An Improved Artificial Bee Colony Algorithm and Its Application in Machine Learning

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Abstract. In order to effectively overcome the problems and shortcomings of the basic improved artificial bee colony algorithm in solving the optimization accuracy of complex standard test functions, the low accuracy of the solution function and the large blindness of the local search strategy, a more basic improved artificial bee colony is proposed. Parameter optimization algorithm. The above artificial bee colony algorithm introduces the conjugate gradient method with strong local optimization search strategy performance in the follow bee stage of the basic improved artificial bee colony algorithm to change the optimization search strategy, and replaces the blind search strategy with a local deterministic optimization search strategy. The sexual optimization search reduces the randomness, enhances the local certainty of the food source of the follower bee and the optimization search ability, and ensures that each update of the follower bee's food source will quickly be substantially improved. This improved artificial bee colony algorithm is widely used in parameter optimization of traditional dengue virus propagation model. The simulation results of the improved standard test function on the problem show that the improved artificial bee colony parameter optimization algorithm has higher optimization and solution function accuracy during simulation than the basic improved artificial bee colony parameter optimization algorithm. The obtained standard test the parameter output corresponding to the dengue virus model parameter output is in good agreement with the actual situation when the data is simulated.

Keywords: Artificial bee colony algorithm; parameter optimization; machine learning.

1. Introduction

In the past two decades, in order to solve the highly complex optimization algorithm search problem, inspired by bioengineering, many crowd artificial intelligence optimization methods have been researched and developed, such as genetic algorithm, ant colony algorithm, particle Swarm algorithm and advanced artificial intelligence bee colony global optimization algorithm, etc. The artificial bee colony global optimization algorithm (ABC) algorithm is a relatively new swarm intelligence optimization method proposed by Carabobo in 2005 based on the research of human bee colony
activities and foraging behavior. It solves various complex algorithm optimization in artificial intelligence. The problem shows that it shows good algorithm search performance. The ABC artificial bee colony algorithm has many advantages such as its few control parameters, strong exploration ability, and easy design and implementation of the algorithm, so it has great potential for application and research. However, for the scale, complexity and scope of the swarm intelligence optimization algorithm problem that continues to expand, the ABC artificial bee colony algorithm also shows its shortcomings, mainly in that as the scale of the global optimization algorithm becomes larger, the speed is slower to converge to the global optimal algorithm solution and the performance of the algorithm search is also poor. Therefore, many experts and scholars have made some important improvements to the three key aspects of the global optimization algorithm after research, and have achieved excellent scientific research results in practice. Among them, in the stage of population initialization, in order to effectively reduce the search time and effectively prevent the population from falling into a local optimal solution, some researchers have used the tent chaotic mapping algorithm to make the population reach an initialized and as uniform Gaussian distribution as possible. At the same time, in order to improve the search global accuracy and convergence of the initialization algorithm, some researchers initialized the application of reverse learning and chaotic mapping algorithms for the initialization population. In the mechanism of determining the cross selection direction, in order to avoid the population flying in the wrong direction, some researchers have effectively adopted the particle swarm cross selection algorithm based on the sorting and testing cross selection mechanism in the stage of initializing the overall population update, and effectively The cross selection method of sorting and exponential increase is used to dynamically adjust the selection pressure [1]. However, some scholars have systematically analyzed and used the mechanism of particle swarm cross selection in the application of differential evolution algorithm to adjust the method of selection pressure to improve the accuracy and precision of the algorithm. In the direction of the search mechanism, in order to avoid the population from falling into a local optimum, some researchers use the method of adjusting the adaptive accuracy of the population through the Gaussian distribution algorithm and use the advantages of the differential evolution operator to make up for the difficulty and limitations of the search, and obtain more precision. High optimal solution. At the same time, some researchers search based on the characteristics of the neighborhood, and use the optimal accuracy as the guiding design principle to balance the exploration and search development. Multi-objective artificial bee colony algorithm

