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An adaptive multi-population differential evolution algorithm for continuous multi-objective optimization

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ABSTRACT

For evolutionary algorithms, the search data during evolution has attracted considerable attention and many kinds of data mining methods have been proposed to derive useful information behind these data so as to guide the evolution search. However, these methods mainly centered on the single objective optimization problems. In this paper, an adaptive differential evolution algorithm based on analysis of search data is developed for the multi-objective optimization problems. In this algorithm, the useful information is firstly derived from the search data during the evolution process by clustering and statistical methods, and then the derived information is used to guide the generation of new population and the local search. In addition, the proposed differential evolution algorithm adopts multiple subpopulations, each of which evolves according to the assigned crossover operator borrowed from genetic algorithms to generate perturbed vectors. During the evolution process, the size of each subpopulation is adaptively adjusted based on the information derived from its search results. The local search consists of two phases that focus on exploration and exploitation, respectively. Computational results on benchmark multi-objective problems show that the improvements of the strategies are positive and that the proposed differential evolution algorithm is competitive or superior to some previous multi-objective evolutionary algorithms in the literature.

1. Introduction

In practical industries, most optimization problems need to deal with multiple objectives simultaneously, which often results in conflict because the improvement in one objective will inevitably cause the deterioration in some other objectives. These problems are referred to as multi-objective optimization problems (MOPs), and multi-objective evolutionary algorithms (MOEAs) have shown a very good performance for these problems [7,8,30]. Due to the good ability of obtaining well distributed solutions, the Pareto-based MOEAs are widely adopted, e.g., NSGA-II [9], microGA [5], SPEA2 [47], MOEA/D [43], multi-objective particle swarm optimization (MOPSO) [6], multi-objective scatter search [21], and hybrid MOEA [34].

Differential evolution (DE) [32] is an evolutionary algorithm, and has shown very good performance for single objective problems (SOPs) [3,24,26,33,35,37,48]. Consequently many researchers have attempted to extend DE to deal with multiple objectives. The first attempt was made by Abbass et al. [1] in which a Pareto DE (PDE) algorithm was developed to solve continuous MOPs. Another multi-objective DE (MODE) similar to PDE is proposed by Madavan [18] through incorporating the

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fast non-dominated sorting and ranking method of NSGA-II into DE. To achieve a balance of convergence and diversity, Robic and Filipic [28] developed a so-called DEMO algorithm that adopts two mechanisms for the convergence and diversity, respectively. Huang et al. [14] extended their self-adaptive DE (SaDE) originally designed for the SOPs to multi-objective space and constructed a multi-objective SaDE (MOSaDE) that can adaptively select an appropriate mutation strategy. Santana-Quintero et al. [29] incorporated a local search based on the use of rough set theory into MODE to solve constrained MOPs, and the computational results showed that the hybrid strategy succeeds to make the MODE robust and efficient. Ali et al. [2] proposed a multi-objective DE algorithm (MODEA), in which the authors adapted the opposition-based learning strategy to generate the initial population, the random localization in the mutation step, and a new strategy based on the PDEA [18] and DEMO [28] in the selection step. Soliman et al. [31] presented a memetic coevolutionary MODE where coevolution and local search are both incorporated. In this algorithm, two populations are maintained, one consisting of solutions and the other storing search directions of solutions, to implement the coevolution. Kukkonen and Lampinen [16] developed a generalized DE (GDE3) by extending the selection operator of canonical DE so that it can handle constrained MOPs.

Although many MODEs have been successfully applied to solve different MOPs, there are still two issues that have not been taken into account by previous researches.

Firstly, in previous MODEs only one population is maintained in the whole evolution process. It is clear that the main disadvantage is that the diversity of the population may be very poor because it is easy for the population to converge to one or several local optimal areas for some MOPs with many local optima. In the literature, some researchers have developed MOEAs with multiple subpopulations and the computational results illustrate that the performance of MOEAs can be considerably improved. In the MOPSO proposed in [25], the population is divided into several subpopulations by a clustering technique, and the computational results reported by the authors showed that the distribution of obtained solutions can be much improved. In another kind of MOPSO proposed by Yen and Leong [39], a dynamic mechanism is designed to adaptively adjust the number of subpopulations. The computational results reported by the authors showed that this strategy can significantly improve the performance of the MOPSO. There are also some papers adopting multiple subpopulations in DE, however, most papers only deal with the SOPs [17,40]. For the MOPs, Zaharie and Petcu [41] developed a parallel adaptive Pareto DE (APDE) algorithm in which the population was divided into several subpopulations and the parallelization was implemented based on an island model and a random connection topology. Parsopoulos et al. [23] also presented a multi-population DE called vector evaluated DE for MOPs in which the parallelization was implemented by a ring topology. Although the multiple subpopulation strategy was adopted in [23,41], the focus of the two algorithms was the parallelization of MODE. In addition, in the two parallel MODEs only one mutation strategy was used during the evolution process. Since different mutation strategies have different search behaviors and performance, how to combine the multi-population strategy with multiple mutation strategies still needs to be studied so as to further improve the performance of MODE.

Secondly, the information contained in the search data during evolution is neglected by most MODEs in the literature, though such information is very valuable and has attracted considerable attentions from researchers. Several kinds of data mining methods have been developed to derive the useful information from the search data so as to guide the evolution to promising regions [3,15,19,22,27,38,42,44]. However, these methods are mainly centered on the SOPs [45]. For DE with data mining techniques, Qin et al. [26] used the statistical method to help DE to adaptively select the most appropriate mutation strategies, and then Huang et al. [14] extended this strategy to MODE. An opposition-based learning method was adopted in Ali et al. [2] to generate a high quality initial population. However, in the above three references the data mining techniques were only focused on the mutation strategy selection and the generation of initial population. The incorporation of data mining techniques into multi-population strategy and local search in MODE still needs to be studied.

Motivated by the above two main issues, in this paper we propose a hybrid DE algorithm for the MOPs, namely an adaptive multi-population DE (AMPDE). The proposed AMPDE has the following three main features with comparison to previous MODEs in the literature.

- The AMPDE adopts multiple populations for MOPs, each of which maintains a different evolution path, so as to improve the search robustness of traditional MODEs. Instead of the canonical mutation strategies used in MODEs, the AMPDE adopts the crossover operators of genetic algorithms to generate perturbed vectors.
- The AMPDE adopts data mining methods such as clustering and statistical method to derive useful information from the search data during the evolution process. The derived information is then used to guide the generation of new population and local search. For example, the size of each subpopulation will be adaptively adjusted based on the information derived from its previous search results.
- The AMPDE adopts a two-phase local search to improve exploration and exploitation abilities: the first phase focuses on the improvement of exploration through the data analysis of the evolution process, and the second phase centers on the improvement of exploitation through the data analysis of current non-dominated solutions.

The remainder of this paper is organized as follows. Section 2 describes some related definitions of multi-objective optimization and DE algorithm. The details of the proposed AMPDE are provided in Section 3. In Section 4, the AMPDE is compared with some other state-of-the-art MOEAs based on bi-objective and tri-objective benchmark MOPs. Finally, the conclusions based on the present study are drawn in Section 5.