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A Novel Fruit Fly Optimization Algorithm with Vision Scanning Search and Extensive Learning Mechanism

Fuqing Zhao,
School of Computer and Communication Technology, Lanzhou University of Technology
Lanzhou 730050,China
Fzhao2000@hotmail.com
(Fuqing Zhao);

Ruiqing Ding,
School of Computer and Communication Technology, Lanzhou University of Technology
Lanzhou 730050,China
rui8932451@163.com
(Ruiqing Ding)

Jianxin Tang,
School of Computer and Communication Technology, Lanzhou University of Technology
Lanzhou 730050,China
jxtang2011@hotmail.com
(Jianxin Tang)

Huan Liu,
School of Computer and Communication Technology, Lanzhou University of Technology
Lanzhou 730050, China
121638449@qq.com
(Huan Liu)

Abstract— **The fruit fly optimization algorithm has drawn various attention to researchers and engineers, due to the simple theory and flexible frame. For solving the complex continuous optimization problems, an improved fruit fly algorithm based on vision scanning search and extensive learning mechanism is proposed in this paper. The vision scanning search strategy is used to scan the potential area by changing the search angle of swarm center. This strategy is utilized to guide the population to jump out the local trap. The extensive learning is using the knowledge of neighboring structure to increase the diversity of population for solving the non-separable issues. Furthermore, a new mutation strategy based on difference vector is proposed to improve the search efficiency of VLFOA. Testified in CEC 2017 benchmark problems, the results show that the VLFOA has a superior performance compared with the original FOA and the state of art variants of the FOA.**

Keywords—fruit fly optimization algorithm, vision scanning search, extensive learning

I. INTRODUCTION

The optimization technique is based on mathematics and used to solve various optimization problems, which has received attention in enormous domains. Especially in recent years, it has been rapidly promoted and applied in immense engineering fields[1], such as aviation manufacturing[2], artificial intelligence[3], production scheduling[4]. These reality engineering problems have the characteristics of high complexity, multiple constraint, non-linearity, multi-extreme values, difficulties in modeling. Afterwards, the solution space is tremendous and the dimensional disaster problems are faced with increasing of problem scale. Therefore, the Blackbox problems, which are the object functions required to be optimized and unknown, is generated.

In the past decades, evolutionary algorithms, which simulates biological or phenomenon of nature, are concerned by scholars and engineering practitioners. Due to the simple, flexible and efficient of evolutionary algorithms, various popular algorithms, including particle swarm optimization algorithm (PSO) [5], ant colony optimization (ACO) [6] [7], biogeography-based optimization (BBO) [8] [9], water wave optimization (WWO) [10] [11], artificial bee colony optimization (ABC) [12] [13], differential evolution (DE) [14], are widely applied in vast domains. As stochastic optimization algorithms, the key to obtaining outperformance is through the balance of exploration and exploitation, which is combined with different strategies and mechanisms.

The fruit fly algorithm (FOA) [15] is proposed by Pan in 2011. Compared with other evolutionary algorithms, FOA is prone to understand and simply achieved by programming. For the framework of algorithm, there are only few parameters and it is convenient to embed various specific search strategies for different problems. The above characteristics are applied to assist FOA to widely use in discrete problems. Ling wang [16] proposed a binary FOA to solve the multidimensional knapsack problem. A hybrid discrete fruit fly optimization proposed by Ling wang [17] to solving permutation flow-shop scheduling problem. Pan proposed modify FOA, which introduced an escaping coefficient to expand the search space in negative spaces. In LGMS_FOA [18], the generated strategy of candidates is changed, and the nonlinear generation replaced by linear generation. Among the algorithms of MFOA [19] IFFO [20], the methods of calculation of smell concentration all replaced by generating candidate solution via one-dimensional coordinate value. IFFO introduced new parameter to control solution generation, and removed the Eq.(5) and Eq.(6). The excitation function of a neural network is used to assisted the search in JSFOA[21]. The cooperation learning strategy in two subswarms is proposed in HACLFOA[22].

The original FOA has superior ability for exploration, while the exploitation is weak. The algorithm is prone to trap in the local optima and difficult to escape the local optimal due to lock efficient perturbation mechanism. The main reasons are summarized as follows.

