Received May 26, 2020, accepted June 7, 2020, date of publication June 10, 2020, date of current version July 20, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3001299

Improved Artificial Bee Colony Algorithm and Its Application to Fundus Retinal Blood Vessel Image Binarization

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This work was supported by the project of the First-Class University and the First-Class Discipline under Grant 10301-018004032301.

ABSTRACT The content of this work is based on the characteristics of standard artificial bee colony(ABC) algorithm with weak local search ability and slow convergence speed. Then, an improved algorithm named KD-ABC is proposed. For improving the diversity and quality of the solution, it changes the generation method of honey source. In the initialization phase, it uses the cluster center generated by the K-MEANS method as the initial honey source instead of the initialization in the standard method. For improving the local optimization ability and the convergence speed without reducing the global search, we proposed a dynamic neighborhood search mechanism based on the number of iterations in terms of ABC search strategy and neighborhood selection stage. In order to find a suitable threshold to divide the grayscale image into blood vessels and background parts, we applied the characteristics of the KD-ABC algorithm to the binary processing stage of the fundus retinal blood vessel image, which lays the foundation for future image recognition.

INDEX TERMS Initialization, clustering algorithm, dynamic neighborhood search, binarization.

I. INTRODUCTION

The research direction of swarm intelligence [1] proposed in "New Generation Artificial Intelligence Development Plan" is essentially the expansion and deepening of the new era of artificial intelligence. In recent years, the research on swarm intelligence has attracted more and more attention from experts and scholars, and its research fields have extended from the research of biological swarm intelligence simulation to swarm intelligence research in the network environment. The research of swarm intelligence can not only promote the theoretical and technological innovation of artificial intelligence, but also provide core driving forces for application innovation, system innovation, management innovation, and business innovation in the entire information society.

Artificial bee colony algorithm is a new type of bionic swarm intelligence algorithm proposed by Karaboga in 2005 [2]. Because of its advantages of fast search speed, few parameters, and easy implementation,it has been successfully applied to solve traveling salesman problems, task scheduling and images. And it provides a good theoretical basis and research ideas for the research of swarm intelligence algorithms.

Inspired by this research result, in recent years, more and more swarm intelligence algorithms have begun to be applied to path planning, such as fuzzy logic, neural networks, ant colony algorithm, particle swarm algorithm, frog jumping algorithm, etc [3]–[9]. However, the standard artificial bee colony algorithm has some disadvantages of being easily trapped into a local optimum and having low search efficiency. Aiming at these problems, this paper proposes an improved artificial bee colony algorithm KD-ABC.

As an important organ of the body, the eye is of great significance. Every year there are many diseases of the eye's blood vessels, and obtaining clear and accurate fundus images is crucial for the study of diseases and other physiological blood vessels. Modern imaging technology [10] can directly observe the microvessel structure of the fundus retina, and the relevant conditions of its vascular network can provide a basis for the study of the physiological characteristics of the retina [11].

At the current stage, the retinal image segmentation method [12] relies heavily on artificial markers to

The associate editor coordinating the review of this manuscript and approving it for publication was Wei Wei.

characterize the difference between blood vessels and background, with strong dependence and unstable accuracy. Nowadays, the difficulty of research lies in how to intelligently identify microvessels and background, accurately and efficiently obtain the contour of fundus retinal vessels, and assist in clinical diagnosis.

Our article organization structure is: the first part is the introduction. This part mainly introduces the development of swarm intelligence and the importance of retinal blood vessels in clinical diagnosis. The second part is related work. This section mainly introduces the research of artificial bee colony algorithm at home and abroad, and then briefly introduces our proposed method. The third part mainly introduces our method in detail. Including the combination with K-MEANS method, dynamic neighborhood search and so on. The fourth part is the experiment and discussion part, which introduces our test objects and experimental results. The fifth part is the conclusion, which summarizes our proposed method.

II. RELATED WORKS

In 2005, Karaboga proposed the artificial bee colony algorithm(ABC). This algorithm finds the optimal solution of the problem through the sharing and communication information of bee colony. The ABC algorithm was originally applied to numerical optimization problems. It widely used in neural networks, data mining, engineering applications, image recognition and other fields because of knowledge, simple operation, few control parameters, easy to implement, good search characteristics and so on. But it also have the following problems. There is a ''premature'' convergence defect. When the global optimal solution is approached, the local search ability is weak and it is easy to fall into the local optimum, resulting in a slower convergence rate in the later stage. In view of the shortcomings of the ABC algorithm, scholars at home and abroad have carried out a lot of research and improvement.

