Synthesis of CCAA using Grey Wolf Optimizer

G.S.K.Gayatri Devi[1], S.Krishnaveni[2],
[1]Dept. of ECE, MallaReddy Engineering College (A), Hyderabad
[2]Dept. of ECE, Gayatri Vidya Parishad College for Degree and PG Courses, School of Engineering, Visakhapatnam

Abstract—This paper presents thinned concentric circular arrays optimized for generating low sidelobe difference patterns. Wireless communication systems now a day require patterns with more directive characteristics with a precise control over sidelobe levels. Concentric Circular Antenna Arrays (CCAA) are drawing the attention of antenna designers as they offer several advantages over linear arrays. In this paper, CCAA are considered and radii of rings are varied and thinning is carried out simultaneously. Grey Wolf Optimization algorithm is used for array optimization. Results are presented for concentric circular arrays of variable number.

Keywords: CCAA, Difference patterns, Grey Wolf Optimization Algorithm,Thinning

I. INTRODUCTION

CCAA are planar arrays which contain various circular arrays of different radii sharing common centre. They provide more degrees of freedom to the antenna designer than linear arrays. The pattern from a circular array can be rotated 360°in azimuth. The symmetry of the array offers beam steering in azimuthal plane without much pattern distortion. This array symmetry also offers another advantage over linear and rectangular arrays that mutual coupling effects need not present a significant problem. These led the antenna designers to opt for concentric circular arrays over the last four decades.

Difference patterns are mainly aimed at detecting radar targets. Sum patterns can also be employed for target detection but the accuracy with which the target is identified depends on where the target exactly falls within the main beam. This calls for generation of highly directive beams. Instead we can employ difference patterns. When the target falls on the deep null between the two principal lobes, its angular position can be precisely revealed. These patterns can be efficiently generated from CCAA.

Thinning is a technique which results in patterns with low sidelobe levels. In this technique, some antenna elements are turned off which reduces power consumption. Since the weight of an array decreases, these are of more interest in large antenna array systems. In addition to the above, thinning also reduces cost and weight. Various thinning techniques are available like thinning based on an analytical formula [1], statistically thinned arrays [2], space or density tapering [3] etc. But the widely used and most well-liked technique is optimization.

Patterns with low side lobes are generated by finding optimized design parameters. A variety of optimization techniques are employed for antenna synthesis problems. Conventional methods do provide solutions but the accuracy depends on the initial solution assumed, that is, they provide local solutions. Chances of locating global solution can be improved only if maximum portion of the solution space is explored. In addition, the conventional methods have time consuming complex numerical equations which complicate the process. In order to overcome these difficulties, a variety of metaheuristic optimization algorithms are being used in recent past.These methods are robust, adaptable and capable of handling multi-optimization problems. Many such methods like Genetic Algorithm, Particle Swarm Optimization, Differential Evolution, Ant-Colony Optimization, Cuckoo Search Algorithm, Bee Algorithm, Bio-Geography Based optimization algorithms have been successfully employed in various antenna synthesis problems.

Many works have been reported earlier on thinning and sidelobe reduction, but they mainly dealt with generation of optimized sum patterns only. To the knowledge of the author, very few works have been reported on generation of low side lobe difference patterns from circular arrays using optimization algorithms. Gayatri Devi et al. [5] generated low side lobe difference patterns from thinned CCAA using amplitude only synthesis method. In this paper, an attempt has been made to find optimized CCAA generating difference patterns with low sidelobes by varying radii. Section II deals with brief description of Grey Wolf Optimization technique. Problem formulation and the fitness equations are presented in Section III. Results are demonstrated and discussed in section IV. Finally section V gives the conclusion.

II. GREYWOLF OPTIMIZATION ALGORITHM

It is a novel meta-heuristic algorithm proposed by Mirzalili et al. [6] inspired by grey wolves. It was suggested on the basis of mimicking the social behavior of wolves in finding their prey. It has maximum potential in finding the optimal solution for many constrained and non-constrained problems. The hierarchy of wolves is as shown in fig.1.

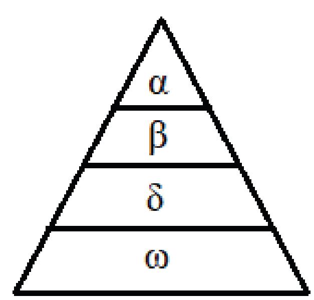

Fig. 1. Grey Wolf Hierarchy

978-1-7281-1423-1/19/$31.00 ©2019 IEEE
DOI 10.1109/ICISGT44072.2019.00035

The leader is male or female called alphas (α). They are the decision makers. They represent first level in the hierarchy. The second level comprises of beta (β) and delta(δ) wolves. These are subordinate wolves which assist alpha wolves in decision making. The lowest ranking wolves are omegas (ω) which are followers. When applied to optimization problem, α represent fittest solution, β and δ wolves represent second and third best solutions. ω wolves represent the candidate solutions.

