Modeling the Neo-Cortex

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***Abstract*— This paper is a study of one of the interesting and most ambiguous parts of the human body, that is the human brain. The concept of how the human brain functions, perceives and learn objects around the world, arrive at patterns out of the learned object to predict and understand new objects is always a burning question among researchers in various fields including neurology, psychology and developmental robotics. There have been various theories about the functioning of the brain by various researches; still we do not have a clear understanding of how the brain processes data, or what algorithm is behind the intelligence of the brain. This project is an attempt to understand how the neo-cortex arranges complex thought from experiences in the light of how a human infant tries to understand the new world around it and how the infant perceives an object and incorporates learning in the earlier phases of brain development.**

***Keywords*—**
Human brain, Development, learning, neo-cortex.

I. INTRODUCTION

The brain is the most complicated organ ever known in the history of human knowledge. Countless attempts have been made to understand how a brain functions with limited success. This understanding of brain is very important for the application in developmental robotics as the main aim is to incorporate human intelligence to machines and far beyond that.

The true complexity of the brain becomes evident when viewing it from a developmental perspective. The brain is an amazing thinking machine, starting with no inherent knowledge at birth [5], and developing this intrinsic intelligence, based on the characteristics that its body and environment has to offer. The dynamics of this automatic development of more and more structured thought along with how information is represented in the brain, are just a couple of the mysteries pertaining to how the brain works.

There has always been a gap between how a machine processes the worldly data and how the human brain perceives the data. For a long time it was assumed that the brain is similar to the CPU of the computer. While the CPU is just the processor, the human brain is capable of both processing and memory storage [1]. Similarly, automated tasks of image processing also process data in terms of exact coordinates and RGB values while the human brain process data in a totally different fashion.

If we are successful in understanding how objects are represented, and how the brain comes to represent those objects, we believe that it would be of great help to understand the functioning, and power of the brain. Successful results would also be a big asset to the world of developmental robotics in the interest of generalized computing. Hence, in this project we approached the following characteristics of brain function:

- Modeling the processes of signal inputs through the brain based on current models of the neo-cortex.
- Explore how our models of the neo-cortex interact with information from the environment.
- Try to understand how an object is represented in the brain of infants say about 2 years old.
- Model this objects and its representation using a network.

Note that when we say the representation of an object we mean what inputs from an object are perceived and stored in the brain of humans. From our interaction and experiment with 2 infants who are about two to three years old, and their parents, an attempt was made to understand what objects in real world are known to them and how these are represented in the brain of these little ones.

We chose to analyze and understand the brain of infants as it is well known that adults know millions of objects and has involved a lot of learning throughout their ages. While infants of the age two has a limited knowledge base of objects in real world and we believe that trying to understand how infants perceive objects would be best applicable to the field of developmental robotics which is also in its early stages of development.

This paper includes our findings of what is the possible knowledge base of infants at around 2 years and we have also tried to come up with a list of object properties as expressed by these infants. We tried to arrive at the general pattern of how the brain comes to acquire this knowledge, and worked on mapping the objects and properties in a network which are believed to be basic inputs to the brain according to this model to implement similar object recognition.

II. Motivation Behind The Idea

The class lectures on brain and its functionality is an important inspiration for this attempt. There are a lot of differences between the robotic intelligence that is possible in today's world and the real human intelligence. If intelligence is what humans possess then intelligence in machines could be redefined or understood to great depth by understanding the essence of human intelligence and by observing the initial stages of brain and other sensory development.

The Hawkins theory [1] on human brain from the book "On Intelligence" explaining the idea of how the human brain is structurally arranged is the motivation of project. The idea of how the various sensory portions of the brain process sensory inputs, and the fact that data is processed the same way using one universal algorithm is a great motivation and inspiring factor for this paper. It made us think of objects not in terms of image recognition and taking up data from the visual and auditory datasets of previous experiments done with robots, rather think of objects that are really familiar to infants and trying to understand a mapping of these objects in human brains. But for the purpose of understanding and maintaining simplicity we have not dealt with all sensory inputs, rather tried with a subset of them.

III. Proposed Idea

One of the main ideas of this project is to look at the neo-cortex like a system interacting with input stimuli, and to understand the relationships between neuron connectivity and leaning. By understanding how signals travel through the brain, we can hypothesize about the internal representations of objects. More simply, when one picks up an apple, we will try to better understand the process causing the recognition of that object.

In order to arrive at a relevant model of how objects are represented in the brain, we must start by understanding the behavior of single neurons, and how those neurons work together to both produce complex thought in the neo-cortex, and arrange themselves to produce complex thoughts only after continued interaction with the environment.

To begin, refer to the diagram of a neuron shown [Figure 1]. In the figure, a signal enters the neurons nucleus from the dendrites. If the sum of all signals at any given time exceeds some threshold, the neuron fires a new signal through its axon. The axon is connected to the dendrites of neighboring neurons, so as the signal leaves one neuron, it enters the next in line. Some neurons can contain thousands of dendrites, so they can be easily arranged in a way that can organize data.

In the book "On Intelligence," [1] Hawkins describes the neo-cortex as a thin wall neurons comparable in size to six stacked business cards, which is on the outer surface of the brain.

