The Improvement of Fruit Fly Optimization Algorithm

——Using Bivariable Function as Example

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***Abstract*—Optimization problems are always the hot issues in various research fields. The aim of this paper is to find the optimal value of the bivariable nonlinear function by means of the improved fruit fly optimization algorithm(G-FOA). Some better results are obtained. Compared with other algorithms, G-FOA is concise, can quickly find the global optimum with the high accuracy and without falling into local extremum. These advantages make the algorithm has good robustness and applicability.**

Keywords-fruit fly optimization algorithm; extremal optimization; local extremum

I. SHORT INSTRUTION OF FRUIT FLY OPTIMIZING CALCULATING

Fruit fly optimization algorithm which was called FOA is the latest evolutionary computation technique which was pointed out by Wenchao Pan in Taiwan. FOA is the new method of swarm intelligence base on the foraging of fruit fly. For fruit fly has advantage in sense organ and feeling, especially in vision and smelling. They can collect all the smell in air ,even can match the food resources out of 40km. When reach the food's location, they will fly to them directly by sense vision and the location confirmed by partner[1].

The basic steps for calculation:

Step 1, confirm the fruit fly group's location by random(X-axis,Y-axis).

Step 2, endow personal fruit fly wih random value for looking food and location(X,Y).

X= X-axis+ Random Value;
Y= Y-axis+ Random Value.

Step 3, caculating the personal fruit fly's distance from the zero point, and find out the S value of density , this value equals to the inverse value of distance.

Dist = $\sqrt{X^2+Y^2}$; S=$1/dist$.

Step 4, bring the smell density Value S to the density judge function, and find out the smell density value of personal fruit fly at confirmed location. Smell=Function(S).

Step 5, repeating the step two to step four, calculating out the smell density of all the fruit flies in the group, and find out the fruit fly with largest and lowest smell density value.

Step 6, keep the smell density value and location (X,Y) of the best fruit fly, and the group fly to that location.

Step 7, enter in the iterative optimization, and repeat step two to step five, and check whether the smell density value better than the previous one, if yes, carry on the step six.

II. THE REALIZATION OF G-FOA

Because the smell density decision value is $S=\frac{1}{\sqrt{X^2+Y^2}}>0$ in the original arithmetic, when bring it to smell density confirming function(S), the function may ask S as negative, which make the FOA has limitation in application.

When applying for the optimizing of binary function $f(x_1,x_2)$, the both two independent variable can be negative. This time, if the fruit fly group has two , X-axis,Y-axis are both planar, using (X-axis(i),Y-axis(i))to check the location coordinate of 'i' fruit fly (i=1,2),and endow a random direction and moving distance for every fruit fly:X= X-axis+ Random Value;Y= Y-axis+ Random Value. And (X(i),Y(i))means the location coordinate of 'i' fruit fly after moving. Make $E=\sqrt{X(1)^2+Y(1)^2}$ and $D=\sqrt{X(2)^2+Y(2)^2}$ as the distance of two fruit flies from zero point, then E and D can be the measure parameters of smell density of fruit fly. Make $F=x_1, T=x_2$,USE (F,T) as the decision parameters of smell density decision function $f(F,T)$, and $F=\text{sign}(\varepsilon)\frac{1}{E}$, $T=\text{sign}(\varepsilon)\frac{1}{D}$, $\text{sign}(\varepsilon)$ is the symbolic function, ε is the random value on point (-1,1) . Then F($=x_1$) and T($=x_2$) can apply to smell density decision function Function= $f(F,T)$ with positive or negative, which is more convenent for iterative optimization according needs. The steps of G-FOA are as following:

Step 1, find a random location of fruit fly group. X-axis=a*rands(1,2);Y-axis= a *rands(1,2),('a' is adjustable parameter).

Step 2, endow the personal fruit fly with random direction and location of searching food by smelling.

