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Compensation of a Squint Free Phased Array Antenna System using Artificial Neural Networks

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Abstract

This paper describes an advanced compensation for non-linear functions designed to remove steering aberrations from phased array antennas. This system alters the steering command applied to the antenna in a way that the appropriate angle commands are given to the array steering software for the antenna to point to the desired position instead of squinting. Artificial neural networks are used to develop the inverse function necessary to correct the aberration. Also a straightforward antenna steering function is implemented with neural networks for the 9-term polynomials of forward steering function. In all cases the aberration is removed resulting in small RMS angular errors across the operational angle space when the actual antenna position is compared with the desired position. The use of neural network model provides a method of producing a non-linear system that can correct antenna performance and demonstrates the feasibility of generating an inverse steering algorithm.

Key Words : Phased Array Antenna, Squint, Aberration, Neural Network

I. Introduction

Many phased array antennas suffer from the so called squint aberration, which is a form of aberration that causes the actual pointing angle of the antenna to be significantly different from the desired angle. In other words, the position of a target can not be measured accurately by an antenna with this aberration. In general this effect is evidenced by a discrepancy between actual azimuth and elevations and the desired azimuth and elevations. This problem can be caused by manufacturing tolerance as well as fundamental electrical characteristics. Most of researchers tried to demonstrate the squint free beam based on an optical equipment controlling phased array antenna [7][8][10][11][12][13]. The squint free receiver steering in 70o azimuth over the full available frequency range was demonstrated by Michael Y. Frankel and Ronald D. Esman from Naval Research Lab [10]. David D. Curtis and Lisa M. Sharpe demonstrated the elimination of phased array beam squint at S-band by means of a single mode fiber-optic beamforming network [16]. J. L. Cruz and his research group demonstrated elimination of the squint error between ±30o in the frequency range 2-6 GHz by using a chirped fiber grating beamformer [8]. The problem of using the hardware such as fiber-optic system is that the manufacturing cost and the characteristic error generated by the use of each hardware could be increased.

An artificial neural network is an information processing system that has certain performance characteristics in common with a biological neural network [1]. The artificial neural network is often used in conjunction with large scaled and complex system having nonlinearity [2]. Antenna systems are complex system whose performance can be improved by using the artificial neural network. For example, the adaptive beam forming function in phased array antennas using the artificial neural networks has been demonstrated in several papers [3][4][5][6][9]. Southhall and his research group exhibited direction finding using neural network beamformer in a phased array antenna [3]. A neural network based on adaptive beamformer for two dimensional array antenna was also demonstrated by Zooghby, Christodoulou, and Geogiopoulos [6].

The antenna system we chose to analyze uses a phase shifting network to position the beam in azimuth and frequency changes to steer the antenna in elevation. This system produces a response curve that is nonlinear in both azimuth and elevation.

Software based neural networks-approach was demonstrated to achieve squint free system in the work [17]. This approach implemented polynomial forward steering function equation first. Then, the inverse model was implemented by artificial neural networks.

In this paper, we suggests more advanced method which implements whole system by neural networks. In other words, 9-term forward steering function is also implemented by artificial neural networks with the number of terms instead of mathematical method. Then, the inverse model is implemented using a combination of the quadratic equation and the artificial neural networks. The results are evaluated in RMS error, and measured for all configurations tested. The network trained to compensate for the nonlinear behavior of the modeled antenna is also discussed.

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2. Design of a Preprocess

2.1 Characterization of Antenna performance

The antenna system we chose to inquire uses a phase shifting network to position the beam in azimuth and frequency changes to steer the antenna in elevation. Actual performance data are shown in Figure 1.

Actual performance azimuth

$$[-700\ -530\ -350\ -190\ 0\ 190\ 350\ 530\ 700]$$

Actual performance elevation

$$\begin{bmatrix} 40 & 41 & 42 & 43 & 44 & 45 & 46 & 47 & 48 \\ 57 & 60 & 63 & 65 & 66 & 67 & 66 & 65 & 63 \\ 71 & 75 & 78 & 82 & 83 & 82 & 81 & 79 & 76 \\ 86 & 93 & 98 & 102 & 103 & 102 & 101 & 97 & 92 \\ 95 & 104 & 107 & 112 & 113 & 112 & 109 & 106 & 100 \end{bmatrix}$$

Figure 1. Actual performance data used

The system described by the above data is non-linear. The system produces a family of response curves in azimuth and elevation.

