Artificial bee colony algorithm improved by centroid strategy

Keming Chen*, Chunping Wang

Mathematics and Computer Science Institute, XinYu University, JiangXi, China

Received 1October 2014, www.cmnt.lv

Abstract

Artificial Bee Colony algorithm was the best optimal algorithm proposed by Karaboga in Karaboga, having the following advantages, such as good stability, excellent ability of solution, less control parameters, simple and easy achievable computation, etc. It also had some disadvantages, such as premature convergence in its later period, poor accuracy in its development, etc. Therefore, a new-typed centroid improvement strategy is introduced in the paper for improving the searching ability of the artificial bee colony algorithm. This research is experimented by the common six kinds of testing functions. The centroid strategy introduced in the paper can effectively enhance the searching ability of the artificial bee colony algorithm in terms of the results so that the continuous development of the algorithm in its later period cannot be prematurely converged and the majority of the testing functions can be obviously improved.

Keywords: artificial bee colony algorithm, the optimal algorithm, evolutionary computation

1 Introduction

As to the emergence of some complicated mathematical problems, such as difficult differential, the possession of multi-partial optimal solution and other problems, scholars begin to try to search for the solution with the random computing method. The method aims to find out the feasible solution approximating to the optimal solution according to the self-learning method. The characteristics of these algorithms are gradually improving the quality of the solution with the method of “Survival of the fittest, the unfit eliminated”, that is called the Evolutionary Computation [1-7].

The Artificial Bee Colony algorithm is an Evolutional Computation introduced in the recent years, possessing the following advantages [8], such as less control parameters, simple computation, good stability, rapid convergent speed, etc. Its excellent efficiency of the solution is proved by many researches and is applied to all kinds of the industrial and commercial fields.

Artificial bee colony algorithm is an optimization method proposed by imitating the behavior of bees, is a cluster of a specific application of intelligent thought. Its main feature is the need to understand the problem of the special information needs only to compare the merits of the issue, by everyone local search behavior of individual bees, culminating in the global optimum manipulation groups come to the fore, with faster convergence [9,10]. In order to solve the multi-variable function optimization problem, Artificial bee colony algorithm (ABC) is proposed by Karaboga.

The Artificial Bee Colony (ABC) algorithm is a swarm based meta-heuristic algorithm that was introduced by Karaboga in 2005 for optimizing numerical problems. It was inspired by the intelligent foraging behavior of honey bees. The algorithm is specifically based on the model proposed by Tereshko and Loengarov for the foraging behavior of honey bee colonies. The model consists of three essential components: employed and unemployed foraging bees, and food sources. The first two components, employed and unemployed foraging bees, search for rich food sources, which is the third component, close to their hive. The model also defines two leading modes of behavior which are necessary for self-organizing and collective intelligence: recruitment of foragers to rich food sources resulting in positive feedback and abandonment of poor sources by foragers causing negative feedback.

In ABC, a colony of artificial forager bees (agents) search for rich artificial food sources (good solutions for a given problem). To apply ABC, the considered optimization problem is first converted to the problem of finding the best parameter vector which minimizes an objective function. Then, the artificial bees randomly discover a population of initial solution vectors and then iteratively improve them by employing the strategies: moving towards better solutions by means of a neighbor search mechanism while abandoning poor solutions [11-15].

The new-typed centroid improvement strategy is proposed in the research and tries to improve the solving ability of the artificial bee colony algorithm by connecting with the Opposition Position Strategy so that the problems of the low precise development can be improved and the capacity of escaping the partial optimal solution in the Artificial Bee Colony algorithm.

2 Literature review

A. The introduction of the Artificial Bee Colony.

Some tasks should be effectively conducted by the specific bee in the real world be colony, and the nectar contents in the beehive should be added to the maximum.

***Corresponding author’s** e-mail: xyuchenkeming@163.com

The Artificial Bee Colony algorithm refers to the optimal algorithm proposed in the Bee Colony Self-organized model of Seeley. The framework of the Artificial Bee Colony include employed bee, observational bee and scout bee. The numbers of the employed bee are the same as the scout bee's. The scout bee is in charge of searching for the source of the nectar and providing the quality information of the food source to the scout bee waiting in the beehive. According to the information offered by the employed bee, the scout bee goes to the food source for searching. When the earning degree of the food source cannot be improved, the scout bee is able to randomly explore in the searching space for obtaining the new food source [16].

