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A Hybrid Intelligent Optimization Algorithm of Fast Convergence

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Abstract

A hybrid intelligent optimization algorithm based on quantum particle swarm is presented to solve the problem that the local search ability of traditional SFLA is poor and converges very slowly. The particle is quantized and introduced chaos mechanism in the algorithm in order to enhance the global search ability, using the escape strategy, the group is divided into three clusters and mutation operation on the cluster within individuals, not only improves the convergence speed and ensure the performance of the algorithm. Experiments show that the improved algorithm has the characteristics of strong optimization capability and performance is improved greatly in whether comparison of the baseline function or analysis of universal database, compared with the other two algorithms have obvious advantages.

Keywords: *SFLA; quantum particle swarm; chaotic sequence; escape strategy; convergence*

1. Introduction

There are some difficulties to solve this problem, which is the nonlinear optimization problem with multiple constraints and extremum by the traditional optimization algorithm, such as linear programming, the least square method. Not only is hard to find the optimal solution, and the convergence speed is slow because of crunching numbers. In recent years, researchers are inspired by social behavior of some biological in nature, many intelligent optimization algorithm for solving complex problems is proposed.

Shuffled frog leaping algorithm (SFLA) is proposed by Eusuff and Lansey in 2003, it is a kind of intelligent optimization algorithm, by simulating the characteristics of information communication in the process of frog foraging to solve combinatorial optimization problems [1-3]. The SFLA algorithm is simple in principle, less parameters, easy realization and strong capability of global search. Based on this, the proposed algorithm has been widely used. But in solving some complex problems, based on the characteristics of the algorithm, the location of the worst individuals has a lot changed in the space about its old and new position. Although enhances the global searching ability, but it is easy to skip the global extremum and trapped in local optimal, which can't achieve the effective search, and the convergence speed is also slower.

This paper proposes an improved shuffled frog leaping algorithm based on quantum particle swarm optimization, in order to accelerate the convergence speed and calculation accuracy of shuffled frog leaping algorithm, namely fuse the quantum behaved particle swarm algorithm in SFLA (QPSO) [4-6]. The algorithm is based on

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quantum mechanics, the particles of clusters has the quantum behavior, and the evolution equation does not consider the velocity direction vector, the search strategy of particle swarm algorithm is simplified, fewer parameters, easier to control. Taking into account the local search ability of SFLA algorithm is weak, solved by particle swarm to complete the local optimal; for the "premature" phenomenon of the P quantum behavior of SO algorithm, introduced escape strategy in the algorithm, to help the particles escape from local bound. The improved algorithm guarantees the individual diversity and stability, improve the convergence speed of the algorithm, the performance also improved, which are testified by the experiments.

2. Shuffled Frog Leaping Algorithm

SFLA simulate the group behavior of frog, thoughts pass in the cluster, in order to achieve the global information exchange [7]. The individual in the group have the same structure, according to the idea of the differences are divided into different clusters, the individual of each cluster have the same thoughts, each frog represents a solution, Set the local extreme value is F_b and global extreme value is F_g, the individuals are close to global and local extreme value in the cluster, the thought kept passing between intra and inter cluster, continue to the convergence condition is satisfied. The basic process of algorithm is as follows:

(1) Set the initial parameters, including population size, number of clusters, maximum number of iterations, *etc*;

(2) Initial population, to determine the fitness function $f(x)$;

(3) On the fitness value of Individual in the group is sorted, to determine the global optimal solution that is O_{gb},in the process of iterative to detect whether meet the convergence conditions, meet is stopped, otherwise do the next step;

(4) Set the population O have m cluster, each cluster have n individuals, divided in sequence, that is m individuals are divided into the corresponding population, $m+1$ individuals start again , until the end of the division;

(5) setting local current value is O_c, Local optimal solution is O_b, The following individual local searching criteria must be observed:

$$O_c^{'} = O_c + \lambda \cdot \varepsilon \cdot | O_b - O_c | \tag{1}$$

In the formula, $\lambda, \varepsilon \in [0,1]$, is a regulatory factor, calculated by $O_c^{'}$ compared with O_b, put O_c update for the optimal solution, and re-initialize O_b, update O_g after each iteration . In particular, if $O_c^{'}$ did not improve, then the system randomly generated $O_c^{''}$, similarly, if $O_c^{''}$ has stronger performance, O_c will updated accordingly.

