An Improved Algorithm of Quantum Particle Swarm Optimization

Yan-xia JIN
North University of China/Department of Computer Science and Technology, Taiyuan, China
Email:jinyanxia_730128@163.com

Jing XUE and Zhi-bin SHI
North University of China/Department of Computer Science and Technology, Taiyuan, China
Email: 150301757@qq.com & shizb@nuc.edu.cn

***Abstract*—Based on the classical particle optimization algorithm and the quantum behavioral theory, this paper proposes an improved QPSO algorithm---GLQPSO to perfect the global and local convergence speed ability and speed of classical particle swarm. To achieve this purpose, the author introduces an improved Logistic chaotic mapping theory [1] to conduct chaotic search for the initial particle and chaotic remolding of the locally optimized particle swarm. The test of the classical function has proved the success of this effort.**

***Index Terms*—quantum behavior, PSO algorithm, chaotic mapping thoughts, local search**

I. INTRODUCTION

In 1995, Kennedy and Eberhart put forward the Particle Swarm Optimization, PSO algorithm. PSO is an evolutionary computation technique, developed for optimization of continuous nonlinear, constrained and unconstrained, non differentiable multimodal functions [2]. It is a random search algorithm of group cooperation and developed by imitating the foraging behavior of Bery. Kennedy and Suganthan [3] analyze the performance of this algorithm in neighborhood operator and its difference from the standard GA. PSO has better computational efficiency, i.e. it requires less memory space and less speed of CPU, and it has less number of parameters to adjust [4]. PSO has gained popularity lately and has been widely applied in different fields [5]. The development of this algorithm benefits from observations of social behaviors of animals, such as bird flocking and fish schooling. PSO was first used to optimize the nonlinear continuous function and train the neural network. Then it is applied to solve the constraint optimizing issue, the multi-objective issue and the dynamic optimizing issue. Now, it gradually becomes a good tool in data classification, clustering, mode recognition, telecommunications Qos management, biological system modeling, flow layout, signal process, robot control [6],vector machines [7], Micro-grid [8], decision support, simulation and system discrimination [9,10].

Despite the great efforts made by many researchers in improving the performance of this algorithm and certain success achieved in this process, the large part of the simplicity and convenience of the algorithm has been sacrificed and its calculated quantity has been increased, which is apparently against the original intention of presenting this optimization algorithm. Therefore, to find a better optimization way while without increasing the calculated quantity becomes pressing.

To solve this issue, the author of this paper introduces an improved logistic chaotic mapping to describe the initial population based on the Quantum PSO, QPSO. The reason is that in spite of its better global convergence ability, the global search capacity of QPSO will be relatively weakened and its local search capacity will be strengthened with the continual increase of iterations, which will result in the local optimal point. When parts of particles reach the local extreme points, the logistic mapping is again introduced to locally initializing these points. It can not only improve the quality of the initial population but also the local optimization ability of the QPSO, and further enhance its computational accuracy.

Ⅱ.BRIFE INTRODUCTION OF THE BASIC PSO

Human being have their own previous experience, set beliefs and set rules of doing some work, based on which they take their actions also human follow the path set by society or group. This path is supposed to be the best according to the whole global best position [11]. Similar to other population-based algorithms, such as evolutionary algorithms, PSO can solve a variety of difficult optimization problems, and has shown a faster convergence rate than other evolutionary algorithms on some problems [12,13]. PSO is an evolutionary computation technique motivated by the simulation of social behavior. Namely, each individual (agent) utilizes two important kinds of information in decision process [14]. PSO is a method for performing numerical optimization without explicit knowledge of gradient of the problem to be optimized. It was originally developed for nonlinear optimization problems with continuous variables so that it can easily be expanded to treat a problem with discrete variables [15].

The basic principle of PSO algorithm is described as the following: in the D-dimensional space, an aggregate of n particles is flying at certain speed. In the search space, each

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particle's movement will be depicted through three parameters: x_i, v_i, p_i [15].

