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Improved Grey Wolf Optimization Algorithm based on SoftPlus Inertia Weight Strategy

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Abstract. In order to solve the problems of the Grey Wolf Optimization (GWO) algorithm, such as low optimization accuracy and low convergence speed, this paper proposes an Improved Grey Wolf Optimization Algorithm Based on SoftPlus Inertia Weight Strategy (SGWO). SGWO combines the nonlinear characteristics of SoftPlus function, and introduces the inertia weight strategy based on SoftPlus function to improve the optimization performance of GWO. Eight classic test functions are used to compare the performance of SGWO with five classical swarm intelligence algorithms. Experimental results show that SGWO is superior to other five-population intelligent algorithms in optimization accuracy and convergence speed.

Keywords: SoftPlus Function; Inertia Weight; Grey Wolf Optimization Algorithm; Optimization Accuracy; Rate of Convergence.

1. Introduction

With the rapid development of computer science and artificial intelligence, optimization algorithm has become one of the important tools to solve complex problems. GWO is a new swarm intelligence optimization algorithm proposed by Seyedali et al. [1] in 2014, which simulated the social behavior and hunting strategy of gray wolves and can solve many optimization problems [2]. Compared with Particle Swarm Optimization (PSO) algorithm [3], Firefly Optimization Algorithm (FA) [4], Ant Lion Optimizer, ALO) [5] and Fruit Fly Optimization Algorithm (FOA) [6], GWO algorithm has the advantages of simple operation, few adjustment parameters and easy programming, so it is widely used in many fields, such as electric vehicle charging duration prediction [7], static and dynamic crack identification [8] and soil liquefaction potential evaluation [9]. Balogun et al. [10] applied the GWO to predict the spatial of landslide susceptibility in western Serbia. Zhou et al. [11] used the GWO to optimize the random forest to evaluate the stability of underground entry-type excavations. Alzaqebah et al. [12] used the improved GWO to adjust the parameters of the high-speed classification method ELM, thus improving the performance of the network intrusion detection system. Yu et al. [13] improved the GWO algorithm by using different population renewal strategies, and applied it to the image segmentation of maize leaf spot. Shaheen et al [14] combined GWO algorithm with PSO algorithm to improve the performance of GWO algorithm, and applied it to the solution of reactive power optimization scheduling problem. Zhao et al. [15] combined the advantages of ENBLS and GWO algorithms, and proposed a performance trend prediction method based on ENBLS and GWO. Yuan et al. [16] improved GWO algorithm by learning based on elite confrontation and chaotic K optimal gravity search strategy, and applied it to the optimization of automobile drum brakes. Although the above work has improved the performance of GWO to a certain extent, it has failed to achieve obvious results in accelerating the convergence speed of the algorithm and avoiding falling into local optimization. In order to further improve the solution to these problems, this paper proposes an improved grey wolf optimization algorithm based on SoftPlus inertia weight strategy. SoftPlus inertial weight strategy combines gradient information, and improves GWO by introducing nonlinear factors, thus enhancing the global search ability and convergence speed of GWO.

2. Grey Wolf Optimization Algorithm

GWO is to simulate the search and cooperation behavior among individuals in the gray wolf population, so that the population gradually concentrates on the position of the optimal solution in the search space [17]. The steps of GWO are as follows:

Step 1: Initialize the grey wolf population, and $\vec{a}$, $\vec{A}$ and $\vec{C}$.

Step 2: Calculate the fitness of each gray wolf individual in the initial gray wolf population, and record the three individuals with the best fitness as wolf α, wolf β and wolf δ respectively.

