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Multiobjective evolutionary algorithm based on vector angle neighborhood

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ABSTRACT

Selection is a major driving force behind evolution and is a key feature of multiobjective evolutionary algorithms. Selection aims at promoting the survival and reproduction of individuals that are most fitted to a given environment. In the presence of multiple objectives, major challenges faced by this operator come from the need to address both the population convergence and diversity, which are conflicting to a certain extent. This paper proposes a new selection scheme for evolutionary multiobjective optimization. Its distinctive feature is a similarity measure for estimating the population diversity, which is based on the angle between the objective vectors. The smaller the angle, the more similar individuals. The concept of similarity is exploited during the mating by defining the neighborhood and the replacement by determining the most crowded region where the worst individual is identified. The latter is performed on the basis of a convergence measure that plays a major role in guiding the population towards the Pareto optimal front. The proposed algorithm is intended to exploit strengths of decomposition-based approaches in promoting diversity among the population while reducing the user's burden of specifying weight vectors before the search. The proposed approach is validated by computational experiments with state-of-the-art algorithms on problems with different characteristics. The obtained results indicate a highly competitive performance of the proposed approach. Significant advantages are revealed when dealing with problems posing substantial difficulties in keeping diversity, including many-objective problems. The relevance of the suggested similarity and convergence measures are shown. The validity of the approach is also demonstrated on engineering problems.

1. Introduction

Evolutionary algorithms proved effective when solving multiobjective optimization problems (MOPs) in different application domains [1]. Similarly to single-objective counterparts, multiobjective evolutionary algorithms (MOEAs) process a population of solutions in a probabilistic manner. This allows to perform the global search with little knowledge about the objectives and to approximate the Pareto set efficiently in a single simulation run. In doing so, MOEAs rely on three major mechanisms such as mating (parent) selection, variation (reproduction) and environmental selection (replacement). In turn, these concepts draw inspiration from natural evolution. Variation aims at exploring the search space by producing new candidate solutions. This process makes use of stochastic operators applied to one or more parent solutions. Overwhelmingly, existing MOEAs simply rely on variation operators initially designed for single-objective optimization. Variation can be adopted without any modifications and plugged into a framework being enable to perform selection in the presence of multiple objectives. This makes selection a key feature of MOEAs, with its effectiveness playing a crucial role in their performance.

In nature, selection is responsible for adaptation of species to their environment. It gives an extra survival and reproduction probability to the most fitted individuals. In MOEAs, selection operators attempt to mimic this process. This is conducted on the basis of some fitness measure designed to reflect how suited individuals are in the context of the environment defined by the problem being solved. Depending on the fitness assignment and selection, most existing MOEAs can be classified into three major category.

Dominance-based MOEAs rely on the concept of the Pareto dominance to direct the search. Selection is motivated by the idea that nondominated individuals are preferred over dominated ones. It typically incorporates some mechanism to promote diversity. A representative MOEA belonging to this category was proposed in [2]. It combines convergence and diversity measures into a scalar fitness value. The former is based on the number of individuals the dominator of a given solution dominates, whereas the latter employs a nearest neighbor technique. Another popular approach ranks the population into different non-domination levels, thereby highlighting nondominated individuals [3]. A diversity preserving mechanism is applied when the last accepted level cannot be completely accommodated.

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Dominance-based MOEAs are often used with variation relying on genetic algorithm concepts. Though, in [4], it was demonstrated that a dominance-based selection is also effective when extending immune clonal algorithm to solving MOPs. The major advantage of dominance-based selection is that it naturally reflects the concepts of optimality in multiobjective optimization. Although such selection often works well for two and three objectives, its performance severely deteriorates in high-dimensional objective spaces [5]. This is caused by the fact that almost all individuals in the population become nondominated. Thus, a selection pressure is significantly decreased. In such circumstances, many diversity preserving mechanisms favor solutions that are far away from the Pareto front. And dominance-based MOEAs can perform even worse than random search algorithms. This issue can be addressed by modifying the dominance relation. In [6], a method for widening the area dominated by a given solution was suggested. In [7], the concept of dominance was applied to the grid in the objective spaces. Defining the grid requires setting the number of devisions for each objective, with an inappropriate value leading to a poor performance. On the other hand, improving a diversity preserving mechanism can increase the scalability of MOEAs [8–11]. Also, the dominance relation can provide a high selection pressure, thereby producing a harmful impact on the search due to the loss of diversity [12]. To improve the population diversity, one can consider the diversity of genetic information as an objective in a nondominated sorting [13]. Overall, the search in the decision space is an important aspect of multiobjective optimization that heavily influences both the population convergence and diversity. This was particularly explored in [14] by suggesting a promising framework based on decision variable analysis that divides and process the decision variables in accordance to their role in the given MOP.