An individual particle i is composed of these vectors: its position in the n-dimensional search space $x_i=(x_{i1}, x_{i2}, \ldots, x_{in})$, the best position that it has individually found $p_i=(p_{i1},p_{i2},\ldots,p_{in})$, and its velocity $v_i=(v_{i1},v_{i2},\ldots,v_{in})$. Particles were originally initialized in a uniform random manner throughout the search space; velocity is also randomly initialized. Each particle adjusts its trajectory toward its own previous best position P_{best} and the previous best position G_{best} attained by the whole swarm [16].

Formula (1) and (2) [17,18]are introduced to get the particle's position and velocity, among which, c_1 and c_2 are called study gene, normally equal to 2; Parameter r and R are two false random numbers evenly distributing in the range [0,1]; x_i and v_i are repeatedly limited within the maximum translocation and maximum velocity.

The modified velocity and position of each particle can be manipulated according to the following equations: where $i=1,2,\ldots,n$; w is a weight factor which controls the velocity's magnitude; c_1 and c_2 are two positive constants, known as acceleration coefficients; r_1 and r_2 are random numbers within the range[0,1][19,20]. The x_i and v_i are limited to the maximum displacement and the corresponding speed.

$$v_i^{k+1} = wv_i^k + c_1r_1(p_i - x_i^k) + c_2r_2(p_g - x_i^k) \quad (1)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (2)$$

The PSO process is given as the followings:

- Initial positions and velocities within the initialization are generated. pi represents the current position of each particle. pg represents the pi of the best value.
- Calculating the fitness value of each particle;
- The fitness value of each particle is compared to the current best position. It is current as the optimal value of the individual particles. The current location update the personal best position;
- The pi and pg of each particle is compared, if the new pg value is better than the previous pg value, the previous pg value is replaced by the new pg value;
- According to Formula (1) and (2), velocity and position of the particles are updated;
- Go to Step 2 until termination condition is reached (Termination condition is generally set to a sufficiently good fitness value or reach a preset maximum number of iterations).

III. Quantum Particle Swarm Optimization Algorithm

In 2004, Sun and other researchers present a new PSO algorithm model from the perspective of quantum mechanics. This model is based on the DELTA trap that the particle has a quantum behavior. Compared with the original PSO algorithm, this new QPSO has only radius vector in its evolution equation [21], which greatly simplifies the equation, reduces its parameters and thereby makes the equation more controllable [22].

In contrast with the classical PSO algorithm, the convergence speed of QPSO is fast and QPSO can not easily fall into the local optimum. This will be helpful for finding the optimal parameters [23]. In the QPSO algorithm, the quantum state of a microscopic particle is described with wave function $\varphi(r, t)$. Once $\varphi(r, t)$ is set, the average value and probability measure of any dynamical variable become certain. That is because, in the quantum world, the moving track of a particle is unlimited. It only changes with the change of time. Its movement can be described with time-dependent Schrodinger equation, which means Particle x_i and v_i cannot be determined simultaneously.

Based on Reference 9, the motion formula (3) of particle is introduced, in which, p、a、$Mbest_i$ and $Mbest^i$ are presented in Formula (4), (5), (6) and (7) respectively[24]. U is a random number in interval [0,1]. Generally, α_1 and α_2 are respectively the beginning and ending value of variable shrinkage factor t. MAXITER is the maximum interactions. Since α_1=2.5，α_2=0.5，in most cases, the value of a is between 0.5 and 2 [25]. $Mbest_i$ represents the average value of each particle when it is in the best position in the local searching. p_{id} reveals the best position of the particle in such a searching, while $Mbest_i$ and p_{id} represent the corresponding number in an overall searching.

