A New Shuffled Frog Leaping Algorithm with Space Zoomed Factor and Gravity Attractor

Deyu Tang[1], Jin Yang[2]
[1]College of Medical Information and Engineering
Guang Dong Pharmaceutical University
Guangzhou, China
[2] College of Computer Science & Engineering
South China University of Technology
Guangzhou, China
scutdy@126.com, goodskyfly@163.com

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ABSTRACT: Shuffled frog leaping algorithm is a new kind of swarm intelligence optimization algorithm. Due to the local search of the basic shuffled frog leaping algorithm which is the only by the worst frog to search and jump, searching ability of which was limited; therefore it had the low precision, slow convergence speed and easy premature convergence etc. Therefore, in order to enhance the ability of the local searching, this paper presented a gravity attractor, all the frogs in the same memeplexe could find the best position under its guidance. Considering the transboundary problems in the frog searching for food process, we introduced a space zoomed factor which made the frog out of the searching space could also be put into the searching space, and the social position relation was not changed, thus it improve the search ability of the SFLA. Through the standard function for testing, and compared with the standard SFLA algorithm and szAPSO algorithm, the experimental results show that the improved algorithm not only improves the convergence speed of the algorithm, enhance the searching capability of the algorithm, but also has better stability.

Categories and Subject Descriptors:
I.2.11 [Distributed Artificial Intelligence]: G.1.2 [Approximation]; Minimax Approximation and Algorithms

General Terms:
Swarm Optimization, Optimization Algorithms

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1. Introduction

Shuffled frog leaping algorithm (SFLA) was presented by the scholar Eusuff and Lansey in 2003, according to the simulated frog searching food process, information was shared and exchanged, so a new swarm intelligence optimization algorithm was produced [1]. SFLA is a heuristic cooperative search algorithm based on the population, the implementation of the algorithm is to simulate natural element evolution behavior. As a new optimization method, SFLA algorithm use the shuffled complex evolution algorithms (SCE) as the breadth search implementation framework, and is combined with genetic memetic evolution algorithm (MA) and the characteristics of particle swarm optimization algorithm based on the bird searching food behavior. So it is easy to understand and has fewer parameters (with less than PSO algorithm parameters), fast calculation speed, good global search ability and is easy to implement. This algorithm has been improved and applicated in widely areas, such as the traveling salesman problem [3], 0-1knapsack problem [4], flowshop scheduling problem [5], image segmentation [6], the grid task scheduling problem [7], economic scheduling problem [8]. However, in the solving problem process by the basic shuffled frog leaping algorithm, for some complex problems, it still has some faults such as the slow convergence speed, low accuracy of optimization, bad local search ability, and as the increase of dimension, eventually affects the efficiency of the algorithm. So the researchers use different methods for the corresponding improvements, such as the paper [9] proposed an improved shuffled frog leaping algorithm based on the PSO algorithm, to a certain extent, improved the effect of shuffled frog leaping algorithm; paper[10] use neighborhood orthogonal crossover operator to enhance the individual diversity, which improve the speed of convergence. The paper [11] combined with the differential evolution algorithm improve the local search speed of the SFLA, has the very good effect. Frog populations in natural evolution process, the worst frog's thought would be influenced by the best frog's thought. The worst frogs tend to jump to the best frog position looking for food. The frog jumping rule of SFLA algorithm is inspired by the social environment in imitation, but it only achieved the worst frog jumps into the best frog position. According to this rule, the worst frog's position is limited in the middle of a line between its current position and the best frog position. Obviously, the frog jumping rules limit each biological evolution process in local search space. And the other frogs do nothing. This restriction is not only to reduce the speed of convergence, but also easy to cause premature. Therefor, we use a gravity attractor, which guide all the frogs to search the best food.

