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An improved particle swarm optimization algorithm with enhanced interference

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ABSTRACT

Particle swarm optimization (PSO) algorithm is favored by scholars because of its simple operation and fast speed, and many improved PSO are proposed on this basis. Although these improved PSO algorithms have made some progress in accuracy, they increase the operation cost and lose the advantages of fast convergence speed and easy operation. To solve these problems, this paper proposes an improved PSO, which is called EIPSO. In comparison to the conventional particle swarm optimization algorithm, the EIPSO (Enhanced Interference Algorithm with Particle Swarm Optimization) eliminates the acceleration coefficient and substitutes the learning factor to diminish the algorithm's reliance on its parameters. It incorporates noise-based perturbations to facilitate the escape from local optima. Subsequently, a multitude of benchmark functions were employed to assess the performance of EIPSO, with experimental outcomes indicating that it achieves greater precision and a quicker convergence rate.

KEYWORDS

Particle swarm optimization; group-based learning; noise-based disturbance

1 Introduction

Particle swarm optimization (PSO) has the characteristics of simple structure and fast convergence because of its unique global mechanism[1]. It has been widely used in various engineering problems and has achieved good results. In order to solve the problem of premature convergence, many improved PSO algorithms have appeared, which can be roughly divided into the following four types.

1) Adjustment parameter. Examples include linear decreasing weights[2], fuzzy adaptive weights[3], and hybrid dynamic weights[4]. This class of parameters has been widely discussed due to its ability to balance exploitation and population exploration.

2) Hybridization optimization. By adding the evolutionary algorithm to the particle swarm optimization algorithm, scholars have prevented it from falling into the local optimal dilemma to the greatest extent, and achieved remarkable results. Ant colony optimization is one of the excellent representatives[5].

3) Neighborhood topology. PSO is mainly divided into global type and local type. The convergence rate of global type is faster but it is easy to fall into local optimal, while local type is the opposite[6].

4) Learning strategy. The learning strategy gives the particle swarm optimization (PSO) simple structure and high search efficiency, but inevitably brings the problem of premature convergence. In order to optimize the algorithm, Liang et al[7]. introduced comprehensive learning into PSO to form

CLPSO.

Although a series of researches by experts and scholars in this field have increased the accuracy of PSO to some extent, they have made the algorithm structure more complex, resulting in lower convergence speed.

An effective interference particle swarm optimization algorithm(EIPSO) is proposed in this paper. The algorithm reduces the parameters while increasing the topology structure, and achieves good results.

For the rest of the article, EIPSO is given in Section 2, experimental date is given in Section 3, and conclusions are given in Section 4.

2 An effective interference particle swarm optimization algorithm

2.1 Learning strategy

In EIPSO, we remove the acceleration coefficient $c_1 c_2$, and introduce a most average value, which is recorded as*Gavg*. *Gavg* is defined by the following formula.

$$gavg(t) = mean\{pbest_1(t), pbest_2(t), \cdots; pbest_N(t)\} \tag{1}$$

With the above.

In EIPSO, the particle evolution formula is constructed as follows.

$$v_i(t+1) = \omega(t) + r_1(pbest_i(t) - x_i(t)) + r_2(gavg(t) - x_i(t)) \tag{2}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{3}$$

Where,

r_1, r_2 and r_3 are three random variables of exponential distribution with parameter $0\lambda = 2$ (the exponential distribution mentioned in this paper is expected to be 0.5).

2.2 Noise-based disturbance

To solve the problem of local optimization of PSO, a noise-based disturbance is introduced in EIPSO. We added a chaotic mapping *gbest*. When the chaotic mapping is enabled, $Nbest = D \times gbest$, and here adopts an elite strategy that *Nbest* is preserved only if the value of the target function corresponding to *Nbest* is better than that of*gbest*. The above steps are described in Eq. (4), (5), and (6) as follows.

$$Nbest = D \times gbest \tag{4}$$

$$D = r(t+1) = 4r(t)(1 - r(t)), r(0) = rand \tag{5}$$

Where $r(0) \neq 0.025, 0.5, 0.75$,and 1.

$$gbest = \begin{matrix} Nbest & f(Nbest)f(gbset) \\ gbset & otherwise \end{matrix} \tag{6}$$

In summary, EIPSO as a variant of PSO is proposed.