The characteristic of artificial bee colony intelligence optimization algorithm is an algorithm that realizes swarm intelligence optimization through heuristics. The basic intelligent optimization idea of the artificial bee colony algorithm is mainly to realize the intelligent optimization process of finding nectar by simulating the intelligent division of labor and information exchange between individuals in the artificial bee colony. Compared with the classic intelligent optimization method of artificial bee colony, the ABC artificial bee colony algorithm has almost no requirements for the search target fitness function and its constraints. It basically does not need to use external information in the search process, and only adapts to the search target. The constraint of degree convergence function is the main basis for its evolution, that is, the algorithm uses the intelligent optimization method of "generation + inspection". This intelligent optimization method is very suitable for solving nap complete problems in search. The ABC artificial bee colony algorithm has the characteristics of simple search operation, fewer control parameters, relatively high search operation accuracy and strong robustness. The artificial bee colony algorithm has strong heuristic search operation performance and weak fitness convergence for the original ABC artificial bee colony. It introduces distance control parameter adaptation based on mobile bees, nearest neighbor based on fitness, and in the following bee phase, the Gaussian search optimization equation is introduced to optimize and improve the fitness and convergence of the artificial bee colony algorithm. It is through the combination of these three intelligent optimization methods that the convergence of the artificial bee colony algorithm can greatly optimize and improve the adaptability and convergence of ABC, thereby also improving the optimization performance of ABC [2].
1.1. Basic principle analysis

1.1.1. The composition of the swarm intelligence model. For a given bee colony optimization intelligence problem, the ABC optimization algorithm uses a colony optimization intelligent food source model algorithm that simulates the bee colony to find better bees and food sources to help find the optimization intelligence problem of the bee colony solution. This simulated swarm optimization intelligence model consists of 3 types of simulated bees and other food source models. The specific smart model definition method is described as follows.

1.1.2. Food sources. The ABC algorithm shows that a food source in a bee colony network may usually be continuous or discrete and liberated in a physical node in a spatial network. The abcd algorithm divides a type of bee colony and other food sources into two components, and two different types of colonies can use different types of colony management strategies at the same time. This method is used to establish and constantly find a new type of bee colony and other food sources. This way of dividing each bee colony usually means that 50% are hired bees for a colony, and 50% is a follower bee.

1.1.3. Hiring Bee. One of the two main categories of bee colonies is hired bees. Hiring bees is a way to find a new food source. The main method is to continue to mine food sources on the basis of the existing food sources. During this mining process, they may be divided into hired follow bees or not hired; The entire mining process of the hired follower bee is the English origin of the name "hire bee".

1.1.4. Follow the bee. The other part of the colony is the bee's follower bee. As the name suggests, the training goal and research task of the follower bee is mainly to finally select a suitable bee colony from multiple bee colonies to hire a bee to keep the bee and to work with one of the other bees in the group to check the location of the other bee colonies. The main regional nectar source or the regional bee colony to carry out tracking research and development.

1.1.5. Scout Bee. When a hired bee begins to think that a new nectar source has no ability and value to continue mining (usually a scout bee thinks that if the nectar source has begun to fall into a local optimal nectar source mining situation), he has the opportunity to re-convert to his own reconnaissance Bee also searched for a new source of hired honey within the scope of the National Security Agency. After selecting a new source of hired honey, the scout bee will have the opportunity to transform into its own hired bee.

1.1.6. The process of ABC algorithm. For a problem where the two dimensions of the analytical subspace are c and d, the process expression of the ABC algorithm is as follows.

\[
\min f(x) = (f_1(x), f_2(x), \ldots, f_m(x))
\]

Among them, the decision vector \( x \in \mathbb{R}^{\text{SN}} \), that is \( x = (x_1, x_2, \ldots, x_{\text{SN}}) \), the target vector \( f(x) \in \mathbb{R}^m \). In multi-objective optimization, each objective usually restricts each other. In multi-objective optimization, each optimization objective usually restricts each other. If an optimization objective is to be effectively optimized, it is often necessary for decision makers to sacrifice the benefits and performance of other optimization objectives at the cost of focusing on multiple objectives. The optimal solution of the problem is optimized reasonably. This paper mainly uses the artificial bee colony optimal solution algorithm based on the artificial bee colony pareto to solve the multi-objective. The number of optimal solutions in the pareto optimal solution set is not comparable to each other. The more targets in the optimal solution number in the solution set, the wider the distribution, and the larger the decision maker's choice, the more likely it is to focus on the actual multiple goals. The optimal solution of the problem is solved reasonably.
1.2. Individual fitness