- The solution space is limited by Eq.(5) and Eq. (6), which are not feasible in negative spaces. The diversity of population has a sudden drop after calculating by Eq.(5).
- All individuals are concentrated on the swarm center, being the current optimal solution.

To further improve the performance of FOA, the contributions of this paper are described as follows.

- The concepts of view angle is introduced to adjust the view angle and help the individuals escape from local optimal solution.
- Extensive learning strategy is used to rise the diversity of population.
- The mutation formula is altered to improve the search capability.

The remainder of this paper is organized as follow: Section 2 is the review of original FOA. Section 3 is the introduce of the proposed algorithm VLFOA in detail. In Section 4 is the result and discussion of experiments, which compares VLFOA with original FOA and two typical variants LGMS_FOA and IFFO. Finally, Section 5 sums up this study, some issues and future work needs to be researched furthermore.

II. THE ORIGINAL FRUIT FLY OPTIMIZATION ALGORITHM

Fruit fly is a common insect in daily life, due to the super olfaction and vision for foraging behavior, the food source is quickly found. In fruit fly swarm, the individual judges the food source by olfactory sensation, and compares the smell concentration with other partners. Then they approach to the individual who is nearest to the food by visual sense. Iterative this process, until they found the food.

The step of the original FOA is described as follows:

Step 1: Initialization.

Initial all parameters, such as size of population in the swarm, the dimension of problems, the swarm location region, the maximum number of evaluations, and random initial fruit fly swarm location.

$$Init\ X_S \tag{1}$$

$$Init\ Y_s \tag{2}$$

Step 2: Olfaction search process.

Step 2.1: The direction and distance of fruit fly individual be given randomly for foraging.

$$X_i = X_S + rand() \tag{3}$$

$$Y_i = Y_S + rand() \tag{4}$$

Step 2.2 Due to the location of food source is unknow, calculate the distance to the origin.

$$D_i = \sqrt{X_i^2 + Y_i^2} \tag{5}$$

Step 2.3 The smell concentration be estimate, which is the count backwards of D_i.

$$S_i = 1/D_i \tag{6}$$

Step 2.4: Substitute the smell concentration to the objective function, and the fitness value be obtained.

$$Smell_i = fitness(S_i) \tag{7}$$

$$[bestsmell, bestindex] = \min(Smell_i) \tag{8}$$

$$X_s = X(bestindex) \tag{9}$$

$$Y_s = Y(bestindex) \tag{10}$$

Step 3: Vision search process

Record the best location of every generation and use vision to close to the current best location.

Step 4: Check termination condition

If the termination condition is satisfied or convergence to a fixed value, finish the loop, return the best solution. Otherwise, the iterative process is continued, repeat the step2-step3.

III. FRUIT FLY OPTIMIZATION ALGORITHM WITH VISON SCANNING MECHANISM

A. *Vison scanning mechanism*

In the original FOA, the vison search was mentioned and not used efficiently. In the original method, the diversity of population are reduced rapidly and individuals are trapped into the local optimal, and which is difficult to jump out .Thus, vison scanning mechanism is adopted to guide search direction. The vison strategy is inspired from white crappies [23], which is characterized by maximum pursuit angle , pursuit distance and pursuit height. In the proposed algorithm, the vison scanning field is simplified and generalized to n-dimensional space, which is characterize by maximum pursuit angle $\theta_{max} \in R^1$ and maximum pursuit distance $\theta_{max} \in R^1$ is explained in Fig.1.

