population genetics, genetic algorithms, premature convergence, genetic drift

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THE INFLUENCE OF POPULATION GENETICS FOR THE REDESIGN OF GENETIC ALGORITHMS

This contribution considers recent results of population genetics in order to present generic extensions to the general concept of a Genetic Algorithm (GA). Consequently a new model for self-adaptive selection pressure steering is presented (Offspring Selection), taking advantage of the interplay between directed genetic drift and selection, resulting in a new class of Genetic Algorithms. As a result we introduce and empirically analyze the generic extensions to the general GA concept, which make genetic search more stable in terms of operators, and allows steering and scaling up of global solution quality to highest quality regions without using problem specific information or local searches.

1. INTRODUCTION

Population genetics has its origin in genetics and evolution biology. The history of evolution biology as an independent discipline dates back to the 17^{th} and 18^{th} century. In contrast to the early years of research of evolution, where selection was considered as the more or less only driving force w.r.t. evolutionary progress, modern population genetics also considers the effects of genetic drift - especially for rather small populations (as it is certainly the case in Evolutionary Computation). Population genetics aims to describe the topology and temporal dynamics of genetic variation in natural populations with the goal to understand the evolutionary forces that act on populations.

Like Evolutionary Computation, population genetics also has an empirical as well as a theoretical component, and especially for scientists in the field of Evolutionary Computation, it should be a very fruitful approach to consider the latest developments of population genetics, which should be kept in mind as the bionic role-model for further developments. Therefore, we summarize some up to date considerations of population genetics which seem relevant for the development of new theoretical GA concepts.

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Concretely this paper aims to describe the effects of genetic drift, selection (selection pressure), and mutation from a population genetics as well as from an Evolutionary Computation inspired point of view and draws some essential interconnections. Especially the interpretation of the consequences of the Hardy-Weinberg Law w.r.t. the interplay between genetic drift and mutation and its effects in terms of global solution quality are considered in more detail. Summarizing we give a brief overview of the newly developed theoretical GA concepts ([1],[2]) and first concrete applications ([3],[11]).

2. SOME BASIC CONSIDERATIONS ABOUT THE GENERAL FUNCTIONING OF GENETIC ALGORITHMS

A very essential aspect in GA theory is the distinction between the problem-specific and the non-problem-specific components of a Genetic Algorithm.

The crossover- and mutation operator depend on the problem codification and therefore on the problem itself. The basic GA model and the corresponding theoretical background introduced by John Holland in the 1970s [6] based upon binary codification. Therefore, the area of application of GAs was quite limited in these days. Over the years plenty a lot of new problems have been attacked by Genetic Algorithms. Together with the new applications new codifications have been developed. As the basic genetic operators (crossover and mutation) depend on the codification of the problem, hundreds of new crossover and mutation operators have been developed by GA researchers in the last decades and it is still a very active field of research to develop new codifications and the corresponding operators respectively new operators for existing codifications.

Selection on the other hand is a totally problem independent mechanism following the same principles for all codifications and operators. In contrast to Evolution Strategies, GA selection is basically implemented as selection for reproduction also denoted as sexual selection or parent selection. This means that above average parents are selected in order to produce new individuals for the ongoing evolutionary process.

As crossover is able to combine attributes of individuals located in very different regions of the search space, GA-search scans the solution space in a much broader sense than algorithms based upon neighborhood search. Therefore, the problem of getting stuck in a local but not global solution is not that serious. So Genetic Algorithms are especially suited for hard and very multimodal problems of combinatorial optimization. But there is a different problem in the theory and application of Genetic Algorithms which is very similar to the situation of getting stuck in a local but not global solution even if the reasons are very different. This problem which will be considered in the following is called premature convergence in GA literature.

3. PREMATURE CONVERGENCE AND GENETIC DRIFT

Ideally speaking premature convergence occurs if the population of a Genetic Algorithm reaches such a suboptimal state that the genetic operators are no longer able to produce offspring that are able to outperform their parents [2].

This happens if the genetic information stored in the individuals of a population does not contain that genetic information which would be necessary in order to further improve the solution quality. Thus, in GA-research the topic of premature convergence is considered to be closely related to the loss of genetic variation in the entire population ([10],[12]).