The procedures of the original Artificial Bee Colony algorithm are as follows:

Step 1: Initiation

Set up the initial parameters, including the numbers of the employed bee, the maximum iteration numbers and the limit value of the unimproved times in each food source.

Randomly place an employed bee in a position in the solution space. (Its randomly placing method is as shown in the Equation (1))

The position is called a food source searched by the bee, and the adaptive value in the food source position is called the earning degree of the food source.

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

where x_{ij} is the initial value of the *i* employed bee in the *j* dimension, $x_{\min}^j$ is the minimum value of the searching value in the j dimension, $x_{\max}^j$ is the maximum value of the searching value in the *j* dimension and rand [0,1] is the random value between 0 and 1.

Step 2: According to the Equation (2), each employed bee moves to the position of the new food source and computes its earning degree of the food source.

$$v_{ij} = x_{ij} + rand[-1,1](x_{ij} - x_{kj})\ , \tag{2}$$

where v_{ij} is the new position after the *i* employed bee in the *j* dimension moves, x_{ij} the position before the *i* employed bee in the *j* dimension moves, x_{kj} is the position randomly selected by the *k* employed bee in the *j* dimension and rand [-1,1] is the random value between -1 and 1. The following Figure 1 is the two-dimensional solution space, that is, the moving route of the employed bee. The employed bee just randomly choose a dimension to move in the original artificial algorithm, but the employed bee are assumed to simultaneously move in the two-dimensional for helping the readers have a better understanding of it.

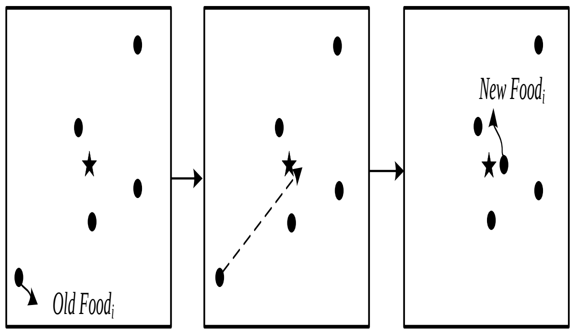

FIGURE 1 The two-dimensional figure of the moving method by the employed bee

Step 3: Make use of the Roulette wheel selection (seen in the Equation 3) to decide that each scout bee should be reached to the food source for assisting its searching behavior. According to the Equation (2), each scout bee moves to the position near to the food source and computes its earning degree of the food source.

$$p_i - \frac{fit_i}{\Sigma_{n-1}^{SN} fit_n}\ , \tag{3}$$

where p_i is the selected probability of the i food source, fit_i is the earning degree of the *i* food source and *SN* is the total number of the food source.

Step 4: When the earning degree of any food source is not improved through limit times searching, the food source should be abandoned. According to the formula (1), a scout bee is dispatched to find a new food source to replace the abandoned food source.

Step 5: Memorize the highest earning degree of the food source so far and record the optimal earning degree of the food sources the optimal solution of the algorithm.

Step 6: The circulation movement is ended until it conforms with the ending condition. Judge whether it conforms with the ending condition (whether the current iteration number is the maximum iteration number). If it conforms with the ending condition, the algorithm can be stopped and the optimal solution should be output. Otherwise, the process should be back to the Step 2.

The employed bee and the observation bee are in charge of the region development in the artificial bee colony algorithm and the scout bee is in charge of the whole region exploration. The method of the region development is moving to the neighboring point in the food source (Equation 2) and the whole exploration is that the scout bee uses the new position to replace the old position in the food source [17]. (Equation 1)

B. The relevant researches in the Artificial Bee Colony Algorithm.

After being introduced by Karaboga in 2005, the Artificial Bee Colony Algorithm attracted many scholars' attention and its various improved researches have been proposed for improving the algorithm's efficiency.

