Chaotic Hybrid Bacterial Colony Chemotaxis Algorithm Based on Tent Map

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***Abstract*—Aiming at improving the global convergence speed of bacterial colony chemotaxis (BCC) optimization algorithm, a new chaotic hybrid bacterial colony chemotaxis (CHBCC) algorithm is introduced through the technique of hybrid algorithm. By integrating elitist strategy and chaotic optimization into bacterial colony chemotaxis optimization algorithm, it greatly enhances the local searching efficiency and global searching performance. Furthermore, the bacteria are divided into two sub-swarms and perform different operations to co-evolve, one sub-swarm searches via BCC and the other searches via chaos algorithm based on Tent Map at the same time. Simulation results on some benchmark functions show that CHBCC is pretty efficient to solve complex problems. It has high optimization efficiency, good global performance, and stable optimization outcomes. The performance of CHBCC is evidently better than BCC and BC.**

***Index Terms*—bacterial colony chemotaxis, elitist strategy, chaotic optimization, Tent Map**

I. INTRODUCTION

In the field of function optimization algorithm, many researchers have been inspired by the behavior of natural systems for decades such as the movement of flocks of birds or the food-searching behavior of ants or honey bee foraging behavior to develop new optimization algorithm methods such as particle swarm optimization Algorithms [1] (PSO) or Ant Colony Algorithms (ACA) [2] or simulated bee colony (SBC) algorithm [3], which are sometimes called meta-heuristic algorithms. These swarm intelligence optimization algorithms have been proved to perform more effectively than the classical heuristic, gradient-based or individual intelligence optimization algorithms, especially when solving the engineering problem of optimizing multimodal, non-differentiable, or discontinuous functions. The Swarm Intelligence optimization algorithms have successfully been used in many fields such as training of neural networks, function optimization, fuzzy control system and so on.

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D. Sibylles et al [4] present an optimization algorithm based on a model of bacterial chemotaxis, which performs similar to standard evolution strategies and worse than evolution strategies with enhanced convergence properties. LI Wei-wu et al [5] present Bacterial Colony Chemotaxis (BCC) algorithm, based on Bacterial Chemotaxis (BC) algorithm, which is a novel heuristic swarm intelligence optimization algorithms. Because BCC algorithm fully makes use of the interactions of the entire colony, it greatly improves the convergence speed and accuracy of BC algorithm and makes it comparable to many other well-used intelligent optimization methods. Nowadays, BCC has widely used in many fields [6] [7].

In this paper, a novel method chaotic hybrid bacterial colony chemotaxis (CHBCC) algorithm based on Tent Map is introduced through the technique of hybrid algorithm. By integrating elitist strategy and chaotic optimization into bacterial colony chemotaxis optimization algorithm, it greatly enhances the local searching efficiency and global searching performance. Furthermore, the bacteria are divided into two sub-swarms and perform different operations to co-evolve, one sub-swarm searches via BCC and the other searches via chaos algorithm at the same time. Simulation results on standard test functions show that CHBCC is pretty efficient to solve complex problems. It has high optimization efficiency, good global performance, and stable optimization outcomes. The performance of CHBCC is evidently better than BCC and BC.

II. BACKGROUND AND RELATED WORK

A. BC algorithm principle

Bacterial Chemotaxis (BC) [4] algorithm is based on the theory of Bacterial Chemotaxis theory, and built up by simulating the movement of a single bacterium. Bacteria are single-cell organisms, which is the simplest form of life developed on earth. But they acquire information about their environment, orient themselves in this environment, and use this information efficiently to survive. So, we can make full use of the interaction between bacteria and their environment to create new optimization algorithm.

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It has been proved that bacteria can share information among bacteria colony, but individuals and social interaction among bacteria are different from the interaction models for the behavior of social insects which are viewed as systems with swarm intelligence which enables organisms to solve problems that are difficult or impossible for single individuals to resolve. This reaction of the organism to its environment has been interested in by many scientists in the field of optimization algorithm. The scientists construct an optimization algorithm based on the simplicity and robustness of the process of bacterial chemotaxis. For optimization purposes, the scientists study microscopic models that consider the chemotaxis of a single bacterium. Several novel features are added to the basic algorithm using evolutionary concepts in order to obtain an improved optimization strategy with strong problem-solving capabilities, called the bacteria chemotaxis (BC) algorithm [4].