X= X-axis+ b*rand()-c;Y= Y-axis+ b*rand() -c,
('b' and 'c' are both adjustable parameter).

Step 3, calculating the smell density Measure parameters (E,D) of personal fruit fly, and calculate the smell density decision parameters (F,T);

$E=\sqrt{X(1)^2+Y(1)^2}$; $D=\sqrt{X(2)^2+Y(2)^2}$; $F=\mathrm{sign}(\varepsilon)/E$; $T=\mathrm{sign}(\varepsilon)/D$, ε is the random value on point (-1,1).

Step 4, apply smell density decision parameters (F,T) to smell density decision function f , and find out the smell density value of that personal fruit fly. $Smell=f(F,T)$.

Step 5, repeating the step two to step four, and calculating the smell density value of every fruit fly in the group size, and find out the fruit fly with best and min value. [bestsmell bestindex]=max(Smell) (or min(Smell)).

Step 6, keep the best smell density value and location parameter. Then let the group fly to that location.

Bestvalue=bestsmell;X-axis=X(bestindex,:);

Y-axis=Y(bestindex,:).

Step 7, enter in the iterative optimization, and back to carry on step two to step five, and check whether the smell density value is better than the previous one, if yes, go on the step six, or carry on the step seven , until match the max iterations , the calculating finished.

III. EXAMPLES ANALYSIS

This article tests the performance of G-FOA by the optimal solution of the below three Binary nonlinear function, the three function are as following :

a) $f_1(x)=e^{-x_1^2-x_2^2}$, $x_1,x_2\in[-2,2]$,

b) $f_2(x)=\dfrac{\sin\sqrt{x_1^2+x_2^2}}{\sqrt{x_1^2+x_2^2}}$, $x_1,x_2\in[-10,10],(x_1,x_2)\neq(0,0)$,

c) $f_3(x)=x_1^4+x_2^4-x_1^2-x_2^2-2x_1x_2$, $x_1,x_2\in[-2,2]$.

A. Optimization results of G-FOA to function $f_1(x)$

Function $f_1(x)$ as Figure. 1, the actual max value of this function is 1, and the related location is $(0,0)$. The iterations of G-FOA is 200, and group size is 30. Adjustable parameter setting: a=10,b=2,c=1. When the iteration of G-FOA to function $f_1(x)$ match 7 times, optimizing match the max value 1, and related location coordinate is (0.0049,0.0049), the location coordinate of group size is (110.6162,105.2353). The time for calculating is 0.069721 seconds.

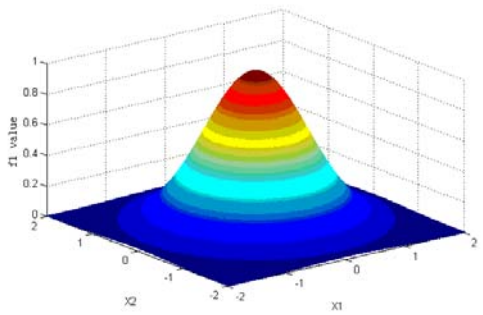

Figure 1. Graph of $f_1(x)$

Iterative optimization process as Figure. 2, the searching line for fruit fly as Figure. 3. For checking the stablility of G-FOA, try to calculating it 5 times continuely, and testing results as Figure. 4 and Table I.

