Hybrid Artificial Bee Colony Algorithm Based on Cuckoo Search Strategy

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***Abstract*—In order to overcome prematurity and local optimum of the artificial bee colony algorithm and enhance the global searching ability, this paper proposes a hybrid artificial bee colony algorithm (CS-ABC) based on Cuckoo search strategy. In the update mechanism, the Cuckoo search strategy is used to conduct the population replacement. Cuckoo search strategy possesses advantages such as rapid global convergence and ability of escaping from local optimum. Through the experiment using classical Benchmark functions and the comparison with other algorithms, the paper shows that the proposed algorithm has excellent global search ability and can avoid prematurity.**

Keywords: Bee Colony Algorithm; Cuckoo Search Strategy; Levy Flight; local optimum

I. INTRODUCTION

Artificial Bee Colony (ABC) algorithm is a relatively new swarm intelligence algorithm, and it's also an active domain based on swarm intelligence optimization in several recent years. Initially, Seeley brought forward the self-organized model of bee colony. Then Karaboga [2] raised in 2005 a kind of complete swarm intelligence mimic algorithm simulating the process that bee colony finds the high-quality nectar source. This algorithm has the advantages such as few control parameters, being easy to accomplish and simple computation, and it has achieved good results in the numerical function optimization [3], traveling salesman problem [4], the network coverage optimization [5] and other engineering optimization applications.

But just as other intelligent optimization algorithms, the classical artificial bee colony algorithm also has some certain shortcomings: it has the problem of premature convergence and it's easy to fall into local optimum. This paper introduces Cuckoo Search Algorithm (CSA) into the classical artificial bee colony algorithm and uses the population updating mechanism of Cuckoo Search Algorithm in the population location updating and neighbourhood searching stage to balance the ratio of local search to global search and enhance the ability to escape from local optimum. By simulation over classical test functions and comparing the classical bee colony algorithm and other improved ones, this paper proves that CS-ABC can effectively prevents artificial bee colony algorithm from being premature and easy to fall into local optimum and also improve the speed of convergence to some extent.

II. BRIEF INTRODUCTION TO ARTIFICIAL BEE COLONY ALGORITHM

Artificial bee colony (ABC) algorithm is to imitate swarm intelligence searching behaviour in the process of bees collecting nectar. In nature, bees find the best food source by carrying out different activities according to their own division of work and sharing information about food source. This process to find food source is the one to find optimal solutions.

The fundamental framework of ABC consists of three parts: food source, employed foragers and unemployed foragers, in which the unemployed foragers can be divided into scouts and onlookers. The number of employed foragers equals to that of food source and onlookers. Every food source's location represents one feasible solution to the optimization problem and the content of nectar in food source corresponds to the fitness value of the optimization problem.

Firstly, the population is initialled. It is to generate N initial feasible solutions at random (N is the number of food source and also that of employed foragers). Every solution $x_i \ (i = 1, 2, \cdots, N)$ is a d-dimension vector, generated by formula (1):

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

In the formula, $j \in \{1, 2, \cdots, d\}$ is a component of the d-dimension vector. $x_{\min}^j$ and $x_{\max}^j$ are respectively the lower limit and the upper limit. After the initialization, employed foragers firstly conduct a neighbourhood search to the food source, and search for new food sources according to formula (2), updating the locations of food sources:

$$v_i^j = x_i^j + \phi_i^j (x_i^j - x_k^j) \tag{2}$$

In the formula, $k \in \{1, 2, \cdots, N\}$, $j \in \{1, 2, \cdots, d\}$, and $k \neq i$. The values of k and j are at random. ϕ_i^j is a uniformly distributed random number between $[-1, 1]$. In the neighbourhood search, bees choose the food source adopting

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the greedy selection mechanism. If the fitness value of a new food source is greater than or equals that of the old food source, then employed foragers accept the location of the new food source otherwise they don't. (After all employed foragers have completed the search, it goes to the selection of food sources. Onlookers select food sources according to their content of nectar (the fitness value), in which the selection is according to formula (3):

$$p_i = \frac{fit_i}{\sum_{n=1}^{N} fit_j} \tag{3}$$

In the formula, p_i is the probability of selection of the i -th solution. fit_i is the fitness value of the i -th solution. Their calculation formula is as (4):

$$fit_i = \begin{cases} \dfrac{1}{1+f_i} & f_i \geq 0 \\ 1+abs(f_i) & f_i < 0 \end{cases} \tag{4}$$

In the formula, f_i is the objective function value of the i -th solution. When a employed forager (a solution) can't find a better food source location after it reaches the threshold value after a defined number of cycles and at the same time the fitness value of this location of food source (the solution) is not a global optimum, then it indicates that this solution falls into local optimum. On this condition, this solution is discarded and regenerate a new food source location randomly to replace the original solution according to formula (1). In the end, the optimal fitness is recorded after cyclic search of employed foragers.

