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Research paper

Quantum-behaved particle swarm optimization with collaborative attractors for nonlinear numerical problems

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ABSTRACT

In this paper, an improved quantum-behaved particle swarm optimization (CL-QPSO), which adopts a new collaborative learning strategy to generate local attractors for particles, is proposed to solve nonlinear numerical problems. Local attractors, which directly determine the convergence behavior of particles, play an important role in quantum-behaved particle swarm optimization (QPSO). In order to get a promising and efficient local attractor for each particle, a collaborative learning strategy is introduced to generate local attractors in the proposed algorithm. Collaborative learning strategy consists of two operators, namely orthogonal operator and comparison operator. For each particle, orthogonal operator is used to discover the useful information that lies in its personal and global best positions, while comparison operator is used to enhance the particle's ability of jumping out of local optima. By using a probability parameter, the two operators cooperate with each other to generate local attractors for particles. A comprehensive comparison of CL-QPSO with some state-of-the-art evolutionary algorithms on nonlinear numeric optimization functions demonstrates the effectiveness of the proposed algorithm.

1. Introduction

Owing to the robustness and parallelism, evolutionary algorithms (EAs) have become powerful tools to solve various optimization problems [1–6]. Among all kinds of EAs, particle swarm optimization (PSO) [7] has been widely used in dealing with many real-world problems because of its simplicity and facile realization [8–10]. However, because of the restricted velocity, the searching area of a particle is limited and diminishing in PSO. Which means, in a PSO system, the searching space cannot cover the whole feasible region and global convergence cannot be guaranteed [11,12]. This is also the main cause of the premature in PSO. In order to dispose of the above mentioned disadvantages of PSO, quantum-behaved particle swarm optimization (QPSO) [13] is proposed. In QPSO, the position of a particle is depicted by its local attractor and a probability density function. In this case, the particles in QPSO have got rid of the limitation of trajectory. Analysis in [14] shows that QPSO is global convergent. Another advantage is that there is only one parameter in QPSO. Hence, QPSO is very easy to implement. In recent years, QPSO has been successfully applied to a lot of optimization problems, such as constrained optimization, multi-objective optimization, engineering design, and so on [15–18].

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For a fixed probability density function, the local attractors of particles have a great influence on the performance of QPSO. In classic QPSO, the local attractor for a particle can be obtained as the weighted sum of its personal and global best positions. It has been found that there are few improvements concentrating on the local attractors in QPSO. In [19], a novel Quantum-behaved particle swarm optimization with Gaussian distributed local attractor point (GAQPSO) is introduced. In GAQPSO, the local attractor is subject to Gaussian distribution whose mean value is the original local attractor that defined in classic QPSO. So the new strategy to get local attractors adopted in GAQPSO is also based on the traditional strategy in classic QPSO. However, the analysis in [20] has demonstrated that the traditional strategy is not an efficient way to make use of the two best positions. For example, some useful information lies in the two positions could be lost. Furthermore, if the personal and global best position of an particle are all the same, then the obtained local attractor of the particle will be exactly the same as its personal best position. In this case, the particle will be held at its personal best position and have weak ability to jump out of local optima.

The word ‘collaborative’ is not new to QPSO. Some improvements which are related to collaborative strategy have been adopted in QPSO. In [21], a cooperative quantum-behaved particle swarm optimization (CQPSO) is presented. In CQPSO, each quantum particle can obtain several individuals by multiple observations at a single generation. Then the obtained individuals cooperate with each other to get a better individual for the next generation. In [22], a revised QPSO with cooperative and competitive mechanism (COQPSO) is introduced. In COQPSO, multiple swarms are adopted. The cooperation and competition among swarms can make the algorithm more efficient. In this paper, a completely different collaborative learning (CL) strategy with the aim of constructing promising local attractor for each particle is introduced. The proposed CL strategy consists of two operators, namely orthogonal operator and comparison operator. The aim of orthogonal operator is to discover useful information that lies in the personal and global best positions of each particle. The orthogonal operator adopted in this paper is designed based on orthogonal experimental design (OED) [23], since OED has demonstrated the ability of discovering the best combination levels for different factors with few test times. Recent studies have also shown the good performance of evolutionary algorithms which cooperate with OED [24–27]. Comparison operator is designed to increase population diversity in QPSO, since it is a universal shortcoming for evolutionary algorithms to run into premature. The detailed procedure of orthogonal operator and comparison operator will be shown in Section 3.2.

In summary, in this paper a novel QPSO (CL-QPSO) with collaborative learning strategy is proposed to solve nonlinear numerical problems including unimodal and multi-modal test functions. The main difference between CL-QPSO and traditional QPSO is that CL-QPSO uses collaborative learning strategy to generate local attractor for each particle. The main contributions of this paper are as follows:

(1) Collaborative learning strategy which consists of two operators (orthogonal and comparison operators) is adopted to generate local attractors.
(2) Orthogonal operator is used to discover the useful information that lies in the two best positions of each particle while comparison searching operator is used to enhance particles’ ability to jump out of local optima.
(3) A probability parameter p is adopted to control the implementation of orthogonal operator and comparison operator in order to achieve the balance between exploitation and exploration in CL strategy.

The rest of the paper is organized as follows. In Section 2, the principle and framework of basic QPSO are introduced and Section 3 describes CL-QPSO in detail. Section 4 analyzes the parameters in CL-QPSO and presents the experimental studies on nonlinear numerical problems. Section 5 is the concluding remarks.

2. Quantum-behaved Particle Swarm Optimization (QPSO)

Inspired by quantum mechanics and the trajectory analysis of PSO, QPSO was proposed in [13]. In QPSO, a particle is updated/evolved according to Eq. (1) and (2).

$$attractor_{i,d} = \varphi \cdot pbest_{i,d} + (1-\varphi) \cdot gbest_d, d = 1, 2, \ldots, D \tag{1}$$

$$x_{i,d}(t+1) = attractor_{i,d} \pm (\alpha \cdot |attractor_{i,d}(t) - x_{i,d}(t)|) \cdot \ln(1/u) \tag{2}$$

Where, $pbest_i$ and $gbest$ are the personal and global best positions for particle x_i, respectively. $attractor_i$ is the local attractor of particle x_i. It can be observed that the local attractor of each particle is constructed according to its corresponding personal and global best positions. D is the dimension of searching space and φ is a random number within [0, 1]. The parameter α is called contraction-expansion coefficient. α can be set to a positive constant or a linearly decreased positive. In order to improve the robustness of the algorithm, α is often set in the latter way. Detailed description of the contraction-expansion coefficient and its impact on particles’ behavior from theoretical and experimental perspectives are provided in [28]. It is shown that the upper bound of the contraction-expansion coefficient is 1.781 approximately when QPSO is used to solve real world problems.

In [29], a global point called mean personal best position of the population, denoted as $mbest$, is introduced to enhance the global searching ability of QPSO. In this case, particle x_i in QPSO is updated as shown in Eq. (3).