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An improved teaching–learning-based optimization algorithm for solving global optimization problem

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ABSTRACT

Teaching–learning-based optimization (TLBO) is a recently proposed population-based algorithm that simulates the process of teaching and learning. Compared with other evolutionary algorithms, TLBO has fewer parameters that must be determined during the renewal process, and is very efficient for certain optimization problems. However, as a population-based algorithm, certain complex problems cause TLBO to exhibit local convergence phenomena. Therefore, to improve the global performance of TLBO, we have designed local learning and self-learning methods to enhance the search ability of TLBO. In the learner phase, every individual learns from both the teacher of the current generation and other individuals. Whether these individuals are neighbours or random individuals from the whole class is determined probabilistically. In the self-learning phase, individuals either renew their positions according to their own gradient information, or randomly exploit new positions according to a design based on the means and variances. To maintain local diversity, all individuals are rearranged after a set number of iterations. The proposed algorithm is tested on a number of functions, and its performance is compared with that of other well-known optimization algorithms. The results indicate that the improved TLBO attains good performance.

1. Introduction

In operations research and computer science, global optimization refers to the procedure of finding the best possible approximate solutions to the relevant objective functions [13]. Such scenarios frequently arise in almost every field of engineering design, applied sciences, and other scientific applications. For global optimization problems, finding the global optima of a function is often difficult, or may even be practically impossible for some complex problems. Indeed, certain classical derivative-based techniques cannot be used to find the global optimal solution. In general, there can be solutions that are locally, but not globally, optimal. This situation appears more frequently in high-dimensional problems or when the function has many local optima [8]. As a result, many intelligent evolutionary algorithms have been developed to solve global optimization problems. Variants of particle swarm optimization (PSO) algorithms are widely used for global optimization problems, although standard PSO [11] can suffer from premature and slow convergence. Many improved PSO algorithms have been proposed for global optimization problems. Some studies have improved the performance of PSO by modifying its parameters. For instance, PSO-w uses the inertia weight in the PSO velocity equation to improve the

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convergence performance of standard PSO [12]. Linearly decreasing inertia weight PSO [23] gradually reduces the inertia weight as the algorithm proceeds, giving a good initial global searching ability, and then enhancing the local searching ability later in the evolution. A constriction factor [5] can also be employed in the particle update equations to improve the convergence of PSO. Peram and Veeramachaneni developed fitness-distance-ratio-based PSO (FDR-PSO), which incorporates near-neighbour interactions [22]. Liang et al. proposed a comprehensive learning PSO (CLPSO) [16] in which the historical best information from all other particles is used to update the particle velocity. Some researchers have improved PSO performance by employing a different population topology. For example, in fully informed PSO [18], the particle update equation uses the stochastic average of the best information from all neighbouring particles, rather than the particle's own best position and the global best. A dynamically adjusted neighbourhood PSO was proposed by Suganthan [24]. In this method, the neighbourhood of a particle gradually increases until it includes all particles. Negative entropy has been added to PSO to discourage premature convergence [37], and a niching PSO was introduced by incorporating a cognitive-only PSO model into a guaranteed convergence PSO algorithm [28]. Speciation-based PSO [14] dynamically adjusts the number and size of swarms by constructing an ordered list of particles, ranked according to their fitness, with spatially close particles joining a particular species. A dynamic neighbourhood learning-based PSO has been developed in which the learner particle either learns knowledge from the historical information of its neighbourhood, or from its own history [21]. A number of hybrid methods have been proposed to solve global optimization problems. For example, a hybrid of a co-evolutionary cultural algorithm and PSO has been reported [25], and a global optimization strategy that combines PSO with the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm was proposed for multimodal functions [15]. In this method, BFGS is integrated into the context of the PSO to improve the particles' local search ability. A hybrid ant particle optimization algorithm [20] combines ant colony optimization (ACO) with PSO to find global minima, and simulated annealing has been combined with an artificial bee colony (ABC) algorithm [4] to improve the exploitation ability. However, there is no theory to guide which algorithms should be blended to derive the best performance; indeed, blending algorithms may even decrease the performance of the individual algorithms.

Teaching–learning-based optimization (TLBO) [33] has recently been proposed for benchmark functions and real models [26,27,31,32,29]. Experimental results indicate that TLBO outperforms the given meta-heuristics. To improve the performance of TLBO, several variants have been introduced. An elitist TLBO (ETLBO) algorithm [34] was proposed to solve complex constrained optimization problems. Rao et al. used a modified version of TLBO [30] for a multi-objective optimization involving heat exchangers. They considered the maximum effectiveness and minimum total cost as the objective functions, and derived an adaptive teaching factor to modulate the TLBO search ability.

In addition, various evolutionary computation algorithms have been designed for global optimization, such as artificial bee colony algorithm (ABC) [10], genetic algorithm (GA) [35], evolution strategy (ES) [38], differential evolution (DE) [9], ant colony optimization (ACO) [6,19]. In this paper, an improved TLBO (ITLBO) is presented. ITLBO enhances the local searching and self-learning ability of TLBO, and improves the global performance by modifying operators in the learner and self-learning phases. In the learner phase, the learners are arranged in a rectangle or square. Every learner learns from the teacher, as well as from neighbouring learners or a randomly selected learner. After the learner phase, the learners teach themselves according to gradient information from the previous two generations, or change their positions according to a designed mean and variance when the gradient is zero. To maintain the diversity of different domains, all learners are randomly rearranged after a given number of iterations. We compare our improved TLBO (ITLBO) with PSO with inertia weight (PSO-w) [12], local version of PSO with constriction factor (PSO-cf-local) [5], FDR-PSO [22], CLPSO [16], local version of PSO with inertia weight (PSO-w-local), jDE [3], ABC [10], TLBO [33], and ETLBO [34].

The rest of this paper is organized as follows. The original TLBO is described in Section 2, before Section 3 presents the improved algorithm. Computational results are discussed and analysed in Section 4, and our conclusions and ideas for future research are given in Section 5.

2. Teaching–learning-based optimization algorithm

Similar to other evolutionary computation algorithms, TLBO is a population-based optimization method. It mimics the teaching and learning process of a typical class. The teacher and learners are vital components of the algorithm—learners learn from the teacher in the teacher phase, and then learn from other learners in the learner phase. The output of the TLBO algorithm is considered in terms of the learners' results or grades, which depend on the quality of the teacher. In the teacher phase, the individual with the best fitness value is selected to be the teacher of the class. A high quality teacher benefits the whole class. Moreover, every learner also learns from a randomly chosen learner in the current class. The main phases are described as follows.

2.1. Teacher phase

During this phase, the teacher attempts to increase the mean grade of the class. For an objective function $f(x)$ with d-dimensional variables, the position of the ith learner can be represented as $X_i = [x_{i1}, x_{i2}, \ldots, x_{id}]$. For a class with m learners, the mean position of the class in the current iteration is presented as $X_{mean} = \frac{1}{m}\left[\sum_{i=1}^{m} x_{i1}, \sum_{i=1}^{m} x_{i2}, \ldots, \sum_{i=1}^{m} x_{id}\right]$. The learner