

Genetic Algorithm Design of Antenna Arrays

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Abstract-Genetic algorithms are capable of optimizing the performance of antenna arrays. They model biological evolution to find the parameters that optimize the output of a function. In this paper, the genetic algorithms find the quantized phase weights that optimize the sidelobe levels of an array over its scanning region.

TABLE OF CONTENTS

1. INTRODUCTION
2. MODELING ANTENNA ARRAYS
3. GENETIC ALGORITHMS
4. RESULTS
5. CONCLUSIONS

1. INTRODUCTION

Antenna arrays in aerospace applications must perform a multitude of complex roles in the radar and communications systems. Optimizing these antennas is quite challenging because of the large number of parameters and the difficulty in calculating performance characteristics. Traditional optimization methods find suboptimum solutions, often require derivative calculations, and cannot optimize with discrete parameters. One relatively new approach to the optimization of complex systems that overcomes the previously mentioned problems is the genetic algorithm. A genetic algorithm models

evolutionary processes on a computer to arrive at an optimum solution. These algorithms are extremely powerful and may be applied to a wide range of engineering design problems. A genetic algorithm searches an extremely large, but finite, solution space to arrive at an optimum solution.

Antenna arrays usually adjust discrete parameters, such as amplitude weights and phase shifters, to give some optimum performance in the far field pattern. A genetic algorithm is perfect for optimizing sidelobe levels, nulls, or other performance characteristics. This paper shows how to design quantized phase tapers for linear arrays with a genetic algorithm. The resulting tapers yield optimum sidelobe performance over the bandwidth of the antenna. For instance, it is possible to find a quantized phase or amplitude taper that produces the lowest possible sidelobe levels over a specified angular region and bandwidth.

2. MODELING ANTENNA ARRAYS

A linear array antenna is a group of equally spaced antennas arranged along a line and whose outputs are added together to provide a single output. Figure 1 shows a diagram of such an array. Mathematically, the array far field pattern is given by [1]

$$ff(\phi) = \underbrace{\frac{1}{N} \sum_{n=1}^N w_n \cos[(n-.5)\Psi]}_{\text{array factor}} \underbrace{\sin \phi}_{\text{element pattern}} \quad (1)$$

where

$w_n = a_n e^{j\delta_n}$ complex weight at element n

$2N$ = number of elements in the array

$\Psi = kd(u-u_0)$

$k = 2\pi/\text{wavelength}$

d = spacing between elements

$u = \cos \phi$

u_0 = steering angle = $\cos \phi_0$

ϕ = angle from x-axis or from the array face

δ_n = nulling phase at element n

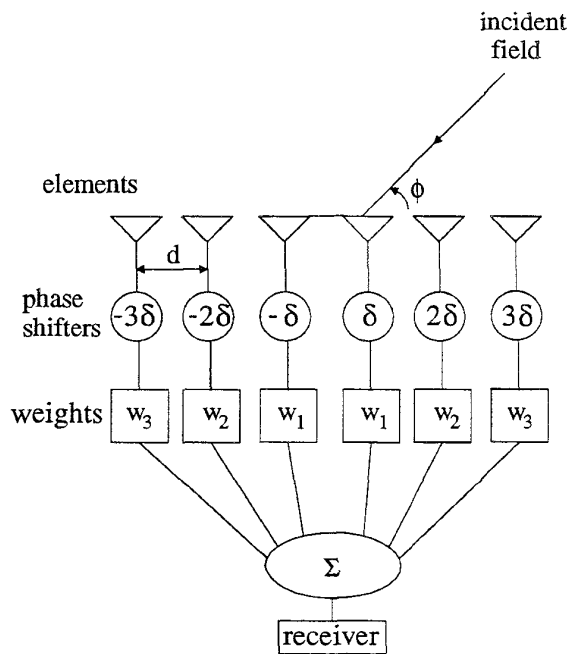


Figure 1. Diagram of a linear phased array of $2N$ equally spaced elements.

Equation (1) assumes the elements have $\sin \phi$ element patterns, typical of elements less than a half wavelength long (e.g. a dipole). The far field pattern is normalized to the peak of the untapered array at broadside.

