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***Journal of Scientific and Engineering Research*, 2019, 6(9):87-91**

Research Article

ISSN: 2394-2630
CODEN(USA): JSERBR

Artificial Bee Colony Algorithm Based on Double Search Strategy

Zhigang Wang

School of Mathematics, Nanjing Normal University, Taizhou College, Jiangsu, China

Abstract Artificial bee colony (ABC) algorithm is an intelligent optimization algorithm which imitates the foraging behavior of honey bees. It has been widely used in many engineering fields. However, like other evolutionary algorithms, ABC algorithm also has the disadvantages of easy falling into local optimum and slow convergence speed. In order to solve these issues, a modified artificial bee colony algorithm based on double search strategy is proposed in this paper. The employed bees and the onlooker bees adopt double search strategy to generate new food source, this method can balance the exploration and the exploitation ability. In addition, we use a more robust calculation to determine and compare the quality of alternative solutions. The comparison results on 8 standard test functions show that the proposed algorithm has higher convergence precision and stronger stability than other ABC-based algorithms.

Keywords Artificial bee colony algorithm; Search strategy; Benchmark function

1. Introduction

In the past decades, people have developed numerous optimization algorithms to deal with complex optimization problems, such as ant colony optimization (ACO) [1] inspired by the foraging behavior of ant colonies, particle swarm optimization (PSO) [2] inspired by the social behavior of bird flocking or fish schooling, grey wolf optimization(GWO) [3] inspired by the social hierarchy and hunting behavior of grey wolves. Inspired by the swarm foraging specific intelligent behavior, Karaboga proposed artificial bee colony algorithm [4] in 2005 becoming the newest and the most popular swarm intelligence optimization algorithm. ABC algorithm has many advantages compared with other optimization algorithm, such as less control parameters, great global optimization ability and easy to carry out. Thus, ABC algorithm was used widely to solve the issues of combinatorial optimization and parameter optimization [5-10]. However, ABC algorithm also faces some problems, such as easy fall into local optimum when solving the complex unimodal problems and the convergence rate is slower than PSO, differential evolution (DE) or other representative optimization algorithms. These weaknesses have limited the pervasive application of ABC algorithm.

To improve the performance of the ABC algorithm, some ABC variations have been proposed. To mention a few, Zhu and Kwong proposed a gbest-guided ABC algorithm [11] guided by global optimum, which merged the information of current best solution with the search strategy of the candidate solution. Gao et al. [12] proposed two ABC-based algorithms that use two update rules of differential evolution called ABC/Best/1 and ABC/Best/2. Gao and Liu [13] was inspired by the differential evolution algorithm, artificial bees searched only around the current optimal solution for enhancing the exploitation. Wang et al. [14] proposed the MEABC algorithm to improve the local and global search capability of the basic ABC algorithm. Banharnsakun et al. [15] described best-so-far selection in ABC algorithm which shared the optimal solution ever discovered in the whole colony and improved the solutions of onlooker bees to make its new candidate solutions get closed to the optimal solution.

In this work, we propose a modified artificial bee colony algorithm based on double search strategy. In our method, the employed bees and the onlooker bees adopt double search strategy to generate new food source. We name the artificial bee colony algorithm based on double search strategy as ABCDSS algorithm for short. In addition, the comparison and the selection of the new solutions are changed from a fitness-based comparison to an objective-valued based.

We organize the rest of this paper as follows. The description about the ABC algorithm is in section2. Section 3 introduces the ABC algorithm based on double search strategy. The experiments and their results are provided in Section 4. Finally, Section 5 offers our conclusions.

2. Artificial bee colony algorithm

ABC algorithm is a newly proposed optimization technique which simulates the intelligent foraging behavior of honey bee swarms. In ABC algorithm, a colony involves three different classes of bees: employed bees, onlooker bees and scout bees. Employed bees are responsible for exploiting the food sources and sharing the information about these food sources. Onlooker bees wait in the hive and take the food source information from employed bees to make a decision on further exploiting the food source. Scout bees randomly search the environment to find a new food source. The position of a food source represents a solution of the optimization problem, and the nectar amount of each food source is the fitness of the corresponding solution. The first half of the colony includes employed bees, and the second half consists of onlookers.

