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Improved PSO based on the Uniform Search Strategy

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Abstract

Particle Swarm Optimization (PSO) algorithm is a new optimization approach, which has been widely used to solve various and complex optimization problems. However, there are still some imperfections, such as premature convergence and low accuracy. To address such defects, an improved PSO is proposed in this paper. The improved PSO algorithm introduces a uniform search strategy that makes particles proceed alternately between basic movement and uniform search movement, which can ensure sufficient search over the entire space as well as the convergence of particles. Meanwhile, the learning object of the particle swarm is no longer a single particle, which is helpful to prevent particles from being trapped in local optima. The experimental results on the typical functions demonstrate that the improved algorithm has good performance in terms of precision and convergence when compared with other variants of PSO.

Keywords: *particle swarm optimization, premature, uniform search strategy, convergence*

1. Introduction

Particle Swarm Optimization (PSO), which was proposed by Kennedy and Eberhart in 1995 [1, 2], is one of the global random search algorithms and derived from the research of birds feeding behavior. Given its advantages of simple method, ease of implementation, few control parameters and fast convergence, PSO has been widely used in function optimization [3], path selection [4], image processing [5, 6] and economic dispatch problem [7, 8] , among others.

Given its similarity to other heuristic algorithms, such as genetic algorithm (GA) [9] and its application [10], ant colony algorithm [11] and its application [12], PSO has defects, such as low accuracy, slow convergence and prematurity when solving complex functions in a high dimensional space. To overcome these defects, scholars have proposed many improved PSOs in three aspects: (1) Increase the diversity of learning objects, such as comprehensive learning PSO (CLPSO) [13], in which particles learn the experience of other randomly selected particles, and the fully informed particle swarm (FIPS) [14] , in which particles learn the experience of all adjacent particles in the topology structure. (2) Maintain the diversity of particles, such as PSO with inertia weight [15], which adjusts inertia weight properly to maintain the diversity of particles, and PSO with particle release and speed limit (PSOPR&SL) [16], which releases particles that may be trapped in local optima. (3) Enhance the traverse ability of particle swarm, such as chaos PSO (CPSO) [17], which makes use of the random thoughts of chaos to search the space around the particles, and intelligent single particle optimizer (ISPO) [18], which enhances the traverse ability of particles by changing the velocity from big to small.

Despite great improvements have been achieved in the above algorithms, their iterative process is more complex, and more parameters are introduced. For example, CLPSO needs to update each dimension of all particles separately; adaptive PSO (APSO) [19]

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requires calculating the distance between each particle and all other particles to select an appropriate velocity update strategy; PSO with neighborhood operator [20] needs to find the optimal neighborhood of each particle in the topology structure. Among the causes, the above algorithms mainly focus on improving the specific movement of particles, and rarely consider the basic principle of search. Therefore, while the comprehensive performance of algorithms has been improved, the particle optimization process becomes more complicated and time-consuming.

In this paper, the principle of searching the globally optimal solution for basic PSO will be presented first. In allusion to the defects of basic PSO, the new improved PSO based on the uniform search strategy will be introduced. Compared fully with basic PSO and CPSO, as shown in figures in Section 3.2, USPSO can perform a more sufficient search over the entire space. The effectiveness of USPSO is well demonstrated by experiments on the typical functions.

2. Basic PSO Algorithm

In PSO, a swarm of particles are represented as potential solutions, and each particle i ($i = 1, 2, \ldots, N$) is associated with two vectors, namely, the velocity vector $v_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$ and the position vector $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$, where D stands for the dimensions of the solution space. So far, the best position of the ith particle is $p_i = (p_{i1}, p_{i2}, \cdots, p_{iD})$ and denoted by $pbest_i$; the best position of the particle swarm is $p_g = (p_{g1}, p_{g2}, \ldots, p_{gD})$ and denoted by $gbest$. The updating equations of velocity and position are

$$v_i^{k+1} = w v_i^k + c_1 \times rand \times (pbest_i - x_i^k) + c_2 \times rand \times (gbest - x_i^k) \tag{1}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{2}$$

where w is the inertia weight that is used to balance the global and local search abilities; c_1 and c_2 are the acceleration coefficients; $rand$ is the random number in the range of [0, 1]; v_i^k and x_i^k are the velocity and position of particle i , respectively, in the kth iteration.

