Squint Free Phased Array Antenna System using Artificial Neural Networks

Young-Ki Kim, Do-Hong Jeon*, Michael Thursby

Abstract

We describe a new method for removing non-linear phased array antenna aberration called "squint" problem. To develop a compensation scheme, theoretical antenna and artificial neural networks were used.

The purpose of using the artificial neural networks is to develop an antenna system model that represents the steering function of an actual array. The artificial neural networks are also used to implement an inverse model which when concatenated with the antenna or antenna model will correct the "squint"problem. Combining the actual steering function and the inverse model contained in the artificial neural network, alters the steering command to the antenna so that the antenna will point to the desired position instead of squinting.

The use of an artificial neural network provides a method of producing a non-linear system that can correct antenna performance. This paper demonstrates the feasibility of generating an inverse steering algorithm with artificial neural networks.

Index Terms--- Squint problem, Phased array, artificial neural network, rms error, beam steering characteristics, adaptive systems

1. 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. Figure 2 shows the example of squint. 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[8][10][15][16][17][18]. The squint free receiver steering in 70° azimuth over the full availablefrequency range was demonstrated by Michael Y. Frankel and Ronald D. Esman from Naval Research Lab [15]. David D. Curtis and Lisa M. Sharpe who discussed elimination of phased array beam squint are demonstrated at S-band by means of a single mode fiber-optic beamforming network [25]. J. L. Cruz and his research group demonstrated elimination of the squint error between 30° in the frequency range 2-6 GHZ by using a chirped fiber grating beamformer [10]. The problem of using the hardware as fiber-optic system is that the manufacturing cost and the characteristic error which is generated with use of each hardware could be increased.

The goal of this research is to apply an artificial neural network, software, to produce squint free phased array antenna system where the basic antenna suffers from aberration.

An artificial neural network is an information

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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 [4][5][7]. Southhall and his research group exhibited direction finding using neural network beamformer in a phased array antenna [4]. A neural network based on adaptive beamformer for two dimensional array antenna was also demonstrated by Zooghby, Christodoulou, and Geogiopoulos [7].

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. See Figure 2.

The inverse model is implemented using a combination of the quadratic equation and the artificial neural networks. The results are evaluated using rms error. The rms errors are measured for all configurations tested.

An artificial neural network provides a method of producing a nonlinear system capable of correcting the antenna performance. The network trained to compensate for the nonlinear behavior of the modeled antenna is also discussed in this research.

2. Background

2.1. Artificial neural networks

An artificial neural network is "an information processing system that has certain performance characteristics in common with biological neural networks and parallel distributed processor that has a natural propensity for storing experimental knowledge"[1]. This is a mathematical model of human cognition or neural biology.

Constituent elements of the artificial neural networks are neurons, connection links, and weight and bias and activation function.

In mathematical terms, we describe a neuron k by writing the following equation:

$$u_k = \sum_{j=1}^{p} w_{kj} x_j$$

$$y_k = \varphi(u_k)$$

A neuron is divided into two separate parts. One is summing junction that sums all input signals, the other is activation function that limits the amplitude of the output of a neuron.

The purpose that uses activation function is to "squashes the amplitude of the output of a neurons"[2]. Typically, the normalized amplitude range of the output is the interval [0,1] or alternatively [-1,1].

We may identify several types of activation function.

2.2. Backpropagation neural networks

Multiple layer feedforward networks that are an important class of neural networks are described by backpropagation. The backpropagation, that has multiple layers networks and non-linear differentiable activation function, was created by inducing the Widrow-Hoff learning rule. This algorithm is known as mutilayer perceptrons that train them in supervised manner. Input vector and the corresponding target vectors are used to train a network until it can approximate a function.

Figure 1 shows architecture of the backpropagation neural networks. Input vectors (x1, x2, x3, . . . xn) are connected to neurons of hidden layer with weights (v11, v12,. . . vnn). Hidden layer (n1, n2,. . . nn) is connected to output layer with another weights (w1,w2, . . . wn). Results of output layer are compared to target pattern. After finishing comparison, delta vectors are backpropagated

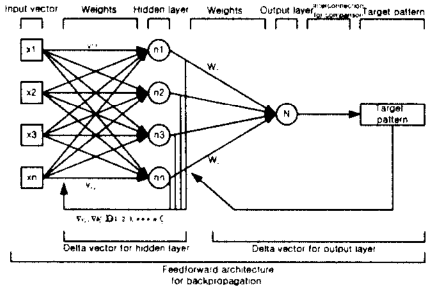


Figure 1. Backpropagation architecture

3. Design

3.1. Antenna performance characterization

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 as follows;

