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Zhiping Ding



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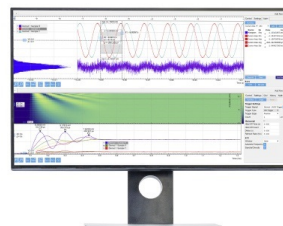
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Research of improved particle swarm optimization algorithm

Zhiping Ding

Department of Computer Application, Qing yuan Polytechnics, Qing yuan, 511510, Guangdong, China

Abstract. Because of the standard particle swarm optimization algorithm (Particle Swarm Optimization PSO) has slow convergence speed and easy to fall into the local minimum problem, in order to solve these problems, this paper proposes a multi-objective particle swarm optimization method based on improved culture. The simulation results show that the proposed algorithm is better in convergence speed and local minimum value, which shows that the improved particle swarm optimization algorithm has a good reference value

Key words: particle swarm optimization; multi-objective; population; algorithm

INTRODUCTION

Particle swarm optimization (PSO) is a kind of artificial intelligence simulation method, which is proposed by Kennedy and Eberhard in 1985. It is a stochastic optimization algorithm based on swarm intelligence theory. Particle swarm optimization (PSO) achieves the evolution of individuals by moving to the optimal individual and the optimal position. In order to overcome the shortcomings of PSO algorithm to improve the local searching ability of the algorithm, the scholars at home and abroad have made a lot of inertia weight particle method in the previous studies, usually with a linear decreasing inertia weight method, but this method cannot adapt to the complex nonlinear optimization problem, the related researches of relatively more optimization of inertia weight, compared with the standard PSO algorithm, this method can improve the convergence speed and optimization accuracy.

But only for the optimization of inertia weight, the improved algorithm still has the possibility of being trapped in local optimum. In order to solve the above problems, this paper proposes a dynamic particle swarm optimization algorithm based on adaptive cultural algorithm. The algorithm combines the global search ability of PSO algorithm and the double layer evolution mechanism of the cultural algorithm, and constructs the cultural particle swarm optimization algorithm.

MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION ALGORITHM

Multi-objective optimization function

Multi objective optimization problems need to optimize multiple objective functions at the same time. The mathematical description of the multi-objective optimization problem is as follows:

$$\begin{aligned} \min F(x) &= [f_1(x), f_2(x), \dots, f_n(x)] \\ s.t. g_i(x) &\leq 0 (or \geq 0) i = 1, 2, \dots, n \\ h_j(x) &= 0 j = 1, 2, \dots, m \end{aligned} \tag{1}$$

Among them, $f_i(x)$ ($i=1,2,\dots,n$) is Objective function, $g_i(x)$ is Inequality constraint, $h_j(x)$ is equality constraint. In this paper, several important concepts of multiobjective optimization are introduced:

Definition one Pareto control: Decision variable x^* dominate x satisfaction: all of $f_i(x^*) \leq f_i(x)$, and at least there is one $f_i(x^*) < f_i(x)$, which $i, j=1,2,\dots,n$.

Definition two Pareto optimum solution :About feasible solution $X^* \in S$, if and only if there is no other feasible solution $X \in S$, all inequalities $f_i(X^*) \leq f_i(X)$ are established, which $i=1,2,\dots,n$, and at least there is one i , all inequalities $f_i(X^*) < f_i(X)$ are established, that is said X^* is a Pareto optimal solution for multiobjective optimization problems

Definition three Pareto front: The combination of all Pareto optimal solutions becomes the Pareto front.

Multi objective particle swarm optimization algorithm

Multi objective optimization is an optimization problem with multiple objectives and constraints. At present, the optimization problems are multi-objective genetic algorithm to solve (GA) and particle swarm optimization (PSO) algorithm, GA as a highly parallel random global search method, can find the global optimum, but the convergence speed is slow, long time to produce new offspring. The convergence speed of PSO algorithm is fast, but it is easy to fall into local optimum. For the first time since 1985 after the evolutionary algorithm is applied to multi-objective optimization, the research in the field of development, many scholars try to improve GA and PSO, such as the use of constrained optimization particle swarm algorithm, vector differential evaluation of genetic algorithm and GA-EO algorithm, the Pareto archive evolution strategy, parallel genetic algorithm and some improved single edge algorithm. Although these algorithms are effective to some extent, these improved algorithms cannot change the nature of GA or PSO itself, and cannot solve the complex spatial problems. A multi-objective particle algorithm steps:

