

Chapter 2

Analysis of Firefly Algorithms and Automatic Parameter Tuning

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ABSTRACT

Many metaheuristic algorithms are nature-inspired, and most are population-based. Particle swarm optimization is a good example as an efficient metaheuristic algorithm. Inspired by PSO, many new algorithms have been developed in recent years. For example, firefly algorithm was inspired by the flashing behaviour of fireflies. In this chapter, the authors analyze the standard firefly algorithm and study the chaos-enhanced firefly algorithm with automatic parameter tuning. They first compare the performance of these algorithms and then use them to solve a benchmark design problem in engineering. Results obtained by other methods are compared and analyzed. The authors also discuss some important topics for further research.

1. INTRODUCTION

Search for optimality in many optimization applications is a challenging task, and search efficiency is one of the most important measures for an optimization algorithm. In addition, an efficient algorithm does not necessarily guarantee the global optimality is reachable. In fact, many optimization algorithms are only efficient in finding local optima. For example, classic hill-climbing or steepest descent method is very efficient for local optimization. Global optimization typically involves objective functions which can be multi-

modal and highly nonlinear. Thus, it is often very challenging to find global optimality, especially for large-scale optimization problems. Recent studies suggest that metaheuristic algorithms such as particle swarm optimization and firefly algorithm are promising in solving these tough optimization problems (Kennedy & Eberhart, 1995; Kennedy et al., 2001; Shi & Eberhart, 1998; Eberhart & Shi, 2000; Yang, 2008; Yang et al., 2013a).

Most metaheuristic algorithms are nature-inspired, from simulated annealing (Kirkpatrick et al., 1983) to firefly algorithm (Yang, 2008; Yang, 2010a), and from particle swarm optimiza-

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tion (Kennedy & Eberhart, 1995; Kennedy et al., 2001) to cuckoo search (Yang & Deb, 2010; Yang, 2014). These algorithms have been applied to almost all areas of optimization, design, scheduling and planning, data mining, machine intelligence, and many others (Gandomi et al., 2013a; Talbi, 2009; Yang, 2010a). On the other hand, chaotic tunneling is an important phenomenon in complex systems (Tomsovic, 1994; Podolskiy & Narmanov, 2003; Kohler et al., 1998; Delande & Zakrzewski, 2003; Shudo & Ikeda, 1998; Shudo et al., 2009). Traditional wisdom in optimization is to avoid numerical instability and chaos. Contemporary studies suggest that chaos can assist some algorithms such as genetic algorithms (Yang & Chen, 2002). For example, metaheuristic algorithms often use randomization techniques to increase the diversity of the solutions generated during search iterations (Talbi, 2009; Yang, 2010a). The most common randomization techniques are probably local random walks and Lévy flights (Gutowski, 2001; Pavlyukevich, 2007; Yang 2010b).

The key challenge for global optimization is that nonlinearity leads to multimodality, which in turns will cause problems to almost all optimization algorithms because the search process may be trapped in any local valley, and thus may cause tremendous difficulty to the search process towards global optimality. Even with most well-established stochastic search algorithms such as simulated annealing (Kirkpatrick et al., 1983), care must be taken to ensure it can escape the local modes/optimalty. Premature convergence may occur in many algorithms including simulated annealing and genetic algorithms. The key ability of an efficient global search algorithm is to escape local optima, to visit all modes and to converge subsequently at the global optimality.

In this paper, we will first analyze the recently developed firefly algorithm (FA) (Yang, 2008; Yang, 2010b). Under the right conditions, FA can have chaotic behaviour, which can be used as an advantage to enhance the search efficiency, because chaos allow fireflies to sample search

space more efficiently. In fact, a chaotic tunnelling feature can be observed in FA simulations when a firefly can tunnel through multimodes and jump from one mode to another modes. This enables the algorithm more versatile in escaping the local optima, and thus can guarantee to find the global optimality. Chaotic tunneling is an important phenomenon in complex systems, but this is the first time that a chaotic tunneling is observed in an optimization algorithm. Through analysis and numerical simulations, we will highlight that intrinsic chaotic characteristics in the FA can enhance the search efficiency. Then, we will introduce automatic parameter tuning to the chaotic firefly algorithm and compare its performance against a set of diverse test functions. Finally, we will apply the FA with automatic parameter tuning to solve a design benchmark whose solutions will be compared with other results in the literature.

2. FIREFLY ALGORITHM

Firefly Algorithm (FA) was developed by Xin-She Yang (Yang, 2008; Yang, 2010b), which was based on the flashing patterns and behaviour of fireflies. In essence, each firefly will be attracted to brighter ones, while at the same time, it explores and searches for prey randomly. In addition, the brightness of a firefly is determined by the landscape of the objective function.

The movement of a firefly i is attracted to another more attractive (brighter) firefly j is determined by

$$x_i^{t+1} = x_i^t + \beta e^{-\gamma r_{ij}^2} (x_j^t - x_i^t) + \alpha \varepsilon_i^t, \quad (1)$$

where α , β and γ are parameters. Here, α controls the scale of randomization, β controls the attractiveness, while γ is a scaling factor. In addition, the second term is due to the attraction. The third term is randomization with α being the random-

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