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An Application of Hierarchical Temporal Memory (HTM)



Prepared for

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Key Words: Cortical micro circuits; Hierarchical Temporal Memory (HTM); Olfactory sensory network; Neocortex; Learning algorithms; Synthetic neuron design, Neuroinformatics, Modeling the brain

DECLARATION

I declare that the work contained in this thesis is my own and no part was created by another party. All references and sources have been appropriately acknowledged.

This work is submitted to the Department of Electrical Engineering, University of Cape Town, in partial fulfilment of the requirements for the degree Master of Science in Electrical Engineering, in the field of Neuromorphic Engineering, and has not been submitted for any other academic purposes before this.

Ashley Liddiard

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-- November 2011

"The point is to understand then build, otherwise you are a cargo cult, building a poor copy of a downed bomber, hoping that the more goodies will fall from the sky" Terry Sejnowski, 1999

"Learning the secret of flight from a bird was a good deal like learning the secret of magic from a magician. After you know the trick and what to look for, you see things you didn't notice when you did not know exactly what to look for." Orville Wright, 1913

ABSTRACT

While a number of neuromorphic studies have been based on understanding and building the brain in software and hardware, a recent theory has been presented from a high level, top down approach, with the view of understanding how the human brain performs higher reasoning, and then designing software infrastructure based on that theory – namely Hierarchical Temporal Memory (HTM). Current opinion raises question marks as to whether this theory is sound, feasible, coherent, logical and correct. This thesis aims to, if not answer some of those questions, at least get closer to understanding the brain and therefore implementing HTM theory in software for further use in an embedded environment.

This paper begins by reviewing the discovery of the sensory input and chemical makeup of the signals in the brain, and then introduces mathematical abstraction to form a software program node. The final output of this thesis is a Hierarchical Temporal node, designed in software, and demonstrating learning using pseudo-random input sensory data and the spatial temporal framework; it verifies that the program operates as it should, and suggests how to create a VLSI circuit implementation of the software and ultimately a silicon chip that can be used in intelligent machines and prostheses.

As this dissertation has taken shape, so has the research backing it. Two fundamental papers, used as references, were published during the writing; lack of published research on HTM has both been a hindrance and a driving factor.

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1 INTRODUCTION

1.1 SUBJECT OF RESEARCH

This research project focuses on a software implementation of the Hierarchical Temporal Memory (HTM) theory recently formulated by Hawkins and Blakeslee (2004) and George and Hawkins (2005, 2009) [1], [2], [3], [4]. The HTM theory hopes to better model the true workings of the cortex and learning mechanisms of human computational intelligence by understanding how the brain works and then designing a protocol that operates as the human brain does. The theory uses a *top down* approach i.e. beginning with the end goal in mind and developing a structure which supports and produces this goal. Simulated, as opposed to recorded, sensory data were used during the design of the software model. The completed program takes inputs of random sensory data, checks that the connections have been made correctly, boosts valid connections, inhibits invalid connections and then assigns permanence values – values associated with memory. The goal of this project was to simulate the overall function of the neocortex using George and Hawkins' mathematical architecture [2].

The following hypothesis was proposed:

“It is possible to design a software algorithm which exhibits intelligent behaviour using Hierarchical Temporal Memory cortical theory, the effectiveness of which can be demonstrated by the reinforcement and recognition of previous input sensory signals.”

What is intelligence? Hawkins and Blakeslee (2004) hypothesise in their book, “On Intelligence” that intelligence is the ability to learn and then to recognise; meaning that after initial introduction of a sensory input, if the input is again introduced to the system it should be recognised, or the incorrect definition of the learned input is corrected with the numerous feedback connections found in the brain [3]. Learning means that once this input is recognised it tends to grow more “permanent” and the surety of what is being viewed is increased – this quantity is hereafter labelled the permanence value.

In most mammals the input discussed here is sensory input.

Up until now HTM theory has mainly been applied to the Visual and Hearing sensory networks in the brain with the majority of published and available work being in Visual networks available through Numenta[®] and collaborations with VitaminD[®] [5]. This study aims to examine the olfactory sensory network, and is the only work of its kind of which we are aware, applying HTM theory to the olfactory sensory network.

This research incorporates the study of sensory networks and current fields of neocortical research, having been initiated with the aim of supporting the development of a silicon chip to perform the functions of HTM theory. Additional investigations of silicon chip design, software and hardware to manage sensory networks, have been reviewed. The goal of this work is to be a building block towards designing a silicon chip that can be used for computational intelligence and prostheses.

1.2 BACKGROUND TO RESEARCH

Study of the brain is seen as an important component to learn about human behaviour, this along with the growing requirement for computers in everyday life, lead to the choice of topic.

Prof. Kwabena Boahen's research group at Stanford University is currently working on designing a hardware system that mimics the neural structure of parts of the Visual Cortex [5]. Although they have successfully built a neuron chip, it is still in the testing stage. The Computational Neuroscience Research Group based at the University of Waterloo headed by Chris Eliasmith uses the Neural Engineering Framework to build simulations that aim to be as realistic as possible, using a proprietary neural simulator called Nengo. The '*Brains in Silicon*' project at Stanford University currently focuses on the visual and hearing cortex, using a method of design based on a bottom up approach [6] i.e. the neurons are first designed and built in silicon – with the intention of building

the human brain from the base up, then introducing networking functions and therefore creating computational intelligence.

As with this research all available works on neuroinformatics have an end goal of understanding how the brain and the neocortex, the center for higher processing and learning, function [7]. It is believed that once the operation of the brain can be replicated its processing power can be applied to different forms of input – such as all sensory data, stock market information, marketing analysis and trends etc. [3].

1.3 OBJECTIVES OF RESEARCH AND DEVELOPMENT

This project aims to satisfy the following objectives:

- Perform research into the field of Neuromorphic Engineering (Section 3).
- Research the brain, its chemical interactions, operations, interaction with the outside world, and find out how HTM theory would be a beneficial theory to be applied here (Section 2).
- Develop and test an HTM cortical learning algorithm software method, using sensory data input (Section 10).
- Investigate the applicability of HTM theory applied to olfactory sensory network (Section 2.3.3).
- Research silicon chip manufacture and fabrication (Section 7.1.5).
- Research the software and protocols used in the formulation of neural networks (in this case possible software that could be used for HTM network formulation) (Section 9).
- Obtain results, test, verify and critically evaluate output (Section 5, 10.1.5).
- Draw conclusions based on the research performed (Section 10.1.7).
- Make recommendations for future development and implementation of a solution for building VLSI chips and software with the intention of constructing

computationally intelligent machines and prostheses – in the electronic and medical fields (Section 10.1.8).

1.3.1 Scope and Limitations

The software implementation of HTM theory described by George and Hawkins (2009) [2] was investigated. Other models have been examined to support this thesis but have not been implemented here.

The sensory input was limited to simulated olfactory data. As experimental data was lacking, randomised input was generated, based on known olfactory principles, but not directly extracted from the olfactory sensory network of a mammal.

Hardware and software implementations of neuroinformatics were investigated, along with development of a silicon VLSI chip to implement HTM theory. These investigations have been mentioned in brief as references for future expansion of this study.

1.4 RESEARCH STRUCTURE OF DISSERTATION

To develop a clear understanding of the structure and workings of the brain, and more specifically the neocortex and olfactory sensory system, as well as the theories that aim to model and replicate brain systems, the following were required:

- An understanding of the mathematical structure behind Hierarchical Temporal Memory, neural systems and brain models.
- All the aspects and concepts required in building a neuromorphic structure that is based on HTM protocol, needed to be understood.
- The hardware currently being used in the design and implementation of neuromorphic structures required investigation.
- An overview of the software platforms and protocols being used to describe neural network systems, and the background to neuromorphic fields and building of silicon chips, in support of designing a neuromorphic chip.

Once this contextual research was completed, the software and mathematical background acquired were used to implement HTM theory and apply it to the olfactory sensory network. The chosen sensory network used as a basis for the design, testing, software recognition and learning processes which confirm operation and success. This was then translated into final results and conclusions based on the test outcomes and findings.

Section 2 of this dissertation describes the biological operation of the neocortex and linking olfactory sensory network. Section 3 introduces the neuromorphic engineering and neuroinformatics community. Section 4 describes previous methods of modelling brain systems. Section 5 takes into account the parallels of HTM theory and that of neuroscience and Section 6 looks at methods in which the brain is being modelled. Sections 7 to 10 undertake the design, development and testing of an HTM node; the final sections of this thesis then outline the neuromorphic research community's related research.

2 THE BRAIN

The mammalian brain is a vast and intricate topic, therefore the research approach needed to reduce the scope of the task, an outline being:

- (i) The neocortex, being the outer most layer of the brain - the place where all reasoning, thought and learning are believed to occur [7]. Section 2.2
- (ii) The olfactory sensory network, being the source of sensory data which was chosen to be used as an input stream or modalities as discussed in Section 2.3.1
- (iii) The route which the olfactory sensory input takes to register in the neocortex. This will play a vital role in justifying the use of HTM theory.

The rat and rabbit sensory networks have been mentioned due to the neuromorphic simulation research that has been completed on them; this is because the structure and operation of the rat and rabbit neocortex is directly comparable to the human neocortex – even though rodent olfactory sensory networks may be better developed than that of humans [8].

2.1 BIOLOGICAL NEURONS

This short description of biological neurons is presented here as an overview and to support further explanations, not all concepts are widely accepted and research, on neurons, is still very much underway.

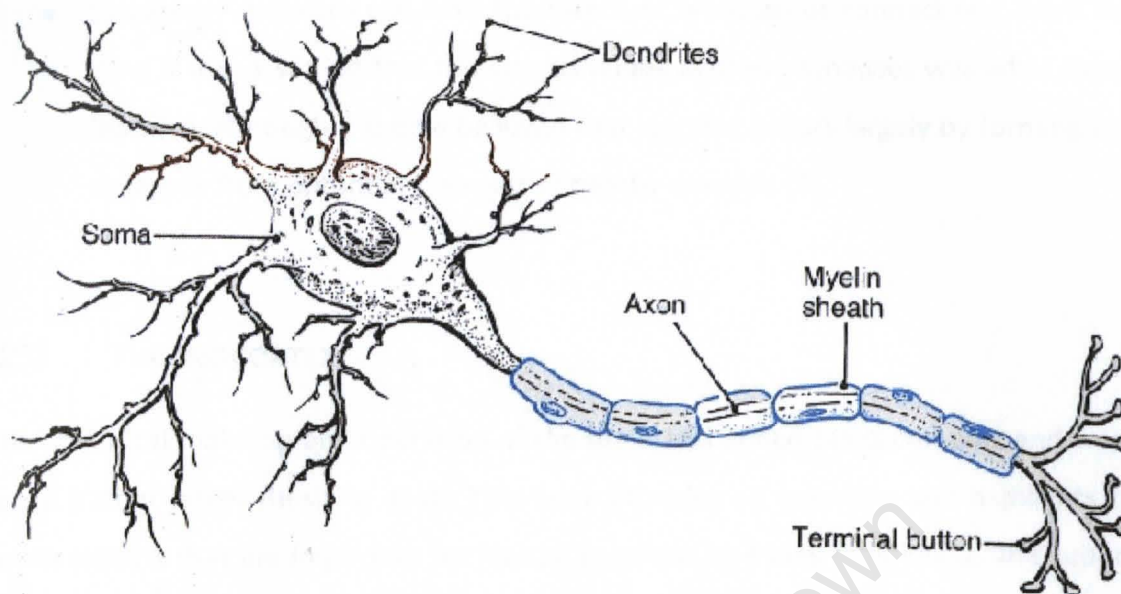


Figure 2.1: Detailed diagram of the neuron. Synapses are formed with the dendrites of one neuron connect another neuron's dendrites [9].

Neurons are the information carriers in the brain, having several parts (above Figure 2.1):

- The Soma or Cell body – is where axons are generated from, and the inputs or connections called synapses form all along the dendrites which feed the cell body.
- The dendrites or branches closest to the cell body are called the proximal dendrites. The feed forward connections to neocortex connect to the proximal dendrites.
- Distal dendrites are further from the cell body and thinner, they can have little effect on the cell body unless they are given large input. They are believed to act like a set of threshold coincidence detectors; proof of this has as yet to be presented though. Distal dendrites form synapses with the surrounding neurons and act as an extension to the cell.

- Synapses – Neurons can have thousands of synapses or connections. For a long time it was assumed that the strengthening of these synapses was what caused learning, although it is now believed that learning occurs largely by forming valid synapses from potential synapses of nearby neurons [9].

2.2 THE NEOCORTEX

The chemical make-up and operation of the brain and neocortex is complex and would be a (rather large) thesis in itself. This work provides an overview and highlights the main aspects that are important for human cognition and how they link to and support Hierarchical Temporal Memory (HTM) theory.

The system that is proposed in this work needs to capture the overall function and architecture of the neocortex, the outer most layer of our brain and the centre of higher level learning and thought [7], [10].

The concept that every brain is made of the same basic parts, and these parts have repeated architecture that perform similar functions but on different input data, is becoming widely known and is reasonably well accepted [10]. Evolution suggests that only when there is a change in an organism's surrounding environment, and current characteristics become disadvantages, is there a need for modification, which then propagates through future generations [11]. Therefore to quantify and qualify the operation of the brain, having developed through a process of evolution in such a way that its micro-circuits are repeated in all different sections of the neocortex, neuroscience has to describe the brain from an external observer's perspective. *"We've got all these tools for studying the cortex,"* Henry Markram of the Blue Brain Project has stated. *"But none of these methods allow us to see what makes the cortex so interesting, which is that it generates worlds. No matter how much I know about your brain, I still won't be able to see what you see."*

Architecture

The neocortex is a thin layer of tissue coating the brain. It is believed to be the location of all higher functions of the brain such as thought, consciousness, awareness, spatial perception etc. It is made up of six layers (I → VI), which in humans are a total of 3–4 mm thick [10], [12]. It has up to 28×10^9 neurons [7].

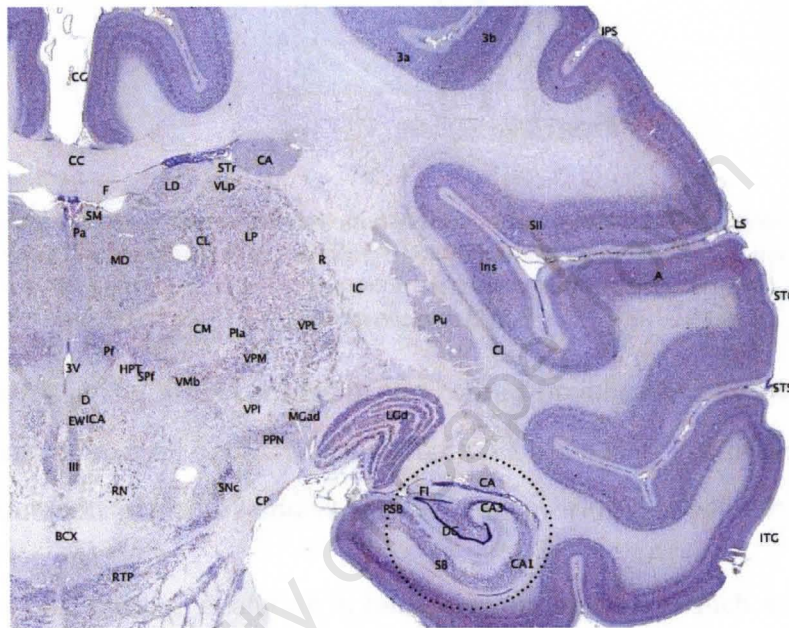


Figure 2.2: The cerebral cortex is the outer layer, viewed here in dark violet, the colour is a Nissel stain which colours cell bodies a brilliant violet, it can be seen from the figure that there is a high concentration of cell bodies situated in the neocortex [13] [14].