$$x_i(t+1) = p \pm a \times \left| Mbest_i - x_i(t) \right| \times \ln(1/u) \quad (3)$$

$$p = (c_1 p_{id} + c_2 p_{gd}^i) / (c_1 + c_2)\ (c_1 + c_2 = 1) \quad (4)$$

$$\alpha = (\alpha_1 - \alpha_2) * ((\text{MAXIER} - t) / \text{MAXIER} + \alpha_2) \quad (5)$$

$$Mbest_i = \frac{1}{M} \sum_{d=1}^{M} p_{id} \quad (6)$$

$$Mbest^i = \frac{1}{M} \sum_{d=1}^{M} p_{gd}^i \quad (7)$$

The procedure of a QPSO is shown as the following:

- The position and speed of each particle in a randomly initialized particle group in the D-dimensional space;
- The overall and local best position of each particle determined based on Formula (6) and (7);
- The present best value of each particle by comparing its overall position with the local one;
- The best value of variable shrinkage factor got by changing t in Formula (5) ;
- Updating the present speed and position of each particle by substituting the result of Step (3) to Formula (1) and (3)[26];
- If the above result fails to exceed the maximum speed and displacement value or the expected best state, please return to Step 2 to repeat the whole process.

IV. The Identical Particle System

In the quantum mechanics, particles of the same type are called identical particles. The exchanging symmetry of such a particle system will set a strong limit on the wave function. In general, wave-function $\psi(q_1, q_2,\ldots, q_n)$ of this system is not necessarily the inherent property of certain p_{ij}. All of the p_{ij} should be equally important. A detailed analysis has proved that the common inherent property of all the p_{ij} exists.

Introduction of the identical particle system, the corresponding wave function must conform to the situation set in Formula (8).

$$p_{ij}^2\varphi = cp_{ij}\varphi = c^2\varphi \quad (P_{ij}^2=1,\ C^2=1,\ i\neq j,\ i=1,2,3,\ldots,n, j=1,2,3,\ldots) \quad (8)$$

Just as what mentioned above, the motion formula of the particle group is changed into Formula (9), which is used to get a new position for the particle in the present position. And the identical particles are introduced to limit the displacement equation of each particle so as to update its displacement and speed.

$$x_i(t+1) = C^2(p \pm a\times|Mbest_i - x_i(t)|\times\ln(1/u)\ (u\in[0,1]) \quad (9)$$

Ⅴ. An improved Logistic Chaotic Mapping

A. Unidimensional nonlinear logistic chaotic mapping

Chaotic is a widely existing nonlinear phenomenon in the nature. Commonly, people call the random motion state got in the deterministic equation as chaotic. Logistic mapping is a typical chaotic system, its iterative formula is shown as Formula (10): in which, μ is control parameter; when μ=4，0≤ z_0≤ 1, Logistic is in a complete chaotic state. Due to the randomness, traversal, and sensitivity to the initial situation of the chaotic motion, the search technology based on chaotic will be more effective that other random search techniques.

$$x_{n+1} = \mu x_n(1-x_n) \quad n=1,2,\ldots \quad \mu\in(2,4] \quad (10)$$

B. An improved chaotic mapping

Because of the pseudo randomness of the chaotic, probability and statistics can be applied to conduct quantitative research on the property of the chaotic sequence. Based on reference [1], the probability distribution density function of such sequence produced through Schuster H.G Formula (11) is:

$$\rho(x)=\begin{cases}\dfrac{1}{\pi\sqrt{x(1-x)}} & 0<x<1\\ 0 & x\le 0, x\ge 1\end{cases} \quad (11)$$

The related experiment proves the inconsistent distribution of Logistic mapping. To get a random system with a consistent distribution, Formula (10) can be changed as the following:

$$y^n = \frac{2}{\pi}sin^{-1}(\sqrt{x_n}), \qquad n=1,2,3,\ldots \quad (12)$$

The time average of x, that is, the average value of the chaotic sequence tracing point is:

$$\bar{x} = \lim_{N\to\infty}\frac{1}{N}\sum_{i=0}^{N-1}x_i = \int_0^0 x\rho(x)dx = 0 \quad (13)$$

The distribution function of variable y is:

$$F\{y\le Y\}=F\{x\le sin(\frac{\pi Y}{2})\}=$$

$$\int_0^{sin\left(\frac{\pi Y}{2}\right)}\rho(x)dx = \int_0^{sin\left(\frac{\pi Y}{2}\right)}\frac{1}{\pi\sqrt{x(1-x)}}dx = Y \quad (14)$$

Formula (12) conforms to the consistent distribution within the (0,1) interval, having better random distribution than Formula (10).

