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USING NEURAL NETWORKS FOR FAULT DETECTION IN PLANAR ANTENNA ARRAYS

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Abstract—A method to diagnose on-off faults in a planar antenna arrays using far field radiation pattern is presented. A systematic approach is suggested for detecting location of faulty elements using Artificial Neural Networks (ANN). Radial Basis Function neural network (RBF) and Probabilistic neural network (PNN) are considered for performance comparison.

1. INTRODUCTION

Antenna arrays are used in many applications such as radio astronomy, satellite antennas, radar and communications which contain large number of radiating elements. Hence, there is always a possibility that one or more elements fail at any time. One kind of fault widely encountered in practical instances is the so-called 'on-off', where the faulty element does not radiate at all. The presence of faulty element changes the radiation pattern causing errors in related systems particularly when it is in the center of the array. Hence it is required to test the array regularly. But it is difficult for inspection of faulty elements in the laboratory because of the large size of the array. Several techniques are reported in the literature to identify faults. A built in performance monitoring method using a transmission line signal injector at the radiating aperture to check the amplitude and phase of the radiating element is suggested by Lee et al. [1]. However such an expensive network must be provided at the design stage of the array and may be affected by faults. Further the size, volume, cost and weight increase by inclusion of monitoring systems. A subtraction method is proposed to identify single faulty element in linear array by Jacob Ronen et al. [2]. This method cannot be extended to multiple faulty elements. Further, detection of faulty element is not accurate if

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there are missing points and measurement errors present in the pattern. Fault diagnosis from near field measurement is also given by Ronen et al. [2]. But this method involves approximation of near field to far field by Fourier transformation and in this only the main beam of the far field radiation pattern is obtained accurately. Hence near field method does not give accurate fault diagnosis. Bucci et al. have reported diagnosis of on-off faults in planar array from noisy far field radiation pattern using global optimization technique [3]. Rodriguez et al. have used genetic algorithm to detect the faulty elements in small size arrays [4]. But the Genetic algorithm has to be run several times to yield high accuracy for large size arrays. Authors of the present paper published a method to detect faults in linear antenna array using artificial neural networks [5–7].

A step wise method is proposed to detect error in phase or amplitude of current in planar arrays by the authors of the present paper [8]. In the present paper the method is extended to detect on-off faults in planar array where the element is turned off completely. The maximum number of faulty elements that can occur in the array at any instant of time is limited to three. The proposed method detects the faults based on the change in the radiation pattern. To begin with the method, radiation pattern is determined for the array with no faulty elements. Further, radiation pattern is derived for 'N' faulty elements in the array. From this the deviation pattern is determined which is the difference between fault free pattern and faulty pattern. A general expression of deviation pattern for N faulty elements is obtained from which the deviation pattern for single, two or three elements can be deduced.

In the present work, a neural network approach is adopted to identify the faulty elements. A neural network is initially trained with some of the possible faulty patterns in the array. Then, it is used to predict the faulty element by giving a test pattern to it.

2. THEORY

A planar array is considered, which consists of N_x rows of elements and each row has N_y elements arranged in a rectangular grid as shown in Figure 1. The spacing between rows is d_x and between elements in a row is d_y. Radiation pattern is given for the array with 'N' faulty elements from which deviation pattern is determined.