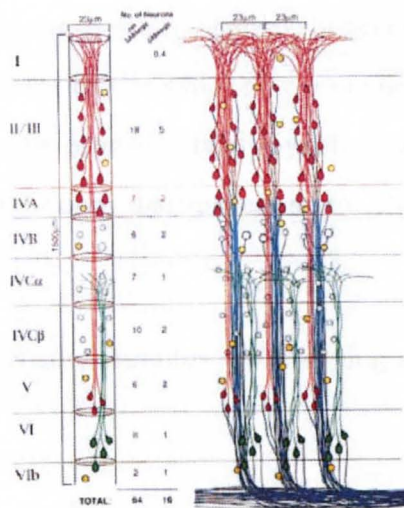


Figure 2.3: Neurons in the neocortex are arranged in a columnar structure. Each layer represents many different processing functions and they are labelled in Roman numeral format. Layers are visualized in the neocortex as I - VI(A), the I layer being the outermost layer and the first recipient of information in the neocortex [7].

The white matter in the brain consists of the coated (myelinated) axons and synapses. The grey matter, so named because brains that have been kept in a preserved state are greyish in colour, consists of cell bodies without the covering or myelin sheath.

The neocortex has, through evolution in homo-sapiens, grown to such an extent that to better use the space provided by the cranial cavity folding itself into grooves named sulci.

Neurons in each of the six layers connect across layers to form cortical microcircuit columns (Figure 2.3). These cortical microcircuits called mini-columns are proposed as the basic functional units of the neocortex [7].

Excitatory neurons make up approximately 80% of neocortical neurons and inhibitory neurons approximately 20%, but there are lots of exceptions to the base structure; for example, in the part of the cortex that controls motor movement, layer IV does not exist. Mostly neurons in the upper layers II and III project their axons to other areas of the neocortex, and those in the deeper layers V and VI project primarily out of the

neocortex, either to other regions of the neocortex, brain or peripheral nervous system. Neurons in layer IV receive most of the synaptic connections from outside the cortex, and make local connections to other cortical layers. Therefore layer IV receives all incoming sensory information and distributes it to the other layers for further processing [15].

Each column responds to a sensory stimulus representing a certain body part or region of sound or vision [7].

This physiological structure of the cortex and its operations is where Hierarchical Temporal Memory (HTM) obtains its reasoning and structure. This is presented in the paper "Towards a mathematical theory of cortical microcircuits", by George and Hawkins (2009) [2], and relates directly to the mathematical and coding relationships presented in both the above paper and the technical review "HTM Cortical learning algorithms", Hawkins and Numenta (2010) [4]. These theories have been studied and used to design the olfactory sensory based node described and developed in this research project.

2.3 THE OLFACTORY SENSORY SYSTEM

The Orbitofrontal cortex (OFC), viewed below, is the receiving point for the primary olfactory neocortex. Input to this area arrives directly from the olfactory system [16].



Figure 2.4: The approximate location of the OFC [17] Obtained from a MRI Scan, location confirmed in Gray's Anatomy Volume IX [18].

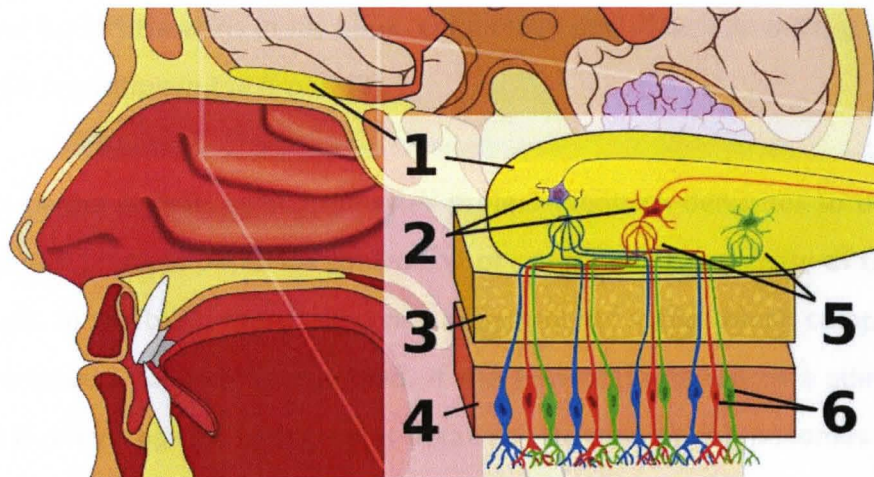


Figure 2.5: The olfactory system [19] [16]. When an odour presents itself it invokes the olfactory receptor neurons (cells) to react or spike. These signals propagate to the olfactory bulb and the axons connect with dendrites of the olfactory network. All these axons merge to form the olfactory tract. (1) Olfactory bulb; (2) Mitral cells; (3) Bone; (4) Nasal epithelium; (5) Glomerulus (6) Olfactory receptor cells

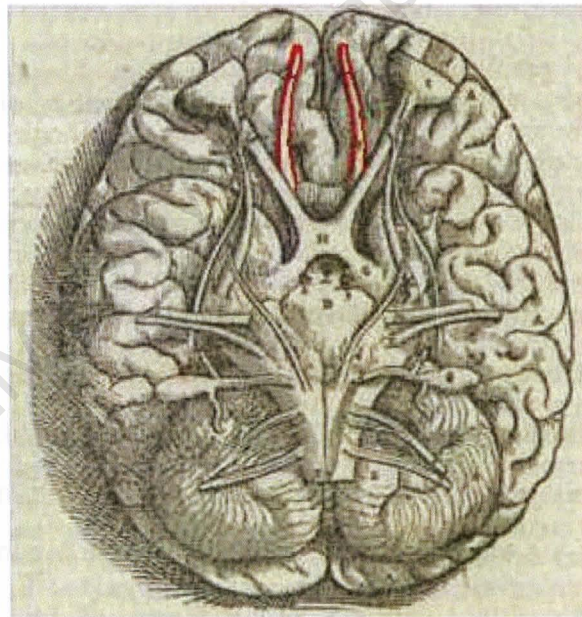


Figure 2.6: This is the view of human brain from below, highlighted in red are the olfactory bulbs, displaying where they are physiologically situated [19] [20].

Aptly stated by Jeff Hawkins in his book 'On intelligence' "*there is nothing static about the flow of information in the brain*" [3].

Most parts of the primary olfactory cortex project feedback dendrites to the olfactory bulb; these are physical paths for controlling or confirming the validity of the received sensory data. In the brain there are constant judgments made, which compare what is being experienced, to what is expected. If the first presentation of a stimulus is not confirmed it is investigated with greater detail or attention until it becomes knowledge, explained in detail by Gottfried and Zald (2005) [16] and in overview, to support HTM theory by Hawkins and Blakeslee (2004) [3].

Without feedback, every time a new stimulus is presented it would seem novel, therefore feedback is intrinsic to any brain-like system and important to include in the design.

HTM theory uses feedback intrinsically to boost signals and to confirm whether what is being presented is correct or incorrect, confirming this through a process of inhibition by modifying permanence values [4].

The above Figure 2.5 and Figure 2.6 are pictorial views of the olfactory sensory bulbs. Neurons found inside these bulbs are the main input neurons to an olfactory bulb. They have a dendrite which receives input from the olfactory receptor neurons, and their axons merge to form the olfactory tract. These axons are the first structures that conduct *negative feedback and positive feed-forward*. There are about 50,000 axons in each bulb in the adult human.

The dendrites merge to form bundles called glomeruli – up to 25 olfactory bulb neurons, namely mitral cells, may send their primary dendrites to a single glomerulus – here they make contact with incoming olfactory nerves.

Cells called periglomerular cells are involved in *lateral inhibition* at the level of the glomeruli or merged dendrites.

The end point of the axons from the olfactory tract is the primary olfactory cortex, in the orbito-frontal section of the neocortex. They originate from merged axons that form the olfactory tract which terminate in the primary olfactory cortex [21].

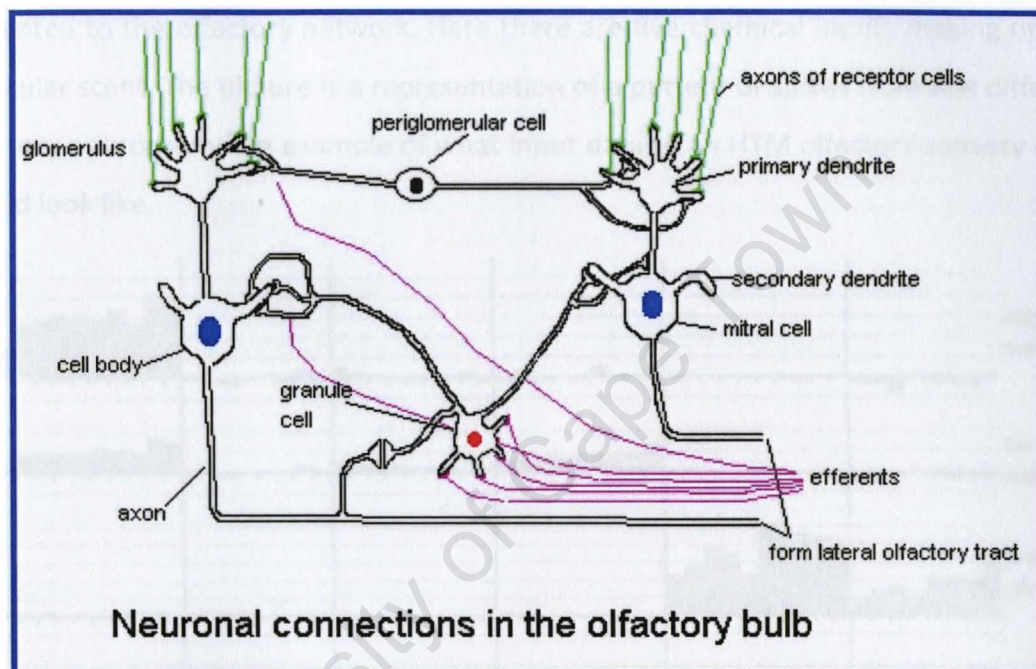


Figure 2.7: Neuronal connections in the olfactory bulb [21]

2.3.1 How does the sense of smell work?

Chemical odorants dissolve in the olfactory mucus and then bind to odorant binding proteins or OBPs. It is thought that these proteins assist the movement of odorants across the mucus layer to the olfactory receptors, and increase the concentration of the odorants in the layer, relative to air [21].

Scent is one of the first senses to form during the process of development [22].

2.3.2 Olfactory sensory patterns

The way in which the brain manages olfactory sensory data is by using a sparse, spatial-temporal pattern classification system [23]. Each HTM node manages input sensory data in the exact same way, the first stage being a spatial pooler and the second a temporal pooler.

Figure 2.8 below is an example of the type of input chemical sensory data that will be presented to the olfactory network. Here there are five chemical inputs making up this particular scent. The picture is a representation of a pattern of spikes from five different olfactory neurons and an example of what input data to an HTM olfactory sensory node should look like.

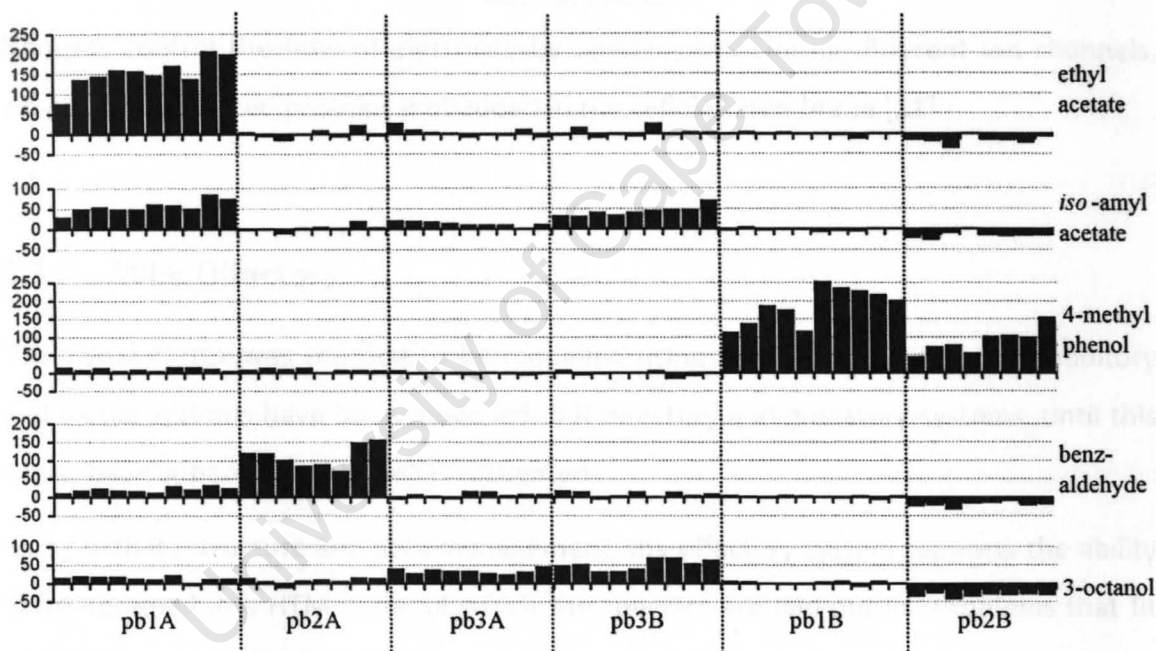


Figure 2.8: Example of a chemical sensory input to the olfactory network. Here there are five chemical inputs making up a particular scent. Each chemical stimulates an olfactory neuron to react with a certain spike pattern when that scent is present [24]. The graph shows the volume (left) of each chemical compound (bottom) found in the cytochromes (right)

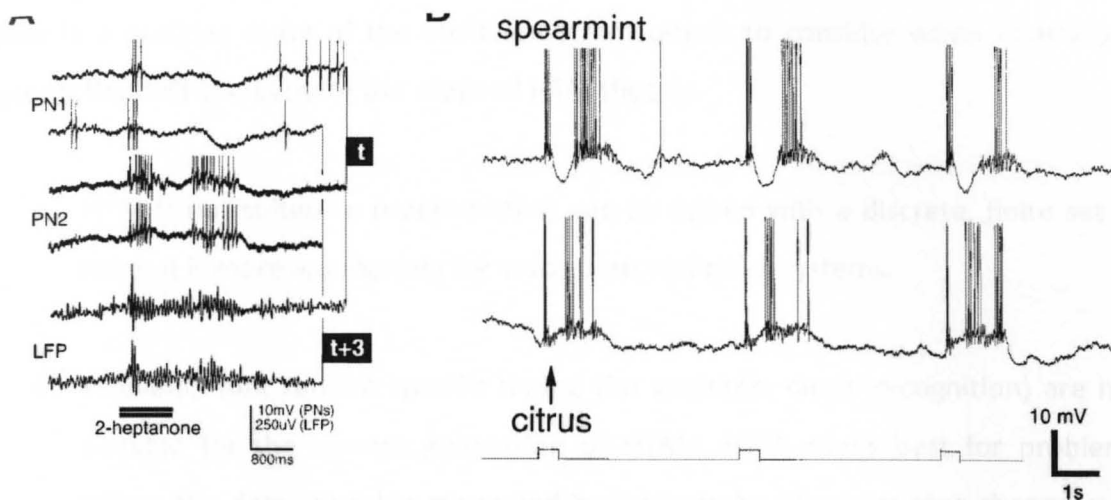


Figure 2.9: Temporal representations of odours in an olfactory network scale seen as 10 mV:1 s [25] displaying neuron outputs, showing that they are electrical processors that represent information as bursts of voltage.