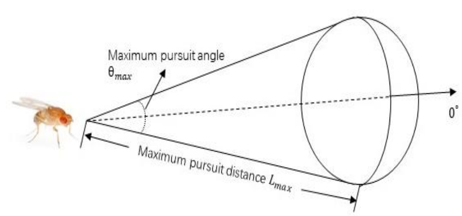

Fig.1 Illustration of maximum pursuit angle and maximum pursuit distance

In the search space of n-dimension, the position of ith fruit fly individual in gth generation is $X_i^g \in R^n$, and the initial angle of this individual is $\boldsymbol{\lambda_i^g} = \left(\lambda^g_{i_1}, \lambda^g_{i_2}, \dots, \lambda^g_{i_{n-1}}\right) \in R^{n-1}$. The search direction of the individual is an direction vector $D_i^g = \left(d^g_{i_1}, d^g_{i_2}, \dots, d^g_n\right) \in R^n$, which is transformed from λ_i^g via a polar to Cartesian coordinate transformation

$$d^k_{i_1} = \prod_{q=1}^{n-1} cos(\lambda^g_{i_q}) \tag{11}$$

$$d^k_{i_j} = sin(\lambda^g_{i_{j-1}}) \prod_{q=1}^{n-1} cos\left(\lambda^g_{i_q}\right) \qquad (j = 2, \dots, n-1) \tag{12}$$

$$d^k_{i_n} = sin\left(\lambda^g_{i_{n-1}}\right) \tag{13}$$

After searching of olfaction, the current best fruit fly individual stays in the current optima, and the scanning mechanism is activated. The initial scanning point is the zero degree, and then turn a random angle at left and right, which is a random lateral search. X_z is the zero point, X_r and X_l is the random point in the right and left-hand side of X_z. The scanning area is fixed by the three points as follows.

$$X_z = X_{axis}{}^g + r_1 * l_{max} D^g_{axis}(\lambda^g) \tag{14}$$

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$$X_r = X_{axis}{}^g + r_1 * l_{max} D_{axis}^g (\lambda^g + r_2 * \theta_{max}/2) \quad (15)$$

$$X_l = X_{axis}{}^g + r_1 * l_{max} D_{axis}^g (\lambda^g - r_2 * \theta_{max}/2) \quad (16)$$

where $r_1 \in R^1$ is random number with normal distribution, which mean is 0 and standard deviation is 1, and $r_2 \in R^{n-1}$ is the rand number in range (0,1).

In the range of the maximum search angle, if the fruit fly individual find a desirable resource of smell concentration than current optima, that means the direction is promising, the swarm fly to the better rescore, and continue the iteration.

$$\lambda^{k+1} = \lambda^k \quad (17)$$

If the individual is find a better solution than current optima, the swarm stay in current location, and turn a random angle, reset the search direction. If the direction still cannot be changed, iteration after n generation, and there is no desirable solution for swam, the direction turns back to zero degree.

$$\lambda^{k+1} = \lambda^k + r_2 * \alpha_{max} \quad (18)$$

where $r_2 \in R^1$ is random number with normal distribution, which mean is 0 and standard deviation is 1, $\alpha_{max} \in R^1$ is maximum turning angle.

B. Extensive learning strategy

To offset all shortcomings mentioned above, in one hand, the Eq. (5) is abandoned, the decision variable x_i is used directly to evaluate fitness value. In the other hand, two strategies describing as follow are introduced.

In the basic FOA, every dimension in all individuals are both learning to corresponding dimension of the same one fruit fly individual. However, indicated in this paper [23], that the phenomenon of 'two steps forward, one step back' is easily cause by the method. Thus in this proposed algorithm, the extension learning strategy is embedded, in which the learning object is not only the current optimal solution, but also the other fruit fly individuals in the neighbor. The following revised fruit fly update formula is proposed as follow:

$$X_i = X_{axis} + rand * (X_i - Nest_i) \quad (19)$$

where $Nest_i$ is the constructive solution, which is acquired from neighbor area by learning.

For these problems in CEC 2017 benchmark, the variables are non-separable. Thus, the effects of introducing multiple neighbor individuals on one individual need to face the possibility of counteracting by each individuals. In order to reduce this effect, each iteration a made fruit fly individual be selected which is met the indicator requirements. The indicator fitness distance ratio (FDR) Eq. (17) based on neighborhood structure is proposed in [18]. Through this indicator, in gth generation, the learning object of ith individuals $Nest_i^g = (nest_1^g, nest_2^g, \dots, nest_n^g) \in R^n$ is obtained.

$$nest_{i_d}^g = \arg\{max\left[\frac{fitness(N_j) - fitness(x_i)}{|n_j^d - x_i^d|}\right]\} \quad (20)$$

where $N_j = (n_j^1, n_j^2, \dots, n_j^d)$ is neighbor area of the individual x_i.

