A Local Best Particle Swarm Optimization Based on Crown Jewel Defense Strategy

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ABSTRACT

Particle swarm optimization (PSO) is a swarm intelligence algorithm well known for its simplicity and high efficiency on various optimization problems. Conventional PSO suffers from premature convergence due to the rapid convergence speed and lack of population diversity. PSO is easy to get trapped in local optimal, which largely deteriorates its performance. It is natural to detect stagnation during the optimization, and reactivate the swarm to search towards the global optimum. In this work the authors impose the reflecting bound-handling scheme and von Neumann topology on PSO to increase the population diversity. A novel Crown Jewel Defense (CJD) strategy is also introduced to restart the swarm when it is trapped in a local optimal. The resultant algorithm named LCJDPSO-rfl is tested on a group of unimodal and multimodal benchmark functions with rotation and shifting, and compared with other state-of-the-art PSO variants. The experimental results demonstrate stability and efficiency of LCJDPSO-rfl on most of the functions.

Keywords: Algorithm, Computational Intelligence, Convergence, Crown Jewel Defense (CJD), Particle Swarm Optimization (PSO)

1. INTRODUCTION

Particle swarm optimization (PSO) was first introduced by Kennedy and Eberhart in 1995 (Eberhart & Kennedy, 1995) based on a social-psychological model of social influence and learning. Like most evolutionary algorithms (EAs), PSO is a population-based stochastic search technique. Each member of the PSO swarm, also called a particle, represents a candidate solution in the search space. During the optimization process, each particle iteratively

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adjusts its flying direction according to its velocity, which is dependent on the best experiences of both the swarm and the particle itself. A fitness value is used to estimate the quality of each particle’s position, and accordingly determine its subsequent flying direction.

PSO is easy to implement, and has been successfully applied to solve various optimization problems such as nearest neighborhood classification (Blackwell & Bentley, 2002), software development (Chang & Huang, 2012), receive-diversity-aided STBC systems (Liu & Li, 2008), mixed discrete nonlinear programming (Nema, Goulermas, Sparrow, & Cook, 2008), economic load dispatch in power systems (Ratnaweera, Halgamuge, & Watson, 2004), and Value-at-Risk based fuzzy random facility location models (Wang & Watada, 2012). However, PSO easily gets trapped in local optimal when solving complex multimodal problems. PSO converges quickly in that information transmits throughout the swarm rapidly, while the search scope is also shrinking rapidly, which usually leads to the lack of population diversity and premature convergence. If the particles happen to be initialized in good positions, PSO can reach a preeminent solution; otherwise it would likely converge to an inferior solution and result in mediocre performance.

Many PSO variants have been proposed to solve the problem by increasing the population diversity (J. J. Liang, Qin, Suganthan, & Baskar, 2006; Peram, Veeramachaneni, & Mohan, 2003; Poli, Kennedy, & Blackwell, 2007; Van den Bergh & Engelbrecht, 2004). In this paper, a reflecting bound-handling scheme is imposed on a local best PSO (LPSO) using von Neumann topological neighborhood, which helps to achieve a better balance between diversity and convergence speed. On top of that, a novel Crown Jewel Defense (CJD) strategy is proposed to direct the algorithm toward a superior solution when particles get trapped. The proposed algorithm is a combination of CJD and LPSO with reflecting bound-handling (rfl) scheme, called LCJDPSO-rfl for short. The performance of LCJDPSO-rfl is evaluated through a series of experiments on benchmark functions. The experimental results demonstrate the stability and efficiency of LCJDPSO-rfl on most of the functions.

The rest of this paper is structured as follows. Section 2 provides a brief review of PSO and its variants. Section 3 describes the details of the proposed LCJDPSO-rfl. In Section 4, four groups of experimental results are analyzed to illustrate the performance of the proposed algorithm. Finally, the paper is concluded in Section 5.

2. PARTICLE SWARM OPTIMIZATION

Inspired by the swarm behavior of birds flocking, Kennedy and Eberhart (Eberhart & Kennedy, 1995) first proposed PSO as a population-based heuristic algorithm to handle complex optimization problems. PSO is invented to exploit the simulation of social interaction instead of the purely individual cognition. In a conventional PSO, a swarm of particles is defined to represent candidate solutions of an optimization problem to be solved. At the beginning of PSO, the swarm is first initialized randomly and then each particle moves iteratively in the direction adjusted by its own personal best position and the global best position. In this way, the particles discover optimal regions of the solution space through learning from the historical information of themselves and the other particles. The moving direction, known as velocity, and the position of each particle are defined as vectors $v_i$ and $x_i$, respectively. In each iteration of PSO, each dimension of $v_i$ and $x_i$, denoted as $v_{id}$ and $x_{id}$, are updated according to the following formulas:

$$v_{id} = v_{id} + c_1 \times r1_{id} \times (pbest_{id} - x_{id}) + c_2 \times r2_{id} \times (nbest - x_{id})$$

(1)

$$x_{id} = x_{id} + v_{id}$$

(2)

where $c_1$ and $c_2$ are acceleration parameters, $r1_{id}$ and $r2_{id}$ are two random numbers in range.
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