Neurons control the flow of electricity by opening and closing different ion channels, which are specialized proteins embedded in the cellular membrane [11].

2.3.3 Why Olfactory

The Visual cortex was the first to be modelled using HTM theory. Since then auditory and tactile systems have been modelled, but olfactory and gustatory systems, until this study, have apparently not been investigated.

Along with its structure and data management, the olfactory system supports the ability to be designed in a HTM node, of which the specifics are laid out in "Problems that fit HTM's" Numenta (2007) [26].

To successfully apply HTM Theory to an olfactory sensory network application there are important aspects to consider in order to ensure that the problem is appropriate and can be formulated precisely.

Here is a outlines some of the most important points to consider when choosing a system that will compliment the usage of HTM theory:

- HTM is not suited to problems that can be solved with a discrete, finite set of rules. It is more appropriate for ambiguous and noisy systems.
- Problems that require specific timing (for example, music recognition) are not suitable for the current generation of HTMs. HTM works best for problems where the data model is generated by a hierarchy of causes that change over time, for example a melody input. Here a *cause* is the *object* that *caused* the HTM input data.
- The problem domain of an HTM node should have an inherent hierarchy and the data should have spatial and temporal correlations, and enough data organized in temporal sequences must be available to perform training.
- The learning process of HTM theory is conducted over a period of time, with reintroductions of the input until it becomes knowledge. The period or the amount of learning that is required depends on a number of aspects discussed in Section 10.1.7, the conclusions section of the spatial pooler of the HTM node designed in this thesis.
- As in the human brain, an HTM network requires a substantial amount of training data. HTM networks handle ambiguity and noise well and can use input from different sources (temperature, speed etc.) to create a picture just as the human brain does, relying on a diverse amount of sensory input data to verify the circumstance. It has been tested and verified that HTM networks do not require symmetry in the input data received [26]. See section 10.1.7.

A system that is organized as a hierarchy of causes has the following properties [4] [26]:

- The first is that it holds *spatial hierarchy*, meaning that if generated data has highly correlated causes, i.e. the sensor readings correlate extensively, but when sensors are separated by distance the correlation coefficient decreases, it is highly likely that the system has spatial hierarchy organization.
- The second property is *temporal hierarchy*, meaning that causes that induce data relate to each other through time, i.e. a trigger or cause will have a before and an after, both defined by an event. If the system can be recognised through input strings relating to each other in before and after occurrences then it has temporal hierarchy organization [27].

2.3.4 The importance of hierarchy

A hierarchy of causes is fundamental to the theory of Hierarchical Temporal Memory (HTM). Common causes can be found in an HTM system only if you are sensing the right information i.e. the information has a causal relationship.

It is expected that much of the work required to formulate a HTM problem will be to experiment with a variety of sensory data. This will enable the HTM system to determine the underlying cause, obvious or not.

3 BACKGROUND OF NEUROMORPHIC ENGINEERING

Neuromorphic engineering is a relatively new field, approximately 20 years old; in which there are a growing number of people and research institutions who are engaging in neuromorphic research. Some of the more widely known institutions are: the Institute of Neuroinformatics: University of Zurich (INI), the École Polytechnique Fédérale de Lausanne (EPFL) in Switzerland, Stanford and Caltech in the USA.

These institutions amongst others are working on:

- Analysing neuronal information representations.
- Interfacing conventional electronics with neurobiology.
- Reproducing neurophysiologic phenomena in silicon.
- Building artificial systems based on neurobiology.

The neuromorphic engineering field has had a number of focuses:

Table 3.1: Neuromorphic Engineering Summary

Medium	Tasks	Aims
Software	<ul style="list-style-type: none"> - Reverse engineering of the Neocortex in Software (e.g. Blue Brain EPFL [28]). 	<ul style="list-style-type: none"> - Replication of the brains functioning [2] [28]. - Use of sensory input to qualify and test outcomes. - To better understand the workings of the brain [2] [28]. - Pharmaceutical testing purposes [28].
Hardware	<ul style="list-style-type: none"> - Design of neuron, reverse engineering of the brain e.g. Brains in silicon [6] . - Design of Hierarchical architecture [1]. - silicon and Imbedded systems that mimic neurons [6]. - Neuron interaction and synapse functioning [6]. 	<ul style="list-style-type: none"> - To better understand the makeup and workings of the brain [6] [2] [28]. - To implement in intelligent machines [6] [2] [28]. - Human brain prostheses and robot operations are the future aim of this dissertation – using HTM theory

This study is thought to be the first of its kind to explore the application of HTM theory to olfactory sensory networks – there are no known publications available linking gustatory or olfactory sensory networks and the use of HTM theories.

3.1 NEUROINFORMATICS

The broad definition of neuroinformatics or neuromorphic engineering is *“Reverse engineering the information representation used by neurobiology, and developing artificial systems that employ these representations in their operation”*. [29] Neuroinformatics is a vast field of research, encompassing mostly, but not restricted to, materials engineering, neuroscience, electronics, software, hardware (silicon chip manufacture, VLSI), psychology, linguistics and human behaviour or anthropology.

Key factors that influence this research and reasons behind the need for this type of research include learning from and then producing systems that can demonstrate brain like abilities, abilities that compute tasks with minimal power and in the presence of high input noise, these tasks include reasoning, knowledge, planning, learning, communication, perception, manipulation of objects and motor control [29], [30].

3.1.1 Current activity in the neuroinformatics community

At present, the major areas of study in the neuroinformatics field can be linked to the research institutes that have dedicated themselves to the study of neuromorphic engineering, in no particular order some of them are named here:

INI – Institute for Neuroinformatics. Housed at the Swiss Federal Institute of Technology in Zurich, the INI aims to explore how brains work and implement these in artificial devices that interact intelligently with the world, having influence in medicine and the development of computational intelligent systems [31].

Some of their current research includes: infrastructure for a reconfigurable asynchronous event-based multi-chip processor; spiking dendrite neuron model; spike-based silicon cochlea's otherwise named multi-sensory fusion & computational modelling; spike-based auditory processing; motion chips; homeostasis in spiking neurons using non-volatile silicon technology; and CAVIAR – an asynchronous vision multi-chip event-based system [32].

INE: Institute of Neuromorphic Engineering. Housed at the University of Maryland, USA, their focus areas include mainly analog VLSI circuit design related to vision and audition: silicon retinas vision chips; silicon neurons AER systems; locomotion; silicon central pattern generation (CPG) circuits; models of lamprey CPG neural circuits with integrate-and-fire neurons; study biological models: ferrets, bats, owls, crickets, humans; extract principles of organization, design, information processing and control; construct computational and physical models; apply to real-world tasks such as sound localization, auditory perception and robot control; study biology of visual transduction, coding, communication, processing and perception; extract computational principles of orientation, motion, stereo, recognition, attention, etc; construct computational and physical models of various modules; apply to visually guided robotics, scene analysis and understanding.

Brains in Silicon, housed at Stanford University, California, USA, has a focus which is to:

“Use existing knowledge of brain function to design an affordable supercomputer—one that can itself serve as a tool to investigate brain function—feeding back, contributing to fundamental, biological understanding of how the brain works” [6].

Systems developed, manufactured and implemented emulate the flow of ions directly in hardware. Their research areas are: audition: spiking; vision: computing efficiently; attention: spike or burst; learning: growing circuits.

The Centre for Neuromorphic Systems Engineering housed at the California Institute of Technology, Caltech, USA has a goal to create an enabling technology useful to industry. From inception, the research has been made to be relevant to industry, and the results of the research have been shared only with industrial partners [33]. The research at CNSE includes: metal nanostructures for optical sensing and signalling; modelling swarm-based, distributed robotic manipulation; networks, evolutions, science and neural systems; CMOS Imager with embedded ue early image processor; spike based saliency detection; fly flight simulator to study visual and rotational stimuli; encoding of depth in parietal reach region (RR); and 47 other such projects

Carver Mead, currently Emeritus Professor of Engineering and Applied Science at Caltech, author of the book “ VLSI and Neural Systems”, developed the first neutrally inspired chips, including the silicone retina and chips that learn from experience [34].

The Blue Brain Project housed at the École Polytechnique Fédérale de Lausanne (EPFL), runs a project they name the Blue Brain, which focuses on modelling of the rat cortex using software [28], [35]. The intention is to provide a platform, for testing prescription and other drugs, that is embodied in silicon and therefore allows non-invasive testing.

At the EPFL they are working on building an exact replica of the brain in software simulation, starting with the most ‘basic’ of building blocks – the neuron – and building outwards -a bottom up approach, to put together the entire structure of the brain.

Numenta is a privately funded institute that is looking to create a new type of computing technology modelled on the operation of the Neocortex, using their own technology called Hierarchical Temporal Memory, or HTM. The study is justified by stating that computers only excel at problems described by using discrete rules. However, rules-based approaches struggle with real-world ambiguity and complexity. They state that:

“An HTM system or node, by contrast, is trained rather than programmed. HTMs learn about objects in the world in the same way that people do, through a stream of sensory

data. By modelling the pattern discovery mechanisms of the human brain, HTMs offer a means to solve pattern recognition and prediction problems in messy, large, real world data sets” [36].

Numenta’s research, performed at their premises, looks to have application areas which include: image and audio recognition; failure prediction in complex systems; web-click prediction; fraud detection; and semantic analysis of text.

The underlying learning algorithms used in HTMs are not specific to particular sensory domains and thus can be applied to a broad set of problems that involve modelling complex sensory data. These problems need to fulfil certain criteria mentioned in section 6.2.1 and laid out in the report “Problems that fit HTM” (2007) [26].

An example of currently published work, implementing HTM theory, is the Vision Toolkit, freely available for download for educational purposes from the Numenta webpage. It is a GUI (Graphical User Interface) that takes a number of input images, and trains with them, after which the user is able to test that the system has learnt correctly through an experimentation and testing page. The final output from the testing page is a screen shot that looks something like this:

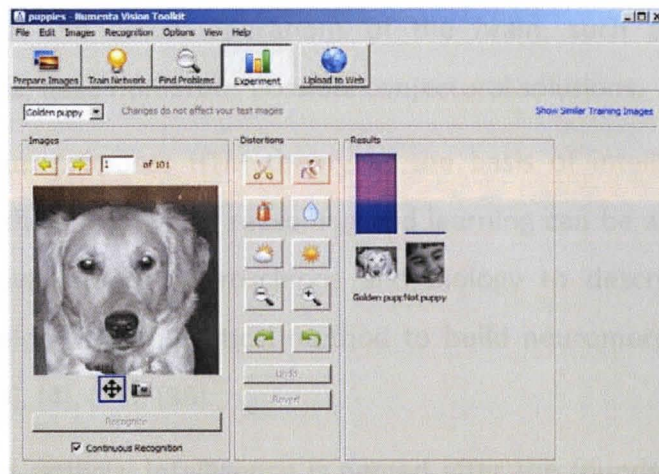


Figure 3.10: Vision toolkit screen shot after training with Vision Tool kit downloaded from www.numenta.com. On the right of the above picture, the two blue bars demonstrate the probability that the picture shown on the left is that of a dog.

One can see clearly on the right hand side that if two different images are presented, the one that is similar to the target (the dog) is chosen with a much higher probability than the one that is not similar. In this case, it was after the system had been trained on 127 pictures of dogs; as with humans, the more images that are introduced the better the accuracy in recognising the correct output.

Vitamin D Inc. (<http://www.vitamindinc.com/>) is a company working in conjunction with Numenta using HTM protocol to design security software for picking up people in the surroundings.

3.1.2 Hierarchical temporal memory (HTM)

Jeff Hawkins and his colleagues founded the company Numenta to back the study of HTM theory – a relatively new concept in the field of neuroinformatics based on work by George, Blakeslee and Hawkins (2005, 2009) [2], [3].

HTM theory is based on the operation of the neocortex, as described in section 2.2. Physically the neocortex is made up of six layers which are well known to

neuroscientists, but the actual operations of the brain, such as its learning and adaptation methods, have numerous possible conjectural solutions.

The Numenta group proposes HTM theory as the basis of intelligence, and as the computational method with which reasoning and learning can be accomplished – they use extensive knowledge of neuroscience and biology to describe how the brain operates and develop a mathematical method to build neuromorphic architecture in software [1], [2], [3], [4], [26], [36].

The original test of artificial intelligence is named after the founder Alan Turing. The Turing test looks to prove intelligence by posing a question: if a machine is hidden and cannot be seen, can the machine trick a human into believing that it is another human [37]? The flaws of the Turing test were initially pointed out by Alan Turing himself, it has since been completely discounted by many later computer scientists, such as Stuart J. Russell and Peter Norvig who wrote a widely used textbook “Artificial Intelligence: A Modern Approach” (2009) [38].

Hawkins and Blakeslee describe what can be interpreted as a test in the book “On Intelligence” [3] (2004), here labelled as “the Hawkins test” and stated as: intelligence is the predictive ability of a hierarchical memory – and not dependant on human reaction or behaviour.

The aim of this thesis is to test the application of HTM to an olfactory sensory network.

4 NEURAL NETWORKS (NN)

Neural Networks (NN) is a broad term originally related to all networks that are based on the mechanics of a biological neuron, and the operation of the brain's higher functioning. Prior to neuroinformatics, neural networks were, chronologically speaking, the most recent effort in attempting Artificial intelligence (AI) [39]. As seen on the same timeline neuromorphic engineering is the follow up, and there is an expectation of successful computational intelligence from this field of research [40].

The general mathematical model describing the input stages of a neural network can be seen in Eq. 4.1

$$v_k = \sum_{j=1}^p w_{kj} x_j \quad (4.1)$$

Where v_k is the output voltage for node k of neural network, p is the total number of input signals to the node and w_{kj} is the weight assigned to the input signal x_j .

This can be visualised as the first stage of the neural network in Figure 4.11 below.