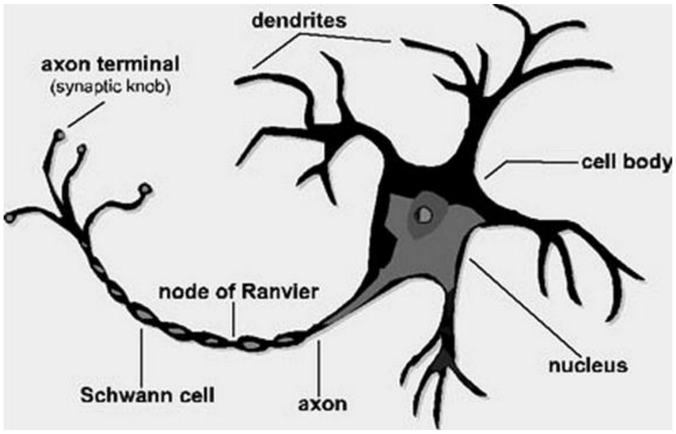


Figure 1 Structure Of A Neuron

It is arranged with six layers of neurons, densely packed on the bottom, and successively less dense toward the top. Hawkins describes this system as a hierarchy where sensory inputs and raw data enter in the bottom of the network, and each layer above represents some more complex representation of the input. As information flows to the top, an object is recognized by the seemingly random inputs. [Figure 2]

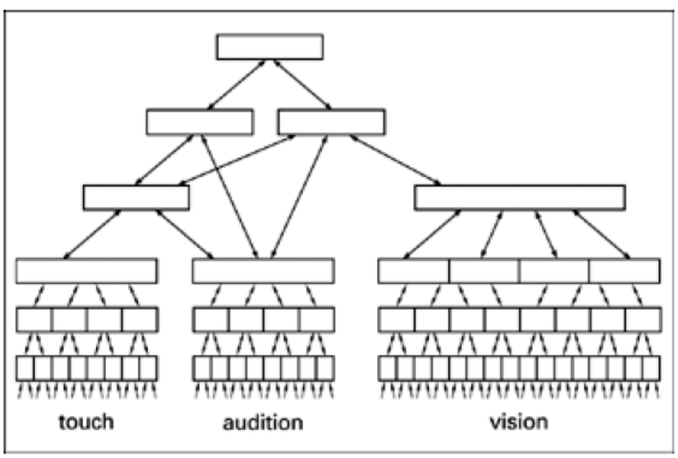


Figure 2 Hawkin's Hierarchial Model

In Figure 2, each box represents a neuron, and each pathway represents an axonal pathway between two neurons of different layer.

Since the introduction of the artificial neurons, shown in the figure above, such hierarchal networks have been employed to solve various computational tasks. These networks are known as artificial neural networks, and they tend to mimic the information flow through the neo-cortex. In this model, sensory information is introduced in the bottom layer and as the signals pass through various neuron connections within the network, a unique signal exits the top which can be thought of as some unique cognitive representation of an object based on the sensory inputs that represent it.

With this conceptual foundation of the functioning of the neo-cortex, our project is broken down into two phases of emphasis.

Phase one focuses on the dynamics of how such networks respond to input stimuli based on how individual neurons react to passing signals. We know that over time, neurons in these networks arrange themselves to result in complex thought. Although there are many approaches to how this works, there is no definitive process known yet. Phase one models one of these approaches focusing on such factors as learning processes, signal flow stability, and output grouping observations.

Phase two will use similar network models; however, emphasis will be put on the representation of objects in early developmental stages, within the networks based on the results obtained from the interaction with infants. For example, say we take an object: a red ball and ask a child who already knows what a ball is to explain what a ball is, then the answer may be a sphere/round shape which I play with.

Say if we ask what an apple is to the same child then the answer would be round and edible. So it is obvious that color and size of an object are least represented in the brain when it comes to identifying an object as we never identify an apple as an apple only if it is 4 cm in diameter or with an exact RGB value of red or green. We also observe that the human infants are able to perceive an elephant in pink color (in cartoons) and identify it exactly as elephants although in reality an elephant would be in grey color. There are various other examples which demonstrate that there is a lenient representation of any object in the human brain versus a very tight representation in the brains of the machines in most cases.

Hence in phase 2, we try to bring out such natural representation of various day today objects in terms of how it is perceived by infants. This study of objects through observation from the infants is an addition to the original idea as we were more interested in trying to model the brain and we decided to make this observation in order to obtain datasets that would depict the way the brain perceives the world rather than taking previous experimental results as suggested in the reviews. That said, we have also implemented an algorithm for shape detection as a proof of concept of the selected attributes.

IV. OBJECTS OF INTEREST

From our initial interaction with kids of age around two we came up with an initial set of knowledge base and the list of objects that were familiar to them. This list of objects and the initial knowledge base might vary between kids as it is purely based on what they observe from their day today activities. As children at this age typically involve learning by interacting with the family and objects at home this is influenced by the setup of the home and based on culture and food habits. For most cases children in the very early stages come to learn about their own body parts and the objects found at home, the food they eat and the toys they interact with.

Based on the above categories here are a few items among the list of objects that we came up with based on different categories. They are apple, banana, orange, table, chair, pen, paper, cat, dog, car and a few others.