The topological neighbor area is divided by Euclidean distance. The neighborhood [24] of the current individual is determined by Eq.(18).

$$\begin{cases} L_i(g) = \{d_{ij}(g) | d_{ij}(g) = \|x_i(g) - x_j(g)\|\}, j \neq i, j \in p_s; \\ N_i(g) = \arg(\min(sort(L_i(g)), n)). \end{cases} \quad (21)$$

where $L_i(g)$ is the distance between the individual j in neighborhood and current position i in gth generation. p_s is the number of neighbors.

C. olfactory search based on learning strategy

In order to overcome the shortcomings mentioned above, in the proposed improved strategy, the difference vectors are used by the fruit flies to move towards the current best location from their different current positions rather than gathering all around the local optima. In this way, the position information of fruit flies is saved for guiding evolution. The convergence speed and diversity are balanced.

$$X_i^{k+1} = X_i^k + r_3 * (X_{axis}^k - X_i^k) \quad (22)$$

where r_3 is a uniform random sequence in the range (0, 1).

Based on the described above, the pseudocode of VLFOA is given as follows.

VLFOA	
Input:	*Sizepop*: size of population *Dim*: dimension *Max_nfes*: maximum number of evaluations *UB, LB*: bound of threshold
Output:	*Smellbest*: the global best fitness *X_axis*: the coordinate of global optimal
Step 1:	Randomly initializing the population, Sizepop new individuals are generated, and the fitness is calculated.
Step 2:	In the olfaction search process, if the probability < 0.2, the individual explore search space by learning from the neighbors used in Eq. (19)-(21).
Step 3:	Else, The population is disturbed by using the Eq.(22),which is using the extensive learning.
Step 4:	In the vision search process, according to the fitness in last generation, judge the search area ,and adjust the search angle by Eq. (14)-(18).
Step 5:	Calculating the fitness of updated swarm. If the maximum number of evaluations is satisfied, output the *Smellbest*, otherwise, continue the loop and jump to step2.

IV. THE EXPERIMENTS AND COMPARISONS

In this paper, the CEC 2017 benchmark is used to evaluate the performance of VLFOV. In the benchmark of CEC 2017, four different categories are divided into functions as follows, $f_1 - f_3$ are Unimodal Functions, $f_4 - f_{10}$ are Simple Multimodal Functions, $f_{11} - f_{20}$ are Hybrid Functions, the remaining 10 functions are Composition Functions. Various detailed information is described in the Table.1. According to this paper, the effect of the proposed function needs confirmation in search space of different dimensions(D=10, 30, 50, 100). Due to the limited length of this article, only the experimental results on the 10-dimensional scale are shown. The experiment of each function has been ran 51 times independently to reduce the chanciness of experimental results. The maximum times of evaluation is required to set to D*10000. The original FOA[15], and two typical variants, LGMS_FOA[18], IFFO[20] and two advanced algorithm JSFOA[21] and HACLFOA[22] are the compare objects of VLFOA.

