

Investigation of Optimal Ratio of Males to Females in Firefly Algorithm

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Abstract

We have proposed a firefly algorithm that distinguishes between males and females. In this algorithm, both males and females exist. In this study, we investigate the features of our proposed algorithm by changing the parameters and the percentage of females. We compare our proposed firefly algorithm with the conventional firefly algorithm using four well-known test functions. Numerical experiments indicate that our proposed firefly algorithm is superior to the conventional firefly algorithm under some conditions.

1. Introduction

The solution of optimization problems has recently become increasingly important. Most optimization problems are non-linear with many constraints. Consequently, optimization algorithms must be efficient to find optimal solutions. Stochastic algorithms, one category of optimization algorithms, are efficient optimization algorithms. Stochastic algorithms have a deterministic component and a random component. Almost all algorithms having only a deterministic component are local search algorithms, for which there is a risk of being trapped at local optima. However, the random component of stochastic algorithms makes it possible to escape from such local optima.

One type of stochastic algorithm is swarm intelligence algorithms, which are based on the behavior of animals and insects. Representative examples are particle swarm optimization (PSO) [1], ant colony optimization (ACO), and the firefly algorithm (FA) [2–4].

In the conventional FA, all fireflies are unisex. However, in the real world, there are males and females. Animals having variation among individuals have a greater chance of surviving than those without variation. In the case of solving optimization problems, we also consider that variation among individuals will lead to a variety of solutions. These solutions may include the global optimal solution. Therefore, we have

proposed a new FA that distinguishes the sex of fireflies [5]. This method is called the firefly algorithm distinguishing between males and females (FADMF). In FADMF, the movements of males and females are defined from their physical differences. Therefore, the movements of males and females are different. We investigate the features of FADMF using four well-known test functions. Numerical experiments indicate that with increasing the percentage of females, FADMF tends to increase randomness.

This study is organized as follows. First, we explain the conventional firefly algorithm in Sect.2, and then, we describe FADMF in detail in Sect.3. In Sect.4, we report the results of numerical experiments. Finally, we conclude this study.

2. Conventional Firefly Algorithm (FA) [2]

The Firefly Algorithm (FA) was developed by Yang and is based on the idealized behavior of the flashing characteristics of fireflies. It is suitable for multipeak optimization problems. The conventional FA idealizes these flashing characteristics using 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 brightness; thus, for any two flashing fireflies, the less brighter one will move towards the brighter one. Both the attractiveness and brightness started above 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.

The attractiveness of firefly β is defined by

$$\beta = \beta_0 e^{-\gamma r_{ij}^2} \quad (1)$$

Algorithm 1 Conventional firefly algorithm (FA)

Objective function $f(x)$, $x = (x_1, \dots, x_d)^T$
Initialize a population of fireflies $x_i (i = 1, 2, \dots, n)$
Define light absorption coefficient γ
while $t < MaxGeneration$ **do**
 for $i = 1$ to n , all n fireflies **do**
 for $j = 1$ to n , all n fireflies **do**
 Light intensity I_i at x_i is determined by $f(x_i)$
 if $I_i > I_j$ **then**
 Move firefly i towards j in all d dimensions
 end if
 Attractiveness varies with distance r via $exp[-\gamma r]$
 Evaluate new solutions and update light intensity
 end for j
 end for i
 Rank the fireflies and find the current best
end while
Postprocess results and visualization

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 located at \mathbf{x}_i and \mathbf{x}_j , respectively. Firefly i is attracted to another more attractive firefly j , and the movement of firefly i is determined by

$$\mathbf{x}_i = \mathbf{x}_i + \Delta \mathbf{x} \quad (2)$$

$$\Delta \mathbf{x} = \beta(\mathbf{x}_j - \mathbf{x}_i) + \alpha \epsilon_i \quad (3)$$

where \mathbf{x}_i is the position vector of firefly i , ϵ_i is the vector of a random variable and $\alpha(t)$ is a randomization parameter. $\alpha(t)$ is defined by

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

where t is the iteration number.

