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Reduction of Dynamic Range Ratio through Competition Over Resources to synthesize planar array antennas

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ABSTRACT

To synthesize planar arrays, a new optimization algorithm namely Competition Over Resources (COR) is presented. This method imposes deeper nulls with the constraint of Side Lobe Level (SLL). COR is a new meta-heuristic algorithm based on competitive behavior of animal groups over food resources. The algorithm restricts Dynamic Range Ratio (DRR) in order to achieve a better control of the mutual coupling and feed network. Simulation results for optimal patterns, possessing multiple and broad nulls, are presented. The approach is implemented based on the position-only and the space/amplitude optimization. Furthermore, in order to find the better performance in imposing deeper nulls and reducing SLL, a comparative evaluation between Particle Swarm Optimization (PSO) and COR is presented. Numerical results show that COR has better performance compared with PSO.

1. Introduction

Planar array antennas find wide applications in radar and communication systems. In this type of antenna, main goal is to determine the physical layout of the array to produce the desired pattern. One of the most important parameters is Side Lobe Level (SLL). Through developments in computer technology, the numerical optimization techniques have been improved. Among these techniques, evolutionary algorithms such as genetic algorithm (GA) [1,2], differential evolution [3], and Particle Swarm Optimization (PSO) [4–6] have been successfully reported. Many synthesis methods are concerned with reducing SLL while preserving the gain of the main beam [7,8]. PSO has been shown to be an effective alternative relative to other evolutionary algorithms in handling certain kinds of optimization problems [9].

Due to increase in electromagnetic environment pollution, using nulls in prescribed direction becomes more and more important to maximize signal-to-interference ratio (SIR) [10–13]. Null steering techniques have been used to control the amplitude, phase, and the spacing to achieve the suppression of interfering signals from prescribed directions [14–17]. Dynamic Range Ratio (DRR) is defined as the ratio maximum and minimum value of the amplitude distribution, is usually high in the low SLL [18–21]. The higher DRR will complicate the design of the feed. A small value of DRR is desirable to achieve a better control of the mutual coupling. Furthermore, the cost of the feeding network is significantly reduced. Whereas the introduced techniques in [12–14] do not allow a DRR reduction, this is a serious drawback to have desired nulls. A simple approach to reduce DRR is eliminating the array elements possessing very small amplitudes [22–28]. However, this is not necessarily sufficient to reduce DRR under the desired threshold. Furthermore, it may produces a pattern distortion sufficient to remove the nulls.

This paper purposes a new scheme based on the evolutionary algorithm inspired by animals' behavior in Competition Over Resources (COR). Proposed algorithm, similar other nature inspired algorithms, has certain features in common with other biology based algorithms. Like GA and PSO, COR shares the information between solutions. In this paper, the multiple and broad nulls are imposed in the direction of interferences to suppress the relative SLLs with simultaneous DRR reduction. However, a lower DRR degrades some of the antenna parameters. This is done by controlling the position-only and the space/amplitude. The phase difference between any two elements is kept zero. Also, a cost function which keeps the nulls and side lobes at lower levels is defined. Two evolutionary optimization techniques, COR and PSO, are used to get the desired pattern.

The rest of the paper is organized as follows: Section 2, reviews similar works in the area of the planner antenna synthesis and optimization. Section 3, states the antenna array design problem. Then, COR algorithm is introduced in Section 4. Simulation results

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are presented in Section 5. Finally, the conclusions of this work along with future lines of the research are presented in Section 6.

2. Related works

In [10] an efficient method for the pattern synthesis of the linear antenna arrays with the prescribed null and multi-lobe beamforming is presented. Multi-lobe pattern and adaptive nulling of the pattern is achieved by controlling only the phase of each array element. The proposed method is based on the sequential quadratic programming algorithm and the linear antenna array synthesis was modelled as a multi-objective optimization problem. In [11] the hybrid differential evolution and enhanced PSO technique are applied for optimizing linear and circular configurations. In [12] a useful and flexible method based on the tabu search algorithm for the pattern synthesis of linear antenna arrays with the prescribed nulls is presented. In [13], an efficient method based on bees algorithm for the pattern synthesis of linear antenna arrays with the prescribed nulls is presented. In [14] differential evolution algorithm is used for null steering of planar array antennas by controlling of each element position. Moreover, differential evolution algorithm is applied to linear array pattern synthesis with prescribed nulls. The only control parameters are array element excitation amplitudes. The method of simulated annealing is adopted in [18] to minimize a cost function involving the SLL of the current far-field pattern and the DRR of the array excitations. In [19], a method to form nulls while reducing DRR is presented for circular arrays. In [20], a real-coded GA is proposed for synthesizing a symmetrical dual-beam pattern with DRR minimization. Two iterative algorithms for the far-field pattern synthesis with DRR constraints are presented in [21], where the author also discussed the consistency between null constraints and DRR constraints. The elements of the array are also assumed to be isotropic radiators and excitation current phases are all constant [29–34].

3. Problem statement

3.1. Planar array formulation

The geometry of a planar antenna array which is placed on the x-y plane is shown in Fig. 1. If the elements are taken to be isotropic sources, the radiation pattern of this array can be described by its array factor. The array factor for N isotropic elements is given by [35]:

$$AF(\theta,\phi) = \sum_{i=1}^{N} a_i e^{j\beta_i} e^{j2\pi dx_i \sin\theta\cos\phi} e^{j2\pi dy_i \sin\theta\sin\phi} \tag{1}$$

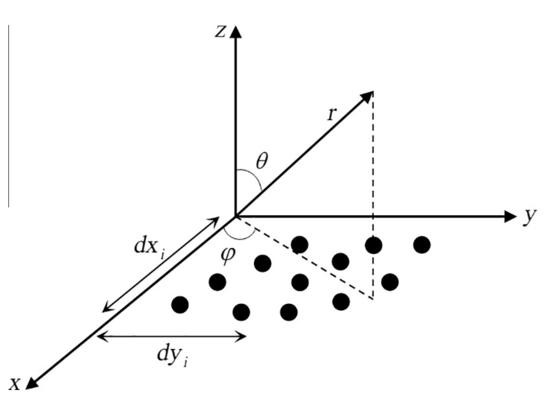


Fig. 1. Geometry of an N elements planar array in x-y plane.

where N is the total number of antenna elements in the array, θ is the elevation angle with respect to z-axis, φ is the azimuth angle with respect to x-axis, a_i is the amplitude of the ith element current and may be either uniform or in any other forms according to the designer's needs and β_i is the phase of ith element current. Also, dx_i and dy_i denote the distance between ith element and y-axis and the distance between ith element and x-axis in wavelength, respectively.

