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Circular And Concentric Circular Antenna Array Synthesis Using CAT Swam Optimization Technique

APARNA BANDLA[1], DR. M.V.S PRASAD[2]

[1]PG Scholar, Dept of ECE, R.V.R & J.C. College of Engineering, Guntur, AP, India.

[2]Professor, Dept of ECE, R.V.R & J.C. College of Engineering, Guntur, AP, India.

Abstract: In this paper the maximum sidelobe level (SLL) reductions without and with central element feeding in various designs of three-ring concentric circular antenna arrays (CCAA) are examined using Particle Swarm Optimization with (PSO) to finally determine the global optimal CCAA design. The present paper assumes non-uniform excitations and uniform spacing of excitation elements in each three-ring CCAA design. Among the various CCAA designs, the three-ring CCAA containing central element and 4, 6 and 8 elements in three successive concentric rings proves to be such global optimal design with global minimum SLL determined by PSO technique.

Keywords: Side Lobe Level(SLL), Concentric Circular Antenna Arrays (CCAA), Particle Swarm Optimization (PSO).

I. INTRODUCTION

An antenna array consists of multiple stationary antenna elements, which are often fed coherently. There is abundant open technical literatures [1-6], bearing a common target - bridging the gap between desired radiation pattern having nil SLL with what is practically achievable. The primary method in all these research works is improvement of array pattern by manipulating the structural geometry to suppress the SLL while preserving the gain of the main beam. Among the different types of antenna arrays, CCAA [1, 5] have become most popular in mobile and wireless communications. In this paper optimization of CCAA design having uniform interelement separations and non-uniform excitations is performed with the help of a novel evolutionary optimization technique. various CCAA design structures are examined to find the best possible design structure using two evolutionary techniques, BGA [4] and PSOCFA [7, 8]. Regarding the comparative effectiveness of the techniques, the newly proposed PSOCFA technique proves to be better in attaining minimum SLL, reduction of major lobe beamwidth and hence minimum “Misfitness” objective function values in the optimization of various CCAA designs. Function Optimization is one of the important fields in the computational intelligence theories. There are many algorithms to find the global and local solutions of the problems. Some of these optimization algorithms were developed based on swarm intelligence.

These algorithms imitate the creature’s swarm behavior and model into algorithm, such as Ant Colony Optimization (ACO) which imitates the behavior of ants [1]-[6], Particle Swarm Optimization (PSO) which imitates the behavior of birds [2], Bee Colony Optimization (BCO) which imitates the behavior of bees [3] and the recent finding, Cat Swarm Optimization (CSO) which imitates the behavior of cats [4] . By simulating the behavior of cats and modeling into two modes, CSO can solve the optimization problems. In the cases of functions optimization, CSO is one of the best algorithms to find the global solution. In comparison with other heuristic algorithms such as PSO and PSO with weighting factor [7], CSO usually achieves better result. But, because of algorithm complexity, solving the problems and finding the optimal solution may take a long process time and sometimes much iteration is needed. The primary method in all these research works is improvement of array pattern by manipulating the structural geometry to suppress the SLL while preserving the gain of the main beam.

II. DESIGN EQUATION

Geometrical configuration is a key factor in the design process of an antenna array. For CCAA, the elements are arranged in such a way that all antenna elements are placed in multiple concentric circular rings, which differ in radii and in number of elements.Fig1 shows the general configuration of CCAA with M concentric circular rings, where the mth (m = 1, 2,…, M) ring has a radius rm and the corresponding number of elements is Nm. If all the elements in all the rings are assumed to be isotopic sources, then the radiation pattern of this array can be written in terms of its array factor only. Referring to Fig.1, the array factor, for the CCAA in xy plane is expressed as:

$$AF(\phi, I) = \sum_{m=1}^{M}\sum_{i=1}^{N_m} I_{mi} \exp\left[j\left(Kr_m \sin\theta \cos(\phi - \phi_{mi}) + \alpha_{mi}\right)\right]$$

where mi I denotes current excitation of the i th element of the m th ring. K = 2π λ , λ being the signal wave-length. θ and φ symbolize the zenith angle from the positive z axis and the azimuth angle from the positive x axis to the orthogonal projection of the observation point respectively. It may be noted that if the elevation angle is assumed to be 90 degrees i.e. θ = 900 then (1) may be written as a periodic function of φ with a period of 2π radian. The angle φ mi is nothing but element to element angular separation measured from the positive x-axis. As the elements in each ring are assumed to be uniformly distributed.