Bao Li etc [13] adopted a strategy based on inverse learning to initialize the population,improving the diversity of targets and the quality of the solution based on the distribution of the solution in space in the initial solution phase. Gao Liu etc [14] combined the difference algorithm to improve the honey source search formula based on the search process of artificial bee colony algorithm. Zhou Xinyu etc [15]–[17] selected the better honey source in the ring neighborhood topology of the honey source for mining,and proposed to adopt a reverse learning strategy to generate a reverse solution of the abandoned food source. Alam etc [18]–[21] proposed an artificial bee colony algorithm(ABC-EDM)based on an exponentially-distributed adaptive variable asynchronous length mechanism to dynamically control the search process to solve the problem of step size in the neighborhood search. Xu Shuangshuang etc [22], [23] adopted the strategy of adaptively adjusting the neighborhood search step size to improve the local search ability of the algorithm.

By analyzing the research and improvement of ABC algorithm by domestic and foreign scholars, there are mainly three directions.

(1) Adjusting the algorithm parameters and propose different improvement methods for different stages of the artificial bee colony algorithm.

(2) Designing a new learning strategy when searching in the neighborhood.

(3) Fusing ABC algorithm with other algorithms.

But there are still the following problems,

(1) There are relatively little research on the ABC algorithm theory, the existing researches focus on the improvement and application of the algorithm.

(2) Existing settings of algorithm parameters are determined based on experience, and they are highly dependent on the environment and specific problems.

A. ABC ALGORITHM

The standard ABC algorithm divides artificial bee colonies into three categories by simulating the actual honey collecting mechanism:leading bees,following bees,and scouting bees.The goal of the entire colony is to find the nectar source with the largest amount of nectar.

Leading bees: they use previous honey source information to find new honey sources and share honey source information with following bees.

Following bees: they are waiting in the hive and collecting honey based on the information shared by the leading bees.

Scouting bees: when a certain honey source is not changed for a limited number of times and is abandoned,the scouting bees randomly look for a new valuable honey source near the hive.

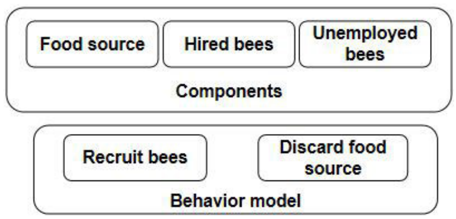

FIGURE 1. Minimal search model for swarm intelligence.

At the initial moment, the population is composed of leading bees and following bees, both of which are equal in number, accounting for half of the bee colony, and the number of leading bees is also the same as the number of honey sources.

$$x_{id} = x_d^{\min} + r\left(x_d^{\max} - x_d^{\min}\right) \tag{1}$$

where, r is a random number on the interval [0,1], $x_d^{\min}$ and $x_d^{\max}$ are the lower and upper bounds on the d-th dimension.

Leading bees fly out of the hive and search the neighborhood around the corresponding food source. Comparing before and after of the search,it uses the greedy algorithm to select the better one.After returning to the hive, leading bees share the information of the honey source with the following bees. And then following bees choose excellent honey sources according to information of honey source.

The probability that a bee is recruited to a nectar source is directly proportional to the fitness value of the nectar source. The richer the nectar source, the greater the probability of being followed by the bee. Then following bees perform neighborhood search and greedy selection again around the honey source.

$$fit(x_i) = \begin{cases} \dfrac{1}{1+fitness_i}, & fitness_i >= 0 \\ 1+|fitnedss_i|, & fitness_i < 0 \end{cases} \tag{2}$$

where, $fit(x_i)$ is the fitness value of honey source x_i(possible solution), $fitness_i$ is the concentration value of honey source x_i, generally related to the objective function.

$$p_i = \frac{fit\,(x_i)}{\sum_{n=1}^{SN} fit\,(x_n)} \tag{3}$$

where, $fit(x_i)$ is the fitness value of the honey source x_i.

$$v_{ij} = x_{ij} + \varphi_{ij}\left(x_{ij} - x_{kj}\right) \tag{4}$$

where, i = 1,2,3…SN; j = 1,2,3…D; k $\neq$ i; v_{ij} is the j-th element of the i-th individual after mutation. v_{ij} is a hired bee randomly choosing a food source different from x_i. φ_{ij} is a random number between -1 and 1.