Inertia weight significantly influences on the search ability of the particle swarm. A large inertia weight is more appropriate for global search, and a small inertia weight facilitates local search. A linearly decreasing inertia weight was introduced by Shi and Eberhart [14], which is represented as follows:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{T} \times t \tag{3}$$

where t is the current iterative generations; T stands for the largest iterative generations; $w_{\max}$ indicates the initial inertia weight, usually set as 0.9; and $w_{\min}$ is the final inertia weight, usually set as 0.4. The PSO with linearly decreasing inertia weight is regarded as basic PSO and has been widely used.

Equation (1) shows that the velocity of one particle in basic PSO is influenced by its own optimum and the entire swarm optimum. When both get trapped in local optima, the particle also falls in the local optima easily. Meanwhile, the traverse ability of particles is limited because it unable to search the space outside the path forward.

3. Improved PSO based on Uniform Search Strategy

3.1. Uniform Search Strategy

When basic PSO imitates the flocking behavior of birds, it assumes that in the early stages of hunting, the birds follow the bird that is closest to the food. This method can quickly centralize the entire population to the space that is close to the food. However, if the current optimal particle is a local one, the entire population will fall into local optima. A phenomenon is analyzed as follows: The birds have a “head” that is closest to the food, and the entire flock follows the “head” to fly; when the birds are preying on food, the entire flock will follow the “head” along the same direction to search the entire space uniformly; after finding the food, the birds will uniformly search other spaces and stay close to the food at the same time. It significantly improves the traverse ability of particle swarm by introducing the “head” effect. In the early iterations, this strategy improves the global search ability of the particles by uniformly searching the feasible space. In the late iterations, this strategy improves the solution accuracy and convergence speed by uniformly searching the space that is close to the global optimum.

The velocity of the particles is determined by three parts: momentum, self-knowledge and social-knowledge, which can be represented as

PSO Learning= Momentum + Self-Knowledge+ Social-Knowledge (4)

In the process of uniform search, the birds would keep their own momentum when following the “head”. Therefore, the birds will learn the self-knowledge and social-knowledge of the “head”, but maintain their own momentum. In the USPSO, the optimal particle in current iterative generations is treated as the entire particle swarm “head”. The velocity updating strategy of particles is defined as

$$v_i^{k+1} = wv_i^k + a_1 \times c_1 \times rand \times (pbest_p - x_p) + a_2 \times c_2 \times rand \times (gbest - x_p) \quad (5)$$

where w , c_1 , c_2 , $rand$ and v_i^k have the same meanings with those in equation (1). However, the velocity of the particle i is determined by the self-knowledge and social-knowledge of particle p , which is the optimal particle in the kth iteration, namely $f(x_p^k) \geq f(x_q^k)$, $q \in [1, n]$, $p = 1, 2, 3....n$ .The a_1 and a_2 represent the learning degree of self-knowledge and social-knowledge, respectively, when particle i learns from particle p , and are called learning factors. Particles can search the entire space uniformly by adjusting a_1 and a_2 appropriately, which can avoid searching blind space and repeat searching space.

The particle swarm selectively learns from the current optimal particle through employing the tournament selection procedure. The location with the best fitness is chosen as the result of traversal. The specific process is as follows:

$$x_i^m = x_i^k + v_i^{k+1} \quad (6)$$

$$x_i^n = x_i^k - v_i^{k+1} \quad (7)$$

where x_i^m and x_i^n are the possible choices of particle i in the kth iteration and the selection process is

If $f(x_i^n) \leq f(x_i^m)$ & $f(x_i^n) \leq f(x_i^k)$

$$x_i^{k+1} = x_i^n \quad (8)$$

If $f(x_i^m) \leq f(x_i^n)$ & $f(x_i^m) \leq f(x_i^k)$

$$x_i^{k+1} = x_i^m \quad (9)$$

Otherwise,

$$x_i^{k+1} = x_i^k \quad (10)$$

Equation (5) shows that the entire flock has the same self-knowledge and social-knowledge, which prompts the entire particle swarm to have the same speed. The search of entire particle swarm can be recognized as a uniform search process because of the high dimension of the search space and the limited number of particles.

