

# An Improved Shuffled Frog Leaping Algorithm with Single Step Search Strategy and Interactive Learning Rule for Continuous Optimization

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**Abstract**—Shuffled frog-leaping algorithm (SFLA) is a heuristic optimization technique based on swarm intelligence that is inspired by foraging behavior of the swarm of frogs. The traditional SFLA is easy to be premature convergence. So, we present an improved shuffled frog-leaping algorithm with single step search strategy and interactive learning rule(called ‘SI-SFLA’). Single step search strategy enhances exploring ability of algorithm for higher dimension and interactive learning rule strengthens the diversity of local memeplexe. The effectiveness of the method is tested on many benchmark problems with different characteristics and the results are compared with other algorithms including PSO,SFLA,DE and TLBO. The experimental results show that SI-SFLA has not only a promising performance of searching for accurate solutions, but also a fast convergence rate, which are evaluated using benchmark functions.

**Index Terms**—shuffled frog-leaping algorithm, single stepsearch strategy, interactive learning rule, continuous optimization, swarm intelligence

## I. INTRODUCTION

Evolutionary computing (EC) is an exciting development in computer science. Over the past several decades, people have developed many optimization computation methods to solve complicated global optimization problems such as genetic algorithm (GA) inspired by the Darwinian law of survival of the fittest [1], particle swarm optimization (PSO) inspired by the social behavior of bird flocking or fish schooling [2][3]; ant colony optimization (ACO) inspired by the foraging behavior of ant colonies [4]; and biogeography-based optimization (BBO) inspired by the migration behavior of island species [5][6]; Differential Evolution (DE) [7][8]

which is similar to GA with specialized crossover and selection method; Teaching-Learning-based Optimization algorithm [9][10][11][12] which imitates the process of the teaching about teacher and students; Shuffled frog leaping algorithm (SFLA) which imitates the foraging behavior of frogs; all these algorithms can be called evolutionary algorithm or swarm intelligence optimization algorithm. Developed by Eusuff and Lansey in 2003, the shuffled frog-leaping algorithm [16] (SFLA) is a meta-heuristic optimisation method spired from the memetic evolution of frogs seeking food in a pond, which combines the advantages of the genetic-based MA [17] and the social behaviour-based particle swarm optimisation(PSO). Memetic algorithms (MAs) are a special class of heuristic searching methods that are derived from the models of adaptation in natural systems that combine the evolutionary adaptation of a population with individual learning within the lifetimes of their members. MAs are based on evolution of memes carried by the interactive individuals. The term memetic algorithm comes from ‘meme’, which is a transmittable information pattern that is replicated by infecting the objects ’s minds and altering their behavior in a parasitic manner. The remarkable characteristic of MAs is that all memes are allowed to gain some experience through a local search before being involved in the evolutionary process.

In general, the SFLA includes two alternating processes: local exploration in the submemeplex and global information exchange among all memeplexes. Local exploration uses the search strategy of PSO and shuffled method was used for global information exchange.

In SFLA algorithm, the whole position vector of frog was updated simultaneously, rather than each

component of the position vector was updated independently in each iteration, so it is difficult to find the best solution in higher dimensional space. So, according to the correlation of data set, the vector can be divided into several sub-vectors, each sub-vector can be updated in cycle. At the same time, the frog analyzes the state of position before the new position was updated, then determines the updating speed of the sub-vector during the updating process.

As everyone knows, in real life, during the learning process of student in a class, in general, there are two ways. one is that the teacher guides the student to access to the new knowledge, the second method is through the interaction between the students, which can improve the learning effect. Therefore, we introduce this interactive learning method into our algorithm. One frog in the population can be associated with arbitrary two frogs in population learning from each other, which improves the global searching ability of SFLA.

In this paper, we introduce an improved SFLA algorithm with a strong searching capabilities. A single step strategy was used to improve the local exploration and an interactive learning rule was utilized to enforce the global searching capability. The rest part of the paper is organized as follows. In Section 2, a brief introduction of SFLA is given. The improved SFLA is introduced in Section 3. In Section 4, Experiments show the result of our algorithm.

