# Neuro-Evolution Using Recombinational Algorithms and Embryogenesis for Robotic Control 

Thesis by<br>Anthony M. Roy

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To Kellie, my future wife

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## Abstract

Control tasks involving dramatic nonlinearities, such as decision making, can be challenging for classical design methods. However, autonomous, stochastic design methods such as evolutionary computation have proved effective. In particular, genetic algorithms that create designs via the application of recombinational rules are robust and highly scalable. Neuro-Evolution Using Recombinational Algorithms and Embryogenesis (NEURAE) is a genetic algorithm that creates $\mathrm{C}^{++}$programs that in turn create neural networks which can function as logic gates. The neural networks created are scalable and robust enough to feature redundancies that allow the network to function despite internal failures. An analysis of NEURAE evinces how biologically inspired phenomena apply to simulated evolution. This allows for an optimization of NEURAE that enables it to create controllers for a simulated swarm of Khepera-inspired robots.

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## Chapter 1

## Introduction

### 1.1 Motivation

Artificial neural networks (ANNs) are able to solve mathematically ill-defined problems with a network of computationally simple elements. Inspired by the architecture of the human brain, McCulloch and Pitts (1943) modeled biological neurons as simple mathematical units capable of comprising large networks. Turing (1950) described the plausibility of a complex computing machine being constructed from simple computational units. Hornik et al. (1989) proved that with the proper architecture, an ANN composed of McCullochPitts neurons can approximate any regular function within a finite space to an arbitrary degree of accuracy.

The potential of ANNs has inspired their application in a wide range of fields. The primary use of neural networks has been for classification purposes. Wu et al. (1993) and Odewahn et al. (1992) showed how ANNs can be used to classify malignant tumors in mammograms and star types in telescopic images, respectively. Waibel (1989) found use of temporal ANNs in the realm of speech recognition. Atiya (2001) detailed how neural networks can be capable tools for analyzing credit risk.

Neural networks have also been used for robotic control. Naito et al. (1997) argued the nonlinearity and distributed information storage of ANNs make them attractive candidates for control. Biewald (1996) used a neural network controller for obstacle avoidance by partitioning the problem into separate path planning and local navigation regions. Cui and Shin (1993) controlled multiple manipulators by using neural networks to approximate the Jacobian at various points of the robots' range of motion. Beer et al. (1992) and Lewis et al. (1994) employed recurrent neural networks to control the gait of a hexapod robot. Hornby
et al. (2001) used ANNs as controllers that are able to evolve alongside the morphology of the controlled robots. Yue and Rind (2006) used a neural network for object recognition in an obstacle avoiding robot.

However, there are limits to what current ANN learning algorithms can accomplish. Convergence of the widely used back propagation algorithm is dependent on network architecture and learning rates (Hecht-Nielsen 1992). The setting of these parameters require significant expertise and a priori knowledge of the problem to be solved. Otherwise, the network is likely to converge to a non-optimal solution or be unduly influenced by the sequence of learning examples that are given (Sutton 1986). Furthermore, training session require large amounts of historical data and are computationally demanding.

Hebb (1949) posited a theory that biological neural networks adapt by repeated firing. As the activation of one neuron coincides with the activation of another several times, the connection between the two strengthens in such a way that it becomes easier for the first neuron to excite the second. Perhaps the most well-known application of Hebbian learning in an ANN is a Hopfield network. Hopfield (1982) proved that an ANN can use Hebbian learning to converge to a local minimum, thus making the network stable. However, stability requires the network be symmetrical, with nodes being connected to each other with identical weights. Even if this constraint is not enforced, Hebbian learning is a capable method for getting ANNs to classify data (Sanger 1989; Oja 1992; Daucé et al. 1998). However, these methods often converge to local minima and are not suited to finding an global optimum.

Real-time reinforcement is yet another scheme for adapting network connections. Onat et al. (1998) showed how positive reinforcement can be used to strengthen connections between neurons when the network is performing as desired. Chialvo and Bak (1999) showed how similar learning occur with negative reinforcement. Bosman et al. (2003) gave a more generalized approach which combined Hebbian and reinforcement learning. However, as evident in the work of Sutton and Barto (1999), there are several learning parameters of the reward function which must be tuned, and these values require expertise or trial and error to set correctly.

Because training ANNs is inherently a trial-and-error process, it was a natural extension to use a genetic algorithm (GA) to train them. Genetic algorithms, also known as evolutionary algorithms, use simulated evolution to design solutions. As conceived by Holland
(1975), GAs are a machine learning paradigm in which the parameters of a possible design solution are varied over time to eventually find a viable solution. Furthermore, many solutions are designed in parallel, and the parameters of one solution may be used, partly or completely, in the parameters of another. As a result, the design solutions within a GA improve over time in a manner similar to biological evolution. Like ANNs, GAs have found applications in a wide range of fields such as circuit design in electrical engineering (Miller et al. 1997), ligand bonding in chemistry (Morris et al. 1998), and granular composites in material science (Fraternali et al. 2009).

Most ANNs designed by evolutionary algorithms involved optimizing the weight of a set network architecture (Montana and Davis 1989; Eberhart and Kennedy 1995). Further work focused on evolving the parameter of various different learning algorithms (Roy et al. 1999; Chen et al. 1999).

Eventually there was an emergence of GAs in which network architecture and connection weights are coevolved in a process known as neuro-evolution. Reed (1999) gives a good overview of many GAs which evolve network architectures through decomposition, where a large, fully connected network has connections and nodes removed. The shortcomings of such schemes were addressed by Angeline et al. (1999) who offered GNARL as an alternative. According to Angeline, decomposition methods often become trapped at local network minima, which causes them to suffer the same non-optimum finding deficiencies GAs were designed to overcome.

More current neuro-evolution efforts include NEAT by Stanley and Miikkulainen (2002), and AGE by Duerr et al. (2006). Both methods utilize genomes that represent the nodes and connections of ANNs. The genomes of NEAT explicitly contain the connection weights. The three tiers of NEAT, gene tracking, speciation, and complexifying, have become so well studied and efficient that Stanley et al. (2005) managed to evolve networks in real time. In AGE, the genome includes a section for each node that, when combined with the similar section of another node, determines the weight of connections. Both NEAT and AGE are able to use evolution to construct networks capable of performing complex control tasks. However, the practical size of evolved networks is limited by the requirement that each node of the network is directly represented in the genome.

There are applications where a large network is necessary, such as the Gammon project (Tesauro 1992). The Gammon project was an attempt to make a neural network a successful
backgammon player. Gammon looks at the current state of the board and possible moves for a given roll of the dice. It then uses the neural net to calculate which possible move for the given dice roll would lead to the highest probability of winning, and moves accordingly. With 198 input units and 40 hidden neurons, it plays on a level even with the best backgammon players in the world. If one were to design such a network with a genetic algorithm, the GA would have to be scalable.

One of the first examples of a scalable GA was introduced by Kitano (1990). In his seminal paper, he used matricies to represent ANN connection weights. He achieved scalability by using single bits to represent small connectivity graphs and allowing recursion of such bits. As a result, a neural network could be represented more compactly with reasonable modularity. Tufte and Haddow (2000) used a similar genome shorthand to evolve large digital circuits.

Theraulaz and Bonabeau (1995) have shown that the reuse of a small set of rules to create a phenotype is an effective alternative to storing and manipulating the large amount of data that describes each individual directly. Bentley and Kumar (1999) have shown that indirect encodings produce solutions to design problems faster and better than their directly encoded counterparts. Federici and Downing (2006) have shown that rule-based encoded designs are more robust as well. Grajdeanu (2007) evolved rules capable of making virtual 2-D organisms with interesting properties such as cell differentiation and repair. Yogev and Antonsson (2007) created 3 -dimensional structures by evolving a set a rules which directs how a single cell should grow through a process called embryogenesis.

Embryogenesis is best described as genetic programming (GP) applied to the evolution of instructions which in turn determines how an artificial embryo should grow (Garis 1992). A genetic program is a genetic algorithm where the evolution is performed on a computer program. In its inception, Fogel et al. (1966) devised a way to use the evolutionary process that allowed the recombination of a computer program into various configurations. Later, LISP programs were evolved by Koza (1989) to create programs which could discover recursive expressions for numerical sequences and pattern recognition. O'Neill and Ryan (2001) went on to make grammatical evolution (GE), which was a scheme for how to do genetic programming in any arbitrary language. However, in GP the program is the end result of evolution. It is when these programs are used to grow something else when true embryogenesis occurs.

Embryogenesis was applied to ANN evolution when Gruau (1992) created cellular encoding (CE), which dictates how a network grows from a single cell. CE was able to create a network of arbitrary size that is capable of detecting logical parity. However, as noted by Luke and Spector (1996), Gruau achieves much of his modularity by using a recursion rule that results in generating nodes with identical inputs and outputs. While his networks are able to perform well for tasks requiring symmetry, his method performs poorly for networks that require asymmetric weights.

Kitano (1995) used his compact representation to encode instructions for the growth of virtual axions and dendrites in graphical ANN. His scheme also implemented cell differentiation. However, this application was geared more towards simulating the growth of a biological neural network instead of creating ANNs for engineering purposes.

Astor and Adami (2000) expanded on the idea of growing neural networks by creating NORGEV, a simulated wet chemistry set. Within their evolutionary algorithm, a network is grown from a single neuron by using cell chemistry and protein diffusion models. One key distinction of their work is that the evolved proteins not only provide growth instructions for the network, but also halt growth. While this method is able to make large neural networks, it can take excessive evolution time as much of the processing power is devoted to simulating chemical diffusion.

Since GAs have been applied successfully in control problems (Yakovenko et al. 2004; Vigraham et al. 2005; Dupuis and Parizeau 2008; Zhang et al. 2008) it may come as now surprise that the synergy of GAs, ANN, and control is a current area of research. Naito et al. (1997) evolved ANN controllers for simulated Khepera (Harlan et al. 2001) robots. Lipson and Pollack (2000); Pollack et al. (2003) have had much success in evolving the morphology and control of robots. Floreano et al. (2007) evolved a swarm of robots which learn complex communication behaviors. Yet, all of these methods use direct representations, and if one were to evolve an ANN complex enough to control an autonomous vehicle(s) (Cremean et al. 2006; Murray 2007), one would need a large ANN and a scalable GA to create it. While Calabretta et al. (1998) and Stanley et al. (2009) have implemented GA with some scalability, their designs scale by using predetermined modules and symmetries, which are not generally known a priori.

### 1.2 Outline

This thesis will detail the methodology, analysis, and implementation of a new genetic algorithm for neuro-evolution. Designs in the GA are grown via a set of variable-length rules that are decoded to create a $\mathrm{C}^{++}$program. The $\mathrm{C}^{++}$programs used to create the ANNs have an If-CONDITION-Then-ACTION structure. Each program has multiple sections that cycle through all pairings of nodes with tests and actions of the form:

If Node $\alpha$ and/or Node $\beta$ meet certain CONDITION(S), Then perform ACTION(S).

The expected result is to create an encoding scheme that, like CE, can take advantage of modularity to create large networks. However, it will also use the innovations of NORGEV to evolve a more controlled growth as well. Having the growth directed by $\mathrm{C}^{++}$ programs comprising various recombinations of $I f$-Then statements instead of solutions of complex diffusion equations will lead to shorter evolution times. While Neuro-Evolution Using Recombinational Algorithms and Embryogenesis, or NEURAE, may seem akin to the GE of Tsoulos et al. (2005), the work presented here is only superficially similar. Limiting the evolution to only If-Then commands constrains the search while remaining flexible enough to explore highly productive regions of the solution space. Furthermore, the programs generated by NEURAE are the rules for embryogenesis, which provide scalability and produce modularity. Conversely, the programs created by conventional GAs are direct representations of an ANN, and do not exhibit such scalability or modularity.

This thesis will show that NEURAE is a unifying GA capable of accomplishing a wide range of neuro-evolutionary goals. Chapter 2 will introduce the methodology of NEURAE after a brief background of artificial neural networks and genetic algorithms. Chapter 3 will show that NEURAE is capable of evolving two types of parity evaluators. The first is a 2 -input XOR gate with many network redundancies. The second is a parity gate of an arbitrary size. The first task has definitive exploration versus exploitation regions, which simplifies the analysis of the evolved rules. Furthermore, it will be shown that modularity can be produced in a randomly changing environment, in opposition to Kashtan and Alon (2005). The second task can be directly compared to existing literature, particularly that of Gruau (1994), and will show how NEURAE can scale well to create large ANNs.

Chapter 4 will analyze how and why NEURAE works in an effort to make the evolutionary process more efficient. Like evolutionary algorithms themselves, many of the mutations used in NEURAE where inspired by natural mutations. Experiments were conducted to verify if and how the artificial mutations actually enhance evolution as well as their biological counterparts are theorized to do. Next is an analysis of the individual created in a good and failed evolution to see what differences lie on a genomic level. Finally, an investigation was conducted to see how different conditions and actions are used, and how their removal affects the GA.

Chapter 5 will give the derivations of the formulas used to create the robotic simulations in Chapter 6 . Chapter 6 will show how NEURAE is able to evolve robotic controllers in deceptive design domains. NEURAE will easily make controllers for a line following robot, and obstacle avoiding robot, and a coordinated swarm without any changes to its core functionality. Chapter 7 will provide a conclusion and the possible future of NEURAE.

## Chapter 2

## Methodology

### 2.1 Background

### 2.1.1 Neural Networks

An artificial neural network (ANN) is a computing paradigm which is a gestalt of simple computational units called neurons or nodes. All ANNs in NEURAE are composed of McCulloch and Pitts (1943) modeled neurons. The input to each neuron is multiplied by some scalar, or weight, $w_{n}$. Next, the weighted inputs are summed and are in turn used as the input, $u$, for a (usually) nonlinear activation function $O(\cdot)$, as shown in Equation 2.1. In the original McCulloch-Pitts model, the nonlinearity could be any bounded function. Due to the desire to make learning algorithms easier to prove and implement, the activation function usually forces the output of the neuron to be within $[-1,1]$. This, however, is not a requirement and an activation function that bounds the output between 0 and 1 can be used. Furthermore, digital networks usually use a discontinuous activation function while $O(\cdot)$ in an analog network would likely be continuous (Kartalopoulos 1996). Finally, neurons usually feature a constant, or bias, which is also summed to the inputs and serves to shift the activation function along the dependent axis.

$$
\begin{equation*}
u=\sum_{i=1}^{n} w_{i} \tag{2.1}
\end{equation*}
$$

The neurons in NEURAE use the activation function shown in Equation 2.2. The activation function, $O(\cdot)$, is a Heaviside function with a bias which acts as a threshold and separates the on/off regions at the constant, $t$. Thus, each neuron in NEURAE is either completely off or on. Even though the bounded output of each neuron may be
weighted before it is used as an input to another node, $O(u)$ for an output neuron is always unweighted, resulting in a binary output for the entire ANN. The model of neurons used in NEURAE is shown in Figure 2.1.

$$
O(u)= \begin{cases}1 & \text { if } u>t  \tag{2.2}\\ 0 & \text { if } u \leq t\end{cases}
$$



Figure 2.1: McCulloch-Pitts neuron model.

### 2.1.2 Genetic Algorithms

Genetic Algorithms (GAs) are a class of evolutionary computation, and repeatedly reiterate randomly created designs to find a desired solution. The design solutions are commonly referred to as individuals, and the goal is to eventually create individuals that are capable of solving the design problem. Figure 2.2 is a simplified flowchart of the various steps contained within a standard GA. GAs begin with an initial population of individuals with randomly created genomes. For all GAs there is a difference between the genotype and phenotype. The genotype dictates the design parameters of the individual, and it is the altering of the genotype that ultimately alters the design parameters of the solution. The phenotype, however, is the realization of the individual, and it is the phenotype which is evaluated. Thus, the individuals' fitnesses are based upon how well their phenotypes complete the design challenge.

However, the randomly created initial population is made up of poorly performing individuals. The best performing of these individuals are selected from the population. These selected individuals are slightly modified to create a new population. This process of eval-
uation, selection, and mutation is repeated until either a prescribed time limit has passed or a good design is found.


Figure 2.2: Steps of a standard genetic algorithm.
(*Denotes an optional step).

The way individuals are represented, or encoded, within a GA is of paramount importance to how they are evolved. As the encoding becomes more complex, the genotype to phenotype mapping becomes a more involved process known as embryogenesis in which the phenotype starts as a small embryo, then grows according to its genome before or even during evaluation. Stanley and Miikkulainen (2003) offer classifications for the different types of genomic encoding within present-day GAs.

- Direct - The design parameters of the phenotype are represented directly within the genotype. The approach works well for optimizing a design parameter, but the one-to-one, genotype to phenotype relationship makes scalability a significant problem. Also, the lack of inherent modularity and symmetry makes it a poor candidate for design synthesis.
- Developmental - The genotype is a compacted representation of the phenotype, and makes the phenotype by using a prescribed set of rules. This can scale well and takes advantage of known modularity and symmetry. However, evolution is unable to discover and exploit unknown symmetries. Furthermore, the way modularity and symmetry are used to compact genomic representation can unduly bias or even limit the solutions acquired.
- Implicit - The genotype is the rules that, when executed, create a phenotype from
an embryo. This approach offers the widest range of possible answers, and thus is the best method for generating completely novel designs. However, optimization is hampered by the strongly non-injective mapping between the genotype and phenotype. Evolution times can also be slowed by extended periods of embryogenesis.

For NEURAE, an implicit encoding scheme was decided to place as little restriction as possible on the type of ANNs created. Thus, many of the examples of NEURAE exemplify the creation of novel network architectures rather than the optimization of well-known ANN problems.

### 2.2 The NEURAE Genotype

### 2.2.1 Overview

Each individual in NEURAE is a digital, feed-forward neural network. However, the implicit encoding scheme of NEURAE means each ANN is created by the execution of the rules encoded in its genome. When the genomes are decoded, the result is a $\mathrm{C}^{++}$program. When the program is compiled and executed, the ANN is created.

The neural networks begin as a few neurons, but are grown according to the instructions encoded within their genomes. All ANNs start as the desired number of input neurons with a threshold of 0 . Each input node is able to create up to seven addition neurons. These subsequent neurons can exist within either the hidden or output layers, and can each make up to seven addition hidden or output neurons. However, once the desired number of output nodes are created, the entire ANN is unable to create any additional neurons.

Each neuron can also make connections, and can continue to do so even after no more neurons can be created. To ensure the ANNs are feed-forward, nodes are only able to make connections to neurons created after themselves. Furthermore, connections to any input node are prohibited. While nodes within the same hidden layer are unable to connect to each other in most ANN applications, no such constraint is imposed here. Neurons within the hidden layer are able to connect to any other node within the hidden layer so long as the receiving node was created after the transmitting node. Finally, each neuron can have a maximum of 99 inputs and 99 outputs.

### 2.2.2 Biological Analog

A biological analogy was the inspiration for the encoding scheme used here. The genome of each individual is a variable-length array of integers which is decoded to create a $\mathrm{C}^{++}$ program. Every digit is analogous to a nucleotide whose value is inclusively between 1 and 100. A collection of six nucleotides forms a complete If-CONDITION-Then-ACTION statement, and are analogous to a codon. These tests in the If-Then statements are not independent, and the sequence of codons will greatly influence how the individual will grow. In particular, the If-Then structure can be arranged such that multiple conditions are tested before an action can be executed. The closure of all If-Then statements, condition tests, and actions form a block analogous to a gene. The resulting (closed) If-Then statements in the $\mathrm{C}^{++}$programs are similar to proteins. These concepts are shown in Figure 2.3.
$\swarrow^{\text {Nucleotide }}$


Figure 2.3: Sample genome and biological analog

### 2.2.3 If Structure Nucleotide



Figure 2.4: Nucleotides of each codon

The first nucleotide of each codon dictates the overall logic of the corresponding $\mathrm{C}^{++}$ program. As shown in Figure 2.5, a simple change in the order or nesting of the If-

CONDITION-Then-ACTION tests can have a large effect on the computational process. This flexibility allows the GA to build complex algorithms from simple building blocks.

The logic corresponding to the numerical value of the first nucleotide is listed below.

- If - Opens an If-Then statement. Adds action to the action stack. Nucleotides [1-25]
- End-If - Writes in and removes last action placed into the action stack. Closes an If-Then statement. Opens another If-Then statement. Adds action to the action stack. Nucleotides [26-40]
- End-End-If - Writes in and removes last action placed into the action stack. Closes an If-Then statement. Executes and removes last action placed into the action stack stack. Closes another If-Then statement. Opens an If-Then statement. Adds action to the action stack. Nucleotides [41-55]
- End - Writes in and removes last action placed into the action stack. Closes an If-Then statement. Nucleotides [56-75]
- End-End - Writes in and removes last action placed into the action stack. Closes an If-Then statement. Executes and removes new last action placed into the action stack stack. Closes an If-Then statement. Nucleotides [76-90]
- End-All - Writes in and removes last action placed into the action stack. Closes an If-Then statement. Repeats until all If-Then statements are closed. Nucleotides [91-100]


Figure 2.5: If structure codon and protein transcription

### 2.2.4 Condition Nucleotides

The next three nucleotides determine which of the ANN states that can cause actions to occur will be tested. The second nucleotide in each codon dictates which attribute will be tested. The attributes are current states of Node $\alpha$ and/or Node $\beta$. Many of these attributes affect the functionality of the neural network, such as the threshold of the neuron or the number of connections it has. However, each node also has a three-part identification number that aids in evolution without affecting the functionality of the neuron. The first part of the identification number (ID1) is denoted by a letter between A and H . Input nodes all have an ID1 of A and output nodes all have an ID1 of H. Hidden nodes can have an ID1 of B through G, which is determined explicitly by the action which creates it. A node's second ID number (ID2) is determined by the parent node which created it. If this is the first node the parent node has made, the new node will have an ID2 of 1. If it is the third node the parent node has made, the new node will have an ID2 of 3. ID2 values can range between 1 and 8 since any node can make, at most, 8 other nodes. ID3 values denote how many nodes within the entire network have the same ID1 and ID2 values. Thus the first node with an ID1 value of B and an ID2 value of 5 will have an ID3 value of 1 , while the second node with the same ID1 and ID2 values will have an ID3 value of 2 . These values can range from 1 to 100 . The result of the three different ID types is that each node will have a unique identification number.

The following list presents all possible node states which can be used by the attribute nucleotide. In addition to using the explicit values of Node $\alpha$ and/or Node $\beta$, relative differences between the two nodes can be considered as well. For values where a state of Node $\alpha$ relative to Node $\beta$ or Rel $\alpha \beta$ are considered, the attribute of Node $\beta$ is subtracted from the value of the same attribute of Node $\alpha$.

Similarly, there are options to consider the attributes of Node $\beta$ relative to Node $\alpha$, or Rel $\beta \alpha$. This can apply to all of the attributes listed above except for the connection weight. The value used for connection weight is the value of the weight from Node $\alpha$ to $\beta$ or vice versa. The nucleotide ranges are for $[$ Node $\alpha][$ Node $\beta][$ Rel $\alpha \beta][$ Rel $\beta \alpha]$. Equation 2.3 is used to get discrete values between $\pm 1$, excluding 0 , where $z$ is the nucleotide and $v$ is the value written into the $\mathrm{C}^{++}$program.

The test attributes corresponding to the numerical value of the second nucleotide are
listed below.

- ID1 - Takes the ID1 value of a node, which can be between A and H. Nucleotides $[1-5][27-31][53-55][77-79]$
- ID2 - Takes the ID2 value of a node, which can be between 1 and 8. Nucleotides $[6-10][32-36][56-58][80-82]$
- ID3 - Takes the ID3 value of a node, which can be between 1 and 100. Nucleotides $[11-14][37-40][59-61][83-85]$
- Threshold - Takes the threshold of a neuron. Due to Equation 2.3, this can be a number in the range $[-1-1] / 0$ in 0.02 increments. Nucleotides $[15-17][41-43][62-$ 64][86-88]
- Number of Nodes Made - The number of subsequent nodes a node has made. Can be between 1 and 8. Nucleotides $[18-20][44-46][65-67][89-91]$
- Number of inputs - Number of inputs into a node. Can be between 0 and 99 . Nucleotides $[21-23][47-49][68-70][92-94]$
- Number of outputs - Number of outputs from a node. Can be between 0 and 99 . Nucleotides $[24-26][50-52][71-73][95-97]$
- Connection weight - Takes the weight of a connection between two nodes. Due to Equation 2.3, this can be a number in the range $[-1-1] / 0$ in 0.02 increments. $\mathrm{Nu}-$ cleotides $[74-76][98-100]$

$$
v(z)=\left\{\begin{array}{lll}
\frac{z-50}{50} & \text { if } & z \geq 51  \tag{2.3}\\
\frac{z-51}{50} & \text { if } & z<51
\end{array}\right.
$$

The third nucleotide writes the appropriate value into the test. In order for a condition test to return textit/true, the attribute (second) nucleotide must be within a certain range of this test value nucleotide. The values written into the program depend on the attribute being tested. If the possible range is $[0,99]$, the number written into the program is the test value nucleotide minus 1. However, attributes that have only 8 possible values require equation 2.4 to convert the test value nucleotide into values suitable for the comparison.

For threshold and connection values, Equation 2.3 is used if the attribute is a connection or the threshold of a neuron. However, if the attribute is the relative threshold of a neuron, Equation 2.5, which gives a range of $[0,1.98]$, is used instead.

$$
\begin{align*}
& v=\left\lfloor\frac{z-1}{12.5}\right\rfloor  \tag{2.4}\\
& v(z)=\frac{z-1}{50} \tag{2.5}
\end{align*}
$$

The fourth nucleotide determines the range over which the attribute can vary from the test value and still have the condition return true. Similar to the test value nucleotide, the test range the nucleotide writes into the code depends on the attribute being tested. For cases where letters are compared, this is the lexicographical range between the letters where two sequential letters have a lexicographical difference of 1 .

### 2.2.5 Action Nucleotides

The final two nucleotides determine which actions are performed if the condition test is true. The fifth nucleotide determines which type of action will be placed into the action stack. As mentioned above, the last in the "stack" of actions is written into the program whenever an If-Then statement is closed. Some nucleotides will result in the creation of a new node. Others will create a connection between Node $\alpha$ and Node $\beta$. In both these cases, the action value nucleotide dictates the threshold of the new node or weight of the connection, respectively. The nucleotide-to-program transcription options are given by Equation 2.3. However, there are also No Action and End Turn action type nucleotides which will not insert any new action commands and end the pairing permutation, respectively. In these cases, the action value nucleotide is not used for anything. Figure 2.6 shows the genetic string used to create a $\mathrm{C}^{++}$program.

### 2.2.6 $\mathrm{C}^{++}$Programs (Proteins)

Each $\mathrm{C}^{++}$program is a collection of proteins that build the phenotype. While the genome creates the bulk of the algorithm, there are a few rules hard-coded into the $\mathrm{C}^{++}$program of every individual. These hard-coded rules are implemented to impose the minimum constraints any viable feed-forward ANN must have, while leaving enough flexibility to create


Figure 2.6: Sample genome and protein pseudocode
a variety of architectures. First, the test statements described in the previous section are always placed within two for loops which cycle through all the different pairs of the ANN. Also, all of the inputs nodes have a ID2 value of 1. As there is no option to create another input, each ANN will have the same number of input nodes.

However, there are also other mandatory conditions that must be met before an action is executed, even if the CONDITION within the genome is true. For actions that make a connection, the first test is to make sure the two nodes are not already connected. Next, the process ensures that the neuron being connected to is not an input to the entire ANN, and that the neuron being connected from is not the output for the entire ANN. Finally, there is a check that the neuron being connected to was made before the neuron which spawned the connection to ensure the ANN is feed-forward.

To keep ANN size reasonable, ANNs have a limited amount of energy available for growth. The act of creating a node or connection consumes one of the predetermined energy units for the entire ANN. Once a pairing executes an action that uses an energy unit, that pairing is over. The individual is considered to be completely developed once the individual uses all 200 energy units or the programs cycles through all pairing permutations without performing any actions. Figure 2.7 shows the development of a NAND gate using the pseudo-code from Figure 2.6. It is important to note that an infinite number of different genomes could have created an identical ANN.

```
for (Node \alpha= 1:ANN.size ) {
    for (Node \beta = 1:ANN.size ) {
        if ( |Node \alpha.ID1 - B| \leq 1 {
            make.connection(-0.5)
        }end
        if ( |Node \beta.ID3-1| < 0 ){
            make.node(H,-0.75)
        } end
    } end
} end
```



Figure 2.7: Protein pseudocode and sample NAND gate


Figure 2.8: Flowchart of protein pseudocode

Step 1:
EMBRYOGENESIS START


Step 3:
Neuron $\alpha=$ A-1-1
Neuron $\beta=\mathrm{A}-1-2$
Action: None


Step 6:
Neuron $\alpha=\mathrm{H}-1-1$
Neuron $\beta=$ A-1-2
Action: None


Step 9:
Neuron $\alpha=$ A-1-1
Neuron $\beta=\mathrm{A}-1-2$
Action: None


Neuron $\alpha=$ A-1-1
Neuron $\beta=$ A-1-1
Action: Make Node


Step 4:
Neuron $\alpha=$ A-1-2
Neuron $\beta=\mathrm{H}-1-1$
Action: Make Connection


Step 7:
Neuron $\alpha=\mathrm{H}-1-1$
Neuron $\beta=\mathrm{H}-1-1$
Action: None


Step 10:
Neuron $\alpha=$ A-1-1
Neuron $\beta=\mathrm{H}-1-1$
Action: Make Connection


Step 2:
Neuron $\alpha=$ A-1-2
Neuron $\beta=$ A-1-1
Action: None


Step 5:
Neuron $\alpha=\mathrm{H}-1-1$
Neuron $\beta=\mathrm{A}-1-1$
Action: None


Step 8:
Neuron $\alpha=$ A-1-1
Neuron $\beta=\mathrm{A}-1-1$
Action: None


EMBRYOGENESIS FINISHED


Figure 2.9: Steps showing the embryogenesis of NAND gate

### 2.3 Evaluation, Mutation, and Selection

Each ANN is evaluated after the embryogenesis of each individual, as described by the method above. Evaluations in NEURAE are performed in tiers to ensure network feasibility and to promote evolution of complex behaviors (Graham et al. 2009).

The first tier ensures the individual grows the correct number of output nodes. If the correct number of outputs are made, the individual advances to the second tier, where the exponent is increased for each output node with a connection. These two requirements, listed in Table 2.1, are the minimum for any possibly viable ANN circuit, and once met, will yield an exponent value of $x-1=1$. The remaining tiers vary depending on the design problem, and are listed alongside the design problem to which they pertain.

Table 2.1: Universal tiers for adjusting fitness exponent $(x)$

| Tier | Test | Change in Exponent |
| :---: | :--- | :--- |
| 1 | Are there enough <br> output nodes? | fraction of desired <br> output nodes |
| 2 | Are there a connec- <br> tions to each out- <br> put node? | + fraction of output <br> nodes with connec- <br> tions |

Another commonality all evaluations share is the fitness function shown in Equation 2.6. While $x$ is a linear comparison of two individuals, the exponential nature of Equation 2.6 magnifies any improvements and greatly improves convergence in NEURAE. Furthermore, the floor function ensures individuals which are unable to pass the first tier have zero fitness, virtually nullifying their odds of survival.

$$
\begin{equation*}
\text { Fitness }=\left\lfloor 2^{x-1}\right\rfloor . \tag{2.6}
\end{equation*}
$$

A roulette style of selection determines which individuals are used for creating the next generation. The population size in each generation is conserved. The probability of selecting an individual is determined using Equation 2.7; where $P_{i}, f_{i}$, and $N$ are the probability of selecting the $i$ th individual, the fitness of the $i$ th individual, and the population size, respectively. A quarter of the population of the current generation survives to the next generation. The remainder of the population is created by using the operations of point
mutation, conjugation, translocation, genome replication, and genome deletion.

$$
\begin{equation*}
P_{i}=\frac{f_{i}}{\sum_{j=1}^{N} f_{j}} . \tag{2.7}
\end{equation*}
$$

As described by Holland (1992), classical GAs change the genotype of future populations through point mutation and crossover of current individuals. Figure 2.10 shows an example of a point mutation in a binary genome where a random bit is flipped. Point mutations are also used in NEURAE, but instead of a binary bit flip, a random nucleotide is replaced with a randomly chosen integer inclusively between 1 and 100 .

$$
11 \underline{1} 0001110 \underline{0} 0 \Rightarrow 11 \underline{0} 0001110 \underline{1} 0
$$

Figure 2.10: Point mutation example. The underlined nucleotides are switched

Crossover mutations require two individuals to make two more individuals and are usually either single-point or two-point crossover. With single-point crossover, two individuals make two new individuals by having their genomes broken and swapped at a random location on the genetic string. In two-point crossover, only a section of the genomes are swapped. Figures 2.11 and 2.12 give an example of both types. For GAs in which all genomes must be the same size, the sections to be swapped must be of identical length. Furthermore, the sections are usually at the same genome locus such that the information being exchanged at that locus has some correlation to its purpose in the phenotype. In NEURAE, however, there is little correlation between the functions of the same section of genome between two different individuals. Furthermore, while crossover may produce one improved individual, they seldom create two. Thus, genetic material is shared during mutations in NEURAE through a process inspired by, and named after, biological conjugation.

$$
\begin{gathered}
111000111000 \\
\mathbf{1 0 1 0 1 0 1 0 1 0 1 0}
\end{gathered} \Rightarrow \begin{aligned}
& 111000101010 \\
& \mathbf{1 0 1 0 1 0 1 1 1 0 0 0}
\end{aligned} \quad 11100011000 \Rightarrow \begin{aligned}
& 111010101000 \\
& \mathbf{1 0 1 0 1 0 1 0 1 0 1 0}
\end{aligned} \Rightarrow \begin{gathered}
101000111010
\end{gathered}
$$

Figure 2.11: Single-point crossover mutation example. Parts of the genome which have been swapped are underlined

Figure 2.12: Two-point crossover mutation example. Parts of the genome which have been swapped are underlined

In biology, conjugation is a process used by many species of bacteria where one bacterium gives part of its DNA to another. Martin and Russell (2002) showed how this type of genomic
exchange may have been key in the evolutionary jump from prokaryotes to eukaryotes and Jain et al. (1999) and Ochman et al. (2000) offer conjugation as a reason for the high adaptability of present-day bacteria. NEURAE uses conjugation in the manner shown in Figure 2.13, where a section of one genome is inserted into the genome into another. Thus, new rules can be exchanged between individuals and, hopefully, the benefits of biological conjugation can also be used by NEURAE.

$$
\begin{gathered}
111000111000 \\
\mathbf{1 0 1 0 1 0 1 0 1 0 1 0 1 0}
\end{gathered} \quad \Rightarrow \quad 111000 \underline{1010111000}
$$

Figure 2.13: Conjugation mutation example. Parts of the genome which have been inserted are underlined

Ohno (1970) introduced the concept of genome duplication as another key component of biological evolution. During replication, portions of the genome are at times copied more than once, resulting in an offspring that has two genes which make the same protein. Ohno theorized this redundancy made the individual more robust to future mutations, because if one gene became non-functional, there is another copy to do the same job. This redundancy was also noted by Britten (2005), who observed that many sections of the human genome have sequences that are too similar to have arisen independently. NEURAE uses a genome duplication process as shown in Figure 2.14, where a section of a genome is copied more than once when it is being replicated.

$$
111000 \underline{111000} \Rightarrow 111000111111000
$$

Figure 2.14: Gene duplication example. The nucleotides copied more than once are underlined

The final two mutation types are gene deletion and translocation. In gene deletion a section of the genome is removed during replication. While gene deletion is an observable phenomenon in biology, its effects are usually damaging (Lewis 2005). However, it was added as a mutation here to counter the concatenating effects of conjugation and gene duplication. Translocation, where a section of the genome is moved to another locus, is yet another observed biological mutation. Regardless of its implications to biological evolution, Figure 2.5 shows that the order of rules are very important in the embryogenesis of an individual, so an operation which varies this order was included. Figures 2.15 and 2.16
show examples of these two processes in NEURAE.

$$
111000 \underline{111000} \Rightarrow 111000000
$$

Figure 2.15: Gene deletion example. The nucleotides deleted are underlined

$$
111000 \underline{111000} \Rightarrow 111 \underline{111000000}
$$

Figure 2.16: Translocation example. The underlined nucleotides are moved to another gene locus

Finally, it was necessary to prevent frame-shift mutations. A frame-shift mutation adds or deletes only part of a codon. The result is a shift in nucleotides that causes all following codons after the mutation to be different. Ohno (1970) detailed how such mutations are almost always deleterious in biology and care is taken to avoid them here.

