Expert Systems With Applications 57 (2016) 192–203

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

A Modified Flower Pollination Algorithm for Global Optimization

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ARTICLE INFO

Article history:
Received 10 November 2015
Revised 24 March 2016
Accepted 24 March 2016
Available online 29 March 2016

Keywords:
Nature-inspired algorithms
Clonal Selection Algorithm
Flower Pollination Algorithm
Global Optimization

ABSTRACT

Expert and intelligent systems try to simulate intelligent human experts in solving complex real-world problems. The domain of problems varies from engineering and industry to medicine and education. In most situations, the system is required to take decisions based on multiple inputs, but the search space is usually very huge so that it will be very hard to use the traditional algorithms to take a decision; at this point, the metaheuristic algorithms can be used as an alternative tool to find near-optimal solutions. Thus, inventing new metaheuristic techniques and enhancing the current algorithms is necessary. In this paper, we introduced an enhanced variant of the Flower Pollination Algorithm (FPA). We hybridized the standard FPA with the Clonal Selection Algorithm (CSA) and tested the new algorithm by applying it to 23 optimization benchmark problems. The proposed algorithm is compared with five famous optimization algorithms, namely, Simulated Annealing, Genetic Algorithm, Flower Pollination Algorithm, Bat Algorithm, and Firefly Algorithm. The results show that the proposed algorithm is able to find more accurate solutions than the standard FPA and the other four techniques. The superiority of the proposed algorithm nominates it for being a part of intelligent and expert systems.

1. Introduction

Nature-inspired metaheuristic algorithms have become very popular in the last two decades; this is due to their success in finding good solutions for complex problems in engineering and industry, especially the NP complete problems. Most of the nature-inspired algorithms lie under the umbrella of stochastic techniques. The stochastic algorithm picks a set of random solutions; these solutions are improved based on the mechanism of the algorithm. The algorithm continues in working till certain stopping criterion. The stochastic algorithms are considered random search, but guided by heuristics to the next iteration. Due to the great success of stochastic algorithms, many algorithms have been proposed in the last few years. Examples of the new stochastic algorithms include Bacterial Foraging Algorithm in 2009 (Das, Biswas, Dasgupta, & Abraham, 2009), Cat Swarm Optimization in 2006 (Chu, Tsai, & Pan, 2006), Artificial Bee Colony Algorithm in 2007(Karaboga & Basturk, 2007), Glowworm Swarm Optimization Algorithm in 2009 (Krishnanand & Ghose, 2009), Cuckoo Search in 2009 (Yang & Deb, 2009), Bat-Inspired Algorithm in 2010 (Yang, 2010b), Firefly Algorithm in 2010 (Yang, 2010a), an Eco-Inspired Evolutionary Algorithm in 2011(Parpinelli & Lopes, 2011), Galaxy-Based Search Algorithm in 2011 (Hosseini, 2011), Brainstorming Process Algorithm in 2011 (Yuhui, 2011), Social Insect Behavior Algorithm in 2011 (Comellas & Martinez-Navarro, 2009), Wolf Search Algorithm in 2012 (Rui, Fong, Xin-She, & Deb, 2012), Krill Herd Algorithm in 2012 (Gandomi & Alavi, 2012), a New Fruit Fly Optimization Algorithm in 2012 (Pan, 2012), Differential Search Algorithm in 2012 (Civicioglu, 2012), Electromagnetism Optimization Algorithm in 2012 (Cuevas, Oliva, Zaldivar, Prez-Cisneros, & Sossa, 2012), Water Cycle Algorithm in 2012 (Eskandar, Sadollah, Bahreininejad, & Hamdi, 2012), Bee Colonies Algorithm in 2012 (Maia, de Castro, & Caminhas, 2012), Flower Pollination Algorithm in 2012 (Yang, 2012), Artificial Cooperative Search Algorithm in 2013 (Civicioglu, 2013), Grey Wolf Optimizer in 2014 (Mirjalili, Mirjalili, & Lewis, 2014), Particle Swarm Optimization and Gravitational Search Algorithm in 2014 (Mirjalili, Wang, & Coelho, 2014), Biogeography-Based Optimization with Chaos in 2014 (Saremi, Mirjalili, & Lewis, 2014), Forest Optimization Algorithm in 2014 (Ghaemi & Feizi-Derakhshi, 2014), An Effective Krill Herd Algorithm with Migration Operator in Biogeography Based Optimization in 2014 (Wang, Gandomi, & Alavi, 2014), Monarch Butterfly Optimization in 2015 (Wang, Deb, & Cui, 2015), Brainstorm Optimization Algorithm in 2015 (Rezaee Jordehi, 2015).

Many techniques are proposed to enhance the performance of stochastic algorithms; one of the most famous techniques is combining an operator imported from certain algorithm with another. One of the most effective operators that enhanced the performance of a set of stochastic algorithms is the cloning operator; the cloning operator is imported from the Clonal Selection Algorithm. The cloning operator enhanced the performance of a lot of

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http://dx.doi.org/10.1016/j.eswa.2016.03.047
0957-4174/

stochastic algorithms and proved to be effective; for example, the clonal operator enhanced the performance of Genetic Algorithms (Ludwig, 2012), Simulated Annealing(Jin, Du, He, & Jiao, 2004), Particle Swarm Optimization (Lu, 2009), Differential Evolution (Qin, Zhou, & Yue, 2010), Biogeography-Based Optimization (Qu & Mo, 2011), Artificial Bee Colony Algorithm (Jia-Ping & Li, 2012), Harmony Search (Wang, Gao, & Ovaska, 2009), Ant Colony Optimization (Gao, Wang, Dai, Li, & Tang, 2008), Bacterial Foraging Optimization (Dong Hwa & Jae Hoon, 2006), Gravitational Search (Gao, Chai, Chen, & Yang, 2013), and Tabu Search (Layeb, 2012).