The local search of shuffled frog leaping algorithm and particle swarm optimization algorithm has similar search method. The transboundary problem of the shuffled frog leaping algorithm has not much research, mainly using the maximum limit method, which is the most simple common method, but is easy to cause the algorithm premature convergence and cannot be guaranteed to frogs be controlled in the search space. In this regard, we studied recent particle swarm optimization algorithm to solve the problem, used for shuffled frog leaping algorithm. In recent years, many scholars put forward different boundary mutation strategy, which is used to solve the problem of particle swarm optimization algorithm. Paper (12) use the physical properties of particle motion to propose three boundary wall: absorption wall, reflecting wall and hide wall; paper (13) integrate the advantage of the absorption wall and hide wall, propose the attenuation wall; paper (14) summarize all these boundary walls and tested the performance of these algorithm and hybrid algorithm. Each frog in the shuffled frog leaping algorithm can be regarded as a particle. Because the frog move behavior directly affects the performance of SFLA algorithm, boundary mutation strategy directly affects the frog move behavior, so using the effective boundary treatment strategy to improve the algorithm's performance is necessary and feasible. In order to solve the defects in SFLA algorithm, this paper use gravity attractor and spatial zoomed factor search strategy, improve the local search ability; and the global shuffled strategy strengthen the individual diversity and evenness in each local cluster. Experiments show that the improved SFLA algorithm greatly improve the accuracy and convergence speed of the algorithm.

2. SFLA Algorithm

Shuffled frog leaping algorithm simulate frog population looking for food process. A frog population was classified into some memeplexes, each memepplex exchage the thought of the flog. Combined with the global information exchange and the local depth search, local search makes thought transfer in local memeplexe among individuals, mixed strategy makes the idea of local memeplexe exchange. In the shuffled frog leaping algorithm, solution set has a group frog (solution) with the same structure. The population is divided into many memeplexes, the memeplexe is considered to be different with different ideological frog collection. According to a certain strategy, frog of memeplexe implement local depth search in the solution space. After the defined numbers of the local search iteration, thought in the mixing process was exchanged. Local search and shuffled process continues until it satisfy the convergence condition of definition.

A balance strategy of Global information exchange and the local depth search make the algorithm can jump out of local extreme point, towards the global optimum direction, which became the most important characteristics of shuffled frog leaping algorithm. In SFLA, population has many frogs, each frog represents a solution, the population is divided into many memeplexes have different ideas. Each memeplexe is carried out local search respectively, the worst individual Q_w close to the local best individual Q_b or the global best individual Q_g through the memetic evolution. When the local search is executed to a certain stage, each memeplexe communicate to implement shuffled process. Repeatedly performs a local search and a shuffling process until they conform to the convergence condition of the definition. The basic SFLA algorithm [1] is as follows:

1. Parameter setting: Size of population, numbers of memeplexe, number of local iteration, numbers of global iterations.

2. Generates an initial population.

3. Determine the fitness function F(x), used to evaluate the quality of the individuals.

4. In the global iteration process, the frog's. Fitness values was arranged in descending order, and determine the global optimal solution Q_g, if it meet the convergence condition, then stop the execution; otherwise, proceed to the next step.

5. Frog populations are divided: the frog population was divided into m memeplexes, each memeplexe contains n frogs, and the number of the population meet $T = m \times n$; then, the first frog is divided into the first memeplexe, the second frog were divided into the second memeplexe, ..., The M frog was divided into the M memeplexe, the $m + 1$ frog is divided into the first clusters, the $m + 2$ frog was divided into the second memeplexe, and so on, until the whole frogs was division. That is:

$$Q_t = \{Q_{t+m(r-1)} \in T \mid 1 \le r \le n\}, (1 \le t \le m)$$

6. Each memeplexe implement local search in the number of the iterations.

1) Determine Q_w, Q_b according to the following formula to update:

$$D = r \cdot rand \cdot (Q_b - Q_w) \quad (1)$$

$$Q_{w(new)} = Q_w + D, D \in [D_{min}, D_{max}], \quad (2)$$
$$rand \in (0, 1], r \text{ is a constant}$$

2) If produce the solution of better performance, then update Q_w with $Q_{w(new)}$; Else use Q_g to replace Q_b, execute formula (1) (2). if produce the solution of better performance, then update Q_w with $Q_{w(new)}$; if Q_w was not improved ,then randomly produce a new solution $Q'_{w(new)}$, if produce the solution of better performance, then update Q_w with $Q_{w(new)}$.

