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Extinction Event Concepts for the Evolutionary Algorithms

***Abstract**. The main goal of this present paper is to propose a structure for a tool helping to determine how algorithm would react in a real live application, by checking it's adaptive capabilities in an extreme situation. Also a different idea of an additional genetic operator is being presented. As Genetic Algorithms are directly inspired by evolution, extinction events, which are elementary in our planet's development history, became a foundation for those concepts.*

***Streszczenie.** Celem autorów jest zaprezentowanie narzędzia, które pomoże określić możliwości adaptacyjne algorytmu ewolucyjnego poprzez sprawdzenie jego możliwości w sytuacji ekstremum. Oprócz tego, został przedstawiony pomysł dodatkowego operatora genetycznego. Obie koncepcje powstały w oparciu o zjawisko wielkiego wymierania w przyrodzie, które to stanowi ważny element w rozwoju życia na Ziemi. (**Możliwości adaptacyjne algorytmu ewolucyjnego przy sprawdzeniu jego stanu w sytuacji ekstremum**)*

Keywords: Evolutionary Algorithms, Modification, Genetic, Operator, Extinction, Event
Słowa kluczowe: Algorytmy Ewolucyjne, Modyfikacja, Operator Genetyczny, Wielkie Wymieranie

Introduction

Genetic Algorithms (GA) are in their foundation evolution inspired computer programs. The terms offspring, mutation, genetic operators and others are being used to describe pieces of coding that try to resemble similar functions that their counterparts take in the biological development of live on Earth. However if one looks into this process, one will discover that the gradual changes aren't steady. Every once in a while we come across to an event that basically reboots the live on earth making the once nurturing environments inhabitable for populations that were previously best adapted.

The authors of this paper inspired by such events have come to a conclusion that the very idea could suit the Genetic Algorithms greatly in terms of analyzing the quality of the algorithm when faced upon a difficult and dynamic challenge (path planning in an unsteady environment[1], predicting stock market behavior, weather, etc). We propose a unified way of grading such algorithms so one can judge its performance in comparison to a different algorithm, or even the same program run under different parameters. This way we can easily grade on how the GA is reacting to drastic changes and if it will manage to adapt to new environment quickly enough (if that is even possible).

Second idea with this backwards engineering process is a proposal of a new genetic operator that is trying to mimic the process of wiping the diversity of live and giving chance to less fitted organisms. Extinction event as a testing procedure is based on the fact that due to extreme changes in the environment, the once well adapted creatures are put into a certain-death conditions. This can be translated into a noticeable change of the value of the fitness function. If we want to treat extinction event as a genetic operator we have to assume that the ultimate evolution goal for live is steady – to develop an organism that would be efficiently able to adapt to any environment and be strong enough to eliminate any other organism, becoming the ultimate creation. This way we can adapt mass extinction concept without changing the fitness function and research if the mechanism has the same improvement capabilities as the original process. We need to remember that it took five great extinction events before the authors of this paper were advanced enough to create this idea.

Genetic Algorithms

Genetic Algorithms (GA) are global optimization methods that scale well to higher dimension problems[2]. The idea behind all evolutionary techniques is roughly the same. Given a population of individuals the environmental pressure causes natural selection – a survival of the fittest – which causes a rise in the fitness of the population. Given a quality function to be maximized we can randomly create a set of candidate solutions – elements of the function's domain and apply the quality function as an abstract fitness measure. Based on this fitness, some of the better candidates are chosen to seed the next generation by applying crossover and/or mutation operators to them.

Crossover is an operator applied to two or more parent solutions which results in one or more new children solutions. Mutation is applied to one solution and results in one new solution. Executing crossover and mutation leads to a set of new candidate solutions, creating w new generation that overrides the old one.

This process can be iterated until a solution with sufficient quality is found or a previously set computational limit is reached. In the process there are two fundamental forces that form the basis of evolutionary systems:
- Genetic operators (crossover and mutation) create the necessary diversity and thereby facilitate novelty, while
- Selection acts as a force pushing quality.

GA can easily be adjusted to the problem at hand. Almost every aspect of the algorithm can be changed and customized. On the other hand, even though a lot of research has been done on which GA is best suited for a given problem, this question has not been answered satisfactorily. While the standard parameters usually provide reasonably good results, different configurations may perform better. Furthermore, premature convergence to a local extreme may result from adverse configuration and not yield (a point near) the global extreme [1].

