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Investigation of Firefly Algorithm Distinguishing between Males and Females for Minimum Optimization Problems

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Abstract

We have proposed 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 algorithm by changing parameters and the rate of females. We compare our proposed Firefly Algorithm with the conventional Firefly Algorithm by using famous four test functions. Numerical experiments indicate that our proposed Firefly Algorithm is superior to the conventional Firefly Algorithm under some conditions.

1. Introduction

The optimization problems has 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. 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 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) [2–4].

On the conventional FA, all fireflies are unisex. However, in the real world, there are males and females. 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 four test functions. Numerical experiments indicate that as increasing the rate of females, FA-DMF tends to increase randomness.

This study is organized as follows: first, we explain the conventional Firefly Algorithm in Section 2, and then, we describe in detail of FA-DMF in Section 3. Followed by, we show numerical experiments. Finally, we conclude in this study.

2. 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

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

Algorithm 1 Firefly Algorithm

```
Objective function f(x), x = (x_1, ..., x_d)^T
Initialize a population of fireflies x_i (i = 1, 2, ..., 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[−γr]
      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 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

$$\boldsymbol{x_i} = \boldsymbol{x_i} + \Delta \boldsymbol{x}, \quad (2)$$

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

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

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

where t is the number of iteration.

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

3. Firefly Algorithm Distinguishing between Males and Females (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.

Algorithm 2 Firefly Algorithm Distinguishing between Males and Females

```
Objective function f(x), x = (x_1, ..., x_d)^T
Initialize a population of male fireflies x_i (i = 1, 2, ..., n)
Initialize a population of female fireflies y_i (i = 1, 2, ..., 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_xi at x_i is determined by f(x_i)
      if I_xi > I_xj 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_yk at y_k is determined by f(y_k)
      if I_xi > I_yk 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[−γr]
    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 $\boldsymbol{x}$ is determined with parameters V and W by

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

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

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

where $\Delta \boldsymbol{x}$ is the same equation (3).

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. Algorithm 2 shows pseudo code of FA-DMF for minimum optimization problems.

4. Numerical Experiments of FA-DMF

We compare FA-DMF to the conventional FA with four test functions (see Table 1). These optimal solutions are $f(x) = 0$ at $x = 0$.

Table 1: The 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	$f(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}}) + 1$	[-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]

In case of solving minimum problem, Sphere and Ackley functions are mono-peak optimization problem, while Rastrigin and Greiwank functions are multi-peak optimization problem. The graphic form of Sphere function is very simple. On the other hands, the graphic form of Ackley function is more complex than Sphere function, because there are a lot of local minimum and local maximum. There are also 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 2. 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.

Almost all of results of the conventional FA for Sphere and Greiwank functions are better than FA-DMF. When females exist 10 percent, FA-DMF obtains better results about average and minimum. In the case of Greiwank function, FA-DMF obtains better results about 10 percent, and minimum and maximum of 20 percent. FA-DMF obtains better results except minimum when 90 percent of swarm are females. FA-DMF obtains better results of Ackley function about average and maximum, while the conventional FA obtains better results about minimum. Therefore, our proposed method is fitted for Rastrigin and Ackley functions.

We make a line graph: the vertical axis shows averages of solutions (log scale) and the horizontal axis shows female percentages (see Fig.1).

As increasing female percentage, the graphs of average of Sphere, Greiwank and Ackley functions are continuously increasing. On the other hands, the graph of average of Rastirigin function decrease slowly from 10 to 30, and the graph increase slightly from 30. According to Fig. 1, FA-DMF is suitable for Rastrigin and Ackley functions. Numerical experiments of Sphere function show that fireflies of the conventional FA converge faster than FA-DMF. FA-DMF obtains better results than the conventional FA about Ackley function. Therefore, we find that fireflies of FA-DMF jump out locality easily. In addition, when the graph has gentle gradient, FA-DMF is inferior to the conventional FA by numerical experiment results of Rastrigin and Greiwank functions.

5. Conclusion

In this study, we investigated the feature of Firefly Algorithm Distinguishing between Males and Females (FA-DMF). We applied our proposed Firefly Algorithm to four test functions. Numerical experiments indicated that FA-DMF is superior to the conventional FA under some conditions. FA-DMF jump out locality more easily than the conventional FA, while FA-DMF is inferior about absorption speed.

In the future work, we improve our proposed Firefly Algorithm, compare to other improved Firefly Algorithms.