To sum up, the main process of artificial bee colony algorithm is as follows.

(1) Initialize the colony, including the number of colonies, the colony's maximum evolution generation and the maximum number of iterations, etc.;

(2) Generate the initial colony at random, calculate fitness values (objective function values) of every individual in the colony and mark them;

(3) Circulate (when the termination condition is not satisfied) or skip to (9);

(4) Employed foragers update the colony according to the neighbourhood function and search strategy. And they select relatively good candidates for solutions of the next generation according to the greedy principle;

(5) Eliminate or reserve the colony according to selection strategy: calculate the probability of being selected according to formula (3) and formula (4);

(6) Onlookers select the locations of food sources according to the probability, update the locations of food sources according to formula (2) and select relatively good candidates for solutions of the next generation according to the greedy principle;

(7) Scouts re-initialized to generate new solutions.

(8) Calculate and record the optimum solution of the current colony and then return to step (3);

(9) End.

III. CUCKOO SEARCH ALGORITHM

Cuckoo Search Algorithm (CSA), is a new kind of global optimization algorithm presented by Xin-she Yang [6] in 2009. It imitates the cuckoo's breeding habits to look for nests to lay eggs. And it can effectively solve optimization problems. The search strategy of the algorithm mainly includes: using the colony location update mechanism based on Lévy flight, and using the merit-based selection mechanism in greedy method. CSA has advantages such as a simple principle, few parameters, high efficiency and good random search paths. And it has been successfully applied into practical problems such as engineering optimization and has become a bright spot in the field of heuristic algorithm.

In nature, animals usually search for food in a random manner. And Lévy flight is one of the best strategies of the random walk model. It is often used to describe the mathematical form of the trajectory consisting of continuous random walk such as the motion of gas molecules and organisms' foraging search trajectory. It is a kind of Non-Gaussian random process, whose step size obeys Lévy distribution. After continuous Fourier transform, its characteristic function can become:

$$p_{\alpha,\beta}(k) = \exp\left[i\mu k - \delta^{\alpha} |k|^{\alpha} \left(1 - i\beta \frac{k}{|k|} \varpi(k,\alpha) \right) \right] \tag{5}$$

$$\varpi(k,\alpha) = \begin{cases} \tan\dfrac{\pi\alpha}{2}, \alpha \in (0,1) \cup (1,2] \\ -\dfrac{2}{\pi} \ln|k|, \alpha = 1 \end{cases} \tag{6}$$

In the expressions, δ is the scale parameter; α is the characteristic parameter; μ is the displacement parameter; β is the skewness parameter. Lévy flight's step size probability density function $L(s)$ is usually simplified as formula (7):

$$L(s) \sim |s|^{-1-\beta}, 0 < \beta \leq 2 \tag{7}$$

In the formula, s is the random Lévy step size, which can be obtained by formula (8):

$$s = \frac{u}{|v|^{1/\beta}} \tag{8}$$

In the formula, u and v obey normal distribution; $u \sim N(0, \sigma_u^2), v \sim N(0, \sigma_v^2)$. The fat-tailed character of Lévy distribution can be found in the step size frequency distribution histogram in fig.1, in which the sample number is 1000.

