**Application Of Neural Networks To Robot Animals**

**Final Project CS547**

Matthew A. Letter

&

Lin sun

University of New Mexico

Neural Networks 547

mletter1@unm.edu

sun@unm.edu

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# Abstract(Todo)

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# 1. Introduction(Todo)

This paper rigorously establishes that neural network design models can be used to manipulate learning on simulated biological system. All the research was done using professor Thomas Caudell’s animal robot environmental model. ADDIN EN.CITE <EndNote><Cite><Author>Thomas Caudell</Author><DisplayText> (Caudell)</DisplayText><record><ref-type name="Generic">13</ref-type><contributors><authors><author>Thomas Caudell</author></authors></contributors><titles/><title>Flatworld</title><periodical/><dates><year/><pub-dates/></dates></record></Cite></EndNote> (Caudell) The research involved 9 architectures, used to establish the parameters of life with respect to the simulated organism and its environment. These provide a basis for analyzing the implemented neural network algorithms, the goal of which is to create a “neuron” based brain for the robot organism to live as long as possible in its environment, and determine what neuronal design structures degrade or enhance this attribute.

# 2. Approach

### 2.1 Architecture 0: No movement, measure lifetime

For the first architecture, we will test the basic metabolic consumption for the robot. The robot’s speed was set to 0; therefore the robot was programmed to do nothing until it dies. Finally the lifespan was measured for analysis of the basic metabolic consumption.

### 2.2 Architecture 1: Movement, measure lifetime as a function of speed without eating food

This test is designed to explore the effect of the robots speed variation on its run lifespan and varying the robots direction correlated to lifespan. The goal of this experiment is to determine a correlation between the speed of the robot and its metabolism. Furthermore, the direction change should yield insight into the world around the robot. The robot will start at the same position where the direction and speed will be varied. To try test different directions, we will turn the neuron head to 5 degree counter-clockwise each time. When the neuron is moving, it will always head to the brightest object in the space, no matter if the food is poisonous or not. The robot will be set to eat nothing in the world.

### 2.3 Architecture 2: Movement, measure lifetime as a function of speed with eating food

This test is designed to explore the effect eating on robot’s lifetime. This is different from Architecture 1 in that neuron will eat all of the food it encounters. When the robot is moving, it will always head to the brightest object in the space, no matter what type of object it is. To get a well-distributed random speed, the initial robot head angle will be changed for each run, but the initial position will be held constant at the point of origination. Actually, this architecture will generate the control experiment for the future architectures. For a new architecture, we need to test if it works well. So we need use the control experiment for comparison to decide if new architecture improve the lifespan for the robot.

### 2.4 Architecture 3: Neuronal Classification of food using Food RGB Values

This test will do classification of food as either good or bad based on whether the food could increase or decrease energy of the robot using LMS neuron architecture. Fig 1 shows the frame for the classification neuron, where the inputs are visual readings as RGB values and output is 0 or 1. If the food increases the energy of the robot, the food is classified as good and the neuron output is 1; otherwise, we say that the food is bad and the output is 0 now. For a simple starting neural architecture an LMS neuron is used to classify the food. It is known that, in order to classify the objects, we should know the weights for classification neuron. Therefore, in this architecture, we will use the objects encountered by the robot to train classification neuron. To pick up objects randomly, we will change the head direction each time, so that the objects encountered by the robot is randomized. The learning rate of classification neuron is 0.01, while the stopping criteria for training is when RMS change between two consecutive life times is less than 0.00000001 or the life time is greater than 3000 to avoid infinite loop.



Fig 1: Network diagram of the LMS neuron for classifying food

### 2.5 Architecture 4: Neuronal Movement towards brightest object

The goal of this architecture is to let the robot move towards the brightest object using a winner-takes-all neuronal network implementation. In our design, movement is the next logical step after classification of food since robot has to have a way of moving toward objects. In order to give the robot the ability to seek out objects a direction neuron will be added that will make a direction choice.