3.2. The Uniform Search PSO

The uniform search strategy enhances the ability to traverse the entire space and significantly prevents prematurity. However, the particles would approach the current global optimum gradually rather than just search the entire space uniformly. Therefore, USPSO will proceed basic search movement and uniform search movement alternately.

To better explain the working principle of the improved algorithm, the update process of one particle for basic PSO and USPSO is illustrated in Figure 1.

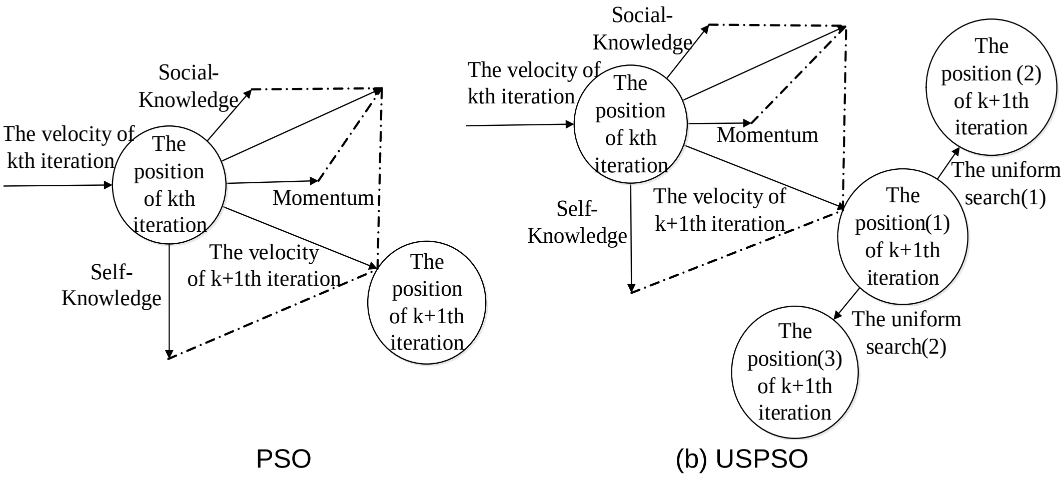


Figure 1. One Iterative Process

In Figure 1(a), the result of the particle in the $k+1\text{th}$ iteration is the combination of three weighted vectors: momentum, self-knowledge and social-knowledge. In Figure 1(b), the particle implements the movement in accordance with the basic PSO at first, and arrives at position (1). Then, the particle explores the space around position (1), and finds out positions (2) and (3). The particle would choose the best one among (1), (2) and (3) as the result of the $k+1\text{th}$ iteration. One iteration process of three particles is taken as an example in Figure 2.

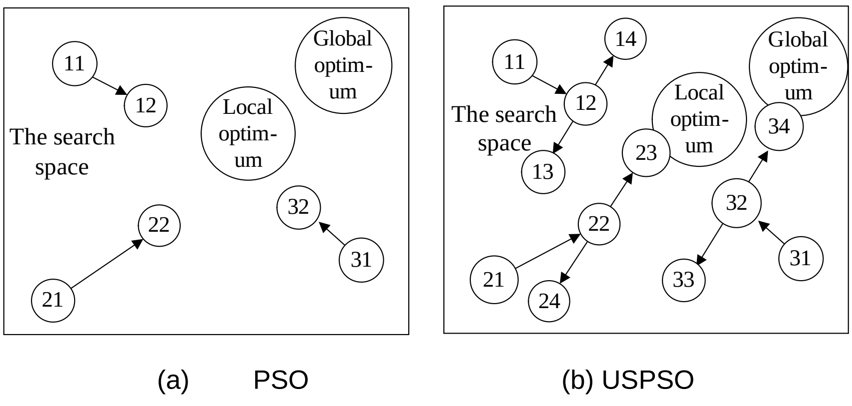
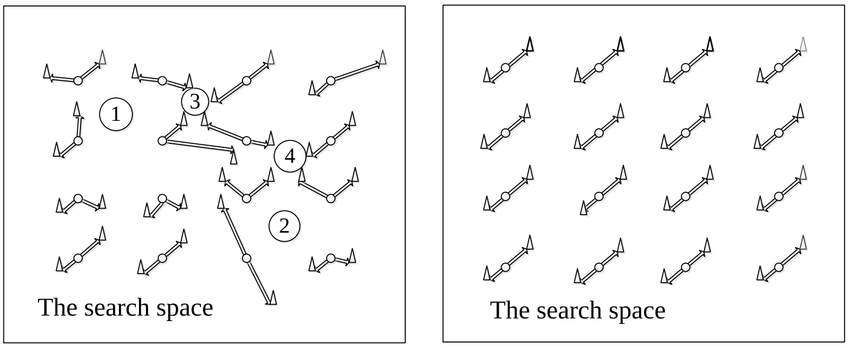


