伝送工学研究会資料
Vol. 2019, No611-3. ,2019 年 10 月

Estimation of Current Distribution by Artificial Neural Network and Eigenmode Currents

Xin Wang, Keisuke Konno,Qiang Chen,(東北大学大学院工学研究科),

Abstract−A method based on ANNs is designed for diagnoses of antenna arrays in this report. Two schemes, direct inverse scheme and eigenmode currents scheme, based on ANNs are proposed to reconstruct the current distribution of array antennas by near field. A dipole array antenna is used to evaluate the proposed twos schemes. It is shows that the proposed EMS works better in terms of correlation function and has a good anti-noise capacity. The optimum number of dominant eigenmode currents are also discussed in this paper.

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. One of the major problems of array antennas is element failure. The existence of the failures in array antennas may reduce its performance.

Reconstructing current distribution of the array antenna themselves using near-field(NF) is one of the most effective app-roaches to diagnose array antenna. A approach based on Amplitude of near field and iterative minimization techniques is used to solve the sources Reconstruction in [1]. And this method has been extended to reconstruct equivalent currents over an arbitrary plane[].The current distribution is rebuilt from eigenmode currents and Near-Field Data is proposed in [2].

One of the major problems regarding the electromagnetic inverse problem is its ill-posed nature. Due to the superiority of building a strong relationship between input data and output data, artificial neural network or Deep neural networks(DNN) have been applied to alleviate ill-posed nature problems. An ANN [3] was put forward for fault finding in antenna array by forming a mapping between the damaged radiation pattern and the

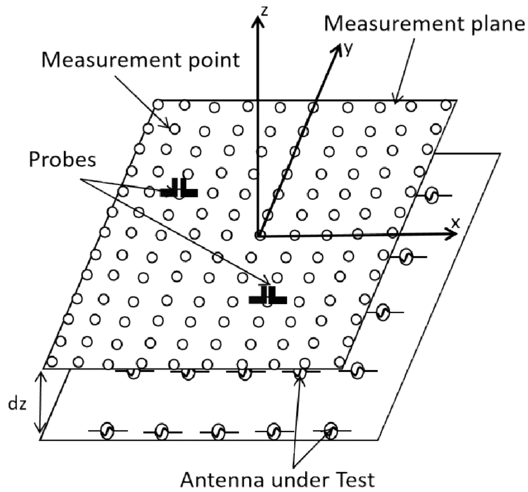


Fig. 1 Geometry of near field measurement

position of the defective elements. [4]designs a deep neural network to solve nonlinear electromagnetic inverse neural network to solve nonlinear electromagnetic inverse scattering problem. Reconstructing permittivity with three different schemes based on DNN is discussed[5].

In this paper, two schemes based on ANNs is proposed to alleviate ill-posed nature problems in source reconstruction. First of all, a direct inversion scheme is designed. Near-field data is directly used to estimate the complex current distribution. What is more. An eigenmode currents scheme is proposed, where the unknown coefficients are obtained from near-field data firstly, and then coefficients and eigenmode vector are used to calculate currents. A dipole array with abnormal ex-citation is used to test two schemes. And it is found that EMS has a better performance than DIS. We also examine the effect of the number of eigenmode currents and probe distance on EMS based ANN. The performance of EMS based ANN shows that it has good robustness.

These paper is organized as fellows. The problem is introduced in Section II. And two schemes are proposed in Section III. Section IV shows a numerical result of the proposed two schemes. Finally, conclusion is obtained in Section V.

II、Problem Statement

An antenna under test is shown in Fig. 1. Let’s consider that the receiving probe scans the rectangular

2019 年 10 月 15 日
東北大学　電気・情報系 2 階大会議室

surface above the AUT and measure the complex near field fields at M specific points.

A. *Connection between ANN and inversion problem*

The proposed problem can be expressed by the electric field integral equation:

$$\mathbf{E}\left(\mathbf{r}\right)=\int_D G(\mathbf{r},\mathbf{r}')I(\mathbf{r}')d\mathbf{r}' \tag{1}$$

Where ***r*** and ***r'*** are the field and source points, respectively. ***E(r)*** is the total near field in measurement face and ***G(r,r')*** denotes the 2-D free space Green's function. I($\mathbf{r}'$) expresses total N segments current distribution on AUT.