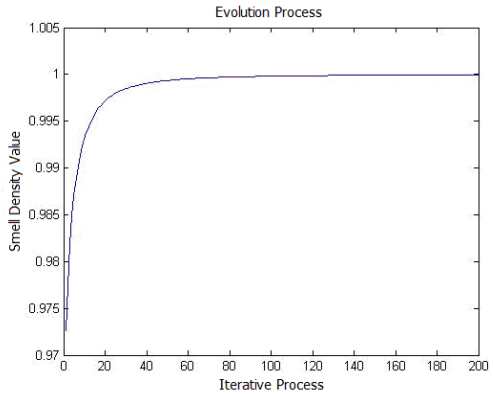

Figure 2. Iterative optimization process of $f_1(x)$

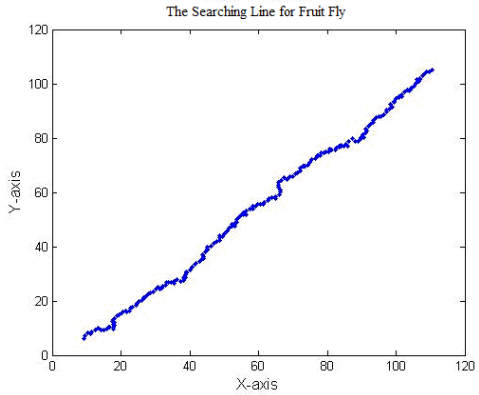

Figure 3. The searching line for fruit fly of $f_1(x)$

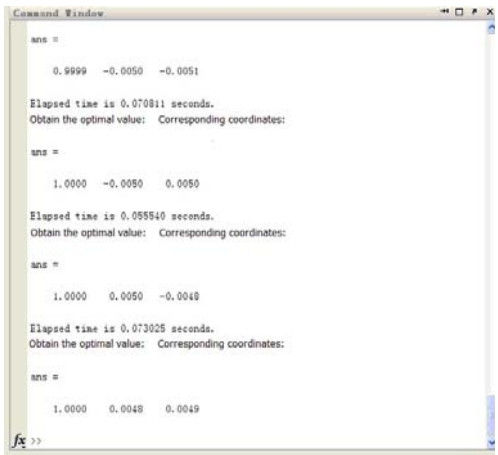

Figure 4. Testing results of calculating $f_1(x)$ 5 times continuely

TABLE I. TESTING RESULTS OF CALCULATING $f_1(x)$ 5 TIMES CONTINUELY BY G-FOA

Test Times	Algorithm Calculating Hour（s）	Acquired Max Value	Location Coordinate Corresponding
1	0.069721	1.0000	（0.0049,0.0049）
2	0.066578	0.9999	（-0.0050,-0.0051）
3	0.070811	1.0000	（-0.0050,0.0050）
4	0.055540	1.0000	（0.0050,-0.0048）
5	0.073025	1.0000	（0.0048,0.0049）

B. Optimization results of G-FOA to function $f_2(x)$

Function $f_2(x)$ ($x_1, x_2 \in [-10,10]$, $(x_1, x_2) \neq (0,0)$)as Figure. 5. This function is multimodal function, has many max value in the whole range. The actual max value is 1, and related location coordinates is $\{(x_1, x_2) | -0.01 \le x_1 \le 0.01, -0.01 \le x_2 \le 0.01\}$, $(x_1, x_2) \neq (0,0)$. Testing way and parameters as section 3.1, the test results as Figure. 6 and Figure. 7, and testing results after 5 times operating asTable 2.