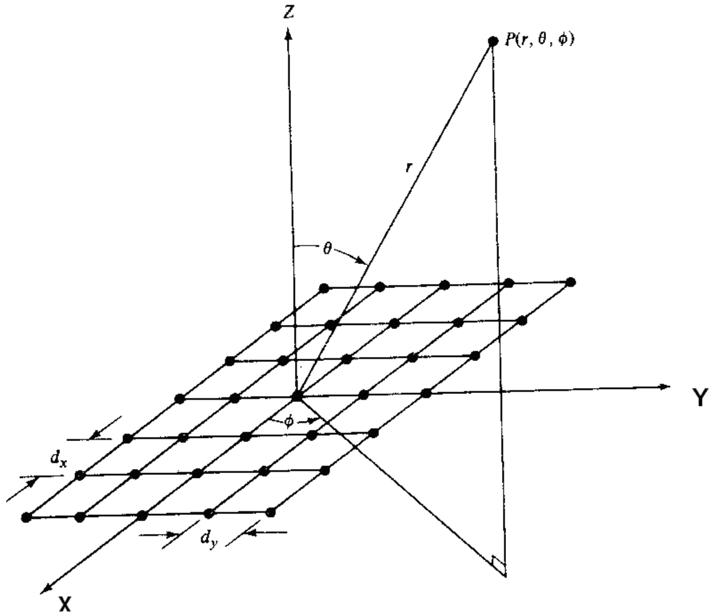

Figure 1. Planar array arranged in rectangular grid.

2.1. Radiation Pattern of Planar Array with out Faulty Elements:

The normalized array factor for the planar array with current excitation of 1 Amp can be written as [9]

$$A(\theta,\phi)=\frac{1}{N_xN_y}\sum_{m=1}^{N_x}\sum_{n=1}^{N_y}e^{jk\sin\theta\left(\left(m-\left(\frac{N_x+1}{2}\right)\right)d_x\cos\phi+\left(n-\left(\frac{N_y+1}{2}\right)\right)d_y\sin\phi\right)} \tag{1}$$

where

N_x is number of rows of elements along X-axis
N_y is number of columns of elements along Y-axis
θ is angle of observation from array normal
ϕ is angle with X-axis
$k=\frac{2\pi}{\lambda}$ is propagation constant
d_x is distance between elements along X-axis
d_y is distance between elements along Y-axis

2.2. Derivation of Deviation Pattern of the Array with 'N' Faulty Elements:

Consider $(r_1, s_1), (r_2, s_2), (r_3, s_3), \ldots, (r_N, s_N)$ are locations of faulty elements occurring in the array. The array factor is provided by

$$A_N(\theta,\phi) = \frac{1}{N_x N_y} \sum_{\substack{m=1 \\ m \neq r1 to rN}}^{N_x} \sum_{\substack{n=1 \\ n \neq s1 to sN}}^{N_y} e^{jk\sin\theta\left(\left(m-\left(\frac{N_x+1}{2}\right)\right)d_x\cos\phi+\left(n-\left(\frac{N_y+1}{2}\right)\right)d_y\sin\phi\right)} \tag{2}$$

Deviation pattern is given by

$$A_d(\theta,\phi) = A(\theta,\phi) - A_N(\theta,\phi)$$

$$A_d(\theta,\phi) = \frac{1}{N_x N_y}\left[\cos\varphi_{rs1} + j\sin\varphi_{rs1} + \cos\varphi_{rs2} + j\sin\varphi_{rs2} + \ldots + \cos\varphi_{rsN} + j\sin\varphi_{rsN}\right] \tag{3}$$

where

$$\varphi_{rs1} = k\sin\theta\left(\left(r1 - \frac{N_x+1}{2}\right)d_x\cos\phi + \left(s1 - \frac{N_y+1}{2}\right)d_y\sin\phi\right)$$

$$\varphi_{rs2} = kd\sin\theta\left(\left(r2 - \frac{N_x+1}{2}\right)d_x\cos\phi + \left(s2 - \frac{N_y+1}{2}\right)d_y\sin\phi\right)$$

$$\ldots$$

$$\varphi_{rsN} = kd\sin\theta\left(\left(rN - \frac{N_x+1}{2}\right)d_x\cos\phi + \left(sN - \frac{N_y+1}{2}\right)d_y\sin\phi\right)$$

$$A_d(\theta,\phi) = B_N(\theta,\phi)\angle\xi_N(\theta,\phi) \tag{4}$$

Amplitude of deviation pattern is derived as

$$B_N(\theta,\phi) = \frac{1}{N_x N_y}\left[N + 2\cos(\varphi_{rs1} - \varphi_{rs2}) + 2\cos(\varphi_{rs2} - \varphi_{rs3}) + \ldots + 2\cos(\varphi_{rsN-1} - \cos\varphi_{rsN})\right]^{1/2} \tag{5}$$