TABLE.1 EXPERIMENT RESULTS OF FOUR ALGORITHMS

FUNCTION	FOA		LGMS_FOA		IFFO		JSFOA		HACLFOA		VLFOA	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
1	2.63E+10	3.08E+09	2.94E+10	6.47E+07	8.25E+09	4.80E+09	1.49E+10	5.00E+09	8.61E+09	2.50E+07	**2.95E+04**	**1.60E+05**
2	2.90E+17	2.49E+17	7.74E+17	1.45E+16	2.35E+11	7.63E+11	2.69E+12	3.16E+12	4.00E+10	3.88E+10	**3.70E-04**	**4.15E-04**
3	3.08E+04	5.37E+04	3.13E+04	2.95E+04	3.62E+04	1.98E+04	6.29E+04	1.51E+04	4.22E+04	6.04E+03	**2.00E-08**	**1.42E-07**
4	4.54E+03	4.89E+02	5.32E+03	3.72E+01	4.79E+02	4.53E+02	1.77E+03	6.81E+02	5.85E+02	3.91E+02	**6.53E+00**	**1.31E+01**
5	2.04E+02	1.30E+01	2.12E+02	**1.92E+00**	5.02E+01	2.05E+01	1.35E+02	1.72E+01	4.63E+01	2.44E+01	**2.82E+01**	1.21E+01
6	1.16E+02	6.19E+00	1.03E+02	**4.89E+00**	2.72E+01	1.27E+01	9.67E+01	1.44E+01	2.62E+01	1.93E+01	**6.37E+00**	5.38E+00
7	2.01E+02	1.46E+01	1.76E+02	**4.99E+00**	2.06E+02	9.20E+01	6.83E+02	1.11E+02	2.14E+02	7.67E+01	**5.29E+01**	1.90E+01
8	1.20E+02	1.17E+01	1.34E+02	**1.94E+00**	5.64E+01	2.19E+01	1.57E+02	1.65E+01	5.86E+01	2.35E+01	**2.80E+01**	1.28E+01
9	2.38E+03	4.95E+02	2.50E+03	**2.45E+02**	8.93E+02	4.57E+02	5.41E+03	1.29E+03	8.57E+02	5.94E+02	**3.24E+02**	3.34E+02
10	4.42E+03	2.53E+02	4.92E+03	**2.57E+01**	1.02E+03	2.95E+02	2.16E+03	1.84E+02	1.11E+03	4.84E+02	**8.07E+02**	2.85E+02
11	2.74E+06	3.70E+06	5.59E+07	3.82E+06	5.35E+03	6.54E+03	1.05E+04	7.26E+03	4.24E+03	3.40E+02	**3.58E+01**	**2.49E+01**
12	4.13E+09	9.12E+08	3.46E+09	2.91E+07	4.78E+08	5.62E+08	6.25E+08	3.98E+08	5.27E+08	1.35E+06	**3.46E+05**	**1.09E+06**
13	1.09E+09	6.98E+08	2.51E+09	2.21E+08	7.69E+07	9.44E+07	5.29E+07	5.72E+07	3.69E+07	1.38E+06	**9.50E+03**	**9.06E+03**
14	3.98E+08	3.97E+08	1.99E+09	1.37E+08	6.11E+03	6.57E+03	2.70E+04	3.41E+04	7.23E+03	7.50E+03	**8.51E+02**	**1.83E+03**
15	9.91E+06	1.58E+07	5.73E+08	1.23E+08	7.25E+04	4.41E+05	3.09E+05	5.32E+05	9.95E+03	2.55E+04	**3.63E+03**	**4.55E+03**
16	1.28E+03	8.97E+01	1.79E+03	**8.63E+00**	5.16E+02	1.86E+02	7.56E+02	1.76E+02	5.26E+02	2.22E+02	**1.55E+02**	1.13E+02
17	1.13E+03	4.37E+02	1.49E+03	**1.49E+01**	2.68E+02	1.46E+02	5.16E+02	1.38E+02	2.69E+02	1.50E+02	**7.21E+01**	4.48E+01
18	8.78E+09	1.26E+09	1.42E+10	5.22E+07	1.53E+08	2.59E+08	2.60E+07	3.43E+07	1.35E+08	3.13E+07	**1.64E+04**	**1.16E+04**
19	5.60E+09	2.45E+09	4.91E+09	9.07E+07	1.00E+07	1.66E+07	1.58E+06	3.10E+06	9.68E+06	1.31E+05	**6.67E+03**	**6.91E+03**
20	1.11E+03	2.25E+01	1.12E+03	**1.24E+01**	1.77E+02	8.96E+01	3.48E+02	6.12E+01	1.76E+02	1.13E+02	**6.70E+01**	4.64E+01
21	6.22E+02	7.90E+01	7.13E+02	**2.57E+00**	2.43E+02	4.77E+01	3.17E+02	4.30E+01	2.41E+02	4.82E+01	**1.86E+02**	6.20E+01
22	2.66E+03	2.91E+02	2.97E+03	**1.55E+01**	8.34E+02	3.63E+02	1.85E+03	4.22E+02	7.60E+02	5.16E+02	**1.00E+02**	1.86E+01
23	1.85E+03	2.12E+02	1.98E+03	1.81E+01	4.21E+02	4.30E+01	4.16E+02	2.35E+01	4.29E+02	4.79E+01	**3.36E+02**	**1.61E+01**
24	9.41E+02	3.18E+01	9.83E+02	**1.58E+00**	4.19E+02	6.36E+01	4.62E+02	2.23E+01	4.22E+02	7.85E+01	**3.18E+02**	1.03E+02
25	2.10E+03	2.20E+02	2.29E+03	**6.23E+00**	8.43E+02	3.44E+02	1.72E+03	5.11E+02	9.41E+02	3.28E+02	**4.19E+02**	8.29E+01
26	3.00E+03	6.16E+01	3.10E+03	**8.06E+00**	1.10E+03	4.37E+02	2.08E+03	3.45E+02	1.12E+03	4.98E+02	**4.36E+02**	2.67E+02
27	1.95E+03	3.02E+02	2.15E+03	3.27E+01	5.18E+02	5.44E+01	4.68E+02	2.48E+01	4.93E+02	6.37E+01	**4.26E+02**	**3.23E+01**
28	1.52E+03	2.11E+02	1.30E+03	**9.12E+01**	7.94E+02	1.34E+02	4.98E+02	2.67E+00	7.83E+02	2.32E+02	**4.68E+02**	1.56E+02
29	1.14E+04	7.19E+03	1.97E+03	4.59E+03	4.94E+02	1.60E+02	7.00E+02	1.14E+02	4.57E+02	1.46E+02	**3.49E+02**	**5.86E+01**
30	3.76E+08	5.46E+07	4.70E+08	1.68E+07	2.59E+06	4.02E+06	6.26E+06	6.44E+06	6.84E+06	1.38E+07	**2.26E+06**	**3.11E+06**