Bacteria algorithm based on the bacterial chemotaxis model, whose mathematical model of BC algorithm is in paper [8] .Take a two-dimensional system for a minimum point as an example, the BC algorithm basic steps are showed in Fig.1and is followed below:

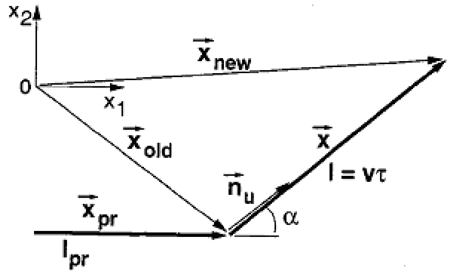

Figure 1. Movement of a bacterium for 2-D model

1) let the velocity v =contst (always 1) (1)

2) Compute the time of the trajectory τ from the distribution of a random variable with an exponential probability density function

$$P(X=\tau)=\frac{1}{T}e^{-\tau/T}. \qquad (2)$$

T is depended on previous position vector $\vec{x}_{pr}$ connecting the previous position and the actual position, and the $l_{pr}=|\vec{x}_{pr}|$.

2) Compute the new direction. The probability density distribution of the angle α between the previous and the new direction is Gaussian and Reads (detailed description in literature [4]).

3) Compute the new position. The length of the path l is given by

$$l=v\tau \qquad (3)$$

The normalized new direction vector $\vec{n}_u$ with $|\vec{n}_u|=1$ is multiplied by l to obtain the new location of the bacterium :

$$\vec{x}_{new}=\vec{x}_{old}+\vec{n}_u l \qquad (4)$$

In summary, the optimization strategy parameters are adjusted on the factual problem.

B. BCC algorithm principle

BCC algorithm is one of novel heuristic colony intelligent optimization algorithm, and it is gained by establishing information interaction between individual bacterial. It is supposed that the bacterium has a sense limit in its environment [4]. BCC algorithm basic steps are following [9]:

Step 1: Initialize the number of bacteria colony and the sense limit. Initialize the position of individual bacterium with random legal values based on the viable intervals. Determine initial starting precision ε_{begin} and the constant of updating precision ε_{cons}.

Step 2: In the initial conditions, the objective function fitness of individual bacterium is calculated based on the individual position; the current optimal value is choose and saved.

Step 3: The bacterium i which moves at the tth step, apperceives the information around it, identifies the center position of other bacteria which have better objective function fitness value in the sense limit, and learns from the center position. The center position is expressed as follow:

center_position(i)=rand() • dis($x_{i,t}$,center($x_{i,t}$)) (5)

where dis($x_{i,t}$,center($x_{i,t}$)) is the distance between the bacteria i and the center_position(i), and rand() is a random number meeting the uniform distribution in interval (0, 1).

Step 4: The bacterium i which moves at the tth step, gains another position bc_position (i) according to single bacterium BC algorithm.

bc_position(i)=current_position(i)+next(i) (6)

where current_position (i) denotes the position of bacteria i at this time; next (i) denotes the expected changing value of the next location:

$$\text{next (i)}=vd\times|\vec{n}_u| \qquad (7)$$

v, d and $|\vec{n}_u|$ α are the velocity, the duration and the normalized new direction vector with $|\vec{n}_u|=1$ respectively.

Step 5: Compare the objective function fitness values of the two positions bc_position(i) and center position(i), then bacteria i moves to the position which value is better at number t+1 step.

Step 6: Update the optimal position and the related parameters. Repeat step 3~5 until the termination conditions satisfied, stop search process and put out he best bacterium as the best solution. The termination condition maybe a maximum number of iterations or a satisfactory fitness value.

C. Chaos search strategy

Chaos is a kind of universal nonlinear phenomena in many systems [10]. Chaotic movement is characterized by ergodicity, randomicity and regularity. So chaotic movement could go through every state in certain scale according to its own regularity and ergodicity, which is better than simple stochastic algorithm. In many optimization algorithms it is always introduced into the optimization strategy to accelerate the optimum seeking operation and find the global optimal solution.

