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Intelligent Design of Arbitrary Bandstop FSS Through Deep Learning and Genetic Algorithm

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***Abstract*—Frequency selective surface (FSS) is used for electromagnetic radiation suppression due to its unique filtering characteristics. However, it still takes some experience and time to design a FSS structure with a specific stopband for actual shielding requirements. In this paper, a method based on deep learning and elite genetic algorithm is proposed, which can realize the automatic design of arbitrary bandstop FSS structure. This method only relies on a basic FSS model and some parameter scanning data to achieve the final design, reducing the need for design experience and the labor cost of repeated iterations.**

Keywords—frequency selective surface; deep learning; genetic algorithm

I. Introduction

Frequency selection surface (FSS) is widely used in the engineering design of various wavebands due to the filtering characteristics of electromagnetic waves [1]-[3]. In the FSS design for practical requirements, the S-parameter curve of a basic FSS structure is generally observed through simulation, and the corresponding structural parameters will be carefully adjusted. However, this time-consuming iterative process is tedious and requires the designer to have a certain design experience to achieve higher parameter tuning efficiency, such as equivalent circuit model [4]. Therefore, an automatic and efficient method is needed to better realize the design of FSS.

In recent years, deep neural networks have attracted a lot of attention due to their excellent fitting ability in highly complex nonlinear problems [5][6]. For the complex correspondence between input and output variables, the deep neural network only needs a certain amount of matched data to fit the corresponding mapping function well.

In our work, a deep neural network is employed to fit the nonlinear function between the FSS structural parameters and the corresponding S-parameter curve, thus an alternative simulation method was further implemented to quickly verify whether the adjustment of the structural parameters was effective. Then, the elite genetic algorithm is used to assist the automatic exploration of structural parameters. Finally, with a given stopband requirement, we use the proposed method to complete the design and carry out simulation verification.

II. Basic FSS model

A. Introduction of FSS Model

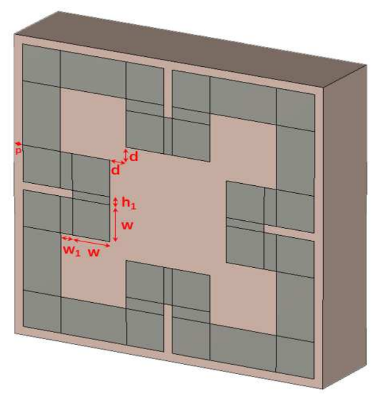

Fig. 1. Configuration of a FSS unit cell and several variable structural parameters

Fig. 1 shows the three-dimensional topology of a FSS unit cell, which consists of one layer of copper and one layer of substrate, the copper layer lies on the top side of the substrate. The layer on the top is a fractal square copper ring. The fractal square ring has a notch lie on the middle of every side with the length of $w + w_1$, and width of h_1. According to equivalent circuit model, FSS structures with different stopbands can be further obtained by adjusting the parameters p, w_1, h_1, d, and w.

B. Data Acquisition and Preprocessing

In order to use the deep neural network to fit the nonlinear relationship between the five structural parameters and the S-parameter curve, a data set was collected by simulation software (CST Studio Suite). Without loss of generality, we carry out equidistant parameter scanning for five structural parameters. Therefore, the value set of the five parameters is uniformly set as [0.1, 0.2, 0.3,0.4,0.5]. And 3125 valid data were finally obtained as training data of the network.

The input of network is a 5-dimensional vector containing structural parameters, and the output is the S_{21} parameter curve of the corresponding structure. It should be noted that the frequency range of the S-parameter curve obtained by the simulation software is 0 to 20 GHz, including 1001 sampling points. To help network training more effectively, an effective sampling point is taken from every ten points as a kind of downsampling. Thus, an S_{21} parameter curve containing 101 sampling points in the frequency range of 0 to 20 GHz, with adjacent sampling points separated by 0.2 GHz, is the expected network output. It is worth mentioning that, to avoid re-adjustment of output characteristic amplitude during network training, the linear value of the S_{21} parameter curve is adopted instead of the dB value.

III. Intelligent design of stopband FSS structure

A. Training and Validation of the Deep Neural Network

In this section, the data collected by simulation is used to train a fully connected deep neural network and verify its generalization performance. Therefore, the complete dataset was divided into training sets and test sets, which contained 2200 and 925 data, respectively. Fig. 2. (a) shows the structure of our proposed network, which contains an input layer with 5 neurons, four fully connected hidden layers with 200 neurons, and an output layer with 101 neurons.

