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A dual-population paradigm for evolutionary multiobjective optimization

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ABSTRACT

Convergence and diversity are two basic issues in evolutionary multiobjective optimization (EMO). However, it is far from trivial to address them simultaneously, especially when tackling problems with complicated Pareto-optimal sets. This paper presents a dual-population paradigm (DPP) that uses two separate and co-evolving populations to deal with convergence and diversity simultaneously. These two populations are respectively maintained by Pareto- and decomposition-based techniques, which arguably have complementary effects in selection. In particular, the so called Pareto-based archive is assumed to maintain a population with competitive selection pressure towards the Pareto-optimal front, while the so called decomposition-based archive is assumed to preserve a population with satisfied diversity in the objective space. In addition, we develop a restricted mating selection mechanism to coordinate the interaction between these two populations. DPP paves an avenue to integrate Pareto- and decomposition-based techniques in a single paradigm. A series of comprehensive experiments is conducted on seventeen benchmark problems with distinct characteristics and complicated Pareto-optimal sets. Empirical results fully demonstrate the effectiveness and competitiveness of the proposed algorithm.

1. Introduction

Multiobjective optimization problems (MOPs) involve more than one objective function to be optimized simultaneously. They typically arise in various fields of science (e.g., [29,1,31]) and engineering (e.g. [33,27,32]) where optimal decisions need to be taken in the presence of trade-offs between two or more conflicting objectives. Maximizing the expected value of portfolio returns and minimizing the potential risk in portfolio management is an example of MOP involving two objectives. Due to the population-based property, evolutionary algorithms (EAs) have been widely recognized as a major approach for multiobjective optimization. Over the last two decades, much effort has been dedicated to developing evolutionary multiobjective optimization (EMO) algorithms, such as non-dominated sorting genetic algorithm II (NSGA-II) [12], improved strength Pareto EA (SPEA2) [42] and multiobjective EA based on decomposition (MOEA/D) [36]. Interested readers can refer to [40] for a more comprehensive survey on recent developments of EMO algorithms.

Generally speaking, there are two distinct goals, common but often conflicting, in multiobjective optimization [30]:

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1. *Convergence*: find a set of solutions that approximates the Pareto-optimal set (PS) as close as possible.
2. *Diversity*: find a set of solutions that represents the entire range of the Pareto-optimal front (PF) as diverse as possible.

Achieving a balance between convergence and diversity is important, but usually far from trivial, in multiobjective optimization.

In traditional Pareto-based EMO algorithms (e.g., NSGA-II and SPEA2), they adopt a convergence first and diversity second selection strategy [23] to fulfill the above two goals. In particular, the convergence issue can be easily achieved by various dominance-preserving techniques, such as the non-dominated sorting in NSGA-II and the Pareto strength value in SPEA2. As for maintaining the population diversity, many diversity-preserving strategies have been proposed to emphasize the solutions in a less crowded niche. However, these diversity-preserving strategies lead to another trade-off between the achievable diversity and the computational complexity. Some algorithms use a quick-but-dirty method (e.g., the crowding distance estimation in NSGA-II) to find a reasonably good distribution quickly; whereas some other ones use a more time consuming strategy (e.g., the clustering analysis in SPEA2) to obtain a better distribution. To achieve both progress towards the PS and coverage over the entire range of PF, some modifications have been introduced to the Pareto dominance relation, such as the ε-dominance [18]. ε-MOEA [11], argued by their authors, achieves a good compromise in terms of convergence towards the PS, well distribution along the PF and small computational complexity. However, its capabilities for solving difficult problems with complicated PSs are still questionable.

Another way to simultaneously consider the convergence and diversity is to apply a set-based indicator, which can evaluate the quality of a PF approximation, as the selection criterion of EMO algorithms. Such indicator can be regarded as a function that assigns a scalar value to each possible PF approximation reflecting its quality and fulfilling certain monotonicity conditions. Hypervolume indicator [43], which provides a combined information about convergence and diversity of the obtained approximation set, is widely used in developing EMO algorithms (e.g., indicator-based EA (IBEA) [41] and $\mathcal{S}$-metric selection EMO algorithm (SMS-EMOA) [4]). However, one of its major criticisms is the large computational complexity, which increases exponentially with the number of objectives. Furthermore, the choice of reference points has a large influence on its calculation result [2]. Unfortunately, in practice, this is far from trivial and is problem dependent.

One other avenue to integrate convergence and diversity into a single criterion is the aggregation-based method (e.g., multiple single objective Pareto sampling (MSOPS) [16] and MOEA/D [36]). As the state-of-the-art, MOEA/D [36] is a representative of this sort. It decomposes a MOP into a number of single objective optimization subproblems through aggregation functions and optimizes them in a collaborative manner. MOEA/D paves a new avenue to balance the convergence and diversity in an efficient manner. Particularly, the convergence of a solution is ensured by the optimum of a subproblem, while the population diversity is guaranteed by the wide distribution of subproblems. During the past few years, MOEA/D, as a major framework to design EMO algorithms, has spawned a large amount of research works, e.g., introducing adaptive mechanism in reproduction [20], hybridizing with local search [34] and incorporating stable matching in selection [22]. Nevertheless, as discussed in [23], MOEA/D struggles to maintain the population diversity when tackling problems with complicated search landscapes. As a consequence, the population might be trapped in some limited regions and fail to achieve a good coverage of the PF.

Based on the above discussions, developing an EMO algorithm that finds a set of well-converged and well-distributed solutions in an efficient manner, especially when tackling problems with complicated PSs [19], is challenging and important. To address these considerations, this paper presents a novel technique, termed dual-population paradigm (DPP), to handle the convergence and diversity in two separate and co-evolving populations. In particular, DPP maintains two populations: one population, termed Pareto-based archive, maintains a repository of solutions with a competitive selection pressure towards the PF; the other one, called decomposition-based archive, preserves an archive of solutions with a satisfied distribution in the objective space. As the name suggests, the Pareto- and decomposition-based archives use the Pareto- and decomposition-based techniques, respectively, to update their populations. In addition, the objective space is divided into several subregions by a set of evenly distributed unit vectors. Each solution in a population is associated with a subregion. Then, a restricted mating selection mechanism is developed to coordinate the interaction between these two co-evolving populations. To validate the effectiveness of DPP, we present four DPP instantiations, which apply the existing Pareto- and decomposition-based techniques in a plug-in manner, for empirical studies. Furthermore, we not only compare each DPP instantiation with its baseline algorithms, we also compare a representative DPP instantiation with four state-of-the-art EMO algorithms. Comprehensive experiments on seventeen benchmark problems with distinct characteristics and complicated PSs fully demonstrate the superiority of the proposed algorithm.

It is worth noting that using two or multiple populations is not a brand new technique in the EMO community. For example, ε-MOEA [11] uses two populations and different archiving mechanisms in evolution. Differently, the idea of DPP is to deal with convergence and diversity by two separate and co-evolving populations. Moreover, by respectively using Pareto- and decomposition-based techniques to update these two populations, DPP paves an avenue to integrate the Pareto- and decomposition-based techniques in EMO. To the best of the authors' knowledge, very few reports [25,28] have addressed this topic in the literature. In [25], a hybrid algorithm is proposed to combine MOEA/D and NSGA-II for solving multiobjective capacitated arc routing problems. In [28], the Pareto-based method is used to build the leaders' archive while a decomposition-based method is used for fitness assignment.

The rest of this paper is organized as follows. Some preliminary knowledge of multiobjective optimization is provided in Section 2. Afterwards, technical details of DPP are illustrated step by step in Section 3, and instantiations of DPP are