An Improved Hybrid Group Intelligent Algorithm Based on Artificial Bee Colony and Particle Swarm Optimization

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***Abstract*—Aiming at the disadvantage of poor convergence performance of PSO and artificial swarm algorithm, an improved hybrid algorithm is proposed to overcome the shortcomings of complex optimization problems. Through the test of four standard function by hybrid algorithm and compared the result with standard particle swarm optimization (PSO) algorithm and Artificial Bee Colony (ABC) algorithm, the convergence rate and convergence precision of the hybrid algorithm are both superior to those of the standard particle swarm algorithm and Artificial Bee Colony algorithm, presenting a better optimal performance.**

Keywords- Particle Swarm Optimization; Artificial Bee Colony; hybrid algorithm; Swarm Intelligence

I. INTRODUCTION

The fusion of intelligent algorithms is a research difficulty yet a promising research direction. The fusion of intelligent algorithm is a new effective method to solve the problem that single intelligent algorithm cannot resolve. At present, scholars at home and abroad have proposed many kinds of fusion algorithms according to different problems. These algorithms are very good to solve some practical problems. These algorithms are very good to solve some practical problems.

Artificial Bee Colony [1] (ABC) is an optimization algorithm based on the intelligent search behavior of honey bee colony. Combining the global search and local search, the performance of ABC algorithm is superior to that of PSO. Particle Swarm Optimization (PSO) [2] has many advantages such as few parameters, simple operation, easy implementation and high efficiency to function optimization, and thus It has been applied in many fields. However the result of PSO inclines to present premature convergence, local optimization, late convergence and poor accuracy. Therefore, a variety of improved algorithms increase the performance of PSO algorithm from different angles. In this paper, the artificial bee colony algorithm is introduced into the particle swarm optimization algorithm, PSO-ABC algorithm. The simulation results show that this fusion algorithm has better performance in performance optimization.

II. ARTIFICIAL BEE COLONY ALGORITHM

A. *The principle of Artificial Bee Colony Algorithm*

In the artificial bee colony algorithm, the bees can be divided into three groups according to the division of labor: honey bees, followers and scout bees. The honey bee's role is to randomly search for nectar within the defined domain, and then share the nectar information with the followers; followers select a better nectar the bees with a certain selection strategy in the vicinity; scout bees are formed by honey bees which abandoned nectar because they collect more than a predetermined number of cycles or collect only a small amount of honey. Scout bees later re-search for new sources of nectar [3-8].

1) The initial stage of the algorithms

Suppose there are m honey bees and m followers, and D-dimensional vector X_{ij} (j = 1, 2, 3,..., D) represents the location of the i-th honey source. Suppose there is only one honey bee working at a honey source, thus there are m honey sources. Initialized as follows:

$$X_{ij} = X_{minj} + \varphi\ (X_{maxj} - X_{minj}) \quad (1)$$

Where X_{ij} is the current position, $i \in \{1,2, ..., m\}$, X_{maxj} and X_{minj} represent the maximum and minimum values in j dimension, and φ is a random number between [0,1].

2) The mining stage of algorithm

After the honey bees find a honey source, the quality of the nectar is measured by the fitness. Fitness is given by the following formula:

$$F_j = \begin{cases} 1/(1+f_j) & f_j \geq 0 \\ 1+abs(f_j) & f_j < 0 \end{cases} \quad (2)$$

Where f_j and F_j are the adaptability and fitness of the i-th honey source respectively.

Followers choose whether to update according to probability P_j, the formula of which is as follows:

$$P_j = \frac{F_i}{\sum_{j=1}^{m} F_i} \quad (3)$$

Honey bees and followers both update values in accordance with

$$V_{ij} = X_{ij} + \varphi\ (X_{ij} - X_{kj}) \quad (4)$$

Where V_{ij} denotes the new position, $k \in \{1,2, ..., m\}$ and $k \neq i$, is a random number.

B. *The algorithm flow of Artificial Bee Colony*

ABC algorithm steps are as follows:

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Step 1: Initialize the basic parameters of the algorithm, according to the formula (1) to generate the initial position of the bees.

Step 2: Honey bees calculate the fitness value according to the formula (2) to, compare and save the optimal value.

Step 3: Followers select the honey bees by formula (3) and update the position of the new honey source according to formula (4). Compare with the fitness of the updated position and save the optimal value.

Step 4: If there is a scout bee, regenerate the initial position by the formula (1) and carry out the update optimization. Otherwise, proceed to step 5.

Step 5: If the number of iterations is less than the preset number of iterations, go to step 2; otherwise, output the optimal solution.

C. The characteristics of Artificial Bee Colony

The characteristics of the ABC algorithm is as follows:

1) It is a kind of random search algorithm, simulation of nature swarm show complex intelligent behavior of honey.