Decomposition-based approaches attempt to decompose an original MOP into a number of subproblems and solve them in parallel. Different possibilities are available for this. On one hand, decomposition can be based on the aggregation of multiple objectives by means of scalarization that involves traditional mathematical techniques [15]. This way, a scalar fitness value is assigned to each population member reflecting its quality. Convergence is provided by minimizing a corresponding scalarizing function, whereas diversity is ensured by a well-distributed weight vectors. MOEA/D [16,12] is a popular framework relying on this principle. When producing offspring, it explores the neighborhood relation defined on the closeness of weight vectors. Replacement is performed favoring better values of the scalarizaing function. Recently, MOEA/D has been extensively investigated, leading to numerous modifications of its framework. The impact of different scalarizion schemes was studied in [17,18], with the results suggesting that a proper choice of scalarizing function is important for the performance of MOEA/D. Also, it was shown that a better exploration of the search space can be achieved by performing replacement in the neighborhood of the subproblem that the best matches offspring [19]. Another important issue in MOEA/D is an efficient allocation of computational resources between different subproblems [20]. For this purpose, the concept of successful solutions, those entering an external archive, was introduced in [21]. For each subproblem, a number of successful solutions is used to calculate a selection probability, thereby allocating computational recourses to most promising subproblems. It was demonstrated that MOEAs relying on scalarization can better balance convergence and diversity [12]. A highly competitive performance for problems with a large number of objectives was also shown [22]. The major advantage of such MOEAs is efficiency, as a little computational effort is needed to compute a scalarizing function value.

On the other hand, directional vectors can be used for defining directions of search. This way, population members are evolved being associated with corresponding directions. In [23], direction vectors uniformly distributed on a hypersphere are utilized to divide the population and assign fitness among subpopulations based on convergence along these vectors. In [24], a diversity preservation mechanism was modified to extend a nondominated sorting genetic algorithm to many-objective optimization. Another MOEA exploiting the dominance and decomposition-based strategies was suggested in [25]. An approach that performs selection considering the distance to the reference direction first and the distance to the reference point second was proposed in [26]. The promising performance exhibited by such algorithms comes with the cost of increasing the human's burden in the form of providing a proper set of vectors before the search. Generating such set may be not an easy task, especially for high-dimensional spaces. Although there are some strategies allowing to automatize this process [27], an arbitrary number of weights cannot be obtained and the population size must be adjusted to the resultant number. Alternatively, polar coordinates can be used to decompose the objective space into a set of grids as suggested in [28], where population members are evolved while maintaining them associated with corresponding grids. A significant drawback of weight vector-based algorithms has been pointed out in [29], showing these algorithms are largely overspecialized for popular test suites such as DTLZ and WFG. This is due to the consistency between the shape of the Pareto front and the shape of the distribution of the weight vectors, which allows doing well on these problems but not in a general case.

The working principle of indicator-based approaches is based on optimizing quality indicators that are often utilized for the performance assessment of MOEAs. Although there have been developed various types of such indicators, the epsilon and hypervolume are the most frequently used ones within MOEAs. A general framework for incorporating quality indicators was proposed in [30]. This approach can use an arbitrary indicator to compare a pair of candidate solutions instead of entire approximation sets. A scheme similar to summing up the indicator values for each population member with respect to the rest of population is used to assign a scalar fitness value reflecting its quality with respect to the convergence and diversity. Indicator-based selection is often used to refine the Pareto dominance relation [31]. In [32], it is shown that maintaining two archives separately, one for diversity and another for convergence with indicator-based selection, can be beneficial. Indicator-based MOEAs are successful in dealing with many-objective problems [33]. The difficulty in their application arises from a high computational cost. As shown in [34], the computation time of the hypervolume grows exponentially with the number of objectives, significantly limiting its applicability. This problem can be mitigated by approximation. For this purpose, a method based on Monte Carlo simulation was proposed in [35], where the hypervolume is approximated by computing a number of dominated point in a sample. This requires to accept some trade-off between accuracy and complexity. Alternatively, a method based on scalarizing functions was suggested in [36], though this necessitates a large number of weight vectors. Another developments make use of computationally less expensive quality indicators [37,38].

In spite of recent advances and numerous existing frameworks for solving MOPs, it is theoretically impossible to have an optimization approach that works the best for all the problems [39]. The only way one approach can outperform another if it implements some characteristics that are particularly suitable for dealing with a problem at hand. This fact stresses the importance of innovative approaches and motivates the research in the field of evolutionary multiobjective optimization. The present study seeks to advance the state-of-the-art by proposing a multiobjective evolutionary algorithm based on vector angle neighborhood (MOEA/VAN). The main novelty of the proposed framework is a selection scheme. In some sense, MOEA/VAN can be viewed as a decomposition-based approach. As opposed to existing MOEAs relying on decomposition, the proposed approach does not use any kind of weight of directional vectors. This alleviates the user's burden and the issue of consistency between the shapes of the Pareto front and the distribution of weight vectors. An important feature of MOEA/VAN is a similarity measure, which is defined on the basis of the angle between population members in the objective space. The