In related researches, Li and other scholars tried controlling the judging mechanism in the partial optimal solution for enhancing the efficiency of searching in the whole region through the Artificial Bee Colony Algorithm. Feng and Ding produced the initial position through the clustering symmetry method and used the Boltzmann selection mechanism to replace the Roulette Wheel selection for improving the Artificial Bee Colony Algorithm. Quan and Shi adopted the fixed point theorem in the compression mapping to produce the new iteration in the Banach space for improving the convergence speed in the Artificial Bee Colony Algorithm. Tsai and other scholars adopted the Newton's universal gravitation theorem to improve the choosing mechanism of the scout bee for making the scout bee have better development capacity. Luojun and Fan Pengcheng adopted the mating strategy in the genetic algorithm to improve the Artificial Bee Colony Algorithm by adding the variety of the food source and enhancing the solution quality and reducing the probability of entering the partial optimal solution. Baoli and Zeng Jianchao improved the Artificial Bee Colony Algorithm by dynamically adjusting the searching space and then gradually reduced the searching region by adopting the chaotic variables to escape the partial optimal solution. Alatas adopted the chaotic concept to improve the Artificial Bee Colony Algorithm and randomly chose the different chaotic map to produce the new iteration for escaping the partial optimal solution. Narasimhan adopted the parallel processing concept to improve the Artificial Bee Colony Algorithm for increasinf the operating speed and the solution quality. Akayand Karaboga referred to the DE algorithm and then added the modification rate and the scaling factor.

Zhun and Kwong proposed Gbest-guided Artificial Bee Colony algorithm and its basic framework was very similar to the original Artificial Bee Colony Algorithm. It used the searched optimal solution as the guidance to make the employed bee and the observation bee search the food source from the direction. The method was very simple but its efficiency was very obvious. Therefore, the paper used the literature as its mainly comparing object.

The searching formula in the GABC algorithm used the Equation (2) as its basic framework, and the current food source as its guidance, is shown as in the Equation (4).

$$\begin{aligned} v_{ij} &= x_{ij} + rand[-1,1](x_{ij} - x_{kj}) \\ &+ rand[0,1.5](y_j - x_{ij}) \end{aligned}, \tag{4}$$

where v_{ij} is the new position after the *i* employed bee in the *j* dimension moves. x_{ij} the position before the *i* employed bee in the *j* dimension moves. x_{kj} is the position randomly selected by the *k* employed bee in the *j* dimension. Rand [-1,1] is the random value between -1 and 1 and the current food source in the *j* dimension, and rand [0,1.5] is the random value between 0 and 1.5.

From the above literature, many scholars have addicted to improving the Artificial Bee Colony algorithm, its mainly improving direction can be divided into the following points: the causing method in the initial iteration, the evolutionary mechanism for the employed bee and the observation bee, the selection bee for the scout bee and others. The paper aims to improve the evolutionary mechanism for the employed bee and the observation bee, the selection bee for the scout bee and hopes to improve the problems of the bad development accuracy during the later period in the Artificial Bee Colony algorithm.

C. Centroid Strategy.

Centroid is the position which has the development potential. The position located in the centroid has better adaptive value and its probability is the whole regions's optimal solution in the whole clustering. In the initial period of the algorithm iteration, the centroid and the whole region's optimal solution respectively belonged to the different positions. With the increasing of the evolutionary iteration times, the distance between the centroid and the whole region's optimal solution can be reduced. When the iteration ended, both of them can be converted to the near position, therefore, the centroid strategy can cause the whole clustering move to the potential region for searching the food source and the convergent speed can be fastened. Xu and other scholars pointed out the particles far away from the centroid and the adaptive values never won the particles near to the centroid. Yi and other scholars pointed put that if the centroid strategy was applied in the clustering algorithm un-properly, the clustering algorithm is easy to fall into the region's optimal solution [18].

D. Relative position strategy.

Tizhoosh introduced the concept of the relative position, and its principle produced the new position in the relative position of the current position. In the multi-dimensional space, n is the solution dimension within the candidate solution ($x_1, x_2, ..., x_n \in R, x_1 \in \{a_i, b_i\}$). a_i is the minimum value in the *i* dimension in the solution space, and b_i is the maximum value in the *i* dimension in the solution space. The relative position $\breve{x}_1, \breve{x}_2, ..., \breve{x}_n$ is as shown in the Equation (5).

$$\breve{x}_1 = a_i + b_i - x_i . \tag{5}$$

The relative position is considered to search for the food source in the solution space range, apart from searching for the food source in terms of the random position produced in the algorithm. Compared with the random position, the relative position has bigger probability to approach the whole region's optimal solution. Zhang and other scholars introduced the symmetric learning initiation for producing a model particle to share the information with other particles. In this way, the particle clustering algorithm can speed up the convergent rate and escape the region's optimal solution. Rahnamayan and other scholars introduced the symmetric learning to improve its initiation and the relative position to escape the strategy. In this way, convergent speed and be fastened and the region's optimal solution can be avoided [19].