The initial knowledge base for children of this age consists of their own body parts like eyes, nose, mouth, hands, body and legs which are learned by constant directions from the parents or caretakers and also basic colors like white, green, red, blue, black. They also tend to have an understanding of basic shapes like line, square, circle while a little more complex ideas like difference between a square and rectangle is not obvious.

Based on these interactions it is also obvious that there is already an unconscious representation of most complex shapes like triangle, hexagon or any other things in terms of basic shapes. For example, a triangle is a combination of three lines. But as the triangle is not in the initial knowledge base the kids are not able to term it exactly as adults do. Hence every complex object in the world is perceived by a kid in terms of simple objects known to the kid from its knowledge base.

This is an interesting finding which was observed through one of the interactions with the kid. When Pranav, a two and a half year old kid who helped us in our study was asked what the shape of a banana is, he replied that the shape is a line which was totally interesting and unexpected. When asked for a reason he drew a banana in the air and showed that it is like a line. This answer from the kid might seem confusing for a while or might even make us wonder if a banana is a line in the infant's brain. But a closer look at this reasoning will make us understand that the child has made a closest match to whatever was already there in the knowledge base. If a five year old kid were asked the same question, we might expect a much refined reply as something similar to an arc, if the arc is a part of the knowledge base.

Hence it is evident that humans keep perceiving objects in terms of what is already known to them and try to make a closest match with it. Other interesting findings as a part of this interaction with these particular kids are as follows.

- There is no distinction between a pen and a pencil at the age of three. It is because of the similarity in shapes and as there is no much usage or exploration of properties in terms of interaction with the object, the difference is not evident.
- An object like boat is only identified correctly when it is in water. This might be because an object is learnt or identified

in terms of its relative position with other objects. So say if a boat is being towed in land then there is no similar identification.

- There is a clear understanding of what the different body parts are but there is not much distinction when it comes to finer details. An example is: There is no distinction or knowledge about the difference between fingers and hands or legs and toes.
- As a part of the interaction, when the kid was asked to draw a picture of a human, the kid started drawing two eyes, a nose and a mouth inside a circle and two ears outside the circle. This was repeated even the next time as the order of nose and mouth were swapped in the process of drawing a face. To the kid it was very clear that a face usually has all these parts but the order of arrangement of the nose and mouth was something which the kid really did not care about at that age.
- Even though there is no exact representation of the face or body of humans in the brain of a kid, they were successful in identifying humans and differentiating between humans and non-humans. But the difference in sex is not at all obvious in this age. There is no clear knowledge about male or female at the age of two while it was observed at an age of three and above. This should be because of the example of male and female from self and from parents. But the distinction is made through voice and other obvious features like hair and clothing. But there could be various scenarios when they get confused when the differences are not obvious or if the person's voice is not heard.
- There is confusion between the television remote and a phone and between a spoon and a fork as the difference between the two in terms of shape is not distinct.
- If two citrus fruits looking similar are given together among which one is known, say an orange then the other fruit which is not orange but of the same color and texture as citrus fruits is also identified the same.
- The sense of smell is also developed at this stage. They are capable of differentiating between milk and any other white liquid which just looks like milk through the sense of smell.

But in most cases the object is identified or perceived by its visual inputs which becomes possible with the knowledge of touch or auditory inputs already perceived through previous interactions with the object.

Also we adults no longer identify an object as woolen by touching and feeling it, rather identify as woolen or silk or cotton just by looking at an object. Or we can easily differentiate between a hard and soft toy just by looking at it without interaction due to the learning obtained from initial stages of interaction with such objects. Hence we are able to perceive most worldly objects of interest to us just through one of the sensory inputs in most cases.

V. Implementation

Within an artificial neural network, the firing of a neuron is determined by the neurons firing in the below layer, and the weights of the connections between those neurons to the current neuron. If the weighted sum of all inputs to a neuron exceeds some threshold value, it fires. Therefore, neural networks learn by either changing the threshold needed for neuron firing, or changing the strengths of various connections between neurons.

Neural networks can be broken down into two categories: supervised and unsupervised networks. Supervised networks tend to use methods where some output solution is known at the top, and an input is known at the bottom. After finding the signal propagation through the network, algorithms change connection weights within the network to match inputs with outputs. It is unlikely that such an advanced algorithm would exist in the brain upon infancy. Unsupervised networks rely on rules that strengthen or weaken connections based on how signals move through neurons. One of the first rules for unsupervised networks is the Hebb's rule, given below.

$$\Delta w_i = \eta x_i y$$

Where ΔW represents the change of weight needed between the i'th and j'th neurons. Ƞ is the learning rate, x is the input, and y is the output. The proper generalization of this rule is "neurons that fire together, wire together" because when both neurons fire together, their connection strength increases. Other rules for unsupervised learning include Oja's rule, generalized Hebbian theory, and BCM theory.

A general process for an unsupervised neural network is outlined below:

1. Create input set, define initial connection strengths, and assign threshold values. (initial conditions)
2. Select an input set and calculate the signal flow through the network
3. Use the signal flow information to re-evaluate the strength between all neurons based on the specific rule such as Hebb's rule, given above.
4. Iterate 2 and 3 many times to simulate the learning stage of the network

The exploration of Hebb's rule led to the implementation of three separate learning strategies all based on the principle of Hebb's rule. The first was implementing Hebb's rule itself. Results of this implementation were inconclusive because the network is clearly unstable. As two neurons continue to fire, their connection can approach infinity, which is an unrealistic model of a neurons characteristics and abilities. The results led to the implication using a modification of Hebb's rule given below:

$$W_{ij}(k) = \alpha W_{ij}(k-1)+(1-\alpha)x_i y$$

Where k is the iteration number and α is a number between zero and one. This model is much more stable because W_{ij} can have a minimum value of zero, and a maximum value of one. This yielded more conclusive results in some ways, but not ideal in other ways.

