Rapid Inverse Design of Nonreciprocal, Space-Time-Modulated Meta-Waveguide Applying Residual Network

Ngoc Hung Phi and Jong-Wook Lee
Department of Electronics and Information Convergence Engineering, Information and Communication System-on-chip (SoC) Research Center, Kyung Hee University

요 약

The fourth generation of metamaterial: space-time metamaterials, provides the critical capability to control the electromagnetic wave. By dynamically manipulating the structure parameters, nonreciprocal transmission can be achieved in the reconfigurable metamaterial. However, because of the system's complexity, it is difficult and time-consuming to investigate this characteristic. Deep learning attracts extensive attention to be applied to the field of material design for clarifying complex problems. In this paper, we introduce a space-time-modulated meta-waveguide that breaks the reciprocity. After that, we apply customized Residual Networks to investigate the relationships between scattering coefficients and the corresponding modulation parameters. The results show that deep neural networks solved the inverse design issue with high accuracy. Moreover, compared to ADS simulation, the computation time can be decreased by 1,500 times.

I. Introduction

For more than two decades, metamaterials have been explored as an encouraging approach to govern magneto-inductive waves, especially at the deep subwavelength scale. Beyond the previous generations, the space-time-modulated metamaterial – the fourth generation exhibits the promising ability of wave propagation control [1]. It has significantly contributed to many physical applications whose representative is nonreciprocity.

In many electronic applications, breaking reciprocity is one of the most crucial tasks. These nonreciprocity devices are integrated into not only the power system whose sources need preventing from reflected signals but also the communication systems that crosstalk between signal paths needs to be canceled. Metamaterials are introduced as a bright method for making the nonreciprocity in electronic systems, which overcome the disadvantage of the previous method, such as bulk, low power handling, or high noise sensitivity [1].

In recent years, deep learning technology has proved its power in solving numerous complex material design problems [2]. The previous approach shows that the deep neural network can forecast the scattering properties with miniature error [3]. However, it is difficult for a deep neural network to converge owing to vanishing gradient problems. Residual Network (ResNet), whose heart is a residual block with a "skip connection" is proposed to relieve this problem [4].

In this work, we propose an inverse modeling paradigm based on ResNet for the space-time-modulated meta-waveguide, which exhibits the powerful capability of cutting off the traveling wave in a backward direction while allowing propagation in the forward direction. After training, the deep ResNet-based model can predict the modulation parameter sets with high accuracy, which means the relationships between electromagnetic responses and the modulation parameters are identified.

Ⅱ. Design

Fig 1(a) illustrates the schematic of the metamaterial waveguide, which supports nonreciprocal transmission. The waveguide is formed from 6 space-time-modulated hexagonal unit cells. To break the reciprocal transferring, the waveguide's characteristic is established by five tunable parameters: the input power to the waveguide (P_{in}); coupling coefficient between two adjacent cells k_c; modulated voltage V_m and modulated frequency f_m; unit cell equivalent capacitance C_S.

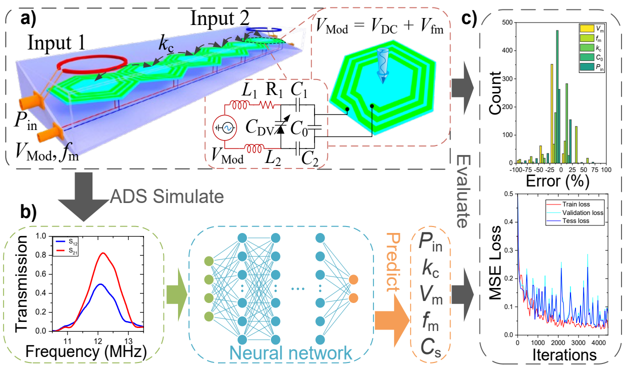

Fig 1. a) Schematic of the RF Isolator device using time-modulated metamaterial and its unit cells. b) Process of the DL network to predict five modulation parameters. c) Variation of loss values.

Fig 1(b) shows a diagram of the overall network. The neural network takes the electromagnetic responses of nonreciprocal transmission (|S21| and |S12|) as its input data samples. The corresponding modulation parameters are forecasted and compared to the actual ones employed by the systems. The neural network is optimized through mean square error loss and mean absolute error loss (Fig 1(c))

The investigated DL models are customized ResNet, which contains a convolution layer and a max pooling layer, followed by a different number of res blocks (RBs) and fully-connected layers (FCLs). 18232 data combinations are divided into a training set, a validation set, and a test set according to the ratios 85, 10, and 5%. The mean square error (MSE) losses of 5 models are shown in Fig 2. Fig 2(f) compares the losses after the final iteration, which indicates that the model contains three RBs and three FCLs converge to the highest accuracy.