## II. SFLA ALGORITHM

Shuffled frog leaping algorithm simulates the process of a group of frogs looking for food. The population was classified into some memplexes (community), in each memplex, frogs exchange their thoughts. SFLA is a heuristic method combined with the shuffled strategy and the local search strategy. The local search strategy makes the thought of frog spread in local search space and the shuffled strategy exchanges the idea of local memplex. In the shuffled frog leaping algorithm, a group of frogs have the same structure which is composed of solution(position) and food(fitness). According to a certain strategy, frogs of memplex implement local search in the solution space. After the number of local search step, thought in the shuffled process was exchanged. Local search and shuffled process continue until the definition of convergence condition was satisfied [15] [16] [17].

A balance strategy of global information exchange and the local search makes the algorithm can jump out of local optimum solution and search toward the global optimum direction, which is the most important characteristics of shuffled frog leaping algorithm. In SFLA, each memplex carry out the local search respectively, the worst individual  $Q_w$ , through the memetic evolution close to the local best individual  $Q_b$  or

the global individual  $Q_g$ . When the local search is executed to a certain stage, frogs in each memplex communicate to implement shuffled process. The basic SFLA algorithm is as follows:

a). parameter settings: population size, numbers of memplexes, maximum of local search iterations, number of global iterations.

b). generates an initial population.

c). determine the fitness function:  $F(x)$ , used to evaluate the quality of the individuals.

d). in the global iteration process, the frog was arranged in descending order by whose fitness, and determine the global optimal solution  $Q_g$ , if it meet the convergence condition, then stop the execution; otherwise, proceed to the next step.

e). frog population was divided: the frog population was divided into  $m$  memplexes, each memplex contains  $n$  frogs, and the number of the population meet  $T=m \times n$ ; then, the first frog is divided into the first memplex, the second frog was divided into the second memplex, ... , The  $M$  frog was divided into the  $M$  memplex, the  $m+1$  frog was divided into the first memplex, the  $m+2$  frog was divided into the second memplex, and so on, until the whole frogs was division. That is:

$$Q_t = \{Q_{t+m(r-1)} \in T \mid 1 \leq r \leq n\}, (1 \leq t \leq m) \quad (1)$$

f). each memplex implement local search in the number of the iterations.

(1) determine  $Q_w, Q_b$ , according to the following formula to update, where  $rand \in (0,1]$ ,  $r$  is a constant.

$$D = r \bullet rand \bullet (Q_b - Q_w) \quad (2)$$

$$Q_{w(new)} = Q_w + D, D \in [D_{min}, D_{max}] \quad (3)$$

(2) If a better solution was produced, then  $Q_w$  was updated by  $Q_{w(new)}$ ; else  $Q_b$  was replaced by  $Q_g$  according to the formula (1)(2). if  $Q_w$  was not improved, then a new solution  $Q'_{w(new)}$  was produced randomly, if it is better, then the  $Q_w$  was updated by  $Q_{w(new)}$ .

## III. IMPROVED SFLA ALGORITHM

### A. Single step Search Strategy

During the updating process, the traditional SFLA algorithm often changes the position of all the dimension at the same time. According to the position of the frog, it can obtain a fitness value, so as to judge the degree of adaptation. This fitness can determine the overall quality of the frog, but can not judge part dimension if it moves to the optimal direction.

For example, on three dimensional function Sphere  $f_1 = x_1^2 + x_2^2 + x_3^2$ , the global optimum value is (0, 0, 0), the initial value of solutions was set (10, 10, 10), the fitness value is 300. Give a random perturbation variable value (1, 0, 1), the initial value was updated to the value (11, 0, 11), and the fitness value is 242. The fitness (242) of the updated solution is less than the initial fitness value(300). So, we can see that, in the next iteration, the solution would be some extent to move toward (11, 0, 11). At this time, although the second dimension moves to the global optimum direction, but the first and third dimension move away from the global optimum. Therefore, for high-dimensional functions, general SFLA algorithm is very difficult to find the best direction of all dimension. In order to solve this problem, the search space of the frogs was divided into several low dimensional space, in specific application, according to the dependence analysis of data set, we can decide the segmentation of the data dimension. The worst frog uses a single step search strategy for each low dimensional space. If a new frog obtains a better solution than the worst frog, then the worst frog position was updated by it, else the worst frog position was updated by it with a small search step. That is as follows formula (4)(5):

