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An enhanced slime mould algorithm

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Abstract

In order to solve the problems of original Slime mould algorithm (SMA), such as easy to be trapped in local optima, slow convergence speed and low optimization accuracy, this paper proposes an enhanced slime mould algorithm (ESMA) based on Levy flight. First, a Tent chaotic map is used to initialize the population and enrich the diversity of the population; then, the Levi flight strategy is introduced to act on the current optimal position to reduce the probability of the algorithm falling into the local optimum and improve the global search ability of the algorithm. In the experiment, nine test functions are used to compare the convergence speed, accuracy and stability of the proposed ESSA with some basic intelligent algorithms. The experimental results show that the ESMA proposed in this paper has better convergence performance, and it also verifies that ESMA has better robustness.

Keywords

Slime mould algorithm, Tent chaotic map, Levy flight, Test function.

1. Introduction

Meta-heuristic algorithm is a new technology used to solve multi-dimensional and complex optimization problems in this century[1]. It mainly simulates the behavior and habits of animals in nature to optimize the solution. For example, Butterfly Optimization Algorithm (BOA)[2], Moth-Flame Optimization Algorithm (MFO)[3] and Whale Optimization Algorithm (WOA)[4], etc., which have been widely used in power dispatch and image Processing, economic load dispatch, photovoltaic cell parameter estimation and feature selection and other fields[5-9].

Slime Mould Algorithm (SMA) is a novel swarm intelligence algorithm proposed by Li et al.[10] in 2020, mainly by simulating the foraging behavior and morphological changes of slime molds. Like other inspiring intelligent algorithms, SMA tends to be trapped in local optima. Given these shortcomings, many scholars have made many improvements. Gholami et al. [11] introduced a mutation mechanism to get rid of local minima and increase the diversity of the population. Qais et al. [12] introduced the squared exponent in the leader position update formula to improve the convergence speed of the algorithm. Teng et al. [13] proposed a gray wolf optimization algorithm based on Tent map, which generated the initial population through chaotic mapping, which increased the diversity of the population. Mandal et al. [14] enhanced the diversity of the particle swarm algorithm population by introducing crazy operators. Wang et al. [15] introduced adaptive inertia weights in the speed formula, so that the bats can dynamically adjust the speed during the search process.

In order to solve the problems of SMA algorithm such as slow convergence speed and insufficient optimization precision, this paper proposes an enhanced slime mould algorithm(ESMA). The paper utilizes the ergodicity and randomness of Tent mapping to initialize the sparrow population primarily so that the sparrow population spreads across the entire search space, thereby enhancing species diversity. The Levy flight mechanism is used to

expand the search range of the current optimal individual and increase the probability of the algorithm jumping out of the local optima. In the experiment, by comparing some performance test indicators of the proposed ESSA and some basic intelligent algorithms, the effectiveness and superiority of SMA are verified.

2. Slime mould algorithm

The SMA algorithm is mainly composed of three stages, namely the approaching food stage, the surrounding food stage and the Grabble food stage.

2.1. Approaching food stage

$$X(t+1)=\begin{cases} X_b(t)+vb\left(W\times X_A(t)-X_B(t)\right), r<p \\ vc\times X(t), r\geq p \end{cases} \tag{1}$$

where, $X(t+1)$ and $X(t)$ describe the positions of slime molds at the $t+1$ and t iterations, respectively, and $X_b(t)$ represents the position with the highest food concentration at the t iteration (the best position), $X_A(t)$ and $X_B(t)$ represent two slime mold individuals randomly selected in the t th iteration; $vb\in[-2,2]$; $a=arctanh(1-(t/T))$, t is the current number of iterations; T is the maximum number of iterations; the range of v is linearly decreasing from 1 to 0; r is a random number between 0 and 1; $p=\tan h(|S(i)-DFD|),(i=1,2,\ldots,N)$; $S(i)$ represents the ith individual slime mold fitness value, DFD represents the optimal fitness value in all iterations; N represents the population size of slime mold; W represents the weight of slime mold, and its formula is as follow:

$$\begin{cases} 1+r\times log\left(\dfrac{bF-S(i)}{bF-wF}+1\right), \text{ condition} \\ 1-r\times log\left(\dfrac{bF-S(i)}{bF-wF}+1\right), \text{ others} \end{cases} \tag{2}$$

$$\text{SortIndex}=sort(S) \tag{3}$$

where condition represents the individuals whose fitness value ranks in the top half of the group, and represents the optimal fitness value and the worst fitness value in the current iteration, respectively, and represents the sequence of the sorted fitness values.

