About the Dynamics of Essential Genetic Information: An Empirical Analysis for Selected GA-Variants

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ABSTRACT

This paper exemplarily points out how essential genetic information evolves during the runs of selected GA-variants. The algorithmic enhancements to a standard genetic algorithm certify the survival of essential genetic information by supporting the survival of relevant alleles rather than the survival of above average chromosomes. This is achieved by defining the survival probability of a new child chromosome depending on the child's fitness in comparison to the fitness values of its own parents. The main aim of this paper is to explain important properties of the discussed algorithm variants in a rather intuitive way. Aspects for meaningful and practically more relevant generalizations as well as more sophisticated experimental analyses are indicated.

Categories and Subject Descriptors

D.2.8 [**Software Engineering**]: Metrics—*Process metrics*; I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search

General Terms

Algorithms, Measurement, Design, Experimentation

Keywords

Genetic Algorithms, Selection, Self-adaptivity, Premature convergence, Population diversity analysis

1. INTRODUCTION

A basic requirement for the analyses presented in this paper is the existence of a unique globally optimal solution which has to be known. Concretely, we aim to observe the distribution of the alleles of the globally optimal solution (denoted as essential genetic information) over the generations in order to observe the ability of the certain algorithmic variants to preserve and possibly regain essential genetic material during the run of the algorithm.

In a broader interpretation of the building block theory ([3], [5]) these alleles should on the one hand be available in the initial population of a GA run, and on the other hand maintained during the run of the algorithm. The tests in this paper show results for a 130 city benchmark TSP, namely the $ch130 - TSP$. In order to observe the situation in the population we display each of the 130 essential edges as a bar indicating the saturation of each allele in the population. The disappearance of a bar therefore indicates the loss of the corresponding allele in the entire population, whereas a full bar indicates that the certain allele occurs in each individual (which is the desired situation at the end of an algorithm run). As a consequence, the relative height of a bar stands for the actual penetration level of the corresponding allele in the individuals of the population. The main characteristics of the considered algorithms could also be observed for many other combinatorial optimization problems and also genetic programming applications in the field of nonlinear structure identification. In order to keep the discussion compact and on an explanatory level, detailed parameter settings and the corresponding statistically relevant result tables are not stated in this paper; detailed results for the TSP tests are given at the website of the book [2][1].

2. BUILDING BLOCK ANALYSIS FOR STANDARD GENETIC ALGORITHMS

For observing the distribution of essential alleles in a standard GA (SGA) we have used the following test strategy:

[1] http://gagp2008.heuristiclab.com/material/statisticsTSP.html

GEC'09, June 12–14, 2009, Shanghai, China.
ACM 978-1-60558-326-6/09/06.

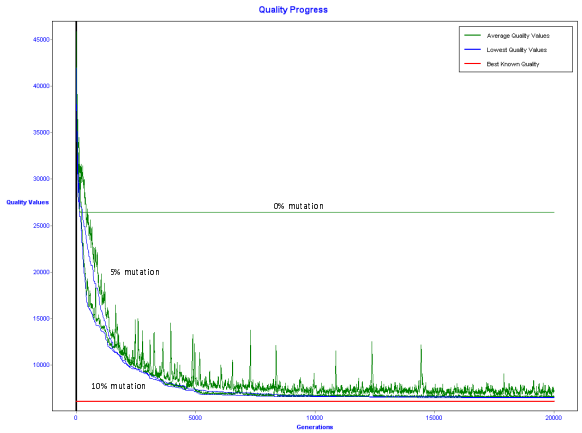

Figure 1: Quality progress for a standard GA with OX crossover for mutation rates of 0%, 5%, and 10%.

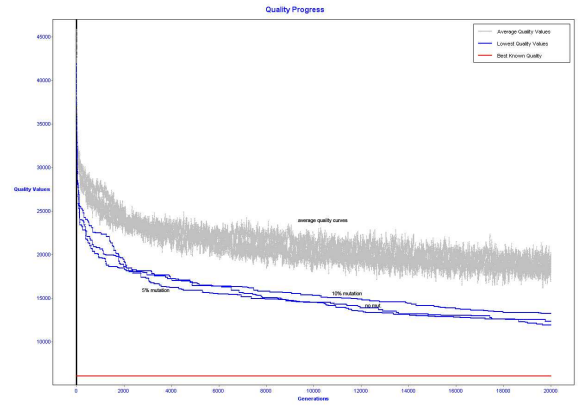

Figure 2: Quality progress for a standard GA with ERX crossover for mutation rates of 0%, 5%, and 10%.

