Pakistan Journal of Applied Sciences 2(3): 380-383, 2002

Design of Adaptive Null Antenna using Genetic Algorithms

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Abstract: This paper describes the design of adaptive null antenna and its implementation through Genetic Algorithm. The step-by-step implementation of GA has been demonstrated using a flow chart to determine the complex excitation co-efficient of adaptive null linear array antenna. This algorithm can avoid the local minima(as observed in LMS) and converges towards the global optimum solution.

Key words: Adaptive Null Antenna, Electromagnetic Optimization, GA for Antennas

Introduction

The radiation pattern of an array antenna can be controlled dynamically. It depends upon, spacing between elements, geometrical configuration of element, element type and their complex weighting co-efficient. The complex weighting coefficients include the amplitude and phase excitation co-efficient. It is important to note that change in the amplitude and phase distribution over the aperture of the array will not only put a main lobe in a given direction but it may change the whole radiation pattern of the array as well, which may not be desirable. Hence, the excitations co-efficient have to be determined through some optimization techniques. Various optimization techniques have been extensively used for antenna design problems. These include LMS, Steepest decent and random search (Windrow and McCool, 1979). The stringent requirements of the user demand more advanced optimization tools to derive the optimum design for a given set of requirements. The emerging techniques include simulated annealing, expert systems, neural network/fuzzy logic and genetic algorithm (Bucci *et al.*, 1994; Barberio and Sabbadini, 1994).

This paper describes the implementation of genetic algorithm for design of adaptive antenna. Genetic algorithm and its application to array antenna design problem are discussed in detail. Various case studies and numerical results are presented.

GA starts from a random initial population and simulates biological evolution for next population. This algorithm can avoid the local minima and converges towards the global minima.

Modeling of Linear Adaptive Antennas: To make an antenna adaptive and to be able to control the antenna pattern without physically moving the antenna it is necessary to use an antenna array. Each element in the array is an isotropic antenna with the same gain. The antenna arrays used for adaptive antennas consist of a number of equal elements and can be of linear, circular or planar form. In this case only the linear array is being considered.

The incoming signal is arriving at an angle of theta from the broadside.

The phase difference between the signals received by two adjacent antenna elements separated by distance d is give by ,

$$\varphi = k.d.\sin\theta \qquad (1)$$

where k is the wave number given by $k = 2\pi/\lambda$

Signals received by the elements are multiplied by complex weights and added together in order to provide adaptivity to the array factor.

We assume that the transmitter is in the far field of the antenna, so a plane wave will appear at the antenna. For a 2N+1 element array the output signal is given by .

$$Y = W^h X \qquad (2)$$

where

$$W = [W_1 \ \ W_2 \ \ W_3 \ \ \ldots \ \ W_{2N+1}]^T,$$

$$X = [X_1 \ \ X_2 \ \ X_3 \ \ \ldots \ \ X_{2N+1}]^T$$

and

$$X_i = e^{(-j(i-1).k.d.\sin\theta)}$$

where

$$j = \sqrt{-1}.$$

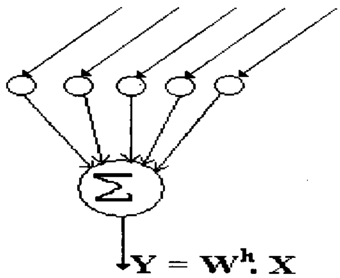

Fig. 1: Weighted addition of signals

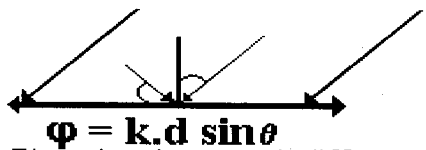

Fig.2 Phase lag due to path difference

Genetic Algorithm: Our main desire is to find the weights that will give us any desired response, in particular the direction of the main beam and the direction of the nulls. A sample of a desired response is given in Fig. 2. The Genetic algorithm is being used to find the weights of the adaptive antenna. We are using 2N+1 number of weights, which are complex, but the center weight is taken as 1. Therefore in each chromosome there are (2N+1) genes. The chromosome is given as a complex weighting vector,

$$W=\begin{bmatrix} w_1 & w_2 & w_3 & \dots & w_{2N+1} \end{bmatrix}^T$$

where w_n belongs to C_n, the set of complex numbers, and is the excitation of nth radiator.
The ordinary rule of thumb for choosing the population size is to choose it five to six times the length of a chromosome. Fig. 3. is the flowchart of the genetic algorithm.