$$Q_{temp} = Q_w(t) + c \cdot rand \cdot (Q_{best}(t) - Q_w(t)) \quad (4)$$

$$\begin{cases} Q_w(t+1) = Q_{temp}, Q_{temp} \cdot fitness \leq Q_w \cdot fitness \\ Q_w(t+1) = rand \cdot Q_{temp}, otherwise \end{cases} \quad (5)$$

**B. Interactive Learning Rule**

In real life, interactive learning is common. For example, students in a class often learn new knowledge through mutual discussions and exchange information for each other [9]. SFLA is a swarm intelligence algorithm. In each memplex(community), the worst frog learns toward the best frog. In traditional SFLA, between memplexes, the frogs were only shuffled, but they do not learn from each other. This reduces the efficiency of learning. Therefore, we use an Interactive learning rule. Firstly, we let frogs in each memplex complete a local search; Secondly, frogs in all memplexes learn from each other to exchange information, then was shuffled. Interactive learning method strengthens the internal information exchange, enhances the global searching ability of the algorithm. Two frogs  $Q_a, Q_b$  was choosed randomly in population. The Interactive learning rule is

as follows:

$$\begin{cases} Q_a(t+1) = Q_a(t) + rand \cdot (Q_b - Q_a(t)), Q_j \cdot fitness \leq Q_i \cdot fitness \\ Q_a(t+1) = Q_a(t) + rand \cdot (Q_a(t) - Q_b), otherwise \end{cases} \quad (6)$$

The improved algorithm as shown in Figure 1. Figure 1 shows frog's searching process with a number of population 30. The population was divided into 5 memplexes, each memplex has 6 frogs. The frogs in each column of table belongs to the same memplex. Frogs implement local search in each memplex, for example: the first column of table with arrows shows that frogs in the same memplex use a one-step search strategy for local search. Interactive learning rule represents the frogs among all the memplexes (population) communicate between each other. For example, to update the position of the frog  $Q_{i+m(j-1)}$ , randomly choose another different frog  $Q_{u+m(v-1)}$  in the whole population respectively, these two frogs communicate with each other and determine how to update it according to the formula (6). The process is as Fig.1.