In addition, normalized power pattern in dB can be expressed as follows:

$$p(\theta,\phi) = 10\log_{10}\left[\frac{|AF(\theta,\phi)|}{|AF_{\max}(\theta,\phi)|}\right]^2 = 20\log_{10}\left[\frac{|AF(\theta,\phi)|}{|AF_{\max}(\theta,\phi)|}\right] \tag{2}$$

3.2. Cost function

We now need to formulate the objective function we want to minimize. The objective function is should be defined in such a way using array factor so that the objective of the optimization is satisfied. For the optimization problem of null placement in the far field pattern of the array, the array factor value at the particular null position must be less. Similarly, for SLL, the array factor values at the side lobe peaks must be less than the reference pattern. To satisfy the objective of this work, the array factor is included in the cost function. The objective function "Cost function" (CF) to be minimized with algorithms for introducing deeper null and the relative SLL reduction is given by [32]:

$$f = \left[\left(\sum_{k=1}^{K} w_k \left||AF_k| - ND_k\right|^2\right) + w_d|d - d_{\min}|^2 + w_s|SLL - SLL_{\max}|^2\right]^{1/2} \tag{3}$$

where K is the number of desired nulls, AF_k is the value of the array factor for the k_{th} direction to be suppressed and ND_k is the desired null depth for the k_{th} null. The weight w_k ($k = 1, \ldots, K$) is set to zero, i.e., $w_{k=0}$, if the condition $|AF_K| \leqslant ND_K$ is satisfied. Also, d and $d_{\min}$ are the minimum distance and the desired minimum distance between the array elements, respectively. If the condition $d \geqslant d_{\min}$ is satisfied then the weight w_d is set to zero. The third term in CF is added to reduce the sidelobe up to a desired level. $SLL_{\max}$ is desired maximum SLL for the overall pattern of the antenna array. The weight w_s is set to zero if the obtained SLL is smaller than $SLL_{\max}$.

An arbitrarily shaped, non-symmetric planar antenna array placed on the x-y plane with uniform excitations and zero phases is considered as the first problem. In this case, for the calculation of AF_k, a_i is taken as 1 and the position of the antenna array elements is selected as the parameter vector to be optimized. As a second case, non-symmetric rectangular lattice of unequal amplitude excitation with zero phased array elements is considered. Consequently, COR and PSO control the amplitude excitation and inter-elements spacing in order to minimize the cost function.

3.3. Fixed Dynamic Range Ratio

DRR is defined by the ratio between the maximum and minimum value of amplitude distribution which is given in the following equation:

$$DRR = \frac{\max_n\{|\alpha_n|\}}{\min_n\{|\alpha_n|\}} \tag{4}$$

By fixing DRR to a lower value, the differences between the successive excitation amplitudes are minimized and hence the effect of coupling between the neighboring elements is reduced. Moreover, the coupling between elements can be better controlled when the amplitude variation is smooth [36,37]. In many optimization procedures, only the pattern of the antenna is considered regardless to DRR effects. For antenna array synthesis, many methods are available to shape the radiation pattern, such as the variation of the amplitude and phase [10], element spacing [9], the variation of only amplitude [17] or phase [13]. Phase-only control is attractive, as usually the elements of a phased array have only phase shifters, while the feeding network determines the amplitude excitations, and furthermore it keeps constant DRR of the excitations. SLL can be reduced to any desired level by tapering the amplitude excitation of the elements. In tapering process the main task is to calculate an appropriate weights vector, which can produce the narrow beam with minimum SLL, but often produces an increase of DRR. To avoid this problem, DRR for an optimized array was restricted and in some example it was optimized. These restrictions will be desirable to achieve a better control of the mutual coupling and to reduce the cost of the feeding network. Hence, effects of the coupling between neighboring array elements are reduced by incorporating an additional term in the objective function in order to minimize the ratio between the maximum and minimum value of the excitation amplitudes.

4. Overview of Competition Over Resources algorithm

Competition Over Resource is a heuristic algorithm inspired by behavioral ecology of animal groups which is introduced by Mohseni and Gholami [38]. This algorithm is developed for solving continuous constrained optimization problems. To compare with other evolutionary techniques, COR is much simpler and easier to implement with feasible convergence. COR has five main phases namely initialization, evaluation, calculating groups' boundaries, search in groups' territory and selection, respectively.

4.1. Behavior of animal groups

Competition is generally understood to refer negative effects caused by the presence of neighbors; usually happens in limited resources situations. Competition is the one of the most important factors to control plant communities, along with resources, disturbance, grazing, and mutualism [39].

In the late 1800s, Darwin wrote extensively about the importance of competition in nature, particularly its role in driving natural selection. Thereafter, interest in the phenomenon grew [39,40]. All living organisms live and interact with other species and are integral members of an ecological community. Both long-term (evolutionary time scale) and short-term (ecological time scale) processes influence the composition of species within a community and the interactions among them [41]. Short term ecological interactions can influence the intensity of an interaction and the presence and abundance of species over the course of a season, a year, or within the lifetime of an organism [42].