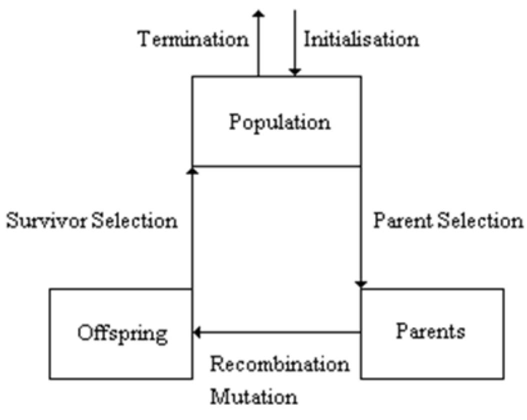

Fig.1. GA basic model

Extinction Events

An extinction event (also known as: mass extinction; extinction-level event (ELE), or biotic crisis) is a drastic decrease in the diversity of macroscopic life. They occur when the rate of extinction increases with respect to the rate of speciation[3].

Over 99% of documented species are now extinct,[4] but extinction occurs at an uneven rate. Based on the fossils, the background rate of extinctions on Earth is about two to five taxonomic families of marine invertebrates and vertebrates every million years. Marine fossils are mostly used to measure extinction rates because of their superior fossil record and stratigraphic range compared to land organisms.

Since life began on Earth, several major mass extinctions have significantly exceeded the background extinction rate. The researches define the 5 greatest events in the following order: Ordovician-Silurian mass extinction, Late Devonian mass extinction, Permian mass extinction, Triassic-Jurassic mass extinction and Cretaceous-Tertiary mass extinction.

Mass extinctions have a tendency to accelerate the evolution of life on Earth. When dominance of particular ecological niches passes from one group of organisms to another, it is rarely because the new dominant group is "superior" to the old and usually because an extinction event eliminates the old dominant group and makes way for the new one.[5][6]

For example mammaliformes ("almost mammals") and then mammals existed throughout the reign of the dinosaurs, but could not compete for the large terrestrial vertebrate niches which dinosaurs monopolized. The end-Cretaceous mass extinction removed the non-avian dinosaurs and made it possible for mammals to expand into the large terrestrial vertebrate niches. Ironically, the dinosaurs themselves had been beneficiaries of a previous mass extinction, the end-Triassic, which eliminated most of their chief rivals, the crurotarsans.

Another point of view put forward in the Escalation hypothesis predicts that species in ecological niches with more organism-to-organism conflict will be less likely to survive extinctions. This is because the very traits that keep a species numerous and viable under fairly static conditions become a burden once population levels fall among competing organisms during the dynamics of an extinction event.

The mechanism of such an event is always based on an extreme and most often sudden change of environment's conditions. This can happen due to eruption of gigantic

Extinction Events Mechanism in GA

As it was already mentioned in chapter I, the authors find the Extinction Event a great challenge for the evolution and live itself. Thus, if a similar mechanism was applied to a Genetic Algorithm one could easily find out the strength of it – so not only its potential to bring the best found solution for a specified problem, but also be able to efficiently provide a new local optimum in case of a drastic fitness function change. The tool described in this paper is meant to provide a unified testing measure that will tell on how well will the Algorithm react in a dynamic environment. Knowing this behaviour is essential before an algorithm can be applied to a real time control task.

To implement a proper testing procedure, one has to simply change the fitness function of the genetic algorithm when it has completed the generation or was close enough with doing so. The change has to be designed to be drastic in order to make sure that the initial best found solution is nowhere near the new optimum, that has to be found.

As an example, one can imagine a situation on a stock market where, based on current data, all points out to the fact that it's best to sell stocks and when the algorithm has a good plan to do this throughout the day, a news appears turning the market upside down and the algorithm has to instantly device a different plan best suited to the updated criteria.

Another example would be a marine vessel path planning optimization task in which a ship has to reach one of two docs with very low fuel reserves in a very crowded area. In this instance an extinction event would mean that as when the ship is half way to dock, the navigator is being informed that the dock is closed and a course to the other marina has to be chosen. As the vessel is low on fuel, a new path has to be planned and it has to meet all the safety restrictions, consider low fuel available and still allow passage between multiple other ships.

