Research on Performance of Artificial Bee Colony Algorithm Based on Benchmark Test Function

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Abstract. Because the artificial bee colony (ABC) algorithm has problems of poor development ability, slow convergence rate and easy to fall into local optimum, an improved ABC algorithm is proposed. The algorithm combines the global optimal guidance strategy, we propose a new location update formula to improve the efficiency of the iterative optimization process, and introduce the mining coefficient in the formula to improve the accuracy of global optimization. In addition, the beta distribution is introduced during the scouting bee phase, which improves the disturbance ability of the algorithm and prevents it from falling into local extremum effectively. Finally, the simulation results of four benchmark functions of Sphere, Rastrigin, Rosenbrock and Griewank show that compared with the traditional algorithm and other improved artificial bee colony algorithm, the proposed algorithm has faster convergence speed and better optimization ability.

1. Introduction
Artificial Bee Colony (ABC) is a stochastic global optimization algorithm proposed by D. Karaboga in 2005[1]. Compared with other optimization algorithms, it has few control parameters, easy implementation, good stability, and strong global search ability, and has been widely used in image signal processing, feature selection, resource scheduling and other scenarios [2]. However, in the process of optimization, when approaching the global optimal solution, the step size of the search strategy is too large, so that it is easy to skip the optimal value and oscillate around the value, thereby reducing the search speed. In addition, for optimization problems with many extreme points. ABC algorithm is easy to fall into local optimum [3].

Based on the above problems, many scholars have proposed improvement schemes on the basis of the original ABC algorithm in recent years. For example, Wang et al. uses dynamic adjustment of the dimension of the search to improve the search efficiency, and combines the characteristics of different search strategies of the ABC algorithm to co-evolve to balance the local search ability and global search ability of the algorithm[4]. Lin et al. adopted dynamic search strategy in the observation stage to achieve the balance between search ability and development ability. In the stage of detecting bees, chaotic variable disturbance is introduced to increase the diversity of the population, so as to realize the global optimum[5]. Zhou et al. generated the new food sources through orthogonal experimental design which enabled the scout bees can save the available information of the abandoned food source and the global optimal solution in different dimensions, so as to improve the search efficiency of the algorithm[6]. Zhao et al. used the current optimal individual as the guidance simplex method to conduct neighborhood search, which enhances the local search ability and adopts the optimal strategy to speed up the convergence of the algorithm[7]. Xiong et al. selectd leading bees by way of two-way
roulette, and adopted the adaptive step size strategy of firefly algorithm in the local search, which improved the convergence speed of the algorithm and enhances the local search ability of the algorithm[8]. The IABC algorithm proposed in the literature [9] uses the maximum and minimum distance product to initialize the bee colony to overcome the randomness of the original ABC algorithm initialization, and uses the new fitness function and the position update formula with global guiding factor to improve the efficiency of iterative optimization.

The improved algorithms in the above documents can improve the performance of the ABC algorithm, but one method cannot effectively solve each problem. In view of the search strategy and the drawbacks that are easy to fall into local optimum. In this work, we propose an ABC algorithm with faster convergence speed and stronger local search ability.

2. Standard artificial bee colony algorithm

ABC algorithm is an optimization algorithm inspired by the intelligent foraging behavior of bee colonies [10]. The algorithm divides the bee colony into three groups according to the different division of labor: employed bee, observation bee and scouting bee [11]. The employed bee is responsible for searching the food source and the observation bee decides the food source to be mined next according to the food source information sought by the employed bee. The scouting bee randomly searches the environment around the hive to find a new food source. If the fitness value of a food source is not updated within the specified number of iterations, the food source will be abandoned by the employed bee, and the employed bee will be turned into a scout to search for a new food source. The location of each food source represents a viable solution to the optimization problem [12].

In the ABC algorithm, we assume that \( N \) is the food source \( \{x_1, x_2, \ldots, x_N\} \), every food source \( x_i \) (\( i=1,2,\ldots,N \)) is a \( d \)-dimensional vector, the maximum number of search cycles is \( \text{Max.Limit} \), the mining limit for each honey source is \( \text{Limit} \). The flow of the ABC algorithm is as follows:

**Initialization phase:** generate a randomly distributed initialized population, the initial position of the food source is generated according to Eq (1):

\[
x_{ij} = x_{\text{min},j} + \text{rand}(0,1)(x_{\text{max},j} - x_{\text{min},j})
\]

where \( x_{\text{min},j} \) and \( x_{\text{max},j} \) are the lower and upper bounds of the solution space, respectively.

**Employed bee phase:** the employed bee is responsible for searching in the neighborhood of the food source and generating a candidate food source according to Eq (2).

\[
V_{ij} = x_{ij} + r_{ij}(x_q - x_k)
\]

where \( V_{ij} \) represents the location of the updated food source. \( k \in \{1,2,\ldots,N\} \), both \( k \) and \( j \) are random numbers. \( r_{ij} \in [-1,1] \) is a random number, which can be used to control the neighborhood range of the search.

**Observation bee phase:** the employed bees share information about the honey content and location of the food source to the observation bee through the swing dance. Based on the roulette principle, the observation bee decides whether to follow the employed bee through the Eq (3). Subsequently, the observation bee will generate a new food source according to Eq (2) in the food source neighborhood, and save the good quality food source by comparing the advantages and disadvantages of the two food sources.

\[
p_i = \frac{\text{fitness}_i}{\sum_{i=1}^{N} \text{fitness}_i}; i = 1,2,\ldots,N
\]
where $fitness_i$ is the fitness of the food source $i$, and $p_i$ is the probability that the bee chooses to employed bee.

