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COMMUNICATIONS

DESIGN OF NON–UNIFORM CIRCULAR ANTENNA ARRAYS USING PARTICLE SWARM OPTIMIZATION

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In this paper, the design of non-uniform circular antenna arrays with optimum side lobe level reduction is presented. The particle swarm optimization (PSO) method, which represents a new approach for optimization problems in electromagnetics, is used in the optimization process. The method of particle swarm optimization is used to determine an optimum set of weights and antenna element separations that provide a radiation pattern with maximum side lobe level reduction with the constraint of a fixed major lobe beamwidth. The results show that the design of non-uniform circular antenna arrays using PSO method provides a side lobe level reduction better than that obtained using genetic algorithms.

K e y w o r d s: antenna arrays, circular arrays, optimization methods, particle swarm optimization

1 INTRODUCTION

In many applications it is necessary to design antennas with very directive characteristics to meet the demands of long distance communication. This can be achieved by forming an assembly of radiating elements in electrical and geometrical configuration, which is referred to as an array. Antenna arrays have been widely used in different applications including radar, sonar, and communications [1]. They are useful in high power transmission, reduced power consumption and enhanced spectral efficiency. To provide a very directive pattern, it is necessary that the fields from the array elements must add constructively in some desired directions and add destructively and cancel each other in the remaining space. This is important to reduce interference from the side lobes of the antenna.

Among the different types of antenna arrays, recently, circular arrays have become more popular in mobile and wireless communications [2-5]. In this paper, we propose the use of the particle swarm optimization (PSO) technique [6, 7] to determine an optimum set of weights and antenna element separations for circular arrays that provide a radiation pattern with maximum side lobe level reduction. First, in section 2, the general design equations for the non-uniform circular array are stated. Then, in section 3, a brief introduction for the PSO algorithm is presented. In section 4, the fitness (or cost) function is given, and finally, numerical results are presented in section 5.

2 GEOMETRY AND ARRAY FACTOR

Consider a circular antenna array of N antenna elements non-uniformly spaced on a circle of radius a in the $x-y$ plane (Fig. 1). The elements in the circular antenna array are taken to be isotropic sources; so the radiation pattern of this array can be described by its array factor. In the $x-y$ plane, the array factor for the circular array shown in Fig. 1 is given by [1]

$$AF(\phi) = \sum_{n=1}^{N} I_n \, e^{j(ka\cos(\phi-\phi_n)+\alpha_n)} \tag{1}$$

$$ka = 2\pi a/\lambda = \sum_{i=1}^{N} d_i, \quad \phi_n = (2\pi/ka)\sum_{i=1}^{n} d_i \tag{2,3}$$

In the above equations, I_n and α_n represent the excitation amplitude and phase of the n-th element, and d_n represents the arc separation (in terms of wavelength) between element n and element $n-1$ (d_1 being the arc distance between the first ($n=1$) and the last ($n=N$) elements), and ϕ_n is the angular position of the n-th element in $x-y$ plane. To direct the peak of the main beam in the ϕ_0 direction, the excitation phase of the n-th element is chosen to be [1]:

$$\alpha_n = -ka\cos(\phi_0-\phi_n) \tag{4}$$

In this case, the array factor can be rewritten as

$$AF(\phi) = \sum_{n=1}^{N} I_n \, exp\{jka[\cos(\phi-\phi_n) - \cos(\phi_0-\phi_n)]\} \tag{5}$$

In our design problem we choose ϕ_0 to be 0, *ie*, the peak of the main beam is in the x direction.

3 THE PARTICLE SWARM OPTIMIZATION

Recently, the PSO technique has been successfully applied to the design of antennas and microwave components [6-9]. The results proved that this method is powerful and effective for optimization problems. PSO is similar in some ways to Genetic Algorithms (GA) and other

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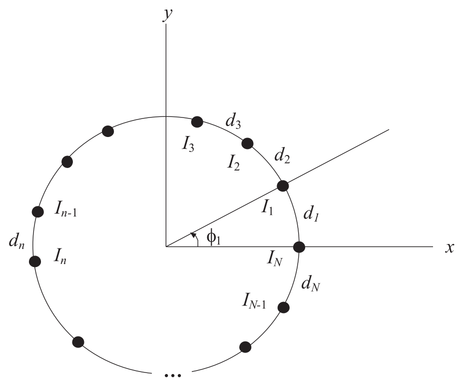

Fig. 1. Geometry of a non-uniform circular antenna array with N isotropic radiators

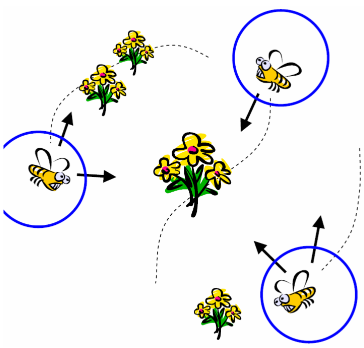

Fig. 2. Particle Swarm Optimization as modeled by a swarm of bees searching for flowers [7]

evolutionary algorithms, but requires less computational bookkeeping and generally fewer lines of code, including the fact that the basic algorithm is very easy to understand and implement.

