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Comparative Study of Horse Swarm Algorithm and Classical Algorithm

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Abstract: *At present, optimization algorithms have been widely used in various scientific fields. These optimization algorithms are usually stimulated by the natural behavior of human, animal, plant, physical or chemical reagents. Most of the algorithms proposed in the past decade are inspired by animal behavior. Based on the horse swarm optimization algorithm, a horse swarm algorithm (WHO), which simulates the social life behavior of horses, is proposed in this paper. The new algorithm integrates the golden sinusoidal guiding mechanism as local operators into WHO algorithm, which improves the accuracy and convergence speed of the algorithm; It avoids the early over convergence of the algorithm. On the challenging CEC2019 test set, the WHO algorithm is comprehensively compared with other improved algorithms. Simulation results show that WHO algorithm has better performance in search efficiency, convergence accuracy and avoiding local optimum for both high-dimensional and fixed-dimensional problems. The results show that compared with other algorithms, this algorithm has strong competitiveness.*

Keywords: *Optimization algorithm; Horse swarm algorithm; Simulation experiment; Sinusoidal guiding mechanism*

1. Introduction

Nowadays, with the improvement of people's living standards, people are faced with more and more complex optimization problems. These complex problems are often complex and abstract, and traditional optimization algorithms cannot find a reliable solution in dealing with complex large-scale data problems. Therefore, the natural heuristic algorithm quasi-bionics principle, processing large amounts of data advantages and attracted the attention of researchers. These algorithms can balance local search and global search and effectively escape the local optimal solution[1].

Genetic algorithm is the beginning of natural heuristic algorithm, which provides a beneficial supplement to the traditional single-point iterative optimization based on analysis and strict theoretical derivation, and puts forward the idea of population iterative evolution and random optimization. The particle swarm optimization (PSO)and ant colony optimization (ACO), which are proposed later, accelerate the development of heuristic algorithms, and make scholars focus on the exploration of optimization mechanism contained in various phenomena in nature. In recent twenty years, heuristic algorithms have developed vigorously. Scholars have put forward many heuristic algorithms to simulate natural, physical and biological phenomena, such as water flow algorithm, raindrop algorithm, weed invasion algorithm, flower pollination algorithm, etc. Gravitational search algorithm, black hole algorithm, etc. Besides PSO and ACO, Grey Wolf Optimization (GWO), Whale Optimization (WOA), Moth to Fire (MFO), Sine-Cosine Algorithm (SCA), etc. Every year, application software computing, expert systems and their applications, knowledge-based systems, neural computing, group and evolutionary computing have been widely reported. The research of SI mainly focuses on three aspects: the new algorithm, the performance improvement of existing algorithms and the expansion of algorithm application domain. Research and use of various domain knowledge, design update strategy, improve the exploration and development ability of SI algorithm, enhance the stochastic optimization performance of SI algorithm[2-3].

In order to better verify the effectiveness of WHO algorithm,essay use CEC2019 test function to test the horse swarm optimization algorithm. CEC2019 benchmark function includes ten test functions, including unimodal function, multimodal function, hybrid function and composite function. Table 1 summarizes the characteristics of CEC2019 function, and Table 2 gives the parameter settings of each of the above algorithms.

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Aiming at the shortcomings of Mustang algorithm, the golden sine mechanismis introduced in the process of individual renewal, accelerate the convergence speed and solution accuracy of the algorithm. Experiments verify the effectiveness of other meta-heuristic algorithms ofWHOonCEC2019test functions. Experimental results show that WHO have higher solution accuracy and convergence speed than other algorithms[4-5].

2. WHO Algorithm

Horse swarm optimization algorithm (WHO) is a new natural heuristic optimization algorithm proposed in 2021, which comes from simulating the social life behavior of horses. The assumption in the Mustang algorithm is that (1) search space exploration is guaranteed by randomly selected leaders and the random movements of horses around them. (2) Because horses break away from the population and mate with horses from other populations, there is a high probability that they can solve the local optimal static problem. (3) The leader directs the horse to the desired area of the search space. (4) saves the best leader in each iteration and compares it with the best leader obtained at that time(optimal). (5) Mustang optimization algorithm is a gradient-free algorithm that regards the problem as a black box.

