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Design of Low Side Lobe Level and Narrow Beam Width Antenna Array using Genetic and Particle Swarm Optimization Methods

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***Abstract*— In antenna array design especially in point-to-point communications, it is frequently desirable, to achieve both a low side lobe level and a narrow beam width. Trying to reduce SLL, results in an increase of beam width and vice versa. Exciting an antenna array according to Chebyshev distribution gives us the smallest beam width for a given SLL and vice versa. But this is not the smallest beam width obtained for any other value of SLL. In this paper, using random stochastic methods like Genetic algorithm based optimization and Particle Swarm Optimization, the SLL and HPBW obtained for a Dolph-Chebyshev linear array designed for a specified SLL are further reduced resulting in a narrow main beam and low side lobe level array.**

***Keywords*— Non-uniform antenna arrays, Side lobe level reduction, Narrow beams, Genetic algorithm, Particle swarm optimization.**

I. Introduction

In point to point communications it is frequently desired to have a narrow main beam followed by a low side lobe level. But in linear arrays, trying to reduce side lobe level results in an increase beam width and vice versa. An optimum compromise between SLL and Beam width is obtained for an antenna array excited according to Chebyshev amplitude distribution. In this paper, a Dolph Chebyshev linear array is designed for a specified side lobe level and taking this Dolph Chebyshev array as reference and using genetic and PSO methods, the SLL and HPBW are further optimized. Comparison between genetic algorithm based optimization and PSO based optimization is done. The optimization is done by varying phase of each element in the array randomly.

The outline of the paper is as follows. The system model is presented in section II. Section III and Section IV describe the genetic algorithm and the particle swarm optimization. In section V, we provide some numerical results. In section VI conclusions are given.

II. Problem Formulation

Consider a broad side non-uniform linear array of N equally spaced isotropic elements in which each element is excited with amplitudes obtained using Chebyshev polynomials with d as a distance between any two adjacent elements . To obtain the radiation perpendicular to the array orientation axis, a broad side linear array is designed. Array factor is referred to as the radiation pattern of the array excluding the element pattern, which is a function of the positions of the antennas in the array and the weights used [4]. By manipulating these parameters the antenna array performance can be optimized to achieve desirable properties.

The array factor of N-element linear array can be written as

$$\sum_{n=1}^{N} a_n e^{j\,(n-1)(\beta d\cos\theta\ +\alpha)}$$

α = 0 corresponds to the broad side array.

Here a_n represents feeding coefficients obtained using Chebyshev polynomials, θ denotes the angle of radiation of electromagnetic plane wave and varies from 0 to π, and d represents the spacing between elements usually taken as 0.5λ.

For large Dolph-Chebyshev arrays with side lobes in the range from -20dB to -60dB, the half-power beam width and directivity can be found by introducing beam broadening factor given approximately by as given in [2]. Here b is major-to-side lobe voltage ratio.

The method used to find beam width is by calculating directivity using above formula. The relation between the beam width and the directivity is given as

$$\text{Beam width}=101.5/D_0 \qquad (1)$$

III. Genetic Algorithm

The genetic algorithm (GA) is a class of adaptive stochastic optimization algorithms involving search and optimization [2]. Population of individuals is generally a set of possible solutions for the optimization. Fitness is simply a degree of adaption of an individual to its environment. Based on natural selection, constrained and unconstrained problems can be solved with the application of genetic algorithm. The genetic algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over the successive generations, the population gives off towards an optimal solution. The genetic algorithm mainly uses three types of components at each step to create the next generation from the current population, namely, selection, crossover and mutation.

GA usually starts from a population of randomly generated individuals, with the population in each iteration called a *generation*. In GA, the population size is (almost always) constant, thus a choice has to be made on which individuals will be allowed in the next generation, which is called as selection process. This decision is based on their fitness values, favoring those with higher quality. *Crossover* also called as recombination, which follows the principle of mating two individuals with different but desirable features, which may produce an offspring which combines both of those features. *Mutation* is a unary variation operator. It is applied to one genotype and delivers a modified mutant, the child or offspring of it. Mutation is a stochastic operator similar to crossover. Performance of GA depends very much on mutation and crossover.