At the beginning, the ABC algorithm generates a randomly distributed population of SN solutions (food source), where SN also represents the number of employed bees or onlooker bees. let $x_i = (x_{i,1}, x_{i,2}, \cdots, x_{i,D})$ represents the i th food source in the population, where D is the number of parameters to be optimized. Each food source is generated within the limited range of j th index by

$$x_i^j = x_{\min}^j + rand(0,1)(x_{\max}^j - x_{\min}^j) \tag{1}$$

where $i = 1, 2, \cdots, SN$, $j = 1, 2, \cdots, D$. $x_{\min}^j$ and $x_{\max}^j$ are the lower and upper bounds for the index j, respectively. $rand(0,1)$ is a random real number within the range $[0,1]$.

In ABC, an employed bee uses the following search strategy to generate a candidate solution v_i from the old one x_i.

$$v_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}) \tag{2}$$

where $j \in \{1, 2, \cdots, D\}$ and $k \in \{1, 2, \cdots, SN\}$ are chosen indexes randomly; k is different from i; φ_{ij} is a random real number in $[-1,1]$. A greedy selection is applied between x_i and v_i by retaining the better one. Then, employed bees will return to their hive and share the information on new solutions with on looker bees.

Onlooker bees select a food source depending on the probability value P_i associated with that food source. The value of P_i is calculated for the i th food source as follows:

$$P_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{3}$$

$$fit_i = \begin{cases} \dfrac{1}{1+f_i}, & f_i \geq 0 \\ 1 + |f_i|, & f_i < 0 \end{cases} \tag{4}$$

where $i = 1, 2, \cdots, SN$ and fit_i is the fitness value of the solution x_i. By using this mechanism, these food sources that have better fitness values will be more likely to be selected for update. Once the onlooker bee chooses the food source, it generates a new solution using Eq. (2). Similar to the employed bees, a greedy selection is carried out between x_i and v_i.

If a food source cannot be improved for a predetermined number of cycles, named *limit*, it is abandoned and the corresponding employed bee becomes a scout bee. The scout bee generates a new food source using Eq. (1).

3. Artificial bee colony algorithm based on double search strategy

According to the solution search equation of ABC algorithm described by Eq. (2), the coefficient φ_{ij} is a random number in the range $[-1,1]$ and x_k is a random individual in the population, therefore, the solution search strategy described by Eq. (2) is good at exploration but poor at exploitation. To improve exploitation ability of the ABC algorithm, literature [12] proposed a modified solution search strategy as follows:

$$v_{ij} = x_{best,j} + \varphi_{ij}(x_{ij} - x_{kj}) \tag{5}$$

where x_{best} is the global best solution of the population.

Based on the above search strategies, we propose a modified solution search strategy for employed bees and onlooker bees as follows:

$$v_{ij} = \begin{cases} x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}) & rand(0,1) < P_1 \\ x_{best,j} + \varphi_{ij}(x_{ij} - x_{kj}) & otherwise \end{cases} \tag{6}$$

where P_1 is a real number in the range $[0,1]$.

Note that the parameter P_1 plays an important role in balancing the exploration and exploitation. When P_1 takes 1, Eq. (6) is identical to Eq. (2); when P_1 takes 0, Eq. (6) is identical to Eq. (5). When P_1 decreases from 1 to 0, the exploration of Eq. (6) will also decrease correspondingly, but the exploitation of Eq. (6) will increase. Therefore, in the early stage, P_1 should be larger to increase exploration, it can prevent bees from falling into the local minimum. At a later stage, P_1 should be smaller to search for local optimum effectively. The parameter P_1 is given as follows:

$$P_1 = 1 - FE / Max.FE \tag{7}$$

where FE is the number of function evaluation, $Max.FE$ is the maximum number of function evaluations.

4. Numerical experiments and results

To investigate the performance and accuracy of the ABCDSS algorithm, the ABCDSS algorithm is applied to optimize 8 benchmark functions with $D = 30$, as shown in Table 1. Summarized in Table 1 are these benchmark functions. $f_1 - f_2$ are the unimodal functions, f_3 is the discontinuous step function, and f_4 is the noisy quartic function. f_5 is the Rosenbrock function which is unimodal for $D = 2$ and 3 but may have multiple minima in the high dimensional cases. $f_6 - f_8$ are multimodal and the number of their local minima increases exponentially with the problem dimension.

The comparisons among ABC algorithm, GABC algorithm [11], ABCbest1 algorithm [12], ABCbest2 algorithm [12], MABC algorithm [13] and ABCDSS algorithm are conducted on 10 benchmark functions. In all simulations, the population size is 40 (i.e., $SN = 20$), *limit* is $SN * D$, the number of maximum function evaluations is set to 150000. All the results reported in this section are obtained based on 30 independent runs.