The Mustang optimization algorithm includes five main steps:

a). Create an initial group, form a horse herd and select leaders; b). Grazing and mating of horses; c). Lead and lead the group by the leader (stallion); d). Communicate and select leaders;

2.1 Population initialization

Similar to other optimization algorithms, population individuals are randomly initialized in the search range, and the leaders of the group are randomly selected at the beginning of the algorithm. In the subsequent stage, the leaders are selected according to the fitness (optimal fitness function) among the group members.

2.2 Grazing behavior

Foals usually spend most of their time grazing in the herd. In order to carry out grazing behavior, we think that stallions are the center of the grazing area, while other members of the herd search around the grazing center. Equation(1)can be used to simulate grazing behavior. Equation(1)causes team members to move and search around the leader at different radii.

$$\bar{X}_{i,G}^{j} = 2Z\cos(2\pi RZ)\times(Stallion^{j} - X_{i,G}^{j}) + Stallion^{j}, \qquad (1)$$

Where $X_{i,G}^{j}$ is the current position of group members (foals or mares), the position of stallions (group leaders), the adaptive mechanism calculated by equation (2), and the uniform random number in the range that causes the group to graze at different angles (360). Take 3.14, COS function through the combination of π and R , and $\bar{X}_{i,G}^{j}$ is the new position of group members when grazing.

$$P = \vec{R}_1 < TDR;\ IDX = (P == 0);\ Z = R_2 \Theta IDX + \vec{R}_3(\sim IDX), \qquad (1)$$

Where P is a vector consisting of 0 and 1, $\vec{R}_1$ and $\vec{R}_3$ are random vectors with a single form distribution in the range[0, 1], R_2 is a random number uniformly distributed in the range[0, 1], the IDX exponent of the random vector $\vec{R}_1$ satisfies the condition $(P == 0)$,TDR is an adaptive parameter, the value starts from 1, decreases during algorithm execution, and according to equation(3)The value of this parameter will reach 0 at the end of algorithm execution.

$$TDR = 1 - iter \times (\frac{1}{\max iter}), \qquad (2)$$

Where iter is the current iteration and maxiter is the maximum number of iterations of the algorithm.

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2.3 Mating Behavior of Horses

Compared with other animals, a unique behavior of horses is to separate foals from the group and mate them. The foals leave the herd before reaching puberty, the male foals join a single herd, and the female foals join another family group, reach puberty and find a mate. This separation is to prevent fathers from mating with daughters or siblings. In order to simulate the departure and mating behavior of horses, the same crossover operator as the mean crossover operator is applied to equation(4).

$$\begin{aligned} &X_{G,k}^{p} = \text{Crossover}(X_{G,i}^{q}, X_{G,j}^{z}) \quad i \neq j \neq k, p = q = \text{end} \\ &\text{Crossover} = \text{Mean} \end{aligned} \tag{3}$$

Where $X_{G,k}^{p}$ is the position of horse pin group k , horse p needs to leave group k and give its position to a horse whose parents have left group i and group j and have reached puberty. They are not related and have mated and reproduced. $X_{G,i}^{q}$ Indicates the position of the foal q in group i . After puberty, it will mate with horses z who leave the $X_{G,j}^{z}$ position in group j .

2.4 Group Leadership

The team leader must lead the group to a suitable place, which we think is the water source. The population needs to advance to the water source. Other groups move to this water source in the same way. Leaders compete for this water source so that groups can use it, while other groups are not allowed to use it until the other party leaves, and then each group goes to the water source and makes the same competitive comparison, with the strong occupying and the weak leaving. We calculate the distance of this method by equation(5).

$$\overline{Stallion_{G_i}} = \begin{cases} 2Z\cos(2\pi RZ)\times(WH - Stallion_{G_i}) + WH & if \ R_3 > 0.5 \\ 2Z\cos(2\pi RZ)\times(WH - Stallion_{G_i}) - WH & if \ R_3 \leq 0.5 \end{cases}, \tag{4}$$

Where $\overline{Stallion_{G_i}}$ represents the next position of the leader of the group i , WH is the position of the water source, $Stallion_{G_i}$ is the current position of the leader of the group i , Z is the adaptive mechanism for calculating the equation(2), R is a uniform random number in the range of[-2, 2], and π takes3.14.