Figure 2. Three Particles in 3 Iterations

In Figure 2, there are three particles which are denoted by particles 1, 2 and 3. The positions of particle i are $i1$, $i2$, $i3$ and $i4$ ($i = 1,2,3$). In Figure 2(a), three particles change their positions as follows: 11 to 12, 21 to 22 and 31 to 32.The particle swarm will choose position 32 of particle 3 as the $gbest$ for the next iteration .Thus the entire particle swarm will get trapped in the local optimum. In Figure 2(b), three particles arrive at positions 12, 22 and 32 at first. Then, the particles explore the space around them along the same direction, and the exploration processes are as follows: 12 to 13 and 12 to 14 for particle 1; 22 to 23 and 22 to 24 for particle2; 32 to 33 and 32 to 34 for particle 3. The particle swarm will choose position 34 of particle 3 as the $gbest$ for the next iteration. Thus the entire particle swarm will get close to the global optimum. As seen in Figure 2, USPSO can ensure a sufficient search over the entire space.

Compared with some typical improved PSOs, such as CPSO, USPSO has more advantages. Particles in CPSO will explore the surrounding space when they arrive at a new position, which strengthens the traverse ability of particles. However, all particles search along different directions, which lead to the problems of repeating search in some certain spaces and leaving spaces without searching. USPSO can search entire space more sufficiently because it takes uniform search strategy. The search strategies of USPSO and CPSO are compared in Figure 3.



(a) CPSO (b) USPSO

o represent the positions of particles in the kth iteration; ⟹ represent the exploration direction; Δ represent the positions that particles search when they implement the course of exploration.

Figure 3. Difference in Search Strategy

In Figure 3(a), the searching blind spaces, such as ①, ②and repeat searching spaces, such as③, ④ appear in CPSO. In Figure 3(b), USPSO can give a uniform search over the entire space.

3.3. Algorithm Steps of USPSO

Concerning the basic principles of improved particle swarm algorithm, the process of USPSO is illustrated in Figure 4.