- The number of copies of a cat produced in seeking mode is called seeking memory pool (SMP).
- The maximum difference between the new and old values in the dimension selected for mutation is called seeking range of selected dimension (SRD).
- The number of dimensions to be mutated is called counts of dimension to change (CDC).
- To guarantee that the cats spend most of their time resting and observing, i.e. most of the time is spent in seeking mode, a term called mixture ratio (MR), which is a fraction of population allocated a very small value.

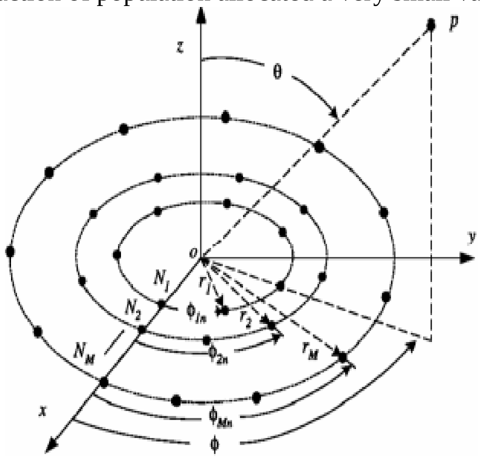

Figure1. Concentric circular antenna array (CCAA).

The steps executed in seeking mode are as follows:

- Select randomly MR fraction of population np as seeking cats; the rest are tracing cats.
- Create SMP copies of ith seeking cat.

Selected by the SRD value chosen, not affected by the velocities and positions. Without the large changes in velocities and positions of seeking mode cats, they are able to focus on an exhaustive search for the local area. Randomly picked dimensions to be mutated based on the CDC value provide a diverse movement of local cats for a better solution. The SMP also provides a proper number of copies of a cat with regard to convergence speed as well as MSE value.

III. CAT SWARM OPTIMIZATION

Cat Swarm Optimization is a new optimization algorithm in the field of swarm intelligence [4]. The CSO algorithm models the behavior of cats into two modes: 'Seeking mode' and 'Tracing mode'. Swarm is made of initial population composed of particles to search in the solution space. For example, we can simulate birds, ants and bees and create Particle swarm optimization, Ant colony optimization and Bee colony optimization respectively. Here, in CSO, we use cats as particles for solving the problems. In CSO, every cat has its own position composed of D dimensions, velocities for each dimension, a fitness value, which represents the accommodation of the cat to the fitness function, and a flag to identify whether the cat is in seeking mode or tracing mode. The final solution would be the best position of one of the cats. The CSO keeps the best solution until it reaches the end of the iterations.

IV. PARTICLE SWARM OPTIMIZATION (PSO)

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. The detailed information will be given in following sections. Compared to GA, the dvantages of PSO are that PSO is easy to implement and there are few parameters to adjust. PSO has been successfully applied in many areas: function optimization, artificial neural network training, fuzzy system control, and other areas where GA can be applied. PSO is a flexible, robust population-based stochastic search/ optimization technique with implicit parallelism, which can easily handle with non-differential objective functions, unlike traditional optimization methods. PSO is less susceptible to getting trapped on local optima unlike GA, Simulated Annealing etc. Eberhart and Shi [7] developed PSO concept similar to the behavior of a swarm of birds. PSO is developed through simulation of bird flocking in multidimensional space. Bird flocking optimizes a certain objective function. Each agent knows its best value so far (pbest).

This information corresponds to personal experiences of each agent. Moreover, each agent knows the best value so far in the group (gbest) among pbests. Namely, each agent tries to modify its position using the following information:

- The distance between the current position and pbest.
- The distance between the current position and gbest. Mathematically, velocities of the particles are modified according to the following equation:

$$V_i^{k+1} = w * V_i^k + C_1 * rand_1 * \left(pbest_i^k - S_i^k\right) + C_2 * rand_2 * \left(gbest^k - S_i^k\right)$$

where k Vi is the velocity of agent i at iteration k ; w is the weighting function; Cj is the weighting factor; rand is the random number between 0 and 1; k i S is the current position of agent i at iteration k; k i pbest is the pbest of agent i; k gbest is the gbest of the group. The searching point in the solution space can be modified by the following equation: +1 +1 = + k i k i k Si S V (6) The first term of (5) is the previous velocity of the agent. The second and third terms are used to change the velocity of the agent. Without the second and third terms, the agent will keep on ''flying'' in the same direction until it hits the boundary. Namely, it corresponds to a kind of inertia and tries to explore new areas. The values of w, C1 and C2 are given in the next section.