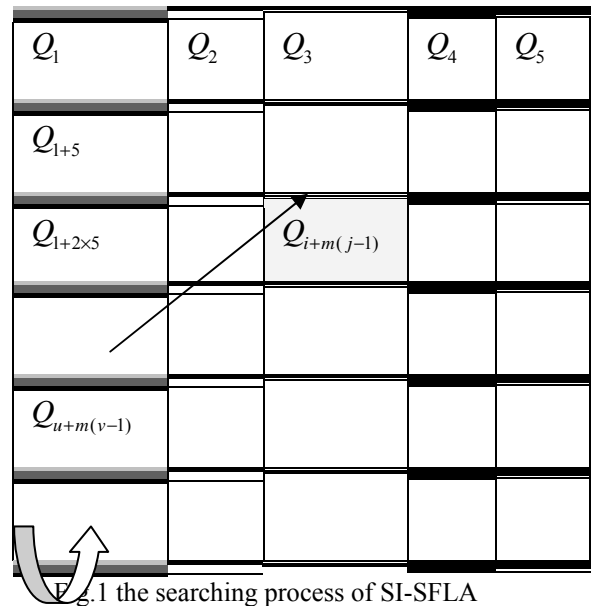


Fig.1 the searching process of SI-SFLA

The pseudo-code is as follows:

```

1.Initialize parameters: m, n, p=m*n, etc.
   Generate population(represented by P frogs )
   randomly;
2.Evaluate fitness of each frog;
3.While( convergence criteria is satisfied)
4.{
5. Sort P frogs in descending order;
   (Shuffled all frogs(construct n groups and each groups
   has m frogs);
6.For
groups
7.{
8.Get the worst frog Qw and the best frog Qb in this
   group;
9.Qtemp =Qw(t)+c.rand.(Qbest(t)-Qw(t) );
10. For each Dimension
11. If Qtemp.fitness < Qw(t).fitness
12. Qw(t+1)= Qtemp ;
13. Else
14. Qw(t+1)= rand.*Qtemp ;
15. End ;
16.end
17.get new frog using mutation;
18.if Qnew.fitness<Qw(t).fitnes
19. Qw=Qnew;
20. end
21.}
22.For each frog in population
23.{
24. get two frogs Qa, Qb randomly from population;
25. Q1=Qa(t)+rand.(Qb-Qa) ;
26. Q2= Qa(t)+rand.(Qa-Qb) ;
27. If Q1.fitness<Q(t).fitness
28. Q(t+1)=Q1;
29. Else
30. Q(t+1)=Q2;
31. End
32 }
33..}
    
```

IV. EXPERIMENTS AND RESULTS

A. Test Functions

In this paper, ten widely used benchmark continuous functions [18] shown in Table 1 with high complexity are tested. Also different benchmark problems are considered having different characteristics such as multimodality. A function is multimodal if it has two or more local optima in their solution space. Complexity increases when the local optima are randomly distributed. Moreover, complexity increases with the increase in the dimensionality.F8~F10 function are multimodality. F7 function is quartic function i.e. Noise. Initialisation dimension, search range and global optimum of these ten functions are given in **Table1**.The SI-SFLA algorithm is compared with standard PSO [2], standard SFLA [16],

standard DE [7] and TLBO [9] to search for the global minima in the solution space. Details of benchmark functions are given in the appendix.

B. Initialisation Parameters Setting

The global parameter is set as follows:the population size is 50 and dimension is 30. For the basic PSO, the acceleration coefficient is set as  $c1 = c2 = 2$ , the inertia weight  $w$  decreases linearly from 0.9 to 0.4. For DE, the coefficient is set as  $F=0.5, CR=0.5$ ; For the basic shuffled frog-leaping algorithm, there are 10 memplexes, each containing 5 frogs. The local exploration in each submemplex is executed for 5 iterations. The parameters settings for SI-SFLA are the same as those of SFLA, with the searching scale parameter  $c$  equal to 2.0; there is not other parameter to be set for TLBO algorithm. Especially the global iteration number is 1000 for PSO,DE and TLBO, and 200 for SFLA and SI-SFLA, because the local iteration number of SFLA and SI-SFLA are 5, then total iteration number of SFLA and SI-SFLA are  $5*200=1000$ .

C. Test Results and Discussion

To test the performance of the improved SFLA (SI-SFLA), ten benchmark functions listed in Table 1 are used here for comparison with PSO, DE, SFLA and TLBO. We had 50 trial runs for every instance and recorded minimum of best fitness, maximum of best fitness, midian of best fitness, mean best fitness and standard deviation.

As shown in Table 2, SI-SFLA is able to evolve in a very efficient manner. Convergence rates of SI-SFLA were strikingly higher than those of PSO, DE, SFLA and TLBO. SI-SFLA also demonstrated its robustness by very consistent performances: across all of the randomly initialized runs on the same test function, SI-SFLA always showed very similar evolution speed and converged to the same point or a small region, whereas for PSO, DE SFLA and TLBO, they sometimes had very diverse behaviors resulting from the random initialization.

Because each function in  $f1\sim f7$  has only a single optimal solution on origin, which usually is employed to test the local search ability of the algorithm. Thus from the result, we can see that SI-SFLA has stronger local search ability than PSO, DE, SFLA and TLBO. Especially,  $f3$  function (Schwefel’s Problem 1.2) has a flat area, so many algorithms do not easy to get its optimal solution. The result in Table2 show that SI-SFLA has a highest accuracy than PSO,DE,SFLA and TLBO.TLBO works better than PSO, DE, SFLA, but it is not stable than SI-SFLA. F8, F9 and F10 function are both multi-modal and usually tested for comparing the global search ability of the algorithm. On F8, F9 and F10 function, the SI-SFLA has better performance than PSO,DE,SFLA and TLBO algorithm; particularly, SI-SFLA can also find the optimal or closer-to-optimal solutions on the complex multimodal functions.