In this architecture, The neuron will choose the direction based on the incoming light intensity. It is known that the light intensity is inversely related to the distance between the robot and an object, which means that objects having higher light intensity are closer to the robot than other objects with lower light intensity. In the simulation world, the robot wants to survive for as long as possible. Therefore, it should try to move towards the objects in the world closest to it. First, to compare the intensity of different lights, we need have a function to calculate the intensity of the light. Equation 1.1 shows how to calculate the intensity of lights based on its RGB values. Based on the thought process above, a neuron with frame in Fig 2 will be implemented. Actually it is a two-layers neuron structure, where the inputs for the neuron are RGB lights bands from 31 directions, while the output is the angle of the lightest object with respect to the horizontal line. The first layer neuron is used to calculate the intensity for each input, and the second layer neuron will pick up the input which generate the highest intensity. So the direction that the robot will change towards is the direction chose by direction neuron based on light intensity.

(eq 1.1)(Todo)



Fig 2: This is a three layer neural network where the RGB circles denote the intensity signal bands being received by the first layer. The second layer is a winner-take all network which selects the brightest cone. The third layer is a neuron, which computes the angle change for movement

### 2.6 Architecture 5: Move robot based on intensity and eat based on classification

Fig 3 shows the frame for architecture 5, where we will integrate classification neuron and direction neuron. Each time the robot stops, classification neuron is activated to classify the objects encountered by the robot. If the objects are not poisonous, the robot will eat it. Otherwise, the robot will just skip the objects. After that, direction neuron is activated to pick up the direction with highest intensity, so that the robot will move towards that direction. If direction neuron can’t find any object, the robot will rotate 45 degree clockwise and then move towards that direction. Because the neuron could classify the objects, the robot will not eat poisonous objects. Therefore, the robot will not waste energy on poisonous objects, which means that robot in this architecture should have larger average lifespan than the robot in architecture 2.



Fig 3: Network diagram of the LMS neuron for classifying food with the caveat of normalized inputs

### 2.7 Architecture 6: Neuronal Classification of food using Food RGB Percentage

In architecture 3, we use RGB values to classify objects. However this does not address a certain problem subset, as robot moves farther away from an object, the light value for that object is decreased uniformly over each signal band. The un-normalized input of RGB values cannot be trusted to classify objects, due to this fact. Moreover, when the robot moves, it will pick up the direction with the highest intensity light value based on equation 1.1. However, it is possible that the direction picked up by direction neuron will lead the robot to poisonous objects; this is because direction is currently only based on the intensity of light not what type of object is producing the light. Therefore, we need to implement a smart direction neuron, which can move towards the direction with the closest nonpoisonous object. To solve this problem we need implement a classification neuron which can classify objects regardless of the distance. Thus, a new classification neuronal network will be created that takes normalized RGB values and classifies these values as either good or bad based on the frame in Fig 4. Similar to classification in architecture 3, the inputs are normalized RGB values instead of original RGB values. The output is 0 or 1. If the objects can increase the energy, the output is 1; otherwise, it is 0. Equation 1.2 is used to normalized RGB values in this architecture. In this architecture, we will train the new classification neuron using objects encountered by the robot. To randomize the objects encountered by the robot, we will change the head direction each time. The learning rate for the classification neuron is still 0.01 while the stopping criteria is when RMS change between two consecutive life time is less than 0.00000001 or the life time is greater than 300 to avoid infinite loop.

(Eq 1.2)(Todo)



Fig 4: Representation of the normalized classification approach

### 2.8 Architecture 7: Eat Objects based on Neuron Classification using RGB Percentage and Choose Direction based on Light Intensity and Classification

In architecture 6, we implements a new classification neuron, which can classify the light based on normalized RGB values. Therefore, for the object to eat, we can ignore the distance factor. It is known that the robot wants to move towards the direction where the objects are closest to it and are non-poisonous. Therefore, we need to implement a upgraded direction neuron, which can select the direction with highest light density and the light is classified as non-poisonous. Fig 5 shows two kinds of neurons we will implement for the robot. To make it easier, we will integrate new classification neuron with direction neuron to make a smarter direction neuron. Each time when the direction checks a light, the classification neuron will classify the neuron first. Then we will multiply the output by classification by the intensity output from first layer direction neuron. Therefore, if the light is classified as poisonous, the intensity is set as 0. So the light which smart direction neuron picks up has the highest intensity and also non-poisonous. Therefore, like architecture 5, each time the robot stops, classification neuron is activated to classify the objects encountered. If it is poisonous, the robot just skip it. Otherwise, the robot will eat it. Then smart direction neuron is activated to choose a direction to move. If there is no suitable direction made from direction neuron, the robot will rotate 45 degrees clockwise, and move towards that direction.



