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Hybrid Method of Genetic Algorithm and Firefly Algorithm Distinguishing between Males and Females

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Abstract—We have proposed Firefly Algorithm Distinguishing between Males and Females (FADMF). This algorithm exists together with males and females. In this study, we propose Firefly Algorithm Distinguishing between Males and Females Combined with Genetic Algorithm (FADCG). This proposed algorithm is applied genetic operators every certain iteration. We compare these two algorithms and the conventional Firefly Algorithm by using 2013 Congress on Evolutionary Computation (CEC) benchmark functions. Numerical experiments indicate that FADCG is effective for complex optimization problems.

1. Introduction

Evolutionary Computing (EC) is a subfield of artificial intelligence (AI) in computer science, and is based on biological mechanisms of evolution. EC technique mainly involves metaheuristic optimization algorithms such as Evolutionary Algorithm (EA) and Swarm Intelligence (SI).

Genetic Algorithm (GA) is one paradigms and most popular technique of major EA. On GA, individuals of a population evolve according to crossover, mutation, and selection from the population. The crossover and mutation create the necessary diversity. On the other hand, selection acts as a force increasing quality. There are two most notable advantage: the ability of dealing with complex problems and parallelism. However, GA also has some minor disadvantages. The choice of important parameters such as the mutation probability and the crossover probability, and the selection criteria of new population should be carefully carried out.

SI algorithm is one of stochastic algorithms. Stochastic algorithms 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. SI algorithms are based on the idealized behavior of animals and insects. Representative examples are Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Firefly Algorithm (FA) [1–3].

On FA, all fireflies are unisex. However, there are males and females in the real world. In our previous study, we have proposed algorithm distinguishing sex of fireflies [4]. This method is called Firefly Algorithm Distinguishing between Males and Females (FADMF). On FADMF, the movements of males and females are different from each other. This proposed algorithm has been applied 27 benchmark functions of Congress on Evolutionary Computation (CEC) 2013. Numerical experiments indicated that FADMF is superior to the conventional FA under some conditions. FADMF jump out locality more easily than the conventional FA, while FA-DMF is inferior about absorption speed.

It is paid many attentions to combine SI algorithm with GA [5, 6]. These hybrid algorithms outperform the standard algorithms. Especially, some hybrid PSO and GA algorithms obtain better results than the conventional PSO and GA. In this study, we propose the hybrid method of FADMF and GA. This method is called Firefly Algorithm Distinguishing between Males and Females Combined with Genetic Algorithm (FADCG). This method involves male and female swarms, and is also performed every certain iteration by using genetic operators. We compare the proposed method and the conventional FA by using 27 benchmark functions of CEC 2013. Numerical experiments indicate that the proposed method is more efficient algorithm than the conventional FA.

This study is organized as follows: first, we explain the conventional Genetic Algorithm in Section 2, and then, we explain the conventional Firefly Algorithm in Section 3. The next, we explain FADMF in Section 4. Followed by, we describe in detail of FADCG. In Section 6, we show numerical experiments. Finally, we conclude in this study.

2. Firefly Algorithm (FA)

Firefly Algorithm (FA) has been developed by Yang, and it was based on the idealized behavior of the flashing characteristics of fireflies. 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

$$\boldsymbol{x_i} = \boldsymbol{x_i} + \Delta\boldsymbol{x}, \Delta\boldsymbol{x} = \beta(\boldsymbol{x_j} - \boldsymbol{x_i}) + \alpha\boldsymbol{\epsilon_i}, \tag{2}$$

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

$$\alpha(t) = \alpha(0)\left(\frac{10^{-4}}{0.9}\right)^{t/t_{max}}, \tag{3}$$

where t is the number of iteration.

3. Genetic Algorithm (GA)

Genetic Algorithm (GA) has been developed by Holland J. and it is a model of biological evolution based on Charles Darwin's theory of nature selection. The conventional GA is often done by the following procedure:

- Creating a population of individuals;
- Evaluating the fitness of all the individuals in the population;
- Updating the population;
- Terminating generation when a maximum number of generations has been produced.