First, our aim was to observe the solution quality achievable with parameter settings that are quite typical for such kinds of GA applications (as given in Table 1) using well known operators for the path representation, namely OX and ERX [4]; each algorithmic variant has been analyzed applying no mutation as well as mutation rates of 5% and 10%.

Table 1: Parameters for test runs using a SGA.

Parameters for the conventional GA tests (Results are graphically presented in Figures 1 and 2)	
Generations	20'000
Population Size	100
Elitism Solutions	1
Mutation Rate	0.00 or 0.05 or 0.1
Selection Operator	Roulette
Crossover Operator	OX (Fig. 1) or ERX (Fig. 2)
Mutation Operator	Simple Inversion

Figures 1 and 2 show the fitness curves (showing best and average solution qualities of the GA's population as well as the best known quality) for a standard GA using order crossover OX (see Figure 1) and edge recombination crossover ERX (Figure 2); the parameter settings used for these experiments are given in Table 1.

For the OX crossover, which achieved the best results with the standard parameter settings, the results are shown in Figure 1; it is observable that the use of mutation rates of 5% and 10% leads to quite good results (about 5% to 10% worse than the global optimum), whereas disabling mutation leads to a rapid loss of genetic diversity so that the solution quality stagnates at a very poor level.

Figure 3 shows the distribution of the 130 essential alleles of the unique globally optimal solution over time for the overall best parameter constellation found in this section, i.e., the use of OX crossover with 5% mutation rate. In order to make the snapshots for the essential allele distribution within the SGA's population comparable to those captured applying the RAPGA, the timestamps are not given in iterations but rather in the number of evaluations (which is in

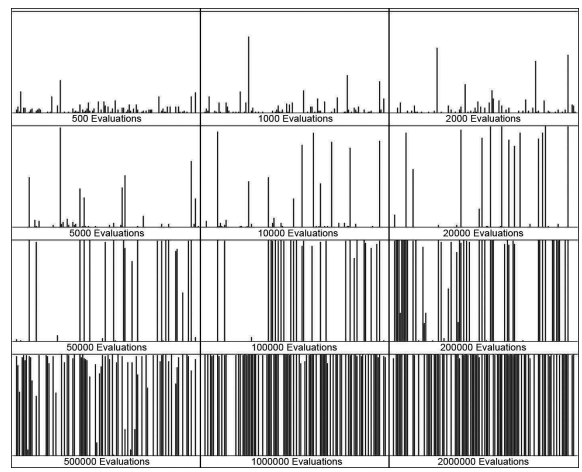

Figure 3: Distribution of the alleles of the global optimal solution over the run of a standard GA using OX crossover and a mutation rate of 5% (remaining parameters are set according to Table 1).

the case of the SGA equal to the population size times the number of generations executed).

Until after about $10,000$ evaluations, i.e. at generation 100, we can observe quite typical behavior, namely the rise of certain bars (representing the existence of edges of the global optimum). However, what happens between the $10,000$th and $20,000$th evaluation is that some of the essential alleles (about 15 in our test run) become fixed whereas the rest (here about $130 - 15 = 115$ in our test run) disappears in the entire population. As we can see in Figure 3, without mutation the genetic search process would already be over at that moment due to the fixation of all alleles; from now on mutation is the driving force behind the search process of the SGA.

The effects of mutation in this context are basically as follows: Sometimes high quality alleles are (by chance) injected into the population, and if those are beneficial (not even necessarily in the mutated individual), then a suited crossover

operator to some degree is able to spread newly introduced essential allele information over the population and achieve a status of fixation quite rapidly. Thus, most of the essential alleles can be reintroduced and fixed approximately between the 2,000th and 2,000,000th evaluation.

