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A new quantum-behaved particle swarm optimization based on cultural evolution mechanism for multiobjective problems

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ABSTRACT

The application of quantum-behaved particle swarm optimization to multiobjective problems has attracted more and more attention recently. However, in order to extend quantum-behaved particle swarm optimization to multiobjective context, two major problems, namely the selection of personal and global best positions and the maintenance of population diversity, need to be taken into consideration. In this paper, a novel Cultural MOQPSO algorithm is proposed, in which cultural evolution mechanism is introduced into quantum-behaved particle swarm optimization to deal with multiobjective problems. In Cultural MOQPSO, the exemplar positions of each particle are obtained according to "belief space," which contains different types of knowledge. Moreover, to increase population diversity and obtain continuous and even-distributed Pareto fronts, a combination-based update operator is proposed to update the external population in this paper. A comprehensive comparison of Cultural MOQPSO with some state-of-the-art evolutionary algorithms on several benchmark test functions, including ZDT, DTLZ and CEC2009 test instances, demonstrates the effectiveness of the proposed algorithm.

1. Introduction

Because of the parallelism characteristic and global searching ability, population-based evolutionary algorithms have been widely used to solve different kinds of optimization problems, such as endmember extraction [1], timetabling [2] and digital circuits design [3] (just to name a few). Since most of the real-word problems are multiobjective optimization problems (MOPs), we have witnessed an enormous interest in solving MOPs by using evolutionary algorithms in recent years. Current multiobjective optimization evolutionary algorithms (MOEAs) can be mainly divided into two categories, i.e. dominance-based algorithms and decomposition-based algorithms. Most of the existing MOEAs belong to the first category, such as NSGA-II [4], SPEA2 [5], PAES [6], AFCMOMA [7], MOPSO [8]. In these MOEAs, the utility of an individual is determined by the dominance relations between the individual and other ones which are visited in the searching history. In the second category, MOEAs are based on decomposition. More specifically, in these MOEAs, the multiobjective optimization problem has been translated into a single-objective optimization problem by aggregation. Some typical MOEAs that belong to the second category are: MOGLS [9], MSOPS [10] and MOEA/D [11]. A novel MOEA/D-M2M, which is also based on decomposition and translates a complex multiobjective problem into a set of simple multiobjective problems, has been proposed in [12].

Quantum-behaved particle swarm optimization (QPSO) [13], as a novel population-based paradigm, has aroused more and more attention because of its simplicity and easy implementation. Up to now, QPSO has been successfully utilized to solve various optimization problems [14–16]. In recent years, there have been growing concerns about the ability of QPSO to handle MOPs [17]. However, to deal with MOPs by QPSO, two problems need to be considered.

- The selection of two exemplar positions (i.e. personal and global best positions) for each particle. In QPSO, each particle moves under the guidance of the attractor position, which is constructed by its two exemplar positions. For MOPs, it is not easy to find the best solution which could optimize all the objectives simultaneously, since the objectives are mutually contradictory. So, the challenge is how to find the appropriate personal and global best positions for each particle.
- The maintenance of population diversity. An important problem in using an evolutionary algorithm is how to maintain the population diversity, so that the algorithm can enhance its ability of jumping out of local optima. In this case, how to increase population diversity in order to get a continuous and

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even-distributed Pareto front is another problem needs to be solved in optimizing MOPs.

Several works have been done to solve the first problem. The most popular strategy for selecting global best positions is proposed by Coello et al. [8]. In their work, the objective space is divided into several hypercubes and the obtained nondominated solutions are distributed into these hypercubes. Then one hypercube is selected according to roulette-wheel selection method. The global best solution is randomly chosen from the nondominated solutions which are distributed in the selected hypercube. This strategy has been widely used in most of the MOPSOs. In addition, a lot of strategies have been proposed to get the global best positions for particles, such as Dynamic Neighborhood strategy [18,19], Sigma method [20], Clustering technique [21], Maximin method [22], Crowding Distance strategy [23,24], Dominate Tree Strategy [25], Prob strategy [26], Niche method [27], Random strategy [28], Particle Angle Division method [29], Hypervolume method [30], Decomposition method [31], Hybrid method based on sigma values and crowding distance [32], Preference Order strategy [33], and so on. For the personal best position of a particle, the most popular way is to hold the personal best position as the best individual found in the particle's searching history [8,17,20,22,32,34]. If the current personal best position and the updated particle are nondominated by each other, then the personal best position will remain unchanged or be replaced by the updated particle randomly. It can be seen that only one personal best position is stored for each particle in this strategy. However, in some algorithms [35,36], a personal archive which stores several personal best positions for each particle is adopted. The personal best position for each particle can be selected from the personal archive by random strategy, WSum strategy, global strategy and diversity strategy.

