Synthesis of Reflectarray Based on Deep Learning Technique

Tao Shan, Maokun Li, Shenheng Xu, Fan Yang
Beijing National Research Center for Information Science and TechnologyBNRist,
Department Of Electronic Engineering, Tsinghua University, Beijing, China
Email: maokunli@tsinghua.edu.cn

***Abstract*—In this work, we investigate feasibility of applying deep learning techniques to synthesis of reflectarrays. A deep convolutional neural network is proposed based on AlexNet to predict phase-shift in an reflectarray antenna given a reflected direction. The proposed network takes radiation pattern and beam direction as input, with training and testing data obtained by array theory. After cafefully training, the proposed network demonstrates strong approximation ability and makes correct prediction of phase-shift. Preliminary numerical experiments show that the prediction error of phase-shift can reach below 0.4%. This paper shows that deep convolutional neural networks can mimic the phase synthesis process of reflectarrays and it has a great potential for real-time phase prediction in more complex problems of array synthesis.**

***Index Terms*—Deep Learning; Synthesis of Reflectarray; Convolutional Neural Network; AlexNet; Array Theory; Array Synthesis**

I. Introduction

Reflectarray is an important type of high-gain antenna that consists of a flat reflecting surface and a feed horn illuminating the array. [1]. Recently, beam-scanning reflectarray has become an increasingly attractive technology due to its advantages over conventional phased array with transmit/receive (TR) modules. Beam-scanning reflectarray can control the reflected angle or shape of beam by offering different phase-shift to elements of reflectarray .

The phase-shift in the beam-scanning reflectarrays is usually obtained by array pattern synthesis techniques. The method can generate the required radiation pattern by adjusting the excitation (phase-shift, etc) of element in the array. In practical applications, the entire computation is usually divided into offline and online process. In the offline process, a set of samples are generated according to various desired patterns and stored in the memory. In the online process, solutions can be obtained directly or interpolated from the pre-stored results. However these solutions may not be optimal and contain inevitable errors. Therefore, it is still very challenging to achieve real-time phase-shift optimization according to practical requirements.

The rapid development of high performance computing enables computation and optimization of multi-layer nerual network with millions of parameters. Recently, the deep neural networks have also been applied to mimic complicated physical systems, sucn as accelerating computation of fluid dynamics [2], and solving Schrödinger equations [3]. These approaches enable neural netwroks learn from data and make correct predictions. In this work, we investigate the feasibility of applying deep learning techniques to reflectarray antennas.

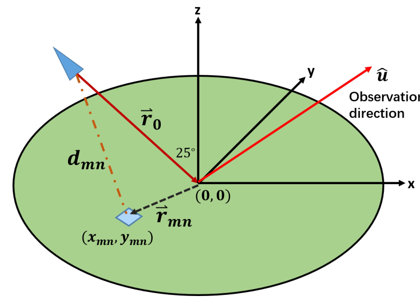

Fig. 1. Reflectarray Modeling Setup

II. Formulation

A. Array-Theory Method

Array-theory method is a typical technique to calculate far-field radiation pattern of reflectarrays. The typical reflectarray model is illustrated in Figure 1. In array-theory, the radiation patterns of both feed horn and individual element in the reflectarray are approximated using a cosine model. Besides, the incident wave is approximated as $e^{-jk_0|\vec{r}_{mn}-\vec{r}_0|}$ and the observation direction is included in $e^{-jk_0\vec{r}_{mn}\cdot\hat{u}}$. With these approximations, the radiation pattern of reflectarray can be formulated using the array-summation technique [4]:

$$E(\theta,\varphi)=\sum_{m=1}^{M}\sum_{n=1}^{N}cos^{q_e}\theta\frac{cos^{q_f}\theta_f(m,n)}{|\vec{r}_{mn}-\vec{r}_0|} e^{-jk_0(|\vec{r}_{mn}-\vec{r}_0|-\vec{r}_{mn}\cdot\hat{u})}cos^{q_e}\theta_e(m,n)e^{j\phi(m,n)} \tag{1}$$

where q_f and q_e are q factor of the feed and element pattern, $\phi(m,n)$ is the phase-shift of element (m,n) in the reflectarray.

The phase-shift of each element in the reflectarray is equal to the phase of reflected field, minus the phase of incident field, as:

$$\phi(m,n)=-k_0sin\theta_r(cos\varphi_r x_{mn}+sin\varphi_r y_{mn})-(-k_0d_{mn}) \tag{2}$$

where $-k_0d_{mn}$ represents the phase introduced by the incident field, $-k_0sin\theta_r(cos\varphi_r x_{mn}+sin\varphi_r y_{mn})$ is the phase distribution of reflected field given the beam direction (θ_r,φ_r) .