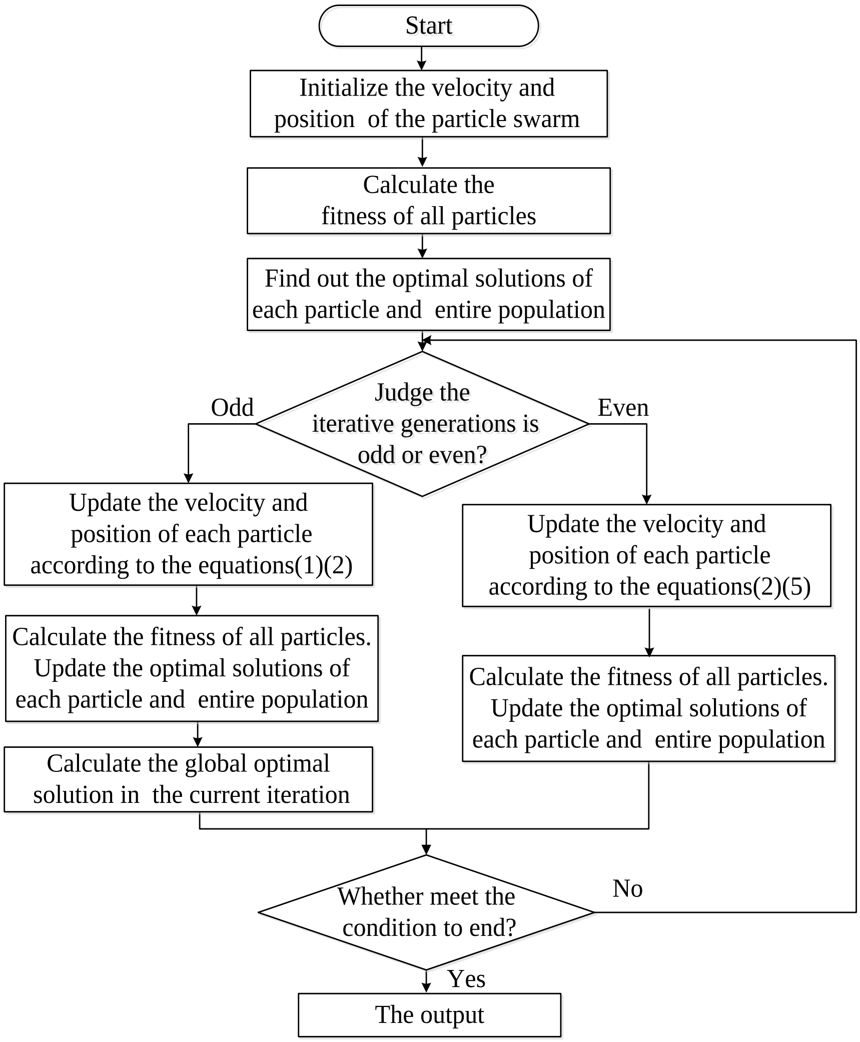


Figure 4. Flowchart of USPSO

Through the above descriptions, the main advantages of USPSO are observed.

(1)Particles search the entire space uniformly, which improves their traverse ability significantly.

(2)The uniform search movement and the basic search movement of particles proceed alternatively, which ensures the convergence of the algorithm as well as the diversity of the particles.

(3)The particle swarm learns from multiple particles rather than a single one, which improves the quality of particles in each generation.

4. Experimental Results and Analysis

To test the performance of USPSO, some general international standard test functions are adopted in Table 1.

Table 1. Standard Test Functions

Function	Dimension	Acceptance	Search space	Global f_{min}
$f_1(x)=\sum_{i=1}^{D} x_i^2$	30	0.01	[-100,100]	0
$f_2(x)=\sum_{i=1}^{D} \lvert x_i \rvert + \prod_{i=1}^{D} \lvert x_i \rvert$	30	0.01	[-10,10]	0
$f_3(x)=\sum_{i=1}^{D} (\sum_{j=1}^{i} x_j)^2$	30	100	[-100,100]	0
$f_4(x)=\sum_{i=1}^{D} -x_i \sin(\sqrt{\lvert x_i \rvert})$	30	-10000	[-500,500]	-12569.5
$f_5(x)=\frac{1}{4000}\sum_{i=1}^{D} x_i^2 - \prod_{i=1}^{D} \cos(\frac{x_i}{\sqrt{i}})+1$	30	0.01	[-600,600]	0
$f_6(x)=-20\exp\{-0.2\sqrt{\frac{1}{30}\sum_{i=1}^{D} x_i^2}\} - \exp\{\frac{1}{30}\sum_{i=1}^{D}\cos 2\pi x_i\}+20+e$	30	0.01	[-32,32]	0

In Table 1, f_1, f_2 and f_3 are unimodal functions; f_4, f_5 and f_6 are multimodal functions. The global optimum of all the test functions is 0 except -12569.5 for f_4.