The FPA is one of the recently proposed algorithms; Unlike the Firefly and Bat Algorithms, the FPA has a very small number of parameters, and it is very easy to implement; at the same time, it has high efficiency (Yang, 2012). The previous properties motivated us to choose the MFPA for enhancement and propose the enhanced algorithm as a new stochastic algorithm.

In this paper, the FPA is combined with the clonal selection operator to investigate the capability of the clonal operator in enhancing the FPA.

The proposed algorithm is validated and tested by solving a set of benchmark problems under the area of continuous global optimization problems. Experimental results show that the Modified Flower Pollination Algorithm (MFPA) outperforms the standard Flower Pollination Algorithm (FPA) beside other four well-established algorithms, namely, the Genetic Algorithm (Mitchell, 1998), Bat Algorithm (Yang, 2010b), Firefly Algorithm (Yang, 2010a), and Simulated Annealing (Kirkpatrick, Gelatt, & Vecchi, 1983).

In this paper, we will first review the main characteristics of the FPA that is developed by Yang (2012) in Section 2, and then we explain the Clonal Selection Algorithm that is developed by De Castro and Timmis (2002) in Section 3. After that, we will explain how to hybridize these two algorithms to produce a new modified version of the Flower Pollination Algorithm in Section 4. The proposed algorithm will be tested using a set of well-known test functions and design benchmarks in Section 5. Discussion and some ideas for possible enhancement of the proposed algorithm are presented in Section 6. Finally, the paper's conclusion is given in Section 7.

Throughout the paper, we use the following abbreviations for the used algorithms instead of the full name:

- Flower Pollination Algorithm: FPA.
- Clonal Selection Algorithm: CSA.
- Modified Flower Pollination Algorithm: MFPA.
- Genetic Algorithm: GA.
- Bat Algorithm: BAT.
- Firefly Algorithm: FF.
- Simulated Annealing: SA.

2. The Flower Pollination Algorithm

Flower pollination is a process associated with transferring flowers' pollens. The main actors of performing such transfer are birds, bats, insects, and other animals. There exist some flowers and insects that have made what we can call a flower-pollinator partnership. These flowers can only attract the birds that are involved in that partnership, and these insects are considered the main pollinators for these flowers (Glover, 2014).

There are two types of pollination: biotic and abiotic. Biotic occupies 90% of flower pollination, while abiotic occupies 10%. Abiotic pollination needs no pollinators. Some insects tend to visit certain types of flowers; at the same time, these insects bypass other species of flowers, and this phenomenon is called: flower constancy (Chittka, Thomson, & Waser, 1999; Waser, 1986). All flowers that own the flower constancy property have the guarantee of reproduction maximization.

Flower pollination process is achieved through cross-pollination or self-pollination. In cross-pollination, pollens are transferred from a different plant. The biotic and cross-pollinations occur at long distances, so they are performed by insects that can fly for long distances such as bees, birds, and bats. The previously mentioned flies are considered as global pollinators. Birds and bees usually follow in their behavior the Levy flight (Pavlyukevich, 2007); from this phenomenon, we can consider their moves as discrete jumps that obey the Levy distribution.

The second type of pollination, by which the fertilization is achieved, is the self-pollination. In self-pollination, pollens from the same flower or the same type of the flower are responsible for the fertilization process. Self-pollination usually needs no pollinators.

The above characteristics of the pollination process, flower constancy, and pollinators' behavior can be idealized in the following rules.

- *(Rule 1)*: The biotic and cross-pollination can be recognized as a global pollination, where the pollinators follow the Levy distribution.
- *(Rule 2)*: The abiotic and self-pollination can be interpreted as a local pollination.
- *(Rule 3)*: The flower constancy property can be considered as a reproduction ratio that is proportional to the degree of similarity between two flowers.
- *(Rule 4)*: Due to the physical proximity and wind, local pollination has a slight advantage over global pollination. Both are controlled by the value of the variable P in [0, 1].

In global pollination, the fittest reproduction is ensured through insects that can travel for long distances; if we represented the fittest as g_*, then the flower constancy and the first rule can be mathematically formulated as follows:

$$x_i^{t+1} = x_i^t + \gamma L\left(g^* - x_i^t\right), \tag{1}$$

In Eq. (1), x_i^t represents the pollen I; in other words, x_i^t is a solution vector at iteration t, g_* is the best found solution at iteration t, γ represents the step size scaling factor, and L is the pollination strength or the step size. The insect's long moves can be mimicked using Levy flight (Pavlyukevich, 2007). For this reason, the step size L is derived from the Levy distribution.

Local pollination, described in *(Rule 2)*, and flower constancy can be formulated as follows:

$$x_i^{t+1} = x_i^t + \epsilon\left(x_j^t - x_k^t\right), \tag{2}$$

where x_j^t and x_k^t are pollens (solution vectors) that are transferred from different flowers, but these flowers belong to a single plant species. This simulates the flower constancy in a small neighborhood. The variable ϵ is derived from a uniform distribution in the range [0, 1].

The pollination process can be either local or global, so a switch probability P is presented to switch between the two types of pollination *(Rule 4)*. The FPA is summarized in Fig. 1.

3. The Clonal Selection Algorithm (CSA)

CSA is inspired by the clonal selection theory that is presented in 1959 (Fekety, 1960). The main characteristics of the immune system can be summarized as follows.

- The immune system has a memory set that remembers the previous attacks.
- The most stimulated antibodies are selected for cloning.
- The poorly and nonstimulated antibodies are removed.
- The activated immune cells have undergone a hypermutation process.