2.5 Communication and Selection of Leaders

First, we randomly select leaders to keep the randomness of algorithm. In the later stage of the algorithm, leader is selected based on fitness. If the fitness of a group of members is better than the current leader, the position of the group leader and members will change according to the equation(6).And introduction Fig.1 for WOA.

$$Stallion_{G_i} = \begin{cases} X_{G,i} & if \ \ \cos t(X_{G,i}) < \cos t(Stallion_{G_i}) \\ Stallion_{G_i} & if \ \ \cos t(X_{G,i}) > \cos t(Stallion_{G_i}) \end{cases}, \tag{5}$$

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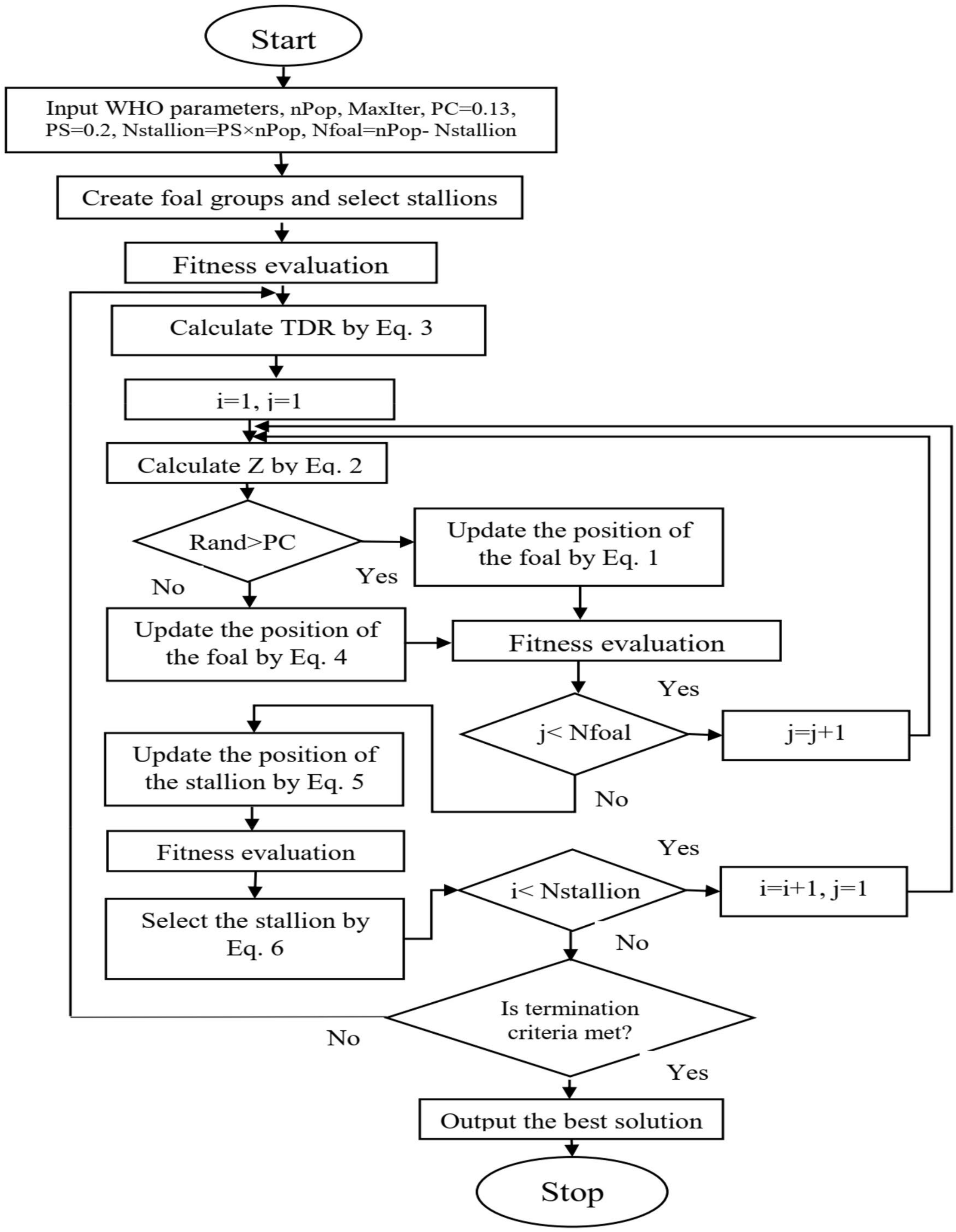

Figure 1: Flow chart of WHO algorithm

3. Simulation Experiment and Result Analysis

In order to better verify the effectiveness of WHO algorithm, we useCEC2019test function to test the horse swarm optimization algorithm. CEC2019 benchmark function contains ten test functions, including bimodal function, multi modal function, hybrid function and composite function. Tablesummarizes the characteristics of CEC2019 function, and Table2 gives parameter settings for each of the above algorithms.