Competition can be described in various ways concerning species interaction with each other. Exploitation competition is when resources used by one species is reduced and negatively affects another species using that same resource [43]. It occurs when a number of organisms utilize common resources which are in short supply. Also density-dependence is a major form of competition that regulates population in an environment [43]. This is a proportional relationship between slowing down or halting the population increase in population density or stopping a decrease in population with a decrease in density. In this process over time, a superior competitor can eliminate an inferior one from the area, resulting in competitive exclusion [44]. In this paper, proposed algorithm is based on such a competitive behavior of group animals, and can be formulated and applied in the optimization.

4.2. COR algorithm

Fig. 2 illustrates the flowchart of the proposed algorithm. Like other evolutionary algorithms, it starts with initial population and ends when reached to satisfactory conditions. In the proposed algorithm, initial population is produced in a random process. Next, the whole population is divided into number of groups. In each group, searching agent with best fitness is called "group best", which determines the territory and survives to the end of iteration to spreads its children in next iterations. Main search coefficients in COR algorithm are number of initial population and groups. Each groups' territory is defined by minimum Euclidean distance between group bests of all adjacent groups:

$$Boundary_m = C_0 \sqrt[n]{(a_1 - b_1)^2 + (a_2 - b_2)^2 + \ldots + (a_n - b_n)^2} \quad (5)$$

which (a) and (b) are two adjacent group best agents in (n) dimension problem. C_0 is equal to 1 when defining inner boundary and equals 1.5 when searching out of the boundary. A number of group members can search out of group boundaries in order to perform random search during the process.

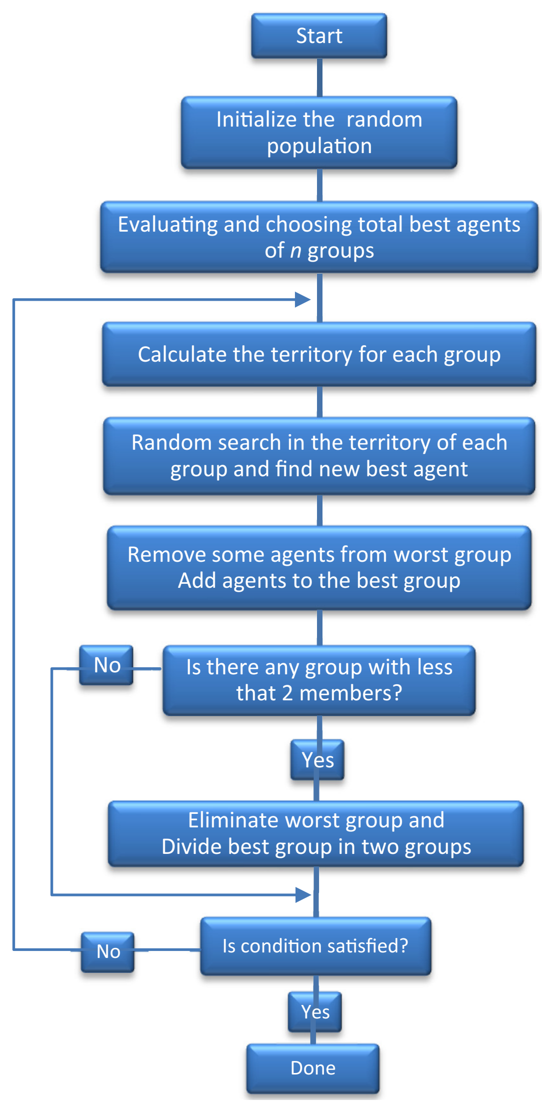


Fig. 2. Flowchart of COR algorithm.

In the boundaries calculations, C_0 is a tunable parameter, but resulting from large number of simulations in this research it is set as 1 and 1.5 for inner and outer boundary search respectively. Fig. 3a indicates an example with population of 10 agents in three groups. Initial population is generated through random seeding. The "group bests", which are three most fitted agents in search space, are marked with triangles. Circles around group bests demonstrate each groups' territory boundary. Agents search their boundary by random distribution, the new agents in each iteration will be evaluated by their fitness. Therefore, in COR algorithm, each group has only two specifications which propagates to the next iteration: group bests position and number of agents.

Groups' territory size will be calculated via distances between adjacent group bests. The minimum distance for each group best is considered as its territory, Fig. 3. In the first iteration all groups are formed with equal number of agents, but in the following iterations, the worst groups' population will be decreased and the best groups' population will be increased by a predefined rate in next iteration. Best and worst groups in each iteration are labeled based on group bests' fitness in problem. This change in group size is shown in Fig. 3b, the blue group gained more population and green color group lost most of its agents. Thus the whole population size will be constant during the execution, but some groups get stronger and some get weaker which results in more focus on specific areas in the search space. Groups with less than two agents will disappear and a new group is formed by separating the best group in two parts and shares information with a new born group. In the operation of partitioning, the second agent with highest fitness in the best group is chosen as a new born group. However, operation of suppressing is based on group population, not any specific agents. Fig. 3c illustrates new groups born from a divided populous group, which adds elitism feature to the algorithm.

As discussed, the Competition Over Resources begins among all groups. Any group, which is not able to find rich resources and increases its population, will be eliminated form competition. The competition gradually results in an increase in population of wealthy groups which gives them more search agents. At last the dividing populous groups minimizes the groups' territory border and gives superior convergence time. Flexible boundary size guarantees the exploration and eliminating worst group gives the exploitation step of the algorithm. Also using group best agents instead of global best in combination with outer boundary search makes sure that the system will not be trapped in a local minimum. From the pseudo code in Fig. 4 it is relative straightforward to implement the COR algorithm.