If the food concentration of the following bees searching for the nectar source is greater than that of the original nectar source, the new nectar source replaces the old nectar source and completes the role swap at the same time. Otherwise, it remains unchanged.

If the honey source does not improve within the preset limit of the number of iterations, the honey source is abandoned.Leading bees become scouting bees and every scouting bee randomly generates some new honey source to replace the original honey source.

$$trial_i = \begin{cases} 0, fit\,(X_i) < fit\,(V_i) \\ trial_i + 1, fit\,(X_i) \geq fit\,(V_i) \end{cases} \tag{5}$$

where, $trial_i$ is the number of records that the honey source x_i has not changed. $fit(X_i)$ is the fitness value of the honey source.

Initially, all the food source locations were discovered by the scouting bees, and then the food of the honey source begin to be mined by the leading bees and following bees. After, the honey source dried up, the leading bees became scouting bees to search for further distance food source. The standard ABC algorithm process is as follows.

1. Initialize the bee colony and its related parameters.
2. Initialize the honey source.
3. while(cycle < MaxCycle){
(1) Leading Bees Phase.
//Leading bees go to the location of the honey source and calculate the richness of the existing honey source
(2) Following Bees Phase.
//Following Bees choose food source, neighborhood search, greedy algorithm selection
(3) Scouting Bees Phase.
//Scouting bees set off, abandoning some honey source, searching in the neighborhood,looking for possible new food source
(4) Memorize the best solution;
}
4. Output the optimal solution.

B. CLUSTERING ALGORITHM

The k-means algorithm [24] is a clustering algorithm. The so-called clustering means that according to the similarity principle, data objects with higher similarity are classified into the same cluster, and data objects with higher dissimilarity are classified into different classes cluster. The biggest difference between clustering and classification is that the clustering process is an unsupervised process, that is, the data object to be processed does not have any prior knowledge. And the classification process is a supervised process, there is a training data set with prior knowledge.

"k" in the k-means algorithm represents the number of clusters, "means" represents the mean of the data objects in the cluster (this mean is a description of the center of the cluster). So the k-means algorithm is also called the k-means algorithm. The k-means algorithm is a clustering algorithm based on partitioning. Distance is used as the standard for measuring similarity between data objects. That is, the smaller the distance between data objects, the higher their similarity, and the more likely they are in the same group. The k-means algorithm usually uses Euclidean distance to calculate the distance between data objects.

$$dist(x^i, x^j) = ||x^i - x^j|| = \sum_{u=1}^{n} |x_u^i - x_u^j| \tag{6}$$

where, x^i, x^j are different sets of points,u = 1,2,3…n.

The k-means algorithm process is as follows.

Input: training data set D = x(1),x(2),…,x(m), the number of clusters is k;

Process: function k-Means(D, k, maxIter).

1: Randomly select k samples from D as the initial "cluster center" vector: μ(1), μ(2),…,, μ(k):

2: repeat

3: Order Ci = Φ(1 $\leq$ i $\leq$ k)

4: j = 1,2,…,m do

5: Calculate the sample Euclidean distance between x(j) and each "cluster center" vector μ(i)(1 $\leq$ i $\leq$ k)

6: Determine the cluster label of x(j) according to the nearest "cluster center" vector

7: Classify the sample x(j) into the corresponding cluster

8: end for

9: for i = 1,2,…,k

10: Calculate a new "cluster center" vector: $(\mu(i))'$ $(1 \leq i \leq k)$
11: if$(\mu(i))' = \mu(i)$then
12: Update the current "cluster center" vector $\mu(i)$ to $(\mu(i))'$
13: else
14: keep the current mean vector unchanged
15: end for
16: Until the current "Cluster Center" vector did not updated
Output: Cluster division C = {C1,C2,...,CK}

C. IMAGE BINARIZATION

Image binarization [25] processing is actually to find an appropriate threshold t, and use this threshold to divide the image to be processed into target and background parts. This feature requires that the gray range of the target and background in the image are not the same. The common binarization global threshold method is as follows. Firstly, setting the threshold as the transformation threshold of the image. In the image, the point greater than the threshold is set to 1, otherwise it is set to 0. The process is as follows:

$$g(x, y) = \begin{cases} 1 & f(x, y) \geq t \\ 0 & f(x, y) < t \end{cases} \tag{7}$$

Threshold selection is essential for binarization. If the selected threshold is large, the target may be ignored. If the threshold is selected small, there will be a lot of background information interference. So a good threshold is satisfied with the following characteristics.

1. Retain the effective features of the image.
2. Strong anti-interference ability, not affected by image type and quality.
3. It can meet the automatic selection of different thresholds.

