Seven-spot Ladybird Optimization Algorithm Based on Bionics Principle

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Abstract. For solving the problems of modern intelligence algorithms such as slow convergence and low precision, a new algorithm based on bionics principle has been proposed which is inspired by the foraging behavior of seven-spot ladybirds in the nature. By analyzing the bionic principle of Seven-spot ladybird Optimization(SLO), we simulate the region search pattern of predation of seven-spot ladybirds ,combining fast extensive search with careful and slow intensive search of the ladybirds,meanwhile we use three kinds of evaluation information to evaluate the solutions one by one ,then the exploration and local approximation in the SLO are balanced. Next,in this paper we analyze the SLO theoretically by mathematics, presenting its specific process and proving the feasibility of SLO. The results based on a set of widely used benchmark functions show that Seven-spot ladybird can converge fast and yield distributed solutions with higher precision.

Keywords: bionics principle,Seven-spot Ladybird Optimization,region search pattern,feasibility analysis ,function optimization

1. Introduction

In the mid-1950s, people founded bionics inspired by the mechanism of biological evolution, and explored a class of heuristic algorithmwhich called intelligent bionic algorithmwith the help of bionic principles.The basic idea of this algorithm is derived from a natural phenomenon or a biological behavior of the simulation.In the existing bionics algorithms, the literature [1] proposed a particle swarm optimization algorithm by simulating the foraging behavior of the birds in the nature(Particle Swarm Optimization, PSO); In the literature [2] , Artificial Bee Colony (ABC) is proposed by simulating the breeding of bees and taking honey. In [3] , the Harmony Search (HS) algorithm is proposed by simulating the principle of a musical performance.There are also some algorithms proposed by some scholarsbased on some animal habits boldlysuch as Chicken Swarm Optimization [4] , Cockroach Swarm Optimization [5] and Mosquito Host-Seeking algorithm [6].Compared with the traditional optimization algorithms, this kind of algorithms does not rely on the nature of the objective function and the limitation of the search space which is easy to realize by programming. Moreover,it is suitable for solving nonlinear problems that traditional methods can not solve and have been widely used in engineering [7-8] . When dealing with the complex problems with multi-dimensions and high-peaks, some of the bionics algorithms usually have a number of problems such as easy to fall into local optimum, poor solution quality and premature convergence and so on .

In this paper, a new intelligent algorithm named Seven-spot Ladybird Optimization (SLO) is proposed based on the predation habit of seven-spot ladybirds. This algorithm makes full use of the group wisdom of the ladybirds. Moreover , the SLO uses a wide area search method with fast positioning when ladybrids are looking for prey and a slow circuitous local search method when ladybirds have found preies .The two methods are combined in order to enhance the search ability and convergence of the SLO.The validity of the algorithm is analyzed by using testing functions.

2. Bionic Principles of the SLO

In the process of searching for preies also known as aphids, the predation method of seven-spots ladybirds has a great breadth and depth, while they often use their visual and olfactory cues to locate prey. To find prey, this kind of insects often turns its head to the left and right alternately,rarely crawling in line and its motion trajectory is staggered. The above-mentioned behavior is called wide-area search. Once preying on their aphids, the ladybirds will reduce search speed while in order to enhance the efficiency of the search,they will increase detour of the route that is around the prey. This behavior is called a geographically centralized search, also known as local search[9].If the predation rate in a certain region is lower than a threshold value or the time between two predation intervals exceeds the giving-up time, the ladybirds will move themselves from the local search to the wide-area search, flying away to a new area, this process is called migration. The giving-up time is defined as the longest time that the ladybids can wait for after the last time predation to leave the area [10].The specific predation process of the ladybirds is shown in Fig1. As the aphids are distributed in groups and they almost have no ability to escape, so behaviors of seven-spot ladybirds which combine local with wide-search method can greatly improve the predation efficiency.

