Journal of Computer and Communications, 2014, 2, 137-141
Published Online March 2014 in SciRes. http://www.scirp.org/journal/jcc
http://dx.doi.org/10.4236/jcc.2014.24018

Parameter Analysis on Fruit Fly Optimization Algorithm

Hazim Iscan, Mesut Gunduz

Computer Engineering Department, Selçuk University, Konya, Turkey
Email: iscan@selcuk.edu.tr, mgunduz@selcuk.edu.tr

Received November 2013

Abstract

Fruit fly algorithm is a novel intelligent optimization algorithm based on foraging behavior of the real fruit flies. In order to find optimum solution for an optimization problem, fixed parameters are obtained as a result of manual test in fruit fly algorithm. In this study, it is aimed to find the optimum solution by analyzing the constant parameter concerning the direction of the algorithm instead of manual defining on initialization stage. The study shows an automated approach for finding the related parameter by utilizing grid search algorithm. According to the experimental results, it can be seen that this approach could be used as an alternative way for finding related parameter or other ones in order to achieve optimum model.

Keywords

Fruit Fly; Optimization

1. Introduction

Intelligent optimization algorithms are attracting the attention of many scholars in recent years. These algorithms with their simple steps and efficient search methods have become the most widely used in optimization problems which require performance. Particle swarm optimization (PSO) [1,2], ant colony optimization (ACO) [3], artificial bee colony algorithm (ABC) [4], Simulated Annealing (SA) algorithm [5], Bacterial Colony Chemotaxis (BCC) [6] and Fruit Fly Optimization algorithm (FOA) [7,8] are some of them. Fruit fly algorithm recently joined the intelligent optimization algorithms group. This algorithm is introduced by Wen Tsao Pan in 2011. The algorithm is originated from foraging behavior of fruit flies. The algorithm can be easily understandable because of its simple structure. Its updating strategy, which used to find best solution, is simpler than other algorithms. However, manually definition of this update strategy causes a disadvantage. A method has been tried to develop for eliminating this disadvantage and improving performance of algorithm. In this method, the manually defined parameters of algorithm, defined with the help of search algorithm. With this new method the functions which tested in Fruit fly algorithm have been used and obtained better results.

2. Fruit Fly Optimization Algorithm

Fruit fly optimization algorithm is the latest evolutionary computation technique which was pointed out by Wen

How to cite this paper: Iscan, H. and Gunduz, M. (2014) Parameter Analysis on Fruit Fly Optimization Algorithm. *Journal of Computer and Communications*, **2**, 137-141. http://dx.doi.org/10.4236/jcc.2014.24018

Tsao Pan in 2011. The Fruit Fly Optimization Algorithm (FOA) is a new intelligent method on the food finding behavior of the fruit fly. The fruit fly itself is superior to other species in sensing and perception, especially in osphresis and vision. The osphresis organs of fruit flies can find all kinds of scents floating in the air; it can even smell food source from 40 km away [7,8]. Then, after it gets close to the food location, it can also use its sensitive vision to find food and the company's flocking location, and fly towards that direction too. The behaviors of the fruit flies could be demonstrated in **Figure 1**.

Fruit fly's food finding characteristics is divided into several necessary steps as shown in **Figure 1**, and the steps of the algorithm could be given as follows [7];

1) Random initial fruit fly swarm location.

Init X_axis

Init Y_axis

2) Search with random direction and distance to the olfactory organ.

X_i = X_axis + RandomValue

Y_i = Y_axis + RandomValue

3) Since food's position is unknown, the distance (Dist) to the origin is estimated first, and the judged value of smell concentration (S), which is the inverse of distance, is then calculated.

$Dist_i = \sqrt{(X_i^2 + Y_i^2)}$

$S_i = 1/Dist_i$

4) Substitute smell concentration judgment value (S) into smell concentration judge 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(S_i)

5) Identifying the position of the best smell concentration (maximum value).

[bestSmellbestIndex] = max(Smell)

6) Keep the best smell concentration value and x, y coordinate, the fruit fly swarm will use vision to fly towards that location.

Smellbest = bestSmell

X_axis = X(bestIndex)

Y_axis = Y(bestIndex)

7) 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 [7].

