Journal of Research in Multidisciplinary Methods and Applications (JRMMA)
ISSN: 2957-3920, Volume 1, Issue 2, June 2022

Particle Swarm Optimization Algorithm Mixed with Wolf Pack Algorithm

Wu Xiangbiao[1], Li Guangzhou[2], Yang Xiaorun[1]

[1] School of Mathematics, Zunyi Normal University, Zunyi, Guizhou, China

[2] School of Mathematical Sciences, Xingyi Normal University for Nationalities, China

Abstract: ***Since particle swarm optimization (PSO) is easy to enter the defect of local optimality, the global optimal solution is not easy to obtain, and the accuracy of the obtained global optimal solution is difficult to meet the standard; The wolf pack algorithm has a relatively high accuracy of the optimal solution and the probability of searching for the optimal solution is also relatively large. Therefore, this paper proposes a new algorithm SVRPSO that combines the wolf pack algorithm and the particle swarm optimization algorithm, which combines the advantages of the wolf pack algorithm and the particle swarm optimization algorithm. Compared with the particle swarm optimization (PSO) algorithm, the SVRPSO algorithm has certain advantages, which can prevent the optimal value update stagnation in the later stage of the PSO algorithm, improve the probability of finding the optimal value, and the optimal value is closer to the theoretical value. Experimental results show that the advantages of the SVRPSO algorithm over the PSO algorithm are that the optimal solution found is closer to the theoretical value and the convergence rate is faster.***

Keywords: particle swarm optimization; wolf pack algorithm; SVRPSO algorithm; global optimal solution.

0 Introduction

The particle swarm optimization algorithm PSO was first proposed by the American electrical engineer Eberhart and the social psychologist Kennedy in 1995, which is an algorithm that simulates the process of foraging birds. Bird foraging process: The starting position, flight speed, and direction of each bird in the flock we do not know, these are random machines, these birds do not know where the food is located, but in the process of finding food, they will continue to accumulate experience like humans, and learn from other birds, therefore, Birds and birds can learn from each other, share information, make progress together, and constantly approach food. During this process, each bird notes the closest position between itself and the food, as well as the closest position of the other birds and food in the flock. In the particle optimization algorithm PSO, each particle is regarded as a bird in the flock, and its initial position, speed, and direction are random, but the "bird" at this time has been regarded as a particle by us, without considering The size and shape of the "bird", but since it has a direction, we can think of it as a vector; How many pieces of food are equivalent to how many solutions, that is, how many dimensions.

Since the particle swarm optimization algorithm PSO is relatively easy to understand for most people, and it is relatively easy to achieve, its convergence rate is not low, so it has a wide range of applications in many fields, for example, in the cooling tower group noise 1 sound control method [1], Hub of neural network[2], permanent magnet linear motor[3], target tracking of SAGBA optimized particle filtering [4], design correction of robot positioning system[5], , distributed generation optimization configuration[6], remote sensing images[7], ice-covered UHV transmission lines[8], etc.

Standard particle swarm optimization algorithms not only have advantages, but also have disadvantages, such as easy to lead to local optimality rather than overall optimality, and we may not find the optimal solution, sometimes the accuracy obtained is not good. In view of this, this paper proposes an improved method: the particle swarm optimization algorithm that integrates the wolf pack algorithm mix, adding the idea of "the weak are subjects, the strong are king" to the particle swarm. Because in the wolf pack, obey the orders of the wolf king, when hunting, they all know what to do, have a clear goal, under the leadership of the leading wolf, constantly approach the prey, surround the prey, therefore, the wolf pack algorithm has a high probability of finding the optimal solution, and the efficiency of the algorithm is also very high, the paper proposed fusion wolf pack algorithm improved particle swarm arithmetic SVRPSO , the optimal solution can be found with a high probability, and the accuracy of the optimal solution and the optimal value can be greatly improved.

