2024 International Applied Computational Electromagnetics Society Symposium (ACES-China) | 979-8-3503-5558-1/24/$31.00 ©2024 IEEE | DOI: 10.1109/ACES-China62474.2024.10699652

Design of Frequency Selective Surface using Residual Network

Yu Xie
Nanjing University of Aeronautics and Astronautics
Nanjing, China
xieyu219@nuaa.edu.cn

Yi Wang
Nanjing University of Aeronautics and Astronautics, Nanjing, China
State Key Laboratory of Millimeter Waves, Nanjing, China
jflsjfls@nuaa.edu.cn

Qi Wang
Hangzhou Institute of Technology, Xidian University, Xi'an, China
wangqi@xidian.edu.cn

***Abstract*—This letter proposes a frequency selective surface (FSS) inverse design method based on a residual learning framework. Traditional FSS designs that meet industrial demands depend on designers' experience and repeated simulation iterations. The proposed method, however, can automatically design the FSS structure parameters that meet specific frequency response requirements. The residual-learning-based method is not only validated by two passband FSS design examples but has shown advantages over the commonly used convoluted neural network-based methods.**

Keywords—frequency selective surface; residual network; inverse design

I. Introduction

Frequency selective surface (FSS) has attracted significant interest and is widely employed in various applications due to its filtering characteristics of electromagnetic waves [1]. The traditional FSS design method is generally based on the design of classic structures and designers' design experiences. A rough structure is proposed for electromagnetic (EM) response to experience parameter scanning or other optimization algorithms until the design goals are achieved. However, this time-consuming iterative process is tedious and largely relies on the designer's experience and contingency factors. Moreover, the equivalent circuit model method makes it difficult to calculate the analytical relationship between complex and irregular unit structures and equivalent lumped components [2].

In recent years, deep neural networks (DNN), as a kind of artificial intelligence technique, have been used to deal with highly complex nonlinear problems [3]-[10]. The DNN only requires enough labeled samples to correctly learn the corresponding mapping function for the hidden relationships between input and output variables. The well-trained DNN could predict new test examples according to the target input. The forward design of FSS has been further developed by building well-trained neural networks to replace full-wave simulations and improve design efficiency [4]. Otherwise, it will be an inverse design; the structure matrixes or parameters can be predicted directly based on the required electromagnetic response [5]-[10].

This paper uses the residual network (ResNet) to bridge EM response data and physical structure data. Once the ResNet model's training process is accomplished, the model is adopted to automatically generate the structure parameters that meet a desired passband requirement. Finally, the predicted results are obtained by performing full-wave simulation verification.

II. Basic FSS Structure

A. The Unit Cell Structure

To achieve the wide passband requirement, a multilayer complementary structure is used as a template of the FSS unit cell, shown in Fig.1. The three-layer metallic arrays are printed on two FR4 dielectric substrates with the same thickness *h*. *D* is the period of the element, *s* represents the gap that separates the metallic square patches, and *w* is the width of the inductive wire grid. According to the equivalent circuit model, the chosen FSS structure has different passbands by adjusting the parameters *D*, *s*, *w*, and *h*.

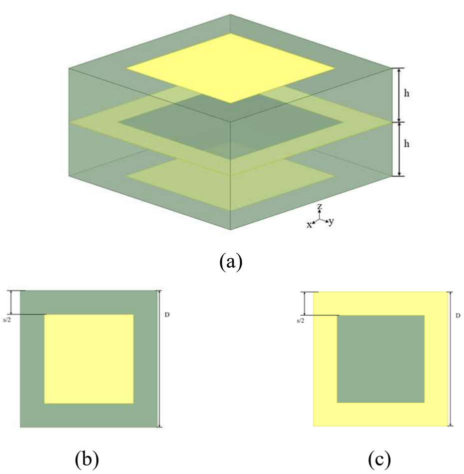

Figure 1. Structure of the proposed FSS. (a) 3-D view. (b) Top layer and bottom layer. (c) Middle layer.

B. Data Set Generation and Preprocessing

Matching data generated by simulation software are prepared to train the neural network. The geometrical dimension parameter *D* of the FSS structure is fixed. Other structural parameters are variables to be swept. The variation ranges are *s* [1.5 mm, 4.5 mm], *w* [1.5 mm, 4.5 mm], *h* [1 mm, 3.5 mm], and the step width of the three variables is 0.25 mm. The dataset is collected by EM simulation, assuming that the TE polarized wave is vertically incident to the surface and that the structure is infinite and periodic. Therefore, 1859 valid data were finally obtained as a network dataset. Then, the dataset is randomly

979-8-3503-5558-1/24/$31.00 ©2024 IEEE

divided into 80% training data and 20% test data. To ensure the dataset is high-quality, the frequency ranges from 1 to 13GHz with 1001 frequency points, and then we only extract the S, C, and X bands, a total of 900 points. To avoid the value transformation of the S-parameters, the data use linear value instead of dB value.

