Investigating Parent Selection Mechanisms In Evolutionary Algorithms for Continuous Function Optimization

Group 65

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1 Introduction

Evolutionary Algorithms (EAs) are population-based, probabilistic search algorithms, that one of the most very popular use is solving multidimensional optimization problems. This family of bio-inspired, metaheuristic algorithms is characterized by the application of an iterative and stochastic process on a maintained population of individuals that represent candidate solutions, where each iteration generates individuals with better quality.

The two main processes that drive the evolution of better solutions within the population of each evolutionary cycle, called a 'generation', are variation operators and selection operators that act to establish a balance between exploration and exploitation of the search space. The role of the selection operators is to focus the evolutionary search on the promising regions of the search space by improving the average quality of the population, measured by a fitness function. In each generation there are two levels of selection. The first level is the selection of individuals to seed the next generation, known as parent selection, and the second is survivor selection.

Typically, parent selection is probabilistic, where the selection probability of each individual is proportional to its quality. Thus, a bias is ensured favouring parents with relatively high fitness to be selected to undergo variation to generate new individuals, as there is a correlation between parental and offspring fitness. There are many different parent selection schemes that exert distinct selection pressures to the population, which is a side-effect of shifting average fitness by introducing offspring with skewed fitness values. This results in...

adjusting the balance of exploration and exploitation, and therefore lead to quality improvement through different mechanisms during the evolutionary search.

In contrast to variation operators, the choice of selection operators is not limited by the representation of the individual. This simplifies the analysis of the parent selection mechanisms as the direct effect of each scheme on the performance of the algorithm can be observed by keeping everything else constant.

In the current work our aim was to evaluate the effect of different parent selection schemes on algorithm performance in multidimensional optimization problems, and dissect the properties of each. We hypothesized that ...

To test our hypothesis we designed and implemented three EAs, differing only in the parent selection mechanism, in maximizing three 10-dimensional continuous optimization problems, known as Bent Cigar, Katsuura, and the Schaffers F7 function. We then compared the performance of each algorithm on each of these problems to assess the effect of each parent selection scheme. In particular, we looked at the effectiveness and efficiency of exponential Ranking Selection, Roulette Selection and Tournament Selection, and used the steady-state model of population management.

2 Experimental Setup

Algorithm Description

Representation	Real-valued vectors
Recombination	One-Point Crossover
Recombination Size	40
Mutation	Uncorrelated mutation with n step sizes
Mutation Size	40
Parent Selection	Uniform, Tournament and different Rankings
Population Management	Steady-state Model
Generational Gap Size	No gap
Survival Selection	Elitism with N = 20
Population Size	100
Number of Offspring	80
Initialization	Uniform distribution on interval [-5, 5]
Termination Condition	Given evaluation limit

Table 1: Algorithm Summary.

Our setup is loosely based on Evolutionary Strategies. We represent the genotype as 10-dimensional Doubles and initialize on a uniform distribution with boundaries [-5, 5]. We recombine by exchanging dimensions after a random point between 1 and 9. The mutation operator is based on this paper [...]. There is no direct overlap of recombination and mutation. We stop the mutation process for the last 5 percent of cycles in order to increase exploitation of good results. For our research question, we analyze 4 different selection mechanisms: Uniform random, tournament as well as exponential ranking and linear ranking based on the roulette wheel implementation. We keep the population size to a constant 100 using the steady-state model and keeping the 20 best individuals from the previous generation. The parameters for variation are kept constant. All offspring are transferred into the next generation. The algorithm is terminated after a function-specific amount of evaluations is reached.

Analysis

To quantify the effectiveness of the different parent selection schemes we used the mean best fitness measure (**MBF**) over all runs. This is the average fitness value of the best individual at termination for each algorithm, in each problem. We run each of the algorithms 100 times for each problem. We also evaluate standard deviation.

To quantify the efficiency of the different parent selection schemes we used the average number of evaluations to a solution (**AES**) measure.

We also produced progress curves for each algorithm on each problem by plotting the MBF against a time axis (units are per evolutionary cycle).

Test problems

Katsuura

$\mathbf{f_{Kat}}$

Schaffers F7 function

$\mathbf{f_{Sch}} = \left[\frac{1}{n-1}\sqrt{s_i} \cdot (sin(50.0 s_i^{\frac{1}{5}}) + 1)\right]^2$

Bent Cigar function

$\mathbf{f_{Cig}} = x_1^2 + 10^6 \sum_{i=2}^{n} x_i^2$

Statistics

In order to obtain statistical significance in our comparisons we used Kruskal-Wallis tests on the results, as all the data sets were non-parametric. The normality of the data distributions was checked using the Kolmogorov-Smirnov test.