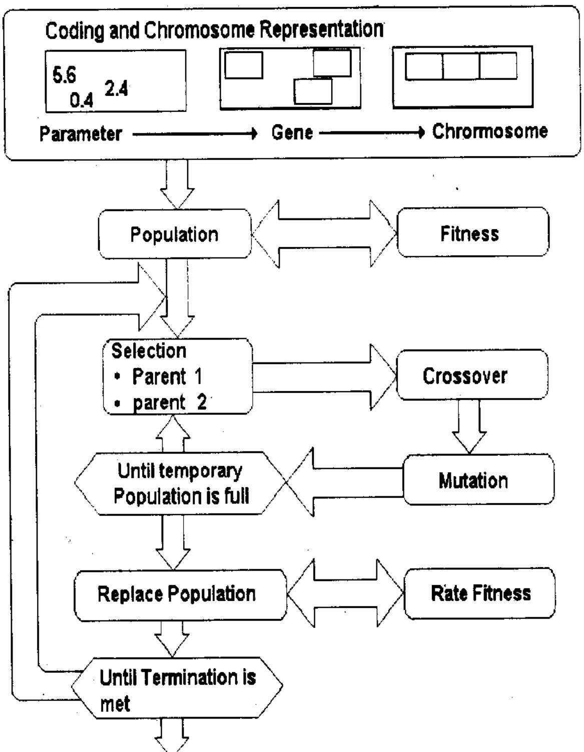

Fig. 3 Flowchart of Genetic Algorithm

Initialization: The real and imaginary parts of the genes representing weights is produced be a pseudo random generator. Values of the genes are real and between 0 and 1.
Fitness Criterion: The fitness criterion denoted by F is taken as

$$F = \frac{1}{1+R} \tag{3}$$

where R is the weighted residual error given as follows

$$R=\sum a(i).e(i) \tag{4}$$

where $a(i)$ are the weightages given to residues, $e(i)$, at different at different points and

$$e(i)=r(i)-s(i) \tag{5}$$

where $r(i)$ is the reference array pattern and $s(i)$ is the actual array pattern given by the chromosome under consideration.
Cross-over, Reproduction and next Generation: The population in a generation is sorted out according to the fitness criterion in a descending order. The top one third are given a chance to produce 5 children per pair as given below

Parent 1: $W1=[w_{11}, w_{12}, w_{13}, \dots\dots\dots]$

Parent 2: $W2=[w_{21}, w_{22}, w_{23}, \dots\dots\dots]$

Child 1 = $\dfrac{(W1+W2)}{2}$,

Child 2 = $\dfrac{(M1.W1-W2)}{2}$,

Child 3 = $\dfrac{(M1.W2-W1)}{2}$,

Child 4 = $\dfrac{(M2.W1-W2)}{2}$

Child 5 = $\dfrac{(M2.W1-W2)}{2}$

where

$M1=2+r1$ and $M2=2+r1+r2$

and $r1$ and $r2$ being random numbers between 0 and 1.

The next one-third is given a chance to produce 3 children per pair. They are similar to child 1,child 2 and child 3 of the given above.
The last one-third is given a chance to produce only one child per pair, as in China, which is similar to child 1.
For selection of a new generation, the rule for the survival of the fittest is being used. All the parents and children are sorted in a descending order of fitness after calculating the fitness of the children. The top ones equal to the number of population are chosen for the next generation. So the new population is a blending and overlap of the previous and the present with no fixed percentage for either generation.
Mutation: We are generally not using mutation. If with every new generation being produced, the fitness criterion does not seem to improve at all, then mutation is being done purely on random basis.
Termination Criterion: When the fitness of the best chromosome in the new population is almost the same as that of the best chromosome in the previous population the program is terminated Quantitatively the criterion for termination is

