Concentric Circular Antenna Array Synthesis Using Biogeography Based Optimization

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ABSTRACT:
Biogeography based optimization (BBO) is a new stochastic force based on the science of biogeography. Biogeography is the schoolwork of geographical allotment of biological organisms. BBO utilizes migration operator to share information between the problem solutions. The problem solutions are known as habitats and sharing of features is called migration. In this paper, BBO algorithm is developed to optimize the current excitations of concentric circular antenna arrays (CCAA). Concentric Circular Antenna Array (CCAA) has numerous attractive features that make it essential in mobile and communication applications. The goal of the optimization is to reduce the side lobe levels and the primary lobe beam width as much as possible. To confirm the capabilities of BBO, three different CCAA antennas of different sizes are taken. The results obtained by BBO are compared with the Real coded Genetic Algorithm (RGA), Craziness based Particle Swarm Optimization (CRPSO) and Hybrid Evolutionary Programming (HEP).

KEYWORDS: Antenna array, concentric circular arrays, biogeography based optimization, metaheuristics, non-uniform excitation.

1. INTRODUCTION

Circular antenna arrays have significant interest in a variety of applications which comprise sonar, radar, and mobile and commercial satellite communications systems [1–4]. A circular array is an arrangement of a number of elements usually omni directional arranged on a circle [1] and can be employed for beam forming in the azimuth plane such as at the base stations of the mobile radio communications system [2-4]. Circular arrays have become popular in recent years over other array geometries because they have the capability to perform the scan in all directions without a considerable change in the beam pattern and provide 3600 azimuth coverage. Moreover, circular arrays are less sensitive to mutual coupling as compared to linear and rectangular arrays since these do not have edge elements [1]. Concentric circular antenna array (CCAA) that contains many concentric circular rings of different radii and number of elements has a number of advantages including the flexibility in array pattern synthesis and design both in narrowband and broadband beam forming applications [2-4]. CCAA is also employed in direction of arrival (DOA) applications since it gives almost invariant azimuth angle coverage. Hence the synthesis of the circular arrays is under active research by many groups. Genetic Algorithm (GA) has been used in [5] to optimize the element placement in CCAA. Particle Swarm Optimization (PSO) [6] has been applied for the optimized synthesis of thinned CCAA. Efficient side lobe reduction techniques have been discussed in [3]. PSO has also been used for obtaining flat-top beam pattern of CCAA [7]. Null synthesis of CCAA has been performed using hybrid Ant Colonial method [8]. CRPSO and RGA have been used to obtain minimum SLL and beam width of CCAA [9]. CCAA with and without central element has been optimized using Hybrid Evolutionary Programming (HEP) [10].

In this paper, biogeography-based optimization (BBO) is applied for the optimization of CCAA. BBO is a population-based evolutionary technique introduced in [11]. It has been applied for the design of linear antenna arrays for obtaining the maximum SLL reduction and null placement in desired directions in [12]. Results obtained using BBO for the linear arrays are encouraging. The BBO method produced a lower value of SLL and better null placement as compared to PSO [13].BBO has also been used for the optimization of Yagi-Uda [14]. The BBO method has been also applied in other areas, such as the power flow problem [15], optimization of gear trains [16], and satellite image classification problems [17]. The aim of this paper is to present the optimization of CCAA using BBO for reducing the maximum SLL and at the same time keeping the beam width as small as possible. To the best of our knowledge, BBO has not been applied for the optimization of the CCAA before. It is well known in general that if the SLL is reduced, the beam width is increased [1]. Therefore, the aim of the optimization in this paper is to minimize the SLL while maintaining minimum possible beam width.

The rest of the paper is organized as follows: Section 2 discusses the geometry and general design for the CCAA. In Section 3, the BBO algorithm is explained. Section 4 presents design examples and the results and in Section 5 conclusions are presented.

2. CONCENTRIC CIRCULAR ANTENNA DESIGN

In CCAA, the elements are arranged in such a manner that all antenna elements are positioned in multiple concentric circular rings, which vary in radii and in number of elements. Figure 1 shows the general configuration of CCAA with M concentric circular rings, where the m^{th} (m = 1, 2,…, M) ring has a radius r_m and the corresponding number of elements is Nm.