Step 3: Update the current position of the gray wolf by formulas 1-7:

$$\vec{D}_{\alpha} = \left|\vec{C}_1 \cdot \vec{X}_{\alpha} - \vec{X}\right| \tag{1}$$

$$\vec{D}_{\beta} = \left|\vec{C}_2 \cdot \vec{X}_{\beta} - \vec{X}\right| \tag{2}$$

$$\vec{D}_{\delta} = \left|\vec{C}_3 \cdot \vec{X}_{\delta} - \vec{X}\right| \tag{3}$$

$$\vec{X}_1 = \vec{X}_{\alpha} - \vec{A}_1 \cdot \vec{D}_{\alpha} \tag{4}$$

$$\vec{X}_2 = \vec{X}_{\beta} - \vec{A}_2 \cdot \vec{D}_{\beta} \tag{5}$$

$$\vec{X}_3 = \vec{X}_{\delta} - \vec{A}_3 \cdot \vec{D}_{\delta} \tag{6}$$

$$X(\vec{t}+1) = \frac{(\vec{X}_1 + \vec{X}_2 + \vec{X}_3)}{3} \tag{7}$$

Step 4: Update the parameters $\vec{a}$, $\vec{A}$ and $\vec{C}$ by formulas 8-10, where Max_iter is the maximum number of iterations:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{8}$$

$$\vec{C} = 2\vec{r}_2 \tag{9}$$

$$\vec{a} = 2 - \frac{2t}{Max\_iter} \tag{10}$$

Step 5: Judge whether the end condition is reached, and if not, return to step 2. Otherwise, end the algorithm and output the optimal result.

3. Improved Grey Wolf Optimization Algorithm based on SoftPlus Inertia Weight Strategy

3.1. SoftPlus Inertia Weight Strategy

In this paper, the inertia weight strategy based on SoftPlus is shown in Formula 11:

$$w = s \cdot (\log(1 + \exp(a - t / t_{\max})))^\wedge b + c \quad (11)$$

Formula 11 is shown in Figure 1:

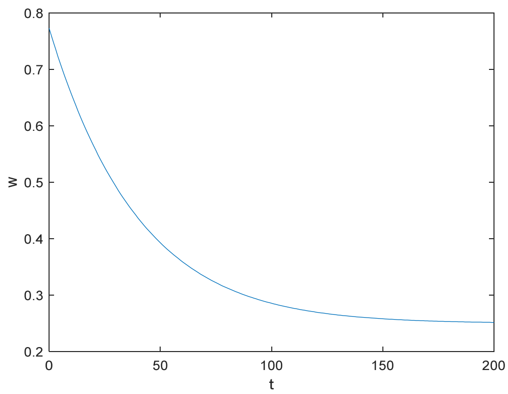


Figure 1. Chart of SoftPlus inertia weight strategy

Figure 1 shows that the curve of SoftPlus inertia weight strategy used in this paper has a large weight at the beginning of the algorithm, which is helpful to expand the search scope of the algorithm, promote the optimal solution of global search, and reduce the chance of falling into the local optimal solution. With the increase of the number of iterations of the algorithm, the curve quickly drops to a smaller value, starts to decrease slowly, and finally tends to be stable, which is beneficial for the algorithm to quickly enter and stabilize in one or several local spaces after searching for the optimal solution in a large range in the early stage and continue to search for the global optimal solution. After transitory iterations in the early stage, the inertia weight curve enters and remains at a small value, which is helpful for the algorithm to retain for a long time to search for the optimal solution in the local space in the later stage. To sum up, SoftPlus inertia weight strategy is beneficial to the algorithm to achieve the balance between global search optimal value and local search optimal value.

3.2. Improved Grey Wolf Optimization Algorithm based on SoftPlus Inertia Weight Strategy

Based on SoftPlus inertia weight strategy, the steps of algorithm of SGWO are as follows:

Step 1: Initialize the grey wolf population, and $\vec{a}$, $\vec{A}$ and $\vec{C}$.

Step 2: Calculate the fitness of each gray wolf individual in the initial gray wolf population, and record the three individuals with the best fitness as wolf α , wolf β and wolf δ respectively.

Step 3: Update the inertia weight w by Formula 11.