$$|F_{new}-F_{prev}|\leq 0.01$$

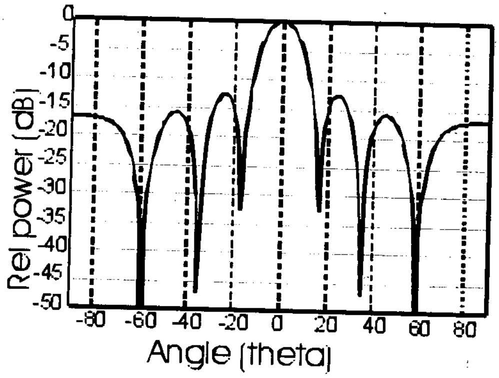

Fig. 4a: Reference Pattern

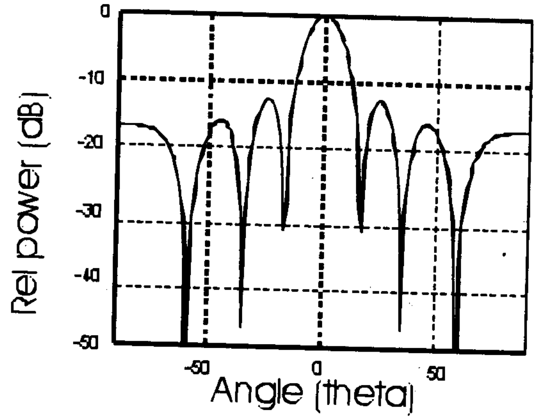

Fig. 5a: Reference Pattern

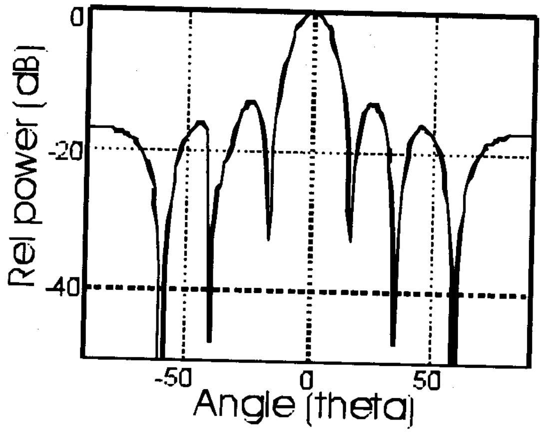

Fig. 4b: The Null at -32° has been Shifted to -40°

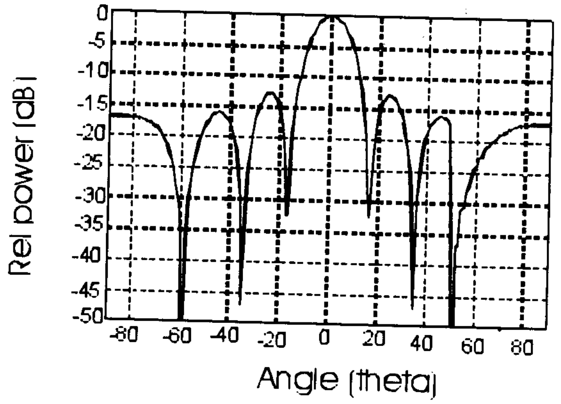

Fig. 5b: The Null at 60° has been Shifted to 50°

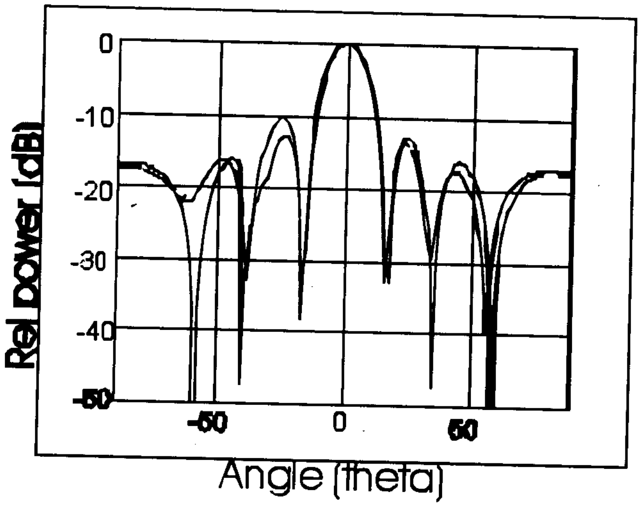

Fig. 4c: (---) Radiation Pattern Obtained Through GA
(-) Targetted Pattern

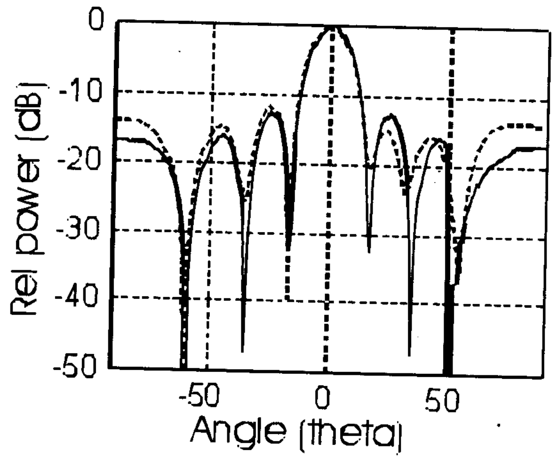

Fig. 5c: (---) Radiation Pattern Obtained Through GA
(-) Targetted Pattern

Results and Discussion

Maximum energy concentrate always in the main lobe and remaining energy is occupied by degrading lobes (side lobes). Shifting of a null to a particular position means generation of "no energy point" at that position. Generation of null at a particular position is not a big problem but generation of energy occupied lobe(at the null position) is the a job. Null steering is allowed upto certain limit, it is because when we steer null then its adjacent lobes adjust their energies with the same energy as they had before shifting. Large degree of null shifting means large span of one adjacent lobe and shrink span of other adjacent lobe.

It is more difficult to steer null to far position as compared to nearby position. Energy re-adjustment in lobes is easier in small spans as compared to large spans. Energy re-adjustment is proportional to span of shifted null. Furthermore when null is shifted to a farther position, then maximum number of remaining lobes and nulls of a regenerated pattern from Genetic Algorithm will be disturbed.

Our proposed scheme can work for even large null shifting.

Further improvement can be obtained by using the combination of Neural network and Genetic algorithm.

Few example are given below from our proposed scheme.

Conclusion

The use of Genetic Algorithm for the design of array antennas has been demonstrated successfully. Certainly, GA is a good optimizer to solve problems of electromagnetic computation and complex antenna design.

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