3. Algorithm Analysis

On the convergence problem of particle swarm optimization, one of the key factors is the particle velocity, too fast or too slow will affect to obtain the optimal solution for [8-11].The fast speed of the particles can effectively escape from local constraints, but it is likely to miss the optimal solution, influence convergence effect; However, The Slow speed of the particles have a better ability to obtain the optimal solution, but it is easy to fall into local optimum. To fix this, the paper from three aspects to be considered: first, improve the global search ability, increase the diversity of solution; second, enhance the ability of local search, improve the convergence rate; Third, improve the search strategy, so that particles can jump out of local optimal bound.

3.1. Chaotic Sequence

Space hash points belong to the category of nonlinear, chaos phenomenon also is such, it has two characteristics: ergodicity and regularity, that can traverse regularly to all state in a given area, and do not repeat [12-13]. If the particles search using chaotic strategy obviously better than simple random search. Search steps are as follows:

(1) Define initial region, given n – vector $R_0 = (R_{01}, R_{02}, \cdots, R_{0N})$, each value of R_0 is adjacent each other, and the difference is very small.

(2) To calculate the initial vector R_0 by using the logistics equation, generating chaotic sequence $c_1, c_2, \cdots, c_n$. After several iterations, the system will be fully in a chaotic state. Vector layer can be expressed as:

$$c_{i+1} = c_i(1 - c_{i-1})\lambda \tag{2}$$

In the formula, λ is an iterative control parameters.

(3) X_i is the space particles, Using formula (2) to get the better location of X_i, denoted as $X_i^{'}$.

$$X_i^{'} = r \cdot rnd \cdot c_j + X_i \tag{3}$$

In the formula, r is the movable radius of particles X_i, $rnd \in [-1,1]$, $j \in [0,n]$.

The main idea of particle swarm optimization algorithm based on chaotic mechanism is embodied in: On the one hand, using the chaos sequence to initialize the particle's position and velocity, because has the characteristics of ergodicity, it was keep the diversity of the particles, and enhance the search ability of the particles; Furthermore, the chaotic state can make the particle motion is persistent.

The particle's chaos initialization: X_i in the type (3) given initial value respectively, and re-fix the speed of the particle swarm iteration:

$$\begin{aligned} v_{i,j}^{'}(t+1) = {} & a v^{''}(t) + b^0(t)(x_{lb}(t) - x_{i,j}(t)) \\ & + b^1(t)(x_{gb}(t) - x_{i,j}(t)) \end{aligned} \tag{4}$$

In the formula, a is constant in $(0,1]$, b is the random number of normal distribution $N[0,1]$, $i \in [1,n]$, $j \in [1,m]$, n is the number of particles, m as the spatial dimension. For $v^{''}(t)$:

$$v^{''}(t) = \begin{cases} v_{i,j}(t) & q = 0 \\ N[0,1] \times \tilde{v} & q = 1 \end{cases} \tag{5}$$

$$q = \begin{cases} 0 & f(x_{gb}(t-1)) > f(x_{gb}(t)) \\ 1 & f(x_{gb}(t)) = f(x_{gb}(t-1)) = \cdots = f(x_{gb}(t-5)) \end{cases} \tag{6}$$

In the formula, $\tilde{v} = v_{\max} ? c_i / 1.1$, $d = f(x_{gb}) - f(x_T)$, c_i is a new chaotic sequence, $f(x_{gb})$ is satisfied solution, $f(x_T)$ is the target solution.