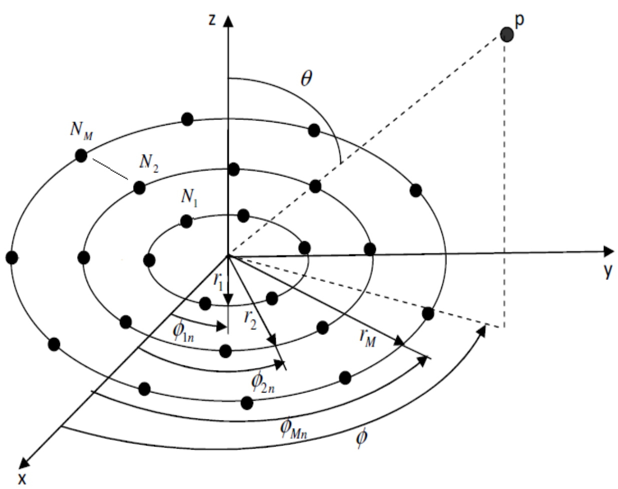

Fig. 1. Concentric Circular Antenna Array.

Assuming that all the elements (in all the rings) are isotopic sources, then the radiation pattern of this array can be written in terms of its array factor only. The array factor (AF) is given by

$$AF(\phi, I) = \sum_{m=1}^{M}\sum_{n=1}^{N_m} I_{mn} \exp[j(kr_m \sin\theta(\cos(\phi - \phi_{mn}) + \alpha_{mn})] \quad (1)$$

where,

k_w is the wave number $= 2\pi / \lambda_w$,

λ_w is the signal wavelength,

r_m is the radius of the m^{th} ring $= N_m d_m / 2\pi$,

d_m =inter element arc spacing of the m^{th} ring

$\phi_{mn} = 2\pi(n-1)/N_m$ is the angular position of the n^{th} element of the m^{th} ring,

I_{mn} is the current excitation of the n^{th} element of the m^{th} ring ,

ϕ and θ are the azimuth and zenith angle respectively ,

$\alpha_{mn} = -k_w r_m \cos(\phi_0 - \phi_{mn})$ is the residual phase,

ϕ_0 is the value of ϕ where main beam is to be directed.

3 BIOGEOGRAPHY-BASED OPTIMIZATION

BBO is a recently developed population-based evolutionary algorithm based on the theory of biogeography. Biogeography is the study of the distribution of the species in nature. The species migrate to different habitats for their survival and better living conditions. BBO imitates this migration phenomenon for solving real-world optimization problems. In common with the GA, the PSO, and many other algorithms, BBO is motivated by natural phenomenon. In along the biogeography, a habitat (*H*) is defined as any ecological area which is geographically isolated from other habitats. Each habitat has its measure of goodness for living which is known as the suitability index (SI). Habitats those are well suited for living has a high SI. The SI of a habitat depends upon a number of factors, such as rainfall, temperature, diversity of species, population of the species, and security. These factors are known as suitability index variables (SIV). The habitats with a high SI have a large population as they are fit for living while the habitats with low SI are not apt or friendly for living and have a thin population. High SI habitats have a low immigration rate λ and high emigration rate μ simply because they are highly populated and can not easily support new species. For the same reason, low SI habitats have a high immigration rate λ , and low emigration rate μ which allows more species to move into these habitats. The habitats with a high SI have many species that emigrate to nearby habitats. The high SI habitats are less dynamic than the low SI habitats. The influx of species to the low SI habitats may raise its SI because the suitability of a habitat is proportional to its biological diversity. But if SI remains low, the habitat may become extinct. Here, Figure 2 illustrates a model of species abundance in a single habitat. Consider the immigration graph of Figure 2. The maximum possible immigration rate to the habitat is I, which occurs when there are zero species in the habitat. If a habitat has less number of species, then much larger amount of species from other habitat can come into that habitat, thus immigration rate is higher at that time. With the increase in the number of species, the habitat becomes densely populated, and fewer species are able to successfully survive after immigration to the habitat, and therefore immigration rate decreases. The largest possible number of species that the habitat can maintain is S_{max}, at which point the immigration rate becomes zero, because no more species can immigrate that habitat after that species count. Now consider the emigration graph. If there are no species in the habitat, then there is no species in that habitat that emigrate other habitat, so the emigration rate must be zero. As the number of species increases, the habitat becomes more crowded, more species are able to leave the habitat to explore other possible residences, and the emigration rate increases. The maximum emigration rate is E, which occurs when number of species is S_{max}. The equilibrium number of species is S_0, at which point the immigration and emigration rates are equal. The immigration and emigration lines in Figure 2 have been shown as straight lines but, in general, they might be more complicated curves. However, the simple model gives us a general description of the process of immigration and emigration. In BBO algorithm, calculation of emigration rate and immigration rate is important as these play vital role to select habitats who's *SIVs* will undergo migration operation.