There are many methods for producing chaos variable [11][12][13], Literatures shows the chaos characteristic of Tent map with contrasting the Logistic map and Tent map, proved that the iteration speed of Tent map is faster than Logistic map, Tent map have the even distribution function, and the initial value sensitivity of its chaos list's probability density distribution function is not strong and its iteration is adapted to the computer. So we consider the use of chaos optimization method based on Tent map. Its equation is as follows:

$$x_{k+1} = \begin{cases} 2x_k, & 0 \le x_k \le 1/2 \\ 2(1-x_k), & 1/2 < x_k \le 1 \end{cases} \quad (8)$$

In this paper, the test suite represented by the ith bacterium produces the discrete chaos series based on Tent map as follows:

Step1. The ith bacterium position x_i is respectively given in equation (8) initial values at random with minor differences, and will get chaos variables with different chaos track. Through M (about 300) times iteration, M numerical values in (0, 1) are obtained.

Step2: calculating chaotic variables in each iteration according to equation (9)

$$\boldsymbol{f(x) = x.|V\max - V\min|} \quad (9)$$

Vmax is the right value of the function interval, and Vmin is the left value of the function interval. Then a chaotic variable in interval $\boldsymbol{(V\min, V\max)}$ can be produced.

D.elitist strategy

The elitist strategy is used to add the best individual in the previous population to the next generation, in place of its worst individual.

Elitist strategy is a method commonly used in genetic algorithms (GA) [14] [15] [16]. It's an iteration process to add the best individual in the previous population to the next generation, in place of its worst individual. Simply, it's a general process of directly copying the corresponding solution to the next cycle. Elitist strategy had been considered as an efficient method for enhancing the performance of evolutionary algorithms. In this paper, Elitist strategy is integrated into the traditional BCC algorithm to improve the speed of the global convergence of the BCC by copying the several better bacteria to replace the corresponding worse bacteria.

III. METHOD

A. overview

Swarm intelligence optimization algorithms are sometimes called metaheuristic algorithms because they provide a high-level framework which can be adapted to solve optimization, search, and related problems, as opposed to providing a stringent set of guidelines for solving a particular problem. So when Swarm intelligence is used to solving a specific problem it must be modified to fit the problem.

Using traditional BCC algorithm to solve the function optimization problem, BCC algorithm has good optimization capabilities, convergence speed, high precision optimization and its performance is better than BC algorithm and some other intelligence optimization algorithms. But for some multimodal function which has not obvious gradient change, the bacterium will get into the local optimum easily and hardly reach the global optimum.

In this paper, a novel chaotic hybrid bacterial colony chemotaxis (CHBCC) algorithm is introduced through the technique of hybrid algorithm. By integrating elitist strategy and chaotic optimization into bacterial colony chemotaxis optimization algorithm, it greatly enhances the local searching efficiency and global searching performance. Furthermore, the bacteria are divided into two sub-swarms and perform different operations to co-evolve, one sub-swarm searches via BCC and the other searches via chaos algorithm at the same time.

B. Integrating elitist strategy into BCC algorithm

The elitist strategy is used to add the best individual in the previous population to the next generation, in place of its worst individual. Elitist strategy had been considered as an efficient method for enhancing the performance of evolutionary algorithms.

In the running process of BCC, individual bacterium will move and gain another fine position in the bacteria movement process, but because of the randomness of bacteria movement, it is easy to destroy the best adaptive individuals in the current bacteria colony, it may impact operating efficiency and convergence of BCC algorithms. While the previous individuals will be replaced by the offspring after movement in BCC algorithm, the basic idea of Elitist Strategy is to have evolutionary operations after movement so that the individuals that the fitness is the best may keep down to the next generation groups. The implementation of the strategy can guarantee that the optimal individuals will not be damaged by the bacteria movement process, but also can guarantee the global convergence of BCC algorithm. As a result of this strategy, even when generating excessive bad bacterial positions after movement, there are the majority of the last bacterial positions and Elitist positions are kept, which help to enhance the convergence of the BCC algorithms.