The paper tried to the relative position strategy to improve the efficiency of the Artificial Bee Colony algorithm by avoiding falling into the characteristics of the optimal solution.

3 Algorithm design

3.1 CENTROID STRATEGY'S DESIGN

The Artificial Bee Colony algorithm adopts the distributed learning method and has the random searching capacity so that it has large range of the exploring capacity. The small range of the developing capacity is lack so that the centroid strategy should be introduced to enhance the searching ability in the small range ad improve the disadvantages of the Artificial Bee Colony algorithm. The computation of the centroid position is as follows:

$$C = \frac{\sum_{i=1}^{SN} X_i}{SN}, \tag{6}$$

where C is the position of the centroid, X_i is the position of the i employed bee, and SN is the number of the food s ource. In the Figure 2, the asterisk is the central point in t he searching space, $Old\ Food$ is the food source in the la st observation bee, $New\ Food$ is the centroid and the last observation bee gives up the $Old\ Food$ to explore in the $New\ Food$ centroid.

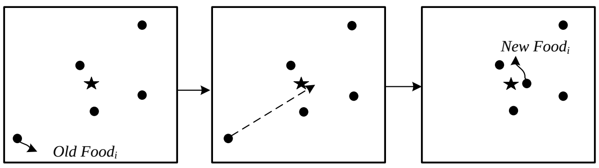

FIGURE 2 The figure of the centroid strategy

3.2 RELATIVE POSITION STRATEGY'S DESIGN

The scout bee produces the new position with the random method in the original Artificial Bee Colony algorithm. The algorithm can effectively escape the partial optimal solution, but a better food source cannot be effectively explored. In order to improve the problem, the paper adopts the relative position strategy which has a better food source to replace the scout bee mechanism in the Artificial Bee Colony algorithm. A large parts of the functions can obtain a better results, as show in in the Figure 3, where asterisk is the central point in the searching space. $Food_{old}$ is the food source which wants to abandoned by the employed bee. $Food_{new}$ is the relative position which has a better food source and the scout bee gives up the $Food_{old}$ to explore in the $Food_{new}$ centroid, as shown in the Equation (7).

$$x_j = x_{\min}^j + x_{\max}^j - x_{best}^j,\ j = 1, 2, ..., n, \tag{7}$$

where x_j is $Food_{new}$'s value in the *j* dimension, $x_{\min}^j$ is the searching space's minimum value in the j dimension, $x_{\max}^j$ is the searching space's maximum value in the *j* dimension and x_{best}^j is the best food source's value in the *j* dimension [20].

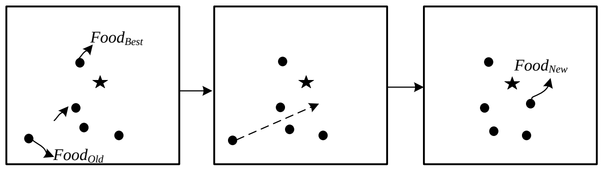

FIGURE 3 The figure of the relative position strategy

3.3 THE IMPROVEMENT OF THE ARTIFICIAL BEE COLONY ALGORITHM BY USING THE CENTROID STRATEGY

The research introduces the algorithm called Centroid-Strategy-based Artificial Bee Colony algorithm. Its complete algorithm description is as follows: Algorithm CSABC.

Step 1: Set up the initial parameter

Step 2: The employed bee conducts the neighboring food source's searching in terms of the Equation (2).

Step 3: The observation bee from the 1 to *SN*-1 selects the food source with the roulette wheel selection.

Step 4: The last one observation bee explore in all food source's centre position. If a better food source is obtained, the worst food source of the employed bee can be noticed and the present food source can be abandoned.

Step 5: The scout bee would explore with the relative position in the current optimal solution.

Step 6: If the ending condition is reached (the iteration times equals to MCN), the optimal solution should be output. Otherwise, the process should be back to the Step 2.

3.4 THE RESEARCH COMBINES WITH OTHER BEE COLONY ALGORITHM

The method is easy to combine with other artificial bee colony algorithms for strengthening the bee colony's searching ability. GABC is a relative improving method, its method is simple but its efficiency is very obvious. Therefore, the GABC introduced in the research combines with the GABC, which are called the CSGABC. Check whether the combination of the two methods is complementary efficiency or use it to test the probability among the CSABC and other methods [21,22].