3.2. Particles Escape

In the running of the PSO algorithm, with the increase in the number of iterations, the particle will gradually become homogeneous, That is to say,the speed continues slow down, close to the global optimum value, Although chaotic mechanism can enhance the search capabilities of particles, but the speed gradually decreases inevitably fall into the local optimum and unable to escape. Once the particles are bound, the move will be more difficult, thereby affecting the entire population, if the extremum is the global extremum, then the algorithm will appear the phenomenon of premature. The traditional particle swarm algorithm does not provide related solutions, this paper introduced the mechanism of chaos to enhance the ergodic of algorithm, at the same time, adopt a new escape strategy, now make the following judgment: in the process of iteration, record the global optimal solution every time, at the same time record the number of times about the change of global optimal solution, when it exceeds a limit value, and the algorithm does not meet the necessary conditions for the end, determine the particle trapping in local optimum.

This paper intends to adopt a mutation operation, that the particles can escape local constraints by using the prior knowledge, the group was divided into three equal size clusters, are defined as: cluster 1, cluster 2, cluster 3. Division rules are: cluster 1 is the particle swarm of highest fitness value; cluster 2 is the particle swarm of relatively high fitness value, mainly to study the particle of cluster 1, these particles carry new information and retain some of the original experience;the particle's position of in clusters 3 remains unchanged, in order to make full use of existing experience.

3.3. Quantum Particle Swarm Optimization Algorithm based on Chaotic Sequence

In order to the chaotic sequence and escape algorithm fusion is better, enhance the global search ability of algorithm, this paper introducing the concept of the quantum particle swarm, the particles are placed in a quantum space by the expression of the wave function, the particles are free to search for possible solutions, its state is not affected by the position and velocity vector. The following is the wave function that marks particle state:

$$\int_{-\infty}^{+\infty} L_p \, dxdydz = 1 \tag{7}$$

The iterative formula of particles obtained by Monte Carlo algorithm converted the quantum state:

$$P_{mb} = \frac{1}{l}\sum_{i=1}^{l} P_i \tag{8}$$

$$P_{mk} = \theta P_{ik} + (1-\theta) P_{gk} \tag{9}$$

$$L_p(t+1) = P_{ik} \pm a \,|\, P_{mk} - L_p(t) \,|\, \ln^{\frac{1}{\lambda}} \tag{10}$$

In the above formula, P_i is current position of particle, P_{gb} is the global extremum, P_{mb} is the optimal intermediate values, l is the number of particles, P_{mk} is a random point between P_{ik} and P_{gk}, a is the expansion contraction factor and a quantitative index, used to control the convergent speed of the algorithm, get a random number from $(0,1)$ in the iterative process, if $a > 0.5$, then take positive values, else take negative values.

In the quantum particle swarm algorithm, a particle can be defined as $x_i^0 = \{v_{i1}, \cdots, v_{ij}, \cdots, v_{im}\}$. In the formula, v_{ij} represents the j cluster center vectors of the i particles, the fitness function is still using the particle swarm optimization objective function $J(u, Z)$, The steps of the algorithm are as follows:

Step 1: The sample data are normalized processing;

Step 2: Initialize the particle swarm, determine the size of population, for each particle determine the clustering center vector in the specified scope of the data vector, set the optimal solution and the global optimal solution of initial individual;

Step 3: Calculate the initial fitness value, according to the fitness function calculate fitness value of each particle, select the best position of particle as the initial iteration position;

Step 4: Referencing fitness value do mutation operation on the particle, and fixed speed of particles by using (3), comparing with extreme value, if it is better, then replace it.

Step 5: Produce individual x_i^t of new generation;

Step 6: referencing particle swarm algorithm set iteration termination condition, Satisfy the condition is terminated, or return to step 3.

Here, introducing concept of the quantum in the particle swarm optimization algorithm only use a to describe the state of particle.

3.4. The Hybrid Algorithm

Chaotic mechanism enhances the quantum particle swarm algorithm's search ability, the implementation of the escape strategy improve the algorithm convergence speed, but the global search ability of algorithm is still weak, SFLA is exactly the opposite, it's local search ability is weak and global search ability is stronger. Based on this, this paper proposes a improved algorithm based on SFLA ISFLA - QPSO. Algorithm is described as follows:

Input: Population size, the number of individuals within a cluster, the local maximum number of iterations, the global maximum number of iterations.