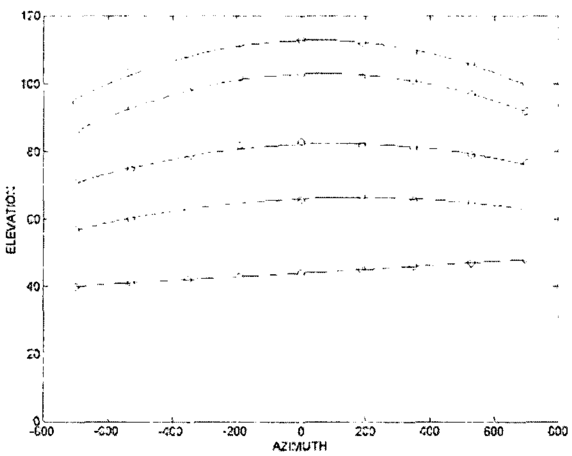

Figure 2. Antenna model function compared with the original measured data set

Figure 2 shows the response curves as a function of elevation. The circles represent the measured angle response of the antenna to angle commands that fall on the dotted lines. Solid curves are based on a least square approximation to the measured data. In other words, they are the optimized curves based on the measured actual data. The response of the antenna at zero azimuth angle is assumed to be the desired elevation while all other azimuth positions produce elevation angles that are in error. First of all, it is necessary to determine the estimated non-linear antenna steering characteristics in terms of a closed form of equation. The curves in Figure 2 are produced by such an equation.

2.2. Design of a straightforward antenna steering function using second order polynomial

We used a multivariate interpolation approach to determine the correct fit based on the MATLAB polyfit and polyval function. Let actual elevation and azimuth in Figure 1 be $\hat{E}$ and A.

For example, for the first row of elevation data we want to fit the polynomial equation 1 where i is the index of row in actually measured elevation, $\hat{E}$.

$$\hat{E}(i) = aA^2 + bA + c \tag{1}$$

If we apply this procedure to each row of data, we get five different second order equations. These equations will be developed with one non linear equation based on desired elevation.

Let E be desired elevation when azimuth is zero. Equation 2 can be implemented by using desired elevation E and coefficients of five second order polynomials as shown in the work [17].

$$\hat{E}(A, E) = PE^2 + QE + C \tag{2}$$

P is an equation that is computed by using coefficients of second order in five different equations and desired elevation. Q is an equation that is computed by using coefficients of first order in five different equations and desired elevation. C is an equation that is computed by using coefficients of zero order and desired elevation.

As a result, we have a forward non linear antenna steering characteristic equation.

$$\begin{aligned}\hat{E}\ (A, E) \cong\ & a_1 + a_2E + a_3A + a_4EA + a_5E^2 \\ & + a_6A^2 + a_7E^2A + a_8EA^2 + a_9E^2A^2\end{aligned} \tag{3}$$

where E, A are the commanded elevation and azimuth in Mils. The first problem is to determine if this general form can be made to fit the data. The coefficients are given in Table 1.

Based on this forward model, an inverse antenna model was implemented with neural networks. The RMS error was computed for the aggregate of all of the known points,

$$e_S = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(\overline{E} - \hat{E})^2} \tag{4}$$

Table 1. Coefficients of antenna model equation

Coefficient	Value
a1	0.10918330E+1
a2	0.96973254E0
a3	0.78333299E-2
a4	-0.57574965E-4
a5	0.17057944E-3
a6	0.26321333E-4
a7	0.14427681E-6
a8	-0.66623847E-6
a9	0.13987143E-8

where $\overline{E}$ was the known data point and $\hat{E}$ was the estimated value from the model equation. The RMS error between the known data point and the estimated value from the model equation was 0.54 Mils(0.030 Degrees).

With this model of antenna performance, we can proceed to develop a compensation system which will allow us to get the desired result in pointing angle. First, the uncompensated antenna model shown in Figure 2-(a) was determined, which has 9-terms polynomial equation[17].

Then, inverse antenna needs to be implemented so that the total system of inverse antenna responds correctly. To do this, the structure shown in Figure 2-(b) was implemented.