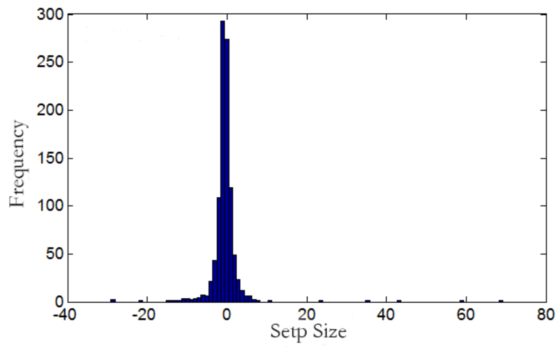

Fig.1 Step size frequency distribution histogram

The variance of Lévy distribution is divergent and grows exponentially. Thus there will be big jumps and shifty direction, whose typical track can be shown as short-distance in-depth local search alternating with occasionally long-distance walk. The trajectory simulation map of Lévy flight is shown in fig.2.

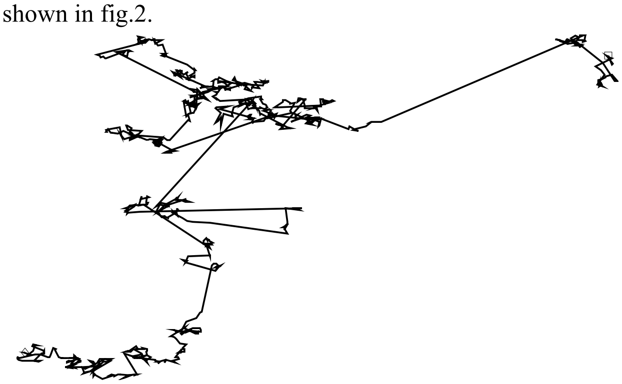

Fig. 2 1000 Lévy flight trajectory simulation map

Step sizes of 1000 Lévy flight is shown in fig.3. It can be seen from fig.3 that one part of solutions are searched for in the vicinity of the current optimal value, which can accelerate local search; and the other part of solutions are searched for in relatively distant space from the optimal value, thereby preventing the algorithm from falling into local optimum.

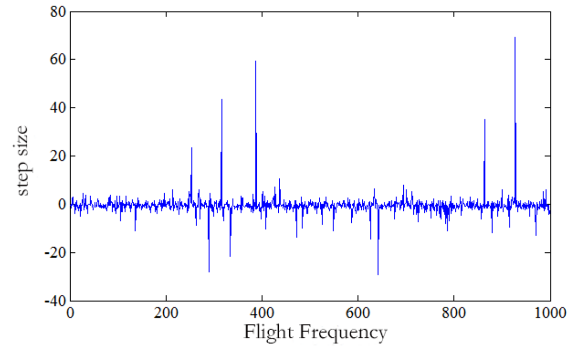

Fig.3 Step sizes of 1000 Lévy flight

IV. Mixed Artificial Bee Colony Algorithm Based on Cuckoo Search Algorithm

Artificial bee colony algorithm and Cuckoo search algorithm all belong to swarm intelligence heuristics. Artificial bee colony algorithm has relatively high convergence rate, but it is easy to fall into local optimum. Cuckoo search algorithm not only has the general characteristics of intelligent algorithm, but also has the rapid global convergence which genetic algorithm and particle swarm optimization can't be compared with. And at the same time, it can effectively escape from local optimum. But it also has problems such as the performance limits to convergence speed caused by the lack of information sharing mechanism among individuals in the population.

This paper puts forward the improvements of artificial bee colony's population update strategy. It is found that the Lévy flight search strategy of Cuckoo search algorithm is a kind of global search operator and can escape from local optimum. And the inferior individuals elimination mechanism can improve population quality advantages. At the same time, artificial bee colony algorithm's effective information sharing mechanism makes up the defects of Cuckoo search algorithm to some extent.

This paper introduces Lévy flight search strategy into update operations to the food source's location of mixed artificial bee colony algorithm to enhance the global search capability of artificial bee colony algorithm, taking full advantage of the random walk characteristic of Lévy flight to have huge leap and several changes in direction, thus it can effectively prevent colony from being bound by local attractors and expand search space. The improved update mode to food sources is as formula (9):

$$x_i^j(t+1) = x_i^j(t) + L(\lambda) \otimes \left(x_i^j(t) - x_{best}^j\right),\ 1 < \lambda \le 3 \tag{9}$$

In the formula, x_{best}^j is the location of the current best food source in the colony; $L(\lambda)$ is the hop path of random search whose step size obeys Lévy distribution and its length and direction are uncertain; Parameter λ is scale parameter and $\lambda = 1+\beta$; $\otimes$ is the vector operator.