Among them, the threshold selection uses the maximum internal variance method (Otsu threshold algorithm)[26]. This method is a classic global threshold method, which can automatically search for the threshold value without manual setting. The image is divided into target and background. And the algorithm is simple.

III. IMPROVED ARTIFICIAL BEE COLONY ALGORITHM KD-ABC

The standard ABC algorithm generates a new solution based only on its old solution, and the calculation is simple,resulting in good information not being able to propagate quickly in the population. At the same time,each mutation only modifies one dimension of the old solution. The change is small, resulting in weak ability, slow convergence speed in local search optimization of ABC, and so on.

Based on domestic and foreign research, the content of this paper is to propose an artificial bee colony improvement algorithm KD-ABC. It based on clustering and dynamic neighborhood search during the initialization stage. It changes the way of generating honey sources and initialize the individuals which are distributed as evenly as possible in the search space. So that it can improve the diversity and quality of the solution. An improved method is proposed for research in order to balance the two processes of exploration and mining without reducing the global search ability in the ABC's search strategies and the neighborhood selection stages. On the basis, it improves the local optimization ability and convergence speed.

A. INITIALIZE BEE SOURCE LOCATION BASED ON CLUSTERING ALGORITHM

The initial solution is the starting point of the algorithm's search. The distribution of individuals in the initial solution space in the candidate solution space has a significant impact on the search performance of the ABC algorithm.

Based on the distribution of the solution in space, Bao Li uses a strategy to initialize the population basing on inverse learning and the idea of interactive learning. But this improvement makes the performance of the algorithm less effective in low-dimensional situations.

This paper applies the idea of clustering algorithm to the initial solution generation process of artificial bee colony algorithm. The clustering method is used to change the generation form of the initial solution,. So that the initialized individuals are distributed as evenly as possible in the search space to improve the diversity and quality of the solution.

The initialization process of the improved ABC algorithm based on the clustering algorithm is as follows.

Firstly, a large amount of data M (M$\gg$N,N is the number of honey sources) is randomly generated in the given area and as the clustering input. And then, the clustering method is adopted for N clusters. Each cluster selects its center as a honey source. Finally the honey sources are initialized. The process is shown in the following figure 2.

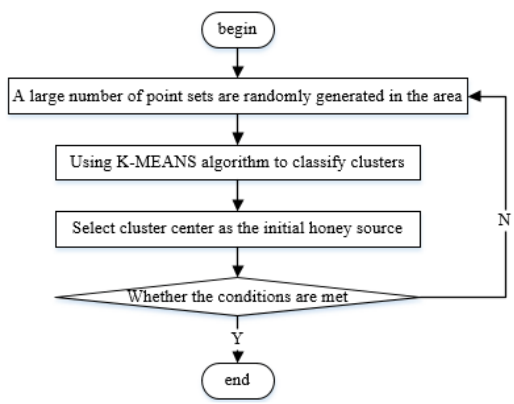

FIGURE 2. Flow chart of cluster in algorithm initialization.

B. IMPROVED ARTIFICIAL BEE COLONY ALGORITHM KD-ABC

The idea of KD-ABC algorithm is as follows. During the initial solution phase, the clustering algorithm k-means method is used to generate NP/2 cluster centers as the initial nectar source (NP is the number of bee colony). The dynamic neighborhood search mechanism are used in the neighborhood searching. The search range changes in different periods that the result improves the ability of the algorithm to jump out of the local extreme value in the early stage, achieves the effect of deep optimization in the later stage and can quickly find the optimal solution.

$$x_{md} = x_d^{\min} + rand(0, 1) * \left(x_d^{\max} - x_d^{\min}\right) \tag{8}$$

where, m = 1,2,3…100000 and rand(0,1) is a random number of 0 to 1.

In the initialization phase of the algorithm, the Eq.1 is no longer used to initialize the solution directly, but the Eq.9 is used to randomly generate a large number of numbers in a given area as the input of the clustering algorithm. The k-means algorithm is used to obtain NP/2 cluster centers as the initial solution.

When the neighborhood is dynamically searched, parameters related to the number of iterations are added to the original search mechanism, which makes the search scope different in different periods.

$$v_{ij} = x_{ij} + f * \varphi_{ij}(x_{kj} - x_{ij}) \tag{9}$$

$$f = \frac{1}{t} \tag{10}$$

On the basis of Eq.2, a weighting function is added to Eq.9, f is an inverse proportional function related to the number of iterations. t is the number of iterations, t = 1,2,3…MaxCycle. And other parameters have the same meaning.

