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Bidirectional teaching and peer-learning particle swarm optimization

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ABSTRACT

Most of the well-established particle swarm optimization (PSO) variants do not provide alternative learning strategies when particles fail to improve their fitness during the searching process. To solve this issue, we improved the state-of-art teaching–learning-based optimization algorithm and adapted the enhanced framework into the PSO. Thus, we developed a bidirectional teaching and peer-learning PSO (BTPLPSO). Specifically, the BTPLPSO uses two learning phases, namely, the teaching and peer-learning phases. The particles first enter the teaching phase and update their velocity based on their personal and global best information. However, when particles fail to improve their fitness in the teaching phase, they enter the peer-learning phase and learn from the selected exemplar. To establish a two-way learning mechanism between the global best particle and the population, we developed an orthogonal experimental design-based elitist learning strategy to improve the global best particle by fully exploiting the useful information of each particle. The proposed BTPLPSO was thoroughly evaluated on 25 benchmark functions with different characteristics. The simulation results confirmed that BTPLPSO significantly outperforms eight well-established PSO variants and six cutting-edge metaheuristic search algorithms.

1. Introduction

The collaborative behavior of bird flocking and fish schooling in searching for food [3,12,16,29] has inspired Kennedy and Eberhart [29] to develop particle swarm optimization (PSO) in 1995. As a population-based metaheuristic search (MS) algorithm, PSO simultaneously evaluates many points in the search space. In PSO, each individual (i.e., particle) represents a potential solution of the optimization problem, whereas the locations of food source are global optimum solutions. While navigating through a multidimensional problem search space independently and stochastically, particles share information with each other and attempt to achieve population convergence in the search space [3,29,30]. These particles could converge towards the optimum, local optimum, or any arbitrary point in the search space [10,45,58]. PSO has been actively applied to many real-world applications with promising results because of its effectiveness and simple implementation in solving multidimensional problems [4,12,30,39].

Similar with other MS algorithms, PSO also has several drawbacks that restrict its wider application in real-world problems. Previous experiments have revealed that PSO suffers from premature convergence because it tends to be trapped in the

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local optima or any arbitrary point in the search space during the early optimization stage, especially when solving complex problems [10,38,45,57,58]. Another challenging issue is the proper control of exploration/exploitation searches. Overemphasis of exploration inhibits swarm convergence, whereas an excessive amount of exploitation leads to premature convergence [52]. In addition, although the neighborhood best particle is crucial in guiding the swarm during the search process, the neighborhood best particle has a poor learning strategy to update itself [32]. The neighborhood and personal best positions of the neighborhood best particle are the same, and this similarity inevitably nullifies its social and cognitive components in the velocity update equation of PSO [10].

In the past decades, scholars have proposed many solutions to address PSO's drawbacks. Parameter adaptation strategy [10,26,35,49,63] is a research hotspot that can improve PSO's performance, considering that the control parameters of PSO are crucial in determining the algorithm's convergence characteristics. Adaptive PSO (APSO) [63] is a PSO variant that was developed via this approach. Specifically, APSO uses the evolutionary state estimation module to identify the evolutionary states and to tune the particles' inertia weight and acceleration coefficients. Another area of focus is to explore the population topology [5,7,27,40–42,46] because the latter decides the information flow rate of the best solution within the swarm [28,31]. The examples of PSO variants developed via this strategy are the fully informed PSO (FIPSO) [41] and the flexible PSO (Flexi-PSO) [27]. The former states that each particle's movement should be influenced by all of its neighborhood members, whereas the latter combines the global and local versions of PSO via the proposed acceleration coefficient heuristic. Learning strategy [6,9,24,25,36,38,55] is another crucial factor that determines the PSO's performance. Comprehensive learning PSO (CLPSO) [38] and feedback-learning PSO with quadratic inertia weight (FLPSO) [55] are examples of PSO variants with modified learning strategy. These two PSO variants allow each particle i to learn from its own best experience or from other particle's historical best position in each dimension.

Although these newly proposed PSO variants have promising search performances, most of these variants preserve population diversity at the cost of slow convergence or complicated algorithmic structures. Solving the conflict between the exploration and exploitation searches without significantly impairing PSO's convergence speed and its simplicity of algorithmic structure remains a challenge. Another notable issue is that most existing PSO variants do not provide alternative learning strategies to particles when they fail to improve their fitness.

Recently, Rao et al. [47,48] proposed a teaching–learning-based optimization (TLBO) algorithm that is motivated by the philosophy of teaching and learning. The TLBO process is divided into two parts, namely, the teacher and learner phases. The development of the original TLBO model, although having a competitive performance, is still incomplete. Several mechanisms used by the original TLBO framework do not accurately reflect actual classical school teaching and learning process scenarios. According to the studies in [1,2], a more accurate modeling of real-world scenario can lead to better natural inspired optimization algorithms. Thus, it could be deduced that the deviation between the modeling and the actual scenarios of the teaching and learning process may restrict the TLBO's search performance. Motivated by these facts, we attempted to modify and improve the existing TLBO and adopt the enhanced framework into PSO, thereby developing bidirectional teaching and peer-learning PSO (BTPLPSO). The latter's essential components are summarized as follows:

(1) Similar to TLBO, BTPLPSO adopts two learning phases, namely, the teaching and peer-learning phases. Each student particle first enters the teaching phase to update its knowledge. A student particle that fails to improve its knowledge in the teaching phase proceeds to the peer-learning phase, whereby an exemplar is selected via the roulette wheel selection technique to guide the student particle to improve its knowledge.
(2) To emulate the knowledge transfer mechanism adopted by the modern school learning paradigm, we proposed an orthogonal experiment design (OED)-based elitist learning strategy (OEDELS). This module enables the student particles that successfully improved their knowledge during the teaching or peer-learning phases to contribute their updated knowledge to the teacher.

The rest of this paper is organized as follows: Section 2 briefly presents several related works. Section 3 presents the methodologies of the BTPLPSO in detail. Section 4 provides the experimental settings and results. Finally, Section 5 concludes this work.

2. Related works

In this section, we describe the mechanism of the basic PSO (BPSO). We then provide a brief description of the TLBO and OED [22,43] techniques. Finally, we review several OED-based PSO variants.

2.1. Basic PSO algorithm

In a D-dimensional problem hyperspace, two vectors are associated with each BPSO particle. The two vectors are the position vector $X_i = [X_{i1}, X_{i2}, \ldots, X_{iD}]$ and the velocity vector $V_i = [V_{i1}, V_{i2}, \ldots, V_{iD}]$. During the search process, the trajectory of each particle is stochastically adjusted based on the particle i's personal best experience $P_i = [P_{i1}, P_{i2}, \ldots, P_{iD}]$ and the group's best experience in the population $P_g = [P_{g1}, P_{g2}, \ldots, P_{gD}]$ [16,29]. At the $(t+1)$-th iteration of the searching process, the d-th dimension of particle i''s velocity, $V_{i,d}\,(t+1)$ and position $X_{i,d}\,(t+1)$ are updated as follows: