

Deep Learning-Based Prediction of Scattering Parameters for Metasurfaces Using Point Clouds

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This paper introduces a novel approach for predicting the scattering parameters (S-parameters) of metasurfaces using a deep learning model based on point clouds. The proposed methodology involves encoding both the spatial and physical characteristics of metasurfaces into point clouds, which are then processed by a proposed deep learning model. The model architecture includes multi-scale pooling layers to retain critical frequency-domain information and dense layers for precise regression. By leveraging a training dataset of 1024 samples and employing efficient feature extraction techniques, the model successfully predicts S-parameters within the 2–12 GHz frequency range of metasurfaces. Experimental results validate the model's high accuracy, with predictions closely aligning with those obtained from full-wave simulations. This work highlights the potential of deep learning to expedite metasurface design and optimization, offering a computationally efficient alternative to traditional numerical methods.

Index Terms—Deep learning, metasurface, point cloud, scattering parameters.

I. INTRODUCTION

ACCURATE PREDICTION of electromagnetic properties is crucial in applications such as antenna design, filter optimization, and metasurface analysis. Traditional methods, including the finite element method (FEM) and finite-difference time-domain (FDTD) method, rely on mesh discretization and complex numerical solving processes to compute scattering parameters (S-parameters). However, these methods are computationally expensive, making them less suitable for large-scale optimization and rapid design tasks. The challenges become particularly prominent when dealing with complex structures where computational efficiency and resource consumption are major bottlenecks.

In recent years, point cloud-based approaches have emerged as promising alternatives. Chen *et al.* proposed a method leveraging point clouds to perform electromagnetic inversion without the need for mesh-based discretization [1]. The test cases in the paper include simulated objects such as digits and chairs, which were used to demonstrate the feasibility of the approach. Li *et al.* proposed a point clouds simulation method based on electromagnetic propagation theory and human electromagnetic scattering characteristics [2]. Kong *et al.* developed the ElectroMagnetic PointNet (EMPNet), which uses point cloud data as input and achieved remarkable reductions in CPU time and memory requirements [3].

Building on the advantages of point cloud-based approaches, this paper presents a novel deep learning-based approach for efficient S-parameters prediction of metasurface. Instead of relying on numerical methods that require intricate meshing and iterative solving, the proposed method uses point cloud data of metasurface elements as input and S-parameters as output to train a predictive model. By bypassing traditional computationally intensive simulations, the trained model can directly and accurately predict the S-parameters of metasurfaces. Experimental results demonstrate that the

proposed method significantly improves computational efficiency while maintaining high prediction accuracy, providing an effective and practical alternative for the design and optimization of metasurfaces.

II. THE PROPOSED METHODOLOGY

In this paper, a novel approach is proposed for predicting the S-parameters of metasurfaces using deep learning. The proposed methodology involves two main parts: (1) simulating metasurface structures to generate training data and representing them as point cloud data, and (2) designing and training a deep learning model to predict the S-parameters based on the point cloud representation.

A. The Metasurface Unit

The metasurface unit in [4] is used. The training dataset is generated by systematically modifying the dimensions of the split ring resonators in the metasurface unit cell, as shown in Fig.1 (a). Four design parameters are adjusted: the width of the outer copper ring s , the gap of the outer copper ring, d , the width of the inner copper ring, p , and the gap of the inner copper ring, g . The output S-parameter data consisted of 1001 frequency points sampled at 0.01 GHz intervals.

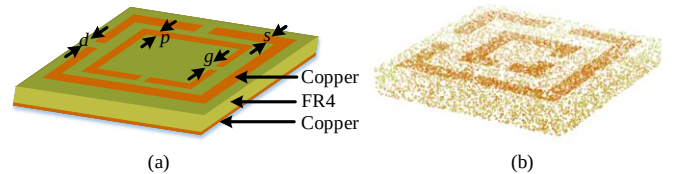


Fig. 1. The metasurface unit, (a) design parameters (b) point clouds representation.

B. Point Clouds Representation

To represent the metasurface and its surrounding environment, point clouds are collected. Sampling is performed uniformly across the metasurface unit, including both the dielectric (FR4) and the surrounding vacuum regions, as shown

in Fig.1 (b). Each point cloud is characterized by its physical properties, including magnetic permeability, permittivity and electrical conductivity. The spatial coordinates of the points are inherently represented by their positions in the dataset, which captured the key geometrical and material properties of the metasurface and its environment, enabling the model to learn the complex interactions within the system.

C. The Proposed Deep Learning Model

The proposed deep learning model is based on convolutional neural network, as shown in Fig. 2, the architecture consists of three primary components: convolutional layers, pooling operations, and dense layers.

