IEEE Workshop on Nonlinear Circuit Networks
December 11-12, 2015

Firefly Algorithm Distinguishing between Males and Females for Minimum Optimization Problems

Masaki Takeuchi
Dept. of Electrical
and Electronic Engineering,
Tokushima University
2-1 Minami-Josanjima,
Tokushima 770–8506, Japan
Email: masaki@ee.tokushima-u.ac.jp

Haruna Matsushita
Dept. of Electronics
and Information Engineering,
Kagawa University
2217-20 Hayashi-cho,
Takamatsu, Kagawa, 761-0396, Japan
Email: haruna@eng.kagawa-u.ac.jp

Yoko Uwate and Yoshifumi Nishio
Dept. of Electrical
and Electronic Engineering,
Tokushima University
2-1 Minami-Josanjima,
Tokushima 770–8506, Japan
Email: {uwate, nishio}@ee.tokushima-u.ac.jp

***Abstract*—We propose Firefly Algorithm Distinguishing between Males and Females. This algorithm exists together with males and females. In this study, we investigate the feature of our proposed Firefly Algorithm by changing parameters and the rate of females. Numerical experiments indicate that our proposed Firefly Algorithm is superior to the conventional Firefly Algorithm under some conditions.**

I. INTRODUCTION

The optimization problems have been important more and more, recently. Most optimization problems are nonlinear with many constraints. Consequently, optimization algorithms require efficiency in order to find optimal solution. Stochastic algorithms, one category of optimization algorithms, are efficient optimization problems. They have a deterministic component and a random component. Algorithms having only the deterministic component are almost all local search algorithms. There is a risk to be trapped at local optima such algorithms. However, stochastic algorithms are possible to jump out such locality by having random component.

One of stochastic algorithms is the swarm intelligence algorithms. The swarm intelligence algorithms are based on the behavior of animals and insects. Representative examples are Particle Swarm Optimization (PSO) [1], Ant Colony Optimization (ACO), and Firefly Algorithm (FA) [2]–[5].

On the conventional FA, all fireflies are unisex. However, there are males and females in the real world. Therefore, we distinguish sex of fireflies. This proposed method is called Firefly Algorithm Distinguishing between Males and Females (FA-DMF). On FA-DMF, the movements of males and females are defined from the physical differences. Therefore, the movements of males and females are different from each other. We investigate the feature of FA-DMF by using famous two test functions. [1] Numerical experiments indicate that FA-DMF tends to increase randomness as increasing the rate of females.

This study is organized as follows: first, we explain the conventional Firefly Algorithm in Section II. Next, we describe in detail of FA-DMF in Section III. Followed by, we show numerical experiments. Finally, we conclude this study.

[1]The extended version of this study is being reviewed for ISCAS'16 [6].

II. THE CONVENTIONAL FIREFLY ALGORITHM (FA) [2]

Firefly Algorithm (FA) has been developed by Yang, and it was based on the idealized behavior of the flashing characteristics of fireflies. It is suitable for multi-peak optimization problems. The conventional FA is idealized these flashing characteristics as the following three rules

- all fireflies are unisex so that one firefly is attracted to other fireflies regardless of their sex;
- Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less brighter one will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If no one is brighter than a particular firefly, it moves randomly;
- The brightness or light intensity of a firefly is affected or determined by the landscape of the objective function to be optimized.

Attractiveness of firefly β is defined by

$$\beta = \beta_0 e^{-\gamma r_{ij}^2} \tag{1}$$

where γ is the light absorption coefficient, β_0 is the attractiveness at $r_{ij} = 0$, and r_{ij} is the distance between any two fireflies i and j at $\boldsymbol{x_i}$ and $\boldsymbol{x_j}$. The movement of the firefly i is attracted to another more attractive firefly j, and is determined by

$$\boldsymbol{x_i} = \boldsymbol{x_i} + \Delta\boldsymbol{x}, \tag{2}$$

$$\Delta\boldsymbol{x} = \beta(\boldsymbol{x_j} - \boldsymbol{x_i}) + \alpha\boldsymbol{\epsilon_i}, \tag{3}$$

where $\boldsymbol{x_i}$ is the position vector of firefly i, ϵ_i is the vector of random variable, and $\alpha(t)$ is the randomization parameter. The parameter $\alpha(t)$ is defined by

$$\alpha(t) = \alpha(0)\left(\frac{10^{-4}}{0.9}\right)^{t/t_{max}}, \tag{4}$$

where t is the number of iteration.