In the following we will denote the genetic information of the global optimal solution as essential genetic information. If parts of this essential genetic information are missing premature convergence is already predetermined in some way. But what are the reasons for premature convergence, or in other words what are the reasons that this essential genetic information is not or no more available:

Firstly, one reason for this loss of essential genetic information may be that these alleles are simply not represented in the initial population of a Genetic Algorithm. Then, especially in the earlier phase of genetic search it frequently happens that essential genetic information is hidden in individuals with bad total fitness and is therefore eliminated due to selection. Furthermore, for the majority of GA applications it is absolutely not guaranteed that the applied crossover operators are able to create new children in a way that the newly evolving child contains exactly the genetic information of its own parents. If this is not guaranteed this fact represents a further reason for a genetic algorithm to loose essential genetic information and therefore cause premature convergence. The only measure in conventional GA-theory to counteract against this phenomenon is mutation and indeed – as will be shown in the experimental part of the paper – this works quite well and a lot of already lost essential genetic information can be recovered by mutation.

This paper aims to take a closer look at population genetics to identify the reasons for premature convergence more exactly in order to counteract against this essential problem of Genetic Algorithms more goal-oriented. Population genetics considers genetic drift as one of the main reasons for the loss of genetic variation in a population [5]. Basically genetic drift is the random drift of alleles in the entire population. Considering one single allele, genetic drift can cause one of the following three possibilities:

An allele may be either fixed in the population, it may get lost in the population, or it may converge to some equilibrium state. Considering the gene eye color as a very simplified example the fixing of the allele brown would mean that all individuals in a population are brown-eyed. On the other hand all other eye colors like blue or green would have disappeared in the entire population and the corresponding alleles are lost. If some specific eye color would converge to an equilibrium state of for example 0.2 the rest 0.8 genes of the population can have other alleles like blue or green.

For reasons of global optimization w.r.t. a static objective function in a GA it is desirable, that alleles of the global optimal solution are fixed in the population and that alleles which are definitely not part of a good solution, are eliminated.

4. SELECTION IN GENETIC ALGORITHMS VS. THE BASIC SELECTION MODEL OF POPULATION GENETICS

In contrast to the theory of Evolution Strategies, selection in Genetic Algorithms is implemented as selection for reproduction which is also denoted as sexual selection or parent selection. This means that above average parents are selected for reproduction. The most commonly used selection schemes in the theory of Genetic Algorithms are proportional selection, linear-rank selection, and tournament selection. The common feature of all these selection mechanisms of Genetic Algorithm theory is that selection takes place only before the reproduction process. This means that only the fitness values of the parents is considered but not the fitness values of the newly evolving offspring.

This represents a major difference to the selection model of population genetics which considers selection of parents rather as a side issue. The basic selection model of population genetics assumes random mating which means no parent selection. Selection happens after reproduction and is determined in the survival probability of the new offspring or in a different formulation: Is the new offspring fit enough to reach the age of producing children and inherit its own genetic information?

We think that this aspect of offspring selection which is not considered in basic Genetic Algorithm research is very important especially for Genetic Algorithms where bad crossover results very often cause a loss of essential genetic information. The new selection model which we have designed for Genetic Algorithms adapts those considerations for the global optimization task of a Genetic Algorithm in a non problem specific way so that it is applicable to all problems treated by Genetic Algorithms and also Genetic Programming.

5. NEW ALGORITHMIC CONCEPTS

A very essential question concerning the general performance of a GA is, whether or not good parents are able to produce children of comparable or even better fitness (the building block hypothesis implicitly relies on this). In natural evolution, this is almost always true. For Genetic Algorithms this property is not so easy to guarantee. The disillusioning fact is that the user has to take care of an appropriate coding in order to make this fundamental property hold.

In order to overcome this strong requirement we have developed an advanced selection mechanism [2] which is based on the idea to consider not only the fitness of the parents, in order to produce a child for the ongoing evolutionary process:

The first selection step of our new selection model operates in exactly the same way as selection in Genetic Algorithms. Parents are selected for reproduction by some selection strategy in order to produce new offspring. In a normal GA the newly generated offspring would be added to the next generation automatically and would therefore have the possibility to inherit its genetic information.

What the new selection model additionally does is to ask if the reproduction of the two parents was really able to generate an offspring that is worth to add its genetic information to the gene pool of the ongoing evolutionary process. The way we have implemented this feature is to ask whether or not the new offspring is able to outperform the fitness value of its own parents. If that is the case and the new offspring is better than its own parents, the new offspring is definitely accepted as a member of the next generation. If the new offspring is not successful it is added to the pool of solution candidates which were not able to outperform their own parents.

This process is repeated until a predefined ratio of the next generation is filled up with successful offspring. The rest of the next population is then simply filled up with individuals from the pool. The technical details concerning the realization and the parameters of these concepts which allow a self-adaptive steering of selection pressure can be found in [2].

Within this model it becomes possible to state selection pressure in a very natural way that is quite similar to the notation of selection pressure in Evolution Strategies. Concretely, we define the actual selection pressure as the ratio of individuals that had to be generated in order to fulfill the success ratio to the population size. For example, if we work with a population size of say 100 and it would be necessary to generate 1000 individuals in order to fulfill the success ratio, the actual selection pressure would have a value of 10.