To verify the effectiveness of the USPSO, five typical improved algorithms, including the PSO with adaptive velocity (VPSO) [21], FIPS, dynamic multi-swarm PSO (DMS-PSO) [22], CLPSO and APSO, are compared with USPSO. VPSO is regarded as a standard PSO, which has been widely used. In FIPS, the URing topology structure is implemented with a weight (wFIPS) for higher successful ratio. DMS-PSO is devoted to improving the topological structure in a dynamic way. CLPSO employs a comprehensive learning strategy, which aims at yielding better performance for multimodal functions. APSO realizes the optimal control of particle swarm through real-time evaluation of distribution of particles and dynamically adjusting weight, acceleration coefficients and other parameters.

For a fair comparison, all improved PSO algorithms are tested with the same population size of 20, a value that is commonly adopted in PSO. Further, the maximum fitness evaluations (FEs) are set at 2.0×10^5 for all test function. All the experiments are carried out on the same machine with Matlab 8.0 and Windows 7 operating system. Each function is independently simulated 30 times to reduce statistical errors.

4.1. Comparisons on Solution Accuracy and Stability

Solution accuracy is usually regarded as an important standard for an optimization algorithm. The parameters of USPSO are set as follows: $c_1 = c_2 = 2.05$; the inertia weight decreased linearly along with $w_{max} = 0.9$ and $w_{min} = 0.4$; $a1 = a2 = 0.1$ for test functions except f_6 that has $a1 = a2 = 0.12$. The parameters of other improved PSOs are set according to [18]. The test results are shown in terms of the mean and standard deviation (SD) of the solutions in Table 2, and the boldface in the table indicates the best result obtained for each function.

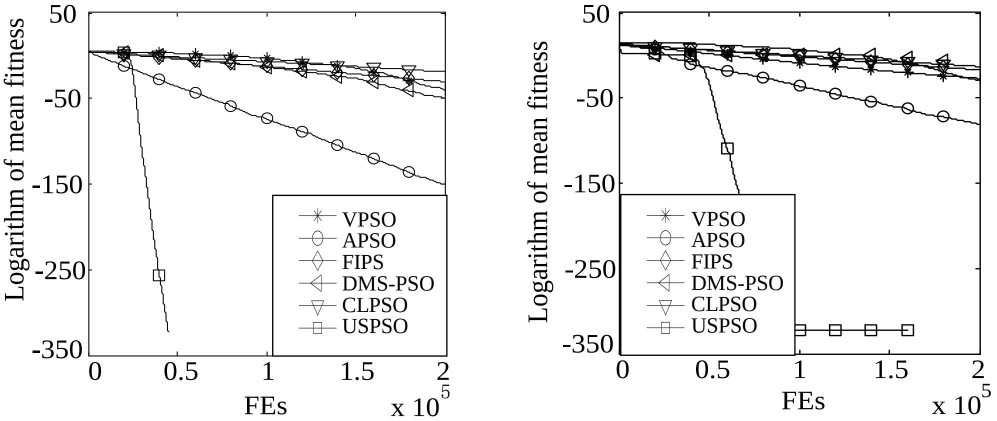
Table 2. Comparisons on Solution Accuracy and Stability

Function		VPSO	FIPS	DMS-PSO	CLPSO	APSO	USPSO
f_1	Mean	5.11e-38	3.21e-30	3.85e-54	1.89e-19	1.45e-150	**0**
	SD	1.91e-37	3.60e-30	1.75e-53	1.49e-19	5.73e-150	**0**
f_2	Mean	6.29e-27	1.32e-17	2.61e-29	1.01e-13	5.15e-84	**0**
	SD	8.68e-27	7.86e-18	6.6e-29	6.51e-14	1.44e-83	**0**
f_3	Mean	1.44	0.77	47.50	395.00	1.00e-10	**5.39e-268**
	SD	1.55	0.86	56.40	142.00	2.13e-10	**2.41e268**
f_4	Mean	-9845.27	-10113.8	-9593.33	-12557.65	-12569.5	**-12569.5**
	SD	588.87	889.58	441	36.2	5.22E-11	**0**
f_5	Mean	1.31e-02	9.04e-04	1.31e-02	3.45e-13	1.67e-02	**0**
	SD	1.35e-02	2.78e-03	1.73e02	2.07e-12	2.14e-02	**0**
f_6	Mean	1.4e-14	7.69e-15	8.52e-15	2.01e-11	1.11e-14	**4.44e-15**
	SD	3.48e-15	9.33e-16	1.79e-15	9.22e-15	3.55e-15	**0**