Mathematically, the concept of migration between habitats can be represented by a probabilistic model. Now, let P_k be probability that the habitat contains exactly *k* species at time *t*. P_s changes from time t to time $t + \Delta t$ as

$$P_s(t+\Delta t) = P_s(t)(1-\lambda_s \Delta t - \mu_s \Delta t) + P_{s-1}\lambda_{s-1}\Delta t + P_{s+1}\mu_{s+1}\Delta t \quad (2)$$

where λ_s and μ_s are the immigration and emigration rates when there are S species in the habitat. This equation holds because in order to have *S* species at time $(t+\Delta t)$ one of the following conditions must be satisfied:

1) There were S species at time t, and no immigration or emigration occurred between t and $t+\Delta t$;
2) There were $(S-1)$ species at time t, and only one species immigrated;
3) There were (S+1) species at time t, and only one species emigrated.

If time Δt is small enough so that the probability of more than one immigration or emigration can be ignored, then taking the limit of (2) as $\Delta t \to 0$ gives

$$\dot{P}_k = \begin{cases} -(\lambda_s+\mu_s)P_s + \mu_{s+1}P_{s+1}, & S=0; \\ -(\lambda_s+\mu_s)P_s + \lambda_{s-1}P_{s-1} + \mu_{s+1}P_{s+1}, & 1 \le S < S_{max}-1; \\ -(\lambda_s+\mu_s)P_s + \lambda_{s-1}P_{s-1}, & S = S_{max}. \end{cases} \quad (3)$$

For the straight-line graph of Figure. 2, the equation for emigration rate and immigration rate for k number of species can be written as:

$$\lambda_k = I_b\left(1-\frac{k}{n}\right) \quad (4)$$

$$\mu_k = \frac{E_b k}{n} \quad (5)$$

where I_b is the maximum possible immigration rate, E_b is the maximum possible emigration rate and $n = S_{max}$ is the maximum number of species.

When, $E_b = I_b$ combining (4) and (5) gives

$$\lambda_k + \mu_k = E_b \quad (6)$$

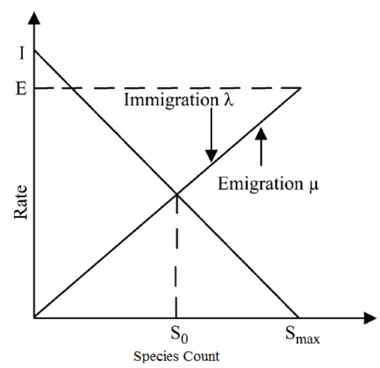

Fig. 2. Linear migration relationships for a habitat

BBO technique imitates nature's way of distributing species, and is analogous to general problem solutions. Suppose that there is an optimization problem with some candidate solutions. The problem can be of any field of life provided that there is a quantifiable measure of the suitability of a given solution. In BBO, for an N_{var}-dimensional optimization problem, a habitat is a 1 X N_{var} array. The population consists of *NP = n* parameter vectors or habitats, where *NP* is the total number of habitats. Habitats consist of solution features named suitability index variables (SIV), corresponding to GA genes. A good solution is equivalent to the high SI habitat while a poor solution is given by the low SI habitat. The value of the SI of a habitat in BBO is similar to the fitness of solution in the other optimization algorithms. In this work, BBO is used to generate discrete numbers i.e. 0 or 1 as such the variable values or SIVs in a habitat are represented as binary numbers. The set of all such vectors is the search space from which the optimum solutions are to be found. The value of the SI is found by evaluating the cost of function at the variables [$SIV_1, \ldots\ldots SIV_{Nvar}$]. Therefore, we have

$$SI = f(Habitat) = f(SIV_1 \ldots SIV_{Nvar}) \quad (7)$$

where *f (Habitat)* represents the value of cost or objective function. The emigration and immigration rates of each solution are used to probabilistically share information between habitats. Each solution is modified depending on the probability P_{mod} which is a user-defined parameter. In BBO, if a given solution is selected for modification, then its immigration rate λ is used to probabilistically decide whether or not to modify each SIV in that solution. If a given SIV is selected for modification, then emigration rates μ of other solutions are used to select which of the solutions should migrate a randomly selected SIV to solution S_i. Similar to other population-based optimization algorithms, elitism is introduced in the BBO to prevent the best p solutions from being corrupted by the migration operation. To this end, p best solutions are kept aside from the migration operation by setting their immigration rate λ equal to zero and therefore these are retained in the population from one generation to the next.