The essential part of GA is formed from genetic operators such as the crossover, mutation, and selection.

Individuals are stochastically selected from the population to create the basis of the next population. The fitter individuals have a more chance of selection than weaker one. There are many ways how to select the best individuals, such as Roulette Wheel Selection, Rank Selection, and Tournament Selection. The crossover selects genes from parent, and creates a new offspring. Commonly, a process of taking two parent genes is used, such as two-point crossover and uniform crossover. After the crossover is performed, individuals are mutated. This process is to prevent falling into a local optima. Genes of the offspring are changed randomly by the mutation.

The crossover probability, the mutation probability, and population size should be carefully carried out.

4. Firefly Algorithm Distinguishing between Males and Females (FADMF)

One of the rules of the conventional FA is 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 $\boldsymbol{x}$ is determined with parameters V and W by

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

$$\beta = \beta_0 e^{-\gamma r_{ij}^2/W}, \tag{5}$$

$$\boldsymbol{x} = \boldsymbol{x} + \Delta\boldsymbol{x}/V. \tag{6}$$

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.

5. Firefly Algorithm Distinguishing between Males and Females Combined with Genetic Algorithm (FADCG)

In this study, we propose the hybrid method of FADMF and GA. This proposed method is called Firefly Algorithm Distinguishing between Males and Females Combined with Genetic Algorithm (FADCG). All fireflies move every iteration according to FADMF. In addition, fireflies are applied genetic operators every certain iteration. We use uniform crossover and the mutation of genetic operators. We define that the crossover probability is 100 percent and the mutation probability is 30 percent.

6. Numerical Experiments

We compare FADCG to the conventional FA and FADMF with benchmark functions of CEC 2013 except function 20 (see Table 1).

Table 1: Benchmark Functions of CEC 2013

No.	Name	$f(\boldsymbol{x}^*)$
Unimodal Functions		
1	Sphere function	−1400
2	Rotated High Conditioned Elliptic Function	−1300
3	Rotated Bent Cigar Function	−1200
4	Rotated Discus Function	−1100
5	Different Powers Function	−1000
Basic Multimodal Functions		
6	Rotated Rosenbrock's Function	−900
7	Rotated Schaffers F7 Function	−800
8	Rotated Ackley's Function	−700
9	Rotated Weierstrass Function	−600
10	Rotated Griewank's Function	−500
11	Rastrigin's Function	−400
12	Rotated Rastrigin's Function	−300
13	Non-Continuous Rotated Rastrigin's Function	−200
14	Schwefel's Function	−100
15	Rotated Schwefel's Function	100
16	Rotated Katsuura Function	200
17	Lunacek Bi Rastrigin Function	300
18	Rotated Lunacek Bi Rastrigin Function	400
19	Expanded Griewank's plus Rosenbrock's Function	500
Composition Functions		
21	Composition Function 1 (n=5, Rotated)	700
22	Composition Function 2 (n=3, Unrotated)	800
23	Composition Function 3 (n=3, Rotated)	900
24	Composition Function 4 (n=3, Rotated)	1000
25	Composition Function 5 (n=3, Rotated)	1100
26	Composition Function 6 (n=5, Rotated)	1200
27	Composition Function 7 (n=5, Rotated)	1300
28	Composition Function 8 (n=5, Rotated)	1400

The optimal solutions $\boldsymbol{x}^*$ of these benchmark functions is shifted from 0, and the global optima $f(\boldsymbol{x}^*)$ are not equal to 0. The search range of these functions is $[-100, 100]^D$, and the dimension N is 30. Each numerical experiment is run 50 times. In each test functions, $t_{max} = 1500$, $V = 3$, $W = 4$. In this study, we change female percentage from 10 to 90 every 10 percentage. The best female percentage of FADCG is 40 percent, while the best female percentage of FADMF is 30 percent. Numerical experiments of the best female percentage are summarized in Table 2. Table 2 shows the average value, minimum value, maximumvalue, and standard deviation.

FADCG obtains a lot of best solutions more than other two algorithms. FADCG performs best on 10 times. In addition, FADCG obtains better results than the conventional FA at 17 times. Therefore, FADCG is superior to the conventional FA and FADMF.

