An adaptive step improved fruit fly optimization algorithm

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Abstract: In order to solve the shortcomings of Fruit Fly Optimization Algorithm (FOA), which is slow and easy to fall into local optimum, can not specify the domain, Fruit Fly Optimization Algorithm and logstic function transformation are combined to propose an adaptive step improved fruit fly optimization algorithm with logistic transform (ASFOALT). The algorithm improves the correctness of the optimal solution range by improving the fitness function of the FOA, and improves the overall performance of the algorithm by adding the adaptive step mechanism. The experimental results show that ASFOALT has a large improvement in global search capability, convergence speed, convergence accuracy and reliability.

1. Introduction

Fruit Fly Optimization Algorithm(FOA) is a grouped intelligence algorithm proposed by Dr. Pan WT in 2011 based on the characteristics of fruit fly foraging behavior and the global optimal solution[1,2].The algorithm improves the diversity of fruit fly melanogaster by olfactory search, increases the search space of fruit fly individuals, and rapidly converges the fruit flies by visual search to achieve the optimal solution. The algorithm has the characteristics of less parameters, fast calculation speed, strong global optimization ability and easy implementation. It can be widely used in science and engineering field, and can be used together with other data mining techniques, It has been successfully applied to BP neural Network clustering analysis[3], support vector machine (SVM) parameter optimization[4], blind source separation[5] and other fields. On the other hand, FOA also has the problem that the domain of optimization can not be specified, the search direction is blind, the optimization is easy to fall into the local optimal, the later convergence speed is slow and the convergence precision is low. Therefore, many scholars have done a different degree of improvement on the FOA.Han JY[6] and others, combining chaos optimization with the fruit fly algorithm, proposed adaptive chaos fruit fly optimization algorithm; Ning Jianping[7] and others, applied the step size of the decreasing algorithm to Fruit Fly Optimization Algorithm, which makes Fruit Fly Optimization Algorithm have strong global search ability at the initial stage, so as to effectively avoid the local optimal problem. Yang Shuquan[8] and others proposed a clustering analysis algorithm(Flow-IFOA) based on the improved fruit fly optimization algorithm and functional flow algorithm, by introducing the fruit fly factor, the search step size of each fruit fly individual is adjusted adaptively according to the distance from the optimal fruit fly, which ensures the search precision and speed of the algorithm.

For the FOA can not specify the domain of optimization, the optimization accuracy is not high and easy to fall into the local optimal characteristics, In this paper, an adaptive step improved fruit fly optimization algorithm with logistic transform (ASFOALT) is proposed by improving the fitness function and fuse the adaptive step size adjustment technology. first, the algorithm corrects the original concentration decision value Js, so that the improved Fruit Fly Optimization Algorithm can be applied to any domain be specified, secondly, used the adaptive step size strategy based on logistic function transformation to overcome the FOA optimization accuracy is not high and easy to fall into the local optimal shortcomings, and thus improving the accuracy and convergence speed of the algorithm.

2. Principle of Algorithm

2.1. Principle of FOA[1-2]

FOA first randomized the initial coordinates of fruit fly swarm, randomly distributed fruit fly individual through their own sense of smell to randomly search for food in a certain range, because the coordinates of the food is unknown, the distance between the fruit fly and the origin is calculated first and take the reciprocal of the distance as smell concentration judgment value, substitute smell concentration judgment value into smell concentration judgment function (or called Fitness function) so as to find the smell concentration of the individual location of the fruit fly and the fruit fly with maximal smell concentration sends a signal to fruit fly swarm, than other fruit flies use vision to fly to the position of the fruit fly with maximal smell concentration. After reaching the current optimal position, the fruit fly swarm re-initializes the location within a certain range and repeats the process until the food is found or Iterations a certain number of times.

The proceed of FOA as follows:

Step1 Random initial fruit fly swarm location is shown in the figure to the right of Fig. 1.