The main phases of hunting are as follows:

- Tracking, chasing and approaching the prey
- Pursuing, encircling and harassing the prey until it stops moving
- Attacking the prey

The mathematical model for encircling behavior is as given below [6] in eq.(1):

$$\overrightarrow{D} = \left|\vec{C}.\overrightarrow{X_p(t)} - \overrightarrow{X(t)}\right| \quad (1)$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}.\vec{D}$$

'*t*' indicates current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\overrightarrow{X_p}$ is position vector of prey and $\vec{X}$ is the position vector of grey wolf. Vectors $\vec{A}$ and $\vec{C}$ are calculated using

$$\vec{A} = 2\vec{a}.\overrightarrow{r_1} - \vec{a} \quad (2)$$

$$\vec{C} = 2.\overrightarrow{r_2}$$

where $\vec{a}$ values are linearly decreased from 2 to 0 over the course of iterations. $\overrightarrow{r_1}$and$\overrightarrow{r_2}$ are random vectors in the range [0,1].

The hunting process (optimization) is usually carried by α wolves but sometimes assisted by β and δ wolves. While exploring the search space for optimum solution (prey), we must assume that α,β, and δ has the best location of the optimum. Therefore the first three best solutions are saved and the remaining search agents update their position according to the position of best search agent.

The following equations are used in this regard:

$$\left.\begin{aligned}
\overrightarrow{D_\alpha} &= \left|\overrightarrow{C_1}.\overrightarrow{X_\alpha} - \vec{X}\right| \\
\overrightarrow{D_\beta} &= \left|\overrightarrow{C_2}.\overrightarrow{X_\beta} - \vec{X}\right| \\
\overrightarrow{D_\delta} &= \left|\overrightarrow{C_3}.\overrightarrow{X_\delta} - \vec{X}\right| \\
\overrightarrow{X_1} &= \overrightarrow{X_\alpha} - \overrightarrow{A_1}.\overrightarrow{D_\alpha} \\
\overrightarrow{X_2} &= \overrightarrow{X_\beta} - \overrightarrow{A_2}.\overrightarrow{D_\beta} \\
\overrightarrow{X_3} &= \overrightarrow{X_\delta} - \overrightarrow{A_3}.\overrightarrow{D_\delta} \\
\vec{X}(t+1) &= \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3}
\end{aligned}\right\} \quad (3)$$

The algorithm steps are summarized as follows:

Step 1: Initially generate a random pool of grey wolves which represent potential solutions to the problem.

Step 2: Set the initial values of other parameters like a, A, C, number of iterations, number of parameters.

Step 3: Calculate the fitness of each search agent (possible solution) and assign the first three best solutions to α, β and δ. The position vector of each possible solution is updated using eq. (3).

Step 4: Update a, A, C using eq. (2).

Step 5: Calculate the fitness of all hunt agents (possible solutions).

Step 6: Update X_α,X_β,$\overrightarrow{X_\delta}$

Step 7: Repeat the steps 3 to 6 if terminating criteria is not satisfied.

Local minima problem can be easily overcome as the wolves change their position based on $\left|\vec{A}\right|$ value. They tend to move away from the solution if $\left|\vec{A}\right|$>1and move towards the solution $\left|\vec{A}\right|$<1.

III. PROBLEM FORMULATION

A CCAA with 'm' rings is shown in fig.2. All ring elements are assumed to be isotropic. Let the number of elements present in m^{th} ring be N_m and let r_m represent the radius of m^{th} ringwhere $m = 1,2,$ ...M. Let the inter element spacing be d_m.

