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Coded antenna radiation pattern prediction network based on DDA algorithm

Zhuoyang Liu(1), Shangyang Li(1), Feng Xu(1)
(1) School of Information Science and Technology, Fudan University, Shanghai, China

Abstract

In the past decades, the interpretability of neural network has gradually become a research hotspot in the fields of deep learning, and the method of combining physical model with neural network is one of its research directions. In this paper, a coded antenna radiation pattern prediction network based on DDA algorithm(ARPN-DA) has been purposed, which replaces part of the approximate calculation in DDA with neural network. Then, it realizes the prediction of antenna pattern under the condition of small samples and few neural network parameters. Compared with pure DNNs, the new system does not rely on massive datasets and has interpretabilitiy. We have implemented the network training and testing on the actual coded antenna platform, and the predictions of antenna pattern are very close to the measured results.

1 Introduction

In the field of remote sensing, how to use radar to complete the task of detecting and sensing targets has always been a very crucial direction in this area. Its detection performance is closely related to the antenna beam scanning form and beam configuration, so we need to achieve flexible beam forming regulation to meet the requirements of radar detection on beam. At present, there are many researches on the use of coded antennas to realized variable beam control. In [1], the coded antenna pattern prediction based on DDA algorithm is proposed, which achieves the antenna pattern prediction on partial code. However, due to the complexity of antenna propagation and coupling in metamaterial, this model is not suitable for all codes. Therefore, the physical model alone cannot solve the problem well.
Based on the deep learning method, end-to-end training method is adopted to realize the mapping between two data sets. In [2], the PReLU network proposed by K. He has for the first time realized the recognition performance of artificial neural network on ImageNet data set [3] beyond the human level. But the learning-based approach relies on the training of massive datasets, and more complex mappings require more complex network models.
Thus we need a hybrid system which combines the physical model and neural network, such as the model-based deep learning in [4, 5, 6, 7]. They use this method to solve many image problems and problems related to inverse scattering. However, no one has used it to predict the antenna radiation pattern at present. In this paper, we proposed a hybrid system, which combines DDA algorithm with full connected layers in neural network. It will be described in detail in the following sections.

2 Formulation of the Problem

At present, the Discrete Dipole Approximation is usually used to calculate the radiation pattern of one-dimensional multiarray antennas.Its main idea is divided into the following three steps. The first step is to excite each antenna unit according to the code and calculate the incident electric field of each unit. Then, according to the coupling relationship between two antenna elements, we can calculate the total electric field of each antenna element. Finally, the radiation pattern of each antenna element is regarded as the pattern of a dipole, we can obtain the pattern of space radiation of the coded antenna elements.

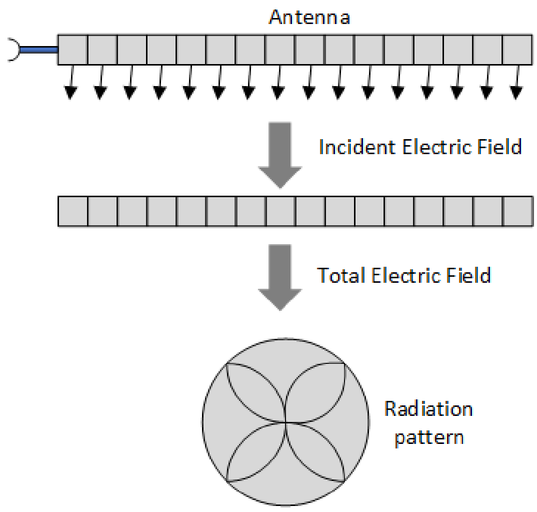


Figure 1. The flow chart of coding antenna radiation pattern prediction based on DDA algorithm.

Fig 1 provides the process of using DDA algorithm to predict the antenna radiation pattern. First of all, according to the condition of coded feed, we can know each antenna is determined to be in an on or off state. The formula of incident electric field $\overline{H}^{inc}$ can be expressed as eq 1.

$$\overline{H}^{inc} = \overline{C} \cdot e^{-jkx} \tag{1}$$

$\overline{C}$, k and x refer to code vector, the wave number inside the antenna array and the position of each antenna element, re-