Output: the optimal solution.

Step 1- step 5 reference the basic steps of SFLA;

Step 6: the part of local search use the improved quantum particle swarm algorithm:

1) Using formula (4), (7), (8) calculates the current position of individual P_i, get the local extremum P_{mb};

2)To Refer type (10)of the quantum particle swarm configured expansion and shrinkage factor a, if $a > 0.5$, then calculate the formula:

$$L_p(t+1) = P_{ik} + a \mid P_{mk} - L_p(t) \mid \ln^{\frac{1}{\lambda}}$$

On the contrary:

$$L_p(t+1) = P_{ik} - a \mid P_{mk} - L_p(t) \mid \ln^{\frac{1}{\lambda}};$$

3) Determine the local search termination condition is satisfied, if the local search is complete, return to step 4.

The pseudo code as follows:

```
void Public ProISFLAQPSO (int i_Population, int i_ClusterCount, int PartN, int GlobalN)
{
  ObjPopulation obj_P;
  Obj_P=fn_initialization(i_Population,i_ClusterCount,PartN,GlobalN);
  while(i< GlobalN)
  {
    obj_P.fitness=fn_cfitness(i_Population);
    P_gb =fn_getOptimal(obj_P.fitness);// compute the globally optimal solution
    if (fn_execEnd( P_gb ,i))
      break;
    While(j<PartN)
    {
      ObjSetChild obj_setChild=fn_divGroup(obj_P);
      fn_execchaoic(j, obj_setChild);
      if (fn_dPart( a ,fn_pLoca(fn_indivCalcu( P_j , P_mb , P_gb ,obj_setChild))))
      // Determine the local search conditions
        break;
    }
  }
}
```

4. Experimental Analysis

The experiment was divided into two parts: the ability of optimization and the effect of cluster. Experiment compare three kinds of algorithms: The traditional particle swarm algorithm, denoted as PSO; Leapfrog algorithm introduced particle swarm, referred to as SFLA-PSO; in this paper, the leapfrog algorithm is proposed fusing chaotic quantum particle swarm, as ISFLA - QPSO. In this paper, in view of the optimization capability of algorithm, we introduce five benchmark functions to test, the size of population set 20. Among them, (1), (2) is the single mode function, there is only one extreme value point within the defined range, it is used to analyze optimization precision of the algorithm and performance; (3), (4), (5) is a multimodal function, defined interval has multiple extreme points, mainly used to test the algorithm's global searching ability, the following are 5 benchmark function definition and value range.

(1)The scope of $Schwefel$ functions is: $[-10,10]^D$, formula is as follows:

$$Schwefel(x) = \sum_{i=1}^{D} (x_i \sin\sqrt{|x_i|})$$

(2)The scope of $Rosenbrock$ functions is: $[-10,10]^D$, formula is as follows:

$$Rosenbrock(x) = \sum_{i=1}^{D} (100(x_{i+1} - x_i^2)^2 + (1 - x_i)^2)$$

(3)The scope of $Noncontinuous\ Rastrigin$ functions is: $[-5.12,5.12]^D$, formula is as follows:

$$Noncontinuous\ Rastrigin = \sum_{i=1}^{D} [x_i^2 - 10\cos 2\pi x_i + 10]$$

$$x_i = \begin{cases} k_i & |k_i| < 0.5 \\ round(2k_i)/2 & |k_i| \geq 0.5 \end{cases}$$

(4)The scope of $Griewank$ functions is: $[-600,600]^D$, formula is as follows:

$$Griewank = \frac{1}{4000}\sum_{i=1}^{D}(x_i)^2 - \prod_{i=1}^{D}\cos(x_i/\sqrt{i}) + 1$$