Step 4: Update the current position of the grey wolf by formulas 1-3, formulas 12-14 and Formula 7 in turn.

$$\vec{X}_1 = w\vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \quad (12)$$

$$\vec{X}_2 = w\vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \quad (13)$$

$$\vec{X}_3 = w\vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \quad (14)$$

Step 5: Update the parameters $\vec{a}$, $\vec{A}$ and $\vec{C}$ by formulas 8-10.

Step 6: Judge whether the maximum number of iterations is reached, and if not, return to step 2. Otherwise, end the algorithm and output the optimal result.

The algorithm flow chart of SGWO is shown in Figure 2:

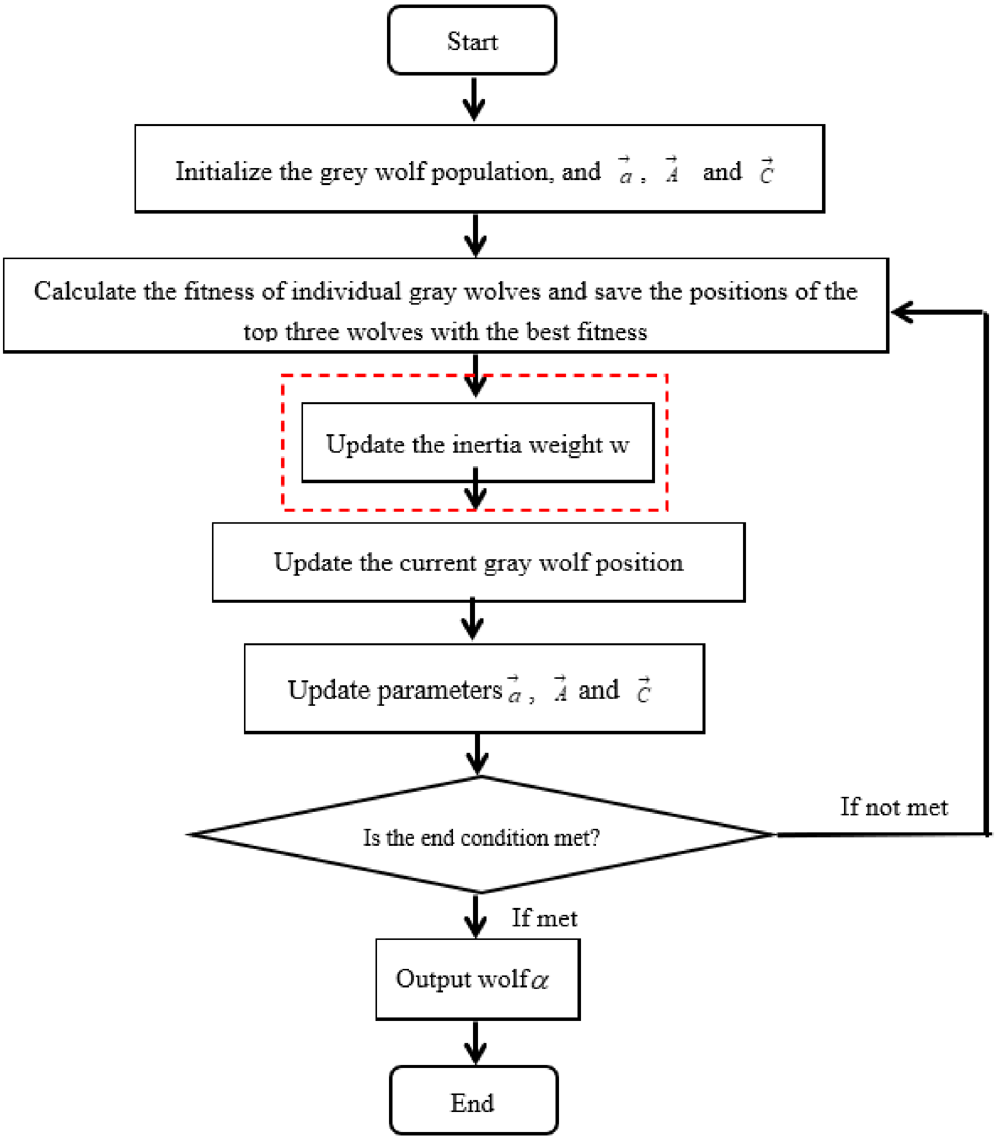


Figure 2. Flow chart of algorithm of SGWO

As can be seen from Figure 2, SGWO improves the inertia weight of GWO, so that the inertia weight of GWO presents a non-linear monotonic decrease with the increase of the number of iteration times. In the short iteration in the early stage, the inertia weight is large, but in the later iterations, the inertia weight gradually decreases and tends to be small, so that GWO can get enough diverse positions in the search space in the early stage, and can dig the global optimal solution in a number of smaller areas in the later stage of iteration.

4. Simulation Experiment and Results

4.1. Experimental Design

Simulation environment: windows11, internal storage 16.00GB, machine basic frequency 3.20GHz, MATLAB R2020b.

In this paper, eight test functions are selected to verify the optimization performance of SGWO. The parameter settings of the test functions are shown in Table 1:

