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Elite opposition-based flower pollination algorithm

Yongquan Zhou [a,b,*], Rui Wang [a], Qifang Luo [a]

[a] College of Information Science and Engineering, Guangxi University for Nationalities, Nanning 530006, China
[b] Key Laboratory of Guangxi High Schools Complex System and Intelligent Computing, Nanning 530006, China

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ABSTRACT

Flower pollination algorithm (FPA) is a novel metaheuristic optimization algorithm with quick convergence, but its population diversity and convergence precision can be limited in some applications. In order to enhance its exploitation and exploration abilities, in this paper, an elite opposition-based flower pollination algorithm (EOFPA) has been applied to functions optimization and structure engineering design problems. The improvement involves two major optimization strategies. Global elite opposition-based learning enhances the diversity of the population, and the local self-adaptive greedy strategy enhances its exploitation ability. An elite opposition-based flower pollination algorithm is validated by 18 benchmark functions and two structure engineering design problems. The results show that the proposed algorithm is able to obtained accurate solution, and it also has a fast convergence speed and a high degree of stability.

1. Introduction

Swarm intelligence optimization algorithm originates from the simulation of various types of biological behavior in nature and has characteristics of simple operation, good optimization performance and strong robustness. Inspired by this idea, there are many bio-inspired swarm intelligent optimization algorithms are proposed, such as, ant colony optimization (ACO) [1], differential evolution (DE) [2], particle swarm optimization(PSO) [3], firefly algorithm (FA) [4], glowworm swarm optimization (GSO) [5], monkey search (MS) [6], harmony search (HS) [7], cuckoo search (CS) [8], bat algorithm (BA) [9], et al. Swarm intelligence optimization algorithm can solve problems which traditional methods cannot handle effectively and have shown excellent performance in many respects, and its application scope has been greatly expanded.

Flower pollination algorithm is proposed by Xin-She Yang in 2012 [10], it is a novel metaheuristic optimization algorithm by simulating flower pollination behavior. Flower pollination behavior stems from the purpose of reproduction. From the biological evolution point of view, the objective of flower pollination is the survival of the fittest and the optimal reproduction of plant species. All these factors and processes of flower pollination interact so as to achieve optimal reproduction of the flowering plants. Self-pollination and cross-pollination are two different ways of pollination [11]. Cross-pollination means pollination can occur from pollen of a flower of a different plant, and self-pollination is just the opposite. Biotic, cross-pollination can occur at long distance, the pollinators of these pollinations such as bees, bats,birds can fly a long distance, thus they can considered as the global pollination. And these pollinators can fly as Lévy flight behavior [12], with fly distance steps obey a Lévy distribution. Thus, this can inspire to design new optimization algorithm. Flower pollination algorithm is an optimization algorithm which simulates the flower pollination behavior above-mentioned, flower pollination algorithm can also be divided into global pollination process and local pollination process. And it has been extensively researched in last two years by scholars. Huang and Yu have proposed a novel alignment-free sequence comparison method based on the numbers of adjacent amino acids based on Normalized feature vectors [13]. Yang and He have used FPA to solve multi-objective engineer optimization problems in 2013 [14,55]; Marwa Sharawi has applied FPA for wireless sensor network lifetime global optimization in 2014 [15]; Osama Abdel-Raouf has used an improved FPA to solve Sudoku Puzzles in 2014 [16]; FPA has also been applied to solve large integer programming problems by Ibrahim EI-henawy in 2014 [17]. In this paper, an elite opposition-based flower pollination algorithm (EOFPA) has been applied to functions optimization and structure engineering design problems. The improvement involves two major optimization strategies. Global elite opposition-based learning enhances the diversity of the population, and the local self-adaptive greedy strategy enhances its exploitation ability. An elite opposition-based flower pollination algorithm is validated by 18 benchmark functions and two structure engineering design problems. The results show that the proposed algorithm is able to obtained accurate solution,

* Corresponding author.
E-mail address: yongquanzhou@126.com (Y. Zhou).

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and it also has a fast convergence speed and a high calculation precision.

The remainder of the paper is organized as follows: Section 2 briefly introduces the original flower pollination algorithm; this is followed in Section 3 by new elite opposition-based flower pollination algorithm (EOFPA); simulation experiments and results analysis are described in Section 4. Finally, conclusion and future works can be found and discussed in Section 5.

2. Flower pollination algorithm (FPA)

Flower pollination algorithm (FPA) is inspired by the flow pollination process of flowering plants are the following rules [10,18]:

Rule 1**:** biotic and cross-pollination can be considered as a process of global pollination process, and pollen-carrying pollinators move in a way that obeys Lévy flights.
Rule 2: for local pollination, a biotic and self-pollination are used.
Rule 3: pollinators such as insects can develop flower constancy, which is equivalent to a reproduction probability that is proportional to the similarity of two flowers involved.
Rule 4**:** the interaction or switching of local pollination and global pollination can be controlled by a switch probability, with a slight bias toward local pollination.