InitX_axis;InitY_axis

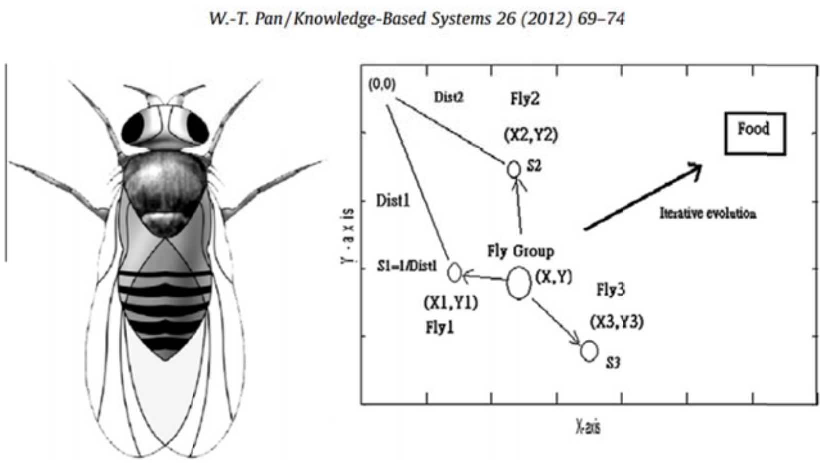

Fig. 1 Illustration of the body look of the fruit fly and group iterative food searching of fruit fly

Step2 Give the random direction and distance(R) for the search of food using osphresis by an individual fruit fly.

$$X_i = X\_axis + R$$

$$Y_i = Y\_axis + R$$

Step3 Since the food location cannot be known, the distance to the origin is thus estimated first (Dist), then the smell concentration judgment value (Js) is calculated, and this value is the reciprocal of distance.

$$Dist = \sqrt{X_i^2 + Y_i^2}$$

$$Js = \frac{1}{Dist}$$

Step4 Substitute smell concentration judgment value (Js) into smell concentration judgment function (or called Fitness function) so as to find the smell concentration ($Smell_i$) of the individual location of the fruit fly.

$$Smell_i = Function(Js_i)$$

Step5 Find out the fruit fly with maximal smell concentration (finding the maximal value Smellbest) among the fruit fly swarm. (Best individual FF_{best}).

$$Smell_{best} = \max(Smell)$$

$$Best = Smell_{best}.index$$

$$FF_{best} = [X_{best}, Y_{best}]$$

Step6 Keep the best smell concentration value and x, y coordinate, and at this moment, the fruit fly swarm will use vision to fly towards that location.

$$BestSmell = Smell_{best}$$

$$[X\_axis, Y\_axis] = FF_{best}$$

Step7 Enter iterative optimization to repeat the implementation of steps 2–5, then judge if the smell concentration is superior to the previous iterative smell concentration, if so, implement step 6.

3. Improvement of Algorithm

3.1. Improvement based on Fruit Fly Optimization Algorithm

In the process of overall iterative optimization, FOA substitute the reciprocal of the distance each fruit fly to the origin into Fitness function to get the optimal solution, so the searching range(or call domain) of fruit fly swarm is not domain of Fitness function, the optimal solution obtained by the fitness function is probably not the solution within the specified range. For example, use FOA to get the minimum value of the sine function $f(x)=\sin(x), x\in[2,4]$ will get the global optimal value $f(x)=-1$ Instead of the optimal value $f(x)=-0.7568$ within domain $x\in[2,4]$, this means that FOA is unable to specify the search range (or call domain). In order to solve this problem, this paper improves the initial range of the fruit fly swarm, the calculation method of smell concentration judgment value and the fitness function of the FOA.

The proceed of the improved fruit fly optimization algorithm as follows:

Step1 Perform the steps 1 to 5 in FOA.

Step2 First, estimated the distance each fruit fly to the origin (Dist), than performs a modulus on 1 to put the value(smell concentration judgment value, Js) in the proper range.

$$Dist = \sqrt{X_i^{\,2} + Y_i^2}$$

$$Js = Dist\%1$$

Step3 Map the smell concentration judgment value(Js) to the domain([Min,Max]).

$$Js = Min + Js \times (Max - Min)$$

Step4 Perform the steps 4 to 7 in FOA.