TABLE 1  
DETAILS OF BENCHMARK FUNCTIONS

Problem	name	Dimension	Search range	Global Optimum
F1	Sphere	30	[-100,100]	0
F2	Schwefel's Problem 2.22	30	[-10,10]	0
F3	Schwefel's Problem 1.2	30	[-100,100]	0
F4	Schwefel's Problem 2.21	30	[-100,100 ]	0
F5	Generalized Rosenbrock's function	30	[-2.048, 2.048]	0
F6	Step function	30	[-100,100]	0
F7	Quartic function i.e. Noise	30	[-1.28,1.28]	0
F8	Generalized Griewank function	30	[-600,600]	0
F9	Generalized Rastrigin's function	30	[-5.12,5.12]	0
F10	Ackley's function	30	[-32,32]	0

TABLE 2  
COMPARISISON OF RESULTS FOR THE MIN,MAX,MIDIAN,MEAN AND THE STANDARD DEVIATION FRO PSO,SFLA,DE,TLBO AND SI-SFLA.

	PSO	SFLA	DE	TLBO	SI-SFLA	
F1	min	0.7101	7.0825e-005	2.2351e-011	2.5400e-015	9.1988e-093
	Max	33.9085	1.4129	2.2091e-010	14.2100	5.0804e-090
	Midian	5.6048	4.0592e-004	4.4524e-011	2.6605e-005	4.0838e-091
	Mean	7.2682	0.0610	5.8090e-011	0.4735	9.4713e-091
	SD.	6.2093	0.2302	3.8643e-011	2.2540	1.2209e-090
F2	min	0.0100	1.2102e-006	4.7970e-013	2.1934e-012	1.2287e-094
	Max	0.3256	100.0000	1.1728e-011	1.0815e+006	5.0111e-092
	Midian	0.0494	7.2865e-006	2.0384e-012	5.5212e-007	3.2693e-093
	Mean	0.0728	4.0002	2.4012e-012	2.1629e+004	5.9400e-093
	SD	0.0751	19.7948	1.9589e-012	1.5294e+005	8.2468e-093
F3	min	4.3075e+004	3.7439e+004	1.3528e+005	3.2865e-010	4.2474e-016
	Max	1.6568e+005	1.6784e+005	4.7575e+005	2.8937e+005	645.9814
	Midian	7.7664e+004	7.7712e+004	2.9498e+005	0.5759	0.5302
	Mean	8.4972e+004	8.0585e+004	2.9151e+005	1.0295e+004	48.9997
	SD	2.9328e+004	2.8036e+004	7.9253e+004	4.3603e+004	115.4962
F4	min	11.2857	3.0528	0.9726	1.0945e-007	3.1176e-072
	Max	27.6603	25.0490	2.1760	0.7453	7.6636e-070
	Midian	21.2735	14.4736	1.4421	0.0158	3.0160e-071
	Mean	20.5526	14.2677	1.4777	0.0720	6.5088e-071
	SD	3.7755	5.0859	0.3142	0.1436	1.2422e-070
F5	min	16.9985	18.6618	23.3310	28.7832	26.2041
	Max	145.7181	83.4157	25.6784	7.5675e+003	28.5672
	Midian	29.2503	28.5246	24.4105	28.9009	27.1582
	Mean	41.8042	35.0193	24.4319	179.6730	27.1621
	SD	27.6833	18.8570	0.5520	1.0661e+003	0.6455
F6	min	2	0	0	0	0
	Max	34	170	0	20	0
	Midian	11	1	0	0	0
	Mean	11.9400	5.5200	0	1.2800	0
	SD	6.6774	24.8261	0	3.3444	0
F7	min	0.0478	0.0158	0.0100	2.3995e-005	1.1186e-005
	Max	0.2660	0.2550	0.0366	0.0045	8.6906e-004
	Midian	0.1316	0.0434	0.0237	6.6088e-004	2.2484e-004
	Mean	0.1325	0.0567	0.0237	9.0397e-004	2.5737e-004
	SD	0.0453	0.0427	0.0059	8.9015e-004	1.7105e-004
F8	min	0.8571	1.4462e-004	5.4495e-011	2.0017e-013	0
	Max	1.1425	1.0344	1.0280e-007	1.3998	0
	Midian	1.0370	0.0028	3.1306e-010	1.1138e-004	0

