

Research on Multiple Particle Swarm Algorithm Based on Analysis of Scientific Materials

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Abstract. This paper proposed an improved particle swarm optimization algorithm based on analysis of scientific materials. The core thesis of MPSO (Multiple Particle Swarm Algorithm) is to improve the single population PSO to interactive multi-swarms, which is used to settle the problem of being trapped into local minima during later iterations because it is lack of diversity. The simulation results show that the convergence rate is fast and the search performance is good, and it has achieved very good results.

Keywords. Swarm intelligence, particle swarm, scientific materials, bacterial foraging optimization

1 Introduction

In order to solve actual problems, a number of methods of algorithmic Swarm intelligence have been worked out, the most effective of which is Particle Swarm Optimization (PSO)[1]. Enlightened by the biological swarming's activities, such as school of fish, in flocks of birds, and even that of mankind's, PSO is an optimization instrument, carried out to settle a variety of function optimization problems. Being a skill to solve problems, the main advantage of PSO is its high speed of convergence, which exceeds that of Evolutionary Algorithms (EA) and the rest global optimization algorithms. However, if PSO is used to settle complicated problems may run into trouble as following: in the evolution of population, premature convergence to the local optimum in former generations may happen to all individuals, which could cause low population diversity of population together with adaptation stagnation in latter generations.[2,3]

The PSO algorithm first randomly initialized a group of particles, in each iteration, the particle is updated by following the two extremes: one is the optimal particle itself to find the solution, called individual best; another is the whole population found in the optimal solution, called global extreme value point, and the local PSO algorithm without the only one part of the population, adjacent particles, is the local extreme in the optimal solution. All the neighbors in the PSO algorithm, the position of the particle represents a potential solution to the optimization problem, the particle velocity indicates the direction and distance of flying particles, each particle at the extent of the position by the particle fitness function the value reflected. Particle velocity and position by tracking individual extreme and global extreme update, each iteration update once, to find the optimal solution or the maximum number of iterations is reached so far.[4,5]

We would analyze this potential by evaluation of MPSO on both mathematical benchmark functions. In our experiments, there are five benchmark functions used to simulation results, which are compared to that of other optimization algorithms, the advantage of the proposed algorithms would be clearly reported in this paper.

2 Basic flow of PSO algorithm

Particle swarm optimization algorithm is simple and easy to implement, compared with other evolutionary algorithms, the algorithm not only retains the global search Ability, but also to simple speed displacement operation model replaced the complex genetic operation, and has the specific memory function according to the current search of dynamic adjustment of the search strategy, is a more efficient parallel search algorithm.[6]The basic particle swarm optimization algorithm is as follows:

The first step: to tell the truth within the scope of random initialization of the particle swarm, including random location and speed.

The second step: to calculate the fitness value of each particle.

The third step: for each particle, the fitness value and the best location fitness value are compared, if better, its value as the particle's best individual historical, personal historical best position is updated with the current position.

The fourth step: for each particle, its historical optimal fitness value and the community or neighborhood experience the best location of the fitness value for comparison, if better, then it as the current best position.

The fifth step: according to the formula (1) and (2) to update the speed and position of the particles.

The sixth step: if the termination condition is reached, then the second step is to be reversed, and the termination condition is generally a good enough fitness value or to achieve a predetermined maximum iterative algebra. [7,8]

3 PSO algorithm related control parameters.

The selection of control parameters is very important, because it can directly affect the performance of the algorithm if the parameters are chosen properly.[9]

(1) Inertia weight

The inertia weight is an important parameter for the global search ability and local search ability of particle balance, from equation (3) and on the section of the velocity update in the interpretation of the inertia weight represents the size of particles retained the speed much of its state of motion. The degree of trust when the inertia weight is zero, the equivalent speed and update the particle velocity is independent of particle, the search space will be greatly reduced, only equivalent to the local search ability, and the particle is easy to flight to the same position, lead to local minima. When the inertia weight increases, which increases the current state of the particle retention, thus expanding the search space of particles, enhances the algorithm the global search ability, therefore, inertia weight changes and the choice of initial value is very important, choose appropriate or not directly related to the performance of the algorithm.[10]

(2) Accelerating factor,

Acceleration coefficient is adjusted parameters of their own experience and the experience of particle groups of particle trajectories. The update formula from the velocity of particle swarm algorithm (3.1) shows that the acceleration coefficient can balance the global search ability and local search ability of particle, when two values were increased, the local search capability of particle increases this, and know the inertia weight is just the opposite. At the same time, known as cognitive acceleration coefficient, represents the effect of particle velocity updating experience of its own, which is more dependent on their own experience of the particle is larger, vice versa; known as social acceleration, on behalf of the particle in the population social experience influence on speed, which is more dependent on the particle of social experience is, vice versa. Therefore, to adjust their own experience with the particle population social experience for speed, acceleration coefficient value is ten Important points.