3. Improved SFLA Algorithm

The search rules of shuffled frog leaping algorithm is a simplified search rule of the traditional PSO algorithm, studying search rules (1) (2), we can get the formula:

$$Q_{w(new)} = Q_w + r1 \cdot rand \cdot (Q_b - Q_w)$$

$$\Leftrightarrow Q_{w(new)} = (1 - r1 \cdot rand) \cdot Q_w + r1 \cdot rand \cdot Q_b$$

$$\Leftrightarrow Q_{w(new)} = \alpha \cdot Q_w + \beta \cdot Q_b,$$

$$\alpha + \beta = 1, \alpha, \in (1 - r1 \cdot rand, 1),$$

$$\beta \in (0, r1 \cdot rand]$$

especially, while $r = 1$, we obtain:

$$Q_{w(new)} = \alpha \cdot Q_w + + \beta \cdot Q_b,$$

$$\alpha + \beta = 1, \alpha, \in (0, 1], \beta \in (0, 1]$$

Therefore, shuffled frog leaping algorithm calculates weighted average position between the current best position of the worst frog and the best frog's position in the present generation, that is to find the gravity of the worst frog's best position, thereby to update the worst frog 's position in the last generation. This method is due only to update the worst frog's position, and restricte the local search ability. In the PSO algorithm, paper [15] proved that, when the individual best value Q_p and the global best value Q_b remain unchanged, the algorithm is asymptotically stable in the position $(Q_p + Q_b)/2$. But because in the process of optimization, Q_p and Q_b is dynamic changed, and at the interaction of the particle motion inertia and the social impact, and the influence of random factors, the particles may not to be the stable position by linear movement, but go to the gravity of weighted average position between individual best position and global best position, around the garvity do spiral motion. So, we improve the local search rule of shuffled frog leaping algorithm, using gravity attractor and space zoomed factor to update all frogs's position in each memeplexe, obtain new search rules, which can be mathematically described as follows:

$$Q_c = \alpha \cdot Q_p(t) + + \beta \cdot Q_b(t),$$

$$\beta = 1 - \alpha, \alpha \in (1 - r1 \cdot and, 1), \quad (3)$$
$$\beta \in 1\,(0, r1 \cdot rand), r1 \text{ is a constant}$$

$$(Q_f(t+1) = Q_e + (Q_f(t) - Q_e)\,\%\,(u_l \times v)/v \quad (4)$$
$$(Q_f(t) - Q_e < 0, u_l = D_{\min}$$

$$(Q_f(t+1) = Q_e + (Q_f(t) - Q_e)\,\%\,(u_r \times v)/v \quad (5)$$
$$(Q_f(t) - Q_e > 0, u_r = D_{\max} - Q_e$$

$$v = k \cdot rand, Q^d \in [D_{\min}, D_{\max}]^d \quad (6)$$

Among formulas above, Q_p is the current best position of frog, Q_b is the best position in the memeplexe, Q_f is the current frog's position. C is the gravity between the current best position of frog and the best position in the memeplexe, K is a constant. The frog's position was updated by the gravity attractor, in order to find the optimal position. Frog was constantly updated, so it may deviate from the gravity and emerge from transboundary. In shuffled frog leaping algorithm, this paper uses the space zoomed method to solve the transboundary problem.