Consider an optimization problem that requires the optimization of a specific fitness function which depends on M variables. A collection or swarm of particles is defined, where each particle is assigned a random position in the M-dimensional problem space so that each particle position corresponds to a candidate solution to the optimization problem. Each of these particle positions is scored to obtain a scalar cost based on how well it solves the problem. These particles then fly through the M-dimensional problem space subject to both deterministic and stochastic update rules to new positions, which are subsequently scored.

As the particles traverse the problem hyperspace, each particle remembers its own personal best position that it has ever found, called its local best and each particle also knows the best position found by any particle in the swarm, called the global best. On successive iterations, particles are "tugged" toward these prior best solutions. Overshoot and undershoot combined with stochastic adjustment explore regions throughout the problem hyperspace, eventually settling down near a good solution

This process can be visualized as a swarm of bees in a field [7]. Their goal is to find the location with the highest density of flowers. Without any knowledge of the field a priori, the bees begin in random locations with random velocities looking for flowers. Each bee can remember the locations where it found the most flowers, and somehow knows the locations where the other bees found an abundance of flowers. Torn between returning to the location where it had personally found the most flowers, or exploring the location reported by others to have the most flowers, the ambivalent bee accelerates in both directions altering its trajectory to fly somewhere between the two points. Along the way, a bee might find a place with a higher concentration of flowers than it had found previously. It would then be drawn to this new location as well as the location of the most flowers found by the whole swarm. Occasionally, one bee may fly over a place with more flowers than had been encountered by any bee in the swarm. The whole swarm would then be drawn toward that location in additional to their own personal discovery. In this way, the bees explore the field. Constantly, they are checking the territory they fly over against previously encountered locations of highest concentration hoping to find the absolute highest concentration of flowers. Eventually, the bees' flight leads them to the one place in the field with the highest concentration of flowers. Soon, all the bees swarm around this point. Unable to find any points of higher flower concentration, they are continually drawn back to the highest flower concentration (Fig 2).

The following steps are accomplished on each particle individually (see Fig. 3):

1 Initialize a population of particles with random positions and velocities in M dimensions in the problem space.

2 For each particle, evaluate the desired optimization fitness function in M variables.

3 Update the particle velocity. The velocity of the particle is changed according to the relative locations of p_{best} and q_{best}. It is accelerated in the directions of these locations of greatest fitness according to the following equation [7]:

$$\begin{aligned} v_n = w * v_n + c_1 \operatorname{rand}() * (g_{\text{best},n} - x_n) \\ +c_2 \operatorname{rand}() * (p_{\text{best},n} - x_n) \end{aligned} \tag{6}$$

where v_n is the velocity of the particle in the n-th dimension and x_n is the particle coordinate in the n-th dimension, c_1 and c_2 are scaling factors that determine the relative "pull" of p_{best} and q_{best} (previous work has shown that a value of 2.0 is a good choice for both parameters [7]), and rand() is a random number uniformly distributed in interval (0,1). The parameter w is a number, called the "inertial weight", in the range [0,1], which specifies the weight by which the particle current velocity depends on its previous velocity and how far the particle is from its personal best and global best positions. Numerical experiments have shown that the PSO algorithm converges faster

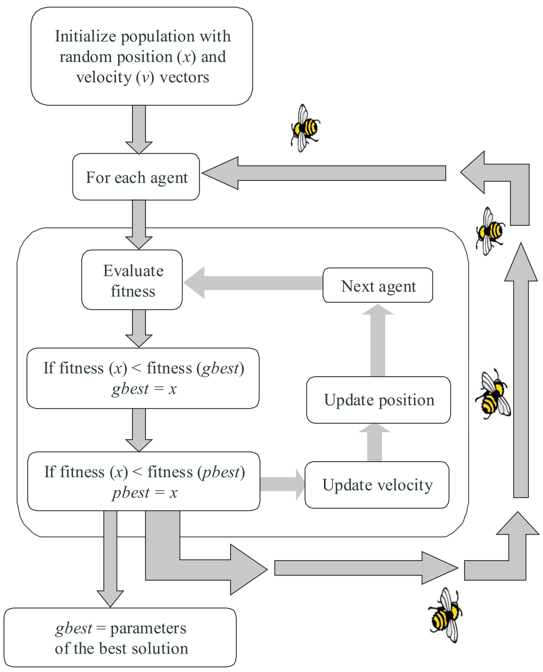

Fig. 3. Flowchart of the PSO algorithm

if w is linearly damped with iterations starting at 0.9 and decreasing linearly to 0.4 at the last iteration.