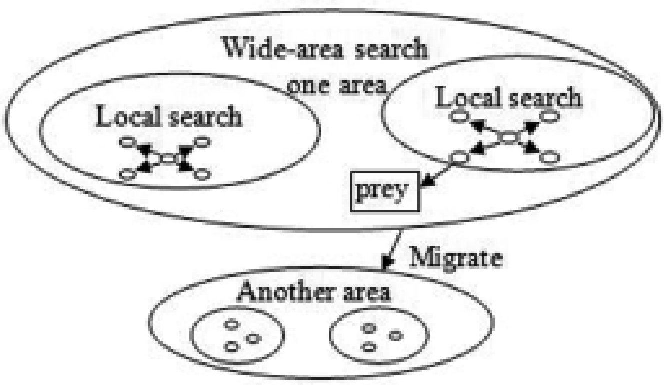


Figure.1 A predation process of Seven-spots ladybirds

Seven-spot Ladybird Optimization is a kind of intelligent optimization algorithm which is constructed by simulating the predation behavior of seven-spot ladybirds, where the specific bionic principle is: seven-spot ladybirds are simulated as feasible solutions in search space; the search method of the partition search mechanism with the combination of local and wide area in the predation process of the ladybirds is simulated into the search process of the algorithm; the location of the ladybirds during foraging is simulated as the objective function of solving the problem; the ladybirds individual survival of the fittest in the nature is simulated into a process of a better solution instead of poor solution in the algorithm, so as to achieve the purpose of searching for optimal solution from space.

3. Seven-Spot Ladybird Optimization Algorithm

3.1 Specific introduction of SLO algorithm

Searching optimization of the algorithm is composed of two methods: local search method and wide area search methods while each search space is divided into sub-spaces at the beginning of the search;the ladybirds are always close to the global optimal solution noted as g_{best} in the solution space and each ladybird will produce its own optimal solution noted as p_{best} in the search process at the same time; since the search space is divided into several subspaces, each subspace will produce a subspace historical optimal solution noted as l_{best} when the subspace is searched by the ladybird. Through the comparison of its current position noted as $present$、l_{best}、p_{best} and g_{best} , the individual updates the next step and finally achieves the purpose of optimization.

For a ladybird in a D-dimensional space, suppose t represents number of current iterations, position of the ladybird is marked as $X_i^t \ni (X_{i1}{}^t, X_{i2}{}^t, X_{i3}{}^t, \ldots, X_{iD}{}^t$; its speed is marked as $V_i \ni (V_{i1}, V_{i2}, V_{i3}, \ldots, V_{iD}$ .The updating formula of the location for ladybird i is,

$$X_i(t+1) = X_i(t) + V_i(t) \quad (1)$$

Where, $V_i(t)$ represents the current speed, $X_i(t)$ represents the current position.

The search methods are divided into local search and wide area search, if the ladybird made a wide area search before, then it will make a local search in this cycle.When the local search is completed, the ladybird will convert itself into a wide area search, so the updating formula of the ladyird in the local search speed is,

$$V_i\left(t\right) = c \times r_1 \times (pbest_i(t) - X_i(t)) + \varepsilon_1 \quad (2)$$

The updating formula of the ladyird in the wide area search speed is,

$$V_i\left(t\right) = c \times r_2 \times (lbest_i(t) - X_i(t)) + \varepsilon_2 \quad (3)$$

Where, r_1、r_2 are random numbers in the [0,1] which obey the uniform distribution so as to increase the randomness of the search; c is a learning coefficient so as to adjust the step length and direction; ε_1、ε_2 are two relatively small random numbers.

If the position has not been improved after a certain cycle, a new solution is substituted for the position near the global optimal solution according to Eq. 4.

$$x'_{i,j} = x_{gbest,j} + \phi\omega \quad (4)$$

Where, ω is the neighborhood of the global optimal solution g_{best} , ϕ is a correction value which is the random number of the interval [-1,1].

The basic flow of the SLO is shown in Fig.2.

