SMARTER NEAT NETS

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Abstract

Smarter NEAT Nets

by

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This paper discusses a modification to improve usability and functionality to a genetic neural net algorithm called NEAT. The modification aims to accomplish its goal by automatically changing parameters used by the algorithm with little input from a user. The advantage of the modification is to reduce the guesswork needed to setup a successful experiment with NEAT that produces a usable Artificial intelligence (AI).

The modified algorithm is tested against the unmodified NEAT with several different setups and the results are discussed. The algorithm shows strengths in some areas but can increase the runtime of NEAT due to the addition of parameters into the solution search space.

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Chapter 1

Introduction

Artificial intelligence (AI) is used in all video games in todays world, but rarely are there games with AI that learns. By using machine learning in video games or other AI applications, AI agents could improve as they compete against users. AI using machine learning or in the case of this paper, genetic algorithms, could create an AI better than any programmer and could do so with little input from a programmer. These genetic algorithms perform well on problems that require searching for a solution that is arrived at by finding the best set of values across a large number of variables.

Machine learning, specifically neural networks, has been used in games recently such as Black White 2 and the NEAT specific NERO [4]. By using machine learning like neural nets programmers can create AI that changes to adapt to the user or even generate content. This paper aims to improve using the NEAT algorithm to allow machine learning to be easier and better to use.

Chapter 2

Background or Related Works

2.1 Genetic Algorithms

Genetic algorithms (GAs) are a system that builds up solutions to a problem space. GAs use a population of individuals that represent a solution to a given problem. These individuals consist of genomes, descriptions of different parts to a solution very much like genetic data (DNA) in biology. Over many generations, GAs weed out bad solutions by only keeping genes from a top percent of the individuals. Most GAs use a method called crossover to mate two parent genomes selecting random genes and creating an offspring.As in biology, a key feature of genetic algorithms is the mutation of genes across individuals. Mutation allows individuals to search for a solution by randomly changing parts of the genome. GAs repeat the process of creating offspring until a solution of acceptable quality is found.

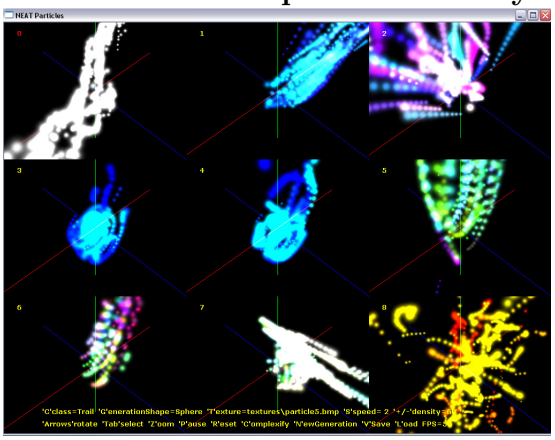
Genetic algorithms show promise in the field of video games with research on genetic AI [11, 6, 8]. Ever since the beginning of genetic research with John

H. Holland, applications of genetic algorithms have been expanding. The new application of GAs in Neural network topology is presented in the algorithms of SANE [10] , ESP [3] , and GNARL [2].

2.2 Galactic Arms Race

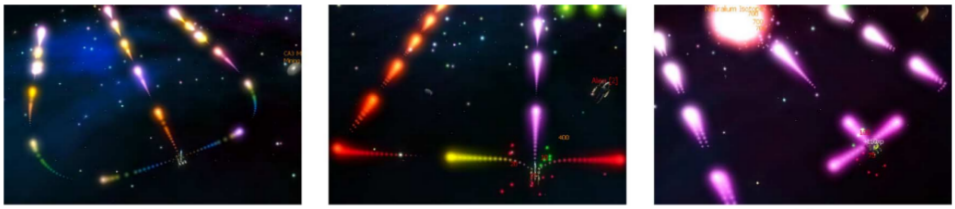
The Galactic Arms Race or GAR incorporates a type of NEAT for generating content in the game called cgNEAT [4]. In this game the player assumes the role of someone fighting aliens and using randomly generated weapons. The genetic algorithm cgNEAT generates the weapons for the player based upon which weapons players in the game are collecting and using. The neural networks created are compositional pattern producing networks that generate the way the weapons looks[4]. Examples can be seen in Figure Figure 2.1.

Figure 2.1: Different weapons created by cgNEAT



GAR starts the users in the game with a set of starter weapons that are preset by the developers. Then players can find weapons spawned in the game world that are created by cgNEAT. Items that are picked up by players and used are then added to the population of offspring that will reproduce. An example of a weapon evolving the game of GAR is shown in Figure 2.2.

Figure 2.2: Evolution of weapons using cgNEAT



Due to players picking weapons that work better for them, later generations perform better than earlier generations as seen in Figure 2.2. GAR shows promising development for genetic algorithms that can create usable content.

2.3 Neural Genetic Agents: NERO

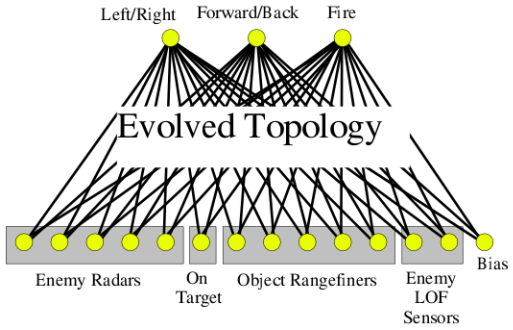
Neuro-Evolving Robotic Operatives or NERO for short, is a game based on the rtNEAT implementation of NEAT[13]. In the NERO game the player trains and uses robot units to complete certain tasks. The main part of the game play is defending and capturing towers against another team of trained robots.

The most interesting aspect of NERO and rtNEAT is that the agents are created in real time. This means that during training or gameplay agents will be removed and replaced with new neural nets derived from the species in the given population. rtNEAT only selects parents for new agents from those that are old enough to have been evaluated. This avoids the problem of removing the fit from the population due to improper evaluation.

Training mode in NERO involves giving the player 50 units to run through a course defined by the player. The player sets a spawn point for the robots where they will have to move from and complete a certain task. After a set amount of time the robots will be restarted from the spawn point with a new brain. The

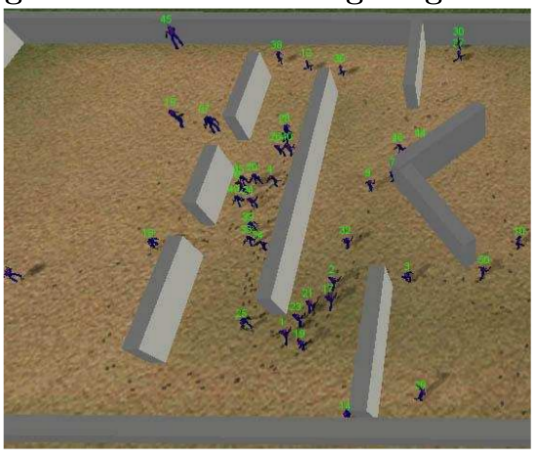
restart is to make sure that no robot is at an advantage when it has its brain replaced. As with the original NEAT neural nets for the initial robots start with a randomly connected topology. The outputs and inputs default to a simple approach with only 3 outputs and 13 inputs as shown in Figure 2.3.