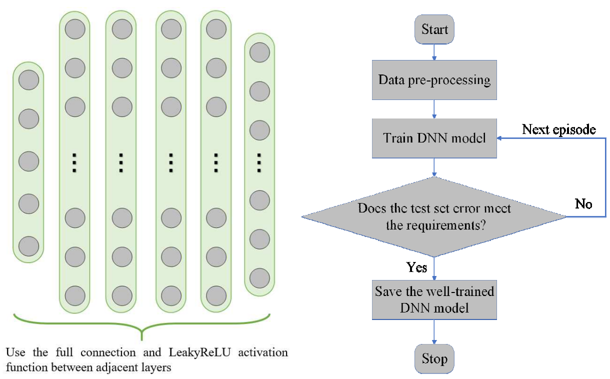

Fig. 2. (a) The structure of the deep neural network, with layers of neurons of 5,200,200,200,200,101, and using the LeakyReLU activation function. (b) Training iteration method for deep neural networks.

It should be noted that the LeakyReLU was used as the activation function after each fully connected hidden layer, which is defined as

$$f(x)=\begin{cases} x & ,when\ x\ >\ 0 \\ 0.01\times x & ,when\ x\ \le\ 0 \end{cases} \qquad (1).$$

The mean-square error between the network predicted and simulated S-parameter curves is selected as the loss function of the network, and the Adam optimizer with a 0.001 learning rate is used to update the network parameters to minimize it. When the accuracy requirement is that the mean square error is less than 0.01, the accuracy of the network in the 925 data of the test set reaches more than 98%.

B. Intelligent Design by Elite Genetic Algorithm

In the previous section, we obtained a well-trained deep neural network, which can quickly and accurately predict the s-parameter curves of structures based on given structural parameters. With the help of such a well-trained deep neural network model, we can achieve faster iteration than simulation and further design the FSS structure to meet the actual needs.

Genetic algorithm (GA) is a global search method based on the theory of biological evolution, which has good exploration and optimization performance in many problem Spaces. Elite genetic algorithm (ELGA) is proposed to prevent the traditional genetic algorithm from losing the best individual of the current population in the next generation, which leads to the failure of convergence to the global optimal solution. The idea is to take the best individuals (called elitists) that have emerged so far in the evolution of the group and copy them directly into the next generation without pairing. We direct interested readers to [7] for more detail of ELGA.

GA minimizes objective function by adjusting structural parameters, so an appropriate objective function selection becomes particularly important. In practical shielding tasks, it is often required to design an FSS structure with a specific stopband.

To design an FSS structure with a stopband peak of 16GHz and the widest possible stopband, a five-dimensional vector $x = [p\ \ w1\ \ h1\ \ dis1\ \ w]^{T}$ is identified as ELGA's exploration space. It should be pointed out that the variation space of each structural parameter is determined as any real number between [0.1, 0.5], instead of discrete values. And the upper and lower bounds are determined by the range of sweep parameters because the well-trained deep neural network is considered to have good generalization performance in this range.

Specifically, a vector x containing five corresponding structural parameters is fed to the well-trained deep neural network to obtain the predicted S-parameter curve. This process is represented as follows:

$$Curve = DNN\left(x\right) \qquad (2).$$

According to our design requirements, the peak of the stopband P_{Curve} and the stopband width W_{Curve} (-10dB) were used as the evaluation index of the *Curve*. Therefore, the ELGA objective function is set as follows:

$$f\left(x\right)=\begin{cases} -W_{DNN(x)} & ,\ if\ \ P_{DNN(x)}=16\ GHz \\ 0, & ,\ else \end{cases} \qquad (3).$$

C. Design Results and Simulation Verification

After 1000 iterations of the elite genetic algorithm, the vector x_0 that minimizes the function $f\left(x\right)$ is equal to $[0.109798,\ 0.10826,\ 0.13673,\ 0.38283,\ 0.352939]^{T}$. To verify the effectiveness of the method, we independently conduct simulation verification for this parameter.