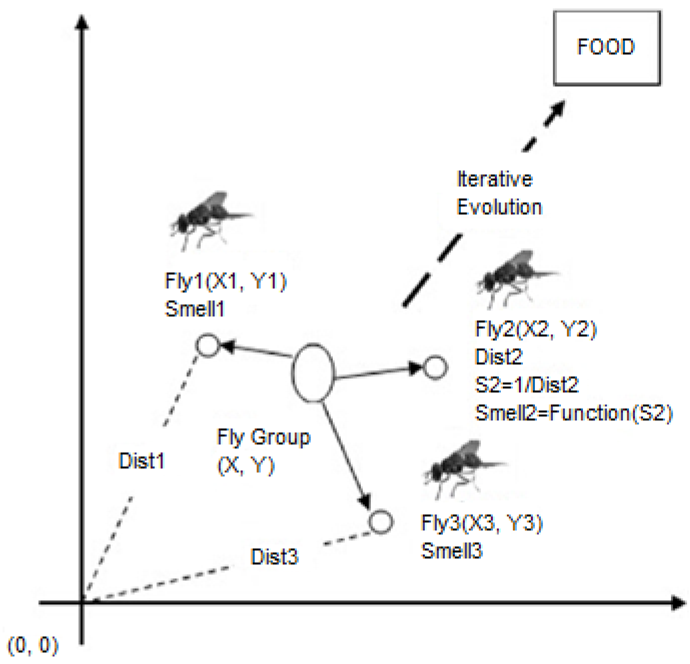

Figure 1. Illustration of the group iterative food searching of fruit fly [9].

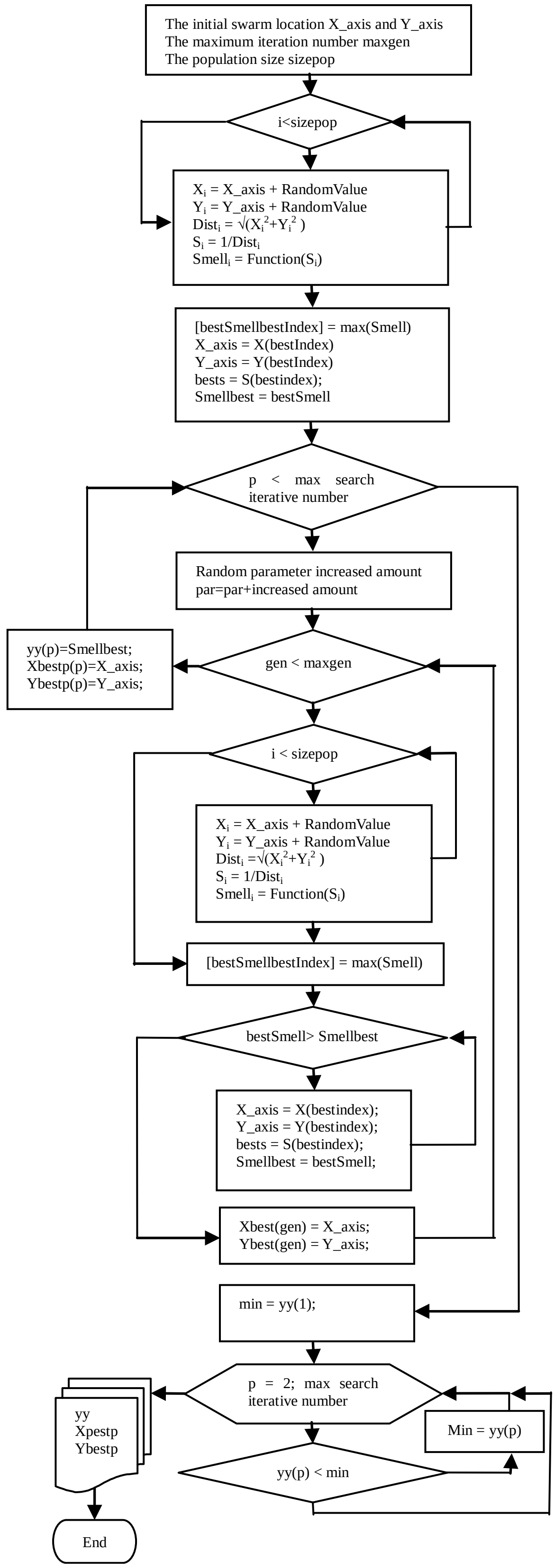

Figure 2. The fruit fly algorithm (proposed).

3. The Proposed Approach

In the fruit fly optimization algorithm, the parameters are employed by pre-defining in the initialization stage. This pre-definition of the parameters are required to be determined manually in order to achieve optimum solution concerning to the problem.

The grid search algorithm is one of the most used parameter estimation algorithms [10]. The parameters are investigated within given ranges and incremental steps. The algorithm is useful and easy on finding the optimum value of the parameter within the given range.

In this study, a constant parameter concerning the direction of the algorithm is investigated using grid search algorithm. In order to show working of the proposed method, a flowchart of the algorithm is drawn in **Figure 2**.

The performance of the proposed approach is evaluated on optimizing 2 different numeric functions given in Equation (1) and Equation (2) in [7]. In this concept, Equation (1) and Equation (2) are minimization and maximization problems respectively.

$$Y = -5 + X^2 \quad (1)$$

$$Y = 2 - X^2 \quad (2)$$

The minimum value of objective function in Equation (1) is −5, and the decision variable (X) should be 0. The maximum value of objective function in Equation (2) is 2, and the decision variable (X) should be 0.

