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A decomposition-based archiving approach for multi-objective evolutionary optimization

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ABSTRACT

External archive can be used to improve the performance of a multi-objective evolutionary algorithm. Various archiving approaches have been developed but with some drawbacks. These drawbacks such as computation-inefficiency, retreating and shrinking, have not yet been well addressed. In this paper, we propose an efficient decomposition-based archiving approach (DAA) inspired from the decomposition strategy for dealing with multi-objective optimization. In DAA, the whole objective space is uniformly divided into a number of subspaces according to a set of weight vectors. At each generation, only one non-dominated solution lying in a subspace is chosen to be used for updating the external archive in consideration of its diversity. A normalized distance-based method, incorporated with the Pareto dominance, is proposed to decide which subspace a new solution should fall into, and whether this solution should replace existing one in this subspace or not. Empirical results on a diverse set of benchmark test problems show that DAA is more efficient than a number of state-of-the-art archiving methods in terms of the diversity of the obtained non-dominated solutions; and DAA can accelerate the convergence speed of the evolutionary search for most test problems.

1. Introduction

Multi-objective optimization problems (MOPs) exist widely in real-world applications. A continuous multi-objective minimization problem can be stated as follows:

$$\begin{aligned} \text{Minimize} \quad & F(X) = (f_1(X), f_2(X), \dots, f_M(X)) \\ & \text{subject to } X \in \Omega \end{aligned} \tag{1}$$

where Ω is the decision space, f_1 –f_M are the M objectives to be optimized. These objectives are assumed to be conflicting with each other. For MOPs, there often exist a set of optimal solutions that are not comparable with each other, i.e. any solution in the set is non-dominated by the others. The set of optimal solutions is called the Pareto front (PF). The two primal goals in multi-objective optimization are to find a set of approximated optimal solutions that (1) are as close as possible to the PF, and (2) are distributed as evenly as possible on the entire PF.

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Classical optimization methods (such as target vector approach [22]) are inefficient for solving multi-objective optimization problems because they can only find one Pareto optimal solution in a single run, meaning that they have to run several times to achieve a set of approximated Pareto optimal solutions [49]. Evolutionary algorithms (EAs) are a population-based, stochastic optimization method with the ability to search for multiple Pareto solutions in one run [4]. Multi-objective evolutionary algorithms (MOEAs) have become popular in multi-objective optimization since the first MOEA [8] developed by Schaffer. From then on, various MOEAs have been designed including the non-dominated sorting genetic algorithm (NSGA) [39], the niched-Pareto genetic algorithm (NPGA) [17], the multi-objective genetic algorithm (MOGA) [14], the multi-objective particle swarm optimization algorithm (MOPSO) [25,40], the multi-objective differential evolution (MODE) [43], the multi-method-based multi-objective evolutionary algorithm [29], the multi-objective teaching-learning optimization algorithm [34], and many others. Interested readers please refer to [51] for recent advances in the development of MOEAs.

In existing MOEAs, an external archive is usually adopted to save elite solutions found during the evolutionary search. For examples, some well-known MOEAs, such as the non-dominated sorting genetic algorithm II (NSGA-II) [11], the strength Pareto evolutionary algorithm (SPEA2) [52], the Pareto archived evolution strategy (PAES) [20], MOEA/D [46], and many others, are equipped with external archives. These studies have shown that such elitism mechanism can provide a monotonically non-degrading performance [9,21,38,53]. It has also been shown that using the external archive to create new solutions can help improve the population diversity, especially for MOPs with complicated PFs [3,33,52].

Though the use of external archive can bring certain advantages to the performance of an MOEA, it also causes some drawbacks. First, to save a candidate solution into the external archive, we need to check the dominance of this solution with respect to all the archived solutions. The time required for this process will grow exponentially along the increase of the archive size. This causes a serious computation efficiency problem. To overcome this drawback, various data structures that permit a fast search over the entire archive are proposed for efficient sortation of the elite solutions, e.g., the dominated tree [13]. However, the time complexity of these approaches is still prohibitively high as the archive size increases. Therefore, an archive with relatively small size is commonly used in existing MOEAs.

With a small-sized archive, the archive pruning (updating) process is a key for preserving its diversity and convergence to the Pareto front. A variety of pruning methods have been proposed in the archive-based MOEAs. Representative methods include the clustering approach [52,53], the adaptive grid approach [5,20], the crowding distance technique [11,45], the ε-dominance-based approach [31], the preference rank-based approach [6,44], and so on. However, drawbacks such as inefficient computation, retreating and shrinking, occur in those approaches. Therefore, it is imperative to propose effective archiving methods.

In this paper, we propose a pruning method based on the decomposition strategy. Decomposition is well-known in traditional multi-objective optimization [26,42]. In 2007, Zhang and Li first employed the decomposition strategy in multi-objective optimization to propose the so-called multi-objective evolutionary algorithm with decomposition (MOEA/D) [46]. In MOEA/D, a MOP is decomposed into a number of scalar optimization sub-problems. Different solutions in the current population are linked with different sub-problems. Hence, the “diversity” among these sub-problems will naturally lead to the diversity of the population. Due to the excellent performance of MOEA/D, the idea of MOEA/D has also been incorporated with some newly proposed MOEAs, such as the reference-point-based many-objective optimization algorithm (NSGA-III) [10], the dual population paradigm [24], and the diversity-first sorting based evolutionary algorithm [19], the decomposition-based self-adaptive multi-objective evolutionary algorithm [35], the decomposition-based multi-objective evolutionary algorithm with epsilon-constraint [1], the multi-objective evolutionary algorithm with mating neighborhood sizes and reproduction operators [48], and others.

Inspired by the decomposition strategy, this paper proposes an efficient archiving approach, called the decomposition-based archiving approach (DAA), to prune the external archive. In DAA, the whole objective space is uniformly divided into a number of subspaces by a set of weight vectors. During the evolution process, only the best solution found so far can be saved into a specific subspace. The size of the archive thus depends on the number of subspaces. To save a newly created solution, we propose a normalized distance to decide which subspace it belongs to, then compare the solution with the archived solutions in the subspace. In this method, we do not need to compare new solutions with all the archived solutions. This can reduce the computational cost significantly. Experimental results on some widely-used benchmark functions show that the proposed method achieves better results in comparison with four state-of-the-art archiving approaches.

The rest of this paper is organized as follows. In Section 2, we briefly review popular archiving approaches. Section 3 formulates the proposed DAA. Experimental results are demonstrated in Section 4. Section 5 concludes the paper, and discusses further research.

2. Related work

Existing archive pruning methods can be classified into two categories: the additional criterion-based approach and the dominance variant-based approach.

2.1. The additional criterion-based approach

This kind of approach imposes some additive criteria or techniques in addition to the Pareto dominance when a non-dominated solution enters the archive [3]. Representative methods include the clustering approach (CA), the adaptive grid approach (AGA), the crowding distance approach (CDA), and others.