The adjustment value of the new solution is large in the early stage of the iteration,which effectively expands the search range, maintains the diversity of the population, improves the ability of the algorithm to jump out of local extreme values, and prevents the occurrence of premature convergence.

As the number of iterations increases, the adjustment part of the new solution gradually becomes smaller, which helps the algorithm to perform deep optimization and quickly finds the optimal solution, improves the algorithm's ability to jump out of local extreme value,and quickly finds the most excellent solution.

1: The function Rand(D, lb, ub) //generating a large number of random numbers as input to kMeans.

2: Function kMeans(D, k, maxIter) //Using k-means method to cluster, and obtain SN cluster centers as initial honey sources.

3: repeat

4: SendEmployedBees() //Leading bees go to the honey source to calculate the richness(probability)of the existing honey source

5: SendOnlookerBees() //Following bees choose food source, dynamic neighborhood search mechanism, greedy algorithm selection

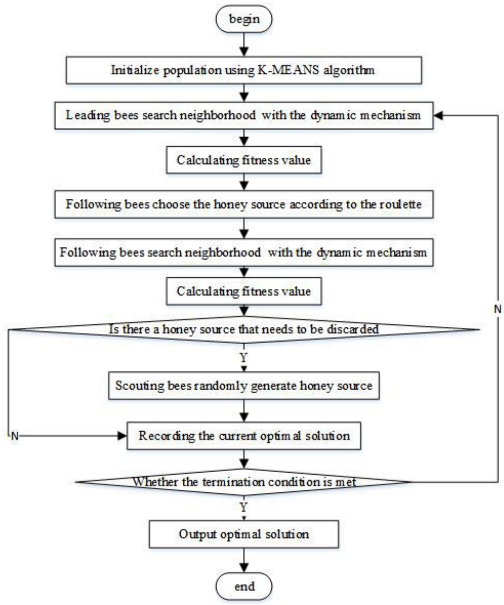

FIGURE 3. Flow chart of KD-ABC.

6: SendScoutBees() //Scouting bees set off, discarding some honey sources, dynamic neighborhood search mechanism, looking for possible new food sources

7: MemorizeBestSource() //Recording the current best honey source

8: until determines whether the termination condition is true.

IV. EXPERIMENTAL SIMULATION

A. EXPERIMENTAL SIMULATION OF IMPROVED KD-ABC ALGORITHM

In this work,we compare the optimal values of each test function iteration in the following.The figures below show the trend of the optimal value of the objective function with the number of iterations.

In Table 1, the optimal value is the minimum value of the objective function. Where, the minimum values of the H5 and H6 functions are negative and are related to the spatial dimensions. We chose these test functions for two main reasons. On the one hand, these test functions are common and public. On the other hand, the value ranges and dimensions of these test functions are different.

In Experiment 1,the number of bees is NP = 60, the number of honey sources is FoodNumber = 30, the number of iterations is maxCycle = 2500, and the number of honey source changes is limit = 100. By adjusting the data dimension D and the test function and its corresponding upper and lower bounds, the change trend of the optimal value of the ABC algorithm before and after improvement is compared. The comparison indicators are:the optimal value of the initial solution before and after the algorithm improvement the optimal value after multiple iterations,and the number of iterations when the specified accuracy is first achieved.

TABLE 1. Test function list.

Function	Formula	the Min
Rastrigin	$y=\sum_{i=1}^{D}[x_i^2-10\cos(2\pi x_i)+10], x_i\in[-5.12,5.12]$	0
Griewank	$y=1+\frac{1}{4000}\sum_{i=1}^{D}x_i^2-\prod_{i=1}^{D}\cos(\frac{x_i}{\sqrt{i}}), x_i\in[-600,600]$	0
Sphere	$y=\sum_{i=1}^{D}x_i^2, x_i\in[-5.12,5.12]$	0
H1	$y=\sum_{i=1}^{D}\left\|\frac{\sin(10x_i\pi)}{10x_i\pi}\right\|, x_i\in[-0.5,0.5]$	0
Step	$y=\sum_{i=1}^{D}(x_i+0.5)^2, x_i\in[-100,100]$	0
H5	$y=-\sum_{i=1}^{D}[x_i\sin(10\pi x_i)], x_i\in[-1,2]$	-1.85D
H6	$y=\sum_{i=1}^{D}[\sin(x_i)+\sin(\frac{2x_i}{3})], x_i\in[3,13]$	-1.21598D
Rosenbrock	$y=\sum_{i=1}^{D}[100(x_{i+1}-x_i^2)^2+(x_i-1)^2], x_i\in[-30,30]$	0
Schwefel	$y=\sum_{i=1}^{D}\|x_i\|+\prod_{i=1}^{D}\|x_i\|, x_i\in[-10,10]$	0
Alpine	$y=\sum_{i=1}^{D}\|x_i\sin(x_i)+0.1x_i\|, x_i\in[-10,10]$	0
Quartic	$y=\sum_{i=1}^{D}ix_i^4+random(0,1), x_i\in[-100,100]$	0
H9	$y=6D+\sum_{i=1}^{D}\lfloor x_i\rfloor, x_i\in[-5.12,5.12]$	0