1 The algorithm principle of particle swarm optimization algorithm PSO

In the particle swarm optimization algorithm PSO, we first initialize the initial position and initial velocity of each particle, that is, to give a set of solutions first, and then constantly through the update of the speed and position of each particle, so that the particles continue to approach the accurate solution, by judging whether to reach the maximum number of iterations to end the algorithm, through continuous iteration, when the algorithm ends We can get the optimal set of solutions. Assuming that the space searched is D dimensional, the total number of particles has M one, $X^i=(x_{i,1},x_{i,2},\dots,x_{i,D})$ and $V^i=(v_{i,1},v_{i,2},\dots,v_{i,D})$ represents the t position and velocity of the first particle, starting with randomly generating the position and velocity of the particles, and then passing through the formulas (1) and (2) Update speed and position.

$$v_i^{(t+1)}=wv_i^{(t)}+c_1r_1\left(p_i^{(t)}-x_i^{(t)}\right)+c_2r_2\left(p_g^{(t)}-x_i^{(t)}\right) \tag{1}$$

$$x_i^{(t+1)}=x_i^{(t)}+v_i^{(t+1)} \tag{2}$$

where the w weights are represented, c_1 and c_2 the learning factors are represented, r_1 and r_2 the numbers that are randomly generated between 0 and 1 t , $t+1$ respectively, represent the iterations t , generations, $t+1$ Represents the $p_i^{(t)}=p_{i,1}^{(t)},p_{i,2}^{(t)},\dots,p_{i,D}^{(t)}$ best position of the t particle when the i algorithm iterates over to the first generation $p_g^{(t)}=p_{g,1}^{(t)},p_{g,2}^{(t)},\dots,p_{g,D}^{(t)}$, and represents the best position of the whole. w Mainly plays a balancing role, looking at the formula (1), we can know that ω is the memory that controls the position of history. If we set it to w 0, then the particle has no memory of the historical position, so it is a search for a small range, and its search ability can only reflect the advantage in this small range, but the search ability for the overall range is not reflected, so the optimal solution obtained is likely to be a local optimal solution. In an algorithm, we want to get the optimal solution of the whole, so we should care about both its local search ability and its overall search ability. For w , we can take advantage of equation (3) that we can reduce w from 0.9 to 0.4. where MT represents the maximum number of iterations.

$$\omega = 0.9 - 0.5\left(\frac{t}{MT}\right) \quad (3)$$

Learning c_1 factors and is c_2 the ability to control particle learning, the accumulation and reference of experience. Particles not only need to learn from themselves, but also from other particles, constantly reducing the distance between themselves and the optimal solution. This document sets both c_1 and c_2 both to 1.2.

2 The principle of the wolf pack algorithm

Wolf pack algorithm is a relatively optimized algorithm [9], it is the use of the characteristics of the wolf pack group of predation, and the wolf in the wolf pack will obey the wolf king's command characteristics, the wolf pack in the hunting imitation, the wolf pack division of labor is clear, can be abstractly divided into the wolf pack to find, convey, besiege these three states, and the wolf king in the wolf pack in the form of production - The winner is the king, you can know that the wolf king has a strong ability, in a wolf pack, the wolf king is constantly changing, as long as there is a stronger wolf production, then the previous wolf king will be replaced and other characteristics of the proposed a new group intelligence algorithm. In the selection method of the main circuit parameters of the converter [10], the analysis and research of the data [11] and other fields have been applied to the wolf pack algorithm, the best performance of the tracking, rounding, and attacking wolves is set to α, β, δ, they act as a guide for other wolves, expanding the space for them to find prey. The location of the wolves throughout the search is reflected in formulas (4) and (5).

$$\mathrm{D} = \left|CX_P(t) - X(t)\right| \quad (4)$$

$$X(t+1) = X_P(t) - AD \quad (5)$$

where t, t+1 indicates the t, t+1 iteration; X_P Indicates the location of the food; $X(t)$ Indicates the location of the wolf, D is the distance between the wolf and the food; A, C represent the coefficient vector, and

$$A = 2ar_1 - a \quad (6)$$

$$C = 2r_2 \quad (7)$$

$$a = 2 - \frac{2t}{MT} \quad (8)$$

Where r_1 sum r_2 is a random number between 0 and 1, a and the number of iterations t is inversely proportional to the parameter that measures the wolf pack's ability to search locally and search as a whole. Since α, β, and δ are better than other wolves, they have stronger search ability, and when they find that the distance between them and food is better than before, they will attract other wolves to move closer to their location. Then they are constantly looking for a better position, and the other wolves are approaching them again, and over and over again, the wolves will surround the prey and continue to approach the prey. Equations (9) through (15) are the basis and methods by which other wolf lambdas update their positions.

