Multi-Criteria Differential Evolution: Treating Multitask Optimization as Multi-Criteria Optimization

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ABSTRACT

Evolutionary multitask optimization (EMTO) has shown great potential and attracted increasing attention for solving multitask optimization problem (MTOP). However, most existing EMTOs still treat the internal tasks just as different related problems, rather than the component problems of the entire MTOP, which is inefficient. Therefore, this paper proposes to treat the entire MTOP as a multi-criteria optimization problem (MCOP), so as to solve the MTOP more efficiently. To be specific, the fitness function of each task in the MTOP is treated as an evaluation criterion in the corresponding MCOP. During the evolutionary process, a round-robin multi-criteria strategy is adopted to better utilize the multiple criteria. This way, we can use different evaluation criteria in different generations or stages to guide the environmental selection and population evolution in ECs, so as to find out the optimal solutions for the criteria of different tasks. Based on the above, a multi-criteria differential evolution algorithm is developed for solving MTOPs. Experiments on widely-used MTOP benchmarks and comparisons with some state-of-the-art algorithms have verified the great effectiveness and efficiency of the proposed algorithm. Therefore, treating MTOPs as MCOPs is a potential and promising direction for solving MTOPs.

CCS CONCEPTS

• **Computing methodologies** → **Randomized search; Continuous space search;** • **Theory of computation** →**Bio-inspired optimization**;

KEYWORDS

Multitask Optimization, Evolutionary Computation, Multi-Criteria Optimization

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1 INTRODUCTION

Multitask optimization (MTO) [1] is a novel and promising paradigm which aims to solve multiple optimization problems (or tasks) simultaneously. Therefore, MTO can be more efficient than the traditional optimization diagram that only optimizes one task independently at a time [1]. When developing efficient MTO algorithms, evolutionary computation (EC) algorithms are usually adopted, which leads to a promising research topic, i.e., evolutionary MTO (EMTO) [2]. This is because that EC algorithms are powerful tools for solving complex optimization problems with various characteristics and difficulties [3]-[5]. Therefore, by integrating EC algorithms with the MTO paradigm, EMTO can solve complex MTOPs more efficiently.

To date, there have been some EMTO algorithms proposed for solving MTOPs [6][7]. However, existing EMTO algorithms, no matter using single or multiple populations, still treat the multiple tasks in the same MTOP as different problems, rather than treating them as the partial components of the entire MTOP. In fact, the fitness function of different tasks can be regarded as different criteria that need to be achieved simultaneously. Inspired by this, we attempt to treat the MTOP as a multi-criteria optimization problem (MCOP) so that the MTOP can be solved more efficiently. That is, we treat the MTOP with multiple tasks as an MCOP with multiple evaluation criteria (i.e., fitness functions) for the selection and the population evolution. By doing so, the challenging problem in MTOP, i.e., how to find the useful knowledge and then transfer them across different tasks, is changed into a simpler issue that how to utilize the multiple evaluation criteria to guide the selection operation and population evolution, so as to find out the optimal solutions for different criteria of different internal tasks. Therefore, this research direction has a great potential of leading to a significant approach for tackling MTOPs and providing great contributions to the developments of related research communities. Furthermore, to the best of our knowledge, this paper is the first that attempts to solve MTOPs by treating them as MCOPs. Therefore, the contribution of this paper should be justified.

To avoid ambiguity, noted that the MCOP in this paper refers to the problem with multiple evaluation criteria, but not the problem where we need to optimize its criteria.

For the experimental study, a multi-criteria differential evolution (MCDE) is developed by using the multi-criteria strategy with the differential evolution algorithm as the optimizer. To evaluate the proposed algorithm, extensive experiments are conducted on widely-used MTOP benchmarks with some state-of-the-art EMTO algorithms.

2 TREATING MTOP AS MCOP

The MTOP naturally has multiple fitness functions that can be adopted as the evaluation criteria for environmental selection and individual evolution. More importantly, the optimal solution of the fitness functions in different tasks may have similarities in some dimensions. In such a situation, using one fitness function as the criterion to guide the evolution can not only benefit the optimization for the corresponding task but also other related tasks. Therefore, the MTOP can be treated as an MCOP with multiple criteria and we can select the proper criterion in different stages to guide the optimization.

To use the multiple criteria efficiently, we propose a multi-criteria strategy that has a round-robin fashion. That is, the multiple criteria are adopted sequentially in a round-robin fashion to guide the evolution. For this, a parameter G is introduced to control the active generation of each criterion. Each criterion will be activated and then used as the current fitness function to guide the evolution for G generation, and every $K \times G$ generations is a complete cycle that all K criteria are activated once. Moreover, to increase the diversity for using criteria, every time all K criteria are used once, the order of these K criteria is randomly shuffled. By doing so, the K criteria will be selected in a different order in the next $K \times G$ generations. Noted that every time the criterion is switched, the population should be re-evaluated by the new criterion.

3 EXPERIMENT STUDIES

In the experiments, six complex MTOPs (i.e., P1-P6) from the commonly-used benchmarks [8] are adopted to investigate the proposed algorithm. As for the parameters of MCDE, the population size is 50, the scale factor F is 0.5, and crossover rate CR is 0.6, as suggested in [7]. Besides, the G is set as 150.

In the comparison, the Wilcoxon's rank sum tests with a significant level α=0.05 [3] and the score metric [8] are used. Then, the symbols '+', '≈', and '-' are used to indicate that the MCDE performs significantly better than, similar to, and significantly worse than other algorithms, respectively.

In this part, the state-of-the-art algorithms MFEA-I [1], MFEA-II [6], and EMT-EGT [7] are adopted for comparisons. For fair comparisons, the total maximum available FEs is 1×10^5 for every algorithm in each run [7]. To reduce statistical errors, each algorithm is run 20 times independently and the average results are adopted for the comparisons.

The comparison results given in Table I show the great efficiency of MCDE. As shown in Table I, the MCDE can obtain the best score on 4 of the 6 problems, while the MFEA-I, MFEA-II, and EMT-EGT only get the best score on 0, 1, and 1 problem, respectively. Moreover, according to the Wilcoxon's rank sum test, the MCDE can significantly outperform MFEA-I, MFEA-II, and EMT-EGT on 7, 7, and 9 tasks, and produce worse results than them only on 5, 5, and 3 tasks. Therefore, the results have verified the efficiency of MCDE, which indicates the potential of solving MTOPs as MCOPs.

Table 1: Comparisons with State-of-the-art Algorithms

Statistical term	MCDE	MFEA-I	MFEA-II	EMT-EGT
+/≈/-/	NA	**7**/0/5	**7**/0/5	**9**/0/3
# number of best score	**4**	0	1	1

4 CONCLUSIONS

In this paper, we have attempted to treat MTOPs as MCOPs and solved them efficiently. The experimental results show that this can be a potential direction for solving MTOPs.

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