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Applying Artificial Neural Network to diagnose Array Antennas

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Abstract−A method based on NNs is designed for diagnosis of antenna arrays in this report. The near-field works as the input and the current of an antenna under test is the output in this model. The robustness of our model is investigated when there are Gauss White noise and more than 3 error elements.The result of numerical simulation shows that the proposed model can estimate the current distribution correctly. As a result, defective elements are detected.

Index Terms − Antenna diagnosis, artificial neural network, array antenna, current distribution, near field, inverse problem

I、Introduction

Due to the requirement of high-speed wireless communication system, modern antenna technologies have been more and more sophisticated. For example, an array antenna is well-known as one of the promising antenna technologies. .(Advantages of array antenna technologies should be described here.) One of the major problems of array antennas is element failure. The existence of the failures in array antennas may reduce its performance. In order to find defective elements in the array antennas, it is necessary to know the current distribution on the array antenna.

Diagnosis of the antenna array using source reconstruction technique is one of the effective approaches to estimate current distribution of the array antenna. A so-called compressive sensing (CS) approach has been introduced for the diagnosis of array antennas [1-2]. And eigenmode current has been used to dignose array antenna [3].

In precious research, so-called Neural Networks (NNs) has been used to solve a large number of EM problems. For example, NNs has been introduced to design antenna through objective gains, far-field patterns,... [4-6]. Radial Basis Function NNs have been made use of calculating straightly estimation for short dipole arrays [7]. NNs combined with Pole-Residue-Based Transfer Function was proposed to solve EM problems [8]. Moreover, many researchers take advantage of NNs to calculate inverse EM problems. NNs and the Finite Element Method(FEM) have been combined to compute inverse EM problems [7]. Inverse NNs model has been utilized for the solution of the inverse loop antenna Radiation Problem [7]. An ANN [8] was put forward for fault finding in antenna array by forming a mapping between the damaged radiation pattern and the position of the defective elements. The method utilizing NNs is effective by structuring the relationship between far-field patterns and the properties of the scatter or the radiator. However, we cannot explain this relation directly.

The object of the present study is to find defective elements in array antennas. Defective elements can be found from reconstructed current distribution of antenna array. If the current is very small, we could consider the element in this position may be broken. To calculate the current, a method based on NNs is proposed for overcoming this inverse EM problems. A full-wave analysis of Method of Moments (MoM) is used in this approach to obtain the training data(near-field distribution) and target data(current distribution of array antennas). The unknown current segments are easily evaluated by measuring the near filed and utilizing the NNs model.

II、Methodology

The proposed method is composed by two steps. Firstly, a NNs is proposed to predict the equivalent current distribution on the equivalent source. Secondly, error segments would be found from the current distribution.

Let us consider that a finite planar measurement surface is parallel to the incoherent source as shown in Fig.1. The near -filed of source can be measured on the surface.

Each measurement point’s electricity field can be written as follows:

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$$\begin{aligned} E_i &= \oint \sum_{j=1}^{M} \overline{G}(r,r') \cdot I_j(r)dr' \\ &= \sum_{j=1}^{M} I_j \cdot \oint \overline{G}(r,r')dr' = \sum_{j=1}^{M} G_{ij} \cdot I_j \end{aligned} \quad (1)$$

Where G is the dyadic Green's function in free space and M is the number of equivalent source points.

There are N measurements points on measurement surface. Thus, equation (1) can be written as the following matrix-vertor:

$$E_{N\times 1} = G_{N\times M} \cdot I_{M\times 1} \quad (2)$$

In order to get current I, we have to solve this inverse problem.

TableI.Inversion Architecture

parameter	value
number of input neurons	576
number of hidden layer1 neurons	400
number of hidden layer2 neurons	300
number of hidden layer3 neurons	200
number of output neurons	100
number of hidden layers	3

III、Artificial Neural networks Model

Several NNs [7-8] have been designed for antenna design and analysis of electromagnetic propagation problems. In these different kinds of NNs, the multilayer perceptrons(MLPs) is one of the most suitable structure to deal with nonlinear electromagnetic problems[9].

The construction of the MLP-NN model which is applied in this report is shown in Fig.2. It is consisted by three departments,input layer, hidden layer and output layer. The input layer assesses N neurons, and the input is the values of $|\mathbf{E_i}(\mathbf{x,y,z})|$. The output layer is consisted by M neurons, and each neuron's value is equal to $|I_i|$.Because complex number cannot be calculated in NNs. All the layers are followed by ReLUs units because of its less train time in backward propagation, except output layer is used sigmoid function as the output is in range (0,1). Highly correlated changes in the summed inputs to the next layer will be influenced heavily by changes in the output of last layer[10]. Therefore, the output data in each layer are normalized by applying layer normalization method. Layer normalization is a new technology, which computes the mean and the variance of the output of each layer and then apply the mean and variance to normalize the output value so that covariate shift problem can be avoided and the efficiency of interaction is able to be enhanced.