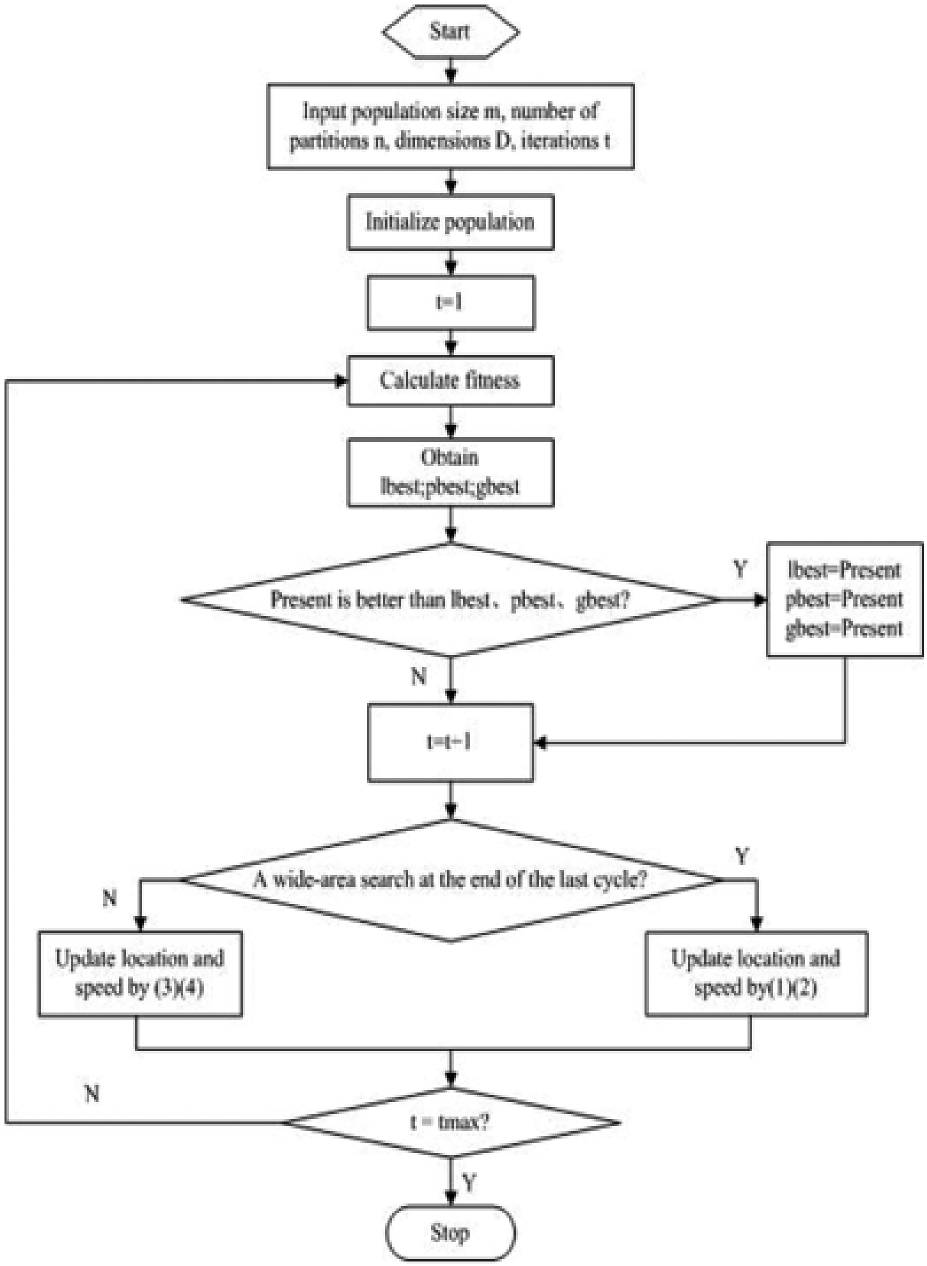
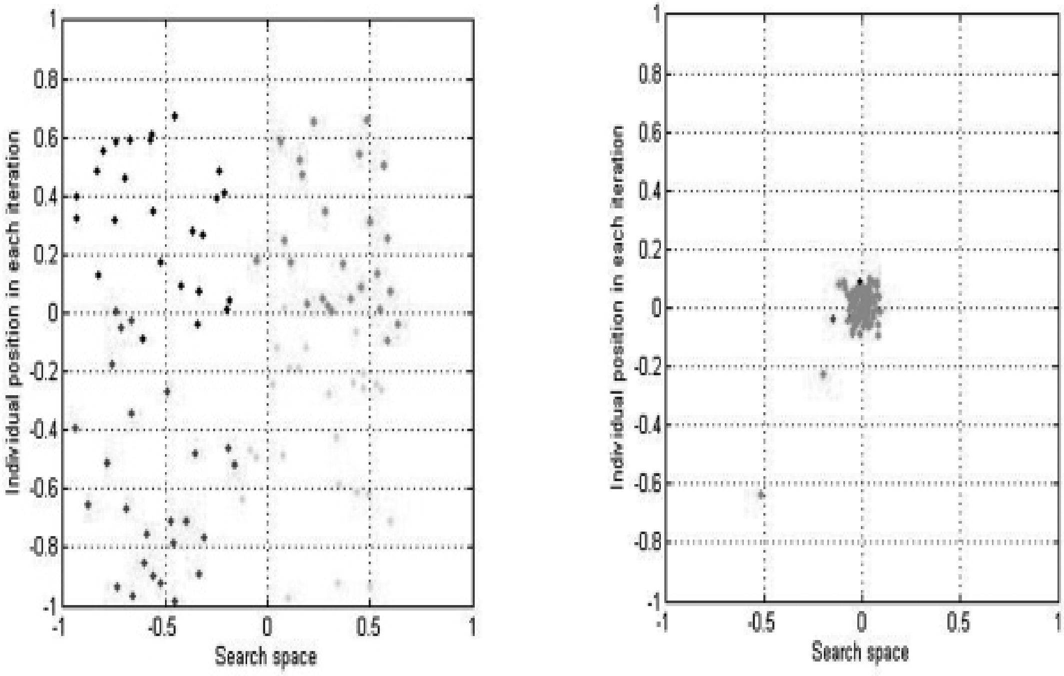


