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Research Article

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An Improved Particle swarm optimization for Global Optimization

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Abstract: Particle swarm optimization (PSO) is a computational method for tackling optimization functions. However, PSO usually suffers from premature convergence, tending to get stuck in local optima, low solution precision and so on. In order to overcome these shortcomings and get better results, an improved particle swarm optimization algorithm is presented in this paper. In our method, the weighted individual best position is introduced to replace the individual best position. In the simulations by using benchmark test functions, experiment data shows that this new algorithm has rapidly convergent in optima search.

Keywords: Particle swarm optimization; Swarm intelligence; Convergence

1. Introduction

Particle swarm optimization (PSO) [1] is a stochastic optimization algorithm based on swarm intelligence. This algorithm inspired by the social behavior of bird flocking or fish schooling. It owns some merits of simple structure, easy implementation and fewer control parameters, so the PSO has been widely used to solve many practical optimization problems since its invention in 1995. However, it was pointed out that PSO usually suffers from premature convergence, tending to get stuck in local optima, low solution precision and so on. In order to overcome these shortcomings and get better results, numerous improvements to PSO have been proposed [2-6]. Compared with the basic algorithm, these modified PSO always have better performance. On the basis of those improvements, this paper presents an improved particle swarm optimization algorithm, named as IPSO, in which using the weighted individual best position to replace the individual best position. The new algorithm strengthens cooperation among the particles by making each particle share more useful information of the others. Experiments are conducted on a set of benchmark functions, and the results demonstrate that the new algorithm has fast convergence and high accuracy.

The remainder of this paper is organized as follows. Section 2 describes the basic PSO algorithm. Section 3 introduces the PSO algorithm using weighted individual best position. Section 4 presents and discusses the experimental results. Finally, conclusions are drawn in Section 5.

2. Basic Particle Swarm Optimization

In the basic particle swarm algorithm, suppose the population size is N . The position vector and the velocity vector of particle i in the D -dimensional search space can be represented as $x_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$ and $v_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$ respectively. The best previous position of particle i is recorded and represented as $p_i = (p_{i1}, p_{i2}, \cdots, p_{iD})$. The best position reached by all the particles in the population so far is represented as $p_g = (p_{g1}, p_{g2}, \cdots, p_{gD})$. The particles are manipulated according to the following equations:

$$v_{id} = wv_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \quad (1)$$

$$x_{id} = x_{id} + v_{id} \quad (2)$$

Where, $i = 1, 2, \cdots, N$, $d = 1, 2, \cdots, D$, w is called inertia weight, c_1, c_2 are acceleration constants, r_1, r_2 are different numbers chosen randomly from the uniform distribution in the range $[0,1]$. The value of v is clamped to the range $[-v_{\max}, v_{\max}]$ to reduce the likelihood that the particle might leave the search space.

3. Particle swarm optimization using weighted individual best position

When particles are exploring the search space, if some particle finds the current best position, the others will fly toward it. If the best position is a local optimum, particles can not explore over again in the search space. In consequence, the algorithm will be trapped into the local optimum, which is called premature convergence phenomenon. The higher dimension of the optimized function is, the easier the algorithm is to appear to this phenomenon.

It is found from the velocity equation (1) that the whole searching process of PSO is the process that particle depends on its “memory” ability and share information mechanism to trace the best particle. Although PSO bases on share information mechanism, particle doesn’t utilize it fully, i.e., particle doesn’t make good use of the information of the others in the swarm.

In this section, we propose an improved PSO algorithm, i.e., the weighted individual best position $p_v = (p_{v1}, p_{v2}, \cdots, p_{vD})$ is introduced to replace p_i in PSO.

Where, $p_{vd} = \sum_{i=1}^{N} \frac{1/f(x_i)}{sum} p_{id}$, $d = 1, 2, \cdots, D$

$$sum = \sum_{i=1}^{N} \frac{1}{f(x_i)}$$

Velocity updating equation:

$$v_{id} = wv_{id} + c_1 r_1 (p_{vd} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \quad (3)$$

The new updating manipulation consists of Eqs. (3) and (2). The other parameters are the same as PSO.