## Chapter 3

## Logic-Gate Evolution

### 3.1 Overview

This chapter will describe how NEURAE creates logic gates. Each evolutionary run begins with the random creation of 200 individuals for 1000 generations. These values were found to give good results in run times around 4 hours on a cluster of 25 dual quad-core, 2.33 GHz computers. Furthermore, each individual started with a genome 300 nucleotides ( 50 codons) long. During evolution, a genome is allowed to double in size before being trimmed to the default length. Genome length was constrained to prevent the well-documented problem of bloat in genetic programming (Koza 1992; Langdon 2000). While this arbitrary setting of genome length may bias evolution, Szathmáry and Smith (1995) have evidence showing that overall genome length of a biological organism has little to do with the complexity of the phenotype.

The first goal is to evolve an ANN that can serve as an XOR logic gate (Table 3.1), even if the ANN suffers multiple failures. This circuit was chosen because its nonlinearity requires the creation of a hidden layer and is a common benchmark in the evolution of ANN logic circuits (Koehn 1996; Ashlock 2006). The next logic gate to be evolved is a parity gate. A parity gate is a standard logic circuit used in simple error detection. An even parity logic circuit will always have an even number of inputs and output active. This design challenge exemplifies NEURAE's capability to make a scalable ANN.

Table 3.1: Desired output pattern for XOR logic-gate

|  |  | Input 2 |  |
| :---: | :---: | :---: | :---: |
|  | 0 | 1 |  |
| Input 1 | 0 | 0 | 1 |
|  | 1 | 1 | 0 |

### 3.2 Robust XOR Gate

### 3.2.1 Evaluation Parameters

Table 3.2 shows the tiers used in evaluating the evolved XOR gates, the exponent gets an additional point for each correct answer. If an individual is able to get to the third tier, the exponent in Equation 2.6 has a value of $x-1=1$. At this point, the network's truth table is compared with that of the desired circuit in tier 3 . If the individual passes tier 3 and is a functional XOR gate, $x=6$ and the individual will have an overall fitness of 32 . In tier 4, a node is randomly removed, and the ANN is compared to the target XOR logic again. Nodes are continually removed until the circuit no longer produces the target logic. This test for robustness is performed for each generation the individual is alive. Because the order in which the nodes are removed changes with each generation, the fitness of an individual is not constant, and the overall robustness will increase.

Table 3.2: Tiers for adjusting fitness exponent $(x)$ in robust XOR evolution

| Tier | Test | Change in Exponent |
| :---: | :--- | :--- |
| 1 | Are there enough <br> output nodes? | fraction of desired <br> output nodes |
| 2 | Are there a connec- <br> tions to each out- <br> put node? | + fraction of output <br> nodes with connec- <br> tions |
| 3 | Compare to the de- <br> sired truth table | + of correct an- <br> swers in each table <br> entry |
| 4 | Break nodes until <br> failure | + fraction of nodes <br> broken |

### 3.2.2 Evolution Results

Figure 3.1 shows the fitness of the best individual of each generation. Figure 3.2 shows the first XOR gate synthesized by evolution in generation 823, and Figure 3.3 shows how it functions. In these figures, a node is filled-in (black) when it is activated. A solid connection indicates a positive weight while a dashed connection is indicative of a negative weight. As shown in Figure 3.3, the activation of either input will activate only the output. Once both nodes are on, three of the four hidden nodes are activated, and their inhibitory connections to the output are enough to deactivate it. However, this ANN is not robust, as all three hidden nodes are needed to counter the activation of both inputs, and the removal of any one will break the entire ANN.


Figure 3.1: Best fitness throughout the evolution of a robust exclusive-OR logic gate

By the end of the evolutionary run, a much larger ANN was created and is shown in Figure 3.4. This ANN comprises 49 nodes and 140 connections. The algorithm created this ANN by taking the smallest possible XOR gate (shown in Figure 3.5) and making duplicate copies of it. The resulting ANN can have all but one hidden node removed, and is as robust to node removal as possible. Furthermore, the ANN used 189 out of the 200 possible energy units, making it close to the maximum size this evolution would allow.

Nevertheless, this is not the largest, fully redundant ANN this genetic algorithm could have made. Figure 3.6 shows a refined version of the individual's code, which shows only the proteins used in making the ANN. The last protein in the code is responsible for making


Figure 3.2: First generated XOR gate


Figure 3.3: Network functionality


Figure 3.4: Best generated XOR gate


Figure 3.5: Network functionality
the output node, which in turn halts all further neuron growth. If the test value is increased from 3 to 5 , and the maximum number of energy units available for growth is not limited, then the 195 node network shown in Figure 3.7 is produced.

```
for (Node \alpha = 1:ANN.size ){
    for(Node \beta = 1:ANN.size ){
        if |Rel }\beta\alpha\mathrm{ .ID1 - 6| < 6{
            if |Rel }\beta\alpha\mathrm{ .threshold - 1.46| < 0.82 {
                make.connection(0.90)
            }
            make.node(D,0.92)
        }
        if |Rel }\beta\alpha\mathrm{ .ID1 - 6| < 4{
            make.connection(-0.94)
        }
        if |Rel }\beta\mathrm{ |.ID2 - 3| < 0{
                make.output(H,0.86)
        }
    }
}
```



Figure 3.7: Larger XOR gate

The results of this experiment show that NEURAE is able to create large and complex network structures. Not only is this GA able to solve the standard benchmark in logic neuroevolution, it was able to expand on it by finding the core module and replicating it. The ability of NEURAE to construct large networks with such regular structure will be key for future applications.

### 3.3 Large Parity Gate

### 3.3.1 Evaluation Parameters

Table 3.3 shows that for the creation of a variable-size parity gate, the exponent is increased by the fraction of entries in the truth table that are correct. Here, a 2-input parity gate will have an exponent of $x-1=2$ and a fitness of 4 . Once 2 -input even parity is developed, the ANN is rebuilt using the same genome, but starts with three inputs. The individual goes through the three tiers again, with the exponent increasing by one for each test. Therefore, a successful three-input parity gate will have an exponent of $x-1=5$ and a fitness of 32 . These three tiers are repeated for up to 21 inputs.

Table 3.3: Tiers for adjusting fitness exponent $(x)$ in scalable parity evolution

| Tier | Test | Change in Exponent |
| :---: | :--- | :--- |
| 1 | Are there enough <br> output nodes? | fraction of desired <br> output nodes |
| 2 | Are there a connec- <br> tions to each out- <br> put node? | + fraction of output <br> nodes with connec- <br> tions |
| 3 | Compare to the de- <br> sired truth table | + fraction of correct <br> answers in each table <br> entry |

### 3.3.2 Evolution Results

The genetic algorithm was also able to create a parity gate for an arbitrary number of inputs. Figure 3.8 shows the fitness of the best performing individual throughout evolution. The particular evolutionary run shown here produced a 2 -input parity (i.e., XOR) gate much more quickly than the run shown in the previous section. This large variability is a by-product of the stochastic nature of GAs. At the 621st generation, NEURAE finally generated a fully scalable individual. However, the discovery of this individual resulted in the halting of the GA due to the excessive time required to evaluate $\sum_{n=2}^{21} 2^{n}$ input configurations. While a more elegant evaluation method could have circumvented this issue (Gruau 1994), the fact still remains that NEURAE was able to solve the problem at hand.

As shown in Figure 3.9, the 2-input parity gate works by having hidden nodes which inhibit the output once both input nodes are activated. The hidden nodes, however, also inhibit the activation of other hidden nodes that were made afterwards. This cascading effect can also be seen in the 4 -input parity gate shown in Figure 3.10. The internal cascading structure of the 2-input network is able to scale accordingly to the 4 -input network by having the number of hidden nodes equal the number of output nodes. Having two inputs active in the 4 -input gate is identical to having two inputs active in the 2-input gate. Activating a third input is able to turn on the output node without activating another hidden node. However, the activation of a fourth input activates another hidden node, which in turn is sufficient to inhibit the excitation of all four inputs. Figure 3.11 shows this cascading effect scales with the number of inputs in an ANN with 13 inputs.

As shown in the code in Figure 3.12 the magnitude of a negative connection is exactly


Figure 3.8: Fitness of best-performing individual throughout the evolution of a scalable parity gate


Figure 3.9: Scalable parity gate with two inputs


Figure 3.10: Scalable parity gate with four inputs


Figure 3.11: Scalable parity gate with 13 inputs
twice the magnitude of a positive connection. Thus the excitation of two input nodes is canceled out by the excitation of one hidden node. Furthermore, as the network begins with more inputs, the number of hidden nodes made during embryogenesis increase as well, providing scalability.

Once again, certain hard limits prevent parity gates of any arbitrarily large size to be created. First, a limit of 200 energy units prevents this network from growing a parity gate with more than 13 inputs. Also, the 99 connection limit placed on the maximum number of inputs and outputs caps the parity gate size at 66 inputs. Fortunately, both these limits were established only to help the evolution process and can be increased as necessary to allow the code in Figure 3.12 to create parity logic for an arbitrary number of inputs.

```
for (Node \alpha = 1:ANN.size() ){
    for(Node \beta = 1:ANN.size() ){
            if |Rel }\beta\alpha\mathrm{ .nodes_made - 0| < 0{
                make.connection(-0.96)
            }
            if |Node\alpha.nodes_made - 1 | 0 0{
                make.node(H,0.02)
            }
            if |Node\beta.ID1 - El < 3{
                make.connection(0.48)
            }
            if |Rel }\beta\alpha.ID2-3| \leq 3{
                make.node(E,0.40)
            }
    }
}
```

Figure 3.12: Code for creating parity gates of arbitrary size

## Chapter 4

## Sensitivity Analysis

### 4.1 Mutation Rates

Many of the values used for the genetic algorithm were heuristic. Fortunately, NEURAE is able to solve the robust XOR problem with a wide range of values. Still, as the design challenges for NEURAE become more difficult, it is important to not disadvantage NEURAE by using suboptimal evolutionary parameters. Some parameters, such as population size and number of generations per evolution, are dependent on the computer resources available. However, the mutation rates were arbitrarily chosen, and are likely not the optimum. Furthermore, these mutation values can be adjusted independently of the hardware used and, hopefully, independently of the problem being solved.

NEURAE has a two-step process in determining mutations. After an individual is selected to produce offspring, its genome is scanned using the overall mutation rate, $\mu \in$ $[0,1]$. Each codon has a probability $\mu$ of undergoing some type of mutation. Based on this random selection, when a mutation will occur, NEURAE then randomly selects from the secondary mutation options the type of mutation the codon will undergo. The possible mutations of point, conjugation, duplication (recopy), deletion, and translocation have the respective rates of $\mu_{P}, \mu_{C}, \mu_{R}, \mu_{D}$, and $\mu_{T}$.

In order to determine the appropriate balance of the various mutation rates, a series of experiments were conducted. Each series was composed of ten evolutionary runs. Because the creation of an XOR gate is feasible by using only point mutations, a series of tests were run to determine the optimal point mutation rate. These tests set the $\mu_{P}$ rate to 1.0 , and varied the $\mu$ rate from 0.05 to 1.0 . The metrics by which the different tests were judged were the number of generations it took to make an XOR gate and the fitness of the
highest-scoring individual at the end of evolution.
Statistical data for the first generation in which an XOR gate was made, or $\alpha$ generation, was fitted to a two-parameter Weibull distribution (Weibull 1951). A Weibull distribution has the cumulative distribution function (CDF) and probability distribution function (PDF) given in Equations 4.1 and 4.2, respectively. In these equations, $k$ is the shape parameter and $\lambda$ is the scale parameter. These parameters were found by performing a least-squares line-fit on the data shown in Figure 4.1, where the slope of the line is $k$, and the x -intercept is $\lambda$. Once these values are found the integral of the PDF (Equation 4.2) is used to determine the likelihood of an XOR gate will being created within 1000 generations.

$$
\begin{gather*}
F(x)=1-e^{-(x / \lambda)^{k}},  \tag{4.1}\\
P(x)=\frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-(x / \lambda)^{k}} . \tag{4.2}
\end{gather*}
$$



Figure 4.1: Log-log plot of $\alpha$ generation vs. $\log \left(\frac{1}{1-F}\right)$ for a point mutation rate of $\mu=0.4$.


Figure 4.2: Probability density function and histogram of $\alpha$ generation for mutation rate of $\mu=0.4$.

The $\Omega$ fitness is the fitness of the best performing individual at the end of the evolutionary run. Because cases where an XOR is never found are capped at 16 , those runs are excluded to focus on the exploitative effects of the mutation rates. This statistical data was found to be best fit to a Gaussian distribution, as shown in Figure 4.3.

Table 4.1 illustrates that evolutions using mutation rates at the extremes are both less likely to make an XOR gate and are worse at optimizing a gate if it does. This is congruent


Figure 4.3: Gaussian distribution of best fitness at the end of evolutionary runs with a point mutation rate of $\mu=0.4$.

Table 4.1: The statistical results for varying mutation rates while only using point mutations

| Case | $\mu$ | Probability $\alpha$ gen $\leq 1000$ | $\Omega$ fit mean | $\Omega$ fit st. dev. |
| :---: | :---: | :---: | :---: | :---: |
| 1 | 0.05 | $73.1 \%$ | 99.67 | 10.36 |
| 2 | 0.1 | $90.2 \%$ | 108.8 | 7.26 |
| 3 | 0.2 | $92.9 \%$ | 106.0 | 8.40 |
| 4 | 0.4 | $97.3 \%$ | 101.1 | 10.12 |
| 5 | 0.6 | $99.5 \%$ | 97.39 | 23.64 |
| 6 | 0.8 | $99.1 \%$ | 94.35 | 18.47 |
| 7 | 1.0 | $88.1 \%$ | 86.70 | 17.76 |

with other literature which shows that extremely high and low mutation rates are often deleterious to GAs (Mühlenbein 1992; Bäck and Schutz 1996).

However, mutation rates between 0.1 and 0.8 offer a trade-off between the likelihood of finding an XOR gate and optimizing an ANN. As shown in Table 4.1, a higher mutation rate makes finding an XOR gate more likely. However, lower mutation rates are generally more capable of exploiting a functional XOR design and making it robust. Thus, a user can either decide whether the problem being solved is more explorative or exploitative in nature, and choose $\mu_{P}$ accordingly, or use variable mutation rates, such as those shown by McGinley et al. (2008).

It may be possible to improve both the explorative and exploitative capabilities of NEURAE without using a variable mutation rate which comes with its own biases and problems (Bäck 1992). It was hoped that other mutations found in nature would be beneficial to include in NEURAE as well. As mentioned in Chapter 2, NEURAE is capable of altering newly created genomes using mutations besides simple point mutations. A sensitivity analysis was conducted to determine the appropriate rates of the rest of the mutation types. However, the mutation rates are interdependent, so the sensitivity analysis was administered in a manner detailed by Montgomery (2004) for studying the effects of dependent variables. Overall, there are 6 variables. However, there are a few constraints that reduce the degrees of freedom.

The first constraint, Equation 4.3, requires the probability of a point mutation to be held at 0.4 . The value of 0.4 was chosen because it is in the middle of the plateau of mutation rates that perform well. Furthermore, the previous experiments prove that the overall mutation rate can be increased without adversely affecting NEURAE.

$$
\begin{equation*}
\mu \cdot \mu_{P}=0.4 . \tag{4.3}
\end{equation*}
$$

Next, the secondary mutation rates must sum to 1, as shown in Equation 4.4. This is to ensure that a mutation happens as the overall mutation rate, $\mu$, dictates. The constraint shown in Equation 4.5 was added because the operations of crossover and gene duplication lengthens the genome while deletion shortens it. Having the mutation rates of these operations balanced makes sure the genomes' lengths are not unduly biased. This constraint, when combined with the constraint that all mutation rates must sum to 1.0 , leads to the


Figure 4.4: The prism is representative of the mutation rate landscape as bounded by the above constraints.
inequality in Equation 4.6.

$$
\begin{equation*}
\mu_{P}+\mu_{C}+\mu_{R}+\mu_{D}+\mu_{T}=1.0 \tag{4.4}
\end{equation*}
$$

$$
\begin{gather*}
\mu_{C}+\mu_{R}=\mu_{D}  \tag{4.5}\\
\mu_{C}+\mu_{R} \leq \frac{1-\mu_{P}}{2} . \tag{4.6}
\end{gather*}
$$

These constraints can be used to create the mutation rate landscape shown in Figure 4.4 and a 3 -dimensional sensitivity analysis can be performed by varying $\mu_{,} \mu_{C}$, and $\mu_{R}$ with data taken at the corners and centroid of the prism to maximize the exploration of the mutation rate landscape. Table 4.2 shows the values used for exploring the mutation rate landscape, which are at the corners and centroid of the prism shown in Figure 4.4.

Table 4.3 offers the results of the mutation rate sensitivity analysis. In general, the excessively high mutation rates $(\mu=1.0)$ were once again the poorest performing. Furthermore, cases that use only point mutations and genome size changing mutations (i.e., conjugation, duplication, and deletion) perform worse than using point mutations alone. However, using only point and translocation mutation with a moderate overall mutation

Table 4.2: Mutation rates for 3-dimensional sensitivity analysis with variables in bold are indicative of the chosen points on Figure 4.4

| Case | $\boldsymbol{\mu}$ | $\mu_{P}$ | $\boldsymbol{\mu}_{\boldsymbol{C}}$ | $\boldsymbol{\mu}_{\boldsymbol{R}}$ | $\mu_{D}$ | $\mu_{T}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 8 | $\mathbf{0 . 6}$ | 0.66 | 0.0 | 0.0 | 0.0 | 0.34 |
| 9 | $\mathbf{1 . 0}$ | 0.40 | $\mathbf{0 . 0}$ | $\mathbf{0 . 0}$ | 0.0 | 0.60 |
| 10 | $\mathbf{0 . 6}$ | 0.66 | $\mathbf{0 . 1 7}$ | $\mathbf{0 . 0}$ | 0.17 | 0.0 |
| 11 | $\mathbf{1 . 0}$ | 0.40 | $\mathbf{0 . 3 0}$ | $\mathbf{0 . 0}$ | 0.30 | 0.0 |
| 12 | $\mathbf{0 . 6}$ | 0.66 | $\mathbf{0 . 0}$ | $\mathbf{0 . 1 7}$ | 0.17 | 0.0 |
| 13 | $\mathbf{1 . 0}$ | 0.40 | $\mathbf{0 . 0}$ | $\mathbf{0 . 3 0}$ | 0.30 | 0.0 |
| 14 | $\mathbf{0 . 8}$ | 0.5 | $\mathbf{0 . 0 7 5}$ | $\mathbf{0 . 0 7 5}$ | 0.15 | 0.20 |

rate, as was done in case 8 , achieved good results. Still, there is a delicate balance between these values since case 9 , which also only used point and translocation mutations, was by far the worst performing test case. This case only had two of the 10 runs produce an XOR gate. Nevertheless, the best combination of mutations rates is case 14, which uses all of the mutation types. These runs have a high probability of discovering an XOR gate ( $99.95 \%$ ) coupled with good optimization. As a result, this became the balance of mutation rates used for future design problems.

Table 4.3: The statistical results for varying mutation rates across the mutation rate landscape given in Figure 4.4

| Case | Probability $\alpha$ gen $\leq 1000$ | $\Omega$ fit mean | $\Omega$ fit St. Dev. |
| :---: | :---: | :---: | :---: |
| 8 | $97.3 \%$ | 106.6 | 8.48 |
| 9 | $19.1 \%$ | 75.7 | 40.6 |
| 10 | $86.1 \%$ | 92.99 | 18.84 |
| 11 | $56.6 \%$ | 100.8 | 8.95 |
| 12 | $71.8 \%$ | 98.34 | 10.52 |
| 13 | $56.5 \%$ | 92.95 | 5.48 |
| 14 | $99.95 \%$ | 102.8 | 10.60 |

### 4.2 Qualities of Productive Evolution

While it is important to see which mutation values optimizes NEURAE, an analysis of why could help make improvements as well. Thus, a look at two different runs from an earlier version of NEURAE (Roy et al. 2008) were analyzed. Both evolutions were performed
using only point mutations, but one case had a moderate mutation rate $\left(\mu=0.2, \mu_{P}=1.0\right)$ which often produced XOR gates. The second group had a higher mutation rate $(\mu=$ $\left.0.8, \mu_{P}=1.0\right)$ which seldom produced an XOR gate. Characteristics of successful, XOR producing runs were compared to those of non-XOR producing, unsuccessful runs. While the quantitative results differ between the two groups, the qualitative results for each group are similar.


Figure 4.5: Genes used by the top $10 \%$ within a successful evolution


Figure 4.6: Genes used by the top $10 \%$ within an unsuccessful evolution

Figures 4.5 and 4.6 show which genes were used by the best individuals (top $10 \%$ ) throughout evolution. Each time a gene is used, a dot is placed that shows in which generation it was used. Furthermore, the figure is overlaid with a plot of the fitness of the best performing individual of each generation.

In Figure 4.5 there are sudden shifts in the genome of the population elite, known as punctuated equilibria (PEs). Eldredge and Gould (1972) describe PEs as sudden shifts in the phenotype of a population that results in speciation happening quickly as opposed to gradually. While this theory was applied to observations of phenotypes within paleological records, Figure 4.5 shows PEs happen on a genomic level in the simulated evolution near generations 270 and 610. The first PE happens shortly after the first jump in fitness of the best individual. The second PE happens after a relatively small change ( $\sim 1 \%$ ) increase in the best fitness. Finally, the majority of fitness improvements do not result in a large shift of the genomes in the population.

The analysis was repeated for poorly performing evolutions with the elevated mutation rate. Figure 4.6 reveals what happens within the genome of the best performing $10 \%$ during
an unsuccessful evolution. Due to the elevated mutation rate, more genes are generated. However, the lack of any PEs show that none of the genes are ever eliminated within the elite population. Thus, there is a correlation between PE and evolutionary progress.


Figure 4.7: Structure of genes used by the top $10 \%$ of each generation during a successful evolution.
(Once nested is at the bottom).


Figure 4.8: Structure of genes used by the top $10 \%$ of each generation during an unsuccessful evolution.
(Once nested is at the bottom).

Figure 4.7 shows how the rules become more complex throughout evolution. The height of the overall bar diagram shows how many different genes were used throughout evolution, grouped for every hundred generations. The number of nestings indicate the number of additional conditions that must test true in order for an action to be executed. Thus, a thrice-nested rule must have four IF statements prove true for its action to execute. Over time, a higher percentage of the rules used have additional nestings. Furthermore, the number of genes used by the best individuals changes as well. As Adami et al. (2000) argues, a more complex gene contains more information about its environment, and genes that require more specified conditions to execute an action contain more information about the required state of the network. The results of Figure 4.7 are contrasted with the unsuccessful results shown in Figure 4.8. The illustration reconfirms that many more genes were generated during the unsuccessful evolution. However, there is little variation throughout evolution. Furthermore, the rules used do not become more complex.

Finally, statistics looking at the structure of the rules are examined. The actions of every codon within each gene that is executed are tallied for each run. It is important to note that the sum of these tallies will be higher than the total number of genes used because nested genes contain multiple codons, and thus, multiple actions. Furthermore, while the
actual numbers are given, it is the relative ratios that remain consistent among similar runs. Table 4.4 reveals that making a connection was the most common action. However, the second most common action was the end turn action, which prevents the growing network from performing tasks. This suggests that the control of growth is nearly as important as growth itself. In other words, evolving rules prohibiting actions may be as important as involving rules that promote actions.

Table 4.4: Actions in executed genes

|  | Make <br> Connection | Make <br> Node | Do <br> Nothing | End <br> Turn |
| :---: | :---: | :---: | :---: | :---: |
| Successful Run | 4297 | 1628 | 1566 | 3981 |
| Unsuccessful Run | 12750 | 4346 | 612 | 8054 |

### 4.3 Variation of Nucleotides within the NEURAE Codon

It was argued earlier that having more complex genomes meant using more information from the environment. Furthermore, the previous section showed that as individuals became more fit, the rules often required a growing ANN to meet more conditions before an action is executed. However, this just means the use of more environmental information is correlated to more successful evolutions, but not necessarily the cause of them. Thus, the following experiment was devised to disable the genome from using any information from the environment for embryogenesis. Every test range (4th) nucleotide was set to write a large number (250) into the $\mathrm{C}^{++}$program. This test range is large enough to encompass all possible ANN states and results in every condition test to be true. With this configuration, the programs in NEURAE run similar to the programs in Gruau's CE, where the order in which actions are executed are completely determined by the sequence of actions in the program.

This change seems to completely break NEURAE, as none of the evolutionary runs produced an XOR gate. While it can be argued that implementing more action options or not resetting the program for each pairing permutation could have produced an XOR gate, it's clear that NEURAE benefits in having information from the environment to correctly apply embryogenesis.

The second experiment tested the effect of growth controls. For this experiment, End Turn action (5th) nucleotides were replaced with Do Nothing nucleotides. This results in a set of rules in which actions cannot be actively halted.

Even though this experiment used the same mutation rates as in case 14, the removal of End Turn nucleotides results in the probability of an XOR gate being created dropping to $88.8 \%$. However, if a desirable circuit was created, the runs were able to optimize it as effectively as the evolutions in case 14 , with an $\Omega$ fitness average at 102.6 and $\Omega$ fitness standard deviation of 10.3. However, one curious side effect is that evolutions without End Turn nucleotides took more than twice the computational time. While computation time was not an explicit evaluation parameter for evolution, clearly using more time to get worse results is undesirable. Thus, its clear that including End Turn action codons is beneficial for the practical application of NEURAE.

## Chapter 5

## Derivation of Simulation Environment

### 5.1 Nomenclature

$A=$ Amplitude of path sinusoid
$\vec{a}=$ Shortest vector from robot center to obstacle wall
$a_{x}=\mathrm{x}$-coordinate of $\vec{a}$
$a_{y}=\mathrm{y}$-coordinate of $\vec{a}$
$\vec{b}=$ Vector coincident with obstacle wall
$b_{x}=\mathrm{x}$-coordinate of $\vec{b}$
$b_{y}=\mathrm{y}$-coordinate of $\vec{b}$
$C=$ Slope of path sinusoid
$c_{1}=$ Chord length of left wheel movement approximation
$c_{2}=$ Chord length of right wheel movement approximation
$d=$ Diameter of robot
$f=$ Frequency for path sinusoid
$g(\cdot)=$ Function which is centerline of path
$h=$ Distance from left wheel to point of rigid body rotation
$\vec{l}=$ Unit vector coincident with LIDAR sensor
$l_{x}=\mathrm{x}$-coordinate of $\vec{l}$
$l_{y}=\mathrm{y}$-coordinate of $\vec{l}$
$\vec{l}_{\perp}=$ Unit vector perpendicular to LIDAR sensor.
$m=$ Slope of line connecting photovoltaic sensor and closest point to path
$\vec{p}_{1}=$ Global position vector to first obstacle vertex
$p_{1 x}=\mathrm{x}$-coordinate of $\vec{p}_{1}$
$p_{1 y}=\mathrm{y}$-coordinate of $\vec{p}_{1}$
$\vec{p}_{2}=$ Global position vector to second obstacle vertex
$p_{2 x}=\mathrm{x}$-coordinate of $\vec{p}_{2}$
$p_{2 y}=\mathrm{y}$-coordinate of $\vec{p}_{2}$
$\vec{q}_{1}=$ Vector from robot center to first obstacle vertex
$q_{1 x}=$ x-coordinate of $\vec{q}_{1}$
$q_{1 y}=\mathrm{y}$-coordinate of $\vec{q}_{1}$
$\vec{q}_{2}=$ Vector from robot center to first obstacle vertex
$q_{2 x}=\mathrm{x}$-coordinate of $\vec{q}_{2}$
$q_{2 y}=\mathrm{y}$-coordinate of $\overrightarrow{q_{2}}$
$r=$ Radius of robot
$s_{1}=$ Arc traversed by left wheel
$s_{2}=$ Arc traversed by right wheel
$t=$ Time
$\vec{v}_{1}=$ Left wheel movement approximation vector
$\vec{v}_{2}=$ Right wheel movement approximation vector
$\vec{v}_{c g}=$ Robot center movement approximation vector
$w=$ Width of the path
$x_{1}=\mathrm{x}$-coordinate of photovoltaic sensor
$x_{2}=\mathrm{x}$-coordinate of path closest to photovoltaic sensor
$\vec{x}_{i}=$ Vector to initial robot global position
$\vec{x}_{f}=$ Vector to final robot global position
$\vec{x}_{t}=$ Vector to test robot global position
$x_{t x}=\mathrm{x}$-coordinate of $\vec{x}_{t}$
$x_{t y}=\mathrm{y}$-coordinate of $\vec{x}_{t}$
$y_{1}=\mathrm{y}$-coordinate of photovoltaic sensor
$y_{2}=\mathrm{y}$-coordinate of path closest to photovoltaic sensor
$\alpha=$ Angle of rigid body rotation
$\beta=$ Angle between $\vec{v}_{2}$ and vector pointing from the left wheel to the right wheel
$\eta=$ Distance from laser origin to wall
$\gamma=$ Angle perpendicular to initial robot orientation
$\theta=$ Angle laser makes with global x-axis.
$\kappa=$ Scalar used to find an arbitrary location along obstacle wall
$\nu_{1}=$ Left wheel translational speed
$\nu_{2}=$ Right wheel translational speed
$\sigma=$ Angle between $\overrightarrow{v_{1}}$ and global x -axis
$\tau=$ Discrete time between simulation steps

$$
\begin{aligned}
& \phi_{i}=\text { Initial robot orientation } \\
& \phi_{f}=\text { Final robot orientation } \\
& \phi_{t}=\text { Test robot orientation }
\end{aligned}
$$

### 5.2 Two-Wheeled Robot Movement



Figure 5.1: Diagram of variables for two-wheeled motion derivation

While the following robots may have varying sensor setups, they all have the same basic movement model. All robots herein have the two-wheeled model shown in Figure 5.1. The assumption that the wheels never slip enables robot movement to be modeled as rotation of a rigid body rotating about some point in the 2-D plane.

As the left wheel travels, it moves along the arc,

$$
\begin{equation*}
s_{1}=h \alpha . \tag{5.1}
\end{equation*}
$$

Figure 5.1 illustrates $\vec{v}_{1}$ and $\vec{v}_{2}$ are respective chords for the $\operatorname{arcs} s_{1}$ and $s_{2}$. Using the

Law of Cosines, the magnitude of the chord, $c_{1}$, squared is

$$
\begin{equation*}
c_{1}^{2}=2 h^{2}-2 h^{2} \cos (\alpha)=2 h^{2}(1-\cos (\alpha)) \tag{5.2}
\end{equation*}
$$

However the Taylor series expansion of $\cos (\alpha)$ about $\alpha=0$ is

$$
\begin{equation*}
\left.\cos (\alpha)\right|_{\alpha=0}=1-\frac{\alpha^{2}}{2!}+\frac{\alpha^{4}}{4!}-H . O . T . \tag{5.3}
\end{equation*}
$$

Plugging the truncation of the Taylor series expansion into Equation 5.2 gives

$$
\begin{gather*}
c_{1}^{2} \approx 2 h^{2}\left(1-\left(1-\frac{\alpha^{2}}{2}+\frac{\alpha^{4}}{24}\right)\right)  \tag{5.4}\\
c_{1} \approx h \alpha-\frac{\alpha^{2}}{2 \sqrt{3}} \tag{5.5}
\end{gather*}
$$

The error between the arc length in Equation 5.1 and the chord length in Equation 5.5 has a maximum error of $\frac{\alpha^{2}}{2 \sqrt{3}}$. If $\alpha$ is small, using the chord to approximate wheel movement in Equation 5.1 is acceptable. Thus, the simulation time steps are kept small and the wheels are assumed to move along the chords instead of the arcs.