Figure 2.3: Inputs and outputs for NERO



Players could set up different scenarios using obstacles such as turrets and walls. The player would then give the robots a fitness score based on certain performances of the robot. By training agents to do different tasks a player could assemble a team of robots to face against another team. An example of of training is shown in Figure 2.3.

Figure 2.4: Robots navigating a maze



By allowing real time replacement the user can see clearly how the training is

affecting the algorithm and is improving the intelligence of the agents. For this reason, NERO is a great way to learn about genetic algorithms and neural net evolution.

2.4 Articial Neural Networks

Neural networks aim to simulate the way the brain works by connecting neurons as nodes to each other using links. In a brain the cells perform some operation on the incoming signals and then send out signals to other neurons. Neural networks have shown themselves to be useful for memorizing patterns and solving parallel logic. Neural nets have shown promise in image recognition from the beginning of its research [9]. Studies on animals have shown that fully connected neural networks are what helps cats eyes recognized shapes [5]. Neural networks are made up of layers of nodes that feed into each other. Usually the input nodes are the first layer that feed to the next layer and so on until the output nodes are reached. Input and Output nodes are connected to the program that is running the network and are ultimately what runs the AI. There are different types of neural networks depending on the connections within them. Neural networks with links from nodes either at the same level or towards the input level are called recurrent networks. There are standard forms of connected neural nets where all nodes are fully connected between each level of nodes. NEAT does not follow this nor any other standard set of topology form, due to its ability to generate topology randomly. Connections in nonstandard graphs can connect from any level to any other level as long as they do not travel towards the input nodes, if they do they are nonstandard recurrent networks. The operation each node performs is a sum across all of its input nodes and an activation function using

threshold logic, a binary function (on or off) or sigmoid function. In NEAT the nodes activation function is always a sigmoid function.

NEAT uses standard fitness sharing to determine how many individuals are to be created from each specie. Fitness sharing simply uses the fitness of the species over the total fitness of all individuals times the current population number to calculate the offspring for the specie.

While NEAT uses simple genetic methods it uses a unique way of comparing structure that allow it to perform efficient evolution of topologies and is the reason it was chosen to study.

2.5 NEAT Background

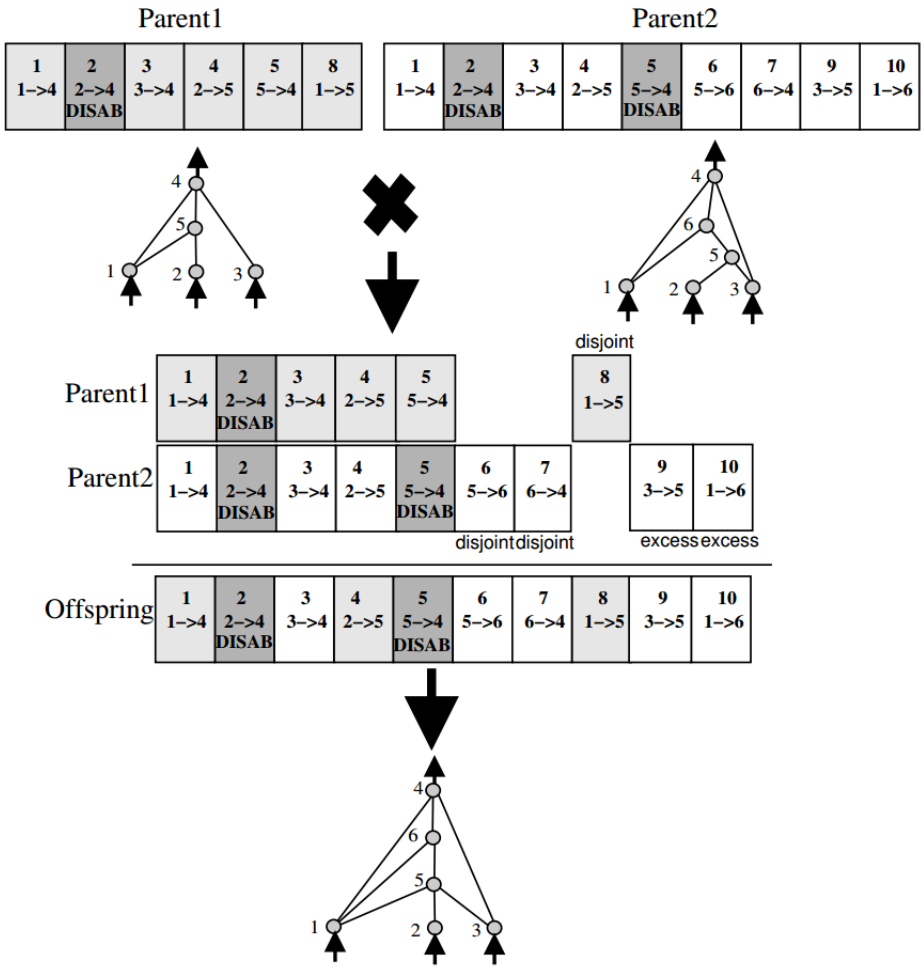
NEAT or NeuroEvolution of Augmenting Topologies was originally developed in 2002 and since then has been used in multiple games and developed extensively [12]. NEAT is a combination of neural nets and genetic algorithms to create an algorithm that build on a simple neural net and evolve it over many generations. NEAT evolves both the connection and weights on nodes incrementally improving the network. These type of algorithms are called Topology and Weight Evolving Articial Neural Networks or TWEANNs. NEAT solves the problem of protecting newly created structures in its genome through speciation. This way topologies can be formed in their own specie and evolve without directly competing with other individuals outside their own specie. Most TWEANNs do not use speciation due to the problem of fitting individuals into distinct species since grouping similar topologies is difficult. NEAT solves this problem by recording historical information about each new gene. Each new gene that is added is given a global innovation number. Each topological change can then be tracked by this number.

Individuals are grouped into species by comparing each individuals connection and node genes. The comparison checks for genes that have the same innovation number in both genomes, the genes that do not match are called excess or disjoint genes. Excess genes are genes that fall beyond the innovation number of the last gene in the first genome being compared. Disjoint genes are merely the genes that do not match innovation numbers, but they numbered at or before the last innovation number in the first parent being compared. An example can be seen in Figure 2.5. In order to fit individual members into species, each member is compared with a previous representative for each past specie. These representatives are chosen at random from the past generation. The individual is placed into the first specie possible if the calculated value of $\frac{c_1 E}{N} + \frac{c_2 D}{N} + c_3 \cdot \overline{W}$ falls below a certain threshold parameter δ , where E are the number of excess genes, D is the number of disjoint genes, and N is the number of genes in the larger genome. Constants $c_1 - c_3$ determine how much each variable affects the comparison. If there is no match when comparing all of the previous species then a new specie is created and the individual is added to that specie.

