Computational Intelligence Coursework Report

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ABSTRACT

This report outlines the results and conclusions of training and testing a neural network, using an evolutionary algorithm, to most effectively land 2D rockets on a launch pad. It was concluded after the testing of many operators that initializing the population with each gene equal to 0, selecting parents using roulette wheel tournaments, using uniform crossover, and replacing the least fit member if the resulting child gives an average fitness higher than other methods.

1. INTRODUCTION

The neural network is designed to have 5 inputs from each of the rocket ships: X position, Y position, X velocity, Y velocity, and remaining fuel. There is then 1 hidden layer, in which the number of nodes is tested and concluded below. Following the hidden layer are 3 outputs for rocket controls: thrust up, left, and right. Each hidden node and output node have an associated bias attached. The resulting chromosome of an individual is outlined in the appendix.

$$Fitness = (D + V + F) / 3$$

The fitness of an individual is measured as shown above. Equal to the average of the distance the ship is from the center of the landing pad, the landing velocity, and remaining fuel. A lower fitness is favored.

Within the evolutionary algorithm, operators were used to guide the evolution. These operators consisted of selection, crossover, mutation, and replacement. Several parameters were used in the tuning of the algorithm: the number of hidden nodes, the maximum and minimum value of each gene, the size of population, the rate of mutation, and the change in gene value when mutated. For all results stated, the number of evaluations was set to 20000.

2. APPROACH

2.1 POPULATION INITIALISATION

The population is initialized within an array list and as it is, the genes of the chromosomes are assigned an initial value. Several options exist for the method of assigning these values.

Each gene could possibly be assigned a random value between the stated minimum and maximum, this option could provide a better fitness in time-sensitive situations where the number of evaluations is limited.

The genes could also be assigned an initial value of 0. This method may provide a better starting point for this specific application (table 1).

2.2 SELECTION OPERATORS

The selection of individuals to be used within the crossover operator is an important process in the algorithm.

Roulette wheel (RW) selection selects an individual based on a probability proportionate to its adjusted fitness, therefore favouring fitter individuals in the population.

Tournament selection selects a number of individuals randomly chosen from the population. A single individual can then be chosen by either selecting the very fittest, or by using a RW

tournament selection, which incorporates the benefits of both RW and tournament selection. The percentage of the individuals used within the tournament can vary and greatly affect the performance of the selector.

In the testing of these selection methods, it is possible that the parents can consist of duplicates of one selected individual, the results in table 2 demonstrate the this and as well as the effects of avoiding this possibility by assuring only unique parents are selected.

2.3 CROSSOVER OPERATORS

Once selected, the parent's chromosomes are mixed in one of many ways, in this report, I have included the results from 6 different methods of crossover.

1-point crossover determines one random point throughout the chromosome, before this point the first parents' genes will be selected and after this point the second parents' genes are selected.

K-point crossover, similar to 1-point, selects K points at which to determine which parents' genes to copy, switching between them at each crossover point.

Another form of crossover included within the results, shown below, involves selecting the genes of the hidden layer from the first parent and the genes of the output layer from the second parent.

Uniform crossover, where each gene is randomly selected independently from either parent, was also tested within the application.

2.4 MUTATION OPERATORS

In regard to mutating the resulting children of the parent, there were few application-specific methods which were viable.

Mutation could be carried out uniformly, wherein each gene of the child's chromosome is either added to or subtracted by the mutate change value. This mutation allows each gene to evolve independently of each other, while other methods do not.

Children's genes could possibly be mutated in pairs or groups collectively, as well as mutating each gene of a layer of the network collectively. Although, these methods do not allow for as much mutation on a gene-by-gene basis for these individuals.

2.5 REPLACEMENT OPERATORS

Few reasonable possibilities in the method of replacement were available. Within the results, several methods were tested which produced varying results.

Children can either be introduced to the population, replacing the weakest, while either taking their own fitness in comparison into account or not. Children who are less fit than the weakest member may be disregarded or further mutated.

The number of children to produce which replace the weakest individuals affects the average fitness of the population and this effect was observed ranging from only one child, to replacing the whole population with children.

2.6 PARAMETER CONFIGURATION

The mutation rate determines the probability that mutation will occur in that instance and mutation change determines the amount in which the gene is either randomly added or subtracted. Each genes value has a certain lower and upper limit.

3. EXPERIMENTS & ANALYSIS

All results shown below are calculated from the average of 15 runs, using 20000 evaluations.

The below results are only indications of how each method performs in relation to each other and not of the fitness when used with other operators.

3.1 POPULATION INITIALISATION RESULTS

Table 1: Methods of initializing population.