In the case of unimodal functions, FADMF performs best on 3 times. FADCG obtains significantly worse results than other two algorithms. Therefore, we assume that FADCG converges slower than the conventional FA and FADMF.

In the case of basic multimodal functions, FADMF and FADCG perform best on 5 times. Therefore, FADMF and FADCG are fitted for basic multimodal functions.

In the case of composition functions, FADCG performs best on 5 times. FADCG is significantly superior to other two algorithms.

7. Conclusion

In this study, we have proposed Firefly Algorithm Distinguishing between Males and Females Combined with Genetic Algorithm (FADCG). This algorithm has male and female swarms which move differently each other, and is applied genetic operators every certain iteration. We have compared FADCG to the conventional FA and FADMF by using benchmark functions of Congress on Evolutionary Computation (CEC) 2013. Numerical experiments indicate that FADCG is superior to other algorithms, while FADMF is superior to other functions for unimodal functions. In other words, FADCG is effective for complex multimodal functions.

In the future work, we investigate parameters of FADCG more details. Furthermore, we compare FADCG to other improved algorithms, and apply to actual optimization problems.

References

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

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

[3] 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.

[4] M. Takeuchi, H. Matsushita, Y. Uwate, and Y. Nishio, *"Investigation of Firefly Algorithm Distinguishing between Males and Females"*,RISP International Workshop on Nonlinear Circuits, Communications and Signal Processing (NCSP'16), 2016.

[5] K. Premalatha, A. M. Natarajan, *"Hybrid PSO and GA for Global Maximization"*, ICSRS Publicaion, 2009.

[6] X. H. Shi, Y. C. Liang, H. P. Lee, C. Lu, L. M. Wang, *"An improved GA and a novel PSO-GA-based hybrid algorithm"*, Information Processing Letters, pp.255-261, 2005.

