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Non-Linear Gradient Descent Algorithm for Smart Antennas

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ABSTRACT: A Nonlinear Gradient Descent algorithm (NGD) is an iterative method that is given an initial point and follows the negative of the gradient in order to move the point towards a critical point, which is hopefully the desired local minimum. Nonlinear gradient descent is a popular algorithm for very large scale optimization problems, because it is easy to implement and can handle black box functions [1]. In Smart Antennas (SA) both Half Power Beam Width (HPBW) and Side Lobe Level (SLL) are low values to get good performance. However to design smart antennas with minimum side lobe level, and HPBW, Nonlinear gradient descent algorithm gives the good performance on HPBW and SLL. This NGD algorithm is used for adaptive array smart antennas, because these arrays allows the antenna to steers the beam pattern in order to enhance the reception of a desired signal, while simultaneously suppressing interfering signals through complex weight selection.

KEYWORDS: NGD algorithm, HPBW, SLL, step size parameter, smart antenna.

I. INTRODUCTION

A Smart antenna is a system that combines multiple antenna elements with a signal processing capability to optimize its radiation and reception pattern with respect to the signal environment. Switched beam smart antennas and adaptive beam arrays are the two basic types of smart antennas. In this paper the nonlinear gradient descent algorithm is used for design of adaptive array smart antennas, because these arrays allow the antenna to steer the beam to any direction of interest while simultaneously suppressing interference signals. The NGD algorithm is used for adaptive array smart antennas, because these arrays allows the antenna to steers the beam pattern in order to enhance the reception of a desired signal, while simultaneously suppressing interfering signals through complex weight selection [2]. However the weight selection is a critical task to get the low SLL and low beam width. It needs to have a low SLL and low beam width to reduce the antenna's energy radiation/reception ability in unintended directions. The weights can be chosen to minimize the SLL and place nulls at certain angles. A vast number of window functions are available to calculate the weights for smart antennas. From the analysis of many of these algorithms, it is observed that there is a compromise between HPBW and SLL [3]-[4]. But in case of smart antennas, both of these parameters must have low values to get good performance. The earlier work it is proposed NGD algorithm in which more control parameters are used thereby optimum values can be obtained for HPBW and SLL. The Butler matrix is a type of beam-forming network. Depending on which of N inputs is accessed, the antenna beam is steered in a specific direction in one plane. The basic smart antenna system with butler matrix as shown in figure 1.

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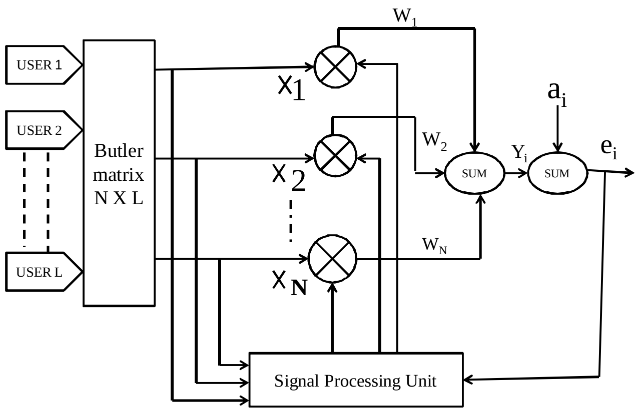

Figure 1. Basic smart antenna

Related work

Dai and Yuan proposed the nonlinear gradient descent method which generates a descent search direction at every iteration. In this paper, is proposed a nonlinear gradient descent method based on the study of Dai and Yuan and show that this method always produces a descent search direction. The numerical results show that this method is very efficient for given standard test problems [5]-[6].

II. PROPOSED ALGORITHM

The equations that describe the nonlinear gradient descent algorithm for a complex-valued dynamical perceptron, with a single output neuron are given by

$$e(k) = d(k) - y(k), \quad y(k) = \Phi(net(k)) \tag{1}$$

where $e(k)$ is the instantaneous output error of the filter at time instant k, y(k) is the output from the nonlinear activation function, d(k) is the desired output, ϕ(net(k) is some holomorphic function that is bounded everywhere in the complex domain [7].