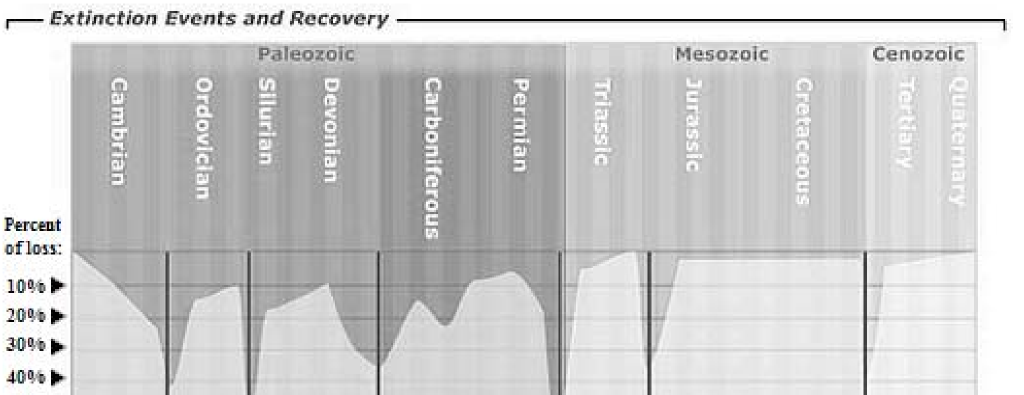

Fig.2. An example of the figure inserted into the text

One could argue that it would be best simply to start the algorithm again and perform a new generation, however that would mean that time would have to be lost on new data entry that could be crucial in such drastic circumstances. However, one needs to remember that we operate under assumption that the efficiency of Genetic Algorithms is based on it being approximation of actual evolutionary mechanisms. Thus, when we observe the process of changes to live on Earth we discover that it would take extremely longer to develop new live from plain amino acids after wiping the entire previous life form population, then it takes to revive a nurturing environment from a few surviving species.

Implementation

To apply this, one has to first measure the mean time (number of generations) which takes the GA to produce an acceptable solution. Most of the algorithms are stable and predictable enough to put confidence in the average value of this parameter (*Mgn* – Mean Generation number). This will be a reference point for measurements taken for the Extinction Event Mechanism. We will also need a second parameter *Pen* – Post Extinction Number: the number of generations needed to achieve a new best found solution, after the an update fitness function in being activated. If the Pen is equal to *Mgn* than that means that algorithm is not really very flexible as it needs to basically repeat the whole process (start the algorithm from the 1st random generation). However one will most often encounter a situation that the solutions (members of the population) are so concentrated around a niche solution, that it will be impossible to leave it in efforts to deliver a new solution, adjusted to updated fitness requirements. Therefore one needs to take two solutions under consideration:

a) To implement the Moment of Extinction (*Moe*) at the generation equal to 70-80% of *Mgn* – when the solutions will be diversified enough to find a solution for a completely new fitness. However then it has to pointed out in the testing sheet.

b) To adjust genetic operators to introduce mutations strong enough to trigger rapid spread of new solutions.

c) Try to emulate actual population behaviour during a great extinction by eliminating the best rated members of the population and replacing them with newly generated random members (that would simulate organisms that did not fit before). This solution makes only sense when one of the original population contains a solution even remotely close to a new solution – otherwise is very similar to actually running the algorithm for the 2nd time.

d) Introduce fitness function scaling [8] to better identify differences in solutions' quality

When everything is in place, we have to run the evolution with extinction scenario at least the same number of times as one did when determining the value of *Mgn* so that a reliable value for Pen can be calculated.

Having Both parameters one can finally calculate the value for the *Drp* – Dynamic reaction parameter.

$$D_{rp} = \frac{P_{en}}{M_{gn}}$$

which will provide a parameter, that would describe the ultimate flexibility of the tested GA and that would give one a very good idea on its performance in a rapidly changing environment

Extinction Event As A Genetic Operator

The second possible approach for mass extinction events that authors found is to implement it as a genetic operator that tries to recreate the evolution in a way similar to what we can observe on Figure 2. In essence our goal is to periodically wipe major part of the population and replace it with random, new members. Those new solutions simulate organisms that were previously poorly adapted but received new chance from evolution. As mentioned previously, in this approach we assume that the ultimate goal is a constant one, however the conditions in which the goal has to be achieved change drastically, thus causing the change in population's diversity.