Figure.2 Flow chart of the SLO

3.2 The feasibility analysis of SLO algorithm

In order to analyze feasibility and observe the optimal effect of the algorithm intuitively, this paper selected *Rastrigin* function to compare its position at the initial and the end after 500 cycles in 2-dimensions where the specific operating principle is: the initial individual position of the algorithm marked as $X_i^t \ni (X_{i1}^t, X_{i2}^t, X_{i3}^t, \ldots, X_{iD}^t$ is a random number between [0,1]. As the number of iterations increases, the individual positions in the population move in the direction of the optimization of the function values according to the SLO steps. The results of the comparison are shown in Figure 4 where 4 (a) and 4(b) show the initial and final positions respectively of the individual of each search space.



(a)Initial distribution of individual positions (b) Final distribution of individual positions

Figure.3 Comparison of the operation results of SLO

It can be seen from Fig.3 that the individual distribution of the search space at the initial time of the optimization is a mess,while it obeys some rules:seven-spot ladybirds are clustered,individuals are closely linked but they are not in collision,which indicates that the algorithm is parallel and easy to share with the population information.Since the test function has a global optrimal value of 0 near($0,0,\cdots,0$),the vast majority of members of the ladybirds are distributed near $(0,0)$ as the algorithm stops which indicates the feasibility of the SLO.

4. Simulation Experiment and Analysis

Six typical testing functions as shown in Table 1 are used to analyze the performance of SLO while compared with PSO, ABC and HS , the basic parameters those algorithms used are set as shown in Table 2. The simulation platform is Windows XP, and the simulation software is Matlab2014 (a).

Table 1 Typical testing functions

Name	Expression	Type	Range	Minimum
Griewank	$f_1(x) = \frac{1}{4000}\sum_{i=1}^{n}(x_i)^2 - \prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}}) + 1$	Multi-modal	[-600,600]	0
Ackley	$f_2(x) = -20e^{-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}} - e^{\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)} + 20 + e$	Multi-modal	[-32,32]	0

Rastrigin	$f_3(x) = \sum_{i=1}^{n} x_i^2 - 10\cos(2\pi x_i) + 10$	Multi-modal	[-10,10]	0
Salomon	$f_4(x) = -\cos 2\pi\sqrt{\sum_{i=1}^{n} x_i^2} + 0.1\sqrt{\sum_{i=1}^{n} x_i^2} + 1$	Multi-modal	[-5,5]	0
Schwefel's	$f_5(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	unimodal	[-10,10]	0
Sphere	$f_6(x) = \sum_{i=1}^{n} x_i^2$	unimodal	[-100,100]	0

Table 2 Testing parameters of each algorithm

Algorithm	PopulationSize(N)	Maxium Iterations (M)	Dimension(D)
SLO	25	500	D=10;30;50
PSO	50	500	
ABC	50	500	
HS	50	500	

To fully reflect the performance of the algorithm, four algorithms are run for 30 times in D=10, 30, 50. And the indices of mean value, optimal value and variance of the algorithm are used to evaluate the optimization properties of the algorithm. The simulation results are shown in table 3-5. In order to observe the convergence of SLO algorithm intuitively, figure 4 shows fitness evolution curves obtained on 6 functions in D =50 that tested by four algorithms to optimize,where the number of iterations is set to the abscissa, the fitness value (base － 10 logarithm) is set to the ordinate.