The third approach was implementing the generalized Hebbian algorithm. This rule is given below.

$$\Delta w_{ij} = \eta \left(y_j x_i - y_j \sum_{k=1}^{j} w_{ik} y_k \right)$$

This is similar to Hebb's rule, however, the second term is a weighted sum of the signals entering the current row of neurons resulting in a better balanced array of neuron connections between neuron layers.

The representation of information through the network is shown in Figure 3.

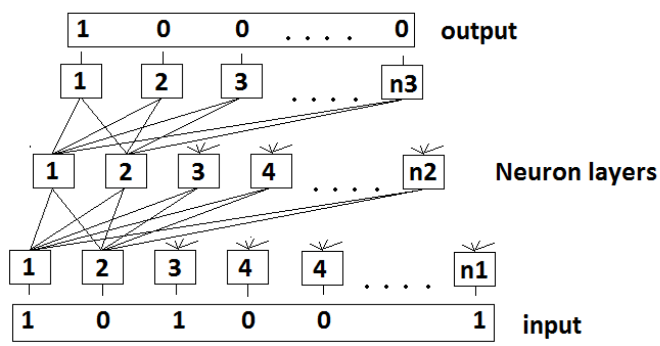


Figure 3 Information Flow

As shown by figure 3, the input and output are just binary sequences of numbers. The idea behind this method of object representation is that every input neuron represents some property. The number 1 or 0 represents the presence or absence of the property, respectively, through some bodily interaction with the object. The idea of internal representation of objects best comes into play when considering the diagram above. The input neurons represent general properties of an object. As one ascends up the network, each layer of neurons represents a higher layer of abstraction, where more and more complicated ideas are expressed by the firing of each neuron. For example, if the input to the network is raw sensory data of a dog, a neuron in the second level may represent fur, a neuron in the fourth layer could represent a leg, and a neuron in the fifth layer could represent the act of running. As the input data moves through the neural network, the hope is that one neuron on the top layer is fired, and that neuron represents the dog.

There is a strong scientific foundation for artificial neural networks. There exists countless books such as [6] and [7] which were used as resources in our research. Other texts such as [8] that give insight to artificial neural networks as applied to robotics, but not developmental robotics. While these resources give great detail into the dynamics and mathematics involved in neural computing, they give little information about how artificial neural networks can be used in artificial intelligence. Many websites such as [9] show countless applications and simulations using artificial neural networks, some of which are very clever in their usage of learning algorithms, but they do not address how intelligence forms within these networks. Other literature such as [1] [5] approaches the brain from an intelligence perspective, but are very limited in computational modeling of such models. Our project is an exploration of the bridge between this gap.

The models above were tested using networks three layers deep, with 30 neurons on the bottom layer, 20 in the middle, and 5 on the top. 5 neurons on the top layer were chosen because there are 120 different output possibilities – plenty of options to allow for unique outputs given only 30 – 50 input sets.

The initial learning tests for these algorithms were created using random number generators. This was only to assess the networks' stability and interaction with input sets in the learning stage. We then applied the algorithms to two sets of data relating sets of common objects and their physical properties. The datasets can be found in appendix 1. Note that these datasets are a drastic oversimplification of ordinary neural inputs for many reasons explained in the appendix, however, they serve as a somewhat realistic tie between the computations done in our model and how they can be applied in the real world.

In the phase two of the project, the emphasis is on understanding what and how the human brain process data in order to identify an object.

From our observation the infant's brain observes the basic object properties to identify an object or identifies a new object by comparing with the objects in the existing knowledge base.

Hence for the purpose of implementation an initial list of object known to a child and the list of properties observed by the child for a particular object is chosen. The child extracts the basic feature sets like color, shape from an object.

The datasets are formed by the using such basic features. The Multilayer perceptron [2] is used to train this network. The data set consisting of thirty instances and forty four attributes is used as input to the network. Each object is trained only once to know the efficiency of the proposed data model. Also testing is based on giving a different set of inputs but referring to the same object. This is because the child automatically recognizes a green apple as an apple even though it has seen only seen red apples beforehand. This model would also be based on the same principle.

As the list of property sets consists of comparison of an objects property with a knowledge base of shapes, colors and other features, an algorithm for shape recognition is implemented as a proof of concept. There are also other features like object movement which is observed from an object over time that is not implemented here to keep the system simple.

The reason for emphasis on shape is that visual input plays an important role in early stages of development and humans learn a lot of things through observation. At later stages of development we tend to become efficient in identifying objects just by sound or touch. There are also complex objects which are identifiable at later stages of development. By complex objects we mean those which could only by the identified using a combination of two or more sensory inputs which are not addressed here due to its complexity.