Actual performance elevation

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

Actual performance azimuth

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

The system described by the above data is non-linear. The system produces a family of response curves in azimuth and elevation. Figure 2 shows the response curves as a function of elevation. In Figure 2, the circles represent the measured angle selected 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 word, they are an optimized curve based on the measured actual data. The response of the antenna at zero azimuth angles is assumed to be the desired elevation. However, all other azimuth positions produce elevation angles that are in error. The purpose of this research is to develop a method to produce an antenna response that falls on straight lines that have the desired elevation angles that is when a particular azimuth and elevation are set the antenna actually points to these coordinates. 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.

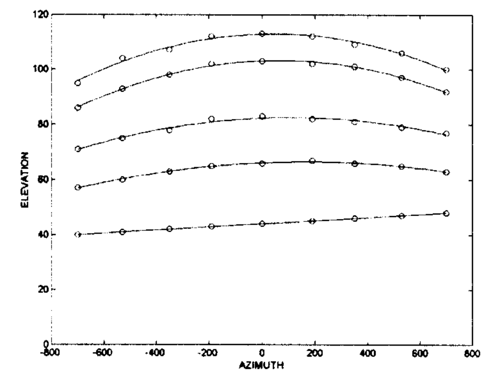


Figure 2. Antenna model function compared with the original measured data set

3.2. Determination of antenna steering characteristics

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

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

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

For example for the first row of elevation data we want to fit this polynomial equation 1 to following set of data.

$$\begin{pmatrix} A \\ \hat{E} \end{pmatrix} = \begin{pmatrix} -700 & -530 & -350 & -190 & 0 & 190 & 350 & 530 & 700 \\ 40 & 41 & 42 & 43 & 44 & 45 & 46 & 47 & 48 \end{pmatrix}$$

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

where i is the index of row in actual measured elevation

$$\hat{E}(A,E) = PE^2 + QE + C \qquad (7)$$

$\hat{E}$

Using MATLAB polyfit function and polyval function, we get follow equation1.

In equation 1, a, b, and c are coefficients of each polynomials. If we apply this procedure to each row of data, we get five different equation 2 through equation 6 for each elevation.

$$\hat{E}(1) = 5.68 \times 10^{-3} A + 44 \qquad (2)$$
$$\hat{E}(2) = -1.28 \times 10^{-5} A^2 + 4.45 \times 10^{-3} A + 66.2 \qquad (3)$$
$$\hat{E}(3) = -1.77 \times 10^{-5} A^2 + 3.96 \times 10^{-3} A + 82.32 \qquad (4)$$
$$\hat{E}(4) = -2.86 \times 10^{-5} A^2 + 2.83 \times 10^{-3} A + 103.02 \qquad (5)$$
$$\hat{E}(5) = -3.07 \times 10^{-5} A^2 + 2.83 \times 10^{-3} A + 112.78 \qquad (6)$$

Equations 2,3,4,5,6 are best-fit equations that include actual elevation of each row in $\hat{E}$ based on azimuth.

Now, These equations will be developed with one non

$$E = [44 \ \ 66 \ \ 83 \ \ 103 \ \ 113]$$

linear equation based on desired elevation. Let E be desired elevation, when azimuth is zero.

Equation 7 can be implemented by using desired elevation E and each coefficient of equation 2, 3, 4, 5, and 6. This equation is as follows;

P is an equation that is computed by using coefficients

of second order in equation 2,3,4,5,6 and desired elevation E. Q is an equation that is computed by using coefficients of first order in equation 2,3,4,5,6 and desired elevation E. C is an equation that is computed by using coefficients of zero order and desired elevation E. This technique can be solved by MATLAB polyfit function.

Consequently, we have a non linear antenna steering characteristic equation 8.

where E,A ; are the commanded elevation and

$$\hat{E}(A,E) \cong a1 + a2E + a3A + a4EA + a5E^2 + a6A^2 + a7E^2A + a8EA^2 + a9E^2A^2 \qquad (8)$$

azimuth in Mils. And are the actual angles in Mils to which the antenna points. The first problem is to determine if this general form can be made to fit the data. Each coefficients are given in Table 1.

