COSC343: Assignment 2 report

Reuben Sweetman-Gough (8271161)
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1 Introduction

The assignment required an implementation of a genetic algorithm, with the purpose of optimising fitness over generations of a creature population. The context for this was a 2d game which placed two teams of creatures against each other. The game grid size, walls, strawberries, and teams sizes were all preset for consistency. The aim of the game was to have more creatures by the end of the game than the opposing team. The creatures had to take into account the walls, strawberries, enemies (as well as their sizes), and friends. Strawberries were used to increase the size of the creatures for that game, and therefore have a higher chance of successfully eating enemies. Therefore an implementation which optimised for eating the other teams creatures whilst having more creatures alive was paramount. The assignment therefore had requirements of a chromosome being mapped to creatures actions, as well as an effective genetic algorithm for improving the overall fitness of the population over generations.

2 Implementation

2.1 Chromosome

Consists of creating a chromosome of size 17 filled with random integers between -9 and 9. The agent function dictates how the chromosome is mapped to the actions. the highest value that results from the chromosome is chosen. index 1 is mapped to eating a strawberry that the creature is on. Each 4 positions afterwards are for directions left, up, right, and down. They become mapped to each subset of the perception of the agent, with the exception of the creature map being split by enemies and friends. This implementation seemed straightforward and easy for changes overtime as apposed to a smaller set of chromosomes which seemed more rigid.

2.2 Agent Function

the agent function's purpose was to maps the creatures chromosomes to actions of four directions to move or whether to eat a strawberry if the creature was in the same square as one. The 75 percepts of the creatures were split into 25x25 grids for creatures, food, and walls. Then looping through and finding which quadrant each of these items were in, such as top left, top right, bottom left, and bottom right. Whenever something was found in any of the sub maps, the chromosome related to the directions would be added to the creatures actions. This resulted in changes in behaviour as creatures chromosomes changed over populations. the expected result being that the chromosome values would change in such a way, that when mapped would result in behaviour that increased the overall populations fitness, and therefore the chance of winning.

3 Genetic Algorithm

3.1 Fitness Function

the fitness function goes through each member of the old population and weights their fitness based on a range of values. The values that determine the fitness of the creature are, whether they survived, otherwise the turn they survived till,how many opposing creatures they killed, and how many strawberries they ate. The attribution of fitness to survival was test over multiple instances, to find a spot which positively related to kills and food eaten. Weighing survival and kills heavily dictated a higher chance of winning in future generations. The fitness function overall played an imperative role in the progression of creating new generations, as it was the determiner for which parents and elites to pick.

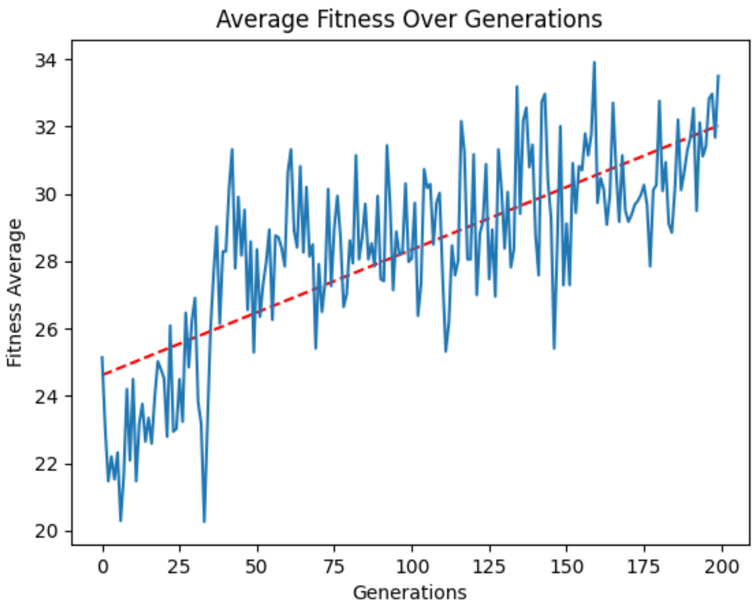

Figure 1: The Average Fitness of creature populations over generations.

3.2 Fitness trend

The figure above shows that as the generations increased so did their fitness. The increase in fitness directly correlated to winning each game, as creatures survived longer and ate more enemies. I relation to that, dips can be seen throughout the generations despite an overall trend of increasing fitness. the dips in the graph, lead to an assumption that the code for attributing fitness was not perfectly configured. Overall the trend is still positive, showing that over the generations the population becomes fitter.

3.3 Parent selection

The parent selection used the tournament selection method where a subset of the population was chosen and the fittest was picked. An issue occurred where sometimes the both parents would be the same creature, which was solved by having a loop that ran until both parents were not the same creature.

3.4 Crossover

The crossover section used a single point crossover with a variable chance for mutation, as it was straightforward to implement and appeared effective. The crossover took both parent's chromosome and found a point in parent 1's chromosome to cut and place the remainder of parent 2's chromosome. This overall created a child with a mixed chromosome, and appeared to increase the fitness of the new populations over time.

3.5 Mutate

this section gave a 10 percent chance to mutate a single position in a child's chromosome. Over the course of the generations the chance went down to 5 percent. The concept behind decreasing the chance of mutation is that less mutations are required as the overall population evolve and their fitness increases. Keeping the chance of mutation this low, meant that the mutation rates would not lead to any drastic changes in the next population, but instead the changes were gradual.

3.6 Elitism

The elites played an important role in the evolving populations and their respective fitness. the elites were chosen from the old population based on which creatures had the highest fitness rating. The individuals were chosen from the fittest 10 percent, which meant over time the fitness of the generations drastically increased over time.

4 Conclusion

The assignments purpose was to create a genetic algorithm which resulted in a population become more fit as the generations increased. This implementation used a common framework with chromosomes, fitness, mutation, crossover, and elitism. The framework used allowed for an initial diverse population to mutate and keep the best of the population, so that as the fitness of the generations increased overtime. In future I would looking at different methods of creating chromosome and mapping them to actions, as well as more testing in terms of a good fitness function. This would overall allow a better rate for improving the fitness over generations.