CSGABC is the new searching method as the employed bee and the observation bee with the Equation (4), and use the Step 2 and Step 3 in the CSABC process. The guidance searching in the whole region's optimal solution is adopted to improve the regions development ability. Its complete algorithm description is as follows: Algorithm CSGABC.

Algorithm CSGABC:

Step 1: Set up the initial parameter.

Step 2: The employed bee conducts the neighboring food source's searching in terms of the Equation (4).

Step 3: The observation bee from the 1 to *SN*-1 selects the food source with the roulette wheel selection. The neighboring food source should be searched in terms of the Equation (4).

Step 4: The last one observation bee explore in all food source's centre position. If a better food source is obtained, the worst food source of the employed bee can be noticed and the present food source can be abandoned.

Step 5: The scout bee would explore with the relative position in the current optimal solution.

Step 6: If the ending condition is reached (the iteration times equals to MCN), the optimal solution should be output. Otherwise, the process should be back to the Step 2.

4 Algorithm design

In this research, the proposed algorithm is CSABC; In addition, we will CSABC algorithm and GABC algorithm [22] as a combination, called CSGABC. We have these two algorithms were compared with ABC and GABC test.

Test CSGABC purpose except to illustrate our method can be used alone or in combination with other bee colony algorithm to achieve the complementary synergy multiplied. The results from the following experiment, there can be found a very excellent CSGABC search capabilities, than is usually used alone CSABC and GABC.

As can be seen from Table 1 (f1) Sphere function test results, CSABC and CSGABC on development capabilities and stability are more ABC and GABC also superior. As can be seen from Figure 4, in the dimension 60, ABC is already at around 2600 on behalf of the convergence, GABC generation in 1600 has stopped development, CSABC and CSGABC retain both ABC and GABC convergence rate, effective and sustained development, and find a better solution.

Rosenbrock function test results (see Table 1 (f2)), CSABC performance is not ideal, but CSGABC still retains a good advantage, its ability to develop and stability are more ABC and GABC also superior. As can be seen from Figure 5, the dimension 3, CSABC in convergence speed is slightly faster than the ABC, but about 300 generations, the development speed will begin to fall, CSGABC can maintain its advantages, in addition to a faster convergence speed can also be continuously and stably developed.

Rastrigin function test results (see Table 1 (f3)), in 30 dimensions, CSABC and CSGABC on development capabilities and stability, are more ABC and GABC also superior, and are able to find the best solution, but in the dimension 60 when, CSABC were more GABC a little weak, but CSGABC will maintain its advantage, and still be able to find the optimal solution. As can be seen from Figure 6, when the dimension 60, ABC at about 3500 generation has been stagnant, GABC is stagnant generation of about 3500, CSABC generation has stagnated at around 3300, however, CSGABC they can effectively continue to develop, and then find the optimal solution.

Griewank function test results (see Table 1 (f4)), CSABC with CSGABC on development capabilities and stability, are also superior compared to ABC and GABC and CSABC and CSGABC are able to find the optimal solution. As can be seen from Figure 7, in the dimension 60 when, ABC in 2800 on behalf of, almost stagnant, while GABC about 3700 generations has also been unable to continue to develop, CSABC and CSGABC are able to maintain stable development capabilities, and are to find the optimal solution.

Ackley function test results (see Table 1 (f5)), CSABC with CSGABC on development capabilities and stability, are more ABC and GABC also superior. As can be seen from Figure 8, in the dimension 60 when, ABC due to the slow pace of convergence, in 4500 generation was stagnant, GABC generation in 2700 has also been unable to continue to develop, CSABC and CSGABC are able to maintain the original ABC and GABC convergence speed, and when ABC stopped development when GABC, CSABC and CSGABC are able to continue to develop and, better results and thus found.

Schwefel function test results (see Table 1 (f6)), CSABC in this function is not desired, while the dimension 30, CSGABC GABC results although with the very close, but when the dimension 60, the result is much better than GABC poor, and CSABC and CSGABC after upgrading the dimensions are better than the ABC. As can be seen from Figure 9, CSABC and CSGABC though it can retain the original ABC and GABC convergence speed, ability but had relatively late in the development GABC vulnerable.