V. RESULT

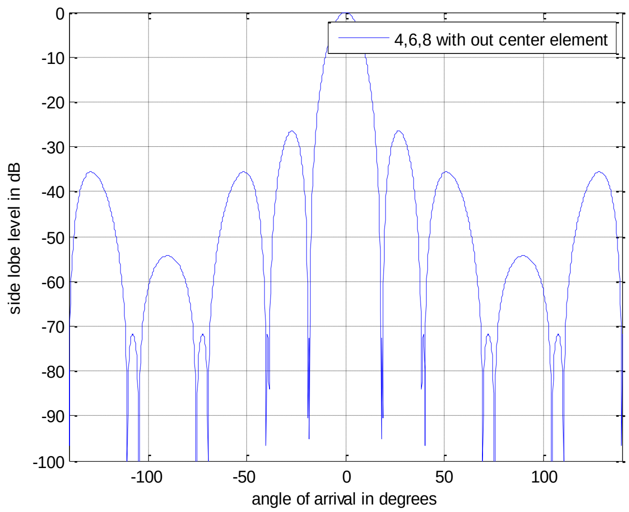

Figure2. Radiation pattern of CCAA for 4, 6, and 8 without center element.

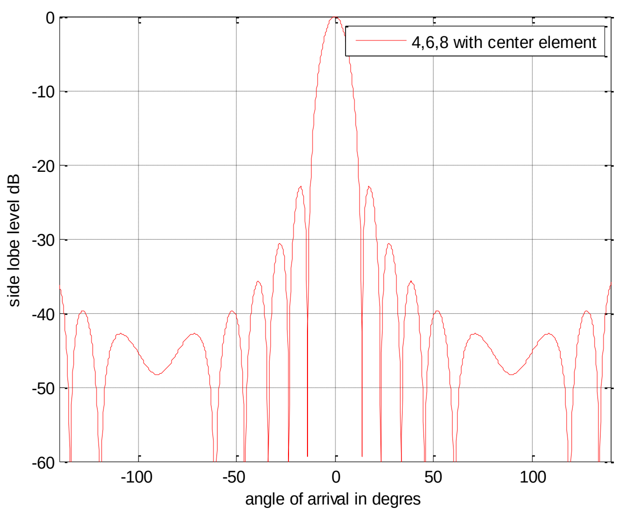

Figure3. radiation pattern of CCAA for 4,6, 8 with center element.

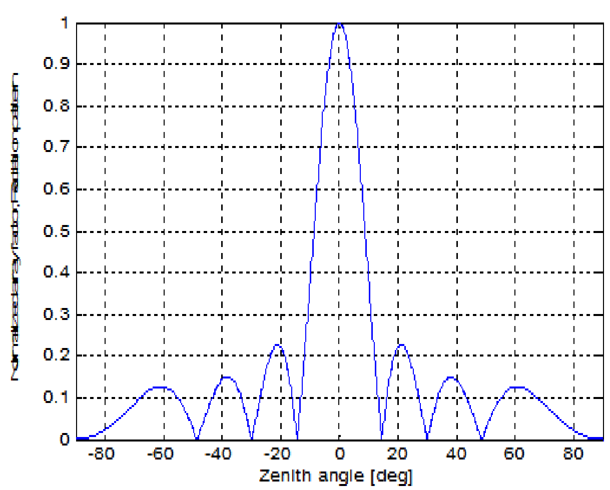

Figure4. Radiation pattern of CAA for N=8.

VI. CONCLUSION

This section gives the experimental results for various CCAA designs obtained by BGA and PSOCFA techniques. For each optimization technique two-ring CCAA structures for two cases as a) without central element feeding and b) with central element feeding in three-ring concentric circular antenna arrays (CCAA) are assumed. Each CCAA maintains a fixed spacing between the elements in each ring (inter-element spacing being different lambda values for first ring, second ring and third ring respectively). These spacings are the means of the values determined for the ten structures for non-uniform spacing and non-uniform excitations in each ring using 25 trial generalized optimization runs for each structure. This generalized optimization is beyond the scope of this paper. For all sets of experiments, the number of elements of the inner most circle is N1 , for outermost circle is N3 , whereas the middle circle consist of N2 number of elements.

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