$$D_\alpha = \left|C_1 X_\alpha - X\right| \quad (9)$$

$$D_\beta = \left|C_2 X_\beta - X\right| \quad (10)$$

$$D_\delta = \left|C_3 X_\delta - X\right| \quad (11)$$

$$X_1 = X_\alpha - A_1 D_\alpha \quad (12)$$

$$X_2 = X_\beta - A_2 D_\beta \quad (13)$$

$$X_3 = X_\delta - A_3 D_\delta \quad (14)$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \quad (15)$$

where X is the position that denotes the θ wolf; A_1 , A_2 and A_3 is a random vector; C_1 , C_2 and are C_3 also random vectors; X_α , X_β and represent the location X_δ of the wolf α, β, and δ, respectively.

3 Converged Improved Algorithm (SVRPSO).

3.1 Fusion of particle swarm and wolf swarm algorithms

The original particle swarm optimization algorithm is easy to converge prematurely and fall into the local optimal trap, mainly because the bird flock does not have a bird king who can lead, and the bird is based on its own learning situation and experience to find the next position to be reached, therefore, it is easy to cause only a search in a small range, the result is not the overall best position, and the degree of convergence is not very high. The wolf pack algorithm is mainly based on the characteristics of the wolf pack "the strong are king", "the weak are slaves" and the characteristics of the wolf pack hunting, and the intelligent optimization algorithm is designed. The wolf pack algorithm has the advantages of searching for the optimal solution with a high probability and the error is relatively low, which can also prevent the stagnation state of the optimization solution update in the later stage of the algorithm; At the same time, because there is no wolf between wolves and wolves that do not share information and learn from each other, resulting in the shortcomings of the poor stability of the wolf pack algorithm. Synthesizing the advantages and disadvantages of particle swarm optimization algorithm and wolf swarm algorithm, a new algorithm SVRPSO that integrates the two algorithms is proposed in this paper. .

SVRPSO algorithm idea: on the basis of the improved particle swarm algorithm fusion wolf pack algorithm, in the particle swarm optimization algorithm, we use the wolf pack "strong is king" feature, for the flock also selected the strongest bird king to lead the flock, the characteristics of mutual learning of the flock is still there, so that not only increase the probability of the optimal value being found, The accuracy of convergence can also be further improved, and stability can also be improved.

3.2 Algorithm Steps

The first step: initialize the position and velocity of the particle swarm particles so that the particles have position and velocity;

Journal of Research in Multidisciplinary Methods and Applications (JRMMA)
ISSN: 2957-3920, Volume 1, Issue 2, June 2022

Step 2: Calculate the fitness of each particle;
Step 3: Find out the top three particles in terms of fitness;
Step 4: Take the position of the top three particles in the fitness degree by comparison, and calculate their average position;
Step 5: Calculate a using formula (8);
Step 6: Use formulas (3), (1), and (2) to update the weights, velocities, and positions of the particles;
Step 7: Use Equations (6), (7), (9) to (15) to calculate the distance between the other particles and the top three particles selected for fitness, and update the position of the particles again;
Step 8: Determine whether the set end conditions are met, if the set end conditions are not met, go back to the fifth step, otherwise, proceed to the next step;
Step 9: Output the optimal solution and the best value.
Figure 1 is a flowchart of the SVRPSO algorithm, from which we can clearly see the process of the SVRPSO algorithm.