The loss function in our model is defined as

$$\text{loss} = \sum_{i=1}^{N} \sum_{j=1}^{M} \left[\left(I^{e}{}_{ij} - I^{o}{}_{ij} \right) / 0.05 \right]^2 \quad (3)$$

where $I^{e}{}_{ij}$ is the exact current distribution obtained by full-wave simulation, $I^{o}{}_{ij}$ is estimated current distribution by the NNs, N is the number of training data and M is the dimension of input.

The setting of gradient descent method has a great influence in training progress. In this report, while training, the weight is updated using a gradient descent technique called Adam and backpropagation during training of the NN.Although compared with other algorithm, Adam has low accuracy, Adam works more quickly than others. The weights are initialized from Xavier distribution and the biases are set to 0 in this model.

IV、Result and Discussion

In this section, a planar dipole array antenna with 10× 10 elements including a couple of defective elements is an antenna under test. The structure of the planar dipole array antenna is shown in Fig.1. Length of the dipole is 0.5 λ , radius of the dipole is 0.015 λ ,array spacing is 0.6 λ ,and distance between each receiving probe is 0.25 λ . Every dipole antenna is excited by a voltage source and its work frequency is 1.5 GHz.

And in this report, the maximum number of defective elements is restricted to three and the defective elements are distributed randomly. Although it is very rare that there are 3 dipoles broken at the same time.

Near-field **E** on a rectangular scanning surface as input data and current distribution **I** as output data were obtained by Method of Moments (MoM). These data is separated into three dataset, training dataset, validation dataset and testing dataset. Before training, dataset was regularized.

The mean absolute percentage error(MAPE) is applied for performance assessment.

$$\text{MAPE} = \frac{1}{N \cdot M} \sum_{i=1}^{N} \sum_{j=1}^{M} \left| \frac{I^{e}{}_{ij} - I^{o}{}_{ij}}{I^{e}{}_{ij}} \right| \times 100\% \quad (4)$$

After the modeling process, the average training MAPEs are 0.842%, while the average validating and testing MAPEs are 1.253% and 1.273%.

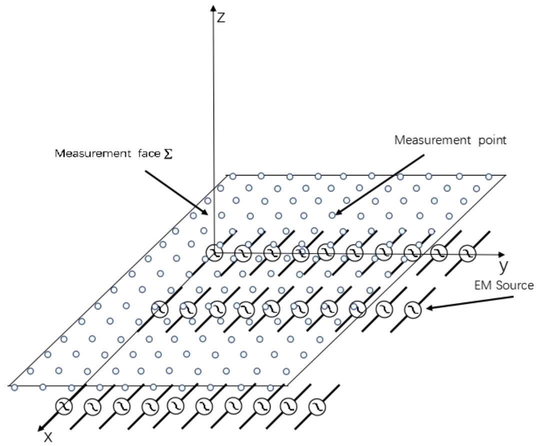

Fig.1 Geometry of near field measurement

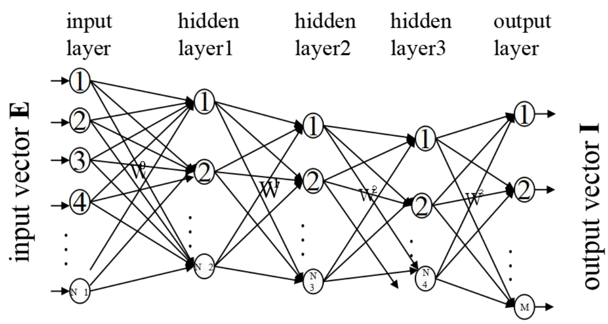

Fig.2 Structure of MLP-NNs

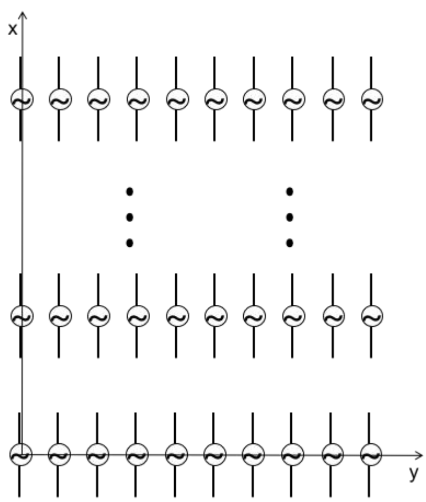

Fig.3 Structure of antenna under test

A、 Test

Fig.4 shows the outputs of one test data from the dipole array antennas with MoM simulation and the proposed model estimation. At this example, the broken dipoles are 35^{th},$73^{th}$and 100^{th},and the average MAPEs are 0.9%. It is clearly shown that the proposed model can perform very well even if the test data is out of the range of the train dataset.

To investigate the robustness of our model, the Gauss White noise, whose mean is 0 and variance is σ^2,are added into the input electric field. As a result, the input data now is consisted by electric field and gauss white noise. And we define the SNR as

$$\mathrm{SNR} = \frac{|\mathbf{E}|_{\max}}{\sqrt{N_R^2 + N_I^2}} = \frac{|\mathbf{E}|_{\max}}{\sqrt{2}\sigma} \tag{5}$$

In this report, the SNR enforced is 20. Inputting the electric field which includes noise into our proposed model, after computing, the average MAPEs are 3.32%. while it is a little larger than the test average MAPEs, compared with the average MAPEs which is larger than 10% if we apply pseudo-inverse to estimate, it is very smaller. Fig.5 reveals that the results predicted from our model are matching closely with simulation data valuated by MoM. Thus, we can conclude that the proposed model has good robustness even though we append noise in the input data.