Table 2: Numerical Experiments

f		FA	FADMF	FADCG
f_1	avg	$\mathbf{6.11\times10^{-4}}$	5.61×10^{-4}	1.06×10^{-3}
	min	3.47×10^{-4}	2.34×10^{-4}	5.70×10^{-4}
	max	9.53×10^{-4}	9.33×10^{-4}	1.64×10^{-3}
	std	1.40×10^{-4}	1.25×10^{-4}	2.44×10^{-4}
f_2	avg	1.09×10^{7}	$\mathbf{3.96\times10^{6}}$	6.59×10^{6}
	min	5.31×10^{6}	1.39×10^{6}	1.94×10^{6}
	max	1.93×10^{7}	7.96×10^{6}	1.50×10^{7}
	std	3.39×10^{6}	1.64×10^{6}	2.97×10^{6}
f_3	avg	1.37×10^{7}	$\mathbf{9.14\times10^{6}}$	1.19×10^{7}
	min	3.77×10^{3}	5.18×10^{3}	2.34×10^{4}
	max	1.74×10^{8}	5.08×10^{7}	9.01×10^{7}
	std	2.54×10^{7}	1.25×10^{7}	1.94×10^{7}
f_4	avg	$\mathbf{1.09\times10^{5}}$	1.38×10^{5}	2.57×10^{5}
	min	6.22×10^{4}	8.09×10^{4}	1.37×10^{5}
	max	1.57×10^{5}	2.09×10^{5}	4.05×10^{5}
	std	2.54×10^{4}	2.87×10^{4}	6.07×10^{4}
f_5	avg	3.89×10^{1}	$\mathbf{1.92\times10^{-2}}$	1.78×10^{-1}
	min	2.28×10^{-2}	1.36×10^{-2}	6.52×10^{-2}
	max	1.53×10^{2}	2.58×10^{-2}	2.87×10^{-1}
	std	3.19×10^{1}	3.46×10^{-3}	5.30×10^{-2}
f_6	avg	2.74×10^{1}	$\mathbf{2.65\times10^{1}}$	2.73×10^{1}
	min	2.60×10^{1}	2.05×10^{1}	2.60×10^{1}
	max	2.92×10^{1}	7.72×10^{1}	2.94×10^{1}
	std	7.23×10^{-1}	7.49×10^{0}	8.15×10^{-1}
f_7	avg	1.16×10^{1}	$\mathbf{4.96\times10^{0}}$	6.35×10^{0}
	min	2.39×10^{0}	4.30×10^{-1}	8.51×10^{-1}
	max	3.01×10^{1}	2.03×10^{1}	1.72×10^{1}
	std	6.14×10^{0}	5.04×10^{0}	4.02×10^{0}
f_8	avg	2.14×10^{1}	2.14×10^{1}	$\mathbf{2.14\times10^{1}}$
	min	2.12×10^{1}	2.12×10^{1}	2.13×10^{1}
	max	2.16×10^{1}	2.16×10^{1}	2.15×10^{1}
	std	7.45×10^{-2}	1.03×10^{-1}	7.11×10^{-2}
f_9	avg	1.00×10^{1}	1.01×10^{1}	$\mathbf{8.74\times10^{0}}$
	min	4.86×10^{0}	4.11×10^{0}	3.25×10^{0}
	max	1.48×10^{1}	1.62×10^{1}	1.45×10^{1}
	std	2.43×10^{0}	2.42×10^{0}	2.40×10^{0}
f_{10}	avg	6.29×10^{-1}	$\mathbf{1.95\times10^{-1}}$	5.50×10^{-1}
	min	7.31×10^{-2}	1.58×10^{-2}	6.22×10^{-2}
	max	2.20×10^{0}	1.03×10^{0}	2.13×10^{0}
	std	5.41×10^{-1}	2.20×10^{-1}	4.99×10^{-1}
f_{11}	avg	2.68×10^{1}	3.88×10^{1}	$\mathbf{2.42\times10^{1}}$
	min	1.29×10^{1}	1.59×10^{1}	15.0×10^{1}
	max	5.07×10^{1}	6.07×10^{1}	3.78×10^{1}
	std	7.12×10^{0}	1.07×10^{1}	4.92×10^{0}
f_{12}	avg	3.01×10^{1}	3.77×10^{1}	$\mathbf{2.96\times10^{1}}$
	min	1.49×10^{1}	1.49×10^{1}	1.49×10^{1}
	max	5.17×10^{1}	6.17×10^{1}	5.17×10^{1}
	std	8.16×10^{0}	9.42×10^{0}	7.95×10^{0}
f_{13}	avg	$\mathbf{6.77\times10^{1}}$	9.43×10^{1}	7.85×10^{1}
	min	1.52×10^{1}	3.96×10^{1}	2.29×10^{1}
	max	1.18×10^{2}	1.53×10^{2}	1.36×10^{2}
	std	2.52×10^{1}	2.83×10^{1}	2.45×10^{1}
f_{14}	avg	2.34×10^{3}	$\mathbf{2.20\times10^{2}}$	1.51×10^{3}
	min	9.36×10^{2}	1.26×10^{3}	6.91×10^{2}