For inverse problem, our target is to reconstruct the current distribution **I** from near field **E(r)**.

Before getting current distribution I, equation (1) can be written as the following matrix-vector:

$$\mathbf{E}_{M\times 1}=\mathbf{G}_{M\times N}\mathbf{I}_{N\times 1} \tag{2}$$

To solve (2), pseudo-inverse can be applied:

$$\mathbf{I}=(\mathbf{G}^{\dagger}\mathbf{G})^{-1}\mathbf{G}^{\dagger}\mathbf{E}=\mathbf{PE}+\mathbf{b} \tag{3}$$

Where $\mathbf{G}^{\dagger}$ is green function **G**'s conjugate transpose. matrix **P** and vector **b** can be decomposed into $\mathbf{P}_1$, $\mathbf{P}_2$,⋯ and $\mathbf{b}_1$, $\mathbf{b}_2$,⋯. Function (3) is similar to a full-connected Artificial neural network, $\mathbf{P}_k$ and $\mathbf{b}_k$is able to be understood as the parameters of number k hidden layers.

According to process of ANN, if a set of date are put into the model, each layer's the parameters $\mathbf{P}_k$ and $\mathbf{b}_k$ will be trained.

B. *structure of ANN*

The construction of the proposed ANN structure is shown in Fig.2. It is consisted by three departments, input layer, hidden layer and output layer. Because the un-known variables are complex number, here, two output layers are utilized. One's outputs are real part of unknown, the others are imaginary part of unknowns. 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]. In order to eliminate co-variate shift problem, Layer normalization is applied at each layer.

III、ANN Schemes for Inverse Problems

A. Direct Inverse Scheme

[6] propose a direct inversion scheme to solve the inverse problems. It considers the inverse problem as a regression of unknowns directly from the measured data. Here,the inputs of our model are the near field measured in measurement face, and the outputs are the complex values of current distribution in AUT. Compared with the proposed DIS model in [6], our model is a little different. Our target is to reconstruct the current distribution on AUT. Therefore, in our scheme, the outputs are the complex values, however, the outputs of it are real number.

B. Eigenmode Currents Scheme

Although it is possible to train a DNN to regress directly from the measured near field to the current distribution on AUT. For inversion problem, solving a great number of unknown variables from limited given quantities will make ill-posed problem. Therefore, to simplify the model and improve the performance of our model, it is important to reduce the number of unknowns.

The Eigenmode current of array antenna is used to source reconstruction[3]. The current distribution of AUT can be expressed by the dominant eigenmode currents whose contributions to the current distribution are relatively huge. Accordingly, to reduce the number of unknowns, eigenmode currents is applied.

Firstly, let's consider about eigenmode before using the eigenmode currents.

As AUT shown in Fig.1, according to the MOM, an N×N matrix equation between mutual impedance **Z** and voltage **V** can be obtained:

$$\mathbf{ZI}=\mathbf{V} \tag{4}$$

Where **I** is an unknown N-dimensional current vector of the AUT, **Z** is the N×N known mutual impedance of AUT And **V** is the known N-dimensional voltage vector of AUT.

Multiplying the conjugate transpose of **Z** on both side of (4), a new matrix equation is gotten:

$$\mathbf{Z}^{\dagger}\mathbf{ZI}=\mathbf{Z}^{\dagger}\mathbf{V} \tag{5}$$

Where $\mathbf{Z}^{\dagger}$is the conjugate transpose of **Z,** $\mathbf{Z}^{\dagger}\mathbf{Z}$ is an Hermitian matrix,which has N different kind of orth-ogonal eigenvevctors, and those eigenvectors are applied as the eigenmode currents of the AUT.

Because each eigenvector is orthogonal to others, the follow equation is available:

$$\mathbf{I_N}\approx\sum_{l=1}^{L}\alpha_l\mathbf{e_l} \tag{6}$$

Where $\mathbf{e}_l$is an N-dimensional *l*th eigenmode current of the AUT, and α_l is its unique unknown coefficient. L is the total number of dominant eigenmode currents. If the coefficient α_l is relative small, it will be omitted and only the dominant eigenmode currents can be left. And how to choose L will be explained in section IV.