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3.1 Numerical Experiment

Table 1: Characteristics of the CEC2019 function

	Uni-modal function	
	F1Shift and Rotational BendCigarFunction100	
	Multi-modal shift and rotation function	
F2	Shift Rotation Schwefel Function	1100
F3	Shift and rotation Lunacek Double grating function	700
F4	Extend Rosenbrock + Griewangk Function	1900
	Mixed function	
F5	Mixed function1 (N=3)	1700
F6	Mixed function2 (N=4)	1600
F7	Mixed function3 (N=5)	2100
	Compound function	
F8	Compound function1 (N=3)	2200
F9	Compound function2 (N=4)	2400
F10	Compound function3 (N=5)	2500

3.1.1 Algorithm Parameter Settings

When WHO is compared with other algorithms, the algorithm parameter settings are shown in Table 2. For fairness, all algorithms use the same experimental parameters, the population size is set to N50, the dimension ofCEC2019 function isDim20, and the maximum iteration times are tmax=50000. Considering the randomness of swarm intelligence algorithm, each algorithm runs independently for 10 times.

Table 2: Parameter Settings for WHO Al versus Other Comparison Algorithms

Algorithm	Parameter setting
General settings	Population size: N50 Maximum number of iterations: tmax=50000 Problem Dimension: Dim20 Number of independent runs:10
WOA	*a* variable linearly decrease from 2 to 0 (default)A 2linearly decrease from-1 to-2 (default)
SCA	a2(default)
GWO	*a* variable decreases linearly from 2 to 0 (default)
MFO	b1, *a* linearly decreases from-1 to-2 (default)
HHO	Beta1.5(Default)
WHO	Crossover rate: PC=0. 13 stallion rate(group number):PS=0. 2 Crossover=Mean
SSA	Leadership update probability is0.5
TSA	=1 and Pmax=4 (default)

3.1.2 Comparison of results obtained by WHO and comparison algorithm on CEC2019

The table3 shows that the WHO algorithm and other algorithms are independently run10times on10CEC2019reference functions, and the optimal value BEST, the worst value WORST and the average value MEAN, standard deviation Std. Dev, where the dimension of the function = 20. The best average is highlighted in bold.

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Table 3: WHO Compare the results obtained by the comparison algorithm on CEC2019