IV. PARTICLE SWARM OPTIMIZATION

PSO is also a population-based stochastic approach for solving continuous and discrete optimization problems. Kennedy and Eberhart in 1995 developed the PSO by studying social and cognitive behavior of ants [3]. Particle Swarm Optimization is an artificial intelligence technique that can be used to find approximate solutions to extremely difficult or impossible numeric maximization and minimization problems. PSO is concerned with the search space. Particles formed at the beginning of the PSO process remain fully functioning until the solution is found.

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. The two factors on which the performance of PSO algorithm depends are global particle-to-particle best solution and the local particle’s iteration-to-iteration best solution. Each particle is updated by these two values in every iteration. The first one is the best solution called pbest referred to as cognitive component. Another "best" value that is tracked by the particle swarm optimizer obtained so far by any particle in the population is global best, gbest also known as social component. The *pbest* and *gbest* are updated for each particle, after each iteration. This process continues, iteratively, until the algorithm achieves the desired result. Particle swarm optimization can be applied to many diverse problems, for instance neural networks training, data mining, signal processing, and optimal design of experiments.

In this algorithm a completely connected swarm, meaning that all the particles share information, any particle knows what is the best position ever visited by any particle in the swarm. Each particle has a position (2) and a velocity (3) which are calculated as follows:

$$X_{i,d}\ (it+1) = X_{i,d}\ (it) + V_{i,d}\ (it+1) \qquad (2)$$

$$\begin{aligned} V_{i,d}\ (it+1) = {} & w(it)V_{i,d}\ (it) \\ & + C_1\ U\left(pb_{i,d}(it) - X_{i,d}\ (it)\right) \\ & + C_2\ U\left(gb_{i,d}(it) - X_{i,d}\ (it)\right) \end{aligned} \qquad (3)$$

where i is the particle index used as a particle identifier, d is the dimension being considered, it represents the iteration, $(X_{i,d}\ , V_{i,d}\ )$ represent the position and the velocity of ith particle, $C_1\ , C_2$ are acceleration constants for the cognitive component usually taken between 0 and 4, U is a uniform random variable between 0 and 1 while $(gb_{i,d}, pb_{i,d})$ represent respectively the best position of ith particle and the position of the best particle in the population and w represents the inertia weight taken between 0 and 1.

The velocity update equation (equation (3)) is a result obtained from the sum of different components, each having a specific meaning. First line represents, the momentum component, which is the previous velocity. Second line has the cognitive component, which depends heavily on the particle's current distance to the best position it has ever visited. Social component is defined on third line which depends heavily on the particle's distance to the best position where any of the swarm's particles has ever been.

V. SIMULATION RESULTS

A Dolph-Chebyshev array consisting of N elements which are optimally fed with excitation coefficients generated using Chebyshev polynomial which are symmetric about the origin is fed with optimal excitation phases obtained as an output of GA and PSO. We use GA and PSO for the minimization of the side lobe level and half power beam width simultaneously.

The algorithm begins by creating an initial population of random phases in the range of 0 to π. The generated phases are substituted in the defined array factor and the performance measures like side lobe level and half power beam width are calculated. The set of phase weights which are favoring those with the higher quality are treated as fittest, which undergoes crossover and mutation in case of GA. Similar to GA, PSO algorithm starts with random population of phases also given with a random velocities and positions. After each iteration, the velocity term is updated, and the particle is moved with some randomness in the direction of its own best position, pbest and the global best position, gbest.

