Balancing Convergence and Diversity in Evolutionary Single, Multi and Many Objectives

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Abstract

Single objective optimization targets only one solution, that is usually the global optimum. On the other hand, the goal of multiobjective optimization is to represent the whole set of trade-off Pareto-optimal solutions to a problem. For over thirty years, researchers have been developing Evolutionary Multiobjective Optimization (EMO) algorithms for solving multiobjective optimization problems. Unfortunately, each of these algorithms were found to work well on a specific range of objective dimensionality, i.e. number of objectives. Most researchers overlooked the idea of creating a cross-dimensional algorithm that can adapt its operation from one level of objective dimensionality to the other. One important aspect of creating such algorithm is achieving a careful balance between convergence and diversity. Researchers proposed several techniques aiming at dividing computational resources uniformly between these two goals. However, in many situations, only either of them is difficult to attain. Also for a new problem, it is difficult to tell beforehand if it will be challenging in terms of convergence, diversity or both. In this study, we propose several extensions to a state-of-the-art evolutionary many-objective optimization algorithm – NSGA-III. Our extensions collectively aim at (i) creating a unified optimization algorithm that dynamically adapts itself to single, multi- and many objectives, and (ii) enabling this algorithm to automatically focus on either convergence, diversity or both, according to the problem being considered. Our approach augments the already existing algorithm with a niching-based selection operator. It also utilizes the recently proposed Karush Kuhn Tucker Proximity Measure to identify ill-converged solutions, and finally, uses several combinations of point-to-point single objective local search procedures to remedy these solutions and enhance both convergence and diversity. Our extensions are shown to produce better results than state-of-the-art algorithms over a set of single, multi- and many-objective problems.