2.6 Mario Platform

Mario from the famous Nintendo game, Super Mario Bros. The platform that is used in this paper is called Mario AI benchmark and has been used in numerous competitions [7]. The platform was chosen as a testbed due to ease of benchmarking and comparing results on a well known game. The platform allows for randomly generated levels, allowing for variety of difficulty. The difficulty can range from a flat level with no pits to large pits with many obstacles. The Mario AI benchmark supplies an API that makes it easy to interact using an AI. The

Figure 2.5: The production of offspring and gene characteristics [12]

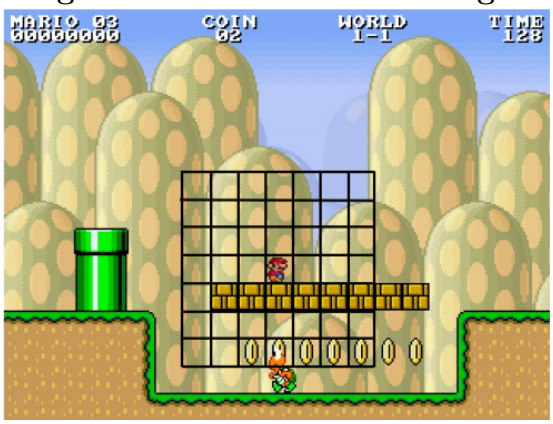


API can supply the AI positions of enemies, blocks, and states that the Mario sprite is in. The grid layout that represents the Mario sprites vision is shown in Figure 2.6. The agent interface supplies a method that outputs Marios buttons presses for each 40ms frame. The allowed buttons are A (jump) , B (run / grab shell) , and the directionals: left, right, up, and down. The benchmark records scores on distance traveled, kills, and items collected so these scores can be used in heuristics and benchmarking.

2.7 Tetris Platform

Tetris is one of the must successful and widely known games. It was created by Alexet Panitnov in 1984 in the Soviet Union. The gameplay of Tetris is a puzzle game where the player must fit different shaped pieces to form lines of blocks. These blocks are then removed that the above blocks slide down. Game pieces are allowed to by rotated into 4 different rotations and move left and right. Application of Tetris in this paper use a Tetris clone developed by professors at Stanford for teaching students about AI [1]. This platform was chosen due to the easy API developed for creating an AI to work with Tetris. The coding platform lets the user define a generic size Tetris board represented by a grid of boolean values. The value of each cell in a grid shows if there is a Tetris block place there or not.

Figure 2.6: The mario vison grid



Chapter 3

Algorithm

In order to asses the difficulty of creating an AI interface for use in the NEAT environment, a Tetris game was reworked with NEAT and the difficulties were recorded. The Tetris game that was used came from a beginning programing class and had an interface for AI that most games would have before implementing any kind of neural nets [1]. Before starting to code the interface between the Tetris AI and the genetic neural algorithm a few hypothesis were made:

- Writing the interface / test harness interface would be simple (only take one try)
- Tetris would perform well compared to normal AI provided

Tetris only took a few hours to code into the testing harness that was already implemented. The most difficult part was changing the Tetris AI interface to accept suitable neural inputs and return some kind of vision to the AI. The AI originally was given a board state then asked for the best move given a piece and a next piece. The move was a position (x,y) and a rotation of the given piece.

This was changed to better suit the neural net, giving it boolean inputs for the board and what the piece looked like. Instead of asking for a move for each piece the AI was asked for a move each cycle of the game, more like what a human would experience while playing. After making these changes, the Tetris AI was tested with the NEAT harness and was able to control the game.

After testing Tetris with the initial inputs and outputs as the whole board, it became apparent that the AI was having trouble figuring out that it should be trying to place pieces to score lines. The AI would at best put pieces to the left then the right. This was due to the setup and shortsightedness of the programmer. Since the neural net had inputs for the whole board (10 by 20 blocks), it was receiving over 200 inputs, much higher than that of the AI mario tests (around 50). In order to achieve a correct move, the neural net would have to memorize exact board states. With 200 inputs the genetic NEAT algorithm would have to randomly create weights for the connecting inputs. After 10 runs, the AI never scored higher than 1 line.

The next implementation used a more roaming eye approach as described in [12]. This approach helps simplify the amount of inputs by giving the AI a small moving subset of vision instead of the whole board. After implementing the modifications to the original AI a series of tests were run to see if there was improvement. Again, the AI failed to gain more than one line.

In order to debug the program to find the reason for failure, I printed out the grid of vision each time the AI was run. I found a small error with converting a grid of booleans to the neural inputs. After fixing the error, the AI still behaved poorly. For further testing, the Tetris pieces the AI was given during testing was set to only vertical bars. While observing the AI, I found it having trouble with the edges of the Tetris board. Vision outside of the tetris board had been set to

empty in the AI code, giving the AI the appearance of a place to put the piece after it had discovered how to place lines. This problem was easily solved by filling the outside of the game area with filled in blocks (as if there were Tetris pieces filling it in).

3.1 NEAT Interface

The genetic description about how to initialize the neural network and how to genetically change the individuals is loaded from a .ga file at startup. The file contains parameters for settings such as the genetic crossover rates and mutation rates. In order to simplify the testing process a GUI was created to automate the experiments, allow easily changing parameters, and observe collected data across runs.

The created interface simplifies the testing process of NEAT and allows the user to change datasets (Mario levels) mid run and observe changes in species and individuals through lists of data. Demos can be run of any individual or individual with the best fitness for that generation. These demos show the neural net structure described by the genome and run the AI on the selected task of Tetris or Mario. The visualization code was supplied by the NEAT4j code base and an example can be seen in Figure 3.1. These demos are threaded so they can be run while still performing the experiment.

Each specie present in the current experiment is displayed in a list showing the number of individuals in each specie. Selecting a specie shows the individuals in that specie. Selecting an individual shows each gene present in the genome and selected information for each gene. If a self-regulation gene is present in the genome then the contents of that gene are shown in a separate box. These infor-

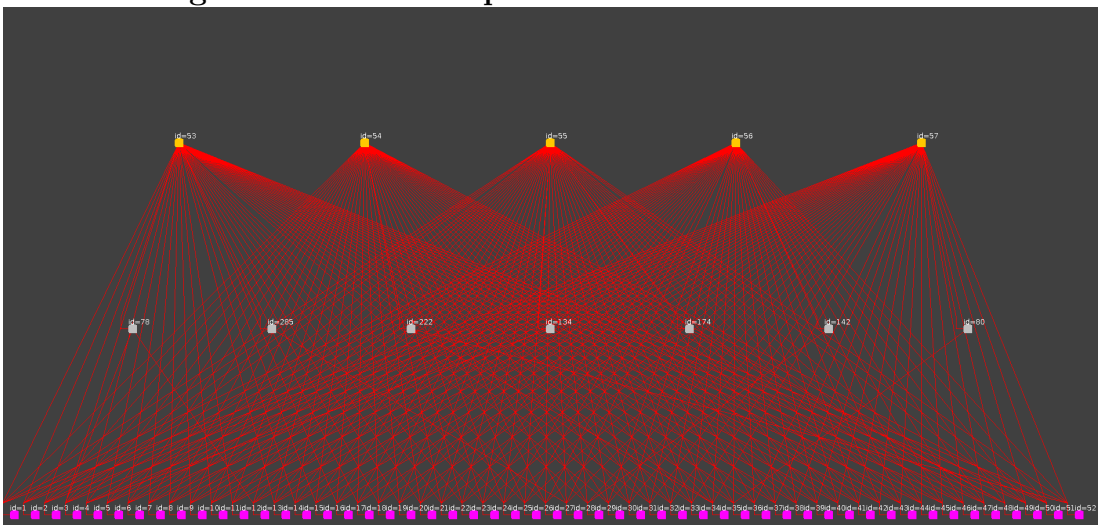
mation boxes are useful for debugging, especially for debugging the self regulation gene's affect on the algorithm.