From a quick look, COR has a significant difference from other similar algorithms. The only parameters, which are kept in memory, are group best agent locations and total number of agents. As a result, it is a low rate memory consumption algorithm, thus it is potentially more general and adapts to a wider class of problems.

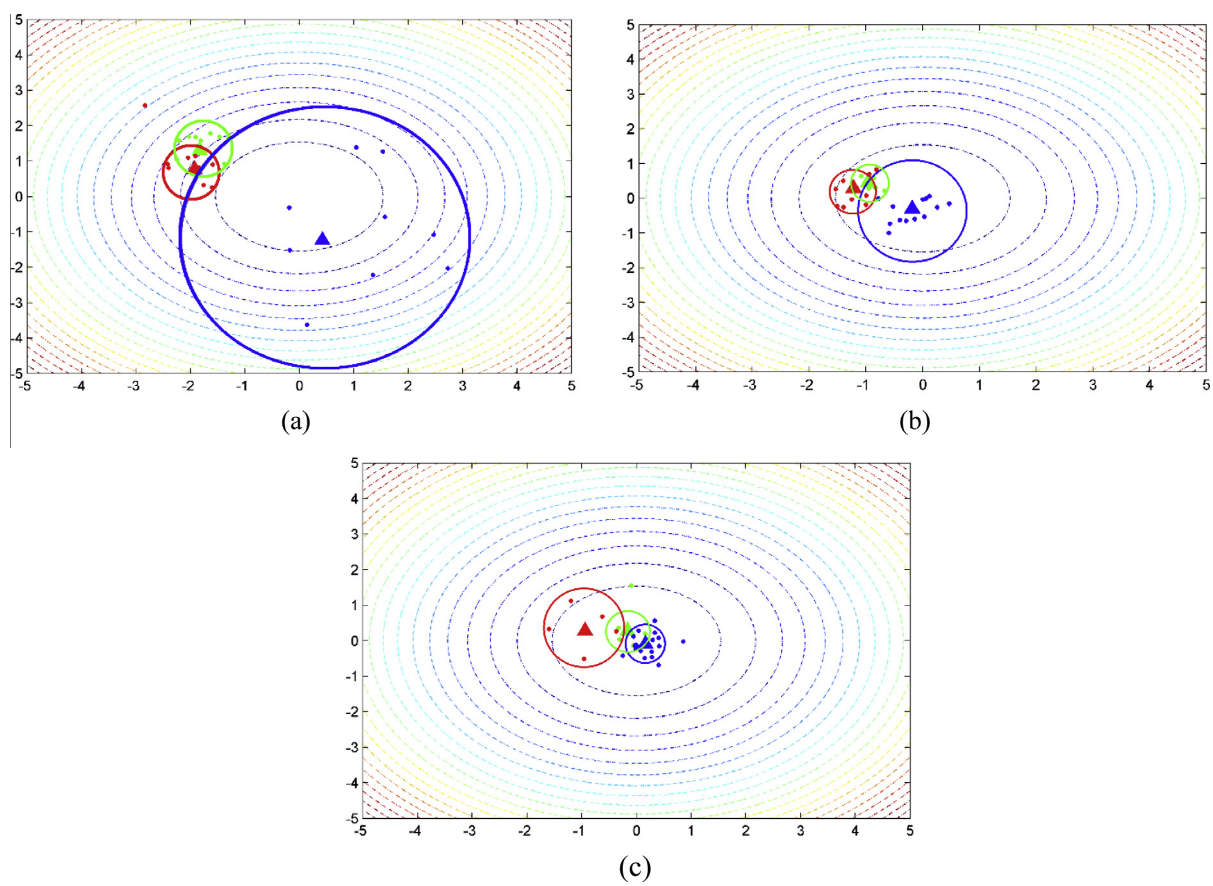


Fig. 3. An example with 30 agents divided in 3 groups and death rate value of 2. Group best agents are shown by a triangle and other agents are small circles. Territory boundary margins shown by color circles, and color markers assign best agents are evaluated for next iteration. (a) Iteration = 2. Number of agents (blue, green, red) = (10, 10, 10). (b) Iteration = 4. Number of agents (blue, green, red) = (14, 6, 10). (c) Iteration = 6. Number of agents (blue, green, red) = (18, 6, 6). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

COR Algorithm

Objective function f(x), x = (x$_1$*,…, x*$_d$*)*
Initialize the whole population of n_Pop agents

Evaluation fitness for each agent
Select n_group best agents (n_group: number of groups)

While *(t < max number of iterations)*

Calculate the Euclidean distance between group heads

For *(i=1 :1: n_group)*

Search in each group territory individually

Rank agents in each group and keep Group best ***End for***

Remove some agents from worst group
Add agents to best group population

If *(group_population < 2)*

Eliminate worst group
Divide best group in two parts

End if

End while

Fig. 4. Pseudo code for basic COR algorithm.