Table 1. Design table of test function parameters

Function number	Function expression	Dimension	Variable range value	Optimal value
F1	$f_1(x)=\sum_{i=1}^{n}x_i^2$	30	[-100,100]	0
F2	$f_2(x)=\sum_{i=1}^{n}\lvert x_i\rvert+\Pi_{i=1}^{n}\lvert x_i\rvert$	30	[-10,10]	0
F3	$f_3(x)=\sum_{i=1}^{n}(\sum_{j=1}^{i}x_j)^2$	30	[-100,100]	0
F4	$f_4(x)=\max_i\{\lvert x_i\rvert,1\le i\le n\}$	30	[-10,10]	0
F5	$f_6(x)=\sum_{i=1}^{n}[x_i^2-10\cos(2\pi x_i)+10]$	30	[-5.12,5.12]	0
F6	$f_5(x)=\sum_{i=1}^{n}ix_i^4+random[0,1)$	30	[-1.28,1.28]	0
F7	$f_7(x)=-20\exp(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2})-\exp(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i))+20+e$	30	[-32,32]	0
F8	$f_8(x)=\frac{1}{4000}\sum_{i=1}^{n}x_i^2-\Pi_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}})+1$	30	[-600,600]	0

To verify the effectiveness of SGWO, eight test functions in Table 1 are used to compare PSO, FA, ALO, FOA and GWO with SGWO. The population size of the six algorithms is 10, the search space dimension is 30, and the maximum number of iterations is 200.

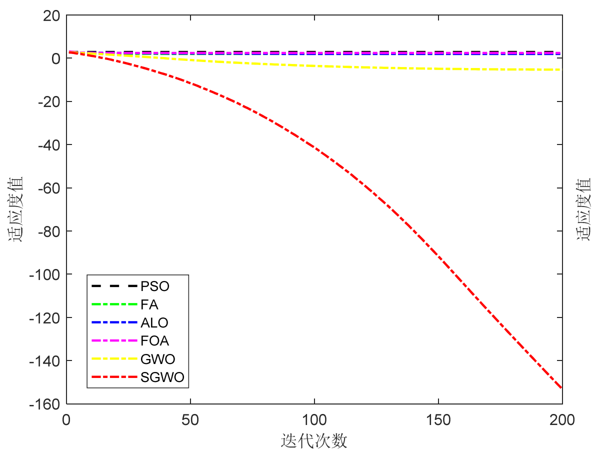
The Logarithmic Mean of Optimal Fitness (LF) of the current optimal fitness of the six algorithms running independently for 50 times is shown in Formula 15:

$$\mathrm{LF}(t)=\frac{1}{G}\sum_{i=1}^{G}\log_{10}\left(\mathrm{sgb}_{(i)}(t)\right) \tag{15}$$

G is the running times of the algorithm, and $sgb_{(i)}(t)$ is the current optimal value of the i-th iteration.

