Multiobjective Differential Evolution Based on Fuzzy Performance Feedback

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ABSTRACT
Differential evolution is often regarded as one of the most efficient evolutionary algorithms to tackle multiobjective optimization problems. The key to success of any multiobjective evolutionary algorithms (MOEAs) is maintaining a delicate balance between exploration and exploitation throughout the evolution process. In this paper, the authors propose a Fuzzy-based Multiobjective Differential Evolution (FMDE) that uses performance metrics, specifically hypervolume, spacing, and maximum spread, to measure the state of the evolution process. The authors apply the fuzzy inference rules to these metrics in order to dynamically adjust the associated control parameters of a chosen mutation strategy used in this algorithm. One parameter controls the degree of greedy or exploitation, while another regulates the degree of diversity or exploration of the reproduction phase. Therefore, the authors can appropriately adjust the degree of exploration and exploitation through performance feedback. The performance of FMDE is evaluated on well-known ZDT and DTLZ test suites. The results validate that the proposed algorithm is competitive with respect to chosen state-of-the-art MOEAs.

Keywords: Differential Evolution, Fuzzy Logic, Hypervolume, Maximum Spread, Multiobjective Performance Metrics, Spacing

INTRODUCTION
Differential Evolution (DE) was proposed by Storn and Price in 1995 as a novel evolutionary algorithm (EA) (Storn & Price, 1995; Storn, 1996; Storn & Price, 1997). It is a stochastic, population-based search approach for optimization over a continuous space (Abbass, 2002). DE is considered one of the most powerful tools for solving optimization problems. DE can handle mixed-type variables, constraints, multimodality, and also multiple-objective. Implementing DE is easier than other EAs such as Genetic Algorithm (GA) even for a beginner in the optimization field. In addition, control parameters in the design of a DE are very few. DE is similar to other evolutionary algorithms, as it starts with a randomly initializing population in the search space. Then the population enters the evolution process: mutation, crossover, and selection operations. These three operations will be repeated until the...
stopping criterion is met. The major difference between DE and other EAs is the powerful use of differences between individuals realized by differential mutation which makes DE unique.

The mutation strategy and the control parameters, namely scaling factor ($F$), crossover rate ($CR$), and population size ($NP$), play the major roles in the success of a DE. Choosing the appropriate mutation operator and parameter values for a particular problem is a difficult task because it is a problem dependent, time-consuming, and trial-and-error process. To address the challenge, references (Abbass, 2002; Huang et al., 2007; Zamuda et al., 2007; Zielinski & Laur, 2007; Zhang & Sanderson, 2008; Huang et al., 2009) proposed adaptive control strategies to adjust the parameter setting of DE during the search process.

In addition, balancing the exploration and exploitation throughout the search is the key to the success of an EA, including a DE. During the evolution process, we may need different mutation strategies. In the beginning of the evolution, we need a higher degree of exploration than exploitation in order to search larger regions in the space. We may choose the mutation operator that possesses higher exploration ability and the associated control parameters that promote the diversity. However, near the end of the evolution we need to promote the local search that is exploitation. The mutation operator that favors local search should be chosen along with the control parameters that emphasize the exploitation. If we know the state of the evolution process, we may decide whether we should emphasize on exploration or exploitation, and choose suitable parameter values or the mutation strategies accordingly. One possible way that we can observe the state of the evolving process is utilizing the performance metrics. Most of the performance metrics are calculated at the end of the evolution in order to assess the quality of the obtained nondominated front. For instance, generational distance needs a complete knowledge about the true Pareto front in order for calculation. Unfortunately, we cannot assume the true Pareto front is available during the evolution search. The quality of the population can be measured by three properties of the obtained nondominated front (Zitzler et al., 2000), namely, the convergence, uniform distribution, and extensiveness. Although there are some proposed running performance metrics (Deb & Jain, 2002) to measure the quality of the current population, there are very few choices to allow us to measure the convergence, uniform distribution, and extensiveness of the population. In this study, we designate three performance metrics, namely hypervolume, spacing, and maximum spread to quantify the three properties of the obtained nondominated solutions. The proposed Evolutionary Algorithm, so called multiobjective differential evolution, exploits three performance metrics feedback, namely hypervolume, spacing, and maximum spread as the input to the fuzzy inference rules. The outputs of fuzzy rules are the greedy factor and the diversity factor for the mutation scheme. These parameters are adaptively adjusted at every generation in order to promptly balance the exploration and exploitation abilities of the population throughout the evolution process independent of the complexity of the optimization problems at hand in characteristics and landscape.

The remainder of this paper is organized as follows. Related Work section describes the background knowledge of DE and gathers some related works presenting the adaptive multiobjective DE and some state-of-the-art Multiobjective Evolutionary Algorithms (MOEAs). Fuzzy Multiobjective Differential Evolution section introduces the proposed fuzzy-based multiobjective DE using performance metrics feedback. Experimental Results section presents the experimental setups and results and draws the relevant observations as justified. Finally, Conclusion section states the conclusion of our work and outlines the future research directions.

RELATED WORK

DE is a simple yet powerful population based optimization algorithm. The fundamental prin-
The Lessons of Human Resource in The Theory of Constraints

The Paradox of the Health Commons: The Benefits and Trouble about Participation and Co-Creation
[www.igi-global.com/article/paradox-health-commons/56340?camid=4v1a](www.igi-global.com/article/paradox-health-commons/56340?camid=4v1a)