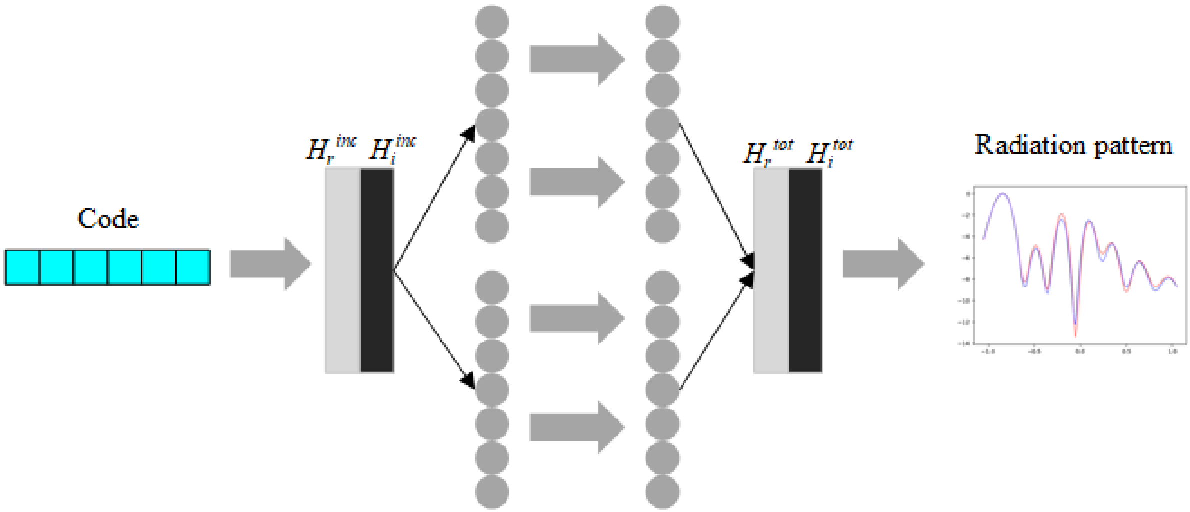


Figure 2. The structure of coded antenna radiation pattern prediction network based on DDA algorithm. Where the H_r^{inc} and H_i^{inc} are the real and imaginary parts of the incident electric field, respectively, and the H_r^{tot} and H_i^{tot} are the real and imaginary parts of the total electric field.

spectively. The polarization of the antenna units need to be approximated, and we use coded zeros and ones to indicate the degree of polarization directly. Then because of the coupling between the antennas, the total electric field $\overline{H}^{tot}$ can be expressed as eq 2.

$$\begin{aligned} &[I-\overline{\overline{G}}\cdot\alpha]\overline{H}^{tot}=\overline{H}^{inc} \\ &\overline{H}^{tot}=[I-\overline{\overline{G}}\cdot\alpha]^{-1}\overline{H}^{inc} \end{aligned} \tag{2}$$

$\overline{\overline{G}}$ represents Green's function, and I is identity matrix. The last step is calculating the radiation pattern. If we consider each antenna unit as a dipole, which its radiation pattern is known as $\cos(\theta)$, the space radiation field $\overline{E}^{tot}$ of the whole coded antenna elements can be written as eq 3.

$$\begin{aligned} \overline{E}^{tot}(\theta) &= \cos(\theta)\sum_{i=1}^{N}\overline{H}_i^{tot}\cdot e^{-j\beta_0 x_i \sin(\theta)} \\ &= \overline{\overline{B}}(\theta)\cdot\overline{H}^{tot} \end{aligned} \tag{3}$$

The propagation factor in free space and the number of antenna units are β_0 and N respectively. Then the two-dimensional matrix $\overline{\overline{B}}$ is given as eq 4

$$\overline{\overline{B}}=\cos(\theta)e^{-j\beta_0 x\sin(\theta)} \tag{4}$$

In this paper, we use the hybrid system which combines DDA algorithm with neural network. Then the process of calculating the total electric field from the incident electric field is replaced by some full connected layers in neural network. Thus, we need the incident electric field information as input and then get total electric field as output. It is used to obtain entire radiation pattern by the formula eq 3 in the end. This hybrid system will be described in detail in the next section.

3 ARPN-DA

In DDA algorithm of antenna pattern prediction, the process of calculating the total electric field according to the Green' function is approximate. In other words, the coupling between antenna elements is much more complicated than the relationship described by the Green's function. Thus, we decide to replace it by full connected layers, in which each neuron indicates the coupling parameters. In this section, 16 antenna units are taken as examples to introduce the principle of combining physical model and neural network in detail.