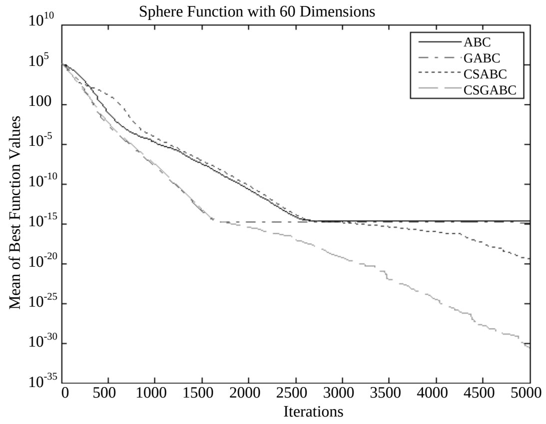

FIGURE 4 Sphere Function 60D

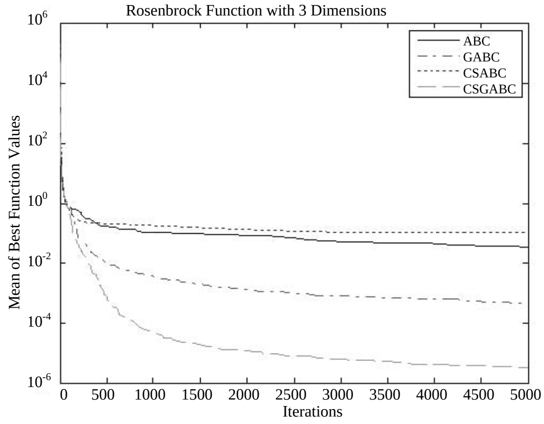

FIGURE 5 Rosenbrock Function 3D

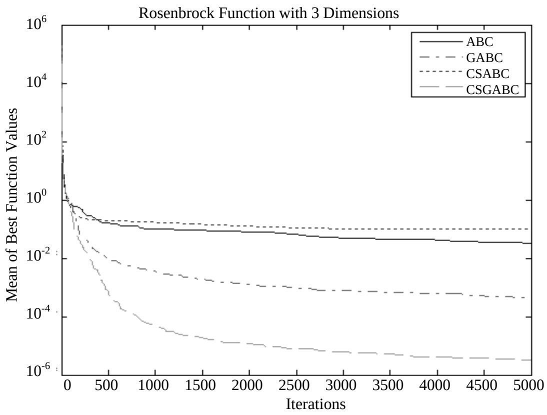

FIGURE 6 Rastrigin Function 60D

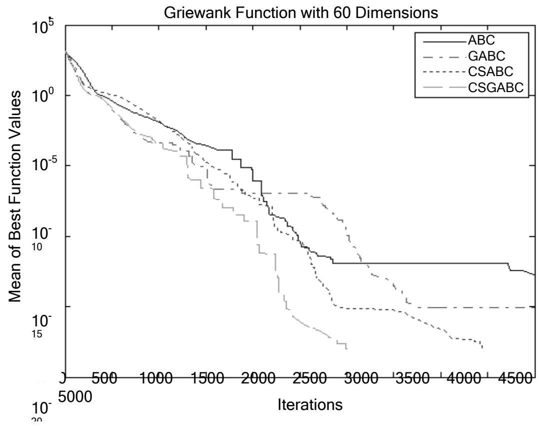

FIGURE 7 Griewank Function 60D

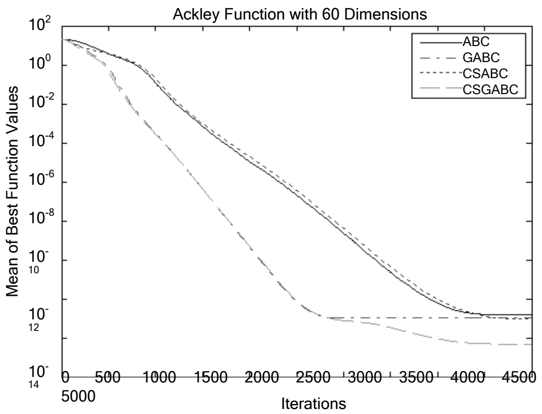

FIGURE 8 Ackley Function 60D

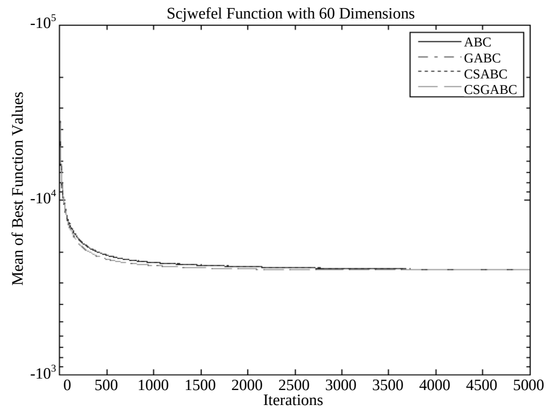

FIGURE 9 Schwefel Function 60D

TABLE 1 Test results

Test function	Algorithms dimension	ABC		GABC		CSABC		CSGABC	
		Mean	Std	Mean	Std	Mean	Std	Mean	Std
f1	30	6.34859e-016	9.71074e-017	4.16236e-016	6.69959e-017	5.29657e-054	5.17198e-053	5.29420e-068	3.10670e-067
	60	2.21062e-015	3.63010e-016	1.34153e-015	1.45550e-016	3.39865e-020	2.21619e-019	2.81780e-031	1.45646e-030
f2	2	5.02329e-003	6.90834e-003	5.06976e-005	7.94764e-005	2.21660e-002	1.80043e-002	3.05066e-009	4.66937e-009
	3	3.27513e-002	4.00285e-002	4.39925e-004	4.84642e-004	9.87035e-002	4.69132e-002	3.14892e-006	3.93273e-006
f3	30	9.89075e-014	5.21229e-014	7.38964e-015	1.92129e-014	0.00000e+000	0.00000e+000	0.00000e+000	0.00000e+000
	60	1.23421e-008	1.11427e-007	3.95630e-013	1.65956e-013	4.06999e-013	2.13259e-013	0.00000e+000	0.00000e+000
f4	30	5.07538e-014	4.94468e-013	5.44009e-017	8.42349e-017	0.00000e+000	0.00000e+000	0.00000e+000	0.00000e+000
	60	1.76553e-013	6.93804e-013	8.20455e-016	4.39267e-016	0.00000e+000	0.00000e+000	0.00000e+000	0.00000e+000
f5	30	4.95959e-014	6.43295e-015	3.47455e-014	3.40446e-015	4.05009e-015	1.11721e-015	4.08562e-015	1.07118e-015
	60	1.58096e-013	2.51842e-014	1.01998e-013	7.95886e-015	9.24061e-014	1.66033e-014	4.68958e-015	1.15756e-015
f6	30	-1.25695e +004	6.51531e-007	-1.25695e +004	1.13581e-011	-1.25694e +004	2.96182e-001	-1.25695e +004	1.11847e-011