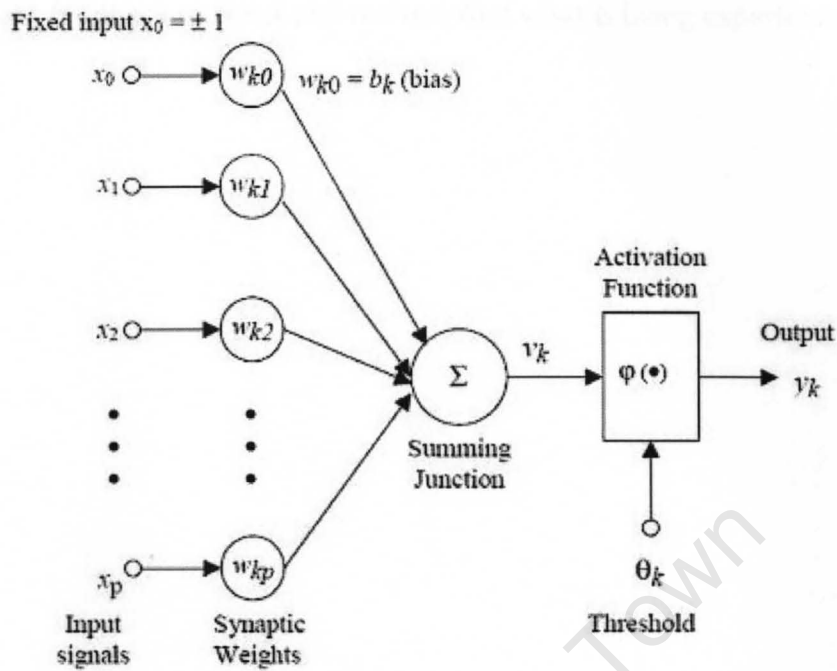


Figure 4.11: Pictorial overview of a simple neural network node k from which the mathematical model in equation 4.1 has been derived [41].

Neural networks are a useful result of previous attempts to model the human brain's higher functioning and reasoning - and are still being implemented in certain fields today. They form the basis of what was originally thought to be the answer to intelligent machines. The following are some common failings of conventional neural networks [42]:

- Neural networks require extremely diverse training for use in the real world [43].
- The fundamentals of neural networks teach that once a computation is completed, an error is broadcast from the output units, and fed back toward the input units, aiming to compensate / correct the error and hence learn. This process only occurs during the learning stage, whereas in our brains there is

constant feedback to check and recheck that what is being experienced is correct [44].

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5 HTM THEORY

All regions of the neocortex form invariant representations of the world [10] or objects using a hierarchical structure. Objects are composed of sub-objects that occur together without fail [45], examples of such are: every door has a handle, every face a nose, every plate a flat surface etc. Memory is considered to be a process of these objects being stored over a hierarchy of cortical regions, and a strengthening of the synapses in these regions [44]. In HTM theory this strengthening is labelled the *permanence value*.

HTM theory states that it is the group name, not just individual patterns, that passes on to higher regions of the cortex. Therefore, the brain can be said to store sequences, develop *names* for the sequences that are known, and then pass these names to the next region, further up in the cortical hierarchy [2].

Representation of simple objects at the bottom of the hierarchy can be used over and over for different high level sequences – avoiding redundancy and making a very efficient way of storing information.

The following steps are important for invariant representations:

- 1) Classify each part of the sequence.
- 2) “Notice” frequently occurring patterns (this is done through the indefinite amount of feedback found in the brain structure).

The brain resolves ambiguity by using the context of known or experienced sequences. It then uses the experiences and constant feedback to modify and strengthen regions.

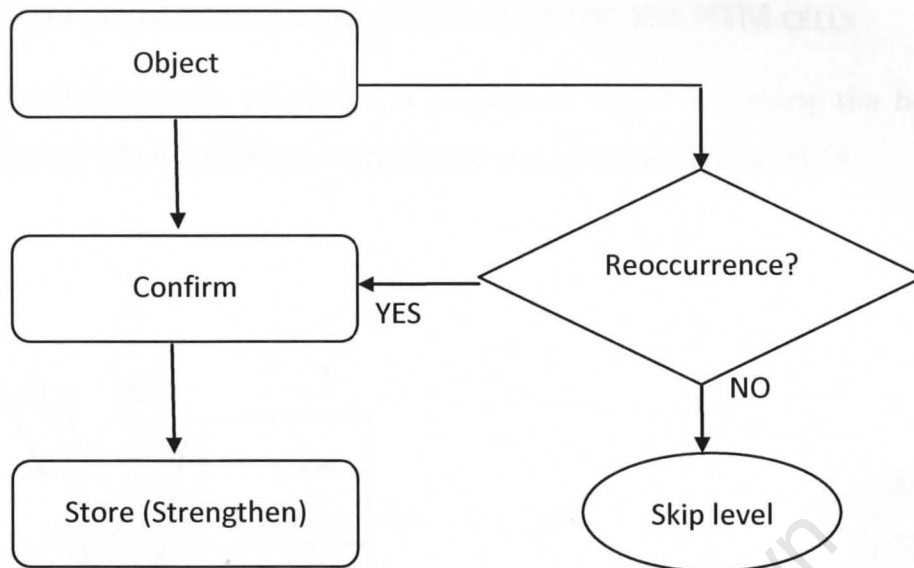


Figure 5.12 Graphical representation of the path a decision would take in an HTM node; representing what happens in the brain and referring to the levels associated with levels in the Neocortex. Graphical representation derived from George and Hawkins (2009) [2].

Through the process of evolution the neocortex has adapted to attach a hierarchical memory system to each sensory system, which models the world and continuously predicts the future – taking patterns that are known and comparing them to what should happen – always confirming truth, and adjusting for incorrect initial perceptions [10].

Using the above natural process as a model, HTM theory states that intelligent machines must behave along the same lines. Starting with a set of senses or inputs, which extract pattern representations of the environment, and using them to create a hierarchical memory system that operates on the same principles as the neocortex – that is to say, train the memory system through repetition, as children learn, and proven thoroughly used in neural network theories [46].

5.1 COMPARISON BETWEEN BIOLOGICAL NEURONS AND HTM CELLS

The aim of HTM theory is to achieve a method or model describing the biological neuronal activity, where others have attempted and failed previously [2], [4].

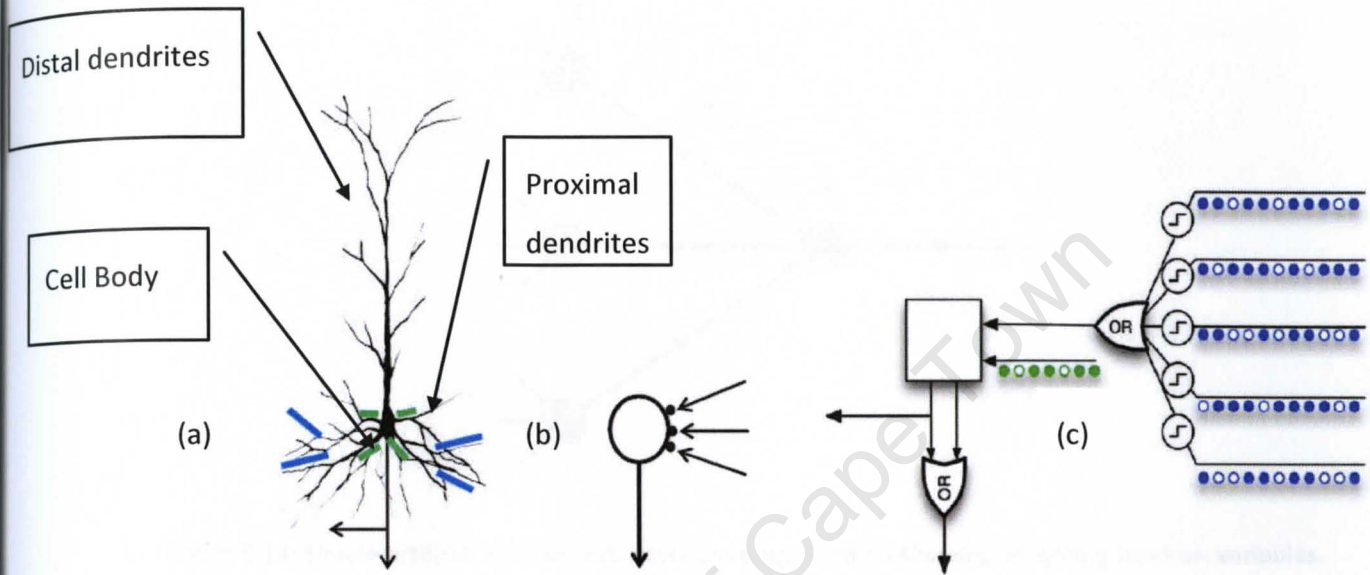


Figure 5.13: Comparison between biological neurons and HTM cells. Above (a) is a biological cell with text describing the different regions of neuron. (b) Is a simple artificial neuron and (c) an HTM neuron or cell with numerous inputs to a 'decision' box (as seen above) and outputs that provide feedback and feed forward mechanisms [4].

SIMPLE ARTIFICIAL NEURONS

The centre illustration in the above figure is of an element used in a number of artificial neural network models and may be familiar.

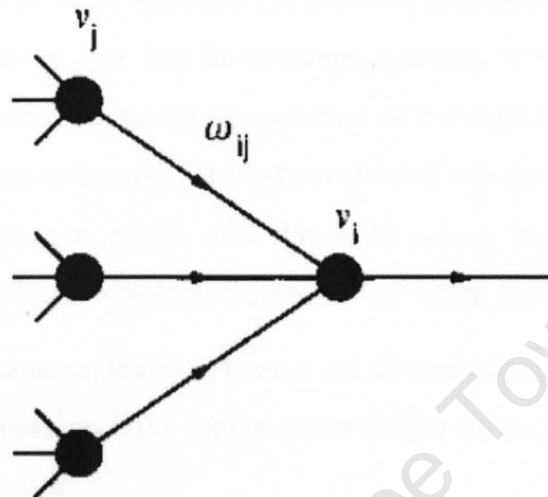


Figure 5.14: Simple artificial neuron with descriptive signal paths showing weighting function variables. where $\omega_{ij} \in \mathbb{R}$ is non-zero for neurons v_j that feed v_i [47].

The above illustration (Figure 5.14) is more descriptive than Figure 5.13. These structures have proven useful in numerous applications; however they do not capture the intricacy of the biological model and its processing. A more sophisticated model is needed for this purpose, one that is believed to be presented in this dissertation.

Simple neuron models work in such a way that each input channel is characterised by a weight. The output is then summed, nonlinearly, and learning happens via adjustment of these weights. This, originally, was the extent of accepted theory to accomplish learning.

HTM CELLS

On the far right of Figure 5.13 is a representation of an HTM cell. It mimics most of the biological neuron, but a few simplifications have been made [4]:

- A biological cell has the ability to modify itself dynamically, to operate in a feed forward manner. An HTM node is fixed and does not, as yet, change dynamically. This is not thought to have a huge impact, and dynamic response can be introduced if need be.
- In the brain, if a cell never wins the competition between neighbouring cells it is deemed unnecessary and dies or becomes inactive. HTM boosts a cell's feed forward activation; if it does not win as often as it should, this maintains its place in the competition, and avoids having to switch off any non-winning cells.
- The HTM permanence values and threshold values can be set and will be maintained, whereas in a biological system they might decay.

Competition between columns, learning from a set of potential synapses, and boosting underutilized columns gives an HTM region some of the same dynamic ability that is seen in the mammalian brain.

HTM nodes have distal dendrite segments that are designed to be threshold detectors. This means that an area will be active if the number of connections or synapses made is above a pre-defined threshold. Fifteen active synapses have been proven to be sufficient to recognise a sensory pattern, much the same as can be seen in Figure 2.8 and Figure 2.9, the minimum number required is 15, for no reason further than a larger sample space the test value used in this thesis is 20 [4].

Synapses in an HTM cell have a binary weight. It is possible to use a scalar value, however due to the distribution of patterns it is also possible to use binary. The permanence value on the other hand is a scalar value that is adjusted in learning. Zero is the permanence value of an invalid potential synapse, and a permanence value of above say 0.2 (accepted threshold relating to 2mV [48]) means it has barely connected and may disconnect. The higher the permanence value, found between 0.0 and 1, the more likely the connection will remain. Biological synapses are made and broken for a

number of different reasons – explanations of these reasons are beyond the scope of this thesis.

5.2 HIERARCHICAL TEMPORAL MEMORY

After an initial review of relevant areas of neuroscience was completed, an argument for using HTM theory was developed, and a collection of published works was analysed and then used to design and implement part of an HTM node. This was the spatial pooler section of the HTM node, which could then be used to learn olfactory sensory input. Here follows a background argument for the use of hierarchical temporal memory theory in this study.

5.2.1 Strengths of HTM across problem domains

HTM systems have some useful attributes that apply to many problem domains [26]. These attributes stem from the fact that they mimic the mammalian brain.

1. HTM nodes handle ambiguity and noise well – they cope with unclear and noisy input data. The hierarchical structure and the use of Bayesian probability techniques lead to the system forming stable conclusions even when there are multiple contradicting inputs – Numenta presents this theory as a conjecture [26].
2. HTM nodes can receive multiple sensory inputs. Like the biological processes in the brain, they have a repeated cortical algorithm that can be applied to the sensory data, and multiple kinds of senses can be used for one HTM [4].

3. It does not matter how far apart sensors are placed, or how close – therefore there is no physical constraint – spatial correlation does not refer to physical surroundings, it refers to the cortical column layout [4]. Therefore HTM structure does not limit the designer to symmetry constraints, in modelling real world systems which are not necessarily symmetrical or constant.

5.2.2 Why HTM?

Though there are several scientific studies focusing on neuroinformatics and the design of the brain, its operations and applying its management of information techniques, the theory of HTM is not well investigated. Although support for this theory is growing, which can be seen in implementation through companies like VitaminD (Section 3.1.2) it is not widely accepted as yet in the scientific community as the answer in the race to figure out how the brain operates.

6 MODELLING THE BRAIN

The neuromorphic field approaches modelling the brain in two domains: (i) Hardware and (ii) Software. Sub categories of these are A) to understand how the brain works and replicate its operation, a seemingly top down method and B) to build the neocortex part of the brain, as a near-exact replica of the biological organ, and use the structure to gain an understanding of its operation, which will in turn allow for its use in intelligent machines. This second sub category is a bottom up method.

6.1 THE HARDWARE APPROACH

6.1.1 Hardware Neuron Models

A biological neuron model, namely the spiking neuron model, describes the properties of nerve cells or neurons in a mathematical formula. Their main purpose is to accurately outline and anticipate biological processes and processing – this is in contrast to the artificial neuron which aims to be effective on a computational level only [49] [50]. The system to be developed in this dissertation is built on computational intelligence, using the biological structure in its reasoning; therefore the aim is to use a biological neuron model.

The input to a neuron is an ion current $I(t)$ which crosses a cell membrane. This happens when neurotransmitters cause an activation of ion channels in the cell membrane. The neuron cell is encased in an insulating cell membrane with a polar distribution of charged ions creating a capacitance C_m . A neuron responds to the input signal with a change in voltage, or potential energy difference, between the cell and its surroundings – this may culminate in an observed voltage V_m spike which is named an “action potential.”

The above description is often simplified as the *integrate and fire* neuron model, being one of the first models introduced by Lapicque in 1907 [49]. The mathematical formula which follows logically is:

$$I(t) = C_m \frac{dV_m}{dt} \quad (6.1)$$

When an input current $I(t)$ is applied, the membrane potential V_m increases as a function of time until it reaches a constant threshold. This induces a delta spike (action potential) after which the membrane potential returns to its resting state with a rate defined by the size of the capacitor C_m .

