Frequency Fitness Assignment: Optimization Without Bias for Good Solutions Can Be Efficient

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***Abstract*—A fitness assignment process transforms the features (such as the objective value) of a candidate solution to a scalar fitness, which then is the basis for selection. Under frequency fitness assignment (FFA), the fitness corresponding to an objective value is its encounter frequency in selection steps and is subject to minimization. FFA creates algorithms that are not biased toward better solutions and are invariant under all injective transformations of the objective function value. We investigate the impact of FFA on the performance of two theory inspired, state-of-the-art evolutionary algorithms, the Greedy $(2+1)$ GA and the self-adjusting $(1+(\lambda,\lambda))$ GA. FFA improves their performance significantly on some problems that are hard for them. In our experiments, one FFA-based algorithm exhibited mean runtimes that appear to be polynomial on the theory-based benchmark problems in our study, including traps, jumps, and plateaus. We propose two hybrid approaches that use both direct and FFA-based optimization and find that they perform well. All FFA-based algorithms also perform better on satisfiability problems than any of the pure algorithm variants.**

***Index Terms*—Evolutionary algorithm (EA), FEA, frequency fitness assignment (FFA), Ising problems, jump problems, linear harmonic functions, MaxSat problem, *N*-queens problem, OneMax, Plateau problems, satisfiability, Trap function, TwoMax, *W*-model benchmark.**

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fitness assignment (FFA), the fitness of a candidate solution is the absolute encounter frequency of its objective value so far during the optimization process [1]. Being subject to minimization, FFA drives the search away from already-discovered objective values and toward solutions with new qualities.

FFA breaks with one of the most fundamental concepts of heuristic optimization: FFA-based algorithms are not biased toward better solutions [2], i.e., they do not prefer better solutions over worse ones. They also are invariant under all injective transformations of the objective function value, which is the strongest invariance property of any nontrivial single-objective optimization algorithm [3].[1] Only random sampling, random walks, and exhaustive enumeration have similar properties and neither of them is considered to be an efficient optimization method.

One would expect that this comes at a significant performance penalty. Yet, FFA performed well in Genetic Programming tasks with their often rugged, deceptive, and highly epistatic landscapes [1], [4] and on a benchmark problem simulating such landscapes [5]. While the $(1+1)$ EA has exp[illegible]ential expected runtime on pro[illegible]blems, such as Jum[illegible] TwoMax [illegible]d Trap, the $(1+1)$ FEA, th[illegible] same al[illegible]thm[illegible] using FFA [illegible]h[illegible]bits mean runtimes that [illegible]ear [illegible] mia[illegible] [illegible]ts [illegible] also s[illegible] M[illegible] [3] [illegible]