2.2. Surrounding food phase

$$X(t+1)=\begin{cases} rand\times(ub-lb)+lb, r<z \\ X_b(t)+vb\left(W\times X_A(t)-X_B(t)\right), r<p \\ vc\times X(t), r\geq p \end{cases} \tag{4}$$

where $rand$ and r represent the random value generated from 0 to 1, ub and lb respectively represent the upper and lower bounds of the search space; z are used to weigh the parameters of the search and development stages, and $z=0.03$.

2.3. Grabble food

The value of oscillates randomly between $[-a,a]$ and gradually approaches 0 as the iterations increase. The value of vc oscillates between [-1,1] and tends to zero eventually.

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3. Enhaned Slime mould algorithm

3.1. Tent chaotic map

Aiming at the loss of group diversity in the late optimization stage of the SMA algorithm, which increases the probability of falling into local extremes and causes insufficient convergence accuracy, this paper uses Tent chaotic map to initialize the muold population, the expression is as follows:

$$x_{t+1}=\begin{cases}\mu x_t, & x_t<0.5\\ \mu(1-x_t), & x_t\geqslant 0.5\end{cases} \tag{5}$$

where $\mu\in(0,2]$ represents the chaos coefficient, when the value is larger, the chaos is considered to be better; therefore, this paper $\mu=2$; $t=1,2,\cdots d$ is the chaotic variable number.

The Bernoulli transformation is as follows:

$$x_{t+1}=(2x_t)\bmod 1 \tag{6}$$

3.2. Levy flight

Considering that SMA is prone to be trapped in local optima, Levy flight is introduced to make the current optimal sparrow individual mould continue to wander, thereby expanding the search range of the algorithm and improving the global optimization ability of the algorithm. The updated location is as follows:

$$X(t+1)=X_b(t)+X_b(t)\times Levy,\ r<p \tag{7}$$

The Levy flight mechanism [16] is as follows:

$$Levy(x)=0.01\times\frac{r_3\times\sigma}{|r_4|^{(1/\xi)}} \tag{8}$$

where $r_3,r_4\in[0,1]$ are random numbers; $\xi=1.5$; the formula of σ is as follows:

$$\sigma=\left(\frac{\Gamma(1+\xi)\times sin(\pi\xi/2)}{\Gamma((1+\xi)/2)\times\xi\times 2^{((\xi-1)/2)}}\right)^{(1/\xi)} \tag{9}$$