Fig 5: Network diagram of the LMS neuron for classifying food with pre-classification before winners take all network layers.

### 2.9 Architecture 8: Eat Objects with Small Mouse based on Neuron Classification using RGB Percentage and Choose Direction based on Light Intensity and Classification

Fig 6 shows the shape of the robot we are controlling in the simulation world. When the robot stops, it will first use classification neuron to classify the objects it encounters. In the architecture, we use the middle light to classify objects, which is the beam in fig 6. However, when robot eat objects, it will eat objects on three sides. Therefore, a new problem comes. Are we sure that the objects on the other two sides are non-poisonous? If the objects on the other two sides are poisonous but the objects on side 0 are good. Then the robots will eat all objects, therefore, the robot is wasting energy on poisonous objects. So in this architecture, we will narrow down the mouse of the robot, so that it can only eat the objects on side 0, which can be classified directly by classification neuron.



Fig 6: Diagram of the new eat direction for the robot.

# 3. Results

### 3.1 Architecture 0: No movement, measure lifetime

| Table 1: Over 200 runs, every run of a stationary robot had a lifespan of 5001 cycles | | |
| --- | --- | --- |
| Speed Rate | Lifetime Mean (Cycles) | Lifetime Standard Deviation |
| 0 | 5001 | 0 |

From Table 1, we see that the robot life is 5001 cycles if it does not move and does not eat any food. The robot needs one cycle to jump out the loop initial start. So totally there are 5000 cycles of life given initially by the world to the robot at birth. Therefore, we could see that the basic metabolic rate should be 0.0002 unit/cycle.

### 3.2 Architecture 1: Movement, measure lifetime as a function of speed without eating food



Figure 7: Shows the max speed of the robot to be 0.1



Figure 8: Linear function of the life cycles with respect to the Robots speed.

From Figure 1, shows lifetime is directly correlated with the robot’s speed. When speed is less than 0.1 and increasing, then the lifetime of the robot has a nearly linear functional correlation with speed, where as speed increases, the lifetime is decreased. Furthermore, when the speed is over 0.1, the lifetime is constant. Therefore, the speed does not change, even though the speed is increasing. Changing the head angle originating from the same origin has limited effect on the life span of the robot, as the life span, with constant speed, showed no change. Therefore, the standard deviation for the lifetime at the same speed with head rotation is 0

### 3.3 Architecture 2: Movement, measure lifetime as a function of speed with eating food



Figure 9: Error bar graph of varying speeds and directions where the standard deviation is represented as bars and the trend line represents the mean.

| **Table 2: Robot lifetime mean and standard deviation for different speed rate for comparison with future architectures.** | | |
| --- | --- | --- |
| Speed Rate | Lifetime Mean (Cycles) | Lifetime Standard Deviation |
| 0.02 | 4541 | 884 |
| 0.04 | 4233 | 973 |
| 0.06 | 3517 | 849 |
| 0.08 | 3093 | 765 |
| 0.10 | 2861 | 832 |
| 0.12 | 2858 | 827 |
| 0.14 | 2858 | 827 |

Figure 3 shows the final result of lifetime vs. speed, with the robot eating food all food it encounters. Like Architecture 1, the lifetime is correlated with speed, further supporting our hypothesis from the previous architecture of their relation. As speed increases, the mean lifetime decreases. When the robots speed goes over 0.1, the mean lifetime is stabilized. There is a standard deviation greater than 0 for this architecture because the robot is eat everything it encounters which is effecting its life either positively or negatively based on the standard deviations range around the trend line lifespan mean.