4.2. Analysis of Experimental Results

4.2.1. Comparison of Average Convergence Curves of Six Algorithms



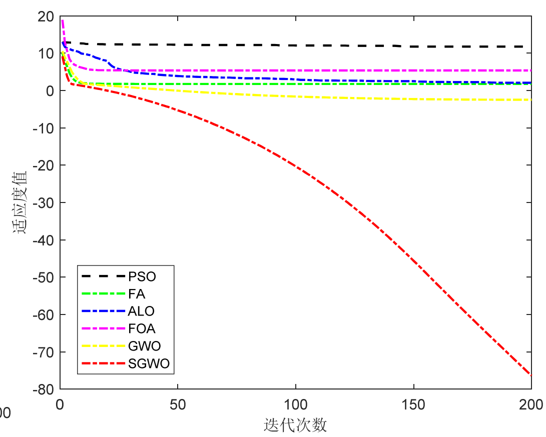
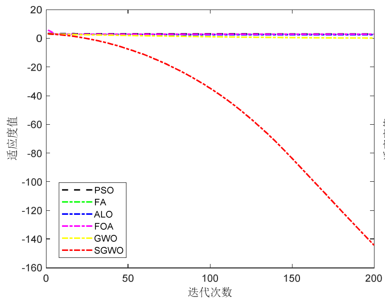


Figure 3. (left) Comparison chart of mean convergence curve of F1

Figure 4. (right) Comparison chart of mean convergence curve of F2

Comparison charts of convergence curves of six algorithms for eight test functions in Table 1 are shown in figures 3-10:



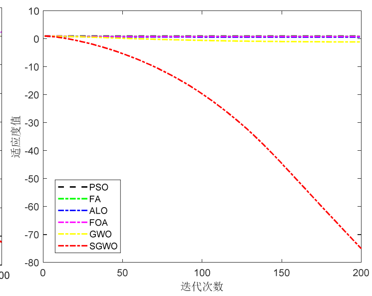
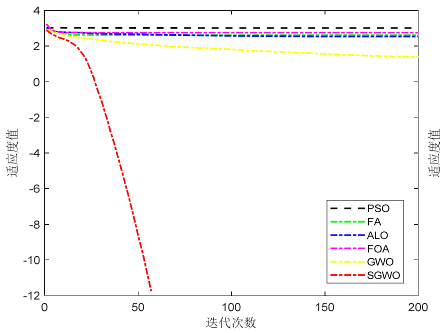


Figure 5. (left) Comparison chart of mean convergence curve of F3

Figure 6. (right) Comparison chart of mean convergence curve of F4



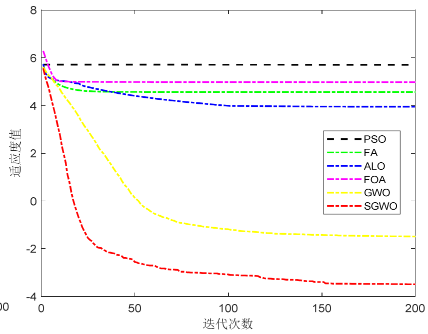
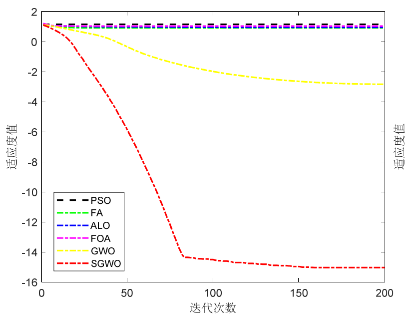