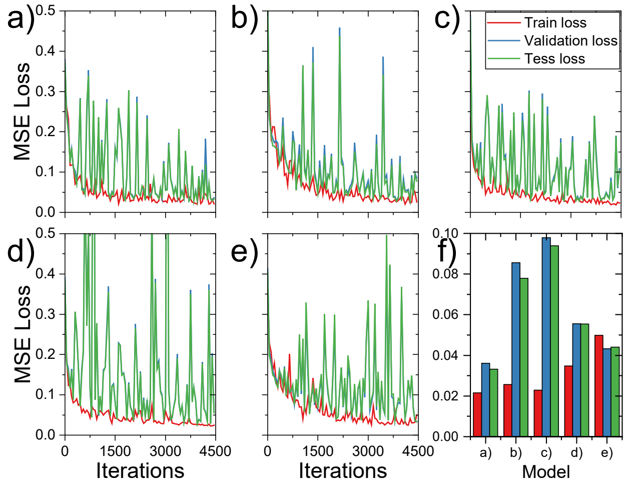

Fig 2. MSE Loss of the model contains a) 3 Res Blocks, 3 FCLs. b) 3 Res Blocks, 2 FCLs. c) 3 Res Blocks, 1 FCLs. d) 2 Res Blocks, 3 FCLs. e) 2 Res Blocks, 2 FCLs. f) Comparation of the final losses of 5 models

Because of its great performance, the model shown in Fig 2(a) is selected to be further explored. Its detailed structure is demonstrated in Fig 3.

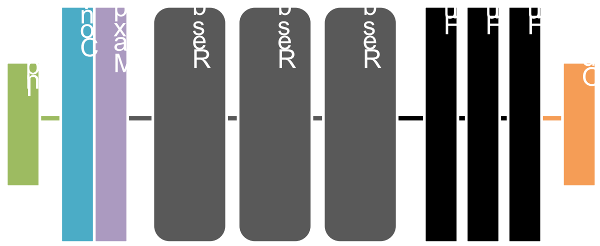

Fig 3. Structure of chosen ResNet-based model.

Finally, five modulation parameters are predicted by the trained model. The analyses of errors between predicted and ground truth values are presented as the histogram distributions in Fig 4. From these error histogram distributions, most errors are within 10% compared to real values, which implies that the model has high accuracy for most cases.

Although the DL model takes an amount of time for training, this cost is even less than the time for simulation of Agilent Advanced Design System on the same computer. Once the training is complete, it proposes a new method for designing a practical meta-waveguide via the deep residual network.

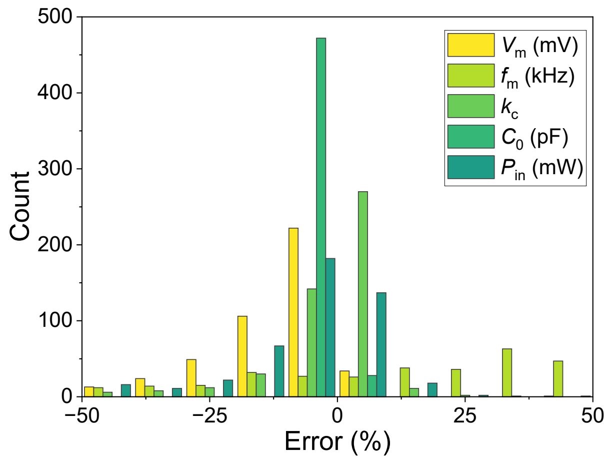

Fig 4. Error histogram distribution of 5 modulation parameters.

Ⅲ. Conclusion

In this work, we propose a ResNet-based framework for achieving space-time-modulated meta-waveguide inverse design. By integrating the transferring response information as a 2D vector, the convolution operations successfully obtain the high-dimension parameter extractions. In addition, the deep neural algorithm solved the design problems with great accuracy during a significant reduction of time can accelerate the development of applications of deep learning in intelligent material design.

ACKNOWLEDGMENT

This work was supported by the Basic Science Research Program through the National Research Foundation of Korea (No. 2021R1A2B5B01001475).

REFERENCES

[1] C. Caloz and Z. Deck-Léger, “Spacetime Metamaterials - Part I: General Concepts,” in IEEE Transactions on Antennas and Propagation, vol. 68, no. 3, pp. 1569-1582 (2020).

[2] R. Vasudevan, G. Pilania, and P. V. Balachandran. “Machine learning for materials design and discovery.” in Journal of Applied Physics 129, no. 7 (2021).

[3] H. N. Bui, J. -S. Kim and J. -W. Lee, “Design of Tunable Metasurface Using Deep Neural Networks for Field Localized Wireless Power Transfer,” in IEEE Access, vol. 8, pp. 194868-194878 (2020).

[4] T. Ying, J. Yang, and X. Liu. “Image super-resolution via deep recursive residual network.” in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 3147-3155. (2017).