C.Integrating chaotic optimization into BCC algorithm

In order to maintain the diversity of bacteria, we add chaos search in original BCC algorithm, which is better at local searching. It would be effective and rational to combine chaos and original BCC algorithm to balance the local and global search. On one hand it can enhance the global search capabilities and get out of the local optimum easily. While on the other hand, it will not reduce the convergence speed and search accuracy at the same time.

When the center position of other bacteria which have better objective function value in the sense limit, the center position is expressed as follow:

$$center\_position(i)=tent() \bullet dis(x_{i,k},center(x_{i,k})) \quad (10)$$

where $dis(x_{i,k},center(x_{i,k}))$ is the distance between the bacteria i and the center_position(i), and tent()is a chaotic sequence number meeting the tent map equation in interval (0, 1).

D.chaos standby database

In order to avoid premature convergence and increase global ergodicity of bacterial movement, we introduce chaos standby database, and uses chaos optimization algorithm based on Tent map to generate a small chaotic standby database (3 to 10 is appropriate) to keep the variety [17]. Chaos standby database is simultaneously updated with the bacteria colony, and in iteration several best bacteria (2 is appropriate) are selected to replace several worst bacteria in current bacteria colony. In this way, the speed of evolution of the bacteria colony is accelerated, its global convergence properties are maintained, and the performance of algorithm is improved to enhance the global convergence.

E. CHBCC Algorithm for function optimization problem

In summary, the novel CHBCC Algorithm for function optimization problem is as following:

Step 1: Initialize the number of bacteria colony, the position of individual bacterium and the sense limit. In particular, the initial position of individual bacterium is generated by Tent map based on chaotic sequence as mentioned above. Determine initial starting precision ε_{begin} and the constant of updating precision ε_{cons}.

Step 2: Initialize chaos standby database with size of n according to section D.

Step 3: In the initial conditions, the objective function fitness of individual bacterium i in the bacteria colony and chaos standby database are calculated.

Step 4: The bacterium i which moves at the kth step, apperceives the information around it, identifies the center position of other bacteria which have better objective function fitness value in the sense limit. The center position is expressed as follow:

$$center\_position(i)=tent()dis(x_{i,k},center(x_{i,k})) \quad (11)$$

where $dis(x_{i,k},center(x_{i,k}))$ is the distance between the bacteria i and the center_position(i), and tent()is a chaotic sequence number is generated by Tent map based on chaotic sequence as mentioned above.

Step 5: The bacterium i which moves at the kth step, gains another position bc_position (i) according to single bacterium BC algorithm.

$$bc\_position(i)= current\_position(i)+ next(i) \quad (12)$$

where current _position(i) denotes the position of bacteria i at this time; next (i) denotes the expected changing value of the next location:

$$next(i)=vd\times|\vec{n_u}| \quad (13)$$

v, d and $|\vec{n_u}|$ α are the velocity, the duration and the normalized new direction vector with $|\vec{n_u}|=1$ respectively.

Step 6:Compare the objective function fitness values of the two positions center_position(i) and bc_position(i), then bacteria i moves to the position which value is better at number k+1 step.

Step 7: Update the position of the bacteria in chaos standby database according to equations (8) (9) at number k+1 step.

Step 8: For each step, several best bacteria (2 is appropriate) in the current chaos standby database are selected to replace several worst bacteria in current bacteria colony.

Step 9: For each step, several elitist bacteria (2 is appropriate) in the current bacteria colony are selected to replace several worst bacteria in current bacteria colony in the next step.