Figure 7. (left) Comparison chart of mean convergence curve of F5

Figure 8. (right) Comparison chart of mean convergence curve of F6



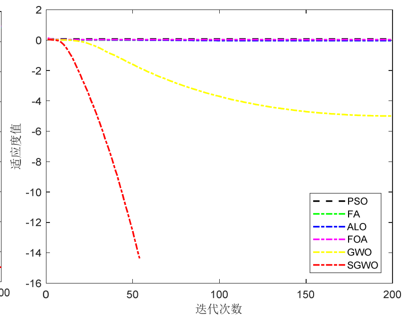


Figure 9. (left) Comparison chart of mean convergence curve of F7

Figure 10. (right) Comparison chart of mean convergence curve of F8

In figures 3-10, the abscissa is the number of iterations of the algorithm, and the ordinate is LF obtained from Formula 15. As can be seen from figures 3-7, with the increase of iteration times, the other five algorithms except SGWO will soon fall into the local optimal solution, and the evolution curve of SGWO is the algorithm with the most obvious decline, the highest solution accuracy and the fastest convergence speed, and will not fall into the local optimal solution. In Figure 8 and Figure 9, although the convergence speed of SGWO in the later iterations will become slower than that in the earlier iterations, the previous iteration can let the population optimal solution of SGWO get high-enough accuracy, and other swarm intelligence algorithms except SGWO will fall into a local optimal solution with relatively low accuracy in the earlier iterations. In Figure 10, the four algorithms except SGWO and GWO will quickly fall into the local optimal solution, while SGWO and GWO will not fall into the local optimal solution, but the convergence speed of SGWO is obviously faster than that of GWO, and the solution accuracy is obviously higher than that of GWO, and SGWO gets the global optimal solution after only about 50 iterations. To sum up, the optimization performance of SGWO is better than the other five algorithms.

4.2.2. Stability Comparison and Analysis of the Six Algorithms

Table 2. Comparison of minimum, maximum, average and standard deviation of six algorithms for solving functions

Test Function	Algorithm	Minimum value	Maximum value	Average value	Standard deviation
F1	PSO	5.57E+02	9.08E+02	7.19E+02	7.23E+01
	FA	3.44E+01	2.31E+02	1.15E+02	4.41E+01
	ALO	8.45E+00	1.68E+02	1.02E+02	3.91E+01
	FOA	1.74E+02	4.06E+02	2.91E+02	5.33E+01
	GWO	5.04E-07	6.09E-05	8.71E-06	1.04E-05
	SGWO	7.79E-156	3.55E-151	1.53E-152	6.02E-152
F2	PSO	6.05E+07	4.14E+14	2.08E+13	6.87E+13
	FA	2.46E+01	3.03E+02	6.26E+01	3.99E+01
	ALO	5.94E+01	1.07E+03	1.32E+02	1.39E+02
	FOA	1.87E+02	6.37E+08	2.17E+07	9.72E+07
	GWO	9.38E-04	7.08E-03	3.59E-03	1.33E-03
	SGWO	6.67E-78	4.63E-76	6.19E-77	7.29E-77
F3	PSO	6.67E+02	1.56E+03	1.03E+03	1.76E+02
	FA	2.37E+02	7.88E+02	4.48E+02	1.37E+02
	ALO	1.01E+02	8.03E+02	3.28E+02	1.41E+02
	FOA	4.14E+02	9.05E+02	6.48E+02	1.12E+02
	GWO	5.87E-02	1.01E+01	1.97E+00	1.72E+00
	SGWO	1.26E-147	1.43E-141	5.35E-143	2.33E-142
F4	PSO	8.12E+00	9.66E+00	9.12E+00	3.66E-01
	FA	4.06E+00	9.15E+00	7.70E+00	1.01E+00
	ALO	2.20E+00	6.14E+00	4.12E+00	7.43E-01
	FOA	5.40E+00	7.01E+00	6.21E+00	3.85E-01
	GWO	1.19E-02	2.34E-01	8.76E-02	5.35E-02
	SGWO	6.71E-77	8.19E-75	1.61E-75	1.73E-75
F5	PSO	7.28E+02	1.19E+03	1.01E+03	8.59E+01
	FA	2.91E+02	5.69E+02	4.28E+02	7.15E+01
	ALO	2.02E+02	4.90E+02	3.30E+02	6.24E+01
	FOA	4.94E+02	6.88E+02	5.81E+02	5.04E+01
	GWO	1.12E+01	5.61E+01	2.71E+01	1.06E+01
	SGWO	0	0	0	0
F6	PSO	3.70E+05	7.45E+05	5.55E+05	1.01E+05
	FA	7.93E+03	1.51E+05	4.68E+04	2.64E+04
	ALO	1.60E+02	2.92E+04	9.36E+03	7.17E+03
	FOA	4.50E+04	1.56E+05	8.96E+04	2.61E+04
	GWO	1.31E-02	6.77E-02	3.45E-02	1.37E-02
	SGWO	8.92E-06	2.36E-03	6.26E-04	5.23E-04
F7	PSO	1.32E+01	1.48E+01	1.43E+01	3.23E-01
	FA	5.51E+00	1.04E+01	8.74E+00	1.00E+00
	ALO	7.56E+00	1.10E+01	9.03E+00	7.94E-01
	FOA	9.42E+00	1.20E+01	1.10E+01	5.19E-01
	GWO	4.49E-04	4.29E-03	1.44E-03	7.29E-04
	SGWO	8.88E-16	8.88E-16	8.88E-16	0.00E+00
F8	PSO	1.13E+00	1.23E+00	1.19E+00	2.36E-02
	FA	9.28E-01	1.05E+00	1.02E+00	2.63E-02
	ALO	4.89E-01	1.04E+00	9.54E-01	1.27E-01
	FOA	1.05E+00	1.09E+00	1.08E+00	1.07E-02
	GWO	1.90E-08	8.07E-02	1.77E-02	2.42E-02
	SGWO	0	0	0	0