According to equation (2) and (6), the relationship between near field E and coefficient αl is available:

$$\mathbf{E}=\mathbf{GI} \approx \sum_{i=1}^{L} \alpha_l \mathbf{Ge}_l \tag{7}$$

In eigenmode current scheme process, the inputs of DNN are the magnitude of near field and the outputs of DNN are the complex values of coefficient α_l. After obtaining coefficient α_l, current distribution will be calculated by (6).

IV、Numerical Results

In this section, the performance of the proposed ANN structure in estimation current distribution is demonstrated. A correlation function is introduced to estimate the performance of the proposed ANN:

$$\gamma = \frac{\left|\sum_{n=1}^{N}(I_n-\bar{I})(I'_n-\bar{I}')^{\dagger}\right|}{\sqrt{\sum_{n=1}^{N}(I_n-\bar{I})(I_n-\bar{I})^{\dagger}}\sqrt{\sum_{n=1}^{N}(I'_n-\bar{I}')(I'_n-\bar{I}')^{\dagger}}} \tag{8}$$

Where† indicates conjugate transpose. I_n and I_n' are the exact current of the nth segment by MOM and the calculated current of the nth segment by the proposed mode respectively. $\bar{I}$ and $\bar{I}'$ represent the average of their current. For comparing, the result computed by pseudo-inverse is thought as counterpart.

A. Training for ANN mode

One numerical example is depicted in Fig.1. A pla-nar dipole array antenna with 5×5 elements including a couple of defective elements is an antenna under test.Parameters for AUT are shown in Table I. In this report, it is important to note that the magnitude of every dipole's excited voltage is 1 V, and if the antenna is broken, its phase of voltage will change. The maximum number of defective elements is restricted to three and the defective elements are distributed randomly. A receiving probe scans the rectangular surface above the AUT, the distance between AUT and measurement face is dz[λ]. Total number of measurement points is P, the polarization of receiving probe is Ex. Gauss white noise is added into measured near field.

10000 dataset, including near field, current distribution and coefficient αare generated by Richmond's MOM. Among them, 7000 of them are used to train ANN, 1500 of them are utilized as validate date to alleviate overfitting, and 1500 of them are used to evaluate the performance of ANN. All the near field, current distribution and coefficient are normalized before training.

For eigenmode scheme, the number of dominant eigenmode currents L affect the performance of mode. Fig. 3 shows the effect of the number of eigenmode currents on correlation function. The growth rate of correlation function is close to gentle as the number of eigenmode currents increases to a specific value. When L=25, the growth rate becomes near 0. As a result, comparing the

Table I PARAMETERS of dipole array

Frequency	1.5GHz
Length of dipole	0.5λ
Radius of dipole	0.003λ
Array spacing	0.6λ
Number of segments in single elements	K=9
Total number of segments	N=225
Probe distance	0.1λ
Distance between AUT and Measurement	dz/λ
Total number of probes	M=961

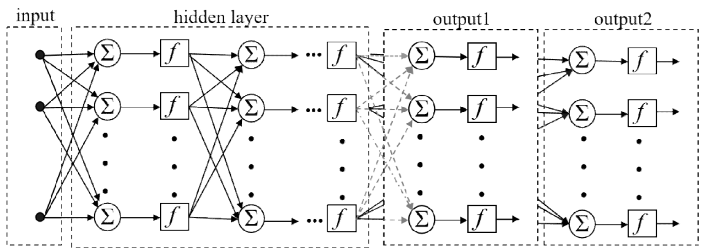


Fig. 2 ANN structure for current reconstruction problem

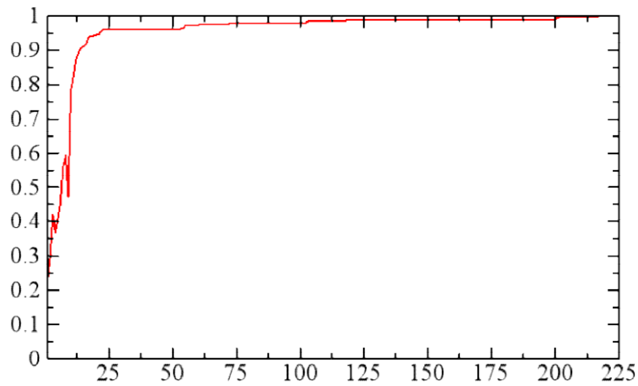


Fig. 3 effect of number of L on correlation function

correlation function and the number of unknowns, we select L=25, while the correlation function is close to 0.962.