Algorithm 1 shows pseudo code of the conventional FA for minimum optimization problems.

3. Firefly Algorithm Distinguishing between Males and Females (FADMF) [5]

In this section, we explain our proposed method [5]. 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 the sex of fireflies, that is, there are two sexes in our proposed method. The movement of females is modeled from the physical characteristics. In the real world, females are larger than males and female eyes are smaller than male eyes. Thus, in our proposed method, females move slower than males, and females have more difficulty detecting the flashes of other distant fireflies. In addition, we give males and females a different randomization parameter.

Algorithm 2 Firefly algorithm distinguishing between males and females (FADMF)

Objective function $f(x)$, $x = (x_1, \dots, x_d)^T$
Initialize a population of male fireflies $x_i (i = 1, 2, \dots, n)$
Initialize a population of female fireflies $y_i (i = 1, 2, \dots, m)$
Define light absorption coefficient γ
while $t < MaxGeneration$ **do**
 for $i = 1$ to n , all n male fireflies **do**
 for $j = 1$ to n , all n male fireflies **do**
 Light intensity I_{x_i} at x_i is determined by $f(x_i)$
 if $I_{x_i} > I_{x_j}$ **then**
 Move male firefly i towards j in all d dimensions
 end if
 end for j
 for $k = 1$ to m , all m female fireflies **do**
 Light intensity I_{y_k} at y_k is determined by $f(y_k)$
 if $I_{x_i} > I_{y_k}$ **then**
 Move male firefly i towards k in all d dimensions
 else
 Move female firefly k towards i in all d dimensions
 end if
 end for k
 Attractiveness varies with distance r via $exp[-\gamma r]$
 Evaluate new solutions and update light intensity
 end for i
 Rank the fireflies and find the current best
end while
Postprocess results and visualization

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

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

$$\beta = \beta_0 e^{-\gamma r_{ij}^2 / W} \quad (6)$$

$$\mathbf{x} = \mathbf{x} + \Delta \mathbf{x} / V \quad (7)$$

where $\Delta \mathbf{x}$ is given by Eq.(3).

In the proposed method, males are attracted to all fireflies, while females are attracted to only males. Males move in the same way as fireflies in the conventional FA. Algorithm 2 shows pseudo code of FADMF for minimum optimization problems.

4. Numerical Experiments on FADMF

We compare FADMF with the conventional FA using four test functions (see Table 1). Their optimal solutions are $f(x) = 0$ at $x = 0$.

In the case of solving minimum problems, the Sphere and Ackley functions are used in monopeak optimization prob-

Table 1: Test functions

Name	Formula	Range
Sphere	$f(x) = \sum_{i=1}^n x_i^2$	[-5.12, 5.12]
Rastrigin	$f(x) = \sum_{i=1}^n (x_i^2 - 10 \cos(2\pi x_i) + 10)$	[-5.12, 5.12]
Griewank	$f(x) = \frac{1}{4000} \sum_{i=1}^n x_i^2 - \prod_{i=1}^n \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	[-600, 600]
Ackley	$f(x) = -20 \exp\left(-\frac{1}{5} \sqrt{\frac{1}{d} \sum_{i=1}^d x_i^2}\right) - \exp\left(\frac{1}{d} \sum_{i=1}^d \cos(2\pi x_i)\right) + 20 + e$	[-30, 30]

lem, while the Rastrigin and Griewank functions are multi-peak optimization problems. The graphic form of the Sphere function is very simple, whereas the graphic form of the Ackley function is more complex because there are many local minima and local maxima. There are also many local minima and local maxima in the Rastrigin and Griewank functions. The graph of the Griewank function has a gentler gradient than that of the Rastrigin function.