Method	Avg start fitness	Avg end fitness
Random	0.353	0.253
0's	0.372	0.051

The results in table 1 show that although the initial average fitness is worse when using 0 Initialisation it does off an advantage at the end of testing. It also provides more accurate test results when measuring the effects of operators.

3.2 SELECTION RESULTS

Table 2: Methods of selection.

Method	Avg fitness
Select random	0.132
Select best	0.073
RW	0.018
Tournament	0.042
Tournament (no same parents)	0.036
RW tournament (no same parents)	0.011

The selection method that performed the worst was when random parents were selected, this is likely due to the fact that it does not promote lower fitness's, instead individuals of different fitness's have an equal chance of producing children. RW selection performed well due to the probability being proportionate to the adjusted fitness. Tournament selection on its own did not outperform RW, but combined the fitness was considerably lower, even more so when no duplicate parents are selected.

3.3 CROSSOVER RESULTS

Table 3: Methods of crossover.

Method	Avg fitness
Clones of parents	0.113
1-cross	0.090
2-cross	0.073
3-cross	0.077
Layer-cross	0.124
uniform	0.058

The crossover method which performed the best on average was uniform crossover, greatly outperforming the tests conducted for K-cross or any other method. Due to the composition of the chromosome, uniform crossover may give an advantage over others as it allows an even split of each parent and also allows the genes to be inherited individually, rather than in groups. Producing children identical to the parent offered the least benefits as it does not allow for the combining of their chromosomes. K-cross crossover performed best at 2 crosses.

3.4 MUTATION RESULTS

Table 4: Methods of mutation.

Method	Avg fitness
Uniform	0.013
In pairs	0.026
By layer	0.046

Uniform mutation provides a clear advantage over other methods tested. Mutation in pairs and groups gave a higher fitness on average. Similar to K-cross and layer crossover, uniform mutation performed the best due to the specific nature of the chromosome as it allowed each gene individuality.

3.5 REPLACEMENT RESULTS

Table 5: Methods of replacement.

Method	Avg fitness
Replace worst	0.019
Replace worst (if child is better)	0.013
Reinitialise all except children	0.227

Reinitialising the population (except for the children) on each evaluation and setting each gene randomly was least effect as it reduced the progress of evolution within the population. Replacing the worst individuals with the children if they are better is clearly the most advantageous method as it encourages the survival of the fittest nature of the population's evolution.

3.6 PARAMETER CONFIGURATION RESULTS

Table 6: configurations of parameters.

Parameter	Value	Avg fitness
Hidden nodes	4	0.0142
	5	0.0124
	7	0.0179
Population size	30	0.0170
	40	0.0124
	50	0.0164
	100	0.0722
Min/max gene	-3.1 to 3.1	0.0224
	-3 to 3	0.0124
	-2.9 to 2.9	0.0247
Mutate rate	0.03	0.0171
	0.04	0.0124
	0.05	0.0122
Mutate change	0.05	0.0252
	0.1	0.0124
	0.2	0.0122
Children	1	0.0802
	2	0.0960
	50% of pop	0.1068

5 nodes in the hidden layer were best, an increase or decrease from this amount was a considerable detriment as it made the network too simplistic or resulted in a chromosome too long for the evaluations limit.

The average fitness was lowest when the population was set to 40.
The genes were best when limited to between -3 and 3, possibly as this would allow for a suitable amount of agility and finesse when landing.
The mutation rate and change were best when kept relatively small, at 0.05 and 0.2, respectively.
The number of children was best when only 1 child was produced, although 2 children was not considerably worse. The number of children shows a positive correlation with the average fitness.

4. CONCLUSION

Throughout the many different methods of selection, crossover, mutation, and replacement there were clear advantages and disadvantages to each. It was clear from the results that using a roulette-wheel tournament and ensuring all selected parents were different gave the best results in the tests conducted.

In regard to the crossover operator, the results from uniform crossover appeared to be far superior to that of any other methods tested.

The mutation operator, similar to the results shown in crossover, showed the biggest advantage when using uniform mutation.

The method of replacement observed to be the most effective was to replace the weakest in the population by the child if the child was fitter.

From the many parameters available to be altered and refined it is fairly unclear as to what combination provides the best results as sufficient testing in this regard would require a further substantial amount of time training. Using 5 hidden nodes with a small population, the genes of which initialized at 0, and keeping the rate and change of mutation (0.05 and 0.2, respectively) low appeared to produce the fittest individuals on average. Using the fore mentioned operators and parameters resulted in the lowest average measured, at 0.0124. 8 out of 8 test rockets were able to land when tested. The activation function used was tanh.

5. FUTURE WORK

As fully comprehensive testing of the combination of parameters was not possible given the time frame, further studies into the possible relationships between them could prove useful in further reducing the average fitness of the populations.