Equation 5.2 can be rewritten to make

$$
\begin{equation*}
\cos (\alpha)=\frac{2 h^{2}-c_{1}^{2}}{2 h^{2}}=1-\frac{c_{1}^{2}}{2 h^{2}} \tag{5.6}
\end{equation*}
$$

Using similar triangles,

$$
\begin{align*}
& \frac{c_{1}}{h}=\frac{c_{2}}{h-d},  \tag{5.7}\\
& h=\frac{c_{1} d}{c_{1}-c_{2}} . \tag{5.8}
\end{align*}
$$

Substituting Equation 5.8 into Equation 5.6 gives

$$
\begin{equation*}
\cos (\alpha)=1-\frac{\left(c_{1}-c_{2}\right)^{2}}{2 d^{2}} \tag{5.9}
\end{equation*}
$$

Now, Equation 5.9 can be solved for $\alpha$ in terms of known qualities,

$$
\begin{equation*}
\alpha=\cos ^{-1}\left(1-\frac{\left(c_{1}-c_{2}\right)^{2}}{2 d^{2}}\right) \tag{5.10}
\end{equation*}
$$

It is necessary to verify that the assumption made in Equation 5.5 is accurate enough. Having the wheels rotate in opposite directions and at equal magnitudes will result in the the robot spinning in place and have the largest possible estimation error of the orientation. If the wheels are assumed to move along the arc, the orientation will change according to Equation 5.11,

$$
\begin{equation*}
\alpha(t)=\frac{s_{1} t}{h} \tag{5.11}
\end{equation*}
$$

The exact movement represented by Equation 5.11 and the approximate movement represented by Equation 5.10 are compared. For the verification of rotational accuracy the following values were given: $\nu_{1}=1 \mathrm{~m} / \mathrm{s}, \nu_{2}=-1 \mathrm{~m} / \mathrm{s}, d=1 \mathrm{~m}, \tau=0.02 \mathrm{~s}$. This leads to the following values of $s_{1}=c_{1}=\tau \nu_{1}=0.02 \mathrm{~m}, c_{2}=\tau \nu_{2}=-0.02 \mathrm{~m}$, and $h=\frac{d}{2}=0.5 \mathrm{~m}$ during each simulation step. The exact and approximated results are shown in Figure 5.2 to be nearly identical with a maximum error of 0.003 rad .

Once it is known how much the robot has changed its orientation during the time step, it is necessary to determine the displacement of its center. Due to the fact that the angles of the isosceles triangle in Figure 5.1 must add up to $\pi, \beta=\frac{\pi-\alpha}{2}$. However, there is a need to account for clockwise or counterclockwise rotations for determining the global orientation of the two displacement vectors, $\vec{v}_{1}$ and $\overrightarrow{v_{2}}$.

$$
\phi_{t}= \begin{cases}\gamma+\beta & \text { if } c_{1}>c_{2}  \tag{5.12}\\ \gamma-\beta+\pi & \text { if } c_{1} \leq c_{2}\end{cases}
$$

By knowing the orientation and magnitude of the displacement of each wheel, $\overrightarrow{v_{1}}$ and $\overrightarrow{v_{2}}$ can be found by Equations 5.13 and 5.14.

$$
\begin{align*}
& \overrightarrow{v_{1}}=\left[\begin{array}{l}
\cos \left(\phi_{t}\right) \\
\sin \left(\phi_{t}\right)
\end{array}\right] c_{1},  \tag{5.13}\\
& \overrightarrow{v_{2}}=\left[\begin{array}{c}
\cos \left(\phi_{t}\right) \\
\sin \left(\phi_{t}\right)
\end{array}\right] c_{2} . \tag{5.14}
\end{align*}
$$



Figure 5.2: Verification of rotational accuracy with and without approximation.

The displacement of the center of the robot is the average of the displacement of the two wheels, so $\vec{v}_{c g}=\frac{\vec{v}_{1}+\vec{v}_{2}}{2}$. Finally, the overall change of the robot position is shown in Equations 5.15 and 5.16.

$$
\begin{gather*}
\phi_{t}=\phi_{i}+\alpha,  \tag{5.15}\\
\vec{x}_{t}=\vec{x}_{i}+\vec{v}_{c g} . \tag{5.16}
\end{gather*}
$$

To verify that the approximations are accurate, two more simulations were run: one with a stationary wheel, and another with the wheels at two different, but constant, speeds. The exact movement results from Equations 5.17-5.22 are compared to the approximation results in Equations 5.15 and 5.16.

$$
\begin{equation*}
\alpha(t)=\frac{c_{1} t}{2 r} . \tag{5.17}
\end{equation*}
$$

$$
\begin{gather*}
x(t)=r \sin \left(\frac{c_{1} t}{2 r}\right) .  \tag{5.18}\\
y(t)=r\left(1-\cos \left(\frac{c_{1} t}{2 r}\right)\right) .  \tag{5.19}\\
\alpha(t)=\frac{c_{1} t}{4 r} .  \tag{5.20}\\
x(t)=3 r \sin \left(\frac{c_{1} t}{4 r}\right) .  \tag{5.21}\\
y(t)=3 r\left(1-\cos \left(\frac{c_{1} t}{4 r}\right)\right) . \tag{5.22}
\end{gather*}
$$



Figure 5.3: Verification of rotational and translational accuracy used the respective left and right wheel speeds of $\nu_{1}=0 \mathrm{~m} / \mathrm{s}$ and $\nu_{2}=1 \mathrm{~m} / \mathrm{s}$. The maximum orientation, $x$-position, and $y$-position errors are $0.017 \mathrm{rad}, 0.0079 \mathrm{~m}$, and 0.0083 m , respectively.


Figure 5.4: Verification of rotational and translational accuracy used the respective left and right wheel speeds of $\nu_{1}=0.5 \mathrm{~m} / \mathrm{s}$ and $\nu_{2}=1 \mathrm{~m} / \mathrm{s}$. The maximum orientation, $x$-position, and $y$-position errors are $0.037 \mathrm{rad}, 0.055 \mathrm{~m}$, and 0.056 m , respectively.

### 5.3 Collision Detection



Figure 5.5: Diagram of variables for obstacle collision check.

The next thing to account for is interactions between the robot and obstacles. All obstacles in the simulation world are polygons. Before the robot moves to the new position determined by Equation 5.16, there is first a check to make sure it does not pass the boundaries of an obstacle, i.e., collide with an obstacle. In Figure 5.5, the point where $\vec{a}$ intersects $\vec{b}$ is shown in Equations 5.23 and 5.24.

$$
\begin{align*}
& \vec{x}_{t}+\vec{a}=\vec{p}_{1}+\kappa \vec{b}  \tag{5.23}\\
& \vec{a}=\vec{p}_{1}+\kappa \vec{b}-\vec{x}_{t} \tag{5.24}
\end{align*}
$$

However, $\vec{a} \perp \vec{b}$, so there dot product is zero, as shown in Equation 5.25.

$$
\begin{equation*}
\vec{a} \cdot \vec{b}=\left(\vec{p}_{1}+\kappa \vec{b}-\vec{x}_{t}\right) \cdot \vec{b}=0 \tag{5.25}
\end{equation*}
$$

Solving Equation 5.25 for $\kappa$ yields the result shown in Equation 5.26.

$$
\begin{equation*}
\kappa=\frac{\left(b_{x} x_{t x}+b_{y} x_{t y}\right)-\left(b_{x} p_{1 x}+b_{y} p_{1 y}\right)}{b_{x}^{2}+b_{y}^{2}} \tag{5.26}
\end{equation*}
$$

If $0<\kappa<1$, then $\vec{a}$ coincides with the line $\vec{b}$ within the line segment of the wall. Equation 5.27 is used to check if the shortest distance from the center of the robots to the wall is greater than the radius of the robot.

$$
\begin{equation*}
\|a\|=\left\|\vec{p}_{1}+\kappa \vec{b}-\vec{x}\right\|>r . \tag{5.27}
\end{equation*}
$$

If $\kappa$ is not within the range $(0,1)$, Equation 5.28 is used to ensure the robot clears the vertices of the obstacle.

$$
\begin{equation*}
\left\|\vec{p}_{1}-\vec{x}\right\|>r \cap\left\|\vec{p}_{2}-\vec{x}\right\|>r . \tag{5.28}
\end{equation*}
$$

If the inequalities in either Equation 5.27 or Equation 5.28 are not satisfied, then the robot will cross a boundary within the next simulation step. To prohibit this, the robot keeps the same position it previously had. However, the robot is free to rotate as it normally would. For verification, the robot is placed in a box and moves and rotates in increments.

### 5.4 Sensor and World Interaction

After the robot moves to the new orientation, the sensors are updated. For the line following robot, photovoltaic sensors are configured to be on if the sensor is positioned above the black line, and off otherwise. The centerline of the line to be followed is a sinusoid with a slope and is governed by Equations 5.29 and 5.30.

$$
\begin{align*}
& g(x)=A \cos (f x)-A-C x,  \tag{5.29}\\
& y_{2}=A \cos \left(f x_{2}\right)-A-C x_{2} . \tag{5.30}
\end{align*}
$$

The line connecting the photovoltaic sensor and the point on the centerline closest to it, as shown in Figure 5.8, is represented by Equation 5.31.

$$
\begin{equation*}
y_{2}=y_{1}+m\left(x_{2}-x_{1}\right) . \tag{5.31}
\end{equation*}
$$

However, the slope of the centerline of the path at $x_{2}$ can be found by Equation 5.32.


Figure 5.6: Collision detection was verified by placing the robot within a small obstacle and having it move around. As shown above, the center of the robot is never closer than 0.5 m (the radius) to the obstacle wall.


Figure 5.7: Model of robot sensor configuration for path following simulations.


Figure 5.8: Diagram of variables used for path detection calculations.

$$
\begin{equation*}
g^{\prime}\left(x_{2}\right)=C-A f \sin (f x) \tag{5.32}
\end{equation*}
$$

This slope, however, is perpendicular to the connecting line shown in Figure 5.8. Thus, the slope, $m$, of the connecting line must be the negative inverse of the slope of the centerline as shown in Equation 5.33.

$$
\begin{equation*}
m=\frac{-1}{\left(g^{\prime}\left(x_{2}\right)\right.}=\frac{1}{A f \sin (f x)-C} . \tag{5.33}
\end{equation*}
$$

Substituting Equations 5.30 and 5.33 into Equation 5.31 yields Equation 5.34.

$$
\begin{equation*}
A \cos \left(f x_{2}\right)-A+C x_{2}=y_{1}+\frac{x_{1}-x_{2}}{C-A f \sin \left(f x_{2}\right)} \tag{5.34}
\end{equation*}
$$

However, Equation 5.34 will have problems when the slope of the sinusoid is 0 . Thus it is converted to the following equation:

$$
\begin{equation*}
x_{1}-x_{2}+\left(C-A f \sin \left(f x_{2}\right)\right)\left(y_{1}+A-A \cos \left(f x_{2}\right)-C x_{2}\right)=0 \tag{5.35}
\end{equation*}
$$

Equation 5.35 is used to solve for $x_{2}$ within the range of $x_{1}-\frac{w}{2}$ and $x_{1}+\frac{w}{2}$ numerically via the secant method. If a zero for $x_{2}$ is not within these bounds, the sensor must be further than $\frac{w}{2}$ away from the centerline and off the path. However, the search region must be broken in two sections to account for multiple roots. Thus, for regions $\left[x_{1}-\frac{w}{2}, x_{1}\right]$ and $\left[x_{1}, x_{1}+\frac{w}{2}\right]$ are searched separately. If a zero is found within these bounds, the secant method finds the root quickly. Once $x_{2}$ is calculated, $y_{2}$ can be found with Equation 5.30. If $\left(\left(x_{1}-x_{2}\right)^{2}+\left(y_{1}-y_{2}\right)^{2}\right) \leq \frac{w^{2}}{4}$ then the sensor is over the line and is consequently activated. Otherwise, the sensor is off.

The fully 2-D robot navigates by using simulated LIDAR sensors which can detect the distance to an obstacle in front of it. $\vec{l}$ is a unit vector collinear with the LIDAR. $\vec{l}_{\perp}$ is used to check if the LIDAR unit intersects $\vec{b}$ within the wall segment with the following inequality,

$$
\begin{equation*}
\left(\vec{l}_{\perp} \cdot \vec{q}_{1}\right) \cdot\left(\vec{l}_{\perp} \cdot \vec{q}_{2}\right) \leq 0 \tag{5.36}
\end{equation*}
$$

If Inequality 5.36 is true, it is necessary to first check if the laser is collinear with the


Figure 5.9: Model of robot sensor configuration for full 2-D navigation.


Figure 5.10: Diagram of variables used for full 2-D navigation.
wall by evaluating Equation 5.37.

$$
\begin{equation*}
\left(\vec{l}_{\perp} \cdot \vec{q}_{1}\right) \cdot\left(\vec{l}_{\perp} \cdot \vec{q}_{2}\right)=0 \tag{5.37}
\end{equation*}
$$

If Equation 5.37 is true, it is necessary to check $\left(\vec{l}_{\perp} \cdot \vec{q}_{1}\right)$ and $\left(\vec{l}_{\perp} \cdot \vec{q}_{2}\right)$ separately. If both equal $0, \eta=\min \left(\left\|\vec{q}_{1}\right\|,\left\|\vec{q}_{2}\right\|\right)$. Otherwise, $\eta=\left\|\vec{q}_{i}\right\|$ for which $\left(\vec{l}_{\perp} \cdot \vec{q}_{i}\right)=0$.

However, if the product of dot products in Equation 5.36 is less than 0, then $\overrightarrow{l_{\perp}}$ intersects $\vec{b}$. To find the distance Equation 5.38 is used.

$$
\begin{equation*}
\vec{q}_{1}+\kappa \vec{b}=\eta \vec{l} \tag{5.38}
\end{equation*}
$$

which becomes the linear equation shown in Equation 5.39.

$$
\left[\begin{array}{l}
l_{x} b_{x}  \tag{5.39}\\
l_{y} b_{y}
\end{array}\right]\left[\begin{array}{l}
\eta \\
-\kappa
\end{array}\right]=\left[\begin{array}{l}
q_{1 x} \\
q_{1 y}
\end{array}\right] .
$$

Then, the distance $\eta$ becomes

$$
\begin{equation*}
\eta=\frac{q_{1 x} b_{y}-q_{1 y} b_{x}}{l_{x} b_{y}-l_{y} b_{x}} \tag{5.40}
\end{equation*}
$$

If $\eta \geq 0$, the LIDAR sensor will hit the wall and return a distance $\eta$. If $\eta<0$, the wall is behind the sensor so there is no reading. This process is repeated for each wall, and the smallest distance is the value that the sensor returns. A value less than the diameter of the robot will cause the corresponding ANN input to active. Figure 5.4 shows the simulated
robot with laser/obstacle interaction.


Figure 5.11: Graphical verification of accurate laser/object interaction. A blue line indicates the corresponding ANN input is inactivate while red line indicates the corresponding ANN input has been activated. The concentric circles are indicative of the desired goal

## Chapter 6

## Robotic-Controller Evolution

### 6.1 Overview

This chapter will describe the evolution of digital controllers for the simulated robots detailed in Chapter 5. All evolutionary runs have a population of 200 individuals with a starting genome length of 150 nucleotides. The mutation rates are set in accordance with the best performing case runs found in Chapter 4, $\mu=0.80, \mu_{P}=0.50, \mu_{C}=0.075, \mu_{R}=$ $0.075, \mu_{D}=0.15$, and $\mu_{T}=0.20$. The design problems to be solved are creating a controller for a line-following robot, creating an obstacle avoiding robot, and creating controllers for a swarm of goal finding robots. As a result, the exponential fitness has the form in Equation 6.1 to further magnify slight improvements in the later tiers.

$$
\begin{equation*}
\text { Fitness }=\left\lfloor 2^{2(x-1)}\right\rfloor . \tag{6.1}
\end{equation*}
$$

### 6.2 Line-Following Robot

### 6.2.1 Evaluation Parameters

Each ANN begins as three input neurons, one for each photovoltaic sensor. Table 6.1 shows the tiers used for the exponent in this simulation. Once again, an individual that passes the second tier has a fitness exponent of $x-1=1$. However, these individuals need to grow and connect two outputs instead of the one in the previous logic evolutions.

Once an individual grows and connects to two outputs, it gets to tier 3 and its line following ability is tested. The path to be followed is a line with a width $w$, and a centerline that satisfies Equation 5.29. The robot starts at the origin facing in the direction of the

| Tier | Test | Change in Exponent |
| :---: | :--- | :--- |
| 1 | Are there enough <br> output nodes? | $\%$ of desired output <br> nodes |
| 2 | Are there a connec- <br> tions to each out- <br> put node? | $+\%$ of output nodes <br> with connections |
| 3 | Simulate robot for <br> 20 seconds | $+\%$ of path followed <br> correctly |

Table 6.1: Tier for adjusting fitness exponent $(x)$ in line following evaluation
positive $x$-axis. The constants are chosen to ensure the line intersects the origin with the center sensor over the line. Furthermore, the curvature of the line is always less than the turning radius of the robot, $r$. An individual is allotted 20 seconds of simulated time. At each time step, it is evaluated by Equation 6.2 where $\epsilon$ is the error between the robot's center and the centerline of the path. These values are summed and divided by the sum of Equation 6.2 if $\epsilon$ were 0 for all time steps. This fraction is then added to the exponent in Equation 6.1.

$$
\begin{equation*}
f(x)=1-\frac{1}{1+e^{-4 \frac{\epsilon-r}{w}}} . \tag{6.2}
\end{equation*}
$$



Figure 6.1: Preference function for position error in line following evaluation

### 6.2.2 Evolution Results

Figure 6.2 shows that the center of the robot traveled along the path and is a capable line follower. The ANN controller of the robot is shown in Figure 6.3. While there was no explicit penalty for building extra neurons, an ANN with a hidden layer could cause a lag in response time which would cause a larger error while following the path.


Figure 6.2: Robot path compared with desired path

INPUTS


Figure 6.3: ANN controller for a line following robot

| Left <br> Sensor | Center <br> Sensor | Right <br> Sensor | Left <br> Wheel | Right <br> Wheel |
| :---: | :---: | :---: | :---: | :---: |
| 0 | 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 | 0 |
| 0 | 1 | 0 | 1 | 1 |
| 0 | 1 | 1 | 1 | 0 or 1 |
| 1 | 0 | 0 | 0 | 1 |
| 1 | 1 | 0 | 0 or 1 | 1 |

Table 6.2: Dominant logic for line following robots

The resulting line-following logic is show in Table 6.2. While some of the entries are self-evident, such as turn right when only the right sensor is active, it was not clear what the right action should be when the line is not sensed. However, it was found through evolution that the best course of action if the line is not detected is to go forward. Given the limited sensing abilities of the robot, this is the best general-purpose line search the robot could perform.

```
for (Node \alpha = 1:ANN.size ){
    for(Node \beta=1:ANN.size ){
            if |Rel }\beta\mathrm{ . inputs - 0| }\leq
            make.output(H,-0.22)
        }
            if |Rel\alpha\beta.inputs - 1| < 1{
                make.connection(-0.50)
        }
        if |Node\alpha.ID3 - 1| \leq 0{
            make.connection(0.24)
        }
        if |Rel }\beta\alpha\mathrm{ .threshold - (-0.26)| }\leq0.14
            end.turn()
        }
        if |Node\alpha.outputs - 1| < 0{
            make.connection(0.10)
        }
    }
}
```

Figure 6.4: Code used to make line following controller

### 6.3 Obstacle-Avoiding Robot

### 6.3.1 Evaluation Parameters

For this problem an ANN was evolved that could function as a controller for a robot that could find a goal within a closed 2-D room. The inputs to the ANN are the goal sensors and LIDAR sensors of the robot. The three goal sensors are configured to be on in accordance to Figure 6.5 with the center sensor having a $45^{\circ}$ arc. These sensors give directional data, but not ranging information. Furthermore, the goal sensors are able to detect the goal regardless of distance or if there is an obstacle between the robot and the goal. As shown in Figure 5.4, there are five LIDAR sensors which are set at equivalent angles in the $120^{\circ}$ arc in front of the robot. Goal sensor inputs for the ANN have an ID1 of A and LIDAR inputs have an ID1 of B . Because an ID1 of B is being used for an input, neurons grown during embryogenesis cannot have an ID1 of B.

Originally, the third tier was a simulation tier of having the robot find the goal in an enclosed room without internal obstacles. However, several individuals were able to find the


Figure 6.5: Goal sensor configuration for the obstacle avoiding robots. Detection is separated into left, center, and right.

| Tier | Test | Change in Exponent |
| :---: | :--- | :--- |
| 1 | Are there enough <br> output nodes? | $\%$ of desired output <br> nodes |
| 2 | Are there a connec- <br> tions to each out- <br> put node? | $+\%$ of output nodes <br> with connections |
| 3 | Logic test | $+\%$ correct answers |
| 4 | Simulate with con- <br> vex obstacle | + summed distance <br> to goal |
| 5 | Simulate with star <br> obstacle | + summed distance <br> to goal |

Table 6.3: Tiers for adjusting fitness exponent $(x)$ in obstacle avoidance evaluation
obstacle without evolving the ability to turn both left and right! Usually, individuals would only be able to sense if the goal was to one side or another, and then use LIDAR detection of the border to make enough turns to compensate. Thus, the third tier was replaced with the logic test shown in Table 6.4. For these tests, it is assumed all the LIDAR inputs are off. This ensured the controller exhibited efficient logic in finding the goal in the absence of obstacles.

Once an ANN controller evinces the logic in Table 6.4, it moves to tier 4. Here, the robot is tested to see if it can find a goal with an obstacle between the starting point and goal. The environment shown in Figure 6.6 starts the robot in a random position and

| Left Goal <br> Sensor | Center Goal <br> Sensor | Right Goal <br> Sensor | Left <br> Wheel | Right <br> Wheel |
| :---: | :---: | :---: | :---: | :---: |
| 0 | 0 | 1 | 1 | 0 |
| 0 | 1 | 0 | 1 | 1 |
| 1 | 0 | 0 | 0 | 1 |

Table 6.4: Logic test goal finding robots are required to pass before simulation. For this test, all LIDAR inputs are inactive
orientation in the upper-right corner, and its movement is simulated for 20 seconds. At each time step, the distance of the robot is evaluated by Equation 6.3, with $\epsilon$ being the distance between the robot and the goal. This distance is doubled if the robot is in contact with an obstacle, providing further evolutionary pressure for obstacle avoidance. As with line following evaluation, this value is summed and divided by the sum of Equation 6.3 if $\epsilon$ is equal to 0 for all time steps. This fraction is then added to the exponent in Equation 6.1. If at the end of the simulation, the robot is within one diameter of the goal, it is allowed to move on to tier 5 .


Figure 6.6: Environment for tier 4 evaluation


Figure 6.7: Environment for tier 5 evaluation

$$
f(x)= \begin{cases}\frac{1}{1+e^{\frac{2 \epsilon-10}{3}}} & \text { if there is a collision, }  \tag{6.3}\\ \frac{\frac{6-10}{1+e^{\frac{\epsilon-10}{3}}}}{} & \text { otherwise }\end{cases}
$$

Tier 5 is almost identical to tier 4, except now the environment includes the star obstacle shown in Figure 6.7. Usually, robots which performed well in tier 4 also performed well here, but this tier did help refine the controllers. Figure 6.7 shows the path taken by a successful individual.

### 6.3.2 Evolution Results

The synthesized controller shown in Figure 6.8 was able to navigate around convex and star obstacles. In the figure, the left three inputs correspond to the goal sensors, and the right five are the inputs from the LIDAR unit. The activation pattern shown in Figure 6.8 is the result of the goal being in front of the robot, but a wall is in close proximity of the two leftmost LIDAR sensors. The corresponding output is to have the left wheel on and the right wheel off, which will cause the robot to turn right, as desired.


Figure 6.8: ANN controller for obstacle avoidance

In order to demonstrate the general capabilities of this controller, the individual was placed in two more simulation environments after evolution was completed. The first is an environment that is densely obstructed. As Figure 6.9 shows, the robot is still able to avoid the obstacles and reach the goal. The next task shown in Figure 6.10 could not be accomplished by the individual. In order to surmount this challenge, the robot had to be able to encounter the obstacle, then move away from the goal as it moved along the contour of the wall. Figure 6.10 shows that the robot was able to trace the wall and is able to follow the wall until the robot is facing the away from the goal. However, the goal sensors indicate the goal is on the right side of the robot, although nearly behind it. As a result, the
robot continues to turn right, looping toward the goal and away from the obstacle. Once it encounters the obstacle again, the cycle is restarted. While there may be a fine-tuned solution to create a feed-forward network for this problem, it is likely that this solution will be brittle. This problem may require a recursive neural network so that the controller can store and use gathered information about the environment.


Figure 6.9: Obstacle avoidance robot in a densely obstructed environment


Figure 6.10: Obstacle avoidance robot in a environment with concave obstacle

### 6.4 Goal-Finding Swarm Robots

### 6.4.1 Evaluation Parameters

A network capable of controlling swarm behavior was the final goal. For this challenge, individuals had the same types of inputs as they did in the previous obstacle avoidance section, but the number of LIDAR input were increased to eight to provide higher fidelity. Furthermore, the goal sensors were reconfigured to not be able to detect the goal if an obstacle is blocking it, as shown in Figure 6.12. Thus, the individual had to evolve logic which enables it to search for the goal, then converge once found.

While, the robots here were unable to detect the goal if there is an obstacle between the two, Figure 6.13 shows that once a robot is able to see the goal, it sends out a signal at its own location, which other robots are able to detect. If the second robot is unable to see the goal, its goal sensors will indicate in what direction the first robot is. However, once a robot is able to detect the goal on its own, the goal sensors will ignore the signal from other goal-detecting robots, and give the direction of the goal.

```
for (Node \alpha= 1:ANN.size ) {
    for(Node \beta = 1:ANN.size ) {
        if |Node }\beta\mathrm{ .inputs - 0| < 0 {
        make.output(H,0.26)
        }
        if |Node\beta.inputs - 2| < 2 {
            if |Rel }\beta\mathrm{ |.inputs - 0| < 0 {
            make.connection(-0.10)
            }
            make.connection(0.44)
        }
        if |Rel }\beta\alpha.\mathrm{ .inputs - 6| < 0 {
            make.connection(-0.08)
        }
        if |Rel\alpha\beta.ID3-0| < 1 {
            make.connection(-0.96)
        }
    }
}
```

Figure 6.11: Code used to make obstacle avoidance controller

Table 6.5 shows the tiers used for evaluating swarm behavior. Rather than forcing a viable ANN to conform to an imposed logic table, the robot was simulated in the convex and star obstacle environments displayed in Figures 6.14 and 6.15.

The fifth tier is the first time swarming behavior is tested. For this challenge, one robot is placed near the goal. A second robot is placed on the other side of a star obstacle. The challenge for the individual is to create a controller where one robot can go toward a global signal without colliding with an obstacle. Figure 6.16 shows that NEURAE produced an individual capable of completing this task.

The sixth and final tier places the swarm in a larger room shown in Figure 6.17. For this tier, both robots are placed outside of detection range of the goal. Eventually, one of the robots finds the goal and the other is able to find it as well. Due to the increased number of tiers present in this evolution, most populations were still improving at the


Figure 6.12: Goal sensor configuration for swarming robots where the goal is obstructed from the entire swarm.


Figure 6.14: A single swarming robot in an environment with a convex obstacle


Figure 6.13: Goal sensor configuration for swarming robots where a member of the swarm can detect the goal.


Figure 6.15: A single swarming robot in an environment with a star obstacle

| Tier | Test | Change in Exponent |
| :---: | :--- | :--- |
| 1 | Are there enough <br> output nodes? | \% of desired output <br> nodes |
| 2 | Are there a connec- <br> tions to each out- <br> put node? | + \% of output nodes <br> with connections |
| 3 | Simulate single <br> robot with convex <br> obstacle | + summed distance <br> to goal |
| 4 | Simulated single <br> robot with star <br> obstacle | $+\%$ summed dis- <br> tance to goal |
| 5 | Simulate swarm <br> with star obstacle | + average summed <br> distance to goal |
| 6 | Simulate swarm in <br> large room | + average summed <br> distance to goal |

Table 6.5: Tiers for adjusting fitness exponent ( $x$ )

1000th generation. As a result, evolutionary runs evolving swarming behavior were allowed to run for 1500 generations.


Figure 6.16: Two swarming robots in an environment with a star obstacle


Figure 6.17: Two swarming robots in a large environment with various obstacles

### 6.4.2 Evolution Results

The individual that could control a swarm of robots as shown above, produced the controller shown in Figure 6.18. This particular ANN eventually evolved the logic to turn right whenever any of the LIDAR sensors detected a wall. As in the previous section, individuals


Figure 6.18: ANN controller for each swarming robot
that had a single robot capable of passing tier 3 seldom had trouble with tier 4 . However, evolving the ability to avoid objects while tracking the signal of a robot in tier 5 was an equivalent challenge to the obstacle avoidance in section 6.3. Tier 6 proved to be an effective trial in which the swarm controllers were further refined.

Figure 6.19 shows the progression of the two robots at various times during the simulation of a successful individual in tier 6. The goal is in the lower left-corner, and the two robots begin in the upper-left and upper-right corners of the environment. For discussion, robot 1 begins in the upper left and robot 2 starts in the upper right. The robots roam about the room avoiding obstacles until, eventually, robot 1 is within direct line of sight of the goal, as shown at time $=31.00 \mathrm{~s}$. The causes robot 1 to emit a signal, shown in Figure 6.19 by the concentric circles, that allows the goal sensors of robot 2 to detect the position of robot 1 . Robot 2 begins to move toward robot 1 , but the L-shaped obstacle prevents it from taking a direct path. Furthermore, at time $=45.00 \mathrm{~s}$, robot 1 loses sight of the goal and both robots reenter their goal searching behavior. Nevertheless, robot 1 quickly reacquires the goal by time $=50.00 \mathrm{~s}$, and moves toward it. Robot 2 once again moves toward robot 1, and begins to maneuver around the vertical obstacle. At time 75.00 s, robot 2 can also detect the goal and by time 80.00 s , both robots circle around the goal,
while avoiding contact with each other.
Once again, the evolved individuals were verified by being presented situations in which they were not explicitly evolved. The first is a revisit to the single robot seeking the goal with a concave obstacle. This time, however, the goal sensors do not cause the robot to loop within the obstacle because the robot is not within line of sight of the goal. As a result, a single robot is able to navigate around the environment to find the goal, as shown in Figure 6.20. Next, a swarm of three robots was placed in the environment shown in Figure 6.21. The entire swarm is once again able to converge at the goal. However, the robots are not able to avoid each other in such close proximity, and end up colliding.


Figure 6.19: Steps showing the movement of an evolved swarm


Figure 6.20: A single swarming robot in an environment with concave obstacle


Figure 6.21: Three swarming robots in a large environment with various obstacles

## Chapter 7

## Conclusion

This dissertation has presented NEURAE, a genetic algorithm capable of generating artificial neural networks via the application of interchangeable rules. Furthermore, these networks have shown to be modular, scalable, and suitable for robotic control. The If-CONDITION-Then-ACTION structure of programs produced by NEURAE allows rules to be easily rearranged and create unanticipated, yet desirable results. In fact, the development of complex rules from simple building blocks may be a key element to the modularity expressed in the phenotypes. The design of the robust XOR gate demonstrates the ability of NEURAE to find and use the inherent modularity within a problem. Having a GA which can discover and use modules on its own is particularly advantageous when these modules are not known beforehand. Furthermore, modules predetermined by a human designer may unintentionally exclude desirable designs. Embryogenesis also provides the scalability required to create parity networks of arbitrary size. NEURAE was able to evolve a genome which could create an even parity logic gate for 2 or 200 inputs. The fact that both ANNs could be made from the same four codons demonstrates that NEURAE can evolve large neural networks in a manner most neuro-evolutionary GAs cannot.

While this was an accomplishment in its own right, NEURAE was honed further through a sensitivity analysis of the mutation rates and types. Experiments were conducted to properly balance the point mutation, conjugation, gene duplication, gene deletion, and translocation mutation rates. As a result, the explorative and exploitative capabilities of NEURAE were optimized. It also shows that biologically inspired mutations, such as gene duplication and conjugation, are important to virtual evolutions as well. These experiments provided further evidence that as evolution used more information from the environment, the designs produced became more complex.

This refined version of NEURAE was used to make robotic controllers. The neural networks for these cases were able to find the correct controller logic by simulating the robot, not by fitting an explicit logic table. As a result, a controller can be designed without having to know the controller's precise functionality but instead by rewarding the higher level behavior.

These goals were achieved even with several constraints placed on NEURAE that are not necessary for future applications. For example, NEURAE is inherently able to make recurrent networks, but that ability was specifically removed in the examples provided here to simplify the evaluation of ANN logic. A version of NEURAE with recursion enabled could exhibit many of desirable properties networks mentioned in the introduction have, but with the modularity and scalability embryogenesis provides. NEURAE is also capable of generated networks that are not purely digital. Most ANN applications use a continuous activation function within each neuron to produce a range of values between -1 and 1 . A particular benefit to using analog networks would be the ability to use Hebbian type learning, for control applications in particular. Nolfi et al. (1994), Stanley et al. (2003), and Soltoggio et al. (2007) have all successfully used reinforcement learning for the real time training of an ANN controller. However, these methods have been used for directly encoded genetic algorithms and are thus impractical for large networks. NEURAE, however, could find the core module necessary for such real-time learning ANNs and replicate it to make large networks.

Future iterations of NEURAE could benefit from other advancements in the field of evolutionary computation. One of the key components of NEAT (Stanley and Miikkulainen 2002) was an evaluation which rewarded robotic controllers for novelty. Instead of dictating a single evolutionary path with evaluation in tiers, rewarding novelty promotes several evolutionary paths at once. Another improvement might be the use of other selection methods. Rather than using the roulette method shown in Equation 2.7, selection can be done via tournaments (Miller and Goldberg 1995) or Pareto optimization (Horn et al. 1994).

These improvements would likely further optimize NEURAE for use in other applications. Many of the classification methods mentioned in the introduction train a large ANN with a set architecture. These training sessions are sensitive to the initial weights and the training sequence. NEURAE has shown it can make large, robust ANNs, and such ANNs would be less sensitive to varying initial weights and training sequences. As a result, better
classifiers could be made, which would have applications in computer vision for robotics, or many of the other fields mentioned in the introduction.

Most promising, the results obtained here may have implications beyond robotics and neuro-evolution. While the importance of point and crossover mutations have been well studied in classical GAs, the effects of gene duplication, gene deletion, and translocation have not. It would be interesting to study how these mutations affect other implicit GAs, and in particular, see if similar results are yielded. Likewise, Davidson (2006) has shown how controlling growth is an important feature of biological regulatory systems, and more work is needed to test the effect of regulatory systems in other GAs which use embryogenesis. Finally, the occurrence and correlation of punctuated equilibrium in an artificial evolution with embryogenesis is not well studied and is likely not unique to NEURAE.

