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Machine-Learning-Assisted Modeling of Millimeter-Wave Channels

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***Abstract*—The conventional physical-statistical models cannot accurately predict the site-specific mmWave channel characteristics when involving complex system configurations and geometric information of transceiver locations. A framework of machine learning assisted channel modeling approach is proposed, in which the statistical models are leveraged for inter-cluster level channel characterization and the propagation properties within each kind of clusters are predicted via a novel set of cluster predictors. In particular, a case study of modeling forward through-vegetation scattering effect is presented using the physics-based and data-driven hybrid approach.**

I. Introduction

As is well known, propagation channel modeling is an essential part of new wireless communication system design, evaluation, and deployment [1]. The cluster-based statistical channel models reveal the mapping results between virtual clusters and physical scatterers, which group the multipath components (MPCs) in both time and angular domains. Consequently, the propagation channels are characterized by several inter- and intra-cluster parameters following specific distributions [2], while the existing standard models disregard the differences in the statistics of intra-cluster parameters among various cluster types [3]. Moreover, the universality and accuracy of the physical-statistical channel models are usually established based on sufficient channel data collected in multiple environments, coupled with the high-resolution channel parameter estimation algorithm. Early studies on machine learning (ML) based modeling of both large-scale and small-scale channel characteristics [4]–[7] show great potential for the improvement of channel prediction accuracy when using the geometric information of transmitter (TX) and receiver (RX) locations as input data. In particular, artificial neural networks (ANNs) have been commonly introduced to find the best functional fit of transceiver settings (including geometric information, antenna patterns, and environmental features) and path loss (or received signal strength) [4], [5]. Only a handful of published works simultaneously fulfill the prediction of path loss and spatialtemporal characteristics, along with more complicated ML algorithms [6], [7].

However, the greatest drawback of these models lies in that they can only be used in the cases having been trained for specific environments. To remedy this situation, an ML-assisted channel modeling approach is proposed, which integrates the advantages of both physical models and ML-based models. It is expected to improve the generalisation properties by leveraging the prior knowledge of the physical structure of concerned environments.

II. The Framework of ML-Assisted Channel Modeling Approach

As shown in Fig. 1, multipath channels are normally modeled by a sum of several clusters propagating through different kinds of scatterers, such as buildings, trees, vehicles, and human body. The interaction of electromagnetic wave and these physical objects products cluster-level channel characterization, including power attenuation and space-time channel dispersions. Fig. 2 depicts the flowchart of the ML-assisted predictive channel modeling approach. We first need to set system configurations (e.g., carrier frequency and antenna field patterns) and geographic information (e.g., scenarios, LoS/OLoS/NLoS, and transceiver locations). Following the standard procedure recommended in [3], the inter-cluster parameters are generated based on the statistical channel model,

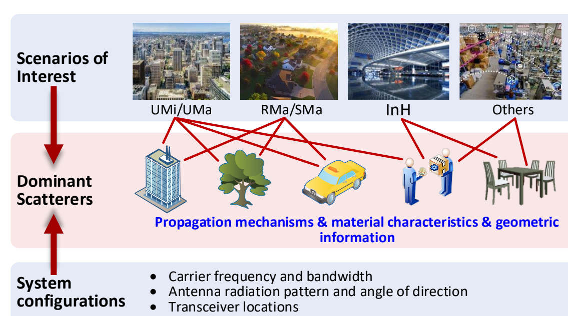


Fig. 1. Dominant scatterers in different indoor and outdoor environments.