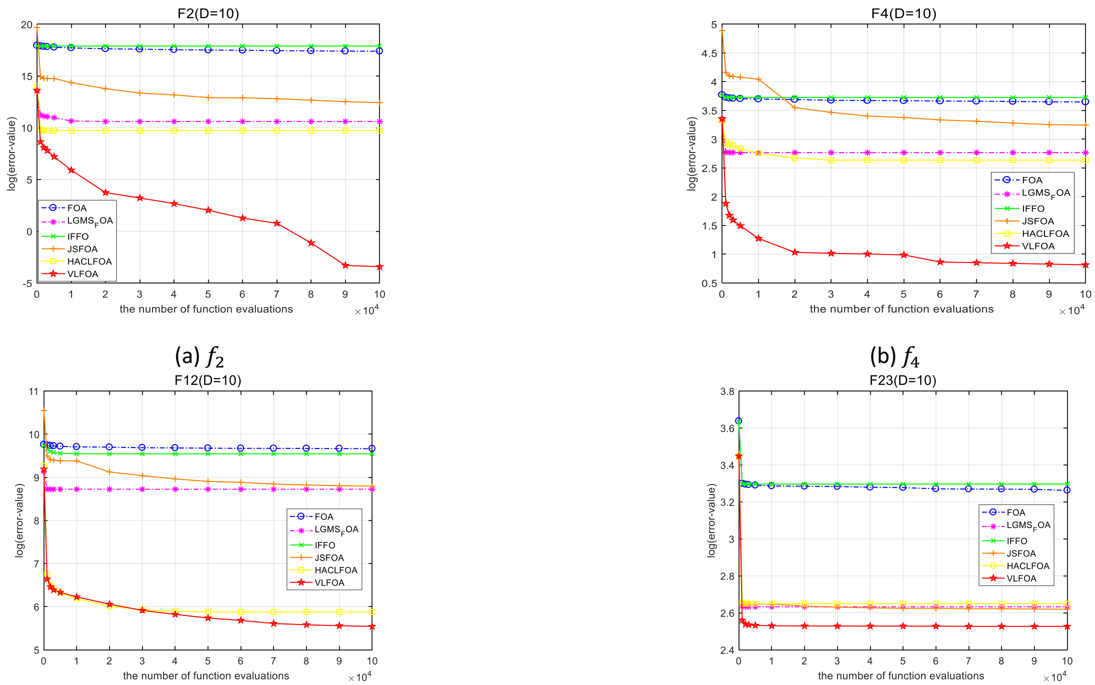
The parameters of those algorithms are set in the corresponding paper. The size of the population both set PS=100. In the VLFOA size of individuals neighborhoods is 20% of PS.