For shape identification, the algorithm [3] is implemented by finding the centroid of an object and the calculating the DFT. The DFT obtained for a particular object is compared with the DFT obtained for the standard shape that is used as the basis for comparison.[4] The DFT is generally used to analyze the frequencies contained in a sampled signal using the below equation.

$$X_k = \sum_{n=0}^{N-1} x_n e^{-\frac{2\pi i}{N} kn} \qquad k = 0, \dots, N-1$$

VI. RESULTS

The evaluation of results in phase one is broken down into the following characteristics.

1. Running various inputs into the system will cause changes in the neural pathways.
2. After repeating the process several times, we will see the changes of neural pathways approach some transient or minimum value. This will indicate that the system has found a way to group the characteristics of each input.
3. Each input will lead to a different unique output neuron firing output on the top layer of the network.

Each of the characteristics given above demonstrates the functionality of the neo-cortex, but a successful model should display all three. This is because a successful model of the neo-cortex is one that arranges itself to recognize how different objects are unique. If the network fails to do this task, complex thought shouldn't be able to result.

The results of the three learning methods were somewhat successful in different ways. These results are best demonstrated by observing the nature of changing connections within the network. Some of these results are shown below, in the order at which their methods were introduced earlier on in the paper.

Method 1: Hebb's Rule

First, the "Hebb's rule" network was trained on a small set of 10 randomly selected input sets. The learned outputs are given in Table 1.

The "all or nothing" cascades in the learned output sets above are typical of this network. Although the initial output has a few unique outputs, the nature of how the network responds to input does not reinforce unique outputs. This problem is most likely due to the unstable nature of Hebb's rule. Figure 4 demonstrates this unstable nature of the network.

The graph shows various connection strengths between one neuron on the second level, and some of its neural connections to the first level. As the learning algorithm approaches 10,000 iterations, the neural connections do not approach any equilibrium, and seem to converge as the iteration approaches infinity. The unstable nature of Hebb's law makes this type of network an unrealistic model of the neo-cortex, as it only one of the three observable characteristics listed above.

Input set	Initial output					Learned output				
1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1
3	0	0	0	0	0	1	1	1	1	1
4	1	0	1	0	1	1	1	1	1	1
5	0	0	0	0	0	1	1	1	1	1
6	1	1	1	1	1	1	1	1	1	1
7	0	0	0	0	0	0	0	0	0	0
8	1	1	1	1	1	1	1	1	1	1
9	1	1	1	1	1	1	1	1	1	1
10	1	1	1	1	1	1	1	1	1	1

Table 1 Hebb's Rule

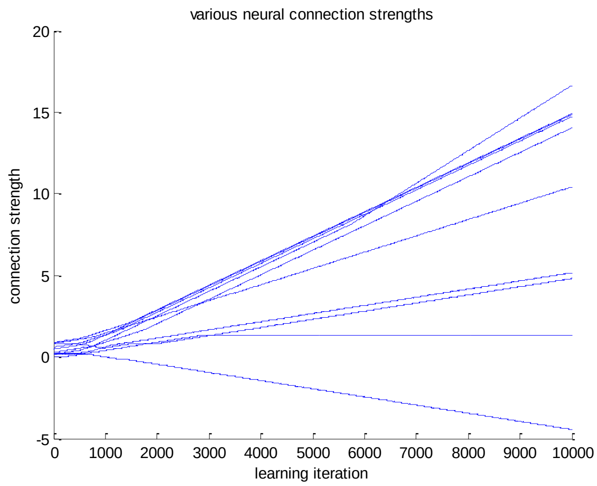


Figure 4 Output Graph

Input set	Initial output					Learned output				
1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1	1	1	1
5	0	0	0	0	0	0	0	0	0	0
6	1	1	1	1	1	1	1	1	1	1
7	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0

Table 2 Modified Hebb's Rule

Method 2: The Modified Hebb's Rule.

A typical output for the modified version of Hebb's rule is in Table 2.

The connection strengths of various neuron are shown in Figure 5.

This model is somewhat more successful. The figure above shows that the neural pathways tend toward transient behavior, but the system outputs are still not unique to their inputs. This however, was found to vary with different network sizes, structures, and number of input sets. A better representation of this networks' output will be shown later in this paper, using a real dataset.
This network satisfies two of the three evaluation characteristics: the network responds to input data, and it approaches some transient state, with stable signal flow characteristics. It is not a realistic model of the neo-cortex because it again, does not produce the unique outputs needed for cognitive abilities.

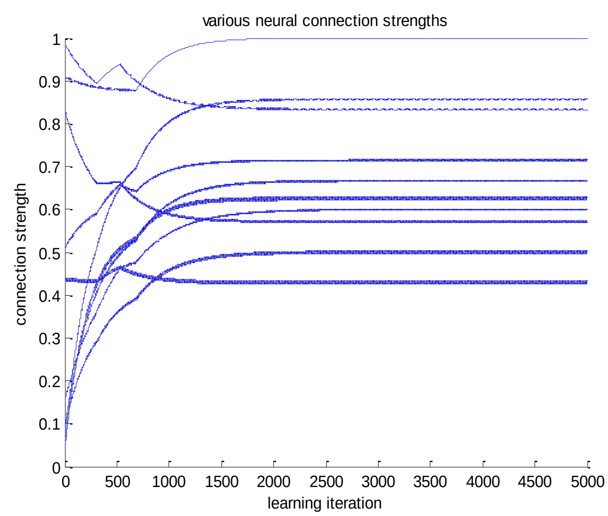


Figure 5 Output Graph

Method 3: Generalized Hebbian algorithm

A typical output for this network is shown in Table 3.

