An improved artificial bee colony algorithm

Yanfei Jia 1,2, a, Xin Wang 3, b and Xiaodong Yang 4, c

¹ College of Electrical and Information, Beihua University, Jilin, China

⁴ Collaborative Research Center, Meisei University, Tokyo, Japan ^a63378617@qq.com, ^b516104653@qq.com, ^cgyoto.yo@meisei_u.ac.jp

Keywords: Artificial bee colony algorithm, chaotic mapping, local optimal value, exploration

Abstract. To improve the performance of artificial bee colony algorithm, a modified artificial bee colony algorithm is proposed. The modified ABC algorithm takes advantage of chaotic mapping to enhance diversity in the bee population, uses information of a better solution to guide the search of candidate solutions toward a promising direction that improves exploitation, and introduces a global solution into the scout stage in order to jump out of the local optimal value. The modified ABC algorithm balances exploration and exploitation, which contradict each other, so that it can achieve optimal performance. Simulation results show the proposed method has more accuracy than the other methods.

1 Introduction

In the recent years, the popular swarm intelligent algorithm, artificial bee colony (ABC) algorithm that is drawn from the intelligent foraging behavior of honey bee is proposed by Karabog [1]. Since the ABC algorithm is simple in concept and structure, is easy to implement, has few control parameters, and has outstanding performance, it has been widely used in many fields, such as optimal filters, chaotic systems, optimal power flow, and blind source separation [2-5]. It was also applied to classify remote sensing images, constraint multi-objective evolutionary, and SVM parameter optimization [6-8]. Karaboga uses ABC method to optimize a large number of test functions [9]. Vafadarnikjoo utilizes ABC to solve the problem of assigning cells to switches in the personal communication services networks [10]. However, the existing ABC algorithms are still insufficient to handle the solution search equation. The search equation of ABC algorithm is good at exploring and bad at exploitation. To further improve the performance of ABC, it is necessary to establish a balance between the two abilities. Therefore, we propose a modified artificial bee colony algorithm by introducing new search mechanisms.

2 Improved ABC algorithm

It is well known that both exploration and exploitation are necessary for population-based optimization algorithms; however, in practice, exploration and exploitation contradict each other. In order to achieve optimal performance, both capabilities should be well balanced.

Initialization of the population is an important part of the evolutionary algorithm, which not only affects convergence speed, but also the quality of the final solution. Since chaotic motion [2] can traverse all states within the specified range without repetition by its own "laws", we fully extract and capture the solution space by chaotic mapping to enhance diversity in the bee population.

In chaotic theory, one-dimensional Logistic mapping is widely used, for which the mathematical equation is:

$$\lambda_{t+1} = \mu \times \lambda_t (1 - \lambda) \tag{1}$$

² College of Information and Communication Engineering, Harbin Engineering University, China

³ Grid information & telecommunication group, Beijing China power information technology CO.LTD, China

where T is a preset maximum number of iterations, λ_r is a random number in the range [0,1] and $\lambda_0 \notin \{0,0.25,0.5,0.75,1\}$, and μ is a control parameter. When $\mu = 4$, the system is completely in a chaotic state.

First, a set of chaotic variables λ_i is generated by equation (1). Second, SN food sources are mapped to the chaos interval $[X_{\max}, X_{\min}]$ according to equation (4) by using the chaotic sequence. X_{\max} and X_{\min} represent the upper and lower bounds of X_i . Finally, the new initialization formula is described as follows:

$$X_{i,j} = X_{\min,j} + \lambda_{i,t} \times (X_{\max,j} - X_{\min,j})$$

$$\tag{2}$$

The merits of evolution strategy have a critical influence on exploration and exploitation; however, in practice, these two abilities are mutually contradictory. The question of how to adjust the search strategy to balance exploration and exploitation, and to improve algorithm accuracy, is a key issue in this study. In the ABC algorithm, X_{kj} is selected at random, which leads to good performance in exploration, but poor exploitation, making these two abilities unbalanced. In order to solve this problem, the following improvement strategies are proposed:

