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# A scattering and repulsive swarm intelligence algorithm for solving global optimization problems

Diptangshu Pandit<sup>a</sup>, Li Zhang<sup>a,\*</sup>, Samiran Chattopadhyay<sup>b</sup>, Chee Peng Lim<sup>c</sup>, Liu Chengyu<sup>d</sup>

<sup>a</sup> Computational Intelligence Research Group, Department of Computer and Information Sciences, Faculty of Engineering and Environment, University of Northumbria,

Newcastle NE1 8ST, UK

<sup>b</sup> Department of Information Technology, Jadavpur University, Kolkata, India

<sup>c</sup> Institute for Intelligent Systems Research and Innovation, Deakin University, Waurn Ponds, VIC 3216, Australia

<sup>d</sup> School of Instrument Science and Engineering, Southeast University, Nanjing 210018, PR China

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#### ABSTRACT

The firefly algorithm (FA), as a metaheuristic search method, is useful for solving diverse optimization problems. However, it is challenging to use FA in tackling high dimensional optimization problems, and the random movement of FA has a high likelihood to be trapped in local optima. In this research, we propose three improved algorithms, i.e., Repulsive Firefly Algorithm (RFA), Scattering Repulsive Firefly Algorithm (SRFA), and Enhanced SRFA (ESRFA), to mitigate the premature convergence problem of the original FA model. RFA adopts a repulsive force strategy to accelerate fireflies (i.e. solutions) to move away from unpromising search regions, in order to reach global optimality in fewer iterations. SRFA employs a scattering mechanism along with the repulsive force strategy to divert weak neighbouring solutions to new search regions, in order to increase global exploration. Motivated by the survival tactics of hawk-moths, ESRFA incorporates a hovering-driven attractiveness operation, an exploration-driven evading mechanism, and a learning scheme based on the historical best experience in the neighbourhood to further enhance SRFA. Standard and CEC2014 benchmark optimization functions are used for evaluation of the proposed FA-based models. The empirical results indicate that ESRFA, SRFA and RFA significantly outperform the original FA model, a number of state-of-the-art FA variants, and other swarm-based algorithms, which include Simulated Annealing, Cuckoo Search, Particle Swarm, Bat Swarm, Dragonfly, and Ant-Lion Optimization, in diverse challenging benchmark functions.

#### 1. Introduction

Nature inspired algorithms have gained popularity and been widely used for solving various global optimization problems. Among them, the firefly algorithm (FA) [1] is a popular metaheuristic search method that has been applied to undertaking diverse optimization problems in engineering, medical, and social sciences [2]. In FA, each firefly represents a solution in the search space. Its light intensity is determined by an objective function. Each firefly moves to the optimal region by following multiple optimal solutions in the neighbourhood. Overall, the FA search strategies enable the fireflies (i.e. solutions) with lower light intensities (i.e. fitness values) to move towards those with higher light intensities in the neighbourhood, in order to achieve global optimality. Although each firefly serves as a search agent to increase global exploration, the empirical results [3,4] indicate that high dimensional optimization problems still pose great challenges to FA, and the random movement of FA has a high likelihood to be trapped in local optima.

One of the limitations of the original FA model is its pure attractiveness force that moves each firefly towards the brighter counterparts in the neighbourhood. If there is no brighter firefly in the neighbourhood, the attractiveness action stagnates, and there is no alternative mechanism to drive the search out of the local optima traps. In other words, there is no effective strategy to avoid poor solutions while moving towards the optimal ones. Moreover, by following the neighbouring brighter fireflies, there is an increased likelihood that part of the population could be clustered in the same region, therefore reducing the possibility of finding the global optimum residing elsewhere. Solving the first issue results in better performance and faster convergence, while resolving the second issue tackles the premature convergence problem. Both challenges constitute the key motivation of this research.

To deal with the abovementioned challenges, this research proposes

\* Corresponding author.

E-mail addresses: d.pandit@northumbria.ac.uk (D. Pandit), li.zhang@northumbria.ac.uk (L. Zhang), samirancju@gmail.com (S. Chattopadhyay), chee.lim@deakin.edu.au (C.P. Lim), bestlcy@sdu.edu.cn (C. Liu).

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three FA variants, i.e., Repulsive Firefly Algorithm (RFA), Scattering Repulsive Firefly Algorithm (SRFA), and Enhanced SRFA (ESRFA). Besides the conventional attractiveness movement of the FA model, RFA uses a repulsive force strategy to drive the search to reach global optimality in fewer iterations. SRFA, in addition to using the repulsive force action, incorporates a scattering mechanism to explore rarely exploited distinctive search spaces to increase search diversity and overcome premature convergence. ESRFA incorporates hawk-moths' local hovering and sharp dive escaping movements to diversify the attractiveness and repulsive force actions of SRFA, as well as exchanges with historical best experiences in the neighbourhood to accelerate convergence. Specifically, the research novelties are five-fold. (1) The proposed repulsive force works together with the original attractive force to enable the search procedure to converge towards the global optima and, at the same time, avoid poor solutions. (2) The scattering strategy overcomes premature convergence by diverting a number of weak solutions to unexploited regions. (3) Exploitation-driven attractiveness and exploration-based evading mechanisms are used to enhance the search operations in diversifying the search process. (4) Interactions with the historical personal best experiences of other fireflies are conducted to accelerate convergence. (5) The proposed strategies cooperate with each other to overcome premature convergence, especially in solving high dimensional optimization problems. We evaluate the three proposed FA models with ten standard and CEC2014 [5] benchmark optimization functions. RFA, SRFA and ESRFA significantly outperform state-of-the-art FA variants and other evolutionary search methods, which include Particle Swarm Optimization (PSO) [6], Simulated Annealing (SA) [7], FA, Bat Swarm Optimization (BSO) [8,9], Cuckoo Search Optimization (CSO) [10], Dragonfly Optimization (DFO) [11] and Ant-Lion Optimization (ALO) [12].