TABLE 2. Results comparison.

Function	D=100					
	Original ABC algorithm			KD-ABC		
	The min before iteration	The min after iteration	The min of iterations with accuracy<E-5	The min before iteration	The min after iteration	The min of iterations with accuracy<E-5
Rastrigin	1684.628512	0.098848175	>2500	929.2525984	0.00126582	>2500
Griewank	2535.683888	1.27E-06	1962	165.6286136	3.11E-08	1569
Sphere	709.0798198	2.57E-07	2085	42.13457333	5.54E-08	1579
Step	269157.4181	1.76E-06	>2500	18443.73016	2.13E-06	2417
H1	13.79282074	-175.948111	0	19.6601007	-166.6542223	0
H5	-28.03993593	-121.5982175	0	-8.87304608	-121.5982173	0
H6	-26.85253758	-121.5982175	0	-20.52663664	-121.5982173	0
Rosenbrock	1134784325	13.20578795	>2500	3852794.386	46.29877299	>2500
H9	481	1	>2500	527	0	1550
Schwefel	206.9352576	0.000617998	>2500	110.5199142	0.000377268	>2500
Alpine	255.5266374	0.047627931	>2500	79.63595576	0.000733691	>2500
Quartic	73575996776	1.45083E-08	2046	368910197.4	2.33408E-10	1261

The honey source dimension D = 100 in Table 2.According to the characteristics of the test function, it can be seen from Table 2 that the improved algorithm uses clusters to initialize clusters. Rastrigin, Griewank, Sphere, Step, Schwefel, Rosenbrock, Alpine, Quartic, the optimal value of the initial solution of these test functions is relatively close to the global optimal value, and the convergence speed and accuracy are also improved. The KD-ABC algorithm is adapted to the above functions.

The honey source dimension D = 30 in Table 3.According to the characteristics of the test function, it can be seen from Table 3 that the improved algorithm uses clusters to initialize clusters. Rastrigin, Griewank, Sphere, Step, Rosenbrock, Schwefel, Alpine, Quartic, the optimal value of the initial solution of these test functions is relatively close to the global optimal value, and the convergence speed and accuracy are also improved. The KD-ABC algorithm is adapted to the above functions.

TABLE 3. Results comparison.

Function	D=30					
	Original ABC algorithm			KD-ABC		
	The min before iteration	The min after iteration	The min of iterations with accuracy<E-5	The min before iteration	The min after iteration	The min of iterations with accuracy<E-5
Rastrigin	383.0108846	1.00E-11	1151	278.0335259	3.73E-10	883
Griewank	616.2835937	9.99E-16	518	152.71956	5.55E-16	398
Sphere	171.5698024	8.63E-16	280	45.01243283	7.59E-16	263
Step	60984.79853	7.76E-16	681	16182.06703	5.55E-16	507
H1	1.955638417	1.17E-15	161	7.837654946	1.17E-15	331
H5	-21.28902732	-58.44750722	0	-4.791278103	-58.50779203	0
H6	-12.96011523	-36.47946525	0	-10.73239647	-36.47946525	0
Rosenbrock	1.92E+08	0.253261647	>2500	1.41E+07	0.032816736	>2500
H9	124	0	206	153	0	257
Schwefel	7147999.691	1.65E-15	1042	46.15899935	2.09E-15	1047
Alpine	62.18360167	3.93E-07	1663	36.31651539	7.05E-09	1541
Quartic	3.22E+09	3.03E-16	418	2.33E+08	2.98E-16	295

From the comparison of the experimental results in Tables 2 and 3, it can be seen that in different dimensions, the H9, Schwefel, Alpine and Quartic test functions can quickly reach a certain accuracy range. That is, they can quickly converge and achieve the optimization effect. The KD-ABC algorithm is suitable for low-dimensional test functions.

