

LMS Algorithm and Neural Network for Optimizing the Phased Array Antenna Radiation Pattern

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Abstract:-

This paper describes a usual application of LMS neural networks algorithm for evolving and optimizing of antenna array. The neural network allows not only establishing important analytical equations for the optimization step, but also a great flexibility between the system parameters in input and output.

This research is based on some software that works on algorithms for the simulation of the beamforming techniques. Furthermore, the research has shown the response of the system before and after the use of adaptive algorithm.

The results showed that the output for four-element antenna array pattern produces a narrower beam with the same amplitude, as that of the main beam before applying neural network. Along with a narrower beam, comes another positive result, that is, the reduction of side-lobes more than 5 decibels in comparison to the related work.

Keywords: LMS, antenna array, neural network,

1- Introduction

Phased array antennas play a significant role in digital signal processing [1]. As the name implies, the essence is of monitoring the information and analyzing and reporting the errors detected and taking the corrective action where the machine itself can perform the functions of communication processing without much of human intervention in monitoring of the events. It should be possible to construct such type of mechanisms in the lines of an artificial neural network structure by making use of

adaptive algorithms for different classes of signal processing like beamformation, side-lobe reduction. In the subsequent sections, brief definitions of concepts of antenna and neural networks are brought in view of understanding the use[2].

Other work have been focused on synthesis of planar array to generate arbitrary 2-dimensional footprint patterns. From the recent literature, such studies are used in the applications of satellite communications. In [3], A fast pattern synthesis method was described for a broadband array antenna using the particle swarm optimization (PSO) and cubic spline interpolation (CSI). A uniform circular array with six broadband dipole elements was examined. The broadband patterns with 60-degree HPBW and the accuracy of the interpolation method were demonstrated. In [1], provides in his paper a comprehensive and detailed treatment of different beam-forming schemes, adaptive algorithms to adjust the required weighting on antennas, direction-of-arrival estimation methods, including their performance comparison, and effects of errors on the performance of an array system, as well as schemes to alleviate them and he brings all aspects of array signal processing. It is presented at a level appropriate to non-experts in the field and contains a large reference list to probe further. In [4], an efficient method for the pattern synthesis of the linear antenna arrays with the prescribed nulls and steering lobe is presented. The proposed method is based on Least Mean Square (LMS) algorithm; provide a comprehensive and detailed treatment of the signal model used for beam forming, as well as, describing adaptive algorithms to adjust the weights of an array. The simulations when compared to that of the LMS algorithm, a 28% overall improvement in the convergence rate is observed. The results suggest that INLMS algorithm can improve the convergence rate and lead to better system efficiency.

2-Antenna Array

The radiation pattern formula in a normalized expression is given by 'Array Radiation Pattern (ARP) [1]:

$$ARP_N = \frac{1}{N} \left[\sin\left(\frac{N*\psi}{2}\right) \right] / \left[\sin\left(\frac{\psi}{2}\right) \right] \quad (1)$$

Where N : the number of antenna elements used (in this project N = 4), ψ : the total phasing factor of antenna radiation pattern, which comprises the formula as:

$$\psi = k * d * \cos(\theta) + \beta \quad (2)$$

where, θ is the angles of rotation in the polar form expressed in values of radians, k is the wave-number of the signal value $k = \frac{2\pi}{\lambda}$, d is indicates the distance between the array elements,

(d measured with respect to λ for example $d = \lambda$, $\frac{\lambda}{2}$, or $\frac{\lambda}{3}$).

where λ is the wave length of the signal ($\lambda = \frac{c}{f}$) where c is the speed of light and f is the frequency of the signal, and as well β denotes the phase excitation between the elements.

By varying the array separation 'd' and also the excitation phase ' β ' between the elements, the field pattern can be controlled.

2.1-Factors of Antenna:

The antenna is chosen depending on the type of application that it will be applied to. Antennas vary in terms of various physical characteristics and electrical characteristics as well [5].