As many tools in GA, mass extinction genetic operator can be designed in a very flexible way:

- extinction points can be either fixed, occur every nth generation or happen absolutely at random.
- extension can occur only under specific conditions (i.e. no major solution improvement after several generations when the Mgn is far from being achieved)
- extinction can be set to take a specific portion of the population, either at random or with some custom approach (50% best, or 50% worst solutions are being replaced).

Further research will try to determine which one of those approaches will be the recommended one.

Initial Research

For the first tests of the concept a graph search evolutionary algorithm was used [8]. The goal of the algorithm is to find a search strategy that uses a minimal number of agents that ensures capture of a fugitive on a graph. The fugitive has unbound speed, is invisible and knows the agents' plan of finding him (He will be found in the last possible location). The pursuer can jump between any two nodes of the graph freely. It was concluded[9] that the approach to solve this problem using the evolutionary method was not a successful one. Thus it could provide enough testing material to determine if the Extinction Event comparison will correctly identify it lack of ability to quickly adjust to the changing conditions.

Normally, the algorithm is set to find the lowest possible number of agents necessary to find an escapee in the graph. However, to embed the Extinction Event mechanism, the ability to switch fitness function to favour solutions with the greatest number of agents necessary to solve the problem was applied. Two test cases were selected – a ladder graph and a square grid graph with a 1000 edges each [9].

For the simulations the mutation chance was set to 25%, population to 40 members and the generations number to 600. The tests were performed using the composition crossover method [9].

Table 1. The results for the Ladder test case

Iteration	Mgn/Solution	Final Solution Generation/Final Solution	Pen
1	110/474	461/519	351
2	176/472	288/521	178
3	223/509	376/520	266
4	167/474	215/524	105
5	80/470	472/518	362
6	134/467	577/521	467
7	69/469	261/520	151
8	87/487	392/522	282
9	50/471	257/572	147
10	25/472	548/522	438
Average	110/-	-	274,7
Drp	**2.5**		

Table 1. The results for the Square Grid test case

Iteration	Mgn/Solution	Final Solution Generation/Final Solution	Pen
1	246/473	543/521	413
2	49/477	492/519	352
3	165/477	320/519	180
4	25/472	372/515	232
5	215/471	479/523	359
6	41/468	404/519	264
7	35/474	232/518	192
8	29/475	390/518	250
9	139/475	175/520	35
10	134/471	456/523	316
Average	140/-	-	259,3
Drp	**2.5**		

Tables 1 and 2 illustrate the process of determining the Drp parameter. After Mgn was set to the level of 110 populations for the ladder case and 140 populations for the square grid case, the Moe was applied at the 80% of those values. The Final Solution Generation/Final solution column shows how long did it take to calculate first the solution for the original fitness function and then the final solution with the modified fitness function in place.

As one can see, algorithm is of a poor quality (which is consistent with the original research) as both approaches produce the Drp parameter high above one. However if we were trying to determine which of the cases analysed were better and more adaptive, one can clearly see that Square Grids performed better. Thus the evaluation of the algorithm in terms of solving quite different problems is independent from the number of generations needed to find the solution. Thanks to the current approach the complexity of the problem is also included in the evaluation.

The Extinction event genetic operator was also tested with the graph search algorithm, however its impact was negligible and will not be presented in this paper. Considering that the genetic operators which were implanted to the algorithm before did not manage to provide acceptable solutions, it is no surprise that additional algorithm's modifications did not manage to improve their works. Further research will focus on implementing the Extinction event genetic operator on various evolutionary algorithms in order to determine its potential to improve the results.

Initial Research

As many of the tools available for Genetic Algorithms, both Extinction Event interpretations won't be useful for every program. However for those who need to compare their scripts in a wide spectrum of different algorithms (Perhaps solving the same problem) or test different configuration for their script, the presented mechanism is ideal to check how adaptive it is, which is obviously a parameter describing Algorithm's quality. It provides a reliable tool to compare programs working under same principal, but facing different objectives.

Also a proposal of a new genetic operator may be something that will greatly improve a program, that would otherwise not be able to provide as good a solution, as with the Extinction Event genetic operator implemented.

Further research will concentrate on implementing presented ideas on a wide range of evolutionary algorithms. This will allow to devise a fixed testing procedure and find the recommended settings for the genetic operator.

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