

Computational Intelligence for Optimization

Project Report



Source: <https://marketingtechnews.net/>

Diana Furtado (m20200590@novaims.unl.pt)
Eliane Zanlorense (m20190802@novaims.unl.pt)
Hiromi Nakashima (m20201025@novaims.unl.pt)

1. INTRODUCTION

In this project we were challenged to apply our Genetic Algorithm (GA) knowledge to solve an optimization problem. The project chosen was to generate an image based on the computer vision techniques.

The project was developed based on the image processing presented in the following process: <https://chriscummins.cc/s/genetics/>.

All the code, dataset and report can be accessed through the following Github repository link: <https://github.com/elianezanlorense/CIFO>

The present report intends to go through the choices made on the implementation of the GA, the parameters tested and their relevance in the outcome and which combination we considered to be the most suitable one. We finalize this report with an overview of the next steps and chances for improvement.

2. IMAGE REPRODUCTION

2.1. Image to Chromosome

The challenge of image reproduction is to represent the image in the GA since images are made of pixels and have two or more dimensions. With this in mind, we started by stacking all the rows of the image matrix into a single 1D vector. In the present project, the image was encoded to optimize the image process.

2.2. Initialization

The following step of the GA image reproduction was to generate a group of random chromosomes to represent the “initial” image. This image is a random mix of pixels in which the GA works to improve it until it reaches the target image.

2.3. Evaluation Solution

The solution reached for this problem was to create a group of chromosomes representing an image. In order to find the best solutions, a fitness function based on the approximation of the generated chromosome and the target image was applied. However, the challenge was that the function must compare improvements with the neighborhood, since the offspring is generated by the best parents of the last generation.

Due to this, the best parent was chosen by the best fitness which means the highest value from fitness function, or the lowest difference between the final chromosome and the target chromosome.

2.4. Crossover

Crossover consists in the change of one or a determined number of characteristics (genes) traded from the parents with the offspring. The goal with this methodology is to have the offspring receiving the best gene from the parents and to improve the evolution. Even in the case where the offspring are not better than the previous generation, the GA will keep the parents to prevent worse solutions to move forward.

2.5. Mutation

The mutation is used to provide for the opportunity of exploration of the search space and guarantees

evolution even when the crossover returns a bad solution. Basically, the mutation randomly changes the values of genes and provides a new offspring with the characteristics of the parents and the evolution of a mutation. Mutation is said to be essential to the GA convergence, while crossover is not.

Mutation is the part of the GA which is related to the “exploration” of the search space. It has been observed that mutation is essential to the convergence of the GA while crossover is not.

3. Test and Analysis

The parent selection is a key step of a GA since this is the process of selecting parents which mate and recombine to create offspring for the next generation. For this reason we have performed different combinations of parameters to understand their impact and the differences in the final result.

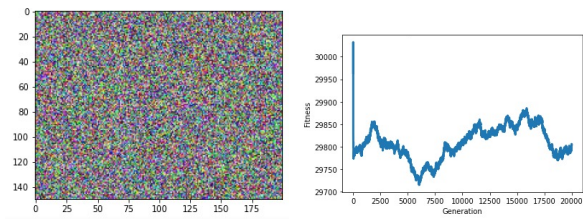
Nine different tests were performed, with an orange image and a bird image, the latter being more colourful. For those tests we kept the single point crossover, but with different parent selection methods (Random, Tournament, Roulette Wheel Selection, Scramble and Steady-State Selection) and mutation types (adaptive and random), to achieve the best result. The other feature that varies between tests is the image colour.

We performed the first test with 20.000 generations, however we then increased it to 100.000 generations since we realised that a lower probability of mutation with a higher number of generations was a stronger combination.

Below we present the parameters and results from each of these tests.

3.1. Orange

3.1.1. Random Selection - i=20K

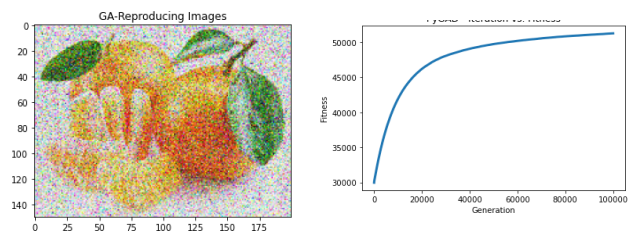


Mutation: Adaptive - Prob: 1%

Crossover: Single point

Best Fitness: 29853.9

3.1.2. Steady-State Selection - i=100K



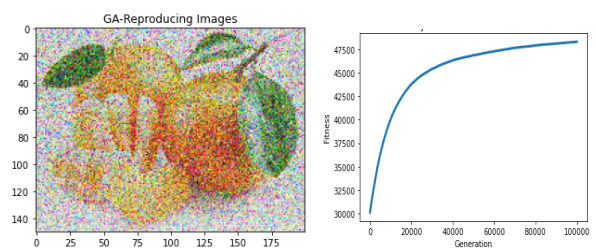
Mutation: Random - Prob: 1%

Crossover= Single

Parents mating 4

Best Fitness: 50772.6

3.1.3. Random Selection - i=100K



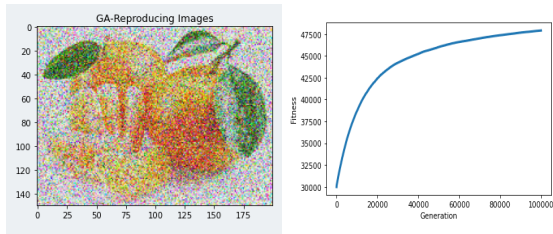
Mutation: Random - Prob: 1%

Crossover= Single

Parents mating 12

Best Fitness: 48275.1

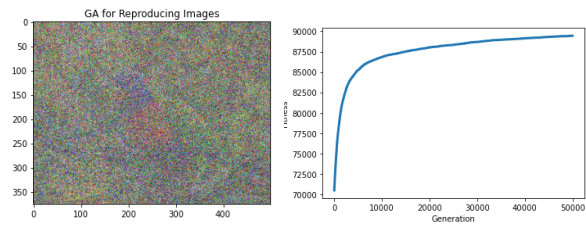
3.1.4. Tournament Selection - i=100K



Mutation: Random - Prob: 1%
Crossover= Single
Parents mating 12
Best Fitness:47903.5