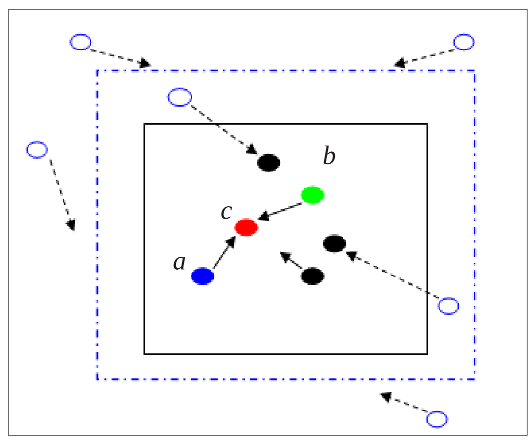

Figure 1. Sketch map of spatial scaling, solid frame is the original search space, the blue line frame is enlarged search space

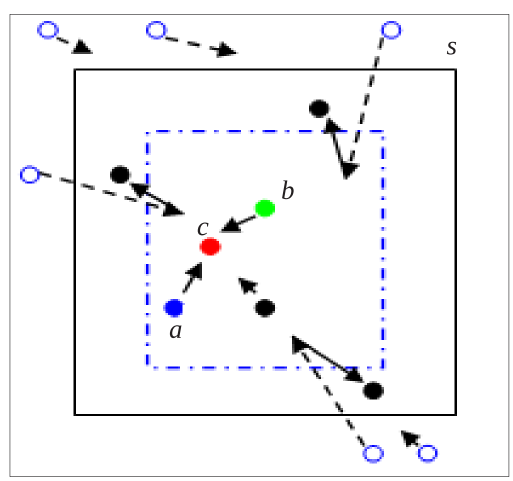

Figure 2. Sketch map of spatial scaling, solid frame is the original search space, the blue line box is the reduced search space

The principle is shown in Figure 1and Figure 2, in Figure 1, the solid line frame is the original search space, the blue point line frame is the enlarged scale space of original search space, The solid ball is the frog in original search space, hollow ball is the frog flying out the original space. The solid red ball *c* is a gravity attractor, blue solid ball *a* is the current best position of the frog, green solid ball *b* is the best frog's position in memeplexe. As you can see from Figure 1, the search space was enlarged, there are two hollow balls (the frog) was put into the blue point line frame; then the search space is reduced, the two hollow balls was put in the original search space, this two hollow balls become two solid black ball, that is say these two transboundary's frog go into the original search space. From the figure 2, we can see, the search space was reduce, the frog of the old search space and the frog out of the old search space all were absorbed into the new search space. (blue point line frame). Figure 2shows, there are three hollow balls (the frog) was placed in the blue point line frame; then as the search space amplification, the three balls go into the original search space (solid frame).

3.1 Space Zoomed Factor

Space zoomed factor $v = t \times rand$, t is an integer greater than zero. When $v > 1$, the search space was firstly expanded and then reduced; when $v < 1$, the search space is firstly reduced and then expanded. In the SFLA, algorithm, each frog is an important one, regardless of its fitness value is bad or best, it will not be eliminated. Direct or indirect social relationship of the frog is complex information transmission way of SFLA algorithm. And the position relationship of the frogs is an important link from the optimization problems to obtain information on the link, so either in the solution of frog's transboundary problem or premature convergence, slow convergence problem, should try to avoid unnecessary interference for population structure in the evolution, which a lot of improvement algorithm does not consider. As seen in Figure 1, the search space is zoomed out, then the frog out of the search space already is also included, becomes effective frog, through the periodic zoomed in or out, all the frogs were controlled in the search space, which not only protect position relationship of frog populations, but also provide a strong guarantee for the algorithm's global search capability.

3.2 Gravity attractor

Gravity attractor *c* is a new centers of social influence. Space zoomed center of SFLA algorithm is not the original search space geometry center, but the center of gravity attractor c, it is the weighted average position of the individual best value and global best value. Under gravity attractor's guidance, interest's region around the center of social influence gather more frogs, greatly improve the convergence speed, enhance local exploitation ability of the algorithm.

