Applied Mathematics and Computation 242 (2014) 265–276

Contents lists available at ScienceDirect

Applied Mathematics and Computation

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

Enhanced comprehensive learning particle swarm optimization

Xiang Yu, Xueqing Zhang *

Department of Civil and Environmental Engineering, The Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong

ARTICLE INFO

Keywords:
Global optimization
Particle swarm optimization
Comprehensive learning

ABSTRACT

Comprehensive learning particle swarm optimization (CLPSO) is a state-of-the-art metaheuristic that encourages a particle to learn from different exemplars on different dimensions. It is able to locate the global optimum region for many complex multimodal problems as it is excellent in preserving the particles' diversity and thus preventing premature convergence. However, CLPSO has been noted for low solution accuracy. This paper proposes two enhancements to CLPSO. First, a perturbation term is added into each particle's velocity update procedure to achieve high performance exploitation. Normative knowledge about dimensional bounds of personal best positions is used to appropriately activate the perturbation based exploitation. Second, the particles' learning probabilities are determined adaptively based on not only rankings of personal best fitness values but also the particles' exploitation progress to facilitate convergence. Experiments conducted on various benchmark functions demonstrate that the two enhancements successfully overcome the low solution accuracy weakness of CLPSO.

1. Introduction

Introduced in 1995 [1], particle swarm optimization (PSO) is a modern metaheuristic that has been applied to solve real-world optimization problems in a wide range of areas. PSO simulates the movements of organisms in a bird flock or fish school. PSO is population-based and finds the optimum using a swarm of particles, with each particle representing a candidate solution. Compared with traditional optimization methods such as linear programming, nonlinear programming, and dynamic programming, PSO does not require the objective and constraints of the optimization problem to be continuous, differentiable, linear, or convex, and PSO usually can efficiently solve large-scale problems. PSO shares many similarities with evolutionary computation based metaheuristics such as genetic algorithm and differential evolution, but PSO basically does not use any evolution operator (e.g. crossover, mutation, or selection), thus PSO is simpler in concept and easier to implement.

In PSO, all the particles "fly" in the search space. Each particle, denoted as i, is associated with a position, a velocity, and a fitness that indicates its performance. PSO relies on iterative learning to find the optimum. In each iteration (or generation), i adjusts its velocity according to its previous velocity, its historical best position (i.e. personal best position), and also the personal best positions of its neighborhood particles. There are many PSO variants that differ in how to use the neighborhood search experiences for the velocity update. In global PSO (GPSO) [2], the historical best position out of the entire swarm (i.e. global best position) is used to update i's velocity. GPSO does not perform well on complex problems, thus various local PSOs (LPSOs) have been studied [3]. In a LPSO, a static topological structure (e.g. ring, pyramid, or von Neumann) is constructed

* Corresponding author.
E-mail addresses: xyuac@ust.hk (X. Yu), zhangxq@ust.hk (X. Zhang).

http://dx.doi.org/10.1016/j.amc.2014.05.044
0096-3003/

and the neighborhood of i consists of i itself and particles that i directly connects to. Instead of referring to the global best position, the historical best position of the neighborhood (i.e. local best position) is used for updating i's velocity. Compared with LPSO, standard PSO (SPSO) [4] maintains a dynamic topological structure. Fully informed PSO (FIPSO) [5] uses a weighted average of the personal best positions of all the particles in i's neighborhood to update i's velocity. For GPSO, LPSO, SPSO, and FIPSO, once the neighborhood related exemplar position has been determined, it is used to update a particle's velocity on all dimensions.

Recently, recognizing the fact that one exemplar does not always offer a good guide on every dimension, two PSO variants, namely comprehensive learning PSO (CLPSO) [6] and orthogonal learning PSO (OLPSO) [7], have been proposed in literature to encourage a particle to learn from different exemplars on different dimensions. In CLPSO, for each particle and on each dimension, a learning probability controls whether to learn from the personal best position of the particle itself or that of some other randomly selected particle. OLPSO adopts orthogonal experimental design to determine the best combination of learning from a particle's personal best position or its neighborhood's historical best position (i.e. global/local best position) on different dimensions with a polynomial number of experimental samples. OLPSO has two versions, global version OLPSO-G and local version OLPSO-L. Zhan et al. [7] compared OLPSO-G, OLPSO-L, CLPSO, and other PSO variants on a number of benchmark functions. The results showed that OLPSO-L and CLPSO significantly outperform OLPSO-G and traditional PSOs (including GPSO, LPSO, SPSO, and FIPSO) on many complex multimodal problems because they are able to preserve the swarm's diversity and thus locate the global optimum region. CLPSO performs worse than traditional PSOs and OLPSO-G on unimodal and simple multimodal problems and OLPSO-L on complex multimodal problems as it is lower in solution accuracy.