Step 1: The initial position of the particle swarm is chosen as the best position $Pbest$ of each individual, and the current best position $Pbest$ of each particle is determined by the following formula:

$$\begin{aligned} V_{ij}(g+1) &= V_{ij}(g) + c_1 r_{1ij}(g)[Pbest_{ij}(g) - x_{ij}(g)] \\ &+ c_2 r_{2ij}(g)[Gbest_j(g) - x_{ij}(g)]; \\ x_{ij}(g+1) &= x_{ij}(g) + V_{ij}(g+1); \\ Pbest_{ij}(g+1) &= \begin{cases} Pbest_{ij}(g), & \text{iff } (x_{ij}(g+1)) \geq f(Pbest_{ij}(g)) \\ x_{ij}(g+1), & \text{iff } (x_{ij}(g+1)) < f(Pbest_{ij}(g)) \end{cases} \end{aligned} \quad (2)$$

Step 2: Updating the spatial position of each particle in the particle swarm

$$Gbest_i(g+1) = \arg \min_{Pbest_{ij}} f(Pbest_{ij}(g+1))$$

In order to balance the global search and local search, Shi, Y. proposed inertia weight, so that, formula (2) becomes:

$$\begin{aligned} V_{ij}(g+1) &= wV_{ij}(g) + c_1 r_{1ij}(g)[Pbest_{ij}(g) - x_{ij}(g)] \\ &+ c_2 r_{2ij}(g)[Gbest_j(g) - x_{ij}(g)], 0 \leq w \leq 1; \end{aligned}$$

Step 3: Update: the external repository for jumping improvement mechanism compares the non-inferior updated non dominated solution and the external repository solution of the particle swarm, to determine the non-inferior solution of the particle swarm is stored into the external archive, and calculate the Euclidean distance;

Step 4: Update the local optimal position of the particle, determine the archive particle;

Step 5: If the termination condition is satisfied, the operation is stopped, otherwise, transfer to the Step2.

IMPROVED PARTICLE SWARM OPTIMIZATION

CBMPSO algorithm description

The literature [1] is inspired by the results of the research of social biology, which is helpful to accomplish the complex task. Consider the cultural factors set up personalized weighting factor and acceleration coefficient, better simulate the polymorphism of particles, this paper proposes a multi-objective particle swarm optimization based on Culture (Cultural-Based Multi-objective Particle Swarm Optimization CBMPSO) algorithm. The core value of the principle of culture in the organization based on the influence function in the belief space of knowledge structure using CBMPSO algorithm (Influence Functions) to accelerate the design of personalized global local acceleration coefficient CG, coefficient CP and inertia coefficient W, maintaining the diversity of the optimal and uniform distribution of files better, improve the ability of complex algorithms to solve multi-objective optimization problems. However, through the study of the design formula and experimental analysis of the influence function, we find that the construction of the influence function is still worthy of improvement. As the global acceleration coefficient, local acceleration coefficient depend on grid relative congestion and increase the step factor α , β , Δ ware constant, cannot fully release the search ability of the algorithm; the current population and the maximum distance selection principle of individual pbest, although is beneficial to improving the global high ability to explore algorithm, but failed to take into account the depth at the same time, the design of global grid search; and the local grid system, the grid system is too complex, the increase of computational time cost etc.

Improved particle swarm optimization

This paper presents a multi-objective particle swarm optimization algorithm based on improved culture, which is called chaos multi-objective particle swarm optimization based on Culture (Cultural-Based Chaos Multi-objective Particle Swarm Optimization, referred to as CBCMPSO) algorithm. The basic flow of the algorithm is as follows:

Step 1 initialization settings, the population size of the population space is N, given the evolution of the population capacity threshold C, particle size n and the maximum number of iterations I, determine the search space $[-x_{\max}, x_{\max}]$ and maximum speed v_{\max} ;

Step 2 initialize the population space and belief space, randomly initialize the initial position of the particle X and the initial velocity v.

Step 3 calculate the fitness value of population space. The optimal position of particle p_{id} is set as its current position, and the global optimal position p_g is set as the position of the optimal particle in the initial population.

Step 4 update the inertia weight according to formula (4), update the new velocity of each particle according to formula (1), update the new position of each particle according to formula (2), and control the speed and position of each particle. If the f_i is better than the fitness value of the p_{id} , the new fitness value is used to replace the optimal position of the previous round. If f_i is better than the fitness value p_g , it is updated to the current position of i .

According to equation (3) evaluation calculation of particle swarm premature convergence degree index ρ , if the calculated value is smaller than a given threshold C and the current population of the optimal fitness value of f_{best} is greater than the theoretical optimal fitness value is f_d , the influence function updates the population space of particle positions. Otherwise turn to step 6.

Step 5: according to the receiver function, the particle with the best fitness of the population space is replaced by the particle with the worst fitness value, and then turn to step 4.

Step 6 determine whether to reach the maximum number of iterations, if not reached, then turn to step 4, otherwise the implementation of step 7.

Step 7 output p_g and f_{best} , and the algorithm runs off.

