Hot Genetic Wheels

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https://github.com/FedeMont/bio_inspired_ai_project

Abstract

This project explores the use of genetic algorithms (GAs) to optimize the structural design of automobiles, focusing on wheel and chassis configurations.

1 Introduction

Rather than employing GAs to facilitate the learning process of cars in driving, in this project, we re-imagined their application by leveraging them to dynamically evolve and optimize the structural design of automobiles, focusing on harnessing the inherent power of GAs to shape the physical attributes of the car, particularly the wheel and chassis configurations.

To assess the performances a fitness-based approach was employed and the generated cars were subjected to benchmark tests on predefined tracks. In order to simulate the behavior and the dynamics of the evolving cars, we utilized the Box2D [1] physics engine. By integrating Box2D into the project, we were able to create realistic physics simulations and evaluate the performances of the evolving car designs in a dynamic environment.

2 Methods

In this section, the steps taken to design, optimize, and evaluate the chassis and wheel configurations are outlined.

2.1 Car structure

Here the information about the design structure of the cars are provided (see Figure 6), where each car is represented by one chromosome, and it's laid out like Table 1.

2.1.1 Chassis

In this project each car's chassis is characterized by a unique design composed of eight vectors, randomly selected with direction and magnitude. These vectors originate from the central point (0,0) and are connected to form a triangular structure, representing the chassis of the car.

2.1.2 Wheels

The wheels, that can be either circular or polygonal in shape, are placed on randomly chosen vertices of the chassis structure. In the case of polygonal wheels, their shape is determined by the number of vertices chosen: to generate a polygonal shape, the circumference is divided evenly based on the specified number of vertices in order to create the desired polygon shape. For each vertex of the polygon, a range is defined to generate random radii. In the case of circular wheels, they are generated by creating circles with a random radius value.

2.1.3 Parameters description

The parameters defining the chromosome of a car are defined as follows:

- **min/max_wheel_density**: this range affect the weight and robustness of the wheel's body;
- **min/max_wheel_radius**: this range determines the size of the wheel;
- **min/max_wheel_vertices_radius**: this range determines the size and the shape of the wheel;
- **min/max_num_wheels_vertices**: this range determines the polygonal shape of the wheels.

These ranges are valid only for the first generation and can be exceeded along the evolution due to mutation:

- **min/max_chassis_axis**: this range influence the overall size and proportions of the car's structure;
- **min/max_chassis_density**: this range affect the weight and robustness of the car's body;
- **min/max_num_wheels**: this range determines the configuration of the wheels on the vehicle;
- **circle_wheel_probability**: probability of having a circular wheel, for the polygonal wheel the probability is one minus this parameter;

	chassis			wheel			
	vertices_x	vertices_y	densities	radii	densities	vertices_r	vertices_theta
1	1.139	0.984	191.211	0.0	0.0	None	None
2	2.455	0.659	112.5845	0.521	169.181	0.947|...|0.811	0|51|...|306
3	0.326	-0.015	158.041	0.0	0.0	0.929|...|0.164	0|120|240
4	-0.259	1.624	174.370	0.247	79.412	None	None
5	-1.191	1.059	75.222	0.329	151.235	0.579|...|0.668	0|72|...|288
6	-2.505	-0.801	192.883	0.432	84.171	0.215|...|0.712	0|90|180|270
7	-1.113	-0.323	90.533	0.0	0.0	None	None
8	0.919	0.276	162.778	0.274	181.665	None	None

Table 1: Car chromosome example. Vertices number 1, 3, and 7 have no wheels; vertices 2, 5, and 6 have polygonal wheels; vertices 4, and 8 have circular wheels.

2.2 Fitness

The fitness value of the car is calculated using the scaling function in the Equation 1, where the fitness is described in the Equation 2.

$$fitness(x) = \begin{cases} tan^{-1}(x) + \frac{\pi}{2} & \text{x} \leq 0 \\ x^{\frac{3}{4}} + \frac{\pi}{2} & \text{otherwise} \end{cases} \tag{1}$$

$$\begin{aligned} x = (&10 \times \text{max\_position} + \\ &- \begin{cases} 50 \times \text{num\_wheels} & \text{num\_wheels} > \text{min\_num\_wheels} \\ 0 & \text{otherwise} \end{cases} + \\ &- \sum_{wheels} \sum_{contacts} \begin{cases} \frac{\mathbf{mcp}}{\mathbf{ct}} \times \text{contacts} + \mathbf{mcp} & \text{contacts} \leq \mathbf{ct} \\ 0 & \text{otherwise} \end{cases} + \\ &- \frac{1}{\text{is\_winner} + 0.10} \times \frac{\text{frames}}{100} - \text{chassis\_mass} + \\ &- 100 \times \text{chassis\_volume} - \frac{\text{wheels\_mass}}{10} + \\ &- 10 \times \text{wheels\_volume} - 10 \times \text{cumulative\_stall\_time}\ ) \end{aligned} \tag{2}$$

Where: **mcp**=max_contacts_penalty, **ct**=contacts_threshold

2.3 Genetic Algorithm Settings

Once designed the fitness function the next step is to implement a GA strategy by means of selection, mutation and crossover.