As shown in Figure 3, the red curve is the prediction result of x_0 by the trained neural network, and the green curve is the simulation result when the structure parameter is set to x_0. Considering the large interval of parameter scanning and the fact that only 101 points are used to approximate the S-parameter curve, which means that the interval frequency of two adjacent points is equal to 0.2GHz, the validity of the proposed method is verified. Specifically, the well-trained deep neural network has good generalization performance in FSS design problems, and the elite genetic algorithm can further effectively complete the desired structure design

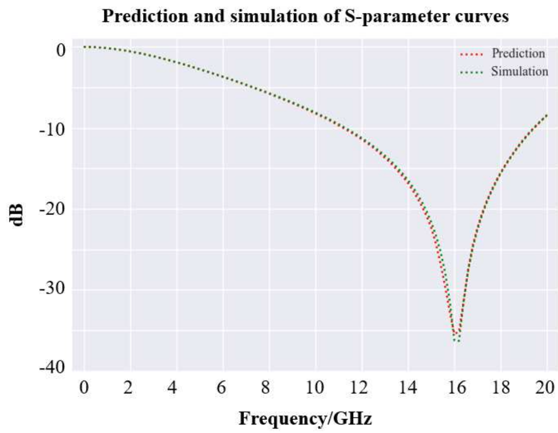

Fig. 3. For the FSS structure with the parameter x_0, the comparison between the prediction results of the well-trained deep neural network and the simulation result.

D. Discussion

However, an inverse deep neural network can also be trained, whose input is the characteristic of the S-parameter curve and output is the corresponding structural parameter, to replace the iterative process of elite genetic algorithm. But predictably, it may face some problems that need to be solved better.

First of all, if a simple cognitive way is used to describe S parameters, such as the peak value of the stopband and the range of the stopband, multiple structural parameters may exist corresponding to a certain S-parameter feature, which further worsens the performance of the network and even makes it difficult to converge. To solve the problem of data inconsistency, we lead interested authors to [8], which introduces a method of combining forward modeling and inverse design in a tandem architecture.

Another approach is to avoid excessive dimensionality reduction of the S-parameter curve caused by cognition-based description. Considering that an actual requirement is often based on the cognitive description, it is a challenge to draw an S-parameter curve that meets the actual requirement as the inverse network input, because the S-parameter curve is drawn randomly based on the requirement that may not be realized by the target structure. In future work, more generative models such as generative adversarial networks rather than discriminant models will be attempted to generate S-parameters satisfying the characteristics of the target structure.

IV. Conclusion

This paper presents an intelligent design method for FSS structure with the desired stopband, which is more effective and simpler than the traditional tuning iteration. For a specific FSS structure and design objective, a deep neural network that can replace the simulation is firstly trained, and then the appropriate structural parameters are obtained by combining the elite genetic algorithm and verified in the simulation software.

References

[1] B. A. Munk, *Frequency Selective Surfaces: Theory and Design*. Hoboken, NJ, USA: Wiley, 2000.

[2] T. -W. Li et al., "A Novel Miniaturized Multiband Strong Coupled-FSS Structure Insensitive to Almost All Angles and All Polarizations," *IEEE Trans. Antennas Propag.*, vol. 69, no. 12, pp. 8470-8478, Dec. 2021.

[3] A. K. Rashid, B. Li, and Z. Shen, “An overview of three-dimensional frequency-selective structures,” *IEEE Trans. Antennas Propag. Mag.*, vol. 56, no. 3, pp. 43–67, Jun. 2014.

[4] D. Li, Z. Shen, and E.-P. Li, ‘‘Spurious-free dual-band bandpass frequency-selective surfaces with large band ratio,’’ *IEEE Trans. Antennas Propag.*, vol. 67, no. 2, pp. 1065–1072, Feb. 2019.

[5] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521,

[6] T. Lu, J. Sun, K. Wu, and Z. Yang, “High-speed channel modeling with machine learning methods for signal integrity analysis,” IEEE Trans.Electromagn. Compat., vol. 60, no. 6, pp. 1957–1964, Dec. 2018.

[7] Ryan (Mohammad) Solgi,genetic algorithm 1.0.2 [Online]. Available: https://pypi.org/project/geneticalgorithm.

[8] D Liu, Tan Y , Khoram E , et al. “Training Deep Neural Networks for the Inverse Design of Nanophotonic Structures,” *ACS Photonics* 2018, 5, 1365−1369.