Application of Perceptron Model for Adaptive Beamforming in Array Antennas

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***Abstract*-In this paper, a single neuron neural network beamformer is proposed. A perceptron model is designed to optimize the weights of a dipole array antenna to steer the beam to desired directions. The objective is to reduce the complexity by using a single neuron neural network and utilize it for adaptive beamforming in dipole array antennas. The optimized coefficients calculated from the single neuron neural network are compared with the optimized coefficients from the traditional Least Mean Square (LMS) method. Matlab is used to optimize the weights in neural network and LMS method as well as display the comparison in graphical format.**

Keywords – Smart Antenna; Adaptive Array; Adaptive Beamforming; Neural Network.

I. INTRODUCTION

Due to its broad range of applications, adaptive array antenna is most popular in the present world. Present world applications require much faster beam steering that cannot be achieved using a mechanical systems. Hence it is required to use more consistent and much faster electronic beam steering techniques such as adaptive arrays. The requirements for almost identical elements results lack of flexibility. On the other hand, adaptivebeamforming methods by means of weight optimization are capable of managing the complexities of distinct elements. The adaptive array can detect, track and allocate narrow beams in the direction of the desired users while nulling unwanted sources of interferences.There are well known traditional techniques for adaptive beamforming in array antenna.

Soft computing techniques namely Artificial Neural Networks (ANN), fuzzy logics, Genetic Algorithms (GAs), provide low cost solutions and robustness to different complex real world problems. ANN is a powerful information processing paradigm that tries to simulate the structure and functionalities of the biological nervous systems. The ANN is used to deal with many applications, and they have proved their effectiveness in several research areas such as image recognition, speech recognition, signal analysis, process control, and robotics. The true power of neural networks lies in their ability to represent both linear and non-linear relationships. ANN, like people, learn by example. Training a neural network is, in most cases, an exercise in numerical optimization of a usually nonlinear function. Basic building block of every artificial neural network is an artificial neuron or perceptron that is a simple mathematical model.

Since neural networks are used in adaptive antenna signal processing[1], [2] because of their general purpose nature, fast convergent rate and large scale integration implementations. Identifying the inherent gains of neural networks, a number of literature are available on neural network based model to calculate the weights of an adaptive array antenna [3-6]. This paper presents a simple single neuron model to optimize the weights of an adaptive array antenna which lead to adaptive beamforming towards the desired users.

II. SINGLE NEURON WEIGHT OPTIMIZATION MODEL (SNWOM)

In this section we briefly describe the single neuron modal to optimize the weights which will be used in adaptive beamforming. In the perceptron model as shown in Fig.1, a single neuron with a linear weighted net function and a threshold activation functionalso known as transfer functionis employed. The model has three parts and at the first part inputs (x_1, x_2 …., x_n) are multiplied with individual weights (w_1, w_2 …w_n). In the second part of simple perceptron is the net function that sums all weighted inputs and bias as in (1).

$$z = b + \sum_{k=1}^{n} w_k x_k \tag{1}$$

In the final part of simple perceptron the sum of previously weighted inputs and bias is passing through a transfer function to get the output. In case of linear activation function artificial neuron is doing simple linear transformation over the sum of weighted inputs and bias$b$. There is no single best method for nonlinear optimization and is based on the characteristics of the problem to be solved.

We simplify the calculation complexity to reduce the processing delay. Hence we have used single neuran for this problem and a nonlinear activation function σ to find out the output y as in (2).

$$y = \sigma(z) \quad = \frac{1}{1+e^{-z}} \tag{2}$$

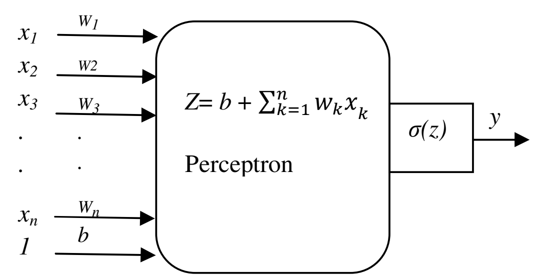

Fig.1: Perceptron model for weight optimization

In order to train the weights to meet the desired output of y_0, the deviation $\Delta$is obtained and the weights are iterated until it reach the trained means error *TMR* is below the predefined value. Where the deviation,and trained means error as in (3) and (4) respectively.

