ON EFFECTS OF FROZEN EVOLUTION IN OPTIMIZATION TASKS

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Abstract: Many optimization algorithms are inspired by evolutionary theories. In this article selected evolutionary theories and their technical implementations are chronologically listed. Frozen evolution is one of the latest theories published firstly in 1998. Despite of all current theories it assumes that species can be found in one of two possible states – elastic (frozen) and plastic. The possible changes in species caused by evolutionary principles strongly differ depending on this state. In my experiments I try to find out whether such behavior, as described in frozen evolution, can be observed under artificial conditions. My experiments are based on solving the problem of symbolic regression by analytical programming.

Keywords: Frozen Evolution, Frozen plasticity, Analytical programing, Symbolic regression

1 INTRODUCTION

There are many algorithms inspired by nature, such as artificial neural networks, genetic algorithms(GA), simulated annealing, ant colony etc. Genetic algorithms inspired by neo-darwinism theory are successfully used for solving various technical problems.

Still new theories arise to explain some problematic aspects of their predecessors. Darwinism and Mendelian genetics were used as base of neo-darwinism. Richard Dawkins introduced Selfish Gene theory. This theory is more gene-centered and explains altruistic behavior. Czech Prof. Jaroslav Flegr proposed new theory named Frozen Evolution in 1998. It is inspired by Selfish Gene theory but it changes meaning of many basic evolutionary processes (e.g. sexual reproduction) and the way of emergence of new species.

GA are based on neo-darwinism. Selfish gene algorithms and Memetic algorithms are based on selfish gene theory. Frozen Evolution hasn't been used for any technical problems so far. It is challenging to find out whether such behaviour, as described in frozen evolution, may be observed in technical implementations based on older theories. If so, some changes in evolutionary-based optimization algorithms may be suggested following the ideas of frozen evolution.

Theory	Algorithm
Lamarckian inheritance	Lamarckian Evolution [8]
Darwinism Neodarwinism	Genetic Algorithms [5]
Selfish gene	Selfish gene algorithms [2] and Memetic [7]
Frozen evolution	None

Table 1: Evolutionary theories and Evolutionary algorithms

2 IMPLEMENTATIONS OF EVOLUTION THEORIES

Biological evolution adjusts structure of an individual (chromosome length, number of chromosomes) as well as parameters of this structure (concrete genes in given structure). Traditional implementation of GA is used for parameters setup only (genes selection). On the other hand Genetic programing and analytical programing could be used to develop individual's structure. Short comparison of Evolutionary algorithms is in table 2.

Algorithm	Optimize
Genetic algoritms [5]	Parameters
Simulated annealing [1]	Parameters
Genetic programing [6]	Structure
Grammatical evolution [9]	Structure
Analytical programming [10]	Parameters + Structure

Table 2: Comparsion of evolutionary algoritms

2.1 Frozen evolution

Theory of frozen evolution (FE)[3] suggests mechanism of the origin of adaptive traits in sexual organisms. FE suggests that sexual species can evolve only when members of populations are genetically uniform. This could occur for example in situation when few members of species arrive on island far away from mainland. After short time expansion, polymorphism appears as result of frequency-dependent selection and sexual reproduction starts working against changes. This plastic phase of evolution corresponds to 1-2%[4] of species existence before becoming extinct.

2.2 Analytical programing

Analytical programing (AP)[10] is method of symbolic regression. Advantage of AP compared to Genetic Programing (GP) and Grammatical Evolution (GE) is that it can use arbitrary type of evolutionary algorithm like simulated annealing, differential evolution or genetic algorithm. AP is based on set of functions, operators and terminals.

All this objects are organized in a set called general functional set (GFS). GFS consists of subsets. Subsets differ from each other by the number of parameters which their objects need. Genes values are used to select objects from GFS.

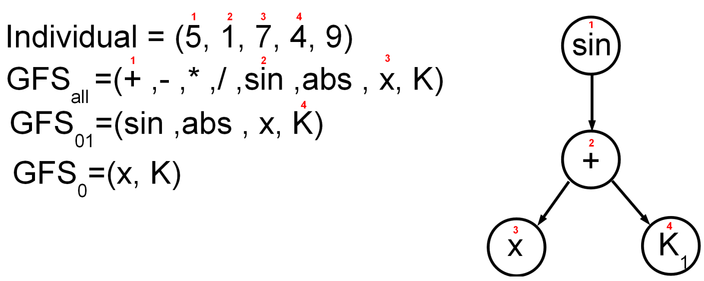

Figure 1: Analytical programing.

There are several variants of AP that differ in method of constant handling. When plain AP is used constants are generated directly from gene value. This approach is fully functional but however of constants is slow process because only mutations on the right parts of chromosome lead to change in constant. Therefore majority of mutations and crossovers lead to different structure of new individual.

AP_{meta} is improved variant of plain AP. In first phase general constants K_1, K_2 etc. are used instead of particular constant. These general constants are fitted with specific values using GA in the second phase. AP_{meta} is quite time-consuming, so second phase was replaced with method of nonlinear fitting in method called AP_{nf}

3 EXPERIMENT SETUP

In this paper AP_{nf} is used in combination with GA. Each individual is represented with integer array of fixed size. Tree types of generic operators are used. Mutation operator alter selected gene with random integer. Multi-point technique is used as crossover operator. Weighted roulette is used as selection operator. Fitness is calculated as multiplicative inverse value of area between original function and function defined by each individual. Used parameters are in table 3. Simple gradient descend was used for constant fitting. Following objects are used to create individuals:

- GFS_2 +, -, * /
- GFS_1 sin, abs
- GFS_0 x, k

Population size	500
Genom size	25
Maximum generations	500
Mutation probability	0.05
Crossover probability	0.05

Table 3: Parameters of used GA

3.1 EXPECTATIONS ACCORDING TO FROZEN EVOLUTION

According to FE major changes are possible only in short time (1-2% [4] of the duration of the species) when species is in plastic state, which means that structure of individual can change. Only minor changes are possible when species is in frozen state. Based on it, it's expected than fitness will change suddenly when new species is created and subsequently minor changes will appear as species pass into frozen state.

