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PSO Algorithm Based on Accumulation Effect and Mutation

Ji Weidong, Zhang Jun
Harbin Normal University, Harbin, China
Corresponding author, e-mail: kingjwd@126.com, hsd_zj@163.com

Abstract

Particle Swarm Optimization (PSO) algorithm is a new swarm intelligence optimization technique, because of its simplicity, fewer parameters and good effects, PSO has been widely used to solve various complex optimization problems. particle swarm optimization (PSO) exist the problems of premature and local convergence, we proposed an improved particle swarm optimization based on aggregation effect and with mutation operator, which determines whether the aggregation occurs in searching, if there is then the Gaussian mutation is detected to the global extremum, to overcome particle swarm optimization falling into local optimal solution defects. Testing the new algorithm by a typical test function, the results show that, compared with the conventional genetic algorithm (SGA), it improves the ability of global optimization, but also effectively avoid the premature convergence.

Keywords: *PSO, aggregation effect, variation, precocious*

1. Introduction

PSO was proposed by Dr. Eberhart and Dr. Kennedy in 1995 [1, 2], which produced the swarmed intelligent and improved guidance algorithm through population, cooperation and competition between particles swarms. Particle Swarms Optimization compared and shared information between individuals. Advantages are simple and easy to understand its ideas, and involving fewer parameters, which has a faster convergence speed and stronger global optimization capability. It is a evolutionary computation method based on swarm intelligence. Particle Swarm Optimization get a wide range of applications and research when it was put forth soon [3-7], However, due to particle swarm optimization algorithm is to trace the location of population by searching iteratively, all particles are near to the best position, they tend to be the same slowly, or making the diverse group damaged seriously, resulting in" mass effect", making convergence speed reduced gradually, even at a standstill, making the algorithm converge in advance and be prematurity. Particle swarm optimization is easy to fall into local optimum, it is difficult to find the global optimum, so the search accuracy is so high. Many experts and scholars studied it and made a number of improved particle swarm optimization algorithm [8-12]. Although some of the above algorithm improved particle swarm optimization performance in varying degrees and improved to varying degrees in the global searching ability, convergence and accuracy, the effect is not very satisfactory.

As PSO is prone to "cluster effect" in late, this paper introduced the idea of judgment mechanism for "cluster effect" and mutation based on the particle swarm mechanism [13], to enhance the particle diversity, improve the ability out of local extreme points, to make them can continue searching in other areas, thus avoiding the deficiencies of being easy to fall into optional values, enhancing the opportunity of searching for global values, to improve the speed and accuracy of late convergence.

2. PSO Algorithm

It is from the simulation of bird predation, is similar with genetic algorithm, PSO algorithm initializes a group of random particles firstly. Every particle is a possible solution of optimization problems; it has its own position and velocity, whose objective function value is its fitness degree [1]. In each iteration, each particle memories, following the best particle

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currently by tracking two ”extreme” to update itself: one is the optimal solution found by particle itself, which id individual extreme *pbest.* Another is the optional solution around the entire population, called the global extremum *gbest*. After finding these two optional values, the particles update their velocity and position iteratively according to the following Equation (1) and (2).

The equation of motion of particle in d-dimensional space can be described commonly by a group of differential equations and constraints. As shown in Equation (1) and (2).

$$v_{i,d}^{(t+1)} = \omega \cdot v_{i,d}^{(t)} + c_1 \cdot r_1 \cdot (pbest_{i,d}^{(t)} - x_{i,d}^{(t)}) + c_2 \cdot r_2 \cdot (gbest_d^{(t)} - x_{i,d}^{(t)}) \quad (1)$$

$$x_{i,d}^{(t+1)} = x_{i,d}^{(t)} + v_{i,d}^{(t+1)} \quad (2)$$

t is number of iterations, ω is inertia factor, $x_{i,d}^{(t)}$ is the position vector particle currently. $v_{i,d}^{(t)}$ is particle velocity, $pbest_{i,d}^{(t)}$ is the best position of particle i reaching d, $gbest_d^{(t)}$ is the best position of population reaching d, c_1 c_2 are acceleration factors, r_1 r_2 are the two random numbers which are distributed uniformly between 0 and 1, the $v_{i,d}^{(t+1)}$ in indicating the current state of the particle; the above formula (1) id made by three items, the first item is “momentum” section, the second item is “cognitive” section, considering the particle own experience;the third item is “society” section, the social role between the particles. Particles move constantly through searching for its own information *pbest* and group information *gbest* until condition is satisfied.