The cost function which is used in training process is defined as follow:

$$cost = \sum_{i=1}^{M}\sum_{j=1}^{N}\left(\frac{I_{ij}-I'_{ij}}{I'_{ij}}\right)^2 + \frac{1}{2}\lambda\|W\|_2^2 \tag{9}$$

Where N_i is the number of batch size. Adam is used to changing learning rate in training, and λ is 0.005. Before training, weights are initialized from Xavier distribution and the biases are set to 0.

The proposed ANN model is constructed by Pytorch with NVIDIA Quadro P5000.

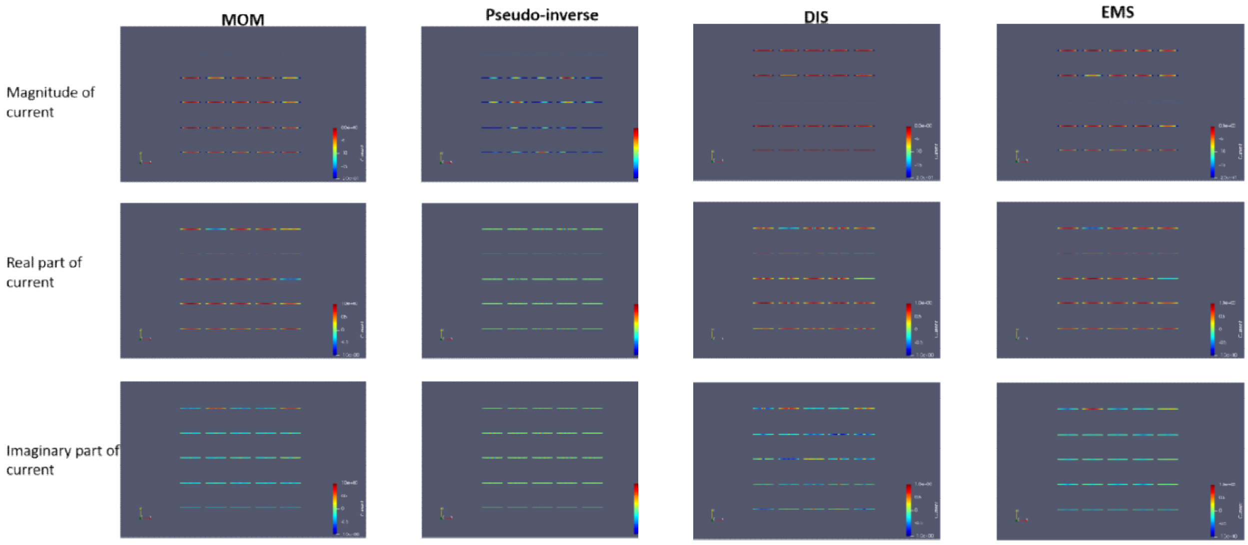


Fig.4 reconstructed current distribution using near-field data with 20dB noise by Pseudo-inverse, DIS and EMS, where MOM is used as ground truth

Table II correlation function for three different schemes

ANN Scheme	DIS	ECS	Pseudo-inverse
γ	0.557	0.900	0.020

Table III The effect of noise on correlation function for DIS and EMS

noise	5dB	10dB	20dB
DIS	0.557	0.331	0.270
EMS	0.686	0.843	0.900

Table IV The effect of L on correlation function by EMS

Number of eigenmode currents L	Correlation function
L=25	0.900
L=55	0.927
L=125	0.950
L=201	0.967
L=225	0.967

B. Test with Trained Networks

Table II shows the correlation function for direct scheme, eigenmode currents scheme and pseudo-inverse.