	max	4.15×10^{3}	3.23×10^{3}	2.75×10^{3}
	std	6.73×10^{2}	4.08×10^{2}	4.21×10^{2}
f_{15}	avg	2.26×10^{3}	$\mathbf{2.23\times10^{3}}$	2.52×10^{3}
	min	1.20×10^{3}	1.22×10^{3}	1.33×10^{3}
	max	3.80×10^{3}	3.44×10^{3}	4.45×10^{3}
	std	5.63×10^{2}	4.76×10^{2}	5.65×10^{2}
f_{16}	avg	$\mathbf{9.28\times10^{-2}}$	1.29×10^{-1}	3.30×10^{-1}
	min	3.17×10^{-2}	4.94×10^{-2}	9.30×10^{-2}
	max	2.28×10^{-1}	2.24×10^{-1}	7.01×10^{-1}
	std	3.99×10^{-2}	4.65×10^{-2}	1.35×10^{-1}
f_{17}	avg	$\mathbf{5.95\times10^{1}}$	8.71×10^{1}	7.59×10^{1}
	min	4.79×10^{1}	7.04×10^{1}	5.88×10^{1}
	max	7.52×10^{1}	1.31×10^{2}	1.12×10^{2}
	std	7.10×10^{0}	1.42×10^{1}	1.14×10^{1}
f_{18}	avg	$\mathbf{6.27\times10^{1}}$	9.16×10^{1}	8.61×10^{1}
	min	4.85×10^{1}	6.69×10^{1}	5.99×10^{1}
	max	8.62×10^{1}	1.27×10^{2}	1.36×10^{2}
	std	8.16×10^{0}	1.47×10^{1}	1.50×10^{1}
f_{19}	avg	3.77×10^{0}	4.01×10^{0}	$\mathbf{3.47\times10^{0}}$
	min	2.44×10^{0}	2.45×10^{0}	2.03×10^{0}
	max	6.13×10^{0}	6.20×10^{0}	4.91×10^{0}
	std	8.19×10^{-1}	9.78×10^{-1}	6.67×10^{-1}
f_{21}	avg	3.30×10^{2}	3.39×10^{2}	$\mathbf{3.12\times10^{2}}$
	min	2.00×10^{2}	1.01×10^{2}	2.00×10^{2}
	max	4.44×10^{2}	4.44×10^{2}	4.44×10^{2}
	std	8.52×10^{1}	9.12×10^{1}	8.82×10^{1}
f_{22}	avg	3.31×10^{3}	2.61×10^{3}	$\mathbf{1.71\times10^{3}}$
	min	1.32×10^{3}	7.27×10^{2}	8.51×10^{2}
	max	6.17×10^{3}	4.51×10^{3}	2.34×10^{3}
	std	1.14×10^{3}	7.70×10^{2}	4.02×10^{2}
f_{23}	avg	3.84×10^{3}	3.31×10^{3}	$\mathbf{2.99\times10^{3}}$
	min	2.40×10^{3}	1.37×10^{3}	1.22×10^{3}
	max	5.75×10^{3}	5.69×10^{3}	4.74×10^{3}
	std	8.43×10^{2}	9.94×10^{2}	7.00×10^{2}
f_{24}	avg	$\mathbf{2.17\times10^{2}}$	2.22×10^{2}	2.23×10^{2}
	min	2.01×10^{2}	2.01×10^{2}	2.03×10^{2}
	max	2.41×10^{2}	2.39×10^{2}	2.34×10^{2}
	std	1.16×10^{1}	9.49×10^{0}	7.52×10^{0}
f_{25}	avg	2.34×10^{2}	2.32×10^{2}	$\mathbf{2.25\times10^{2}}$
	min	2.20×10^{2}	2.01×10^{2}	2.14×10^{2}
	max	2.51×10^{2}	2.53×10^{2}	2.40×10^{2}
	std	7.73×10^{0}	1.23×10^{1}	5.47×10^{0}
f_{26}	avg	2.89×10^{2}	$\mathbf{2.85\times10^{2}}$	3.00×10^{2}
	min	2.00×10^{2}	2.00×10^{2}	2.00×10^{2}
	max	3.34×10^{2}	3.35×10^{2}	3.34×10^{2}
	std	4.78×10^{1}	5.34×10^{1}	4.39×10^{1}
f_{27}	avg	$\mathbf{4.56\times10^{2}}$	5.17×10^{2}	4.85×10^{2}
	min	3.13×10^{2}	3.14×10^{2}	3.26×10^{2}
	max	6.59×10^{2}	7.28×10^{2}	6.23×10^{2}
	std	1.17×10^{2}	9.32×10^{1}	9.08×10^{1}
f_{28}	avg	3.06×10^{2}	3.09×10^{2}	$\mathbf{2.97\times10^{2}}$
	min	1.01×10^{2}	1.00×10^{2}	1.01×10^{2}
	max	1.36×10^{3}	1.32×10^{3}	3.02×10^{2}
	std	1.60×10^{2}	2.17×10^{2}	2.81×10^{1}

f	FA	FADMF	FADCG
best solution	8	9	10
more than the conventional FA		13	17