The SI of a habitat can change suddenly due to some cataclysmic events due to which the species count in a habitat changes rapidly from its equilibrium value. Therefore, these random events can result in an abrupt change in the SI of a habitat. This is modelled in the BBO as SIV mutation. The species count probabilities are used to determine the mutation rate. The probabilities of each species count are determined by the differential equation in (3). Every habitat member has an associated probability, which represents the chances that it exists as a solution for a given problem. The solutions having high SI and low SI are equally improbable. On the other hand, solutions with medium SI are relatively probable. If a given solution S has a low probability P_s, then it is surprising that it exists as a solution. It is, therefore, likely to mutate to some other solution. Conversely, a solution with a high probability is less likely to mutate to a different solution. This can be realized as a mutation rate m that is inversely proportional to the solution probability

$$m_s = m_{\max}\left(1 - \frac{P_s}{P_{\max}}\right) \quad (8)$$

where $m_{\max}$ is a user-defined parameter and P_s is a function of S. This mutation scheme is likely to increase the diversity of the population. Without this variation, the highly probable solutions will have a tendency to be more dominant in the population. This mutation operation makes both low and high SI solutions likely to mutate, which gives a chance of improving both types of solutions in comparison to their earlier value. Elitism is introduced so that the best solutions are retained in the population. Elitism helps in reverting back to an old solution (solution before mutation) if a solution is ruined by the mutation process [11]. The algorithm of BBO is shown in Figure 3.

The migration of species among a group of neighboring habitats, combined with mutation of the individual species, will have a propensity over many generations to produce habitats that attract and keep large numbers of species through immigration. Habitats with low SI lose species through the extinction or emigration and will sometimes become uninhabited. The BBO algorithm emulates this behaviour in a manner that causes an "optimal" habitat to come out from the original population of habitats.