In addition to, the antenna model equation 8 is represented by matrix form.

$$\hat{E}(A,E) = \begin{pmatrix} 1 & A & A^2 \end{pmatrix} \begin{pmatrix} a1 & a2 & a5 \\ a3 & a4 & a7 \\ a6 & a8 & a9 \end{pmatrix} \begin{pmatrix} 1 \\ E \\ E^2 \end{pmatrix} \qquad (9)$$

Coefficient	Value
a1	1.09183305717 18166
a2	0.96973254045285
a3	0.7833329970133X10-2
a4	-0.5757496594X10-4
a5	0.17057944026X10-3
a6	0.263213339494 72X10-4
a7	0.14427681X10-6
a8	-0.666238479155X10-6
a9	0.1398714352X10-8

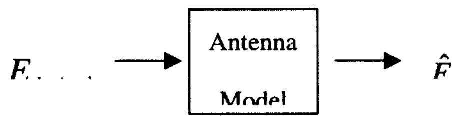
Table 1.Coefficients of antenna model equation

This equation was then tested against the known data by computing values for the output of the antenna model equation and comparing them with the known points. An interpolated curve was generated to provide estimates for the response of the antenna in between the known data points. The rms error was computed for the aggregate of all of the known points,

$$e_{rms} = \sqrt{\frac{1}{N} \sum_{k=1}^{N} \left(\overline{E} - \hat{E} \right)^2}$$

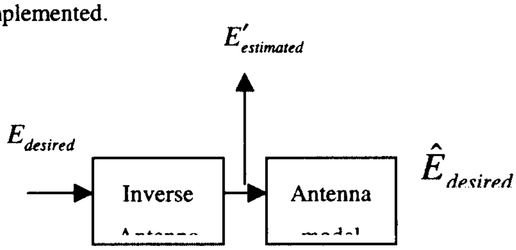
where $\overline{E}$ was the known data point and $\hat{E}$ was the estimated value from the model equation. The rms error was 0.54 Mils(0.030 Degrees). A plot of the response of the model equation and the data points is shown in Figure 3. Symbol x is the estimated value from antenna model equation and symbol o is the known data point.

With this model of antennaperformance we can proceed to develop a compensation system which when applied to the antenna steering commands will allow us to get the desired result in pointing angle. First the uncompensated antenna model shown in the following figure was determined.



$\hat{E}_{desired} \neq E_{desired}$

Now we will prefilter an input antenna (Inverse antenna) so that the total system inverse antenna responds correctly. To do this, the following will be implemented.



$\hat{E}_{desired} = E_{desired}$

This structure is the design concept of this research. Next we will discuss the methods used to form the inverse antenna function and then the results of using the method.

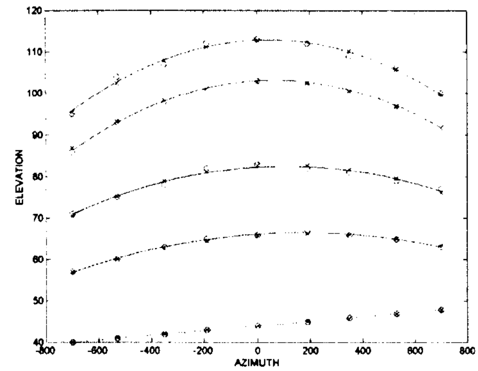
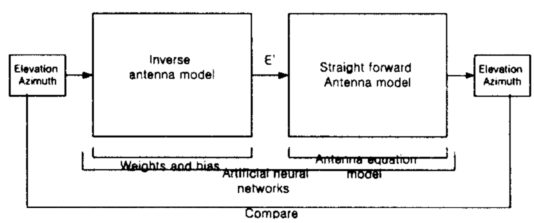


Figure 3. Estimated data point from antenna model (symbol x)

3.3. Inverse antenna model using artificial neural networks

First, mathematical method using quadratic theory was used to develop inverse equation model.

This mathematical way is the most basic method to solve inverse function. If the way using quadratic theory does not give us good solution, we try to find a new method to have good solution.



As a result, the antenna elevation calculated from the antenna model equation results that deviated from the elevations measured by the actual antenna. Rms error is about 4.5Mils. This is a big error between calculated elevation and measured elevation.

Consequently, it is necessary for another method to compensate inverse model equation using quadratic theory. The use of artificial neural networks provides a more direct method for forming the inverse for this equation.