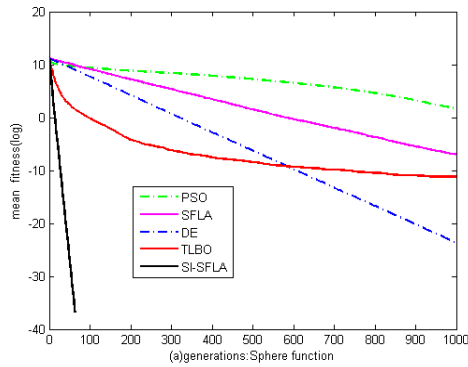
Mean	1.0292	0.0533	3.5514e-009	0.0915	0
SD	0.0529	0.1674	1.5102e-008	0.2771	0
F9 min	33.4843	27.6249	98.1627	1.2260e-010	0
Max	116.9836	226.2016	145.0373	165.9932	0
Midian	64.3820	81.5295	134.4844	7.5345e-004	0
Mean	65.8825	95.3020	132.0604	9.2961	0
SD	17.8519	53.0519	9.7593	34.6402	0
F10 min	0.7373	0.0029	1.1695e-006	3.6651e-008	8.8818e-016
Max	3.1276	4.6982	4.1530e-006	5.4371	8.8818e-016
Midian	1.9979	0.9379	2.0644e-006	0.0028	8.8818e-016
Mean	1.9632	1.2461	2.2340e-006	0.2293	8.8818e-016
SD	0.6116	1.2581	7.0297e-007	0.8739	0

Fig 2 gives the comparison of convergence processes of SI-SFLA, PSO, SFLA, DE and TLBO in the above six benchmark functions (F1, F3, F7, F8, F9, F10) averaged on 50 trial runs, when the population size is 50 and the maximum generation is 1000 according to the dimension 30. For SFLA and SI-SFLA, the maximum generation=5\*200. (local iteration number is 5 and global iteration number is 200). The result show that SI-SFLA has a quick convergence speed than PSO,SFLA,DE and TLBO, especially, for F1, F8, F9, F10 function, SI-SFLA

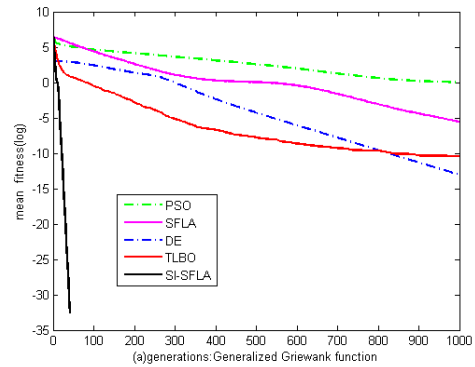
obtains global solution or closer-to-global solution in iteration 100.

#### D. Change of Difference in Efficiency with Increasing Dimensionality

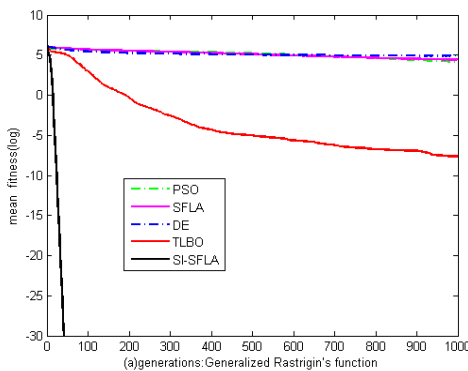
To further demonstrate its efficiency and effectiveness on high-dimensional problems, we also compared SI-SFLA with PSO, SFLA, DE and TLBO. SI-SFLA has a more smaller value of the mean and the standard deviation than PSO, SFLA, DE and TLBO, when the dimension is 10, 30 and 50 as TABLE 3~6.