In the SFLA algorithm, when $Q_p = Q_b$, it is no longer subject to other frogs by the formula (3), and begin to stagnate, does not favor the evolution of the population. Therefore, the improved SFLA algorithm always use the attractor of the global optimal frog as a perturbation, give gravity attractor $Q_c = r2 \times Q_b + r3$, in which a random number is .$r2$ (0.5, 1.5), $r3 \in (-1, 1)$. This is benefit to increase activity of global optimal frog, and help to maintain the diversity of the population.

3.3 zgSFLA Algorithm's Pseudo code

Pseudo code is as follows:

```
input: Number of global iterations glo, global best solution
       Qg, number of local iterations loc, local best
       solution Qb; the number of memeplexe m, number
       of frogs in each memeplexe n, population Q(m * n).

output: global best solution Qg
 GlobalSFLA ()
 {
 For i = 1 to glo
     Sort Shuffle (Q (m * n));
     get (Qg);
     For j = 1 to loc
     For u = 1: m
            For v = 1: n
                 Get (Qb);
        Qc = r1*Qp (v) + (1- r1) * Qb; //gravity
        Qf = Qp;
       If Qc = Qb
        Qc = r2 * Qb + r3;
          // update the best frog in the memeplexe
        end
       LocalSearch (Qc, & Qf );
              if f (Qf ) < f (Qp)
                  Qp = Qf ;
              end
       End//n
            end//m
            end//loc
        End //g
        }

  Input: gravity attractor Qc, current frog Qf in the
         generation t
  Output: new frog Qf in generation t + 1

 LocalSearch (Qc, & Qf )
  {For w = 1: d//d is dimention
    If Qc (w) > Dmax
//transboundary processing for gravity attractor Qc
      Qc (w) = Dmax;
     If Qf (w) > Dmax
// transboundary processing for current frog
      Qf (w) = Dmax
     end
    Elseif Qc (w) < Dmin
      Qc (w) = Dmin;
     If Qf (w) < Dmin
      Qf (w) = Dmin;
     end
```

Else

If $Qf(w) < Qc(w)$

$Ul = Qc(w) - Dmin;$

$Qf(w) = (Qf(c) - Qc(w)) \% (ul * v) * v + Qc(w);$

//space zoomed processing

Else

$ur = Dmax - Qc(w);$

$Qf(w) = (Qf(c) - Qc(w)) \% (ur * v) * v + Qc(w);$

// space zoomed processing

End

End

}

4. Experiments Analysis

Experiment and simulation is to abstain the minimum value of 5 benchmark functions (the optimal value is 0), Testing software platform is MATLAB7.8 and Windows XP, machine frequency is P4 (210GHz), memory is 3G, hard disk is 120G .The SFLA, szAPSO and zgSFLA algorithms are tested, in order to enhance the comparability of the test, all of the following public parameter settings are the same. The number of global iteration $T = 500$, population number is $P = 200$, memeplexe's number is $m = 20$, individual frog's number in each memeplexe $n = 10$, the number ot local iteration $r = 10$, To szAPSO algorithm for the same comparison, we adds an inner loop, the number of cycle is $r = 10$. zgSFLA algorithm parameter $v = 100$, random number $r1 \in (0, 1)$ $r2 \in (0.5, 1.5)$, $r3 \in (-1, 1)$, variable dimension d=30. Three algorithms were run 30 times, We obtain the optimal solution after 30 times continuous operation of the five functions, the global optimal value, the average of the global optimal values, standard deviation is as evaluating indices of the algorithm performance.

(1). Sphere function: $f1 = \sum_{i=1}^{n} x_i^2, (x_i \in [-100, 100])$

(2). Rastrigin function: $f2 = \sum_{i=1}^{n} (x_i^2 - 10\cos(2\pi x_i) + 10]),$ $(x_i \in [-5.12, 5.12])$

(3). Ackley function:

$$f3 = -20\exp\left(-20\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e, (x_i \in [-32, 32])$$

(4). Griewang k function:

$$f4 = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \; (x_i \in [-600, 600])$$

(5). Rosenbroch k function:

$$f5 = \sum_{i=1}^{n-1} 100 \bullet (x_{i+1} - x_i^2)^2 + (1 - x_i)^2 \; (x_i \in [-2.048, 2.048])$$

Table 1 lists test results of the above 3 kinds of algorithm. Table 1 shows that the convergence speed of zgSFL algorithm is good, improve the quality of solution; improved SFLA algorithm improves the convergence accuracy, and has good robustness, and can effectively avoid the algorithm being trapped in local optimal solution.