The purpose of this section is to define an inverse antenna model of an antenna whose performance is described by an Equation 8, using the artificial neural network. The artificial neural network can give a more accurate method for implementing the inverse model. The most logical approach seems to be to assume a form for the inverse that is of the same form as the forward equation and then determine the best fit coefficients that will provide the desired output. In this case the desired output is the same as the input. The network suggested is shown in Figure 4. We used a linear network and pre-processed the inputs into the form of the model equation (e.g. A, E, AE, A^2, E^2, AE^2, A^2E, and A^2E^2).

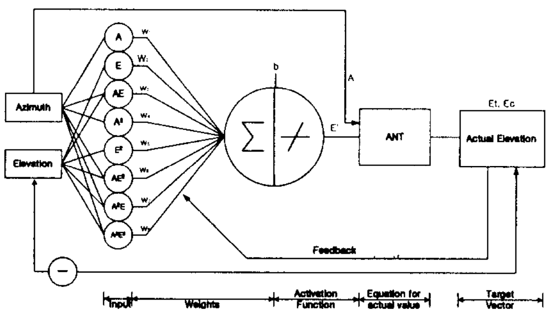


Figure 4. Architecture used for the determination the inverse equation

In Figure 4, coefficients of the inverse model are weights and bias of the artificial neural networks, Note the artificial neural network has only one neuron and linear activation function. This activation function is F(x) = x. we also know E'is the desired elevation from Figure 4. Figure 5 shows a block diagram of Figure 4 including the training path. After training the neural networks, input elevation and output elevation were tested and compared.

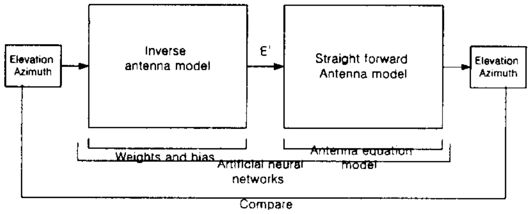


Figure 5. Block diagram of figure 4

With this type of pre-processing the nature of the non-linearity was preserved, while allowing the flexibility of an optimization scheme such as back propagation to determine the exact coefficients. The neurons used in this first method were linear, as we have already incorporated the non-linearities into the preprocessing of the input data. The output of the network was then passed through the antenna equation, and this output was used to determine the error, (the difference between the desired position of the beam and the actual position.) The error was then used in the conventional manner to perform learning. The learning process for our neural network follows the delta rule that is briefly described below.

The error term *e* is computed by;

$$e = Et - Ec$$

where *Et*: Target elevation
Ec: Computed

Weight changes are computed by;
where $f(x) = 1$ for linear cases

$$\Delta w_i = \alpha e f'(y\_in) x_i$$

Bias changes are calculated by;

$$\Delta b = \alpha e f'(y\_in)$$

Forward propagation (output computation) is;

$$y\_in = b + \sum_{i=1}^{n} x_i w_i$$

$$Ec = \hat{E}(A, f(y\_in))$$

Algorithm for weight change (learning) is

$$w_i(new) = w_i(old) + \Delta w_i$$

$$b(new) = b(old) + \Delta b$$

The results of this type of approach provide a set of coefficients that give an adjusted coordinate that when applied to the antenna steering system position the antenna correctly

3.4. Training, test of the artificial neural networks and experimental results

Training of the inverse antenna modelwas implemented using MATLAB and the back-propagation algorithm. The points chosen were those given in the performance data. The neural network was trained successfully and the rms error was computed from all of the training points. The error was 0.28 Mils (0.0157 degrees). Figure 6 shows the result of the trained antenna model combined with the training data set. The "O"symbol show the original measured antenna data points and the "X" symbol show the results from trained neural networks.

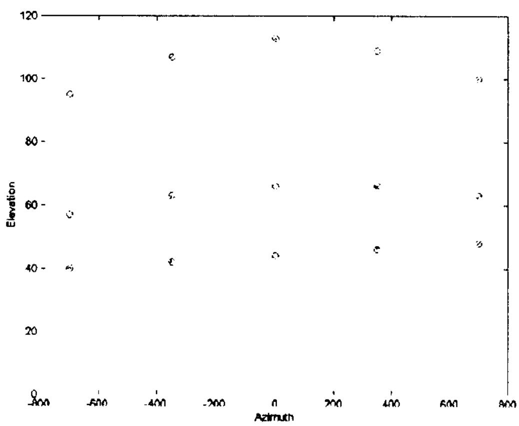


Figure 6. Results of training the inverse network. Data plotted as x's and circles represent the original antenna data points RMS error is0.28 Mils, 0.016 deg

As mentioned above, the weights and bias of the trained neural network become the coefficients of the inverse antenna model. The linear artificial neural networks, which have one neuron, provide a small but sufficient number of coefficients necessary to program the control algorithm into a digital computer associated with the antenna. Therefore, the weights and the bias have very important meaning in the neural networks.