3. PSO is based on Accumulation Effect and Mutation

3.1. PSO: The Determined Mechanism when “cluster effect”

Several definitions are given to determine.

Definition 1: PSO group fitness variance can be defined as Equation (3).

$$\delta^2 = \sum_{i=1}^{n} \left| \frac{f_i - f_{avg}}{f} \right|^2 \quad (3)$$

Among them, f_i is the fitness degree of i-th, f_{avg} is current average fitness degrees of swarm, according to the formulation (4) to solve, f is used to limit the size of δ^2, its value can be defined as formula (5).

$$f_{avg} = \frac{\sum_{i}^{n} f_i}{n} \quad (4)$$

$$f = \max\left\{1, \max\left\{\left| f_i - f_{avg} \right|\right\}\right\} \quad (5)$$

Fitness variance can reflect the degree of convergence in the swarm of particles, the smaller the δ^2 is, the greater the degree of aggregation of PSO, then the more convergent the particle swarm is. On the contrary, particles are in the random search stage.

Definition 2: Particle is the maximum distance (MaxDist), is the current distance between the position of the global optimum maximum Euclidean distance, can be defined as formula (6):

$$MaxDist = \max \sqrt{\sum_{d=1}^{m} \left(p_{gd} - x_{id} \right)^2} \qquad i = 1, 2..., n \tag{6}$$

There, n is the number of particles in the particle swarm, m is the dimension of the particle, p_{gd} is best position by the particle swarm, x_{id} means the current searching position by i-th particle.

Definition 3: Average particle aggregation distance (MeanDist), the average particle swarm Euclidean distance, can be defined as Equation (7):

$$MeanDist = \frac{\sqrt{\sum_{d=1}^{m} \left(p_{gd} - x_{id} \right)^2}}{n} \qquad i = 1, 2, \ldots, n \tag{7}$$

Whether it is local or global convergence, particle convergence will happen "gather" phenomenon. In the iterative process, the particles of the “gathering” are not a bad phenomenon, it can promote the optimization of the particle, what we need to address are those who do not meet the conditions: the early "gathering" phenomenon. When a particle moving at a rate equal to 0, particles come together, very difficult to move, if p_{gd} is not obtained for the global optimal solution, then the algorithm will fall into a local optimum. We can determine whether aggregation occurs by the times of position unchanged and the change of optimal location, we determine the Aggregation happens if the number is greater than the optimal threshold or less than a certain threshold position. You can also know that by Fitness variance, the aggregation effect occurs when less than the set threshold. This paper was based on Determination on δ^2 and MaxDist MeanDist.

Aggregation, effect, the judge mechanism is shown in Figure 1:

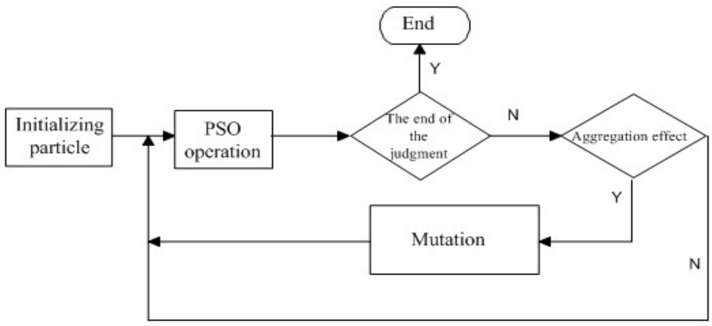

Figure 1. Judgment Mechanism of Aggregation Effect

When δ^2 tends 0:

(1) If the maximum distance is less than the average aggregation distance.

$MaxDist < MeanDist$

Believes that particle reaches global convergence.

(2) If the maximum distance is greater than the average aggregation distance.

$MaxDist > MeanDist$

Believes that is "cluster effect", falling into local convergence.

3.2. Mutation Operator

When the swarm aggregation occurs, the particles tend to homogenization, then the introduction of mutation operator to makes the PSO increase diversity, enhance the ability to jump out of local optimal answer, continuing searching in other areas, it is possible to find the global optimal solution [14]. This article will introduce the Gaussian mutation into particle swarm optimization algorithm, added disturbances in the place of optimal value received, this algorithm was combined with stronger ability out of local extrema of Gaussian algorithm based on global searching capability and easy to achieve, it is possible to find the global optimal solution.