	60	-2.50286e +004	7.34310e+001	-2.51390e +004	1.16255e-001	-2.50344e +004	7.28883e+001	-2.51354e +004	2.03058e+001

5 Conclusions and future research

CSABC proposed by this research, in order to group the relative position of the centre of strategies and policies improved artificial bee colony algorithm, in terms of observing the dispatch centre position last one bee to observe all food sources to search, in order to strengthen small-scale search capabilities; in the utilization of the relative position of scouts strategy to enhance the ability of the algorithm to escape local optima. In addition, this improved method and GABC another algorithm proposed by combining CSGABC, between the present study to test the possibility of his ways and binding.

Through experiments, we found that CSABC with CSGABC algorithm in most of the test function has a very good performance, showing the relative position of the group centre strategies and policies proposed by this research, in addition can be used alone, can also be combined with other bee colony algorithm to achieve complementary synergy multiplied.

Experiments of this research, the main test dimensions of 30 and 60; future research may be experimental for different parameters, especially high-dimensional tests (for example, 300, 500), so that a more comprehensive view of the performance of the performance of this method.

In this paper, the use of cluster centre and the relative positions of the strategy to strengthen the algorithm in the solution space search capability. Future scholars can also try using different algorithms concepts (for example, genes, particle swarm and ant algorithm) to improve bee colony algorithm, I believe will have the opportunity to get more breakthroughs.