Based on the experimental data, plot the change trend of the function. In the experiment, the following function parameters are the number of bees NP = 60, the number of honey sources FoodNumber = 30, the number of iterations maxCycle = 2500, the number of honey source changes limit = 100, and the honey source dimension D = 100.

It can be seen from Table 1 that the minimum value of the H5 and H6 functions is negative, and the minimum value of the other test functions is 0, which results in different positions of the abscissa of the trend graphs of the H5 and H6 functions.

As can be seen from the above figures. Firstly, the KD-ABC algorithm uses clustering method to initialize the honey source. And the objective function value of the initial iteration stage is better than the original ABC algorithm's objective function value, which shortens the optimization time to a certain extent. Secondly, Compared with the original ABC algorithm,the optimal value is found faster, and the optimization speed is improved. The KD-ABC algorithm in the figures have a sudden change in the target function value. The improvement of the dynamic neighborhood search has reached the local optimum. To achieve the goal of finding the global optimum.

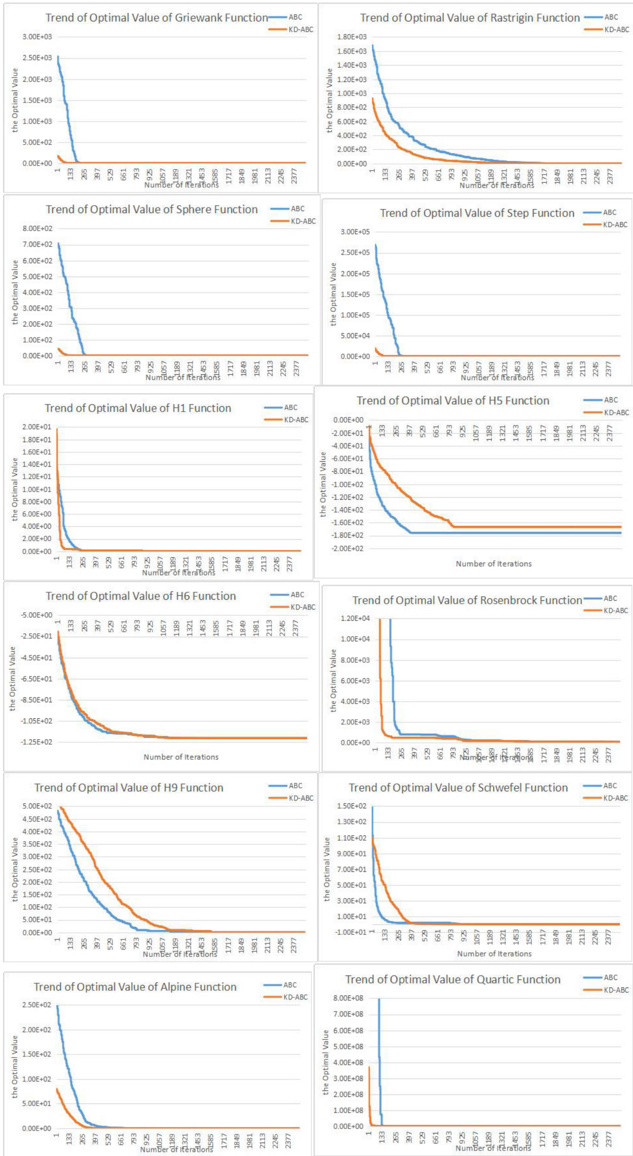

FIGURE 4. The trend graph of function.

B. FUNDUS RETINAL BLOOD VESSEL IMAGE BINARIZATION COMBINED WITH IMPROVED KD-ABC ALGORITHM

The selected images are from the DRIVE (Digital Retina Image for Blood Vessel Extraction) data set. Firstly, it is necessary to preprocess the image grayscale [27], [28]. Secondly, the improved KD-ABC algorithm is applied to the maximum internal variance method to quickly find the threshold value, thereby realizing the image binarization processing. Figure 5 is a flowchart of the algorithm.

In the verification experiment, the number of bee colonies NP = 60, the number of honey sources FoodNumber = 30, the number of iterations maxCycle = 500, the number of honey source changes limit = 10, D = 10. According to the distribution and clarity of the fundus blood vessels, we chosen three different situations.The original images and experimental results are shown in the following figures.