The improved fruit fly optimization algorithm can overcome the defects in FOA that can not specify the search range by mapping the smell concentration judgment value(Js) within the range [0,1] to the specified domain. In the following experimental section, the effectiveness of this improvement will be verified by multiple functions.

3.2. Adaptive step size based on logistic transform

In each iteration, Fruit Fly Optimization Algorithm take the best individual of last iteration as the center and take the random distance(R) as the radius to search the food, but the random distance(R) is a fixed value. If R is a large value, the algorithm will get better performance in global optimization, can quickly locate the approximate range of the optimal solution, but in the process of local optimization, convergence accuracy and search efficiency of the algorithm can not be guaranteed. If R is a smaller value, the algorithm is easily trapped in the local optimum and appeared premature convergence, whole search efficiency is limited even in unimodal functions.

In order to resolve this problem, we have introduced a function based on Logistic Function transformation.

$$LT = \frac{1}{1 + e^{20(x-0.5)}} \quad x \in [0,1] \tag{1}$$

Set the Adaptive step size(RV).

$$RV = R \times LT\left(\frac{Gen}{Maxgen}\right) \tag{2}$$

In this formula, R is the initial step size(or call random distance) of FOA, Gen is iterations, Maxgen is maximum number of iterations, function LT is a correction function and the graph as shown in the Fig.2.

adaptive step size adjustment technology can make Fruit Fly Optimization Algorithm have a larger random step value(RV) in early iterations to avoid premature convergence, as the number of iterations increases RV will decreased by Logistic Function curve; in later iterations, smaller step size make Fruit Fly Optimization Algorithm have powerful local optimization performance.

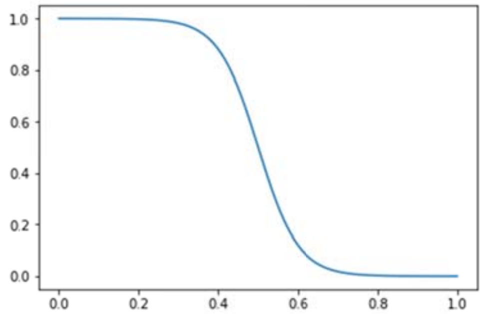

Fig. 2 The correction function graph

4. An adaptive step improved fruit fly optimization algorithm

In this paper, the improved fruit fly optimization algorithm and adaptive step size adjustment techniques combined, proposed an adaptive step improved fruit fly optimization algorithm with logistic transform (ASFOALT). This optimization is base on the improved fruit fly optimization algorithm above and use adaptive step size adjustment technology to global optimization. On the one hand, the improved fruit fly optimization algorithm overcome the disadvantage of unable to specify the search range, on the other hand, adaptive step size adjustment technology can effectively overcome premature convergence, increase global optimization capability and precision of solutions.

The proceed of ASFOALT as follows:

Step1 Set initialization parameters of population size(S), domain([Min,Max]), maximum number of iterations(Maxgen), initial step size(R), initial fruit fly swarm location([X_axis,Y_axis]).

Step2 Simultaneous formula.1 and formula.2 to get adaptive step size(RV) for the search of food using osphresis by an individual fruit fly.

$$RV = R \times LT(\frac{Gen}{Maxgen})$$

$$X_i = X\_axis + RV$$

$$Y_i = Y\_axis + RV$$

Step3 estimated the distance each fruit fly to the origin(Dist) and performs a modulus on 1 to put the value(the smell concentration judgment value, Js) in the proper range([0,1]).

$$Dist = \sqrt{X_i^2 + Y_i^2}$$

$$Js = Dist\%1$$

Step4 Map the smell concentration judgment value(Js) to the domain([Min,Max]).

$$Js = Min + Js \times (Max - Min)$$

Step5 Substitute smell concentration judgment value (Js) into smell concentration judgment function (or called Fitness function) so as to find the smell concentration ($Smell_i$) of the individual location of the fruit fly.

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$$Smell_{best} = \max(Smell)$$

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Step7 Keep the best smell concentration value and x, y coordinate, and at this moment, the fruit fly swarm will use vision to fly towards that location.

$$BestSmell = Smell_{best}$$

$$[X\_axis, Y\_axis] = FF_{best}$$

Step8 Enter iterative optimization to repeat the implementation of steps 2–6, then judge if the smell concentration is superior to the previous iterative smell concentration, if so, implement step 7.