Via these means we are already in a position to attack one of the reasons for premature convergence. Furthermore, this strategy has proven to act as a precise mechanism for self-adaptive selection pressure steering, which is of major importance in the migration phases of parallel evolutionary algorithms. All these new generic concepts are very promisingly combined in the parallel SASEGASA-algorithm ([1],[2]).

6. EXPERIMENTS

The experimental discussions of this paper aim to point out some characteristical features of Genetic Algorithms in general as well as some main properties of the newly discussed methods. The results are mainly shown on the basis of diagrams and give only a brief description of introduced operators, parameter settings, and test environments. For a more detailed experimental discussion the interested reader is referred to [1] and [2].

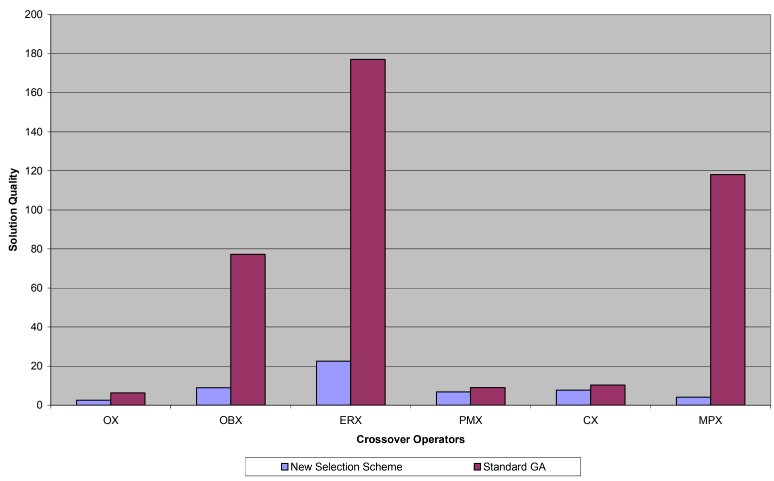

Figure 1. Performance of different crossover operators for the ch130 benchmark TSP.

The first experiments (Figure 1) show the improvements which are achievable when using the new selection principle for the ch130 TSP benchmark problem taken from the TSPLib [9]. The bar chart shows the average results of ten different test runs of a standard GA (using standard parameter settings as proposed in [7] or [8], i.e. population size of 100, mutation rate of 5%, generational replacement, proportional selection) against the results achieved with the new selection concept for a couple of standard crossover operators for the path representation of a TSP. As it can be seen, especially that operators that perform rather weak in case of the standard GA were able to achieve results in the region of the best operators when being equipped with the new selection mechanism. Due to the enhanced selection concepts weaker operators are therefore still able to produce high-quality results as long as the operator is able to produce advantageous crossings at least sometimes.

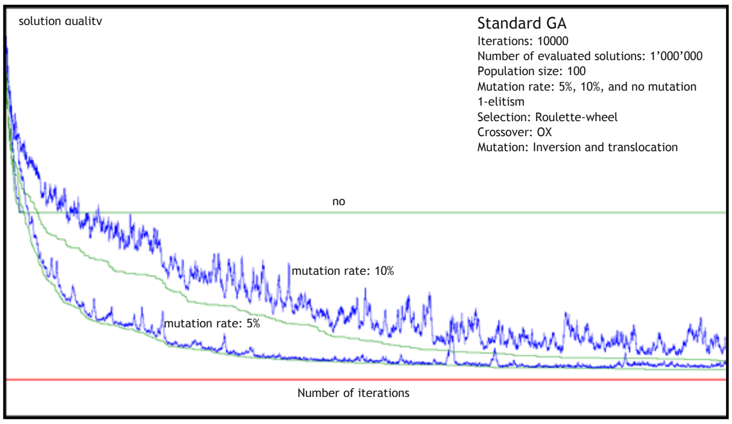

Figure 2. The effect of mutation in case of a standard GA for the ch130 benchmark TSP.

The results displayed in Figure 2 show the effect of mutation for reintroducing already lost genetic information. The horizontal line of the diagram shows the number of iterations and the vertical line stands for the solution quality. The bottom line indicates the global optimal solution which is known for this benchmark test case.

The three curves of the diagram show the performance of a Genetic Algorithm with no mutation, with a typical value of 5% mutation as well as a rather high mutation rate of 10%. For each of the three curves the lower line stands for the best solution of the actual population and the upper line shows the average fitness value of the population members.