A phased array has many advantages over other antennas, including higher gain than a single element, electronic beam steering, and control over the antenna pattern. Varying the weights leads to an antenna pattern with lower sidelobes and/or nulls in the directions of interference or jamming. Finding the weights for the optimum antenna pattern is a long established art; however, this art is being improved as computers become more powerful.

When optimizing an array, the parameters and cost function must be specified. The parameters are the amplitude and phase controls at each element. The cost function is the quantity to be minimized. Some cost function alternatives are

- sidelobe level
- null depth in specified direction
- beamwidth or gain

The cost function may also include

- scan angles
- bandwidth
- quantization parameters

3. GENETIC ALGORITHMS

Genetic algorithms are a subset of evolutionary computations. Evolutionary computations attempt to use biological processes for the basis of a computer algorithm that optimizes highly complex problems. Figure 2 is a flow chart of a simple genetic algorithm.

Genetic Algorithm Flow Chart

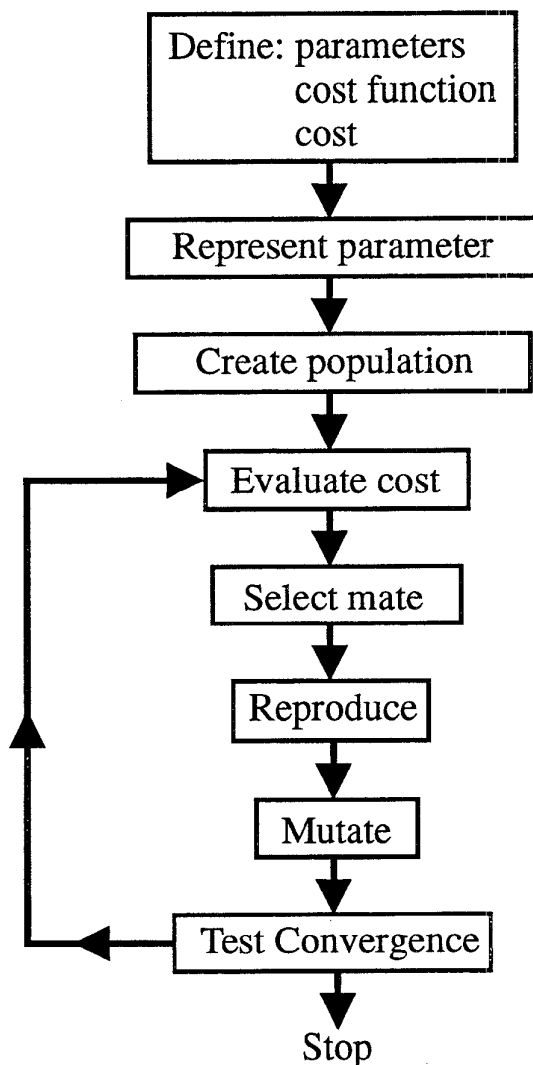


Figure 2. Flow chart of a genetic algorithm.

A genetic algorithm usually encodes each parameter in a binary sequence called a gene and places the genes in an array known as a chromosome. For instance, $(x,y)=(32,1)$ can be encoded as

chromosome = (100000000001).

The algorithm begins with a population in the form of a random matrix of ones and zeros

where each row is a chromosome. Next, the fitness or cost function for each chromosome is calculated. The chromosomes are ranked from best to worst according to their fitness values. Mating takes place between the most fit chromosomes. Offspring or new chromosomes produced from mating contain parts of the two parents. A simple crossover scheme randomly picks a point in the chromosome. Two offspring result by keeping the binary strings to the left of the crossover point for each parent and swapping the binary strings to the right of the crossover point. Consider two parent chromosomes given by

parent #1 = [1010|1010]

parent #2 = [1111|0000]

If the random crossover point occurs between bits four and five, the offspring are

offspring #1 = [10100000]

offspring #2 = [11111010]

The fitness of the new offspring are computed. Mutations change a small percentage of the bits from "1" to "0" or visa versa. The new list is ranked from best to worst and the process repeated. The algorithm stops when an acceptable solution is found or a set number of iterations has lapsed. Many variations and improvements to this process are possible.