III. Intelligent Design of Passband FSS

A. *Residual Neural Network Model*

Shortcut connections are inserted based on the regular convolutional neural network, which turns the network into its counterpart residual version. From Fig. 2, residual blocks allow information to jump directly between different layers, which enables the network to learn identity mapping directly and more effectively approach the objective function. By introducing residual connections, gradients can more easily propagate to shallower layers, thus solving the problem of vanishing gradients. At the same time, due to the better propagation of gradients, the convergence speed of the network is faster, and the training process is more stable.

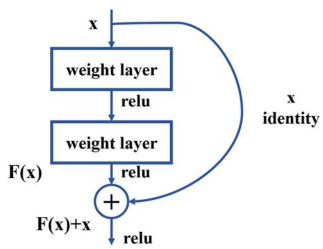

Figure 2. Residual block.

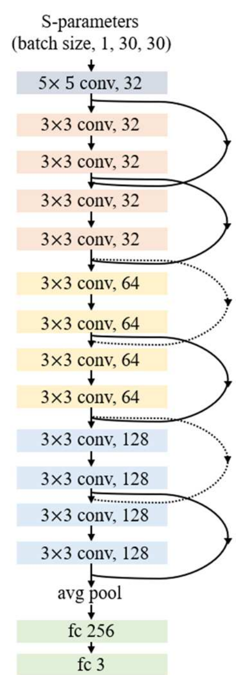

Figure 3. Architecture for a residual network.

The residual network's framework includes 1 prime stage, 3 residual blocks, and one fully connected layer. Fig. 3 and Table 1 show the details of the ResNet structure. The S-parameters curves need to be reshaped to a matrix (1, 30, 30) that is the same as the grayscale image, then input the network.

TABLE I. Parameters of Residual Network

Layer name	Output size	13-layer
Conv1	28×28	5×5, 32, stride 1, padding 1
Conv2_x	14×14	$\begin{bmatrix} 3\times3, 32 \\ 3\times3, 32 \end{bmatrix}\times2$
Conv3_x	7×7	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$
Conv4_x	4×4	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$
	1×1	average pool, 256-d fc

PyTorch is chosen to achieve network training and optimization on a computer with an NVIDIA GeForce RTX 4090 graphic processing unit (GPU).

The MSE (mean square error) is the network's loss function, and the Adam optimizer with a 0.001 learning rate is used to update the network weight and bias parameters and minimize MSE. In equation (1), n represents the number of samples, $\hat{y}_i$ presents the predicted value, and y_i represents the actual value.

$$\mathrm{MSE}=\frac{1}{n}\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2 \tag{1}$$

One hundred twenty-eight labeled samples are taken from the dataset as a batch to update each kernel's weights, with 300 training epochs performed. Fig. 4 displays the learning curves for the residual network model to evaluate the models' performance. The model's training MSE is 0.00084, and the test MSE is 0.0017. This demonstrates the model's successful training and generalization capabilities. It is noted that in the first 15 epochs, there is a rebound of loss curves. That is a normal phenomenon during the iteration process.

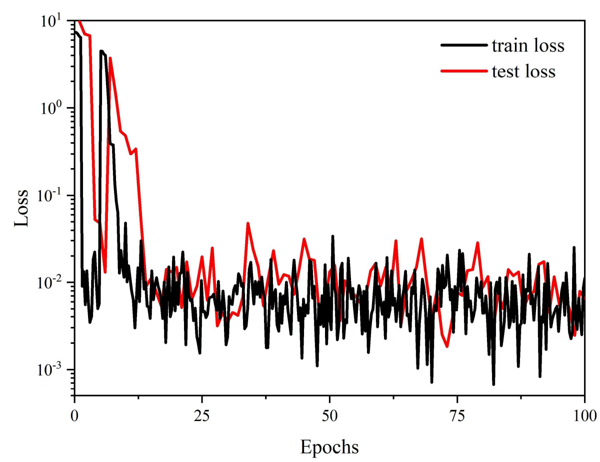

Figure 4. Evaluation of the neural network model.

B. *Prediction Results and Simulation Verification*

To further verify the feasibility of the residual network in FSS structure design, target curves are input to neural network prediction. The required passband responses are the S-band (2-4GHz) and the C band (4-8GHz), while the other band is cut off. The output structure parameters of the residual model are [3.3734 1.7136 2.4112] and [0.1596 2.4033 2.0927], respectively, representing *s*, *w*, and *h*. Fig.5 provides a comprehensive illustration of the performance of neural networks by comparing the desired responses and predicted responses.