Table 3 Simulation testing results in 10-D

Name	Dimensio	Indice	SLO	PSO	HS	ABC
f_1	10	*Best*	2.1440e-9	5.2795e-2	3.0476e-3	4.6420e-5
		Mean	1.6659e-3	8.2021e-3	2.9927e-2	4.3921e-3
		Std	4.3248e-4	3.2789e-4	2.2576e-3	3.9486e-3
f_2	10	*Best*	-5.3363e-3	7.8205e-1	1.9480e-1	9.5212e-1
		Mean	2.2968e-2	9.5397e-1	8.4129e-1	9.5234e-1
		Std	2.5353e-2	9.9953e-2	7.8991e-1	1.7728e-4

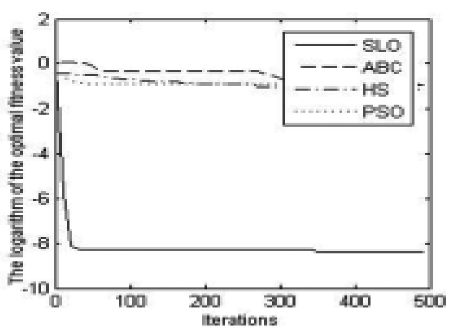
f_3	10	*Best*	1.0106e-6	7.6108	3.5556	1.4492e-8
		Mean	6.3989e-2	9.1032	1.4079e+1	1.4255
		Std	3.0174e+1	3.8023e+1	2.5889e+2	9.3210e+3
f_4	10	*Best*	1.0610e-5	1.4987e-1	1.7989e-1	1.9042e-2
		Mean	2.8664e-3	1.5268e-1	1.8293e-1	4.5964e-2
		Std	5.8336e-4	2.9980e-4	1.0474e-3	4.8746e-2
f_5	10	*Best*	1.0513e-8	5.4643e-2	2.1235e-2	4.5642e-4
		Mean	1.1560e-2	7.9289e-2	2.3097e-1	1.0244e-2
		Std	1.9061e-2	1.8648e-2	1.7274e-1	2.1923e-2
f_6	10	*Best*	1.1317e-8	3.3975e-2	1.8063e-2	1.0975e-14
		Mean	1.7325e-2	6.4460e-2	2.6815e-1	5.2047e-2
		Std	4.2551e-2	4.2218e-2	2.1377e-1	6.1868

Table 4 Simulation testing results in 30-D

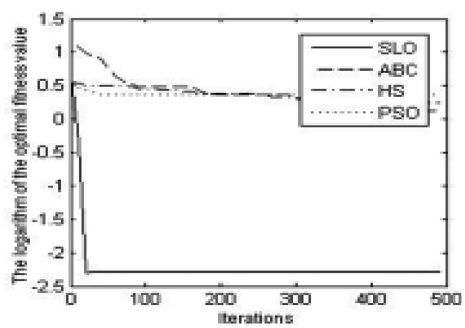
Name	Dimensio	Indice	SLO	PSO	HS	ABC
f_1	30	*Best*	3.2145e-9	5.1580e-2	2.5236e-2	8.3693e-4
		Mean	3.0745e-3	5.7688e-3	9.8092e-2	1.9574e-2
		Std	1.2382e-4	1.2240e-3	5.6659e-3	1.0006e-1
f_2	30	*Best*	-5.2700e-3	1.3903	5.1606e-1	9.5212e-1
		Mean	3.0349e-2	1.4547	1.2872e-1	9.5239e-1
		Std	1.1078e-1	8.0031e-2	8.0880e-1	1.2064e-4
f_3	30	*Best*	1.2925e-6	1.3288e+2	4.4681e+1	4.1044e-1
		Mean	2.2453e-3	1.3780e+2	9.6527e+1	6.1215e+1
		Std	4.4413e+2	3.0818e+2	3.2336e+3	2.6165e+6
f_4	30	*Best*	2.6855e-5	3.0987e-1	2.9991e-1	1.3817e-1
		Mean	4.9253e-3	3.1226e-1	3.0286e-1	2.4424e-2
		Std	1.5897e-3	3.5566e-4	8.9552e-4	7.5598e-1
f_5	30	*Best*	6.3100e-8	1.2141	7.9248e-1	2.2403e-2
		Mean	5.2142e-2	1.3213	1.8964	1.0684e-1
		Std	3.3865e-1	3.2974e-1	1.8693	3.6342e-1
f_6	30	*Best*	6.5532e-8	1.4428	8.4510e-1	2.5147e-7
		Mean	9.6317e-2	1.5879	2.1980	3.9218e-1
		Std	1.1237	8.0026e-1	2.7285	1.6467e+2