It shows that ECS has better ability to reconstruct the current distribution when 20dB gauss white noise is present in near field. Reconstructed current distributions by three ways are shown in Fig.4. DIS and EMS both of them can reconstruct the magnitude of current distribution well. And EMS is better than DIS in estimating the currents in the position where antenna is fault. From the current distribution, it is easy for us to diagnose the broken elements easily. Compared with the complex current calculated by DIS and ECS, it can be concluded that DIS has a good performance in estimating the magnitude of current

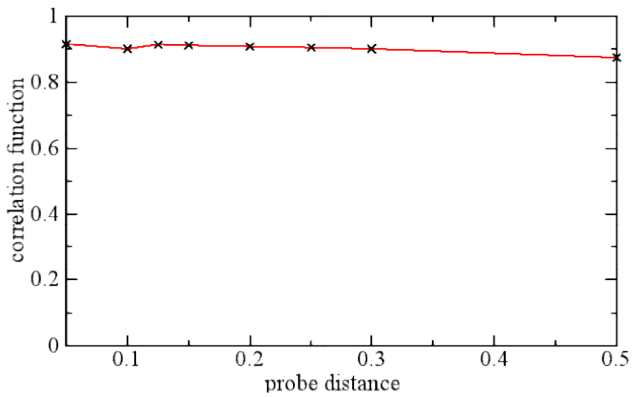


Fig.5 the effect of correlation function on probe distance

distribution, however, ECS can not only calculate the real part of current distribution, but also estimate the imaginary part of current distribution.

Anti-noise capacity of DIS and ECS are considered in tableV. When SNR is from 20dB to 5dB, the correlation function of ECS reduces from 0.900 to 0.686, while DIS's decreases from 0.557 to 0.27. Both of them do not have a good behavior in high noise level environment. EMS has a better performance when SNR is equal to 5 dB than using DIS when SNR is equal to 20 dB. As a result, it can be concluded that ANN based on EMS possesses a better robustness.

In ECS, the number of dominant eigenmode currents L will affect the correlation function. In other words, L determine the performance of our model. Table V shows the effect of L on correlation function. It shows that the performance becomes better with the increasing of dominant eigenmode current, and when L=201 and L=225, the correlation function is nearly same. Because the last 25 coefficients are so small and their contribution to current distribution can be omitted. Fig.6 shows the reconstructed current distribution in different L. Their relative errors are 23.8%, 18.4%, 14.3%, 14.6% and 12.3%, respectively. To keep then balance between accuracy, memory and time consuming, L= 125 is the optimum in this example which mean we can using half unknowns to reconstruct current distribution by EMS.

When we use the near-field or far- filed to diagnose the array antenna, a great number of measurement data should be input so that a good result can be obtained. A large number of measurements and, consequently, a long measurement time incase of arrays with a large number of elements.And more input data, more memories are occupied. Therefore, it is of great importance to reduce the number of measured probes without deteriorating result. In this paper, the influence of probe distance on the proposed modelis discussed. Fig.4 shows the correlation function of EMS when probe distance increases from 0.05λ to 0.5λ. Even when probe distance is 0.5 λ, EMS is able to obtain satisfying results. It means that EMS is robust with the changing of input near field.

V、Conclusion

In this paper, two schemes based on Artificial Neural Network are proposed to solve Electromagnetic inverse problem. Compared with pseudo-inverse method, direct scheme and eigenmode currents scheme based on ANN have a better performance to estimated current distribution when noise is considered in near field. However, ECS can not only obtain details on magnitude of currents distribution,but also can reconstruct the phase of currents, while DIS is just good at reconstructing the magnitude of currents. The robustness of ECS and DIS is thought, and DIS has a better anti-noise capacity. The effect of L on ESM is discussed, more dominant eigenmode currents, a better result will be obtained. Finally, this paper provides a new method for source reconstruction using EMS when there are limited near field message.

References

[1] L. J. Foged, L. Scialacqua, F. Saccardi, J. L. A. Quijano, G. Vecchi, andM. Sabbadini, “Practical application of the equivalent source method aa an antenna diagnostics tool [AMTA Corner],” IEEE Antennas Propag.Mag., vol. 54, no. 5, pp. 243–249, Oct. 2012.

[2] Q. J. Zhang and K. C. Gupta, Neural Networks for RF and Microwave Design. Norwood, MA, USA: Artech House, 2000, pp. 151, 312–315, and 336.