In this paper, a -26dB Chebyshev pattern for a given number of (say N) equispaced elements with an inter element spacing of 0.5λ was taken as reference. For example, for the Chebyshev array of 11 elements, the side lobe level and half power 3-dBbeam width are -26dB and 9.4080^{o} respectively. The half power 3-dB beam width are calculated using the equation (1). The side lobe level can be calculated using the ratio of first maximum side lobe level to main lobe level which can be obtained from the plot. The excitation coefficients and the optimized phase weights for number of array elements N = 11 obtained after applying GA and PSO are shown in Table 1. Fig1 and Fig2 represents the optimized radiation pattern obtained after applying GA and PSO respectively.

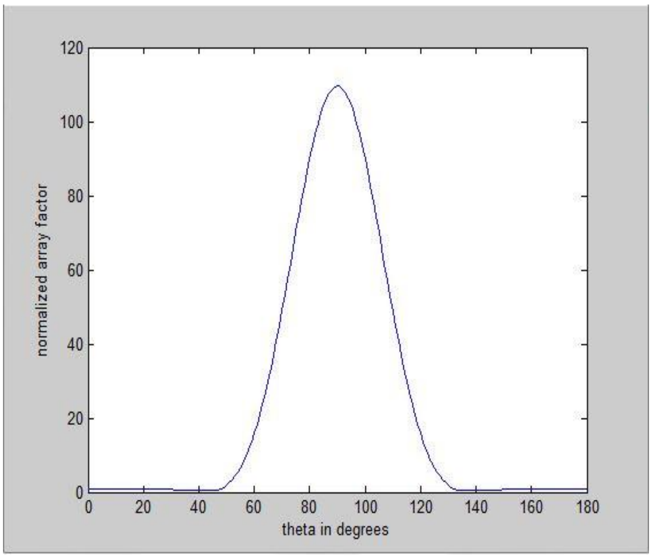

Fig 1: Optimized radiation pattern using GA for N=11

Table 1: Optimized Phase Weights using GA and PSO

a_n	Excitation coefficients	Optimized phases using GA(in radians)	Optimized phases using PSO(in radians)
a_1	1.0000	1.1345	0
a_2	1.2444	1.3788	2.8574
a_3	1.7863	1.3963	2.6786
a_4	2.2698	2.0769	2.0636
a_5	2.6044	1.2566	3.4332
a_6	2.7240	2.2864	0.9782
a_7	2.6044	1.0996	3.3051
a_8	2.2698	2.1817	1.9481
a_9	1.7863	0.9076	2.6387
a_{10}	1.2444	1.7104	2.1111
a_{11}	1.0000	0.0349	1.3752