Phase of deviation pattern is

$$\xi_N(\theta,\phi) = \sin^{-1}\left(\frac{\sin\varphi_{rs1} + \sin\varphi_{rs2} + \ldots + \sin\varphi_{rsN}}{N_x N_y B_N(\theta,\phi)}\right) \tag{6}$$

Amplitude and phase of deviation pattern along $\phi = 0^\circ$ plane are given by

$$B_N(\theta,0) = \frac{1}{N_x N_y}\begin{bmatrix} N+2\cos(\varphi_{x1}-\varphi_{x2})+2\cos(\varphi_{x2}-\varphi_{x3}) \\ +\ldots+2\cos(\varphi_{xN-1}-\varphi_{xN}) \end{bmatrix}^{1/2} \tag{7}$$

$$\xi_N(\theta,0) = \sin^{-1}\left(\frac{\sin\varphi_{x1} + \sin\varphi_{x2} + \ldots + \sin\varphi_{xN}}{N_x N_y B_N(\theta,0)}\right) \tag{8}$$

where

$$\begin{aligned}
\varphi_{x1} &= k \sin\theta \left(r1 - \frac{N_x+1}{2}\right) d_x \\
\varphi_{x2} &= kd \sin\theta \left(r2 - \frac{N_x+1}{2}\right) d_x \\
&\dots \\
\varphi_{xN} &= kd \sin\theta \left(rN - \frac{N_x+1}{2}\right) d_x
\end{aligned}$$

Amplitude and phase of deviation pattern along $\phi = 90^\circ$ plane are given by

$$B_N(\theta, 90) = \frac{1}{N_x N_y}\begin{bmatrix} N+2\cos(\varphi_{y1}-\varphi_{y2})+2\cos(\varphi_{y2}-\varphi_{y3}) \\ +\ldots+2\cos(\varphi_{yN-1}-\varphi_{yN}) \end{bmatrix}^{1/2} \tag{9}$$

$$\xi_N(\theta, 90) = \sin^{-1}\left(\frac{\sin\varphi_{y1}+\sin\varphi_{y2}+\ldots+\sin\varphi_{yN}}{N_x N_y B_N(\theta, 90)}\right) \tag{10}$$

where

$$\begin{aligned}
\varphi_{y1} &= k \sin\theta \left(c1 - \frac{N_y+1}{2}\right) d_y \\
\varphi_{y2} &= kd \sin\theta \left(c2 - \frac{Ny+1}{2}\right) d_y \\
&\dots \\
\varphi_{yN} &= kd \sin\theta \left(CN - \frac{N_y+1}{2}\right) d_y
\end{aligned}$$

The deviation pattern along $\phi = 0^\circ$ plane illustrates location of the rows of faulty elements. The location of columns is depicted by deviation pattern along $\phi = 90^\circ$ plane. It can be stated that amplitude of deviation pattern specifies the distance between faulty elements locations and phase of deviation pattern represents the location of faulty elements. A random variable is introduced in the deviation pattern to account for noise and measurement error.

3. ARTIFICIAL NEURAL NETWORKS

Two artificial neural networks architectures are considered for classifying the faulty element locations.

3.1. Radial Basis Function

Radial basis function network is nonlinear, layered and feed forward network. It consists of three layers namely input layer, hidden layer and output layer. The input layer consists of source nodes. The second layer, called hidden layer, is of high enough dimension. The output layer supplies the response of the network to the activation patterns applied to the input layer. The transformation from the input space to the hidden space is by nonlinear radial basis function and that from hidden space to the output space is by linear weights. The centers of radial basis function and weights of the nodes are determined from different learning techniques. Two learning strategies applied to train RBF network with the given training data set are mentioned below.