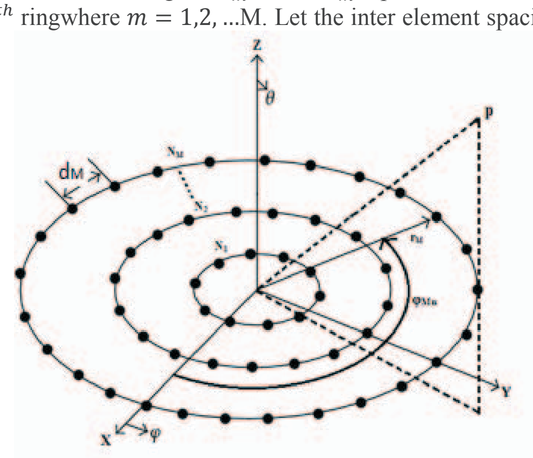

Fig. 2. Geometry of Concentric circular array

The generalized array factor for the array [7] is given by

$$E(\theta,\varphi) = \sum_{m=1}^{M}\sum_{n=1}^{N_m} I_{mn}\,\mathrm{A_{mn}}\exp(jkr_m\sin\theta\cos(\varphi - \varphi_{mn})) \quad (4)$$

Here

M = number of rings

N_m = number of elements in ring m

A_{mn} = Amplitude excitation of n^{th} element of m^{th} ring

I_{mn} = excitation of n^{th} element of m^{th} ring= $\begin{cases}1 & ON\\ 0 & OFF\end{cases}$

r_m = radius of ring m

φ_{mn} = angular position of n^{th} element of m^{th} ring

$$= \frac{2\pi(m-1)}{N_m} \quad (5)$$

$$K = \frac{2\pi}{\lambda}$$

θ = elevation angle

φ = Azimuthal angle

In 'u' domain

$$E(u)_{|\varphi=constant} = \sum_{m=1}^{M}\sum_{n=1}^{N_m} I_{mn}\, A_{mn} \exp(jkr_m u \cos(\varphi - \varphi_{mn}))$$

where u=sin(θ)

The radius of m^{th} ring is given by

$$r_m = m\frac{\lambda}{2} \quad (6)$$

In this paper ring radii are not calculated using the above equation but optimized for reducing peak side lobe levels (PSLL).

The inter element spacing is assumed to be approximately $\frac{\lambda}{2}$ i.e. $d_m = \frac{\lambda}{2}$.

The number of equally spaced elements present in ring 'm' is given by

$$N_m = 8*m \quad (7)$$

All the elements have uniform excitation phase of zero degrees. For attaining the difference patterns, half the array must be excited in out of phase. Hence the resultant expression for the array factor is given by

$$AF(u) = |E_1(u) - E_2(u)| \quad (8)$$

where

$$E_1(u) = \sum_{m=1}^{M}\sum_{n=1}^{N_m/2} I_{mn}\, \mathrm{A_{mn}} \exp(jkr_m u \cos(\varphi - \varphi_{mn}))$$

$$E_2(u) = \sum_{m=1}^{M}\sum_{n=\left(\frac{N_m}{2}+1\right)}^{N_m} I_{mn}\, \mathrm{A_{mn}} \exp(jkr_m u \cos(\varphi - \varphi_{mn}))$$

In the above equations, φ is assumed to be constant.

METHOD OF SIDELOBE REDUCTION:

Thinning of the array reduces the sidelobe levels. In this paper, in addition to array thinning, radii of concentric rings is varied to minimize sidelobe levels. The GWO algorithm is used to find the optimum ring radii as well as thinning coefficients.

The cost function which is to be minimized for finding the optimum solution is as follows:

$$Fit = w1 * (PSLL_o - SLL_d) + w2 * (FF_o - FF_d) \quad (9)$$

where

$PSLL_o = Max\left[20\log\left|\frac{AF(u)}{AF_{Max}(u)}\right|\right]$ = Obtained Peak Sidelobe level

u∈ side lobe region.

SLL_d =Desired Sidelobe level

$AF_{max}(u)$= Main beam peak value

FF_o is the obtained Fill factor, FF_d is the desired Fill factor. Fill factor is defined as the number of turned on elements divided by total number of elements present. w1 and w2 are weighing factors for controlling the amount of significance given to each term in eq.(9).

IV. RESULTS

This section presents computational results for 8 ring CCAA. GWO algorithm is used to optimize the concentric circular arrays. The algorithm is implemented using Matlab Simulation software. An initial population of 30 is taken. The number of iterations is set to 500. Table 1 shows the optimum values of radii and the number of elements present in each ring for a 8 ring CCAA. Fig.3 depicts the radiation pattern. Half of the elements are excited out of phase to get difference pattern. This is illustrated in Fig.4.The '+' sign indicates zero phase whereas a 'o' sign indicates out of phase. A peak SLL of -17.67dB is obtained. Fig.5 gives the distribution of ON elements in the array. Out of 288 elements, 164 elements are turned OFF i.e. the ON percentage is 43.06%. Less than half of total number of elements are turned ON.