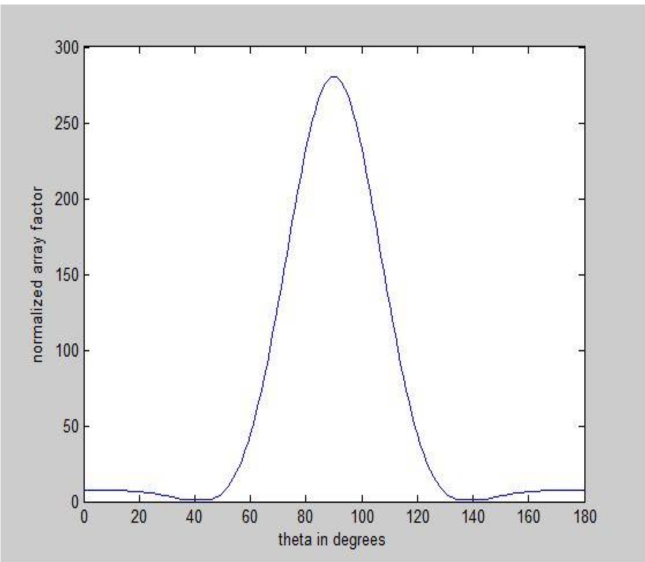

Fig 2: Optimized radiation pattern using PSO for N=11

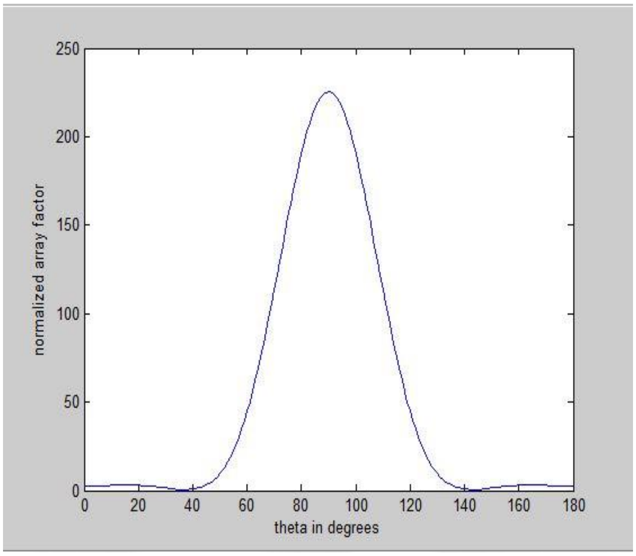

Fig 3: optimized radiation pattern using GA for N=9

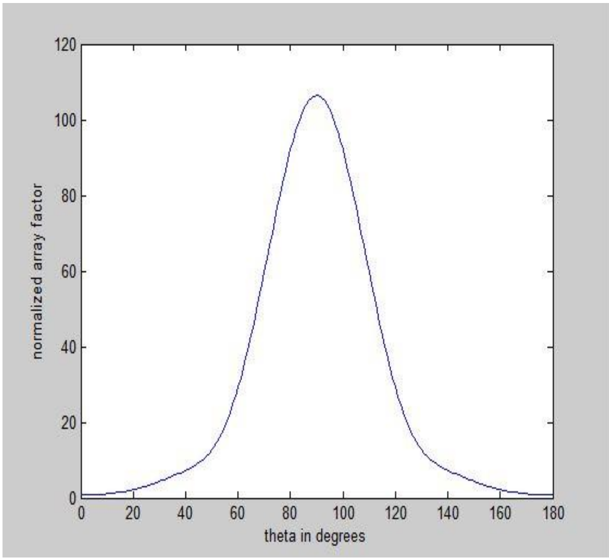

Fig 4: optimized radiation pattern using PSO for N=9

A comparison between the results obtained from GA and PSO is given in Tables 2, 3, 4.

Table 2

Number of elements in array	Dolph-Chebyshev array	
	SLL(dB)	HPBW(deg)
7	-26.0000	14.7112
8	-26.0000	12.8884
9	-26.0000	11.4704
11	-26.0000	9.4080

Table 3

Number of elements in array	Optimized values when GA is applied	
	SLL(dB)	HPBW(deg)
7	-40.6021	12.6511
8	-39.6801	11.0844
9	-37.3323	9.8856
11	-41.1465	8.0465

Table 4

Number of elements in array	Optimized values when PSO is applied	
	SLL(dB)	HPBW(deg)
7	-51.9767	12.5185
8	-49.5684	10.9686
9	-57.6230	9.7190
11	-46.9331	7.9936

VI. CONCLUSIONS AND FUTURE WORK

In this paper, the SLL and HPBW of a Dolph-Chebyshev array designed for a specified SLL are further optimized using genetic algorithm based optimization and particle swarm optimization methods.

The best values of SLL and HPBW obtained by applying PSO for 11 element array (reference- values: SLL=-26dB, HPBW=9.4080deg) are -46.9331 dB and 7.9936 deg respectively. Similarly, for the case of GA, the best values of SLL and HPBW are -41.1465 dB and 8.0465 deg respectively. PSO yields better results and is more efficient computationally. In this work relative phase of each element is randomly varied. This work can be extended by varying spacing between the elements along with the relative phase which might result in further reduction in HPBW.

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