Multi-Objective Evolutionary Algorithms

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INTRODUCTION

Real world optimization problems are often too complex to be solved through analytical means. Evolutionary algorithms, a class of algorithms that borrow paradigms from nature, are particularly well suited to address such problems. These algorithms are stochastic methods of optimization that have become immensely popular recently, because they are derivative-free methods, are not as prone to getting trapped in local minima (as they are population based), and are shown to work well for many complex optimization problems.

Although evolutionary algorithms have conventionally focussed on optimizing single objective functions, most practical problems in engineering are inherently multi-objective in nature. Multi-objective evolutionary optimization is a relatively new, and rapidly expanding area of research in evolutionary computation that looks at ways to address these problems.

In this chapter, we provide an overview of some of the most significant issues in multi-objective optimization (Deb, 2001).

BACKGROUND

Arguably, Genetic Algorithms (GAs) are one of the most common evolutionary optimization approaches. These algorithms maintain a population of candidate solutions in each generation, called chromosomes. Each chromosome corresponds to a point in the algorithm's search space. GAs use three Darwinian operators – selection, mutation, and crossover to perform their search (Mitchell, 1998). Each generation is improved by systematically removing the poorer solutions while retaining the better ones, based on a fitness measure. This process is called selection. Binary tournament selection and roulette wheel selection are two popular methods of selection. In binary tournament selection,

two solutions, called parents, are picked randomly from the population, with replacement, and their fitness compared, while in roulette wheel selection, the probability of a solution to be picked, is made to be directly proportional to its fitness.

Following selection, the crossover operator is applied. Usually, two parent solutions from the current generation are picked randomly for producing offspring to populate the next generation of solutions. The offspring are created from the parent solutions in such a manner that they bear characteristics from both. The offspring chromosomes are probabilistically subject to another operator called mutation, which is the addition of small random perturbations. Only a few solutions undergo mutation. Evolutionary Strategies (ES) forms another class of evolutionary algorithms that is closely related to GAs and uses similar operators as well.

Particle Swarm Optimization (PSO) is a more recent approach (Clerc, 2005). It is modeled after the social behavior of organisms such as a flock of birds or a school of fish, and thus only loosely classified as an evolutionary approach. Each solution within the population in PSO, called a particle, has a unique position in the search space. In each generation, the position of each particle is updated by the addition of the particle's own velocity to it. The velocity of a particle, a vector, is then incremented towards best location encountered in the particle's own history (called the individual best), as well as the best position in the current iteration (called the global best).

EVOLUTIONARY ALGORITHMS FOR MULTI-OBJECTIVE OPTIMIZATION

Multi-Objective Optimization

When dealing with optimization problems with multiple objectives, the conventional theories of optimality can-

Figure 1. An illustration of convergence and diversity concepts in multi-objective optimization algorithms. The objective functions f_1 and f_2 are to be minimized.
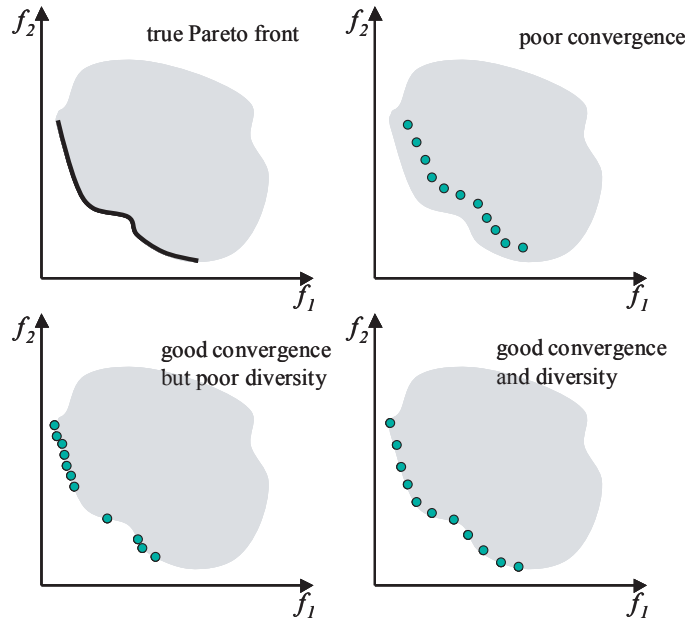
not be applied. Instead, the concepts of dominance and Pareto-optimality are used. Without a loss of generality, we will assume that the optimization problem involves the simultaneous minimization of several objectives only. If these objective functions are $f_i(.)$, $i = 1,...,M$, a solution x is said to *dominate* another solution y if and only if for all i, $f_i(x) \leq f_i(y)$ with at least one of the inequalities being strict. In other words, x dominates y if and only if x is as good as y for all objectives and better in at least one. This relationship is written $x \succ y$. In the set of all feasible solutions, that subset whose members are not dominated by any other in the set, is called the *Pareto set*. In other words, if **S** is the search space, the Pareto set **P** is given by, $\mathbf{P} = \{x \in \mathbf{S} \mid \forall y \in \mathbf{S}, y \succ x \text{ is false}\}$. The image of the Pareto set **P** in the M dimensional objective function space is called the *Pareto front*, **F**. Thus, $\mathbf{F} = \{(f_1(x), f_2(x),...f_M(x)) \mid x \in \mathbf{P}\}$.

The goal of a multi-objective optimization algorithm is twofold. Firstly, its output, the set of non-dominated solutions in the population, must be as close to the true Pareto front as possible. This feature is called *convergence*. Secondly, in addition to good convergence, the multi-objective evolutionary algorithm should also yield solutions that sample the front at approximately

regularly spaced intervals, a feature that is usually referred to as *diversity*. Outputs, where the solutions are clustered in a few regions of the front while other regions are either omitted or poorly sampled, are not desirable. Figure 1 illustrates the concepts of good convergence and diversity.

In order to handle multi-objective optimization tasks, an evolutionary algorithm must be equipped to discriminate between solutions using either convergence or diversity as the criterion for comparison. When using convergence, the majority of current evolutionary algorithms make use of one of two basic ranking schemes that were originally put forth by Goldberg (Goldberg, 1989). The first is a method that shall be referred to here as *domination counting*. Within a population of solutions, the rank of any solution is the number of other solutions in the population that dominate it. Clearly, the non-dominated solutions in the population are assigned counts of zero. The second approach will be called *non-dominated sorting*. Here, ranks are assigned to each solution in a population, in such a manner that solutions that have the same rank do not dominate one another, each solution is assigned a lower rank than another that it dominates, and, in turn, is ranked higher

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