B、 The effect of the number of broken antenna

TABLE II

MAPE of the current distribution for the proposed model VS number of error dipoles

Broken dipoles \ **Model**	**NN3**
1	0.867%
2	0.929%
3	1.273%
4	2.164%
5	3.842%
6	6.082%

In this part, robustness of the devised method is discussed when there are more than 3 broken elements. A lot of test data are collected by applying (1) with different amount of fault elements. Table II shows the average MAPE of different number of fault dipoles. When broken segments are less than 3, the average MAPE is less than 1.273% and increase slowly with enlarging the quantity of errors. However, the average MAPEs increase dramatically while there are more than 3 broken antennas. Consequently, it reveals that our model cannot work very well when the number of dipoles which do not work is out of the range in training data. In other words, the less error antennas, the better performance would be achieved. Nevertheless, it is impossible that a great number of dipoles failure at the same time. Therefore, it is able to be concluded that our model can complete good accuracy in most conditions.

One test data, which is chosen out of the training data and validate date, is selected to be as an example. There are 6 deficiency dipoles in this array antenna where the broken ones are 20^{th},37^{th},49^{th},54^{th},$57^{th}$and 61^{th} , the average MAPEs is 4.182% which is a little smaller than data's average MAPEs. Fig.6 shows the current distribution estimated by MoM and by our model. It is obvious that the evaluation of current distribution in some position where antennas works is similar to the current distribution evaluated by MoM. This outcome conforms to our target, because our loss function is defined that if I^{e}_{ij} is larger, the weight factor in loss function is bigger so that the current distribution can be predicted more exactly, because most antenna under test usually work . And the current measured in broken segments is a little larger than estimated by MoM. Therefore, the huge MAPEs is caused by bad estimated for mistaken antennas. to get better MAPEs or result, a new cost function should be defined to reduce the residual for current at broken antennas. Although the MAPEs is quite vast when there are 6 dipoles which are damaged, it is evident that the disable ones would be detected form the current distribution clearly. Generally speaking, our model can achieve high accuracy even though there are a lot of fault segments which is out of the training data.

V、Conclusion

In this report, a NNs has been designed to find defective elements in an array antenna. The robustness of our model is discussed when the electric field is influenced by the Gauss White noise and there are more than three diploes which is broken. It has been demonstrated that the designed NNs has good robustness and enable build a closely relationship between electric field and current. And then, the error elements can be detected easily from the estimated current distribution.

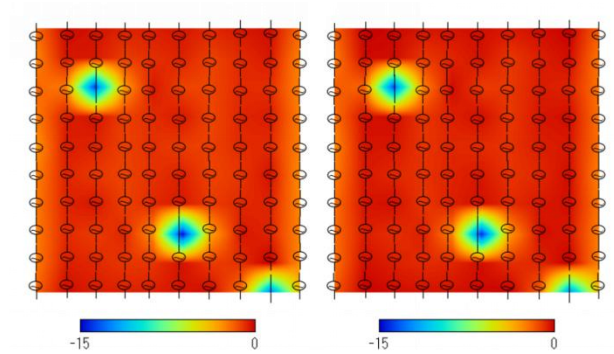

Fig.4 (a) current distribution by MoM (b) current distribution estimated by Model

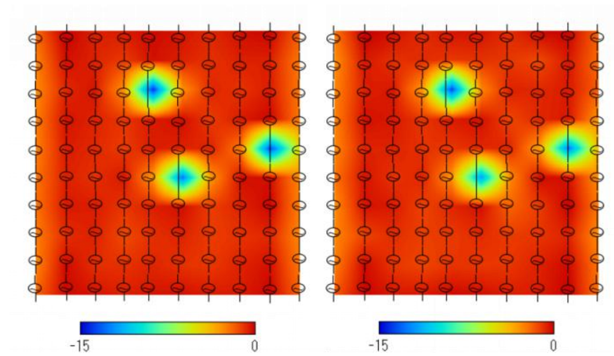

Fig.5 (a) current distribution by MoM (b) current distribution estimated by Model

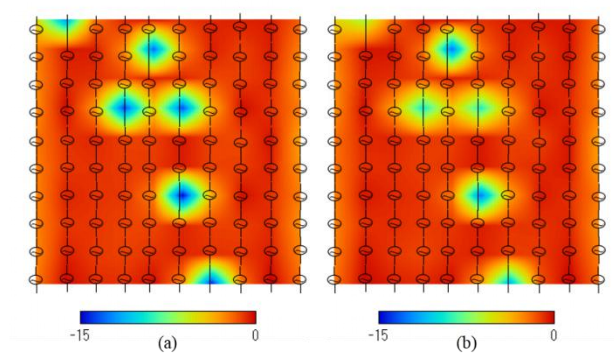

Fig.6(a) current distribution by MoM (b) current distribution estimated by Model

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