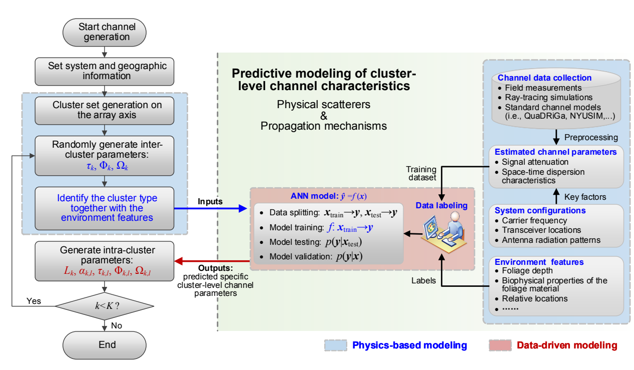
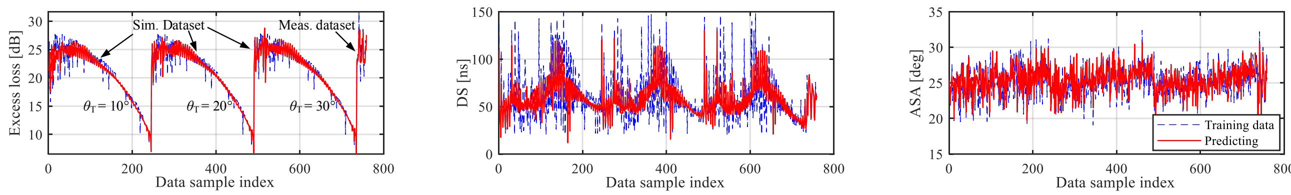


Fig. 2. Flowchart of the ML-assisted channel modeling.



(a) (b) (c)

Fig. 3. Comparison of training data and predicting results for the forward through-vegetation scattering cluster. (a) vegetation attenuation; (b) DS; (c) ASA.

and in turn, clusters are placed in parameter space. In particular, the cluster type is assigned to each cluster together with its physical characteristics. This step enables the differences of spatio-temporal dispersion parameters between clusters to be distinguished. Due to the fact that each cluster could be mapped to the objects in physical space, it is reasonable to separately characterize the cluster-level channel interacting with the corresponding scatterers. By leveraging a set of ML-based predictors, the intra-cluster space-time channel parameters can be sequentially generated for different cluster types.

This framework tries to show that, when predicting mmWave channel characteristics in multiple environments, limited site-specific channel data can be used to train the networks for the predictive modeling of cluster-level channel characteristics along with the environmental features. Another advantage of this framework is that it naturally integrates the blockage effect in cluster generation rather than adding more steps for the application of blockage model [3]. To enable this framework, we first need to promote a novel set of cluster predictors, that can predict the complex intra-cluster level propagation characteristics over different kinds of physical objects.

III. A Case Study of Modeling Through-Vegetation Scatting Effect

In particular, the mmWave propagation characteristics of the forward vegetation scattering cluster is investigated in this work using hybrid physics-based and data-driven modeling approach. Based on the channel data collected from field measurements and ray-tracing simulation, several channel parameters can be estimated together with the key impact factors of system configurations. Consequently, these channel data is labeled with environment features and used for training the data-driven model.

For instance, ANN model is employed to predict vegetation attenuation and spatio-temporal spreads of the forward through-vegetation cluster. The network is trained with directional channel sounding and simulation data collected in the identical vegetated street canyon environment at 28 GHz (total 759 effective channel data samples), combining with the inputs of several key impact factors extracted from physics-based observations (e.g., three TX antenna downtilt of 10°, 20°, and 30°). Apart from the basic geometric information of transceivers (TX and RX coordinates), two propagation environment features c_1 and c_2 are converted as inputs to the ANN (i.e., c_1 labels the RX inside or outside vegetation and c_2 indicates whether the RX location is directly below the foliage), which could greatly enhance its predicting performance to the variation of propagation environments. The outputs of the ANN include the estimated channel parameters, such as vegetation attenuation, delay spread (DS), and azimuth angular spread of arrival (ASA). Fig. 3 shows the training results with the optimal number of hidden neurons of 10 in terms of the overall regression R values and sufficient mean square error (MSE).

IV. Conclusion

In this paper, a framework of the ML-assisted modeling approach has been proposed, which is expected to provide a scalable and robust channel model for multiple environments. To enable this framework, the scattering effect of the forward vegetated cluster is predicted using hybrid physics-based and data-driven modeling approach. Comparing with the physical-statistical model, training results show that the proposed hybrid predictive model has higher prediction accuracy and greater generalization ability in terms of the site-specific through-vegetation cluster parameters, such as vegetation attenuation, delay spread, and angular spread.

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