Step9 This process is iterated until the function convergesor or the number of iterations reaches the maximum number of iterations(Maxgen).

5. Experiment and result analysis

5.1. The testing functions

In order to illustrate ASPHALT can specify the search range, this paper add the sine function and sine rate function(the graph as shown in the Fig.3 and 4) on the basis of the six classical testing functions, the performances of ASFOALT and FOA will be compared by simulation experiments. The function name, function form, search domain, optimum solution and target precision of the testing functions are shown in Table.1. Test platform is Inter Core i5-6300HQ CPU @ 2.30GHz 16GB Windows7.

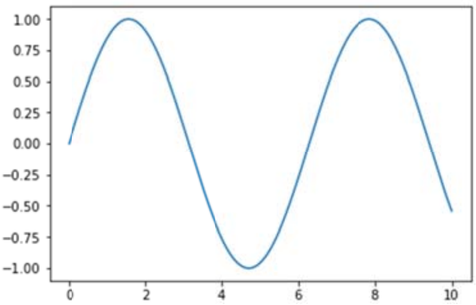

Fig. 3 Sine

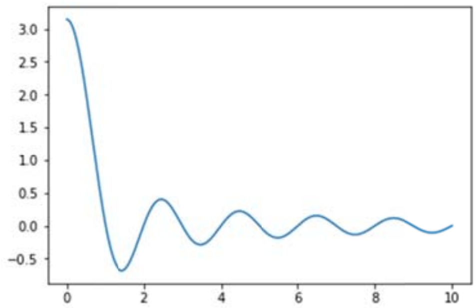

Fig. 4 Sine Rate

5.2. Result analysis.

Set initialization parameters, population size(S)=30, maximum number of iterations (Maxgen)=200, initial step size(R)=0.5, The objective of this experiment is determine minimum value of the test functions, Shaffer, Sine, Sine Rate of the test functions are 2 dimensional function and other test functions are 30 dimensional. The minimum, maximum, average and standard deviation were used as the evaluation indexes of this experiment, take the average value of FOA and ASFOALT two algorithms run independently 20 times as a result to eliminate random error to get a better precision and the results are shown in the Table.2.

The results with the indces showed that ASFOALT has a significant improvement over FOA and obtained the theoretical extreme value of Schaffer function and Griewank function. It is worth noting that many of the other algorithms in the literature[9-10] did not perform well in Rosenbrock function, but ASFOALT raise 8 orders of magnitude at least than FOA. In addition, the optimal solution obtained of sine Function by FOA is not within the specified domain([2,4]), but ASFOALT successfully converged to the optimal value, this also proves that FOA is unable to specify the domain. Sine Rate is a multimodal function, because FOA can not specify the domain and the search step is fixed value, this algorithm is not stable and the standard deviation is large, the effect of convergence accuracy far from ideal. Unlike FOA, ASFOALT effectively overcome premature convergence by adaptive step size adjustment technology and increase global optimization capability and precision of solutions.

Table. 1 Test function

Name	Function form	Domain	Optimum solution	Target precision
Sphere	$f=\sum_{i=1}^{n}x^2$	[-100,100]	0	10^{-5}
Rosenbrock	$f=\sum_{i=1}^{n-1}(100(x_{i+1}^2-x_i)^2+(x_i-1)^2)$	[-30,30]	0	30
Schaffer	$f=\dfrac{\sin^2\sqrt{x_1^2+x_2^2}-0.5}{(1+0.001(x_1^2+x_2^2))^2}-0.5$	[-100,100]	-1	10^{-5}
Rastrigin	$f=\sum_{i=1}^{n}(x_i^2-10\cos(2\pi x_i)+10)$	[-5.12,5.12]	0	10^{-4}
Ackley	$f=-20e^{-\frac{1}{5}\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}}-e^{\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)}+20+e$	[-32,32]	0	10^{-5}
Griewank	$f_2=\frac{1}{4000}\sum_{i=1}^{n}x^2-\prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}})+1$	[-600,600]	0	10^{-6}
Sine	$f_7=\sin(x)$	[2,4]	-0.75680	10^{-5}
Sine Rate	$f_8=\sin(\pi x)/x$	[2,6]	-0.28690	10^{-5}