When "premature" phenomenon appears, according to Equation (8) for mutation.

$$P_{gd} = P_{gd} * (1+\eta) \tag{8}$$

Wherein, η obeys the Gaussian distribution, $\eta \sim Gauss(0,1)$. Thus, there is particle swarm optimization algorithm GPSO.

3.3. Basic Process of Optimization with Mutation Particle Swarm

Step1: init position and speed of PSO population,

$$V \in [-V_{\max}, V_{\max}], \qquad X \in [-X_{\max}, X_{\max}],$$

Initialize population parameters, set swarm size N, set dimension is D, Sets the maximum number of iterations $T_{\max}$, The initial frequency t = 0.

Step 2: calculate the fitness value of every particle F_i; update individual optimum P_i and global optimum P_g.

Step 3: Update the particle velocity and position according to the formula (1) and (2), adjust the inertia weight according to the formula (9) ω [15],

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} \times iter \tag{9}$$

$iter_{\max}$ is maximum evolution algebra, $iter$ is Current evolution algebra.

Step 4: Determine whether the algorithm reaches the maximum number of iterations $T_{\max}$.

If it does then turn Step 8, otherwise, do Step 5;

Step 5: Determine whether the particle swarm aggregation occurs, calculate the particle swarm fitness variance according to the formula (3), (4), (5), if δ^2 tends 0, the aggregation occurs, do Step 6, otherwise go to Step 3;

Step 6: According to Equation (6), (7), calculate MaxDist, MeanDist, if $MaxDist < MeanDist$, then turn up to step8, if $MaxDist > MeanDist$, turn up to Step 7;

Step 7: According to the formula (8) make variations on Global optimum, turn Step 3;

Step 8: output P_g.

4. Experimental Study

In order to assess the effectiveness of the proposed method GPSO, this article will compared GPSO and SGA, select four benchmarks functions to solve it [16]:

(1) Schwefel function is shown in Equation (10), (11) as follows:

$$f_1(x) = \sum_{i=1}^{n} |x_i| + \prod_{i=1}^{n} |x_i| \tag{10}$$

$$f_2(x) = \sum_{i=1}^{n} \left(\sum_{j=1}^{i} x_j \right)^2 \tag{11}$$

(2) Griewank function is shown in Equation (12) below:

$$f_3(x)=\frac{1}{4000}\sum_{i=1}^{n}x_i^2-\prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}})+1 \quad (12)$$

(3) Ackley function is shown in Equation (13) below:

$$f_4(x)=-20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}\right)-\exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right)+20+\exp(1) \quad (13)$$

Schwefel function $f_1(x)$、$f_2(x)$ are unimodal function. Griewank function $f_3(x)$ can not be separated, variable it is multimodal function, Function Ackley $f_4(x)$ is a continuous, rotational, and inseparable multimodal test function. Mainly through a cosine exponential waveform to adjust the exponential function. Its global optimal value falls on the edge ,if the initial value of the algorithm falls on the edge, it will be very easy to solve this kind of problem. Its topology is characterized by: since the outer region dominated function is an exponential function, so is very flat. Because of the cosine waveform adjusts in the middle, it will turn up a aperture or a summit, and turns out to be not flat. The multimodal function has large amount of partial optimal point. The four functions are required to get minimum. Function dimension and feasible solution space as shown in Table 1.

Table 1. Three Test Functions

Test function	Dimension	Feasible solution Space
$f_1(x)=\sum_{i=1}^{n}\lvert x_i\rvert+\prod_{i=1}^{n}\lvert x_i\rvert$	30	$[-10,\ 10]^n$
$f_2(x)=\sum_{i=1}^{n}\left(\sum_{j=1}^{i}x_j\right)^2$	30	$[-100,\ 100]^n$
$f_3(x)=\frac{1}{4000}\sum_{i=1}^{n}x_i^2-\prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}})+1$	30	$[-600,\ 600]^n$
$f_4(x)=-20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}\right)-\exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right)+20+\exp(1)$	30	$[-32,\ 32]^n$

Experiment parameters:

GPSO algorithm parameter is set to:

Particle swarm size $n=40$

Dimension $d=30$,

$c_1=c_2=2$, $\omega_{\max}=0.9$, $\omega_{\min}=0.4$, $V_{\max}=2$.