Both the Tetris and Mario mode of the interface are threaded to decrease the runtime of long experiments. Only the testing phase of the genetic algorithm is multi-threaded as this is where most of the runtime is located.

For the Mario testing there is a level queue that allows setting up any number of levels at any difficulty. Marios vision parameters can be changed as well as all the parameters as described in the NEAT4j section. Each run can be set to automatically restart at a set breakpoint of a number of generation or a maximum score reached.

There is a graphing tab in the GUI interface that allows for viewing the total fitness of the population over a history of runs. The graph tool is useful for debugging changes to the NEAT algorithm as well as the AI interface between the neural net and the game it is controlling. For example, while creating the AI interface between Tetris and the neural net there was a clear improvement when allowing the neural net to use the level of the current Tetris block as an input.

Figure 3.1: An example of a neural network demo



Chapter 4

Algorithm: Experiments with NEAT and Mario

In this section the process of implementing a system that allows the application of NEAT to a general set of AI problems will be discussed. The software that was modified for this was the NEAT4J implementation of NEAT written in Java. The NEAT algorithm was selected due to its success in NERO and other games.

Heuristics that help promote a correct solution are critically important for GAs to work correctly. Finding heuristics that work appropriately for GAs can be tedious or impossible to find if the search space for the neural network is too large. In order to solve the aforementioned problems, the first experiment was to allow for each genome run to determine its own heuristics. A new genotype was added called a self regulation gene. This gene contains numerical values for the heuristics in the Mario game. The default heuristics that were used are shown in 4.1. Although for the Mario game the number of different heuristics was short,

the number could be much greater in more complex games. While experimenting with NEAT, the amount of set up and tweaking of variables seemed to be too much of a hassle for a normal user. I tried a couple of modifications to the NEAT algorithm to alleviate the difficulty of using NEAT. These modifications added a new gene that determined specific heuristic changes to be used during the speciation process where only the individuals with the highest fitness are used to populate the next generation.

Each specie would use its highest fitness individuals self regulation gene to determine the heuristics for all individuals that fit into the specie. The reason behind this was to not allow an individual to just give themselves larger and larger heuristic values. The self rating was called the self fitness value. This value was then averaged with a baseline default heuristic value to further prevent self heuristic inflation. The results are shown later in Chapter 5.

The first algorithm explored gave each individual in generation 0 a random heuristic values so each gene would be a unique set of heuristic values. This would work well for small sets of heuristic values to search through or situations where changing the heuristics mid-run will ruin the population. If the ability for heuristics to change dynamically was added then the GA would be able to change as needed to improve the overall fitness while adjusting specific heuristics within each specie. This was the hypothesis that led to another change that would let the self regulation gene guide the whole genetic algorithm while changing parameters for NEAT dynamically. These parameters that would be changed are listed in Table 7.1. As well as containing these parameters, the self regulation gene would contain additional parameters for mutating all parameters in the self regulation gene. For example, the pMutatateRegulationHeuristics variable would change the probability that a heuristic is changed by at most the variable PerturbRegulation.

4.1 Initial Agent Implementation

Most of the implementation work involved creating the framework to allow NEAT to control Mario agents in Infinite Mario. I used the NEATGATraining-Manager class in NEAT4J as a starting place to create and evaluate agents. After figuring out how to run experiments I created an agent for Infinite Mario that took in a neural net from NEAT and connected the appropriate inputs and outputs. Once Mario started jumping around with a default configuration I moved to tweaking the program to get a Mario that could complete static levels. In order to make sure the algorithm was creating good Mario agents I set up a system that allowed the user to see each agent's fitness score at the end of its test and every time a Mario completed a level it would display that Mario net actually doing the level. NEAT also let me visualize the neural net topologies that were being generated. That way I could see how each setting changed how the neural nets were formed. Eventually, the heuristic values shown in Table 4.1 were found to result in well performing Mario AIs.

Heuristic	Default Value
Distance travelled	1
Mushrooms collected	0
Flowers collected	0
Coins collected	0
Stomp kills	200
Shell kills	500
Connection genes	0
Total Nodes	0

Table 4.1: Table of default heuristics for the Mario genetic algorithm

Chapter 5

Results

The goal of this experiment was to create a modification to the neat algorithm that would automatically vary parameters for NEAT rather spending hours tweaking settings files. The results show improvements in some areas, however this method has some pitfalls and shortcomings as revealed by experiments.

All tests using the Mario testbed were implemented by giving a vision grid with one block behind Mario and 5 blocks ahead of Mario, 3 blocks above Mario and 5 blocks below Mario. Other inputs include a bias input of 0, an input if Mario is carrying a shell, an input that determined if Mario can jump and an input if Mario is on the ground. These inputs totaled to 52 inputs with 5 outputs for each button Mario could press. Mario was also given the ability to jump by continuously holding the jump button down, making the logic more simple to evolve.

5.1 Results for Mario Running NEAT with the Same Heurisitics

The Mario benchmark was run with various setting for NEAT4j and a population size of 500. All heuristic values were set to 1 across these experiments. As a base for comparison a run with the default parameters values as listed in Table 7.1 is presented. For the base run the total fitness graph Figure 5.1 shows a problem keeping fitness as the number of species changes. This is due to the compatibility threshold fluctuating to compensate for the number of species which started at 500, the same as the population number. The algorithm is trying to keep the number of species to 15 by changing the θ value as seen in Figure 5.2. As this value changes genes can be lost as species combine with others, which is why a fluctuation in average fitness is observed.

In comparison to using a limited feature set of the self regulation gene and compatibility change enabled, the default parameters configuration converged to a solution in about 10 generations while the self regulation implementation takes 50 to 80 generations as seen in Figure 5.3 and Figure 5.4. This is due to the starting parameters of the self regulation genes starting at much smaller mutation rates than the default parameters. The self regulation gene is set this way to avoid creating species that mutate too fast too early. When the level difficulty is changed to a harder level the self regulation gene helps increase mutation rates. As shown in Figure 5.5 and Figure 5.6 the normal NEAT algorithm has parameters set too low to develop any solutions to the problems it is facing.

The best improvement is seen when all the parameters for the self regulation genes are randomly chose as each gene is created. This allows for a larger diversity of parameters and sometimes a faster convergence on a solution. graph

Figure 5.7 shows that seeding random values for self regulation parameters helps improve the chance of finding a solution as compared with self regulation without randomization. The graph also shows that using this method will not always yield the same result, since run 1 and run 2 of the algorithm in Figure 5.7 did not find the same solution.

The tests using the Mario platform revealed that the self regulation gene helped in cases where the difficulty of finding a solution was higher than expected and NEAT parameters needed to be adjusted to compensate. Otherwise, the self regulation gene improved the overall fitness of the algorithm and slightly decreased the best fitness.