5. Computational experiments and results

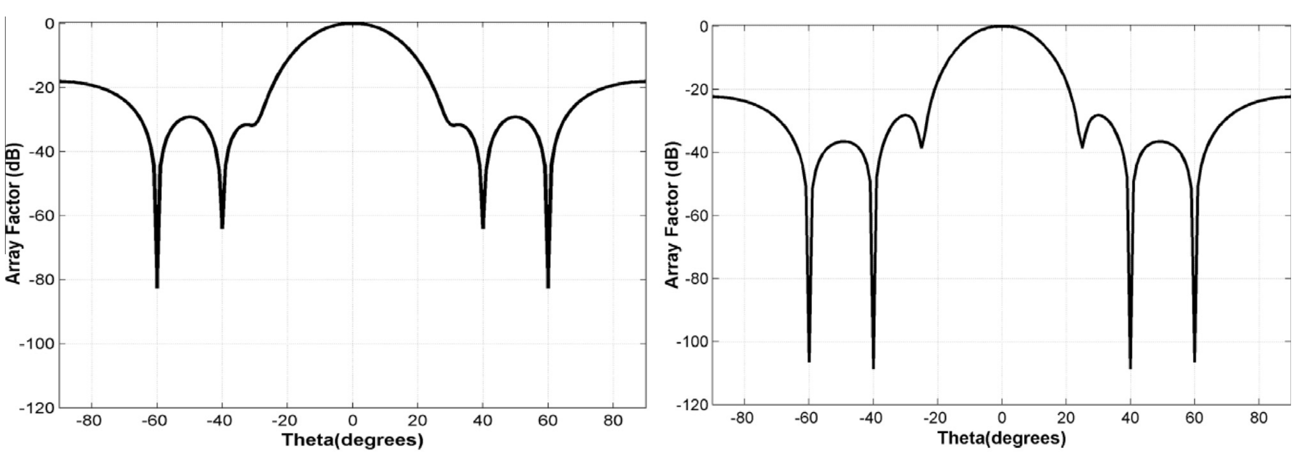
5.1. Multiple nulls imposing

5.1.1. Position only optimization

To illustrate the capability of COR algorithm for obtaining multiple nulls and reducing SLLs by controlling the position and amplitude, an illustrative example of a planar array with 36 elements have been simulated. In the first example, the pattern nulling is achieved by controlling only the inter-element spacing. In the second example, forming nulls in the pattern is achieved by controlling both the position and amplitude of each array element.

In both algorithms, some parameters of CF such as ND, $d_{\min}$, and $SLL_{\max}$ are similar. For example, in this case, the desired null depth level, i.e., ND, are set to −100 dB for each nulls. Furthermore, the desired minimum distance between array elements, i.e., $d_{\min}$, is fixed to 0.2λ. Also, for the overall pattern, $SLL_{\max}$, is selected to −20 dB. All weight coefficients are equal and set as $w_k = w_d = w_s = 1$. Also for planar array structure, the coordinates are required to be between $0 \leqslant x, y \leqslant 3\lambda$. In addition, some parameters of the COR algorithm such as the maximum number of iteration and the initial population have been taken as 250 and 40, respectively. For PSO method, these parameters have been chosen 300 and 100, respectively. Specifically for COR, the predefined conditions, such as the group numbers and the death rate have been chosen 4 and 1 respectively.

In the first example, the resultant patterns, by using of the position-only control, are shown in Fig. 5 for double nulls patterns. It illustrates the obtaining of a deep nulls at $\varphi = 30°$, $\theta = 40°$ and



(a) (b)

Fig. 5. Normalized array factor of 36 elements planar array synthesized for double nulls using a) PSO and b) COR (position-only).

Table 1
Normalized positions of the elements in wavelengths synthesized for double nulls pattern using PSO (Position only).

El. Num.	dx_i	dy_i		dx_i	dy_i		dx_i	dy_i
1	0.82	0.88	**13**	0.90	1.85	**25**	0.66	2.05
2	0.49	0.47	**14**	0.65	2.44	**26**	0.06	1.20
3	2.44	1.48	**15**	0.64	0.81	**27**	1.50	1.84
4	1.48	0.91	**16**	0.40	0.42	**28**	1.48	1.86
5	1.52	2.77	**17**	0.82	1.26	**29**	1.08	0.55
6	1.44	3.45	**18**	1.38	1.57	**30**	1.49	1.17
7	1.67	0.69	**19**	1.08	1.08	**31**	2.64	1.99
8	1.70	1.75	**20**	2.34	0.74	**32**	1.69	2.31
9	1.53	2.42	**21**	1.30	2.74	**33**	1.39	0.74
10	1.60	1.50	**22**	2.70	1.24	**34**	0.59	1.15
11	1.23	2.17	**23**	2.55	2.23	**35**	2.22	1.35
12	2.55	1.52	**24**	2.78	1.35	**36**	1.08	2.53

Table 2
Normalized positions of the elements in wavelengths synthesized for double nulls pattern using COR (Position only).

El. Num.	dx_i	dy_i		dx_i	dy_i		dx_i	dy_i
1	0.04	0.55	**13**	0.17	0.11	**25**	2.00	2.45
2	1.37	0.97	**14**	1.64	1.37	**26**	2.46	0.52
3	2.71	0.13	**15**	0.87	2.70	**27**	2.91	0.41
4	2.25	0.95	**16**	0.09	1.01	**28**	1.20	0.27
5	0.74	1.25	**17**	1.86	1.09	**29**	2.27	0.16
6	1.76	0.01	**18**	0.29	1.44	**30**	0.51	0.70
7	0.61	2.02	**19**	1.05	2.01	**31**	2.31	1.77
8	2.10	1.28	**20**	2.30	2.86	**32**	2.21	2.01
9	0.02	2.38	**21**	1.33	0.53	**33**	2.81	1.10
10	2.50	1.60	**22**	0.37	1.01	**34**	0.02	2.91
11	2.84	2.45	**23**	1.65	0.32	**35**	0.95	2.25
12	1.02	0.15	**24**	0.42	2.99	**36**	0.88	2.96