Observing the transmission curves, the target response (4-8GHz) has a passband response with two transmission poles in 5.1GHz and 7.0GHz, with 4.23GHz bandwidth. The corresponding predicted result could be seen to coincide with the required S-parameters curve, which meets the design requirements. Although the expected response (2-4GHz) differs from the desired curve, it covers frequency from 2.4 to 3.9GHz with 3dB insertion loss (IL) and has excellent roll-off and suppression characteristics.

The frequency offset is caused by the small dataset and the selection of sample points by equidistant sampling, which makes it difficult for neural networks to capture the features of the passband.

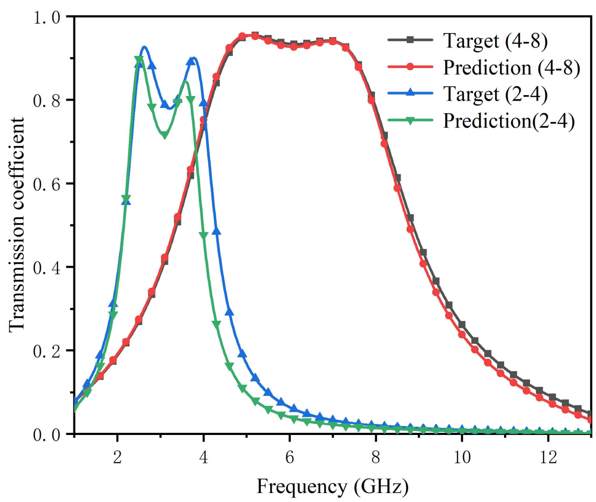

Figure 5. Comparison of target and predicted results.

IV. Conclusion

An innovative bandpass frequency selective surface inverse design method combining residual learning is proposed in this paper. This model can rapidly design FSS structure parameters that meet the requirements based on the expected passband curve of the input. Two wide passband FSSs operating in the S and C bands have been designed for verification. However, the latter work needs to focus on improving design freedom, using pixel structure instead of fixed structure. As for a one-to-many mapping problem in an inverse design, unsupervised learning is a robust network that could extract features and reduce the dimensionality of data.

Acknowledgment

This work is supported by the open research funds of the State Key Laboratory of Millimeter Waves K202324, the Key Laboratory of Radar Imaging and Microwave Photonics, Ministry of Education, China, No. NJ20230007 and Postgraduate Research & Practice Innovation Program of NUAA,No.xcxjh20230408.

References

[1] B. A. Munk, "Frequency selective surfaces: theory and design," John Wiley & Sons, 2005.

[2] M. Zhao, H. Li, Z. Wu, et al., "Wideband second-order bandpass frequency selective surface with high selectivity," Microwave and Optical Technology Letters, 2023.

[3] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 770-778.

[4] T. Yuze, L. Hai, and Z. Qinglin, "On the application of deep learning in modeling metasurface," in 2019 International Applied Computational Electromagnetics Society Symposium - China (ACES), Nanjing, China, 2019.

[5] J. Hou et al., "Customized Inverse Design of Metamaterial Absorber Based on Target-Driven Deep Learning Method," IEEE Access, vol. 8, pp. 211849-211859, 2020.

[6] S. Gu, J. Su, and Z. Li, "Pixelated Electromagnetic Surface Design Based on Deep Learning," in 2021 IEEE MTT-S International Microwave Workshop Series on Advanced Materials and Processes for RF and THz Applications (IMWS-AMP), Chongqing, China, 2021, pp. 385-387.

[7] E. Zhu, Z. Wei, X. Xu, and W.-Y. Yin, "Fourier Subspace-Based Deep Learning Method for Inverse Design of Frequency Selective Surface," IEEE Transactions on Antennas and Propagation, vol. 70, no. 7, pp. 5130-5143, July 2022.

[8] R. Cong, N. Liu, X. Li, H. Wang and X. Sheng, "Design of Wideband Frequency Selective Surface Based on the Combination of the Equivalent Circuit Model and Deep Learning," IEEE Antennas and Wireless Propagation Letters, vol. 22, no. 9, pp. 2110-2114, Sept. 2023.

[9] X. Fang, H. Li and Q. Cao, "Design of Reconfigurable Periodic Structures Based on Machine Learning," IEEE Transactions on Microwave Theory and Techniques, vol. 71, no. 8, pp. 3341-3351, Aug. 2023.

[10] L. Y. Xiao, Y. Cheng, Y. F. Liu, et al., "An Inverse Topological Design Method (ITDM) Based on Machine Learning for Frequency-Selective-Surface (FSS) Structures," IEEE Transactions on Antennas and Propagation, vol. 72, no. 1, pp. 653-663, Jan. 2024.