Figure 5.1: Average fitness using default parameters

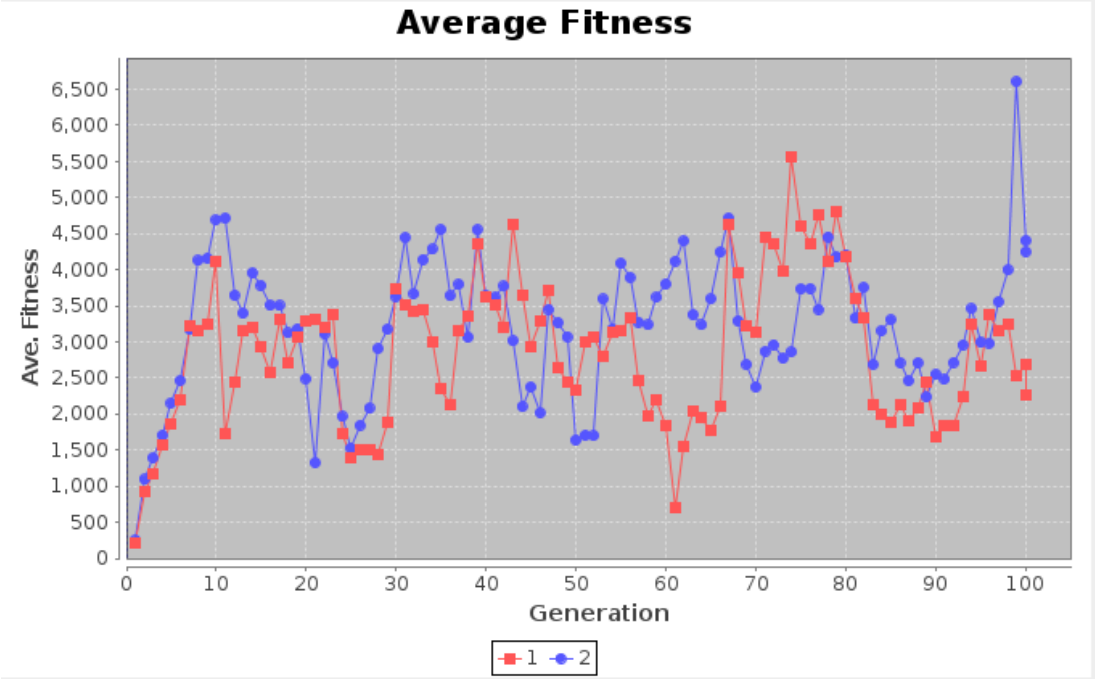
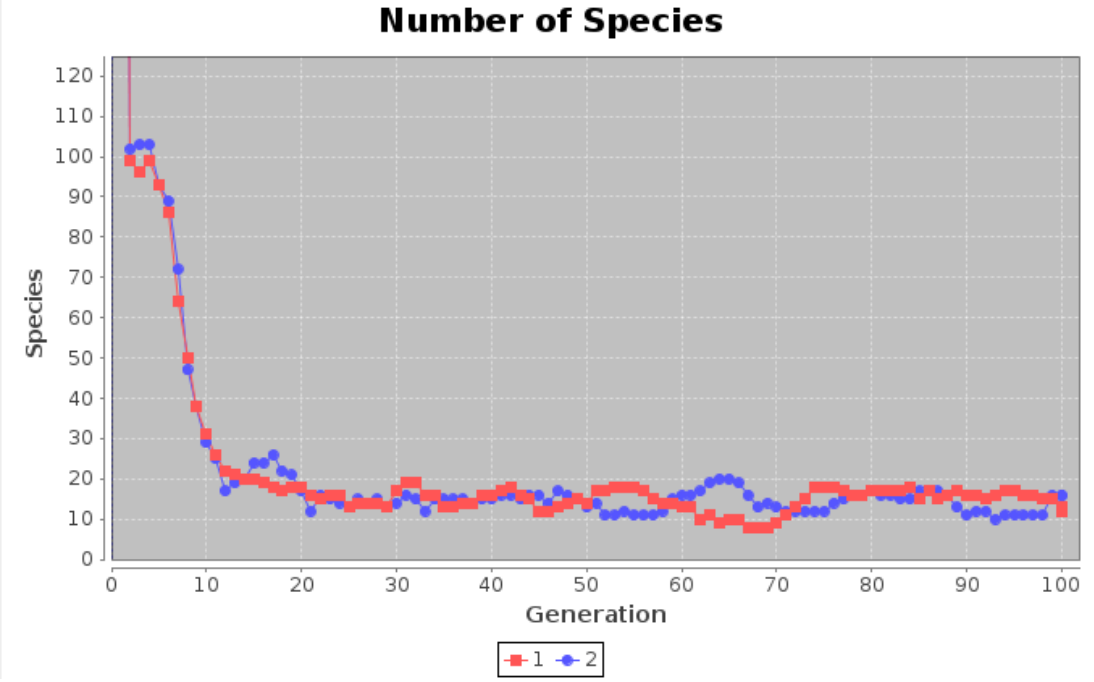


Figure 5.2: Number of species using default parameters

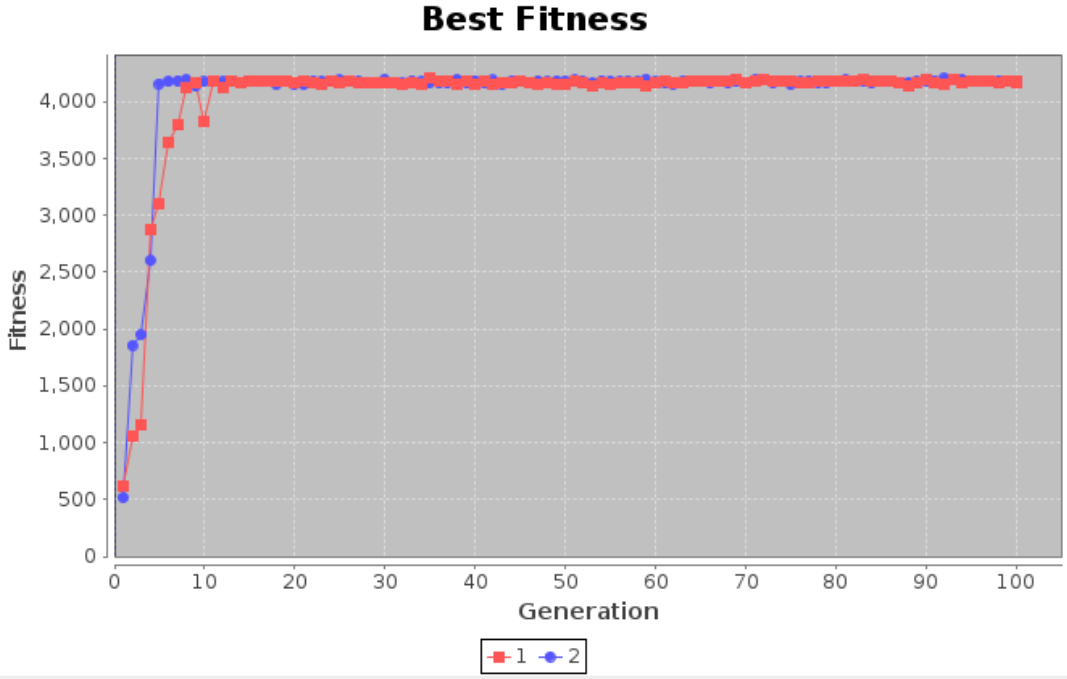


5.2 Results for Tetris Running NEAT

For these tests the Tetris environment has a board set to height of 6 by a width of 10, since height is not a factor. For the heuristic values a line is given a value of 10 and a piece placed is given a value of 1. There is a board rater that rates a given board state and gives a value. The board raters score is added for the last tick of the AI as the game ends. For each generation each individual is run against three levels: one with a seed of 0, one with a seed of 2, and one with a random seed. The resulting fitness score is the sum of all the levels.