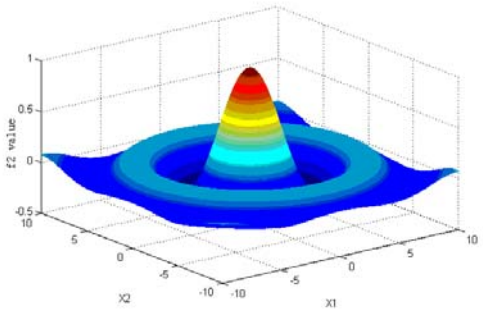

Figure 5. Graph of $f_2(x)$

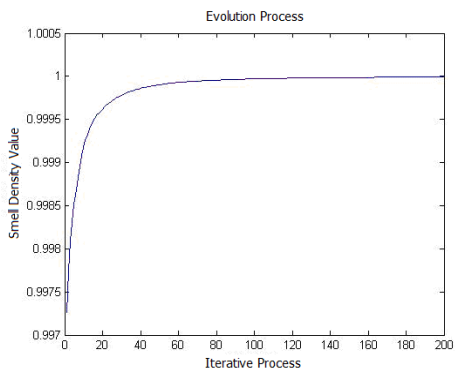

Figure 6. Iterative optimization process of $f_2(x)$

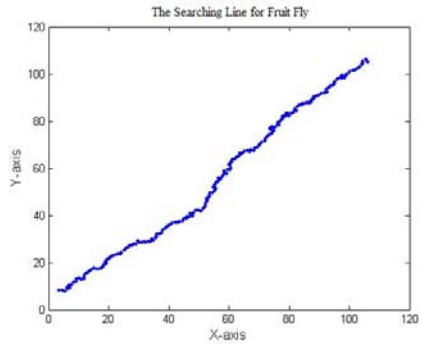

Figure 7. The searching line for fruit fly of $f_2(x)$

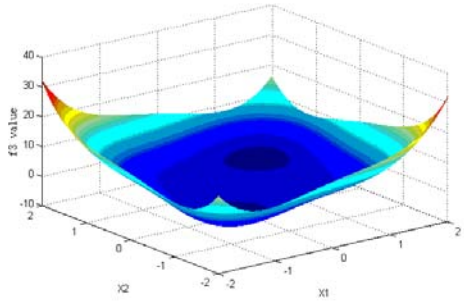

Figure 8. Graph of $f_3(x)$

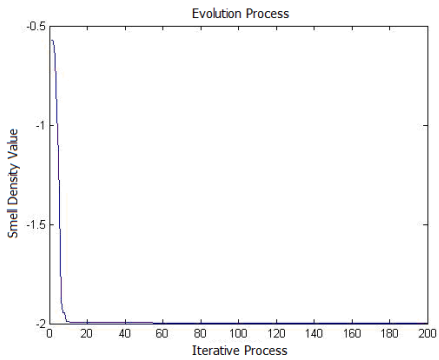

Figure 9. terative optimization process of $f_3(x)$

TABLE II. TESTING RESULTS OF CALCULATING $f_2(x)$ 5 TIMES CONTINUELY BY G-FOA

Test Times	Algorithm Calculating Hour（s）	Acquired Max Value	Location Coordinate Corresponding
1	0.027103	1.0000	（0.0048,0.0049）
2	0.026718	1.0000	（ -0.0051,-0.0051）
3	0.058381	1.0000	（0.0050,-0.0051）
4	0.051700	1.0000	（0.0049,0.0049）

5	0.037639	1.0000	（-0.0050,0.0050）

C. Optimization results of G-FOA to function $f_3(x)$

Function $f_3(x)$， $x_1, x_2 \in [-2,2]$ is multimodal function too, the min value of whole range is -2, and related location coordinates is $(-1,-1)$ & $(1,1)$ as Figure. 8. Same, the calculating results as Figure. 9 to Figure. 10, the results of operating 5 times continuely as table 3 .

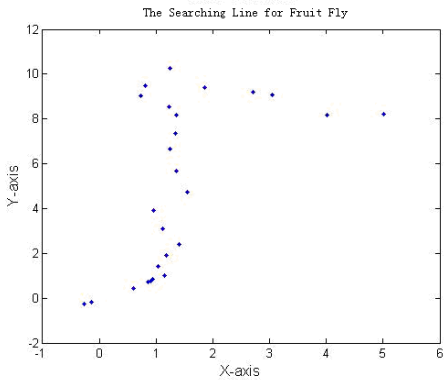

Figure 10. The searching line for fruit fly of $f_3(x)$

TABLE III. TESTING RESULTS OF CALCULATING $f_3(x)$ 5 TIMES CONTINUELY BY G-FOA

Test Times	Algorithm Calculating Hour（s）	Acquired Min Value	Location Coordinate Corresponding
1	0.084104	-1.9999	（-1.0042, -0.9987）
2	0.095729	-1.9999	（-1.0039, -1.0039）
3	0.098602	-1.9996	（0.999, 1.0086）
4	0.087864	-1.9996	（-1.0041, -0.9927）
5	0.089189	-1.9975	（1.0158, 1.0193）

