Fig.2(a). This comparison shows that, with the inclusion of measurement, GAN can improve the received power simulation and make it closer to the real measurement data in urban environments when RF signal is at relatively low frequencies.



(a) (b)

Figure 2. At the low frequencies, the cumulative distribution of the absolute difference between (a) simulation data and measurement data and (b) GAN prediction and measurement data.

Fig.3(a) compares the simulation results and GAN results at the high-frequency range from 1GHz to 6GHz. Fig.3(a) shows that 90-percentile value of the absolute differences between simulation data and real measurement data is within 27.47dB. Fig.3(b) compares the GAN-predicted results and measurement results; 90-percentile of the differences between GAN data and measurement data is less than 14.39dB, which is 13.08dB better compared to Fig 3(a).



(a) (b)

Figure 3. At the high frequencies, the cumulative distribution of the absolute difference between (a) simulation data and measurement data and (b) GAN prediction and measurement data.

IV. Conclusion

In this paper, we proposed a GAN-based approach for real-time prediction of RF signal strength by leveraging both simulated and limited real-world measurement data. Our model effectively generates accurate signal strength predictions across urban environments, addressing the challenges of conventional propagation models. Performance evaluations against actual measurement data validate the effectiveness of our approach, demonstrating its potential for enhancing wireless network planning and optimization. By improving prediction accuracy while reducing the need for extensive measurements, the proposed method offers a promising solution for efficient and data-driven wireless communication system design.

References

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