4 Move the particle. Once the velocity has been determined, it is simple to move the particle to its next location. The new coordinate is computed for each of the dimensions according the following equation $x_n \leftarrow x_n + v_n$

5 Loop to step (2) until a criterion is met, usually a sufficiently good fitness or a maximum number of iterations.

4 FITNESS FUNCTION

In antenna array problems, there are many parameters that can be used to evaluate the fitness (or cost) function such as gain, side lobe level, radiation pattern, and size. Here, we are interested in designing a circular antenna array with minimum side lobes levels for a specific first null beamwidth (FNBW). Thus, the following fitness function is used

$$Fitness = F_1 + F_2 + F_3 \tag{7}$$

$$F_1 = |AF(\phi_{nu1}| + |AF(\phi_{nu2}| \tag{8}$$

$$F_2 = \frac{1}{\pi + \phi_{nu1}} \int_{-\pi}^{\phi_{nu1}} |AF\phi| \mathrm{d}\phi + \frac{1}{\pi - \phi_{nu2}} \int_{\phi_{nu2}}^{\pi} |AF\phi| \mathrm{d}\phi \tag{9}$$

$$F_3 = |AF(\phi_{ms1}| + |AF(\phi_{ms2}| \tag{10}$$

where ϕ_{nu} — is the angle at a null. Here, we minimize the array factor at the two angles ϕ_{nu1} and ϕ_{nu2} defining the major lobe, *ie*, the first null beamwidth $FNBW = \phi_{nu2} - \phi_{nu1}$.

ϕ_{ms1} — is the angle where the maximum side lobe level is attained during swarming in the lower band (from $-\pi$ to ϕ_{nu1}). Minimizing the maximum side lobe level provides simultaneous reduction of the levels of all side lobes in this region.

ϕ_{ms2} — is the angle where the maximum side lobe level is attained during swarming in the upper band (from ϕ_{nu2} to π). Minimizing this maximum side lobe level provides simultaneous reduction of the levels of all side lobes in this region.

It should be noted that besides minimizing the maximum side lobe level through minimizing F_3, we are also minimizing the average side lobes level through minimizing F_2. Thus, the optimization problem is to search for the current amplitudes (I'_ns) and the arc distances between the elements (d'_ns) that minimize the above fitness function.

5 RESULTS

Several cases are considered with different number of antenna elements ($N = 8, 10, 12$). The swarm size used is 20-30; the number of iterations needed to reach an acceptable solution is 20000-30000. The experiments are performed for a specific FNBW, which corresponds to a uniform circular array with a uniform $\lambda/2$ element-spacing and the same number of elements [4]. Table 1 shows the results obtained using PSO. The weightings for the array elements are normalized to $max(I) = 1$, and it shows that many of the excitation elements are close to 1 which is practically desirable. The same cases were considered in [4] using genetic algorithm for optimization. The array factor obtained using the results of the PSO will be compared to the array factor obtained using genetic algorithm (GA) results given in [4].

Figure 4 shows the array factor obtained using the results in Table 1 for $N = 8$ as compared to that obtained using GA results in [4].

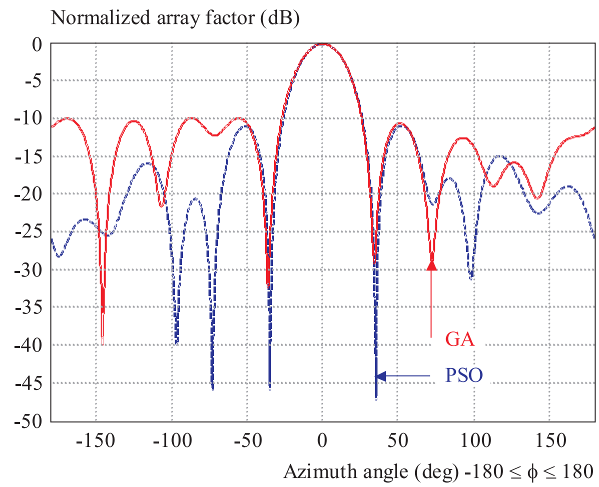

Fig. 4. Radiation pattern for $N = 8$ using the PSO results as compared to the GA results from [4]

