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IMPROVED ARTIFICIAL BEE COLONY FOR DESIGN OF A RECONFIGURABLE ANTENNA ARRAY WITH DISCRETE PHASE SHIFTERS

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Abstract—Multi-beam antenna arrays have important applications in the field of communications and radar. The reconfigurable design problem is to find the element in a sector pattern main beam with side lobes. The same excitation amplitudes applied to the array with zero-phase should be in a high directivity, low side lobe pencil shaped main beam. This paper presents a new method of designing a reconfigurable antenna with quantized phase excitations using an improved artificial bee colony, called IABC. Compared with subsequent quantization, experimental results indicate that the performance of the discrete realization of the phase-excitation value can be improved.

1. INTRODUCTION

The problem of reconfigurable antenna arrays involves radiating multiple patterns using a single power-divided network. In the past decades, this problem has been one of the most active and prolific research areas since the pioneering work of Bucci et al. [1, 2]. Moreover, this problem has also been a central and well studied problem with a strong engineering background in the field of manufacturing and telecommunications science [3, 4]. In order to solve this problem, many methods have been proposed to obtain the multi-pattern arrays in previous literatures [4–8].

Traditionally, exact algorithms such as branch and bound methods and mixed integer linear programming methods have been widely used in early days to solve the problem. However, because the computational time of these methods is always unacceptable, these

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methods can only solve problems of relatively small size. On the other hand, evolutionary algorithms perform population-based probabilistic searches with a high speed of convergence rate, and have been proved to be very successful in solving problems of large scale. When it comes to solve reconfigurable antenna problems, compared with traditional algorithms, evolutionary algorithms have the ability of obtaining excitation phases and amplitudes that can be practically implemented more easily by imposing additional constraints. So it is not uncommon, in the past decade, to see that different kinds of evolutionary algorithms, such as simulated annealing (SA) [4], genetic algorithm (GA) [5, 6], particle swarm optimization algorithm (PSO) [7, 8], and tabu search algorithm [9], have been advanced to handle reconfigurable antenna problems, especially for the problems of large scale.

Recently, artificial bee colony algorithm [15], ABC for short, is proposed as a population-based heuristic evolutionary algorithm inspired by the intelligent foraging behaviour of the honeybee swarm. In ABC, a honey bee colony consists of three kinds of bees: employed bee, onlooker bees, and scout bees. Among them, employed bees are responsible for exploiting the nectar sources explored before, sharing their information with onlookers within the hive, onlooker bees wait in the hive and decide on a food source to exploit based on the information shared by the employed bee colony, and scout bees choose one of the most inactive solutions and then replace it by a new randomly generated solution.

In evolutionary algorithm based antenna-array synthesis producers, phased excitations are always represented by continuous values, and discrete phase shifters are used to realize the phase excitation sometimes. Therefore, the excitation phase values obtained by these approaches are subsequently quantized to the nearest n-bit phase shifter excitation values. In order to solve the reconfigurable antenna array with quantized phase excitations, Baskar et al. proposed a mixed integer optimization method for the first time using an evolutionary search method, as called the generalized generation-gap model GA (G3-GA) [10]. The aim is to optimize real-valued amplitude excitations and quantized phase excitations [11]. Akdagli et al. proposed a method called the clone selection algorithm (CLONALG) to design a reconfigurable dual-beam linear antenna array with excitation distributions differing only in phase [12]. From the practical implementation viewpoints, the proposed method took discrete phase shifters into account during synthesis. However, GA and CLONALG usually trap into the local minima easily. In [13], we proposed a new method of designing a reconfigurable with quantized phase excitations using an evolutionary algorithm called differential evolution. Compared with the continuous realization and subsequent quantization, experimental results indicate better performance of the discrete realization of the phase-excitation value of the proposed algorithm.

In this paper, we propose a novel best search mechanism to improve original ABC algorithm. In this way, the newly generated candidate solutions are always around the random solutions of the previous iteration. Moreover, a controlled parameter is introduced to control the frequency of perturbation. By combing these methods, an improved algorithm as called IABC is proposed. Then we will use IABC to perform reconfigurable antenna array optimization with quantized phase excitations. In order to demonstrate the advantages of the proposed design, the results obtained using discrete-phase excitations followed are compared. Experimental results show our algorithm is both effective and efficient.