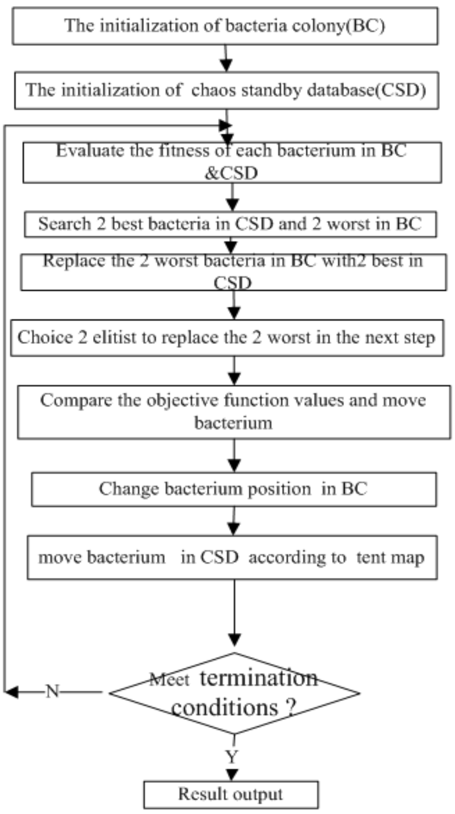

Figure 2. Flow chart of novel CHBCC algorithm

Step 10: Update the optimal position and the related parameters. Repeat step 4~9, until the termination conditions satisfied, jump out of the cycle. The termination condition maybe a maximum number of iterations or a satisfactory function fitness value.

In summary, the flow chart of a novel CHBCC Algorithm for function optimization problem is shown in Fig. 2.

IV. NUMERICAL EXPERIMENTS

To test the performance of the novel CHBCC algorithm for solving the function optimization problem, the author developed program for it. The novel CHBCC algorithm discussed here has been developed in MATLAB R2007a platform on an Intel(R) Core(TM) Duo T75002.2GHz PC, with 1GB of main memory in Windows XP Professional SP3 environment. In this paper, the typical example in literature [4] [5] is adopted and the experiment results are compared with result of this paper.

Note: the data with * are from literature [4] [5].

Concerning the CHBCC algorithm, simulation experiment parameters are as follows: the scale of bacterial colony is 20, the chaos standby database size is 6, and the maximum iterative times are 250, the precision e=0.000001 and the initial position of bacterium is generated by Tent map based on chaotic sequence.

Tests on following function for search minimization:

(1) $F_1(x,y) = (x^2+y^2)^{0.25} \bullet (\sin^2(50(x^2+y^2)^{0.1}) + 1.0)$

$(x,y) \in [-20, 20]$

The function $F_1(x,y)$ reaches the global minimum value 0 at point (0, 0). There are innumerable local minimum points in function interval[20，20], the general optimization algorithm can easily fall into those local minimum. So, we can test the global convergence ability of the proposed algorithm through the example. Fig. 3 is the Function $F_1(x,y)$ space graph. Fig. 4 is each bacterium current location at the 20th iteration. As can be seen, some bacterium current locations have almost reached the global minimum point. Fig. 4 is each bacterium current location after the 50th iteration. As can be seen, most bacterium current locations have almost reached the global minimum point. So the CHBCC has fast convergence rate.