The bar charts for comparing MBF display mean, and the error bars represent standard deviation. Statistical significance is indicated on graphs using standard conventions: n.s. (non-significant): $p > 0.05, *p \leq 0.05, **P \leq 0.01, ***P \leq 0.001$. All experiments were repeated 100 times.

The analyses were performed using Prism 5 (GraphPad Software). The significance level was set at $p = 0.05$.

3 Experimental Results

We began by assessing the MBF of each algorithm throughout each independent run on each test function to identify any difference in effectiveness between them.

For $\mathbf{f_{Cig}}$ we found that there was a statistically significant difference between the Uniform (M = 0.005743 ± 0.03411), Roulette L. (M = 7.915 ± 0.7509), Roulette E. (M = 9.629 ± 0.7064) and Tournament (M = 6.974 ± 2.201) algorithms, as determined by a Kruskal-Wallis test (H = 306.2, p < 0.0001). A Dunn's multiple comparison post-hoc test revealed that there was a significant difference between all algorithm comparisons except in the Roulette L. vs Tournament comparison, where ... Results are displayed in Table 2 and Table 3, and graphically in Figure ...

For $\mathbf{f_{Sch}}$ we found that there was a statistically significant difference between the Uniform (M=0.007566 ± 0.01424), Roulette L. (M=6.886 ± 1.437), Roulette E. (M=8.907 ± 2.513) and Tournament (M=2.400 ± 1.504) algorithms, as determined by a Kruskal-Wallis test ($H = 337.0$, $p < 0.0001$). A Dunn's multiple comparison post-hoc test revealed that there was a significant difference between all algorithm comparisons. Results are displayed in Table 2 and Table 3, and graphically in Figure ...

For $\mathbf{f_{Kat}}$ we found that there was a statistically significant difference between the Uniform (M=0.04792 ± 0.1207), Roulette L. (M=0.1686 ± 0.2919), Roulette E. (M=0.2935 ± 0.3694) and Tournament (M=0.1803 ± 0.3285) algorithms, as determined by a Kruskal-Wallis test ($H = 8.281$, $p = 0.0405$). A Dunn's multiple comparison post-hoc test revealed that there was a significant difference between all algorithm comparisons. Results are displayed in Table 2 and Table 3, and graphically in Figure ...

Alg.	$\mathbf{f_{Kat}}$	$\mathbf{f_{Sch}}$	$\mathbf{f_{Cig}}$	$\mathbf{f_{Sph}}$
Uniform Selection	0,012758797	0.002292568	4.51359E-05	4.67663E-15
Tournament Selection	0,162084203	2.358272578	7.136120668	9.80817282
Roulette Wheel LIN	0.547753839	7.168785174	5.94773506	9.626834766
Roulette Wheel EXP	0,152676164	9.194072313	9.892989737	9.986059675

Table 2: Computational results. MBF

Alg.	$\mathbf{f_{Kat}}$	$\mathbf{f_{Sch}}$	$\mathbf{f_{Cig}}$	$\mathbf{f_{Sph}}$
Uniform Selection	0,013096551	0.022787459	0.118243171	0.131635551
Tournament Selection	0,194757816	2.094653517	2.086194371	0.334941158
Roulette Wheel LIN	0.279425874	1.352295728	0.925856185	0.165664615
Roulette Wheel EXP	0,581567107	2.045591844	0.627768231	0.019229561

Table 3: Computational results. Standard deviation of MBF

We also

Alg.	$\mathbf{f_{Kat}}$	$\mathbf{f_{Sch}}$	$\mathbf{f_{Cig}}$	$\mathbf{f_{Sph}}$
Uniform Selection	521,453125	72.30321236	15.15921972	7.10543E-15
Tournament Selection	2677,865234	458.4262989	92.84570209	97.01096076
Roulette Wheel LIN	9337.882813	778.6028246	88.45548721	76.00371446
Roulette Wheel EXP	5610,929688	935.4808941	96.04011702	97.46491229

Table 4: Computational results. AES

4 Analysis and Discussion

We used the ranked-based selection scheme to assign selection probabilities to each individual. For the individual of rank i, it's selection probability is given by either a linear or exponential ranking.

Probabilities are then sampled by the Roulette Wheel algorithm. Uniform Random and Tournament Selection do not include probabilities.

Interpretation of Results

selection pressure, form the book why linear fails etc

NEED TO PLACE THE RESULTS OF EACH ALGO IN A PROBLEM SOLVING CONTEXT

Results vs. Literature

Limitations

Parameters (population/recombination/mutation/elitism size), may favour one of the selection schemes.

Future Work

Future studies — To analyze the influence of each scheme on the search process dynamics of the EAs the interaction of the scheme on the fitness distribution should be examined. This framework allows the derivation of several insights in the properties of each selection method.

5 Conclusions

Each selection scheme draws a mating pool from the population where each individual is selected based on different criteria; thus pushing the search process in different directions.

6 Bibliography

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