2.3.1 Selection

In GAs, the selection process determines which individuals from the current generation become parents for the next one. Here are the key parameters and their roles in this problem:

- **num_parents**: determines the initial number of individuals in the population;
- **num_offspring**: determines the number of offspring created from the selected parents;
- **elitism**: percentage of top performing parents that are carried over to the next generation without undergoing any mutation or crossover operation;
- **selection_type**: set to "$\mu + \lambda$" meaning that the next generation includes both offspring and elite individuals from the parents;
- **lifespan**: decreases with number of survived generation. When it reaches zero, the individual is not selected for next generation, promoting exploration by introducing new individuals.

2.3.2 Mutation

Mutation is an important mechanism that introduces diversity into the population and promotes exploration of the search space. To control the scale of Gaussian mutations, the parameters are as follows:

- **mutation_rate**: higher mutation rate increases the likelihood of gene modifications, while a lower rate promotes stability and convergence;
- **mutation_rate_type**: used in "static" mode, the mutation rate remains constant throughout the generations;
- **gaussian_mutation_scale**: by multiplying the mutation value with this parameter, it is possible to adjust the mutation magnitude and potentially limit it to smaller values.

The gaussian mutation described above is applied only to the portion of the chromosome that does not involve the wheel vertices (table 1, first 5 columns). For polygonal wheels then, a random mutation affects the vertices in terms of their distance from the center (r) and their angle (θ) and can both remove or add a vertex.

If a vertex is removed from a polygonal wheel with min_num_wheels_vertices the whole wheel is removed from that chassis vertex. If a vertex is added to a polygonal wheel with max_num_wheels_vertices then the polygonal wheel becomes a circular one.

2.3.3 Crossover

When it comes to the crossover process of GAs, there are some specific parameters that control how the genetic material of parents, in this case the chromosome defined in table 1, is combined to produce offsprings:

- **crossover_probability**: determines the rate at which crossover occurs using a technique called "single-point binary crossover" (SBX);

- **crossover_selection**: a competitive tournament is conducted among a subset of individuals, and the winners are selected as parents for crossover;
- **tournament_size**: specifies the number of individuals participating in each tournament during parent selection.

3 Experiments and results

To test the GA, different environments have been implemented, which are analyzed in detail below. Note that for sake of space we decided to show only one graph per experiment, the other ones will be shown during the presentation along with the train and test part.

These runs have been implemented with params **num_of_parents** of 50, **num_of_offsprings** of 50, **mutation_rate** of 20%, a **crossover_probability** of 30%, **elitism** of 5%, **tournament_size** of 5 individuals for a total of 50 **generations**.

3.1 Irregular road

The algorithm has been tested on an irregular path where the tiles have variable inclination angles (see Figure 6

3.1.1 Equal probability wheels

From the graph in Figure 1, it is possible to observe how, as the generations increase, the vehicles are able to adapt to the track and successfully complete it. Despite both types of wheels being equally probable in the first generation, in the later generations, the top-performing individuals tend to favor polygonal wheels. Furthermore, it has emerged that in vehicles with high scores the average number of wheels is three. It has also been observed that there has been an adaptation in terms of masses: initially, all vehicles had similar values for the chassis and wheel masses, while in the later generations heavier wheels and lighter chassis provide greater stability and, consequently, a higher probability of completing the track.

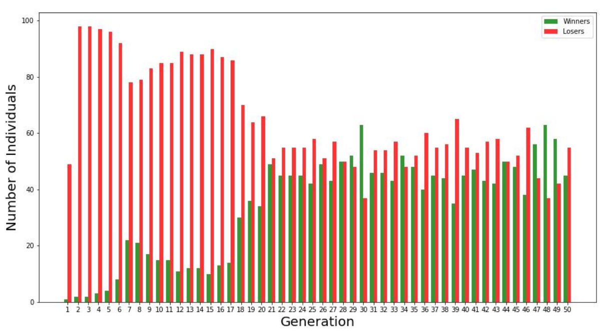

Figure 1: Number of winners per generation

3.1.2 Inhibited polygonal wheels

In this section, the study is presented in the case where polygonal wheels were inhibited in the initial generation. Despite this initial configuration, individuals were still able to complete the course. Polygonal wheels emerged in subsequent generations due to mutation, persisting and surpassing the percentage of circular wheels that initially constituted all the wheels as noticeabale in the left part of Figure 2. However, their number throughout the generations was lower compared to the previously discussed equiprobable case (Figure 1).