The rest of this paper is organized as follows: in Section 2 we will introduce the problem formulation. Section 3 describes the fitness function. Section 4 describes the ABC. Section 5 describes the improved ABC. Corresponding experimental results are given in Section 6. In the last section we conclude this paper and point out some future research directions.

2. PROBLEM FORMULATION

The problem described is as follows: in order to design a reconfigurable dual-beam antenna array, an amplitude distribution can generate either a pencil-shaped or a sector power pattern, when the phase distribution of the array is modified appropriately. All excitation phases are set to be 0° for the pencil-shaped beam, and vary in the range $-180° \leq \phi \leq 180°$ for the sector pattern [7]. If the excitation is symmetrical about the centre of the linear array, the array with even number of uniformly spaced isotropic elements ($2N$) can be written as [10]:

$$F(\theta) = 2\sum_{k=1}^{N} \left(a_{kR}\cos\phi_k - a_{kl}\sin\phi_k\right) \tag{1}$$

With

$$\phi_k = \frac{2\pi}{\lambda} d_k \sin\theta \tag{2}$$

where d_k is the distance between the position of the kth element and the centre, θ is the scanning angle from broadside, a_{kR} is the real parts of the kth element excitation, a_{kI} is the imaginary parts of the kth element excitation, and a_{kR} and a_{kI} are setted within the range [0, 1] and [−1, 1], respectively. N excitation amplitude and phase coefficients are chosen to optimize the desired pattern. The pencil and sector patterns have a high directivity; low side lobe pencil shaped main beam and a wide sector beam.

3. FITNESS FUNCTION EVALUATION

For the reconfigurable dual-beam optimization, the objective of the fitness function is to qualify the entire array radiation pattern. The calculated pattern can be described in terms of the criteria of the desired pattern. The fitness function for the dual-beam optimization can be described as follows [7]:

$$E(P) = \sum_{i=1}^{3} \left(P_{i,d}^{(p)} - P_i^{(i)} \right)^2 + \sum_{i=1}^{4} \left(P_{i,d}^{(s)} - P_i^{(s)} \right)^2 \quad (3)$$

where the superscript p is the design specification for the pencil pattern, the superscripts s is the design specification of the sector pattern, the superscript d indicates the desired value of the design specification, the superscript represents the ith individual, and P indicates the applicable fitness factor in Table 1. The first part of this fitness function is summarized in the first column of Table 1, and the other part of this function is summarized in the second column. Different from the fitness function of the pencil beam pattern, the sector pattern needs to calculate the pattern ripple.

In order to decrease the effect of coupling between elements, an additional term is included in the objective function Equation (4) [10]. The ratio is used to minimize the coupling effect between the maximum and minimum excitation amplitudes. The minimization of the amplitude-excitation dynamic range (ARD) can reduce the mutual coupling problem [17, 18]. The objective function can be expressed as

Table 1. Design specifications.

Design Parameters	Pencil Pattern	Sector Pattern
Side-lobe level (SLL)	−30 **dB**	−25 **dB**
Half-power bandwidth (HPBW)	**6.8°**	**24°**
Bandwidth at SLL	**20°**	**40°**
Ripple	**NA**	**0.5 dB**

follows:

$$Ec(P) = \sum_{i=1}^{3} \left(P_{i,d}^{(p)} - P_i^{(i)} \right)^2 + \sum_{i=1}^{4} \left(P_{i,d}^{(s)} - P_i^{(s)} \right)^2 + \mathrm{ADR} \quad (4)$$

where the superscript p is the design specification for the pencil pattern, the superscripts s is the design specification of the sector pattern, the superscript d indicates the desired value of the design specification, the superscript represents the ith individual, P indicates the applicable fitness factor, and ADR is the amplitude-dynamic ratio. The ADR is defined as the ratio between the maximum excitation amplitude to the minimum excitation amplitude. The differences among the excitation amplitudes are minimized by minimizing the ADR; therefore, the effect of coupling can be minimized.