This paper mainly adopts the density method combining double comprehensive sorting and self-adaptation to assign a value to the individual's surrounding fitness. First, according to the surrounding domination time relationship of the group pareto, each individual in the group is double-sorted, and then according to the surrounding congestion is calculated comprehensively to calculate the surrounding fitness and the assignment of the density method, and finally the surrounding fitness is determined according to the comprehensive calculation result. Calculate the rank $R(i)$ of each individual I in the group $Q$:

$$R'(i) = \left| \left\{ j \mid j \in Q, j \neq i \right\} \right| \quad \forall i \in Q$$  \hspace{1cm} (2)

Among them, the symbol $\neq$ represents the Pareto dominance relationship, that is, the above formula represents the number of dominating individuals I in the current group Q. Sort $R(i)$ of individual i:

$$R(i) = R'(i) + \sum_{j \in Q(i)} R'(j) \quad \forall i \in Q$$  \hspace{1cm} (3)

The above formula shows that the ranking number $R(i)$ of individual I is equal to the sum of the pseudo ranking number of individuals I and the pseudo ranking numbers of all individuals dominating individual I. According to the size of the population SN, the target space is divided into $e^e e^e e^e$ grids, $n_e$ represents the number of grids in each dimension of the target space, and the integer part of $\sqrt{SN}$ is $a$, and the decimal part is $r$.

$$n_e = \begin{cases} a & r = 0 \\ a+1 & r \neq 0 \end{cases}$$  \hspace{1cm} (4)

The number of individuals in the grid area where each individual is located is used as the density value for the individual. Individual fitness value:

$$\text{fit}_i = \frac{1}{\exp(R(i) \cdot \rho(i))}$$  \hspace{1cm} (5)

In the formula, $R(i)$ represents the ranking number of individuals I, and $\rho(i)$ represents the density value of individual I.

1.3. Artificial bee colony algorithm based on Pareto

This paper mainly studies and uses the calculation concept of amaretto’s optimal honey seed fitness, and comprehensively calculates the various probabilities and values of the honey seed's optimal honey seed fitness for the honey seed better than a certain honey individual as the honey seed The value of the individual's optimal nectar fitness, a value that mainly depends on the optimal selection rate of the individual observer bee and the value of the optimal adaptation probability of the individual nectar source, and the value of the optimal adaptation probability and adaptation to the individual nectar source The numerical value of the degree, and the specific probability calculation operation method is briefly described as follows:

$$p_i = \frac{\text{fit}_i}{\sum_{i=1}^{SN} \text{fit}_i}$$  \hspace{1cm} (6)

Among them, $\text{fit}_i$ is the fitness value of individual I, and SN is the number of honeybees (or the number of nectar sources). In order to generate a new honey source location from the memory, the ABC algorithm uses the following expression:

$$v_j = x_j + \phi_j (x_y - x_j)$$  \hspace{1cm} (7)

Here $k \in \{1,2,SN\} \quad j \in \{1,2,D\}$ is a randomly selected subscript, and $k \neq i; \phi$ is a random number between $[-1,1]$; it controls the generation of new nectar $x_j$ sources in the field and represents the position of bees on two nectar sources within two visible ranges. From the comparison of (7), it can
be seen that as the gap between $x_{ij}$ and $x_{kj}$ decreases, the disturbance to position $x_{ij}$ becomes smaller. Therefore, as the optimal solution approaches in the solution space, the step size will be correspondingly cut back. In the artificial bee colony algorithm, if a nectar source location cannot be improved even after a limited number of cycles, then the picker bee at the nectar source becomes a scout bee, and the nectar source location will be replaced by a randomly generated location in the solution space. Assuming that the position of the abandoned nectar source is $x_i$, the operation of the scout bee to find a new nectar source and replace $x_i$ is as follows:

$$x_i' = x_{\text{min}} + \text{rand}[0,1](x_{\text{max}} - x_{\text{min}})$$  

(8)