Table. 2 Result of the experiment

Name	Algorithm	Min	Max	Mean	Std Dev
Sphere	FOA	2.4733e-06	0.0158	0.0035	0.0054
	ASFOALT	2.8564e-12	6.0076e-11	3.4597e-12	1.5677e-12
Rosenbrock	FOA	28.5742	29.3921	28.7633	0.2741
	ASFOALT	1.0122e-13	6.6795e-08	1.1501e-10	4.2457e-09
Schaffer	FOA	-0.9999	-0.9998	-0.9999	2.1645e-06
	ASFOALT	-1	-1	-1	0
Rastrigin	FOA	0.0012	0.0022	0.0015	3.2615e-05
	ASFOALT	0	2.9624e-12	2.3182e-15	1.5426e-14
Ackley	FOA	0.0031	0.0547	0.0293	1.1521e-04
	ASFOALT	2.6501e-15	7.5648e-15	4.3350e-15	1.8448e-17
Griewank	FOA	7.3842e-06	4.3715e-05	1.2016e-06	6.3257e-07
	ASFOALT	0	0	0	0
Sine	FOA	-0.9999e-10	-0.9999e-9	-0.9999e-10	1.1622e-11
	ASFOALT	-0.75680	-0.75680	-0.75680	1.6975e-15
Sine rate	FOA	-0.68245	-0.67272	-0.67957	1.7332e-03
	ASFOALT	-0.28690	-0.28690	-0.28690	6.0562e-16

6. Conclusion

For the FOA can not specify the domain of optimization, the optimization accuracy is not high and easy to fall into the local optimal characteristics, by the improved fruit fly optimization algorithm and adaptive step size adjustment techniques combined, proposed an adaptive step improved fruit fly optimization algorithm with logistic transform (ASFOALT). And the experiments show that the proposed algorithm(ASFOALT) can specify the search range and on this basis,it has a lot of improvements than FOA in global search capability, convergence speed, convergence accuracy and reliability.

References

[1] Pan WT. A new evolutionary computation approach: Fruit fly optimization algorithm[C].Conference of Digital Technology and Innovation Management, 2011

[2] Pan WT. A new Fruit Fly Optimization Algorithm: Taking the financial distress model as an example. Knowledge-Based Systems, 2012,26(2): 69-74

[3] Yu XR, Zhang SR, Wang XH,Chen J. Back analysis on dam mechanical parameters based on fruit fly-BP neural network algorithm. Water Resources and Hydropower Engineering. 2014.45(9):52

[4] Li HZ, Guo S, Li CJ. A Hybrid Forecasting Model Based on Fruit Fly Optimization Algorithm and Least Squares Support Vector Machine: -the Case of Logistics Demand Forecasting of China. Journal of Quantitative Economics, 2012, 29(3):103-106

[5] Xiao ZA. Application of improved FOA on audio signal blind separation [J].Computer Engineering and Applications, 2013, 49(16):201-204

[6] Han JY,Liu CZ. Adaptive chaos fruit fly optimization algorithm [J]. Journal of Computer Applications, 2013,33(5):1313-1316.

[7] Ning JP, Wang B, Li HG, Xu BH. Research on and application of diminishing step fruit fly optimization

algorithm[J]. Journal of Shenzhen University [Science&engineering],2014,31(4):367-373

[8]Yang SQ, Shu Q, He C. A MODIFIED FRUIT FLY ALGORITHM AND ITS APPLICATION IN PPI NETWORK [J]. Computer Applications and Software, 2014(12):291-294

[9] Zhang QT, Fang LQ, Zhao YL. Double subgroups fruit fly optimization algorithm with characteristics of levy flight [J].Journal of Computer Applications, 2015,35(5):1348-1352

[10] Zhang CH, Pan GZ. Fruit fly optimization algorithm based on non-uniform mutation and adaptive escape[J]. Computer Engineering and Design, 2016,37(8):2093-2097