### 3.4 Architecture 3: Neuronal Classification of food

| **Table 3: Root mean squared error (RMSE) vs. lifetime training result** | | | | |
| --- | --- | --- | --- | --- |
| Weight Index | 0 | 1 | 2 | 3 |
| Value | -0.0593627 | -0.0574903 | 0.643285 | -0.0570887 |

Fig 10 shows the training results for the classification neuron. We could see that at the beginning the RMS drops very quickly and dramatically. However, after a few cycles, the RMS values is stabilized but still tremble within 0.2 and 0.35. So we could see that the neuron is trained well after that. Table … shows the weight for the final trained neuron using RGB values. Therefore, in the following experience, we could use these weight to classify the objects robot meets and decide if robot should eat the objects or not.

Figure 10: Direction decision neuron checking with a 5o rotation change after each life. This graph shows the RMSE dropping from 0.9 to asymptote around 0.3 suggesting that the LSM neuron has learned to classify objects it has encountered.

### 3.5 Architecture 4: Neuronal Movement towards brightest object

In section 2.5, we postulated a theory about neuronal directionality decision-making. We now need to verify the neuronal algorithms correctness. There is an internally implemented function, called intensity\_winner\_takes\_all, which returns the index of the receptor that has the highest intensity. We will compare the result from our implementation of a neuronal function with that of the internally coded function to see if they have the same result. Figure 5 shows the result of this comparison. We can see that the neuron implemented here generates the same result as the internal functions. Therefore, our neuronal function yields the same result as the internally coded function.

Figure 11: Intensity receptor index comparison between the internal function and the implemented neuronal function.

### 3.6 Architecture 5: Eat objects based on neuronal classification

In this architecture, the neuron architecture will classify food will be eaten based on the classification. Also, a direction change will be made based on the network in figure 3.

| **Table 4: Robot lifetime mean and standard deviation for different speed rate for comparison with future architectures.** | | |
| --- | --- | --- |
| Speed Rate | Lifetime Mean (Cycles) | Lifetime Standard Deviation |
| 0.02 | 4353 | 878.8 |
| 0.04 | 4323 | 965.2 |
| 0.06 | 3709 | 963.7 |
| 0.08 | 3661 | 1044.4 |
| 0.10 | 4884 | 1661.2 |
| 0.12 | 4862 | 1644.7 |
| 0.14 | 4862 | 1644.7 |

Table 4 shows a significant improvement over the mean lifespan found in table 2. This is attributed to the classification of food before eating, thereby helping the robot selectively choose only food that is classified as good by the LMS neuron.



Figure 12: Standard deviation plotted as a line. We can see the standard deviation levels out once the speed is constant.



Figure 13: Intensity Receptor Index Comparison between the internal function and the implemented neuronal function. Note that the highest life span of the robot was 8000 and the minimum lifespan was 2500.

### 3.7 Architecture 6: Neuronal Classification of food using Food RGB Percentage

| Table 5 Classification Neuron Weights after training with normalized inputs | | | | |
| --- | --- | --- | --- | --- |
| Weight Index | 0 | 1 | 2 | 3 |
| Value | 0.0364013 | -0.462995 | 1.26562 | -0.833772 |



Figure 14: RMSE error drops as the LMS neuron adjusts its weights and learns how to classify objects found in its environment.

Normalization of the data appears to not be detrimental to the overall performance of the classification of incoming light based off figure 13. The large oscillation is hypothesized to be from classification of good food in front of the robot while there is bad food to the sides of the robot, since the robot classified the food as good all the food around it gets eaten. This will be addressed as a fine-tuning to architecture 7 with architecture 8. Take note that a biased input was included in the classification of the objects.