(5)The scope of $Generalized\ Penalized$ functions is: $[-50,50]^D$, formula is as follows:

$$\begin{aligned} Generalized\ Penalized = {} & \frac{\pi}{D}\{10\sin^2(\pi y_i) \\ & + \sum_{i=1}^{D}(y_i - 1)^2[1 + 10\sin^2(\pi y_{i+1}) \\ & + (y_D - 1)^2]\} + \sum_{i=1}^{D}u(x_i) \end{aligned}$$

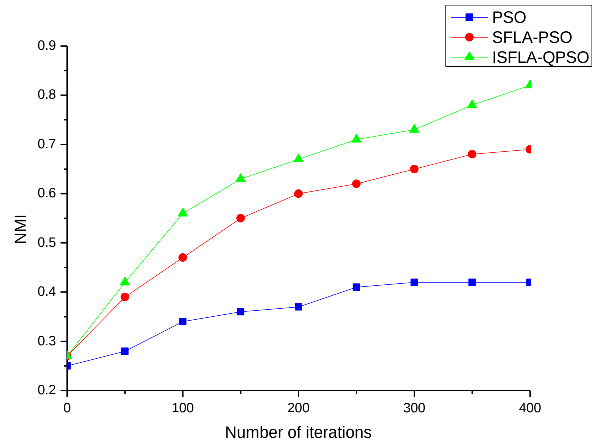
$$y_i = 1 + \frac{1}{4}(x_i + 1)$$

$$u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m \\ 0 \\ k(-x_i - a)^m \end{cases}$$

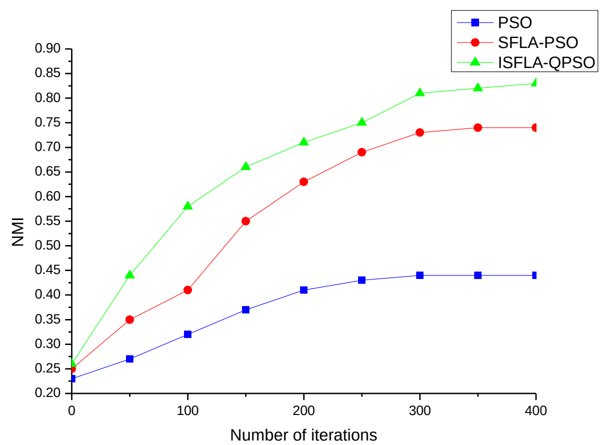
Each function were random testing, the number is100 times, using the average value to verify, evaluation criteria adopt two indexes: Mean Best Fitness (MBF) and Standard Deviation (SD). Investigation on the clustering effect, data source come from UCI general database, the data set is Iris, Balance and Similar. Among them, the Iris is a low dimensional data set, the dimension is 4, can be divided into 3 categories, each sample's number is 50. The Balance is a low dimensional data set, the dimension is 4, the sample's number is 585. The similar is a high dimensional data set, the dimension is 16090, the sample's number is 280. The maximum number of iteration is 400, evaluation criteria adopt two indexes: Normalized Mutual Information (NMI) and the convergence. The former is a kind of evaluation index about the effect of clustering, reflect the degree of similarity between the sample's clustering results and the real class division, range set$^{[0,1]}$, the higher the value, the better the clustering. The larger the value, the better the effect of clustering; the latter test the stability and speed of the algorithm, the gentler the better while ensure speed. Table 1 is the comparison results of benchmark function test, Figure 1 is the comparison results of PCM values, Figure 2 is the comparison result of algorithm convergence.