Thus, the probability density function of the variable y is:

$$\rho(Y)=\frac{dF}{dY}\{y\le Y\}=1 \quad (15)$$

Ⅵ. An QPSO algorith based on the improved Logistic chaotic mapping

In recent years, researchers both home and abroad have raised a lot of versions of PSO algorithms, with many of which use normal, Cauchy, uniform and exponential distribution to produce random sequence to update the speed of this algorithm. In this paper, a QPSO algorithm based on the improved Logistic chaotic mapping is proposed. The foundation of chaotic theory is to use the traversal of the chaotic motion to produce a large amount of particle population and select the optimal ones from them. It can further prevent the particles from beginning to conduct local search too early and help them to find their optimal position.

In QPSO algorithm, the chaotic sequence replaces the random sequence to achieve the diversity of QPSO population and the improved performance of this algorithm, which is very useful in restrain the minimization of local convergence. The improved Logistic chaotic mapping mentioned in Reference[1] means transforming Formula (10) into Formula (12), which can result in more even variable distribution and better randomness. By applying the above improved algorithm to QPSO, the author can not only ensure the even distribution of the particle in their initial situation, but also further initialize part of the local extreme points in the later local convergence process. The detailed procedure is shown as the following:

- Based on the improved one-dimensional Logistic chaotic mapping system presented in Reference[1], a large number of initial population are produced and the best of them are selected;
- Using the formula (17) to determine the position of each particle in the identical particle system [27];
- Using the formula (16) and (17) to determine the global and local optimal position of each particle respectively, in which, pgd is their global optimal position and pid is the local one; Then comparing the two positions of each particle to select the best value as the present optimal value of this particle.

$$Mbest = \frac{1}{M}\sum_{i=1}^{N} p_{gd}^{i} \qquad (16)$$

$$Mbest_i = \frac{1}{M}\sum_{i=1}^{N} p_{id} \qquad (17)$$

- Subtracting the local and global optimal value of each particle; if the result is smaller than certain order of magnitude or is a minus, it means this particle has fallen into the local minimum sector and the improved Logistic system can be used to locally optimize this part of particles, thereby to prevent them from beginning local minimization too soon and from failing to find their optimal positions. That is why this new search technology is more effective than other techniques of the same type;
- Substituting the result of Step (3) into Formula (9) to update the present position of the particle;
- If the above result does not exceed the maximum value of the speed and displacement or fails to achieve the expected state, return to the Step 2 to repeat the procedure.

Ⅶ.PERFORMANCE ANALYSIS OF THE IMPROVED QPSO ALGORITHM

In the following, the property of GLQPSO is tested by comparing with that of PSO, CPSO (Chaos particle swarm optimization) and QPSO through optimizing the Ackley, Rosenbrock and Rastrigin function when they are in their ten-dimensional conditions. According to Reference [28], the globally optimal value of Rastrigin function is 0. It is a nonlinear unction of multiple peak values, having many local optimal points and very difficult of find its globally optimal value and therefore also very difficult to be optimized by the optimization algorithm. The globally optimal values of Griewank, Ackley functions are also 0. They are invariably nonlinear functions of multiple peak values. Their local optimal points are distributed regularly, whose quantity gradually setting of the parameters in the algorithm: $c_1=c_2=2$, the value of w will drop from 0.9 linearity to 0.4 with the change of iteration step, its maximum iteration is 1000; that of a will drop from 1.0 to 0.5.

