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Search space-based multi-objective optimization evolutionary algorithm☆

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ABSTRACT

Evolutionary multi-objective optimization (EMO) algorithms are actively used for answering optimization problems with multiple contradictory objectives and scheming interpretable and precise real-time applications. A majority of existing EMO algorithms performs better on two or three objectives non-dominated problems; however, they meet complications in managing and maintaining a set of optimal solutions to multi-objective optimization problems. This paper proposes a search space-based multi-objective evolutionary algorithm (SSMOEA) for multi-objective optimization problems. To accomplish the potential of the search space-based method for solving multi-objective optimization problems and to reinforce the selection procedure toward the ideal direction while sustaining an extensive and uniform distribution of solutions is our key objective. To the best of our knowledge, this paper is the first attempt to propose a search space-based multi-objective evolutionary algorithm for multi-objective optimization. The experimental setup used showed that the proposed algorithm is good and competitive in comparison to the existing EMO algorithms from the viewpoint of finding a scattered and estimated solution set in multi-objective optimization problems. SSMOEA can achieve a good trade-off between search space convergence and search space diversity in the appropriate experimental setup.

1. Introduction

In several practical applications, evolutionary algorithms are treated as one of the efficient way for discovering multi-objective optimization problems (MOP). In MOP, there are more than three objectives to be optimized for the same instance of time. Generally, there is no distinct optimal solution for MOP due to the contradictory nature of objectives; however, there is a set of alternate solutions, and such alternative solutions are known as the Pareto set for multi-objective optimization problems. Evolutionary algorithms (EAs) have been accepted to be appropriately well-matched for MOPs because of their population-based property of attaining an approximation of the Pareto set in a particular run [1]. Over the past few years, several advanced evolutionary multi-objective optimization (EMO) algorithms have been suggested by researchers and practitioners. All of these algorithms converge at two objectives – reducing the distance of possible results to the optimum front, which is treated as convergence, and making the best use of the broadcasting of possible solutions over the optimal front, which is termed as diversity.

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This paper offers a search space based multi-objective optimization evolutionary algorithm (SSMOEA) to solve the multi-objective optimization problems. The key objective of the paper is to accomplish the potential of the search space-based methodology so as to support the MOPs and achieve source node position confidentiality in optimum direction while conserving an identical and comprehensive movement of roaming users among wireless search space areas [2]. A search space area is the least cloaked area that conceals the confidentiality of a specific roaming wireless object from unauthorized roaming wireless objects contained within the respective least cloaked area [3,4]. A search space area has an intrinsic characteristic of reproducing the convergence facts and diversity information concurrently. Every possible optimum solution in the search space has a deterministic position. The performance of an optimum solution concerning convergence may be evaluated by its search space position in contrast to the other possible solutions; whereas the performance of an optimum solution about diversity might be assessed by the number of possible solutions whose search space positions are similar or match with its search space position. Moreover, in contradiction to the Pareto dominance standard, a search space-based standard may not only qualitatively relate to possible solutions but also provide quantifiable difference in every objective among them. This appears to be more appropriate for MOPs, in view of the increase in the selection pressure from the countable comparison of objective values among solutions.

Due to the huge search space of a high dimensional multi-objective problem, MOP significantly deteriorates the effect of an evolutionary operative like mutation, crossover and recombination. In literature, there are five classes of multi-objective evolutionary algorithms (MOEAs) that have been presented for answering multi-objective problems. The first class comes with algorithms that modify the Pareto dominance concept to adapt it to higher dimensional space encompassing Pareto α-dominance, Pareto ϵ-dominance and Pareto cone ϵ-dominance [5]. The experimentally selected constraints are integrated into all these approaches. The second class is an impression of quality indicators. A fitness value is allocated to every individual by means of these quality indicators. The Hyper-volume estimation (HypE) algorithm [6] is the classic solution from this category. Some other tactics like S-metric selection EMO algorithm, volume dominance [7], and indicator-based evolutionary algorithm [8] are covered in this class. The third class is based on the decomposition-based design like MOEA on the basis of decomposition (MOEA/D) [9]. Here, the multi-objective problem is decomposed into several scalar optimization sub-problems and optimizes MOPs concurrently. For fitness assignment, Achievement Scalarizing Function (ASF) [10] is applied. The resultant fitness standards are applied to choose entities instead of Pareto-dominance. Consequently, this tactic may be overextended to solve MOPs. The fourth class is grid-based approaches [1,11]. Grid-based evolutionary algorithm (GrEA) [1] accomplishes the prospective of the grid-based method in order to reinforce and support the selection pressure in the optimal direction, conserving identical distribution amongst possible solutions. The fifth class is diversity prominence tactics. Diversity is treated as the main standard in the evolutionary process as an alternative of convergence. Convergence may be taken care by means of Pareto dominance or some other approaches.

Following are the key contributions of the proposed EMO algorithm SSMOEA:

1) An intricate density estimator of an individual in the population is planned, that considers the number of its neighbors as well as the distance variance amongst respective individual and its neighbors.
2) An idea of search space dominance is announced to equate individuals in environmental selection processes.
3) An enhanced fitness tuning method is established to evade fractional congestion in addition to direct the search in diverse directions in the record set.

In this paper, we use a multi-objective static clustering that seeks partition optimized with respect to two optimization objectives: minimal communication between clusters and outstandingly equivalent coordination traffic within groups of individuals. Furthermore, systematic experimentations are accomplished to compare SSMOEA with six other advanced evolutionary algorithms on several groups of MOPs.

The rest of this paper is structured as follows. In Section 2, the motivation of making use of a search space for solving MOPs and the related works on search space-based and grid-based methods are described in brief. Section 3 is dedicated to the detailed description of the search space-based multi-objective optimization procedure. Section 4 defines the structure of the proposed strategy and explains the proposed algorithm (SSMOEA). Section 5 describes the experimental settings, performance metrics and three groups of test problems used for performance evaluation. The detailed experimental results and discussions are specified in Section 6. Lastly, Section 7 conveys concluding remarks and comments on future work.

2. Related literature

A number of MOPs appears in engineering and industrial design like water control system design, industrial planning and scheduling problems, molecular design, resource engineering, and many more [9]. Many associated methods and techniques have been established in the EMO domain comprising performance evaluation metrics appropriate for a high dimensional space, test functions scalable to any number of contradictory objectives and visualization tools intended for the display of solutions with three or more objectives. These have made it conceivable to genuinely inspect and study the performance of existing algorithms on multi-objective problems. Consequently, several investigational and analytical studies have been offered, and some novel interpretations and implications have been prepared for the multi-objective optimization scenario [9,12].

It is not easy to balance convergence and diversity in multi-objective optimization. Several traditional Pareto-based EMO algorithms, for instance the strength Pareto EA2 (SPEA2) [13] and the non-dominance sorting genetic algorithm II (NSGA-II)