The magnitude of the output current increases linearly without bound, indefinitely and therefore this neuron model is fundamentally flawed; this neuron would have to be monitored and refreshed throughout the system's life.

So far there is no exact method of modelling a neuron, and there are a number of contradicting theories. Regardless, the integrate and fire neuron model has been implemented successfully to design the neural network system used in a small number of consumer products today, the most noteworthy being mice and pointing devices by Synaptics and Logitech. This design was first implemented in silicon by Carver Mead and his research group at Caltech in 1989 [51] [52].

Spiking neuron modelling incorporates a spectrum of biological constraints, with current studies supporting spike timing and its importance in neural-computations [53]. There have been a number of tools that can be used to simulate spiking neural networks, and these tools are used to accurately simulate a variety of systems [54]. However there are so many challenges relating to spiking neurons that the representations are just as vast; as an example, when intracellular electrophysiological measurements need to be reproduced, conductance based models like the Hodgkin and Huxley (1952) have been

used [55]; in other cases, where realistic spiking does not have to be captured, then simpler models like the integrate and fire neurons suffice, as they are quick to simulate and have been proven effective in large and small scale simulations [56].

6.2 LEARNING MODELS

This is a brief overview of current learning models. The models below are thought to be the most relevant to this study.

6.2.1 Hebbian learning

The rules for adjusting synapses to be more or less permanent in HTM are similar to the Hebbian learning rules [4].

Hebbian learning is the most common method used to train neural networks. It is an unsupervised way of learning and is named after its original proposer, Canadian neuropsychologist Donald O. Hebb.

$$\omega_{ij} = x_i x_j \quad (6.2)$$

The above equation describes the weight (ω_{ij}) of the connections between two units x_i and x_j and demonstrates the Hebbian learning constraint that the weight should be increased or decreased in proportion to the product of their activation [46].

This theory and formula is based on the learning rule by Hebb who said that connections between two neurons might be strengthened if the neurons fire simultaneously, meaning that, two nearby neurons that fire together may be considered to have a causal relationship [57]. The Hebbian rule works *iff* all the input patterns are orthogonal and uncorrelated – these criteria place rather large limitations on the learning rule. D.E Rumelhart and J.L McClelland of the PDP research group confirmed that a more powerful rule for neural network training is the delta (Δ) rule, which calculates the error between the actual input and the previous output [57].

These rules define a standard neural network training method, and are limited by:

- Neural networks are known to generalise, however the amount of data required to train the network exceeds that of an HTM node.
- Following from the previous point, by increasing the input space, the required storage capacity and power usage for the system increases. The biological neocortex and HTM network are able to reduce those requirements by using sparsity [2].
- Hebbian learning uses correlation between units in an associative network. Sometimes these “unitwise” correlations are not sufficient enough to learn correct associations between whole input patterns and thereby to formulate the correct responses [46].

6.2.2 Hierarchical Temporal Memory (HTM)

HTM learning theory is the basis of this study. George Dileep and Jeff Hawkins (2009) describe the essence of learning in the cortex in that regions can be, and are, modified by experience. Forming new classifications and new sequences is how the world around is remembered and recalled [2].

Two current input processes for design of the input neuron signal will suffice for this study, namely synchronous (clock driven) where the neurons are updated at the same time every clock cycle, or event driven neurons (asynchronous) where the neurons are updated only when a spike is received or emitted. HTM theory leans towards a hybrid system which is event based using the first input received to initialise the system [58].

HTM networks use discrete neuron spikes as the initial inputs to the system or node; from there mathematical manipulations use this data to create Markov chains by arranging the input signals into coincidence patterns, hence relating the Markov chains through spatial and temporal means.

The process of learning an HTM model for spatio-temporal data is the process of learning the coincidence patterns and Markov chains in each node at every level of hierarchy. The basic process can be summarized using two operations:

- 1) Memorization of coincidence patterns and
- 2) Learning a mixture of Markov chains over the space of coincidence patterns.

The coincidence patterns generated are two or more inputs that have occurred at the same time - the coincidence of them co-occurring places them in a position in a set of coincidence patterns that can be used to formulate a matrix of Markov chains describing the system. The Markov chain of a specific occurrence is a subset of the coincidence patterns, or an overlapping of coincidence patterns.

6.3 MATHEMATICAL THEORY OF CORTICAL MICRO CIRCUITS

"Towards a mathematical theory of cortical micro circuits" by Dileep George and Jeff Hawkins [2], is the first peer-reviewed published work to be presented on the Hierarchical Temporal Memory theory and defines, mathematically, the management of information in the neocortex. As the name suggests the paper is an unproven conjecture that aims to lay out a mathematical theory towards the design of a micro circuit that can produce intelligent reasoning and recognition, and a suggestion as to how higher cognition occurs in the brain.

The paper supports the accepted mathematical theory of hierarchical Bayesian inference for understanding cortical computation, and fits Bayesian belief propagation to a spatial-temporal (governed in space and time) hierarchical model. This method is abstracted mathematically in the white paper, and a year later in the technical report *"HTM Cortical Learning Algorithms"* [4]. Numenta produces pseudo code that has been used in this work to build a learning algorithm that operates as the Neocortex does.

6.3.1 Markov Chains

As part of the study of HTM's, the mathematical stochastic process Markov Chains were investigated. These chains describe a system or space of the transition from one state to another, very basically, by having knowledge of two parts: (i) the initial state and (ii) a matrix called the "transition matrix".

A more mathematical description perhaps is: a Markov chain is a random process that possesses the so called "*Markov property*". This property states that the conditional probability distribution for the system at the next step – and all future steps – given its current state, depends only on the current state of the system, and not on the state of the system at any previous step [59].

These Markov chains take the input spikes (delta function $\delta(x)$) of the sensory neurons and use them in this case as input to a HTM network [1].

Markov chains are defined in the following way:

For a finite state space Ω , it is said that a sequence of random variables (X_t) on Ω is a Markov chain if $\forall t$ all $x_0, \dots, x_t, y \in \Omega$ meet the requirement:

$$\Pr(X_{t+1} = y | X_0 = x_0, X_1 = x_1, \dots, X_t = x_t) = \Pr(X_{t+1} = y | X_t = x_t), \quad (6.3)$$

Therefore transitions are independent of time and have a transition matrix denoted as:

$$P(x, y) = P(X_{t+1} = y | X_t = x) \quad (6.4)$$

Here time is measured from the first moment of interaction, or the inception of the signal [59].

In terms of sensory input, the Markov chain is an array of probabilities that the next moment in time a spike will be generated. The transition from one point to another is defined by the transition matrix specific to the system.

The transition probability matrix for the above set of Markov chains is denoted by:

$$P(c_i(t)|c_j(t-1), g_r) \quad (6.5)$$

Where c_i is a coincidence pattern and g_r are the Markov chains of the system.

In summary a Markov chain represents a dynamic process as a transition probability matrix. For each stimulus presented, a matrix is constructed; the array of each row representing a state of a neuron receptor, and the column arrays representing the probabilities of transition from the current state to the next state of the neuron in the next transition step. The result is a set of binary conditional probability distributions, one for each state of the sensory neuron.

As the system changes under random conditions, it is not possible to predict what the future state will be, however using the statistical properties of neural sensory streams and derived Markov chains, it is possible to determine what the next stage will be.

In Hierarchical Temporal Memory systems each Markov chain is defined over a subset of coincidence patterns of the input data. A coincidence pattern in a node represents the co-activation of the Markov chains of its child nodes. A coincidence pattern that is generated by sampling a Markov chain in a higher level node, concurrently, activates Markov chains in the lower level nodes [2]. The process of learning in an HTM model using spatio-temporal data is the process of learning the coincidence patterns and Markov chains in each node at every level of the hierarchy. This translates into a set of input data and *Permanence values* which are demonstrated in the development of an HTM node [2], [4].

The use of Markov chains is not new in the neuroinformatics field. Bernardete Ribeiro, Rudolf F. Albrecht and Andrej Dobnikar designed a Markov chain representation of a neural network in their book "*Adaptive and natural computing algorithms*" (2005) [60].

6.4 HTM CORTICAL LEARNING ALGORITHMS

In the Technical Report "*HTM Cortical Learning Algorithms*" [4] Numenta sheds light on the previously submitted white paper "*Towards a mathematical theory of Cortical Microcircuits*" [2], by introducing the concepts of the spatial pooler and temporal pooler, which is the theory needed to design an HTM node and correctly simulate the workings of the neocortex.

The HTM theory demonstrates that each building block of every level of the neocortex possesses a spatial and a temporal pooler. The spatial pooler receives the input data, comparing it to feedback streams, and learning by strengthening the synaptic connections. The temporal pooler then organises the data with respect to previously experienced events and situations, and compares what is expected to what is being experienced [4].

6.4.1 Spatial Pooler

The inputs to the spatial pooler are arrays of binary data. This data either describes sensory information from input sensory systems, or the previous level temporal pooler output.

It computes a list of columns that *win* based on previously defined criteria and the bottom up input at time t . Each column consists of a stack of cell bodies of neurons, comparable to the biological neocortex. The winning column is one that has a threshold number of input synapses that have been found to be connected exceeding a preset, and definable strength or *permanence* value. This reduces the sensitivity of each column, reducing the effect of noise in the system.

There are three phases to the spatial pooler after initialization:

1. Compute the overlap with the current input for each column.
2. Compute the winning columns after inhibition.
3. Update synapse permanence and internal values.

Initialization

A region is initialised by working out a list of initial potential synapses. This is a random set of inputs selected from the input space. Each input is then represented by a synapse and assigned a random permanence value.

There is a predefined permanence value with which a synapse is considered to be “connected”. This allows potential synapses to be connected or disconnected after a small number of training iterations.

Phase 1: Overlap

With the input vector the “overlap” of each column is calculated. This is the number of connected synapses with active inputs, multiplied by a boost function – the boost function is a confirmation of the threshold value or an inhibition value if the threshold of connected synapses has not been met. If the latter is true then the overlap value is set to zero.

Phase 2: Inhibition

This returns the columns that remain active after the inhibition stage.

Phase 3: Learning

This phase updates the permanence values of all the connected synapses as needed. If a synapse is active the permanence value will either be incremented or decremented. Permanence values range between 0 and 1.

As learning was the required output of this thesis, the spatial pooler is designed and tested here. The temporal pooler is the second stage to be used in further computing mechanisms in olfactory sensory networks and embedded systems.

The information here on the temporal pooler is for interest only, and will not be explored in detail.

6.4.2 Temporal Pooler

The input to the temporal pooler is the output of the previous layer's spatial pooler, or the sensory input to the system if the temporal pooler is the first stage; and the output of each temporal pooler is the input to the spatial pooler of the next stage. Here the active and predictive state for each cell at its current time step, t , is computed.

Two of the three phases of the temporal pooler discussed here are:

1. Compute the active state for each cell.
2. Compute the predictive state for each cell.

Phase one: Computing the active state

For every winning column from the Spatial pooler the following cell that is required to become active is computed. Here if the prediction state is 1 i.e. the input was expected, then certain cells become active, and if the input is unexpected then each cell in the column is set and therefore becomes active.

Phase 2: Computing the predictive state

A cell will "turn on" a predictive state if enough of its lateral connections are firing due to the feed-forward input.

7 INVESTIGATIONS

7.1 HARDWARE

In Carver Mead's words, *"You cannot fully understand anything unless you can build it"*. The hardware and software investigated here support the development of a HTM network in an embedded system, and ultimately the design of a VLSI chip, which both follow on from this work. Various methods were considered to accomplish these goals and are described in the following sections.

7.1.1 Parallel vs. Serial Processing

The network designed in this dissertation is restricted to serial algorithms, as standard computer interfaces were used. However it is believed necessary to mention that parallel processing hardware, which was considered, mimics the nature of signal management in the brain and should be used in preference to serial processing hardware.

7.1.2 FPGA

Field programmable logic arrays are, as the name suggests, logical arrays of circuitry that are configurable to implement any logical function.

FPGA's are parallel programmable logic at its best: whereas a microcontroller runs sequentially, so that only by introducing more cores to a microcontroller do you increase the parallelism, the multi-core structure is intrinsic to an FPGA. Because the brain works at a high level of real time digital signal processing and parallelism, if a dedicated silicon chip is not going to be designed, then a FPGA is the best solution for implementation of an HTM node.

An FPGA was investigated in this exercise – both in respect of the development code and platform – but this was found to have a huge impact on the time scale of this project and for this reason was discarded from the scope of this thesis.

7.1.3 ColdFire V1 M52211EVB

From the perspective of customization, the first choice to design an HTM node would be to use VLSI (Very Large Scale Integration) design methods and build a silicon chip; the second an FPGA; and the third a microprocessor. A number of different options were investigated before settling on the ColdFire[®] V1 M52211EVB microprocessor board.

The systems under consideration needed the following features (keeping the biological system in mind):

- use input pins with an ADC (use to digital converter) fast enough to account for input neuron spiking. Here the Nyquist-Shannon criteria for sampling would be the minimum activation requirement, and is simply stated:

$$f_s > 2B \quad (7.1)$$

Where f_s is the sampling frequency and B the highest frequency of the input signal. The ColdFire V1 M52211EVB runs at 2.1 MIPS (million instructions per second) at 50 MHz, while synapses run rather slowly in comparison - the maximum frequency of odours evoked in a moth run at around 50 Hz [61].

- Low power consumption is intrinsic to the way in which the HTM architecture is designed; even so, this particular microprocessor has a very low power consumption per operation. The brain is estimated to run at between 11W and 30W at full capacity, and it is assumed that a lot of this is not used for computation, therefore 10W is deemed a reasonable value to equate the computational power energy usage in higher processing regions of the brain. For

interest only, a nerve impulse which propagates 1 mm requires around 5×10^{-15} joules [30].

- The input channels of an olfactory sensory network, at the point of entry, map chemical stimuli onto olfactory glomeruli. There are thousands of these inputs. Even though the entire system will not be represented here, a quantity of input pins is needed to give the scope of developing a system that can simulate a subset of these inputs. The ColdFire V1 M52211EVB has 56 general purpose I/O pins, a 32 bit core, and a 24 bit address bus which assist with management of the large amount of input sensory data that is required for this relatively small simulation of sensory system management in the brain.

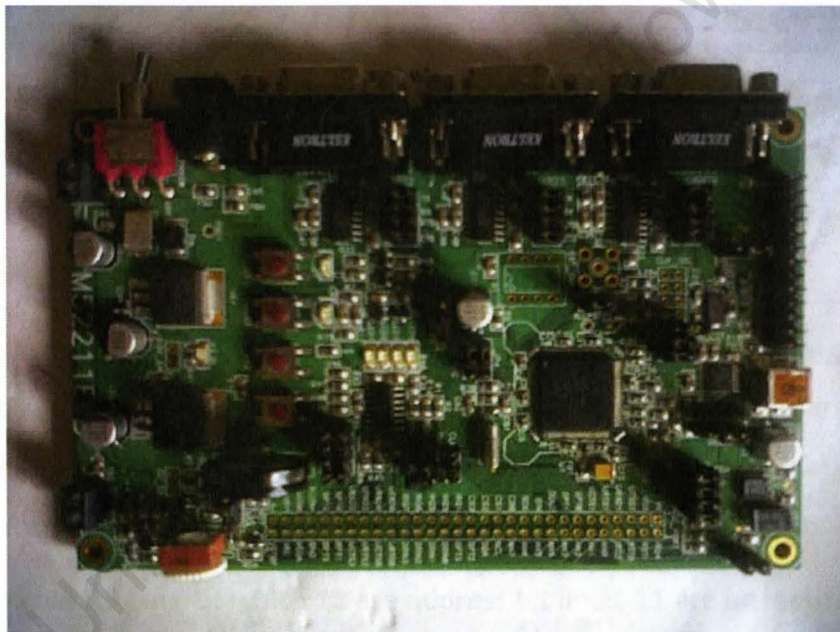


Figure 7.15: ColdFire V1 M52211EVB

7.1.4 IFAT

The IFAT chip is a custom chip designed primarily for individuals that require large arrays of neurons [62].