TABLE Ⅰ.
THE INITIAL VALUES OF RASTRIGIN , ACKLEY AND GRIEWANK TRIAL FUNCTION

test function	search interval	initialization interval	space dimension
Ackley	(-32.768,32.768)	(-32.768,32.768)	10,3
Rastrigin	[-10,10]	[-10,10]	10,3
Rosenbrock	[-5,10]	(-5,10)	10,3

$$\text{Rastrigin} \quad \sum_{i=1}^{n}(x_i^2 - 10\cos(2\pi x_i)) + 10 \qquad (18)$$

$$\text{Rosenbrock} \quad \sum_{i=1}^{n-1}[100(x_i^2 - x_{i+1})^2 + (x_i - 1)^2] \qquad (19)$$

$$\text{Ackley} \quad 20 + e - 20\exp(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}) - \exp(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)) \qquad (20)$$

TABLE Ⅱ.
THE COMPARED OF PSO、CPSO、QPSO 、GLQPSO RESULTS

		global optimum value（max）	global optimum value（min）	Mean global optimum value	Global optimum value variance
Ackley	PSO	2.3172	0.0001201	1.1898	0.64965
	CPSO	3.0271	0.000472	1.0604	0.82805
	QPSO	0.02339	5.46E-02	4.0053	1.23
	GLQPSO	0.011339	9.46E-05	0.002382	1.14E-05
Rosenbrock	PSO	9.5865	0.24229	6.3559	4.4032
	CPSO	9.7047	0.25196	6.7629	5.1954
	QPSO	4.6148	2.97E-07	0.5778	0.60297
	GLQPSO	4.1003	5.94E-10	0.16944	0.63E-04
Rastrigin	PSO	38.803	1.99	17.003	67.836
	CPSO	32.841	4.0241	15.274	27.937
	QPSO	23.0337	7.26E-06	5.4415	35.472
	GLQPSO	19.9	2.74E-07	5.3436	24.568

Table 1 lists the value range of variable initialization of the three functions. Table 2 lists the optimization results of the four algorithms with the number of iterations being 1000. It reveals that arranging from high to low, the order of their convergence values should be that of GLQPSO, of QPSO, of CPSO and of PSO, which means GLQPSO has the best convergent tendency of the four. As for their speed to reach the global optimum the order is quite the same, with GLQPSO being the fastest. It proves that the employment of the probability density function helps to improve the chaotic randomness, restrain the local convergence, increase the iterations and facilitate the group to reach the global optimum quicker. Mean square error refers to the distance square of each datum drifting from the average, disclosing the dispersion degree of a Datasets. Among the four algorithms, GLQPSO's mean square error is the lowest because this algorithm can not only help to improve the quality of the initial population through the identical particle, but also use the bettered chaotic system to prevent the particle from beginning the local minimum search, improve its local search ability, save the search time and thus make it find the optimal position faster. And this, in turn, can improve the local optimization ability and convergence. And all this has also been proven through the related experiment. In addition, the convergence of the four algorithms is also tested in this essay by optimizing the three functions when they are in their three-dimensional conditions. The result finds that among the four algorithms, QPSO has the highest speed to reach the global optimum.

Figure 1~2 show the simulation results of the one experiment. The two figures show the change in the average fitness curve and global optimal cure of the particle population when the number of particle changes while the iteration time remains the same. Due to the fewness of the particle number and their sparse distribution, the fluctuation of the curve in Figure1 is larger than

Figure2. In these two figures, there will appear an upward fluctuation when the iteration times reach 50~200 interval. That is because GLQPSO has increased the diversity of the population and enhanced the trial period of the particle. In addition, by using the chaotic sequence to initialize the population and the chaotic disturbance to improve the optimization ability, too early local optimization process can be avoided and the search efficiency can be greatly raised.