1.4. Elite selection

The paper claims that $x \in [a,b]$ is the Pareto optimal solution of the multi-objective optimization problem. If $y \in [a,b]$ does not exist, it makes $f_i(y) \leq f_i(x)$, $i=1,2,\ldots,m$ and at least one strict inequality hold. Based on the above ideas, using the idea of elite selection to improve the artificial bee colony algorithm can speed up the algorithm's search speed and effectively find accurate solutions. The basic steps of the algorithm are as follows:

Initialize the population: Given the number of bees collected $n_0$ and the number of observed bees $n_1$, randomly generate $SN = n_0 + n_1$ solutions; evaluate the initial population and select $n_0$ from them to constitute the initial nectar source position (solution); determine the position of abandoning the nectar source, if there is such nectar source. The basic idea of elite selection comes from the entire elite selection strategy of genetic algorithm. The so-called elite selection strategy is the optimization process of retaining excellent potential problem solutions from the previous generation group to the next generation of the group in the iterative optimization process of the genetic algorithm, and simply copying the corresponding potential solutions of the next generation from the previous generation to the group. For the next generation, this is the usual elite selection method. From the perspective of the basic idea of the entire elite selection strategy of genetic algorithm, the selection strategy of elites is an important basic guarantee to optimize the convergence and optimization of the best group problem to the optimal solution of the next generation. If the best next-generation individual fitness value of the best next-generation group is much smaller than the next-generation fitness value of the best individual of the current next-generation group, then the best individual or fitness value of the current next-generation group is greater than that of the current next-generation group. The best individual or multiple next-generation individuals with fitness value directly replace or replicate to the next generation of the group, and randomly select to replace or replace the next generation of the worst group or replace the next generation of the corresponding group number. In order to further improve the optimization quality of the multi-objective solution and the efficiency of the bee colony algorithm and the speed of convergence optimization, this paper further proposes a multi-objective bee colony optimization algorithm based on the selection of a single-objective elite population to solve the problem of multi-objective elite population optimization. The definition is as follows: the set of elite population individuals that each single species needs to generate to solve the multi-objective optimization problem is called the sub-elite population, and the combination of all sub-elite populations is called the multi-target elite population, and each but the target sub-elite population The scales of individuals are the same, and a new set of elite individuals can be established to generate and preserve the optimal solution of a new generation of pareto. After each single population generates a new generation of multi-objective elite populations, all individual optimal solutions in the new generation of elite population optimization problems will be updated once according to the following definitions to ensure the individual optimal solutions in each elite population optimization problem Both are considered to be the best solutions of the new generation of pareto in the true sense.
2. Analysis of experimental results

In order to analyze and verify the proposed problem, as well as the design and performance of artificial intelligence and bee colony algorithm before and after the improvement, the following five more typical unconstrained optimization problem algorithms were used for numerical simulation. In the artificial intelligence ABC algorithm before and after the design and improvement, the maximum number of loop operations is 2000. In order to verify the average error and mean value of the statistical algorithm convergence, each test function needs to do 30 experiments. Each time the loop operation is performed, the observation bees and the collected bees obtain the maximum population size with an error of 50% [3].

2.1. Comparison of ABC algorithm, GABC algorithm and FABC algorithm

F1-f5 is performed on the objective function, and the fabc algorithm in the algorithm and the gabc algorithm in the basic fabc algorithm are compared and analyzed under a fixed number of iterations. The basic structure of the flow chart of the fabc test algorithm is shown in Figure 1. The gabc algorithm uses the current best food source location information as the basis and guidance for leading the innovative way of food source search to further improve the accuracy of food source search. In this experiment, the specific parameter setting method is as follows: the test food source np is 20, the setting dimension d of the test target food source function value is 30, the maximum number of iterative mining times is 3000, and the mining time limit limit=npd. The test method uses the limatlabr2014a method to carry out a numerical experiment on the basis of the laboratory test platform, and conduct 30 independent tests on the test questions of each platform, and obtain the average function solution and standard of the target food source function value obtained from the test results. The results of poor, worst average difference and best average solution are compared. The statistics of the test results are shown in Table 1.