3 Experiment and result analysis

In our experiment, we chose 12 test functions, including unimodal function, multimodal function, translational rotation function and engineering function. The optimal value of the test function is represented by opt-f. In addition, six advanced PSO variant algorithms were used to validate the performance of EIPSO. They are FDR-PSO [8], IPSO [9], SPSO [10], FIPS [11], MPSO[12], and UPSO[13].

Table 1 Some variants of the PSO algorithm.

Algorithm	Parameter setting
FDR_PSO[8]	$\omega = 0.9 - 0.4, c_1 = c_2 = 2, c_3 = 2$
IPSO[9]	$\omega = 0.9 - 0.4, c_1 = c_2 = 2$
SPSO[10]	$\omega = 0.9 - 0.4, c_1 = c_2 = 2$
FIPS[11]	$\omega = 0.7298, \phi_1 = \phi_2 = 2.05$
MPSO[12]	$\omega = 0 - 0.4, c_1 = c_2 = 2$
UPSO[13]	$\omega = 0.9 - 0.4, u = 0.7$
EIPSO	$\omega = 0.9 - 0.4$

In order to make the experimental results more reliable, we uniformly set the algorithm size to 200 and run it independently on the test function 50 times. All algorithms are terminated on the condition that the particle reaches the maximum number of evaluations of fitness. Maximum number of evaluations of fitness((FES) of updates is$D \times 1E4$). The averages, variances, and optimal values of the 50-run date are shown in Table 1.

In this section, 12 functions were selected to detect the performance of EIPSO in high-dimensional states. EIPSO is run in 200-dimensional states, and the results are compared with the variants of PSO. Table 2 shows the performance of EIPSO and variants of PSO on the 200-dimensional problem. It can be seen from it that the convergence of EIPSO is significantly better than the variants of PSO. This indicates that the disturbance mechanism embedded in EIPSO can to some extent assist particles in jumping out of local optima. In addition, EIPSO performs weaker than FDR_PSO on f_{11} but still outperforms IPSO,SPSO, FIPS, MPSO, and UPSO.

Table 2 Comparison of results in the 200-dimensional state($FES = D \times 1E4$).

		FDR_PSO	IPSO	SPSO	FIPS	MPSO	UPSO	EIPSO	opt_f
	Mean	4.61E+03	3.11E+03	3.27E+03	2.98E+03	3.48E+03	3.34E+03	2.70E+03	
	Std	1.87E+02	4.05E+02	1.57E+02	3.50E+02	2.99E+02	3.89E+02	2.39E+02	
f_1	Min	4.16E+03	2.20E+03	2.91E+03	2.21E+03	2.83E+03	2.53E+03	2.17E+03	0
	rank	7	3	4	2	6	5	1	
	Mean	3.73E+03	2.95E+03	2.81E+03	2.84E+03	3.38E+03	3.12E+03	2.66E+03	
	Std	1.18E+02	2.82E+02	1.61E+02	1.96E+02	2.09E+02	2.46E+02	1.78E+02	
f_2	Min	3.44E+03	2.28E+03	2.21E+03	2.45E+03	2.98E+03	2.65E+03	2.19E+03	0
	rank	7	4	2	3	6	5	1	
	Mean	6.02E+06	1.07E+06	3.50E+06	8.21E+05	2.16E+06	1.96E+06	4.72E+05	
	Std	1.66E+06	8.41E+05	1.14E+06	3.83E+05	1.06E+06	2.02E+06	1.80E+05	
f_3	Min	2.59E+06	1.68E+05	1.61E+06	1.26E+05	4.42E+05	2.19E+05	1.19E+05	0
	rank	7	3	6	2	5	4	1	
	Mean	3.31E+04	7.49E+04	6.94E+04	2.48E+05	1.84E+06	4.69E+05	1.33E+04	
	Std	9.93E+03	2.24E+05	2.39E+04	7.04E+04	2.31E+06	1.34E+06	3.27E+03	
f_4	Min	1.06E+04	2.49E+03	3.42E+04	1.23E+05	2.72E+04	3.11E+03	5.15E+03	0
		2	3	4	5	7	6	1	
	Mean	3.87E+03	2.86E+03	2.82E+03	3.17E+03	3.09E+03	2.98E+03	2.58E+03	
	Std	1.01E+02	3.07E+02	1.23E+02	1.44E+02	2.29E+02	2.11E+02	1.70E+02	
f_5	Min	3.64E+03	2.26E+03	2.58E+03	2.81E+03	2.47E+03	2.57E+03	2.10E+03	0
	rank	7	3	2	6	5	4	1	
	Mean	2.70E+03	2.45E+03	2.61E+03	2.55E+03	2.55E+03	2.46E+03	2.43E+03	
	Std	1.61E+01	3.26E+01	1.51E+01	4.63E+01	2.23E+01	2.84E+01	1.75E+01	
f_6	Min	2.65E+03	2.39E+03	2.58E+03	2.40E+03	2.49E+03	2.40E+03	2.39E+03	0
	rank	7	2	6	4	5	3	1	