A. Analysis and discussion

The results of 30 functions are shown in Table.1, which records in detail information of mean and standard deviation of each function. The VLFOA is outperformed in the 30 functions. Significantly, VLFOA almost find the global optimal solution of f_3 in 51 times, and in f_2, f_4, f_6 the optimal solution are very closed to the optimal point. Due to the limited pages, the four different types functions f_2, f_4, f_{12} and f_{23} are selected to represented the four categories functions in CEC 2017 benchmark. The Fig.2 is represented to show the convergence characteristics of those algorithms in these representative functions in 10 D. It is observed clearly that, compare with the three algorithms, the VLFOA declines to a lower level. When the other algorithms have converged prematurely, the VLFOA still has ability of exploration and exploitation. This phenomenon is due to two reasons, in one hand, the extensive learning based on individuals neighbor area increase diversity of population, and improve the ability of exploration, which also avoid the swarm convergence prematurely. In the other hand, the angle of visual scanning search was adjusted in time to change the search direction of the population to a potential search which help the individuals escape from local optima. The box plots of VLFOA and the other compared algorithms for f_2, f_4, f_{12}, and f_{23} are shown in Fig.3,which expresses the stability and precision of VLFOA. It can be seen from the Fig.3, VLFOA has better performance than the other three algorithms.

TABLE.2 p-VALUE OF WILCOXON'S RANK-SUM TEST FOR D = 10

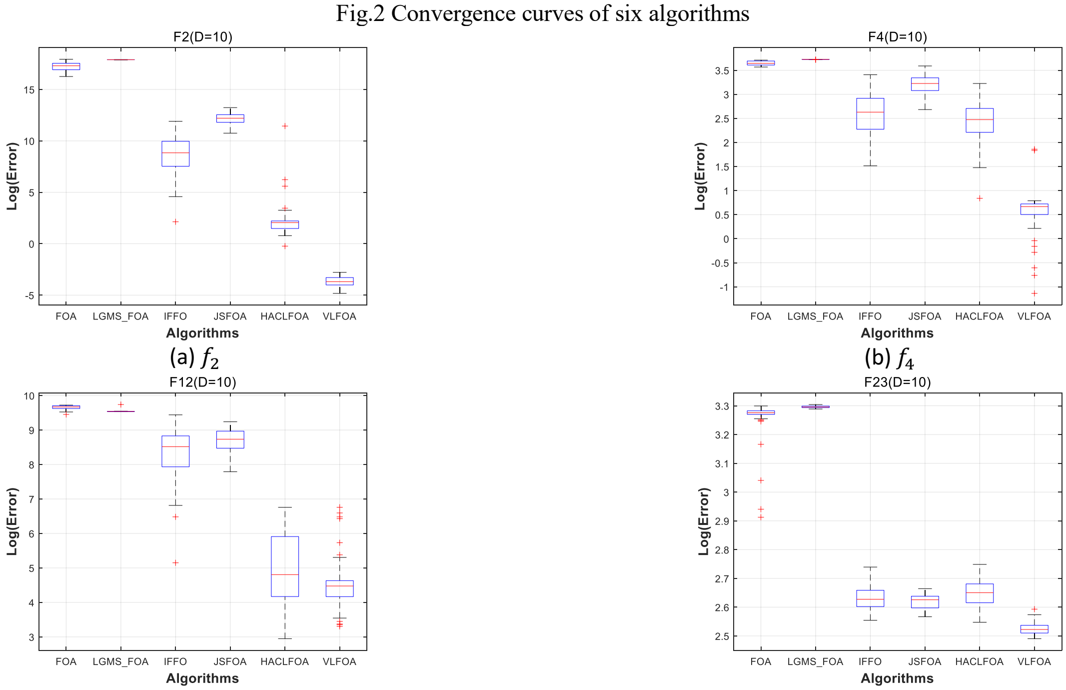
D	VLFOA vs.	+	-	R+	R-	p-value	α= 0.5	α= 0.1
10	FOA	30	0	465	0.000	2.00E-06	Yes	Yes
	LGMS_ FOA	30	0	465	0.000	2.00E-06	Yes	Yes
	IFFO	30	0	465	0.000	2.00E-06	Yes	Yes
	JSFOA	30	0	465	0.000	2.00E-06	Yes	Yes
	HACL FOA	30	0	465	0.000	2.00E-06	Yes	Yes