(3) Population size M

The population size m , that the number of particles in a population. When the population size M is 1, namely only one particle in the search. At this time there is no groups between information sharing and cooperation to speak; when increasing the population size m , mutual collaboration cooperation of particle is more, the search algorithm can power will increase; when the population size is too large, it is clear, the search process of the algorithm is also more complex, the calculation time of the algorithm will increase a lot, so convergence speed will slow. Therefore, the size of the population size also need to according to the practical application of the selection of appropriate.[11]

(4) Maximum speed

Maximum speed is used to restrict the particle's velocity parameters, that define the maximum distance of particle in every iteration moves. When the maximum speed is too large, the moving distance of each particle will corresponding is too large, although the search speed of particles increases. Global search ability is enhanced, however, particles are easy to miss the optimal solution.[12,13]

4 The proposed multiple particle swarm optimization algorithm

MPSO modify the single population PSO to the interactive multiple swarms model by incorporating the behaviors of cooperation and competition in bacterial swarming. In the MPSO, respective individual moving in the range of solution space by 3 attractors:

- (a) The particle previously best position.
- (b) Best position of the particle in its own swarm.
- (c) Best position of the particle in neighbor swarms.

By imitating cooperation and competition in bacterial swarming process, MPSO algorithm is proposed. Firstly, the section will introduce two kinds of operation, and then gives the specific implementation steps.[14]

In MPSO, the definition of cooperative operation is similar to standard PSO, each particle close to their optimal positions of its and population. The competitive operation indicates the worst position of particle and population in history. The update algorithm of particle velocity is as follows:

$$v_{id}^k(t) = \chi(v_{id}^k(t-1) + R_1c_1(W_{id} - x_{id}^k(t-1)) + \quad (1)$$

$$R_2c_2(W_{gd} - x_{id}^k(t-1)) + R_3c_3(P_{gd}^{\theta} - x_{id}^k(t-1)))$$

$$x_{id}^k(t) = x_{id}^k(t-1) + v_{id}^k(t) \quad (2)$$

W_{id} is the worst position of population, P_{gd}^{θ} is the worst position of its history, P_{gd} is the optimal position of global.

5 Summary

In summary, MPSO modifies the single population PSO to interactive multi-swarms model based on analysis of scientific materials.[15]With the theoretical analysis, we've got the results of experiment showing that the MPSO reaches remarkably better results on all the test functions. In order to make a clear demonstration for the MPSO algorithm's performance, we compared it with optimization on several benchmark functions. Then comparison of experimental results shows that the MPSO algorithm is superior to the PSO in terms of accuracy and speed of convergence.

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References

1. J. Kennedy and R. C. Eberhart, *Swarm Intelligence*, Morgan Kaufmann, San Francisco (2001).
2. Y. Xin. Improved firefly algorithm approach applied to chiller loading for energy conservation. *Energy and Buildings*, Vol **59** (2013),p.273-278.
3. M.H. Horng. Multilevel minimum cross entropy threshold selection based on the firefly algorithm. *Expert Systems with Applications*, Vol **38** (2011), p.14805-14811.
4. W. Peng, Image segmentation method based on firefly algorithm and maximum entropy method. *Computer Engineering and Applications*, Vol **12** (2014), p.115-119.
5. H. W. Tian, F. Xie, and J. M. Ni, *Computer Technology and Development* **21**, 22 (2011).
6. M. Clerc and J. Kennedy, *IEEE Transactions on Evolutionary Computation* **6**, 58 (2002).
7. Y. Liu, X. H. Wang, C. M. Xing, and S. Wang, *Computer Technology and Development* **21**, 19 (2011).
8. D. M. Li and H. H. Shi, A Hierarchical Load Balancing Scheduling Model Based on Rules *Computer Science* **30**, 16 (2003).
9. R. C. Eberchart and J. Kennedy, A new optimizer using par-ticle swarm theory, *Proceeding of the 6th International Sympo-sium on Micromachine and Human Science*, Nagoya, Japan (1995), p. 39–43.
10. Z. H. Zhang and X. J. Zhang, A load balancing mechanism based on ant population and complex network theory in open cloud com-puting federation, *2010 2nd International Conference on Industrial Mechatronics and Automation*, Wuhan, China (2010), p. 240–243.
11. J. F. Schutte, Particle swarms in sizing and global optimization, Master's Thesis, University of Pretoria, Department of Mechanical Engineering (2002).
12. Y. Shi and R. C. Eberhart, A modified particle swarm optimizer, *Proceedings of the IEEE International Conference on Evolution-ary Computation*, Anchorage, Alaska, IEEE Press, Piscataway, USA (1998), p. 69–73.
13. Y. Shi and R. C. Eberhart, Parameter selection in particle swarm optimization, *Evolutionary Programming VII*, edited by V. W. Porto, N. Saravanan, D. Waagen, and A. E. Eiben, *Lecture Notes in Com-puter Science*, Springer, Berlin (1998), Vol. **1447**, p. 591–600.
14. Tao,X.M, Xu,J.and Yang,L.B. An Improved Hybrid Algorithm Based on Particle Swarm Optimization and K-means Algorithm. *Journal of Electronics &Information Technology*. **32**, 1,(2010),p.92-94.
15. Suresh,S. Sundararajan,N. Saratchandran, P. A sequential multi-category classifier using radial basis function networks, *Neurocomputing* **71**, (2008) p.1345–1358.