$$S_{ij} = \frac{Fit_{best} \cdot X_{best,j} + Fit_i \cdot X_{i,j}}{Fit_{best} + Fit_i}$$
(3)

$$V_{ij} = X_{best,i} + (X_{i,j} - X_{ki})\phi_{ij} + (S_{ij} - X_{ij})\phi_{ij}$$
(4)

where $j \in \{1, 2, \dots, D\}$, $k \in \{1, 2, \dots, SN\}$ and $k \neq i$, SN is the number of the initial solution and is equal to one-half the number of bees, Fit_{best} is the fitness value of the *best* solution, $X_{best,j}$ is the *j*th individual of the best solution in each iteration, Fit_i is the fitness value of the *i*th solution, $X_{i,j}$ is the *j*th individual in X_i , $X_{k,j}$ is the *j*th individual in X_k , ϕ_{ij} is a random number in the range [-1,1], and ϕ_{ij} is a random number in the range [0,1].

As observed in (3)-(4), the best solution in each iteration can drive the new candidate solution towards the best solution; therefore, the modified search equation can improve exploitation, and at the same time, the new equation maintains the advantage of selecting solutions randomly and ensures diversity in the population. In order to establish a balance between exploration and exploitation, S_{ij} is introduced to the search equation, on one side, which guides the search toward the promising region and away from being trapped in a local optimum. On the other hand, it reduces the guiding role of the optimal solution to a certain extent, which avoids good exploitation but poor exploration.

In the ABC algorithm, when a solution cannot be improved in a predetermined cycle, it is abandoned since this solution has fallen into a local optimum value. The next generation will search new sources near the extreme value, which is straightforward in a state of stagnation. This not only weakens the ability to explore the population, but also hinders the entire population's convergence to the global optimal value. By taking into account that the nature of scouts is to escape from the local optimal value, a global optimal solution is introduced to update the solution. In this way, the bee population will jump out of the local optimal value. The modified equation is described as follows:

$$V_{bj} = \varphi_{ij} X_{gbest,j} + (X_{gbest,j} - X_{bj}) \phi_{ij}$$

$$\tag{5}$$

where $X_{gbest,j}$ is the *j*th individual of the global optimal solution, X_{bj} is the *j*th individual of the solution that is not improved at present, and φ_{ij} and ϕ_{ij} are the same as above.

3 Simulation and discussion

In order to evaluate the performance of the modified algorithm GBABC, we use six benchmark functions with D=5 or D=30 [11], as listed in Table 1 and Fig 1. By comparing the performance of GBABC, ABC[1], and ABCbest [11], it is shown that the proposed algorithm has higher precision and stability. Simulations were completed in Matlab 7.0. Some of the parameters are set as follows:

population scale is 100, number of limit is 50, the three algorithms are run 20 times for each benchmark function, and all of the best values of the functions are zero.

As shown in Table 1, the optimized results of the three algorithms obtained with three benchmark functions are listed, and the mean and standard deviation are recorded. The mean shows the precision and speed of convergence, and the standard deviation reflects the stability of the algorithm. Results show that when the dimension increases from 5 to 30, exploitation of the GBABC algorithm is all enhanced compared with ABCbest and ABC. For Schwefel and Rosenbrock functions, all compared ABC algorithms can obtain similar results, GBABC also overcomes ABC and ABCbest algorithms in general. For Griewank function, GBABC outperforms than any other compared algorithms.

Table 1 Comparison of performance among time argorithms			
Function	Method	Mean	Std
Schwefel	GBABC	1.5605e-03	1.0586e-03
(D=5)	ABCbest	1.5617e-03	8.1077e-03
	ABC	7.7653e-03	5.5648e-03
Rosenbrock	GBABC	1.1213e-03	3.1613e-03
(D=5)	ABCbest	1.2837e-03	3.2844e-03
	ABC	5.8421e-02	4.4883e-02
Griewank (D=5)	GBABC	0	0
	ABCbest	0	0
	ABC	3.3862e-14	4.7731e-14
Schwefel (D=30)	GBABC	4.6632e-03	4.3822e-03
	ABCbest	4.2456e-02	3.2342e-02
	ABC	4.9873e-01	8.3431e-01
Rosenbrock	GBABC	1.0011e-02	6.4832e-03
(D=30)	ABCbest	3.5011e-01	7.7621e-01
	ABC	5.7372e-02	2.6853e-02
Griewank (D=30)	GBABC	3.3861e-13	2.4873e-13
	ABCbest	1.7674e-10	2.5125e-10
	ABC	1.3492e-08	7.4678e-09