The complexity of memorizing pieces and places to put the pieces seems to be difficult for NEAT. All of the tests show that at best out a of a population of 500 there is at least one individual that scores a 90 as seen in Figure 5.8 and Figure 5.9. This is the equivalent to scoring 9 rows across 3 levels of Tetris. In

Figure 5.3: The best fit individual using default parameters



previous test runs NEAT was able to converge on solutions to levels with only line pieces showing that the AI could solve simple problems.

Figure 5.4: The best fit individual using self regulation gene

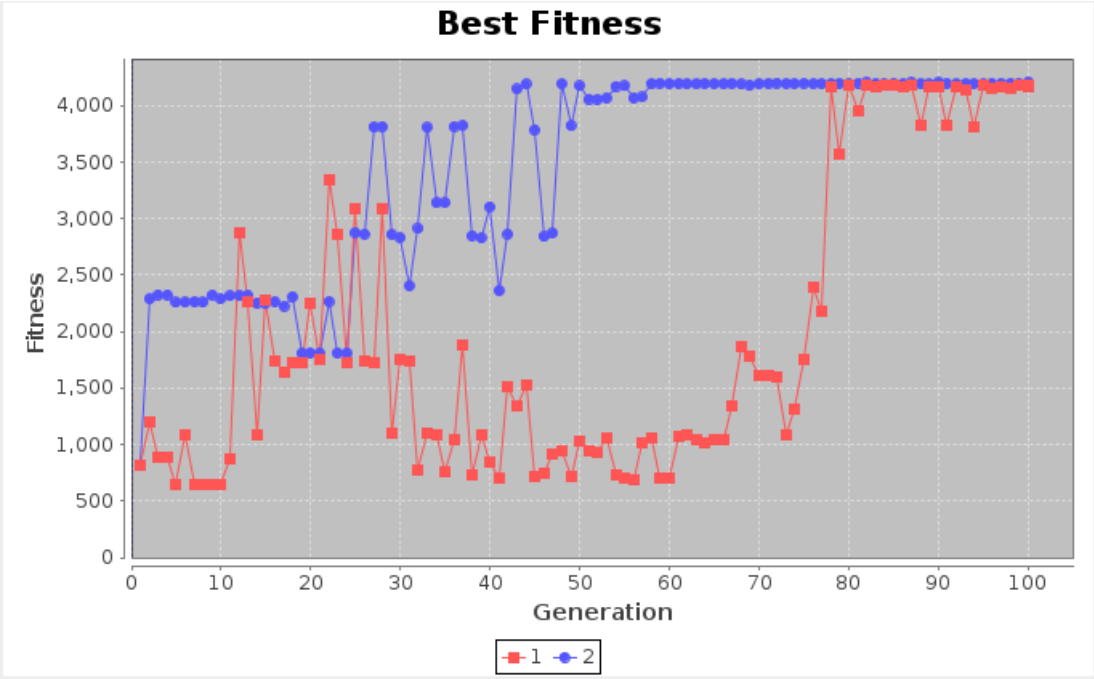


Figure 5.5: The best fit individual using self regulation gene on hard difficulty

