Designing Nonuniform Antenna Arrays by Adaptive Variable Differential Artificial Bee Colony Algorithm

Xin Zhang[1,2], and Xiu Zhang[1,2*]

[1]Tianjin Key Laboratory of Wireless Mobile Communications and Power Transmission, Tianjin Normal University
[2]College of Electronic and Communication Engineering, Tianjin Normal University, Tianjin 300387, China
Corresponding author: zhang210@126.com

Nonuniform antenna array is very useful to attain narrow beam and low sidelobe, while keeping a low manufacturing cost. For the design of nonuniform antenna arrays, the positions of array elements, excitation amplitude and phase distribution are the key factors to be determined. Artificial bee colony algorithm (ABC) has shown good performance in solving electromagnetic inverse problems. However, the ABC algorithm costs too much number of iterations and converges slowly in the design of sparse nonuniform antenna arrays. This paper proposes an adaptive variable differential method for ABC (AVDABC). This method adaptively decides the number of decision variables to be mutated. Existing modified ABC algorithms employ the same search equation in one iteration. The proposed adaptive variable method assigns different search equations to chosen decision variables in one iteration. The proposed AVDABC algorithm is more diverse than existing ABC algorithms. Through numerical simulation on mathematical functions, AVDABC converges faster than ABC. Moreover, demonstrated by the design of sparse nonuniform antenna array, the AVDABC algorithm achieves promising performance than several existing ABC algorithms. Thus, the proposed algorithm is helpful to solve antenna array design problems.

Index Terms—Antenna design, artificial bee colony, differential vector, sparse antenna array

I. INTRODUCTION

NONUNIFORM SPACING antenna array has been studied for decades, though the synthesis of sparse nonuniform arrays is still not resolved. Given the number of array elements and array response, the synthesis refers to determine proper array element position and excitation distribution such that the resulting antenna array has minimal peak sidelobe level. These designs are usually formulated to nonlinear optimization problems [1].

As antenna array designs are simulation-based and their simulation often costs a long computer time. Swarm intelligence algorithms are suitable to solve such design problems [2]. Artificial bee colony (ABC) is a kind of swarm intelligence algorithm. It shows good performance in solving electromagnetic inverse problems. Standard ABC costs too much number of iterations to converge to optimal or desirable solution. Hence, it is not suitable for handling the design of nonuniform antenna arrays.

To accelerate the convergence rate of ABC algorithm, an adaptive variable differential method is proposed to promote gene information exchange among current solutions. The resulting algorithm is first tested on mathematical functions, and then is verified on a design example of sparse nonuniform antenna array, which is discussed in the following sections.

II. OPTIMIZATION ALGORITHM

In standard ABC algorithm, a feasible solution set is randomly created within search space. Denote N_s as the size of solution set. Without loss of generality, antenna array design is assumed to be a minimization model. The objective function values of N_s solutions are evaluated based on given minimization model. Smaller objective value is seen as a fitter solution than greater value. The target of ABC is to refine the initialized solutions as fitter as possible. The refining process is realized by the main cycle of ABC, which is comprised of employed bee stage, onlooker bee stage and scout stage.

In employed bee stage, $N_s/2$ honey bees are sent out exploring for new locations, which is carried out as follows:

$$v_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{n1}), \ i = 1,2, \ldots, N_s/2 , \quad (1)$$

where x_{ij} refers to the j-th decision variable of solution $\mathbf{x}_i$. Denote D as the number of decision variables of antenna design problem. Index j is randomly chosen between 1 and D.

In onlooker bee stage, probability values of all solutions are calculated according to their fitness. Fitter solutions are designated to higher probability than worse solutions. $N_s/2$ honey bees fly out to exploit solutions which are selected based on their probability values. The search of onlooker bees is carried out by the same equation as (1).

In scout stage, the number of scouts is determined by an algorithmic parameter called *limit*. This parameter counts the number of continuous search trials of a solution. If a solution is not refined in continuous *limit* iterations, it is discarded and replaced by a new solution. New solution is created by:

$$\mathbf{x}_i = \mathbf{x}_i^{min} + \mathbf{r}_i(\mathbf{x}_i^{max} - \mathbf{x}_i^{min}), \ i = 1,2, \ldots, N_s , \quad (2)$$

where search space Ω is surrounded by $\mathbf{x}_i^{min}$ and $\mathbf{x}_i^{max}$, $\mathbf{r}_i$ is a vector of random numbers generated between 0 and 1.

For standard ABC, the refining process is repeated until some desirable solutions are returned. It can be seen that a solution is mutated on one variable in each iteration, and employed bee stage and scout stage are good at exploring search space. This character makes the ABC algorithm ineffective in handling design problems with a large number of variables.

Convergence rate of the ABC algorithm could be accelerated from two aspects. One is to replace (1) and (2) by exploitative search equations. The other is to mutate multiple variables in each iteration. An adaptive variable differential

method is proposed to speed up the ABC algorithm from both aspects. The method is detailed as follows.

Two exploitative search equations are used:

$$v_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{n1}) + \varphi_{ij}(x_j^{best} - x_{n2}) \ , \qquad (3)$$

$$v_{ij} = x_{ij} + \varphi_{ij} f^{best}(x_{ij} - x_j^{best}) \ , \qquad (4)$$

where x_j^{best} is the j-th variable of the best so far solution and f^{best} is the fitness value of $\mathbf{x}^{best}$. Equations (3) and (4) could speed up the convergence of ABC as evolutionary search is guided towards to the best so far solution [3], [4].