Table 1 Comparison of performance among three algorithms

4 Conclusion

In order to analyze voltage flicker, a new ICA algorithm is proposed based on a modified ABC algorithm (GBABC). The major contribution of this paper is that the proposed ABC algorithm can achieve good exploration and better exploitation by adopting chaotic mapping for initialization. The search strategies have been improved for employed bees and the onlookers phase. A global optimal solution has been introduced to guide the search direction for scouts, in order to avoid falling into local optimal solutions. The simulation results show that new proposed ABC algorithm has good performance than other ABC algorithms in most case. It may be also worthy to apply other optimization algorithms such as NSGA-II, NSGA-III, MOPSO [12-13] to optimize ICA algorithm.

Acknowledgement

In this paper, the research was sponsored by the Foundation of Jilin Educational Committee (2017135).

References

- [1] Karaboga Dervis, Basturk, B. On the performance of artificial colony algorithm [J]. Applied soft computing, 2008 8(1) 687-697.
- [2] Vural R A, Yildirim T, Kadioglu T. Performance Evaluation of Evolutionary Algorithms for Optimal Filter Design[J]. IEEE Transactions on Evolutionary Computation, 2012 16(1)135-147.

- [3] Gao W F, Liu S Y, Jiang F. An improved artificial bee colony algorithm for directing orbits of chaotic systems[J]. Applied Mathematics & Computation, 2011 218(7)3868-3879.
- [4] Liu Q, Huiming X U, Chao S. Research on power flow optimization based on multi-objective artificial bee colony algorithm[J]. Dianli Xitong Baohu Yu Kongzhi/power System Protection & Control, 2015 43(8)1-7.
- [5] Zhang Y X, Tian X M, Deng X G. Blind Source Separation Based on Modified Artificial Bee Colony Algorithm[J]. Acta Electronica Sinica, 2012 40(10)2026-2030.
- [6] M.Cao, Z. L. Shi, J. Y. Yang; A innovative method to classify remote sensing images using artificial bee colony algorithm [J], Acta Geodaetica et Cartographica Sinica, 2013 42(5) 745-750.
- [7] Xiao-Jun B I, Wang Y J. Constraint multi-objective evolutionary algorithm based on artificial bee colony algorithm[J]. Journal of Jilin University, 2013 43(2)397-403..
- [8] Ming Y U, Yue-Qiao A I. SVM parameter optimization and application based on artificial bee colony algorithm [J]. Journal of Optoelectronics Laser, 2012 23(2)374-378.
- [9] Karaboga D, Akay B. A comparative study of Artificial Bee Colony algorithm [J]. Applied Mathematics & Computation, 2009 214(1)108-132.
- [10] Vafadamik joo A, Khatami M, Mobin M, Roshani A. A Meta-Heuristic approach to locate optimal switch locations in cellular mobile networks [C]. Proceedings of the 2015 American Society of Engineering Management Conference (ASEM2015), Indiana, USA, 2015. 203-212.
- [11] Gao W F, Huang L L, Liu S Y, et al. Artificial Bee Colony Algorithm Based on Information Learning[J]. IEEE Transactions on Cybernetics, 2015 45(12) 2827-2837.
- [12] Zhaojun Li, Mohammadsadegh Mobin, Thomas Keyser. Multi-Objective and Multi-Stage Reliability Growth Planning in Early Product-Development Stage [J]. IEEE Transactions on Reliability, 2016 65(2)769-781.
- [13] Mobin M, Mobin M, et al. Multi-objective control chart design optimization using NSGA-III and MOPSO enhanced with DEA and TOPSIS [J]. Expert Systems with Applications An International Journal, 2016 50(C)17-39.