This network was the first one implemented that develops unique outputs. As shown in Table 3, the 80% of the outputs are unique. This network is also interesting because the initial state of the network stops most signals from passing, however, over time, unique signal outputs emerge.

The behavior shown in Figure 6 is very erratic compared to the previous two models. The data presented here are more complicated as well. This network changes neuron threshold values in its learning process, so the connection strengths presented above are as a ratio to their individual neurons threshold value. The connection strengths shown in Figure 7, were also smoothened out using a simple Kalman filter, seen in red.

Input set	Initial output					Learned output				
1	0	0	0	0	0	0	1	0	1	1
2	0	0	0	0	0	0	1	0	1	1
3	0	0	0	0	0	0	1	0	0	1
4	0	0	0	0	0	0	1	1	1	1
5	0	0	0	0	0	0	0	0	1	0
6	0	0	0	0	0	0	0	0	0	1
7	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	1	0	1
9	0	0	0	0	0	1	0	1	0	1
10	0	0	0	0	0	0	0	0	0	0

Table 3 Generalized Hebbian algorithm

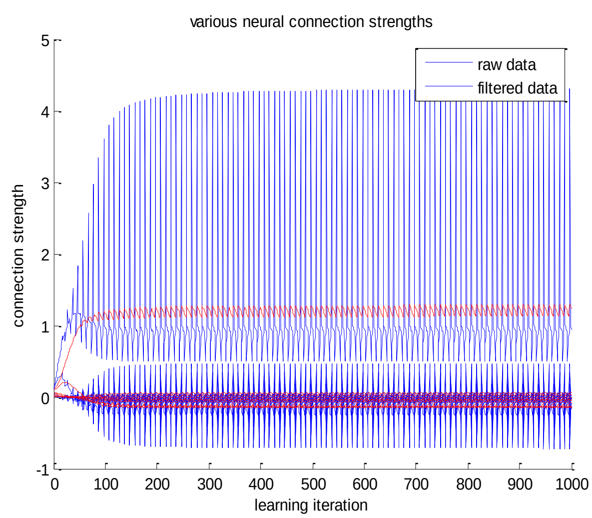


Figure 6 Output Graph

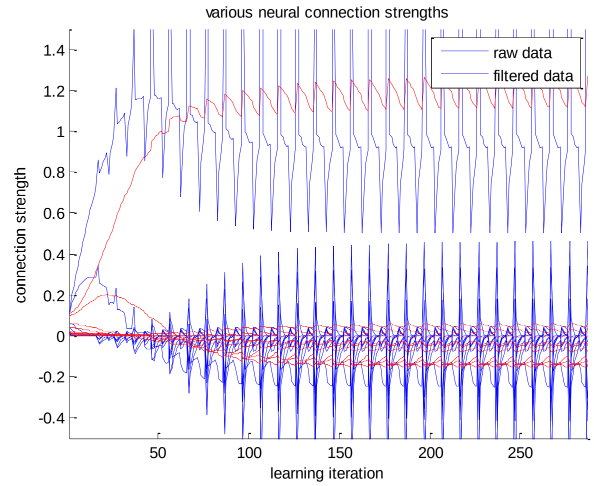


Figure 7 Output Graph
[Finer Details Of The Output]

The behavior shown above is very erratic compared to the previous two models. The data presented here are more complicated as well. This network changes neuron threshold values in its learning process, so the connection strengths presented above are as a ratio to their individual neurons threshold value. The connection strengths shown above, were also smoothened out using a simple Kalman filter, seen in red. This network satisfies all three evaluation characteristics. Not only does it respond well to signal inputs, and display transient nature, but it also creates unique outputs in its learning stage. This network is a worthy candidate in modeling the neo-cortex. Although this network displays the three characteristics given above, there is one case where this network is unrealistic. In order for the network to remain stable, the connection between two neurons is modified based on the outputs of all other neurons of the same layer. This may be a far assumption since neurons can't know the state of every other neuron on any layer, but it is sufficient for the purposes of this project.

After deciding on the most accurate model of the neo-cortex, the next stage in phase one was to test the network using a set of real objects and properties. A property table and list of objects can be found in appendix 1. In making our list of objects, we picked many everyday household objects that a two year old may interact with on a frequent basis. Many of the objects were selected from [10] because the paper uses a wide range of household items. Other items were added to the list that had some properties, not displayed by the objects in the paper. Some of these objects included animals and food since they offer characteristics such as locomotion, warmth, or taste. The input values were selected to be general properties that describe the object. Most of the properties could be experimentally determined without extremely heavy computation, thus making the input properties raw data. In creating the input sets, objects were chosen to display a property if an infant could experience that property through some interaction with the object. For example, the property 'sweet' is selected for an apple because if an infant puts the apple in its mouth, it tastes the 'sweetness' of the apple. The property 'large' is assigned to the block of wood because when an infant tries to pick it up; it won't fit in the infant's hand.

The network was trained using the 38 datasets mentioned above and resulted in 11 different unique outputs. Refer to the table below, showing the output codes and the objects grouped to those outputs.