In order to formulate updating formulas, we have to convert the aforementioned rules into updating equations. For example, in the global pollination step, flower pollen gametes are carried by pollinators such as insects, and pollen can travel over a long distance because insects can often fly and move in a much longer range. Therefore, Rule 1 and flower constancy can be represented mathematically as:

$$x_i^{t+1} = x_i^t + \gamma L(\lambda)(x_i^t - B) \tag{1}$$

where x_i^t is pollen i or solution vector x_i at iteration t, and B is the current best solution found among all solutions at the current generation/iteration. Here γ is a scaling factor to control the step size. In addition, $L(\lambda)$ is the parameter that corresponds to the strength of the pollination, which essentially is also the step size. Since insects may move over a long distance with various distance steps, we can use a Lévy flight to imitate this characteristic efficiently. That is, we draw $L > 0$ from a Lévy distribution:

$$L \sim \frac{\lambda \Gamma(\lambda) \sin(\pi\lambda/2)}{\pi} \frac{1}{S^{1+\lambda}}, (S > > S_0 > 0) \tag{2}$$

Here, $\Gamma(\lambda)$ is the standard gamma function, and this distribution is valid for large steps $s > 0$. Then, to model the local pollination, both Rule 2 and Rule 3 can be represented as

$$x_i^{t+1} = x_i^t + U(x_j^t - x_k^t) \tag{3}$$

where x_j^t and x_k^t are pollen from different flowers of the same plant species. This essentially imitates the flower constancy in a limited neighborhood. Mathematically, if x_j^t and x_k^t comes from the same species or selected from the same population, this equivalently becomes a local random walk if we draw U from a uniform distribution in [0, 1]. Though flower pollination activities can occur at all scales, both local and global, adjacent flower patches or flowers in the not-so-far-away neighborhood are more likely to be pollinated by local flower pollen than those faraway. In order to imitate this, we can effectively use the switch probability like in Rule 4 or the proximity probability p to switch between common global pollination to intensive local pollination. To begin with, we can use a naïve value of $p = 0.5$ as an initially value. A preliminary parametric showed that $p = 0.8$ might work better for most applications [10]. Specific implementation steps of the Standard Flower Pollination Algorithm (FPA) can be summarized in the pseudo code shown in Algorithm 1.

Algorithm 1. Flower pollination algorithm

```
Define objective function f(x), x = (x_1, x_2, ..., x_d)
Initialize a population of n flowers/pollen gametes with random solutions;
Find the best solution B in the initial population;
Define a switch probability p ∈ (0, 1);
Define a stopping criterion (either a fixed number of generations/iterations or accuracy)
while (t < MaxGeneration)
    for i = 1 : n (all n flowers in the population)
        if rand < p
            Draw a (d-dimensional) step vector L which obeys a Lévy distribution;
            Global pollination via Eq. (1) and get new solution x_i;
        else
            Draw U form a uniform distribution in (0,1);
            Do local pollination via Eq. (3) and get new solution x_i ;
        endif
        Evaluate the new solutions;
        If new solutions are better, update them in the population;
    endfor
        Find the current best solution B;
end while
Output the best solution found
```

3. Elite opposition-based flower pollination algorithm (EOFPA)

Flower pollination algorithm can easily solve low-dimensional unimodal optimization problems. Whereas when handling the high-dimensional and multi-modal optimization problems, we can clearly discover that the solutions obtained by FPA are not good enough. In order to enhance the global searching and local searching abilities, we append three optimization strategies to basic flower pollination algorithm (FPA). There are global elite opposition-based learning strategy (GEOLS), local self-adaptive greedy strategy (LSGS) and dynamic switching probability strategy (DSPS).

3.1. Global elite opposition-based learning strategy (GEOLS)

Basic flower pollination algorithm use Lévy flight in global search process. It is simulated by Lévy distribution. As we know that it is a stochastic process, the probability of getting a good solution is relatively low. For increasing the probability of obtained a better solution to the problem in global search process and expand the searching space, this strategy is applied to the proposed EOFPA. In essence, it is a greedy strategy.

Elite opposition-based Learning is a new technique in the field of intelligence computation. Its main ideology is: for a feasible solution, calculate and evaluate the opposite solution at the same time, and choose the better one as the individual of next generation. In this paper, individual with the best fitness value in the population is viewed as the elite individual. For explaining the definition of elite opposition-based solution, an example should be exhibited. If we suppose that the elite individual of the population is $X_e = (x_{e,1} x_{e,2}, ..., x_{e,D})$. For the individual $X_i = (x_{i,1} x_{i,2}, ..., x_{i,D})$, the elite opposition-based solution of X_i can be defined as $X_i' =$