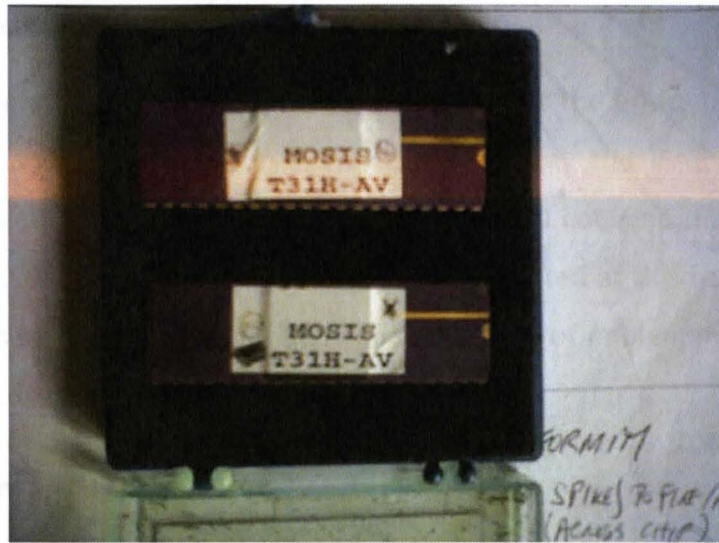


Figure 7.16 2 x IFAT chips

The chip consists of matrices of 2400 neuromorphic integrate and fire neurons. There are no physical synaptic connections on the chip; they are implemented virtually by an off-chip look up table. Serial communication manages input and output *events*, which use a proprietary address-event representation (AER) protocol.

An arbiter is responsible for selecting a single spiking neuron out of a large number of simultaneously spiking neurons, and putting that neuron's address on the output pads. Most of the arbitration circuit is self-timed, waiting only for an external confirmation that the address was received before going on to process additional spikes.

The IFAT chip has 40 pins, of which 12 are address bit lines, 11 are ue inputs such as bias voltages, and there are arbiter pull-ups, resets, thresholds, and 6 digital inputs. These include the acknowledge signal which polls high once a spike is seen. Other pins implement synaptic weights that are shared between neurons in an array, and notifications as to whether the chip is in input or output mode.

Results and conclusions regarding the IFAT chip

It was first thought that this chip could be put to use for the entire implementation of the HTM node and network theory. However, the way the IFAT chip maintains a weighting between neurons lends itself more towards a conventional neural network implementation. The investigation into the IFAT chip halted at this realisation. It is still believed that using the LIF neurons there may be ways of implementing HTM theory, but it would need a more higher level approach.

7.1.5 Custom VLSI Chip

The end goal of this investigation would be to develop a custom VLSI chip that is designed to support the HTM protocol, so hence this study delved into CMOS chip design and the associated platform and design software requirements. The full design of such a chip is beyond the scope of this thesis.

Software

There are a number of software tools that can be used in the design process of CMOS chips. Below is a table with most of the available options and an explanatory overview:

Table 7.2: Microsystems CAD Tools: Summary of software requirements for design and production of a silicon chip implementing HTM [63]

Function	Comments	Free / Low cost	Commercial full cost
Mask Layout	general purpose VLSI and IC design	MAGIC / IRSIM XCircuit Microwind / Dsch Electric	Tanner Tools CADENCE CMOSedu.com
	quick mask design		Photoshop
Circuit Simulation	CaZM	CaZM	Tanner TSPICE
	some of the programs include the macromodeling and behavioral extensions	SPICE from Berkeley B2-Spice WinSpice PSPICE LTSpice TopSPICE	SPECTRE HSPICE PSPICE ICAP
Mathematical Modeling	Matrix analysis and computation		MATLAB

Due to financial constraints only software available for free / with student licensing options were investigated.

The first of these programs is Electric, which is freely downloadable, well documented, and supported via the CMOSedu.com website.

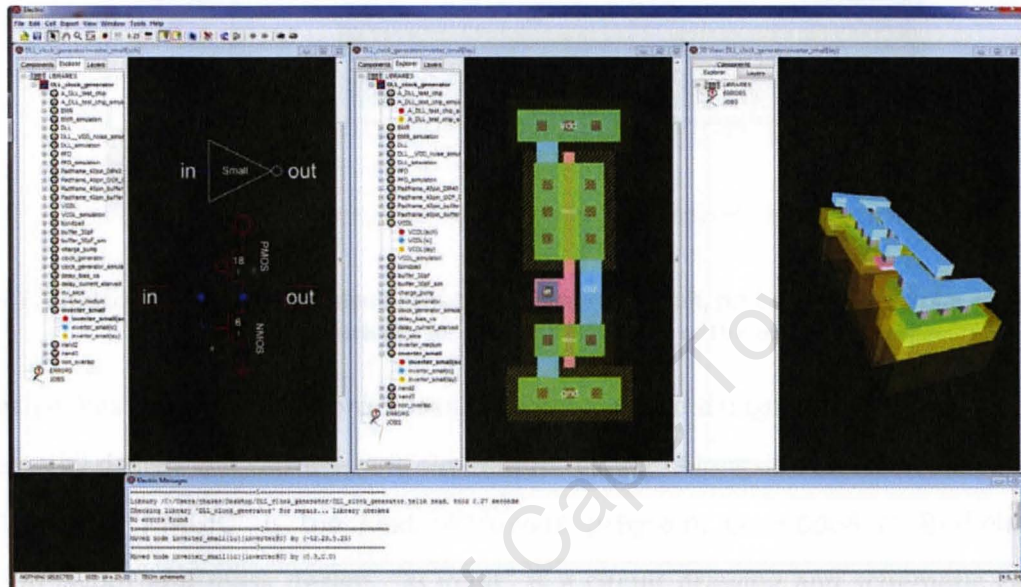


Figure 7.17: Electric screen shot #1 showing on the left the schematic view of an op-amp circuit, in the middle a 2D silicon layout of the circuit and on the right a 3D orientated view of the circuit.

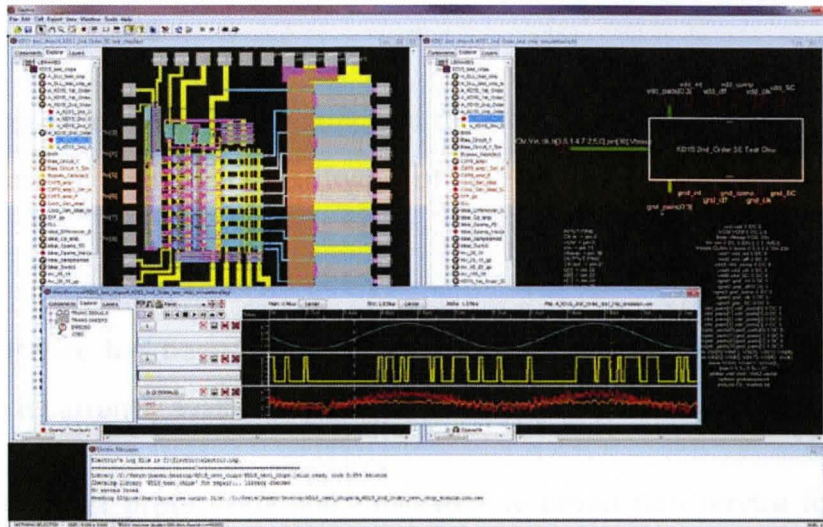


Figure 7.18: Electric screen shot #2 demonstrating a chip view circuit, probes have been placed to show signal outputs which can be seen at the bottom of the screen shot.

IC design has a number of processes, including mask design for fabrication, circuit (schematic) design and capture, and simulation testing. Alongside Electric (developed at Oracle, Inc.), "MAGIC" is the next shareware program, developed at Berkeley, for physical layout and mask design. "XCircuit" is a circuit drawing and schematic capture program developed by Tim Edwards. A large percentage of the other alternatives are for commercial usage; Tanner LEDIT is a low cost option and has student licensing options with affiliated universities. "Cadence" is the gold standard and therefore expensive design system used mainly in commercial silicon chip architecture and design.

All the above programs will produce the CIF or GDS-II files that are necessary for fabrication. Steve Rubin's "Electric VLSI Design System" [64] is a complete set of VLSI design tools for Unix, Windows and Macintosh OS.

Circuit Simulation and Models:

LTSPICE was investigated for design simulation and testing; it is an easy to use program that bridges the gap between what is expected and what is designed. It was also designed at Berkeley and is available freely for education purposes.

Mathematical Modeling

MATLAB is a program used for scientific and technical computing, and has been used in the current research to design the software of the HTM node's Spatial Pooler.

MOSIS

Once the software has been chosen to design and test a silicon chip, the process to manufacture is currently available through a company called MOSIS.

MOSIS is a low-cost prototyping and small-volume production service for VLSI circuit development. They basically offer a commercial service which produces marketable silicon wafers, in which parts of the board that are not bought can be re-assigned for research purposes at a fraction of the cost.

Summary and conclusions on custom CMOS chip manufacture

Manufacturing a CMOS chip to implement HTM may be a viable option, and it is suggested that this avenue be investigated further.

8 DESIGN SPECIFICATION

In selecting a suitable test problem to experiment with HTM, the following process was followed:

1. There must be a convincing answer to the question "What is being solved?" Two classes of problems that HTM can currently solve are:
 - Discovering causes in sensory data.
 - Inferring or concluding the cause of novel input.
2. Ideally HTM predictions will be able to drive external behaviour, such as robotics; however the current focus is just to determine causes.
 - The data should correspond to a spatial and temporal hierarchy.

In summary and justification for applying HTM theory to the olfactory system:

- The olfactory system is supported by the repeating structures and information management in the brain, as mentioned in section 2.3.3
- HTM theory has been said to be modifiable to all mammalian sensory inputs [4] [26], however this has not, as yet, been proven, and the olfactory system is one of the unknown cases.

This thesis aims to present an argument that HTM can be successfully applied to the olfactory sensory network.

8.1 SCOPE OF DESIGN

The objective of this design is to produce a software simulation capable of demonstrating HTM theory applied to the olfactory sensory network, that can serve as a model for a future hardware implementation. This could be a microprocessor or FPGA system, and hopefully ultimately a silicon chip, implementing a neuromorphic HTM node.

The olfactory sensory network was chosen due to the uniqueness of the subject matter, both from a software and hardware perspective. The following specification was created by analysis, deliberation of procedures being experimented on at Numenta, and constraints dictated by the required functionality. The scope of this work does not extend past the development of the spatial pooler, and hence demonstrates the learning ability of the node, but not the temporal reasoning; this fits the functional characteristic requirements.

Development with the intention of CMOS chip manufacture was considered during the design, but has been regarded as a secondary goal; the focus is to establish a working model showing the capabilities of implementing HTM theory.

8.2 FUNCTIONAL CHARACTERISTICS

The following are functional characteristics that the design is required to fulfil:

- It must have the capability of receiving olfactory sensory data.
- It must model the biological architecture and operation of some small part of the neocortex.
 - It must demonstrate learning; inference; but not necessarily prediction (as this is in the temporal pooler stage).
- It must follow the current mathematical models that underlie HTM and neuromorphic theory.
- It must implement spatial pooling by performing an initialization sequence including three distinct phases, as follows:
 - Initialize the region.
 - Phase 1: Compute the overlap with the current input for each column.

- Phase 2: Compute the winning columns after inhibition.
- Phase 3: Update synapse permanence and internal variables (learning).
- The behaviour of the system must replicate that of the human model.

8.3 RELIABILITY AND MAINTAINABILITY

Code should be reliable in the sense of being repeatable, and comments should be presented in such a way to support in the way that it operates and act as information and guides to the process.

8.4 ECONOMIC FACTORS

This software should be thought of as the first step towards building a CMOS chip that implements the HTM protocol, and it should be written with the intention of being modified, only slightly, for an embedded system and ultimately a custom microchip.

Future impact could be to use a chip of this design in truly intelligent machines, and possibly assist in brain prostheses.

8.5 ACCEPTANCE TEST REQUIREMENTS

The following are the minimum requirements for the software design for acceptance:

- Software should be able to take in the data repeatedly, and without storing the data should be able to then recognise the data string as having been previously received.
- Recognition of data should be demonstrated by either increasing or decreasing the permanence values, the final output being the storing of the original data string in memory; i.e. the reintroduction of the original data string should cause

the system to output the memory, organisation of which is then to be managed in the spatial pooler at a later stage.

- Data should be able to be corrupted with noise and still produce the same results; this should confirm the theory that if only a small proportion, such as 10%, of the columns are active the message should still be transferred correctly to the next level in the hierarchy. [4]

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9 SOFTWARE DESIGN

9.1 INTRODUCTION TO SOFTWARE DESIGN

Previous versions of developed software have been based on the visual cortex [36]. Numenta has published all of its research, with the intention that others working in the field, can publish their findings and a collective audience could be used to investigate and test these findings. HTM is also proprietary in nature, meaning that to implement the instructions laid out, a platform had to be chosen that is widely used. Due to the author's prior working knowledge of Matlab© and the way in which Matlab© manages data and matrices, it was the chosen platform.

Valuable time was spent coming up with concepts for an approach to this project, and the best way to represent a solution which would convincingly demonstrate the HTM theory. All parts of the specifications were considered however these specifications do not take into account time limitations on the research, so that where there was an idea that would take too long to implement, and was beyond the scope of this study, it was discarded.

The software design process followed this plan:

1. Construct the structure of mathematical hierarchy for system.
2. Confirm the Spatial Pooler parallels to mathematical structure and reasoning.
3. Confirm the fidelity to biological reasoning and background.
4. Translate into code.
5. Test with pseudo random olfactory inputs, based on representations of data available.
6. Monitor the output and confirm the correct operation in terms of the graphs and data produced.
7. Test the system's ability in recognition and learning.
8. Test the system's capacity for noise management and linearity.

9. Conclude with an evaluation of systems robustness and other findings.

The software developed had to achieve the goals presented in the specifications.

Previous methods of software designed based on HTM theory have been proprietary in nature. By using Matlab®, a widely recognized programming language, which intrinsically works by manipulation of matrices, it is possible to reach out to a large part of the research community and using the power of the collective to save time, gain insight over and above one's own efforts.

9.1.1 Code requirements

The coding must have comments and be such that it can be related back to the text, in order to be clear and logical.