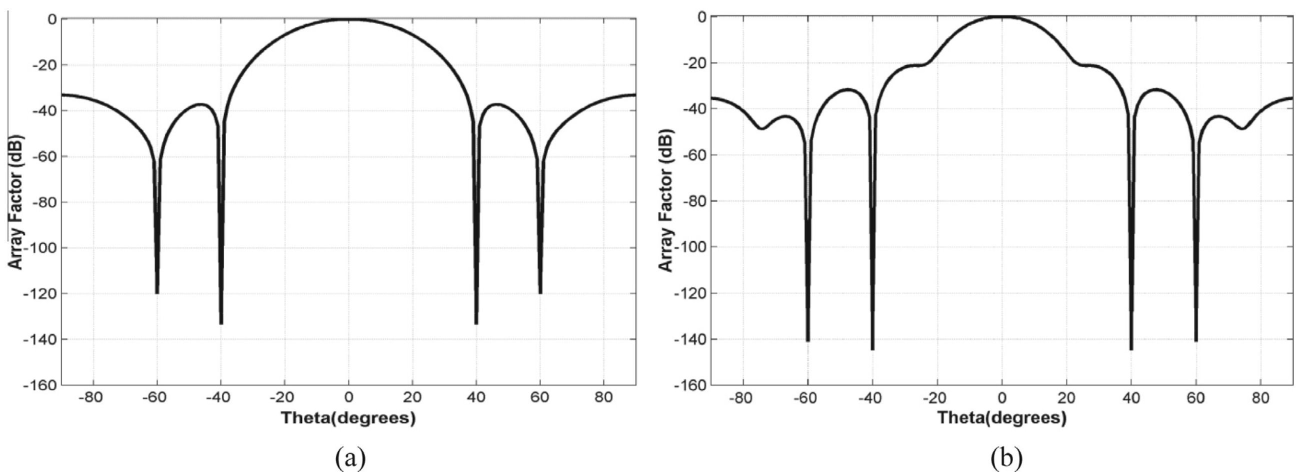


Fig. 6. Normalized array factor of 36 elements planar array synthesized for double nulls using a) PSO and b) COR (Position and Amplitude).

Table 3
Normalized positions of the elements in wavelengths synthesized for double nulls pattern using PSO (Position and Amplitude).

El. Num.	dx_i	dy_i		dx_i	dy_i		dx_i	dy_i
1	2.50	1.60	**13**	0.22	1.19	**25**	1.51	1.89
2	1.53	1.84	**14**	0.36	1.83	**26**	0.87	1.83
3	1.82	1.97	**15**	0.52	2.08	**27**	1.18	0.84
4	1.92	1.21	**16**	0.63	1.32	**28**	1.46	2.23
5	2.31	1.18	**17**	1.24	2.25	**29**	0.64	1.86
6	1.73	2.44	**18**	0.68	0.60	**30**	2.50	2.03
7	1.39	1.64	**19**	1.04	1.32	**31**	1.77	2.35
8	1.40	1.10	**20**	1.25	1.01	**32**	1.68	1.82
9	1.57	0.74	**21**	0.70	0.47	**33**	1.91	1.60
10	1.15	0.77	**22**	1.92	1.76	**34**	0.39	1.90
11	2.04	2.45	**23**	0.37	1.42	**35**	2.44	2.09
12	1.14	1.69	**24**	1.85	1.10	**36**	1.34	1.42

$\theta = 60°$. For PSO as can be seen in Fig. 5(a), it is evident that the desired nulls are deeper than −64 dB and −82 dB at $\theta = 40°$ and $\theta = 60°$ respectively. For COR, the nulls have been imposed up to −109 dB and −107 dB as well as the maximum SLL is obtained −22 dB. The results shown in Fig. 5(b) indicate the ability of the proposed algorithm for array pattern synthesis with double nulls imposed in the prescribed interference directions as well as SLL reduction.

Table 1 shows the exact element positions of the planar array for double nulls patterns using PSO. These positions are normalized to λ. Also, these exact values optimized by COR method are shown in Table 2.

5.1.2. Position and amplitude optimization

In the second example, the pattern including two nulls is obtained by controlling both the position and amplitude of the elements. Although the number of variable to be optimized is increased, the resultant patterns are more efficient in terms of SLL and DRR. The resultant patterns that make the use of both position and amplitude control are shown in Fig. 6. For PSO, the null depth level of the patterns are obtained −136 dB and −120 dB at $\theta = 40°$ and $\theta = 60°$ respectively. Furthermore, the maximum SLL is obtained as −34 dB. In addition, after running the program for COR, the results in Fig. 6 confirm that our proposed AF of COR method has −36 dB SLL and the nulls have been imposed up to −142 dB and −140 dB at $\theta = 40°$ and $\theta = 60°$, respectively. To achieve the broad-band interference suppression with DRR minimization, as it illustrated in Tables 4 and 6, the excitation amplitude DRR is found to be 4.36 and 4.08 for PSO and COR, respectively. Indeed, COR pattern confirms that about −20 dB improvement for each null is obtained in comparison with PSO pattern even with less value of DRR. The results depicted in

Table 4
Normalized amplitudes of the elements in synthesized for double nulls pattern using PSO (Position and Amplitude).

El. Num.	Opt. Amp.	El. Num.	Opt. Amp.	El. Num.	Opt. Amp.	El. Num.	Opt. Amp.
1	0.56	**10**	0.45	**19**	0.30	**28**	0.45
2	0.21	**11**	0.48	**20**	0.25	**29**	0.50
3	0.70	**12**	0.78	**21**	0.40	**30**	0.63
4	0.23	**13**	0.22	**22**	0.41	**31**	0.49
5	0.19	**14**	0.36	**23**	0.45	**32**	0.29
6	0.30	**15**	0.52	**24**	0.65	**33**	0.68
7	0.83	**16**	0.40	**25**	0.70	**34**	0.35
8	0.66	**17**	0.47	**26**	0.61	**35**	0.41
9	0.45	**18**	0.23	**27**	0.80	**36**	0.77

Table 5
Normalized positions of the elements in wavelengths synthesized for double nulls pattern using COR (Position and Amplitude).