4. ARTIFICIAL BEE COLONY

Artificial Bee colony is an evolutionary algorithm first introduced by Karaboga [15] in 2005. This algorithm simulates the foraging behavior of the bee colony. In this algorithm, the model of the ABC algorithm consists of three groups of bees: employed bees, onlooker bees, and scout bees. Main steps of the ABC algorithm simulating these behaviors are listed below:

procedure *Artificial bee colony Algorithm*

begin

Initialize

Repeat

Step 1: Move the employed bees onto their food sources and determine their nectar amounts.

Step 2: Move the onlookers onto the food sources and determine their necta-r amounts.

Step 3: Move the scouts for searching new food sources.

Step 4: Memorize the best food source found so far.

UNTIL (requirement are met)

end.

As we can see in the algorithm, each cycle of the search consists of three steps: moving the employed and onlooker bees onto the food sources, calculating their nectar amounts respectively, and then determining the scout bees and moving them randomly onto the possible food source. Here, a food source stands for a potential solution of the problem to be optimized. The ABC algorithm is an iterative algorithm, starting by associating all employed bees with randomly generated food solutions. The initial population of solutions is filled with SN number of randomly generated n dimensions. Let $X_i = \{x_{i1}, x_{i2}, \ldots, x_{\text{in}}\}$ represent the ith food source in the population, and SN be the number of food source equal to the number of the employed bees and onlooker bees. Each food source is generated as follows:

$$x_{ij} = LB_j + (UB_j - LB_j) \times r \tag{5}$$

where $i \in \{1, 2, \ldots, SN\}$ and $j \in \{1, 2, \ldots, n\}$ are randomly chosen indexes, r is a uniform random number in the range $[0, 1]$, and LB_j and UB_j are lower and upper bounds for the dimension j respectively.

Each employed bee x_{ij} generates a new food source v_{ij} in the neighborhood of its present position as follows.

$$\begin{aligned} v_{ij} &= x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}) \\ k &= \text{int}(\text{rand} * (SN - 1)) + 1; \end{aligned} \tag{6}$$

where $\varphi_{ij} = (\text{rand} - 0.5) \times 2$ is a uniformly distributed real random number within the range $[-1, 1]$, $i \in \{1, 2, \ldots, SN\}$, $k \in \{1, 2, \ldots, SN\}$ and $k \neq i$, and $j \in \{1, 2, \ldots, n\}$ are randomly chosen indexes. The new solution v_i will be accepted as a new basic solution, if the objective fitness of v_i is smaller than the fitness of x_i, otherwise x_i would be obtained.

When all employed bees finish this process, an onlooker bee can obtain the information of the food sources from all employed bees and choose a food source according to the probability value associated with the food source, using the following expression:

$$p_i = 0.9 \times \frac{\text{fitness}_i}{\max(\text{fitness}_i)} + 0.1 \tag{7}$$

where fitness_i is the fitness value of the solution i evaluated by its employed bee. Obviously, when the maximum value of the food source decreases, the probability with the preferred source of an onlooker bee decreases proportionally. Then the onlooker bee produces a new source according to Equation (6). The new source will be evaluated and compared with the primary food solution, and it will be accepted if it has a better nectar amount than the primary food solution.

After all onlookers have finished this process, sources are checked to determine whether they are to be abandoned. If the food source does not improve after a determined number of the trails "limit", the food source is abandoned. Its employed bee will become a scout and then will search for a food source randomly as follows:

$$x_{ij} = LB_j + (UB_j - LB_j) \times r \tag{8}$$

where r is a uniform random number in the range $[0, 1]$.

After the new source is produced, another iteration of the ABC algorithm will begin. The whole process repeats again till the termination condition is met.

5. IMPROVED ARTIFICIAL BEE COLONY ALGORITHM

Inspired by the differential evolution, in this section, we propose a best search mechanism to improve the original ABC algorithm. As we know, differential evolution is an evolutionary algorithm first introduced by Storn and Price [14]. Similar to other evolutionary algorithms, particularly genetic algorithm, DE uses some evolutionary operators like selection recombination and mutation operators. Different from genetic algorithm, DE uses distance and direction information from the current population to guide the search process. The crucial idea behind DE is a scheme for producing trial vectors according to the manipulation of target vector and difference vector. If the trail vector yields a lower fitness than a predetermined population member, the newly trail vector will be accepted and be compared in the following generation. Different kinds of strategies of DE have been proposed based on both the target vector selected and the number of difference vectors used. The following is a mutation strategy frequently used in the literature:

DE/rand/1:

$$v_i = x_a + F(x_b - x_c) \tag{9}$$

where a, b and c are mutually different random integer indices selected from $\{1, \ldots, SN\}$, and F is a positive real number denoting the scaling factor or amplification factor.