The improved algorithm strengthens cooperation among the particles by making each particle share more useful information of the others.

The framework of the improved PSO as follows:

Begin
Initialize population
While (termination condition=false)
Do
For $i = 1$ to Population Size N
if $f(x_i) < f(p_i)$ then $p_i = x_i$
$p_g = \min(p_i)$
For $d = 1$ to Dimension D
$v_{id} = wv_{id} + c_1 r_1 (p_{vd} - x_{id}) + c_2 r_2 (p_{gd} - x_{id})$
if $v_i > v_{\max}$ then $v_i = v_{\max}$
else if $v_i < -v_{\max}$ then $v_i = -v_{\max}$
$x_{id} = x_{id} + v_{id}$
Next d

Next i
End do
End

4. Experiments and comparisons

Benchmark functions and parameter settings

Table 1： Benchmark functions used in experiments

Function	Search range	Min
$f_1(x)=\sum_{i=1}^{D}x_i^2$	[-100,100]	0
$f_2(x)=\sum_{i=1}^{D-1}[100(x_{i+1}-x_i^2)^2+(1-x_i)^2]$	[-100,100]	0
$f_3(x)=\sum_{i=1}^{D}(x_i^2-10\cos(2\pi x_i)+10)$	[-100,100]	0
$f_4(x)=\frac{1}{4000}\sum_{i=1}^{D}x_i^2-\prod_{i=1}^{D}\cos(\frac{x_i}{\sqrt{i}})+1$	[-600,600]	0
$f_5(x)=20+e-20\exp\{-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D}x_i^2}\}-\exp\{\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\}$	[-32.8,32.8]	0

In this section, five scalable benchmark functions with $D=30$ as an example to show the performances of the PSO, MPSO [4] and IPSO, these benchmark functions are shown in Table 1. The parameters of PSO are $w_1=0.9$, $w_2=0.4$, $c_1=c_2=2$; MPSO and IPSO have used the same parameters, where $w=0.729$, $c_1=c_2=2.05$. For each function, dimension is 30. Population size of the algorithms is 30. The maximum number of iterations allowed is 3000. Each algorithm for each of the functions executed 30 times to compare its mean and the standard deviation, and the results are presented in Table2.

Table 2: Result comparisons of PSOS on 30-dimensional basic functions

Fun	Metric	PSO	MPSO	IPSO
f_1	Mean	1.21E-16	2.62E-43	5.80E-57
	Std	3.25E-16	7.91E-43	1.28E-56
f_2	Mean	7.78E+01	3.76E+01	2.18E+01
	Std	6.94E+01	4.07E+01	3.02E+01
f_3	Mean	4.77E+01	9.55E+01	6.36E+00
	Std	1.21E+01	3.41E+01	4.39E+00
f_4	Mean	1.29E-02	1.89E-02	4.06E-03
	Std	1.61E-02	2.47E-02	7.63E-03
f_5	Mean	4.82E-09	1.35E+00	1.10E-13
	Std	7.26E-09	8.26E-01	3.17E-13

As is shown in Table 2, under a fixed number of iterations, IPSO is obviously better than PSO and MPSO for all the test functions, not matter which is unimodal function or multimodal function. This shows that IPSO is superior to all of the other algorithms in solution quality. The experimental results show that IPSO is more effective and reliable than the other algorithms mentioned in this paper.

5. Conclusion

PSO is a population-based evolutionary computation technique. In order to improve these shortcomings of PSO: premature convergence, tending to get stuck in local optima and low solution precision when solving high-dimension functions, an improved particle swarm optimization algorithm using weighted individual best position is proposed in this paper. The experimental result indicates that the improved algorithm increases the ability to break away from the local optimum.

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