where $\Gamma(x)=(x-1)!$

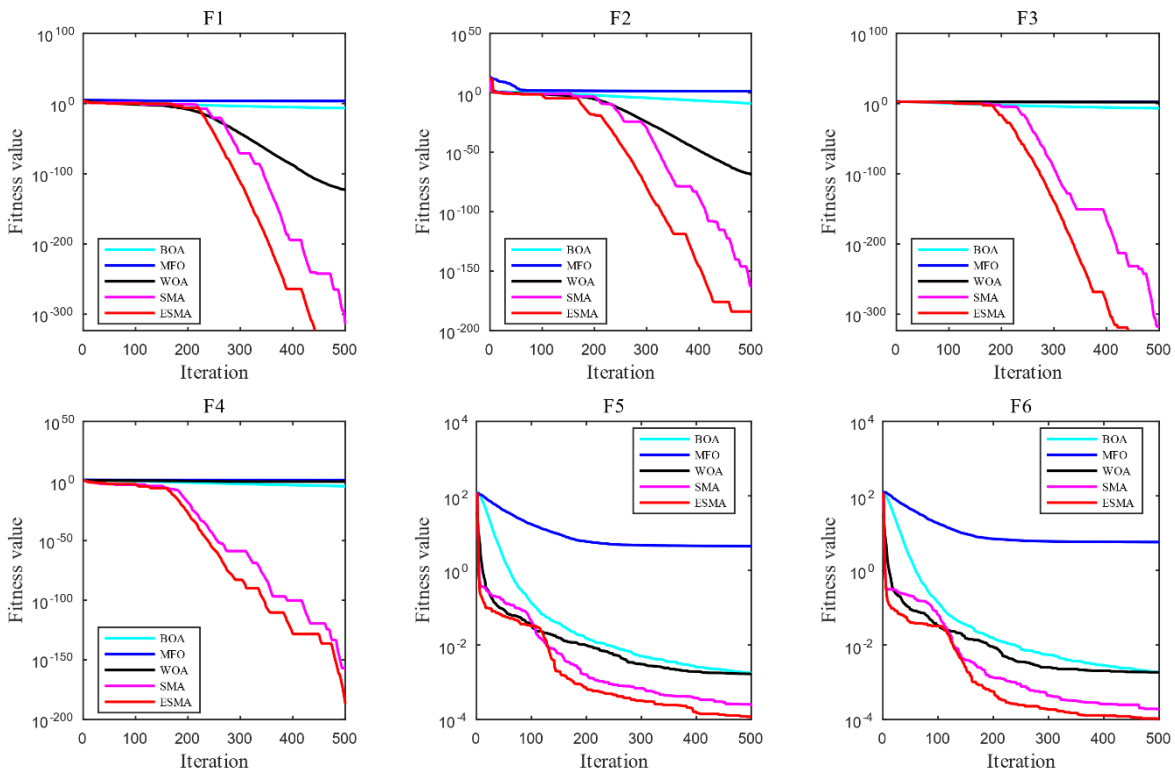
4. Experimental results

In order to verify the effectiveness of the ESMA proposed in this paper, 12 representative functions are selected for testing, as shown in Table 1. The performance of several intelligent algorithms of BOA, MFO, WOA, and SMA are compared. To ensure the fairness of comparison, the population size of the above 6 algorithms is 30, the dimension dim=30, and the maximum number of iterations is 500. To describe the convergence of various algorithms in detail, it is achieved through the convergence curve. The above five algorithms are independently run 30 times under the above conditions, and the convergence curve in Figure 1 is obtained. When the curve is no longer displayed as the number of iterations increases, it means that the algorithm has obtained the theoretical optimal solution 0.

Table1 Test function

Function	Search range	Fmin
$F_1(x)=\sum_{1}^{n}x_i^2$	[-100,100]	0

$F_2(x)=\sum_{i=1}^{n}\lvert x_i\rvert+\prod_{i=1}^{n}\lvert x_i\rvert$	[-10,10]	0
$F_3(x)=\sum_{i=1}^{n}\left(\sum_{i=1}^{n}\lvert x_i\rvert\right)^2$	[-100,100]	0
$F_4(x)=max_i\left\{\lvert x_i\rvert,-1<i<n\right\}$	[-100,100]	0
$F_5(x)=\sum_{i=1}^{n}\left(\left[x_i+0.5\right]\right)^2$	[-100,100]	0
$F_6(x)=\sum_{i=1}^{n}ix_i^4+random[0,1)$	[-1.28,1.28]	0
$F_7(x)=\sum_{1}^{n}ix_i^2$	[-10,10]	0
$F_8(x)=\sum_{i=1}^{n-1}\left[100\left(x_{i+1}-x_i^2\right)^2+\left(x_i-1\right)^2\right]$	[-30,30]	0
$F_9(x)=\sum_{i=1}^{n}x_i^2+\left(\sum_{i=1}^{n}0.5ix_i\right)^2+\left(\sum_{i=1}^{n}0.5ix_i\right)^4$	[-5.12,5.12]	0