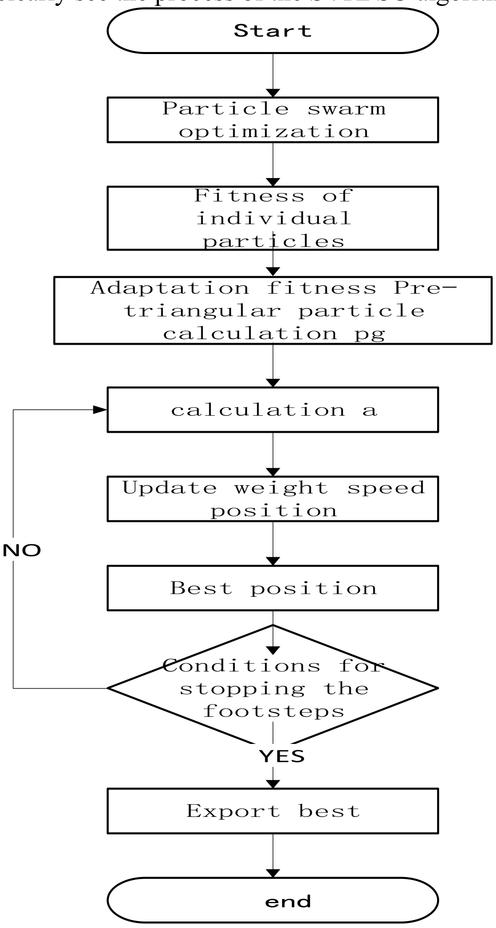


Fig. 1 Flowchart of the SVRPSO algorithm

4 Experimental design and results analysis

4.1 Experimental design

Table 1 is a selection of 10 test functions[12] to test the performance of the SVRPSO algorithm and the PSO algorithm. The first four functions have only one peak point and are unipolar functions, and the last six functions have multiple peak points and are multimodal functions. Multimodal functions can easily cause the dilemma of local optimization, which is one of the methods to detect a better optimization performance ratio of an algorithm, and is a test of the algorithm's search ability. The dimension in the experimental parameters of this experiment D is set to 30 dimensions, the maximum number of iterations MT is 1000 times, the number of learning $c_1 = c_2 = 1.2$ factors, and the number of particles $N = 200$; The SVRPSO algorithm and the PSO algorithm were run independently 30 times each.

Table 1 Test functions

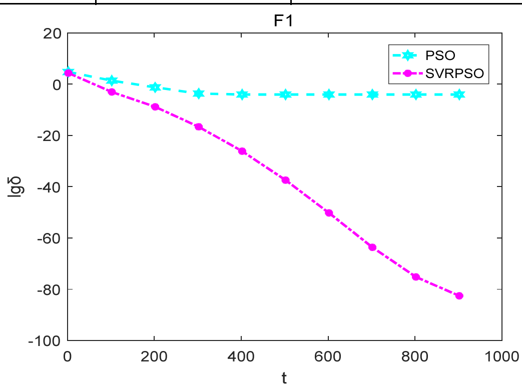
Function name	Function expressions	Search for spaces	X*	$f(x^*)$
Ball	$F_1(x)=\sum_{i=1}^{D}\left\|x_i^2\right\|$	[-100,100]	$\{0\}^D$	0.0
Schwefer P2.22	$F_2(x)=\sum_{i=1}^{D}\left\|x_i^2\right\|+\prod_{i=1}^{D}\left\|x_i\right\|$	[-10,10]	$\{0\}^D$	0.0
Rosenbrook	$F_3(x)=\sum_{i=1}^{D}\left(100\left(x_{i+1}-x_i^2\right)^2+\left(1-x_i\right)^2\right)$	[-10,10]	$\{1.0\}^D$	0.0
Power difference	$F_4(x)=\sum_{i=1}^{D}\left\|x_i\right\|^{(i+1)}$	[-10,10]	$\{0\}^D$	0.0