## Bibliography

Adami, C., Ofria, C., and Collier, T. C. (2000). Evolution of biological complexity. Proceeding of the National Academy of Sciences, 97(9):4463-4468.

Angeline, P. J., Saunders, G. M., and Pollack, J. B. (1999). An evolutionary algorithm that constructs recurrent neural networks. IEEE Transactions on Neural Networks, 5(1):5465.

Ashlock, D. (2006). Optimization and Modeling with Evolutionary Computation. SpringerVerlag.

Astor, J. C. and Adami, C. (2000). A developmental model for the evolution of artificial neural networks. Artificial Life, 6(3):189-218.

Atiya, A. F. (2001). Bankruptcy prediction for credit risk using neural networks: A survey and new results. IEEE Transactions on Neural Networks, 12:929-935.

Bäck, T. (1992). Self-adaptation in genetic algorithm. In Proceedings of the 1st European Conference on Artificial Life, pages 263-271.

Bäck, T. and Schutz, M. (1996). Intellegent mutation rate control in canonical gas. In Proceeding of Foundation of Intellegent Systems 9th International Symposium, volume 2, pages 158-167.

Beer, R. D., Chiel, H. J., Quinn, R. D., Espenschied, K. S., and Larsson, P. (1992). A distributed neural network architecture for hexapod robot locomotion. Neural Computation, 4(3):356-365.

Bentley, P. and Kumar, S. (1999). Three ways to grow designs: A comparison of embryogenesis for an evolutionary design problem. In Genetic and Evolutionary Computation Conference, pages 35-43, New York, NY, USA. ACM.

Biewald, R. (1996). A neural network controller for the navigation and obstacle avoidance of a mobile robot. In Zalzala, A. M. S. and Morris, A. S., editors, Neural network for robotic control, pages 162-191. Ellis Horwood, Upper Saddle River, NJ, USA.

Bosman, R. J. C., van Leeuwen, W. A., and Wemmenhove, B. (2003). Combining hebbian and reinforcement learning in a minibrain model. Neural Networks, 17:29-36.

Britten, R. J. (2005). The majority of human genes have regions repeated in other human genes. Proceeding of the National Academy of Sciences, 102(15):5466-5470.

Calabretta, R., Nolfi, S., Parisi, D., and Wagner, G. P. (1998). Emergence of functional modularity in robots. In Proceedings of the fifth international conference on simulation of adaptive behavior on From animals to animats, pages 497-504.

Chen, S., Wu, Y., and Luk, B. L. (1999). Combined genetic algorithm optimization and regularized orthogonal least squares learning for radial basis function networks. IEEE Transactions on Neural Networks, 10(5):1239-1243.

Chialvo, D. R. and Bak, P. (1999). Learning from mistakes. Neuroscience, 90(4):1137-1167.

Cremean, L. B., Foote, T. B., Gillula, J. H., Hines, G. H., Kogan, D., Kriechbaum, K. L., Lamb, J. C., Leibs, J., Lindzey, L., Rasmussen, C. E., Stewart, A. D., Burdick, J. W., and Murray, R. M. (2006). Alice: An information-rich autonomous vehicle for high-speed desert navigation. Journal of Field Robotics, 23(9):777-810.

Cui, X. and Shin, K. G. (1993). Direct control and coordination using neural networks. IEEE Transactions on Systems, Man and Cybernetics, 23:686-697.

Daucé, E., Quoy, M., Cessac, B., and Samuelides, M. (1998). Self-organization and patterninduced reduction of dynamics in recurrent networks. Neural Networks, 11:521-533.

Davidson, E. H. (2006). The Regulatory Genome: Gene Regulatory Networks in Development and Evolution. Elsevier, London, UK.

Duerr, P., Mattiussi, C., and Floreano, D. (2006). Neuroevolution with analog genetic encoding. In Parallel Problem Solving from Nature, volume 9, pages $671-680$.

Dupuis, J.-F. and Parizeau, M. (2008). Evolving a vision-based line-following robot controller. In Proceedings of the Third Canadian Conference on Computer and Robot Vision, pages 75-81.

Eberhart, R. and Kennedy, J. (1995). A new optimizer using particles swarm theory. In Proceedings of the Sixth International Symposium on Micro Machine and Human Science, pages 39-43, Piscataway, NJ. IEEE Press.

Eldredge, N. and Gould, S. J. (1972). Punctuated equilibria: An alternative to phyletic gradualism. In Schopf, T. J., editor, Models in Paleobiology, chapter 5, pages 82-115. Freeman, Cooper and Company, San Francisco, U.S.A.

Federici, D. and Downing, K. (2006). Evolution and development of a multicellular organism: Scalability, resilience, and neutral complexification. Artificial Life, 12(3):381-409.

Floreano, D., Mitri, S., and Magnenat, S. (2007). Evolutionary conditions for the emergence of communication in robots. Crruent Biology, 17(6):514-519.

Fogel, L. J., Owens, A. J., and Walsh, M. J. (1966). Artifical intiellegence through simulation evolution. Wiley, New York, NY, USA.

Fraternali, F., Porter, M. A., and Daraio, C. (2009). Optimal design of composite granular protectors. Mechanics of Advanced Materials and Structures. In Press.

Garis, H. D. (1992). Artificial embryology - the genetic programming of an artificial embryo. In Soucek, B. and IRIS, editors, Dynamic, Genetic, and Chaotic Programming, chapter 14, pages 373-393. Wiley, New York, NY, USA.

Graham, L., Cattral, R., and Oppacher, F. (2009). Beneficial preadaptation in the evolution of a 2d agent control system with genetic programming. In Proceedings of the 12 th European Conference on Genetic Programming, pages 303-314.

Grajdeanu, A. (2007). Methods for open-box analysis in artificial development. In Genetic and Evolutionary Computation Conference, pages 1005-1012, New York, NY, USA. ACM.

Gruau, F. (1992). Genetic synthesis of boolean neural networks with a cell rewriting developmental process. In International Workshop on Combinations of Genetic Algorithms and Neural Networks, 1992 (COGANN-92), pages 55-74.

Gruau, F. (1994). Neural Network Synthesis using Cellular Encoding and the Genetic Algorithm. PhD thesis, Laboratoire de l'Informatique du Parallilisme, Ecole Normale Supirieure de Lyon, France.

Harlan, R. M., Levine, D. B., and McClarigan, S. (2001). Evolving neural networks. ACM SIGCSE Bulletin, 33(1):105-109.

Hebb, D. (1949). The Organization of Behavior. Wiley, New York, NY, USA.

Hecht-Nielsen, R. (1992). Theory of the backpropagation neural network. Neural Network for Perception, 2:65-93.

Holland, J. (1975). Adaptation in Natural and Artificial Systems. University of Michigan Press, Ann Arbor, MI, USA.

Holland, J. (1992). Genetic algorithms. Scientific American, 267(1):66-72.

Hopfield, J. J. (1982). Neural networks and physical systems with emergent collective computational abilities. Proceeding of the National Academy of Sciences, 79(8):25542558.

Horn, J., Nafpliotis, N., and Goldberg, D. E. (1994). A niched pareto genetic algorithm for multiobjective optimization. In Proceedings of the First IEEE Conference on Evolutionary Computation, pages 82-87.

Hornby, G. S., Lipson, H., and Pollack, J. B. (2001). Evolution of generative design systems for modular physical robots. IEEE International Conference on Robotics and Automation, pages 4146 - 4151 .

Hornik, K., Stinchcombe, M. B., and White, H. (1989). Multilayer feedforward networks are universal approximators. Neural Networks, 2:359-366.

Jain, R., Rivera, M. C., and Lake, J. A. (1999). Horizontal gene transfer among genomes: The complexity hypothesis. Proceeding of the National Academy of Sciences, 96(7):38013806.

Kartalopoulos, S. V. (1996). Understanding Neural Networks and Fuzzy Logic. IEEE Press, Piscataway, NJ.

Kashtan, N. and Alon, U. (2005). Spontaneous evolution of modularity and network motifs. Proceeding of the National Academy of Sciences, 102(39):13773-13778.

Kitano, H. (1990). Designing neural networks using genetic algorithms with graph generation system. Complex Systems, 4(4):461-476.

Kitano, H. (1995). A simple model of neurogenesis and cell differentialtion based on evolutionary large-scale choas. Artificial Life, 2(1):79-97.

Koehn, P. (1996). Genetic encoding strategies for neural networks. In Proceedings of Information Processing and Management of Uncertainty in Knowledge-Based Systems.

Koza, J. R. (1989). Hierarchical genetic algorithms operating on populations of computer programs. In Proceedings of the Eleventh International Joint Conference on Artificial Intelligence, pages 768-774, San Mateo, CA, USA. Morgan Kaufman.

Koza, J. R. (1992). Genetic Programming: On the Programming of Computers by Means of Natural Selection. MIT Press, Cambridge, MA, USA.

Langdon, W. B. (2000). Quadratic bloat in genetic programming. In Proceedings of the Genetic and Evolutionary Computation Conference, pages 451-458.

Lewis, M. A., Fagg, A. H., and Bekey, G. A. (1994). Genetic algorithms for gait synthesis in a hexapod robot. In Zheng, Y. F., editor, Recent Trends in Mobile Robots. World Scientific, New Jersey, USA.

Lewis, R. (2005). Human Genetics: Concepts and Applications. McGraw-Hill.
Lipson, H. and Pollack, J. B. (2000). Automatic design and manufacture of robotic lifeforms. Nature, 406:974-977.

Luke, S. and Spector, L. (1996). Evolving graphs and networks with edge encoding: Preliminary report. In Late Breaking Papers at the Genetic Programming 1996 Conference, pages 117-124.

Martin, W. and Russell, M. J. (2002). On the origins of cells: a hypothesis for the evolutionary transition from abiotic geochemistry to chemoautotropic prokaryotes, and from prokaryotes to nucleated cells. Philosophical Transactions of the Royal Society, 358:59-85.

McCulloch, W. and Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. Bulletin of Mathematical Biophysics, 5:115-133.

McGinley, B., Morgan, F., and O'Riordan, C. (2008). Maintaining diversity through adaptive selection, crossover and mutation. In Genetic and Evolutionary Computation Conference, pages 1127-1128, New York, NY, USA. ACM.

Miller, B. L. and Goldberg, D. E. (1995). Genetic algorithms, tournament selection, and the effects of noise. Complex Systems, 9(3):193-212.

Miller, J. F., P.Thomson, and Fogarty, T. (1997). Designing electronic circuits using evolutionary algorithms. arithmetic circuits: A case study. In Quagliarella, D., Periaux, J., Poloni, C., and Winter, G., editors, Genetic Algorithms and Evolution Strategies in Engineering and Computer Science: Recent Advancements and Industrial Applications. Wiley, New York, NY, USA.

Montana, D. J. and Davis, L. (1989). Training feedforward neural networks using genetic algorithms. In Proceedings of the Eleventh International Joint Conference on Artificial Intelligence, pages 762-767, San Mateo, CA,USA. Morgan Kaufmann.

Montgomery, D. C. (2004). Design and Analysis of Experiments. Wiley, New York, NY, USA, 6 edition.

Morris, G. M., Goodsell, D. S., Halliday, R. S., Huey, R., Hart, W. E., Belew, R. K., and Olson, A. J. (1998). Automated docking using a lamarckian genetic algorithm and an empirical binding free energy function. Journal of Computational Chemistry, 19(14):16391662.

Mühlenbein, H. (1992). How genetic algorithms really work I: Mutation and hillclimbing. In Parallel Problem Solving from Nature, volume 2, pages 15-25.

Murray, R. M. (2007). Recent research in cooperative controls of mulit-vehicle sytems. ASME Journal of Dynamic Systems Measurement and control, 129(5):571-582.

Naito, T., Odagiri, R., Matsunaga, Y., Tanifuji, M., and Murase, K. (1997). Genetic evolution of a logic circuit which controls an autonomous mobile robot. Lecture Notes in Computer Science, 1259:210-219.

Nolfi, S., Miglino, O., and Parisi, D. (1994). Phenotypic plasticity in evolving neural networks. In Proceedings of the First Conference Frome Perception to Action, pages 146-157. IEEE Computer Society Press.

Ochman, H., Lawrence, J. G., and Groisman, E. A. (2000). Lateral gene transfer and the nature of bacterial innovation. Nature, 405:299-304.

Odewahn, S. C., Pennington, E. B. S. R. L., Humphreys, R. M., and Zumach, W. A. (1992). Automated star / galaxy discrimination with neural networks. Astronomical Journal, 103(1):318-331.

Ohno, S. (1970). Evolution by gene duplication. Springer-Verlag.

Oja, E. (1992). Princle components, minor components, and linear neural networks. Neural Networks, 5:927-935.

Onat, A., Kita, H., and Nishikawa, Y. (1998). Recurrent neural networks for reinforcement learning: architecture, learning algorithms and internal representation. In $I E E E$ International Joint Conference on Neural Networks, pages 2010-2015.

O'Neill, M. and Ryan, C. (2001). Grammatical evolution. IEEE Transactions on Evolutionary Computation, 5:349-358.

Pollack, J. B., Hornby, G. S., Lipson, H., and Funes, P. (2003). Computer creativity in the automatic design of robots. Leonardo, 36(2):115-121.

Reed, R. (1999). Pruning algorithms - a survey. IEEE Transactions on Neural Networks, 4(5):740-744.

Roy, A., Govil, S., and Miranda, R. (1999). A neural-network learning theory and a polynomial time rbf algorithm. IEEE Transactions on Neural Networks, 8(6):1301-1306.

Roy, A. M., Antonsson, E. K., and Shapiro, A. A. (2008). An investigation into the structure of genomes within an evolution that uses empryogenesis. In Genetic and Evolutionary Computation Conference: Late Breaking Papers, pages 2137-2142, New York, NY, USA. ACM.

Sanger, T. D. (1989). Optimal unsupervised learning in a single-layer linear feedforward neural network. Neural Networks, 2:459-473.

Soltoggio, A., Peter Dü, r., Mattiussi, C., and Floreano, D. (2007). Evolving neuromodularity topologies for reinforcement learning-like problems. In IEEE International Joint Conference on Neural Networks, pages 2010-2015.

Stanley, K. O., Bryant, B. D., and Miikkulainen, R. (2003). Evolving adaptive neural networks with and without adaptive synapses. In Proceedings of the IEEE Congress on Evolutionary Computation, CEC 2003, pages 2557-2564.

Stanley, K. O., Bryant, B. D., and Miikkulainen, R. (2005). Real-time neuroevolution in the nero video game. IEEE Transactions on Evolutionary Computation, 9(6):653-693.

Stanley, K. O., D'Ambrosio, D., and Gauci, J. (2009). A hypercube-based indirect encoding for evolving large-scale neural networks. Artificial Life, 15(2):185-223.

Stanley, K. O. and Miikkulainen, R. (2002). Evolving neural networks through augmenting topologies. Evolutionary Computation, 10(2):99-127.

Stanley, K. O. and Miikkulainen, R. (2003). A taxonomy for artificial embryogeny. Artificial Life, 9(2):93-130.

Sutton, R. S. (1986). Two problems with backpropogation and other steepest-descent learning procedures for networks. In Proceeding of the Eighth Annual Conference of the Cognitive Science Society, pages 823-831.

Sutton, R. S. and Barto, A. G. (1999). Reinforcement learning. Journal of cognitive neuroscience, 11:126-134.

Szathmáry, E. and Smith, J. M. (1995). The major evolutionary transitions. Nature, 374:227-232.

Tesauro, G. (1992). Practical issues in temporal difference learning. Machine Learning, 8:257-277.

Theraulaz, G. and Bonabeau, E. (1995). Coordination in distributed building. Science, 269(5224):686-688.

Tsoulos, I. G., Gavrili, D., and Glavas, E. (2005). Neural network construction using grammatical evolution. In IEEE International Symposium on Signal Processing and Information Technology, pages 827-831.

Tufte, G. and Haddow, P. C. (2000). An evolvable hardware fpga for adaptive hardware. In Proceedings of the 2000 Conference on Evolutionary Computation, pages 553-560.

Turing, A. (1950). Computing machinery and intelligence. Mind, 59(236):433-460.
Vigraham, S. A., Gallagher, J. C., and Boddhu, S. K. (2005). Evolving analog controllers for correcting thermoacoustic instability in real hardware. In Genetic and Evolutionary Computation Conference, pages 933-940, New York, NY, USA. ACM.

Waibel, A. (1989). Modular construction of time-delay neural networks for speech recognition. Neural Computation, 1:39-46.

Weibull, W. (1951). A statistical distribution function of wide applicability. Journal of applied mechanics, 18:292-297.

Wu, Y., Giger, M. L., Doi, K., and Vyborny, K. (1993). Artificial neural networks in mammography: Application to decision making in the diagnosis of breast cancer. Radiology, 187(1):81.

Yakovenko, S., Gritsenko, V., and Prochazka, A. (2004). Contribution of strech reflexes to locomotor control: a modeling study. Biological Cybernetics, 90:146-155.

Yogev, O. and Antonsson, E. K. (2007). Growth and development of continuous structures. In Genetic and Evolutionary Computation Conference, pages 1064-1065, New York, NY, USA. ACM.

Yue, S. and Rind, F. C. (2006). Collision detection in complex dynamic scenes using an lgmd-based visual neural network with feature enhancement. IEEE TRANSACTIONS ON NEURAL NETWORKS, 17(3):705-716.

Zhang, Y., Antonsson, E. K., and Martinoli, A. (2008). Evolutionary engineering design synthesis of on-board traffic monitoring sensors. Research in engineering design, 19:113125.

## Appendix

Included in the appendix is the source code used to make NEURAE work. Because many different version of NEURAE were developed in the process of this thesis, the codes have several sections which were obsolete or never finished. Furthermore, the first three programs listed were for evolving the robust XOR logic gate, while the final library was used for the evolution of swarming robot controllers.

- Evovle.cpp is the executable program, and contains the various libraries listed afterwards. This is the program which conducted the genetic algorithm. Pages 86 106
- node_lib. $h$ is a libraries which defined the node and neural network object class, as well as useful functions for both. Pages 107-115
- evo_lib.h contains many useful functions used throughout evolution, such as those used for evaluation and mutation. It also contains the definition for an individual as well. Furthermore, the make_protien function contained within evo_lib.h was responsible for transcibing the integers of an individual's genome into a compilable $\mathrm{C}^{++}$program. Pages 116-163
- robot_lib.h contains the definition and functions needed for robot simulations. Pages 164-180

```
//This is the main script that will control evolution
#include <iostream>
#include <fstream>
#include <vector>
#include <string>
#include <sstream>
#include <ctime>
#include <math.h>
#include "chimera_lib.h"
#include "node_lib_omega4.h"
#include "evo_lib_omega4.h"
#include <mpi.h>
using namespace std;
int main(int argc, char *argv[]){
    //----- These values are set by arguments during
    program calls ---------------
    //Template for new runs:
    // Evolve.exe N last_generation default genome
    length
    //Template for continuing runs
    // Evolve.exe -c N last_generation
    restarting_generation
    char restart; //This determines whether evolution will k
        start from scratch or a member of Ark.txt
    int N; //The number of individuals per generation
    int default_genome_length;
    int last_generation; //Max number of generations
    int start_gen,counter; //Used for regenesis
    vector<int> restart_individuals; //Used for regenesis
    //------------------------------------------------
    //--- Number of inputs and outputs for each ANN ------ K
    --
    const int no_of_inputs = 2;
    const int max_no_of_outputs = 1;
    const int max_connections = 99;
    //------ Mutation Rates & Values -----------
    const float mu = 1.0; //Chance of mutation at each \boldsymbol{k}
    reading frame
    vector < vector<float> > mutation_ratios; //Ratio for k
        each case. The # of cases determines the number of
    children each individual can have
    vector<float> mu_ratio (5, 1.0); //Mutation rate of
    each mutator. Make sure they add up to 1.0
    mu_ratio[0] = 0.40;mu_ratio[1] = 0.30;mu_ratio[2] = 0.k
    00;mu_ratio[3] = 0.30;mu_ratio[4] = 0.00;
    mutation_ratios.push_back(mu_ratio);
    mu_ratio[0] = 0.40;mu_ratio[1] = 0.30;mu_ratio[2] = 0.k
    00;mu_ratio[3] = 0.30;mu_ratio[4] = 0.00;
```

    mutation_ratios.push_back(mu_ratio);
    mu_ratio[0] = 0.40;mu_ratio[1] = 0.30;mu_ratio[2] = 0. \(\kappa\)
    \(00 ; \mathrm{mu}_{-}\)ratio[3] = 0.30;mu_ratio[4] = 0.00;
    mutation_ratios.push_back(mu_ratio);
    float mu_point_mutation;
    float mu_conjugation;
    float mu_recopy;
    float mu_deletion;
    float mu_translocation;
    //-----------------------------
    //---- Random Seeding
    time_t start,end, seed;
    int dif_t;
    time (\&start); //Sets the start time for this 反
    evolution run
    time (\&seed);
    //seed = 1244495693;
    srand(seed); //Seeds the randomizer
    //------------------------
    //------Used for organizing individuals throughout 反
    evolution
    int generation \(=0 ; / / T h e ~ c u r r e n t ~ g e n e r a t i o n ~\)
    int newly_made, vets,reduced; //keeps track of the 反
    number of individuals made each generation
    int Ark_no, my_Ark_no, Ark_no2; //Used to keep track
    of Ark numbers within the hub and satellite computers
    int genome_size;
    vector<int> recalled_genome; //Used for regenesis
    vector<individual> Ark; //Holds all the individuals
    vector<individual> my_Ark; //Array for satellite
    computers that has its individuals
    vector<int> my_Ark_conversion; //Ark_conversion[i] on
    satellite comp == Ark_no on comp 0
    int Ark_search; //Used to find the right Ark_no on 反
    satellites
    
-----
//----- Used for selection in survival and proceation
vector<int> procreation; //For selecting whose genes
will be passed on
vector<int> unmade; //Individuals whose ANN's haven't
been made
vector<int> alive; // All individuals alive this
generation
vector<int> still_alive; // Individuals that were k
alive this generation and will live onto the next
vector<int> stay_alive; //Individuals that have been 反
selected during death and procreation loops
float all_fitness,max_fitness;
int lucky_one, newbies, mutation_method;
vector< vector<int\gg mutation_info; //The individuals $\swarrow$
' subject number and the method of its mutation
vector< vector<int\gg mutation_Ark; //The individuals $\leqslant$
genomes
float low_fit, high_fit, range_fit, num_fit;
int selection_q, low_int, high_int, range_int, num_int $\swarrow$
;

// -----.- Declared here and used to temporarily
hold info
int junk_int;
char junk_char;
float junk_float;
vector<int> junk_ints;
//------------------------------
//MPI Variables
MPI: :Init(argc, argv);
int dest, noProcesses, processID, tag, src;
int hub = 0;
vector<int> mutationID, embryogenesisID;
tag $=0$;
MPI_Status status;
noProcesses = MPI::COMM_WORLD.Get_size();
processID = MPI::COMM_WORLD.Get_rank();
int data_pack[2]; //Used to hold info when sending 反
info to other comps
int data_pack2[3]; //Also used to hold info when 反
sending info to other comps in mutation loop
int back_size; //Tells hub how much info is being sent $\boldsymbol{k}$
back
vector<int> temp_genome; //Used as a temp place holder $\boldsymbol{k}$
for sending genomes to other comps
vector<int> temp_genome2;
vector<int> sub_back; //Used to send subject numbers દ
back to computer hub
vector<float> fit_back; //Used to send fitnesses back $\boldsymbol{\swarrow}$
to computer hub
vector<int> ruleset_length_back; //Used to prep 反
computer hub for the number of rules coming back
vector<int> ruleset_back; //Rules creating in making $\boldsymbol{\kappa}$
each ANN.
int ruleset_back_size; //Same as ruleset_back.size(), 反
but shorter way can't be used alone
//----------//
if((processID\%8) == 0)\{ //This is a fix for GARUDA so $\boldsymbol{k}$
each computer does this only once
//Cleans up scratch if anything is there
//Copies necessary libraries to /scratch
directories of each comp

------------------------
system("scp /home/roy/chimera_lib.h /scratch/ chimera_lib.h");
system("scp /home/roy/Evolution/Version_omega4/ node_lib_omega4.h /scratch/node_lib_omega4.h");
\}
else\{
system("sleep 5");
\}

//This if/else loop determines if we are continuing from a past evo run or starting a new one, then sets $\boldsymbol{k}$ the variables accordingly
if(argc == 5) \{
$\mathrm{N}=$ atoi(argv[2]);
last_generation = atoi(argv[3]);
start_gen = atoi(argv[4]);
counter $=0 ; / / T r a c k s ~ h o w ~ m a n y ~ i n d i v u a l s ~ h a v e ~ b e e n ~ 反 ~$ restarted

Ark_no = 0;
if (processID == hub) \{
//First, we read the Chronograph to see which individuals were alive at the given gen
ifstream infile1("Chronograph.txt");
for(int i=0;i<start_gen;i++)\{ //Skips down the $\swarrow$ right gen
infile1>>junk_int; //Gets the gen
for(int j=0;j<N;j++)\{
infile1>>junk_int; //Gets the subject
number
infile1>>junk_float; //Get the fitness \}
\}
infile1>>junk_int; //Gets the gen again for(int i=0;i<N;i++)\{ //Gets and saves the subject numbers infile1>>junk_int; //Gets the subject number
restart_individuals.push_back(junk_int);
infile1>>junk_float; //Get the fitness
\}
if(restart_individuals.size()!= N)\{ //Check cout<<"There was a problem with determining which individuals were alive at generation $\boldsymbol{\swarrow}$ "<<start_gen<<endl;
return 0;
\}
sort_vector(restart_individuals);
cout<<"Individuals to be restarted from generation "<<start_gen<<": "<<endl;
print_vector(restart_individuals);
system("cp ./Ark.txt ./Arktmp.txt"); //Creates a temp file to read from system("rm Ark.txt"); system("rm Chronograph.txt");
ofstream datafile_temp("Ark.txt");
datafile_temp<<seed<<endl; //Gets the seed ifstream infile2("Arktmp.txt");
//Now we read through the Ark and compares the $\boldsymbol{\swarrow}$ subject number of the Ark with the individuals marked $\boldsymbol{\kappa}$ for restart
infile2>>junk_int; //Gets the old seed while (counter<N) \{
if(any(restart_individuals,Ark_no)) \{//Save the individual
infile2>>junk_int;
infile2>>junk_int;
infile2>>junk_int;
infile2>>junk_char;
infile2>>genome_size;
for(int j=0;j<genome_size;j++)\{ infile2>>junk_int; recalled_genome.push_back

```
(junk_int);
```

    \}
    generate_designed(Ark, recalled_genome, \(\swarrow\)
    generation);
recalled_genome.clear();
Ark_Load(Ark[counter]);
unmade.push_back(counter);
alive.push_back(counter);
cout<<"Individual "<<Ark_no<<" was k
reborn as "<<Ark[counter].get_fcall()<<endl;
counter++;
\}
else\{//Discards it
infile2>>junk_int;
infile2>>junk_int;
infile2>>junk_int;
infile2>>junk_char;
infile2>>genome_size;
for(int j=0;j<genome_size;j++)\{
infile2>>junk_int;
\}
\}
Ark_no++;// Moves onto next individual in $\boldsymbol{\swarrow}$
the Ark
\}
system("rm Arktmp.txt");
newly_made = unmade.size();
vets = 0;
reduced $=0$;
\}

```
}
```

else\{
$\mathrm{N}=$ atoi(argv[1]);
last_generation = atoi(argv[2]);
default_genome_length = atoi(argv[3]);
if (processID == hub) \{
system("rm Ark.txt");
system("rm Chronograph.txt");
ofstream datafile_temp("Ark.txt");
datafile_temp<<seed<<endl;
for (int $\bar{i}=0 ; i<N ; i++)\{/ / T h i s ~ w i l l ~ g e n e r a t e ~ N ~ ட ~$
random individuals
generate_random(Ark,default_genome_length, $\boldsymbol{\swarrow}$
generation);
Ark_Load(Ark[i]);
unmade.push_back(i);
alive.push_back(i);
\}
newly_made = unmade.size();
vets = 0;
reduced $=0$;
\}
\}

// --- This partions the satellites into evaluators 反
and mutators ----------
if((int(N/24)+2)<noProcesses) \{
for(int i=0;i<N/24;i++)\{
mutationID.push_back(i+1);
\}
if(mutationID.size()==0) \{ //A fix for small runs $\boldsymbol{K}$
where there would be no mutation processor
mutationID.push_back(1);
\}
for(int i=(mutationID.size()+1);i<noProcesses;i++) ட
$\{$
embryogenesisID.push_back(i);
\}
\}
else\{
cout<<"Use more processors or this will be VERY
slow"<<endl;
mutationID.push_back(1);
for(int i=1;i<noProcesses;i++)\{
embryogenesisID.push_back(i);
\}
\}

-----
MPI: :COMM_WORLD.Bcast(\&newly_made, 1, MPI: :INT, hub);
MPI: : COMM_WORLD.Bcast(\&vets, 1, MPI: :INT, hub);
MPI : : COMM_WORLD.Bcast(\&reduced,1,MPI: :INT, hub);

```
    //
    ---------------------
    // ------------ BEGINNING OF EVOLUTION LOOP
    //
    for(generation;generation<last_generation;generation+
    +) {
        if(processID == hub){
            cout<<"Generation: "<<generation<<endl;
            assert((still_alive.size()+unmade.size())==N);
            assert(alive.size()==N);
        }
        // --- Re-evaluates the individuals that lived
        from last generation ---
        if(generation != 0){
            for(int i=0;i<vets;i++){
                    if(processID == hub){
                    Ark_no = still_alive[i];
            }
            MPI::COMM_WORLD.Bcast(&Ark_no,1,MPI::INT,
        hub);
            dest = embryogenesisID[Ark_no%
        (embryogenesisID.size())]; //See page 20 Vol. 2 for
        logic
            if(processID == hub){
                Ark_no = still_alive[i];
                            MPI::COMM_WORLD.Send(&Ark_no,1,MPI::
        INT,dest,tag);
            }
            if(processID == dest){
                    MPI::COMM_WORLD.Recv(&Ark_no,1,MPI:: k
    INT,hub,tag);
                    Ark_search = -1;
                    int my_Ark_counter = 0;
                    while(Ark_search < Ark_no){
                    Ark_search = my_Ark_conversion
    [my_Ark_counter];
                            my_Ark_counter++;
                    }
                            my_Ark_no = my_Ark_counter-1;
                            //cout<<"Process "<<processID<<" is re k
        -evaluating "<<my_Ark[my_Ark_no].get_fcall()<<endl;
                    if(my_Ark[my_Ark_no].get_fitness() >=
    pow(2.0,(2*max_no_of_outputs - 1))){ //Repeats if a
    good ANN is made
```

                my_Ark[my_Ark_no].eval_robustness
            ();
                \}
                    sub_back.push_back(Ark_no);
    get_fitness())
\}
if(any(embryogenesisID, processID)) \{ //Sends
results to process the hub
back_size = sub_back.size();
MPI::COMM_WORLD.Send(\&back_size,1,MPI: :INT
, hub, tag);
MPI: : COMM_WORLD.Send(\&sub_back[0],
back_size, MPI:: INT, hub, tag);
MPI: : COMM_WORLD.Send(\&fit_back[0],
back_size,MPI::FLOAT,hub,tag);
//cout<<"Process ID "<<processID<<" sent 反
back (from re-evaluation):"<<endl;
//print_vector(sub_back);
sub_back.clear();
fit_back.clear();
\}
if(processID == hub)\{ //The hub collects k
results
for(int i=0; i<embryogenesisID.size(); i+
+ ) \{
src = embryogenesisID[i];
MPI: : COMM_WORLD.Recv(\&back_size,1, MPI:
: INT, src, tag);
sub_back.resize(back_size);
fit_back.resize(back_size);
MPI: : COMM_WORLD.Recv(\&sub_back[0],
back_size, MPI::INT, src,tag);
MPI: : COMM_WORLD.Recv(\&fit_back[0],
back_size, MPI: :FLOAT, src,tag);
//cout<<"Hub received ";
//print_vector(sub_back);
//cout<<" from process "<<src<<endl;
for(int j=0;j<back_size;j++)\{
Ark[sub_back[j]].make_fitness
(fit_back[j]);//Gives the individual sub_back[i] the
fitness fit_back[i]
\}
sub_back.clear();
fit_back.clear();
\}
\}
\}
// ------------ End of re-evaluating survivors --
// -----------------------------------------------
// ------ Sends out indivuals for embryogenesis
and evaluation----

```
            for(int i=0;i<(newly_made+reduced);i++){
            if(processID == hub){
                Ark_no = unmade[i];
            }
            MPI::COMM_WORLD.Bcast(&Ark_no,1,MPI::INT, hub);
            dest = embryogenesisID[Ark_no%(embryogenesisID \swarrow
.size())]; //See page 20 Vol. 2 for logic
            // --- Hub loop -------
            if(processID == hub){
                Ark_no = unmade[i];
                genome_size = Ark[Ark_no].
get_genome_length();
                                    data_pack[0] = Ark_no;
                                    data_pack[1] = genome_size;
                                    //cout<<Ark[Ark_no].get_fcall()<<" was
                                    sent to process "<<dest<<" for evaluation."<<endl;
                                    for(int j=0;j<genome_size;j++)
                    temp_genome.push_back(Ark[Ark_no].
get_genome(j));
                                    MPI::COMM_WORLD.Send(&data_pack,2,MPI::INT к
    ,dest,tag);
                            MPI::COMM_WORLD.Send(&temp_genome[0],
    genome_size,MPI::INT,dest,tag);
                                    temp_genome.clear(); //Empties for next <
    time
            }
            // ------------------------------------------------- K
                            // ------------- Satellite Loop
                            L
                            if(processID == dest){
                            MPI::COMM_WORLD.Recv(&data_pack[0],2,MPI:: ц
    INT,hub,tag);
        Ark_no = data_pack[0];
        my_Ark_conversion.push_back(Ark_no);
        my_Ark_no = my_Ark.size();
        genome_size = data_pack[1];
        temp_genome.resize(genome_size);
        MPI::COMM_WORLD.Recv(&temp_genome[0], <
        genome_size,MPI::INT,hub,tag);
        generate_satellite(my_Ark,temp_genome,
        generation,Ark_no);
        make_protein(my_Ark[my_Ark_no],
        no_of_inputs,max_no_of_outputs,max_connections,
        processID);
            my_Ark[my_Ark_no].make_ANN(processID);
            my_Ark[my_Ark_no].eval_XOR_logic();
            my_Ark[my_Ark_no].eval_robustness();
            //cout<<"Process ID = "<<processID<<"
        Ark_no = "<<Ark_no<<" my_Ark_no = "<<my_Ark_no<<endl;
```

sub_back.push_back(Ark_no);
fit_back.push_back(my_Ark[my_Ark_no].
get_fitness());
ruleset_length_back.push_back(my_Ark
[my_Ark_no].get_rules_length());
for $\left(i n t \quad j=0 ; j<m y \_A r k\left[m y \_A r k \_n o\right]\right.$.
get_rules_length();j++)\{
ruleset_back.push_back(my_Ark
[my_Ark_no].get_rule(j));
\}
\}