The results of numerical experiments are shown in Table 2. Each numerical experiment is run 100 times. For each test function, we define the number of dimensions $N = 30$, $t_{max} = 1000$, $V = 3$ and $W = 4$. In this study, we change the female percentage from 10% to 90% in increments of 10%.

Almost all the results of the conventional FA for the Sphere and Griewank functions are better than those of FADMF. When 10% of fireflies are females, FADMF obtains better results for the average and minimum. In the case of the Rastrigin function, FADMF obtains better results except for the minimum when 90% of the swarm are females. FADMF obtains better results for the Ackley function for the average and maximum, while the conventional FA obtains better results for the minimum. Therefore, our proposed method is suitable for the Rastrigin and Ackley functions.

We formed line graphs in which the vertical axis shows the average value of solutions (log scale) and the horizontal axis shows the female percentage (see Fig.1).

With increasing female percentage, the average value of solutions for the Sphere, Griewank and Ackley functions continuously increase. On the other hand, the graph for the Rastrigin function decreases slowly from 10% to 30%, then increases slightly from 30%. According to Fig.1, FADMF is suitable for the Rastrigin and Ackley functions. Numerical experiments for the Sphere function show that fireflies of the conventional FA converge faster than those of FADMF. FADMF obtains better results than the conventional FA for the Ackley function. Therefore, we find that the fireflies of FADMF easily escape from local optima. In addition, when the graph has a gentle gradient, FADMF is inferior to the con-

ventional FA according to the numerical experimental results for the Rastrigin and Griewank functions.

5. Conclusions

In this study, we investigated the features of our proposed firefly algorithm (FADMF) by applying it to four well-known test functions. Numerical experiments indicated that FADMF is superior to the conventional FA under some conditions. FADMF escapes from local optima more easily than the conventional FA, while it has a lower convergence speed.

In future work, we will improve our proposed FADMF.

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Table 2: Numerical experimental results of FADMF

name		conventional FA	FADMF								
female percentage			10	20	30	40	50	60	70	80	90
Sphere	ave	2.80×10^{-7}	2.79×10^{-7}	3.03×10^{-7}	3.33×10^{-7}	3.55×10^{-7}	4.04×10^{-7}	4.36×10^{-7}	5.64×10^{-7}	7.09×10^{-7}	2.90×10^{-6}
	min	1.69×10^{-7}	1.53×10^{-7}	1.83×10^{-7}	2.21×10^{-7}	2.30×10^{-7}	1.88×10^{-7}	2.50×10^{-7}	3.21×10^{-7}	3.67×10^{-7}	1.35×10^{-6}
	max	3.90×10^{-7}	4.08×10^{-7}	4.12×10^{-7}	4.43×10^{-7}	5.13×10^{-7}	6.01×10^{-7}	6.78×10^{-7}	8.24×10^{-7}	1.10×10^{-6}	5.85×10^{-6}
Rastrigin	ave	2.63×10^1	2.22×10^1	2.07×10^1	1.83×10^1	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	7.96×10^0	1.09×10^1	7.96×10^0	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	2.79×10^1	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}	2.83×10^{-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}	1.21×10^{-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}	7.65×10^{-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
Ackley	ave	6.35×10^0	2.29×10^{-3}	2.41×10^{-3}	2.49×10^{-3}	2.58×10^{-3}	2.68×10^{-3}	2.83×10^{-3}	3.16×10^{-3}	1.72×10^{-2}	4.39×10^0
	min	9.82×10^{-4}	1.83×10^{-3}	1.83×10^{-3}	1.80×10^{-3}	2.11×10^{-3}	1.74×10^{-3}	2.01×10^{-3}	2.47×10^{-3}	2.86×10^{-3}	2.66×10^0
	max	2.00×10^1	2.80×10^{-3}	2.84×10^{-3}	2.97×10^{-3}	3.21×10^{-3}	3.26×10^{-3}	3.54×10^{-3}	4.00×10^{-3}	1.34×10^0	5.62×10^0