The implementation process of mixed artificial bee colony algorithm is as follows:

(1) Set the initial parameters, including the number of colonies N, the colony's maximum evolution generation, the maximum number of iterations and colony's group information;

(2) Randomly initialize the bee colony (food source) $X_0(N)$, and calculate fitness values of individuals in population.

(3) Circulate (when the loop condition is satisfied) or skip to (9);

(4) Employed foragers conduct a global search to generate new locations according to formula (9), and select relatively good candidates for solutions of the next generation according to the merit-based selection mechanism.

(5) Eliminate or reserve the colony according to selection strategy: calculate the probability of being selected according to formula (3) and formula (4);

(6) Onlookers select the locations of food sources according to p_i , update the locations of food sources according to formula (9) and select relatively good candidates for solutions of the next generation according to the greedy principle;

(7) Scouts re-initialized to generate new solutions.

(8) Calculate and record the optimum solution of the current colony and then return to step (3);

(9) End.

V. SIMULATION AND ANALYSIS

In order to verify CS-ABC's performance, this paper conducts simulation to compare CS-ABC with classical ABC and several other improved algorithms. The testing environment is: Matlab 2013a software, Windows server 2008 operating system, 16GB memory, Intel Xeon CPU E5-2620 and 2.0GHZ CPU main frequency. The contents compared in the simulation testing include: iterative evolutionary curve, convergence performance comparison and comparison with other improved algorithms.

To test the performance of CS-ABC proposed in this paper, Benchmark functions [7] are chosen to conduct simulation, as fig.4. In this figure, Sphere is a unimodal function, usually used to test the algorithm's precision of optimization; Griewank is a multimodal function, usually applied to evaluate an algorithm's global optimization capability. Rastrigin is a multimodal function, commonly used to test an algorithm's global search capability and ability to avoid prematurity. In the actual simulation test, the parameter setting is as follows: the population size is 60; the maximum number of cycles is 200; the maximum number of iterations is 2000; and every algorithm runs 30 times randomly.

Test problem	Description	Range1
Sphere	$\min_x f_1(x) = \sum_{i=1}^{n} x_i^2$	$[-100,100]^n$
Rosenbrock	$\min_x f_2(x) = \sum_{i=1}^{n-1}\left[100\left(x_{i+1}-x_i^2\right)^2+\left(x_i-1\right)^2\right]$	$[-10,10]^n$
Ackley	$\min_x f_3(x) = -20\exp\left(-0.02\sqrt{n^{-1}\sum_{i=1}^{n} x_i^2}\right)-\exp\left(n^{-1}\sum_{i=1}^{n}\cos(2\pi x_i)\right)+20+e$	$[-30,30]^n$
Griewank	$\min_x f_4(x) = \sum_{i=1}^{n}\frac{x_i^2}{4000}-\prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right)$	$[-600,600]^n$
Rastrigin	$\min_x f_5(x) = \sum_{i=1}^{D}\left(x_i^2-10\cos(2\pi x_i)+10\right)$	$[-5.12,5.12]^n$

Fig. 4 Benchmark functions

According to Benchmark functions in Fig. 4, three types of them are selected to conduct the test. The obtained average evolution curves of ABC and CS-ABC are as Fig. 5, Fig. 6 and Fig. 7. In the figures, the horizontal axis is the number of iterations and the vertical axis is the objective function value. It can be seen from them that CS-ABC has the better convergence ability and the faster convergence speed.