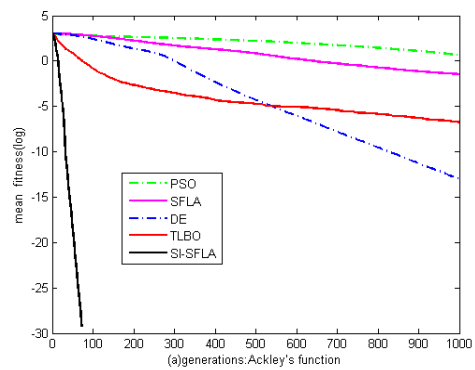
(a) Sphere



(c) Griewank



(b) Rastrigin



(d) Ackley

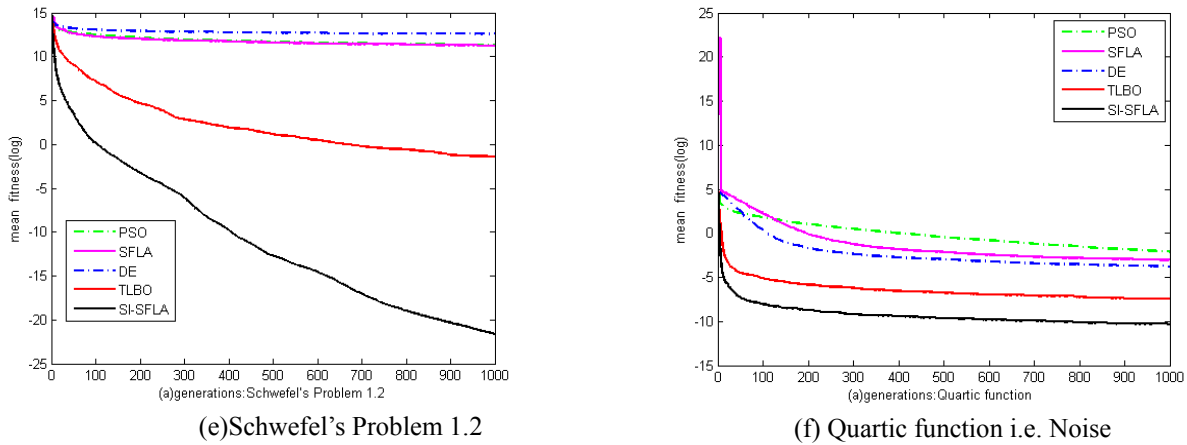


Fig 2 Convergence curve for different benchmark problems

TABLE 3  
NUMERICAL EXPERIMENT RESULTS OF SPHERE FUNCTION(F1)

Dimension	PSO	SFLA	DE	TLBO	SI-SFLA
10Mean	5.7236e-012	2.7017e-025	1.2459e-045	0.0428	5.6119e-110
SD	1.3761e-011	7.7906e-025	2.5355e-045	0.1863	1.2353e-109
30Mean	7.2682	4.6363e-005	5.8090e-011	0.4735	9.4713e-091
SD	6.2093	2.8341e-004	3.8643e-011	2.2540	1.2209e-090
50Mean	524.7095	32.6081	0.0038	0.6408	4.8316e-086
SD	196.9751	92.6275	0.0013	3.4093	6.0995e-086

TABLE 4  
NUMERICAL EXPERIMENT RESULTS OF GENERALIZED RASTRIGIN'S FUNCTION(F9)

Dimension	PSO	SFLA	DE	TLBO	SI-SFLA
10Mean	3.2778	7.2302	3.8369e-015	2.2046	0
SD	1.6819	3.6425	1.4140e-014	5.9969	0
30Mean	65.8825	59.7707	132.0604	9.2961	0
SD	17.8519	24.0783	9.7593	34.6402	0
50Mean	195.5192	298.5764	335.7978	4.0913	0
SD	38.6663	99.2877	13.9482	19.6936	0

TABLE 5  
NUMERICAL EXPERIMENT RESULTS OF ACKLEY'S FUNCTION9F(10)

