A Multi-objective Niching Co-evolutionary Algorithm (MNCA) for Identifying Diverse Sets of Non-dominated Solutions

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ABSTRACT

Many engineering design problems must optimize multiple objectives. While many objectives are explicit and can be mathematically modeled, some goals are subjective and cannot be included in a mathematical model of the optimization problem. A set of alternative Pareto fronts that represent multiple optima for problem solution can be identified to provide insight about the decision space and to provide options and alternatives for decision-making. This paper presents the Multi-objective Niching Co-evolutionary Algorithm (MNCA) that identifies a set of Pareto-optimal solutions which are maximally different in their decision vectors and are located in the same non-inferior regions of the Pareto front. MNCA is demonstrated for a set of multi-modal multi-objective test problems to identify a set of Pareto fronts with maximum difference in decision vectors.

Categories and Subject Descriptors

G.1.6 [**Mathematics of Computing**]: Optimization—*Global optimization*

General Terms

Algorithms

Keywords

diversity, decision space, alternatives generation

1. INTRODUCTION

Many real-world optimization engineering problems involve multiple objectives that should be addressed simultaneously. A set of Pareto-optimal solutions that represents the trade-off among conflicting objectives should be identified to provide knowledge about the performance of alternative solutions for design and management problems [1]. Many multi-objective evolutionary algorithms (MOEAs) have been developed and designed to efficiently identify a set of non-dominated solutions, and these algorithms have been successfully applied for realistic engineering problems. The fitness landscapes for realistic design problems, however, are often non-linear, complex, and multi-modal. Alternate optima or local optima may exist in the search space and, when identified as alternative solutions, they can provide both additional insight to the problem and options for implementation.

While MOEAs typically utilize a mechanism for preserving diversity, such as niching, to ensure that solutions are spread out uniformly along the Pareto front, they do not include an explicit mechanism to identify alternative Pareto-optimal or alternative nearly Pareto-optimal solutions. To provide additional insights for decision-making, a secondary set of solutions can be identified that provide an array or range of alternative decisions that could be made, while achieving an acceptable level of performance for the objectives. These solutions should be identified by searching explicitly for solutions that originate in diverse regions of the decision space while satisfying objectives to the same degree. The Multi-objective Niching Co-evolutionary Algorithm (MNCA) is a new algorithm that is developed and demonstrated here to identify alternative Pareto fronts with maximum genotypic diversity. Fronts are identified that are similarly close to a true Pareto front, while the decision vectors represented by each front are located in diverse regions of the decision space. MNCA is based on an evolutionary algorithm-based framework, Evolutionary Algorithm to Generate Alternatives (EAGA) [2], that uses a set of subpopulations to identify an array of alternative solutions for single-objective problems. MNCA extends the EAGA framework by using a set of subpopulations to converge simultaneously to Pareto fronts that are maximally different in genotypic space from other subpopulations of solutions. MNCA is demonstrated here to identify alternate Pareto fronts for a suite of test problems.

2. MULTI-OBJECTIVE NICHING CO-EVOLUTIONARY ALGORITHM

To initialize MNCA, a set of subpopulations are generated, and the first subpopulation searches for a Pareto front, while secondary subpopulations search for alternative sets of non-dominated solutions that are diverse in decision space while approximating the Pareto front. In the first subpopulation, any MOEA can be used to identify an optimal Pareto front, while specialized operators are required in secondary subpopulations. At each generation, a *target front* is created based on the non-dominated set from the first popu-

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lation. To create the target front, each solution from the non-dominated front is copied into an array, and the objective values of each solution are reduced using a target value, while the decision variable values are discarded. In the remaining subpopulations, which are labeled as secondary subpopulations, solutions are tagged as *feasible* if they dominate the target front. To calculate a difference metric, a solution should be compared to solutions in other subpopulations that are located in similar regions of the objective space. All solutions are grouped into clusters based on their similarities in phenotypic space, using k-means clustering. A solution in a secondary subpopulation is assigned a difference metric based on its genotypic distance to solutions which are in the same cluster, but in other subpopulations. Solutions in secondary subpopulations are selected to survive based on feasibility, the difference metric, and non-dominance.

In this implementation, the MOEA that is used to identify a Pareto front in the first subpopulation is the Hypervolume Maximizing Multiobjective Evolutionary Algorithm (HM2EA) [4]. The hypervolume is defined as the space that is covered by all the solutions in the non-dominated front with respect to a worst point [3]. HM2EA uses non-dominated sorting and hypervolume calculations in the selection operator and combines child and parent populations at each generation. The combined population is sorted into fronts using non-dominated sorting, and fronts are selected in order of decreasing non-dominance to allow solutions to survive into the next generation. If there are more solutions in a front than the number of solutions that are needed for the next generation, solutions are selected from the front based on an S-metric value, which is the incremental contribution of each solution to the hypervolume. For selection in secondary subpopulations, HM2EA is altered to allow consideration of the feasibility of solutions and to incorporate a modified definition of the hypervolume and S-metric.

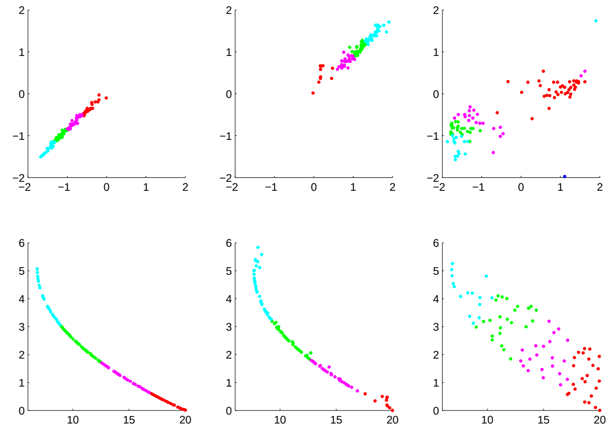

Figure 1: Results for Two-on-One. Upper row - Genotype space as x_2 vs. x_1. Lower row - Objective space as f_2 vs f_1. Columns (left to right) represent subpopulations 1-3. Colors indicate five clusters.

3. RESULTS

MNCA was tested for the Two-on-One function (Fig. 1) [5] and identified three alternative sets of non-dominated solutions. The target was set at 80% for identifying non-dominated solutions in secondary subpopulations. The second subpopulation identifies solutions that are very different from the first subpopulation in the decision space, located across the origin from the solutions in the first subpopulation. The Pareto front of the second subpopulation is only slightly dominated by the first subpopulation and has a greater spread along the f_2 axis. The third subpopulation identifies solutions that are different from both the first and second subpopulations, but the Pareto front shows a large loss in quality when compared to the Pareto fronts identified by the first and second subpopulations.

4. DISCUSSION

The purpose of MNCA is to identify diverse solution characteristics for Pareto-optimal solutions in the same region of the Pareto front. The MNCA framework uses subpopulations of solutions, a conventional MOEA, a clustering algorithm, and a new selection operator for identifying diverse and Pareto-optimal solutions. The MOEA for finding Pareto-optimality in the first subpopulation and the clustering method can be easily replaced with other similar algorithms to explore new results. MNCA requires few additional algorithmic parameters, including the number of alternative Pareto fronts that should be identified, and a target, which represents the level of degradation in the Pareto front that would be acceptable. The target can have a significant influence on the type of results that are identified, depending on the characteristics of the fitness landscape. As MNCA is designed to address the complexities of decision-making for engineering design problems, further work will apply MNCA for realistic multi-objective engineering problems.

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