Fixed centers learning: The centers of Gaussian function are determined from the data set and weights of second layer are found by pseudo inverse matrix [10].

Self organized selection of centers:

This learning consists of two different stages.

a) Self organized learning stage, the purpose of which is to estimate appropriate locations for the centers of the radial basis functions in the hidden layer. The centers are determined by using K-means clustering algorithm.
b) Supervised learning stage, which computes the linear weights of the output layer.

The fault diagnosis of planar antenna array involves in identifying locations of rows and columns of faulty elements. From amplitude of deviation pattern the number of faulty elements is classified as one, two or three. If the faulty element is one, the location of faulty element is found from phase of deviation pattern. If the faulty elements are two or three then distance between elements is found from amplitude of deviation pattern. For the given distance between elements, location of faulty elements is determined from phase of deviation pattern. The method of fault detection of planar array is done with RBF network having fixed centers training, RBF network with self organized centers training and PNN network.

4. RESULTS & DISCUSSION

To establish the validity, a planar array with 5×5 and 8×8 isotropic elements having uniform excitation and uniform distance between successive elements ($d = \lambda/2$) is considered. The radiation pattern is sampled at 32 points between angles $-90°$ to $90°$. Parameters of array are mentioned in Table 1.

Amplitude and phase of deviation pattern for one, two and three faulty elements along $\phi = 0°$ plane are shown in Figures 2 and 3 for 5×5 elements array. Figures 4 and 5 show the amplitude and phase

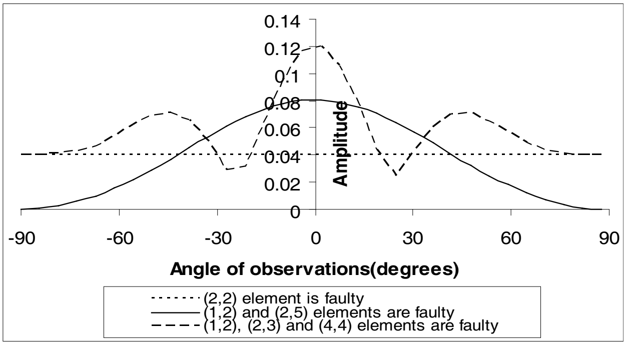

Figure 2. Amplitude of deviation pattern for one, two and three faulty elements in 5×5 elements array along $\phi = 0°$ plane.

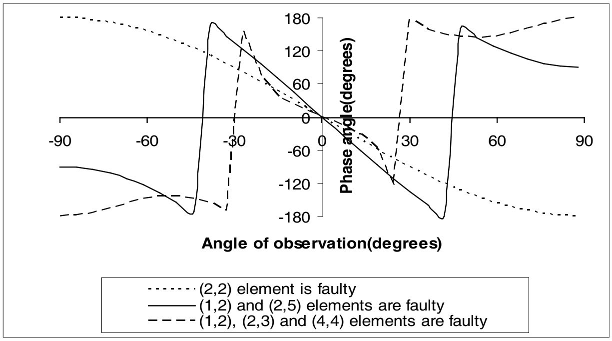

Figure 3. Phase of deviation pattern for one, two and three faulty elements in 5×5 elements array along $\phi = 0°$ plane.

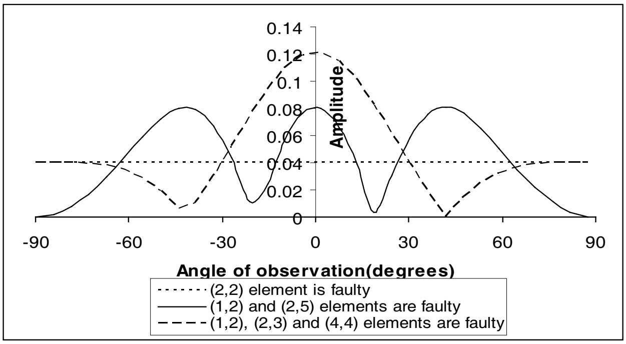

Figure 4. Amplitude of deviation pattern for one, two and three faulty elements in 5×5 elements array along $\phi = 90°$ plane.