It can be seen in Table 2 that USPSO achieves better performance than any other improved algorithms in both accuracy and stability. For the unimodal functions, the solution accuracy of USPSO is much higher than that of other algorithms, especially for f_1 and f_2 whose solution accuracy is 0. As for the multimodal functions, USPSO algorithm shows a stronger ability in achieving the global optimum, and f_4 and f_5 obtain the global optimum. Although USPSO has a similar performance with FIPS on f_6 in terms of solution accuracy, it outperforms FIPS in stability.

4.2. Comparisons on the Convergence Speed and Reliability

To display the convergence process of USPSO and other improved algorithms more intuitively, the convergence processes of all improved algorithms are shown in Figure 5. The parameters of all improved PSOs are the same as those in section 4.1.



(a) f_1 (b) f_2

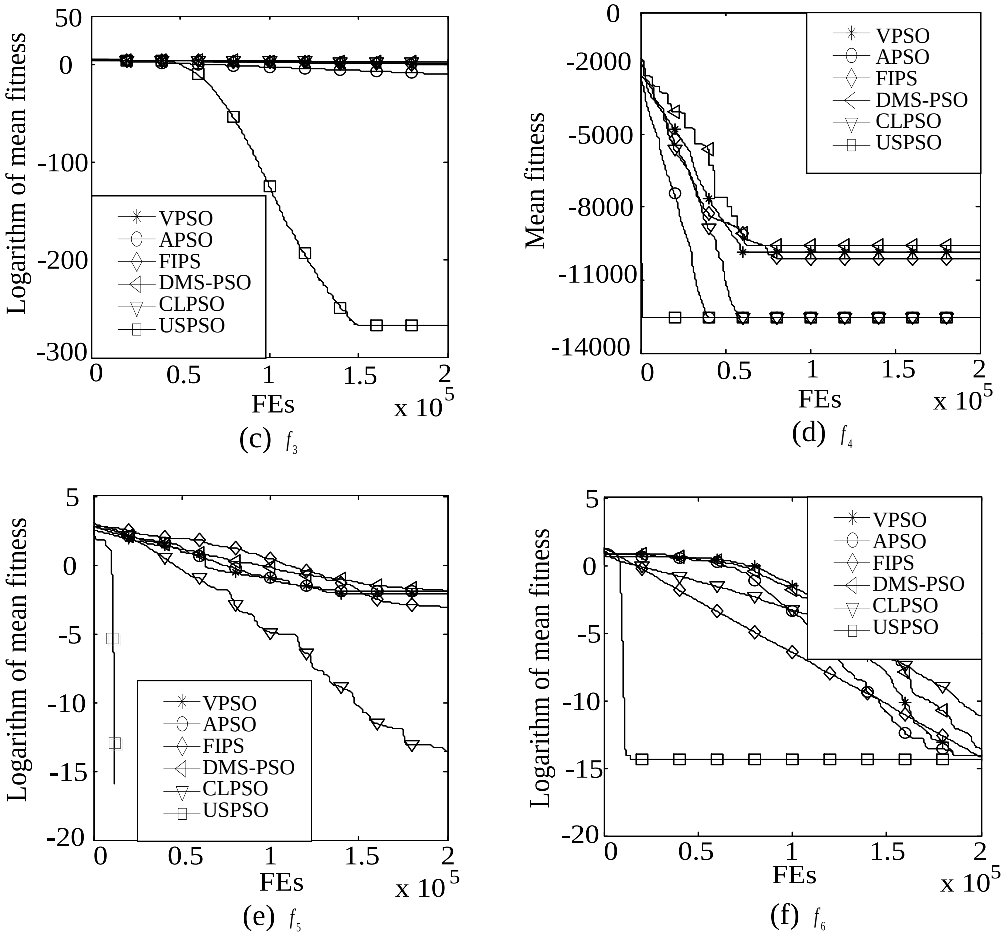


Figure 5. Convergence Performance of the 6 different PSOs on the 6 Test Functions