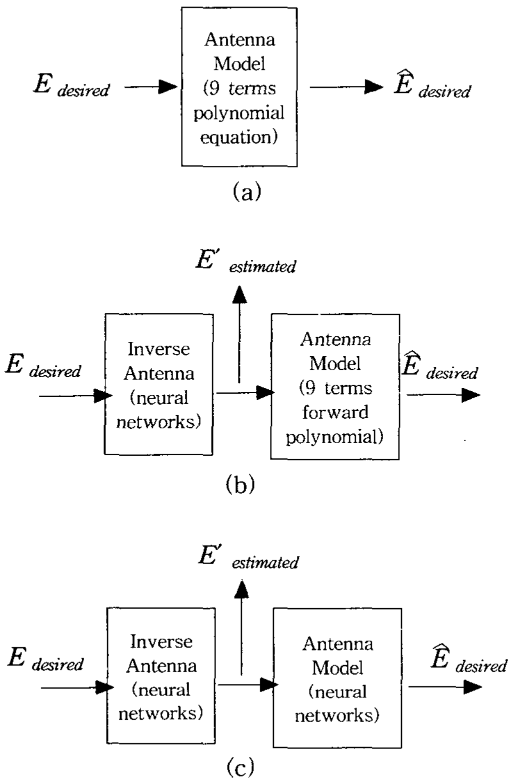

Figure 2. Models to be implemented

Next, the forward antenna model based on a mathematical method is also implemented by artificial neural networks as shown in Figure 2-(c).

The third structure is the main interest of this research since the first two concepts were done in previous work [17].

3. Design of Neural Networks and Experiments

3.1. Design of a straightforward antenna steering function and experimental results

The terms of the straightforward antenna model using a second order polynomial were used for this design. Figure 3 shows the architecture of the straightforward antenna model that is implemented by using the neural network.

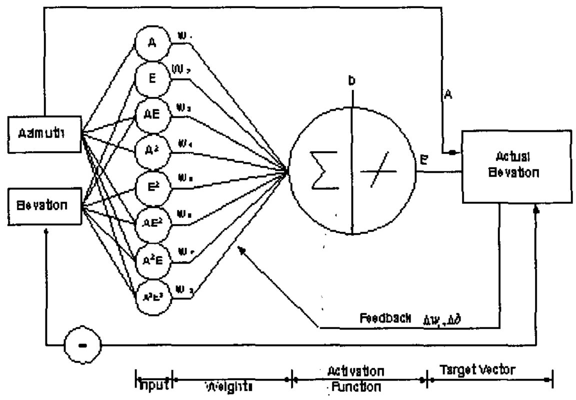

Figure 3. Architecture of the straightforward antenna model

Actual data used are the ones in Figure 1. The network is trained on this data and the coefficients of the straightforward antenna model are determined. Figure 4 shows response achieved by the neural networks.

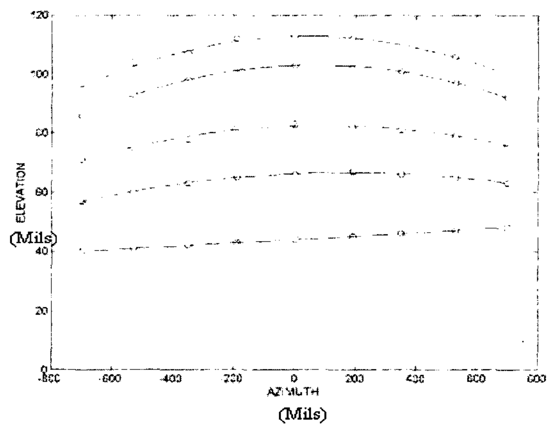

Figure 4. Response of neural networks after training

The actual response of our antenna is represented by symbol O's in Figure 4. Solid curves are a least squares curve fitting based on target response after training. The result of trained neural network are represented by symbol X's. RMS error is 0.427 Mils (0.024 degrees) between the actual response and the result of neural networks trained. After training, a new antenna steering model that uses neural networks is produced and new coefficients for this model are determined.

3.2. Design of an inverse antenna steering function and experimental results

The equivalent training and testing scheme is used to define the inverse of the antenna model equation in this section. The most logical approach seems to be to assume a form for the inverse that is of the same form of the forward equation and then determine the best fit coefficients that will provide the desired output.