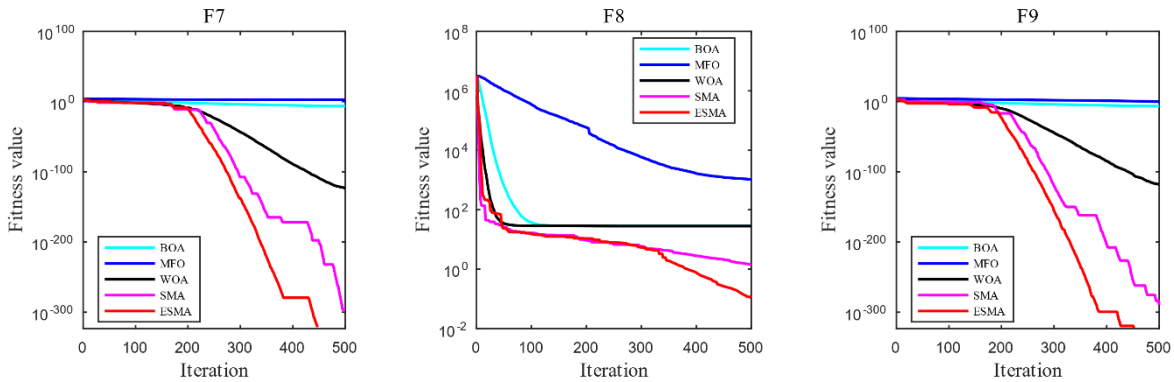


Figure 1:Convergence curve of 5 models

It can be clearly seen from Figure 1 that when solving the test function F1-12, SMA has obvious advantages in convergence speed and convergence accuracy compared to the three traditional intelligent algorithms of BOA, MFO, and WO except for F12 and F10. Shows that SMA has certain performance advantages. The ESMA proposed in this paper is significantly better than the original SMA in terms of convergence speed and optimization accuracy. When solving the test functions F1, F3, F7, F9, F10, and F12, ESAM can find the optimal value 0, which shows its good search performance.

In order to be able to clearly compare the optimization accuracy and stability of the algorithms, four performance indicators of Min, Max, Mean, and Std are selected for comparison. Min, Max, and Mean represent the optimal value, worst value and average value of fitness value, respectively. Std represents the variance of the fitness value and can also characterize the stability of the algorithm.

Table 2 Comparisons of ESMA and other algorithms

Fun	Alogorithm	Min	Max	Mean	Std
	BOA	1.51E-07	4.57E-07	3.36E-07	6.83E-08
	MFO	6.10E-01	3.00E+04	4.01E+03	6.75E+03
F1	WOA	2.47E-132	5.61E-122	2.85E-123	1.08E-122
	SMA	0.00E+00	6.35e-313	2.14E-314	0.00E+00
	ESMA	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	BOA	5.83E-12	2.32E-08	1.26E-09	4.26E-09
	MFO	1.50E-01	9.00E+01	2.95E+01	2.51E+01
F2	WOA	6.89E-76	3.58E-68	2.65E-69	8.09E-69
	SMA	9.79E-298	7.14E-162	2.38E-163	0.00E+00
	ESMA	0.00E+00	2.93E-183	9.77E-185	0.00E+00
	BOA	5.24E-08	3.14E-07	1.75E-07	5.90E-08
	MFO	3.78E+01	4.07E+02	1.97E+02	1.19E+02
F3	WOA	3.53E-02	2.70E+02	9.68E+01	7.67E+01
	SMA	0.00E+00	1.46E-316	4.87e-318	0.00E+00
	ESMA	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	BOA	3.03E-05	6.52E-05	4.67E-05	7.46E-06