$$net(k) = \sum_{n=1}^{N} x_n(k) w_n(k) = X^T(k)\, w(k) \tag{2}$$

Where x(k) denotes the input such that

$$x_n(k) = x(k - n + 1), \; n = 1\ldots\ldots\ldots,N.$$

W(k) is the weight vector and is equals to $[w_1(k),\ldots\ldots,w_N(k)]$ rise to the power T, and N is the number of array elements used. For simplicity we state that,

$$\Phi(net(k)) = \Phi^r(net(k)) + j\, \Phi^i(net(k)) = u(k) + jv(k) \tag{3}$$

Where the superscripts $(.)^r$ and $(.)^i$ respectively, denotes the real and imaginary parts of a complex quantity, and j $=\sqrt{-1}$. It can be split up the error term in equation (1), into its real and imaginary parts as

$$e^r(k) = d^r(k) - u(k), \quad e^i(k) = d^i(k) - v(k) \tag{4}$$

$$E(k) = \frac{1}{2}|e(k)|^2 = \frac{1}{2}[e(k)e^*(k)] = \frac{1}{2}[(e^r)^2(k) + (e^i)^2(k)] \tag{5}$$

Where E(k) is the conventional cost function and $(.)^*$ denotes the complex conjugate. The weight adaptation in the NGD algorithm is therefore given by equation (3)

$$w_n(k+1) = w_n(k) + \Delta w_n(k), \quad n = 1, 2,\ldots..,N \tag{6}$$

$$\Delta w_n(k) = -\eta \nabla_w [E(k)]_{w=w_n(k)}$$
$$= \eta\, e(k)(\Phi^{/}[net(k)])^* x_n^*(k) \tag{7}$$

Where η is the learning rate. The NGD algorithm can be written in the compact form as

$$W(k+1) = w(k) + \eta\, e(k)(\Phi^{/}[net(k)])^* x_n^*(k). \tag{8}$$

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Learning rate is a decreasing function of time [8]. Two forms that are commonly used are a linear function of time and a function that is inversely proportional to the time t.

III. Simulation Results

The simulations are carried out with an input signal $x_s(k) = \cos(2wt)$ at frequency of 1kHz along with a random noise. When the values of N and μ (step size parameter) are varied, one can generate main lobe in required direction with low SLL and HPBW [9]-[10]. At N=8, Signal to Noise Ratio (SNR) =45, when the μ value is increased it is observed that HPBW is also increasing simultaneously reducing SLL, as shown in table 1.

Table 1. Performance of HPBW and SLL by increasing μ values.

Step size(μ)	Half power beam width(HPBW)	Side lobe level (SLL)	Symmetrical number of side lobes
0	0	0	0
0.01	6.9	0.128	7
0.02	7.3	0.09002	7
0.03	7.7	0.08	7
0.04	8.3	0.0765	6
0.05	8.7	0.06471	6
0.06	9.1	0.0582	5
0.07	9.3	0.0546	4
0.08	10.1	0.0531	4
0.09	10.3	0.0520	4
0.1	12.3	0.0460	3

In order to simulate the real time environment of smart antenna system, the noise component has been considered in addition to the input signal and the performance of the Nonlinear gradient descent algorithm have been analyzed with different values of N and constant step size (μ), as result in decreasing HPBW, SLL as shown in below table 2.

Table 2. Performance of HPBW and SLL by increasing N values.

Number of array element (N)	Half power beam width (HPBW)	Side lobe level (SLL)
1	60	-
2	26.5	0.2577
3	17.5	0.2143
4	13.3	0.1792
5	10.8	0.1548
6	10.1	0.133
7	8.1	0.0999
8	7.3	0.09168
9	6.7	0.0842
10	6.3	0.07202

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IV. CHARACTERISTICS OF SMART ANTENNA WITH NGD ALGORITHM

The characteristics of normalized array factor is plotted, for N=8, μ=0.02, by taken, angle (in degree) on x-axis, normalized array factor on y-axis, the corresponding results for HPBW and SLL are 7.3 and 0.08977 respectively, as shown in figure 2. For the above mentioned values of N and μ, the comparison of array output of NGD algorithm (shown in dotted line), with desired output (shown in thick line), by taken number of iterations on x-axis and normalized signal amplitude on y-axis, corresponding characteristics are as shown in figure 3.

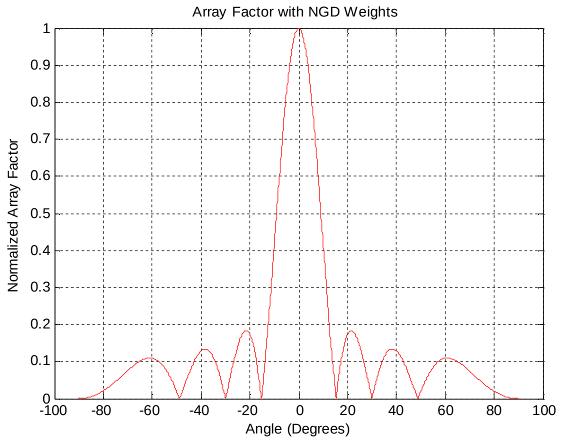

Figure 2. Normalized Array factor generated with NGD algorithm.