Table 1. Parameters of array.

Serial No.	Parameter	Value	Value
1	No. of isotropic elements	5×5	8×8
2	Distance between successive elements	$\lambda/2$	$\lambda/2$
3	Excitation	1 Amp	1 Amp
4	No. of samples of radiation pattern between angles -90 to 90 degrees	32	32
5	No. of possible faulty patterns for one faulty element array	25	64
8	No. of possible faulty patterns for two faulty elements array	300	2016
9	No. of possible faulty patterns for three faulty elements array	2300	41664

Table 2. Parameters of ANN.

Parameter	RBF (fixed centers)	RBF (self organisation of centers)	PNN
Number of input nodes	32	32	32
Number of hidden layers	1	1	2
Number of nodes in hidden layers	32	32	32, number of classes
Number of output nodes	1	1	number of classes
Spread of centers	3	3	1.5
No. of epoch for training	1	300	300

of deviation pattern along $\phi = 90^\circ$ plane for 5×5 elements array. The parameters of ANN are given in Table 2.

The neural networks are trained by faulty patterns with 0% measurement error. The efficiency of the networks when tested by faulty patterns with 3% and 6% measurement error is given in Figure 6. It can be observed that variation of success rate is almost constant for all measurement errors for a PNN network. Further it is also observed that the efficiency with PNN network is better compared to the RBF algorithms.

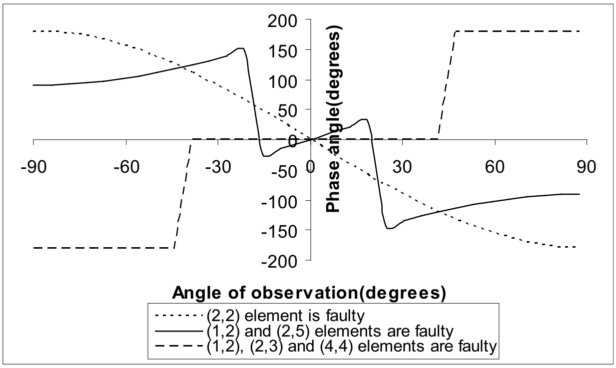

Figure 5. Phase of deviation pattern for one, two and three faulty elements in 5×5 elements array along $\phi = 90^\circ$ plane.

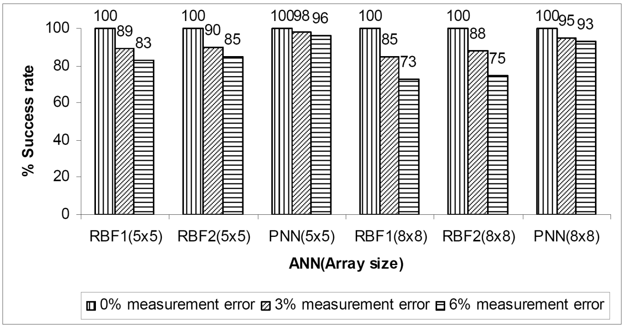

Figure 6. Success rate of the method for PNN and RBF neural networks for 5×5 and 8×8 elements array. RBF1-RBF network trained with fixed centers learning. RBF2-RBF network trained with self organisation of centers. PNN-PNN network trained with self organisation of centers.

5. CONCLUSIONS

RBF and PNN neural network models are applied to predict the location of faulty elements. This approach makes use of a neural network that can be trained off line for any number of elements, spacing and excitation. Although training the network is time consuming, it is usually completed in advance and done only once. The high success rate displayed in the numerical results establishes the validity of the suggested method. This approach can be extended to identify location of any number of faulty elements and to any size of array.

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