![Fig.1 FABC algorithm flow chart](image-url)
Table 1. Objective function test results

| function | algorithm | Average solution | Standard deviation | Worst solution | Best solution |
|----------|-----------|------------------|--------------------|---------------|---------------|
| f1       | ABC       | 1.74E-08         | 3.21E-08           | 1.15E-07      | 1.20E-11      |
|          | GABC      | 4.59E-16         | 8.08E-17           | 5.50E-16      | 2.76E-16      |
|          | FABC      | 0                | 0                  | 0             | 0             |
| f2       | ABC       | 0.006718         | 0.013941           | 0.05868       | 1.27E-14      |
|          | GABC      | 0.001887         | 0.005906           | 0.029481      | 0             |
|          | FABC      | 3.01E-12         | 1.63E-11           | 8.94E-11      | 0             |
| f3       | ABC       | 59.25084         | 36.43943           | 145.9423      | 9.62575       |
|          | GABC      | 0.653402         | 1.025764           | 3.941282      | 0.007605      |
|          | FABC      | 7.77E-12         | 2.43E-12           | 1.42E-11      | 9.69E-13      |
| f4       | ABC       | 0.124223         | 0.322976           | 1.352479      | 1.85E-07      |
|          | GABC      | 2.73E-14         | 7.22E-14           | 3.84E-13      | 0             |
|          | FABC      | 0                | 0                  | 0             | 0             |
| f5       | ABC       | 0.122307         | 0.153112           | 0.633494      | 1.77E-04      |
|          | GABC      | 1.43E-08         | 1.33E-08           | 5.74E-08      | 8.39E-13      |
|          | FABC      | 1.88E-14         | 2.13E-14           | 9.13E-14      | 2.10E-15      |

It can be clearly seen from Table 2 of the results of this test and experiment that compared with the worst solution of the fabc algorithm and the algorithm obtained from the gabc analysis, the fabc algorithm is in terms of the stability and accuracy of the theoretical worst solution obtained by the analysis. All have greater evolution and improvement. For the unimodal functions f2 and f1, both the best solution accuracy and the worst solution are successfully solved and the theoretical optimal solution 0 is found; for the complex multimodal objective functions f2 and f5, the ABC analysis algorithm and the gabc analysis result The accuracy of the worst solution and the best deviation solution of the algorithm is very different, indicating that the worst solution of these three algorithms is extremely unstable, and the worst solution and the best solution of the fabc algorithm are very close, and the standard deviation shows that these three This algorithm is relatively stable; for the unimodal functions f2 and f3, the best deviation solution of the algorithm obtained by fabc analysis has greatly improved the accuracy of the best deviation solution of the other two analytical algorithms; for the multimodal functions f3 and f4 , The worst solution of the algorithm obtained by fabc analysis has found the theoretically optimal deviation solution 0 obtained from the analysis. Figure 2-Figure 5 respectively show the evolution curves of the average optimal solution of the three algorithms to the objective functions obtained from different analyses [4].

![Fig. 2 The average optimal evolution curve of objective function f1](image)

From Figure 2, we can clearly see that for the target conjugate function f1, the fabc algorithm quickly reached the theoretical optimal value. The basic data on the figure shows that it is almost impossible to see the change speed curve of the target function; from In Figure 3, we can clearly see that for the target
conjugate function $f_2$, the fabc algorithm has reached a solution accuracy of $1e-10$ within a few milliseconds of 1000 times, while the accuracy of the ABC algorithm and the gabc algorithm is still not very good at about 3000 times. Good; from Figure 4 we can clearly see that for the theoretical solution accuracy of the target conjugate function $f_3$, the fabc algorithm has completely reached $1e-12$ at about 2400 times, while the ABC algorithm and the gabc algorithm are still very poor at 3000 times; From Figure 5, we can clearly see that for the objective function $f_4$, the fabc algorithm has successfully found the theoretical optimal solution about 1400 times, while the ABC algorithm and the gabc algorithm have not fully reached the target function after 3000 times. Therefore, Table 2 and Figure 2 to Figure 5 show that it is actually feasible to introduce the conjugate function gradient calculation algorithm, an algorithm that conforms to the traditional theoretical optimization, and integrate it into the ABC algorithm optimized by the swarm intelligence theory. Its advantage is that it can greatly improve the theoretical optimization calculation ability of the ABC algorithm [5].