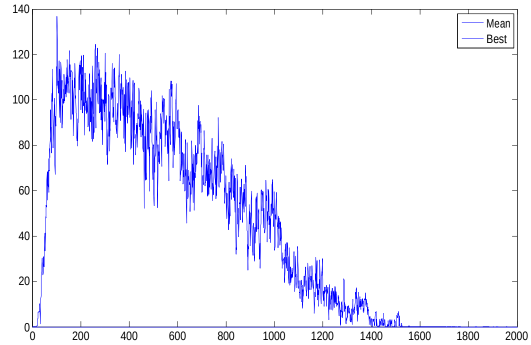

Figure1. the simulation result of the GLQPSO algorithm in the two-dimensional space with its iteration times being 2000 and the number of particle being 30 (Rastrigin Function)

Figure 3~8 show the simulation results of 50 experiments. Fig3, 4 and 5 shows the convergence curves of the three functions in their ten- dimensional conditions. They reveal that GLQPSO has the fastest convergence speed. Fig 6~8 show the same type of curves when these functions are in their three-dimensional conditions. The weakness of GLQPSO can be found clearly in these curves, which means that despite its great convergence in the high dimension, this ability will be weakened in the low dimension.

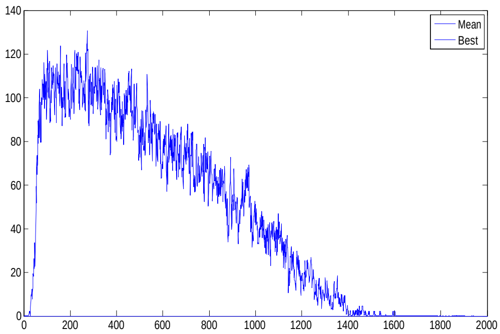

Figure2. the simulation result of the GLQPSO algorithm in the two-dimensional space with its iteration times being 2000 and the number of particle being 45 (Rastrigin Function)

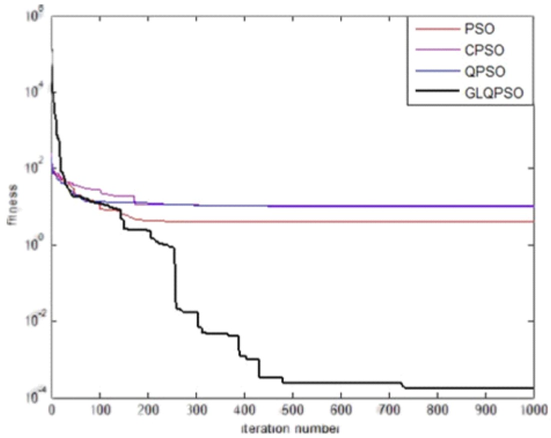

Figure3. the simulation results of the four algorithms in the ten-dimensional space with its iteration times being 1000 and the number of particle being 30 (Rosenbrock Function)

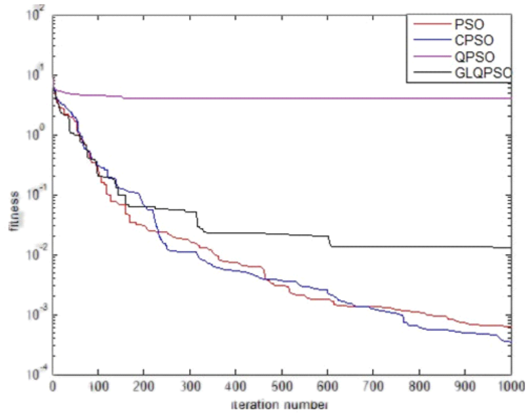

Figure4. the simulation results of the four algorithms in the ten-dimensional space with its iteration times being 1000 and the number of particle being 30 (Ackley Function)

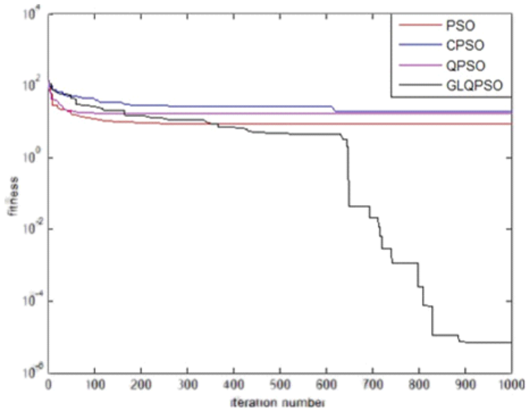

Figure5. the simulation results of the four algorithms in the ten-dimensional space with its iteration times being 1000 and the number of particle being 30 (Rastrigin Function)