The research contributions are summarized, as follows:

- Three FA variants, i.e., RFA, SRFA and ESRFA, are proposed. RFA incorporates a repulsive force strategy to enable fireflies with higher light intensities to jump out of unpromising search regions to achieve fast convergence.
- SRFA employs the repulsive force action and a scattering mechanism to avoid local optima. The latter diverts a proportion of weak neighbouring solutions to an unexploited distinctive search space to increase search diversity. The repulsive behaviour and the scattering mechanism in SRFA work cooperatively to mitigate premature convergence of the original FA model. On one hand, when the repulsive force action stagnates, the scattering mechanism is able to extend the search to rarely explored regions to reduce the probability of premature convergence. On the other hand, when the scattering behaviour is unable to generate fitter solutions, the repulsive force action enables each firefly to conduct long jumps to move towards optimal regions to escape from local optima.
- · ESRFA incorporates exploitation and exploration coefficients to diversify the attractiveness and repulsive operations of SRFA, respectively, and interacts with neighbouring historical best experiences to accelerate convergence. It has three key properties. Firstly, the exploitation factor simulates the mid-air hovering of hawkmoths around attraction, which enables a refined random examination of a promising neighbourhood and overcomes the local optima traps, as compared with the original attractiveness operation in FA. Secondly, the exploration-driven escaping coefficient simulates a sharp dive of moths in response to predators, which enables the search to explore a wider search space while evading from the worse solutions. The newly proposed attractiveness operation increases local exploitation while the updated evading action increases global exploration. In other words, both properties enable the search process to balance well between local exploitation and global exploration. Thirdly, a distinctive attractiveness-based operation guided by the historical personal best experiences of neighbouring fireflies is conducted to accelerate convergence.

• A comprehensive evaluation with diverse unimodal, multimodal and challenging CEC2014 optimization functions is conducted. The proposed RFA, SRFA and ESRFA models outperform the original FA model and advanced FA variants, as well as other metaheuristic search methods, significantly. They also show great robustness and superiority in dealing with complex high dimensional optimization problems.

The paper is organised as follows. A literature review on related work is presented in Section 2. The proposed RFA, SRFA and ESRFA models are introduced in detail in Section 3. Comprehensive experiments for evaluation of three proposed models are presented in Section 4. Finally, conclusions and directions for future work are given in Section 5.

#### 2. Related work

Swarm intelligence (SI) based optimization methods have gained popularity recently [13,14]. As a recent SI algorithm, FA is an effective metaheuristic search method on par with other existing models, in solving diverse optimization problems, which include PSO, Genetic Algorithm (GA), CSO, Artificial Bee Colony (ABC) and Ant Colony Optimization (ACO). In this section, we discuss the basic concepts of FA, different FA variants, and other recently proposed metaheuristic search methods.

#### 2.1. Firefly algorithm

Introduced by Yang [1], FA is inspired by the movement of fireflies based on their bioluminescence. It employs three strategies to guide the search process: (1) fireflies are unisex, and are attracted to each other; (2) attraction is proportional to the degree of brightness and inversely proportional to the distance between a pair of fireflies. As a result, less bright fireflies move towards the brighter ones in the neighbourhood. The brightest firefly moves randomly; (3) the brightness of each firefly represents the solution quality. In FA, each firefly represents a solution, which is characterised by its position and light intensity (the fitness value). The light intensity decreases as the distance to its source increases. The variation of light intensity is defined by

$$I(r) = I_0 e^{-\gamma r^2} \tag{1}$$

where *r* denotes the distance and  $I_0$  represents the original light intensity when the distance r = 0.  $\gamma$  represents a fixed light absorption coefficient. The attractiveness of a firefly is defined by

$$\beta(r) = \beta_0 e^{-\gamma r^2} \tag{2}$$

where  $\beta_0$  indicates the initial attractiveness when the distance r = 0. Eq. (3) illustrates the position updating formula of each firefly, which moves a firefly, *i*, with a lower light intensity towards a brighter one, *j*, in the neighbourhood, i.e.,

$$x_{i}^{t+1} = x_{i}^{t} + \beta_{0} e^{-\gamma r_{ij}^{2}} (x_{j}^{t} - x_{i}^{t}) + \alpha_{t} \varepsilon_{t}$$
(3)

where  $x_i^t$  and  $x_j^t$  denote the positions of fireflies *i* and *j* at the *t*-th iteration, respectively.  $r_{ij}$  denotes the distance between two fireflies, *i* and *j*.  $\alpha_t$  is a randomization parameter that controls the step size of the randomized move with  $\varepsilon_t$  as a random walk behaviour defined by a Gaussian (or other) distribution. The second term in Eq. (3) denotes the attractiveness behaviour while the third term implements random exploitation. The pseudo-code of the FA model [1] is presented in Algorithm 1.

FA has several distinctive advantages. FA performs automatic subdivision of the population into subgroups. Unlike the particles in PSO, which purely follow the global best solution, each firefly in FA is a search agent, and follows multiple brighter fireflies (i.e. optimal solutions) in the neighbourhood to increase global exploration. Therefore, Download English Version:

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