SGA algorithm parameter is set to:

Using fitness proportional selection operator, arithmetic crossover and uniform mutation operator,

Where crossover probability $p_c=0.8$

Mutation probability $p_m=0.02$

GPSO algorithm and SGA were used, which are tested on three test functions 20 times, find the average fitness value and standard deviation. Test results are shown in Table 2, GPSO, SGA of the four function to solve the optimization of the simulation curves shown in Figure 2, 3, 4, and 5.

Table 2. Test Results

Test Function	Average fitness value (standard deviation) GPSO	SGA	Global minimum
F_1	3. 9125E-115 (2. 0841E-114)	2. 6624E-1 (6. 3625E-2)	0
F_2	8. 7445E-181 (0)	671. 3289 (122. 4790)	0
F_3	2. 4797E-14 (1. 1206E-13)	4. 8423 (1. 1184)	0
F_4	1.1685E-13 (2.1318E-13)	5.9209 (6.4707E-1)	0

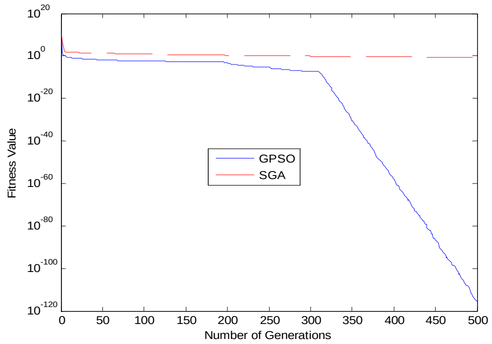

Figure 2. Fitness Value Comparison Chart of F1 in 2 Algorithms

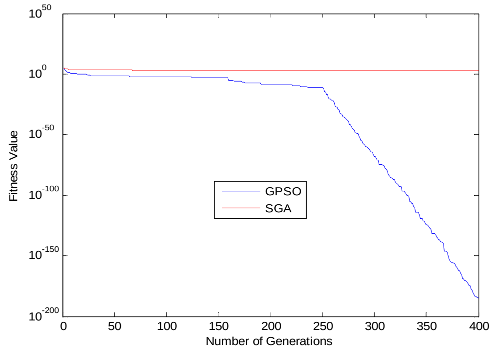

Figure 3. Fitness Value Comparison Chart of F2 in 2 Algorithms

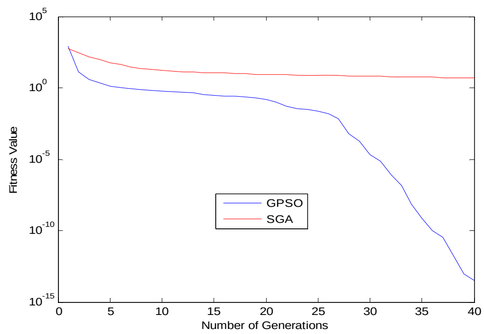

Figure 4. Fitness Value Comparison Chart of F3 in 2 Algorithms

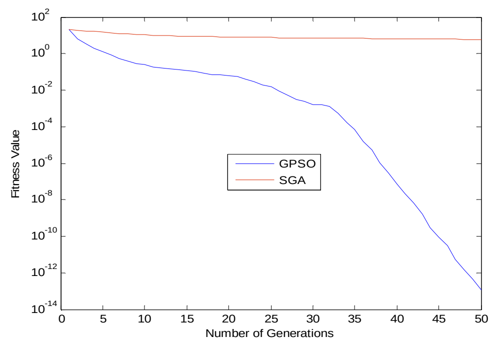

Figure 5. Fitness Value Comparison Chart of F4 in 2 Algorithms

The experimental results were analyzed and compared. We can know it from 2 Algorithms for 4 test functions, GPSO can get a smaller answer than SGA through 4 functions, indicating GPSO algorithm can search for better solution, and avoiding premature particles falling into local point. Through the analysis of the standard deviation, GPSO algorithm is better than SGA algorithm, it can obtain smaller standard deviation, so it has better stability. Therefore, the algorithm in solving accuracy and robustness of GPSO are better than SGA algorithm. After analyzing the fitness value comparison chart, we see, although the two kinds of algorithms are not getting the global optimal value within the set maximum number of iterations, GPSO algorithm convergence accuracy is much better than SGA algorithm, unlike that SGA algorithm into local point prematurely, results of GPSO algorithm are very close to the target value. Simulation experiments show GPSO algorithm for improving the quality of solutions have validity.