Based on DE algorithm and the property of ABC, we propose a novel best search mechanism to improve ABC:

$$\begin{aligned} v_{ij} &= x_{aj} + \varphi_{ij}(x_{ij} - x_{bj}) \\ k &= \text{int}(\text{rand} * (SN - 1)) + 1; \end{aligned} \tag{10}$$

where $\varphi_{ij} = (\text{rand} - 0.5) \times 2$ is a uniformly distributed real random number within the range $[-1, 1]$, $i \in \{1, 2, \ldots, SN\}$, $k \in \{1, 2, \ldots, SN\}$ and $k \neq i$, and $j \in \{1, 2, \ldots, n\}$ are randomly chosen indexes. The new search method can generate the new candidate solutions only around the random solutions of the previous iteration.

Akay and Karaboga [16] proposed a modified ABC algorithm by controlling the frequency of perturbation. Inspired by this algorithm, we also use a control parameter, i.e., modification rate (MR), in our algorithm. In order to produce a candidate food position v_{ij} from the current memorized x_{ij}, IABC algorithm uses the following expression:

$$v_{ij} = \begin{cases} x_{aj} + \varphi_{ij}(x_{ij} - x_{bj}), & \text{if } r_{ij} \le MR \\ x_{ij} & \text{otherwise} \end{cases} \tag{11}$$

where r_{ij} is a uniformly distributed real random number within the range [0, 1]. The algorithm can be described as follows:

procedure *Algorithm description of IABC*

begin

Step 1*: Set the generation counter $G = 0$; and randomly initialize a population of SN individuals X_i. Initialize the parameter limit.*

Step 2*: Evaluate the fitness for each individual in P.*

Step 3*:* ***while*** *stopping criteria is not satisfied* ***do***

%% ***employed bee colony***

for *$i = 1$ to NP*

Select randomly $a \neq b \neq i$

$$v_{ij} = \begin{cases} x_{aj} + \varphi_{ij}(x_{ij} - x_{bj}) & if\ r_{ij \le MR} \\ x_{ij} & otherwise \end{cases}$$

Apply the greedy selection process between v_i and x_j, select the better ones.

If the solution x_i, does not improve $trial_i = trial_i + 1$; Otherwise $trial_i = 0$.

end for

%% ***Onlooker bee colony***

$i = 1$;

$t = 0$;

which *$t \le NP$*

if *$rand < prob(i)$*

t=t+1;

Select randomly $a \neq b \neq i$

$$v_{ij} = \begin{cases} x_{aj} + \varphi_{ij}(x_{ij} - x_{bj}) & if\ r_{ij \le MR} \\ x_{ij} & otherwise \end{cases}$$

Apply the greedy selection process between v_i and x_i, select the better ones.

If the solution x_i does not improve $trial_i = trial_i + 1$; Otherwise $trial_i = 0$.

end if

$i = i + 1$

if *$i == NP + 1$*

$i = 1$;

end if

end while

*%% **Scout bee colony***
If $\max(\boldsymbol{trial_i} > \boldsymbol{limit})$
Replace x_i with a new randomly produced solution by
$x_{ij} = l_j + (u_j - l_j) \times r$
end if
Step 4 : end while
end

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6. SIMULATION RESULTS

To evaluate the performance of the IABC, an experiment is conducted in this paper. The benchmark problems for the experiments have also been used in [10]. In the experiment, for each instance, there are twenty design parameters. Among them, ten phase coefficients are represented as discrete variables, and the other ten are represented as continuous variables.

In the experiment, 10-phase excitations are indicated as quantized values corresponding to the n-bit phase shifter used. Therefore, the values of the phase excitation are quantized between $-180°$ and $180°$. For simulating IABC, the population size *SN* is 10, *MR* is 0.6, and the number of the maximum function evaluations is 20000. For simulating differential evolution algorithm and generalized generation gap GA (G3-GA), the population size *NP* is 20, the number of the maximum function evaluations is 20000, the crossover rate CR is 0.9, and the scale factor F is 0.5. In G3-GA, the number of the offspring $\lambda = 6$, the number of the maximum function evaluations is 20000, the population size *NP* is 500, and $\sigma_\alpha = \sigma_\beta = 0.25$. In order to compare the algorithms fairly, we set these algorithms the same fitness evaluations.