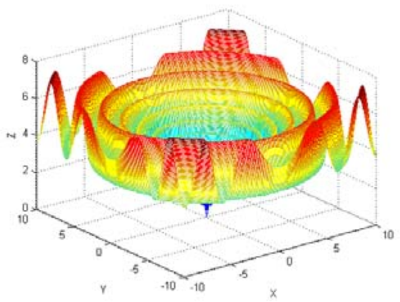

Figure 3. Function $F_1(x,y)$ space graph

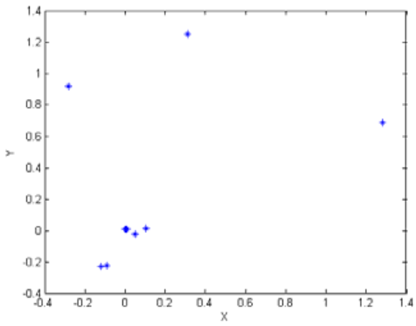

Figure 4. Bacterium location at the 20th iteration

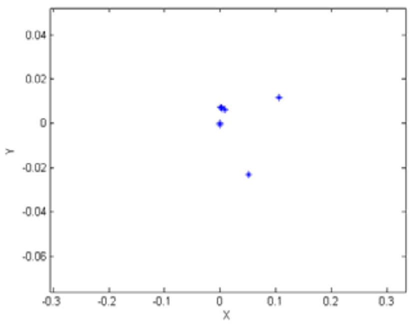

Figure 5. Bacterium location at the 50th iteration

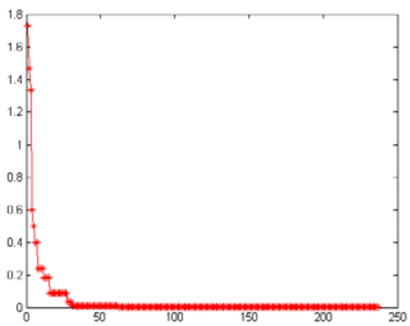

Figure 6. Global optimal fitness of function $F_1(x,y)$

Fig. 6 gives the global optimal fitness of function $F_1(x,y)$ changing with steps during an iterative process. The bacterial colony, using CHBCC algorithm, carry out about 56 iterations to get a result with a precision of 10^{-6}, while the bacterial colony, using BCC algorithm, need about 200* iterations to get a result with a precision of 10^{-3}. Generally speaking, in contrast with BCC algorithm and standard genetic algorithm (SGA) the number of iterations is less and the convergence speed is faster. So the convergence of this algorithm is effective.

(2) $F_2(x,y) = 20 + (x^2 - 10\cos(2\pi x) + y^2 - 10\cos(2\pi y))$

$\mathbf{(x, y) \in [-4, 4]}$

The function $F_2(x,y)$ reaches the global minimum value 0 at point (0, 0). Fig. 7 is the Function $F_2(x,y)$ space graph. There are innumerable local minimum points in function interval, the general optimization algorithm can easily fall into those local minimum. Fig.8 is each bacterium current location after the 20th iteration. As can be seen, some bacterium current locations have almost reached the global minimum point.

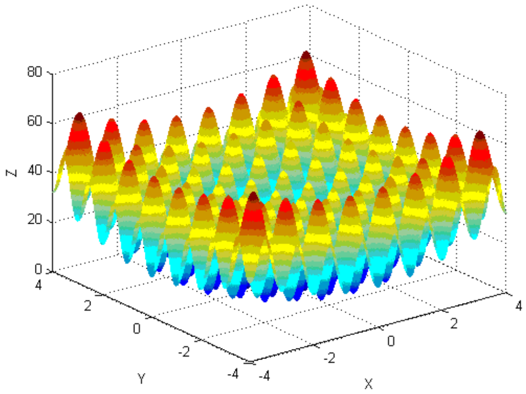

Figure 7. Function $F_2(x, y)$ space graph

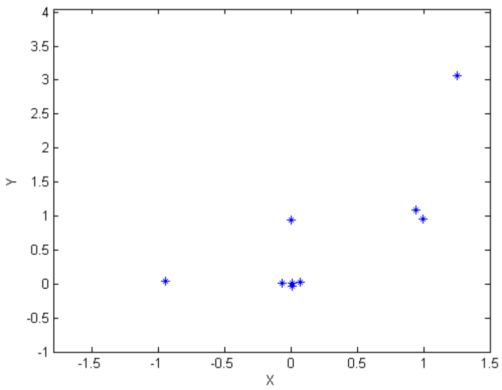

Figure 8. Bacterium location at the 20th iteration

Fig. 9 is each bacterium current location after the 50th iteration. As can be seen, most bacterium current locations have almost reached the global minimum point. Fig. 10 gives the global optimal fitness of function $F_2(x, y)$ changing with steps during an iterative process. As can be seen, the Global optimal fitness of function rapidly decreases from 62 to 10^{-6}.at 46^{th} step, eventually the optimal position is obtained. So the convergence speed of the CHBCC is fast, especially at the starting.