Table 5 Simulation testing results in50-D

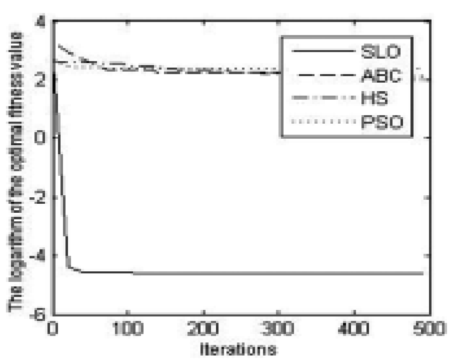
Name	Dimension	Indice	SLO	PSO	HS	ABC
f_1	50	*Best* *Mean* *Std*	4.2234e-9 3.3346e-3 1.7208e-3	1.0877e-1 1.1647e-1 1.6674e-3	7.2478e-2 1.4481e-1 6.6099e-3	8.6653e-4 1.4424e-2 6.3858e-3
f_2	50	*Best* *Mean* *Std*	-5.2503e-3 3.0943e-2 1.2542e-2	2.3162 2.3602 4.1347e-2	1.7489 2.4828 2.9499e-1	1.2566e-1 1.7553e-1 2.9604e-1
f_3	50	*Best* *Mean* *Std*	1.6812e-5 2.5915e-1 4.2107e+2	2.8364e+2 2.8867e+2 3.8855e+2	1.1483e-2 2.1223e-2 9.0867e-3	4.7141 1.2258e+1 4.2271e+3
f_4	50	*Best* *Mean* *Std*	4.0342e-5 5.4999e-3 2.8011e-3	3.7987e-1 3.8255e-1 4.8918e-4	3.9133e-1 3.9196e-1 2.8373e-4	1.6191e-1 1.6731e-1 3.0765e-2
f_5	50	*Best* *Mean* *Std*	1.3577e-7 1.0479e-1 1.3230	2.9843 3.6012 1.2198	2.5168 4.7555 5.7054	1.2382e-1 1.6924e-1 3.6047e-1
f_6	50	*Best* *Mean* *Std*	1.3321e-7 1.7205e-1 3.8914	3.3803 3.6575 2.6320	2.7070 5.3044 9.2624	4.6932e-2 3.7246 2.2524e+3