The architecture and platform must maintain a logical connection with current biological thinking and findings, and it must be based on the HTM theory presented in both the paper and technical review published by Numenta; namely, the spatial pooler.

Synapses

In a hierarchical temporal memory system, synapses have only binary weights. As mentioned in section 2.3.2, the important factor here is how permanent the signal is; and the permanence value is a value between 0.0 and 1.0.

Dendrite segments

Synapses connect to these segments, of which there are two types:

- 1) Proximal dendrites: synaptic inputs to these are summed.
- 2) Distal dendrites: If the sum of active cells on a distal dendrite is above a certain threshold, then its cell body becomes active – when there are more than one distal dendrite the cell body becomes active as an OR function.

9.2 PRINCIPLES OF HTM

HTM is built with the understanding that each cell or component in a hierarchy operates in the same manner - its connections may differ, but its fundamental operation is identical to any other part of the hierarchy.

9.2.1 Hierarchical structure

An HTM region is typically one level in a hierarchy – each level converges the level below it; this is so that when it reaches the top most level the input signal is “named”. The same works as the hierarchy is descended, in that the feedback information is dispersed.

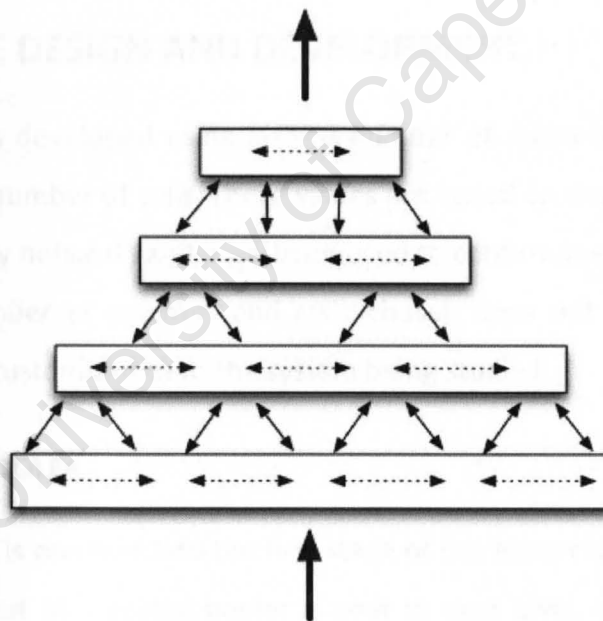


Figure 9.19: Flow of information in a simplified HTM structure. Each level consists of a number of HTM nodes, and each HTM node consists of a spatial and temporal pooler. The output of an HTM spatial pooler is the input to its own nodes' temporal pooler. The output of a temporal pooler is the input to the next layer in the hierarchy's spatial pooler.

For illustration, and to give an idea of what happens when senses rely on each other to complete a verification task - it is possible to combine regions:

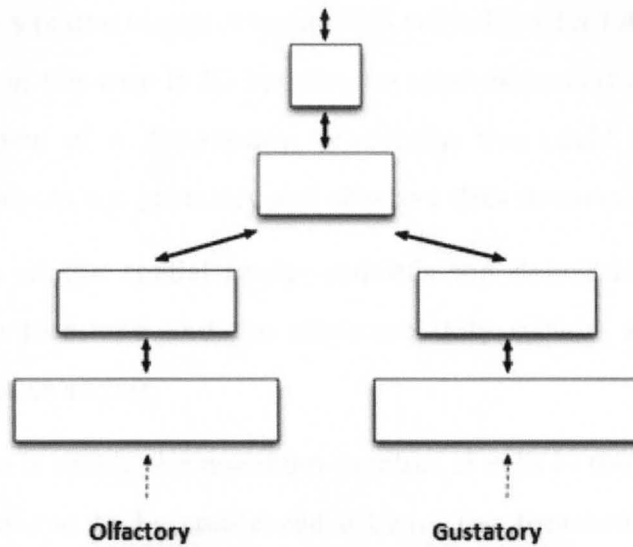


Figure 9.20: An example of converging of sensory input regions that work in parallel and support each other in the brain

10 SOFTWARE DESIGN AND DEVELOPMENT

This HTM node was developed using a fixed number of micro-cortical columns, each made up of a fixed number of cells. These values are based on the biological makeup of the olfactory sensory network, and have been used to confirm the validity of the node's operation. The number of columns and cells chosen does not impact the recorded output, and can be customized to fit the system being studied.

10.1 SPATIAL POOLER

Initial sensory input is received into the first stage of the hierarchical temporal memory hierarchy. The output of a spatial pooler is sent to next level, which is the temporal pooler.

10.1.1 Phase 1: Overlap

Here either a sensory input or the output of the previous level's temporal pooler is received, in the form of an array of binary inputs. When the input is sensory, each cell of

the input array refers to one neuronal input. This cell will hold a 1 if it is active and a 0 if it is not. The array in this case is 1D but can, be extended to 2D and 3D. (The system allows for a mapping of n dimensions; practically, this could be done by adding numerous sensory inputs e.g. gustatory and olfactory data streams.)

The overlap phase of the spatial pooler requires the definition of the number of columns, cells, the threshold and the minimum duty cycle – all of which can be arguments in a function setting.

The threshold value is simply the minimum number of cells in the input array that are required for the column to be considered active. The threshold value is important because anything below the threshold value is ignored or considered useless, which reduces the amount of data to be sifted in the brain, and decreases the amount of storage space and processing power required.

Each input synapse has an associated permanence value defining the strength with which a synapse is connected; this value is between 0.0 and 1, 0.0 being not connected and 1 being permanent. There is a second threshold introduced here of 0.2; this value relates to the permanence requirement i.e. the connection must not only be active but it must also be valid – this removes connections that are too weak to be considered permanent, and again reduces the operating power requirements and data storage.

A column is considered active when it has more cells than the required threshold and those cells are connected with a higher than required permanence value. The columns with higher values than those around it will be considered 'stronger' and therefore inhibit those around it. The column must be active for a longer interval than a minimum duty cycle for it inhibits those around it; if this is the case then it is assigned a boost value, which ensures that the activity of the column is registered and processed further.

The overlap, being the output of phase 1, is then seen as the number of valid connected synapses in each column, multiplied by the relative boost.

10.1.2 Phase 2: Inhibition

The phase returns those columns which are inhibitors, and which are inactive or columns to be inhibited. It does this by taking the current highest overlap value computed in the previous phase and returning it if it is larger than the desired local activity.

The desired local activity works within a defined radius and is another threshold input that can be system dependent; it relates to the sensitivity of the system – by reducing the sensitivity (increasing the radius of inhibition) the computing power and storage requirements are reduced.

10.1.3 Phase 3: Learning

This phase updates the permanence values of all synapses as necessary, as well as the boost and inhibition radius. If a synapse is active, valid, and is located in an inhibitory column then its permanence value is incremented, otherwise it is decremented.

This is done with a simple *for* or *while* loop, and the outputs are plotted (they being the input signal, the overlap and the permanence values).

10.1.4 Threshold values

Threshold level choices are required for the active synapses in a column; in this case the value of 3 active synapses were used to qualify an active column.

The minimum permanence value to deem a synapse to be active as well as valid was chosen to be 0.2.

The boost value assigned to a cell to confirm inhibitory status was 0.2, i.e. $1 + 0.2$ which is what the connection value will be boosted by.

10.1.5 Noise and Filtration

Noise in signal processing or computing can be considered as data without meaning; that is, data that is not being used to transmit a signal, but simply produced as an unwanted by-product of other activities. Noise blocks, distorts and changes the meaning of a message in both human and electronic communication.

In an olfactory network, noise could mean an inclusion of random scents, or chemicals that interact with what is being experienced, and which distort and mix with the correct chemicals; that is why when the scent is smelt repeatedly the incorrect noise signal can be filtered out, thereby correcting the recorded scent.

In an HTM system, noise relating to the recording mechanism of sensory input should be taken into account. The efficiency of sensory pick up neurons cannot be calculated, and these will be used as comparative signals or input signals to the HTM nodes.

10.1.6 Results

Introduction of noise

Noise was added by modifying the bits at intervals between 0 and 20%, based on the current literature and the time available to perform this testing.

Table 10.3: Introduction of noise for testing purposes

Amount of noise introduced to input	Iterations required for stability - Minimum number of times input introduced to system.	Success rate
0	5	System demonstrated learning after 5 iterations of input signal; this is the benchmark under the current threshold criteria.
1%	5	System demonstrated learning after 5 iterations of input signal.
2.5%	6	System less stable, demonstrating learning after 6 iterations of input signal.
5%	7	System attempts to correct itself as initially the incorrect values are displayed, only after 7 iterations does it manage to correct itself.
10%	7	Values correspond to 5% noise
20%	7	System demonstrated correction after 5 iterations of input signal

Below are step progression pictures displaying reaction time in a learning sequence with 10% noise. 10% noise is found by taking the full signal of 500 outputs and modifying the bit at every 10% interval. For the same input signal the connected synapses and overlap remain the same, as they are set on the first presentation of the signal. The permanence

value demonstrates learning, and therefore modifies within the system to show the learning process.

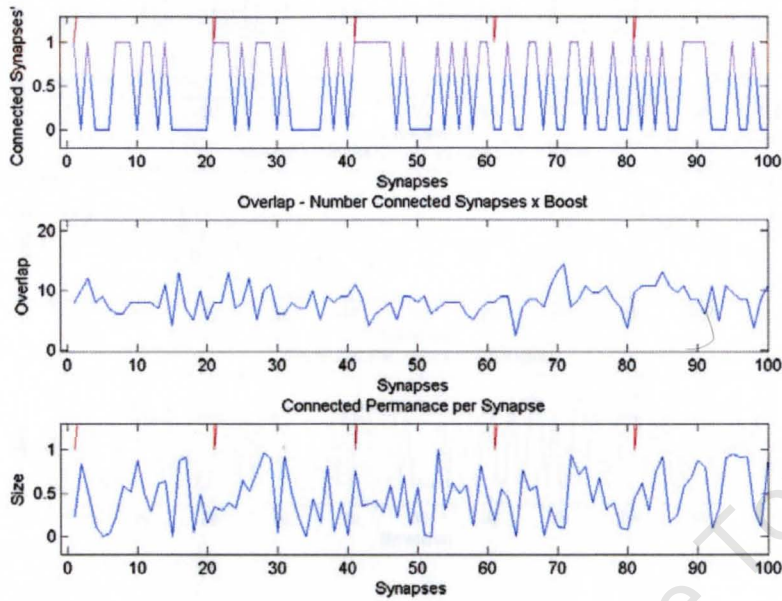


Figure 10.21: 1st introduction of the sensory signal. Here there was no modification or manipulation of the original input sensory data. The following four graphs show the progression of learning within the HTM node designed.

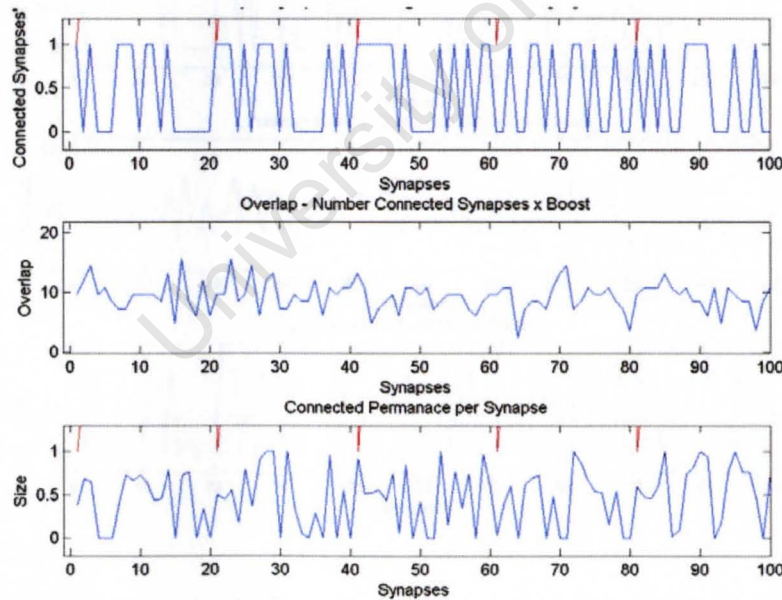


Figure 10.22: 5th introduction of sensory signal, the top graph showing the original signal, the middle graph the column overlap and the last graph shows the progressing output signal. For learning the last

graph needs to start looking like the first one, showing that the system is recognising and classifying the signal as expected.

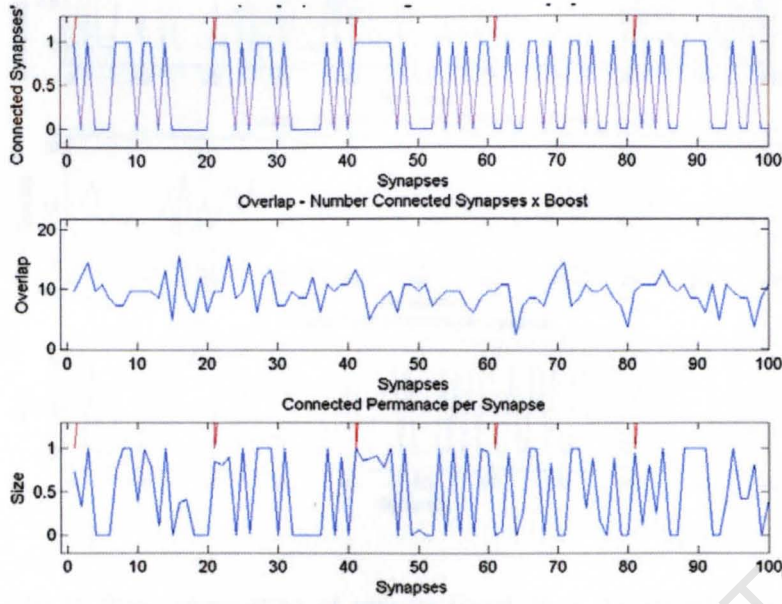


Figure 10.23: 12th introduction of sensory signal. The bottom graph shows the recognition of the initial signal, displayed in the top graph

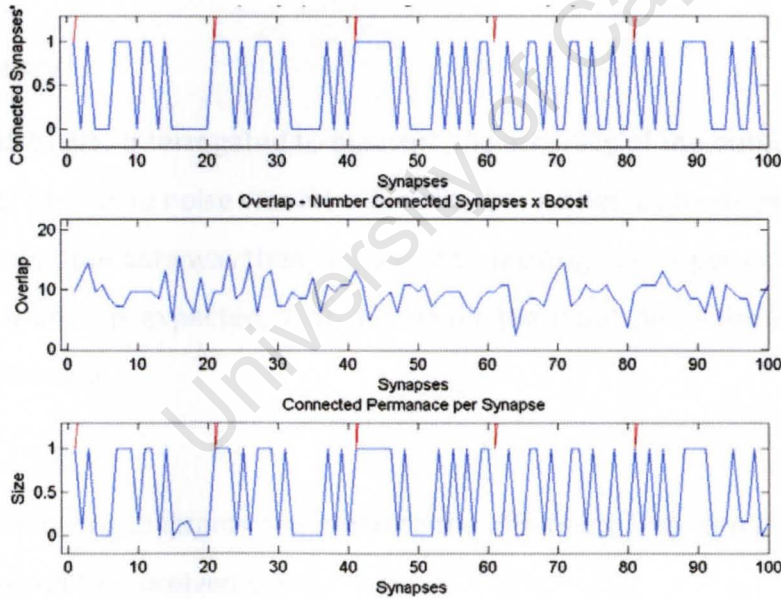


Figure 10.24: 17th introduction of sensory signal. Here almost complete recognition has taken place, demonstrating that with 10% noise it takes up to 17 iterations or experiences of the signal for recognition to take place.