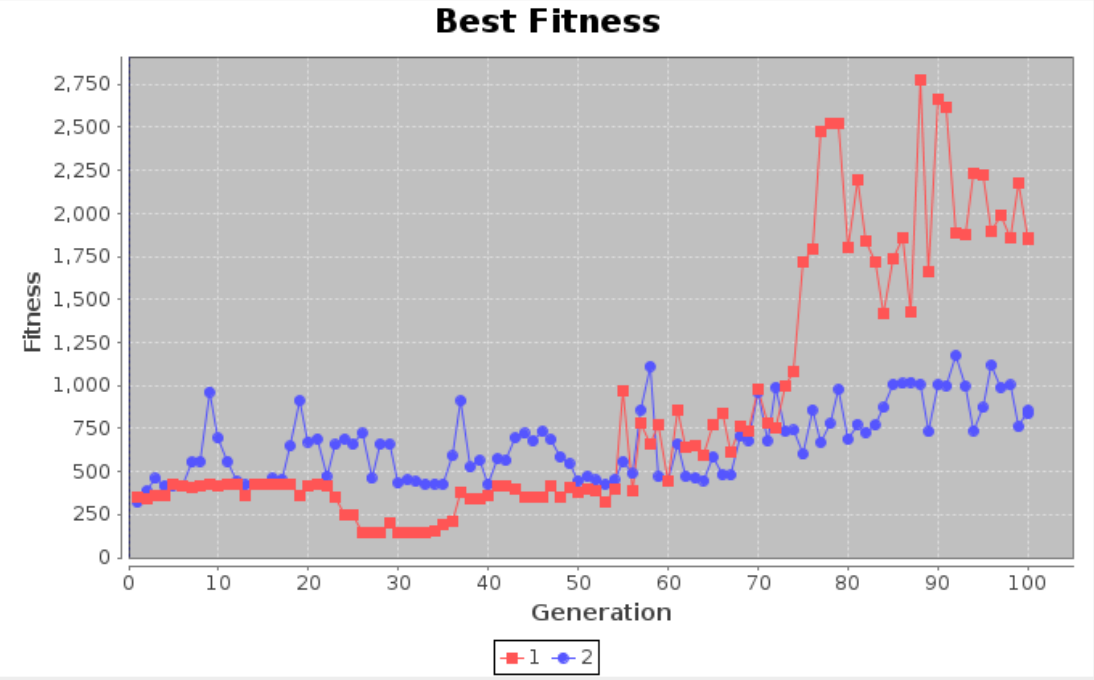


Figure 5.6: The best fit individual using default parameters on hard difficulty

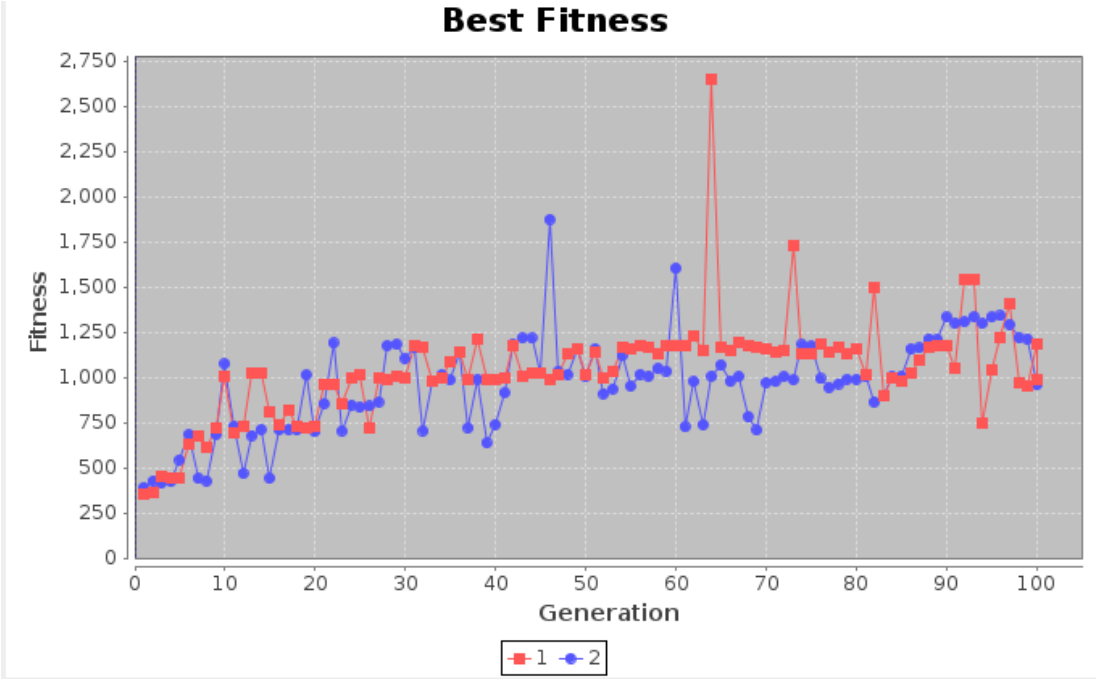


Figure 5.7: The best fit individual using self regulation gene with random parameters on hard difficulty

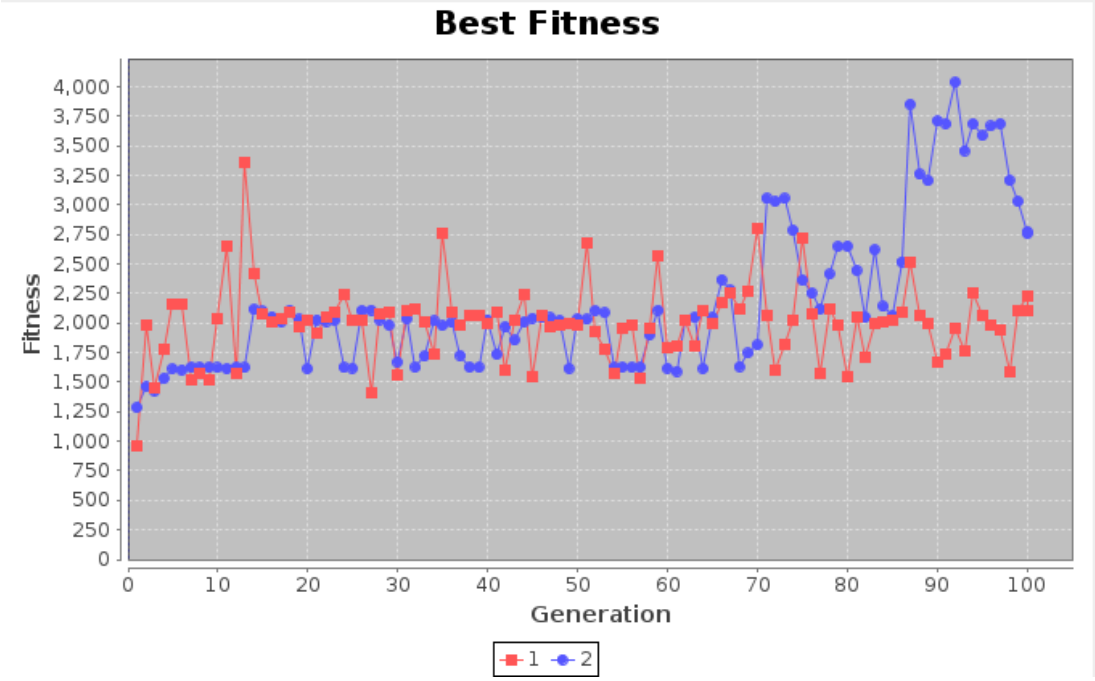


Figure 5.8: The best fit individual using default paramters for Tetris

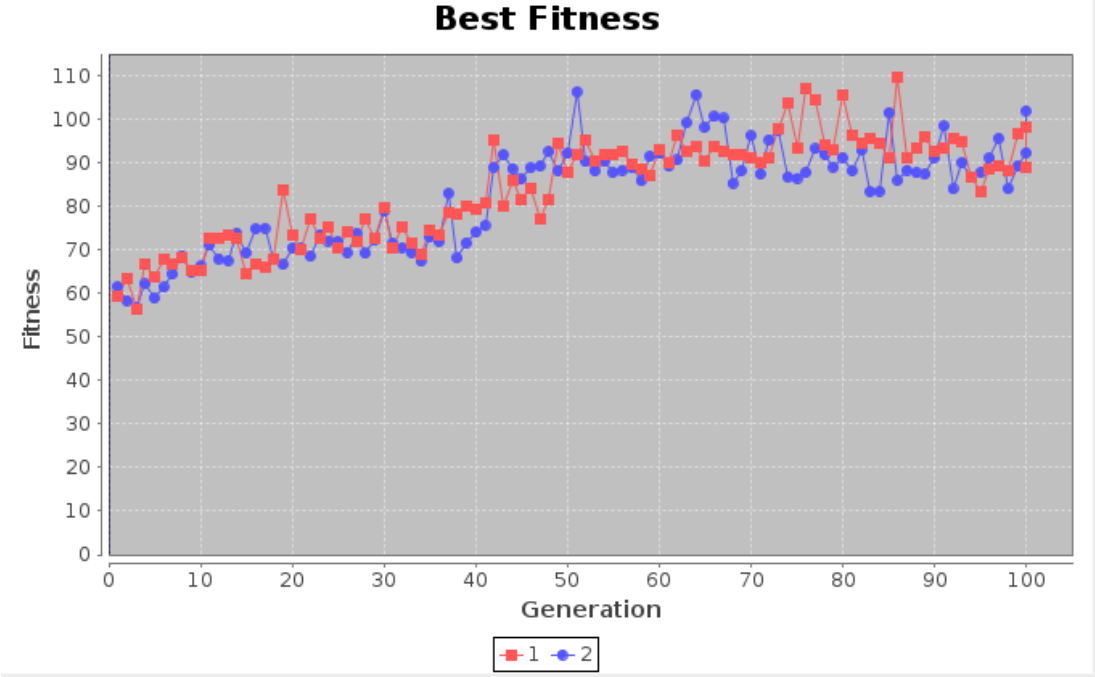
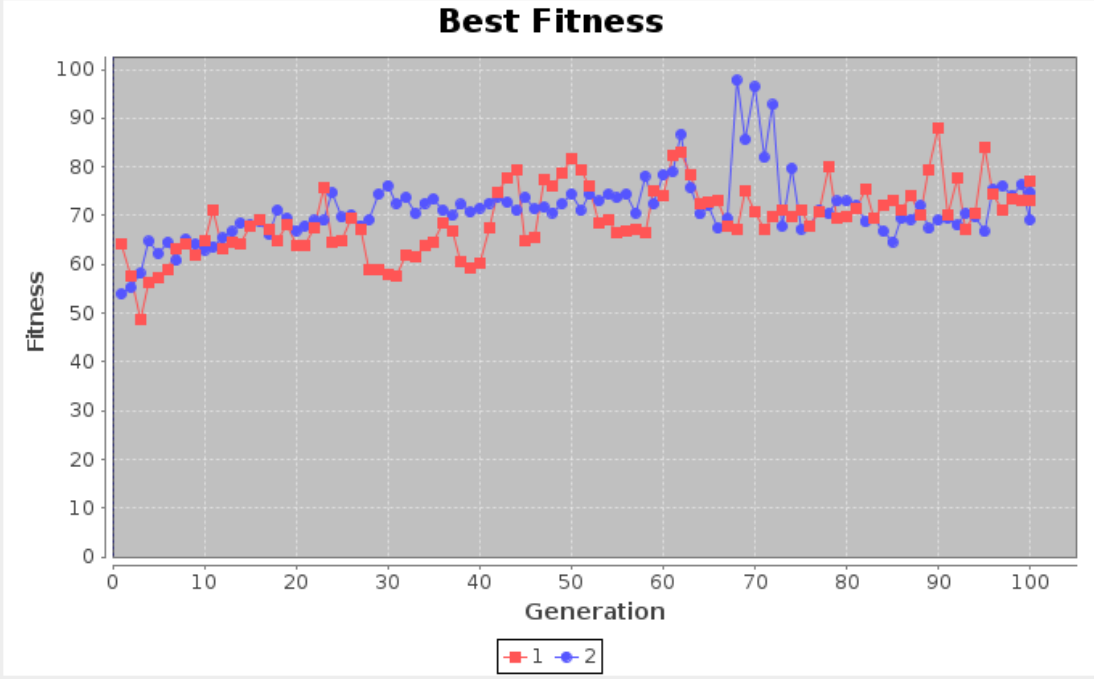