Acknowledgements

Supported by Category: The Education Department of Jiangxi Province, 2014 year science and technology project. Project name: Research on key technology of large scale unexpected network public opinion monitoring (NO: GJJ14773)

References

[1] Bao L, Zeng J-c 2010 Self-adapting search space chaos-artificial bee colony algorithm *Application Research Of Computers* **27**(4) 1330-4

[2] Luo J, Fan P-c 2009 Improved particle swarm optimization based on genetic hybrid genes *Application Research Of Computers* **26**(10) 6-3717

[3] Akay B, Karaboga D 2012 A modified artificial bee colony algorithm for real-parameter optimization *Information Sciences* 192 120-42

[4] Alatas B 2010 Chaotic bee colony algorithms for global numerical optimization *Expert Systems with Applications* **37**(8) 5682-7

[5] Basturk B, Karaboga D 2006 An Artificial Bee Colony (ABC) algorithm for numeric function optimization *Proceedings of IEEE Swarm Intelligence Symposium (SIS 2006) Indiana USA* 12-14

[6] Feng Q X, Ding H J 2008 Bee colony algorithm for the function optimization, Science Paper Online available at http://www.paper.edu.cn/en/paper.php?serial_ number=200808-448 (accessed 25 November 2013)

[7] Karaboga D 2005 An idea based on honey bee swarm for numerical optimization *Technical Report-TR06 Erciyes Univ. Press Erciyes*

[8] Karaboga D, Akay B 2008 Solving large scale numerical problems using artificial bee colony algorithm *Proceedings of the Sixth International Symposium on Intelligent and Manufacturing Systems Features, Strategies and Innovation Sakarya Turkiye* 14-17

[9] Karaboga D, Basturk B 2007 A powerful and efficient algorithm for numerical function optimization: Artificial Bee Colony (ABC) algorithm *Journal of Global Optimization* **39**(3) 459-71

[10] Karaboga D, Basturk B 2008 On the performance of artificial bee colony (ABC) algorithm *Applied Soft Computing* **8**(1) 687-97

[11] Li F L, Ding H J, Fang X 2007 The parameter improvement of bee colony algorithm in TSP problem *Science Paper Online available at*

http://www.paper. edu.cn/en/paper.php?serial_number=200711-226 (accessed 25 November 2013)

[12] Liu Y, Qin Z, Shi Z, Lu J 2007 Center particle swarm optimization *Neurocomputing* **70**(4-6) 672-9

[13] Narasimhan H 2009 Parallel Artificial Bee Colony (PABC) algorithm, World *Congress on Nature & Biologically Inspired Computing(NABIC 2009), Coimbatore, India* 306-11

[14] Quan H, Shi X 2008 On the analysis of performance of the improved artificial-bee-colony algorithm *Proceedings of Fourth IEEE International Conference on Natural Computation Jinan China* 25-7

[15] Rahnamayan S, Tizhoosh *H R*, Salama M M A 2006 Opposition-based differential evolution algorithms *Proceedings of IEEE Congress on Evolutionary Computation (CEC 2006) Vancouver Canada* 2010-7

[16] Rahnamayan S, Tizhoosh H R, Salama M M A Opposition versus randomness in soft computing techniques *Applied Soft Computing Journal* **8**(2) 906-18

[17] Tizhoosh H R 2005 Opposition-based learning: a new scheme for machine intelligence *Proceedings of the Computational Intelligence for Modeling Control and Automation (CIMCA.2005) Vienna Austria* 695-701

[18] Tsai P W, Pan J S, Liao B Y, Chu S C 2009 Enhanced Artificial Bee Colony Optimization *International Journal of Innovative Computing, Information and Control* **5**(12) 5081-92

[19] Xu L, Krzyzak A, Oja E 1993 Rival penalized competitive learning for clustering analysis, RBF net, and curve detection *IEEE Transactions on Neural Networks* **4**(4) 636-49

[20] Yi B, Qiao H Q, Yang F, Xu C W 2010 An improved initialization center algorithm for K-means clustering *Proceedings of 2010 International Conference on Computational Intelligence and Software Engineering (CISE 2010) Wuhan China* 1-4

[21] Zhang C, Ni Z W, Wu Z J, Gu L C 2009 A novel swarm model with quasi-oppositional particle *Proceedings of International Forum on Information Technology and Applications (IFITA 2009) Chengdu Chinay* 325-30

[22] Zhu G, Kwong S 2010 Gbest-guided artificial bee colony algorithm for numerical function optimization *Applied Mathematics and Computation* **217**(7) 3166-73

Authors

Keming Chen, 1979-08-23, ShangRao City, JiangXi Province, China.

Current position, grades: associate professor in XinYu University.
University studies: computer science.
Scientific interest: database technology.

Chunping Wang, 1979-01-27, XinYu City, JiangXi Province, China.

Current position, grades: lecturer in XinYu University
University studies: computer science.
Scientific interest: database technology.