2) With the roles in the process of evolution and transition,Different roles in the ABC algorithm has different tasks.They are according to the optimal situation between different role conversion optimization work together with each other.

3) IT has high robustness.The rules of probability and random selection in the process of searching are for ways to find food sources.It can not consider prior knowledge. It has high robustness and adaptability.

III. PARTICLE SWARM OPTIMIZATION ALGORITHM

A. The Principle of PSO algorithm

Particle Swarm Optimization (PSO) is an iterative random search algorithm. Each solution is an individual particle with no volume and no mass in the search space. At each iteration, the particle updates itself according to the two pieces of extremum information. One is the individual optimal value pbest found by the individual particle, and the other is the global optimal value gbest found by the population. In this way, the particle population can approach the individual particle that has good adaptive value and find the optimal solution in the end [9-12].

PSO algorithm can be described as follows: Suppose in a D-dimensional target search space, N particles form a particle population, the position and velocity of the i-th particle are expressed as: $x_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$ and $v_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$. The individual optimal position of the individual particle is: $p_i = (p_{i1}, p_{i2}, \cdots, p_{iD})$(pbest), The global optimal position of the whole particle population is: $p_g = (p_{g1}, p_{g2}, \cdots, p_{gD})$ (gbest). Each particle updates the speed and position iteratively according to the following formula:

$$v_{id}^{t+1} = \omega v_{id}^t + c_1 r_1 (p_{id}^t - x_{id}^t) + c_2 r_2 (p_{gd}^t - x_{id}^t) \quad (5)$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \quad (6)$$

In which, i=(1,2,......N)， d=(1,2,......D)； ω is Inertia weight; c_1 and c_2 are Acceleration constants; $r_1$and r_2 are evenly distributed random numbers between 0 and 1; v_{id}^t is the current velocity of particle i ; v_{id}^{t+1} is the updated velocity of particle i ; x_{id}^t is current position of particle i; x_{id}^{t+1} is the updated position of particle i.

B. The algorithm flow of particle swarm

PSO algorithm steps are as follows:

Step 1: Initialize the particle swarm, randomly generate the position and velocity of a set of particles, initialize the individual optimal pbest value and the global optimal gbest value;

Step 2: Calculate the objective function value of each particle and use it as the fitness value of the particle;

Step 3: Compare the fitness value of each particle with its individual optimum pbest value, and if the current particle fitness value is better, the individual optimal pbest value will be replaced;

Step 4: Compare the individual optimal pbest value of the updated particle with the current optimal gbest value of the population. If it is superior to the gbest value, attribute it to the new current group optimal gbest value;

Step 5: Update the velocity and the position of the particle according to the formula (5) and the formula (6).

Step 6: Decide whether the termination condition is satisfied. If satisfied, stop the algorithm and output gbest. If not satisfied, return to step 2.

IV. HYBRID ALGORITHM

A. ABC-PSO algorithm principle

Particle swarm hybrid algorithm, first divide the particles into M subgroups of equal size, each subgroup evolves following the artificial bee algorithm model; then, form a new group by the best particles of each subgroup, and evolve according to the particle group algorithm model evolution, to find the best particles [13-15] . The algorithm utilizes the local and global search properties of the ABC algorithm to narrow the search range [16]. The position feedback of the global best particle in the artificial bee colony algorithm is introduced into the updated velocity formula of the particle swarm, which effectively leads the PSO to avoid the problem of local optimum.

B. ABC-PSO algorithm flow

ABC-PSO algorithm steps are as follows:

Step 1: Initialize the artificial bees, set the relevant parameters;

Step 2: The population was divided into M groups, each group of N individuals;

Step 3: Calculate the fitness value of each individual, and then select the nectar source is according to the fitness value. Find the optimal solution after the finite number of iterations;

Step 4: Take the optimal solution of each group as the initial particle of PSO;

Step 5: Update particles according to the updated particle swarm formula and find the optimal solution.

Step 6: If the termination condition is satisfied, the optimal solution is output; otherwise, the process returns to step 3;

Figure 1 shows the flow chart of the PSO-ABC algorithm.