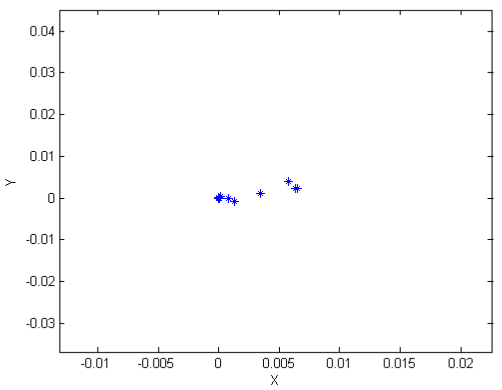

Figure 9. Bacterium location at the 50th iteration

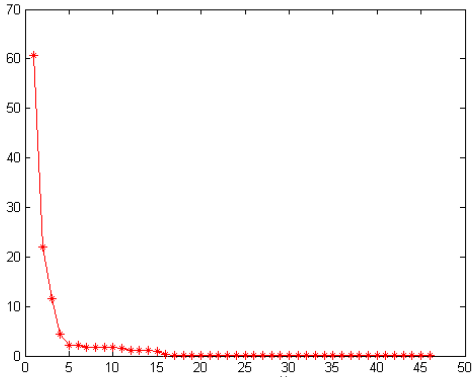

Figure 10. Gobal optimal fitness of function $F_2(x, y)$

TABLE I. COMPARISON OF OPTIMAL PERFORMENCE OF F_2(X,Y) AMONG DIFFERENT ALGORITHMS

algorithms	number of iteration	precision	rate of success
CMA-ES	50000*	0.9*	33%*
ES	50000*	0.9*	37%*
PRS	50000*	0.9*	0.1%*
BC	50000*	0.9*	10%*
BCC	500*	10^{-6*}	100%*
CHBCC	46	10^{-6}	100%

The function $F_2(x, y)$ is solved respectively by CMA-ES algorithm, ES algorithm, PRS algorithm, BC algorithm, BCC algorithm and this novel CHBCC algorithm .The simulation results are shown in Tab.1. As can be seen from Tab.1, The CHBCC algorithm for solving the function optimal problem always find the best result and can obtain more precise optimal solutions than other algorithms. Moreover the number of iterations is less and the convergence speed is faster. So the novel CHBCC algorithm is stable and effective.

$$(3)\ F_3(x, y) = \frac{(\sin\sqrt{x^2 + y^2})^2 - 0.5}{(1 + 0.001(x^2 + y^2))^2} + 0.5$$

The function reaches the global minimum value 0 at point (0, 0). Fig. 11 is the Function $F_3(x, y)$ space graph. There are two rings of points near the point (0, 0), with values 0.009716* and 0.003724* respectively, the general optimization algorithm can easily fall into this two local minimum. Fig. 12 is each bacterium current location after the 20th iteration. As can be seen, some bacterium current locations have almost reached the global minimum point .Fig.13 is each bacterium current location after the 50th iteration. As can be seen, some bacterium current locations have almost reached the global minimum point. Fig. 14 gives the global optimal fitness of function $F_3(x, y)$ changing with steps during an iterative process. Generally speaking in contrast with BCC algorithm and other algorithms the number of iterations is less and the convergence speed is faster.

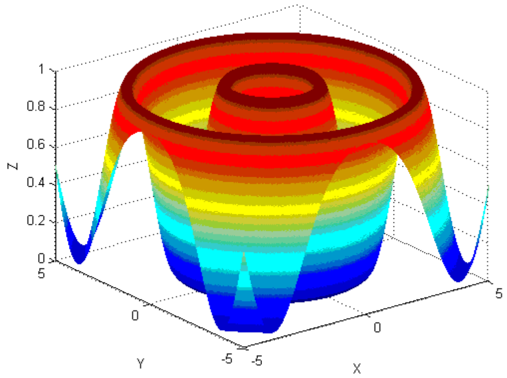

Figure 11. Function $F_3(x,y)$ space graph

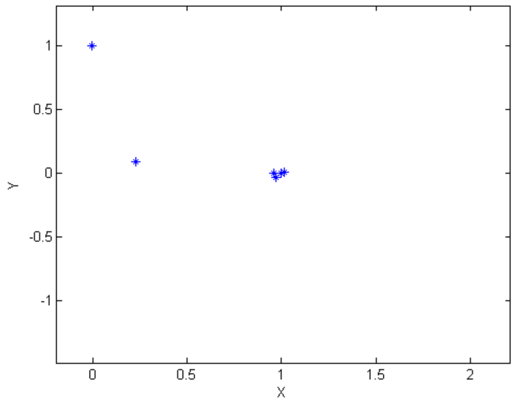

Figure 12. Bacterium location at the 20th iteration

The function $F_3(x,y)$ is solved respectively by PSO algorithm and this novel CHBCC algorithm .The simulation results are shown in Tab.2. As can be seen from Tab.2, the number of iterations for solving the function optimal problem is less and the convergence speed is faster than PSO. So the convergence speed of the novel CHBCC algorithm is faster and more effective.