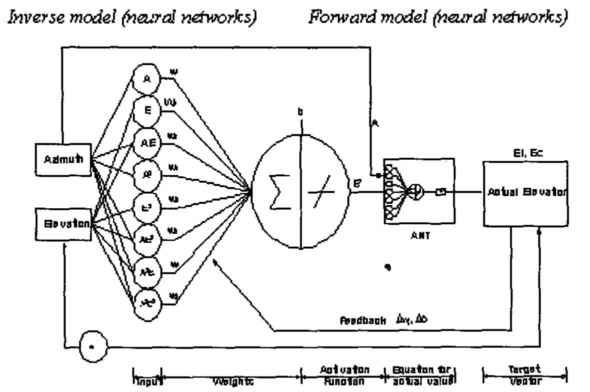

Figure 5. Architecture of inverse model based on forward model implemented with neural networks

The network architecture is shown in Figure 5. We use a linear network and pre-processed inputs into the form of the model equation. In Figure 5, the coefficients of the inverse model are the weights and biases of neural networks. Also, ANT is the straightforward antenna model using neural networks. After training the networks, input and output elevations are compared and tested. The output of the network is processed through the antenna equation, and this output is used to determine the error, the difference between the desired position of the beam and the actual position. The error is then used in the conventional mode to perform learning.

Training was achieved by back-propagation algorithm. The networks were trained successfully and RMS error, 0.52 Mils (0.0293 degrees), was computed from all of the training points. Figure 6 shows the response of the trained compensated antenna model when applied to the training data set. Symbol O's are originally measured antenna data points and X's are the results after training.

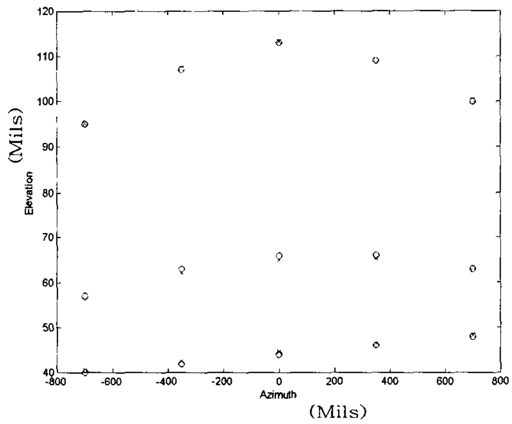

Figure 6. Results of trained inverse antenna model

As mentioned above, the coefficients of the inverse antenna model are set by the weights and bias of the network after training. Table 2 shows the coefficients of the inverse antenna model. It may be possible to remove one or more of the coefficients and still compensate the antenna adequately. This issue is not discussed in this work.

Table 2. Coefficient table of inverse model

Coefficient	Value
a1	2.5445786E-3
a2	9.2133621E-1
a3	-2.4581556E-3
a4	7.9408134E-2
a5	5.2254107E-1
a6	-1.9002436E-3
a7	-5.6014754E-1
a8	6.5833916E-2
a9	-4.5901183E-1

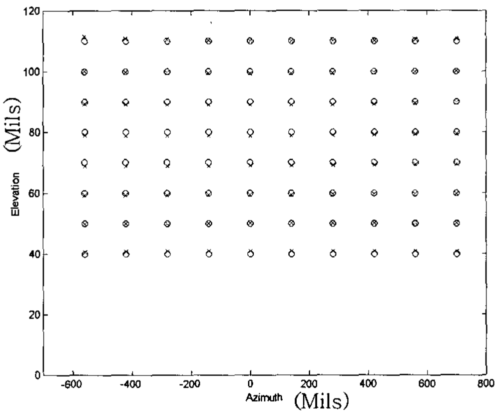

Figure 7. Response of the neural networks

After training, the inverse antenna model is tested. Data points that were not used as training data are selected for test. Therefore the points of test data set are taken from within the whole measurement space. Figure 7 shows the response of the neural network from test data. The RMS error of the test set is 0.70 Mils (0.0394 degrees).

4. Conclusion

With the completion of the total neural network system, squint free antenna system was achieved. The use of a neural network to compensate for the non-linear performance of a phased array antenna is feasible. The neural network designed, trained and tested in this research successfully removed squint from the antenna steering characteristics. The measured accuracy gives us an RMS error of approximately 0.4 Mils.