3. BUILDING BLOCK ANALYSIS FOR THE RELEVANT ALLELES PRESERVING GA (RAPGA)

Similar to the previous section we aim to highlight some of the most characteristic features of the relevant alleles preserving GA (RAPGA) [1]. The RAPGA ideally works in such a way that new child solutions are added to the new population as long as it is possible to generate unique and successful offspring stemming from the gene pool of the last generation.

This idea is implemented using ad hoc population size adjustment in that sense that potential offspring generated by the basic genetic operators are accepted as members of the next generation if and only if they are able to outperform the fitness of their own parents. Additionally, in order to be accepted, offspring have to be new in that sense that their chromosome consists of a concrete allele alignment that is not represented yet in an individual of the next generation. As long as new and (with respect to the definition given in the context of offspring selection) ŞsuccessfulŤ individuals can be created from the gene pool of the actual generation, the population size is allowed to grow up to a maximum size. Similar to offspring selection [2], a potential offspring which is not able to fulfill these requirements is simply not considered for the gene pool of the next generation.

Still a lower as well as an upper limit of population size are necessary in order to achieve efficient algorithmic performance. In order to terminate the run of a certain generation in case it is not possible to fill up the maximally allowed population size with new successful individuals, an upper limit of effort in terms of generated individuals is also necessary. This maximum effort per generation is the maximum number of newly generated chromosomes per generation (no matter if these have been accepted or not). In order to terminate the run of a certain generation in case it is not possible to fill up the maximally allowed population size with new successful individuals, an upper limit of effort in terms of generated individuals is necessary. This maximum effort per generation is the maximum number of newly generated chromosomes per generation (no matter if these have been accepted or not).The question, whether or not an offspring is better than its parents, is answered in the same way as in the context of offspring selection.

The following experiments are set up in the following way: Firstly, the considered operators OX, and ERX as well as the combination (OX, MXP, ERX) are applied to the *ch130* benchmark TSP problem taken from the TSPLib. Then the most successful operator or operator combination, respectively, is also exemplarily considered without mutation in order to show that the RAPGA like offspring selection does not rely on mutation to such an extent as conventional GAs.

Already the experiments using OX show good results (approximately 5% – 10% worse than the globally optimal solution) which are even slightly better than the corresponding offspring selection results. Even if only single test runs are shown in this paper it has to be pointed out that the authors have taken care that characteristical runs are shown. Besides, as described in the more systematical experiments described in [2], especially due to the increased robustness caused by offspring selection and RAPGA the variance of the results' qualities is quite small.

Table 2: Parameters for test runs using the relevant alleles preserving genetic algorithm.

Parameters for the RAPGA tests (Results presented in Fig.4 and Fig.5	
Max. Generations	1'000
Initial Population Size	500
Mutation Rate	0.00 or 0.05
Elitism Rate	1
Male Selection	Roulette
Female Selection	Random
Crossover Operator	OX ERX combined (OX, ERX and MPX)
Mutation Operator	Simple Inversion
Minimum Population Size	5
Maximum Population Size	700
Effort	20'000
Attenuation	0

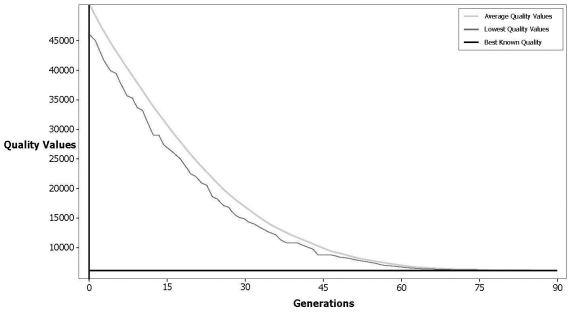

Figure 4: Fitness curve for a relevant alleles preserving GA using a combination of OX, ERX and MPX and a mutation rate of 5%.

Similar to what we stated for the OS analyses, also for the RAPGA the best results could be achieved using ERX as well as using the combination of OX, ERX and MXP (see Figures 4 and 5). The achieved results using these these operators are about 1% or even less worse than the global optimal solution. In the case of the RAPGA the operator combination turned out to be slightly better than ERX (in 18 of 20 test runs). Therefore, this is the operator combination we have also considered for a detailed building block analysis without mutation as well as applying 5% mutation.