\}

// ----------- Collects the info at the hub ---- $\boldsymbol{k}$

if(any(embryogenesisID, processID)) \{ //Sends results to process 0
back_size = sub_back.size();
MPI: :COMM_WORLD.Send(\&back_size,1,MPI: :INT, hub $\kappa$ , tag);

MPI: : COMM_WORLD. Send(\&sub_back[0], back_size, MPI: :INT, hub, tag);

MPI: : COMM_WORLD.Send(\&fit_back[0],back_size, 久 MPI: :FLOAT, hub, tag);

MPI: : COMM_WORLD.Send(\&ruleset_length_back[0], к back_size,MPI: :INT, 0,tag);
//cout<<"Process ID "<<processID<<" sent back: "<<endl;
//print_vector(sub_back);
ruleset_back_size = 0;
for(int j=0;j<back_size;j++)\{
ruleset_back_size = ruleset_back_size + $\boldsymbol{\kappa}$ ruleset_length_back[j];
\}
MPI: : COMM_WORLD.Send(\&ruleset_back[0], ruleset_back_size,MPI: :INT, 0, tag);
sub_back.clear();
fit_back.clear();
ruleset_length_back.resize(0);
ruleset_back.resize(0);
\}

// ---------- Hub loop
if(processID == hub)\{ //If rank is 0, collect results and preps for next gen
for(int i=0; i<embryogenesisID.size(); i++)\{
src = embryogenesisID[i];
MPI: : COMM_WORLD.Recv(\&back_size,1,MPI: :INT $\swarrow$ , src,tag);
sub_back.resize(back_size);
fit_back.resize(back_size);
ruleset_length_back.resize(back_size);
MPI: : COMM_WORLD.Recv(\&sub_back[0], back_size, MPI::INT,src,tag);

MPI: : COMM_WORLD.Recv(\&fit_back[0], back_size,MPI: :FLOAT, src,tag); MPI: : COMM_WORLD.Recv(\&ruleset_length_back [0],back_size,MPI::INT,src,tag); ruleset_back_size $=0$; for(int j=0; j<back_size;j++) \{
ruleset_back_size = ruleset_back_size + ruleset_length_back[j];
\}
ruleset_back.resize(ruleset_back_size);
MPI: : COMM_WORLD.Recv(\&ruleset_back[0], ruleset_back_size, MPI::INT,src,tag);
int rule_pointer $=0$;
for(int j=0;j<back_size;j++)\{
Ark[sub_back[j]].make_fitness(fit_back к [j]);//Gives the individual sub_pack[i] the fitness k fit_pack[i]
for(int $k=0 ; k<r u l e s e t \_l e n g t h \_b a c k[j] ; k \kappa$ ++ ) \{

Ark[sub_back[j]].save_rule
$K$
(ruleset_back[rule_pointer+k]);
\}
rule_pointer = rule_pointer + ruleset_length_back[j];
\}
sub_back.clear();
fit_back.clear();
ruleset_length_back.resize(0);
ruleset_back.resize(0);
\}
Record_Gen(Ark, still_alive, unmade, generation); //Saves final state
newly_made $=0$;
reduced $=0$;
unmade.clear(); //Empties unmade...
\}

// --- The hub selectes the survivors and parents for the next generation ---------
if(processID == hub)\{ //If rank is 0, collect results and preps for next gen
//All that are alive have a chance to
procreate
procreation.clear();
for(int i=0;i<alive.size();i++)\{
Ark_no = alive[i];
procreation.push_back(Ark_no);
\}
/*

for(int i=0;i<alive.size();i++)\{
cout<<Ark[alive[i]].get_fcall()<<" has a
fitness of "<<Ark[alive[i]].get_fitness()<<endl;
$\}$
$*$
//-----------------------------DEATH LOOP----
while(stay_alive.size()<N/4)\{
all_fitness = 0;
max_fitness = 0;
for(int i=0;i<alive.size();i++)\{
Ark_no = alive[i];
if(!any(stay_alive,Ark_no)) \{
all_fitness += Ark[Ark_no].
get_fitness();
\}
if(Ark[Ark_no].get_fitness()==-1)\{
cout<<Ark[Ark_no].get_fcall()<<"
wasn't evaluated. Ending program."<<endl;
return 0;
\}
// -----------The fittest one last
made is always pardoned!--------------
if((Ark[Ark_no].get_fitness()>=
max_fitness)\&\&(stay_alive.size()==0))\{
max_fitness = Ark[Ark_no].
get_fitness();
\}
\}
all_fitness -= max_fitness;
//Max fitness is always 0 if something has
been pardoned
//This does the actually pardoning of the
fittest one last made
if(stay_alive.size() == 0)\{
stay_alive.push_back(lucky_one);
cout<<Ark[lucky_one].get_fcall()<<"
has stayed alive (ELITE) with fitness: "<<Ark
[lucky_one].get_fitness()<<endl;
\}
//----------End of elite selection------- と
//cout<<"End of elite selection"<<endl;
if(all_fitness!=0)\{
num_fit $=$ random_float(.000001,
all_fitness);
selection_q $=0$;
while(num_fit>0)\{
Ark_no = alive[selection_q];
if(!any(stay_alive,Ark_no)) \{
num_fit -= Ark[Ark_no].
get_fitness();
\}
selection_q++;
\}
stay_alive.push_back(Ark_no);//
PARDONED!!
cout<<Ark[Ark_no].get_fcall()<<" has
stayed alive with fitness: "<<Ark[Ark_no].get_fitness
()<<endl;
\}
else\{
//cout<<"Zero fitness"<<endl;
low_int = 0;
high_int = alive.size()-1;
vector<int> exclude;
for(int i=0;i<alive.size();i++)\{
if(any(stay_alive, alive[i])) \{
exclude.push_back(i);
\}
\}
num_int = random_int(low_int,high_int, $\leqslant$
exclude);
Ark_no = alive[num_int];
stay_alive.push_back(Ark_no); //
PARDONED (Zero Fitness)!!
cout<<Ark[Ark_no].get_fcall()<<" has
randomly stayed alive with "<<Ark[Ark_no].get_fitness 反
()<<" (zero) fitness."<<endl;
\}
\}
for(int i=0;i<alive.size();i++)\{
if(!any(stay_alive, alive[i]))\{
Ark[alive[i]].kill(generation); //COLD
-BLOODED!!
//cout<<Ark[alive[i]].get_fcall()<<"
did not make it across the river."<<endl;
\}
\}
alive.clear(); //Empties alive...
still_alive.clear();//...and empties
still_alive...
for(int i=0;i<stay_alive.size();i++)\{//...then $\kappa$

```
        refills them with stay alive
            alive.push_back(stay_alive[i]);
```

            //cout<<Ark[stay_alive[i]].get_fcall()<<"
    is alive."<<endl;
                            still_alive.push_back(stay_alive[i]);
                            //cout<<Ark[stay_alive[i]].get_fcall()<<"
    is still alive."<<endl;
\}
stay_alive.clear();
vets = still_alive.size();

\}
MPI::COMM_WORLD.Bcast(\&vets,1,MPI::INT, hub);
//---------------Procreation Selection Loop(s)---
//This (these) loops will select a primary and
secondary parent for each loop
//The number of loops is determined by the number $\boldsymbol{k}$
of mutation ratio sets
if(processID == hub) \{
N) ) \{
while((newly_made+reduced+still_alive.size() <
for(int i=0;i<mutation_ratios.size();i++)\{ $\swarrow$
vector<int> primary_parents;
vector<int> secondary_parents;
while((secondary_parents.size()<((N- к
(reduced+still_alive.size()))/mutation_ratios.size
( ) ) ) ) \{
first
++ ) \{

Ark_no ) ) \{
.get_fitness();
,all_fitness);
[selection_q];
Ark_no) ) \{
//The primary parent is selected $\boldsymbol{\swarrow}$
all_fitness = 0;
for(int j=0;j<procreation.size();j $\boldsymbol{k}$

```
        Ark_no = procreation[j];
``` if(!any(primary_parents,
all_fitness += Ark[Ark_no] \(\swarrow\) \}

\section*{\}}
if(all_fitness!=0) \{ num_fit \(=\) random_float(.000001 \(\leqslant\) selection_q = 0; while(num_fit>0)\{ Ark_no = procreation
if(!any(primary_parents,
```

.get_fitness();

```
(Ark_no);
    ()<<" with fitness "<<Ark[Ark_no].get_fitness()<<" was k
    selected as primary parent for selection loop "<<i< 反
    <endl;
        \}
        else\{
                            //cout<<"Zero fitness loop for \(\boldsymbol{\swarrow}\)
        primary parent in selection loop "<<i<<endl;
                            low_int = 0;
                            high_int = procreation.size()- \(\boldsymbol{\Sigma}\)
        \(1 ;\)
    vector<int> exclude;
    for(int i=0;i<procreation.size \(\leqslant\)
        ();i++)\{
    procreation[i]))\{
        if(any(primary_parents,
    high_int,exclude);
        (Ark_no);
    primary_parents.push_back
    //cout<<Ark[Ark_no].get_fcall
        ()<<" has been randomly selection for primary parent \(\boldsymbol{k}\)
        with "<<Ark[Ark_no].get_fitness()<<" (zero) fitness."<
        <endl;
        \}
                        //Repeat for secondary parents
                all_fitness = 0;
                    for(int j=0;j<procreation.size();j \(\swarrow\)
                        Ark_no = procreation[j];
                            if((!any(secondary_parents,
        Ark_no))\&\&Ark_no!=primary_parents.back()) \{ //Skips
        already chosen secodanry parents and the primary
        parent that was last chosen
            all_fitness += Ark[Ark_no]
        .get_fitness();
        ,all_fitness);
selection_q = 0;
while(num_fit>0)\{
Ark_no = procreation
[selection_q];
if((!any(secondary_parents
, Ark_no))\&\&Ark_no!=primary_parents.back())\{ //Skips already chosen secodanry parents and the primary parent that was last chosen
num_fit -= Ark[Ark_no]
```

.get_fitness();

```
\}
selection_q++;
\}
secondary_parents.push_back
(Ark_no);
//cout<<Ark[Ark_no].get_fcall ()<<" with fitness "<<Ark[Ark_no].get_fitness()<<" was \(\boldsymbol{k}\) selected as secondary parent for selection loop "<<i< \(\boldsymbol{k}\) <endl;
\}
else\{
//cout<<"Zero fitness loop for \(\boldsymbol{\Sigma}\) secondary parent in selection loop "<<i<<endl;
low_int \(=0\);
high_int = procreation.size()1;
vector<int> exclude;
//I want to exclude the
primary parent that was just chosen
exclude.push_back(num_int);
for(int i=0;i<procreation.size \(\leqslant\)
();i++) \{
procreation[i]))\{
high_int,exclude);
(Ark_no);
()<<" has been randomly selection for secondary parent with "<<Ark[Ark_no].get_fitness()<<" (zero) fitness." <<endl;
\}
\}
//Check to make sure an equal number of primary and seconday parents were chosen
if(primary_parents.size()!=
```

```
secondary_parents.size()){
```

```
secondary_parents.size()){
                                    cout<<"An equal number of primary
                                    cout<<"An equal number of primary
    and seconday parents were chosen"<<endl;
    and seconday parents were chosen"<<endl;
                                    return 0;
                                    return 0;
                                    }
                                    }
                                    //Place primary parent, secondary
                                    //Place primary parent, secondary
parent, and mutation method into mutation info
parent, and mutation method into mutation info
                                    for(int j=0;j<secondary_parents.size() <
                                    for(int j=0;j<secondary_parents.size() <
    ;j++){
    ;j++){
    (primary_parents[j]);
    (primary_parents[j]);
        junk_ints.push_back
        junk_ints.push_back
    (secondary_parents[j]);
    (secondary_parents[j]);
                                    junk_ints.push_back(i);
                                    junk_ints.push_back(i);
                                    mutation_info.push_back(junk_ints) \swarrow
                                    mutation_info.push_back(junk_ints) \swarrow
    ;
    ;
                        newly_made++;
                        newly_made++;
                junk_ints.clear();
                junk_ints.clear();
                    }
                    }
                    primary_parents.clear();
                    primary_parents.clear();
                    secondary_parents.clear();
                    secondary_parents.clear();
                        }
                        }
            }
            }
        }
        }
    //------------------------------------------------- K
```

```
    //------------------------------------------------- K
```

```
614
615
    for(int i=0;i<newly_made;i++)\{
        ------------------------
    //----------------------------------------------
    MPI: :COMM_WORLD.Bcast(\&newly_made,1, MPI: :INT, hub);
    //---------------------Sends genomes to be
    mutated
    See page 20 Vol. 2 for logic
        if(processid == hub)\{
            Ark_no = mutation_info[i][0];
            genome_size = Ark[Ark_no].
    get_genome_length();
        data_pack2[0] = Ark_no;
        data_pack2[1] = mutation_info[i][2];
        data_pack2[2] = genome_size;
        for(int j=0;j<genome_size;j++)\{
            temp_genome.push_back(Ark[Ark_no].
        get_genome(j));
                        \}
                            MPI::COMM_WORLD.Send(\&data_pack2,3,MPI::
        INT, dest,tag);

MPI::COMM_WORLD.Send(\&temp_genome[0], ட genome_size, MPI: :INT, dest, tag);
temp_genome.clear(); //Empties for next \(\boldsymbol{k}\)
time
//This sends another genome selected for a \(\boldsymbol{k}\)
mutation
Ark_no = mutation_info[i][1];
genome_size = Ark[Ark_no].
get_genome_length();
data_pack[0] = Ark_no;
data_pack[1] = genome_size;
for (int \(j=0 ; j<g e n o m e=s i z e ; j++)\{\)
temp_genome.push_back(Ark[Ark_no]. к
get_genome(j));
\}
MPI: :COMM_WORLD.Send(\&data_pack,2,MPI: :INT \(<\)
, dest, tag);
MPI: : COMM_WORLD.Send(\&temp_genome[0],
genome_size, MPI: :INT, dest, tag);
temp_genome.clear(); //Empties for next \(\boldsymbol{\swarrow}\)
time
\}
if(processID == dest)\{
MPI: : COMM_WORLD.Recv(\&data_pack2[0],3,MPI: : INT, hub, tag);

Ark_no = data_pack2[0];
mutation_method = data_pack2[1];
genome_size = data_pack2[2];
temp_genome.resize(genome_size);
MPI: : COMM_WORLD.Recv(\&temp_genome[0],
genome_size, MPI:: INT, hub, tag);
MPI: : COMM_WORLD.Recv(\&data_pack[0],2,MPI:: ц
INT, hub, tag);
Ark_no2 = data_pack[0];
genome_size = data_pack[1];
temp_genome2.resize(genome_size);
MPI: : COMM_WORLD.Recv(\&temp_genome2[0], genome_size, MPI: : INT, hub, tag);
mu_point_mutation = mu_ratio[0];
mu_conjugation = mu_ratio[1];
mu_recopy = mu_ratio[2];
mu_deletion = mu_ratio[3];
mu_translocation = mu_ratio[4];
mutator (temp_genome, temp_genome2, mu, mu_point_mutation,mu_conjugation,mu_recopy,mu_deletion \(\swarrow\) , mu_translocation);
junk_ints.push_back(Ark_no);
junk_ints.push_back(Ark_no2);
junk_ints.push_back(mutation_method);
mutation_info.push_back(junk_ints);
mutation_Ark.push_back(temp_genome);
                    junk_ints.clear();
                temp_genome.clear();
                temp_genome2.clear();
            \}
        \}
        //Satallites send the new genomes back to the hub
        if(any(mutationID, processID))\{
            back_size = mutation_Ark.size();
            MPI: :COMM_WORLD.Send(\&back_size,1, MPI: : INT, hub
, tag);
            for(int j=0;j<back_size;j++)\{
                    data_pack2[0] = mutation_info[j][0];
                    data_pack2[1] = mutation_info[j][1];
                    data_pack2[2] = mutation_info[j][2];
                            MPI::COMM_WORLD.Send(\&data_pack2,3,MPI: :
INT, hub, tag);
                            genome_size = mutation_Ark[j].size();
                            MPI : : COMM_WORLD.Send(\&genome_size,1,MPI:: k
INT, hub, tag);
                            MPI: : COMM_WORLD.Send(\&mutation_Ark[j][0], <
genome_size,MPI: :INT, hub, tag);
            \}
                mutation_info.clear();
                mutation_Ark.clear();
            \}
            if(processID == hub)\{
            //Collects and places new individuals into the \(\boldsymbol{K}\)
    Ark
            mutation_info.clear();
            mutation_Ark.clear();
            for(int i=0;i<mutationID.size();i++)\{
            src = mutationID[i];
            MPI::COMM_WORLD.Recv(\&back_size,1,MPI: :INT \(\swarrow\)
,src,tag);
            for(int j=0;j<back_size;j++)\{
                            MPI: :COMM_WORLD.Recv(\&data_pack2[0],3, к
MPI: :INT, src,tag);
                                    Ark_no = data_pack2[0];
                                    Ark_no2 = data_pack2[1];
                                    mutation_method = data_pack2[2];
            junk_ints.push_back(Ark_no);
            junk_ints.push_back(Ark_no2);
            junk_ints.push_back(mutation_method);
            mutation_info.push_back(junk_ints);
            junk_ints.clear();
                            MPI: :COMM_WORLD.Recv(\&genome_size,1, k
MPI: :INT, src,tag);
                            temp_genome.resize(genome_size);
                            MPI: :COMM_WORLD.Recv(\&temp_genome[0], к
```

genome_size,MPI::INT,src,tag);
mutation_Ark.push_back(temp_genome);
temp_genome.clear();
}
}
for(int i=0;i<mutation_Ark.size();i++){
Ark_no = mutation_info[i][0];
Ark_no2 = mutation_info[i][1];
generate_offspring(Ark,mutation_Ark[i],
Ark_no,Ark_no2,(generation+1));
Ark_Load(Ark[Ark.size()-1]);
unmade.push_back(Ark.size()-1);
//cout<<Ark[Ark.size()-1].get_fcall()<<"
is unmade."<<endl;
alive.push_back(Ark.size()-1);
//cout<<Ark[Ark.size()-1].get_fcall()<<"
is alive (2)."<<endl;
}
mutation_info.clear();
mutation_Ark.clear();
}

```

```

    // ------ This echoes the Final results
    if(processID==hub){
    cout<<"----------FINAL RESULTS------------"<<<
    <endl;
    time (&end);
    dif_t = int(difftime(end,start));
    int hr,min,sec;
    hr = int(dif_t/3600);
    min = int((dif_t%3600)/60);
    sec = dif_t%60;
    cout<<"Evolution took "<<hr<<" hours, "<<min<<"
    minutes and "<<sec<<" seconds."<<endl;
    //Echo back certain results for debugging
    /*
    for(int i=0;i<Ark.size();i++)
    cout<<Ark[i].get_fcall()<<" "<<Ark[i].get_fitness
        ()<<endl;
    for(int i=0;i<unmade.size();i++)
    cout<<unmade[i]<<" ";
    cout<<endl;
    for(int i=0;i<alive.size();i++)
    cout<<alive[i]<<" ";
    cout<<endl;
    */
    Record_Gen(Ark,still_alive,unmade,generation); //
    ```
```

Saves final state
}
MPI::Finalize();
return 0;

```
757
758
759
760 \}
761
```

using namespace std;
//-----------------Classes for Neural Nets------------------ K
class connection
{private:
float weight;
int node_from;
int node_to;
float Heb_rate;
float random_rate;
public:
connection()
{}
void operator = (const connection\& right){
if (this != \&right){
weight = right.weight;
node_from = right.node_from;
node_to = right.node_to;
Heb_rate = right.Heb_rate;
random_rate = right.random_rate;
}
}
void make_connection_private(int n_from,int n_to,float k
w,float h, float r)//Used with make_connection
function
{
weight = w;
node_from = n_from;
node_to = n_to;
Heb_rate = h;
random_rate = r;
}
float get_weight(){
return(weight);
}
void set_weight_private(float x){
weight = x;
}
int get_node_from(){
return(node_from);
}
int get_node_to(){
return(node_to);
}
float get_Hebbian_rate(){
return(Heb_rate);
}
float get_random_rate(){
return(random_rate);
}

```

50 \}
51
52 class node
53 \{private:
54 float bias;
55 float slope;
56 char layer; //Denote whether a node is an input (I), hidden (H), or an output(O) Don't confuse with type 1
int type1; //Denotes the type of node. Integer corralates \(\boldsymbol{\kappa}\) to A - H
int type2; //Also denotes numerical order of the node
int type3;
int nodes_made; //Records the number of new nodes a node \(\boldsymbol{\Sigma}\) has made
float activation; //Tells us the activation level of a node
public:
node()
\{ \}
//It works, but I get an warning evrytime it's compiled void operator \(=\) (const node\& right)\{
if (this != \&right)\{
bias = right.bias; slope = right.slope; layer = right.layer; type1 = right.type1; type2 = right.type2; type3 = right.type3; nodes_made = right.nodes_made; activation \(=\) right.activation;
\} \}
void make_node_private(char l,int t1,int t2,int t3, float s,float b)\{//Used with make_node function layer = l; type1 = t1; bias = b; slope = s; type2 = t2; type3 = t3; nodes_made \(=0\); activation \(=0.0\);
        \}
        char get_layer()\{
            return(layer);
        \}
        int get_nodes_made()\{
            return(nodes_made);
        \}
        void inc_nodes_made() \{
            nodes_made++;

97
98
99
100
101
\}
float get_bias() \{ return(bias);
\}
float get_slope() \{ return(slope);
\}
int get_type1() \{
return(type1);
\}
int get_type2()\{ return(type2);
\}
int get_type3()\{ return(type3);
\}
float get_activation_private()\{
return(activation);
\}
void set_activation_private(float x)\{
activation \(=x\);
\}
\};
class neural_net
\{private:
vector<connection> connections;
compiled
if (this != \&right) \{ nodes \(=\) right.nodes;
\}
\}
void clear_ANN()\{ connections.clear();
nodes.clear();
\}
node get_node(int n)\{
return(nodes[n]);
\}
float get_activation(int \(n\) ) \{
//It works, but I get an warning everytime it's
void operator= (const neural_net\& right)\{ connections \(=\) right.connections;
return(nodes[n].get_activation_private());
\}
```

void set_activation(int n, float x){

```
        nodes[n].set_activation_private(x);
    \}
    void make_node(int p_node,char l,int t1,float s,float
    b) \{
            int t2,t3;
            int counter = 0;
            node new_node;
            t2 \(=\) nodes[p_node].get_nodes_made();
            for(int \(i=0 ; i<n o d e s . s i z e() ; i++)\{\)
                    if((nodes[i].get_type1()== t1)\&\&(nodes[i]. \(\leqslant\)
    get_type2()== t2) )\{
                counter++;
                    \(\}\)
        \}
        t3 = counter\%100;
        new_node.make_node_private(1, t1, t2, t3, s, b) ;
        nodes.push_back(new_node);
        nodes[p_node].inc_nodes_made();
    \}
        void make_input(int t1)\{
            int t2,t3;
            int counter = 0;
            node new_node;
            t2 = 0;
            for(int i=0;i<nodes.size();i++)\{
            if(nodes[i].get_type1()== t1 )\{
                counter++;
            \}
        \}
        t3 = counter\%100;
    new_node.make_node_private('I',t1, t2, t3, 0, 0);
    nodes.push_back(new_node);
    \}
    void make_output(int p_node,int t1,float s,float b)\{
    int t2,t3;
    int counter = 0;
    node new_node;
    t2 = nodes[p_node].get_nodes_made();
    for(int i=0;i<nodes.size();i++)\{
            if((nodes[i].get_type1()== t1)\&\&(nodes[i].
        get_type2()== t2) ) \{
                counter++;
            \}
    \}
    t3 = counter\%100;
    new_node.make_node_private('0',t1,t2,t3,s,b);
    nodes.push_back(new_node);
    nodes[p_node].inc_nodes_made();
\}
int get_total_connections()\{
return(connections.size());
\}
connection get_connection(int \(n\) ) \{
return(connections[n]);
\}
void set_weight(int n,float x)\{
connections[n].set_weight_private(x);
\}
void make_connection(int n_from,int n_to,float w,float \(\kappa\) h,float r)\{
connection new_connection;
new_connection.make_connection_private(n_from, n_to \(\boldsymbol{K}\) , w, h, r) ;
connections.push_back(new_connection);
\}
int get_total_inputs() \{
int count \(=0\);
node temp_node;
for(int i=0;i<nodes.size();i++)\{
temp_node = nodes[i];
if(temp_node.get_layer()=='I')\{ count++;
\}
\}
return(count);
\}
int get_total_outputs()\{
int count \(=0\);
node temp_node;
for(int i=0;i<nodes.size();i++)\{
temp_node \(=\) nodes[i];
if(temp_node.get_layer()=='0')\{
count++;
\}
\}
return(count);
\}
float get_reinforcement() \{
return(reinforcement);
\}
void set_reinforcement(float x)\{
reinforcement \(=x\);
\}
int get_inputs_to(int n)\{
int ins = 0;
for(int i=0;i<connections.size();i++)\{
if(connections[i].get_node_to()==n) \{
ins++;
\}
\}
        return(ins);
\}
int get_outputs_from(int n)\{
        int outs = 0;
        for(int i=0;i<connections.size();i++)\{
            if(connections[i].get_node_from()==n)\{
                outs++;
        \}
    \}
        return(outs);
\}
float sum_inputs_to(int n)\{
        float ins \(=0\);
        for(int i=0;i<connections.size();i++)\{
            if(connections[i].get_node_to()==n) \{
                ins \(=\) ins + connections[i].get_weight();
            \}
        \}
        return(ins);
\}
float sum_outputs_from(int n)\{
    float outs = 0;
    for(int i=0;i<connections.size();i++)\{
                if(connections[i].get_node_from( )==n) \{
                outs \(=\) outs + connections[i].get_weight();
            \}
        \}
        return(outs);
    \}
float get_connection_weight(int i,int j)\{
    //float w = 0;
    float \(w=-100 ; / / C h a n g e d ~ t o ~ t h i s ~ s o ~ i t ~ w i l l ~\)
return a non-working answer if there is no connection
    for(int i=0;i<connections.size();i++)\{
(connections[i].get_node_to()==j))\{
                \(w=\) connections[i].get_weight();
            \}
        \}
        return(w);
    \}
void print_net()\{
    cout<<"Node: \tLayer t tType: \tBias: \tSlope: \n";
    for(int i=0;i<nodes.size();i++)\{
        cout<<i<<"\t"<<nodes[i].get_layer()<<"\t"\ll
<nodes[i].get_type1()<<nodes[i].get_type2();
            cout<<"\t"<<nodes[i].get_bias()<<"\t"<<nodes
        [i].get_slope()<<endl;
        \}
        cout<<"Conn: \tFrom\tTo:\tWeight:\tHeb:\tRand:\n";
        for(int i=0;i<connections.size();i++)\{
        cout<<i<<"\t"<<connections[i].get_node_from()<
```

<"\t"<<connections[i].get_node_to();
cout<<"\t"<<connections[i].get_weight()<<"\t"< <
<connections[i].get_Hebbian_rate();
cout<<"\t"<<connections[i].get_random_rate()< <
<endl;
}
}
void write_net(string\& filename){
ofstream ANNfile(\&filename[0]);
ANNfile<<nodes.size()<<endl;
for(int i=0;i<nodes.size();i++){
ANNfile<<i<<" "<<nodes[i].get_layer()<<" "< <
<nodes[i].get_type1()<<" "<<nodes[i].get_type2()<<" "< к
<nodes[i].get_type3();
ANNfile<<" "<<nodes[i].get_bias()<<" "<<nodes
[i].get_slope()<<" "<<nodes[i].get_nodes_made()<<endl;
}
ANNfile<<connections.size()<<endl;
for(int i=0;i<connections.size();i++){
ANNfile<<i<<"\t"<<connections[i].get_node_from K
()<<"\t"<<connections[i].get_node_to();
ANNfile<<"\t"<<connections[i].get_weight()<<"\ <
t"<<connections[i].get_Hebbian_rate();
ANNfile<<"\t"<<connections[i].get_random_rate к
()<<endl;
}
}
void read_net(string\& filename){
ifstream ANNfile(\&filename[0]);
int number_of_nodes,nodes_made,
number_of_connections;
int junk_int,type1,type2,type3,node_from,node_to;
char layer;
float bias,slope,weight,Heb,rand;
node temp_node;
connection temp_conn;
ANNfile>>number_of_nodes;
for(int i=0;i<number_oof_nodes;i++){
ANNfile>>junk_int;
ANNfile>>layer;
ANNfile>>type1;
ANNfile>>type2;
ANNfile>>type3;
ANNfile>>bias;
ANNfile>>slope;
ANNfile>>nodes_made;
temp_node.make_node_private(layer,type1,type2, к
type3,slope,bias);
nodes.push_back(temp_node);
for(int j=0;j<nodes_made;j++){
nodes[i].inc_nodes_made();
}

```

\section*{\}}

ANNfile>>number_of_connections;
for(int i=0;i<numbēr_of_connections;i++) \{
ANNfile>>junk_int;
ANNfile>>node_from;
ANNfile>>node_to;
ANNfile>>weight;
ANNfile>>Heb;
ANNfile>>rand;
temp_conn.make_connection_private(node_from,
node_to, weight, Heb, rand);
connections.push_back(temp_conn);
\}
\}
\};

//------------Functions for making and using ANN Matricies----------------
```

bool make_node_check(neural_net ANN,int n,int max_outs){
node temp_node = ANN.get_node(n);
int outs = ANN.get_total_outputs();
bool verdict = false;
if((temp_node.get_nodes_made()<7) \&\&(outs < max_outs)) 反
{

```
            verdict = true;
        \}
        return(verdict);
\}
bool make_connection_check(neural_net ANN,int n_from,int \(\boldsymbol{\kappa}\)
    n_to,int max_conns) \{
    bool verdict = true;
    connection temp_conn;
    node from_node = ANN.get_node(n_from);
    node to_nóde = ANN.get_node(n_tō);
    int from_counter = 0;
    int to_counter \(=0\);
        for(int i=0;i<ANN.get_total_connections();i++)\{
        temp_conn = ANN.get_connection(i);
        if(temp_conn.get_node_from() == n_from) \{
            from_counter++;
        \}
            if(temp_conn.get_node_to() == n_to) \{
            to_counter++;
        \}
            if((temp_conn.get_node_from() == n_from)\&\&
        (temp_conn.get_node_to() == n_to)) \{
            verdict = false;
        \}
```

C:\Documents and Settings\...\node_lib_omega4.h
9
380 }
381 if(n_to <= n_from){
382 verdict = false;
393 return(verdict);
396 //----------------------------------------------------------------------

```
383
384
385
386
387
388
389
390
391
392
394 \}
395
397

1 // This is the library that contains functions necessary for manipulating individuals thoughout evolution
5 using namespace std;
6
7
8
9

10
                S - Say Again */
int death; //Tells the last generation in which an
        individual appeared, thus a -1 means it is still
        alive
neural_net ANN; //The individual's neural net
vector< vector<float\gg ANN_weights; //The individual's
    neural net weight in matrix form
vector<float> ANN_biases; //The individual's neural net
    biases in vector form
vector<float> ANN_slopes; //The individual's neural net
    slopes in vector form
public:
    individual()\{\} //Default Constructor
    individual(int sega[3], vector<int> genes) \{ //
    Constructor - given creation info and genome
        genome_length = genes.size();
        genome = genes;
        fcall = "Subject-1.cpp";
        fitness = -1;
        genesis[0] = sega[0];
        genesis[1] = sega[1];
        genesis[2] = sega[2];
        method = 'I';
```