References

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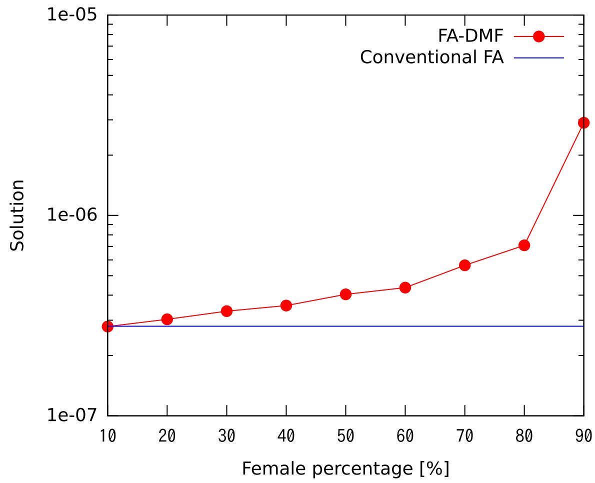
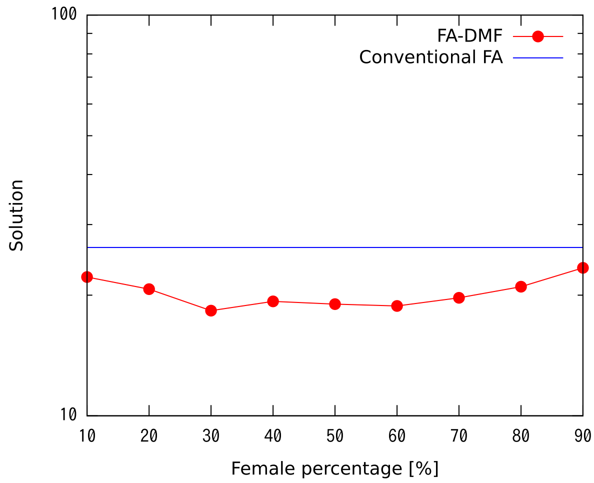
Table 2: Numerical Experiment Results of FA-DMF

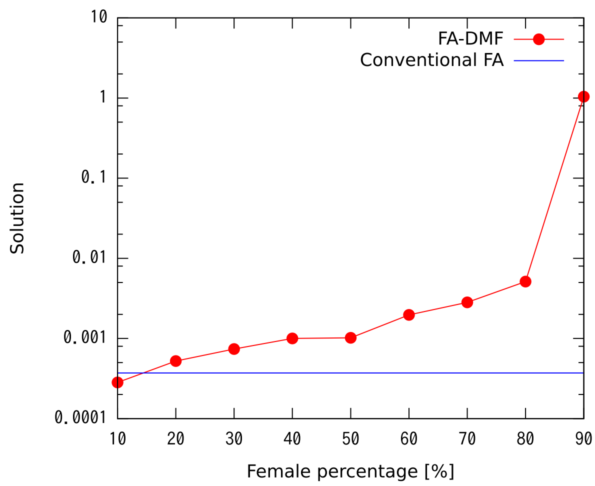
name		conventional FA	FA-DMF								
female percentage			10	20	30	40	50	60	70	80	90
Sphere	ave	2.80×10^{-7}	$\mathbf{2.79 \times 10^{-7}}$	3.03×10^{-7}	3.33×10^{-7}	3.55×10^{-7}	4.04×10^{-7}	4.36×10^{-7}	5.64×10^{-7}	7.09×10^{-7}	2.90×10^{-6}
	min	1.69×10^{-7}	$\mathbf{1.53 \times 10^{-7}}$	1.83×10^{-7}	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	$\mathbf{3.90 \times 10^{-7}}$	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}	$\mathbf{1.83 \times 10^{1}}$	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}
Ackley	ave	6.35×10^{0}	$\mathbf{2.29 \times 10^{-3}}$	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	$\mathbf{9.82 \times 10^{-4}}$	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}	$\mathbf{2.80 \times 10^{-3}}$	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}



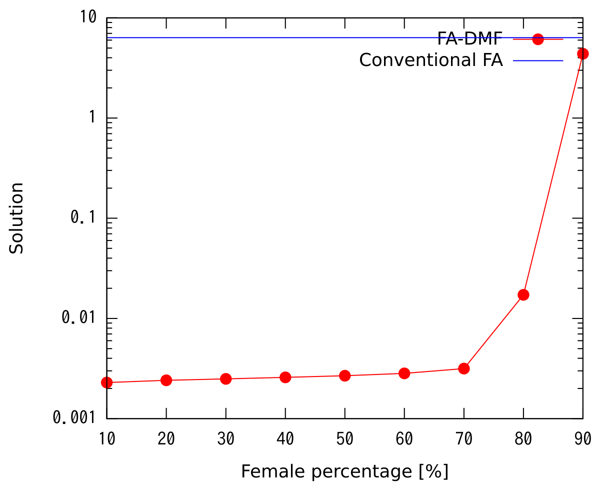
(a) Sphere function.



(b) Rastrigin function.



(c) Greiwank function.



(d) Ackley function.

Figure 1: Example of numerical experiments.