Figure 5 shows that USPSO is slower in unimodal functions than other improved algorithms in the early stage, especially for APSO, which is mainly because the USPSO algorithm carries out uniform search strategy over the entire space at first rather than approaches the optimal particle quickly. However, USPSO achieves higher accuracy in the final stage because it conducted sufficient search around the optimal particle. As for the multimodal functions, USPSO converges faster than any other improved PSO, especially for the f_4 that achieves the global optimum in the 2953th iteration.

Sometimes, achieving an acceptable solution as quickly as possible is more important than obtaining a very high accuracy. Meanwhile, it is essential for algorithm to exhibit high reliability in some cases, such as adjusting weights of neural network by PSO. Then the iterative generations, times and reliability for all improved PSOs are measured when the functions achieve acceptable solutions. The population size of all improved PSOs is 20. Parameters of USPSO are set differently depend on the test functions. For all functions, $c_1 = c_2 = 2.05$, $a_1 = a_2 = 0.1$. The weight decreased linearly for f_5 and f_6 along with $w_{max} = 0.9$ and $w_{min} = 0.4$; $w = 0.7$ for f_1 , f_2 , f_3 and f_4 .Parameters of other improved PSOs are set according to [18]. The experiment takes the average of 30 times, and the results are shown in Table 3. Boldface in the table indicates the best result for each function.

Table 3. Comparison in Time and Iterations

Function		VPSO	FIPS	DMS-PSO	CLPSO	APSO	USPSO
f_1	Mean FEs	112408	32561	91496	72081	7074	**363**
	Ratio(%)	100.0	100.0	100.0	100.0	100.0	100.0
	Time（sec）	21.50	4.84	17.57	10.12	4.55	**0.23**
f_2	Mean FEs	109849	36322	91354	66525	7900	**443**
	Ratio(%)	100.0	100.0	100.0	100.0	100.0	100.0
	Time（sec）	18.63	6.16	15.41	11.34	5.19	**0.28**
f_3	Mean FEs	147133	73790	185588	—	21166	**1945**
	Ratio(%)	100.0	100.0	86.7	0.0	100.0	100.0
	Time（sec）	69.55	42.99	32.78	—	33.03	**3.44**
f_4	Mean FEs	91811	122210	101829	23861	5159	**664**
	Ratio(%)	40	66.7	20	100.0	100.0	100.0
	Time（sec）	31.90	28.15	37.18	8.87	4.96	**0.96**
f_5	Mean FEs	117946	42604	97213	81422	7568	**1391**
	Ratio(%)	96.7	100.0	100.0	100.0	100.0	100.0
	Time（sec）	33.99	14.75	26.09	33.34	9.02	**1.81**
f_6	Mean FEs	118926	38356	100000	76646	40736	**1485**
	Ratio(%)	46.7	100.0	56.7	100.0	66.7	100.0
	Time（sec）	34.81	13.10	27.21	31.31	40.80	**1.65**
Mean Reliability		80.56%	100%	77.23%	83.331%	94.45%	100%

Table 3 shows that USPSO achieves better results than any other improved PSOs in terms of convergence and reliability. As for unimodal functions, USPSO costs 10 to 20 times less than other improved PSOs in time and number of iterations. As for the multimodal test functions, USPSO costs 40 times less than other improved PSOs.

5. Conclusions

This paper proposes USPSO, an improved particle swarm algorithm based on uniform search strategy. It introduces the uniform search strategy firstly, breaking the uniqueness of movement of particles, and combines the basic search strategy and uniform search strategy. The experimental results show that USPSO achieves significant improvement in preventing prematurity, and improving the convergence speed and solution accuracy. Another advantage of USPSO is that it improves the comprehensive performance without making the optimization process redundant. Therefore, most improvements based on the basic PSO can be applied to USPSO to achieve a better performance.

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