What makes these algorithms so good? Some of the advantages they have over conventional algorithms are

1. They can work with discrete parameters. Deterministic algorithms work with continuous parameters. Many engineering problems have a finite number of parameter values. For example, designing an electronic circuit from resistors, capacitors, inductors, and transistors available in a laboratory or from a vendor may

have a rather large, but finite number of parameter values.

2. They are not as likely to get stuck in local minima. An initial random set of genes samples the parameter space. Crossover and mutation keep the search from narrowing to a particular region too quickly.

3. They can optimize a problem with a large number of parameters. The search space has far too many local minima for conventional optimization methods when the number of parameters gets large.

4. They are simple to understand and program.

References [2] and [3] provide more details on the algorithm.

4. RESULTS

Phased arrays often use digital phase shifters to steer the main beam. It is possible to use these same phase shifters to lower the sidelobe levels [4], [5]. Phase tapers can be superimposed on the beamsteering phase without degrading beam pointing accuracy. Reference [5] extended the work of [4] to digital phase shifters, and this paper extends [5] to include beam steering.

If the elements had isotropic element patterns and the phase shifters were analog, then a low sidelobe phase taper optimized at broadside would provide the same low sidelobes as the beam steered to some angle. The element patterns reduce the main beam amplitude and increase the sidelobe levels of sidelobes near broadside. Consequently, the relative sidelobe level goes up. In addition, an undesirable quantization lobe enters the pattern as the beam is steered [6].

As an example, consider a 60 element linear array with the elements spaced one half of a

wavelength apart. The broadside array far field pattern is shown in Figure 3. Its aperture efficiency is $\eta=1$, and the aperture efficiency at broadside for a linear array of isotropic point sources spaced $d=0.5\lambda$ is defined as [1]

$$\eta = \frac{\left| \sum_{n=1}^N w_n \right|^2}{N \sum_{n=1}^N w_n w_n^*} \quad (2)$$

where w_n^* is the complex conjugate of the array weight. The peak relative sidelobe level is approximately 13.5 dB below the peak of the main beam. Steering the beam with infinite

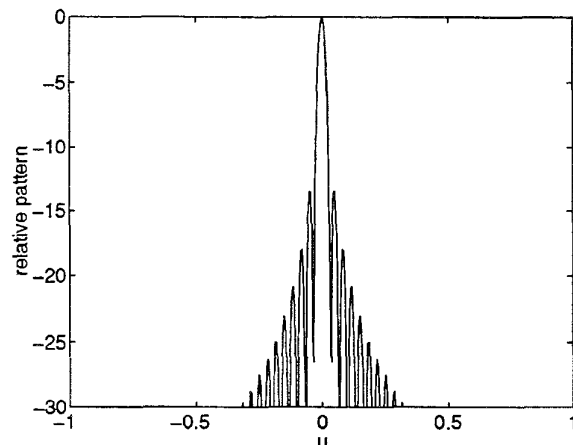


Figure 3. Far field pattern of a 60 element array of point sources with $\sin\phi$ element patterns and elements spaced $d=0.5\lambda$

precision phase shifters to $\phi = 60^\circ$ results in a reduction in the main beam and a general increase in sidelobe levels as shown in Figure 4. The main beam is 1.25 dB lower than the broadside case and the maximum relative sidelobe level is -13.2 dB. These performance reductions are due to the element patterns and not the array factor. If the phase shifters are quantized to three bits, then the beam does not precisely point to $\phi = 60^\circ$ and quantization lobes appear as shown in Figure 5. The

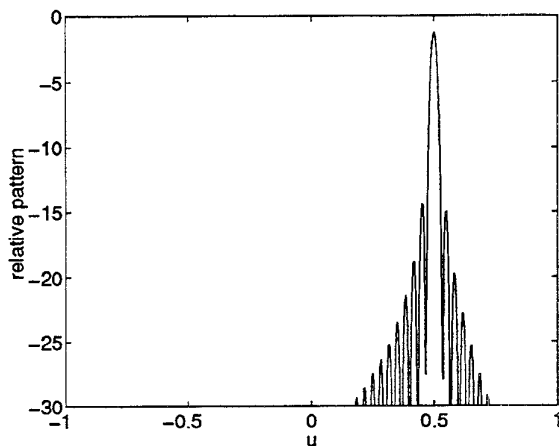


Figure 4. Far field pattern of a 60 element array with the main beam steered to $\phi=60^\circ$ with analog phase shifters.

quantization lobe at $u=0.5$ is at about 14 dB below the peak of the main beam.