This constraint also influenced the evolution of the mass of the cars. It was observed that individuals paid more attention to the evolution of the chassis mass compared to the mass of the wheels, which remained more or less constant. Unlike the previous scenario, in this configuration, the better cars were those with a heavier chassis mass compared to the cumulative mass of the wheels. Additionally, it was noticed that even in this configuration, the average number of wheels is three.

Params have been modified to **mutation_rate** of 50%, a **crossover_probability** of 50% to promote the exploration.

3.1.3 Inhibited circular wheels

Along with the previous scenario, the right part of Figure 2 represent the situation where circular wheels were inhibited in the initial generation. It was observed that circular wheels appeared in subsequent generations due to mutations. However, like before, they were unable to prevail over polygonal wheels, which constituted the majority of the wheels in the subsequent generations and proved to be the best wheel type for this type of course.

Params have been modified to **mutation_rate** of 50%, a **crossover_probability** of 50% to promote the exploration.

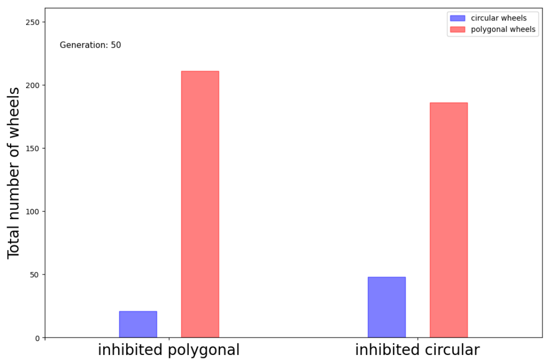

Figure 2: Wheels comparison (different road seed)

3.2 Bumpy road

The path in this scenario was inspired by one of the exhibits at the National Museum of Mathematics

[2]. It features a horizontal path with semi-circular humps (see Figure 7). The evolution of individuals has confirmed that for this particular type of path, polygonal wheels are undeniably superior, to the point that circular wheels have disappeared in some generations. Most wheels have a number of vertices ranging from four to six. As shown in Figure 3 wheels with seven or eight vertices are less common, indicating a tendency for individuals to choose polygonal wheels that are not too different from the square, which has been demonstrated to be the optimal shape for this scenerio.

Here the parameters are the same as the ones in the scenario of section 3.1.1.

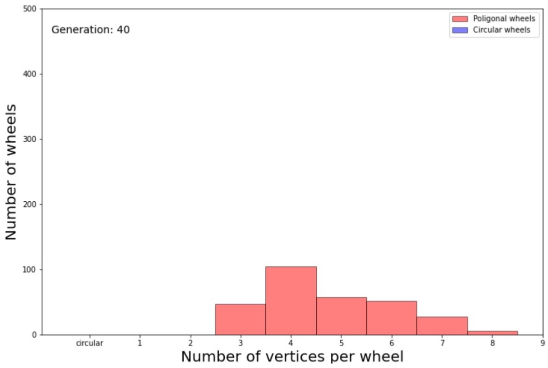

Figure 3: Wheels vertices distribution

3.3 Stairway road

In this section, the results obtained using a path with gradually higher steps are presented (see Figure 8). It was observed that in this task, individuals evolved in such a way as to progressively overcome more and more steps, as can be seen from the Figure 4.

Despite an equal probability in the initial generation, the number of polygonal wheels in the subsequent generations was consistently higher. This can be attributed to the fact that polygonal wheels provide greater grip for climbing.

As expected, evolution also influenced the shape of the chassis as well as the mass of the vehicles. Specifically, it was observed that in the early generations facing lower steps, the chassis mass and the cumulative mass of the wheels evolved symbiotically. In contrast, in the later generations facing higher obstacles, individuals favored heavier chassis to avoid tipping over and achieve greater stability.

3.4 Holes road

In this scenario, a path with progressively wider holes has been considered (see Figure 9). As the path advances, the width of the holes gradually increases. As observed from the "step-wise fitness" in Figure 5, the individuals are able to evolve and progressively overcome all the holes to reach the end of the path.

It is particularly interesting to note that the shape of the chassis has been strongly adapted to the task, with the most successful cars having longer chassis. These scenarios, along with the previous ones, have demonstrated how GAs can deal with obstacles becoming more challenging to navigate as the individuals progress along the path.