Fig.3 The average optimal evolution curve of objective function $f_2$

Fig.4 Average optimal evolution curve of objective function $f_3$

Fig.5 Average optimal evolution curve of objective function $f_4$
2.2. Comparison of optimization results of other improved algorithms

For the five objective functions, the fabc algorithm is compared with the mace algorithm, the Abcde algorithm, and the cabcde algorithm in the dimension, and the dimension is 30. By changing the control parameter mr, the mabc algorithm can change multiple control variables at the same time during the bee-following stage, thereby greatly improving the global convergence performance of the co-evolution algorithm; the abcd differential evolution algorithm introduces differential convergence evolution in order to improve the accuracy of the global convergence of the co-evolution algorithm; the cabcde algorithm is a calculation method that uses the co-evolution method to calculate the alternate convergence optimization of the variable multiplier vector and the function lagrange multiplier vector, which improves the performance of the co-evolution algorithm and the global optimization convergence ability [6].

![Fig.6 The average optimal evolution curve of objective function f5](image)

**Table 2. Comparison of results of different improved algorithms**

|   | f1 | f2 | f3 | f4 | f5 |
|---|---|---|---|---|---|
| Mean | 2.22E-22 | 7.37E-33 | 2.64E-51 | 2.30E-50 | 0 |
| Std, Dev | 1.15E-22 | 6.44E-33 | 2.37E-51 | 3.42E-50 | 0 |
| Std, Dev | 7.16E-07 | 1.78E-17 | 0 | 4.25E-12 | 1.40E-13 |
| Std, Dev | 1.45E-06 | 8.88E-17 | 0 | 2.08E-11 | 3.49E-13 |
| Std, Dev | 1.45E+05 | 3.05E+00 | 4.40E+01 | 8.54E-02 | 1.10E-07 |
| Std, Dev | 4.13E+05 | 8.13E+00 | 2.94E+01 | 8.00E-03 | 9.98E-08 |
| Std, Dev | 4.50E+01 | 0 | 1.19E+00 | 0 | 0 |
| Std, Dev | 1.23E+02 | 0 | 1.23E+00 | 0 | 0 |
| Std, Dev | 1.98E+01 | 1.52E-14 | 4.26E-15 | 3.55E-15 | 5.59E-15 |
| Std, Dev | 6.40E-02 | 2.62E-15 | 1.45E-15 | 0 | 8.95E-15 |

From the comparison results in Table 2 above, we can clearly see that the fabc algorithm performs well in the results obtained from the objective function f1-f5. For the objective function f2 and f1, only one fabc algorithm has found the theoretical best The optimal value is 0; for the objective function f1 and f2, the accuracy of the fabc algorithm is significantly higher than that of other mabc algorithms and other cabc and other algorithms; for the objective function f3, the accuracy of the fabc algorithm to find the optimal solution is obviously better Compared with other algorithms, it is better close to the optimal solution; for the objective function f4, the fabc algorithm and other gabc algorithms, and the cabc algorithm are better to find the theoretical optimal value; for the objective function f4 and f5, except for mabc and In addition to other algorithms, the fabc algorithm and other algorithms have found the optimal solution with higher accuracy.
3. Conclusion

This paper first proposes an algorithm for improving the fitness of the optimal solution of the artificial bee colony. The artificial bee colony algorithm directly embeds the method selected by the current elite population number into the iterative process to ensure the performance of the artificial bee colony algorithm. Each optimal solution can be the current pareto optimal solution in the true sense. This article finally verifies the results through three basic test functions. The results show that the artificial bee colony algorithm in this paper is obviously better than the improved artificial bee colony algorithm under the actual situation of large elite population.

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