	MFO	4.84E+00	8.33E+00	6.97E+00	9.55E-01
F4	WOA	3.36E-05	3.55E+00	3.82E-01	7.73E-01
	SMA	4.48E-310	2.04E-156	6.78E-158	3.72E-157
	ESMA	4.90E-324	3.02E-186	1.56E-187	0.00E+00
	BOA	4.49E+00	6.30E+00	5.35E+00	3.90E-01
	MFO	5.89E-03	1.10E+02	1.97E+01	3.95E+01
F5	WOA	4.61E-02	1.66E-01	8.59E-02	3.24E-02
	SMA	1.08E-05	5.89E-03	1.67E-03	1.36E-03
	ESMA	2.66E-06	2.04E-03	6.46E-04	4.61E-04
	BOA	3.51E-04	3.17E-03	1.87E-03	8.17E-04
	MFO	7.12E-02	3.24E+01	5.77E+00	9.65E+00
F6	WOA	2.22E-05	1.15E-02	1.84E-03	2.35E-03
	SMA	1.49E-05	7.28E-04	1.83E-04	1.79E-04
	ESMA	7.16E-06	3.35E-04	1.02E-04	8.27E-05
	BOA	1.59E-07	4.82E-07	2.69E-07	7.22E-08
	MFO	1.70E-01	2.00E+03	4.50E+02	5.85E+02
F7	WOA	9.89E-134	1.28E-122	8.52E-124	3.00E-123
	SMA	0.00E+00	1.97E-295	6.59E-297	0.00E+00
	ESMA	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	BOA	2.88E+01	2.90E+01	2.89E+01	2.65E-02
	MFO	4.29E+01	1.01E+04	1.05E+03	2.56E+03
F8	WOA	2.77E+01	2.87E+01	2.81E+01	3.12E-01
	SMA	7.36E-05	2.78E+01	1.38E+00	5.01E+00
	ESMA	9.84E-04	4.05E-01	1.09E-01	1.04E-01
	BOA	1.51E-07	4.44E-07	2.55E-07	7.36E-08
	MFO	7.29E-02	2.73E+00	7.68E-01	7.17E-01
F9	WOA	4.30E-135	4.28E-117	1.43E-118	7.81E-118
	SMA	0.00E+00	3.11E-289	1.04E-290	0.00E+00
	ESMA	0.00E+00	0.00E+00	0.00E+00	0.00E+00

It can be seen from Table 2 that the four performance indicators of Min, Max, Mean, and Std can all perform best, when the test functions F1-F9 are solved for 30 times. Among them, in F1, F3, F7, and F9, the values of the four performance indicators are all 0, and the algorithm can get the theoretical optimal solution 0 and shows good stability. In F2, Min is 0, which means that the optimal solution can be obtained at a certain number of solving times, and Std is 0, which means that it can also show excellent stability when solving F2. Similar to F2, solving F4 in ESMA can also show excellent stability. Although it failed to obtain 0 in solving F5, F6, and F8, when compared with BOA, MFO, WOA, SMA has a certain improvement in convergence accuracy and stability. Therefore, the experiment generally verifies that the algorithm shows good optimization accuracy and robustness in solving the test functions F1-F9.

In summary, Figure 1 and Table 2 can show that performance of ESAM in optimization convergence accuracy, convergence speed and robustness is due to other algorithms, mainly because the introduction of Tent chaotic mapping increases the diversity of the algorithm and reduces the probability of the algorithm falling into premature convergence, In addition, the using of Levy flight improves the global optimization ability of the algorithm.

5. Conclusion

This paper proposes an enhanced sparrow search algorithm based on Levy flight. Tent chaotic map is introduced into the population initialization to make the population evenly distributed and increase the diversity of the population, thus improving the global optimization ability and convergence speed of the algorithm. Through experimental tests, the ESMA and BOA, MFO, WOA, SMA algorithms are comprehensively compared in terms of convergence speed, accuracy, and stability among the 9 classic test functions. The experimental results verify that the local development of ESMA proposed in this article has better performance, and it is also prove the effectiveness and reliability of the improvement strategy. The following work considers applying SCSSA to the steelmaking process to solve practical problems.

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