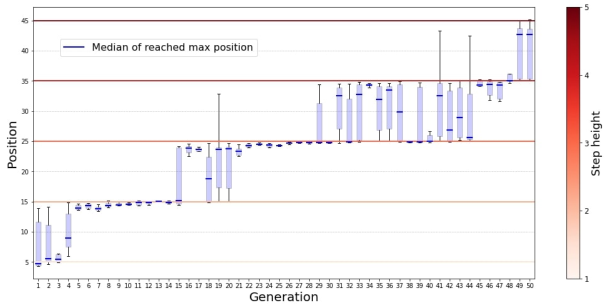

Figure 4: Walls Max Position

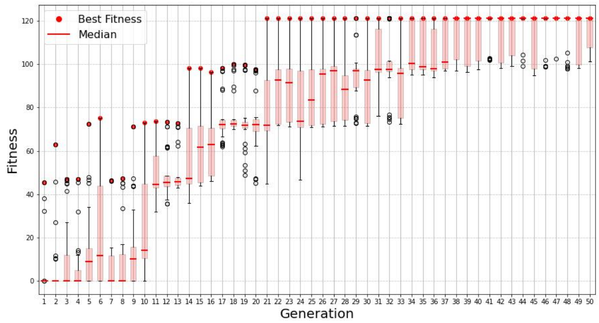

Figure 5: Holes Road Fitness

4 Conclusions

One of the main challenges encountered was to implement a chromosome representation that was compatible with crossover and mutation operations, while also maintaining physical meaningfulness within the context of the environment. Furthermore, another challenge was to find parameter configurations that could yield somewhat satisfactory and interpretable results.

Among the various things learned in this project, one of the most important is undoubtedly the remarkable adaptability demonstrated by genetic algorithms, even in tasks that may initially seem unsolvable with this type of approach.

In this work we have investigated the optimization of machine structure using genetic algorithms. Experimental results show that these algorithms are adaptable and can efficiently find practical solutions to the given problem.

Future work

In the future, it would be interesting to implement the competitive coevolution of the environment. This would allow us to observe whether the machines adapt dynamically and competitively to the changing terrain.

This type of implementation would provide an environment where both the machines and the terrain mutually influence each other during the evolutionary process, enabling us to evaluate the adaptability of the machines to different terrain conditions.

Contibutions

First of all, we would like to say that all the decisions made in this project were taken from all the members of the group. Between brackets the people who contributed more to the task.

Mainly, we divided our work into these tasks:

- Chromosome encoding (Federico)
- Fitness composition (Everyone)
- Mutation, Crossover, Selection, Elitism improvement (Everyone)
- Different type of wheels (circular and polygonal) in which the car can mutate (Alice, Luca)
- Different types of roads: irregular, ramp, jagged, holes, walls and flat (Mattia)
- Different type of tiles: linear, circular, triangular and polygonal (Mattia)
- Replay and testing (Federico)
- Graphs (Luca)
- Graphic upgrades (Alice)

We took inspiration from the work of the github repository [3], for what concerns the user interface we just added new features, while for the algorithmic part we changed all the things that we mentioned above.

We have implemented the replay, where the best machine from each generation is shown using the same type of terrain and random seed. While in the testing we only shows the final generation using the same type of terrain but with a different random seed to see if the machine can adapt to a different road.

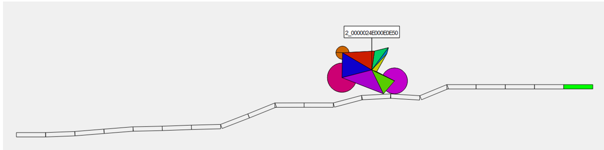

Figure 6: Irregular Road example

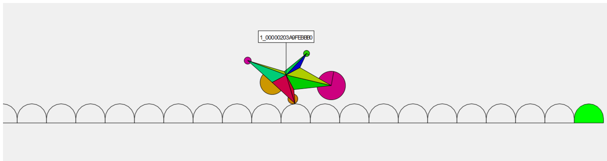

Figure 7: Bumpy Road example

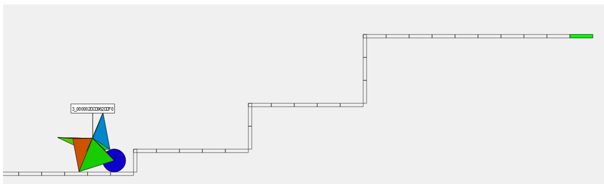

Figure 8: Stairway Road example

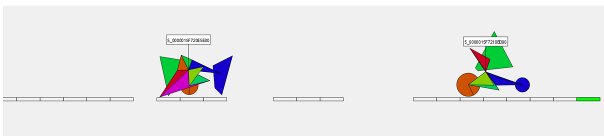

Figure 9: Holes Road example

References

[1] Box2D. https://github.com/erincatto/box2d.

[2] Esame di Stato 2018. https://momath.org/16-square-wheeled-trike-3/.

[3] Chrispresso. PyGenoCar. https://github.com/Chrispresso/PyGenoCar.