To mention few key words from the factors of the antenna, in brevity, (referred to fig1) as stated by [5]:

1. “Main lobe is defined as the direction of the maximum radiation from the array pattern of the antenna. The peak of the main lobe is called the bore sight of the antenna and the concepts of efficiency of the antenna and the beam-width of the antenna are related to the main lobe alone”.
2. “Side lobes, are characterized by their low level intensity which is below the boresight gain and their angular positions relative to the boresight. They are sometimes also defined as peaks”.

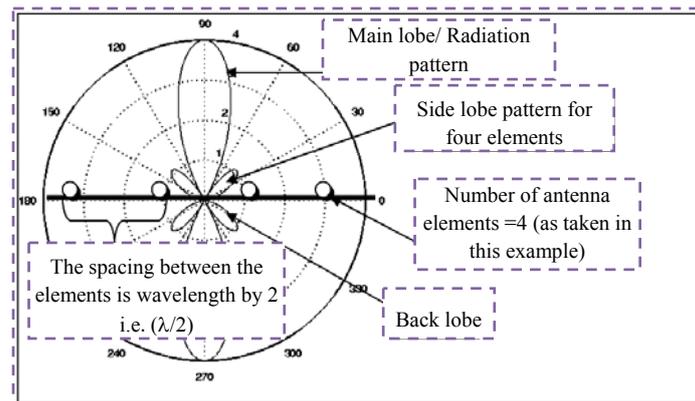


Fig 1. In this diagram, it shows a beam-formation taken for example: the spacing between the array sensors as 0.5λ and the number of array elements = 4. It also depicts the main lobe, side lobe and back lobes of the radiation pattern [5].

To make the linear array more optimized in terms of radiation pattern, the broadside array category is selected for better signal tracking, processing and transmission.

3-A Connection between Neural Network and array Antenna

The antenna architecture in basic format can be superimposed with the architecture of the neural networks like[2]:

- Input neurons of the neural network as array elements of the antenna in the number as desired by the user.

- Hidden neurons as weight segment in case of neural network and as well in antenna array structure, where updating of weights takes place basing on the statistical measures for optimization of the beamformation.
- Desired responses or reference signals for obtaining optimum solution by minimizing errors through proper weight updating and weight convergence that allows adapting to the situation and optimizing the status in both cases of neural architecture and smart-antenna system.
- Output neurons as the output signal from signal processing of the antenna structure after optimization to form a noiseless, distortion-less and desirable behavioral pattern.

Fig (2) shows a comparative diagram between phased array antenna architecture and neural network architecture in the form of multilayer back-propagation neural network.

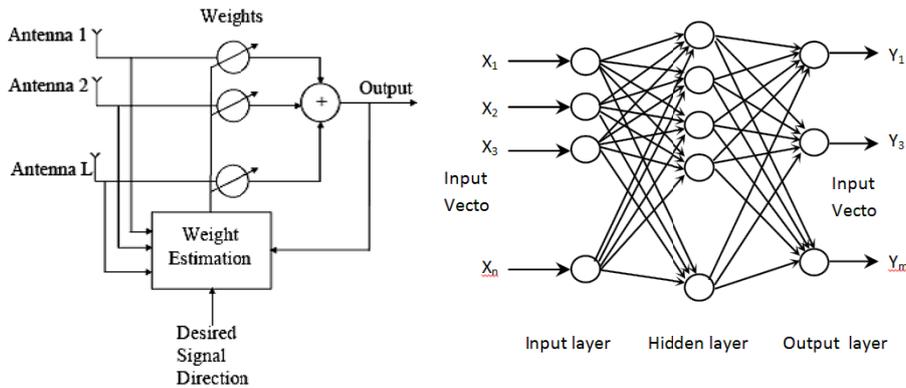


Fig 2. (a) Phased array antenna architecture, (b) Neural Network architecture (The Multilayer Back-Propagation NN).