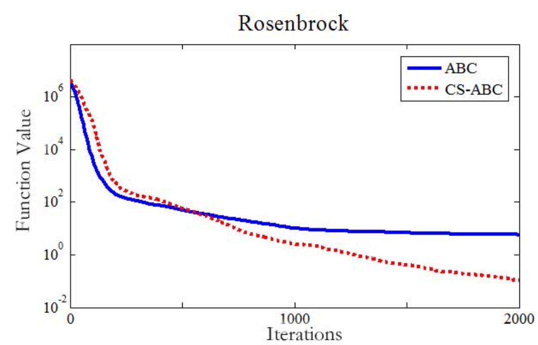

Fig. 5 Rosenbrock function

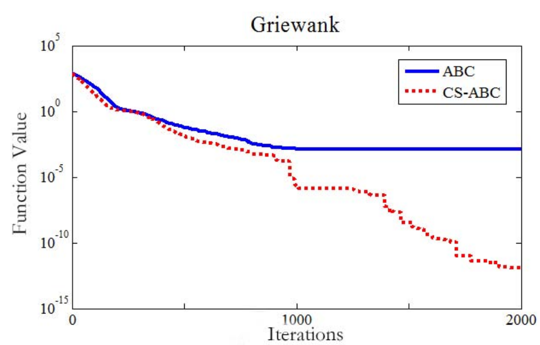

Fig. 6 Griewank function

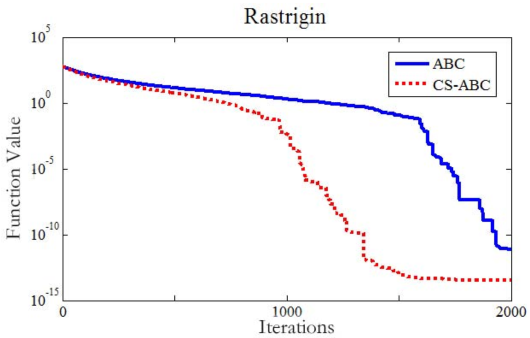

Fig. 7 Rastrigin function

The comparison of algorithms' convergence performance results are as Fig. 8. The results of CS-ABC are better than classical ABC algorithm. It illustrates that adopting Cuckoo search strategy could improve the quality of solutions and the convergence speed.

Function	Alg	Max	Min	Mean	Std
f_1	ABC	1.15000e-10	4.62752e-14	3.26778e-12	2.96497e-11
	CS-ABC	1.09409e-14	6.17399e-16	8.43004e-15	1.25419e-15
f_2	ABC	76.2333	0.00553661	5.74636	17.2772
	CS-ABC	0.305005	0.00133821	0.105068	0.0789793
f_3	ABC	4.898e-09	6.9186e-10	1.95289e-09	9.84625e-10
	CS-ABC	3.49321e-12	1.11644e-12	2.03375e-12	6.46762e-13
f_4	ABC	0.0175506	4.44089e-16	0.00124734	0.00417769
	CS-ABC	6.77236e-15	0	4.12777e-16	7.31023e-15
f_5	ABC	4.60432e-11	5.68434e-14	6.87237e-12	1.47058e-11
	CS-ABC	1.13687e-13	0	3.78956e-14	3.10747e-14

Fig. 8 Comparison of algorithms' performance

In order to further investigate this algorithm's performance, this paper compares this algorithm with OABC [8] and PABC [9], selecting three functions in Fig. 4 to conduct the test.

Fig. 9 shows the results of performance comparison of the three algorithms. It can be seen by comparing average data and the best one in the figure.

Function	Alg	Max	Min	Mean	Std
f_2	OABC	43.9468	0.00952678	2.4516	9.77015
	PABC	58.1103	0.11710813	1.019174	1.938589
	CS-ABC	0.305005	0.00133821	0.105068	0.0789793
f_4	OABC	5.99909e-10	4.44089e-16	3.43689e-11	1.342e-10
	PABC	2.44582e-13	0	1.28508e-14	5.45515e-14
	CS-ABC	6.77236e-15	0	4.12777e-16	7.31023e-15
f_5	OABC	1.00044e-11	0	1.6712e-12	2.68668e-12
	PABC	2.14135e-11	1.61621e-14	5.32824e-12	4.13177e-13
	CS-ABC	1.13687e-13	0	3.78956e-14	3.10747e-14

Fig. 9 Comparison of performance of improved algorithms

VI. CONCLUSION

This paper, on the base of researching the optimization of artificial bee colony algorithm, analyses the original algorithm's limitation and refers to research results in recent years, finding that the improved strategy based on Cuckoo Search Algorithm can enhance the quality of solutions, accelerate the convergence process and avoid prematurity. The results of simulation also shows that CS-ABC has faster convergence and higher precision of optimization. It also avoids prematurity effectively compared with other improved algorithms. The optimization and application of artificial bee colony algorithm are still in the research stage and there are many issues to be explored and solved by people, such as convergence analysis to the algorithm and the fusion with other optimization algorithms. How to apply this algorithm to actual fields such as face recognition and image processing can be the future work.

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