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Create a random set of habitats (population) H1, H2,….. Hn;
Calculate SI values;
While the halting criterion is not satisfied do
    Compute immigration rate λ and emigration rate μ for each habitat based on SI;
    For each habitat (solution)
        For each SIV (solution feature)
            Select habitat Hi with probability α λi;
            If Hi is selected then
                Select Hj with probability α μj;
                If Hj is selected then
                    Hi (SIV) ← Hj (SIV);
                End if
            End if
            Select Hi (SIV) based on mutation probability mi;
            If Hi (SIV) is selected then
                Replace Hi (SIV) with randomly generated SIV;
            End if
        Next for
        Recalculate SI values;
    Next for
End while
```

Fig. 3. BBO algorithm

Similar to GA and PSO, BBO share its information between solutions. Therefore, BBO can be applied to many of the similar types of problems that GA and PSO are used for. But, BBO also has some distinct features which separates it from the other algorithms. One of them is that the original population is not discarded after each generation. It is rather modified by migration. Also, for each generation, BBO employs the fitness of each solution to determine its emigration and immigration rates [11].

4. DESIGN EXAMPLES

In this section, the proposed BBO algorithm is applied to the three CCAA with different numbers of elements. The goal of the synthesis of the antenna in this work is to determine array structure for having the radiation pattern with the minimum SLL and narrower beam width. This is done by manipulating the excitation current of the elements of each ring. The objective function to achieve the desired pattern using BBO is given by

$$F = w_1 * SLL + w_2 * BW \quad (9)$$

where w_1 and w_2 are the weighting coefficients, SLL and BW are he side lobe level (in decibels) and beam width (in degrees) In this work, the beam width is determined computationally from the radiation pattern data. The optimization problem can be summarized as the minimization of function F to obtain a set of element amplitudes $[I_{11}, I_{12}, ...I_{mn}]$. The values of the element amplitudes are allowed to vary between [0, 1]. The BBO algorithm is applied to three CCAA designs having of M=3 rings. For each CCAA design, the number of elements for the inner most ring is N_1, the middle ring consists of N_2 number of elements whereas for the outermost ring is N_3 The elements in each ring of CCAA are equally spaced (inter-element spacing) and the value of spacing is 0.55λ, 0.61λ and 0.75λ for first ring, second ring and third ring respectively. These spacings are optimized values of element spacing given in [9].The main lobe is steered at ϕ_0 =0. After many runs of the optimization, the following parameters that yield satisfactory results are chosen for the BBO algorithm as follows:

- Number of habitats or population : N_{pop} =150
- Iterations or Generations =120
- Mutation probability: m_{max}=.005
- Elitism parameter p =2
- Maximum Migration Rates E_b=1 and I_b=1
- w_1=1 and w_2=2

In the first case, the CCAA with three rings (M=3) and (N_1, N_2, N_3) = (4, 6, 8) elements is optimized with BBO. The number of parameters to be optimized are eighteen i.e. eighteen current element excitations of elements in each ring. The number of habitats is equal to the population size and it is taken as 150. Each habitat consists of eighteen SIVs made up of i.e.

$$X = (I_{11}, I_{12,} ...I_{14}, I_{21}, ...I_{26}, I_{31}, ...I_{38}) \quad (10)$$