Function	Measure	WOA	SCA	GWO	MFO	HHO	SSA	TSA	**WHO**
F1	BEST	2.09×10^{3}	2.75×10^{3}	1.51×10^{2}	2.89×10^{-3}	0.00×10^{0}	3.28×10^{3}	2.80×10^{-14}	0.00×10^{0}
	WORST	4.87×10^{3}	2.07×10^{3}	6.26×10^{2}	1.46×10^{4}	0.00×10^{0}	4.36×10^{3}	1.08×10^{-10}	4.05×10^{2}
	MEAN	3.44×10^{3}	8.47×10^{3}	8.74×10^{1}	2.07×10^{3}	0.00×10^{0}	4.14×10^{3}	1.68×10^{-11}	7.29×10^{1}
	Std.Dev	1.00×10^{3}	5.76×10^{3}	1.92×10^{2}	4.40×10^{3}	0.00×10^{0}	3.99×10^{2}	3.57×10^{-11}	1.42×10^{2}
F2	BEST	5.43×10^{0}	7.98 55×10^{0}	2.20×10^{0}	1.32×10^{0}	2.21×10^{0}	9.87×10^{0}	2.19×10^{0}	1.85×10^{0}
	WORST	2.47×10^{1}	2.26×10^{1}	3.53×10^{0}	3.52×10^{0}	2.37×10^{0}	2.26×10^{1}	3.00×10^{0}	2.36×10^{0}
	MEAN	1.48×10^{1}	1.42×10^{1}	2.64×10^{0}	2.39×10^{0}	2.27×10^{0}	1.60×10^{1}	2.63×10^{0}	2.11×10^{0}
	Std.Dev	6.78×10^{0}	4.84×10^{0}	4.75×10^{-1}	7.55×10^{-1}	5.36×10^{-2}	4.72×10^{0}	3.88×10^{-1}	1.77×10^{-1}
F3	BEST	9.71×10^{0}	1.17×10^{1}	1.04×10^{1}	9.71×10^{0}	9.71×10^{0}	1.17×10^{1}	9.71×10^{0}	9.71×10^{0}
	WORST	1.17×10^{1}	1.17×10^{1}	1.22×10^{1}	1.17×10^{1}	9.71×10^{0}	1.18×10^{1}	1.07×10^{1}	1.17×10^{1}
	MEAN	1.07×10^{1}	1.17×10^{1}	1.16×10^{1}	1.04×10^{1}	9.71×10^{0}	1.17×10^{1}	9.99×10^{0}	1.15×10^{1}
	Std.Dev	1.05×10^{0}	1.01×10^{-2}	4.72×10^{-1}	9.48×10^{-1}	1.10×10^{-9}	3.25×10^{-2}	4.35×10^{-1}	6.32×10^{-1}
F4	BEST	2.19×10^{1}	5.31×10^{1}	2.09×10^{1}	1.93×10^{1}	3.50×10^{1}	3.93×10^{1}	4.14×10^{1}	3.98×10^{0}
	WORST	6.67×10^{1}	7.40×10^{1}	4.14×10^{1}	3.62×10^{1}	5.31×10^{1}	5.66×10^{1}	6.82×10^{1}	1.59×10^{1}
	MEAN	4.21×10^{1}	6.27×10^{1}	2.81×10^{1}	2.82×10^{1}	4.43×10^{1}	4.81×10^{1}	5.58×10^{1}	9.85×10^{0}
	Std.Dev	1.41×10^{1}	6.78×10^{0}	6.29×10^{0}	4.93×10^{0}	7.12×10^{0}	5.98×10^{0}	8.58×10^{0}	3.85×10^{0}
F5	BEST	3.72×10^{-1}	2.37×10^{1}	1.55×10^{0}	2.22×10^{-2}	6.84×10^{-1}	4.87×10^{0}	4.54×10^{0}	7.78×10^{-5}
	WORST	8.45×10^{-1}	3.90×10^{1}	4.69×10^{0}	8.92×10^{0}	1.43×10^{0}	2.31×10^{1}	3.23×10^{1}	7.92×10^{-2}
	MEAN	5.90×10^{-1}	2.96×10^{1}	2.40×10^{0}	1.04×10^{0}	9.85×10^{-1}	1.43×10^{1}	1.45×10^{1}	3.06×10^{-2}
	Std.Dev	1.62×10^{-1}	5.81×10^{0}	9.26×10^{-1}	2.78×10^{0}	2.67×10^{-1}	5.50×10^{0}	1.06×10^{1}	2.42×10^{-2}