Three 3-dimensional (3D) convolutional layers are employed with a kernel size of (4, 4, 2) to capture spatial and frequency-domain features effectively, which reduces computation along the frequency axis while retaining critical information. Each convolutional layer uses ReLU activation to introduce non-linearity. Max-pooling layers are modified to have a kernel size of (4, 4, 1) and a stride of (4, 4, 1), ensuring that frequency-domain information is preserved while reducing spatial dimensions. Additional pooling layers are used in auxiliary paths, with kernel sizes (1, 13, 1) and (5, 12), to extract multi-scale features. The fused features are passed through three dense layers. The first two layers each contain 2048 nodes, while the final layer have 1001 nodes, corresponding to the S-parameter predictions for the 2–12 GHz frequency range.

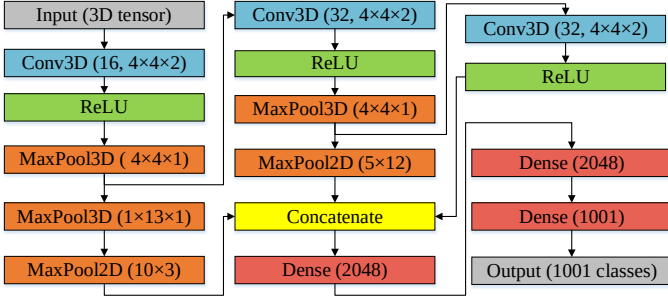


Fig. 2. The proposed deep learning model architecture.

III. EXPERIMENTS AND ANALYSIS

To evaluate the performance of the proposed method, 1024 unique metasurface configurations are created firstly. For each configuration, the corresponding S-parameters are computed over a frequency range of 2 to 12 GHz using full-wave electromagnetic simulations. The stochastic gradient descent optimizer is employed for efficient gradient descent, with an initial learning rate of 0.001. The training dataset, consisting of 1024 samples, is split into 80% for training and 20% for validation. The model is trained for 1000 epochs and the mean squared error (MSE) is utilized as the loss function. As shown in Fig. 3, the MSE decreased rapidly during the initial epochs and gradually stabilized as the model converged, demonstrating the model's ability to generalize well to unseen data, with the final test loss reaching 0.107.

Secondly, the trained model is evaluated on the test dataset, and the predicted S11 samples are compared to the ground truth S11 obtained from full-wave electromagnetic simulations, as

depicted in Fig. 4. The predicted S11 and the simulated values are nearly identical, indicating a high level of prediction accuracy. Notably, the model successfully captures key resonant features, with minimal error across the spectrum. The discrepancy between the predicted and simulated values is negligible, even at critical resonant points. This highlights the robustness of the proposed model in predicting complex electromagnetic behaviors of metasurfaces. While a single full-wave electromagnetic simulation typically requires an average of 1 minute to compute the S-parameters, the trained model can predict the results in just 0.0023 seconds. The minimal loss and high accuracy suggest that the model is suitable for real-time metasurface design and optimization tasks, and the results demonstrate its capability to accurately predict the S-parameters of metasurfaces across the frequency range of 2–12 GHz.

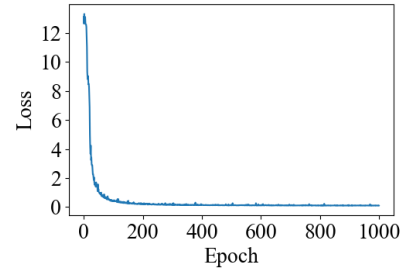


Fig. 3. Training loss (MSE) vs epochs.

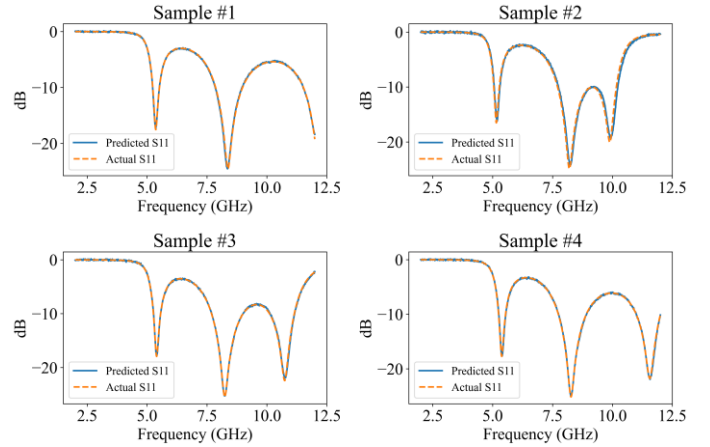


Fig. 4. S11-parameter prediction performance on selected samples.

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