For each instance, the average running time on the 30 runs are recorded. The computational conditions are listed as follows.

System: Windows XP

* CPU: Intel(R) Core(TM) 2 Quad

* RAM: 1 G

* Language: Matlab

* Compiler: Matlab 7.0

6.1. Optimization without ARD and with ARD

In this section, we will use IABC to solve the reconfigurable antenna-array design without the coupling effects using the objective function (3), and to solve the problems with the coupling effects using the objective function (4). Table 2 shows the results of the excitation amplitude and phase. The best of optimal results for the experiment are also listed in Table 2. The Table also illustrates the ADR of the optimized excitation amplitudes and fitness function value. As can be seen in Table 2, the ARD is reduced from 7.13 without coupling effect to 4.26 with coupling effect. For the fitness, it reduces from 0.16 to 0.09. Therefore, we can reduce the coupling effects by minimizing the dynamic rang ratio. The optimized excitation patterns and dual-beam patterns without coupling effect are shown in Figures 1 and 2, respectively. Figure 2 illustrates the satisfaction of designed parameters simultaneously for both pencil and sector beam. Figures 3 and 4 show the excitation pattern and dual-beam pattern with coupling effect obtained in the experiment.

Table 2. Optimum results without ADR and with ADR.

Element Number	without ADR Amplitude	Phase[deg.]	With ADR Amplitude	Phase[deg.]
1/20	0.128	−174.3	0.227	−174.3
2/19	0.215	−162.9	0.227	−145.7
3/18	0.246	−151.4	0.234	−145.7
4/17	0.288	151.4	0.389	−111.4
5/16	0.454	−54.3	0.464	-111.4
6/15	0.572	60	0.620	111.4
7/14	0.636	−88.6	0.724	−65.7
8/13	0.825	−82.9	0.848	94.3
9/12	0.816	94.3	0.921	111.4
10/11	0.915	82.9	0.968	82.9
ADR	7.14		4.26	
Fitness value	0.16		0.09	

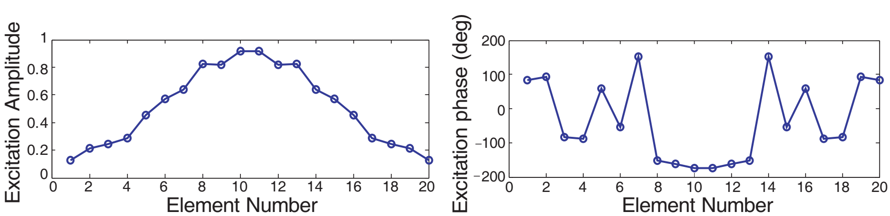

Figure 1. Dual-beam array pattern without coupling.

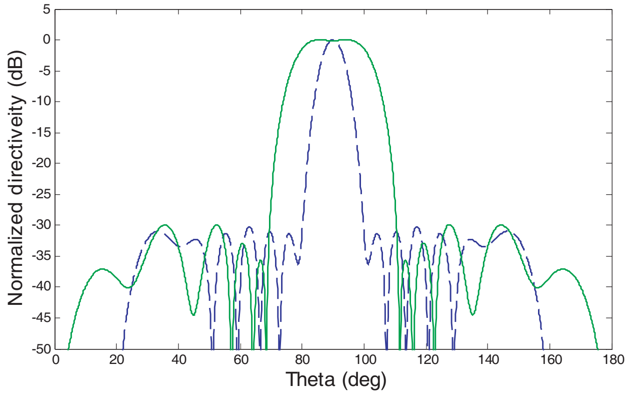

Figure 2. Amplitude and phase excitation without coupling effect.