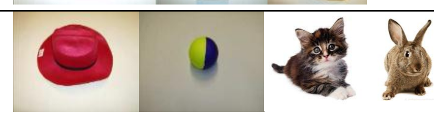
Output code						Object groups
Output 1	1	0	1	0	1	
Output 2	1	0	1	1	1	
Output 3	1	0	0	1	1	
Output 4	1	1	1	1	1	
Output 5	0	0	1	0	0	
Output 6	0	1	0	0	0	
Output 7	1	0	0	0	1	
Output 8	1	1	0	0	1	
Output 9	1	1	1	0	1	
Output 10	0	0	0	0	0	
Output 11	0	0	1	0	1	

Table 4: Object grouping results

When considering the grouping capabilities of the network, this is a pretty unsuccessful result. Some output sets such as 3 and 10 show similarities, but others such as 1 and 5 show little if any relationship. These results can be expected with a network only three layers deep. The results also lead us to the realization that best links phase one to phase two. Most of the output codes include more than one neuron firing. Given that the representation of the object is still in terms of many neurons means that each neuron could still only represent certain abstract properties of the objects, rather than the objects themselves. Phase two approaches this by creating a network, and defining datasets in terms of properties that one may find in say, the third or fourth level of neurons in the neo-cortex where more detailed and abstract concepts can be represented by a neuron. The generalized hebbian algorithm was tested with the above input set using networks of varying sizes and complexities. The smallest was a 3 layer network with 5 outputs, while the largest was a 5 layer network with 40 outputs. Though the results varied somewhat, they all tended to result in different combinations of neurons firing at the top level, making it impossible to designate one object to each output neuron. Therefore, it may be necessary to explore datasets of higher abstraction in order to arrive at the idea of single neurons represent objects.

The next phase in the project was to test the networks using a set of real objects and properties. It has results related to shape and object identification. When talking about the shapes that are known to a child that are used for object identification, it is not only square or circle but also the shapes of legs, hands and human body as the child is successful in identifying another human as human in this stage. Another concern when it comes to shape identification is identifying similar shapes although they might be in different sizes. The DFT algorithm implemented is used to identify the shape of an object irrespective of the size as the graph obtained by plotting the DFTs for various sizes of the same shape matches closely.

Figure 8 is a comparison of DFT of the same object but in various sizes like smaller, larger, and mediocre in comparison with the original size chosen.

With respect to the dataset, the Multilayer Perceptron was chosen to train the network .The datasets provided for training has a good ROC (>0.6) which indicates effective learning. The pairwise confusion matrix estimated for this model is shown in Figure 8.

VII. Conclusion and Future work

In this project we have modeled many aspects of the neo-cortex ranging from information propagation through the network, Hebbian based learning strategies, and internal representations of objects. We have arrived at a computational model demonstrating how neural networks such as the neo-cortex develop over time, allowing us to arrive at the knowledge that we acquire over our lives. We made an attempt to simulate the computational power of the neo-cortex by modeling of neural networks, using real physical input data. This serves as an advancement to robotics because it connects real life sensory input to the power of artificial neural network based models of the neo-cortex. We presented some interesting observations which were noticed as a part of the interaction with children. We also worked on simulating a network based on this objects and properties.

In the future we would like to work on how to enable such human perception of object properties using algorithms in Robots to enable same level of perceptual skills and make it less rigid to progress towards the real known form of intelligence which is the human brain.

Acknowledgement

We wholeheartedly thank Dr. Alexander Stoytchev, Assistnat Professor, Department of Electrical and Computer Engineering, Iowa State University, for motivating us to take up this project as part of the HCI 585X Developmental Robotics course.