In the case where the inverse trained from a single antenna model was tested against the same model throughout the operational angle space, the performance shows excellent result. The determination of a set of coefficients allows one embed an equation of the form of the inverse into the antenna control software and thus internally compensate for the aberration as part of the steering command system.

Also this paper shows the basis of the adaptive beam forming smart antenna system. In other world, neural phase shifter can be applied to get smart beam forming after removing squint problem in phase array antenna.

References

[1] Laurene Fausett, Fundametals of Neural Networks: Ar chitecture, Algorithms and Applications, Prentice Hall, 1994.

[2] Simon Haykin, Neural Networks: A Comprehensive Foundation, Macmillan Publishing Co., 1994.

[3] Hugh L. Southall, Jeffrey A. Simmers, and Teresa H. O'Donnell, "Direction Finding in Phased Arrays with a Neural Network Beamformer", IEEE Transactions on Antenna and Propagation, Vol. 43, No. 12, 1995.

[4] T. O'donnell, J. simmer, and D. J. Jacavanco, "Neural Beamforming for Phased array antennas", in Proc. 1992 Antenna Appl. Symp., Griffiss AFB, NY, USAF HQ Rome Laboratory, Sep. 1992.

[5] R. K. Mishra, and A. Patnaik, "Neural Network-Based CAD Model for the Design of Square Patch Antennas", IEEE Transaction on Antenna s and Propagation, Vol. 46, No. 12, 1998.

[6] A. H. El Zooghby, C. G. Christodoulou, and M. Georgiopoulos, "Performance of Radial Basis Function networks for Direction of Arrival Estimation with Antenna Array", IEEE Transaction on Antennas and propagation, Vol. 45, p 1611-1617, 1997.

[7] Hong Wang, Emad S. Ebbini, O'donnel, M, and Charles A. Cain, "Phase aberration correction and motion compensation for ultrasonic hypertheria phased arrays: experimental results", IEEE Transaction on Ultrasonics, Ferroelectronics, and Frequency Control, Vol 41, p 34-43, 1994.

[8] J. L. Cruz, B. Ortega, M. V. Andres, B. Gimeno, J. Capmany, and L. Dong, "Array factor of a phased array antenna steered by a chirped fiber grating beamformer", IEEE Photonics Technology Letters, Vol 10, p 1153-1155, 1998.

[9] A. Patnaik, R. K. Mishra, G. K. Patra, and S. K. Dash, "An Artificial Neural Network Model for Effective Dielectric Constant of Microstrip Line", IEEE Transactions on Antennas and Propagation, Vol. 45, No. 11, 1997.

[10] Michael Y. Frankel, Ronald D. Esman, "True time-delay fiber-optic control of an ultrawideband array transmitter/ receiver with multibeam capability", IEEE Transactions on Microwave Theory and Techniques, p 2387-2394, 1995.

[11] Paul J. Matthews, Michael Y. Frankel, "Wide-band fiber-optic true time steered array receiver capable of multiple independent simultaneous beams", IEEE Photonics Technology Letters, Vol 10, p 722-724, 1998.

[12] Michael Y. Frankel, Ronald D. Esman, "Fiber optic true time steering of an ultrawide-band receive array", IEEE transaction on Microwave Theory and Techniques, Vol 45, p 1522-1526, 1997.

[13] Paul J. Matthews, Michael Y. Frankel, "Wideband fiber-optic, true time steered array receiver", IEEE MTT-S International Microwave Symposium Digest, Vol 1, p 347-350, 1997.

[14] N. V. Jeperson, P. R. Herczfeld, "Phased array antennas with phasers and true time delay phase shifters", AP-S International Symposium Digest, Vol 2, p 778-781, May, 1990.

[15] W. Ng, "Optical steering of dual band microwave phased array antenna using semiconductor laser switching", Electronics Letters, Vol 26, p 791-793, 1990.

[16] David D. Curtis and Lisa M. Sharp, "True time delay beamforming using fiber optic delay lines", IEEE AP-S International Symposium, Vol 2, p 766-769, May, 1990.

[17] Young-Ki Kim, Michael Thursby, and Do-Hong Jeon, "Squint Free Phased Array Antenna System using Artificial Neural Networks", The Journal of Korean Association of Computer Education, Vol. 6, No. 3, p 47-56, 2003.

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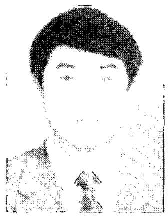

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