The solution scale is 10, and the number of iterations is 200. six algorithms run independently for 50 times, and the maximum, minimum, average and standard deviation of the optimal fitness obtained by the six algorithms are compared, as shown in Table 2:

From Table 2, it can be seen that SGWO can get smaller minimum, maximum and average values of optimal fitness than other five population intelligent algorithms, which shows that SGWO has higher solution accuracy and faster convergence speed than other five population intelligent algorithms. Compared with other five population intelligent algorithms, SGWO can get smaller standard deviation of optimal fitness, which shows that SGWO has higher stability than other five population intelligent algorithms. In Summary, SGWO has better optimization performance than the other five algorithms.

4.2.3. Time Complexity Analysis

The time complexity of GWO algorithm is O(N×S×d), where N is the number of gray wolves in the gray wolf population, S is the maximum number of iterations of the algorithm, and d is the spatial dimension of the algorithm. For SGWO, on the basis of the GWO algorithm, in its iterative process, it linearly multiplies an inertia weight function w, which is equivalent to linearly multiplying a constant on the basis of the original formula. This does not increase the time complexity of GWO, so the time complexity of SGWO is O(N×S×d). As can be seen from Table 2, under the same accuracy requirement, SGWO needs fewer iterations to solve the same accuracy than GWO, so the time complexity of SGWO is lower than that of GWO algorithm.

5. Conclusion

In this paper, an improved grey wolf optimization algorithm based on SoftPlus inertia weight strategy is proposed to solve the problems of low optimization accuracy and low convergence speed of grey wolf optimization algorithm. SGWO uses the nonlinear characteristics of SoftPlus function to adjust the inertia weight, which balances the global search ability and local search ability of the algorithm and improves the search efficiency of the algorithm. The simulation results show that compared with the classical swarm intelligence algorithms, SGWO has the characteristics of high optimization accuracy and fast convergence speed, and has a good application prospect in practical industrial applications.

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