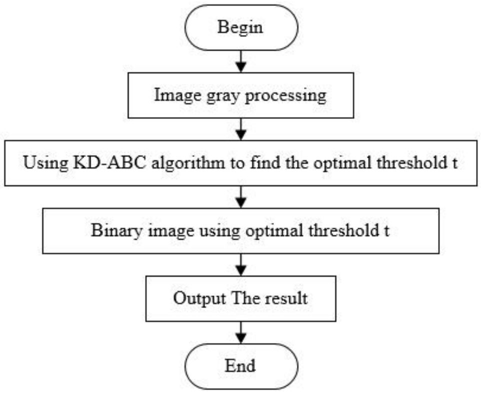

FIGURE 5. Flow chart of image binarization combined with improved KD-ABC algorithm.

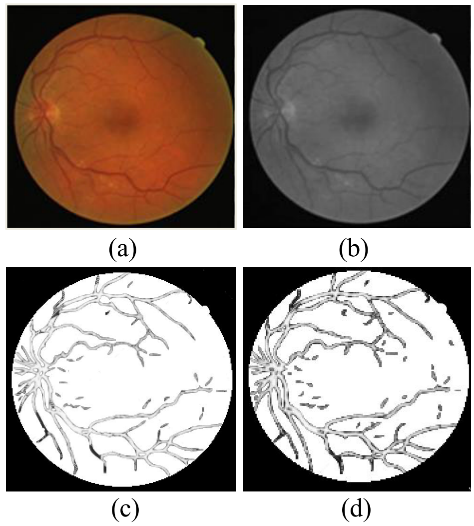

FIGURE 6. Image binary comparison results (I) Original image (b) Grayscale (c) Binary processing combined with ABC algorithm (d) Binary processing combined with KD-ABC algorithm.

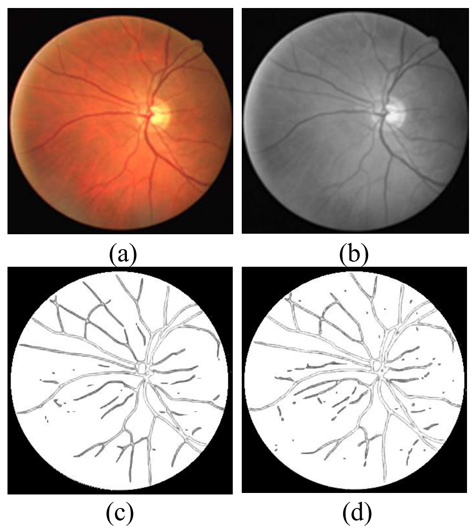

FIGURE 7. Image binary comparison results (II) (a) Original image (b) Grayscale (c) Binary processing combined with ABC algorithm (d) Binary processing combined with KD-ABC algorithm.

Figure 6-8 are experimental verification of some images on the DRIVE data set. By binarizing the grayscale image,

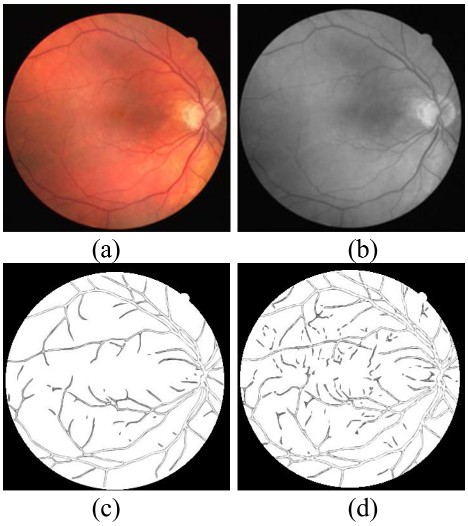

FIGURE 8. Image binary comparison results (III) (a) Original image (b) Grayscale (c) Binary processing combined with ABC algorithm (d) Binary processing combined with KD-ABC algorithm.

the improved KD-ABC algorithm processing results proposed in this work are more levels compared with the original ABC algorithm processing results.In other words, the threshold t is better, so that more details are retained, and the overall processing result is clearer and more accurate.

V. CONCLUSIONS

From the above experiment and its data, it can be seen that the improved algorithm has better test function adaptability at low dimensions, and has better effect when implementing image binarization. Secondly, the existing settings of algorithm population parameters are determined based on experience. In addition, researches on bee colony search strategies and honey source selection mechanisms can be continued to optimize the algorithm and improve the convergence speed of ABC. Finally, in the future, the improved artificial bee colony algorithm can be further expanded and studied in the field of image recognition and segmentation to provide a basis for medical research.

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