El. Num.	dx_i	dy_i		dx_i	dy_i		dx_i	dy_i
1	0.21	0.25	**13**	0.82	0.50	**25**	1.36	2.65
2	1.31	1.91	**14**	0.78	0.86	**26**	2.99	2.80
3	1.57	2.32	**15**	1.73	1.66	**27**	0.59	1.66
4	1.70	2.24	**16**	1.06	0.14	**28**	2.16	1.25
5	1.84	0.02	**17**	2.40	1.75	**29**	2.12	1.54
6	1.89	0.9	**18**	2.87	0.82	**30**	1.75	0.06
7	1.45	1.21	**19**	0.36	1.07	**31**	2.25	2.60
8	0.82	2.97	**20**	2.42	1.84	**32**	1.67	2.57
9	0.14	0.15	**21**	0.81	0.56	**33**	0.98	2.36
10	2.98	2.63	**22**	1.39	0.47	**34**	0.64	0.58
11	0.70	2.24	**23**	1.37	2.06	**35**	2.75	2.04
12	0.02	1.49	**24**	2.33	1.43	**36**	0.32	0.46

Table 6
Normalized amplitudes of the elements in synthesized for double nulls pattern using COR (Position and Amplitude).

El. Num.	Opt. Amp.	El. Num.	Opt. Amp.	El. Num.	Opt. Amp.	El. Num.	Opt. Amp.
1	0.74	**10**	0.25	**19**	0.61	**28**	0.35
2	0.46	**11**	0.26	**20**	0.64	**29**	0.97
3	0.47	**12**	0.88	**21**	0.27	**30**	0.87
4	0.24	**13**	0.85	**22**	0.57	**31**	0.98
5	0.35	**14**	0.64	**23**	0.32	**32**	0.15
6	0.62	**15**	0.74	**24**	0.65	**33**	0.43
7	0.38	**16**	0.52	**25**	0.77	**34**	0.93
8	0.46	**17**	0.31	**26**	0.19	**35**	0.24
9	0.30	**18**	0.71	**27**	0.70	**36**	0.68

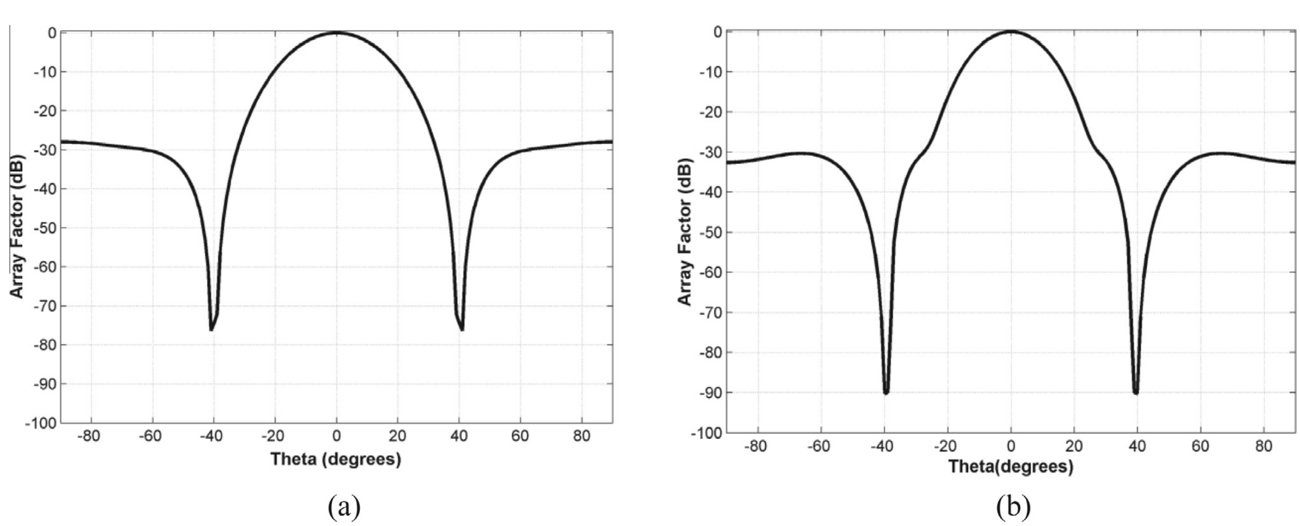


Fig. 7. Normalized array factor of 36 elements planar array synthesized for broad null at $\theta = 40^{\circ}$ using a) PSO and b) COR (Position and Amplitude).

Table 7
Normalized positions of the elements in wavelengths synthesized for broad null pattern using PSO (Position and Amplitude).

El. Num.	dx_i	dy_i		dx_i	dy_i		dx_i	dy_i
1	2.53	2.41	**13**	1.15	1.19	**25**	0.55	0.56
2	0.81	0.80	**14**	1.72	1.77	**26**	1.38	2.19
3	1.37	0.27	**15**	2.16	2.88	**27**	2.11	1.69
4	1.34	0.92	**16**	1.58	1.87	**28**	2.33	1.38
5	1.08	2.99	**17**	1.44	1.11	**29**	2.02	1.44
6	1.44	0.74	**18**	2.07	2.02	**30**	1.56	1.30
7	1.82	0.77	**19**	1.79	1.94	**31**	1.70	1.36
8	1.77	3.00	**20**	1.50	1.98	**32**	1.35	1.01
9	0.76	0.81	**21**	0.92	1.25	**33**	0.87	2.03
10	1.54	2.17	**22**	2.18	0.40	**34**	0.47	1.31
11	1.06	2.04	**23**	0.81	2.21	**35**	2.15	2.12
12	0.33	1.48	**24**	1.26	2.09	**36**	0.79	1.46

Table 8
Normalized amplitudes of the elements in synthesized for broad null pattern using PSO (Position and Amplitude).

El. Num.	Opt. Amp.	El. Num.	Opt. Amp.	El. Num.	Opt. Amp.	El. Num.	Opt. Amp.
1	0.48	**10**	0.82	**19**	0.58	**28**	0.14
2	0.59	**11**	0.48	**20**	0.56	**29**	0.73
3	0.42	**12**	0.46	**21**	0.14	**30**	0.12
4	0.61	**13**	0.35	**22**	0.60	**31**	0.32
5	0.38	**14**	0.40	**23**	0.76	**32**	0.53
6	0.62	**15**	0.71	**24**	0.21	**33**	0.59
7	0.46	**16**	0.70	**25**	0.46	**34**	0.50
8	0.69	**17**	0.47	**26**	0.45	**35**	0.88
9	0.25	**18**	0.53	**27**	0.68	**36**	0.42

Table 9
Normalized positions of the elements in wavelengths synthesized for broad null pattern using COR (Position and Amplitude).