}

```
void operator= (const individual\& right)\{
    if (this != \&right)\{
                genome = right.genome;
                ruleset = right.ruleset;
                fcall = right.fcall;
                fitness = right.fitness;
                genesis[0] = right.genesis[0];
                genesis[1] = right.genesis[1];
                genesis[2] = right.genesis[2];
                method = right.method;
                death = right.death;
                ANN = right.ANN;
                ANN_weights.resize(0); ANN_weights.assign
(right.ANN_weights.begin(), right.ANN_weights.end());
            ANN_biases.resize(0); ANN_biases.assign(right
.ANN_biases.begin(),right.ANN_biases.end());
                    ANN_slopes.resize(0); ANN_slopes.assign(right \(\kappa\)
.ANN_slopes.begin(),right.ANN_slopes.end());
        \}
    \}
int get_genome(int n) \{
        return(genome[n]);
    \}
int get_genome_length()\{
        return(genome_length);
    \}
int get_nucleotide(int n) \{
    return(genome[n]);
\}
void save_rule(int rule)\{
    ruleset.push_back(rule);
    \}
int get_rule(int n)\{
    return(ruleset[n]);
\}
int get_rules_length() \{
        return(ruleset.size());
    \}
string get_fcall()\{
    return(fcall);
    \}
float get_fitness()\{
    return(fitness);
    \}
    void make_fitness(float x)\{
        fitness \(=x\);
    \}
void inc_fitness(float x)\{
        fitness \(=\) fitness \(+x ;\)
    \}
    void mult_fitness(float x)\{
        fitness \(=\) fitness*x;
    \}
    void dec_fitness(float x)\{
        fitness \(=\) fitness - \(x\);
    \}
    int get_genesis(int n)\{
        return(genesis[n]);
    \}
    char get_method() \{
        return(method);
    \}
    int get_death()\{
        return(death);
    \}
    void kill(int gen)\{
        death = gen;
    \}
    bool alive()\{
        if(death == -1)
            return(true);
        else
            return(false);
    \}
    void generate_random_private(int l,int gen,int sub)\{ \(\boldsymbol{\kappa}\)
    //Will generate a random genome of length l
            int lowest=1, highest=100;
            int range=(highest-lowest)+1;
            int temp;
            for (int i=0; i<l; i++) \{
                    temp \(=\) lowest+int \(\left(\right.\) range* \(\left(r a n d() /\left(R A N D \_M A X+1 \kappa\right.\right.\)
    .0)) );
                    genome.push_back(temp);
        \}
        genome_length = l;
        string num = int2string(sub);
        fcall = "Subject" + num + ".cpp";
        fitness = -1;
        genesis[0] = gen;
        genesis[1] = 0;
        genesis[2] = 0;
        method = 'R';
        death \(=-1\);
    \}
    void generate_designed_private(int arr[],int gen,int
    sub)\{ //Will generate an individual with the given
    genome
        int find_array_length(int[]);
        int \(1=\) find_array_length(arr);
        for (int i=0; i<l; i++)\{
            genome.push_back(arr[i]);
        \}
        genome_length = l;
        string num \(=\) int2string(sub);
        fcall = "Subject" + num + ".cpp";
        fitness = -1;
        genesis[0] = gen;
        genesis[1] = 0;
        genesis[2] = 0;
        method \(=\) 'I';
        death \(=-1\);
        \}
        void generate_designed_private(vector<int> arr,int \(\boldsymbol{\swarrow}\)
        gen,int sub)\{ //Will generate an individual with the \(\boldsymbol{\kappa}\)
        given genome
            int \(1=\) arr.size();
            for(int i=0; i<l; i++)\{
            genome.push_back(arr[i]);
        \}
        genome_length = l;
        string num = int2string(sub);
        fcall = "Subject" + num + ".cpp";
        fitness = -1;
        genesis[0] = gen;
        genesis[1] \(=0\);
        genesis[2] \(=0\);
        method = 'I';
        death \(=-1\);
    \}
    void generate_reduced_private(vector<int> arr,int gen
        , int sub,int parent)\{ //Will generate an individual
        with the given genome
            int \(\quad=\) arr.size();
            for(int i=0; i<l; i++)\{
            \(i f((\operatorname{arr}[i]>=1) \& \&(\operatorname{arr}[i]<=100))\{\)
                    genome.push_back(arr[i]);
            \}
            else\{
                    int temp_int;
                    temp_int = random_int(1,100);
                    genome.push_back(temp_int);
                    cout<<"The invalid nucleotide "<<arr[i]<
    <" was replaced with "<<temp_int<<endl;
            \}
        \}
        genome_length = 1;
        string num \(=\) int2string(sub);
        fcall = "Subject" + num + ".cpp";
        fitness = -1;
        genesis[0] = gen;
        genesis[1] = parent;
        genesis[2] = parent;
        method = 'S';
        death = -1;
    \}
    void generate_offspring_private(vector<int> arr,int \(\boldsymbol{k}\)
    gen,int sub,int indy1,int indy2)\{ //Will generate an \(k\)
        individual with the given genome
            int l = arr.size();
            for(int i=0; i<l; i++)\{
            genome.push_back(arr[i]);
        \}
            genome_length = l;
            string num = int2string(sub);
            fcall = "Subject" + num + ".cpp";
            fitness = -1;
            genesis[0] = gen;
            genesis[1] = indy1;
            genesis[2] = indy2;
            method = '0';
            death = -1;
\}
void Say_Again_private(int sega[], char meth, vector
<int> arr)\{
    int \(1=\) arr.size();
    for (int i=0; i<l; i++)
                    genome.push_back(arr[i]);
    genome_length = genome.size();
    fcall = "Subject-1.cpp";
    fitness = -1;
    genesis[0] = sega[0];
    genesis[1] = sega[1];
    genesis[2] = sega[2];
    method = meth;
    death = -1;
    \}
    void show_genome()\{ //The following prints out the \(\boldsymbol{k}\)
    genomes
        for(int i=0; i<genome.size(); i++)
            cout << genome[i] << " ";
            cout << endl;
    \}
    void show_rules()\{ //The following prints frames as \(\boldsymbol{k}\)
    they are used
    for(int i=0; i<ruleset.size(); i++)\{
        if(ruleset[i]!=-1)\{
                    cout<<ruleset[i]<<' ';
                for (int \(j=0 ; j<6 ; j++\) )
                cout<<genome[ruleset[i]+j]<<' ';
                cout<<endl;
```

            }
                else
                    cout <<endl;
    }
    }
void reduce_rules(vector< vector <int> >\&
reduced_protein_table){
//This will show which frame numbers made the
individual
reduced_protein_table.clear();
if(ruleset.size()==0){
return;
}
vector< vector<int> >used_proteins_table;
vector< vector<int> >sorted_used_proteins_table;
vector <int> test_protein;
int lowest_rule = 100000;
int lowest_rule_size = 100000;
int lowest_rule_index = -1;
vector <int> used_indexes;
for(int i=0;i<ruleset.size();i++){
if(ruleset[i]!= -1){
test_protein.push_back(ruleset[i]);
}
else{
if(!any(test_protein,
K
used_proteins_table)){
used_proteins_table.push_back
(test_protein);
}
test_protein.clear();
}
}
//print_matrix(used_proteins_table);
while(sorted_used_proteins_table.size() <
used_proteins_table.size()){
for(int i=0;i<used_proteins_table.size();i++) \swarrow
{
if((used_proteins_table[i][0]
<lowest_rule)\&\&(!any(i,used_indexes))){
lowest_rule = used_proteins_table[i]
[0];
lowest_rule_size =
used_proteins_table[i].size();
lowest_rule_index = i;
}
else if((used_proteins_table[i][0]==
lowest_rule)\&\&(used_proteins_table[i].size()
K
K
<lowest_rule_size)\&\&(!any(i,used_indexes))){
lowest_rule = used_proteins_table[i] к
[0];

```
```

                lowest_rule_size =
    used_proteins_table[i].size();
                lowest_rule_index = i;
            }
            else if((used_proteins_table[i][0]==
    lowest_rule)&&(used_proteins_table[i].size()==
    lowest_rule_size)&&(!any(i,used_indexes))){
                for(int j=i;j<used_proteins_table[i]. K
    size();j++){
            if(used_proteins_table[i][j]
    <used_proteins_table[lowest_rule_index][j]){
                            lowest_rule =
        used_proteins_table[i][0];
                            lowest_rule_size =
        used_proteins_table[i].size();
                            lowest_rule_index = i;
                                    }
                }
            }
        }
        sorted_used_proteins_table.push_back
    (used_proteins_table[lowest_rule_index]);
        used_indexes.push_back(lowest_rule_index);
        lowest_rule = 100000;
        lowest_rule_size = 100000;
    }
    //print_matrix(sorted_used_proteins_table);
    for(int i=0;i<(sorted_used_proteins_table.size()- к
        1);i++){
        if(sorted_used_proteins_table[i].size()==
    sorted_used_proteins_table[i+1].size()){
                                    reduced_protein_table.push_back
    (sorted_used_proteins_table[i]);
        }
        else{
            for(int j=0;j<sorted_used_proteins_table
        [i].size();j++){
            if(sorted_used_proteins_table[i][j]!= К
        sorted_used_proteins_table[i+1][j]){
                            reduced_protein_table.push_back <
        (sorted_used_proteins_table[i]);
                                    break;
                    }
                }
            }
        }
        reduced_protein_table.push_back
        K
        (sorted_used_proteins_table[
        K
    (sorted_used_proteins_table.size()-1)]);
        //print_matrix(reduced_protein_table);
    }
    ```
```

void reduce_rules(){
vector< vector <int> > reduced_protein_table;
//This will show which frame numbers made the
individual
if(ruleset.size()==0){
return;
}
vector< vector<int> >used_proteins_table;
vector< vector<int> >sorted_used_proteins_table;
vector <int> test_protein;
int lowest_rule = 100000;
int lowest_rule_size = 100000;
int lowest_rule_index = -1;
vector <int> used_indexes;
for(int i=0;i<ruleset.size();i++){
if(ruleset[i]!= -1){
test_protein.push_back(ruleset[i]);
}
else{
if(!any(test_protein,
used_proteins_table)){
used_proteins_table.push_back <
(test_protein);
}
test_protein.clear();
}
}
//print_matrix(used_proteins_table);
while(sorted_used_proteins_table.size() <
used_proteins_tab}le.size()){
for(int i=0;i<used_proteins_table.size();i++) k
{
if((used_proteins_table[i][0]
<lowest_rule)\&\&(!any(i,used_indexes))){
lowest_rule = used_proteins_table[i] к
[0];
lowest_rule_size =
used_proteins_table[i].size();
lowest_rule_index = i;
}
else if((used_proteins_table[i][0]==
K
lowest_rule)\&\&(used_proteins_table[i].size()
K
<lowest_rule_size)\&\&(!any(i,used_indexes))){
lowest_rule = used_proteins_table[i] \swarrow
[0];
lowest_rule_size =
used_proteins_table[i].size();
lowest_rule_index = i;
}
else if((used_proteins_table[i][0]==
lowest_rule)\&\&(used_proteins_table[i].size()==
K
lowest_rule_size)\&\&(!any(i,used_indexes))){

```
for(int j=i;j<used_proteins_table[i]. \(\kappa\) size();j++)\{
<used_proteins_table[lowest_rule_index][j])\{
lowest_rule =
used_proteins_table[i][0];
lowest_rule_size =
used_proteins_table[i].size();
lowest_rule_index = i;
\} \}
\}
\}
sorted_used_proteins_table.push_back
(used_proteins_table[lowest_rule_index]);
used_indexes.push_back(lowest_rule_index);
lowest_rule = 100000; lowest_rule_size = 100000;
\}
//print_matrix(sorted_used_proteins_table);
for(int i=0;i<(sorted_used_proteins_table.size()- к 1);i++)\{
if(sorted_used_proteins_table[i].size()==
sorted_used_proteins_table[i+1].size())\{
reduced_protein_table.push_back
(sorted_used_proteins_table[i]);
\}
else\{
for(int j=0;j<sorted_used_proteins_table
[i].size();j++)\{
if(sorted_used_proteins_table[i][j]!= sorted_used_proteins_table[i+1][j])\{
reduced_protein_table.push_back
(sorted_used_proteins_table[i]);
break;
\}
\}
\}
\}
reduced_protein_table.push_back (sorted_used_proteins_table[
(sorted_used_proteins_table.size()-1)]); print_matrix(reduced_protein_table); \}


 COMMANDS

\(\qquad\)
        print_matrix(reduced_protein_table);
        \}

\(K\)


                        \}
        
        \}
        print_matrix(reduced_protein_table)
```

neural_net get_neural_net(){
return(ANN);
}
void make_ANN(int rank_no){
ANN.clear_ANN();
string pcall = "/scratch/subject"+int2string \swarrow
(rank_no)+".exe";
string pmake = "g++ -o " + pcall + " /scratch/"+ к
fcall;
string ANNfilename = "/scratch/ANN"+int2string
(rank_no)+".dat";
string Rulecall = "/scratch/Rules"+int2string K
(rank_no)+".dat";
char *syscall;
syscall = \&pmake[0];
system(syscall);
syscall = \&pcall[0];
system(syscall);
ANN.read_net(ANNfilename);
ANN_weights.resize(0);
ANN_biases.resize(0);
ANN_slopes.resize(0);
ruleset.resize(0);
vector<float> w_fill(ANN.get_ANN_size(),0);
node temp_node;
connection temp_conn;
float temp_slopes,temp_biases,temp_w;
int node_to,node_from;
for(int i=0;i<ANN.get_ANN_size();i++){
ANN_weights.push_back(w_fill);
temp_node = ANN.get_node(i);
ANN_biases.push_back(temp_node.get_bias());
ANN_slopes.push_back(temp_node.get_slope());
}
for(int i=0;i<ANN.get_total_connections();i++){
temp_conn = ANN.get_connection(i);
node_to = temp_conn.get_node_to();
node_from = temp_conn.get_node_from();
temp_w = temp_conn.get_weight();
ANN_weights[node_from][node_to] = temp_w;

```
        \}
        ifstream infile2(\&Rulecall[0]);
        int temprule;
        while(!infile2.eof())\{
            infile2 >> temprule;
            ruleset.push_back(temprule);
        \}
        ruleset.pop_back(); //For some reason, it always \(\boldsymbol{\kappa}\)
        saves an extra -1

C:\Documents and Settings\...\evo_lib_omega4.h 11

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\}
void make_ANN_matrix()\{
    ANN_weights.resize (0);
    ANN_biases.resize(0);
    ANN_slopes.resize(0);
    vector<float> w_fill(ANN.get_ANN_size(), 0);
    node temp_node;
    connection temp_conn;
    float temp_slopes,temp_biases,temp_w;
    int node_to, node_from;
    for(int i=0;i<ANN.get_ANN_size();i++)\{
        ANN_weights.push_back(w_fill);
        temp_node = ANN.get_node(i);
        ANN_biases.push_back(temp_node.get_bias());
        ANN_slopes.push_back(temp_node.get_slope());
        \}
    for(int i=0;i<ANN.get_total_connections();i++)\{
            temp_conn = ANN.get_connection(i);
            node_to = temp_conn.get_node_to();
            node_from = temp_conn.get_node_from();
            temp_w = temp_conn.get_weight();
            ANN_weights[node_from][node_to] = temp_w;
        \}
    \}
        void show_ANN_matrix() \{
        int type1;
        for(int i=0;i<ANN.get_ANN_size();i++)\{
            node temp_node = ANN.get_node(i);
            for (int j=0;j<ANN.get_ANN_size();j++)\{
            cout<<ANN_weights[i][j]<<" \t";
        \}
        cout<<" \t"<<ANN_biases[i];
        //cout<<" \t"<<ANN_slopes[i];
        type1 = temp_node.get_type1();
        cout<<" \t";
        if(type1 == 0)
            cout<<"A";
            else if (type1 == 1)
            cout<<"B";
            else if (type1 == 2)
            cout<<"C";
            else if (type1 == 3)
            cout<<"D";
            else if (type1 == 4)
                    cout<<"E";
            else if (type1 == 5)
                    cout<<"F";
            else if (type1 == 6)
```

            cout<<"G";
            else if (type1 == 7)
            cout<<"H";
            cout<<temp_node.get_type2()<<" - "<<temp_node.
    get_type3()<<endl;
}
}
void break_node_off(int n){
ANN_biases[n] = 1000;
}
void break_node_on(int n){
ANN_biases[\overline{n}]=-1000;
}
void break_connection(int i, int j){
ANN_weights[i][j] = 0;
}
float get_ANN_weight(int i, int j){
return(ANN_weights[i][j]);
}
float get_ANN_bias(int i){
return(ANN_biases[i]);
}
float get_ANN_slope(int i){
return(ANN_slopes[i]);
}
void Matlab_ANN(){
//This puts the matrix weights, biases, and
slopes into a Matlab script
//Rearanges the Matrix so inputs are first,
outputs are last, and hidden nodes are in between
float Matlab_weights[ANN.get_ANN_size()][ANN.
get_ANN_size()];
float Matlab_biases[ANN.get_ANN_size()];
float Matlab_slopes[ANN.get_ANN_size()];
vector< vector <int> > translation; //Holds the
old node number [0] and the new one [1] The [0] entry k
is just the index and isn't necessary, but it makes
it easier to decipher
node temp_node;
int temp_int;
float temp_float;
vector< int > temp_vect;
for(int i=0;i<ANN.get_ANN_size();i++){
temp_node = ANN.get_node(i);
if(temp_node.get_layer()== 'I'){
temp_int = translation.size();
temp_vect.push_back(temp_int);
temp_vect.push_back(i);
translation.push_back(temp_vect);
temp_vect.clear();
}
}

```
for(int i=0;i<ANN.get_ANN_size();i++)\{
            temp_node = ANN.get_node(i);
            if(temp_node.get_layer()== 'H')\{
                    temp_int = translation.size();
                    temp_vect.push_back(temp_int);
                    temp_vect.push_back(i);
                    translation.push_back(temp_vect);
                    temp_vect.clear();
        \}
    \}
    for(int i=0;i<ANN.get_ANN_size();i++)\{
        temp_node = ANN.get_node(i);
        if(temp_node.get_layer()== '0')\{
            temp_int = translation.size();
                    temp_vect.push_back(temp_int);
                    temp_vect.push_back(i);
                    translation. push_back(temp_vect);
                    temp_vect.clear();
            \}
        \}
    if(translation.size()!= ANN.get_ANN_size())\{
        cout<<"ERROR: The nodes were not recorded
    properly"<<endl;
    \}
    for(int i=0;i<translation.size();i++)\{
    [1]];
        Matlab_biases[i] = ANN_biases[translation[i] 反
    [1]];
        Matlab_slopes[i] = ANN_slopes[translation[i] \(\boldsymbol{K}\)
            for(int \(j=0 ; j<t r a n s l a t i o n . s i z e() ; j++)\{\)
            Matlab_weights[i][j] = ANN_weights
        [translation[i][1]][translation[j][1]];
            \}
        \}
    ofstream ANNfile("ANN.m");
    ANNfile<<"W=[";
    for(int i=0;i<translation.size();i++)\{
        for(int j=0;j<translation.size();j++)\{
            ANNfile<<Matlab_weights[i][j]<<" ";
        \}
        ANNfile<<";";
    \}
    ANNfile<<"] \n";
    ANNfile<<"B=[";
    for(int i=0;i<translation.size();i++)\{
        ANNfile<<Matlab_biases[i]<<"; ";
    \}
    ANNfile<<"]\n";
    ANNfile<<"S=[";
    for(int i=0;i<translation.size();i++)\{
    ANNfile<<Matlab_slopes[i]<<"; ";
\}
ANNfile<<"]\n";
\}
void Matlab_ANN_growth()\{
//This records the order and type of rules used \(\boldsymbol{\swarrow}\)
so the growth of the ANN can be seen
vector<float> Matlab_rules;
int action_nucleotide, action_value_nucleotide,
action_type, nodes_made, outputs_made, max_outputs;
float action_value;
int make_connection[] = \{1,20\};
int do_nothing[] = \(\{21,35\}\);
int end_turn[] = \(\{36,50\}\);
int make_node[] \(=\{51,100\}\);
int make_nodeH[] \(=\{86,100\}\);
nodes_made = 0;
outputs_made \(=0\);
max_outputs = 0;
node temp_node;
for(int i=0;i<ANN.get_ANN_size();i++)\{
temp_node = ANN.get_node(i);
if(temp_node.get_layer()== 'I')\{ nodes_made++;
\}
else if(temp_node.get_layer()== '0')\{ max_outputs++;
\}
\}
ofstream ANNfile("ANN_growth.m");
ANNfile<<"rules = [";
for(int i \(=0 ; i<r u l e s e t . s i z e() ; ~ i++)\{\)
if(ruleset[i]!=-1)\{
if(ruleset[i+1]==-1)\{
action_nucleotide \(=\) genome[ruleset[i] \(\leqslant\)
+4];
[ruleset[i]+5];
action_value_nucleotide = genome \(\boldsymbol{\kappa}\)
if ((make_node[0]<=action_nucleotide) K
\&\&(make_node[1]>=action_nucleotide)\&\&(outputs_made
<max_outputs)) \{
action_type = 0;
nodes_made++;
if ((make_nodeH[0]<=
action_nucleotide)\&\&(make_nodeH[1]>= action_nucleotide))\{
action_value = 2;
outputs_made++;
\}
else \{
action_value = 1;
\}
\}
else if ((make_connection[0]<= action_nucleotide)\&\&(make_connection[1]>= action_nucleotide))\{
action_type = 1;
if(action_value_nucleotide >= 51)
\{
(action_value_nucleotide-50.0)/50.0;
\}
else\{
action_value = float
(action_value_nucleotide-51.0)/50.0;
\}
\}
else if ((do_nothing[0]<= action_nucleotide)\&\&(do_nothing[1]>= action_nucleotide))\{
//Do nothing
\}
else \{
action_type = 2;
action_value = random_int(1,
nodes_made);
\}
ANNfile<<action_type<<" "< <action_value<<";";
\}
\}
\}
ANNfile<<"]; \({ }^{\prime}\) ";
\}
void show_ANN_states()\{
node temp_node;
for(int i=0;i<ANN.get_ANN_size();i++)\{
cout<<ANN.get_activation(i)<<" ";
\}
cout<<endl;
\}
void update_ANN(vector<float> input,bool learning, float r_signal)\{
float unbounded_next,bias,slope,h_rate,r_rate, と old_weight,del_weight;
int node_to, node_from, activated_inputs;
int ANN_size = ANN.get_ANN_size();
int total_inputs = ANN.get_total_inputs();
vector<float> node_activation_levels(ANN_size, 0.
\(K\)

nodes_made);
            )
            \}
        ANNfile<<"]; \({ }^{\prime}\) ";
    \}
    vector<float> node_activation_levels(ANN_size, 0.
\(0)\);
```

            vector<float> new_activation_levels(ANN_size,0.0)
    ```
    ;
    node temp_node;
    connection temp_connection;
    for(int i=0;i<ANN_size;i++) \{
        node_activation_levels[i] = ANN.
        get_activation(i);
            \}
            activated_inputs = 0;
            for(int i=0;i<ANN_size;i++) \{
            assert(activated_inputs<=ANN.get_total_inputs
        () );
            unbounded_next = 0;
            temp_node = ANN.get_node(i);
            bias = ANN_biases[i];
            slope = ANN_slopes[i];
            for(int \(\left.j=0 ; j<A N N \_s i z e ; j++\right)\{\)
                unbounded_next = unbounded_next + к
    ANN_weights[j][i]*node_activation_levels[j];
            \}
            if(temp_node.get_layer() == 'I')\{//An input \(\boldsymbol{\swarrow}\)
        stays unbounded
                                new_activation_levels[i] = unbounded_next
    + input[activated_inputs] - bias;
                                    activated_inputs++;
            \}
            else\{
                //new_activation_levels[i] = tanh( \(\boldsymbol{K}\)
    (unbounded_next-bias)/(2*slope)); //For a range of -1 к
    to 1
                //For digital nodes ranged \(0-1\)
                if(unbounded_next>bias)\{
                    new_activation_levels[i] = 1;
                \}
                else\{
                    new_activation_levels[i] = 0;
                \}
            \}
            \}
            for(int i=0;i<ANN_size;i++)\{
            ANN.set_activation(i, new_activation_levels
        [i]);
            \}
            if(!learning) \{
            return; //Stops here so weights don't change
        \}
            for(int i=0;i<ANN.get_total_connections();i++)\{
            temp_connection = ANN.get_connection(i);
            node_to = temp_connection.get_node_to();
            node_from = temp_connection.get_node_from();
            h_rate = temp_connection.get_Hebbian_rate();
r_rate = temp_connection.get_random_rate();
old_weight = temp_connection.get_weight();
ANN.set_reinforcement(r_signal);
del_weight = 0;
//Hebbian Learning
del_weight \(=\left(1-r \_s i g n a l\right) * h \_r a t e * f a b s\) (old_weight)*ANN.get_activation(node_from)*ANN. get_activation(node_to);
//Random Reinforcement
del_weight \(=\) del_weight \(+\left(1-r \_s i g n a l\right) *(1-\quad \kappa\)
r_signal)*r_rate*fabs(old_weight)*random_float(-1,1);
ANN.set_weight(i,(old_weight-del_weight));
\}
make_ANN_matrix();
//temp_connection = ANN.get_connection(0);
//cout<<"To: "<<temp_connection.get_node_to()<<" From: "<<temp_connection.get_node_from();
//cout<<" Weight: "<<temp_connection.get_weight() <<" H Rate: "<<temp_connection.get_Hebbian_rate()< <endl;
\}
void eval_XOR_logic()\{
int no_of_inputs = 2;
float desíred_no_of_outputs = 1;
float exponent \(=-1\);
vector<int> connected_outputs;
connection test_conn;
node test_node;
vector<float> test_input(no_of_inputs, 0);
bool learning = false;
float r_signal = 0;
int desired_answer;
//Tier 1 - check for number of outputs
if(ANN.get_total_outputs() == 0)\{
fitness \(=0\);
return;
\}
exponent += ANN.get_total_outputs()/ desired_no_of_outputs;
if(exponent < 0)\{
fitness \(=\) pow(2.0, exponent);
return;
\}
//Tier 2 - outputs with connections
for(int i=0;i<ANN.get_total_connections();i++)\{
test_conn = ANN.get_connection(i);
test_node \(=\) ANN.get_node(test_conn. get_node_to());
if((test_node.get_layer()=='0')\&\&(!any
(connected_outputs, test_conn.get_node_to())))\{ connected_outputs.push_back(test_conn. к get_node_to());
```

            }
        }
        exponent += connected_outputs.size()/
    desired_no_of_outputs;
if(exponent < 1){
fitness = pow(2.0,exponent);
return;
}
// Tier 3 - Logic test
for(int test_no = 0;test_no<pow(2.0,no_of_inputs)
;test_no++){
int2binary(test_no,test_input);
desired_answer = 0;
for(int i=0;i<test_input.size();i++){
if(test_input[i] == 1){
desired_answer++;
}
}
desired_answer = desired_answer%2;
for(float t=0;t<1;t+=0.01){
update_ANN(test_input,learning,r_signal);
}
for(int i=0;i<ANN.get_ANN_size();i++){
test_node = ANN.get_node(i);
if(test_node.get_layer()=='0'){
if(within_range(0.01,ANN.
get_activation(i),desired_answer)){
exponent++;
}
break;
}
}
}
fitness = pow(2.0,exponent);
}
void eval_robustness(){
//Tier 4 test - remove nodes until logic fails
int no_of_inputs = 2;
int no_of_outputs = 1;
node test_node;
float exponent;
float tier_4_exponent = 1 + pow(2.0,no_of_inputs)
;
if(fitness < pow(2.0,tier_4_exponent)){
return;
}
int node_break;
vector<int> broken_nodes;
broken_nodes.clear();
bool keep_breaking_nodes = true;
vector<float> test_input(no_of_inputs,0);

```
```

        int desired_answer;
        bool learning = false;
        float r_signal = 0;
        for(int i=0;i<ANN.get_ANN_size();i++){
            node test_node = ANN.get_node(i);
            if((test_node.get_layer()=='I')|(test_node.
    get_layer()=='0')){
broken_nodes.push_back(i);
}
}
while((keep_breaking_nodes)\&\&(broken_nodes.size() \swarrow
<ANN.get_ANN_size())){
node_break = random_int(0,ANN.get_ANN_size()- к
1,broken_nodes);
break_node_off(node_break);
broken_nodes.push_back(node_break);
//print_vector(broken_nodes);
//Logic retested
for(int test_no = 0;test_no<pow(2.0,
no_of_inputs);test_no++){
int2binary(test_no,test_input);
desired_answer = 0;
for(int i=0;i<test_input.size();i++){
if(test_input[i] == 1){
desired_answer++;
}
}
desired_answer = desired_answer%2;
for(float t=0;t<1;t+=0.01){
update_ANN(test_input,learning,
r_signal);
}
for(int i=0;i<ANN.get_ANN_size();i++){
test_node = ANN.get_node(i);
if(test_node.get_layer()=='0'){
if(!within_range(0.01,ANN.
get_activation(i),desired_answer)){
keep_breaking_nodes = false;
broken_nodes.pop_back();
}
break;
}
}
}
}
make_ANN_matrix(); //Rebuilds ANN
//print_vector(broken_nodes);
//cout<<"ANN size ="<<<ANN.get_ANN_size()<<endl;

```
            <int> arr, int gen)
        Ark size = Ark.size()
        Ark.push_back(individual());
        int subject = Ark_size;
        Ark[Ark_size].generate_designed_private(arr,gen,
        subject);
868 \}

869
870 void generate_satellite(vector<individual>\& Ark,int arr[] \(\swarrow\)
    ,int gen,int subject)
\{
int Ark_size = Ark.size();
Ark.push_back(individual());
Ark[Ark_size].generate_designed_private(arr,gen, subject);
\}
void generate_satellite(vector<individual>\& Ark, vector <int> arr,int gen,int subject)
\{
int Ark_size = Ark.size(); Ark.push_back(individual()); Ark[Ark_size].generate_designed_private(arr,gen, subject);
\}
void generate_reduced(vector<individual>\& Ark, vector<int> \(\swarrow\) arr,int gen,int parent)
\{
int Ark_size = Ark.size();
Ark.push_back(individual());
int subject = Ark_size;
Ark[Ark_size].generate_reduced_private(arr,gen, subject,parent);
\}
void mutator(vector<int>\& genome, vector<int> genome2, float mu, float p_mu, float c_mu, float r_mu, float d_mu, float t_mu)
\{
vector<int> proto_genome;
vector<int> codon;
int skip_to_codon = 0;
vector< vector<int\gg translocated_codons;
vector<int> translocation_codon_numbers;
float x,y;
int start,stop,temp_int; //Start and stop FRAME K numbers
float mu_point_mutation, mu_recopy, mu_deletion, mu_conjugation, mu_translocation;
//If there is a mutation within the codon, odds of that mutation being of this given type mu_point_mutation = p_mu; //Make sure mu_conjugation = c_mu; //these add mu_recopy = r_mu; //up to 1.0 mu_deletion = d_mu; mu_translocation = t_mu;
for (int i=0;i<genome.size();i+=6)\{
for (int \(j=0 ; j<6 ; j++)\{\)
if((i+j)<genome.size())\{
            codon.push_back(genome[i+j]);
            \}
            else\{ //Fills genome with dummy nucleotides
        if genome is too short
            codon. push_back(100);
            \}
    \}
    x = rand();
    \(y=x / R A N D \_M A X ;\)
    if(i<(skip_to_codon*6)) \{
            codon.clear();
        \}
        else if(y > mu)\{
            for(int j=0;j<6;j++)\{
                proto_genome.push_back(codon[j]);
            \}
            codon.clear();
        \}
        else\{ //Perform a mutation
            y = y/mu; // y is now a random number between
        0 and 1
            if( y <= mu_point_mutation) \{
                //This will change exactly one nucleotide
        within the reading frame
        vector<int> old_nuc;
        int change_nuc;
        change_nuc = random_int(0,5);
        old_nuc.push_back(codon[change_nuc]);
        codon[change_nuc] = random_int(1,100,
        old_nuc);
        for(int j=0;j<6;j++)\{
                proto_genome.push_back(codon[j]);
            \}
            codon.clear();
        \}
        else if(y < (mu_point_mutation+
        mu_conjugation)) \{
                            //This will insert a section from the
        secondary parent
            int lowest, highest;
            lowest = 0;
            highest = int((genome2.size())/6);
            start = random_int(lowest,highest);
            stop \(=\) random_int(start,highest);
            for (int j=(start*6);j<(stop*6);j++) \{
                proto_genome.push_back(genome2[j]);
            \}
            for(int j=0;j<6;j++)\{
                proto_genome.push_back(codon[j]);
            \}
            codon.clear();
            \}
            else if(y < (mu_point_mutation+mu_conjugation \(\boldsymbol{\kappa}\)
        +mu_recopy))\{
                                    //This will duplicate a section of the
        genome
            start = i/6;
            stop \(=\) random_int(start,int(genome.size() と
        /6) ) ;
            for(int j=(start*6);j<(stop*6);j++)\{
            proto_genome.push_back(genome[j]);
            \}
            for(int j=0;j<6;j++)\{
                proto_genome.push_back(codon[j]);
                    \}
                    codon.clear();
            \}
            else if(y < (mu_point_mutation+mu_conjugation \(\boldsymbol{\kappa}\)
        +mu_recopy+mu_deletion))\{
                    //This will delete a section of the \(\boldsymbol{K}\)
    genome
                            start = i/6;
                            skip_to_codon = random_int(start,int
        (genome.size()/6));
            codon.clear();
        \}
                            else if(y <= (mu_point_mutation+
        mu_conjugation+mu_recopy+mu_deletion+ 反
        mu_translocation))\{
            //This will delete a section of the \(\boldsymbol{K}\)
        genome and save for later insertion
            start = i/6;
                            skip_to_codon = random_int(start,int と
        (genome.size()/6));
            for(int \(j=((s t a r t+1) * 6) ; j<\left(s k i p \_t o \_c o d o n * ~ k\right.\)
        6); j++)\{
                        codon.push_back(genome[j]);
            \}
            translocated_codons.push_back(codon);
                    codon.clear();
                \}
        \}
    \}
    genome.clear();
    int counter = 0;
    while((counter<translocated_codons.size())\&\& K
    (translocation_codon_numbers.size()<=int(proto_genome 反
    .size()/6)))\{
        temp_int \(=\) random_int(0,int(proto_genome.size()/ \(\leqslant\)
        \(6)\), translocation_codon_numbers);
            translocation_codon_numbers.push_back(temp_int);
            counter++;
        \}
        //If the genome is too short, this check will delete 反
    extra translocations
    if(translocation_codon_numbers.size()
    <translocated_codons.size())\{
    translocated_codons.resize
    (translocation_codon_numbers.size());
    \}
    for(int i=0;i<proto_genome.size();i++)\{
    if((i\%6 == 0)\&\&any(translocation_codon_numbers, ,
    int(i/6)))\{
                for (int j=0;j<translocation_codon_numbers.
    size(); j++)\{
        if((i/6) == translocation_codon_numbers \(\swarrow\)
    [j])\{
                        temp_int = j;
                \}
        \}
        for(int j=0;j<translocated_codons[temp_int].
    size();j++)\{
                                    genome.push_back(translocated_codons
    [temp_int][j]);
        \}
        \}
        genome.push_back(proto_genome[i]);
    \}
    for(int i=0;i<translocation_codon_numbers.size();i++) K
    \{
            //Inserts translocations
            if(translocation_codon_numbers[i] == int
    (proto_genome.size()/6))\{
                for(int j=0;j<translocated_codons[i].size();j
    ++ ) \{
                                    genome.push_back(translocated_codons[i] と
    [j]);
                \}
            \}
    \}
    if(genome.size()<6)\{
            for (int i=genome.size(); i<6; i++)\{
                genome.push_back(100);
            \}
        \}
    if (genome.size()>600)
            genome.resize(300);
    /*
    for(int i = 0;i<genome.size();i++)
    cout<<genome[i]<<" ";
    cout<<endl;
    * /
void focused_mutator (vector<int>\& genome, vector<int> \(\swarrow\)
        genome2, float mu, float p_mu, float c_mu, float r_mu 反
```