3.2 RESULTS

Solving of symbolic regression of polynom was implemented. In figure 3 we can see fitness function of best individual in every generation. Tested polynom is in equation (1).

$$y = 2x^5 + 4x^3 \tag{1}$$

Graph shows that fitness functions often changes in large steps followed by small adjustments and long periods without any changes. Sometimes there appears single individual with better fitness than in previous generation, but disappears in next one. From 500 generations 80 (16%) exhibit fitness change greater than 1% (Highest fitness achieved in generation T over highest achieved fitness in generation T-1).

Resulting individuals are often more complicated than necessary. For example the individual in figure 2 contain an expression $sin((sin(abs(64.697255))+66.160679))$ which could be replaced with single constant.

$$((((((x*x)-sin((sin(abs(64.697255))+66.160679)))*(x*x))+1.448234)*x)*2.096112)$$

Figure 2: Example of individual

Main aim of this work was to find out if behavior described in FE could be observed under artificial conditions, therefore comparison of different optimization methods and their settings wasn't carried out.

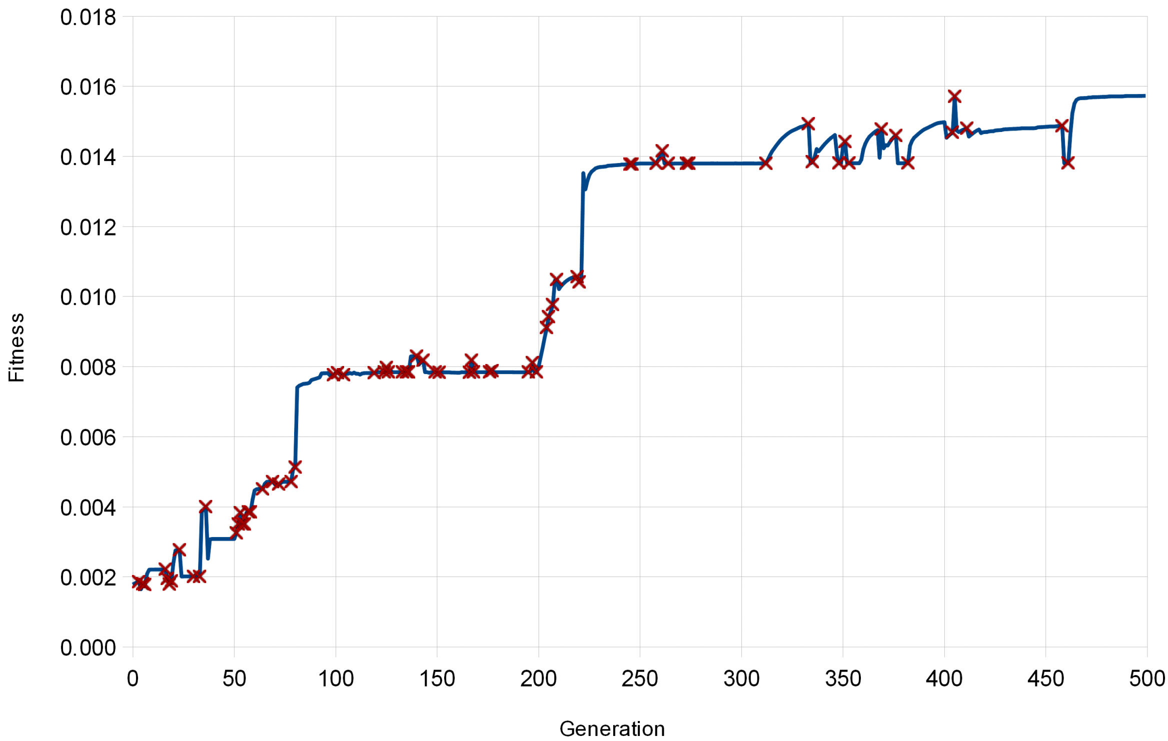

Figure 3: Fitness of best individual; crosses are used to mark creation of new structure; the steps in graph may be viewed as proof of concept that assumptions are valid

4 DISCUSION

In the graph in figure 3 the dependency between fitness function of the best individual and time in generations is shown. The shape of the graph fulfills the frozen evolution assumptions. Significant changes in fitness occur in steps rather than continuously. Theoretically the significant changes should occur in 2% of generations, in the presented experiments they occur more frequently, approximately in 16% of generations. Some of the best individuals did not exceed one generation. Based on the frozen evolution such situation arises when the new individual differs too strongly from the others and the children produced by the sexual reproduction of this different individual with some average one brings low quality offspring into being. In some cases the structures of best solutions contain useless or even unused substructures. Such phenomenon has its biological equivalent e.g. in blindworms, which belong among lizards despite of their similarity to snakes. It doesn't have any visible limbs but its skeleton has vestigial limbs.

5 CONCLUSION

In the results of the experiment it is possible to observe behavior that can be described by the theory of frozen evolution. The results of the experiment are not sufficient to draw any conclusions due to simplifications in the experiment, but indicate relevance of further study of this topic. In the future work I intend to focus on effects of population size and migration.

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