TABLE II
NUMERICAL EXPERIMENT RESULTS OF FA-DMF

name		conventional FA	FA-DMF								
female percentage			10	20	30	40	50	60	70	80	90
Rastrigin	ave	2.63×10^1	2.22×10^1	2.07×10^1	$\mathbf{1.83 \times 10^1}$	1.93×10^1	1.90×10^1	1.88×10^1	1.97×10^1	2.10×10^1	2.34×10^1
	min	1.21×10^1	9.95×10^0	1.09×10^1	$\mathbf{7.96 \times 10^0}$	1.09×10^1	$\mathbf{7.96 \times 10^0}$	1.09×10^1	1.09×10^1	1.19×10^1	1.39×10^1
	max	4.66×10^1	4.28×10^1	3.68×10^1	$\mathbf{2.79 \times 10^1}$	3.48×10^1	3.18×10^1	2.98×10^1	3.28×10^1	3.48×10^1	4.08×10^1
Griewank	ave	3.71×10^{-4}	$\mathbf{2.83 \times 10^{-4}}$	5.23×10^{-4}	7.39×10^{-4}	1.00×10^{-3}	1.02×10^{-3}	1.97×10^{-3}	2.82×10^{-3}	5.13×10^{-3}	1.04×10^0
	min	1.29×10^{-4}	1.23×10^{-4}	$\mathbf{1.21 \times 10^{-4}}$	1.41×10^{-4}	1.50×10^{-3}	1.58×10^{-4}	2.07×10^{-4}	1.77×10^{-4}	3.75×10^{-4}	1.03×10^0
	max	8.59×10^{-3}	7.68×10^{-3}	$\mathbf{7.65 \times 10^{-3}}$	1.02×10^{-2}	7.75×10^{-3}	1.51×10^{-2}	1.27×10^{-2}	2.00×10^{-2}	2.55×10^{-2}	1.06×10^0

III. FA-DMF

One of the rules of the conventional FA is that all fireflies are unisex. However, males and females exist in the real world. Therefore, we distinguish sex of fireflies, that is, there are two swarms in our proposed method. We call our proposed method Firefly Algorithm Distinguishing between Males and Females (FA-DMF). The movement of female is modeled from the physical differences. In the real world, females are bigger than males and female eyes are smaller than male. Thus, in our proposed method, females move slower than males, and females have difficulty finding the flashes of other distant fireflies. In addition, we change the randomization parameter of female.

The female parameters $\alpha(t)$ and β, and the female movement $\boldsymbol{x}$ are determined with parameters V and W by

$$\alpha(t) = \alpha(0)\left(\frac{10^4}{0.9}\right)^{t/2t_{max}}, \tag{5}$$

$$\beta = \beta_0 e^{-\gamma r_{ij}^2/W}, \tag{6}$$

$$\boldsymbol{x} = \boldsymbol{x} + \Delta\boldsymbol{x}/V. \tag{7}$$

In the proposed method, males are attracted to all fireflies, while females are attracted to only males. Males move the same as fireflies of the conventional FA.

IV. NUMERICAL EXPERIMENTS OF FA-DMF

We compare FA-DMF to the conventional FA with two test functions (see Table I). These optimal solutions are $f(x) = 0$ at $x = 0$.

TABLE I
THE TEST FUNCTIONS

name	Formula	range
Rastrigin	$f(x) = \sum_{i=1}^{n} (x_i^2 - 10\cos(2\pi x_i) + 10)$	[-5.12,5.12]
Griewank	$f(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos(\frac{x_i}{\sqrt{i}}) + 1$	[-600,600]

In case of solving minimum problem, Rastrigin and Greiwank functions are multi-peak optimization problem. There are a lot of local minimum and local maximum in Rastrigin and Greiwank functions. The graph of Greiwank function has gentler gradient than Rastrigin function.

Numerical experiment results are shown in Table II. Each numerical experiment is run 100 times. In each test function, we define the number of dimensions $N = 30$, $t_{max} = 1000$, $V = 3$ and $W = 4$. In this study, we change female percentage from 10 to 90 every 10 percentage.

As increasing female percentage, average of Greiwank function is continuously increasing. On the other hands, average of Rastirigin function decrease slowly from 10 to 30, and increase slightly from 30.

In case of numerical experiment of Rastrigin function, FA-DMF is almost superior to the conventional FA. In case of numerical experiment of Greiwank function, FA-DMF is superior to the conventional FA when female percentage is ten. In addition, FA-DMF is superior to the conventional FA about minimum and maximum when females percentage is twenty. Therefore, when the graph has gentle gradient, FA-DMF is inferior to the conventional FA.

V. CONCLUSION

In this study, we investigated the feature of Firefly Algorithm Distinguishing between Males and Females (FA-DMF). We apply our proposed Firefly Algorithm to two test functions. Numerical experiments indicate that FA-DMF is superior to the conventional FA under some conditions.

In the future work, we improve our proposed Firefly Algorithm, compare to other improved Firefly Algorithms, and apply to actual optimization problems.

REFERENCES

[1] J. Kennedy, R. Eberhart, *"Particle Swarm Optimization"*, Proceedings of the IEEE international conference on neural networks, pp. 1942—1948, 1995.

[2] Yang, X.S., *"Nature-Inspired Metaheuristic Algorithms Second Edition"*, Luniver Press, 2010.

[3] Yang, X.S., *"Firefly Algorithms for multimodal Optimization"*, Int. J. Bio-Inspired Computation, Vol. 2, No. 2, pp.78-84, 2010.

[4] H. Matsushita, *"Firefly Algorithm with Dynamically Changing Connections"*, Proceedings of International Symposium on Nonlinear Theory and its Application, pp.906-909, 2014.

[5] S. Lukasik, S. Zak, *"Firefly Algorithm for Continuous Constrained Optimization Tasks"*, Computational Collective Intelligence. Semantic Web, Social Networks and Multiagent Systems, Vol. 5796 of the series Lecture Notes in Computer Science, pp.97-106, 2009.

[6] M. Takeuchi, H. Matsushita, Y. Uwate, Y.Nishio, *"Investigation of Firefly Algorithm Distinguishing between Males and Females"*, IEEE International Symposium on Circuits and Systems(ISCAS), 2016. (being submitted)