A Modified Artificial Bee Colony Algorithm for Function Optimization Strategy

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Abstract. Artificial Bee Colony (ABC) algorithm has received wide attention due to the outstanding performance in solving complex optimization problems. However, the further application of ABC is still hindered due to some bottlenecks, such as slow convergence velocity, poor global search ability and low accuracy of solution. To overcome these problems, an improved ABC (CT-ABC) is proposed in this paper by using both a chaotic map and a tolerance based search equation (TSE). Some standard test functions are chosen to verify the performance by implementing the proposed modified ABC algorithm, basic ABC and another modified ABC (WABC). Simulation results reveal the proposed CT-ABC algorithm is able to obtain the faster convergence speeds and better accurate approximate solution.

1. Introduction
Swarm Intelligence (SI) [1] is briefly defined as the self-organizing, adaptive, and social division of labor as well as intelligent behavior of social life in group living creatures. Being a classical SI algorithm, ABC was proposed by Karaboga in 2005, which based on the bees foraging behavior [1]. Compared to other SI algorithms, ABC has shown good features and signs. However, some clear disadvantages such as “slow convergence and low accuracy of solutions” [2], hinder the further researches of ABC. In order to address these shortages, an improved ABC (CT-ABC) is proposed in this manuscript to improve the convergence speed and accuracy of solutions as well as balance exploration and exploitation ability by using chaotic map to adjust the inertial weight and tolerance based search equation (TSE) to help the colony get grid of the local optimum.

To verify the feasibility and properties of CT-ABC, four famous standard benchmark functions are applied to test CT-ABC’s performance and results are compared with basic ABC and one ABC variant (WABC). The rest of this paper is arranged as follows: in Section 2, the original ABC algorithm is presented. Section 3 described and analyzed the proposed CT-ABC in detail, which include three parts. The simulation experiments are conducted and results are discussed in Section 4. The conclusion of research and future study is summarized in Section 5.

2. Basic artificial bee colony algorithm
In ABC algorithm, there are three kinds of bees [1-6]: employed bees, onlooker bees, and scout bees. Employed bees take charge of moving nectar to the hive and dancing in waiting area to share information of nectar source with onlooker bees. Onlooker bees wait in the hive to get information
from employed bees and decide which food source to select. Scout bees searched the new food source in the neighbourhood of the hive [2-5].

The fundamental steps of basic ABC algorithm are described as follows:

1. Initialization of parameters \((N, D, \text{Limit}, \text{iter}, \text{iter}_{\text{max}})\);

2. Generate the initial solutions \(X^*_n (m = 1, 2 \cdots, N)\)

\[
X^*_n = X^*_{\min} + \text{rand} (0, 1)(X^*_n - X^*_{\min})
\]  

3. Search new solutions in the neighbourhood;

\[
\text{new}_n X^*_n = X^*_n + \text{rand} (0, 1)(X^*_n - X^*_i)
\]  

4. Update the solutions according to Greedy Selection;

\[
\text{new}_n X_n = \begin{cases} 
1, & f(\text{new}_n X_n) \geq f(X_n) \\
0, & f(\text{new}_n X_n) \leq f(X_n)
\end{cases}
\]  

5. Onlooker bees choose the employed bees to follow;

\[
P_n = \frac{\beta_n}{\sum_{k=1}^{N} \beta_k}
\]  

6. After limit times search, the solutions still no update. The employed bee will transform into scout bees, and generate a new solution randomly.

\[
X^*_n (k) = X^*_{\max} + \text{rand} (0, 1)(X^*_{\max} - X^*_{\min}), \text{Bas}_n \geq \text{Limit}
\]  

3. The proposed modified artificial bee colony

In this section, three improved strategies are utilized to modified the original ABC. First, an inertial weight based adjustment strategy is applied to enhance the diversity of the nectar resource. Second, a chaotic map is selected to tune inertial weight. Thirdly, a tolerance based search equation (TSE) is proposed to avoid the colony from sinking into local optimum and change the search direction a when it needs.

3.1. Inertial weight based ABC

In order to improve the diversity of the nectar source, Lei et al, add an inertial weight \(\omega\) to the basic ABC, which was inspired by PSO evolution equation and its improving strategy. This process can be defined by equations (6) and (7) as follow:

\[
\text{new}_n X^*_n = \omega X^*_n + \text{rand} (0, 1)(X^*_n - X^*_i)
\]  

\[
\omega = (\omega_{\text{start}} - \omega_{\text{end}}) \times (\text{iter}_{\max} - \text{iter}) / \text{iter}_{\max} + \omega_{\text{end}}
\]  

Where \(\omega_{\text{start}}\) is the initialized value of inertial weight, and \(\omega_{\text{end}}\) is the final value. iter stands for the number of iteration, and \(\text{iter}_{\max}\) is the max iteration number of the algorithm [6].