Table 1. The Comparison Results of Benchmark Function Test

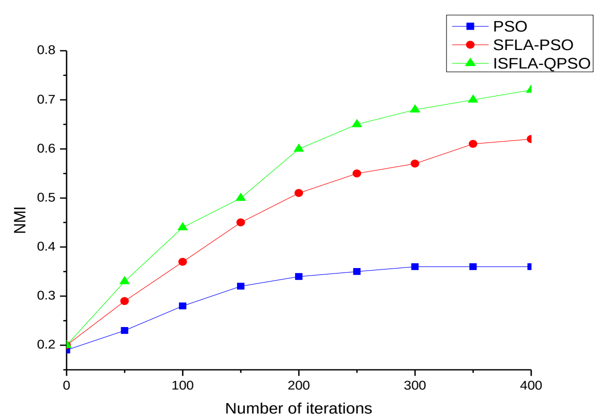
benchmark function	index type	PSO	SFLA-PSO	ISFLA-QPSO
Schwefel	MBF	1.98e-33	1.02e-13	1.09e-12
	SD	2.12e-58	5.62e-13	1.95e-19
Rosenbrock	MBF	25.4	10.3	10.7
	SD	28.0	13.9	11.2
Noncontinuous	MBF	19.5	0.35	0.48
Rastrigin	SD	7.8	0.42	0.69
Griewank	MBF	2.32e-19	5.61e-31	1.32e-47
	SD	1.88e-20	1.36e-30	6.71e-29
Generalized	MBF	5.81e-22	1.76e-45	1.03e-55
Penalized	SD	1.32e-21	2.19e-45	7.01e-23



(a) The Comparison of the NMI Value in Iris Dataset



(b) The Comparison of the NMI Value in Balance Dataset



(c) The Comparison of the NMI Value in Similar Dataset

Figure 1. The Comparison Result of the NMI Value

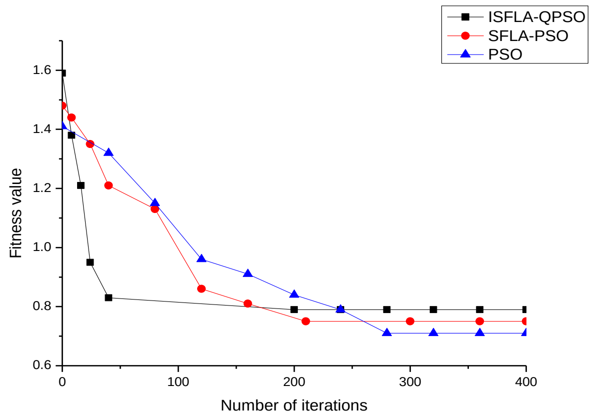


Figure 2. The Comparison Result of Algorithm Convergence

Results can be found from Table 1, the quality of the optimal solution and algorithm stability, the improved ISFLA - QPSO algorithm is obvious advantages, optimization ability have a certain increase compared with other two kinds of algorithm, for *Noncontinuous Rastrigin* function, although the optimization result than SFLA - PSO is a bit poor, but the stability of algorithm have advantages and other functions are obtained the optimal solution, because chaotic mechanism is introduced, and the application of local escape algorithm enhance the search ability of the individual.

Figure 1 analysis the NMI value of Iris, Balance and Similar data set in the UCI, the experimental results show that three kinds of algorithm basically no room for improvement when the iteration number is 0, the NMI value is consistent, with increasing number of iterations, the traditional PSO algorithm behind the other two algorithms, in comparison, ISFLA-QPSO algorithm has the best performance. When the iteration number more than 150, the improved effect is gradually apparent, and when the iteration number more than 350, ISFLA - QPSO still keep the rise of a certain range, it is obvious that the improved effect of algorithm is very prominent.

Figure 2 is the comparison result of algorithm convergence. From the velocity analysis, the convergence rate of ISFLA-QPSO algorithm significantly faster than the other two algorithms. In terms of stability, the improved algorithm remained stable when the number of iterations reach 200, embodies the advantages of escape strategy.

5. Conclusion

The local search ability of traditional leapfrog algorithm is weak, a hybrid algorithm is proposed to remedy its defects, based on this, this paper proposes a hybrid algorithm that leapfrog combined with particle swarm, in order to avoid the prematurity of the algorithm, using the escape strategy, so that the individual has the ability to jump out of the shackles of local extreme points When local search; algorithm is also introduced the chaos mechanism and the quantized particles, improve the convergence speed at the same time, keep the stability of the algorithm. The optimization ability and performance of improved algorithm are testified by the experiments. In addition, the algorithm also has the certain space to improve, such as adaptive learning, mutation operator, *etc*.

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