### 3. 8 Architecture 7: Eat Objects based on Neuron Classification using RGB Percentage

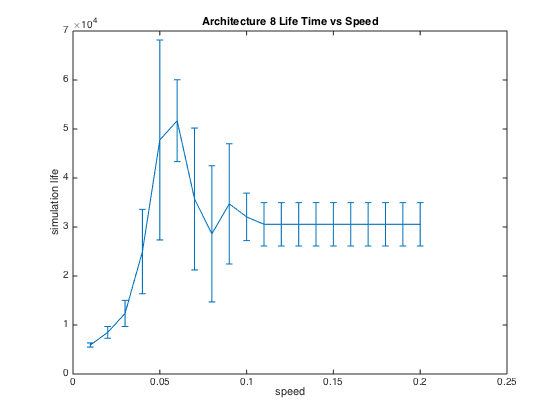
| Table 5 Robot Lifetime Mean and Standard Deviation for Different Speed Rate with Direction selection for food | | |
| --- | --- | --- |
| Speed Rate | Lifetime Mean (Cycles) | Lifetime Standard Deviation |
| 0.02 | 7337 | 1253 |
| 0.04 | 12763 | 4349 |
| 0.06 | 33165 | 15722 |
| 0.08 | 28193 | 11208 |
| 0.10 | 23935 | 9429 |
| 0.12 | 23911 | 9543 |
| 0.14 | 23911 | 9543 |
| 0.16 | 23911 | 9543 |
| 0.18 | 23911 | 9543 |
| 0.20 | 23911 | 9543 |



Figure 14: Mean lifespan trend line with standard deviation bars.

### 3. 9 Architecture 8: Eat Few Objects based on Neuron Classification using RGB Percentage

| Table 5 Robot Lifetime Mean and Standard Deviation for Different Speed Rate with Direction selection for food | | |
| --- | --- | --- |
| Speed Rate | Lifetime Mean (Cycles) | Lifetime Standard Deviation |
| 0.02 | 8491 | 1200 |
| 0.04 | 24987 | 8612 |
| 0.06 | 51701 | 8355 |
| 0.08 | 28601 | 13893 |
| 0.10 | 32059 | 4848 |
| 0.12 | 30550 | 4426 |
| 0.14 | 30550 | 4426 |
| 0.16 | 30550 | 4426 |
| 0.18 | 30550 | 4426 |
| 0.20 | 30550 | 4426 |



# 4. Discussion

# 5. Summaries and Conclusion

# 6. Acknowledgements

# 7. References

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1. Caudell, Thomas. "Flatworld."
2. Haykin, Simon S. *Neural Networks: A Comprehensive Foundation*. Upper Saddle River, NJ: Prentice Hall, 1999. Print

# 8. Appendix A

1. Perceptron.h

/\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*/

/\* Perceptron header file \*/

/\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*/

#ifndef PERCEPTRON

#define PERCEPTRON

typedef struct perceptron

{

int input\_num;

double \*weights;

double v;

double output;

double error;

int is\_inner\_neuron; /\*inner neuron has no error, but sigma instead\*/

void \*param; /\*Reserved variable for future use\*/

}perceptron;

/\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*/

/\* Global variable \*/

/\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*/

/\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*/

/\* Exportable functions \*/

/\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*/

void perceptron\_default(perceptron \*neuron);

void perceptron\_clear(perceptron \*neuron);

#endif

2. Perceptron.c

#include "Perceptron.h"

#include <stdlib.h>

/\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*/

/\* Exportable functions \*/

/\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*/

void perceptron\_default(perceptron \*neuron)

{

neuron->weights = (double \*)malloc(sizeof(double) \* (neuron->input\_num + 1));

}

void perceptron\_clear(perceptron \*neuron)

{

free(neuron->weights);

}

3. LMSAlgorithm.h

/\*

\* LMSAlgorithm.h

\*

\* Created on: Oct 24, 2014

\* Author: lin

\*/

#include "Perceptron.h"

#include <math.h>

#ifndef LMSALGORITHM\_H\_

#define LMSALGORITHM\_H\_

extern perceptron neuron\_brain;

extern double accumulated\_rms;

/\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*/

/\* Exportable functions \*/

/\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*/

int LMScalculate(float \*inputs, int input\_num, int isCal, float expected);

#endif /\* LMSALGORITHM\_H\_ \*/

4. LMSAlgorithm.c

/\*

\* LMSAlgorithm.c

\*

\* Created on: Oct 24, 2014

\* Author: lin

\*/

#define OUTPUT\_NUM 1

#define LEARNING\_RATE 0.01

#define NEURON\_NUM 1

#include "LMSAlgorithm.h"