Table 1

M	Radius(λ)	Number of elements in each ring
1	0.567	8
2	1.139	16
3	1.652	24
4	2.167	32
5	2.685	40
6	3.192	48
7	3.717	56
8	4.271	64

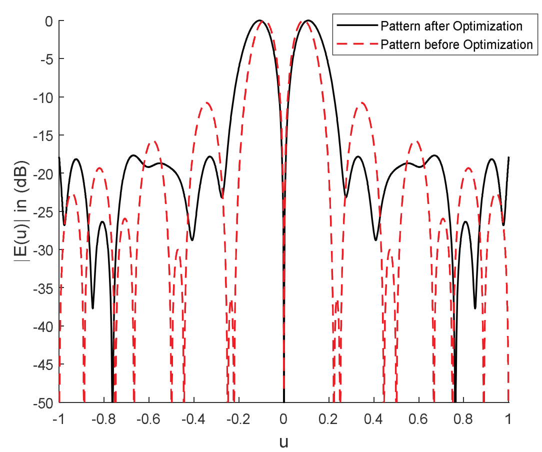

Fig.3 Plot comparing patterns before and after Optimization

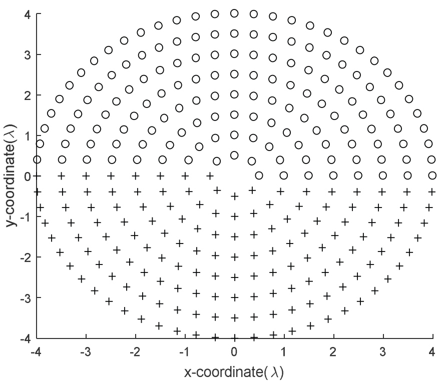

Fig.4. Half of the array excited out of phase

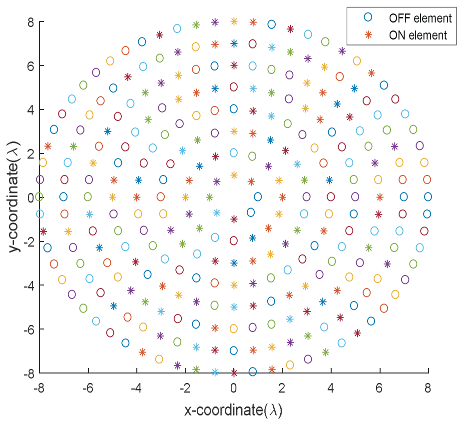

Fig.5 Aperture layout of ON elements

V. CONCLUSION

A novel Grey wolf algorithm is used to optimize thinned Concentric Circular Antenna Arrays. Optimized difference patterns are generated for 8 ring CCAA by taking ring radii and thinning coefficients as the variables. A uniform aperture distribution is assumed for ON elements. Simulation results are presented for 8 ring CCAA. The results show that the obtained patterns have deep null and peak SLL is also minimized. These patterns are very useful in radar applications. The work can be extended for thinning practical arrays.

REFERENCES

[1] S. J. Blank, and M. F. Hutt, "On the empirical optimization of antenna arrays," IEEE Antennas and Propagation Magazine, vol. 47, no. 2, pp. 58-67, April 2005.

[2] R. J. Mailloux, and E. Cohen, "Statistically thinned arrays with quantized element weights", IEEE Trans. Antennas and Propagation, vol. 39, no. 4, pp. 436-447, April 1991.

[3] W.P.M. N Keizer, "Synthesis of thinned planar circular and square arrays using density tapering", IEEE Trans. on Antenna and Propagation, vol. 62, no. 4, pp. 1555-1563, April 2014.

[4] W.P.M.N.Keizer, "Amplitude-Only Low Sidelobe Synthesis for Large Thinned Circular Array Antennas," *IEEE Transactions on Antennas and Propagation*, vol. 60, no. 2, pp. 1157–1161, February 2012.

[5] G. S. K. Gayatri Devi, G. S. N. Raju, P. V. Sridevi, "Design of Concentric Circular Antenna Arrays for Sidelobe Reduction using Differential Evolution Algorithm", AMSE JOURNALS–2016-Series: Modelling A, vol. 89; No. 1, pp. 45-57, March 2016.

[6] S.Mirjalili, S.M.Mirjalili, A. Lewis, "Grey Wolf Optimizer" , Advances in Engineering Software, vol. 69, pp. 46-61, March 2014.

[7] R. L. Haupt, "Optimized element spacing for low sidelobe concentric ring arrays," *IEEE Trans. Antennas Propag.*, vol. 56, No.1, pp. 266–268, Jan. 2008.