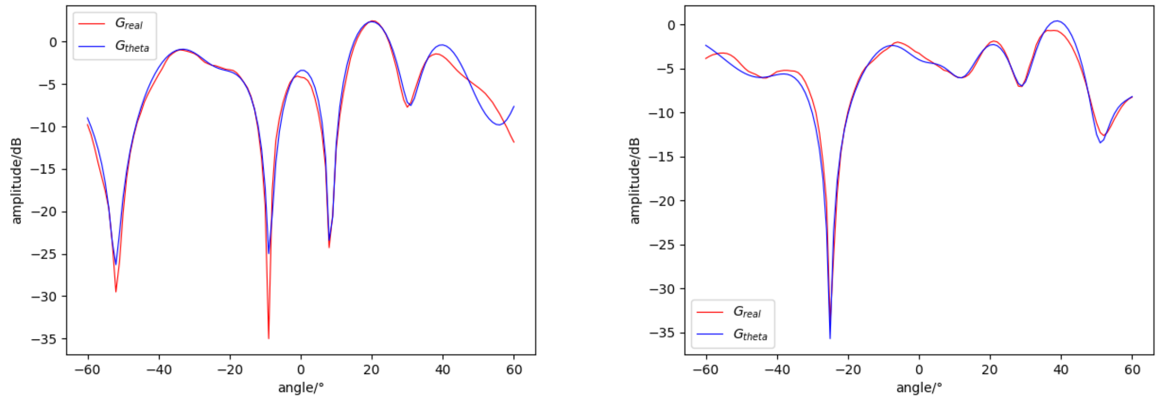
3.1 Principle of Hybrid System

The incident electric field information of each antenna unit and the coupling relationship between each two antennas need to be taken into account, when calculating the total field of the coded antenna. Fig 2 shows the structure of coded antenna radiation pattern prediction network based on DDA algorithm(ARPN-DA). Then each antenna element has 16 coupling factors, and 16 antenna elements array correspond to 256 coupling factors. Thus, we need at least 256 neurons in each full connected layer to ensure that the coupling between each two antenna elements is involved. One form of this hybrid system can be expressed as eq 5.

$$\begin{aligned} \overline{E}^{tot} &= \overline{\overline{B}}\cdot\overline{\overline{W}}\cdot\overline{H}^{inc} \\ &= \overline{\overline{B}}\cdot\overline{\overline{W}}_{16\times256}\cdot f(\overline{\overline{W}}_{256\times256}\cdot f(\overline{\overline{W}}_{256\times16}\cdot\overline{H}^{inc})) \end{aligned} \tag{5}$$

Where $\overline{\overline{W}}$ is variable weight, $f(\cdot)$ is activation function. We use leakyReLU as activation function to add nonlinearity to the full connected network, and its expression is given here.

$$f(x)=\begin{cases} 0.02x & \text{if } x<0, \\ x & \text{if } x\geq 0. \end{cases} \tag{6}$$



(a) Code-0111 0111 1101 1011

(b) Code-1010 0101 1001 1001

Figure 3. Coded antenna radiation pattern prediction results and their measured results. The blue line and red line represent the predictions and true values respectively. By the way, the codes are randomly selected from the full code data.

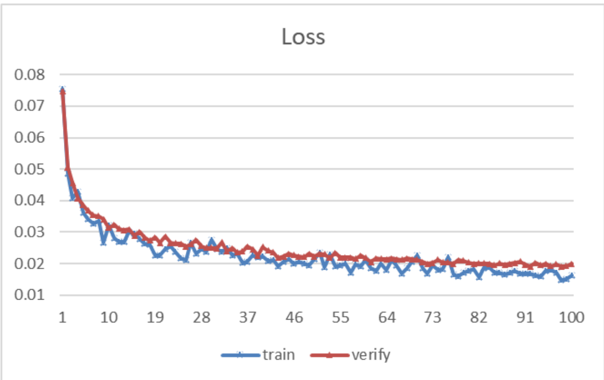


Figure 4. The joint loss reduction diagram of training and verification

The incident electric field is complex data, so it needs to be divided into real and imaginary parts and input into the neural network at the same time. Then the forward propagation of network is depended on the principle of complex data calculation. Accordingly, the weight parameters in the full connected layers need to be complex data and the formula for the whole hybrid system can be written as:

$$\begin{aligned}\overline{E}^{tot} =& \overline{\overline{B}} \cdot \overline{\overline{W}}_{16\times256} \cdot f((\overline{\overline{W}}_3 + j\overline{\overline{W}}_4) \\ & \cdot f((\overline{\overline{W}}_1 + j\overline{\overline{W}}_2) \cdot (\overline{H}_r^{inc} + j\overline{H}_i^{inc})))\end{aligned} \tag{7}$$

where the H_r^{inc} and H_i^{inc} are the real and imaginary parts of the incident electric field, respectively. We only take the amplitude of the antenna radiation field $\mathrm{R}(\overline{E}^{tot})$ as the prediction results finally.

3.2 Parameter of Neural Network

In this hybrid system, it combines physical model-based with deep-learning, so that the network parameters include the neural network parameters and the coefficients in physical model. The former one is the neurons in the full connected layers, and their physical meaning can be expressed by eq 2. The parameters in physical model include code vector and the radiation pattern of an antenna unit, and the antenna element pattern is the ideal result. An example of using this network to predict antenna pattern is presented in the next section.

4 Experiment Results

The network training data are from the measured true values of 25% full code data, and their corresponding radiation pattern has gain in dB domain. The full code data refer to all possible coded results of 16-bit binary. We have trained the proposed network according to the parameters given in the table 1. In this training experiment, it need to be trained for 100 rounds and in each round it has 131 times iterations. The initial learning rate is set as 1e-3 and we reduced the learning rate of each round to 0.99 times that of the last epoch.In this paper, 5% of full code data is used as verification, and 5%, 10%, 15%, and 20% of measurement corresponding to the whole code data are used to train the ARPN-DA respectively. Then, we use a pure neural network with the same size of parameters in ARPN-DA to make comparisons. Finally, the ARPN-DA is trained by MSE loss function and Loss2, and the formula of it can be

Table 1. Neural network training parameters

Network parameters	Value
Data sets	16383
Train sets	5%, 10%, 15%, 20%
Linear layers	$256 \times 16, 256 \times 256$
Minibatch	50
Learning rate	1e-3, 0.99/131
Epoch	100

expressed as:

$$Loss2 = 0.7(1 - COE) + 0.3MSE \tag{8}$$

where the COE is correlation coefficient. Fig 4 provides the loss reduction diagram of training and verification. We give some visual comparisons of the predictions and the true values in Fig 3 and MSE comparison diagram of verification results obtained by different network training methods in Fig 5. Compared with pure neural network, the ARPN-DA proposed does not rely on massive datasets, it can perform well with small samples and few parameters.

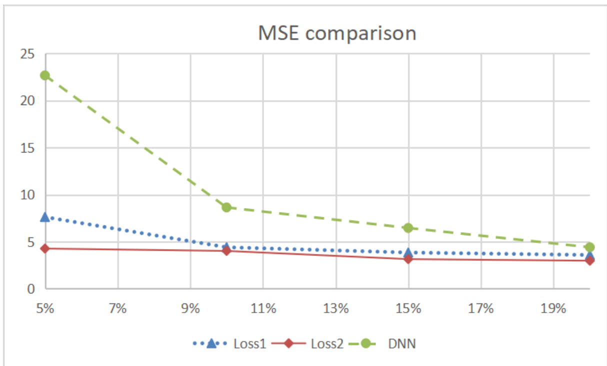


Figure 5. The MSE of the predictions and true values of the code used for testing. The label Loss1 refers to the test results obtained by training with MSE as a loss function. The label Loss2 refers to the results obtained by training with joint loss function. And the last one is the results of pure neural network.

5 Conclusion

This paper mainly focused on the ARPN-DA which combines the physical model of DDA with neural network of full connected layers, and its purpose is to realize antenna pattern prediction. According to our experiment results, this hybrid system complete the task of predicting the pattern of the coded antenna. Moreover, it achieves the effect that the MSE between the network predictions and the true value is less than 4 dB^2 in the case of small samples. However, the physical model is usually approximate. If the part containing the approximation is not modified, the neural network based on the physical model will reach a limit, which has nothing to do with the number of parameters, but is only related to the approximate calculation in the model. It means that the neural network based on physical model, may not achieve the results close to the pure neural network, or even far from the pure neural network, in the case of big data and multi-network parameters.Therefore, if we want the network to preform better, we need to do more constraints for the physical model.

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