#include "Perceptron.h"

int initialized = 0;

perceptron neuron\_brain;

double accumulated\_rms = 0;

float forwardspeed;

void v\_function(float\* inputs, struct perceptron\* p)

{

int it = 0;

p->v = 0;

p->v += p->weights[0];/\*Bias\*/

for(it = 0; it < p->input\_num; it++)

{

p->v += (inputs[it] \* p->weights[it+1]);

}

}

void y\_function(struct perceptron\* p)

{

p->output = p->v;

}

void adjust\_function(float\* inputs, struct perceptron\* p, void \*params)

{

double target =\*((double \*) params);

int idx = 0;

p->error = target - p->output;

p->weights[0] += (p->error \* 1 \* LEARNING\_RATE);/\*Bias\*/

for(idx = 0; idx < p->input\_num; idx++)

{

p->weights[idx+1] += (p->error \* inputs[idx] \* LEARNING\_RATE);

}

}

void initialize(int input\_num)

{

int idx = 0;

neuron\_brain.input\_num = input\_num;

perceptron\_default(&neuron\_brain);

/\*This part uses the old data\*/

neuron\_brain.weights[0] = 0.493975;

neuron\_brain.weights[1] = -0.658991;

neuron\_brain.weights[2] = 0.720632;

neuron\_brain.weights[3] = -0.144448;

/\*This part is used to train the neuron\*/

// for(idx = 0; idx <= input\_num; idx++)

// {

// neuron\_brain.weights[idx] = 0.1 \* (rand()%10);

// }

}

/\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*/

/\* Exportable functions \*/

/\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*/

int LMScalculate(float \*original\_inputs, int input\_num, int isCal, float expected)

{

int ret = 0;

double e = (double)expected;

float \*inputs = (float\*)malloc(input\_num \* sizeof(float));

memcpy(inputs, original\_inputs, sizeof(float) \* ( input\_num));

if(!initialized)

{

initialize(input\_num);

initialized = 1;

}

v\_function(inputs, &neuron\_brain);

y\_function(&neuron\_brain);

if(neuron\_brain.output > 0)

ret = 1;

if(isCal)

{

adjust\_function(inputs, &neuron\_brain, &e);

/\*Log rms\*/

accumulated\_rms += (pow(neuron\_brain.error, 2));

}

else

{

}

return ret;

}

void reset()

{

accumulated\_rms = 0;

}

5. DirectionControlNeuron.c

//

// DirectionControlNeuron.c

// FlatWorldIIV1.0ClassVersion\_dist2014

//

// Created by lin sun on 11/22/14.

// Copyright (c) 2014 lin sun. All rights reserved.

//

int set\_direction(WORLD\_TYPE \*world, AGENT\_TYPE \*agent, int eye\_idx)

{

VISUAL\_SENSOR\_TYPE \*\*eyes = agent->instate->eyes;

int num\_receptors;

int num\_bands;

int receptor\_idx = 0;

int band\_idx = 0;

int max\_receptor = -1 ;

float intensity = 0;

float maxintensity = 0;

float bodyx = 0;

float bodyy = 0;

float bodyh = 0;

int ret = 0;

num\_receptors = eyes[0]->nreceptors ;

num\_bands = eyes[0]->nbands ;

read\_visual\_sensor(world, agent) ;

extract\_visual\_receptor\_values\_pointer(agent, 0) ;

for(receptor\_idx = 0; receptor\_idx < num\_receptors; receptor\_idx++)

{

intensity = 0 ;

for(band\_idx = 0; band\_idx < num\_bands; band\_idx++)

intensity += eyes[0]->values[receptor\_idx][band\_idx] ;

ret = LMScalculate(eyes[0]->values[receptor\_idx], agent->instate->eyes[0]->nbands, 0, 0);

if(intensity > maxintensity && ret == 1)

{

max\_receptor = receptor\_idx;

maxintensity = intensity ;

}

}

return max\_receptor;

}

6. Controller.c