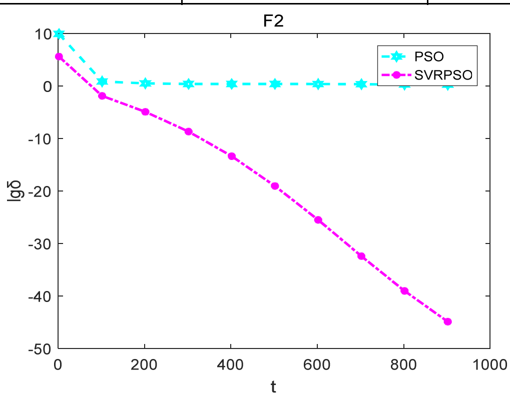
Acre	$F_5(x) = -20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right)$, e is the natural constant $+20+e$	[-32,32]	$\{0\}^D$	0.0
Grimvank	$F_6(x) = \sum_{i=1}^{D} \frac{x_i^2}{4000} - \prod_{i=1}^{D} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	[-600,600]	$\{0\}^D$	0.0
Rastreen	$F_7(x) = \sum_{i=1}^{D} \left(x_i^2 - 10\cos(2\pi x_i) + 10\right)$	[-5.12, 5.12]	$\{0\}^D$	0.0
Schwefer P1.2	$F_8(x) = 418.98234D - \sum_{i=1}^{D} x_i \sin\left(\sqrt{\lvert x_i \rvert}\right)$	[-500,500]	$\{420.96\}^D$	0.0
Mountains	$F_9(x) = \sum_{i=1}^{D} \lvert x_i \sin(x_i) + 0.1x_i \rvert$	[-10,10]	$\{0\}^D$	0.0
Solomon	$F_{10}(x) = -\cos\left(2\pi\sqrt{\sum_{i=1}^{D} x_i^2}\right) + 0.1\times\sqrt{\sum_{i=1}^{D} x_i^2} + 1$	[-100,100]	$\{0\}^D$	0.0

4.2 Results and Analysis

Table 2 Comparison of the results of functions run under PSO algorithm and SVRPSO algorithm

Function name	algorithm	Meaning Dress	Venereal disease.	best	worst
ball	interrupter	9.17197E-05	0.000117477	2.13482E-06	0.000525204
	SVRPSO	1.2877E-87	4.18875E-87	1.46124E-91	1.79483E-86
Schwefer P2.22	interrupter	1.851586052	1.019931888	0.460676858	4.156593739
	SVRPSO	1.54453E-49	2.28931E-49	1.50485E-51	7.95452E-49
Rosenbrook	interrupter	36.3912085	22.06246432	19.00569035	107.0368858
	SVRPSO	28.81013116	0.26850148	28.18023381	29
Power difference	interrupter	8.13438E-10	1.15529E-09	1.43502E-11	4.92537E-09
	SVRPSO	3.1892E-161	1,572E-160	9.8531E-174	8.6008E-160
Acre	interrupter	16.56815786	0.821110671	15.44093903	18.14800027
	SVRPSO	10.50719902	0.235210856	10.19253893	10.94480717
Grimvank	interrupter	3.55274E-06	6.85372E-06	6.55048E-08	3.46676E-05
	SVRPSO	0	0	0	0
Rastreen	interrupter	61.58810125	18.18218095	30.84376447	113.4246761
	SVRPSO	0	0	0	0
Schwefer P1.2	interrupter	-4.12324E+57	-1.23599E+59	-8.60008E+35	2.25654E+58
	SVRPSO	-11518.83718	-13516.89437	-9896.939614	923.5338439
Mountains	interrupter	3.614895641	1.911339126	0.843030805	8.335878013
	SVRPSO	4.80284E-50	1.77741E-49	4.96416E-53	9.70461E-49
Solomon	interrupter	1.669873346	0.297286579	0.899873346	2.299873346
	SVRPSO	0.026632892	0.044920678	0	0.099873346





Journal of Research in Multidisciplinary Methods and Applications (JRMMA)
ISSN: 2957-3920, Volume 1, Issue 2, June 2022