Figure 3-7 is the evolution curves of average optimal fitness above 5 functions by using 3 kinds of algorithm to run 30times. The 5 figures show that converges of our zgSFLA algorithm is much faster than SFLA algorithm and szAPSO algorithm, for the Rastrigin function, the SFLA algorithm is superior to szAPSO algorithm; in five different function, zgSFLA algorithm is rarely have flat, which is the key of global shuffled method. To sum up, the proposed algorithm has better convergence speed for either single peak function or multi peak function, it is a kind of reliable and effective global optimization algorithm.

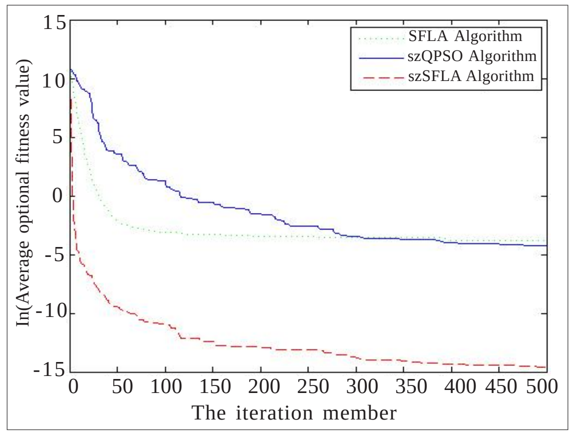

Figure 3. Running result of Sphere function

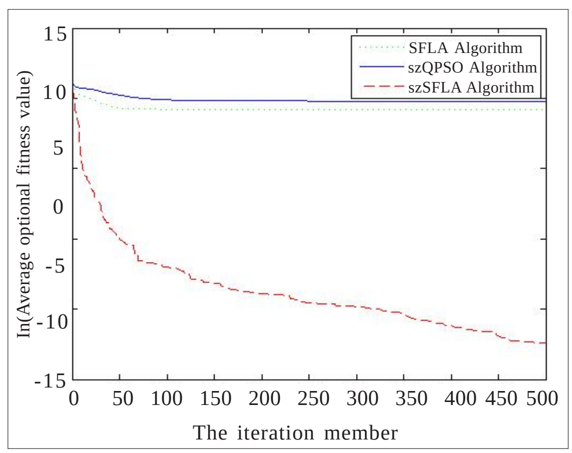

Figure 4. Running result of Rastrigin function

5. Conclusion

zgSFLA algorithm is a new swarm intelligence optimization algorithm. This paper introduces the gravity attractor and spatial zoomed factor, improve local search strategy of SFLA. Gravity attractor guide all the frogs in looking for the right position at the same time, for the frog out of the search space, the use of space zoomed

Function name	Algorithm	Optimal Solution	Avarage Optimal Solution	Standard Deviation
Sphere	SFLA	0.0039	0.0941	0.1468
	szAPSO	0.00261001526766287	0.0144361854215652	0.0114897963880160
	zgSFLA	4.00414326291755e-08	4.74190641563352e-07	5.79608233656781e-07
Rastrigin	SFLA	45.6290	66.6608285714286	13.3567704395829
	szAPSO	102.264708133047	115.812061102363	6.9321881700543
	zgSFLA	7.40185464920273e-07	4.09512859578242e-06	4.26352440805383e-06
Ackley	SFLA	3.3166	3.61070000000000	0.357775674596993
	szAPSO	0.0233864936012945	0.100580661986391	0.0862204848018264
	zgSFLA	6.46043930929708e-05	9.75981389510495e-05	5.21470439189532e-05
Griewangk	SFLA	1.2738	1.61213333333333	0.199129251157801
	szAPSO	0.000590715949187470	0.00124642471856920	0.000638025521970245
	zgSFLA	7.57585882915635e-10	7.97861499091113e-09	1.04726278240278e-08
Rosenbrock's	SFLA	31.6832	35.2519333333333	4.33031065105804
	szAPSO	0.00576824248496783	0.0429264796326555	0.0568200276632366
	zgSFLA	4.17959480221189e-08	6.67220369290168e-06	1.19510506638086e-05

