

Frequency Fitness Assignment

Thomas Weise, *Member, IEEE*, Mingxu Wan, Pu Wang, *Member, IEEE*, Ke Tang, *Senior Member, IEEE*, Alexandre Devert, and Xin Yao, *Fellow, IEEE*

Abstract—Metaheuristic optimization procedures such as evolutionary algorithms are usually driven by an objective function that rates the quality of a candidate solution. However, it is not clear in practice whether an objective function adequately rewards intermediate solutions on the path to the global optimum and it may exhibit deceptiveness, epistasis, neutrality, ruggedness, and a lack of causality. In this paper, we introduce the frequency fitness H , subject to minimization, which rates how often solutions with the same objective value have been discovered so far. The ideas behind this method are that good solutions are difficult to find and that if an algorithm gets stuck at a local optimum, the frequency of the objective values of the surrounding solutions will increase over time, which will eventually allow it to leave that region again. We substitute a frequency fitness assignment process (FFA) for the objective function into several different optimization algorithms. We conduct a comprehensive set of experiments: the synthesis of algorithms with genetic programming (GP), the solution of MAX-3SAT problems with genetic algorithms, classification with Memetic Genetic Programming, and numerical optimization with a (1+1) Evolution Strategy, to verify the utility of FFA. Given that they have no access to the original objective function at all, it is surprising that for some problems (e.g., the algorithm synthesis task) the FFA-based algorithm variants perform significantly better. However, this cannot be guaranteed for all tested problems. Thus, we also analyze scenarios where algorithms using FFA do not perform better or perform even worse than with the original objective functions.

Index Terms—Combinatorial optimization, diversity, fitness assignment, frequency, genetic programming (GP), numerical optimization.

I. INTRODUCTION

SINGLE-OBJECTIVE optimization is a process with the goal of finding (ideally) i.e., (local) solutions x

from within a space \mathbb{X} of possible solutions. An objective function f serves as quality measure guiding the search. Black-box metaheuristic approaches are methods that only require such an objective function and search operations to solve an optimization problem without any further insight into their structure. The most prominent family of these methods are evolutionary algorithms, which have wide applications ranging from engineering, planning and scheduling, numerical optimization, to even program synthesis.

Most metaheuristic optimization methods start with a randomly generated set of candidate solutions. New points in the search space are derived by modifying or combining promising existing solutions. Promising here means having a better objective value than the other points visited so far, maybe combined with some considerations about diversity. The rationale is that in the ideal case, solutions that have better objective values should be closer to the global optimum or, at least, may have even better solutions in their vicinity.

The principle of tending to choose areas of the solution space for sampling where points with better objective values have previously been discovered is one of the most universally applied ideas in black-box optimization. Lehman and Stanley [1] argued that increasing fitness does not always reveal the best path through the search space. Building on their work, we believe that there is at least one other fundamental principle inherent to non-trivial optimization problems to be exploited to solve them: good solutions (and hence objective values) are hard to find.

If we consider optimization as sampling of the space, we could exploit frequency