The results with no mutation are extremely weak and the quality curve stagnates very soon and far away from the global optimum. The best and average solution quality is the same and no further evolutionary process is possible – premature convergence has occurred. As already stated before, mutation is the essential feature of standard GAs in order to avoid premature convergence. But also a rather high mutation rate of 10% produces results which are not very satisfying and indeed the best results are achieved with a mutation rate which is very typical for GA applications – namely a mutation rate of 5%

This indicates that the effect of mutation is very strong and also very sensible for avoiding premature convergence. But let us take a closer look at the distribution of essential genetic information in the population.

The next curve (Figure 3, left chart) shows the quality curve and the distribution of essential genetic information (the 130 edges of the optimal tour) for a GA with the enhanced selection model with 5% mutation which was able to achieve the best results in case of a standard GA.

When applying the GA with the new selection principle to the same benchmark test case one can see that the global optimal solution is detected in only about 100 iterations. Nevertheless, the computational effort is comparable to the standard GA as much more individuals have to be evaluated at each iteration step due to the higher selection pressure.

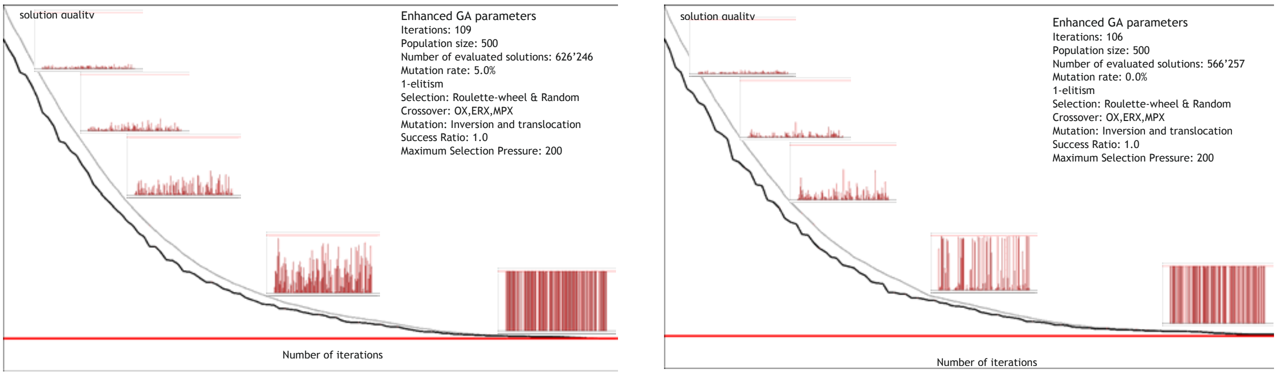

Figure 3. The distribution of essential genetic information when using the enhanced selection concept with and without mutation considering the ch130 benchmark TSP.

Considering the distribution of essential alleles we see a totally different situation. Almost no essential alleles get lost but it also takes longer to fix some of the essential genetic information. The ratio of the essential alleles slowly increases in order to end up with a final population that contains almost all pieces of essential genetic information and therefore achieving a very good solution.

This indicates that the essential alleles are preserved much more effectively and the influence of mutation should be much less. But is this really the case? In order to answer this question, let us consider the same example with the same settings – only without mutation.

And indeed the assumption holds and also without mutation (Figure 3, right chart) the algorithm finds a solution which is very close to the global optimum. The essential alleles interfuse the population more and more and almost all of them are members of the final population. Reconsidering the standard GA without mutation the algorithm was prematurely converging very soon with a very bad total quality.

CONCLUSION

Possibly the most important feature of the newly introduced concepts is that the achievable solution quality can be improved in a non-problem specific manner so that it can be applied to all areas of application for which the theory of Genetic Algorithms and Genetic Programming provides suitable operators. Further aspects worth mentioning concern the robustness and self-adaptiveness of the population genetics inspired measures: Basically weak operators become powerful and the selection pressure is steered self-adaptively in a way that the amount of selection pressure actually applied is that high that further progress of evolutionary search can be achieved.

Nevertheless the newly developed selection technique is not problem specific and as we have already found out for several other problems of combinatorial optimization like timetabling or scheduling problems the basic characteristics are the same as shown here for the TSP. Even under very different kinds of codifications like the optimization of n-dimensional real-valued test functions [2] and even under codifications for Genetic

Programming applications [11] the new concepts show the same potential and improvements in global solution quality as shown here for the TSP.

Possible future research topics in that area are certainly to open new areas of application due to the increased robustness and also more theoretical topics like the analysis of various aspects of population genetics and their interaction with concrete applications of Evolutionary Computation. Especially for the theory of parallel Genetic Algorithms the interactions between genetic drift and migration should be a very fruitful field of research.

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