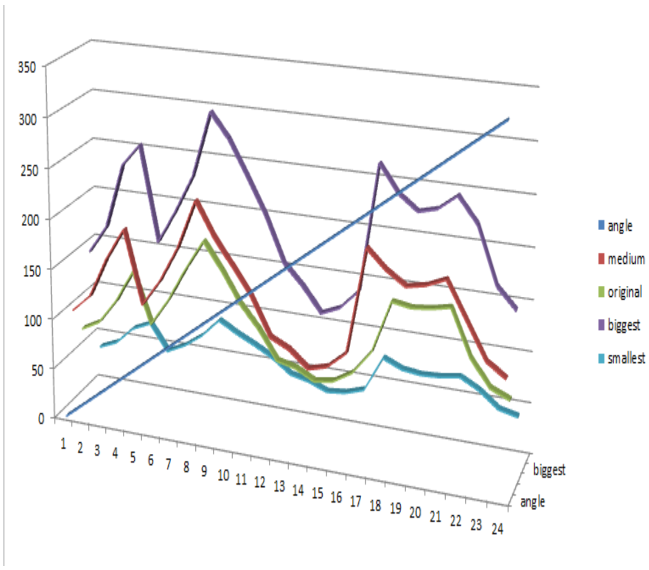


Figure 7 DFT Graph For Different Sizes

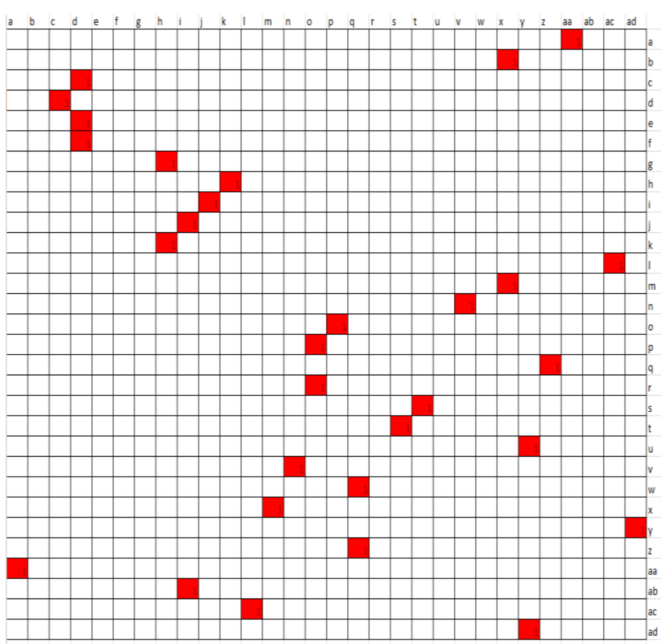


Figure 8 Confusion Matrix

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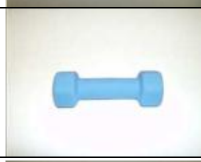
Appendix

The list of objects used in phase 1 is given below. Their ids correspond to the datasets given in the next chart. The list of data sets used is from Dr. Alex's experiment, but the properties have been redefined.

Input object id's	Object pictures				
1 - 5					
6-10					
11-15					
16-20					
21-25					
26-30					
31-35					
36-38					

	Visual inputs														Taste			Audial			Tactical inputs									
Input object id's	Bright	Dark	Mixed colors	Red	Green	Blue	Small (less than palm of hand)	Medium (size of hand)	Large (larger than head)	Shiny	Fuzzy	Motion	Round - t least one dimension	Sharp edges	Sweet	Sour	Bitter	A0 - A4 (low pitch)	A4 – A8 (high pitch)	Loudness	Hot	Cold	Heavy (over 1 lb. in weight)	Light (under 1 lb. in weight)	Firm	Soft	Jagged	Smooth	Abrasive	Grip/ stickiness
1	1	0	1	0	1	0	0	1	0	1	0	0	1	1	0	0	0	0	1	1	0	0	0	1	0	1	0	1	0	0
2	1	0	1	1	0	0	0	1	0	0	0	0	1	1	0	0	0	0	1	1	0	0	0	1	0	1	0	1	0	0
3	1	0	1	0	1	0	0	0	1	1	0	0	1	0	0	0	0	1	0	1	0	0	0	1	1	0	0	1	0	0
4	0	1	1	0	1	0	0	0	1	1	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	1	0	1	0	0
5	1	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	1	0	1	0	0
6	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	1
7	1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	1	0	1	1	0	0	1	0	0	1	1	1	1	0
8	1	0	0	0	0	1	0	1	0	1	0	1	1	0	0	0	0	0	1	1	0	0	0	1	0	1	0	1	0	0
9	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	1	1	0	0	1	0	0	1	0	1	0	0
10	0	1	1	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	1	0	1	1
11	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1	1	0	0	0	1	0	1	0	1	0	0
12	1	1	1	0	0	1	0	1	0	0	0	1	1	0	0	0	0	1	0	0	0	0	0	1	1	0	0	0	0	1
13	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	1	1	1	0	0	0	1
14	1	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0	1	0	1	0	0
15	1	0	1	1	0	0	0	0	1	0	0	0	1	0	0	0	0	1	1	1	0	0	1	0	0	1	0	1	0	0
16	1	0	1	1	0	0	0	0	1	0	0	0	1	1	0	0	0	1	0	0	0	0	0	1	1	0	0	1	0	1
17	1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	1	0	0	1	0	0	1	0	1	0	0
18	1	0	0	1	0	0	0	1	0	1	0	0	1	0	0	0	0	0	1	1	0	0	0	1	0	1	0	1	0	0
19	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	1	0	0	1	0	0	1	0	1	0	0
20	0	1	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	1	1	0	0	1	0	0	1	0	1	0	0
21	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
22	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	1	0	1	0	0
23	1	0	0	0	0	1	0	0	1	0	0	0	1	0	0	0	0	0	1	1	0	0	0	1	0	1	0	1	0	0
24	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	1	0	0	1	0	0	1	0	1	0	0
25	1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	1	0	0	0	1	0	0	1	1	0	1	0
26	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	0	0	1	1	0	0	1	0	0	1	0	1	0	0
27	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	1	1	0	0	1	0	0	1	0	1	1	0
28	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	1	1	0	0	1	0	0
29	1	0	0	0	1	0	0	1	0	0	0	0	1	0	1	0	0	1	0	0	0	0	1	0	0	1	0	1	0	0
30	0	1	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	1	1	1	0	1	0	1	0	0	0	0	0
31	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	0	0	0
32	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0
33	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	1	0	0	1	0	0	1	0	1	0	0
34	1	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	1	1	1	0	1	0	1	0	0	0	0	0
35	0	1	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0
36	0	1	0	1	0	0	1	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	1	0	1	0	1	0	0
37	1	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	1
38	1	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0