In order to obtain the experimental results for FFO and proposed approach, the methods are evaluated 10 times and the obtained results are given in **Table 1** and **Figure 3**.

4. Results and Discussion

Based on characteristics of the optimization problem, the basic FFO needs to optimize constant value of coefficient while calculating step size. In the study, we propose the grid search to obtain the optimum value of coefficient. The experimental results show that proposed FFO is better than the basic FFO in terms of solution quality. The proposed method automatically adjusts the coefficient for each numeric benchmark function by using grid search, and this adapts the behavior of the method according to the problem. Therefore the more successful results are obtained by the proposed method.

5. Conclusion and Future Works

In this study, an adaptable version for basic FFO algorithm is proposed and the performance of the proposed

Table 1. Experimental results.

Function	FFO	Proposed Approach
$Y = -5 + X^2$	−4.9999	−5.00
$Y = 2 - X^2$	1.9999	2.00

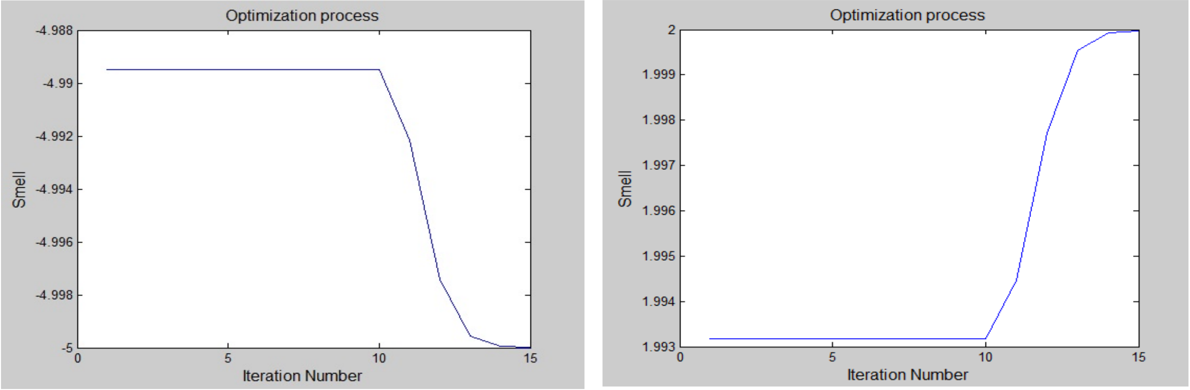

Figure 3. Solution curves.

method is examined on the numerical benchmark functions. According to experimental results, proposed method is better than the basic FFO algorithm. Future works include applying the proposed method to different optimazation problems such as energy estimation.

Acknowledgements

This study has been supported by Coordinatorship of Scientific Research Projects of Selcuk University.

References

[1] Kennedy, J. and Eberhart, R.C. (1995) Particle Swarm Optimization. *Proceedings of IEEE International Conference on Neural Networks*, Perth, 1942-1948.

[2] Shi, Y.H. and Eberhart, R.C. (1998) Parameter Selection in Particle Swarm Optimization. *Proceedings of the 7th International Conference on Evolutionary Programming VII*, 591-600.

[3] Dorigo, M. and Stützle, T. (2004) Ant Colony Optimization. MIT Press, Cambridge. http://dx.doi.org/10.1007/b99492

[4] Karaboga, D. (2005) An Idea Based on Honey Bee Swarm for Numerical Optimization. *Technical Report-TR*06, Erciyes University, Engineering Faculty, Department of Computer Engineering.

[5] Kirkpatrick, S., Gelatt, Jr., C.D. and Vecchi, M.P. (1983) Optimization by Simulated Annealing. *Science*, **220**, 671-680. http://dx.doi.org/10.1126/science.220.4598.671

[6] Li, W.W., Wang, H., Zou, Z.J. and Qian, J.X. (2005) Function Optimization Method Based on Bacterial Colony Chemotaxis. *Journal of Circuits and Systems*, **10**, 58-63.

[7] Pan, W.T. (2011) A New Fruit Fly Optimization Algorithm: Taking the Financial Distress Model as an Example. *Knowledge-Based Systems*, **26**, 69-74. http://dx.doi.org/10.1016/j.knosys.2011.07.001

[8] Pan, W.T. (2011) A New Evolutionary Computation Approach: Fruit Fly Optimization Algorithm. *Conference of Digital Technology and Innovation Management*, Taipei. http://www.oitecshop.byethost16.com/FOA.html

[9] Lin, S.-M. (2013) Analysis of Service Satisfaction in Web Auction Logistics Service Using a Combination of Fruit Fly Optimization Algorithm and General Regression Neural Network. *Neural Computing and Applications*, **22**, 783-791. http://dx.doi.org/10.1007/s00521-011-0769-1

[10] Cormen, T.H., Leiserson, C.E., Rivest, R.L. and Stein, C. (2001) Introduction to Algorithms. 2nd Edition, MIT Press.