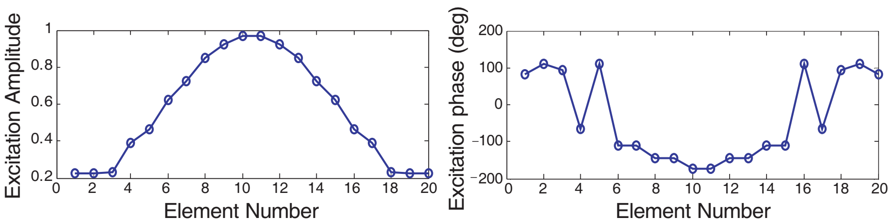

Figure 3. Amplitude and phase excitation with coupling effect.

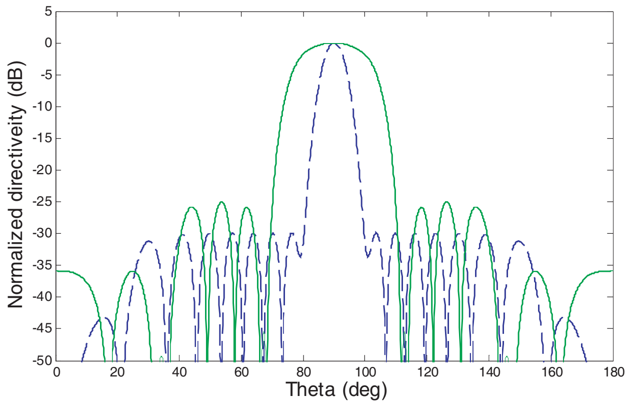

Figure 4. Dual-beam array pattern with coupling effect.

6.2. Comparison with IABC with DE, G3-GA [10] and MABC for Reconfigurable Antenna-array Design with Discrete Variable

In order to study the effect of the IABC, we carry out a scalability study to compare the algorithm with the generalized generation gap genetic

Table 3. Comparison of G3-GA, DE with IABC for reconfigurable antenna array with discrete variable.

Algorithm	without ADR fitness	with ADR ADR	fitness
G3-GA [10]	0.619	5.8026	0.2630
DE [13]	0.36	4.7190	0.16
MABC [16]	0.16	4.76	0.22
IABC	**0.16**	**4.26**	**0.09**

algorithm, differential evolution and modified artificial bee colony [16]. The experiment is conducted for the determination of amplitude and phase excitation patterns for the dual beam optimization with quantization. The best fitness is reported in Table 3. From Table 3, we can find that the IABC can obtain better solutions for the experiment, especially for the reconfigurable antenna-array design with the coupling effects. For the problems without the coupling effects, the IABC can obtain the value of o.16 better than the G3-GA's value of 0.618, the DE's value of 0.36 and the MABC's value of 0.36. By minimizing the dynamic ratio, we can find that the IABC can provide the 4.26 (ARD) and 0.09 (fitness) better than those of G3-GA, DE and MABC. This demonstrates IABC is well suitable to solve the dual beam optimization problem.

6.3. Comparison with IABC with DE, G3-GA [10] and MABC for Reconfigurable Antenna-array Design with Continuous Variable

In order to show the efficiency of the IABC, we compare the algorithms for reconfigurable antenna-array design with continuous variable. The experiment is conducted for the determination of amplitude and phase excitation patterns for the dual beam optimization. As can be seen in Table 4, we can find that the IABC can obtain better solutions for the experiment, especially for the reconfigurable antenna-array design with the coupling effects. For the problems without the coupling effects, all algorithms can find the best solutions. By minimizing the dynamic ratio, we can find the IABC can provide the 4.30 (ADR) better than those of G3-GA, DE and MABC. DE gives the better fitness than other algorithm. But, the smallest of the ADR + fitness is obtained by the IABC. This demonstrates IABC can better solve the dual beam optimization problem.

Table 4. Comparison of G3-GA, DE with IABC for reconfigurable antenna array with continuous variable.