Some researchers have worked on improving the performance of CLPSO on single-objective global optimization problems and extending CLPSO to multiobjective optimization. Liang and Suganthan [8] proposed an adaptive CLPSO with history learning, wherein the particles' learning probabilities are adjusted adaptively based on the value that has achieved the biggest improvement in past several generations and the particle velocity update takes into account the historical improving direction. Zheng et al. [9] introduced a mechanism to CLPSO that adaptively sets the values of the inertia weight and acceleration coefficient based on evolutionary information of the particles. In [10], through combining chaotic local search with CLPSO, a memetic scheme enables stagnant particles that cannot be improved by the comprehensive learning strategy to escape from local optima and enables some elite particles to do fine-grained local searches around promising regions. The Pareto dominance concept was integrated with CLPSO to handle multiobjective optimization problems in [11–13].

This paper proposes two novel enhancements to CLPSO to improve the algorithm performance in terms of solution accuracy. The enhanced method is called enhanced CLPSO (ECLPSO). The two enhancements are respectively perturbation based exploitation and adaptive learning probabilities. Specifically, a perturbation term is added into each particle's velocity update procedure to achieve high performance exploitation, with normative knowledge about dimensional bounds of the personal best positions used to appropriately activate the perturbation based exploitation; and the particles' learning probabilities are adaptively determined based on not only rankings of the personal best fitness values but also the particles' exploitation progress to facilitate convergence.

The rest of this paper is organized as follows. In Section 2, CLPSO and research trends on PSO are reviewed. Section 3 elaborates the rationales and implementation details of the two enhancements made in ECLPSO and the algorithm framework of ECLPSO. In Section 4, the performance of ECLPSO is evaluated on fourteen typical unimodal, multimodal, and rotated benchmark functions. Section 5 concludes the paper.

2. Background

2.1. Comprehensive learning particle swarm optimization

Let there be D decision variables, the swarm of particles move in a D-dimensional space. Each particle i is associated with a D-dimensional position $X_i = (X_{i,1}, X_{i,2},\ldots,X_{i,D})$ and a D-dimensional velocity $V_i = (V_{i,1}, V_{i,2},\ldots,V_{i,D})$. In each generation, V_i and X_i on each dimension are updated as described in (1) and (2).

$$V_{i,d} = wV_{i,d} + cr_d(E_{i,d} - X_{i,d}) \tag{1}$$

$$X_{i,d} = X_{i,d} + V_{i,d} \tag{2}$$

where d is the dimension index; w is the inertia weight; $E_i = (E_{i,1}, E_{i,2},\ldots,E_{i,D})$ is the guidance vector of exemplars; c is the acceleration coefficient and usually $c = 1.5$ [6,7]; and r_d is a random number in [0, 1]. $V_{i,d}$ is usually clamped to a pre-specified positive value V_d^{max}. If $V_{i,d} > V_d^{max}$, then $V_{i,d}$ is set to V_d^{max}; or if $V_{i,d} < -V_d^{max}$, then $V_{i,d}$ is set to $-V_d^{max}$. Let $\underline{X_d}$ and $\overline{X_d}$, respectively be the lower and upper bounds of the search space on the dth dimension, V_d^{max} is usually set as 20% of $\overline{X_d} - \underline{X_d}$ [7]. The personal best position of particle i is denoted as $P_i = (P_{i,1}, P_{i,2},\ldots,P_{i,D})$. After X_i is updated, X_i is evaluated and will replace P_i if it has a better fitness value.

PSO possesses two important characteristics: exploration and exploitation. Exploration is the ability to search different regions for locating a good solution, while exploitation is the ability to concentrate the search around a small region for refining a hopeful solution. The inertia weight w linearly decreases during the run of CLPSO in order to balance exploration and