, float d_mu, float t_mu)

```
\{
```

    vector<int> proto_genome;
    ```
    vector<int> codon;
    int skip_to_codon = 0;
    vector< vector<int\gg translocated_codons;
    vector<int> translocation_codon_numbers;
    float x,y;
    int start,stop,temp_int; //Start and stop FRAME K
    numbers
    float mu_point_mutation, mu_recopy, mu_deletion,
    mu_conjugation, mu_translocation;
    bool connection_codon;
    int make_connection[] = \{1,25\};
    int action_nucleotide;
    //If there is a mutation within the codon, odds of
    that mutation being of this given type
    mu_point_mutation = p_mu; //Make sure
    mu_conjugation = c_mu; //these add
    mu_recopy = r_mu; //up to 1.0
    mu_deletion = d_mu;
    mu_translocation = t_mu;
    for(int i=0;i<genome.size();i+=6)\{
    for (int \(j=0 ; j<6 ; j++)\{\)
        if( (i+j)<genome.size()) \{
                                    codon.push_back(genome[i+j]);
        \}
        else\{ //Fills genome with dummy nucleotides \(\boldsymbol{K}\)
    if genome is too short
                codon.push_back(100);
            \}
            if(j==5) \{
                action_nucleotide = genome[i+j];
            \}
        \}
        connection_codon = false;
        if((make_connection[0]<=action_nucleotide) \&\&
        (make_connection[1]>=action_nucleotide))\{
            connection_codon = true;
    \}
    x = rand();
    y = x/RAND_MAX;
    if(i<(skip_to_codon*6))\{
        codon.clear();
    \}
    else if(y > mu)\{
        for(int j=0;j<6;j++)\{
                proto_genome.push_back(codon[j]);
            \}
            codon.clear();
    \}
    else\{ //Perform a mutation
```

    //The following will always mutate a
    connection weight
    if(connection_codon){
        codon[5] = random_int(1,100);
        }
    y = y/mu; // y is now a random number between
    0 and 1
        if( y <= mu_point_mutation){
        //This will change exactly one nucleotide 
        within the reading frame
        vector<int> old_nuc;
        int change_nuc;
        change_nuc = random_int(0,5);
        old_nuc.push_back(codon[change_nuc]);
        codon[change_nuc] = random_int(1,100,
        old_nuc);
        for(int j=0;j<6;j++){
            proto_genome.push_back(codon[j]);
        }
        codon.clear();
        }
        else if(y < (mu_point_mutation+ <
        mu_conjugation)){
                            //This will insert a section from the k
        secondary parent
        int lowest, highest;
        lowest = 0;
        highest = int((genome2.size())/6);
        start = random_int(lowest,highest);
        stop = random_int(start,highest);
        for(int j=(start*6);j<(stop*6);j++){
                proto_genome.push_back(genome2[j]);
            }
            for(int j=0;j<6;j++){
                proto_genome.push_back(codon[j]);
            }
            codon.clear();
        }
    else if(y < (mu_point_mutation+mu_conjugation \swarrow
        +mu_recopy)){
                                    //This will duplicate a section of the
        genome
        /6));
            start = i/6;
            stop = random_int(start,int(genome.size()k
            for(int j=(start*6);j<(stop*6);j++){
            proto_genome.push_back(genome[j]);
            }
            for(int j=0;j<6;j++){
            proto_genome.push_back(codon[j]);
    ```
\}
codon.clear();
\}
else if(y < (mu_point_mutation+mu_conjugation +mu_recopy+mu_deletion))\{
genome
//This will delete a section of the
start = i/6;
skip_to_codon = random_int(start,int
(genome.size()/6));
codon.clear();
\}
else if(y <= (mu_point_mutation+
K
mu_conjugation+mu_recopy+mu_deletion+
mu_translocation)) \{
//This will delete a section of the
genome and save for later insertion
start = i/6;
skip_to_codon = random_int(start,int と
(genome.size()/6));
for(int \(j=((s t a r t+1) * 6) ; j<\left(s k i p \_t o \_c o d o n * ~ K\right.\) \(6) ; j++\) ) \(\{\)
```

                                    codon.push_back(genome[j]);
    ```
                \}
                translocated_codons.push_back(codon);
                    codon.clear();
            \}
    \}
    \}
    genome.clear();
    int counter \(=0\);
    while((counter<translocated_codons.size())\&\& K
    (translocation_codon_numbers.size()<=int(proto_genome \(\boldsymbol{k}\)
    .size()/6)))\{
        temp_int \(=\) random_int(0,int(proto_genome.size()/
        \(6)\), translocation_codon_numbers);
            translocation_codon_numbers.push_back(temp_int);
    counter++;
    \}
    //If the genome is too short, this check will delete
    K
    extra translocations
    if(translocation_codon_numbers.size() к
    <translocated_codons.size()) \{
    translocated_codons.resize
    (translocation_codon_numbers.size());
    \}
    for(int i=0;i<proto_genome.size();i++)\{
    if((i\%6 == 0)\&\&any(translocation_codon_numbers, レ
    int(i/6)))\{
            for (int j=0;j<translocation_codon_numbers.
        size();j++)\{
                                if((i/6) == translocation_codon_numbers
[j])\{
```

                                    temp_int = j;
                    }
                    }
                    for(int j=0;j<translocated_codons[temp_int].
    size();j++){
    [temp_int][j]);
                }
            }
            genome.push_back(proto_genome[i]);
    }
    for(int i=0;i<translocation_codon_numbers.size();i++) k
    {
            //Inserts translocations
            if(translocation_codon_numbers[i] == int
        (proto_genome.size()/6)){
                                    for(int j=0;j<translocated_codons[i].size();j к
    ++ ) {
    [j]);
                }
            }
    }
    if(genome.size()<6){
            for(int i=genome.size(); i<6; i++){
                    genome.push_back(100);
            }
    }
    if (genome.size()>600)
            genome.resize(300);
    /*
    for(int i = 0;i<genome.size();i++)
    cout<<genome[i]<<" ";
    cout<<endl;
    */
    }
void reduce_genome(vector<int>\& genome,vector< vector
<int> > rule_table){
//This operation will reduce the genome into the
rules that actually produced the ANN
vector <int> new_genome;
int reading_frame,temp_int;
for(int i=0;i<rule_table.size();i++){
for(int j=0;j<rule_table[i].size();j++){
reading_frame = rule_table[i][j];
for(int k=0;k<6;k++){
if(k==0){
new_genome.push_back(1); //
Homogenizes IF's
}

```

1233 //The script that transform the genome into proteins/ programs
1234 void make_protein(individual indy,int no_of_inputs,int outputs,int max_conns,int rank_no)\{
1235 int genome_length = indy.get_genome_length();
1236 int l,openifs,g;
1237 vector<int> genome;
1238 for(int i=0;i<genome_length;i++)\{
\(1239 \quad g=\) indy.get_genome(i);
1240
1241
\}
1242
1243
fil
filename2 = \&filename1[0];
1245 ofstream file(filename2);
//-------------Protien Primer
    file << "\#include <iostream>\n";
    file << "\#include <fstream>\n";
    file << "\#include <vector>\n";
    file << "\#include <string>\n";
    file << "\#include <sstream>\n";
    file << "\#include <ctime>\n";
    file << "\#include <math.h>\n";
    file << "\#include \"chimera_lib.h\"\n";
    file << "\#include \"node_lib_omega4.h\"\n"; //WILL k
    HAVE TO CHANGE THIS LINE TO MATCH VERSION
    file << "using namespace std; \n";
    file << "int main() \n\{\n";
        file << "neural_net ANN; \n";
        file << "string rules; \n";
        file << "int no_of_inputs = "<<no_of_inputs<<"; \n";
        file << "int Max_Outputs = "<<outputs<<"; \n";
        file << "int Max_Connections = "<<max_conns<<"; \n";
        file << "int ANN_Size; \n";
        file << "float bias, weight; \n";
        file << "int NodeA_type1, NodeA_type2, NodeA_type3,
        NodeA_bias, NodeA_nodes_made, NodeA_inputs,
        NodeA_outputs; \n";
        file << "int NodeB_type1,NodeB_type2,NodeB_type3,
        NodeB_bias,NodeB_nodes_made,NodeB_inputs,
        NodeB_outputs; \n";
        file << "int relAB_type1,relAB_type2,relAB_type3,
        relAB_bias,relAB_nodes_made,relAB_inputs,
        relAB_outputs,relAB_connection; \n";
        file << "int relBA_type1, relBA_type2, relBA_type3,
        relBA_bias,relBA_nodes_made, relBA_inputs,
        relBA_outputs,relBA_connection; \n";
        file << "bool keep_going=true; \n";
        file << "bool turn_over=false; \n";
        file << "int no_of_outputs = 0; \n";
        file << "int energy_units = 200; \n";
        // For looped input creation
        file << "for(int i=0;i<no_of_inputs;i++) \n" ;
        file << "ANN.make_input(0); \n";
        file << "while(keep_going \&\& energy_units > 0)\{\n";
        file << "keep_going = false; \n";
        file << "ANN_Size = ANN.get_ANN_size(); \n";
        file << "for(int i=0;i<ANN_Size;i++)\{\n";
        file << "turn_over = false; \(\backslash n " ;\)
        file << "node NodeA = ANN.get_node(i); \n";
        file << "NodeA_type1 = NodeA.get_type1(); \n";
        file << "NodeA_type2 = NodeA.get_type2(); \n";
        file << "NodeA_type3 = NodeA.get_type3(); \n";
        //Need to change bias into an integer
        file << "bias = NodeA.get_bias(); \n";
        file << "if(bias>0)\{\n";
    file << "NodeA_bias = int(50*bias+50+0.5); \n\} \nelse\{\k
    n";
    file << "NodeA_bias = int(50*bias+51+0.5);\n\}\n";
    file << "NodeA_nodes_made = NodeA.get_nodes_made(); \n к
    ";
    file << "NodeA_inputs = ANN.get_inputs_to(i); \n";
    file << "NodeA_outputs = ANN.get_outputs_from(i); \({ }^{\prime}{ }^{\prime} " ;\)
    file << "for(int j=0;j<ANN_Size;j++)\{\n";
    file << "node NodeB = ANN.get_node(j); \n";
    file << "if(turn_over)\n";
    file << "break; \n";
    file \(\ll\) "NodeB_type1 = NodeB.get_type1(); \({ }^{\text {n }}\) ";
    file << "NodeB_type2 = NodeB.get_type2(); \n";
    file << "NodeB_type3 = NodeB.get_type3(); \n";
    //Need to change bias into an integer
    file << "bias = NodeB.get_bias(); \n";
    file << "if(bias>0)\{\n";
    file << "NodeB_bias = int(50*bias+50+0.5); \n\}\nelse\{\k
    n";
    file << "NodeB_bias = int(50*bias+51+0.5); \n\}\n";
    file << "NodeB_nodes_made = NodeB.get_nodes_made(); \n \(\boldsymbol{\kappa}\)
    ";
    file << "NodeB_inputs = ANN.get_inputs_to(j); \n";
    file << "NodeB_outputs = ANN.get_outputs_from(j); \n";
    file << "relAB_type1 = NodeA_type1 - NodeB_type1; \n";
    file << "relAB_type2 = NodeA_type2 - NodeB_type2; \n";
    file << "relAB_type3 = NodeA_type3 - NodeB_type3; \n";
    file << "relAB_bias = NodeA_bias - NodeB_bias;\n";
    file << "relAB_nodes_made = NodeA_nodes_made -
    NodeB_nodes_made; \n";
    file << "relAB_inputs = NodeB_inputs - NodeA_inputs; \(\boldsymbol{k}\)
    n";
    file << "relAB_outputs = NodeB_outputs -
    NodeA_outputs; \n";
    file << "weight = ANN.get_connection_weight(i,j);\n";
    file << "if(weight>0)\{\n";
    file << "relAB_connection = int(50*weight+50+0.5); \n\}
    \nelse\{\n";
    file << "relAB_connection = int(50*weight+51+0.5);\n\}
    \n";
    file << "relBA_type1 = NodeB_type1 - NodeA_type1; \n";
    file << "relBA_type2 = NodeB_type2 - NodeA_type2; \n";
    file << "relBA_type3 = NodeB_type3 - NodeA_type3; \n";
    file << "relBA_bias = NodeB_bias - NodeA_bias; \n";
    file << "relBA_nodes_made = NodeB_nodes_made -
    NodeA_nodes_made; \n";
    file << "relBA_inputs = NodeA_inputs - NodeB_inputs; \(\boldsymbol{\Sigma}\)
    n";
    file << "relBA_outputs = NodeA_outputs -
    NodeB_outputs; \n";
    file << "weight = ANN.get_connection_weight(j,i);\n";
    file << "if(weight>0)\{\n";
```

file << "relBA_connection = int(50*weight+50+0.5);\n} 反
\nelse{\n";
file << "relBA_connection = int(50*weight+51+0.5);\n}
\n";

```

```

    openifs = 0;
    int if_struct_nucleotide;
    int criterion_nucleotide;
    int test_value_nucleotide;
    int test_range_nucleotide;
    int action_nucleotide;
    int action_value_nucleotide;
    vector<string> action_stack;
    vector<int> rule_stack;
    l = genome_length - (genome_length%6);
    bool action_commented;
    for(int i=0;i<l;i+=6){
    if_struct_nucleotide = genome[i];
    criterion_nucleotide = genome[i+1];
    test_value_nucleotide = genome[i+2];
    test_range_nucleotide = genome[i+3];
    action_nucleotide = genome[i+4];
    action_value_nucleotide = genome[i+5];
    //---------------IF STRUCTURE ALGORITHM--------- к
    ```
    int make_if[] = \{1,38\};
    int make_end_if[] = \{39,54\};
    int make_end_end_if[] = \{55,70\};
    int make_end[] = \(\{71,80\}\);
    int make_end_end[] = \{81,90\};
    int make_end_all[] = \{91,100\};
    if ((make_if[0]<=if_struct_nucleotide)\&\&(make_if
    [1]>=if_struct_nucleotide)) \{
        action_commented = false;
        file <<"if(";
        openifs++;
    \}
    else if ((make_end_if[0]<=if_struct_nucleotide)\&\& \(k\)
    (make_end_if[1]>=if_struct_nucleotide)) \{
        action_commented = false;
        if(openifs == 0)\{
                file <<" if(";
                openifs++;
            \}
            else\{
                file << action_stack.back();
                file << "if(turn_over)\{\n";
                file << "rules = rules + \"";
            for (int j=0;j<rule_stack.size();j++)\{
                                    file << int2string(rule_stack[j]) + "
    ";
    \}
    file << "-1 \\n\"; \n";
    file << "break; \n\}\n";
    action_stack.pop_back();
    file<<"/*";
    for(int j=0;j<rule_stack.size();j++)
        file << rule_stack[j]<<" ";
    file<<"*/";
    rule_stack.pop_back();
        //file << "\}//stack is "<<action_stack. K
size()<<"\n if(";
    file << "\}\n if(";
        \}
        \}
        else if((make_end_end_if[0]<=
if_struct_nucleotide)\&\&(make_end_end_if[1]>=
if_struct_nucleotide))\{
        action_commented = false;
        if(openifs == 0)\{
            file <<" if(";
            openifs++;
            \}
                else if(openifs == 1)\{
                    file << action_stack.back();
                    file << "if(turn_over)\{\n";
                    file << "rules = rules + \"";
                    for (int j=0;j<rule_stack.size();j++)\{
                            file << int2string(rule_stack[j]) + "
    ";
            \}
            file << "-1 \\n\"; \n";
            file << "break; \n\}\n";
            action_stack.pop_back();
            file<<"/*";
            for(int j=0;j<rule_stack.size();j++)
                    file << rule_stack[j]<<" ";
            file<<"*/";
            rule_stack.pop_back();
            //file << "\}//stack is "<<action_stack. K
size()<<"\n if(";
            file << "\}\n if(";
        \}
        else\{
            file << action_stack.back();
            file << "if(turn_over)\{\n";
            file << "rules = rules + \"";
            for (int j=0;j<rule_stack.size();j++)\{
                    file << int2string(rule_stack[j]) + "
    ";
\}
file << "-1 \\n\"; \n";
file << "break; \n\}\n";
action_stack.pop_back();
file<<"/*";
for(int \(\left.j=0 ; j<r u l e \_s t a c k . s i z e() ; j++\right)\)
file << rule_stack[j]<<" ";
file<<"*/";
rule_stack.pop_back();
//file << "\}//stack is "<<action_stack. size()<<"\n";
file << "\}\n";
file << action_stack.back();
file << "if(turn_over)\{\n";
file << "rules = rules + \"";
for (int \(\left.j=0 ; j<r u l e \_s t a c k . s i z e() ; j++\right)\{\)
file << int2string(rule_stack[j]) + "
";
\}
file << "-1 \\n\"; \n";
file << "break; \n\}\n";
action_stack.pop_back();
file<<"/*";
for(int j=0;j<rule_stack.size();j++)
file << rule_stack[j]<<" ";
file<<"*/";
rule_stack.pop_back();
//file << "\}//stack is "<<action_stack. к size()<<"\n if(";
file << "\}\n if(";
openifs--;
\}
\}
else if((make_end_all[0]<=if_struct_nucleotide)\&\& \(\kappa\) (make_end_all[1]>=if_struct_nucleotide))\{
action_commented = true;
if(openifs == 0)
file <<"//";
else\{
for(int j=0;j<openifs;j++)\{
file << action_stack.back();
file << "if(turn_over)\{\n"; file << "rules = rules + \""; for (int \(\left.k=0 ; k<r u l e \_s t a c k . s i z e() ; k++\right) k\)
\{
file << int2string(rule_stack[k]) 反
+ " ";
\}
file << "-1 \\n\"; \n";
file << "break; \n\}\n";
action_stack.pop_back();
file<<"/*";
```

            for(int k=0;k<rule_stack.size();k++)
            file << rule_stack[k]<<" ";
                    file<<"*/";
                rule_stack.pop_back();
                //file << "\}//stack is "<
    ```
<action_stack.size()<<"\n";
                                    file << "\}\n";
                            \}
                            file << "// FORCED END OF GENE stack size \(\swarrow\)
    is "<<action_stack.size()<<".";
                    openifs \(=0 ;\)
            \}
            \}
            else if((make_end[0]<=if_struct_nucleotide)\&\&
(make_end[1]>=if_struct_nucleotide)) \{
            action_commented = true;
                    if(openifs == 0)
                    file <<"//";
                    else \{
                            file << action_stack.back();
                    file << "if(turn_over)\{\n";
                    file << "rules = rules + \"";
                            for (int j=0;j<rule_stack.size();j++)\{
                            file << int2string(rule_stack[j]) + "
    ";
            \}
                    file << "-1 \\n\"; \n";
                    file << "break; \n\}\n";
                    action_stack.pop_back();
                    file<<"/*";
                    for(int \(\left.j=0 ; j<r u l e \_s t a c k . s i z e() ; j++\right)\)
                    file << rule_stack[j]<<" ";
                    file<<"*/";
                            rule_stack.pop_back();
                            //file << "\}//stack is "<<action_stack.
size()<<"\n //";
            file << "\}\n //";
            openifs = openifs - 1;
            \}
        \}
            else if((make_end_end[0]<=if_struct_nucleotide)\&\& \(\kappa\)
        (make_end_end[1]>=if_struct_nucleotide)) \{
            action_commented = true;
            if(openifs == 0)
                file <<"//";
            else if(openifs == 1)\{
                    file << action_stack.back();
                    file << "if(turn_over)\{\n";
                    file << "rules = rules + \"";
                    for (int j=0;j<rule_stack.size();j++)\{
                    file << int2string(rule_stack[j]) + "
```

";

```
```

            }
                            file << "-1 \\n\";\n";
                            file << "break;\n}\n";
                            action_stack.pop_back();
                            file<<"/*";
                            for(int j=0;j<rule_stack.size();j++)
                            file << rule_stack[j]<<" ";
                            file<<"*/";
                            rule_stack.pop_back();
                            //file << "}//stack is "<<action_stack.
    size()<<"\n //";
file << "}\n //";
openifs = 0;
}
else{
action_commented = true;
file << action_stack.back();
file << "if(turn_over){\n";
file << "rules = rules + \"";
for (int j=0;j<rule_stack.size();j++){
file << int2string(rule_stack[j]) + " к
";
}
file << "-1 <br>n\";\n";
file << "break;\n}\n";
action_stack.pop_back();
file<<"/*";
for(int j=0;j<rule_stack.size();j++)
file << rule_stack[j]<<" ";
file<<"*/";
rule_stack.pop_back();
//file << "}//stack is "<<action_stack.
size()<<"\n";
file << "}\n";
file << action_stack.back();
file << "if(turn_over){\n";
file << "rules = rules + \"";
for (int j=0;j<rule_stack.size();j++){
file << int2string(rule_stack[j]) + " K
";
}
file << "-1 <br>n\";\n";
file << "break;\n}\n";
action_stack.pop_back();
file<<"/*";
for(int j=0;j<rule_stack.size();j++)
file << rule_stack[j]<<" ";
file<<"*/";
rule_stack.pop_back();
//file << "//stack is "<<action_stack. K
size()<<"\n //";

```

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file << "\}\n //";
                openifs = openifs - 2;
            \}
    \}
        else \{
            cout<<indy.get_fcall()<<" ";
            cout<<"If structure did not use the following
    nucleotide: "<<if_struct_nucleotide<<endl;
        \}
    //cout<<if_struct_nucleotide<<"\t";

    file << "abs(";
    //---------CRITERION AND VALUE SET UP ALGORITHM-- と
    int NodeA_Type1[] = \(\{1,5\}\);
        int NodeA_Type2[] = \(\{6,10\}\);
        int NodeA_Type3[] = \{11,14\};
        int NodeA_Bias[] = \{15,17\};
        int NodeA_nodes_made[] = \{18, 20\};
        int NodeA_inputs[] = \{21,23\};
        int NodeA_outputs[] \(=\{24,26\}\);
        int NodeB_Type1[] = \{27,31\};
        int NodeB_Type2[] \(=\{32,36\}\);
        int NodeB_Type3[] = \(\{37,40\}\);
        int NodeB_Bias[] \(=\{41,43\}\);
        int NodeB_nodes_made[] \(=\{44,46\}\);
        int NodeB_inputs[] \(=\{47,49\}\);
        int NodeB_outputs[] \(=\{50,52\}\);
        int RelAB_Type1[] \(=\{53,55\}\);
        int RelAB_Type2[] \(=\{56,58\}\);
        int RelAB_Type3[] \(=\{59,61\}\);
        int RelAB_Bias[] = \(\{62,64\}\);
        int RelAB_nodes_made[] = \{65,67\};
        int RelAB_inputs[] = \{68,70\};
        int RelAB_outputs[] = \{71,73\};
        int RelAB_connection[] \(=\{74,76\}\);
        int RelBA_Type1[] = \(\{77,79\}\);
        int RelBA_Type2[] = \{80,82\};
        int RelBA_Type3[] = \(\{83,85\}\);
        int RelBA_Bias[] = \{86,88\};
        int RelBA_nodes_made[] = \{89,91\};
        int RelBA_inputs[] = \(\{92,94\}\);
        int RelBA_outputs[] \(=\{95,97\}\);
    int RelBA_connection[] = \{98,100\};
    string value_type;
    if((NodeA_Type1[0]<=criterion_nucleotide)\&\&
(NodeA_Type1[1]>=criterion_nucleotide))\{
            file<<"NodeA_type1 ";
            value_type = "Type1";
    \}
    else if((NodeA_Type2[0]<=criterion_nucleotide)\&\&
(NodeA_Type2[1]>=criterion_nucleotide)) \{
                            file<<"NodeA_type2 ";
            value_type = "Type2";
    \}
    else if((NodeA_Type3[0]<=criterion_nucleotide)\&\&
(NodeA_Type3[1]>=criterion_nucleotide))\{
            file<<"NodeA_type3 ";
            value_type = "Туре3";
    \}
    else if((NodeA_Bias[0]<=criterion_nucleotide)\&\&
(NodeA_Bias[1]>=criterion_nucleotide))\{
            file<<"NodeA_bias ";
            value_type = "Bias";
    \}
    else if((NodeA_nodes_made[0]<=
criterion_nucleotide)\&\&(NodeA_nodes_made[1]>=
criterion_nucleotide)) \{
        file<<"NodeA_nodes_made ";
        value_type = "nodes_made";
    \}
    else if((NodeA_inputs[0]<=criterion_nucleotide)\&\&
(NodeA_inputs[1]>=criterion_nucleotide))\{
            file<<"NodeA_inputs ";
            value_type = "connections";
    \}
    else if((NodeA_outputs[0]<=criterion_nucleotide)\& \(\kappa\)
\&(NodeA_outputs[1]>=criterion_nucleotide)) \{
            file<<"NodeA_outputs ";
            value_type = "connections";
    \}
    else if((NodeB_Type1[0]<=criterion_nucleotide)\&\&
(NodeB_Type1[1]>=criterion_nucleotide)) \{
            file<<"NodeB_type1 ";
            value_type = "Type1";
    \}
    else if((NodeB_Type2[0]<=criterion_nucleotide)\&\&
(NodeB_Type2[1]>=criterion_nucleotide))\{
            file<<"NodeB_type2 ";
            value_type = "Type2";
    \}
    else if((NodeB_Type3[0]<=criterion_nucleotide)\&\&
(NodeB_Type3[1]>=criterion_nucleotide))\{
                                    file<<"NodeB_type3 ";
            value_type = "Type3";
\}
else if((NodeB_Bias[0]<=criterion_nucleotide)\&\&
(NodeB_Bias[1]>=criterion_nucleotide)) \{
file<<"NodeB_bias ";
value_type = "Bias";
\}
else if((NodeB_nodes_made[0]<=
criterion_nucleotide)\&\&(NodeB_nodes_made[1]>=
criterion_nucleotide)) \{
file<<"NodeB_nodes_made ";
value_type =-"nodes_made";
\}
else if((NodeB_inputs[0]<=criterion_nucleotide)\&\& \(\kappa\)
(NodeB_inputs[1]>=criterion_nucleotide))\{
file<<"NodeB_inputs ";
value_type = "connections";
\}
else if((NodeB_outputs[0]<=criterion_nucleotide)\& \(\kappa\)
\&(NodeB_outputs[1]>=criterion_nucleotide)) \{
file<<"NodeB_outputs ";
value_type = "connections";
\}
else if((RelAB_Type1[0]<=criterion_nucleotide)\&\&
(RelAB_Type1[1]>=criterion_nucleotide))\{
file<<"relAB_type1 ";
value_type = "Type1";
\}
else if((RelAB_Type2[0]<=criterion_nucleotide)\&\&
(RelAB_Type2[1]>=criterion_nucleotide)) \{
file<<"relAB_type2 ";
value_type = "Type2";
\}
else if((RelAB_Type3[0]<=criterion_nucleotide)\&\& (RelAB_Type3[1]>=criterion_nucleotide)) \{
file<<"relAB_type3 ";
value_type = "Турез";
\}
else if((RelAB_Bias[0]<=criterion_nucleotide)\&\& (RelAB_Bias[1]>=criterion_nucleotide)) \{
file<<"relAB_bias ";
value_type = "Bias";
\}
else if((RelAB_nodes_made[0]<= criterion_nucleotide)\&\&(RelAB_nodes_made[1]>= criterion_nucleotide)) \{
file<<"relAB_nodes_made ";
value_type = "nodes_made";
\}
else if((RelAB_inputs[0]<=criterion_nucleotide)\&\& (RelAB_inputs[1]>=criterion_nucleotide))\{
file<<"relAB_inputs ";
            value_type = "connections";
        \}
        else if((RelAB_outputs[0]<=criterion_nucleotide)\&
    \&(RelAB_outputs[1]>=criterion_nucleotide)) \{
            file<<"relAB_outputs ";
            value_type = "connections";
    \}
    else if((RelAB_connection[0]<=
    criterion_nucleotide)\&\&(RelAB_connection[1]>=
criterion_nucleotide))\{
            file<<"relAB_connection ";
            value_type = "Bias";
    \}
    else if((RelBA_Type1[0]<=criterion_nucleotide)\&\&
(RelBA_Type1[1]>=criterion_nucleotide)) \{
            file<<"relBA_type1 ";
            value_type = "Type1";
    \}
    else if((RelBA_Type2[0]<=criterion_nucleotide) \&\&
(RelBA_Type2[1]>=criterion_nucleotide)) \{
            file<<"relBA_type2 ";
            value_type = "Type2";
    \}
    else if((RelBA_Type3[0]<=criterion_nucleotide)\&\&
(RelBA_Type3[1]>=criterion_nucleotide)) \{
            file<<"relBA_type3 "
            value_type = "Type3";
    \}
    else if((RelBA_Bias[0]<=criterion_nucleotide)\&\&
(RelBA_Bias[1]>=criterion_nucleotide)) \{
            file<<"relBA_bias ";
            value_type = "Bias";
    \}
    else if((RelBA_nodes_made[0]<=
        \(K\)
    criterion_nucleotide)\&\&(RelBA_nodes_made[1]>= к
    criterion_nucleotide))\{
            file<<"relBA_nodes_made ";
            value_type = "nodes_made";
            \}
            else if((RelBA_inputs[0]<=criterion_nucleotide)\&\& \(ட\)
        (RelBA_inputs[1]>=criterion_nucleotide)) \{
            file<<"relBA_inputs ";
            value_type = "connections";
    \}
    else if((RelBA_outputs[0]<=criterion_nucleotide)\& \(\swarrow\)
\&(RelBA_outputs[1]>=criterion_nucleotide)) \{
            file<<"relBA_outputs ";
            value_type = "connections";
    \}
    else if((RelBA_connection[0]<=
        criterion_nucleotide) \&\&(RelBA_connection[1]>=
```

            file<<"relBA_connection ";
        value_type = "Bias";
    }
    else {
        cout<<"Criterion did not use the following
    nucleotide: "<<criterion_nucleotide<<endl;
}
//cout<<criterion_nucleotide<<"\t";
//-------------------VALUE ALGORITHM------------ K
if((value_type == "Type1")||(value_type ==
"relType1")||(value_type == "Type2")||(value_type == к
"nodes_made")){
int num;
num = int((test_value_nucleotide-1)/12.5);
file<<"- "<<num<<")";
}
else if(value_type == "Bias"){
int num;
num = test_value_nucleotide;
file<<"- "<<num<<")";
}
else if((value_type == "Type3")||(value_type ==
"connections")){
int num;
num = test_value_nucleotide-1;
file<<"- "<<num<<")";
}
else{
cout<<indy.get_fcall()<<" ";
cout<<"Value type ("<<value_type<<") did not <
use the following nucleotide: "<
<test_value_nucleotide<<endl;
}
//cout<<test_value_nucleotide<<"\t";
//----------------------------.- K
if((value_type == "Type1")||(value_type ==
"relType1")||(value_type == "Type2")||(value_type == к
"nodes_made")){
int num;
num = int((test_range_nucleotide-1)/12.5);
file<<" <= "<<num<<"){\n";
}
else if(value_type == "Bias"){
int num;
num = test_range_nucleotide;
file<<" <= "<<num<<"){\n";
}
else if((value_type == "Type3")||(value_type == к
"connections")){
int num;

```
            num = test_range_nucleotide-1;
            file<<" <= "<<num<<")\{\n";
        \}
        else\{
            cout<<indy.get_fcall()<<" ";
            cout<<"Value type ("<<value_type<<") did not
use the following nucleotide: "\ll
                                    K
<test_range_nucleotide<<endl;
    \}
    //cout<<test_nucleotide<<"\t";

    int make_connection[] = \{1,20\};
    int do_nothing[] = \{21,35\};
    int end_turn[] = \(\{36,50\}\);
    int make_node[] = \{51,100\};
    int make_nodeB[] = \(\{51,55\}\);
    int make_nodec []\(=\{56,61\}\);
    int make_nodeD[] = \(\{62,67\}\);
    int make_nodeE[] = \{68,73\};
    int make_nodeF[] = \{74,79\};
    int make_nodeG[] = \{80,85\};
    int make_nodeH[] = \{86,100\};
    if(!action_commented)\{ //Determined by
if_structure codon to comment out rule
                            rule_stack.push_back(i);
    \}
    string temp_stack = " ";
    if ((make_connection[0]<=action_nucleotide)\&\&
(make_connection[1]>=action_nucleotide)) \{
                            temp_stack += "if(make_connection_check(ANN, i \(\boldsymbol{\kappa}\)
, j, Max_Connections))\{\n";
    temp_stack += "ANN.make_connection(i,j,";
    float \(x, w, h ;\)
    if(action_value_nucleotide >= 51)\{
                \(w=\) float(action_value_nucleotide-50.0)/ \(\kappa\)
50.0;
        \}
        else\{
                w = float(action_value_nucleotide-51.0)/
50.0;
    \}
    //w = fabs(w); //Makes evolution of XOR gate \(\boldsymbol{k}\)
impossible
    \(x=\) float(action_nucleotide);
    h = x*0.1/64;
    temp_stack += float2string(w); //Base weight
    temp_stack += ",";
        temp_stack += float2string(h); //Hebbian rate
        temp_stack += ",";
        temp_stack += float2string(0.0); //Random к
```

    rate
    ```
            temp_stack += "); \nkeep_going = true;
    nturn_over = true; \nenergy_units--; \n\}\n";
        \}
        else if ((end_turn[0]<=action_nucleotide)\&\&
    (end_turn[1]>=action_nucleotide)) \{
            temp_stack += "turn_over = true; \n";
        \}
        else if ((make_node[0]<=action_nucleotide)\&\&
                            K
    (make_node[1]>=action_nucleotide)) \{
    if ((make_nodeB[0]<=action_nucleotide)\&\&
    (make_nodeB[1]>=action_nucleotide)) \{
                            temp_stack += "if(make_node_check(ANN,i, \(\boldsymbol{\kappa}\)
    Max_Outputs))\{\n";
            temp_stack += "ANN.make_node(i,'H',1,";
    \}
    else if ((make_nodeC[0]<=action_nucleotide)\&\&
    (make_nodec[1]>=action_nucleotide)) \{
                            temp_stack += "if(make_node_check(ANN,i, \(\boldsymbol{\kappa}\)
    Max_Outputs))\{\n";
                                    temp_stack += "ANN.make_node(i,'H',2,";
    \}
    else if ((make_nodeD[0]<=action_nucleotide)\&\&
    (make_nodeD[1]>=action_nucleotide)) \{
        temp_stack += "if(make_node_check(ANN,i, 反
    Max_Outputs)) \{\n";
                                    temp_stack += "ANN.make_node(i,'H',3,";
    \}
    else if ((make_nodeE[0]<=action_nucleotide)\&\&
    (make_nodeE[1]>=action_nucleotide)) \{
                                    temp_stack += "if(make_node_check(ANN,i, к
    Max_Outputs)) \{\n";
                                    temp_stack += "ANN.make_node(i,'H',4,";
    \}
    else if ((make_nodeF[0]<=action_nucleotide)\&\& \(\boldsymbol{K}\)
    (make_nodeF[1]>=action_nucleotide)) \{
                                    temp_stack += "if(make_node_check(ANN,i,
    Max_Outputs))\{\n";
                            temp_stack += "ANN.make_node(i,'H',5,";
    \}
    else if ((make_nodeG[0]<=action_nucleotide)\&\& \(\kappa\)
    (make_nodeG[1]>=action_nucleotide)) \{
                                    temp_stack += "if(make_node_check(ANN,i, \(\boldsymbol{\Sigma}\)
    Max_Outputs))\{\n";
                    temp_stack += "ANN.make_node(i,'H', 6,";
    \}
    else if ((make_nodeH[0]<=action_nucleotide)\&\& \(\boldsymbol{K}\)
    (make_nodeH[1]>=action_nucleotide)) \{
                            temp_stack += "if(make_node_check(ANN,i, \(\boldsymbol{\kappa}\)
        Max_Outputs))\{\n";
            temp_stack += "ANN.make_output(i,7,";
    \}
            float s;
        \(\mathrm{s}=\operatorname{pow}(10.0,0.0)\);
        temp_stack += float2string(s);
        /*
        if(action_codon1[2] == 1)\{
        float s;
        \(\mathrm{s}=\operatorname{pow}(10.0,-2.0)\);
        temp_stack += float2string(s);
        \}
        else if(action_codon1[2] == 2)\{
        float s;
        \(s=\operatorname{pow}(10.0,-0.5)\);
        temp_stack += float2string(s);
        \}
        else if(action_codon1[2] == 3)\{
        float s;
        \(\mathrm{s}=\mathrm{pow}(10.0,0.0)\);
        temp_stack += float2string(s);
        \}
        else if(action_codon1[2] == 4)\{
        float s;
        s = pow(10.0,0.5);
        temp_stack += float2string(s);
        \}
        else\{
        cout<<indy.get_fcall()<<" ";
        cout<<"did not use the following slope
    nucleotide:"<<action_codon1[2]<<endl;
        \(\underset{*}{\}} /\)
        temp_stack += ",";
        float b;
        if(action_value_nucleotide >= 51)\{
            b = float(action_value_nucleotide-50.0)/
        50.0;
            \}
        else\{
                b = float(action_value_nucleotide-51.0)/ к
    50.0;
        \}
        temp_stack += float2string(b);
        temp_stack += "); \nkeep_going = true;
        nturn_over = true; \nenergy_units--; \(\backslash n\} \backslash n " ;\)
        \}
        else\{// A 'Do nothing' is added to the stack. It \(\boldsymbol{k}\)
        does nothing
            temp_stack += "//Do nothing \n";
        \}
            if(!action_commented) \{ //Determined by
        if_structure codon to comment out action
        action_stack.push_back(temp_stack);
    \}
```