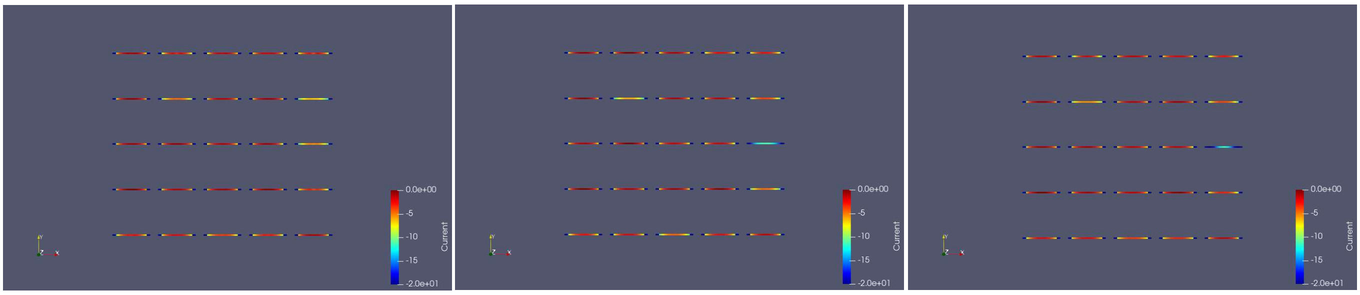
[2] K.Konno,S.i Asano, T. Umenai, and Q. Chen, “Diagnosis of Array Antennas Using Eigenmode”,IEEE Trans. Antennas Propag., vol. 66, no. 11, pp. 5982 – 5989, Nov. 2018.

[3] A.Patnaik,B.Choudhury, P.Pradhan, R.K.Mishra, and C. Christodoulou, “An ANN Application for Fault Finding in Antenna Arrays,”IEEE Trans. Antennas Propag., vol.55,no. 3, pp. 775-777, March 2008

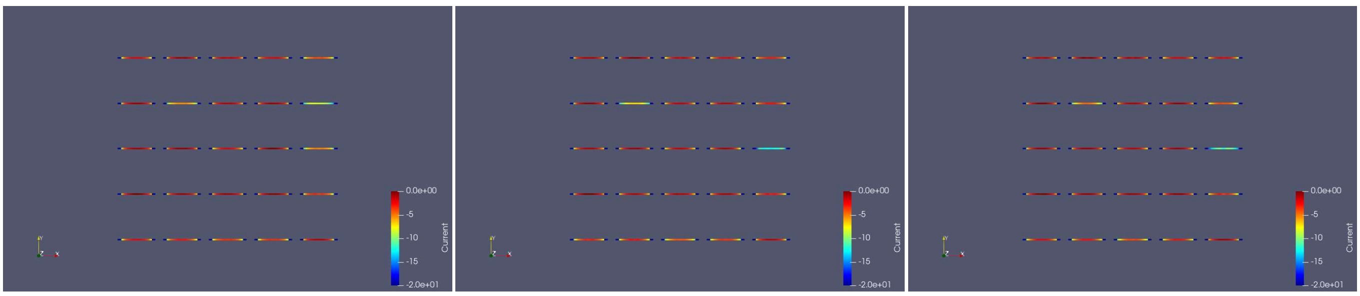
[4] L.L.Li,”DeepNIS: Deep Neural Network for Nonlinear Electro-magnetic Inverse Scattering”,IEEE Trans. Antennas Propag., vol. 67, no. 3, pp. 1819 – 1825, Mar. 2019

[5] Z.Wei, X.D.Chen ”Deep-Learning Schemes for Full-Wave NonlinearInverse Scattering Problems”,IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 57, NO. 4, PP. 1849-1860 ,APRIL. 2019

[6] X. Wang,K,Q. Chen,”Diagnosis of Array Antennas with Defective Elements Using Artificial Neural Network”, IEICE general conference,MARCH.2019



MOM(ground truth)　　L=25(23.8%)　　L=55(18.4%)



L=125(14.3%)　　L=201(14.6%)　　L=225(12.3%)

Fig.6 reconstructed current distribution by EMS when L=25,55,125,201,225