Parameter-less Evolutionary Portfolio: First Experiments

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ABSTRACT

A portfolio of parameter-less evolutionary algorithms called *Parameter-less Evolutionary Portfolio* is proposed. This portfolio implements a heuristic that performs adaptive selection of parameter-less evolutionary algorithms in accordance with performance criteria that are measured during running time. Initial experiments show that the parameter-less portfolio can solve various classes of problems without the need for any prior parameter setting technique and with an increase in computational effort that can be considered acceptable.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search

Keywords

Algorithm Portfolios, Black-box Optimization

1. INTRODUCTION

The key idea of algorithm portfolios is to devise new heuristics that combine known individual algorithms in ways that allow to tackle broad classes of problems with the most suitable technique. In recent years, the development of algorithm portfolios has gained significant traction in many fields of search and optimization techniques. This progress can be explained in part by the vast and increasing number of various types of algorithms that are currently available to be aggregated into portfolios and by the mounting pressure to lessen the need of (costly) specialized knowledge to operate those same individual algorithms.

The portfolio approach to optimization explicitly trades efficiency for applicability and it is naturally related to the black-box optimization paradigm and to the design of parameter-less algorithms in particular.

In this paper we present a portfolio of parameter-less evolutionary algorithms (P-EAs) called the *Parameter-less Evolutionary Portfolio* (P-EP). This portfolio performs adaptive selection of P-EAs as suggested in [5] using a heuristic inspired by the parameter-less genetic algorithm [4].

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2. PARAMETER-LESS EVOLUTIONARY PORTFOLIO

The Parameter-less Evolutionary Portfolio implements a heuristic for adaptive selection of P-EAs first proposed by Lobo and Lima in [5]. We direct the interested reader to their paper for a more general and detailed description of the heuristic itself.

Initial experiments were done with a portfolio consisting of three parameter-less Estimation of Distribution Algorithms (EDAs): Parameter-less Univariate Marginal Distribution Algorithm (P-UMDA) [6], Parameter-less Extended Compact Genetic Algorithm (P-ECGA) [3], and Parameter-less Hierarchical Bayesian Optimization Algorithm (P-HBOA) [8]. This three P-EAs can be informally, but quantifiably, ordered by their increasing "complexity": P-UMDA, P-ECGA, and P-HBOA, with the more complex ones capable of tackling more difficult problems at the expense of using an increased cost in model building. Following this order, P-EP alternates between each algorithm on a continuous loop, giving the same amount of CPU time to all three P-EAs in each iteration. Starting with a chosen initial time, T_0, the allowed CPU time is updated at each loop iteration to at least match the maximum time spent in one generation by any of the P-EAs. At the same time, because they are able to advance further in the search due to faster model building, simpler P-EAs are eliminated from the loop as soon as their current best average fitness is lower than the best average fitness of a more complex P-EA. The use of parameter-less algorithms allows P-EP to work as a black-box algorithm, without the need for any prior parameter settings.

3. EXPERIMENTAL RESULTS

The results of our initial experiments with P-EP are presented in Table 1 where all shown values are averaged over 30 independent runs of P-EP. Three well known problems with increasing "difficulty" (see, for instance, [7]) were used: Onemax, Concatenated Trap-5 (TRAP-5), and Hierarchical Trap One (H-TRAP). The dimensions (n) of the problems are, respectively, 500, 150, and 243. These dimensions were chosen such that the problems at hand can be considered as good representatives of significant sets of theoretical problems commonly used to gauge the behaviour of EAs.

P-EA	P-UMDA			P-ECGA			P-HBOA			P-EP		
Problem	Best	Fit. Calls	Time	Best	Fit. Calls	Time	Best	Fit. Calls	Time	Best	Fit. Calls	Time
ONEMAX (n = 500)	**500**	**18** **(98.1%)**	**1** **(18.7%)**	293	0.2 (0.9%)	0.7 (13.7%)	291	0.2 (0.9%)	3 (67.6%)	500	19 (100.0%)	5 (100.0%)
TRAP-5 (n = 150)	121	4786 (70.9%)	176 (4.1%)	**150**	**880** **(13.0%)**	**2241** **(51.9%)**	135	1084 (16.1%)	1905 (44.0%)	150	6750 (100.0%)	4322 (100.0%)
H-TRAP (n = 243)	1191	7455 (59.9%)	414 (1.3%)	1191	1890 (15.2%)	15903 (51.7%)	**1215**	**3110** **(24.9%)**	**14466** **(47.0%)**	1215	12455 (100.0%)	30783 (100.0%)

Table 1: Results for P-EP initial experiments. 'Best' denotes the fitness of the best individual found by each P-EA. The number of fitness calls is measured in thousands ($\times$1000). The CPU time is rounded to seconds.

P-EP was run until the global optimum was found. P-EP performed as expected, being able to eventually reach the global optimum with the most adequate P-EA (see the results highlighted in **blue** in Table 1). In the TRAP-5 and H-TRAP problems the time spent running the adequate P-EA and running the sub-optimal P-EAs is about the same. This is an acceptable increase in computational effort if we consider that P-EP was able to automatically select the best P-EA and find the optimal solution without any prior knowledge of the given problem. On the other hand, P-EP was able to solve the ONEMAX problem using exclusively the P-UMDA in 23 of the 30 runs performed, but the time spent by the P-ECGA and the P-HBOA in the remaining 7 runs was sufficient to significantly inflate the corresponding results. However, had the initial time allowed to each P-EA been slightly higher (we set $T_0 = 1$s in the reported experiments), the exclusive use of the P-UMDA would become more prevalent and this inflation would vanish. We are currently working in the design of an empirical rule that adapts T_0 relative to the dimension of the problem at hand.

4. CONCLUSIONS

The initial experiments presented in this paper show that P-EP can solve various classes of problems without the need for any prior parameter setting technique and with an increase in computational effort that can be considered acceptable. Naturally, there are improvements that can be made, such as the adaptation of the initial time allowed to each P-EA, relative to the dimension of the problem at hand. More importantly, the portfolio P-EAs can easily be changed to integrate other algorithms such as hillclimbers, the self-adaptive $(1 + (\lambda, \lambda))$ [1] and a parameter-less version of the Linkage Tree Genetic Algorithm [9, 10] which will enhance significantly the applicability and the effectiveness

Finally, we could not end this paper without due reference to the recently proposed Parameter-less Population Pyramid (P3) [2] which delivered excellent results in a black-box optimization context. The P3 algorithm "[...] unlike other parameter-less techniques [...] appears to be at least a constant factor *improvement* over comparable, optimally configured, optimization methods." [2]. This improvement directly challenges the trade-off between efficiency and applicability that is (was) one of the defining characteristics of black-box optimization techniques. We are currently studying what new possibilities the P3 method opens to our research with P-EP.

5. ACKNOWLEDGMENTS

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