1929 //---------------------END OF MAKE_PROTIEN--------------- K

```

1931

    if(openifs != 0)\{
            for(int j=0;j<openifs;j++)\{
            for(int \(\left.k=\left(a c t i o n \_s t a c k . s i z e()-1\right) ; k>=0 ; k--\right)\{\)
                    file << action_stack[k];
                    file << "if(turn_over)\{\n";
                    file << "rules = rules + \"";
                    for (int I=0;I<rule_stack.size(); I++)\{
                                    file << int2string(rule_stack[I]) + " K
            ";
                \}
                    file << "-1 \\n\"; \({ }^{\text {n"; }}\)
                    file << "break; \n\}\n";
            \}
            action_stack.pop_back();
            file<<"/*";
            for(int j=0;j<rule_stack.size();j++)
                    file << rule_stack[j]<<" ";
            file<<"*/";
            rule_stack.pop_back();
            file << "\}\n";
        \}
        \}
        file<<"\}\n\}\n\}\n";
        file<<"string ANNfilename = \"/scratch/ANN"+
        int2string(rank_no)+".dat\"; \({ }^{2}\) ";
        file<<"ANN.write_net(ANNfilename); \n";
        string rulesfilename = "/scratch/Rules"+int2string K
        (rank_no)+".dat";
        file<<"ofstream outfile2(\""<<rulesfilename<<"\"); \n" K
        ;
        file<<"outfile2<<rules; \(\ n " ;\)
        //file<<"ANN.print_net();\n"; \\Prints ANN to screen
        //file<<rules;\n"; \\Prints rules to screen
        file<<"return 0; \n\}\n";

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1933
1934
1935
1936

    //This function will record the Ark_no and fitness of the \(\boldsymbol{\Sigma}\)
        population at each generation
    void Record_Gen(vector<individual> Ark, vector<int> old,
    vector<int> young, int gen)\{
    ofstream datafile;
    datafile.open("Chronograph.txt",ios_base: :app);
    datafile<<gen<<endl;
    for(int i=0;i<old.size();i++)\{
        datafile<<old[i]<<' ';
        datafile<<Ark[old[i]].get_fitness()<<' ';
        datafile<<endl;
        \}
        for(int i=0;i<young.size();i++)\{
            datafile<<young[i]<<' ';
            datafile<<Ark[young[i]].get_fitness()<<' ';
            datafile<<endl;
        \}
        datafile.close();
    \}

    //This function will get the state of the last generation \(\mathfrak{\swarrow}\)
        in Chronograph.txt
    void Read_Last_Gen(int \(N, v e c t o r<i n t>\& ~ u n m a d e, ~ v e c t o r<i n t>k\)
        \& alive, vector<int>\& still_alive, int gen)\{
        ifstream datafile;
        int temp_gen,temp_sub;
        float temp_fit;
        datafile.open("Chronograph.txt");
        datafile>>temp_gen;
        while((temp_gen <= gen)\&\&(!datafile.eof())) \{
            if(temp_gen < gen) \(\{/ / D o n ' t ~ s a v e ~ r e s u l t s ~\)
                    for (int i=0;i<N;i++)\{
                    datafile>>temp_sub;
                    datafile>>temp_fit;
                    \}
                datafile>>temp_gen;
        \}
        else\{ //Save results
                        for(int i=0;i<N;i++)\{
                    datafile>>temp_sub;
                    alive.push_back(temp_sub);

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2025 datafile.close();
2026 \}
2027
```

using namespace std;
//----------------- Robot Classes
--------
class signal_robot //A bot of 0 size that sends out a
signal
{private:
float position[2]; //The [0] and [1] are x-y location.
public:
signal_robot(){ //Default Constructor
position[0] = 0;
position[1] = 0;
}
signal_robot(float x,float y){ //Constructor - given
starting position and error
position[0] = x;
position[1] = y;
}
float get_x(){
return(position[0]);
}
float get_y(){
return(position[1]);
}
void set_position(float x, float y){
position[0] = x;
position[1] = y;
}
};
class laser_robot
{private:
float dia; //The diameter of the robot in meters (m)
float max_vel; //Maximum magnitude of output velocity (m/ <
s)
float position[3]; //The [0] and [1] are x-y location. [2]
is heading in degrees. 0 is right/east/x-positive
float left_wheel; //The output speed of left wheel
float right_wheel; //The output speed of right wheel
vector <float> goal_sensors; //Activation of goal input
nodes
vector <float> lasers; //Activation of obstacle input
nodes
bool goal_line_of_sight;
public:
laser_robot(){ //Default constructor
dia = 1;
max_vel = .5;
position[0] = 0;
position[1] = 0;
position[2] = 0;

```
```

    left_wheel = 0;
    right_wheel = 0;
    vector<float> default_lasers(8,0.0);
    lasers = default_lasers;
    vector<float> default_goal_sensors(3,0.0);
    goal_sensors = default_goal_sensors;
    goal_line_of_sight = false;
    }
laser_robot(float start_x,float start_y,float
start_ang){ //Constructor - given starting position
dia = 1;
max_vel = .5;
position[0] = start_x;
position[1] = start_y;
position[2] = start_ang;
left_wheel = 0;
right_wheel = 0;
vector<float> default_lasers(8,0.0);
lasers = default_lasers;
vector<float> default_goal_sensors(3,0.0);
goal_sensors = default_goal_sensors;
goal_line_of_sight = false;
}
laser_robot(int l_s,float start_x,float start_y,float
start_ang){ //Constructor - laser size given starting
position
dia = 1;
max_vel = .5;
position[0] = start_x;
position[1] = start_y;
position[2] = start_ang;
left_wheel = 0;
right_wheel = 0;
vector<float> default_lasers(l_s,0.0);
lasers = default_lasers;
vector<float> default_goal_sensors(3,0.0);
goal_sensors = default_goal_sensors;
goal_line_of_sight = false;
}
laser_robot(float d,float v,int l_s){ //Constructor - к
given diameter, max velocity and laser size
dia = d;
max_vel = v;
position[0] = 0;
position[1] = 0;
position[2] = 0;
left_wheel = 0;
right_wheel = 0;
vector<float> default_lasers(l_s,0.0);
lasers = default_lasers;
vector<float> default_goal_sensors(3,0.0);
goal_sensors = default_goal_sensors;

```
```

    goal_line_of_sight = false;
    ```
    \}
    laser_robot(float d,float v,int l_s,float start_x,
    float start_y,float start_ang)\{ //Constructor - given
    diameter, max velocity, sensor info, and starting
    position
        dia = d;
        max_vel = v;
        position[0] = start_x;
        position[1] = start_y;
        position[2] = start_ang;
        left_wheel = 0;
        right_wheel = 0;
        vector<float> default_lasers(l_s,0.0);
        lasers = default_lasers;
        vector<float> default_goal_sensors(3,0.0);
        goal_sensors = default_goal_sensors;
        goal_line_of_sight = false;
    \}
    laser_robot(float d,float v,int l_s,float start_x,
    float start_y,float start_ang,float left_vel,float
    right_vel)\{ //Constructor - given diameter, max
    velocity, sensor info, starting position and velocity
    dia = d;
    max_vel = v;
    position[0] = start_x;
    position[1] = start_y;
    position[2] = start_ang;
    left_wheel = left_vel;
    right_wheel = right_vel;
    vector<float> default_lasers(l_s,0.0);
    lasers = default_lasers;
    vector<float> default_goal_sensors(3,0.0);
    goal_sensors = default_goal_sensors;
    goal_line_of_sight = false;
    \}
    void operator= (const laser_robot\& right)\{
    if (this != \&right)\{
        dia = right.dia;
        max_vel = right.max_vel;
        position[0] = right.position[0];
        position[1] = right.position[1];
        position[2] = right.position[2];
        left_wheel = right.left_wheel;
        right_wheel = right.right_wheel;
        lasers = right.lasers;
        goal_sensors = right.goal_sensors;
        goal_line_of_sight = right.goal_line_of_sight;
        \}
    \}
    float get_diameter()\{
        return(dia);
    \}
    float get_max_velocity()\{
        return(max_vel);
    \}
    float get_x()\{
        return(position[0]);
    \}
    float get_y()\{
        return(position[1]);
    \}
    float get_heading() \{
        return(position[2]);
    \}
void set_position(float x, float y,float ang)\{
    position[0] \(=x\);
    position[1] = y;
    position[2] \(=\) ang;
    \}
    float get_left_wheel() \{
        return(left_wheel);
    \}
    void set_left_wheel(float x)\{
        left_wheel = x;
    \}
    float get_right_wheel()\{
        return(right_wheel);
    \}
    void set_right_wheel(float x)\{
        right_wheel = x;
    \}
    void get_goal_sensors(vector<float>\& s)\{
        s = goal_sensors;
    \}
    void set_goal_sensors(vector<float> s)\{
        goal_sensors = s;
    \}
    int get_number_of_goal_sensors()\{
        int temp_int = goal_sensors.size();
        return(temp_int);
    \}
    void get_lasers(vector<float>\& l)\{
        l = lasers;
    \}
    void set_lasers(vector<float> l)\{
        lasers = l;
    \}
    int get_number_of_lasers()\{
        int temp_int = lasers.size();
        return(temp_int);
    \}
    void set_goal_visible_on()\{
        goal_line_of_sight = true;
    \}
    void set_goal_visible_off()\{
        goal_line_of_sight = false;
    \}
    bool get_goal_visible()\{
        return(goal_line_of_sight);
    \}
\};

    ---- -

    class simulation_world
    \{private:
    vector<vector<float\gg obstacles;
    vector<laser_robot> laserbots;
    vector<signal_robot> sigbots;
    public:
        simulation_world() \{
        \}
        simulation_world(vector<vector<float\gg obs)\{ //
    Constructor - given the obstacles
        for(int i=0;i<obs.size();i++)\{
                            //Makes sure obstacles have an even number of \(\boldsymbol{K}\)
    coordinates and there are at least 3 of them
            assert((obs[i].size()\%2)==0);
            assert(obs[i].size() >= 6);
        \}
        obstacles = obs;
        laserbots.clear();
        sigbots.clear();
    \}
    simulation_world(vector<float> obs)\{ //Constructor - K
    given one obstacle
        //Makes sure obstacle has an even number of
    coordinates and there are at least 3 of them
        assert((obs.size()\%2)==0);
        assert(obs.size() >= 6);
        obstacles.clear();
        obstacles.push_back(obs);
        laserbots.clear();
        sigbots.clear();
    \}
    simulation_world(vector<laser_robot> bots)\{ //
    Constructor - given the laser robots
        obstacles.clear();
        laserbots = bots;
        sigbots.clear();
    \}
```

simulation_world(vector<signal_robot> bots){ //
Constructor - given the signal robots
obstacles.clear();
laserbots.clear();
sigbots = bots;
}
simulation_world(vector<laser_robot> lbots, vector
<signal_robot> sbots){ //Constructor - given the laser <
and signal robots
obstacles.clear();
laserbots = lbots;
sigbots = sbots;
}
simulation_world(vector<vector<float> > obs, vector
<laser_robot> lbots, vector<signal_robot> sbots){ //
Constructor - given the obstacles and robots
for(int i=0;i<obs.size();i++){
//Makes sure obstacles have an even number of
coordinates and there are at least 3 of them
assert((obs[i].size()%2)==0);
assert(obs[i].size() >= 6);
}
obstacles = obs;
laserbots = lbots;
sigbots = sbots;
}
void operator= (const simulation_world\& right){
if (this != \&right){
obstacles = right.obstacles;
laserbots = right.laserbots;
sigbots = right.sigbots;
}
}
void build_obstacle(vector<float> obs){
//Makes sure obstacle has an even number of
coordinates and there are at least 3 of them
assert((obs.size()%2)==0);
assert(obs.size() >= 6);
obstacles.push_back(obs);
}
void build_obstacle(float obs[],int obs_size){
//Makes sure obstacle has an even number of
coordinates and there are at least 3 of them
assert((obs_size%2)==0);
assert(obs_size >= 6);
vector<float> new_obstacle;
for(int i=0;i<obs_size;i++){
new_obstacle.push_back(obs[i]);
}
obstacles.push_back(new_obstacle);
}
void build_obstacle(const float obs[],int obs_size){

```
        //Makes sure obstacle has an even number of
        coordinates and there are at least 3 of them
        assert((obs_size\%2)==0);
        assert(obs_size >= 6);
        vector<float> new_obstacle;
        for(int i=0;i<obs_size;i++)\{
            new_obstacle.push_back(obs[i]);
        \}
        obstacles.push_back(new_obstacle);
\}
int no_of_obstacles() \{
    return(obstacles.size());
\}
void get_obstacle(int n, vector<float>\& obs)\{
    assert(n<obstacles.size());
    obs.clear();
    obs = obstacles[n];
\}
void get_all_obstacles(vector< vector<float\gg\& obs)\{
    obs = obstacles;
    \}
void clear_all_obstacles()\{
    obstacles.clear();
\}
void clear_internal_obstacles()\{
    vector<float> border = obstacles[0];
    obstacles.clear();
    obstacles.push_back(border);
\}
int get_no_of_laser_robots() \{
    return(laserbots.size());
    \}
void add_laser_robot(laser_robot new_bot)\{
    laserbots.push_back(new_bot);
    \}
    void add_signal_robot(signal_robot new_bot)\{
    sigbots.push_back(new_bot);
    \}
    void move_laser_robot(int n,float x,float y,float ang) \(反\)
    \{
        assert(n<laserbots.size());
        laserbots[n].set_position(x,y,ang);
    \}
    void update_laser_bot_actuators(int n,float x1,float 反
    x2) \{
        assert(n<laserbots.size());
        laserbots[n].set_left_wheel(x1);
        laserbots[n].set_right_wheel(x2);
    \}
    void move_signal_robot(int n,float \(x, f l o a t ~ y)\{\)
    assert(n<sigbots.size());
    sigbots[n].set_position( \(x, y\) );
\}
laser_robot get_laser_robot(int n)\{
    assert(n<laserbots.size());
    return(laserbots[n]);
    \}
    signal_robot get_signal_robot(int n)\{
    assert(n<sigbots.size());
        return(sigbots[n]);
    \}
    void clear_all_laser_robots()\{
    laserbots.clear();
    \}
    void clear_all_signal_robots()\{
        sigbots.clear();
    \}
    void clear_all_robots()\{
        laserbots.clear();
        sigbots.clear();
    \}
    bool update_world(float dt)\{
        //Gets actuator states and moves each bots, then \(\boldsymbol{K}\)
        updates sensor states for each bot.
        laser_robot bot, bot_2;
        vector<float> obs;
        bool collision;
        //The following vectors are labeled in Vol 4 pg 10 k
        - 13
            float diameter, v1, v2, x,y,heading,r;
    float alpha,gamma,beta, theta; //Used for
determining new states
    float test_x, test_y, bot_2x, bot_2y;
    //The following vectors are labeled in Vol 3 pg 98
    float p0x, p0y, p1x, p1y, p2x, p2y,bx,by, ax, ay, A;
        //The following vectors are labeled in Vol 3 pg 95 к
        \& 100
            float lx, ly, lpx, lpy, v1x, v1y, v2x, v2y, hx, hy, range,
        test_range, phi;
        //The following vectors are labeled in Vol 4 pg と
        109
        float \(n x, n y ;\)
        int ob_hit; //Used for debugging
        int no_lasers;
        vector<float> new_lasers;
        int no_goal_sensors = bot.
        get_number_of_goal_sensors();
        assert(no_goal_sensors==3); //As of now, logic k
        works ONLY if there are 3 sensors
        vector<float> new_goal_sensors(no_goal_sensors,0. к
        \(0)\);
            float sx,sy, sensor_angle,goal_dist, swarmx, swarmy;
    bool swarm_sees_goal;
    int no_of_swarm_sees_goal;
            for(int i=0;i<laserbots.size();i++)\{
            collision = false;
            //Getting actuator states
            bot = laserbots[i];
            diameter = bot.get_diameter();
            \(r=\) diameter/2;
            v1 = dt*bot.get_left_wheel();
            v2 = dt*bot.get_right_wheel();
            \(x=\) bot.get_x();y = bot.get_y();heading = bot. \(k\)
    get_heading();
                            //Finds new spot - logic on Vol 4 pg. 10 - 13
                            \(\operatorname{assert}\left(\left(1-((\mathrm{v} 1-\mathrm{v} 2) *(\mathrm{v} 1-\mathrm{v} 2)) /\left(2^{*}\right.\right.\right.\) diameter \(\left.\left.)\right)>=-1\right) k\)
;
    assert((1-((v1-v2)*(v1-v2))/(2*diameter))<=1);
    alpha \(=\operatorname{acos}\left(1-((\mathrm{v} 1-\mathrm{v} 2) *(\mathrm{v} 1-\mathrm{v} 2)) /\left(2^{*}\right.\right.\) diameter* \(k\)
diameter));
    //Accounts for CW or no rotations
    if(v1==v2) \{
                alpha \(=0\);
    \}else if(v1>v2)\{
                alpha = -alpha;
    \}
    gamma \(=\) atan2(-cos(heading), sin(heading));
    beta \(=(p i()-f a b s(a l p h a)) / 2\);
    if(v1 > v2) \{
                theta \(=\) gamma + beta;
    \}
    else\{
        theta \(=\) gamma + pi() - beta;
    \}
    test_x \(=x+\left(v 1^{*} \cos (\right.\) theta \()+v 2^{*} \cos (\) theta) \() / 2 k\)
    ; //New test position
    test_y \(=y+\left(v 1^{*} \sin (t h e t a)+v 2 * \sin (t h e t a)\right) / 2 k\)
    ;
    heading = heading + alpha; //New heading.
    Robot can always turn even if it hits an obstacle
    //The follow ensure heading is within +/- pi
    while(heading > pi()) \{
        heading -= 2*pi();
    \}
    while(heading <= -pi())\{
        heading += 2*pi();
    \}
    //Check to make sure new spot isn't within an \(\boldsymbol{\kappa}\)
        obstacle
            //Logic on Vol 3 pg 97-98
            p0x = test_x; p0y = test_y;
            for(int j=0;j<obstacles.size();j++)\{
                if(collision) \{
                    break;
        \}
        obs = obstacles[j];
            for(int k=0;k<obs.size();k+=2)\{
        if((k+3)<obs.size())\{
            \(\mathrm{p} 1 \mathrm{x}=\mathrm{obs}[\mathrm{k}]\);
            p1y \(=\) obs \([k+1] ;\)
            p2x = obs \([k+2] ;\)
            p2y = obs[k+3];
        \}
        else\{
            p1x = obs[k];
            p1y = obs[k+1];
            p2x = obs[0];
            p2y = obs[1];
            \}
            bx = p2x - p1x;
            by = p2y - p1y;
            gamma \(=\left(\left(b x^{*} p 0 x+b y * p 0 y\right)-\left(b x^{*} p 1 x+b y *\right.\right.\)
p1y))/(bx*bx+by*by);
            if \(((0<\) gamma \() \& \&(\) gamma<1) \()\{\)
                //Bot may hit the wall
                        \(a x=p 1 x+g a m m a * b x-p 0 x ;\)
                        ay = p1y + gamma*by - p0y;
                A = ax*ax + ay*ay;
            if ( \(\left.\mathrm{A}<\left(\mathrm{r}^{*} \mathrm{r}\right)\right)\{\)
                collision = true;
                /*
                cout<<"COLLISION!"<<endl;
                cout<<"Robot "<<i<<" hit
obstacle "<<j;
defined at (";
                                    cout<<" wall with verticies
                                    cout<<p1x<<", "<<p1y<<") and (" к
<<p2x<<", "<<p2y<<")"<<endl;
                                    */
            \}
            \}
            else\{
                //Bot may still hit a vertex
            ax = p0x - p1x; ay = p0y - p1y;
            \(\mathrm{A}=\mathrm{ax*} \mathrm{ax}+\mathrm{ay*} \mathrm{ay}\);
            if ( \(\left.\mathrm{A}<\left(\mathrm{r}^{*} \mathrm{r}\right)\right)\{\)
                                    collision = true;
                    /*
                    cout<<"COLLISION!"<<endl;
                    cout<<"Robot "<<i<<" hit
obstacle "<<j;
                    cout<<" at vertex ("<<p1x<<"," к
<<p1y<<")"<<endl;
                    */
                    \}
                    ax = p0x - p2x; ay = p0y - p2y;
                    A = ax*ax + ay*ay;
                    if \((A<(r * r))\{\)
                collision = true;
                    /*
                    cout<<"COLLISION!"<<endl;
                        cout<<"Robot "<<i<<" hit
obstacle "<<j;
<<p2y<<")"<<endl;
                            cout<<" at vertex ("<<p2x<<","
                        */
                    \}
                    \}
                \}
            \}
                //Checks to make sure it won't hit another ц
robot
                                for(int \(j=0 ; j<l a s e r b o t s . s i z e() ; j++)\{\)
                if(i!=j)\{
                bot_2 = laserbots[j];
                    bot_2x = bot_2.get_x();bot_2y = bot_2.
get_y();
                    ax = test_x - bot_2x;
                    ay = test_y - bot_2y;
                    A = ax*ax + ay*ay;
                    if \(\left(A<\left(4^{*} r * r\right)\right)\{\)
                                    collision \(=\) true;
                                    /*
                                    cout<<"COLLISION!"<<endl;
                                    cout<<"Robot "<<i<<" hit Robot "< と
<j<<endl;
                                */
                    \}
            \}
        \}
        if(!collision) \{
                        x = test_x; y = test_y;
        \}
        laserbots[i].set_position(x,y,heading);//
    Updates the robot's position
        \}
        //After each bot has moved, the sensors of each
bot are updated
    for(int i=0;i<laserbots.size();i++)\{
pg 95 \& 100
                                    //cout<<"Robot: "<<i<<endl;
                                    bot = laserbots[i];
                                    no_lasers = bot.get_number_of_lasers();
            new_lasers.clear();
            new_lasers.resize(no_lasers);
            phi = pi()/(no_lasers+1);
            \(p 0 x=\) bot.get_x(); p0y = bot.get_y();
            heading = bot.get_heading();
```

for(int j=0;j<no_lasers;j++){
theta = heading + pi()/2 - (j+1)*phi;

```
    \(l x=\cos (t h e t a) ; l y=\sin (t h e t a) ;\)
    \(l p x=-\sin (t h e t a) ; l p y=\cos (t h e t a) ;\)
    range = RAND_MAX;
    ob_hit = -1;
    //Checks obstacles
    for(int \(k=0 ; k<o b s t a c l e s . s i z e() ; k++)\{\)
        obs = obstacles[k];
        for (int \(m=0 ; m<o b s . s i z e() ; m+=2)\{\)
        if( (m+3)<obs.size())\{
                                    p1x = obs[m];
                                    p1y = obs[m+1];
                                    \(p 2 x=o b s[m+2]\);
                            \(\mathrm{p} 2 \mathrm{y}=\mathrm{obs}[\mathrm{m}+3]\);
        \}
        else\{
                p1x = obs[m];
                p1y = obs[m+1];
                p2x = obs[0];
                p2y = obs[1];
            \}
                v1x = p1x-p0x; v1y = p1y-p0y;
                \(v 2 x=p 2 x-p 0 x ; v 2 y=p 2 y-p 0 y ;\)
            if(((lpx*v1x+lpy*v1y)*(lpx*v2x+lpy к
                    *v2y ) )<=0 ) \{
\(+1 p y * v 2 y)\) ) \(==0\) ) \{
                                if(((lpx*v1x+lpy*v1y)*(lpx*v2x
\(\&((1 p x * v 2 x+l p y * v 2 y)==0))\{\)
                    \(i f(((l p x * v 1 x+l p y * v 1 y)==0) \& ~ k\)
                    test_range \(=\) min((v1x* \(\boldsymbol{k}\)
v1x+v1y*v1y),(v2x*v2x+v2y*v2y));
(test_range, 0.5)) \{
                    if(range > pow
                        range \(=\) pow
(test_range, 0.5);
\[
\{
\]
;
\}
\[
==0 \text { ) \{ }
\]
v1x+v1y*v1y), 0.5);
else if ((lpx*v1x+lpy*v1y) ட
test_range \(=\) pow ( \(\left(v 1 x^{*}\right.\) к
if(range > test_range) \(\swarrow\) range \(=\) test_range \(\kappa\)
        ob_hit = k;
\}

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C:\Documents and Settings\...\robot_lib_omega6.h
\}
else if ((lpx*v2x+lpy*v2y) と
\[
==0 \text { ) \{ }
\]
                            test_range \(=\) pow ((v2x* \(\kappa\)
\[
v 2 x+v 2 y * v 2 y), 0.5) ;
\]
                    if(range > test_range) \(\swarrow\)
\[
\{
\]
                range \(=\) test_range \(\swarrow\)
;
                                    ob_hit = k;
                                    \}
                            \}
                    \}
                    else\{
                            \(h x=v 2 x-v 1 x ; h y=v 2 y-v 1 y\) к
;
                            test_range \(=(v 1 x * h y-v 1 y *\)
\[
h x) /(l x * h y-l y * h x) ;
\]
                            if((range > test_range)\&\& \(\swarrow\)
\[
(\text { test_range>0)) \{ }
\]
                            range = test_range;
                            ob_hit = k;
                            \}
                                    \}
                \}
            \}
                \}
                //Checks other robots
                    for(int k=0;k<laserbots.size();k++)\{
                    if(k!=i) \{
                    \(n x=\) laserbots[k].get_x();
                    ny \(=\) laserbots[k].get_y();
                    test_range \(=\left(l x^{*}(n x-p 0 x)+l y *(n y-\right.\)
p0y) )/(lx*lx+ly+ly);
                    \(a x=n x-p 0 x-t e s t \_r a n g e * l x ;\)
                    ay = ny - p0y - test_range*ly;
                    if \(\left(\left(\left(a x^{*} a x+a y * a y\right)<\left(r^{*} r\right)\right) \& \&(r\right.\) ange \(>\)
test_range)\&\&(test_range>0))\{
                                    range = test_range;
                                    ob_hit = k;
                    \}
            \}
            \}
            if (range == RAND_MAX) \{
                    cout<<"WARNING: Laser "<<j<<" did not 反
detect any obstacles"<<endl;
                    new_lasers[j] = 0;
                    \}
                    else\{
            new_lasers[j] = range;
\}
/*
<endl;
lx<<" "<<range*ly<<"]"<<endl;
*/
\}
laserbots[i].set_lasers(new_lasers); //Goal sensors are updated p1x = sigbots[0].get_x(); p1y = sigbots[0].get_y(); sx = p1x - p0x; sy = p1y - p0y; goal_dist = pow((sx*sx+sy*sy),0.5); //Finds if goal is within robot line of sight theta \(=\) atan2(sy, sx);
\(l x=\cos (t h e t a) ; l y=\sin (t h e t a) ;\) lpx = -sin(theta); lpy = cos(theta);
range = RAND_MAX;
ob_hit = -1;
for (int \(\mathrm{j=0}\); \(\mathrm{j}<\mathrm{obstacles.size();j++)} \mathrm{\{ }\)
obs = obstacles[j];
for(int \(\mathrm{m}=0\); \(\mathrm{m}<\mathrm{obs}\).size(); \(\mathrm{m}+=2\) ) \{
if((m+3)<obs.size())\{
p1x = obs[m];
p1y = obs[m+1];
p2x = obs[m+2];
p2y = obs[m+3];
\}
else\{
p1x = obs[m];
p1y = obs[m+1];
p2x = obs[0];
p2y = obs[1];
\}
v1x = p1x-p0x; v1y = p1y-p0y;
\(\mathrm{v} 2 \mathrm{x}=\mathrm{p} 2 \mathrm{x}-\mathrm{p} 0 \mathrm{x} ; \mathrm{v} 2 \mathrm{y}=\mathrm{p} 2 \mathrm{y}-\mathrm{p} 0 \mathrm{y}\);
if(((lpx*v1x+lpy*v1y)*(lpx*v2x+lpy* K
v2y) )<=0) \{
*v2y) \(==0\) ) \{
if(((lpx*v1x+lpy*v1y)*(lpx*v2x+lpy k
\((l p x * v 2 x+l p y * v 2 y)==0)\) ) \{
if(((lpx*v1x+lpy*v1y)==0)\&\&(
v1y*v1y), (v2x*v2x+v2y*v2y));
test_range = min((v1x*v1x+ \(\kappa\)
if(range > pow(test_range, \(k\) 0.5))\{
,0.5);
```

                    ob_hit = j;
        }
        }
        else if ((lpx*v1x+lpy*v1y)==0) <
    {
    v1y*v1y),0.5);
    {
    v2y*v2y),0.5);
        else if ((lpx*v2x+lpy*v2y)==0)k
            test_range = pow((v2x*v2x+ к
            if(range > test_range){
            range = test_range;
                            ob_hit = j;
                            }
            }
        }
            else{
                hx = v2x-v1x; hy = v2y-v1y;
                test_range = (v1x*hy-v1y*hx)/k
    (lx*hy-ly*hx);
(test_range>0)){
if((range > test_range)\&\&
range = test_range;
ob_hit = j;
}
}
}
}
}
if(range < goal_dist){
laserbots[i].set_goal_visible_off();
}
else{
laserbots[i].set_goal_visible_on();
}
if(laserbots[i].get_goal_visible()){//If it
can see the goal, go to it
sensor_angle = atan2(sy,sx) - heading;
//The follow ensure sensor_angle is within к
+/- pi
while(sensor_angle > pi()){
sensor_angle -= 2*pi();
}
while(sensor_angle <= -pi()){

```
                    sensor_angle += 2*pi();
            \}
            //cout<<"sensor_angle = "<<(sensor_angle*
180/pi())<<endl;
            if(fabs(sensor_angle)<=pi()/8)\{
                                    new_goal_sensors[0] = 0;
                                    new_goal_sensors[1] = 1;
            new_goal_sensors[2] = 0;
            \}
            else if(sensor_angle < 0) \{
                    assert (fabs(sensor_angle) \(>\) pi()/8);
                    new_goal_sensors[0] \(=0\);
                    new_goal_sensors[1] = 0;
            new_goal_sensors[2] = 1;
            \}
            else if(sensor_angle > 0)\{
                    assert(fabs(sensor_angle)>pi()/8);
                    new_goal_sensors[0] = 1;
                    new_goal_sensors[1] = 0;
            new_goal_sensors[2] \(=0\);
            \}
        \}
        else\{
            swarm_sees_goal = false;
            no_of_swarm_sees_goal = 0;
            swarmx = 0;
            swarmy = 0;
            for(int j=0;j<laserbots.size();j++)\{//See
if others see the goal...
                                if(laserbots[j].get_goal_visible()) \{
                        swarm_sees_goal = true;
                    no_of_swarm_sees_goal++;
                    swarmx += laserbots[j].get_x();
                    swarmy += laserbots[j].get_y();
            \}
            \}
            if(swarm_sees_goal)\{ //If so, go to center \(\boldsymbol{\swarrow}\)
        of others
        assert(no_of_swarm_sees_goal != 0);
        swarmx = swarmx/float
(no_of_swarm_sees_goal) - p0x; //Gives relative
position
    swarmy = swarmy/float
    (no_of_swarm_sees_goal) - p0y; //Gives relative K
                            \(K\)
position
    heading;
        within +/- pi
        sensor_angle = atan2(swarmy,swarmx) - \(\boldsymbol{\kappa}\)
        //The follow ensure sensor_angle is
    while(sensor_angle > pi())\{

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```