For the second problem, most of the MOPSOs and MOQPSOs use perturbation operators (i.e. turbulence or mutation operators), to increase population diversity [20,25,37]. In this case, the mutation methods adopted in QPSOs and other EAs may also be useful as perturbation operators for MOQPSO. In [38], a specific particle is reset at a certain number of generations in order to increase population diversity in MOPSO. In [39], a multi-swarms strategy has been proposed to enhance the global searching ability and prevent premature convergence. In [40], a concept of 'fuzzy global best' is introduced to maintain population diversity. Besides, the tuning of parameters and selection of personal and global best positions also have an influence on the population diversity in MOPSOs and MOQPSOs.

In this paper, a Cultural MOQPSO is proposed, in which the cultural evolution mechanism [41] is introduced to solve multi-objective optimization problems. Cultural evolution mechanism is an evolutionary computation technique which extracts different types of knowledge during the evolution process to improve performance. Inspired by the framework of cultural evolution mechanism, Cultural MOQPSO has two spaces: population space and belief space. Population space contains some information that is related to the evolving population whilst belief space contains the knowledge extracted from population space. By using the knowledge in belief space, this paper proposes a local-search-based strategy and a combination-based update operator to enhance the ability of handling multiobjective problems. The main contributions of this paper are listed below:

(1) Belief space, which contains three types of knowledge extracted from population space, is introduced into QPSO to guide the evolution process.
(2) A local-search-based strategy is proposed to get the personal best position for each particle. Because of the intrinsic searching ability, this strategy can also enhance the algorithm's ability of jumping out of local optima.
(3) In this paper, a combination-based update operator is proposed to update the external population in order to increase population diversity and obtain continuous and even-distributed Pareto fronts.

The rest of this paper is organized as follows. Section 2 introduces the background knowledge of Cultural evolution mechanism and QPSO. Section 3 gives a detailed description of the proposed Cultural MOQPSO algorithm. Section 4 shows the comparative experiments and achieved results. Section 5 presents the concluding remarks.

2. Related works

2.1. Cultural evolution mechanism

Cultural evolution mechanism, inspired by the cultural evolution process of human, has been formulated as cultural algorithm (CA) [41]. CA consists of two spaces: population space and belief space. Population space contains information of the evolving population, such as individual solutions, objective values of solutions, and so on. Belief space contains knowledge extracted from population space. There exists a continuous cycle between population space and belief space until the termination condition is met. More specifically, the knowledge in belief space is extracted from population space, then population space evolves by using the obtained knowledge. Generally, five types of knowledge are usually used, including normative knowledge, situational knowledge, domain knowledge, historical knowledge and topographical knowledge. Normative knowledge records a set of variable ranges which can lead individuals to the promising regions. Situational knowledge gives a set of exemplary cases, which can lead individuals to 'move towards the exemplars'. Domain knowledge is related to the problem needs to be optimized, and records the problem domain information. Historical knowledge records the important events in the searching history. Topographical knowledge records the spatial characteristics which can guide individuals towards the best performing area in searching space. In recent years, CA has been successfully adopted to solve various optimization problems by combining with intelligence optimization algorithms [35,42–44].

2.2. Quantum-behaved particle swarm optimization (QPSO)

QPSO is a probability search technology, which was proposed in 2004 [13]. For particle x_i in the swarm, its two exemplar positions, namely the personal and global best positions, are represented as $pbest_i$ and $gbest_i$ respectively. In QPSO, each particle moves according to its attractor [45], which is constructed by the two exemplar positions as shown in Eq. (1). D is the dimension of the searching space and φ is a random number within range [0, 1].

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

In QPSO [46], particle x_i is updated as follows:

$$mbest(t) = \left(\frac{1}{N}\sum_{i=1}^{N}(pbest_{i,1}(t)), \frac{1}{N}\sum_{i=1}^{N}(pbest_{i,2}(t)), \ldots, \frac{1}{N} \times \sum_{i=1}^{N}(pbest_{i,D}(t))\right)$$

$$x_{i,d}(t+1) = attractor_{i,d}(t) \pm \beta \cdot |mbest_{i,d}(t) - x_{i,d}(t)| \cdot \ln\left(\frac{1}{u}\right) \tag{2}$$

where N is the population size and u is a random number within [0, 1]. β decreases linearly with the running of QPSO [13,47]. The detailed procedure of QPSO is shown in Algorithm 1.