IV. COMPARATIVE STUDY AND RESULTS ANALYSIS

For optimization problem processing is always the hot point of every reserching area [2-6],the way to solving optimization problem includes genetic algorithm[6,7] 、 Particle swarm algorithm [8-11] and simulated annealing algorithm[12,13] etc. For the restrition of article length, this article only use classic nonlinear multimode state Rastrigin function as exemple, to have comparative study, to show the performance of G-FOA. The expression is :

$$f(x,y) = x^2 + y^2 - 10\cos(2\pi x) - 10\cos(2\pi y) + 20 .$$

This function is multiple hump function (as Figure. 11), find the min value 0 on point (0,0) there are about 20 local minimum value at point $x, y \in (-5.12, 5.12)$, has very large searching space, always taken as the complicated Nonlinear multimodal problems which is hard to handle of optimization algorithm, so it is difficlut to find the globally optimal solution.

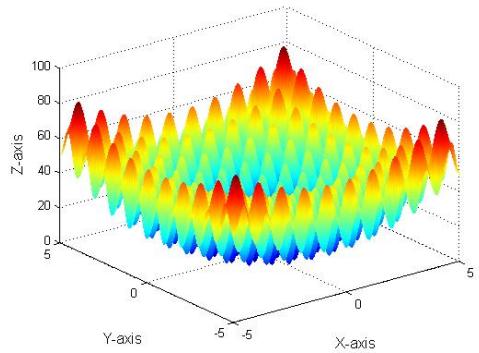

Figure 11. Binary function graph of Rastrigin

For making it more easy to compare with all the optimization algorithm, setting all the iterations as 500 times, and group size is 50, optimal boundary is $[-5,5]$, the other parameters is default,and the results of optimizing as table 4.

TABLE IV. THE RESULTS' COMPARISON OF EACH ALGORITHM OPTIMIZING

Optimization Algorithm	Algorithm Calculating Hour（s）	Acquired Min Value	Location Coordinate Corresponding
G-FOA	0.219159	3.6754e-04	（ -9.6505e-04, -9.5983e-04）
Particle swarm algorithm	3.234407	4.6289e-04	（ -2.2560e-04, 0.0015）
Genetic algorithm	9.248884	3.1251e-04	（ 8.7780e-04,-8.9704e-04）
Simulated annealing algorithm	4.461261	0.0095	（0.0049, -0.0049）

According to this comparison, G-FOA, particle swarm optimization and genetic algorithm can find the global optimum well, and G-FOA has better convergence. During the optimization process, genetic algorithm and particle swarm optimization and simulated annealing algorithm trap in local extremum many times, the common faults for all these arithmetic is : complicated calculus process, not easy to control for new learner, and difficult to popularize. Comparring with these arithmetic,G-FOA is more simple to operate, can find the global optimum quickly, and population without degradation when using for iterative optimization of multivariate function, keep the variety of group size, which make the optimizing results more accurate and not easy to trap in the local extremum.

V. CONCLUSIONS

Though the original FOA shown a better performance during global optimization and parameter optimization[2], but the shortage of semll density value decision value setting make it has some restriction in popularizing. The G-FOA in this article broaden the application ability of original

arithmetic, has better robustness and application ability. And this arithmetic can be used together with other data mining , such as fuzzy mathematics, grey system, artificial neural network etc,can use in the army, engeneer , medical science, management, finance area etc.

The common shortage for G-FOA and original FOA is that the optimization ability will be effected by parameter 'a','b','c',group size and iterations , adjustable parameter will be a little much. But when using for application, just need to setting a suitable parameter, G-FOA still can be a very excellent optimization algorithm.

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