The BBO algorithm is applied to the CCAA problem which consists of migration operator followed by mutation. The duplicate solutions are removed at each generation and restored with random mutations. The elitism operation is applied for preserving two fittest habitats from each generation. The stopping criterion for BBO is the maximum number of generations. The BBO method took around 13 minutes to complete this optimization on a computer with a Pentium Core 2 Duo and 2 GB of RAM. The results obtained for this optimization are given in Table 1. Along with the BBO results, the optimized excitations using a RGA [9], CRPSO [9], HEP [10] and uniform excited antenna are also listed for comparison. The maximum SLL obtained by BBO is -33.64 dB and the beam width is 28.6^0. Obviously, BBO offers improved SLL and beam width than other techniques. The SLL given by BBO is enhanced by -16.43 dB, -1 dB, -5.54 dB, and -1.21 dB than those by the uniform excited array, CRPSO, RGA, and HEP optimized arrays, respectively. The obtained beam width is also narrower by 0.8^0 0.2^0, 0.54^0, 0.4^0 than the uniform array, CRPSO, RGA, and HEP arrays respectively. The radiation pattern of the array obtained by BBO is plotted in the Figure 4 along with the radiation patterns of the uniform excited, the RGA and the CRPSO and the HEP methods.

Table 1. Normalized current excitations of CCAA with (N_1=4, N_2=6, N_3=8) elements

Method	Current excitations weights for the array elements (I_{11}, I_{12}, I_{13},……….. I_{mn})	
Uniform	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	SLL=-17.17 3dB BW=29.4
RGA[9]	0.3773 0.9491 0.3830 0.7861 0.5661 0.6932 0.9638 0.6275 0.5465 0.9349 0.4878 0.7220 0.5123 0.2850 0.6041 0.7300 0.5016 0.2799	SLL=-28.06 3dB BW=29.06
CRPSO[9]	0.0906 0.6250 0.0986 0.6904 0.4267 0.4139 1.0000 0.4145 0.4393 0.9604 0.4979 0.6600 0.4866 0.2423 0.5017 0.6475 0.5020 0.2387	SLL=-32.61 3dB BW=28.8
HEP[10]	0.0192 0.4230 0.0233 0.4009 0.2530 0.2507 0.6606 0.2746 0.2473 0.6098 0.2956 0.4095 0.3052 0.1664 0.3213 0.4082 0.3124 0.1514	SLL=-32.39 3dB BW=29
BBO	0.1105 0.6413 0.0964 0.6438 0.4017 0.3942 0.9661 0.3923 0.3981 0.9564 0.4699 0.6872 0.4646 0.2339 0.4680 0.6681 0.4738 0.2214	SLL=-33.64 3dB BW=- 28.6

In the next example, the BBO algorithm is employed to optimize a CCAA with three rings (M=3) and (N_1, N_2 N_3) = (6, 8, 10) elements for the same objective and parameters. The constraints are also the same as in the previous example. The results achieved are given in Table 2. These are again judged against with the results of uniform excited array, CRPSO [9], the RGA [9], and the HEP [10] methods. Again, the BBO has surpassed the other algorithms. The obtained maximum SLL is better by -10.73 dB, -1.75 dB, -1.64 dB and, -1 dB than those achieved by the uniform excited array, the CRPSO, the RGA and the HEP methods, respectively. Moreover, the beam width obtained by the BBO is smaller by .2^0, 2^0, than those by the CRPSO and the RGA methods, respectively. The optimized radiation pattern of the BBO array for this case is plotted in Figure 5. For comparison, the radiation patterns of the uniform excited antenna and antennas obtained by the RGA, the CRPSO, and the HEP techniques are also plotted in Figure 5. The radiation pattern clearly shows that BBO accomplishes excellent results.

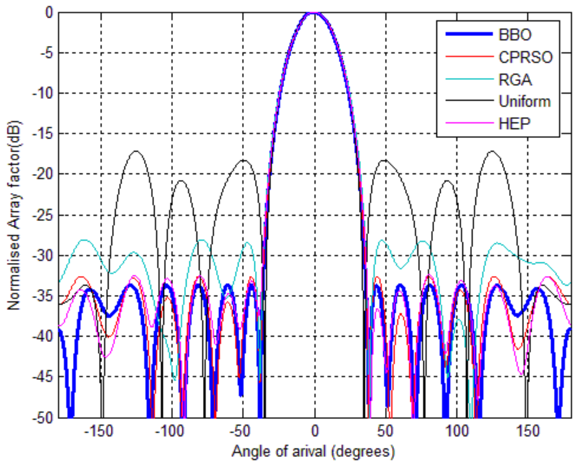

Fig. 4. Radiation pattern of CCAA (N_1=4, N_2=6, N_3=8)