4- LMS Structure and Function

The algorithm to be used in this paper is summarized in simpler form as indicated in table 1 which indicates that the use of LMS searches for the optimum or near optimum filter weights by performing the following iterative operation:

$$\text{New weights} = \text{previous weights} + (\mu) \times (\text{previous error}) \times (\text{current input vector}) \quad (3)$$

where,

$$\text{Previous error} = (\text{previous desired output}) - (\text{previous actual output}). \quad (4)$$

Table 1. Summary of LMS (least mean squares) algorithm [6].

1	Training Sample	Input signal vector = $u(n)$ Desired response = $d(n)$
2	User selected parameter	μ (also known as learning rate parameter)
3	Initialization	set $w(0) = 0$
4	Computation	for $n = 1, 2, \dots$, compute $e(n) = d(n) - w^T(n) * u(n)$ $w(n+1) = w(n) + \mu * u(n) * e(n)$

4.1-LMS Algorithm

As stated by [6], the practical applications of LMS are highly diverse, with each other application having different solutions and are uncommon in nature. In this algorithm the input signal is defined as $u(n)$. These input signals are then multiplied by the input weights $w(1), w(2), \dots, w(n)$, which in this case are complex. The output signal is the weighted sum of the input signals, i.e.

$$y(n) = w^T(n) * x(n) \quad (5)$$

where w^T is the transpose of the weight vector $W = [w(1) \ w(2) \ w(3) \ \dots \ w(n)]^T$.

In order that the adaptation takes place a reference signal $d(n)$ must be supplied by the adaptive array. There are numerous ways to generate the reference signal. [7, 8] discusses numerous techniques for generating this reference signal. The difference between the desired response and the output response forms the error signal $e(k)$, i.e.

$$e(n) = d(n) - w^T(n) * u(n) \tag{6}$$

$$e(n) = d(n) - y(n) \tag{7}$$

This signal is used as the control signal for the weight adjustment and adaptation. The purpose of the weight adaptation is to find a set of weights that will permit the output response of the adaptive element at each instant of iteration to be equal to, or as close as possible to the desire response. Moreover, this is an iterative process and will continue until all the weights in the array converge.

The notation of the data expressed in complex form is as follows (as mentioned in [6]):

For each instance of iteration: $n = 1, 2, \dots, \dots$, compute:

Tap-input vector: $u(n) = u_i(n) + iu_q(n)$

Desired response: $d(n) = d_i(n) + id_q(n)$

Tap-weight vector: $w(n) = \hat{w}_i(n) + i\hat{w}_q(n)$

Output vector: $y(n) = y_i(n) + iy_q(n)$

Estimation error: $e(n) = e_i(n) + ie_q(n)$

The subscripts in the complex form ‘I’ and ‘Q’ are denoted as ‘In-phase’ and ‘Quadrature’ components i.e. real and imaginary parts, respectively. Such that, these equations are then expanded and equated with the respective real and imaginary parts [6]. To implement its workability the equations were equated to the respective I and Q components as well. Therefore, the resultant equations with the final updated weight vectors of I and Q components are as follows [6]:

$$\begin{aligned} y_i(n) &= \hat{w}_i^T(n) * u_i(n) - \hat{w}_q^T(n) u_q(n) & y_q(n) &= \hat{w}_i^T(n) * u_q(n) - \hat{w}_q^T(n) u_i(n) \\ e_i(n) &= d_i(n) - y_i(n) & e_q(n) &= d_q(n) - y_q(n) \\ \hat{w}_i(n+1) &= \hat{w}_i(n) + \mu * [e_i(n) * u_i(n) - e_q(n) * u_q(n)] & \hat{w}_q(n+1) &= \hat{w}_q(n) + \mu * [e_i(n) * u_q(n) - e_q(n) * u_i(n)] \end{aligned}$$

Learning rate parameter is given as μ , where it lies in-between the range 0 to 0.2

The LMS algorithm does not require squaring, averaging or differentiating and hence, can be implemented in most practical systems. Its popularity is accredited to the fact that it is simple, easy to compute and efficient [8].

