Statistical Channel Modeling for Indoor Environments Using Generative Neural Networks - Project Plan

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I. Problem Statement

A. Background

The vast amounts of bandwidth (over tens of GHz) offered by the Millimeter-wave (mmWave) and Terahertz (THz) spectrum [1] have the potential to support rapidly increasing mobile traffic demand throughout the world, which is expected to reach 77 exabytes per month by 2022 [2]. Advancements in technologies that operate in these frequencies (e.g. massive multiple input output (MIMO)) aims to support such stringent demands, but introduce more difficulties and challenges. Conventional channel modeling approaches may not accurately characterize the wireless channel given the increased number of complex modeling components. Thus, deep learning is considered to be a potential solution to this problem from a data-driven perspective. This project aims to employ a generative neural network to predict statistical channel information by using the simulated channels generated from a ray tracer as the training data.

B. Conventional Channel Modeling

A received signal is commonly viewed as a superposition of multiple replicas of the transmitted signal with different delays and angles for any wireless propagation channel. Conventional channel modeling approaches can be classified into two types: deterministic approach and statistical approach. Deterministic approach describes the channel by modeling each propagation paths through free space propagation, reflection, diffraction, and scattering. Given a site-specific environment, the dimensions and building materials are required to generate propagation paths. Such deterministic approach is also well known as ray tracing, and high computation complexity and demanding requirements on the details of the environment are major concerns.

Instead, the statistical modeling approach considers the channel as a random variable, which usually cannot accurately recreate the channel conditions in a certain environment, but is capable of realizing the probabilistic distribution of a type of environment. A widely used cluster-based statistical channel model is given by

$$h(t,\overrightarrow{\Theta},\overrightarrow{\Phi})=\sum_{n=1}^{N}\sum_{m=1}^{M_n}a_{m,n}e^{j\varphi_{m,n}}\cdot\delta(t-\tau_{m,n})\cdot\delta(\overrightarrow{\Theta}-\overrightarrow{\Theta_{m,n}})\cdot\delta(\overrightarrow{\Phi}-\overrightarrow{\Phi_{m,n}}), \tag{1}$$

where t is the absolute propagation time, $\overrightarrow{\Theta}=(\phi_{\text{AOD}},\theta_{\text{ZOD}})$ is the angle of departure (AOD) vector, and $\overrightarrow{\Phi}=(\phi_{\text{AOA}},\theta_{\text{ZOA}})$ is the angle of arrival (AOA) vector. N and M_n denote the number of clusters and the number of subpaths within each cluster, respectively. For the mth subpath in the nth cluster, $a_{m,n}$, $\varphi_{m,n}$, $\tau_{m,n}$, $\overrightarrow{\Theta_{m,n}}$, and $\overrightarrow{\Phi_{m,n}}$ represent the magnitude, phase, absolute time delay, AOD vector and AOA vector, respectively. As shown above, each channel parameter is fitted by some distribution, but the correlations among these channel parameters may not be accurately reserved.

C. Generative Channel Modeling

As the advent of deep learning, people start thinking about how deep learning techniques can be leveraged in wireless communications. Our idea is to train neural networks so that the neural networks can generate life-like channel information given a set of input parameters such as frequency, environment type, and separation distance.

A commercial ray tracer, Remcom, is used to generate the channel realization in an indoor multi-floor factory scenario and an indoor residential home scenario at 60 GHz. Many transmitter (TX) and receiver (RX) locations are selected in the environment. Then, the ray tracer simulates the channels between each pair of the TX and RX, which can output the path loss, the number of paths, the delay, power, and angle of each path, etc. These channel information must be carefully pre-processed and fed in the generative neural networks. The data pre-processing is expected to be interesting and non-trivial, and the best pre-processing algorithms may be found by trial-and-error using some domain expert knowledge.

Currently, we consider two potential network structures, generative adversarial network (GAN) [3] and variational autoencoder (VAE) [4]. GANs consist of a pair of models called the generator and discriminator [3]. The generative models can be thought of as a thief trying to generate couterfeit currency whereas the discriminative model can be thought of as police trying to detect the counterfeit currency. Therefore, the entire framework resembles a two-player minimax game where the generator tries minimize its objective function and the discriminator tries to maximize its objective function. Through a min-max objective function, the generator tries to approximate the distribution of input data using the latent variables. This approximation approach sets GANs apart from variational autoencoders and Boltzmann machines [3].

For the variational autoencoder, we have a generative model $x = g_\theta(u, z)$ where x is the data of interest, g is the generating function given parameters θ, u is the condition variable, and z is the latent random variable. So given θ, we have a conditional density $p_\theta(x|u)$ which defines a relation between our link conditions and the path data x. The problem then becomes how to find parameters θ to match $p(x|u)$ given training data $(u_i, x_i), i = 1, \ldots, n$. The variational autoencoder employs an encoder-decoder structure, where q_θ gives the distribution of the latent variable z given the condition and data (encoder) and p_θ gives the distribution of path parameters x given the condition and latent variable (decoder). These are jointly minimized using the Evidence Lower Bound (ELBO) given by:

$$ELBO(\theta) = \mathbb{E}\{q_\theta(z|x, u) \log p(x|z, u)\} - D(q_\theta(z|x, u)||p(z)) \tag{2}$$

where $D(q_\theta(z|x, u)||p(z))$ is the Kullback–Leibler divergence between distributions $q_\theta(z|x, u)$ and $p(z)$. The latent random variable z is initialized with some known distribution (e.g. $z \sim N(0, I)$), and its mean and covariance matrices are updated during training. Heuristically, the input data is mapped from the input space to a latent representation with typically smaller dimensionality, and then reconstructed into the output space (reconstructed samples). The goal then is the learn the conditional distribution between the input data and latent representation, and the conditional distribution between the latent representation and the output reconstruction.

Some preliminary performance metrics are the generated cumulative probability functions of path loss, shadow fading, LOS/NLOS condition, root mean square (RMS) delay spread and angular spread. We will use the distributions of new samples from our designed generative model and compare them to the distributions of the data set from the Remcom simulator. This will give us a good indicator of whether our model is able to generate wireless communication channels that are representative of the environments they are trained on.

II. List of Deliverables

- A literature survey on the state-of-art development in generative models, especially GANs and VAEs. The survey also includes the limited attempts of generative models in wireless communications [5]–[7].
- A full data set of path information generated from Wireless Insite including received power, delays, and angles of arrival of each path of communication links distributed in both the factory and residential house environments.
- Weights and structure of a generative neural network that can create realistic channel information given the input parameters in both of the target scenarios.
- A detailed performance evaluation will be provided in terms of key channel characteristics such as path loss, LOS/NLOS condition, delay spread, and angular spread.

III. Timeline

Weeks	Work Items
8-9	Literature review on GANs and VAEs. Run open-source GAN and VAE implementation.
10-11	Generate training datasets using the ray tracer for two different scenarios at 60 GHz. Pre-processing generated channel data.
12	Write code for the network model, and perform initial training and test
13	Based on the preliminary results, update the pre-processing algorithms and investigate the potential improvement in network architecture
14-15	Finalize the design and provide detailed performance evaluation. Point out future works and directions

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