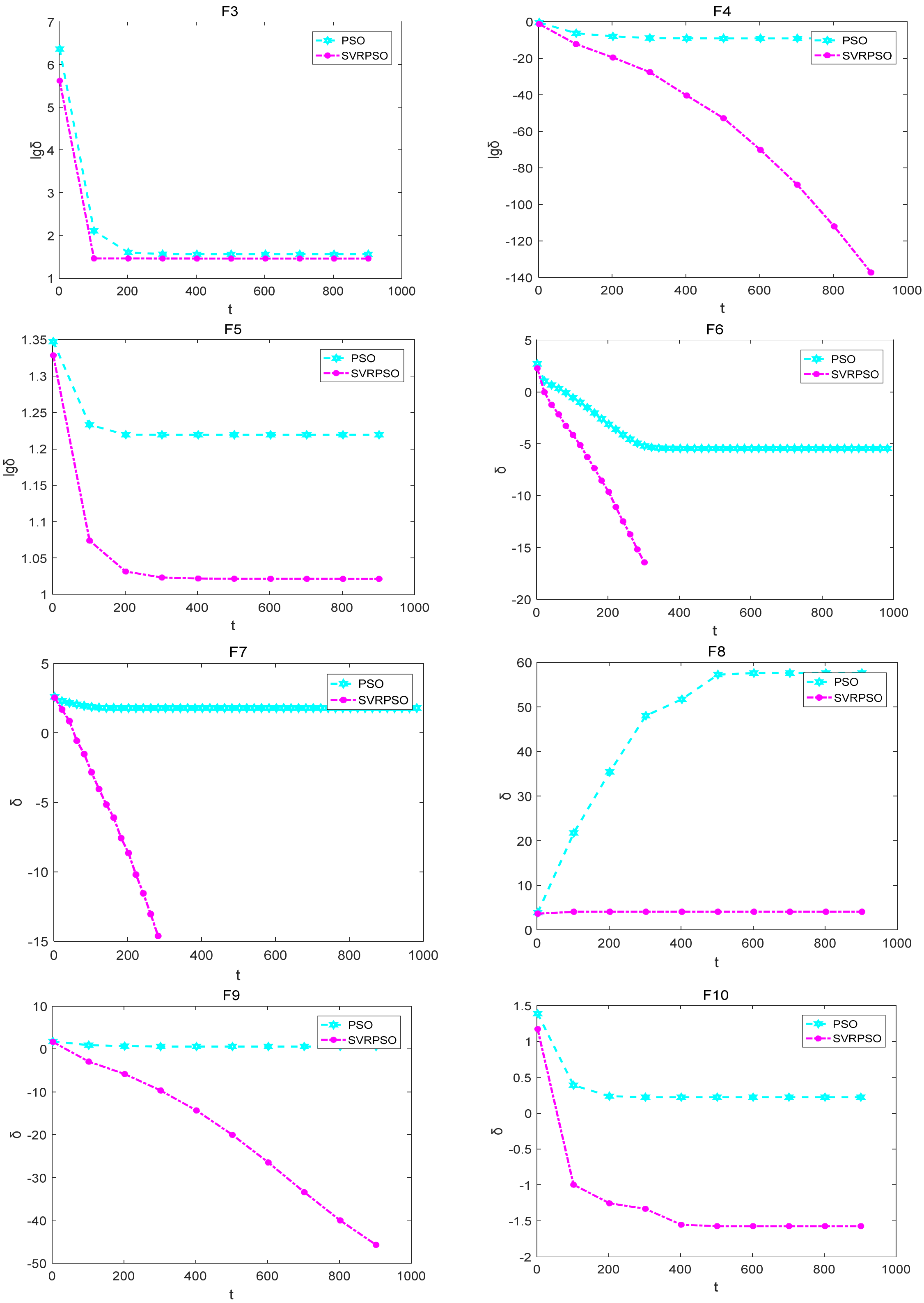


Fig.2 The above 10 images are the results of the 10 functions running under the SVRPSO algorithm and the PSO algorithm, respectively.

From Table 2 and the 10 images above, it can be seen that the SVRPSO algorithm is better optimized than the PSO algorithm, for the ten functions selected (including single peak function, multi-peak function), SVRPSO The effect of the algorithm on convergence speed and convergence accuracy is obviously better than that of PSO algorithm. It can be seen that the SVRPSO algorithm is better in the comparison between the local search capability and the overall search capability and the PSO algorithm.