F6	BEST	3.24×10^{0}	7.46×10^{0}	2.48×10^{0}	2.60×10^{0}	3.31×10^{0}	6.62×10^{0}	5.94×10^{0}	1.25×10^{-3}
	WORST	8.91×10^{0}	1.00×10^{1}	5.86×10^{0}	6.83×10^{0}	8.22×10^{0}	9.95×10^{0}	8.66×10^{0}	1.81×10^{0}
	MEAN	6.69×10^{0}	8.75×10^{0}	3.50×10^{0}	5.08×10^{0}	6.07×10^{0}	8.29×10^{0}	7.32×10^{0}	8.52×10^{-1}
	Std.Dev	1.87×10^{0}	8.57×10^{-1}	1.06×10^{0}	1.44×10^{0}	1.30×10^{0}	1.21×10^{0}	9.96×10^{-1}	7.06×10^{-1}
F7	BEST	6.35×10^{2}	9.24×10^{2}	8.14×10^{2}	4.85×10^{2}	5.44×10^{2}	1.26×10^{3}	1.48×10^{3}	2.44×10^{2}
	WORST	1.50×10^{3}	1.78×10^{3}	1.51×10^{3}	1.31×10^{3}	1.26×10^{3}	1.75×10^{3}	2.03×10^{3}	9.07×10^{2}
	MEAN	1.04×10^{3}	1.50×10^{3}	$1. 13\times10^{3}$	8.26×10^{2}	7.99×10^{2}	1.52×10^{3}	1.82×10^{3}	6.14×10^{2}
	Std.De	2.98×10^{2}	2.49×10^{2}	2.41×10^{2}	2.79×10^{2}	2.10×10^{2}	1.71×10^{2}	1.77×10^{2}	2.02×10^{2}
F8	BEST	3.50×10^{0}	3.63×10^{0}	2.52×10^{0}	3.21×10^{0}	3.51×10^{0}	2.87×10^{0}	3.55×10^{0}	2.09×10^{0}
	WORST	3.80×10^{0}	3.86×10^{0}	3.65×10^{0}	3.67×10^{0}	3.96×10^{0}	3.74×10^{0}	3.98×10^{0}	3.38×10^{0}
	MEAN	3.61×10^{0}	3.75×10^{0}	2.99×10^{0}	3.46×10^{0}	3.71×10^{0}	3.37×10^{0}	3.86×10^{0}	2.72×10^{0}
	Std.Dev	1.10×10^{-1}	7.08×10^{-2}	3.58×10^{-1}	1.31×10^{-1}	1.51×10^{-1}	2.38×10^{-1}	1.65×10^{-1}	3.85×10^{-1}
F9	BEST	3.23×10^{-1}	1.28×10^{0}	1.96×10^{-1}	1.40×10^{-1}	4.22×10^{-1}	4.42×10^{-1}	2.41×10^{-1}	8.16×10^{-2}
	WORST	7.31×10^{-1}	1.82×10^{0}	4.65×10^{-1}	4.49×10^{-1}	9.95×10^{-1}	1.05×10^{0}	6.37×10^{-1}	2.74×10^{-1}
	MEAN	5.17×10^{-1}	1.58×10^{0}	3.00×10^{-1}	2.82×10^{-1}	6.05×10^{-1}	8.08×10^{-1}	4.12×10^{-1}	1.49×10^{-1}
	Std.Dev	1.26×10^{-1}	1.65×10^{-1}	6.86×10^{-2}	1.15×10^{-1}	1.75×10^{-1}	2.00×10^{-1}	1.26×10^{-1}	6.38×10^{-2}
F10	BEST	2.00×10^{1}	2.02×10^{1}	2.02×10^{1}	2.00×10^{1}	2.00×10^{1}	2.03×10^{1}	2.03×10^{1}	2.00×10^{1}
	WORST	2.02×10^{1}	2.05×10^{1}	2.05×10^{1}	2.04×10^{1}	2.02×10^{1}	2.06×10^{1}	2.05×10^{1}	2.00×10^{1}
	MEAN	2.01×10^{1}	2.04×10^{1}	2.04×10^{1}	2.00×10^{1}	2.01×10^{1}	2.04×10^{1}	2.04×10^{1}	2.00×10^{1}
	Std.Dev	5.02×10^{-2}	9.26×10^{-2}	6.63×10^{-2}	1.34×10^{-1}	4.20×10^{-2}	8.05×10^{-2}	6.68×10^{-2}	6.94×10^{-4}