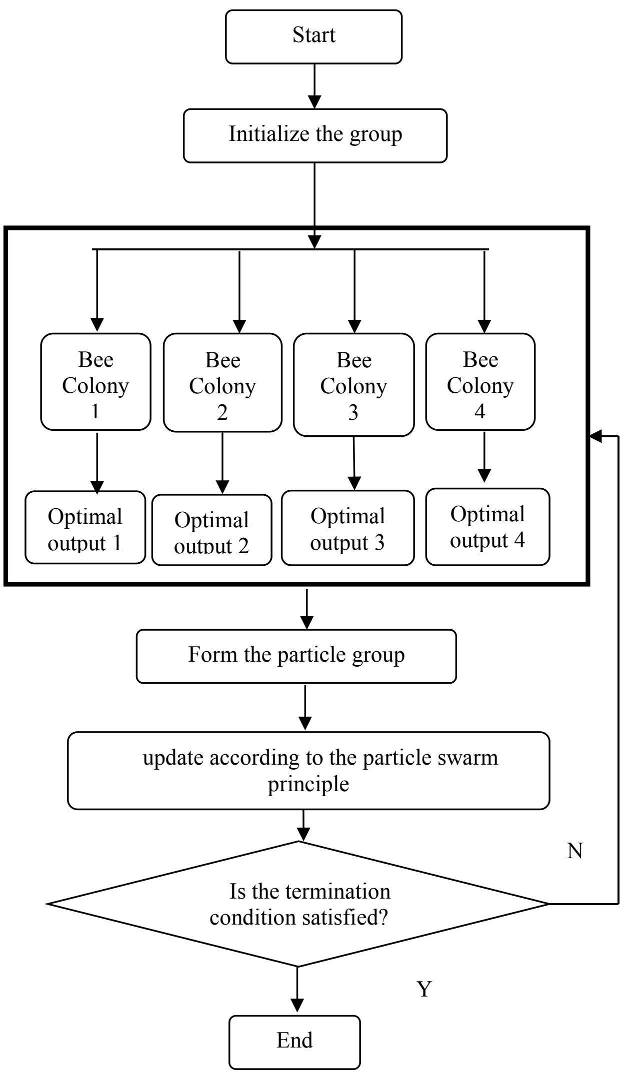

Figure 1. The chart of the PSO-ABC algorithm

V. SIMULATION EXPERIMENT

A. Experiment design

In order to test the performance of the algorithm, four classical benchmark functions, two unimodal functions and two multimodal functions, are chosen for simulation experiments [17]. The test environment is Matlab7.0 and Windows 7. As is shown in Table 1.

Table 1. Four classical benchmark functions

	函数名	测试函数	范围	维数	最优值	收敛值
单峰函数	sphere	$f(x)=\sum_{i=1}^{n} x_i^2$	[-100,100]	30/100	0	0.01
	rosenbrock	$f(x)=\sum_{i=1}^{n}[100(x_{i+1}-x_i^2)^2 + (x_i-1)^2]$	[-2.048,2.048]	30/100	0	100
多峰函数	rastrigin	$f(x)=\sum_{i=1}^{n}[x_i^2-10\cos 2\pi x_i + 10]$	[-5.12,5.12]	30/100	0	50
	griewank	$f(x) = {}^{1}/_{4000}\sum_{i=1}^{n}(x_i)^2 - \prod_{i=1}^{n}\cos\left({}^{x_i}/_{\sqrt{i}}\right)+1$	[-600,600]	30/100	0	0.01

B. Experimental results and analysis

In order to verify the performance of the algorithm, run the function of PSO-ABC algorithm, PSO algorithm and ABC algorithm for 30 times each, and then take the average as the optimization results [18-20]. The experimental results are in Table 2. From the test results we can see: PSO-ABC algorithm in most functions on the test results is significantly better than other contrast algorithms.

Table 2. Experimental results

FunctioN	Algorithm	Average Adaptive value	Maximum Adaptive Value	Minimum Adaptive Value
sphere	ABC-PSO	8.9034	49.55	0.000133406
	PSO	179.63	3987.56	0.004550
	ABC	89.96	2306.65	0.002061
rosenbrock	ABC-PSO	4123.57	5928.6	8.2337
	PSO	70334.8	2566045	0.002387
	ABC	52334.6	9899.65	0.001843
rastrigin	ABC-PSO	147.37	327.266	0.2441
	PSO	158.96	364.87	0.0002317
	ABC	136.68	355.29	0.00564
griewank	ABC-PSO	0.43362	0.79662	0.001766
	PSO	2.5777	36.8992	0.006653

	ABC	1.8532	12.553	0.0047

VI. CONCLUSIONS

The PSO-ABC fusion algorithm proposed in this paper is simple and easy to implement. The algorithm has good performance in both single peak and multi-peak test functions, and has better global searching ability and faster convergence speed. Compared with the artificial swarm algorithm, the standard particle swarm has the advantage of both the particle swarm and the artificial bee colony algorithm. The global optimal solution can be found more quickly on the single peak function. In the complex multi-peak function, it can effectively escape the local extreme. The performance of the new algorithm is improved to a certain degree both in the standard particle swarm and the artificial bee colony.

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