Barely surprising, the results of RAPGA with the operator combination consisting of OX, ERX, and MPX turned out to be quite similar to those achieved using offspring selection and the ERX operator. Due to the essential aspect of relevant allele preservation, disabling mutation (see Figure 5) has almost no consequences concerning achievable global solution quality. Even without mutation the results are just 1-2% worse than the global optimum. The distributions of essential alleles over the generations of the RAPGA run (as shown in Figure 6) also show quite similar behavior as already observed in the corresponding analyses of the effects

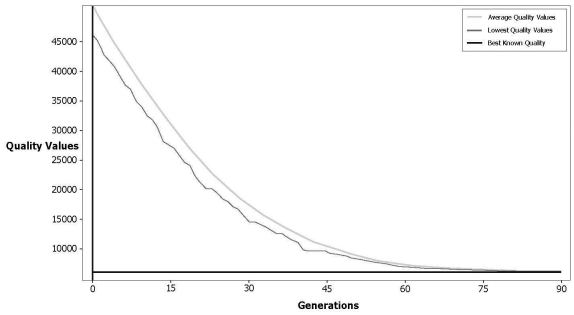

Figure 5: Fitness curve for a relevant alleles preserving GA using a combination of OX, ERX and MPX and mutation switched off.

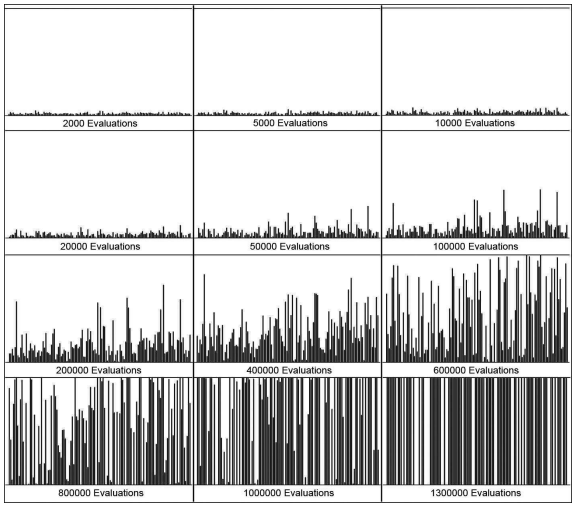

Figure 6: Distribution of the alleles of the global optimal solution over the run of a relevant alleles preserving GA using a combination of OX, ERX and MPX without mutation (remaining are set parameters according to Table 2).

of offspring selection. Almost all essential alleles are represented in the first populations and their diffusion is slowly growing over the GA run, and even without mutation the vast majority of essential alleles is fixed by the end of the RAPGA runs.

Summarizing the test results, we can state that quite similar convergence behavior is observed for a GA with offspring selection and the RAPGA, which is characterized by efficient maintenance of essential genetic information. As shown in Section 2, this behavior (which we would intuitively expect from any GA) cannot be guaranteed in general for GA applications where it was mainly mutation which helped to find acceptable solution qualities.

4. CONCLUSIONS

In this paper we have exemplarily opposed the characteristical behavior of conventional GA with the typical functioning of generic hybrids based upon self adaptive selection pressure steering. The shown experiments are not comprehensive at all as only snapshot results are shown under somehow idealized conditions which use the knowledge of the known unique optimal solution; nevertheless these tests represent a compressed summary of the algorithm's properties which are discussed in depth in [2]. In [2] it is also shown that the observed behavior is not restricted to the TSP, but can be also observed also in other combinatorial optimization problems like the CVRP(TW) and especially in genetic programming applications. Extensive empirical studies for the TSP, which are also relevant in view of the results of this paper, are provided at the website[2] of the book where also tests for the CVRP(TW) and genetic programming applications are documented.

5. ACKNOWLEDGMENTS

The work described in this paper was done within the Josef Ressel centre for heuristic optimization sponsored by the Austrian Research Promotion Agency (FFG).

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