5. Conclusion

In this paper, PSO algorithm has been improved, we put ideas of aggregation effect and variation ideas into PSO, proposed an improved particle swarm optimization based on accumulation effect and mutation operator. Testing to standard genetic algorithm and improved particle swarm with complex Schwefel function, Griewank function and Ackley function, the results show that improved PSO is better than the standard genetic algorithm in convergence speed and global search capability, avoiding falling into a premature and local convergence.

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References

[1] J Kennedy, R Eberhart. *Particle Swarm Optimization.* Proc. IEEEInt. Conf. Neural Networks. 1995; 1942-1948.
[2] YW Leung, YP Wang. An Orthogonal Genetic Algorithm with Quantization for Global Numerical Optimization. *IEEE Transactions on Evolutionary Computation*. 2001; 5(1): 41–53.
[3] Das Sharma K, Chatterjee A, Rakshit A. A Random Spatial lbest PSO-Based Hybrid Strategy for Designing Adaptive Fuzzy Controllers for a Class of Nonlinear Systems. *IEEE Transactions on Instrumentation and Measurement*. 2012; 61(6): 1605–1621.
[4] Chia-Nan Ko, Ying-Pin Chang, Chia-Ju Wu. A PSO Method with Nonlinear Time-Varying Evolution for Optimal Design of Harmonic Filters. *IEEE Transactions on Power Systems*. 2009; 24(1): 437-444.
[5] Vlachogiannis JG, Lee KY. Economic Load Dispatch. A Comparative Study on Heuristic Optimization Techniques with an Improved Coordinated Aggregation-Based PSO. *IEEE Transactions on Power Systems*. 2009; 24(2): 991–1001.
[6] Benzheng Wei, Zhimin Zhao, Xin Peng. Spatial Information Based Medical Image Registration using Mutual Information. *Journal of Multimedia.* 2009; 6(3): 236-243.
[7] Xiaohui Chen, Canfeng Gong, Jiangbo Min. A Node Localization Algorithm for Wireless Sensor Networks based on Particle Swarm Algorithm. *Journal of Networks*. 2012; 7(11); 1860-1867.
[8] Zhang Feizhou, Cao Xuejun, Yang Dongkai. Intelligent scheduling of public traffic vehicles based on a hybrid genetic algorithm. *Tsinghua Science and Technology*. 2008; 13(5): 625–631.
[9] Taejin Park, Kwang Ryel Ryu. A Dual-Population Genetic Algorithm for Adaptive Diversity Control. *IEEE Transactions on Evolutionary Computation*. 2010; 14(6): 865–884.
[10] Xiao Min Hu, Jun Zhang, Yan Yu, et al. Hybrid Genetic Algorithm Using a Forward Encoding Scheme for Lifetime Maximization of Wireless Sensor Networks. *IEEE Transactions on Evolutionary Computation*. 2010; 15(4): 766–781.
[11] Yi-Tung Kao, Erwie Zahara. A hybrid genetic algorithm and particle swarm optimization for multimodal functions. *Applied Soft Computing.* 2008; 8: 849-857.
[12] Shutao Li Mingkui Tan, Tsang IW, et al. A Hybrid PSO-BFGS Strategy for Global Optimization of Multimodal Functions. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*. 2011; 41(4): 1003–1014.
[13] MG Epitropakis, DK Tasoulis, NG Pavlidis. Enhancing Differential Evolution Utilizing Proximity-Based Mutation Operators. *IEEE Transactions on Evolutionary Computation*. 2011; 15(1): 99-119.
[14] S Das, A Abraham, UK Chakraborty, A Konar. Differential Evolution Using a Neighborhood-Based Mutation Operator. *IEEE Transactions on Evolutionary Computation*. 2009; 13(3): 526-553.
[15] Y Shi, RC Eberhart. *A Modified Particle Swarm Optimizer.* Proceedings of IEEE International Conference on Evolutionary Computation. Anchorage, AK, USA. 1998; 69–73.
[16] YW Leung, YP Wang. An Orthogonal Genetic Algorithm with Quantization for Global Numerical Optimization. *IEEE Transactions on Evolutionary Computation*. 2001; 5(1): 41–53.