El. Num.	dx_i	dy_i		dx_i	dy_i		dx_i	dy_i
1	0.92	2.53	**13**	2.61	0.94	**25**	1.10	2.21
2	0.32	1.78	**14**	1.45	0.27	**26**	2.14	0.18
3	1.92	2.67	**15**	0.82	2.94	**27**	0.48	2.72
4	0.81	1.19	**16**	2.93	1.68	**28**	2.64	0.32
5	2.31	1.12	**17**	1.28	1.18	**29**	0.03	1.61
6	0.84	1.33	**18**	1.05	0.28	**30**	1.40	1.26
7	2.51	0.56	**19**	0.21	0.49	**31**	0.07	0.12
8	0.66	2.90	**20**	1.20	1.41	**32**	2.48	0.00
9	0.26	1.05	**21**	1.00	1.64	**33**	2.42	2.56
10	2.62	0.79	**22**	2.35	2.17	**34**	0.64	2.00
11	0.11	1.11	**23**	0.85	0.85	**35**	2.03	1.34
12	2.05	2.16	**24**	0.71	2.64	**36**	1.28	0.28

Table 10
Normalized amplitudes of the elements in synthesized for broad null pattern using COR (Position and Amplitude).

El. Num.	**Opt. Amp.**	**El. Num.**	**Opt. Amp.**	**El. Num.**	**Opt. Amp.**	**El. Num.**	**Opt. Amp.**
1	0.77	**10**	0.64	**19**	0.28	**28**	0.17
2	0.86	**11**	0.87	**20**	0.57	**29**	0.60
3	0.17	**12**	0.48	**21**	0.38	**30**	0.81
4	0.52	**13**	0.73	**22**	0.65	**31**	0.90
5	0.47	**14**	0.46	**23**	0.50	**32**	0.38
6	0.19	**15**	0.14	**24**	0.86	**33**	0.65
7	0.45	**16**	0.32	**25**	0.77	**34**	0.66
8	0.60	**17**	0.74	**26**	0.95	**35**	0.71
9	0.26	**18**	0.37	**27**	0.24	**36**	0.95

Fig. 6 show significant DRR restriction can be obtained while maintaining satisfactory patterns, including double nulls and SLL reduction. Therefore, in practice, it is possible to reduce the coupling effect by minimizing DRR. From the null depth and maximum SLL points of view, the performances of the patterns are very good. For accomplishment of numerical results, the exact optimized values of the positions and amplitudes of the synthesized patterns using PSO are shown in Tables 3 and 4, respectively. It is also noted that the excitation coefficient values given in Table 4 are normalized. Also, the exact optimized values of element positions and amplitudes of the synthesized patterns using COR are shown in Tables 5 and 6, respectively.

5.2. Broad null imposing

It is well known that the broad nulls are needed when the direction of the unwanted interference may vary slightly or may not be known exactly. Furthermore, a null would require continuous steering for obtaining a reasonable value for the signal-to-noise ratio. To illustrate the broad-band interference suppression capability of the nulling method, the patterns having a broad null located at 40° with $\Delta\theta = 3°$ are achieved by PSO and COR shown in Fig. 7. As can be seen, a null depth level smaller than −70 dB is obtained over the spatial region of interest. This simulation clearly shows the capacity of algorithms to synthesize the array pattern with broad null. In addition, the maximum SLL are obtained less than −28 dB. The exact optimized element positions and normalized amplitudes of broad null pattern are shown in Tables 7 and 8 for PSO. Also, the exact optimized values of element positions and amplitudes of the synthesized pattern of Fig. 7(b) using COR are shown in Tables 9 and 10, respectively. To show the broad-band interference suppression with DRR minimization, the excitation amplitude DRR is found to be 6.28 and 5.58 for PSO and COR, respectively. Indeed, Fig. 7 confirms that a 15 dB null improvement is achieved by COR in comparison with PSO even with less value of DRR. Fig. 7 show that the significant restriction can be obtained while maintaining satisfactory patterns, including broad null imposing and SLL reduction. In addition, from the null depth and the maximum SLL points of view, the performances of the patterns are very good.

6. Conclusion

This paper illustrated the use of COR optimization algorithm in the synthesis of planar array geometry in order to SLL reduction and null placement with DRR constraints. COR is a memory-less algorithm with having accurate response due to its novel neighborhood set. Pattern nulling is achieved by position-only optimizing and both amplitude and position optimizing of the array elements. The effect of coupling between antenna array elements is reduced by minimizing the excitation amplitude DRR, without compromising on the design specifications. To prove the superiority of the COR algorithm in the term of accuracy and the number of function evaluations, the obtaining results are compared with PSO. Consequently, two different multiple nulls imposing problems are simulated. The pattern nulls and SLL of COR are improved significantly compared to that of the PSO. In addition, to achieve broad null pattern, both amplitudes and positions have been chosen as optimization variables in COR, which resulted in a 15 dB null improvement in comparison to the case of PSO even with less value of DRR. Numerical results reveal that design of non-uniform planar arrays using COR provides a considerable SLL reduction and a satisfactory null depth with DRR constraint, simultaneously. It is worth noting that, although the algorithms proposed here are implemented to constrain synthesis of a planar array, one can see from the proposed technique that, they are not limited to this case. Therefore, both of these optimization algorithms can easily be implemented to conformal antenna arrays with different geometries for various array patterns synthesis.

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