The mean and the standard deviation of the results get by each algorithm are summarized in Table 2. According to Table 2 results, it can be seen that the compared methods have most reliably found the minimum of the function f_3. It is a region rather than a point in f_3 that is the optimum. Hence, this problem relatively be easy to solve with a 100% success rate. For the rest of the functions, ABC algorithm performs best on function f_5.

GABC algorithm, ABCbest1 algorithm, ABCbest2 algorithm, MABC algorithm and ABCDSS algorithm perform better than ABC algorithm on most benchmark functions.

Table 1: Benchmark functions used in experiments

Function	Search range	Min
$f_1(x)=\sum_{i=1}^{D}x_i^2$	[-100,100]	0
$f_2(x)=\max_i\{\lvert x_i\rvert,1\le i\le D\}$	[-100,100]	0
$f_3(x)=\sum_{i=1}^{D}(\lfloor x_i+0.5\rfloor)^2$	[-100,100]	0
$f_4(x)=\sum_{i=1}^{D}ix_i^4+\text{random}[0,1)$	[-1.28,1.28]	0
$f_5(x)=\sum_{i=1}^{D-1}[100(x_{i+1}-x_i^2)^2+(1-x_i)^2]$	[-10,10]	0
$f_6(x)=0.5+\dfrac{\sin^2\left(\sqrt{\sum_{i=1}^{D}x_i^2}\right)-0.5}{\left(1+0.001\sum_{i=1}^{D}x_i^2\right)^2}$	[-100,100]	0
$f_7(x)=\dfrac{1}{4000}\sum_{i=1}^{D}x_i^2-\prod_{i=1}^{D}\cos(\dfrac{x_i}{\sqrt{i}})+1$	[-600,600]	0
$f_8(x)=20+e-20\exp\{-0.2\sqrt{\dfrac{1}{D}\sum_{i=1}^{D}x_i^2}\}-\exp\{\dfrac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\}$	[-32,32]	0

Table 2: Result comparisons of ABCS on 30-dimensional basic functions

Fun	Metric	ABC	GABC	ABCbest1	ABCbest2	MABC	ABCDSS
f_1	Mean	5.19E-16	4.62E-16	3.11E-47	5.96E-35	9.43E-32	1.19E-52
	Std	8.21E-17	7.12E-17	3.44E-47	3.61E-35	6.67E-32	3.53E-52
f_2	Mean	7.82E-01	2.18E-01	2.18E+00	3.55E+00	1.02E+01	2.04E-01
	Std	3.50E-01	4.01E-02	3.27E-01	4.79E-01	1.49E+00	5.73E-02
f_3	Mean	0	0	0	0	0	0
	Std	0	0	0	0	0	0
f_4	Mean	4.90E-02	2.03E-02	2.06E-02	2.53E-02	3.71E-02	1.95E-02
	Std	8.52E-03	5.74E-03	4.75E-03	4.67E-03	8.53E-03	4.32E-03
f_5	Mean	4.07E-02	3.21E-01	1.49E+01	5.45E+00	6.11E-01	7.31E-02
	Std	3.88E-02	8.21E-01	2.87E+0	8.40E+00	4.55E-01	2.41E-01
f_6	Mean	3.30E-01	2.66E-01	2.39E-01	2.81E-01	2.95E-01	2.32E-01
	Std	3.64E-02	4.39E-02	6.13E-02	3.92E-02	3.17E-02	4.99E-02
f_7	Mean	6.46E-11	3.70E-17	0	1.81E-08	0	0
	Std	3.25E-10	5.32E-17	0	6.29E-08	0	0
f_8	Mean	3.72E-14	3.20E-14	3.01E-14	3.07E-14	4.13E-14	2.89E-14
	Std	3.20E-15	3.36E-15	2.91E-15	3.43E-15	2.17E-15	3.23E-15

5. Conclusion

This work proposed a novel artificial bee colony algorithm based on double search strategy, called ABCDSS algorithm. The employed bees and the onlooker bees adopt double search strategy to maintain the balance between exploitation and exploration in ABCDSS algorithm. A suite of unimodal/multimodal benchmark functions were employed in order to benchmark the performance of the proposed algorithm. The results show that the ABCDSS algorithm was able to provide highly competitive results compared to other ABC-based algorithms. As a consequence, it is desirable to further apply ABCDSS to solve those more complex real-world optimization problems, such as clustering, data mining, design and optimization of communication networks. How to extend ABCDSS to handle the combinatorial optimization problems is also very interesting.

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