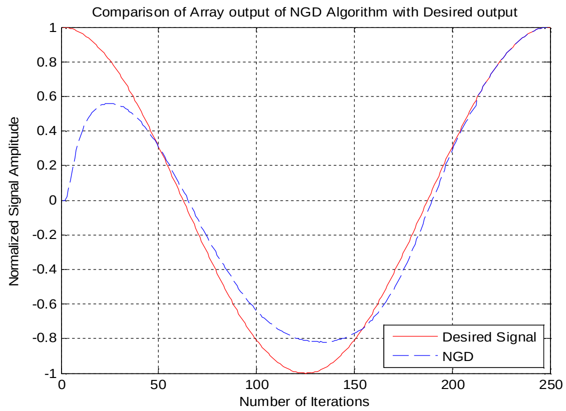

Figure 3 Comparison of array output of NGD algorithm, with desired output.

The Mean Square Error (MSE) of an estimator measures the average of the squares of the "errors", that is, the difference between the estimator and what is estimated. MSE is a risk_function, corresponding to the expected value of the squared error loss or quadratic loss [11]. By taken number of iterations on x- axis, normalized MSE amplitude on y-axis, the corresponding characteristics as shown in figure 4. At different values of N, the characteristics of normalized array factor and it's corresponding side lobe levels are plotted by taking angles on x- axis, normalized array factor on y-axis as shown in figure 5.

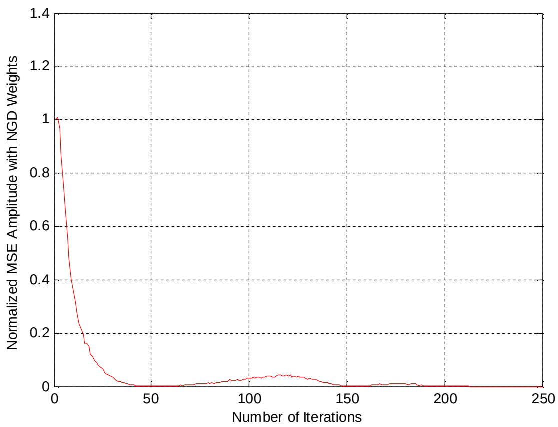

Figure 4. Normalized mean square error generated with NGD algorithm.

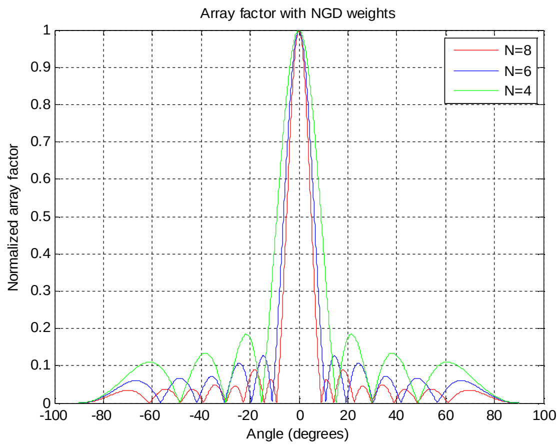

Figure 5. Normalized Array factor generated with NGD algorithm.

By taken number of iterations on x- axis, normalized MSE amplitude on y- axis, the corresponding characteristics at different values of N, as shown in figure 6. For the different values of N, the comparison of array output of NGD algorithm, with desired output, plotted by taken number of iterations on x-axis and normalized signal amplitude on y-axis, corresponding characteristics are as shown in figure 7.

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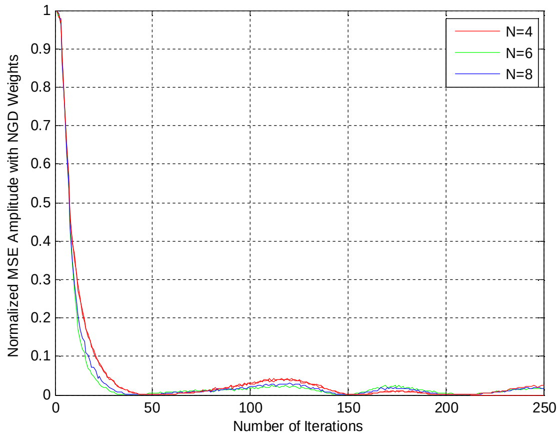