After training the neural network, the coefficients of the inverse antenna model are determined from weights and bias. Table 2 shows the nine coefficients of the inverse antenna model equation. The removal of squint of the antenna can be achieved using nine coefficients. It may be possible to reduce the number of coefficients and get

$$\hat{E}(A.E) \cong a1 + a2E + a3A + a4EA + a5E^2 + a6A^2 + a7E^2A + a8EA^2 + a9E^2A^2 \quad (8)$$

maintains squint compensation.

Coefficients	Value
a1	-1.1236547
a2	-8.66676609X10-3
a3	9.4962465X10-1
a4	2.966443X10-2
a5	6.4287039X10-3
a6	5.7103463X10-1
a7	1.6140672X10-1
a8	-2.6462807X10-1
a9	9.41091X10-1

Table 2. Coefficients of the inverse antenna model equation

After training, it is necessary to test whether the performance of the trained neural networks is as desired or not. Data that are not in the training set need to be used for testing. The testing set has data points spacing the whole measurement space but not including training data points

Testing azimuth	-560 -420 -280 -140 0 140 280 420 700									
	40	40	40	40	40	40	40	40	40	40
	50	50	50	50	50	50	50	50	50	50
	60	60	60	60	60	60	60	60	60	60
Testing elevation	70	70	70	70	70	70	70	70	70	70
	80	80	80	80	80	80	80	80	80	80
	90	90	90	90	90	90	90	90	90	90
	100	100	100	100	100	100	100	100	100	100
	110	110	110	110	110	110	110	110	110	110

Table 3. Test set

Table 3 shows test set which have data point with in whole measured space. The result is reliable. Figure 7 and figure 8 show the response of testing neural network and rms error mesh plot.

Table 3 shows test set which have data point with in whole measured space. The result is reliable. Figure 7

and figure 8 show the response of testing neural network and rms error mesh plot.

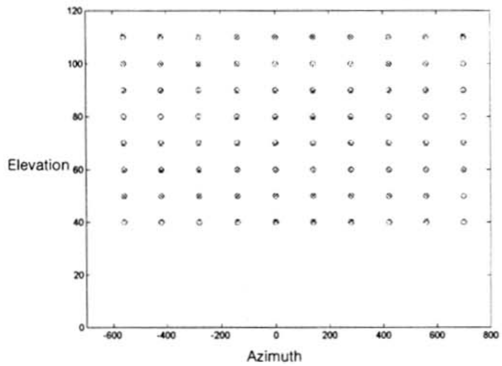


Figure 7response of testing neural network

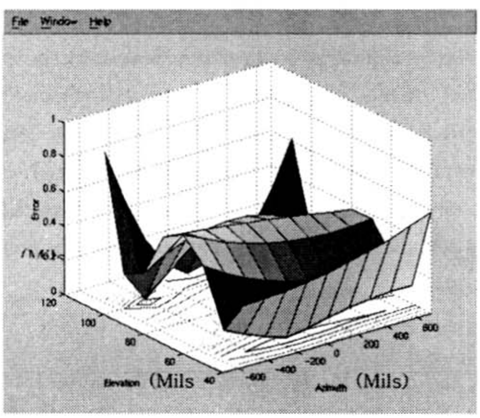


Figure 8 Rms error mesh

6. Conclusion

The artificial neural network designed, trained and tested in this research successfully removed squint from the antenna steering characteristics.

The results of training the artificial neural networks described in this research showed that the goal of this research, i.e. a squint free compensated antenna model of a phased array antenna system using artificial neural networks, has been demonstrated. With calibration of the phased array antenna system, it becomes the basis for adaptive beam forming using an over arching artificial neural network. If a radar can point to the location of a target accurately, a receiver can detect the target correctly. Use of the backpropagation neural network for calibrating phased array antenna can decrease antenna manufacturing and maintenance costs by reducing complexity.

Further works is needed to develop an antenna robust model using random number. This would allow all kinds of different antenna models having slightly different characteristics to be controlled by a robust antenna model.

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