EXPERIMENTAL SIMULATION AND RESULT ANALYSIS

The function selection of experiment

To verify the effectiveness of the algorithm. The following formula gives the definition of function, the range of values and the global optimal solution.

$$\text{Sphere function: } f_1(x) = \sum_{i=1}^{30} x_i^2 \quad (3)$$

Among which, $-100 \leq x_i \leq 100$, dimension is 30, global minimizer is $x^* = (0, 0, \dots, 0)$, minimum value $f(x^*)=0$.

$$\text{Rosen Brock function: } f_2(x) = \sum_{i=1}^n \left[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2 \right] \quad (4)$$

Among which, $-100 \leq x_i \leq 100$, dimension is 30, optimum solution is $x^* = (1, 1, \dots, 1)$, minimum value $f(x^*)=0$.

$$\text{Rastrigrin function: } f_3(x) = \sum_{i=1}^n \left[x_i^2 - 10 \cos(2\pi x_i) + 10 \right] \quad (5)$$

Among which, $-100 \leq x_i \leq 100$, dimension is 30, global minimizer is $x^* = (0, 0, \dots, 0)$, minimum value $f(x^*)=0$.

$$\text{Schaffer function: } f_4(x) = \frac{\sin^2 \sqrt{x_1^2 + x_2^2} - 0.5}{\left[1 + 0.001(x_1^2 + x_2^2) \right]^2} + 0.1 \quad (6)$$

Among which, $-100 \leq x_i \leq 100$, dimension is 30, global minimizer is $x^* = (0, 0, \dots, 0)$, minimum value $f(x^*)=0$.

Experimental results and analysis of the improved algorithm

In order to analyze the algorithm's global search ability and convergence speed, this paper based on the basic PSO algorithm with inertia weight PSO algorithm of linear decreasing strategy on the basic PSO algorithm, a particle swarm optimization algorithm proposed in the literature of culture (CPSO) and only by using the influence function adaptive particle swarm algorithm AG-CPSO culture were compared and record the results. The experimental results are compared with the results of the CBCMPSO algorithm in this paper. In the experiment, the total number of particles $N=30$, the maximum number of iterations $I=3000$, acceleration factor $c1=c2=2$. The inertia weight of the basic PSO algorithm decreases linearly from 0.9 to 0.4, and the evolutionary ability threshold of CBCMPSO algorithm is $C(0.05)$. Because the performance of the algorithm may be affected by the internal random operation, 30 experiments were carried out in order to eliminate the influence. The experimental results are shown in table 1.

TABLE 1 Comparison of CBCMPSO and other algorithms in test function

test function	PSO		CPSO		AG-CPSO		CBCMPSO	
	Average optimal value	standard deviation	Average optimal value	standard deviation	Average optimal value	standard deviation	Average optimal value	standard deviation
f1	4.5805e-16	2.6490e-16	5.7214e-16	3.2523e-16	7.7318e-17	4.3218e-17	2.1499e-25	3.1206e-25
f2	7.6756e+03	3.7868e+05	7.4032e+03	5.7441e+05	4.9156e+03	7.1543e+05	3.1554e+03	2.0154e+05
f3	1.7056e+01	3.2729e+01	1.4333e+01	4.9354e+01	2.1521e+00	2.5596e+01	1.7054e+00	1.2501e+01
f4	6.2621e-01	5.5953e-02	9.7710e-01	7.4316e-02	5.6509e-02	3.7683e-02	1.2548e-02	2.4315e-02

As can be seen from table 1, after the average fitness value calculated by the 30 experiments, the proposed improved algorithm is better than PSO, CPSO and AG-CPSO algorithm. This is because the reliability of this

algorithm using spatial influence function of population space particle swarm algorithm for adaptive guidance, enhance the diversity of particles, and using dynamic inertia weight adjustment strategy, according to the degree of convergence of adaptive population adjustment, so that the algorithm has strong global optimization ability.

Fitness variance to judge the convergence state population space using the AG-CPSO algorithm, the algorithm convergence in population space, the influence function of population space particle mutation operation, this method improves the convergence speed and convergence accuracy, but for the population space of the particle swarm algorithm, using linear decreasing inertia weight, the inertia weight changes linearly decreasing is too single, and the search process of particle swarm algorithm is very complex and nonlinear, so it is for the complex problem of adaptability and adjustment capabilities are very limited. Therefore, the accuracy of AG-CPSO algorithm is lower than that of the algorithm.

SUMMARY

Aiming at the disadvantage that PSO algorithm is easy to fall into premature, the particle swarm optimization algorithm is introduced into the cultural algorithm framework, and a multi-objective particle swarm optimization algorithm is proposed in this paper. The simulation results show that the improved algorithm not only has good global optimization performance, but also can avoid the local optimum.

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