As reported in literature, mutating multiple variables in an iteration is able to improve the performance of the ABC algorithm, though, mutating all variables in an iteration does not show performance improvement according to our preliminary experiment. The number of variables to be mutated in an iteration is adaptively generated based on Poisson distribution. In Poisson distribution, the number of mutating variables is discrete random variable, $\xi \sim P(u)$. Parameter u represents the average frequency of the number of mutating variables. The choice of u will be discussed in the next section.

In adaptive variable differential method, a number ξ_i is generated for each honey bee, if fitness improvement is obtained, ξ_i is kept and used in the next iteration of the honey bee; otherwise, a new number is generated for the honey bee.

III. NUMERICAL EXPERIMENT

A. Mathematical function

The adaptive variable differential ABC algorithm (AVDABC) is tested on Rastrigin function with numerous local optima. The target of this simulation is to find the relation of u and D.
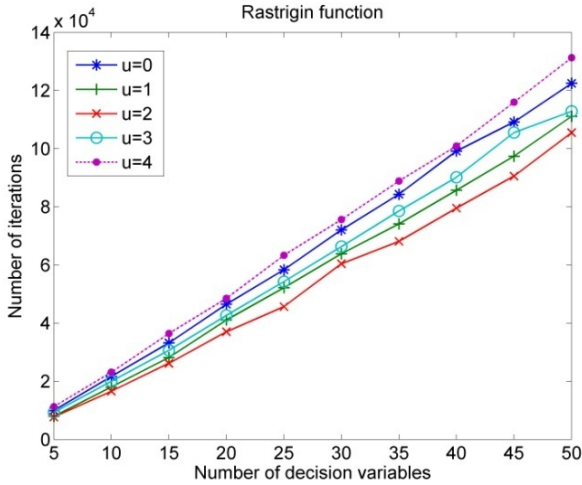

Fig. 1. The number of iterations cost by the AVDABC algorithm with different u values tested on Rastrigin function.

The results of AVDABC with different u values are shown in Fig. 1, where $u=0$ corresponds to standard ABC. It can be seen that the curves of AVDABC with $u=1$, 2, and 3 lie below standard ABC. This means AVDABC costs less iterations to reach global optimum of Rastrigin function than ABC. The results also suggest that $u=2$ should be the default setting for AVDABC.

B. Designing a sparse nonuniform antenna array

Given the number of array elements N and array aperture L, sparse nonuniform antenna array design can be formulated to:

$$\begin{aligned} \min \quad & f = \sum_{i=1}^{N} I_i e^{j\varphi_i} e^{jkw\,d_i} \mathrm{elpat}(i) \\ \text{s.t.} \quad & d_i - d_k \geq \mathrm{d_c} > 0, 1 \leq k < i \leq N \\ & w = \cos\theta - \cos\theta_0 \\ & \sum_{i=1}^{N-1} d_i = L \end{aligned} \qquad (5)$$

Where I_i and φ_i are the excitation amplitude and phase of the i-th array element, and d_i are the position of the i-th element. This model is simulated by setting N=17 and L=9.744λ, while I_i and φ_i are set as constant.

Both ABC and AVDABC algorithms are independently tested 10 times. The best peak sidelobe level attained by ABC is -18.57 dB, while AVDABC reaches -19.80 dB. This means that the proposed algorithm shows better performance than the ABC algorithm. Additional simulation results will be reported in the full paper.

IV. CONCLUSION

Designing sparse nonuniform antenna arrays is a nonlinear optimization problem. To solve such problem, an adaptive variable differential method is proposed under the paradigm of artificial bee colony algorithm, called AVDABC. Standard artificial bee colony (ABC) algorithm could not accomplish the task of solving the design of sparse arrays, because standard ABC converges slowly to the region of optimal solution and could not fulfill the requirements as antenna design is a time consuming task.

The proposed AVDABC algorithm is good at exploiting gene information of existing solutions. It adaptively decides the number of decision variables to be mutated in each iteration. Moreover, the chosen decision variables could conduct mutation based on different search formula. The goodness of AVDABC is demonstrated on an example of designing a sparse nonuniform antenna array. It attains promising performance compared with several modified ABC algorithms.

REFERENCES

[1] G. G. Lema, G. T. Tesfamariam, and M. I. Mohammed, "A novel elliptical-cylindrical antenna array for radar applications," *IEEE Trans. Antennas Propagat.*, vol. 64, no. 5, pp. 1681-1688, 2016.

[2] K. Choi, D. H. Jang, S. I. Kang, J. H. Lee, T. K. Chung, and H. S. Kim, "Hybrid algorithm combing genetic algorithm with evolution strategy for antenna design," *IEEE Trans. Magn.*, vol. 52, no. 3, Article No. 7209004, 2016.

[3] Xiu Zhang, Xin Zhang, S. L. Ho, and W. N. Fu, "A modification of artificial bee colony algorithm applied to loudspeaker design problem," *IEEE Trans. Magn.*, vol. 50, no. 2, Article No. 7018204, 2014.

[4] A. Banharnsakun, T. Achalakul, and B. Sirinaovakul, "The best-so-far selection in artificial bee colony algorithm," *Applied Soft Computing*, vol. 11, pp. 2888-2901, 2011.