The goal is to optimize a phase taper to reduce the maximum sidelobe level of the array for all steering angles. First, the genetic algorithm finds a phase taper for the broadside case. Figure 6 shows the convergence of the algorithm. The upper curve is the average maximum sidelobe level for a population of 200 chromosomes, while the lower curve is the

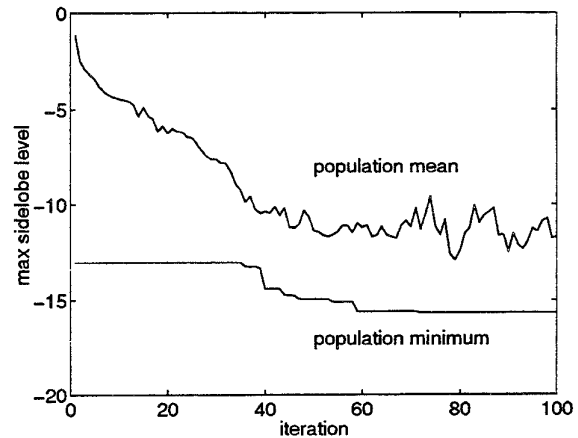


Figure 6. Genetic algorithm convergence.

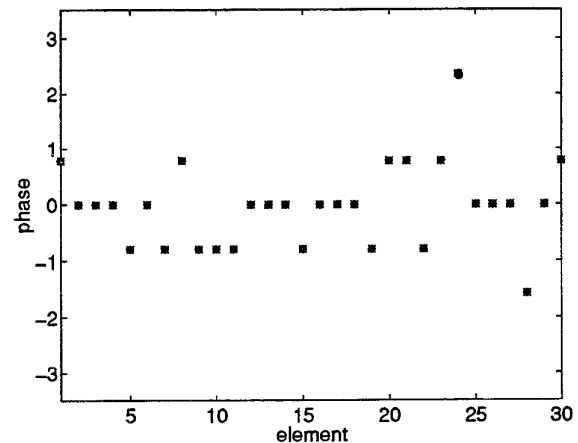


Figure 7. Optimized phase taper from broadside pattern.

minimum maximum sidelobe level for the population. The phase taper that results from this optimization has an aperture efficiency of $\eta=0.60$ and is shown in Figure 7. The corresponding far field pattern appears in Figure 8 and has a peak relative sidelobe level of -15.8 dB.

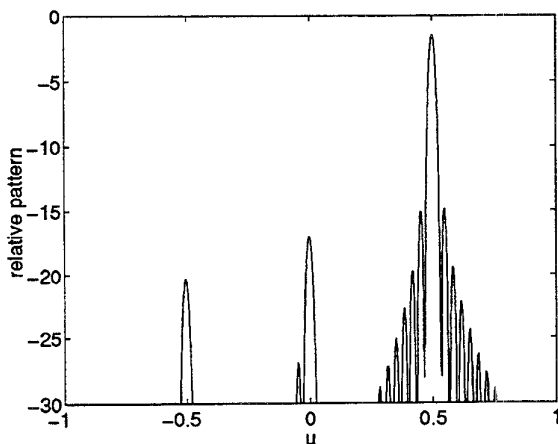


Figure 5. Far field pattern of a 60 element array with the main beam steered to $\phi=60^\circ$ with digital phase shifters.