Dimension	PSO	SFLA	DE	TLBO	SI-SFLA
10Mean	6.8402e-007	0.3334	4.4409e-015	0.3614	8.8818e-016
SD	6.5761e-007	0.5923	0	1.1992	0
30Mean	1.9632	1.1479	2.3458e-006	0.2293	8.8818e-016
SD	0.6116	1.2890	7.5809e-007	0.8739	0
50Mean	6.1583	3.8771	0.0154	19.6936	8.8818e-016
SD	0.8369	2.7107	0.0031	1.3180	0

TABLE 6  
NUMERICAL EXPERIMENT RESULTS OF GENERALIZED GRIEWANK FUNCTION(F8)

Dimension	PSO	SFLA	DE	TLBO	SI-SFLA
10Mean	0.1129	0.0464	2.7145e-004	0.2009	0
SD	0.0711	0.0275	0.0019	0.2608	0
30Mean	1.0292	0.0533	3.5514e-009	0.0915	0
SD	0.0529	0.1674	1.5102e-008	0.2771	0
50Mean	6.0022	1.2027	0.0063	0.1114	0
SD	2.4769	0.7862	0.0037	0.3256	0

Especially, SI-SFLA has a good fitness for F8, F9, F10 function, which have many local best fitness, regardless of dimension is 10, 30 or 50. That is to say, our algorithm

has a good robustness.

V. CONCLUSION

SFLA algorithm was an heuristic algorithm which combined PSO[19][20][21] with MA algorithm. This paper presents a novel improved SFLA algorithm (called SI-SFLA) to improve the stability and global search ability for high-dimensional continuous function optimisation. Single step search strategy and interactive learning rule was introduced to improved SFLA Algorithm. Single step search strategy is based on multidimensional data correlation to determine the search direction, which improved the search accuracy of SFLA algorithm, and interactive learning rule makes all the frogs find new important information which strengthen the global searching ability of the SFLA algorithm. The performance of the proposed SI-SFLA method is checked with the recent and well-known optimization algorithms such as PSO, SFLA, DE, TLBO, etc. by experimenting with different benchmark problems with different characteristics like, multimodality and dimensionality. The effectiveness of SI-SFLA method is also checked for different performance criteria, like median, standard deviation, mean solution, average function evaluations required, convergence rate, etc. The results show better performance of SI-SFLA method over other nature-inspired optimization methods for the considered benchmark functions. This method can be used for the optimization of engineering design applications.

APPENDIX BENCHMARK FUNCTION

1. F1 Sphere

$$f_1 = \sum_{i=1}^n x_i^2$$

2. F2 Schwefel's Problem 2.22

$$f_2(x) = \sum_{i=1}^n |x_i^2| + \prod_{i=1}^{30} |x_i|$$

3. F3 Schwefel's Problem 1.2

$$f_3(x) = \sum_{i=1}^n \left( \sum_{j=1}^i x_j \right)^2$$

4. F4 Schwefel's Problem 2.21

$$f_4(x) = \max \{ |x_i|, i \in [1, n] \}$$

5. F5 Generalized Rosenbrock's function

$$f_5(x) = \sum_{i=1}^{n-1} 100 \cdot (x_{i+1} - x_i^2)^2 + (1 - x_i)^2$$

6. F6 Step function

$$f_6(x) = \sum_{i=1}^n (\lfloor x_i + 0.5 \rfloor)^2$$

7. F7 Quartic function i.e. Noise

$$f_7(x) = \sum_{i=1}^n ix_i^4 + \text{random}[0,1)$$

8. F8 Generalized Griewank function

$$f_8(x) = \frac{1}{4000} \sum_{i=1}^n x_i^2 - \prod_{i=1}^n \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$$

9. F9 Generalized Rastrigin's function

$$f_9(x) = \sum_{i=1}^n (x_i^2 - 10 \cos(2\pi x_i) + 10)$$

10. F10 Ackley's function

$$f_{10}(x) = -20 \exp\left(-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2}\right) - \exp\left(\frac{1}{n} \sum_{i=1}^n \cos(2\pi x_i)\right) + 20 + e$$

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