The Table 3 shows that compared with other algorithms, WHO has significant advantages in solving CEC2019 reference functions

3.2 Convergence analysis

Convergence analysis is an important test to evaluate the stability of optimization algorithms. Therefore, this paper analyzes the WHO algorithm and compares it with other competitive algorithms. fig.2 shows the convergence curve of WHO algorithm and its corresponding CEC2019 function. It can be clearly seen from the figure that the WHO algorithm has reached a stable point for all functions. In addition, for all CEC2019 benchmark functions, through a small number of function evaluations, this algorithm can reach the lowest average of global solutions faster than other algorithms[6-7].

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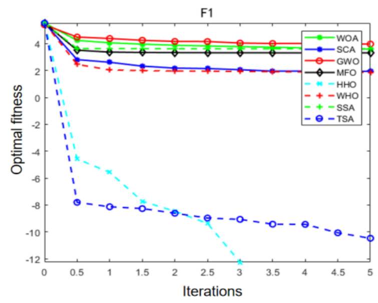

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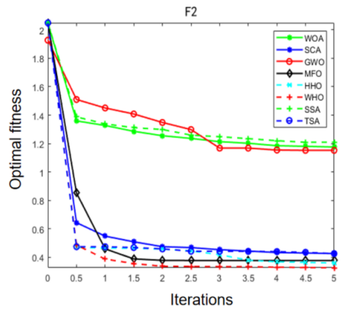

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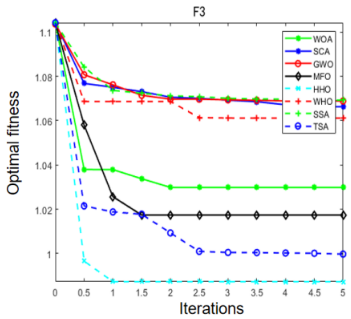

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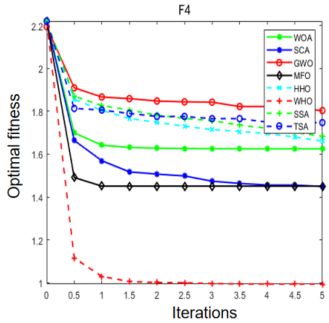

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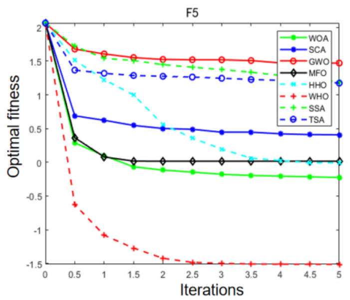

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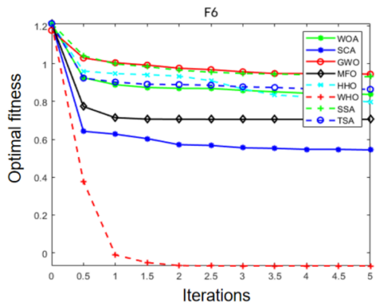

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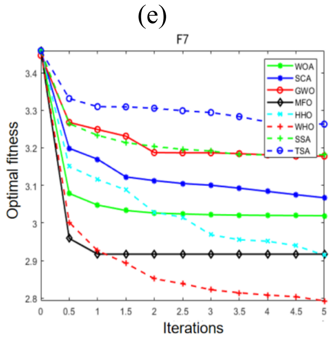

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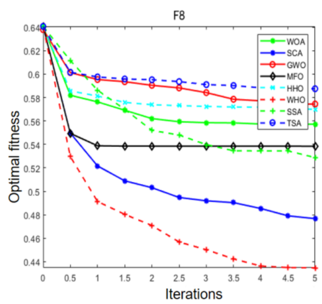

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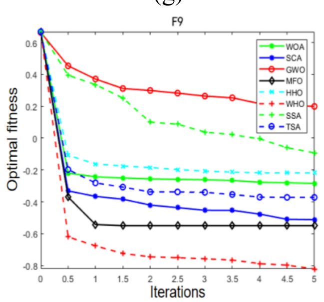

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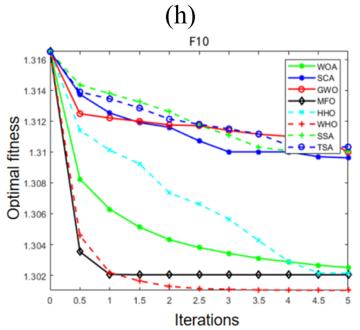

(j)

Figure 2: Function Average Convergence

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4. Conclusions

This paper reviews the herd optimization algorithm and simulates the behavior horses in nature. The characteristic of this algorithm is the special and unique mating behavior of horses. So that members of a family can't mate with each other. When puberty comes, they will leave the group and join other groups to find their own spouses. Another important behavior is herding, grouping around stallions or leaders. In order to improve the effectiveness of the algorithm, adaptive parameters are used to help solve complex problems better, and the effectiveness, unimodal, multimodality, mixing and recombination of the algorithm are verified. In order to verify the effectiveness of WHO algorithm, a group of experiments were designed. The first group of experiments verified the effectiveness of WHO and other meta heuristic algorithms on CEC2019 test function. The experimental results show that WHO has higher precision and convergence speed than other algorithms. The convergence curve also further shows that WHO has higher stability.

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