In conclusion, this strategy can transfer the local searching process of colony into global searching and mean while balances the two sides, which can make the converge process close the optimal solution more effectively.
3.2. Chaotic map and tolerance search equation based adjustment mechanism
The chaotic map has the characteristics of sensitivity, non-repetition and ergodicity; It can help the algorithm to increase the population diversity and achieve high-quality solutions. Here, we choose sine map to tune inertial weight [5]. The logistic equation is given as follows:

\[ a_{k+1} = A \cdot \sin(\pi a_k), \quad a_k \in (0,1), \quad 0 < A \leq 1, \quad k = 1,2,\cdots,M_{\text{max}} \]  

(8)

Where \( k \) is the current iteration number.
In the basic ABC, the employed bees will abandon the original food source when it can’t be updated with limit times search, which will decrease the accuracy of solution. So, we propose a tolerance based search equation to decide when we need adjust the search direction. The tolerance search equation as follows:

\[ P_{c} = \frac{\exp(T) - 1}{\exp(10) - 1} \]  

(9)

Where \( P_{c} \) is the probability of making adjustments. If \( P_{c} > \text{rand()} \), the colony will abandon the original food source and adjust its search direction.

With the help of chaotic map and TSE strategies, the algorithm can make full use of the potential leading ability to help the colony step out of the local optimum.

4. Experiments

4.1 Test problems
In this section, in order to verify the validity of the proposed CT-ABC algorithm, we apply four classical benchmark functions as test functions. Descriptions for the aforementioned test problems are listed in Table 1, where D is the solution space dimension, Opt denotes the global optimum[2,4-7].

\begin{table}[h]
\centering
\begin{tabular}{|l|l|l|l|}
\hline
Function & Formulation & Search range & Opt & D \\
\hline
Sphere & \( f_1(x) = \sum_{i=1}^{D} x_i^2 \) & \([-100,100]\) & 0 & 30 \\
rosenbrock & \( f_2(x) = \sum_{i=1}^{D-1} [100(x_{i+1} - x_i)^2 + (x_i - 1)^2] \) & \([-30,30]\) & 0 & 30 \\
rastrigin & \( f_3(x) = \sum_{i=1}^{D} [x_i^2 - 10 \cos(2\pi x_i) + 10] \) & \([-5.12,5.12]\) & 0 & 30 \\
griewank & \( f_4(x) = \frac{1}{4000} \sum_{i=1}^{D} x_i^2 - \prod_{i=1}^{D} \cos(\frac{x_i}{\sqrt{i}}) + 1 \) & \([-600,600]\) & 0 & 30 \\
\hline
\end{tabular}
\caption{Five classic benchmark functions in experiments}
\end{table}

4.2. Comparison of CT-ABC with ABC and WABC
The comparison results on the solution accuracy and convergence speed including mean fitness value and value’s standard deviation (std) which are listed in Table 2 [7]. We mark the best mean of the objective values on each test functions with bold font, and mark the best standard deviations of them with underlined.
Table 2. Results of the basic ABC, WABC, CT-ABC over classic benchmark functions

|   | ABC         | WABC        | CT-ABC       |
|---|-------------|-------------|--------------|
| $f_1$ | Mean: 71.4394, Std.: 67.4375 | Mean: 59.3259, Std.: 57.1724 | Mean: 55.1843, Std.: 52.1769 |
| $f_2$ | Mean: 3.23684e-07, Std.: 2.01436e-13 | Mean: 2.41975e-06, Std.: 1.69174e-17 | Mean: 1.03776e-05, Std.: 1.01436e-09 |
| $f_3$ | Mean: 13.569, Std.: 12.134 | Mean: 12.651, Std.: 10.087 | Mean: 11.363, Std.: 9.542 |
| $f_4$ | Mean: 15.3759e-11, Std.: 14.2517e-13 | Mean: 5.1963e-09, Std.: 3.2751e-11 | Mean: 4.7407e-06, Std.: 2.6524e-19 |

As the results shown in Table 2, we can see that no matter in the mean of fitness value or the standard deviation, CT-ABC can achieve the best value compared to other two algorithms. So we can get the initial conclusion that proposed strategies can help the original ABC to improve the accuracy of solution, as well as solve existed poor global search ability problem.

Fig. 1 (a-d) Convergence curves of ABC, WABC, CT-ABC on first four (f1-f4) test functions.

Fig. 1 graphically present the convergence characteristics of ABC, WABC, as well as CT-ABC on four selected test functions. Through analyzing the experiment result of Sphere function in Fig.1 (a), we can find in the first 50 iterations three algorithms almost achieved the same solution, however CT-ABC performed much better than other two algorithms in the following process except an abnormal change between the 400 - 440 iterations. From Fig.1 (b) we can see in the rosenbrock function, the
proposed CT-ABC can achieve the best solution in each iteration of the whole process. Both ABC and WABC fall into local optimum in the early time of the optimization, respectively, in 100th and 350th iteration. After comparing the performance of CT-ABC with ABC and WABC in Fig.1 (c) and (d), we can see CT-ABC has a better performance in both griewank and rastrigin functions. The experimental results confirm that proposed strategies can significantly improve the accuracy of solution and increase the convergence speed on all test functions.

5. Conclusion and future study
In the present work, in order to enhance the search performance of ABC and acquire good global solution, we proposed a modified ABC algorithm which is based on chaotic map inertia weight adjustment strategy and tolerance-based search equation (TSE). To verify the performance of CT-ABC, we compared it with basic ABC and inertial weight-based ABC on four representative test functions. Experimental results show that the CT-ABC combined chaotic map strategy and TSE strategy can get better convergence accuracy as well as faster convergence speed.

As future work, the study of CT-ABC algorithm will be expanded to include modifying the way of getting initial solution. In addition, the CT-ABC algorithm will be applied to various optimization fields such as pattern recognition and artificial intelligence, etc.

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