Table 1. Experimental Results

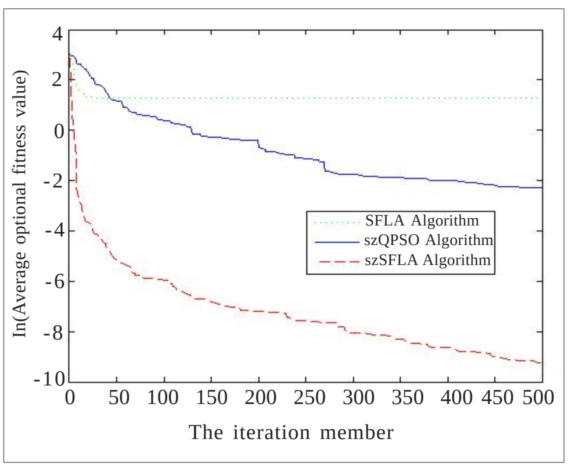

Figure 5. Running result of Ackley function

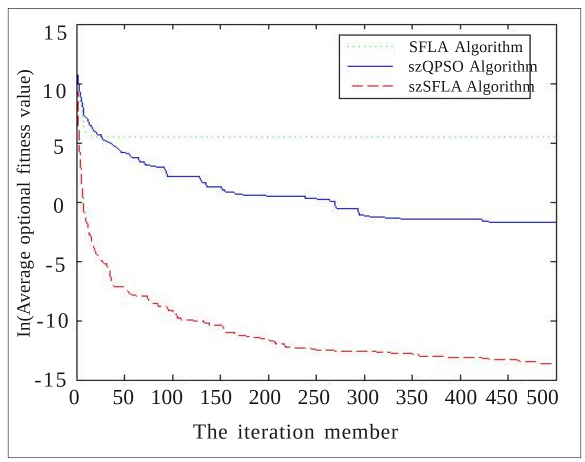

Figure 7. Running result of Griewangk function

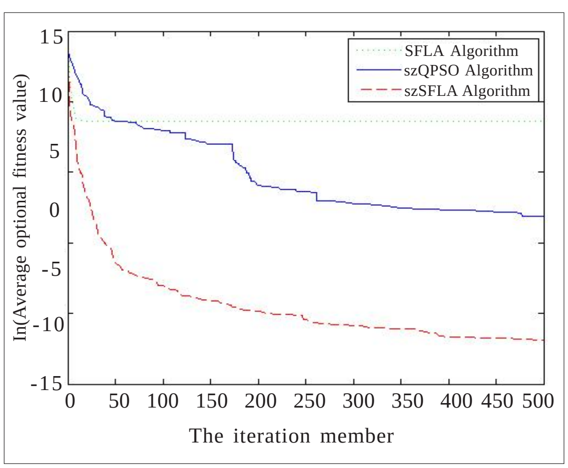

Figure 6. Running result of Rosenbrock's function

method, makes the frog can also be exploited and search, greatly improving the search capability. For gravity attractor parameter $r1 > 1$, which can improve the search scope of frog. Selection of $r1$ is related to application field. Experimental results show that, the improved algorithm has strong search ability, can effectively avoid the premature convergence, has fast convergence speed, good stability. At later work, the algorithm can be applied to many fields.

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