Algorithm	without ADR fitness	with ADR ADR	fitness
G3-GA [10]	0.16	4.4137	0.1028
DE [13]	0.16	4.3470	**0.04**
MABC [16]	0.16	4.358	0.042
IABC	**0.16**	**4.302**	0.06

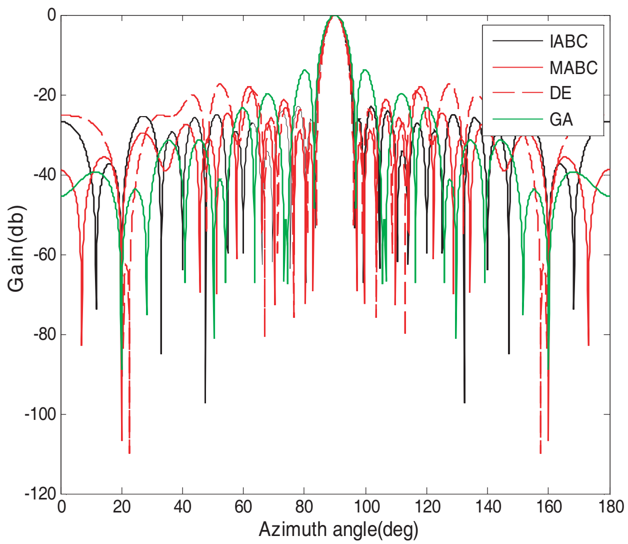

Figure 5. 13 Element array for minimum SLL [0°, 82°] and [98°, 180°] and NULL 20°.

6.4. Experimental Results of the Linear Antenna Array

In this experiment, for the artificial bee colony, MR is 0.6, limit = 100. The parameter of DE uses $F = 0.3$ and $C_r = 0.7$ over the problem. For genetic algorithm, crossover probability is 1, mutation probability is 0.01. For all algorithms, in order to comparison fair, the population size is 50 and the maximum fitness = 50000. In this case, we are required to design a 26 element array with minimum SLL in bands [0°, 82°] and [98°, 180°] and null direction in 20°. The array patter from IABC algorithm is shown in Figure 5, along with patterns obtained using other algorithms. From Figure 5, it is obviously that IABC suppresses

Table 5. Geometry of the 26 element linear array, normalized numbers with respect to $\lambda/2$ and null at 20°.

IABC	±0.337	±0.990	±1.589	±2.429	±2.675	±3.793	
MABC	±0.330	±0.979	±1.821	±2.039	±3.267	±2.897	
DE	±0.472	±1.049	±2.090	±2.058	±2.897	±3.799	
GA	±0.306	±1.253	±1.792	±2.545	±3.059	±3.452	
IABC	±4.206	±6.068	±5.272	±7.224	±8.237	±9.558	±11.114
MABC	±4.151	6.574	±7.749	±4.880	±5.799	±9.544	±10.909
DE	±4.825	±6.318	±5.373	±7.475	±8.61	±10.231	±11.558
GA	±4.369	±5.480	±4.3	±5.901	±6.961	±7.565	±8.684

Table 6. Mean final objective function value, standard deviation, best, worst, median, and the Rank for problem 2.

Algorithm	IABC	MABC	DE	GA
Mean	**0.0177**	0.0235	0.02763	0.0405
Best	**0.0131**	0.0182	0.01984	0.0223
Median	0.0167	0.252	0.02915	0.0403
Worst	0.0224	0.0291	0.03396	0.0663
std	0.0039	0.0044	0.00368	0.0120
Rank	1	2	3	4

the side lobes to the greatest extent. Moreover, it also generates lowest gain at the desired null of 20°. The position coordinates of the array elements (normalized to $\lambda/2$) are listed in Table 5. Table 6 shows the mean objective function values, best objective function values, worst objective function values, median objective function values, standard deviation obtained and ranks of the algorithms. Tables 5 and 6 show that IABC can beat all other algorithms for the same objective function.

7. CONCLUSIONS

In this paper, we propose a novel best search mechanism to improve original ABC algorithm. Moreover, a controlled parameter is introduced to control the frequency of perturbation of ABC. By combing these methods, an improved algorithm as called IABC is proposed. Application of IABC for the reconfigurable antenna array with quantized phase shifter is then discussed in this paper. The effectiveness of the proposed algorithm is demonstrated on the design of a reconfigurable antenna array with the quantized phase excitations, a reconfigurable antenna array with continuous variable and a linear array antenna. In order to reduce the effect of mutual coupling between the antenna-array elements, the dynamic range ratio is minimized. The simulation results clearly indicate superior performance of the proposed algorithm in comparison to some recent optimization algorithms. In ther future, we will devote to applying our algorithm to slove some realistic problems, and we hope that this paper will spark a new venue of research in the problem of solving reconfigurable antenna array.

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