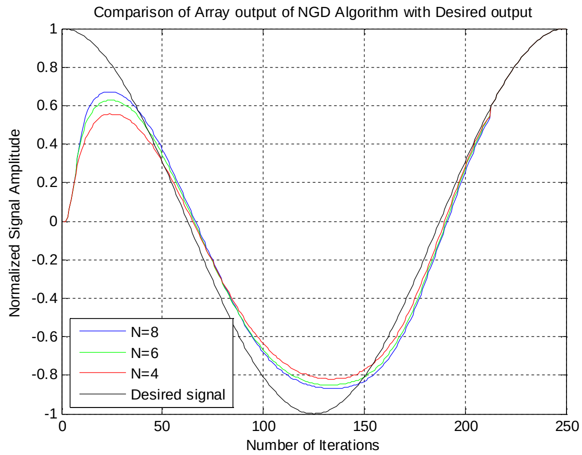
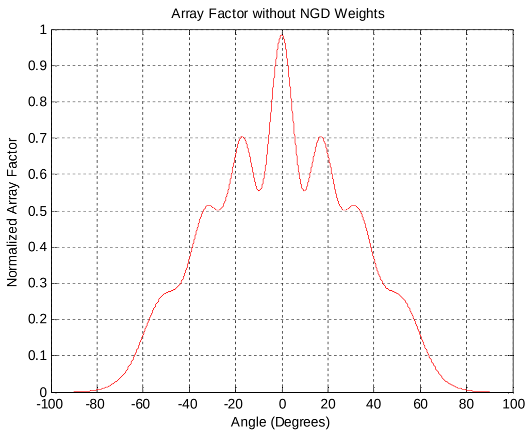


Figure 6. Normalized mean square error (MSE) generated with NGD algorithm. Figure 7. Comparison of array output of NGD with desired output.

V. COMPARISON OF WEIGHTED AND UNWEIGHTED OUTPUTS

Number of array elements and step size are fixed at the values of, 8 and 0.02 respectively, the characteristics of normalized array factor obtained with un-weighted, as shown in figure 8. For the above mentioned values of N and μ, the comparison of array output for un-weighted (shown in dotted line), with desired output (shown in thick line), corresponding characteristics are as shown in figure 9.



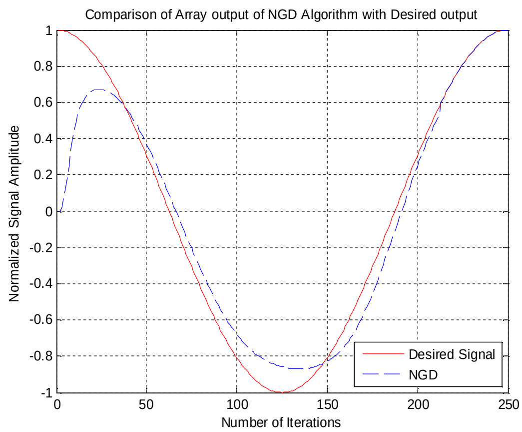


Figure 8. Normalized Array factor generated without NGD algorithm. Figure 9. Comparison of array output of NGD algorithm, with desired output.

Normalized MSE amplitude for un-weighted can be plotted, By chosen number of iterations on x- axis, normalized MSE amplitude on y- axis, the corresponding characteristics as shown in figure 10.

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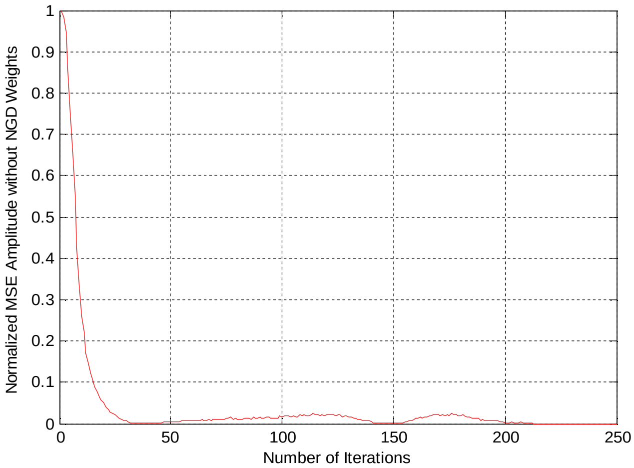

Figure 10. Normalized mean square error generated for un-weighted.

VI. CONCLUSION AND FUTURE WORK

Nonlinear gradient decent algorithm is considered for adaptive beam forming of signals in smart antennas, with various parameters such as number of array elements, learning rate, step size of adaptive amplitude, have been considered under noiseless and noisy environments. From the analysis with NGD weights have better performance in the convergence of desired signal, in giving low HPBW and SLL in noiseless environment.

However un-weighted has no control over adaptation of HPBW and SLL. At the same time NGD weights has good control over adaptation of these two parameters with η and μ. By using NGD weights we designed a smart antenna with minimum half power beam width and side lobe level.

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