Research on Particle Swarm Optimization Algorithm

Shouya Wang, Jiabing Zhu*, Xiaobo Shen, Qianchun Wang, Renyi Shu and Jun Cai

School of Electronic Engineering, Huainan Normal University, Huainan, Anhui, 232038, China.

Corresponding author’s e-mail: renyi_shu@hnnu.edu.cn

Abstract: Aiming at the unsatisfactory performance of the particle swarm optimization algorithm in the optimization process of complex problems and being easy to fall into premature convergence, a power law function to improve the weight value of the particle swarm algorithm is proposed in the paper. It is compared with the linearly decreasing weight particle swarm algorithm, and the test is performed on four typical single-peak and multi-peak functions. The test results show that the particle swarm optimization algorithm in this paper has a better optimization effect.

1. Introduction

Particle Swarm Optimization (PSO) [1] is an efficient and intelligent search algorithm proposed by Eberhart and Kennedy based on the foraging behavior of birds. Because the algorithm has the advantages of simple implementation and fast convergence speed, it has been widely used in many aspects [2-4].

In the process of optimizing complex problems, the particle swarm algorithm may fall into the problems of local optimization and slow convergence speed. Many scholars have made certain improvements to the particle swarm algorithm to solve related problems. Huang Zhen et al. [5] introduced complex networks to increase the speed of convergence. Dai Wenzhi et al. [6] introduced adaptive strategies, which can jump out of local extremes to a certain extent. Chen Qiulian et al. [7] combined neural networks to reduce the iterative search Optimal times. Qiu Feiyeu et al. [8] combined with adaptive learning factors to improve the convergence performance of the algorithm. The choice of the inertia weight value $\omega$ has a great influence on the optimization result of the particle swarm algorithm. A power law function to improve the weight value of the particle swarm algorithm is proposed in the paper. It is simple to implement, and is tested on a typical test function. The test results show that the particle swarm optimization algorithm in this paper has a better optimization effect.

2. Particle Swarm Optimization

The particle swarm optimization algorithm first needs to initialize a group of particles randomly, and then find the optimal solution through iterative optimization. The particle swarm optimization algorithm updates the velocity and position by the following formulas:

\[ v_{id}(k+1) = \omega \cdot v_{id}(k) + c_1 r_1 (p_{id}(k) - x_{id}(k)) + c_2 r_2 (p_{gd}(k) - x_{id}(k)) \]  

\[ x_{id}(k+1) = x_{id}(k) + v_{id}(k) \]

Formula: $\omega$ is the inertia weight, $c_1$ and $c_2$ are the learning factors, $r_1$ and $r_2$ are random...
numbers between [0, 1], \( v_{id}(k) \) is the search speed of the \( i \) particle at time \( k \) in \( d \) dimensions, and \( x_{id}(k) \) is the search speed at time \( k \) and \( i \) The position of each particle in the \( d \) dimension, \( p_{id}(k) \) is the optimal position of the \( i \) particle in the \( d \) dimension at time \( k \), and \( p_{gd}(k) \) is the optimal position of the entire particle swarm in the \( d \) dimension at time \( k \).

3. Improved Particle Swarm Optimization Algorithm

3.1. Weights Value
In the early stage of particle swarm optimization, a larger optimization speed is required to increase the optimization speed. In the later stage of the optimization, a smaller optimization speed is required to improve the search accuracy. This paper combines the power law function to improve the weight value of \( \omega \), and takes into account the search Excellent speed and accuracy, compared with the typical linear weighting method, the simulation result of \( \omega \) is shown in Figure 1.

![figure 1. Numerical comparison of \( \omega \)](image)

3.2. Algorithm Performance Test
Comparing the improved particle swarm algorithm with the typical linear decreasing weight particle swarm algorithm, the running test functions are the typical single-peak function: step function and sphere function; the classic multi-peak function: griewank function and rastrigin function. The minimum values of the four test functions are all 0.

Experimental parameter settings are as follows. The population size is set to 50. The number of iterations is set to 100. The dimensionality is set to 30. The learning factor is \( c_1 = 1.5 \) and \( c_2 = 2.5 \). The minimum inertia weight is \( \omega_{\text{min}} = 0.4 \), and the maximum is \( \omega_{\text{max}} = 0.8 \). The iterative optimization performance of the improved particle swarm algorithm and the typical linearly decreasing weight particle swarm algorithm are tested in Figures 2 to 5.
It can be seen from Figure 2 that the particle swarm optimization algorithm proposed in this paper can find the optimal solution faster when testing function of step. It can be seen from Figure 3 that when testing function of sphere, the particle swarm optimization algorithm proposed in this paper can find the optimal solution faster, and at the same time better jump out of the local optimal solution. It can be seen from Figure 4, when testing function of griewank, the particle swarm optimization algorithm proposed in this paper has a relatively large value at the beginning of the iteration, but the optimal value can be found very quickly. From Figure 5, it can be seen that the particle swarm optimization algorithm proposed in this paper has a significantly better optimization effect when testing function of rastrigin. On the whole, the particle swarm optimization algorithm proposed in this paper can show better optimization performance in the optimization process of typical single-peak and multi-peak functions, and the algorithm is simple and easy to implement.
4. Conclusion
This paper proposes the power law function to improve the inertia weight value $\omega$ of the typical particle swarm algorithm, then compares it with the typical and common linear decreasing weight particle swarm algorithm, and tests the optimization performance on four typical test functions, which can be seen through experiments. As a result, the improved particle swarm algorithm has better performance, faster optimization speed, higher accuracy, and can better jump out of the local optimal solution. It provides a certain theoretical reference value for the practical application of particle swarm algorithm.

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