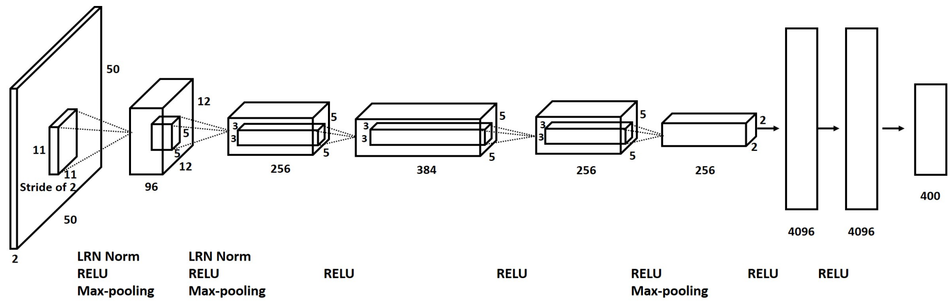

Fig. 2. The proposed convolutional neural network architecture based on AlexNet

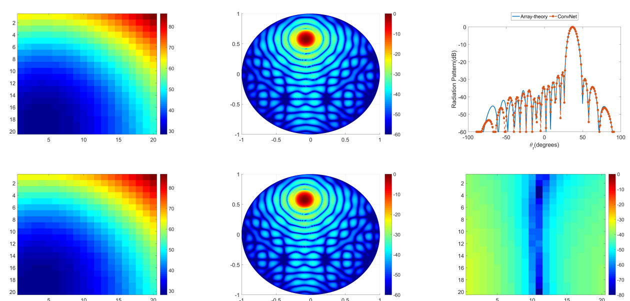

Fig. 3. Results (from *Left* to *Right*): *Row 1*: 'True' phase-shift, 'True' radiation pattern, Radiation pattern in Principle Plane 1 (P.P.1); *Row 2*: Predicted phase-shift, Predicted radiation pattern, error distribution.

B. ConvNet Model based on AlexNet

Convolutional neural network has demonstrated strong capability of approximating complex functions [2]. The proposed ConvNet model is based on the AlexNet [5]. AlexNet has proven to be a successful deep convolutional neural network model and demonstrated distinguished capacity of learning and prediction. The architecture of the proposed convolution neural network model is summarized in Figure 2. It is composed of five convolutional layers and three fully connected layers. Five convolutional layers are bound to extract main features from the input while three fully connected layers are to make correct approximations.

The input of the proposed ConvNet model includes the sampling radiation pattern of reflectarray and information of reflected direction (θ, φ). The output of the proposed deep convolutional neural network is phase-shift of each element. The optimization process of the ConvNet model is to adjust parameter values in the network and minimize the difference between 'true' phase-shift and 'predicted' phase-shift. In this paper, the cost function for optimization is designed as:

$$f_{obj} = ||log10(\phi) - log10(\widehat{\phi})||^2 \tag{3}$$

where $\widehat{\phi}$ is phase-shift obtained by array theory approach and ϕ is the predicted phase-shift.

III. Results and Analysis

A circular-aperture reflectarray is taken as a numerical example, as shown in Figure 1. The operation frequency of this reflectarray is 12.5 GHz and the diameter of circular aperture is 10λ. The incident direction of this reflectarray is fixed at $\varphi_i = 180°, \theta_i = 25°$.

The ConvNet model takes two 50×50 arrays as input and the output is a 20×20 array representing the phase-shift of each element in the reflectarray. For a more detailed comparison, the average relative error is used to evaluate the accuracy of the ConvNet model prediction and it can be written as:

$$err_{aver} = 20\log 10\left(\frac{\sum_{m,n} \frac{|\phi(m,n) - \widehat{\phi}(m,n)|}{\widehat{\phi}(m,n)}}{mn}\right), \tag{4}$$

where $\widehat{\phi}(m,n)$ is the 'real' ideal phase-shift of mn-th element obtained by array theory and $\phi(m,n)$ is the predicted ideal phase-shift of the mn-th element.

One sample prediction is shown in the Figure 3. The predicted phase-shift agrees well with the 'true' phase-shift and the final average relative error reaches -49.3dB.

IV. Conclusion

The feasibility of synthesizing the reflectarray using deep learning techniques is verified. As a starting point, we aim to compute the phase-shift of reflectarray given the main beam's direction. A deep convolutional neural network is proposed based on AlexNet and it can make accurate prediction of element phase-shift with the average relative error below 0.4%. This study shows a great potential for real-time phase synthesis for complex reflectarrays based on deep learning techniques.

Acknowledgment

The authors would like to thank supports from National Science Foundation of China under contract 61490693 and 61571264.

References

[1] J. Huang and J. A. Encinar, *Reflectarray antenna*. Hoboken, NJ, USA:Wiley, 2007.

[2] J. Tompson, K. Schlachter, P. Sprechmann, and K. Perlin, "Accelerating eulerian fluid simulation with convolutional networks," *CoRR*, vol. abs/1607.03597, 2016.

[3] K. Mills, M. Spanner, and I. Tamblyn, "Deep learning and the Schrödinger equation," *ArXiv e-prints*, Feb. 2017.

[4] P. Nayeri, A. Z. Elsherbeni, and F. Yang, "Radiation analysis approaches for reflectarray antennas [antenna designer's notebook]," *IEEE Antennas and Propagation Magazine*, vol. 55, no. 1, pp. 127–134, 2013.

[5] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in neural information processing systems*, 2012, pp. 1097–1105.