In the last example, the BBO method is used to optimize a CCAA for three rings (M =3) and (N_1, N_2, N_3) = (8, 10, 12) elements. The results attained after optimization are shown in Table 3. Yet again, the BBO technique gives results which are better to the other algorithms. The maximum SLL is lower than those accomplished by the other algorithms. The improvement in the SLL is significant and it is lower by -14.7 dB, -1.8 dB, -2.6 dB, and -1.6 dB than those from uniform excited antenna and the optimized antennas by the the CRPSO [9], the RGA [9], and the HEP [10] techniques, respectively. The obtained beam width is also better than those accomplished by the CRPSO, the RGA, and the HEP techniques. It is narrower by 7.4^0, 0.4^0, and 0.2 as compared to CRPSO, RGA, and HEP optimized arrays respectively. The radiation patterns for the antennas obtained by BBO, uniform excited antenna, RGA, CRPSO and HEP are plotted in Figure 6. Certainly, BBO has again done better than the other techniques in obtaining the required antennas.

5. CONCLUSIONS

In this paper, the design of a non-uniformly excited concentric circular antenna array with uniform spacing between the elements has been illustrated using the BBO technique. As compared with previous published results of CRPSO and HEP, BBO has obtained better results. The design of CCAA using BBO offers improvement in SLL reduction along with reduced beam width. The main benefit of the BBO is its simplicity that provides an easy, quick, and efficient resolution of medium and large problems The BBO method has proved to be an efficient algorithm for the antenna optimization problems.

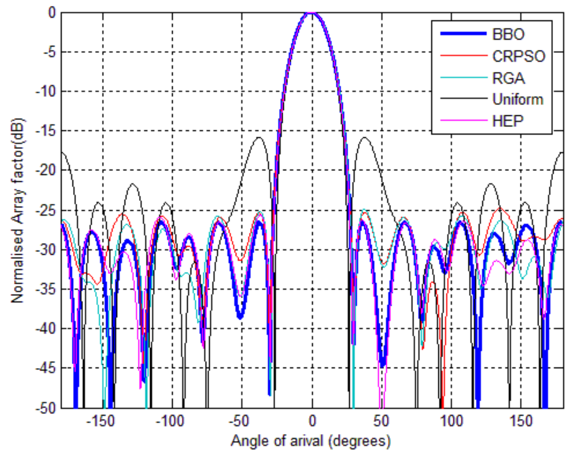

Fig. 5. Radiation pattern of CCAA (N_1=6, N_2=8, N3=10)

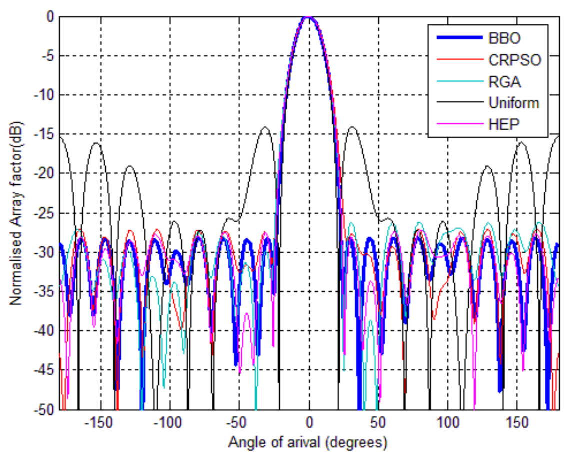

Fig. 6. Radiation pattern of CCAA (N_1=8, N_2=10, N_3=12)

Table 2. Normalized current excitations of CCAA with(N_1=6, N_2=8, N_3=10)elements

Method	Current excitations weights for the array elements (I_{11}, I_{12}, I_{13},……….. I_{mn})	
Uniform	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	SLL=-15.84 3dB BW=23.4
RGA[9]	0.5513 0.4810 0.6504 0.5254 0.7093 0.9878 0.9240 0.0206 0.7129 0.9853 0.8481 0.0006 0.8226 0.9933 0.4945 0.7770 0.6438 0.4928 0.6184 0.4075 0.9723 0.8552 0.4231 0.5006	SLL=-24.93 3dB BW=23.8
CRPSO[9]	0.6462 0.7146 0.8599 0.6331 0.5285 0.9829 0.9326 0 0.8051 0.9424 0.8323 0.0000 1.0000 0.9999 0.4039 0.8987 0.8780 0.3347 0.6025 0.5059 0.8089 0.8498 0.5761 0.6353	SLL=-24.82 3dB BW=23.8
HEP[10]	0.2539 0.1643 0.2535 0.1615 0.1837 0 .4012 0.4195 0 0.3601 0.5418 0.3092 0 0.4333 0.5739 0.1976 0.4085 0.4174 0.2424 0.3586 0.2639 0.3406 0.4188 0.2275 0.2450	SLL=-25.57 3dB BW=23.4
BBO	0.4073 0.2687 0.4759 0.2694 0.3495 0.6715 0.7029 0.0008 0.6814 0.9961 0.5479 0.0002 0.7029 0.9955 0.4055 0.6973 0.7377 0.4156 0.6119 0.4560 0.5953 0.6779 0.4317 0.4858	SLL=-26.57 3dB BW=23.6

Table 3. Normalized current excitations of CCAA with(N_1=8, N_2=10, N_3=12)elements

Method	Current excitations weights for the array elements (I_{11}, I_{12}, I_{13},……….. I_{mn})	
Uniform	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	SLL=-14.08 3dB BW=19.2 44
RGA[9]	0.7507 0.3438 0.7676 0.9471 0.8357 0.4322 0.8105 0.9816 0.4392 0.1996 0.2429 0.8479 0.5903 0.6827 0.0409 0.0649 0.9464 0.5148 0.5861 0.0744 0.9357 0.3858 0.4818 0.4177 0.2614 0.5137 0.9845 0.6134 0.3000 0.5170	SLL=-26.11 3dB BW=20
CRPSO[9]	0.6779 0.3910 0.6668 1.0000 1.0000 0.3036 0.9360 0.9757 0.5663 0.2201 0.2306 0.6152 0.6135 0.8425 0.1443 0.1248 0.6574 0.5085 0.4546 0.2234 0.9887 0.2936 0.4100 0.4502 0.3979 0.4542 1.0000 0.3310 0.4025 0.5632	SLL=-27.0223 3dB BW=27.023 54.40
HEP[10]	0.3356 0.1697 0.2629 0.2719 0.3039 0.1342 0.3562 0.4342 0.3223 0.0657 0.0444 0.1575 0.1418 0.1738 0.0445 0.0721 0.3286 0.2282 0.1509 0.1533 0.3812 0.0685 0.1776 0.1759 0.1427 0.1064 0.3736 0.1897 0.1265 0.1526	SLL=-27.20 3dB BW=20 54.40
BBO	0.5010 0.2061 0.7080 0.9853 0.7087 0.2578 0.4922 0.2692 0.1598 0.0875 0.0988 0.7985 0.5707 0.8017 0.1171 0.1028 0.1845 0.2894 0.2793 0.1256 0.8306 0.4473 0.3715 0.3938 0.3647 0.4450 0.8956 0.1373 0.2646 0.4306	SLL=-28.80 3dB BW=19.6 51.2

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