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Superior solution guided particle swarm optimization combined with local search techniques

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ABSTRACT

Particle swarm optimization (PSO) is an evolutionary algorithm known for its simplicity and effectiveness in solving various optimization problems. PSO should have strong yet balanced exploration and exploitation capabilities to enhance its performance. A superior solution guided PSO (SSG-PSO) framework integrated with an individual level based mutation operator and different local search techniques is proposed in this study. In SSG-PSO, a collection of superior solutions is maintained and updated with the evolutionary process, such that each particle can comprehensively learn from the recorded superior solutions. In addition, to maintain the diversity of the particle swarm, SSG-PSO is combined with an individual level based mutation operator, which will be invoked when a particle is trapped in a local optimum (determined by the fitness and position states of the particle), thereby improving the adaptation and flexibility of each individual particle. Moreover, two gradient-based local search techniques, namely, the Broyden–Fletcher–Goldfarb–Shanno (BFGS) and Davidon–Fletcher–Powell (DFP) Quasi–Newton methods, and two derivative-free local search techniques, namely, pattern search and Nelder–Mead simplex search, are incorporated into SSG-PSO. The performances of SSG-PSO and that of its local search enhanced variants are extensively and comparatively studied on a suit of benchmark optimization functions.

1. Introduction

Optimization is important in scientific research, management, and industry because numerous real-world problems can be essentially modelled as optimization tasks. "Traditional" mathematical programming methods (e.g., gradient-based methods) are no longer completely effective in solving complex optimization problems characterised by multi-modality, discontinuity, and high dimensionality. Thus, many evolutionary algorithms (EAs), such as genetic algorithm (GA) and ant colony optimization (ACO), have emerged. Particle swarm optimization (PSO), developed by Kennedy and Eberhart (Eberhart & Kennedy, 1995; Kennedy & Eberhart, 1995), is a competitive population-based algorithm, which is particularly efficient in dealing with numerical optimization problems. PSO is a bio-inspired (Eberhart, Shi, & Kennedy, 2001) algorithm which mimics swarm behaviours, such as bird flocking and fish schooling (Zhan, Zhang, Li, & Shi, 2011). Particles in PSO adjust their movements by learning from their own past experience and that of their neighbours in an attempt to identify better positions in a cooperative manner.

PSO has attracted significant attention since its inception because of its simplicity and effectiveness in solving various optimization problems. Various strategies, including parameter tuning (Chatterjee & Siarry, 2006; Ismail & Engelbrecht, 2012; Parsopoulos & Vrahatis, 2007; Ratnaweera, Halgamuge, & Watson, 2004; Shi & Eberhart, 1998b; Shi & Eberhart, 2001), topology structure adjustment (Hu & Eberhart, 2002; Kennedy, 1999; Kennedy & Mendes, 2002; Liang & Suganthan, 2005; Suganthan, 1999), intelligent combination of various search strategies (Li, Yang, & Nguyen, 2012; Hu, Wu, & Weir, 2012; Zhan, Zhang, Li, & Chung, 2009), and hybridisation with other optimization techniques (Angeline, 1998; Poli, Di Chio, & Langdon, 2005; Wei, He, Zhang, & Pei, 2002; Yao, Liu, & Lin, 1999), have recently been developed to strengthen the performance of PSO (Wu et al., 2014). Although noticeable progress and fruitful achievements have been attained, successfully balancing the exploration and exploitation capabilities of PSO to determine high-quality solutions for complex optimization problems, especially those with multimodal landscapes or high-relevance variables, remains a fundamental challenge.

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Exploration and exploitation capabilities are two key aspects in the design of efficient EAs (Das & Suganthan, 2011). However, balancing the exploration and exploitation capabilities of an EA is challenging because these capabilities generally contradict each other. Three methods are used to obtain an exploration- and exploitation-balanced EA. The first is integrating diversification strategies (e.g., utilisation of mutation strategies) into an EA which suffers from premature convergence (Andrews, 2006; Gao & Xu, 2011; Pehlivanoglu, 2013). The second is dynamically adjusting the parameters of EA in accordance with evolutionary states (Ismail & Engelbrecht, 2012; Zhan et al., 2009). The third is designing effective exploration and exploitation strategies and then reasonably organising them into an EA.

Our work in this study conforms to the third method. A superior solution guided particle swarm optimization with local search techniques is proposed in this study. The newly presented algorithm consists of three parts, namely, a superior solution guided PSO as framework, an individual level based mutation strategy, and different local search techniques.

Two strategies are adopted in the superior solution guided PSO framework. First, a collection of superior solutions was maintained as learning sources for each particle. Similar techniques, such as niching (Qu, Liang, & Suganthan, 2012; Li, 2010) and example particles (Huang, Qin, Hao, & Lim, 2012), have demonstrated effectiveness in enabling particles to have high exploration capability. The superior solution collection in this study is composed of two solutions; the local best particle solutions and the solutions with high-quality objective function values. Second, each particle comprehensively learns from all recorded superior solutions. Comprehensive learning is particularly effective in dealing with multimodal optimization problems (Liang, Qin, Suganthan, & Baskar, 2006).