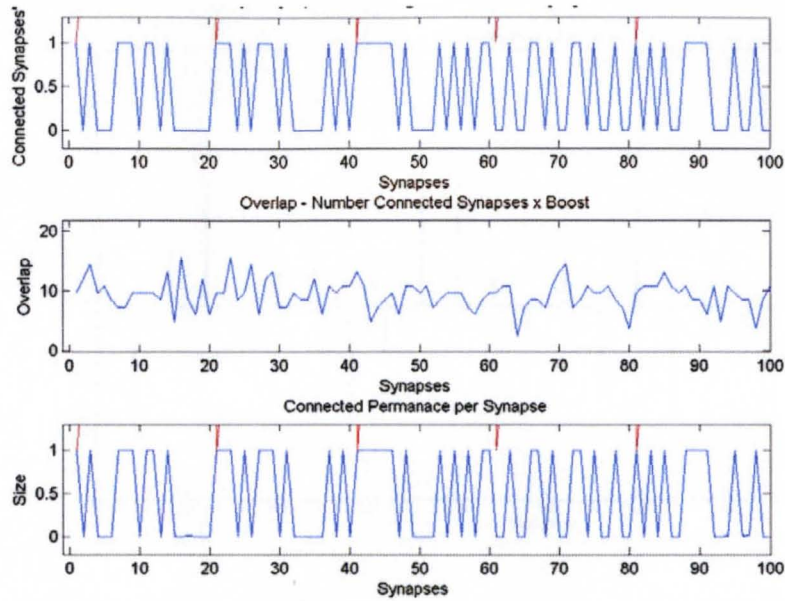


Figure 10.25: 20th introduction of sensory signal. Here the classification of the signal is complete. Clearly the permanence values have reached their expected limits, displaying confirmation of input connection synapses and correct classification of the signal

Accuracy

The data was interrogated to measure the accuracy of the output signal as per the input noise. Each time noise was introduced to the system by modifying bits at the percentage intervals, the data was then compared to the original output and the results recorded. It was found, as expected, that the higher the input noise the less accurate the output data became.

The following diagrams demonstrate the difference between the expected permanence value and the received value.

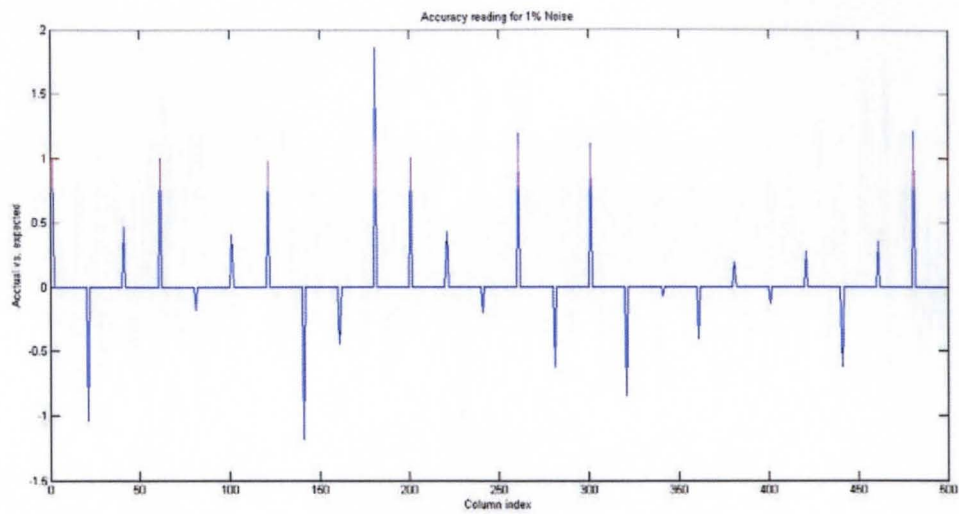


Figure 10.26: This figure plots the difference between the received signal with 1% noise introduction, and the original unmodified signal. The y axis displays the difference between the permanence values summed over each column, where each column has a total of 20 cells or neurons. The x axis shows the column index.

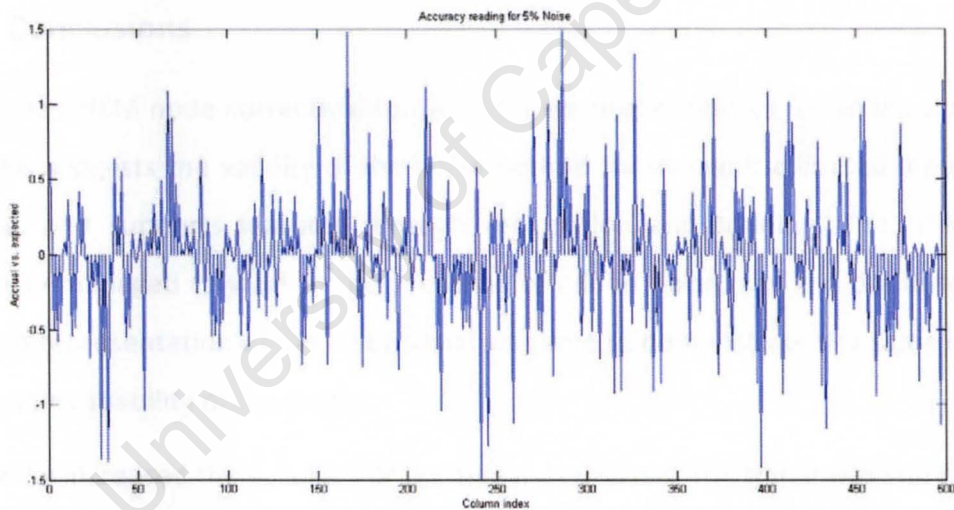


Figure 10.27: This figure shows the difference between the expected signal and the received signal after the introduction of 5% noise. The y axis shows the difference of permanence values per column summed, and the x axis demonstrates the column index.

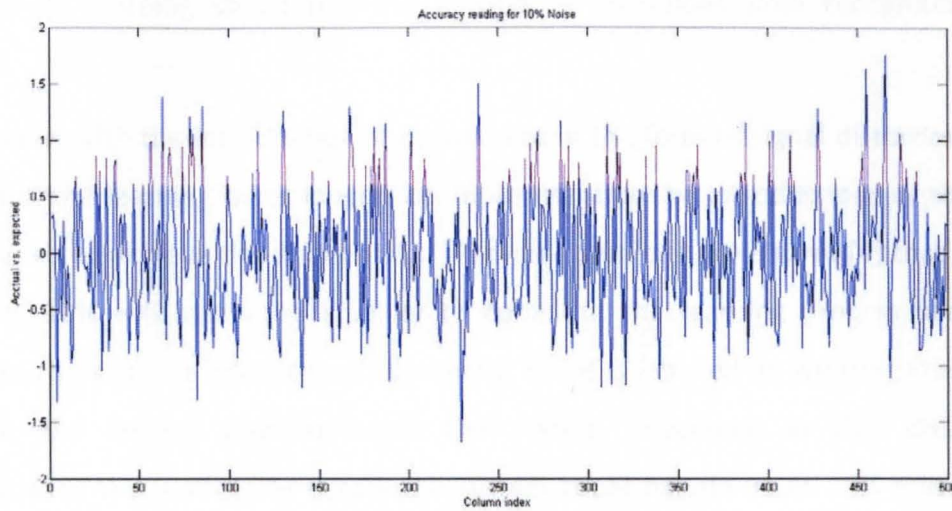


Figure 10.28: After 10% noise is introduced the signal's accuracy declines rapidly. Previously it was shown that the signal is recognised correctly at 10% noise, however the accuracy of the signal is questionable. Here the y axis shows the difference of the permanence values summed over each column, and on the x axis the column index is shown.

10.1.7 Conclusions

The designed HTM node correctly displayed the learning attributes for an input sensory signal; this suggests the validity of the HTM method for use with a limited input space and data, and supports learning through recognition and training. The HTM node successfully managed to work in the presence of added noise, and the optimisation of the sparse representation of the input signal was able to demonstrate the same learning and dynamic capability of the cortex.

As the noise increased the accuracy of the signal decreased. The signal was still correctly recognised with 10% noise, but the accuracy of the reading decreased which meant that it took longer for the recognition process to occur.

Spatial pooler phase 1: Overlap

It was found that by increasing and decreasing the boost, permanence threshold, minimum active cell threshold and active duty cycle, the system either decreases or

increases its learning speed (i.e. the number of iterations until recognition), and stability.

Additionally, with the introduction of more noise in the form of signal distortion, it was found that the learning takes longer, i.e. more iterations or introductions of the signal are required to achieve the final output. Previous studies have shown [4] that noise in excess of 10% will mean the inability to complete the learning process accurately, therefore the signal is interpreted incorrectly, i.e. it is labelled as another input signal and not the correct one. However the system developed in this dissertation demonstrated that with HTM theory the system could handle up to 20% noise before being reclassified as a different signal, and interpreted incorrectly.

It was also noted that after 20% noise introduction the output was recorded as a 'scent'; even though it was not the 'correct' classification, it was a classification. The mammalian brain re-classifies input signals with their re-introduction. This is why it is possible to have the wrong impression of an input signal – that will later be corrected in memory.

It was found that if the signal was kept constant, and no noise was introduced, the output signal was repeated consistently and therefore HTM node performed well - reproducing a consistent output.

False Assumptions Made

Several assumptions were showed to be false:

- It was thought that the system would re-classify the signal i.e. another name and output would be awarded once recognition occurred, however what was found was that the HTM node classifies the signal as close to the input as possible. The only difference is the method by which it is stored, and the lower power and space requirements needed to classify or name or recognise the signal.

Successful Aspects of the Design

The following aspects of the design were shown to be successful:

- Signal recognition was successfully achieved.
- Repeatability: the HTM node was able to perform to original specifications, no matter how many times it was run.
- Learning and recognition capability was demonstrated, without departing significantly from the mammalian brain.
- It was found that even with 20% additive noise the HTM node was still able to classify the input signal with minor increases in the number of iterations. With higher noise content, the signal took longer to recognise the signal, but even initial mistakes / misclassifications were ironed out.

Failed Aspects of the Design

The following aspects of the design were considered to be a failure:

- Optimisation of the code was not performed due to time constraints; therefore the full power of Matlab®'s matrix and parallel processing capability was not utilised.
- Our inability to acquire actual sensory spike sequences for input uses meant using pseudo-random simulated sensory sequences, and therefore recognition and confirmation of actual data – to compare to the brain's output – could not be completed.
- The temporal pooler was considered, but not developed; for the full demonstration of HTM theory and capability, this would be required as the next phase, along with development of a CMOS chip and embedded neuromorphic system.

10.1.8 Recommendations

Future Research

The following are aspects of the design that should be further investigated if this design were to be made more suitable.

- Further testing should be performed – limits should be taken for each noise criterion, so as to create a better understanding of the learning and recognition process. Only once the entire olfactory HTM network has been built and tested, will the output values be able to be compared with the human brain – and therefore lead towards an intelligent cognitive system.
- It would be beneficial to see just how much noise this system can handle before 'break point' i.e. at what point the input signal becomes incoherent. A study on how the permanence values and the noise values correlate is suggested – to confirm thoughts on intelligence and attention correlation.
- The range of threshold values should be investigated. Currently the accepted permanence value noted for a successful synaptic connection is 0.2 – this can be modified, and is thought to then have implications on the number of iterations required for recognition. However by increasing this value, the effect on linearity of the previous signal should be monitored and may prove to have a knock on effect further up the recognition hierarchy.
- Development of the temporal pooler is considered imperative.

Further Steps in the Current Design

Further investigation into the design must be conducted, especially relating to the following:

- An input data acquisition system.
- A CMOS chip design, and its fabrication.

11 THE NEUROMORPHIC RESEARCH COMMUNITY AND RELATED RESEARCH

The key to advancing efficiently in the field of neuromorphic engineering is to continue to use research from all aspects of the neuroscience and neuroinformatics spheres, and maintain fidelity with the biological operation of the brain in justification for completing any task that aims to model the brain.

It is clear that a significant amount of research is being done worldwide to understand how the brain works, and how to replicate its operation. Once the tools have been built, both in hardware and software, there are a multitude of tasks that they can be used for.

It is not a secret that the brain is an amazing structure and when its operation is harnessed, machines will become truly useful.

One of the biggest problems faced in the neuromorphic research community is the extraction of sensory data and hence its availability. In order to create a working HTM network it is imperative that all fields are represented in the research team – from materials engineers through to neuroscientists.

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GLOSSARY

Dynamic Programming	<p>In mathematics and computer science, dynamic programming is a method of solving complex problems by breaking them down into simpler steps.</p> <p>Top-down dynamic programming simply means storing the results of certain calculations, which are then re-used later because the same calculation is a sub-problem in a larger calculation. Bottom-up dynamic programming involves formulating a complex calculation as a recursive series of simpler calculations.</p>
AI	Artificial Intelligence - At first seemingly real, but without actual learning based intelligence.
RI	Real Intelligence – Based on Human architecture and human interaction with the surrounding environment.
Latency	Latency, in this case, is a time delay between the moment something is initiated, and the moment one of its effects begins or becomes detectable.
ADC	Analogue-to-digital converter. Process of converting Analogue signals to a digital representation
Topology	As in network topology. The geometric physical or electrical configuration describing a local communication network; the shape or arrangement of a system.
In Vivo	<i>In vivo</i> (Latin for "within the living") is experimentation

using a whole, living organism as opposed to a partial or dead organism

Neural network	Any network based on the functioning of neurons – a broad term which up until now has been used mainly in the studies only loosely associated with the working of the brain
Markov Chain	A stochastic process with a finite number of states in which the probability of occurrence of a future state is conditional only upon the current state; past states are inconsequential.
Stochastic Process	A system that evolves in time according to probabilistic equations, that is, the behaviour of the system is determined by one or more time-dependent random variables.
Sparse distribution	A small percentage of neurons are active at one time. Representation of the whole distribution.
Distributed neurons	Activations of many neurons are required in order to represent input. A single active neuron conveys some meaning but it must be interpreted within the context of a population of neurons to convey the full meaning.
Primates	An animal order including lemurs and tarsiers and monkeys and apes and human beings

HTM	Hierarchical temporal memory
Fuzzy Logic	A form of mathematical logic in which truth can assume a continuum of values between 0 and 1
VLSI	Very Large Scale integration
Inference	The reasoning involved in drawing a conclusion or making a logical judgement on the basis of circumstantial evidence and prior conclusions rather than direct observation

APPENDIX A – Software DVD

A Software DVD accompanies this thesis. The DVD contains the folders listed below. Further explanation of the contents of a folder is documented within that folder.

- A1 Test Data and Diagrams**
- A2 Thesis Document**
- A3 References**
- A5 Software install kits and data sheets**
- A6 Matlab Software and Code**