5- Simulations and Results

Indoing the simulations, mathematical formula are used to produce the experimental results. The formula was briefly highlighted in the previous sections for an idea about beamformation and the LMS algorithm. The LMS formula is shown with less complexity to have brief overview of its core function. The basic parameters for the experimental set up for the software to function:

Table 2. Summary of fixed parametric values as a standard, for running simulations in this paper.

1	No. of elements	4
2	Antenna type	Broad-side
3	Beam direction	Vertical (pointing at 90°)
4	Frequency under considerations	F=15 GHz
5	Wavelength	$\lambda= 0.02$ m
6	Distance between antenna elements	$d=0.5 \lambda$
7	Step size (learning rate)	$\mu= 0.01$
8	Number of training samples	N=1250

The parametric values in table-2 were chosen based on the initial experiments, (initial experiments means that the experiments were performed with all specified values indicated above but took longer time to test and hence the chosen values were considered for convenience towards quicker and better evaluations).

The diagrammatic simulations are performed on a four-element array. Fig (3) (a and c) depicts the polar and Cartesian coordinate systems of the main-beam radiation to visualize the height of the side-lobe level at 21 dB, before using the LMS algorithm. In comparison to it, fig(3) (b and d) depicts the polar

and Cartesian coordinate systems of the main-beam radiation to visualize the height of the side-lobe level falling down to 5 dB, after using the LMS algorithm.

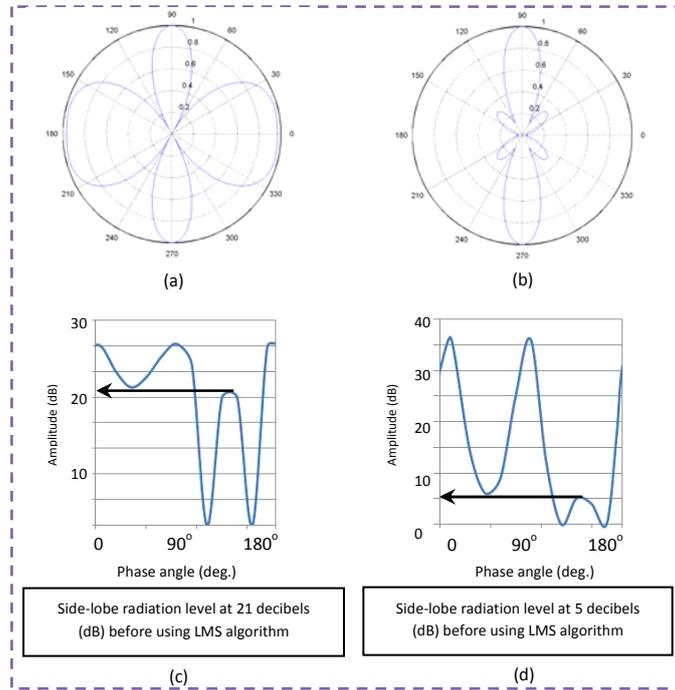


Fig 3.The above diagrams illustrate the comparison analysis for the clarity in side-lobe level reduction before and after using LMS algorithm

Another diagram shown in Fig (4) and (5). Fig (4) depicts the beamformation in two aspects: (a) before using LMS (b) after using LMS; for the number of elements=4; angle of radiation=30°; number of training samples =1250; the learning rate parameter = 0.01 (constant).

It also shows the mean-square error against the number of training samples (fig (4-c)). In this diagram, the adaptation rate's noise has fairly reduced for the number of training samples, in contrast to the previous case.