Table 2 Comparison of results in the 200-dimensional state(FES=D×1E4).(Continued).

		FDR_PSO	IPSO	SPSO	FIPS	MPSO	UPSO	EIPSO	opt_f
f_7	Mean	1.48E+04	8.66E+03	1.14E+04	9.34E+03	1.19E+04	9.18E+03	4.78E+03	-4.50E+03
	Std	3.17E+03	1.28E+03	1.99E+03	5.87E+03	1.58E+03	7.63E+02	3.16E+03	
	Min	3.54E+03	3.34E+03	6.18E+03	2.30E+03	8.80E+03	7.91E+03	2.31E+03	
	rank	7	2	6	4	6	3	1	
f_8	Mean	3.14E+03	3.09E+03	3.06E+03	2.96E+03	3.29E+03	2.98E+03	2.91E+03	0
	Std	1.58E+01	9.24E+01	1.25E+01	6.39E+01	6.84E+01	4.42E+01	2.69E+01	
	Min	3.10E+03	2.93E+03	3.02E+03	2.84E+03	3.16E+03	2.89E+03	2.86E+03	
	rank	6	5	4	2	7	3	1	
f_9	Mean	3.31E+03	3.35E+03	3.30E+03	3.09E+03	3.44E+03	3.15E+03	3.03E+03	0
	Std	1.47E+01	1.53E+02	1.64E+01	7.26E+01	5.82E+01	4.68E+01	3.17E+01	
	Min	3.25E+03	3.12E+03	3.26E+03	2.95E+03	3.29E+03	3.04E+03	2.95E+03	
	rank	5	6	4	2	7	3	1	
f_{10}	Mean	7.84E+03	5.79E+03	6.96E+03	4.87E+03	9.96E+03	6.44E+03	4.69E+03	0
	Std	1.97E+02	1.11E+03	1.13E+02	1.10E+03	1.03E+03	4.87E+02	7.11E+02	
	Min	7.33E+03	3.21E+03	6.67E+03	2.90E+03	7.64E+03	5.24E+03	3.76E+03	
	rank	6	3	5	2	7	4	1	
f_{11}	Mean	3.31E+03	3.59E+03	3.61E+03	3.48E+03	3.76E+03	3.62E+03	3.43E+03	0
	Std	2.07E+01	1.65E+02	2.56E+01	3.88E+01	1.08E+02	1.40E+02	6.48E+01	
	Min	3.27E+03	3.29E+03	3.54E+03	3.40E+03	3.50E+03	3.42E+03	3.29E+03	
	rank	1	4	5	3	7	6	2	
f_{12}	Mean	4.89E+03	4.24E+03	4.36E+03	4.41E+03	5.07E+03	4.69E+03	3.96E+03	0
	Std	1.81E+02	3.16E+02	1.15E+02	1.80E+02	4.43E+02	4.16E+02	1.88E+02	
	Min	4.41E+03	3.59E+03	4.08E+03	3.92E+03	4.15E+03	3.75E+03	3.53E+03	
	rank	6	2	3	4	7	5	1	

4 Conclusion

In this paper, an improved particle swarm optimization algorithm is proposed, which is called EIPSO. Meanwhile, On this basis, noise interference is introduced. After that, we selected 20 test functions to test the 200-dimensional EIPSO with the maximum number of fitness evaluations as the stopping condition. It can be found that EIPSO has obvious advantages. However, EIPSO cannot achieve the desires in terms of rotation and translation functions, which will be addressed in our future work.In subsequent experiments, we will test the performance of EIPSO on more dimensional Spaces in order to find out the optimal operation mode of the algorithm. In addition, providing theoretical support for EIPSO is also part of our future research.

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