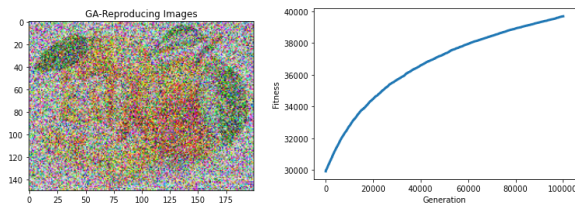
3.2. Bird

3.2.1. Random Selection



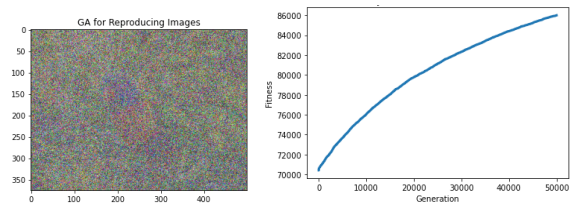
Mutation: Random - Prob: 10%
Crossover= Single
In=50000
Best Fitness:89448.3

3.1.5. Roulette Wheel Selection - i=100K



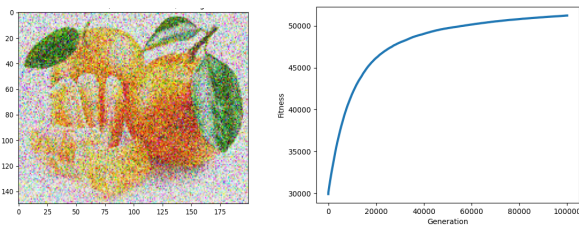
Mutation: Random - Prob: 1%
Crossover= Single
Parents mating 4
Best Fitness: 39683.5

3.2.2. Random Selection



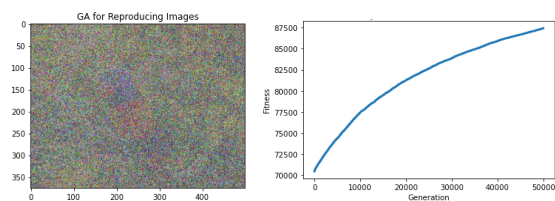
Mutation: Random - Prob: 1%
Crossover= Single
In=50000
Parents mating 4
Best Fitness:86005,1

3.1.6. Scramble - i=100K



Mutation: Random - Prob: 1%
Crossover= Single - Prob: 75%
Parents mating 4
Best Fitness:50903.5

3.2.3. Random Selection



Mutation: Random - Prob: 1%
Crossover= Single
In=50000
Best Fitness:87412.3
Parents mating 12

4. CONCLUSION

We opted for not performing elitism because we opted for applying random initializations, meaning it is not ensured that the first iteration will have enough quality to be taken forward. Given this, we believe it would make sense to apply elitism on image recognition, not in image reproduction.

The quality of the outcomes is measured by the best fitness, which is computed by the sum of the differences between the chromosomes of the reproduced image and the initial image.

A summary of the outcomes is shown in the following table:

Tests	Image	Parent selection	Mutation	Crossover	Iterations	Parents mating	Best fitness
1	Orange	Random	Random (1% Prob)	Single point	20,000	-	29853.9
2	Orange	SSS	Random (1% Prob)	Single point	100,000	4	50772.6
3	Orange	Random	Random (1% Prob)	Single point	100,000	12	48275.1
4	Orange	Tournament	Random (1% Prob)	Single point	100,000	12	47903.5
5	Orange	RWS	Random (1% Prob)	Single point	100,000	4	39683.5
6	Orange	Scramble	Random (1% Prob)	Single point / 75%	100,000	4	50903.5
7	Bird	Random	Random (10% Prob)	Single point	50,000	-	89448.3
8	Bird	Random	Random (1% Prob)	Single point	50,000	4	86005.1
9	Bird	Random	Random (1% Prob)	Single point	50,000	12	87412.3

From the table above, we can conclude that there is a clear improvement when applying a higher number of generations (test 1 only ran 20.000 iterations and the outcome image is unrecognizable).

Regarding the tests with a higher number of iterations (100.000) and still with the same image

(orange), the test achieving the worst performance used Roulette Wheel Selection as the parent selection method and random mutation with probability of 1%, test 5.

The best results were achieved in test 2, when combining Steady-State Selection as parent selection with 100.000 generations and 1% of mutation; and test 6, combining Scramble parent selection with random mutation of probability 1%.

Regarding the bird image, a more colourful image, the best result was achieved in test 7, with random mutation of probability 10%.

5. NEXT STEPS

In this section we present some suggested points that could be taken forward to develop the present analysis:

- Perform additional tests increasing the number of iterations;
- Perform tests with the bird image, with Steady-state selection and Scramble as parent selection methods;
- Perform additional tests on the orange image reproduction with the random mutation probability set to 10%;
- Perform a test applying the 75% crossover probability on the bird image.