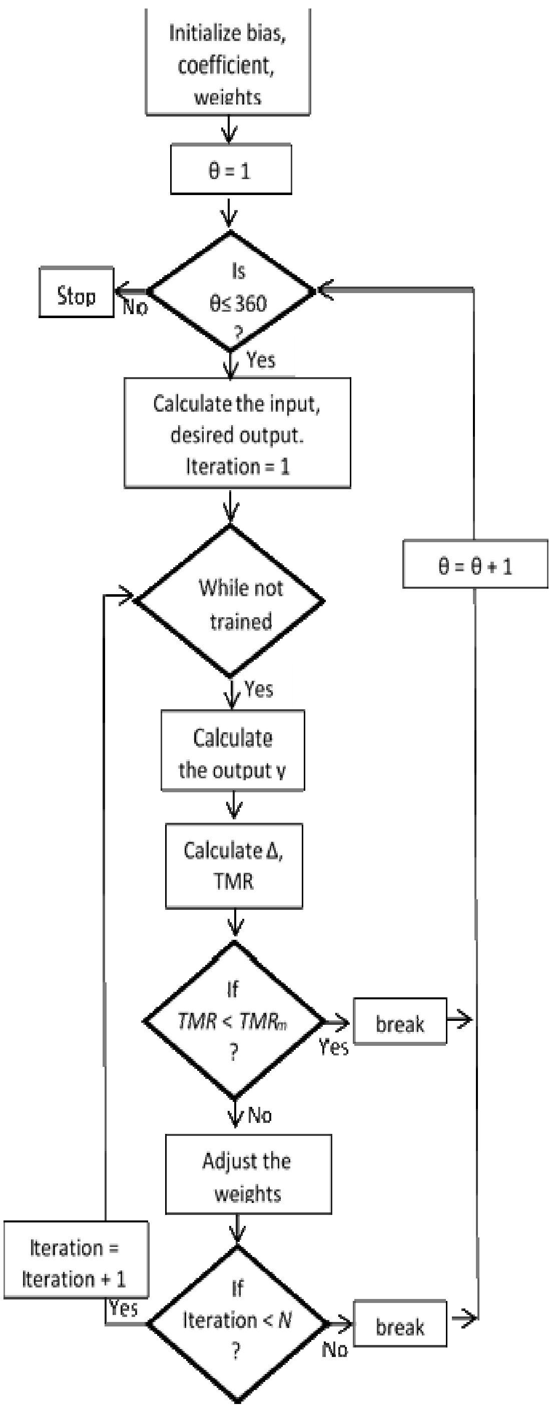

Fig.2. The SNWOM weight optimization flowchart

$$\Delta = y_0 - y \tag{3}$$

$$TMR = \frac{\Delta}{y_0} * 100 \tag{4}$$

Also the weights are adjusted in every iteration using the deviation and the selected learning rate also known as coefficient k_0 as given in (5).

$$w_i = w_i + k_0 \Delta x_i \tag{5}$$

The iteration is allowed either it reaches the *TMR* below the predefined valueTMR_m or the defined maximum number *N* of iterations. The SNWOM weight optimization flowchart is given in Fig. 2.

III. ADAPTIVE ARRAY MODEL

A simple array of dipoles placed in a straight line as shown in Fig.3 is considered as the array model. We have tested array models with five and seven elements placed in the straight line. The array model equation with respective coefficients can be given for five elements array could be given as in (6).

$$\begin{aligned} &w_1 e^{2j\beta d\cos\phi} + w_2 e^{j\beta d\cos\phi} + w_3 \\ &+ w_4 e^{-j\beta d\cos\phi} + w_5 e^{-2j\beta d\cos\phi} = f(\phi) \end{aligned} \tag{6}$$

Similarly, we can write the seven elements model as in (7).

$$\begin{aligned} &w_1 e^{3j\beta d\cos\phi} + w_2 e^{2j\beta d\cos\phi} + w_3 e^{j\beta d\cos\phi} \\ &+ w_4 + w_5 e^{-j\beta d\cos\phi} + w_6 e^{-2j\beta d\cos\phi} \\ &+ w_7 e^{-3j\beta d\cos\phi} = f(\phi) \end{aligned} \tag{7}$$

where $f(\phi)$ is the desired beam function.

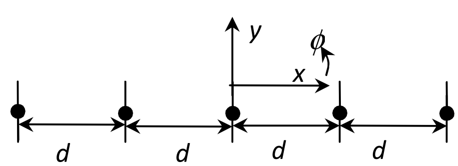

Fig.3. Schematic diagram of the five element array model.

IV. RESULTS AND DISCUSSION

Fixing the desired beam function $f(\phi)$ as $\cos 2\phi$ and taking the distance between two elements as half wavelength, we have optimized the weights for five and seven elementsto find the actual output using the above

SNWOM model with initial weights, bias and learning rate also known as coefficient. For training, we have used different angles ϕ in the range of 0^0 to 360^0. During the testing process we have used different angles ϕ in the range of 0^0 to 360^0.Having obtained the optimized weights after convergence, we have drawn the radiation patterns using optimized weights and compared with the radiation patterns of the desired beamfor five elements array as shown in the Fig.4.

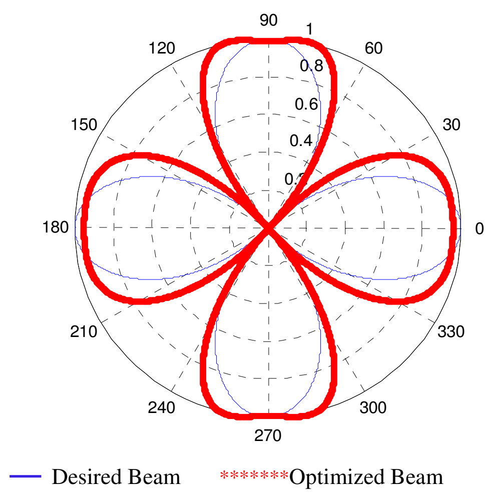

Fig. 4. Comparison of Radiation pattern between optimized beam and desired beam obtained by SNWOM when the number of adaptive array elements is five.