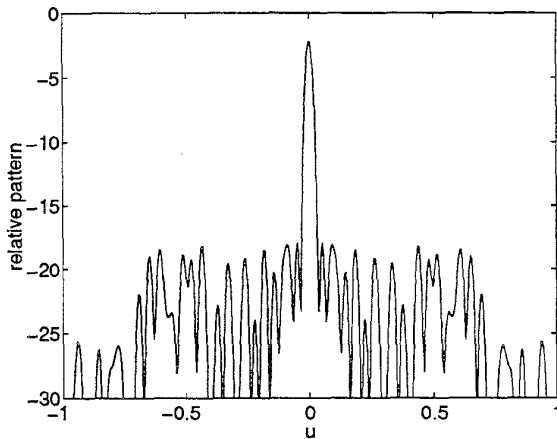


Figure 8. Optimized far field pattern at broadside.

Steering the beam to $\phi = 60^\circ$ while keeping the low sidelobe phase taper results in the far field pattern shown in Figure 9. Again, the quantization lobe appears and is only 9.8 dB below the peak of the main beam. Optimizing the phase taper at $\phi = 60^\circ$ results in the phase taper shown in Figure 10 and the far field pattern in Figure 11. The maximum relative sidelobe level is -12.9 dB, and the aperture has an efficiency of $\eta=0.56$.

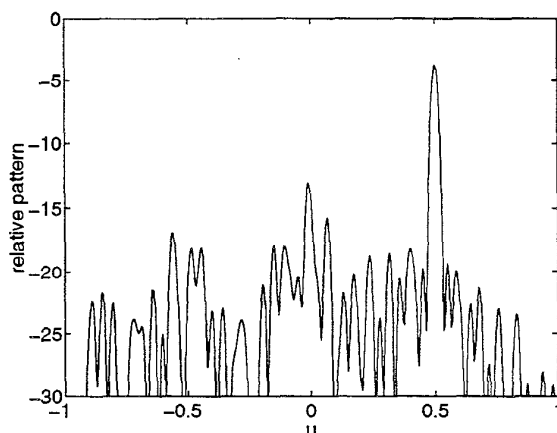


Figure 9. Optimized broadside pattern steered to $\phi=60^\circ$.

5. CONCLUSIONS

This paper has shown how to apply a genetic algorithm to find low sidelobe phase tapers that take into account beam steering. The phase tapers are different for each steering angle and can be stored in a lookup table. Applying the phase taper results in reduced sidelobe level but decreases aperture efficiency as well. Unlike conventional optimization algorithms, the genetic algorithm can work with a large number of discrete parameters.

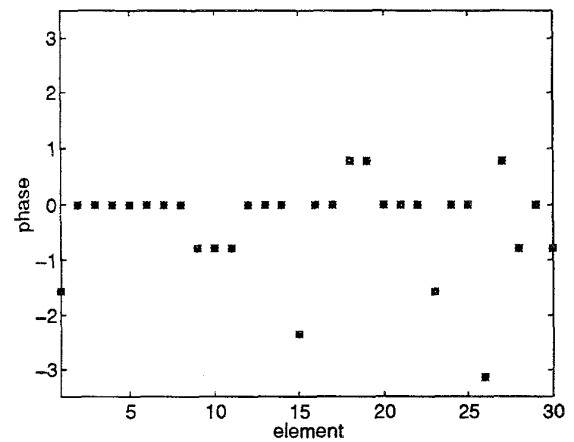


Figure 10. Optimized phase taper for main beam steered to $\phi=60^\circ$.

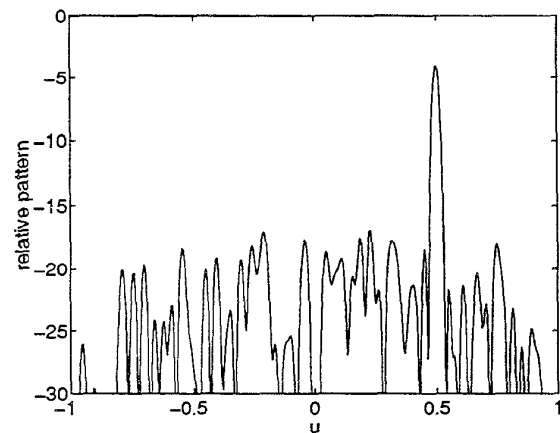


Figure 11. Optimized far field pattern when main beam is steered to $\phi=60^\circ$.

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