Scouting bee phase: if the employed bee does not update the food source after a continuous cycle, the food source is discarded and turned into a scout bee, and the new food source position is randomly generated by the Eq (1).

3. Improved artificial bee colony algorithm

3.1 Location update equation

The location update equation determines whether the bee can quickly and accurately find a new source of honey. Equation (2) has strong search ability, but its exploration ability is weak, and it has the disadvantages of blindness and low convergence rate when searching for neighborhoods. In response to this problem, this paper will introduce the global optimal guiding factor based on the original equation. The improved equation is shown in Eq (4):

$$V_{ij} = x_{best,j} + \lambda r_{ij} \left( \frac{x_{best,j} + x_{ij}}{2} - x_{ij} \right)$$

where $r_{ij} \in [-1, 1]$ is a random number, $\lambda$ is the mining coefficient, $x_{best,j}$ is the global optimal solution.

Equation (2) can only obtain the historical optimal position and current position information in the neighborhood search, and lacks the global optimal consideration for the bee colony. The first term on the right side of Eq (4) can speed up the convergence of the algorithm to the optimal solution, and the second term replaces the current solution with a linear combination of the current optimal solution and the current solution. In this way, the useful information of itself and the global position can be fully utilized to guide the bees in the population to approach the optimal solution, so that the direction and purpose of the bee search are more clear.

Inspired by Ref [13], the value of the cosine function varies between $[-1, 1]$, which can reduce the impact of the jump caused by the difference, to control the search quality of the bee, thereby improving the accuracy of the global optimization of the algorithm. Based on this, equation (4) can be further improved to:

$$V_{ij} = x_{best,j} + \cos \left( \frac{x_{best,j} + x_{ij}}{2} / x_{ij} \right) r_{ij} \left( \frac{x_{best,j} + x_{ij}}{2} - x_{ij} \right)$$

Note that the equation (5) for observation bee phase is very similar to the equation in Ref [14], namely:

$$V_{ij} = \left( x_{best,j} + x_{e,j} \right) / 2 + \phi_{e,j} \cdot \left( x_{best,j} - x_{k,j} \right)$$

Compared with Eq (6), equation (5) uses the current optimal solution as the first term of the equation, which makes the observation bee approach the optimal honey source, accelerates the convergence speed of the algorithm, and the control of the cosine function makes the algorithm more accurate.

3.2 Scouting bees search for new solutions based on beta distribution

The beta distribution is introduced in the scouting stage to increase the perturbation ability of the algorithm so that it can jump out of the local optimum. The beta distribution refers to a set of continuous probability distributions defined in the $(0, 1)$ interval. The probability density function of the beta distribution is shown in Eq (7):
\[ f(x; a, b) = \frac{x^{a-1}(1-x)^{b-1}}{B(a,b)} \]  

(7)

where parameter \(a, b > 0\). It can be seen from Fig. 1 that when the parameter \(a, b\) takes different values, the probability density function of the beta distribution can fit different probability distributions.

The specific expression of the scout bee search is shown in Eq (8). Add the adjustment factor \(\mu\) before betarnd function to control the search level so that the value of the search level is more reasonable.

\[ x_{ij} = x_{\text{min},j} + \text{rand}(0,1)(x_{\text{max},j} - x_{\text{min},j}) + \mu \text{betarnd}(a, b) \]  

(8)

4. Simulation and analysis

The simulation experiment is based on the Windows 10 version 64-bit operating system and is programmed by Matlab R2019a.

In order to verify the performance of the improved algorithm, the proposed algorithm is simulated with the original ABC algorithm and the IABC algorithm in Ref [9] on the four benchmark functions of Sphere, Rastrigin, Rosenbrock and Griewank, and the simulation results are analyzed. Each test function is shown in Table 1. For fair comparison, the relevant parameter settings of each algorithm are equal, where the population size is 20, the number of honey source update limit \(\text{Limit}\) is 100, the maximum number of \(\text{cycles}\) is 2000, \(\mu\) is 0.1, \(a\) is equal to 1, and \(b\) is equal to 2. The fitness curve of the four benchmark functions is shown in Figure 2-5.

| Function  | Search range | Minimum value |
|-----------|--------------|---------------|
| Sphere    | [-100,100]   | 0             |
| Rastrigin | [-5.12,5.12] | 0             |
| Rosenbrock| [-100,100]   | 0             |
| Griewank  | [-600,600]   | 0             |
It can be seen from Figs. 2-5 that the original ABC algorithm converges slowly on four test functions, and ABC algorithm is easy to fall into local optimum. Compared with the original ABC algorithm, the Ref [14] algorithm has a significantly faster convergence rate and fewer iterations, but it still lacks in global optimization. The improved algorithm in this paper adopts a new location update formula, which effectively avoids the blindness when searching for neighborhoods, and makes the direction and purpose of bee search more clear. By introducing the beta distribution, the algorithm is easy to jump out of local extremum. Therefore, it can be seen from Fig. 2 and Fig. 4 that the algorithm can find a better position. In Fig. 3 and Fig. 5, the algorithm has the least number of iterations in the process of finding the optimal position, which saves the running time of the algorithm.

5. Conclusion
In order to improve the shortcomings of ABC algorithm development, slow convergence and easy to fall into local optimum, a global optimal guidance strategy is proposed and a beta distribution is introduced. The optimization results of the four benchmark functions show that the improved artificial bee colony algorithm has faster convergence speed, fewer iterations and better optimization precision. The next step is to use the improved algorithm in this paper for the study of image super-resolution reconstruction.
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