Figure 5.9: The best fit individual using self regulation for Tetris



Chapter 6

Conclusions and Future Works

6.1 Conclusions

The self regulation gene has the potential to reduce the time needed to configure an experiment with NEAT, as long as the experiment is difficult enough that the normal parameters are not sufficient.

Defining useful heuristics is still important since there isn't a way to use the self regulation gene to assign heuristic values used in calculating specie size. As seen with the development of the Tetris interface, it is important to provide inputs that work well with neural networks.

Overall the self regulation gene is an improvement to NEAT, but should only be used in situations where a default setup is not providing results.

6.2 Future Works

6.2.1 Different Genes

An alternate approach to the implementation of the self regulation gene using multiple genes containing information on specific parameters could lead to improved convergence on parameters. This improvement would allow for genes to be used only where they are needed, instead of using all the parameters present in NEAT.

6.2.2 Dynamic Data Set Selection

In addition to generating heuristic values for the datasets or levels used to run the AI against, datasets or level could be selected from a set to improve AI creation. Selections could be made on the difficulty the AI has solving certain levels or levels that are shown to have a history of producing high fitness individuals.

6.2.3 Improved Specie Allocation

There are a few parts of the NEAT algorithm that conflict with goals of the modification. The distribution of individuals could be improved so that genes are protected better during dynamic speciation. In some of the tests it was apparent that too many species were being created and destroyed in order to keep the number of species constant. This led to a large drop in the total fitness of whole population. Either creating a modification to the dynamic compatibility threshold algorithm or allowing the self regulation gene to have more control over speciation could be explored to solve this issue.

6.2.4 Aging

Allowing the self regulation gene was tested in preliminary experiments and showed problems due to species developing higher and higher youth boost parameters. Species would inflate their own fitness without actually improving anything. If this problem could be fixed then the aging functionality, allowing modification of the specie age threshold, the specie youth threshold, the specie old penalty , the specie age threshold, and the specie youth threshold could be dynamically changed and solved.

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Chapter 7

Appendix

Parameter Name	Parameter Description	Range	Ex
PROBABILITY.MUTATION	This value controls the mutation of connection weights and the sigmoid factor of the neurons.	0 - 1	0
PROBABILITY.CROSSOVER	This value controls the rate at which individuals, within the same specie, perform a GA crossover operation as defined in the NEAT algorithm.	0 - 1	
PROBABILITY.ADDLINK	This is the rate at which new links are added between neurons. It does not take into account the recurrent parameter as this check is performed at the end of a mutation.	0 - 1	0

PROBABILITY.ADDNODE	This is the rate at which new neuron is added to an enabled link.	0 - 1	0
PROBABILITY.MUTATEBIAS	Each neuron has a bias value. This parameter controls the rate at which they are mutated.	0 - 1	
PROBABILITY.TOGGLELINK	A link (neuron-neuron connection) has two states, enabled and disabled. This paramter controls the rate at which a link might toggle its state.	0 - 1	
PROBABILITY.WEIGHT.REPLACED	A link can have its weight reset to some arbitrary value regardless of its current value. This parameter controls the rate at which this happens.	0 - 1	
EXCESS.COEFFICIENT	A NEAT specific coefficient that provides a measure of importance to the excess of genes, within a chromosome, when it comes to calculating the compatibility between two chromosomes.	>=0	

DISJOINT.COEFFICIENT	A NEAT specific coefficient that privides a measure of importance to the difference of genes, within a chromosome, when it comes to calculating the compatibility between two chromosomes.	>=0	
WEIGHT.COEFFICIENT	A NEAT specific coefficient that provides a measure of importance to the weight differences of link genes, within a chromosome, when it comes to calculating the compatibility between two chromosomes.	>=0	
COMPATABILITY.THRESHOLD	A speciation parameter that is used when deciding if a given chromosome should go in a given species.	>=0	

COMPATABILITY.CHANGE	If this is 0, then the COMPATABILITY.THRESHOLD will not change at all. This means that the number of species will be not controlled. If this is greater than 0, then the COMPATABILITY.THRESHOLD will by dynamically changed (*up or down) by this change value to try and keep the number of species to be SPECIE.COUNT.	>=0	
SPECIE.COUNT	A speciation parameter that is used when deciding if a given chromosome should go in a given species.	>=1	
SPECIE.COUNT	A speciation parameter that is used when deciding if a given chromosome should go in a given species.	>=1	

SURVIVAL.THRESHOLD	During mating within a species, this value defines the fraction of the top specie members that are allowed to mate. For example, if the value was 0.2, then only the fittest 20% of the specie would be allowed to mate.	>=0	
SPECIE.AGE.THRESHOLD	Once a species age reaches this value, the fitness of the specie members will be multiplied by SPECIE.OLD.PENALTY.	>=1	
SPECIE.YOUTH.THRESHOLD	Whilst a species age is less than this value, the fitnesses of the specie members will be multiplied by SPECIE.YOUTH.BOOST	>=1	
SPECIE.OLD.PENALTY	The penalty applied to the fitness of a given species members. Note, if NATURAL.ORDER.STRATEGY is true, this should be >= 1 else <= 1	>=1 or <= 1	

Table 7.1: Table of Parameters for NEAT4J