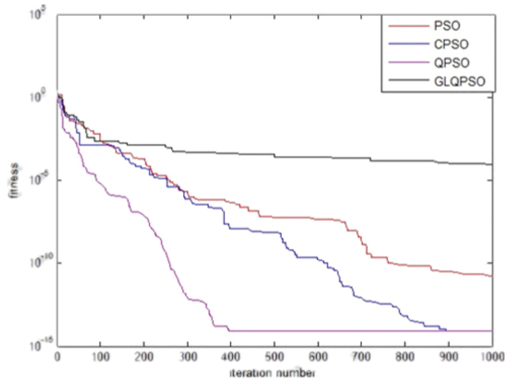

Figure6. the simulation results of the four algorithms in the three-dimensional space with its iteration times being 1000 and the number of particle being 30 (Ackley Function)

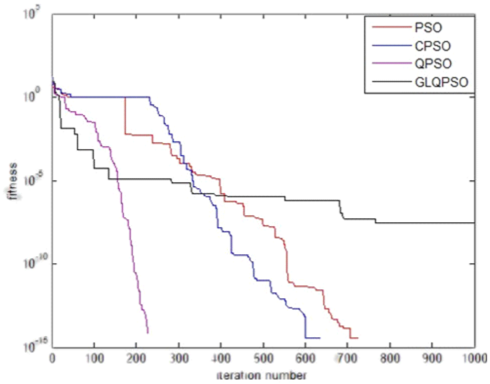

Figure7. the simulation results of the four algorithms in the three-dimensional space with its iteration times being 1000 and the number of particle being 30 (Rastrigin Function)

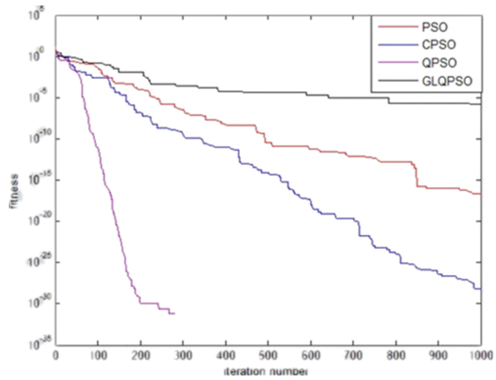

Figure8. the simulation results of the four algorithms in the three-dimensional space with its iteration times being 1000 and the number of particle being 30 (Rosenbrock Function)

Ⅷ. CONCLUSION

This paper proposes a new PSO algorithm based on the improved quantum behavior---GLQPSO algorithm by using identical particle system to update the particle position and the chaotic theory to conduct chaotic disturbance and initialization on each particle. The test shows that compared with the classical PSO, CPSO and QPSO, the new algorithm greatly improves the local search capacity and convergence speed of the particle swarm. The author hopes that this algorithm can be further perfected in the future application.

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My name is Yan-xia JIN. I am 40 years old, born in shanxi province in china. I am Associate professor. I got my bachelor degree from NORTH UNIVERSITY OF CHINA in 1997.I am master instructor. My major is computer. In 2004, i got master degree from NORTH UNIVERSITY OF CHINA in shanxi province. My major is measuring and testing technology and instruments. In 2010, i got doctor from NORTH UNIVERSITY OF CHINA. My major is measuring and testing technology and instruments too. My major field of study should be virtual reality, image processing and optimization theory. (E-mail:jinyanxia_730128@163.com)

The past five years, i have main results: 10 papers, including one by SCI, four by EI, two textbooks, a book, a national invention patent.

The second author is Jing XUE. He is a graduate.

The third author is Zhi-bin SHI. She is Associate professor. She has main results: 10 papers, including three by EI, one textbook.