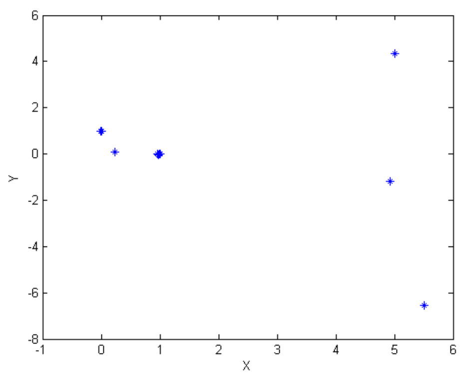

Figure 13. Bacterium location at the 50th iteration

TABLE II. COMPARISON OF OPTIMAL PERFORMENCE OF F_3(X,Y) AMONG DIFFERENT ALGORITHMS

algorithms	PSO Compression (Vmax=100000)	PSO Compression (Vmax=Xmax)	PSO Compression (inertia weights)	BCC	CHBCC
Average iterations	430.55*	532.4*	512.35*	308.75 *	102.4

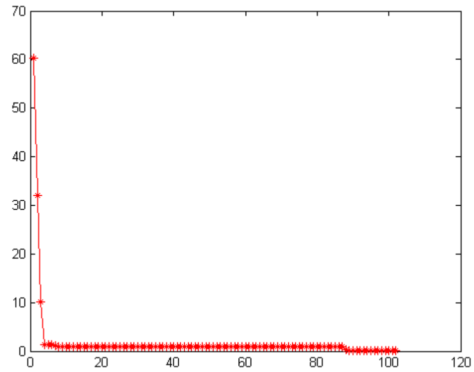

Figure 14. Gobal optimal fitness of function $F_3(x,y)$

(4) $F_4(x,y)=(x-1)^2+(y-1)^2$

Global minimum: F (1, 1) =0

(5) $F_5(x,y)=(x-1)^4+(y-1)^4$

Global minimum: F (1, 1) =0

(6) $F_6(x,y)=100(x^2-y)^2+(1-x)^2$

Global minimum: F (1, 1) =0

(7) $F_7(x,y)=(x-1)^6+(y-1)^6$

Global minimum: F (1, 1) =0

The function $F_4(x,y)$ ~ $F_7(x,y)$ is solved by BC algorithm and this novel CHBCC algorithm. The simulation results are shown in Tab.3. As can be seen from Tab.3, the number of iterations for solving the function optimal problem is less and the convergence speed is faster than BC. So the convergence speed of the novel CHBCC algorithm is faster than BC.

TABLE III. AVERAGE NUMBER TO REACH THE OPTIMIZATION GOAL FOR DIFFERENT ALGORITHMS

algorithms	$F_4(x,y)$	$F_5(x,y)$	$F_6(x,y)$	$F_7(x,y)$
BC	389*	386*	15025.5*	1256*
CHBCC	37	36	165	125

V. CONCLUSIONS

This paper presents a novel chaotic hybrid bacterial colony chemotaxis (CHBCC) algorithm for the function optimization problem, By integrating elitist strategy and chaotic optimization into bacterial colony chemotaxis optimization algorithm, it greatly enhances the local searching efficiency and global searching performance. Simulation results on standard test functions show that CHBCC is pretty efficient to solve complex problems. It has high optimization efficiency, good global performance, and stable optimization outcomes. The performance of CHBCC is evidently better than BCC and BC. Therefore, the CHBCC algorithm provides the function optimization problem with a novel and efficient solution.

In our future research, we will improve the performance of our algorithm and apply the algorithm to other fields for solving complex and urgent problems.

ACKNOWLEDGMENTS

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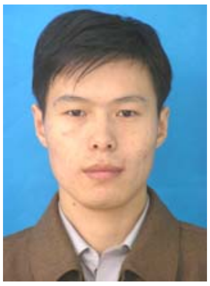

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