5 Conclusion

This paper proposes a new algorithm SVRPSO algorithm that integrates the improved particle swarm optimization algorithm of the wolf pack algorithm, which not only has the advantages of information sharing and mutual learning when the birds are hunting, but also has the characteristics of the wolf pack hunting and encircling the prey, and the "strong is king" in the wolf pack. In order to evaluate the optimization effect of SVRPSO algorithm, 10 functions are selected to test, and through the analysis and summary of experimental results and results, we know that the effect of SVRPSO algorithm is indeed better than that of PSO algorithm. The algorithm improves the convergence speed and accuracy.

Funds

Fund Project: Zunyi Normal University Teaching Content and Curriculum System Reform and Construction Cultivation Project (JGPY2021042); Guizhou Provincial Department of Education Project (Qianjiaohe KY Character [2020] 214).

References

[1] ZHOU Xuefeng,CHENG Xingping,PENG Wenchuan,SUN Lishan,LU Jun. Noise control method of cooling tower group based on particle swarm optimization algorithm[J]. Journal of Xi'an Polytechnic University,2019,33(05):568-574.] [J]. Journal of Zhejiang University (Engineering Science), 2018, 52(02): 367-378+405

[2] Ge Yan, Liu Xingxing, Xie Junbiao Improved wheel hub classification algorithm for particle swarm optimization BP neural network[J]. China Science and Technology Papers,2019,14(07):773-777+788.]

[3] Xu Xiaozhuo, Fu Huiqi, Liu Zhuli, Wang Xudong Study on Particle Swarm Optimization PID Control of Primary Permanent Magnet Linear Motor[J/OL]. Journal of Henan Polytechnic University (Natural Science Edition), 2020(01):101-106[2019-12-12].https://doi.org/10.16186/j.cnki.1673-9787.2020.1.13.

[4] Lu Siyao, Zhou Wuneng, Li Longlong Target tracking based on SAGBA optimized particle filtering [J/OL]. Computer Technology and Development, 2020(02):1-5[2019-11-28].http://kns.cnki.net/kcms/detail/61.1450.TP.20191107.0912.052.html

[5] Tang Lin, Liu Tong Design of positioning system for weeding robots—Particle swarm optimization based on jump distance correction and WSN[J]. Agricultural Mechanization Research,2020,42(08):231-235.]

[6] Cao Shen, Su Shiwei, Cao Wenkang, Yang Xuan Optimal configuration of distributed power generation based on artificial immune particle swarm algorithm[J]. Power Science and Engineering

[7] Chen Yingxia, Chen Yan, Liu Cong Remote sensing image fusion AIHS conversion and particle swarm optimization algorithm[J]. Journal of Geomatics,2019,48(10):1296-1304.,2019,35(10):57-61.

[8] Wu Junjun, Song Gang, Lu Binfang Calculation of icing unbalance tension of UHV transmission line based on particle swarm optimization algorithm[J]. Zhejiang Electric Power, 2019, 38(03): 59-64

[9] Zhao Hong, Li Weipeng, Liu Tiejun Wolf pack algorithm based on improved Levi flight and its application in airfoil aerodynamic optimization design[J]. Science Technology and Engineering,2019,19(18):315-323.]

[10] LIU Ji,ZHANG Xiaoping,ZHANG Ruirui. Adaptive optimization method of buck-Boost matrix converter main circuit parameter with current quota[J]. Information and Control, 2019, 48(05): 545-551

[11] Yang Wenjing Analysis and research of clustering algorithm based on wolf pack optimization in big data environment[J]. Modern Electronics Technology, 2019, 42(17): 106-108

[12] ZHANG Qingke,MENG Xiangxu,ZHANG Huaxiang,YANG Bo,LIU Weiguo. Particle swarm optimization algorithm based on random dimension division and learning[J]. Journal of Zhejiang University (Engineering Science), 2018, 52(02): 367-378+405