Chapter 6
An Analysis on Fireworks Algorithm Solving Problems With Shifts in the Decision Space and Objective Space

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ABSTRACT

Fireworks algorithms for solving problems with the optima shifts in decision space and/or objective space are analyzed. The standard benchmark problems have several weaknesses in the research of swarm intelligence algorithms for solving single objective problems. The optimum shift in decision space and/or objective space will increase the difficulty of problem solving. Modular arithmetic mapping is utilized in the original fireworks algorithm to handle solutions out of search range. The solutions are implicitly guided to the center of search range for problems with symmetrical search range via this strategy. The optimization performance of fireworks algorithm on shift functions may be affected by this strategy. Four kinds of mapping strategies are compared on problems with different dimensions and different optimum shift range. From experimental results, the fireworks algorithms with mapping to the boundary or mapping to limited stochastic region obtain good performance on problems with the optimum shift. This is probably because the search tendency is kept in these two strategies.

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1. INTRODUCTION

An optimization problem in $\mathcal{R}^n$, or simply an optimization problem, is a mapping $f : \mathcal{R}^n \rightarrow \mathcal{R}^k$, where $\mathcal{R}^n$ is termed as decision space (Adra, Dodd, & Griffin, *et al*., 2009) (or parameter space (Jin & Sendhoff, 2009), problem space), and $\mathcal{R}^k$ is termed as objective space (Sundaram, 1996). Swarm intelligence is based on a population of individuals (Kennedy, Eberhart, & Shi, 2001). In swarm intelligence, an algorithm maintains and successively improves a collection of potential solutions until some stopping condition is met. The solutions are initialized randomly in the search space. The search information is propagated through the interaction among solutions. With solutions' converging and/or diverging behaviors, solutions are guided toward the better and better areas.

In swarm intelligence algorithms, there is a population of solutions which exist at the same time. The premature convergence may happen due to solutions getting clustered together too fast. The population diversity is a measure of exploration and exploitation status. Based on the population diversity changing measurement, the state of exploration and exploitation can be obtained. The population diversity definition is the first step to give an accurate observation of the search state. Many studies of population diversity in evolutionary computation algorithms and swarm intelligence have been developed (Burke, Gustafson, & Kendall, 2002; Cheng, & Shi, 2011; Cheng, Shi, & Qin, 2011; Cheng, 2013; Cheng, Shi, & Qin, 2013; Mauldin, 1984; Shi, & Eberhart, 2008; Shi, & Eberhart, 2009).

The concept of developmental swarm intelligence algorithms was proposed in Shi (2014). The developmental swarm intelligence algorithm should have two kinds of ability: capability learning and capacity developing. The Capacity Developing focuses on moving the algorithm's search to the area(s) where higher searching potential may be possessed, while the capability learning focuses on its actual searching from the current solution for single point based optimization algorithms and from the current population for population-based swarm intelligence algorithms.

The capacity developing is a top-level learning or macro-level learning. The capacity developing could be the learning ability of an algorithm to adaptively change its parameters, structures, and/or its learning potential according to the search states on the problem to be solved. In other words, the capacity developing is the search strength possessed by an algorithm. The capability learning is a bottom-level learning or micro-level learning. The capability learning is the ability for an algorithm to find better solution(s) from current solution(s) with the learning capacity it is possessing (Shi, 2014).

The Fireworks algorithm (FWA) (Tan, & Zhu, 2010; Tan, Yu, & Zheng, *et al*., 2013) and brain storm optimization (BSO) (Cheng, Shi, & Qin, *et al*., 2014; Shi, 2011a; Shi, 2011b; Cheng, Qin, & Chen, *et al*., 2016;) algorithm are two good examples of developmental swarm intelligence (DSI) algorithms. The "good enough" optimum could be obtained through solutions' diverging and converging in the search space. In FWA algorithm, mimicking the fireworks exploration, the new solutions are generated by the exploration of existed solutions. While in BSO algorithm, the solutions are clustered into several categories, and new solutions are generated by the mutation of clusters or existed solutions. The capacity developing, i.e., the adaptation in search, is another common feature in these two algorithms.

Swarm intelligence is based on a population of individuals. In swarm intelligence, an algorithm maintains and successively improves a collection of potential solutions until some stopping condition is met. The solutions are initialized randomly in the search space, and are guided toward the better and better areas through the interaction among solutions. Mathematically, the updating process of population