Similarly, we have optimized the weights using stated SNWOM. The optimized results are shown for seven elements as in Fig.5. As we have expected, with increased number of elements, the adaptive array beamforming is verymuch close to the desired beam. However the amplitudes in the 0^o and $180^o$are better in five elements array than seven elements array that due to the characterstic of the desired beam selected.

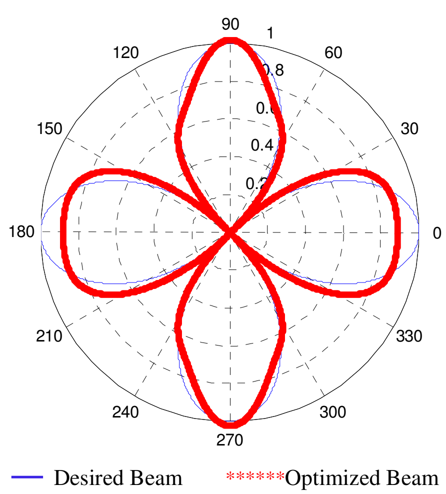

Fig. 5. Comparison of Radiation pattern between optimized beam and desired beam obtained by SNWOM when the number of adaptive array elements is seven.

In order to have the comparison betweenaccuracy of weights optimized from SNWOM method with the weights optimized from traditional LMS method, the weights are calculated for five elements and seven elements array antenna using LMS optimization. The radiation patterns for five and seven elements optimized from LMS methods are shown in Fig.6 and Fig.7, respectively.

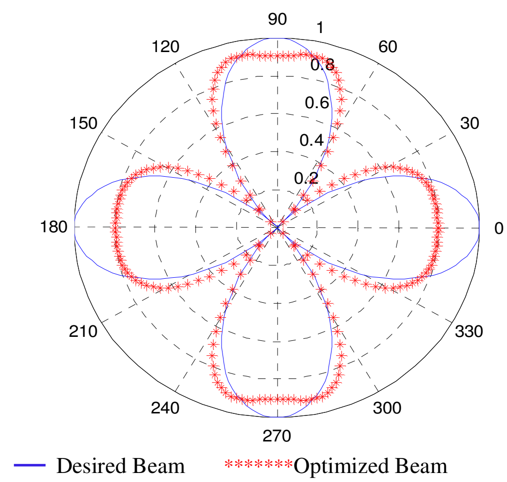

Fig. 6.Comparison of Radiation pattern between optimized beam and desired beam when the number of adaptive array elements is five.

Comparison of Fig.4 and Fig.6 displays that the results obtained from SNWOM has better match than LMS method though significant difference cannot be observed between Fig.5 and Fig.7.

Even though, the precisionof the SNWOM is depending on the dipole placement and the characteristics of the desired beam selected, it is a fast, efficient and simple method for the weight optimization compare to the previously proposed neural network based adaptive beamforming methods.

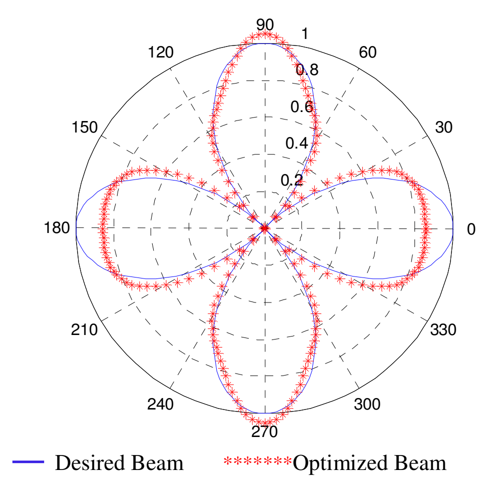

Fig. 7.Comparison of Radiation pattern between optimized beam and desired beam when the number of adaptive array elements is seven.

V. CONCLUSIONS

A simple, accurate and efficient approach to the problem of adaptive beamforming was proposed and implemented using single neuron neural network. The weights were optimized using SNWOM and compared with that of traditional LMS method for the comparison of performance. The radiation patterns obtained from optimized weights were close match with the desired radiation patterns though it was depending on the characteristics of the desired beam selected.

VI. FUTURE WORK

When the dipoles are placed in straight line along with the selected desired beam function (even function respect to azimuthal angle), the weight coefficients turned to be real values. For the present setup, the selected nonlinear activation function matched very well and weight coefficients could be optimised easily. However, it will not be the case in real time application where the dipole placement and desired beam function may not be as taken in this model where the expected weight coefficients would be complex values. In order to optimise complex weigh coefficients, the present nonlinear activation function may not be suitable. Therefore, the future work can be focused on selecting appropriate nonlinear activation function in order to optimise complex weights coefficients.

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