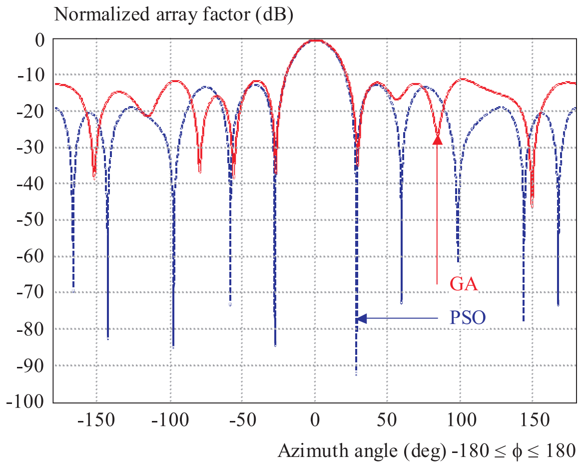

Fig. 5. Radiation pattern for $N = 10$ using the PSO results as compared to the GA results from [4]

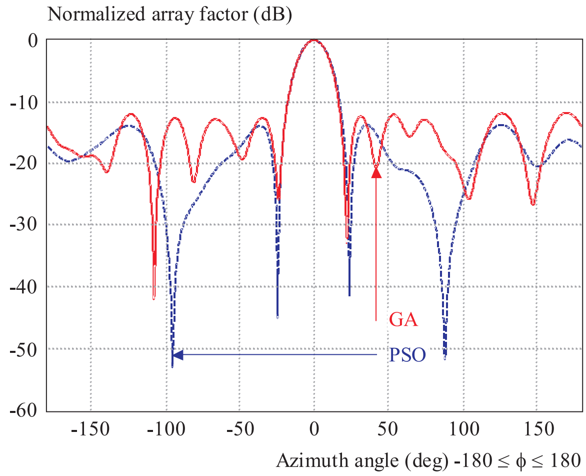

Fig. 6. Radiation pattern for $N = 12$ using the PSO results as compared to the GA results from [4]

Table 1. Examples of non-uniform circular antenna array optimized using PSO technique

N	FNBW (deg)	$[dm_1, dm_2, dm_3, \dots, dm_N]$ in λ's $[I_1, I_2, I_3, \dots, I_N]$
8	70.27	$[0.3590, 0.5756, 0.2494, 0.7638, 0.6025, 0.8311, 0.7809, 0.3308] \to \sum = 4.4931$ $[0.7765, 0.3928, 0.6069, 0.8446, 1.0000, 0.7015, 0.9321, 0.3583]$
10	55.85	$[0.3170, 0.9654, 0.3859, 0.9654, 0.3185, 0.3164, 0.9657, 0.3862, 0.9650, 0.3174] \to \sum = 5.9029$ $[1.0000, 0.7529, 0.7519, 1.0000, 0.5062, 1.0000, 0.7501, 0.7524, 1.0000, 0.5067]$
12	46.26	$[0.2569, 0.8509, 0.6607, 0.7057, 0.8540, 0.3734, 0.1609, 0.8321, 0.6464, 0.7079, 0.8330, 0.2682] \to \sum = 7.1501$ $[0.9554, 0.6641, 0.7109, 0.7769, 1.0000, 1.0000, 0.3958, 0.7162, 0.6746, 0.7695, 0.9398, 0.6415]$

It can be seen that using the above fitness function along with the PSO method gives a radiation pattern which is generally better than that obtained from the GA results. Specifically, all side lobes (except the first one adjacent to the major lobe) have levels less than -15 dB.

Similarly, Figure 5 shows the array factor obtained using the results in Table 1 for $N = 10$ as compared to that obtained using GA results in [4]. Again, the PSO results are, in general, better than the GA results. Moreover, the PSO array factor shows better symmetry around $\phi = 0$. It is worth mentioning that a uniform circular array with the same number of elements and $\lambda/2$ element-to-element spacing has a maximum side lobe level of -3.6 dB [4].

Lastly, figure 6 shows the array factor obtained using the results in Table 1 for $N = 12$ as compared to that obtained using GA results in [4].

The three cases presented in this paper show a nearly symmetric pattern in comparison to the results presented in [4]. Such symmetry is usually desirable in many applications. It should be noted that for the $N = 8$ case, the size of the circular array obtained using the PSO (circumference $= 4.4931\ \lambda$) is slightly larger than that obtained using the GA (circumference $= 4.409\ \lambda$) [4]. On the other hand, $N = 10$ case (circumference $= 5.9029\ \lambda$) and $N = 12$ case (circumference $= 7.1501\ \lambda$) show better side lobe suppression with somewhat smaller size than those presented in [4] ($6.0886\ \lambda$ and $7.77\ \lambda$, respectively).

6 CONCLUSIONS

In this paper, the PSO method was used to adjust the position and the excitation of each element in the circular array to obtain better side lobe suppression. We have presented a pattern synthesis method of non-uniform circular antenna arrays for simultaneous reduction of the side lobe level, required smaller circumference and nearly symmetrical pattern. Array patterns obtained from PSO results are generally better than those presented in [4] which were obtained using GA. At the present time, we are investigating the application of the PSO method to optimize the side lobe level of concentric circular arrays [10].

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