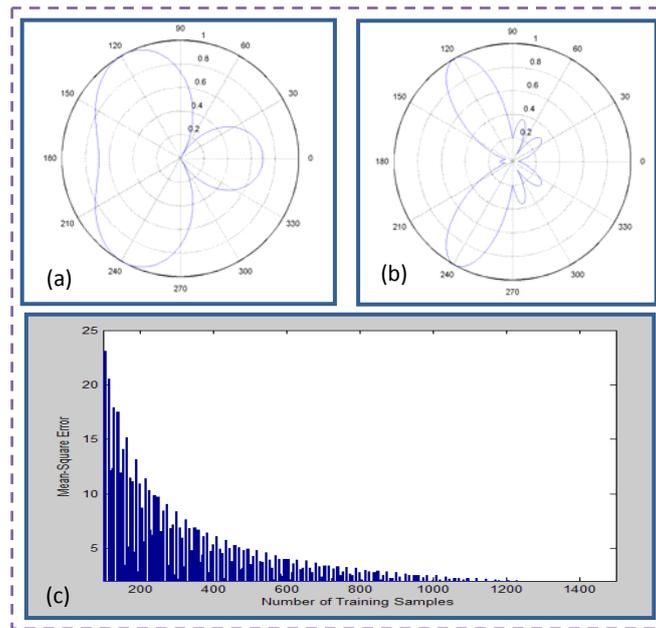


Fig4. Illustrates the comparison analysis of polar system in side-lobe level reduction and as well the narrowing of the main-beam, before (a) and after (b) using the adaptive algorithm LMS. It also shows window plots (c) of the behavior of the learning rate parametric value.

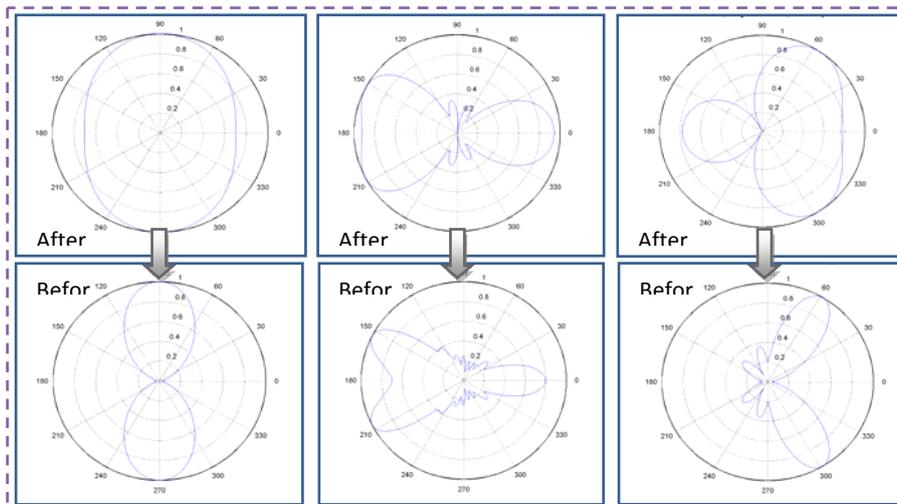


Fig5. Another cases of side-lobe level reduction and as well the narrowing of the main-beam before and after using the adaptive algorithm LMS (Least Mean Squares).

6- Conclusions

This paper evaluates the potential of using the neural network techniques in a complex real-time environment like signal-processing in phased array antennas. The aim of this work is to evaluate the adaptive algorithm LMS, to evolve the functionality of an antenna. Also, study the antenna in its behavioral pattern of its main beam radiation and as well side-lobes formed along with it. It is not to prove here, to solve trivial problems with approaches that have already been proven theoretically by other researchers. The results showed that the output of the four-element antenna array pattern produces a narrower beam with the same amplitude, as that of the main beam before applying LMS. Along with a narrower beam, comes another positive result, that is, the reduction of side-lobes more than 5 dB in comparison to the related work mentioned in previous sections

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