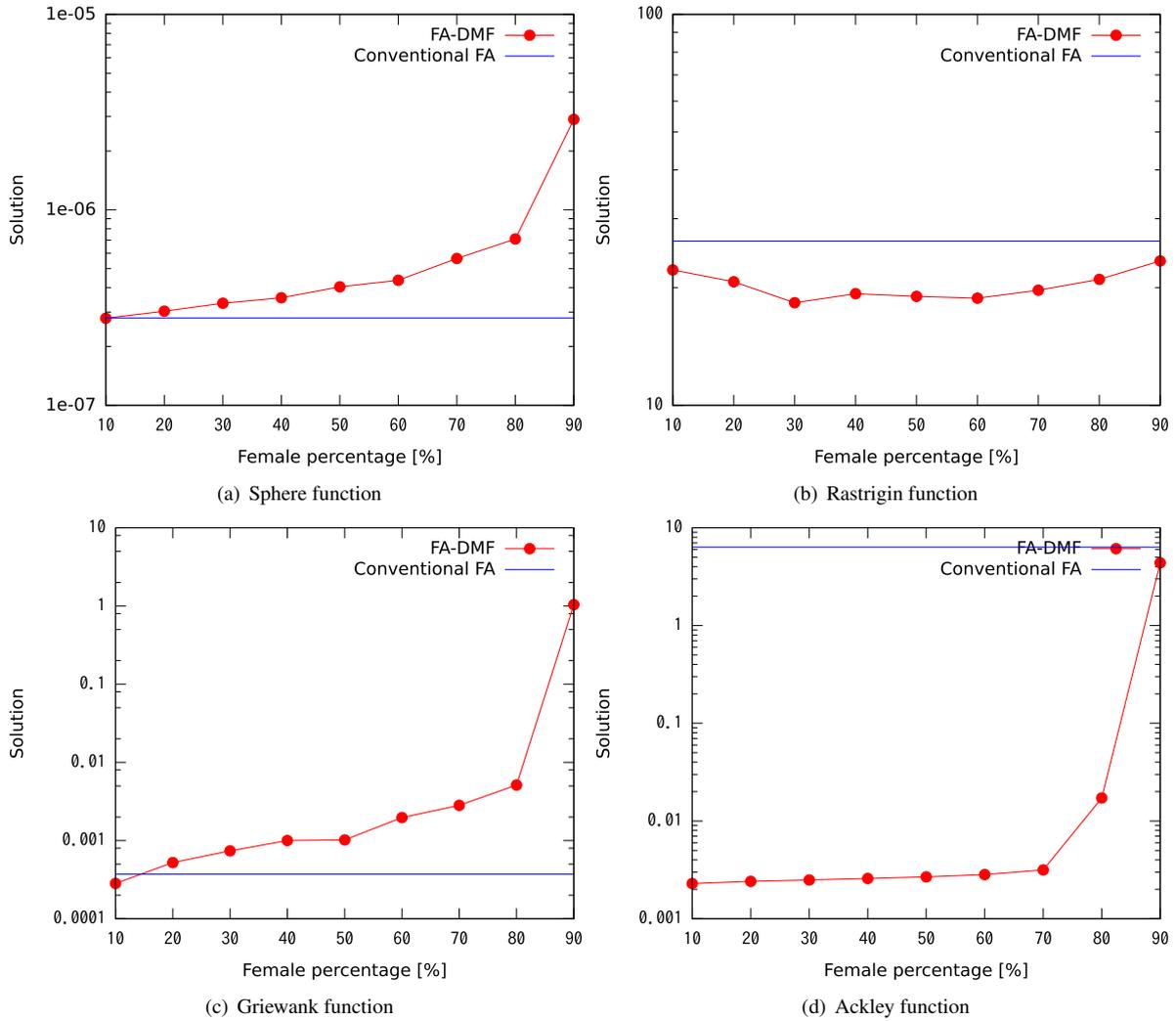


Figure 1: Examples of results of numerical experiments