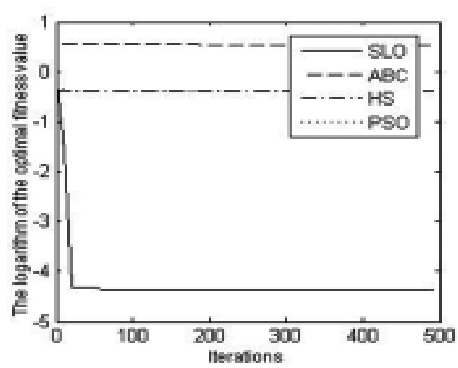
(a)Griewank function



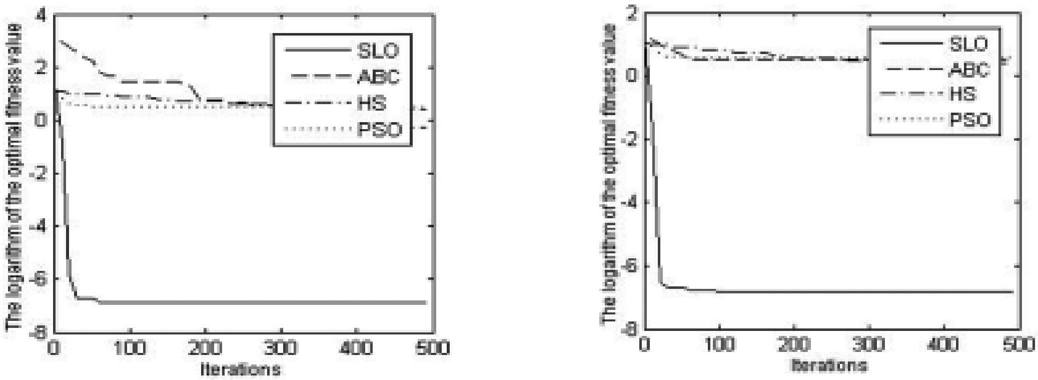
(b) Ackley function



(c) Rastrigin function



(d) Salomon function



(e) Schwefel’s function (f) Sphere function

Figure.4. Optimization iterative curves of test functions of the SLO

The optimal value marked as $Best$, mean value marked as $Mean$ in table 3 ~ 5 can reflect the convergence precision and optimization ability of the algorithm while variance marked as Std which can reflect the stability of the algorithm.From table 3 we can see that SLO is better than the other three algorithms for functions f_1, f_2, f_4, f_5 in low-dimension (D = 10).Especially, the accuracy of SLO is more than e-9 for multi-modal function f_1. Although accuracy of the SLO is not as high as that of ABC in terms of f_3 and f_6 , stability of the SLO is much higher than the latter and SLO also performed well. As the dimension increases, the search space becomes more complex, and it is more challenging referred to the search ability of algorithm.When the dimension increases to 30 and 50, the optimal accuracy and mean optimal value of SLO are better than the other three algorithms for all functions as shown in table 4~5 . It is worth noting that convergence accuracy of f_1、f_5、f_6 in the SLO is more than e-7 which is obviously better than that of the other three algorithms.

The optimization iteration curves of the testing functions can directly reflect the convergence speed and accuracy of the algorithm. It can be seen from fig. 4 that SLO has high convergence speed and high precision for the functions f_4 and f_6 , which shows that SLO has good searching ability;SLO can smoothly pass through a large number of local optimal points in f_1 and f_3 ; SLO can cross the traps of local optimal almost effortlessly in f_2 and f_5 . All of the above can show that SLO is not easy to fall into local optimum.Generally, the convergence performance of SLO is better than that of PSO 、 HS and ABC under the same number of iterations.

5. Conclusions

As to the problems of falling into local optimum and low solution precision in exsiting algorithms, this paper proposed a new bionic algorithm by simulating the predatory process of seven-spot ladybirds. The SLO makes full use of the characteristics of the partition search mechanism and combination of the local and wide area search of the ladybirds when searching for preies which achieves a good balance between global exploration and local exploitation. Compared with the three representative biomimetic intelligent algorithms, the results show that the SLO has good convergence precision ,high stability and fast convergence speed in dealing with low - dimensional and high - dimensional problems.

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References

[1] J. Kennedy, R. Eberhart. Particle swarm optimization. Proceedings of the IEEE International Conference on Neural Networks, Perth: IEEE, 1995: 1942-1948.

[2] Karaboga D.An idea based on honey bee swarm for numerical optimization,Technical Report-TR06[R].Kayseri:Erciyes University,Engineering Faculty,Computer Engineering Department,2005.

[3] Geem ZW,Kim JH,Loganatham GV. A new heuristic optimization algorithm: harmony search[J]. Simulation,2001,76(2):60-68.

[4] MENG X B,LIU Y,Gao X Z,et al. A new bio-inspired algorithm: chicken swarm optimization [C]//5th International Conference on Swarm Intelligence .Hefei: Springer International Publishing,2014:86-94.

[5] CHENG L. New bionic algorithm： cockroach swarm optimization[J].Computer Engineering and Applications, 2008,44(34):44-46.

[6] Feng X, Zhang J W, Yu H Q. Mosquito Host-Seeking Algorithm for TSP problem[J].Chinese Journal of computers,2014,37(8):1794-1808.

[7] Cheng X B.Multi-target Tracking Based on Improved Simlified Particle Swarm Optimization[J]. Computer Engineering,2016,42(08):282-288.

[8] Yang X H,Xue Jian,Wang Y L.Deployment Optimization of Intergrated Network Node Based on Improved Artificial Bee colony Algorithm[J].Computer Engineering, 2016,42(03):116-120.

[9] Wang G. Foraging behavior of predatory ladybugs [J]. Entomological Knowledge,1991,28(5):316-319.

[10] J.L.Hemptinne,M Gaudin,et al.Social Feeding in ladybird beetles:adaptive significance and mechanism[J].Chemoecology.2000(10):149-152.