A Novel Differential Evolution Algorithm Based on ϵ-Domination and Orthogonal Design Method for Multiobjective Optimization

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Abstract. To find solutions as close to the Pareto front as possible, and to make them as diverse as possible in the obtained non-dominated front is a challenging task for any multiobjective optimization algorithm.ϵ-dominance is a concept which can make genetic algorithm obtain a good distribution of Pareto-optimal solutions and has low computational time complexity,and the orthogonal design method can generate an initial population of points that are scattered uniformly over the feasible solution space.In this paper, combining ϵ-dominance and orthogonal design method, we propose a novel Differential Evolution (DE) algorithm for multiobjective optimization .Experiments on a number of two- and three-objective test problems of diverse complexities show that our approach is able to obtain a good distribution with a small computational time in all cases. Compared with several other state-of-the-art evolutionary algorithms, it achieves not only comparable results in terms of convergence and diversity metrics, but also a considerable reduction of the computational effort.

1 Introduction

Evolutionary Algorithms (EAs) (including genetic algorithms, evolution strategies, evolutionary programming, and genetic programming) are heuristics that have been successfully applied in a wide set of areas. In real-world optimization applications, it is often hard to formulate the optimization goal as a scalar function. Typically, there are several criteria or objectives, and not unusually, these objectives stay in conflict with each other. Simply combining the different associated objective functions in a linear way is usually unsatisfactory. Instead, one is interested in a so-called Pareto optimal set of solutions, i.e., any solution that cannot be improved with respect to one objective without worsening the situation with respect to the other objectives. Consequently, there are two goals in multiobjective optimization: (i) to find solutions as close to the Pareto front as possible, and (ii) to find solutions as diverse as possible in the obtained non-dominated front. Satisfying the two goals is a challenging task for any multiobjective optimization algorithm. Special strategies are therefore needed to deal with such multiobjective optimization problems. Since EAs work on populations of candidate solutions, they represent a promising basic framework for multiobjective optimization.

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In the last few years, many variants and extensions of classical EAs have been developed for Multiobjective Optimization Problems (MOPs). Such as Nondominated Sorting GA (NSGA-II) [1], Strength Pareto EA (SPEA2) [2], Vector Evaluated GA (VEGA) [3], Hajela and Lins GA (HLGA) [4], Pareto-based Ranking Procedure(FFGA) [5], Niched Pareto GA (NPGA) [6], Pareto Archived Evolution Strategy (PAES) [7], and so on. Among these, the NSGA-II by Deb *et al.* [1] and SPEA2 by Zitzler *et al.* [2] are the most popular approaches.

Differential evolution (DE) [8] is a novel evolutionary algorithm for faster optimization, which mutation operator is based on the distribution of solutions in the population. And DE has won the third place at the first International Contest on Evolutionary Computation on a real-valued function test-suite. Unlike Genetic Algorithm (GA) that uses binary coding to represent problem parameters, DE is a simple yet powerful population based, direct search algorithm with the generation-and-test feature for globally optimizing functions using real valued parameters. Among the DE's advantages are its simple structure, ease of use, speed and robustness. Price & Storn [8] gave the working principle of DE with single strategy. Later on, they suggested ten different strategies of DE [9]. It has been successfully used in solving single-objective optimization problems [10]. Hence, several researchers have tried to extend it to handle MOPs. Such as Pareto DE (PDE) [11,12], Pareto DE Approach (PDEA) [13], Multiobjective DE (MODE) [14], and DE for Multiobjective Optimization (DEMO) [15].

Combing orthogonal array (OA) and factor analysis (such as the statistical optimal method),Orthogonal design method [16] is developed to sample a small and representative set for all possible combinations to obtain good combinations. Recently, some researchers applied the orthogonal design method incorporated with EAs to solve optimization problems. Leung and Wang [17] incorporated orthogonal design in genetic algorithm for numerical optimization problems and found such method was more robust and statistically sound than the classical GAs. OMOEA [18] and OMOEA-II [19] presented by Sangyou Zeng *et al.* adopted the orthogonal design method to solve the MOPs. Numerical results demonstrated the efficiency of the two tools.

ϵ-MOEA [20] is a steady-state Multiobjective EA (MOEA) based on the ϵ-dominance concept introduced in [21]. Also, it incorporated efficient parent and archive update strategies to obtain a good distribution of Pareto-optimal solutions within less computational time. The ϵ-dominance does not allow two solutions with a difference ϵ_i in the i-th objective to be nondominated to each other, thereby allowing a good diversity to be maintained in the population. Besides, the method is quite pragmatic, because it allows the user to choose a suitable ϵ_i depending on the desired resolution in the i-th objective [20].

Inspired by the ideas from OGA/Q [17] and ϵ-MOEA [20], in this paper, we propose an extension of DE algorithm based on the ϵ-dominance concept and orthogonal design method. Our proposed DE algorithm is named ϵ-ODEMO. Our algorithm has three novelties. Firstly, the proposed approach adopts orthogonal design method with quantization technique to generate an initial population of points. And then, it uses the DE/rand/1/exp strategy to produce new candidate solutions. Thirdly, ϵ-dominance concept and efficient parent and archive update strategies introduced in [20] are used to