(a) f_2 (b) f_4

(c) f_{12} (d) f_{23}

Fig.2 Convergence curves of six algorithms



(a) f_2 (b) f_4

(c) f_{12} (d) f_{23}

Fig.3 Boxplots of six algorithms

The Wilcoxon's test, which is a nonparametric statistical tests, is used to testify the performance of VLFOA furtherly. The statistical analysis result of the Wilcoxon's test is shown in Table 2, the p -values of Wilcoxon's rank-sum test are calculated by comparing different algorithms in pair. In the experiment, the confidence level is to be set as 0.95 and 0,99. There is a null hypothesis that means the compared algorithms have the same performance. R^+ is the sum of the rank that represented the VLFOA is superior to the compared algorithm. R^- is the sum of the rank that represented the VLFOA is inferior to the compared algorithm. The '+' and '-' is the number of function that VLFOA has better performance than the comparing algorithm and worse than the comparing algorithm respectively. In the 30 functions test set, the VLFOA both has a high performance compared pairwise with the other five algorithms. Thus, the p-value which is represented the distinctiveness is same. And because the p-value is smaller than 0.01, the results are show that the null hypothesis is false, there is an obvious distinctiveness between the VLFOA and comparing algorithm, and the VLFOA is both superior than the other comparing algorithms in the 95% and 99% confidence level. The 'Yes' is the employed to shown the p-value whether less than 0.01 and 0.05.

For analyzing the important of the proposed three strategies, the algorithm is split to FOA1, FOA2, FOA3, and FOA4. The FOA1 is the original FOA, FOA2 is the FOA only combined with the extensive learning strategy, FOA3 is FOA integrated with extensive learning and scanning search, FOA4 is the proposed VLFOA. Due to the limit pages, the function f_3 is chosen as example to shown the efficiency of proposed strategies. As shown in the convergence curves below, the accuracy and convergence rate is improved step by step with the inset of the proposed three strategies. The diversity of population is improved by the extensive learning strategy. And the convergence rate is speed up with the addition of scanning search strategy and mutation strategy.

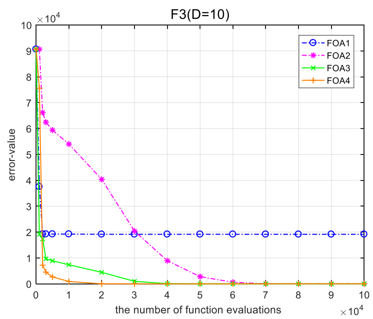


Fig.4 Convergence curves of FOA inserted different strategy

It can be seen from the results above, the VLFOA has excellent performance compared with the variant and original algorithm of FOA in CEC 2017 benchmark for D = 10.

V. Conclusion

In this paper, a variant of FOA based on efficient visual search and extensive learning is proposed to solve the complex continuous optimization problems. The VLFOA performing well in the exploration stage is owed to an improvement of vision search with visual angle is proposed to escape from local optima. The learning indicator FDR is introduced to increase the diversity of population and efficiency of non-separable problems. The algorithms are executed in CEC 2017 benchmark, and the experimental results show that the VLFOA has superior performance in all 30 functions compared with other three compared algorithms. But much work needs to be done in the cooperation in different strategies, and the convergence speed is required to be further improved. Those problems are raised further for future investigations on this topic. It is to be hoped that researchers continue to pursue this research agenda for discrete optimization, multi-objective optimization, uncertain optimization.

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