An individual level based mutation operator is incorporated into the superior solution guided PSO framework. Mutation operators, such as Gaussian mutation, Cauchy Mutation, Lévy Mutation and Michalewicz's non-uniform mutation, are useful in maintaining the diversity of the swarm, thereby preventing PSO from premature convergence (Gao & Xu, 2011; Wang, Wang, & Wu, 2013; Andrews, 2006; Pehlivanoglu, 2013). Previously, mutation operators have been conducted based on population level, i.e., the whole population is mutated with a certain probability (Andrews, 2006), or the mutation operators are triggered according to the fitness value changes of the local best or global best solutions (Wang et al., 2008; Krohling, 2005; Wang et al., 2013). However, shortcomings are still encountered. First, probability based mutation operations without considering the evolutionary states of particles may destroy the consistence of the search behaviours of particles because a particle may be forced to be mutated although it is not trapped or moving to the better solution area. Second, mutation operations in terms of fitness changes of local best or global best solutions also have a problem in which fitness stagnation does not necessarily mean that particles get trapped because particles may still be exploring the solution space.

In our study, mutation is performed at the individual level and trigged by the satisfaction of two conditions. One condition is that a particle does not improve its fitness in a certain number of generations. The second condition is that the movements of the particle are restricted in a small area. That is, the mean distance between the current position of the particle and its previous certain number of positions is smaller than a threshold value. When both conditions are satisfied, the particle is trapped and should execute the mutation operator. The mutation strategy presented in this study can provide more accurate guidance for the diversification of particles while improving the adaptation and flexibility of each single particle.

Different local search techniques are combined into the superior solution guided PSO framework and comparatively studied to enhance the performance of the algorithm. However, compared with conventional mathematical programming (MP) methods, PSO has global search capability. Therefore, it is a natural idea to reasonably combine PSO with traditional MP methods to solve optimization problems to benefit from both the exploration capability of PSO and exploitation capability of MP. The combination of local search techniques and evolutionary algorithms has been investigated in some papers. For example, the gradient-based local search method (Hu et al., 2012; Noel, 2012; Plevris & Papadrakakis, 2011; Xie, Yu, & Zou, 2012) and derivative-free local search method (Fan & Zahara, 2007; Qu et al., 2012) have been employed in EAs to provide stronger exploitation capability. However, these methods have not been comprehensively and comparatively studied yet. In the present study, four gradient-based and derivative-free local search techniques, including the Broyden–Fletcher–Goldfarb–Shanno (BFGS) and Davidon–Fletcher–Powell (DFP) Quasi-Newton methods (gradient-based), Pattern Search (derivative-free), and Nelder–Mead simplex search (derivative-free) method are integrated into the algorithm, respectively.

The paper is structured as follows: Section 2 briefly introduces the basic PSO and reviews the related work. Section 3 describes the superior solutions guided PSO framework. Section 4 briefly introduces the four adopted local search techniques. Section 5 provides details of the proposed individual level based mutation operator. Section 6 provides the algorithm framework of SSG-PSO with different local search techniques. Section 7 conducts experimental and comparative studies on a suit of 21 benchmark optimization problems. Section 8 provides the conclusion of this paper.

2. Related studies

PSO has undergone a significant progress since its introduction in 1995. A large number of PSO variants have been proposed to improve the performance of traditional PSO (Wu et al., 2014). Comprehensive reviews of PSO can be found in (Banks, Vincent, & Anyakoha, 2007; Banks, Vincent, & Anyakoha, 2008; Poli, Kennedy, & Blackwell, 2007). In addition, del Valle, Venayagamoorthy, Mohagheghi, Hernandez, and Harley (2008) surveyed PSO along with its basic concepts, variants, and applications in power systems. Rana, Jasola, and Kumar (2011) reviewed PSO and its application to data clustering. In this section, this study briefly introduces the basic PSO, and then surveys the recent major PSO variants.

2.1. Basic PSO

Analogous to other evolutionary algorithms, such as GA and ACO, PSO is a population-based stochastic optimization algorithm. A swarm of particles attempt to search for superior solutions through learning, communication and interaction. The position of each particle refers to a solution. The position moving process of a particle in the solution space then relates to a solution search process. The state of particle i is described by its current position $\mathbf{x_i} = [x_{i1}, x_{i2}, \ldots x_{iD}]$ and velocity $\mathbf{v_i} = [v_{i1}, v_{i2}, \ldots v_{iD}]$, where D is the number of variables encountered in the optimization problem. In the generic PSO with inertia weight (Shi & Eberhart, 1998a), the position and velocity of particle i are updated during the evolutionary process:

$$v_i^d = w \times v_i^d + c_1 \times r_1^d \times (pBest_i^d - x_i^d) + c_2 \times r_2^d \times (gBest^d - x_i^d), \tag{1}$$

$$x_i^d = x_i^d + v_i^d, \tag{2}$$

where x_i^d is the dth variable (or dimension) of the position of particle i; v_i^d is the dth variable of the velocity of particle i; $pBest_i^d$ is the