# EDGE DETECTION BY ARTIFICIAL VISUAL CORTEX

*LT COL RAJAT BHATNAGAR*

# Edge Detection by Artificial Visual Cortex

Thesis submitted in partial fulfillment of the
requirements for award of the degree of

**Master of Technology**

in

**Information Technology**

By

**Lt Col Rajat Bhatnagar**

**[10IT60D02]**

Under the supervision of

**Dr. D Samanta**

**School of Information Technology**

**Indian Institute of Technology Kharagpur**

**Kharagpur - 721302**

**April 2012**

# DECLARATION

I, **Lt Col Rajat Bhatnagar**, Roll no **10IT60D02** registered as a student of **M.Tech.** in the **School of Information Technology, Indian Institute of Technology, Kharagpur**, India (hereinafter referred to as the 'Institute')do hereby submit my thesis, title:

**Edge Detection by Artificial Visual Cortex**

(hereinafter referred to as 'my thesis') in a printed as well as in an electronic version for holding in the library of record of the Institute.
I hereby declare that:

1. The electronic version of my thesis submitted herewith on CDROM is in PDF format.

2. My thesis is my original work of which the copyright vest in me and my thesis does not infringe or violate the rights of anyone else.

3. The contents of the electronic version of my thesis submitted herewith are the same as that submitted as final hard copy of my thesis after my viva-voce and adjudication of my thesis on 13-04-2012.

4. I agree to abide by the terms and conditions of the Institute Policy on Intellectual Property (hereinafter Policy) currently in effect, as approved by the competent authority of the Institute.

5. I agree to allow the Institute to make available the abstract of my thesis in both hard copy (printed) and electronic form.

6. For the Institutes's own, non-commercial, academic use I grant to the Institute the non-exclusive license to make limited copies of my thesis in whole or in part and to loan such copies at the Institutes's discretion to academic persons and bodies approved of from time to time by the Institute for non-commercial academic use. All usage under this clause will be governed by the relevant fair use provisions in the Policy and by the Indian Copyright Act in force at the time of submission of the thesis.

7. Furthermore (*strike out whichever is not applicable*)

   (a) I agree / do not agree to allow the Institute to place such copies of the electronic version of my thesis on the private Intranet maintained by the Institute for its own academic community.

   (b) I agree / do not agree to allow the Institute to publish such copies of the electronic version of my thesis on a public access website of the Internet should it so desire.

8. That in keeping with the said Policy of the Institute I agree to assign to the Institute (or its Designee/s) according to the following categories all rights in inventions, discoveries or rights of patent and/or similar property rights derived from my thesis where my thesis has been completed (tick whichever relevant):

   (a) with use of Institute-supported resources as defined by the Policy and revisions thereof,

   (b) with support, in part or whole, from a sponsored project or program, vide clause 6(m) of the Policy.

   I further recognize that:

   (c) All rights in intellectual property described in my thesis where my work does not qualify under sub-clauses 8(a) and/or 8(b) remain with me.

9. The Institute will evaluate my thesis under clause 6(b1) of the Policy. If intellectual property described in my thesis qualifies under clause 6(b1) (ii) as Institute-owned intellectual property, the Institute will proceed for commercialization of the property under clause 6(b4)of the Policy. I agree to maintain confidentiality as per clause 6(b4) of the Policy.

10. If the Institute does not wish to file a patent based on my thesis, and it is my opinion that my thesis describes patentable intellectual property to which I wish to restrict access, I agree to notify the Institute to that effect. In such a case no part of my thesis may be disclosed by the Institute to

any person(s) without my written authorization for one year after the date of submission of the thesis or the period necessary for sealing the patent, whichever is earlier.

**Lt Col Rajat Bhatnagar**
(Name of the Student)

**Dr. D Samanta**
(Name of Supervisor)

Department/School/Centre:**School of Information Technology**

**Signature of the Head of the Department/Centre/School**

**School of Information Technology**
**Indian Institute of Technology**
**Kharagpur - 721302**

## CERTIFICATE

This is to certify that this thesis entitled **"Edge Detection by Artificial Visual Cortex"** submitted by Lt Col Rajat Bhatnagar, to the School of Information Technology, in partial fulfillment for the award of the degree of **Master of Technology** (**Information Technology**), is a record of bonafide research work carried out by him under my supervision during the period 2011-2012. The thesis has fulfilled all the requirements as per the regulations of the Institute and, in my opinion, has reached the standard needed for submission.

**Dr. D Samanta**
School of Information Technology
Indian Institute of Technology
Kharagpur-721302, INDIA

# Acknowledgements

In the first place I would like to express sincere gratitude to my advisor Dr. D Samanta for his invaluable guidance and constant encouragement during the project work giving me extraordinary experiences through out the work. It is indeed an honor and a great privilege for me to have learned from his expertise and experiences which exceptionally inspire and enrich my growth as a student.

I would also like to express my thank to Dr AS Mandal, Senior Principle Scientist, CEERI, Pilani, who, I was very lucky to have as my co-guide. I fortunately got associated with such a remarkable person, who's consistant guidance helped me alot in persuing my work.

I owe my deepest gratitude to the entire faculty members of School of Information Technology for providing an excellent academic environment and support.

Nothing would have been possible without the constant support of my wife and two daughters, whose loving support and encouragement have always been there for me. I feel deep sense of gratitude for my parents for their inspiration and blessing.

I also express my thanks to all my classmates specially Darshan Trivedi and Jyotirmay Dewangan for their support during the course of my work.

I remember the Almighty with humbleness for his blessings upon me during the course.



Lt Col Rajat Bhatnagar<br>
School of Information Technology<br>
Indian Institute of Technology, Kharagpur<br>
Date:

# Abstract

Hubel and Wiesel pioneered a significant progress in the field of study of the visual cortex and added a new dimension of understanding about the human visual system by discovering Simple and Complex cells. Visual cortex being one of the complex part of brain, has a lots of short and long-range vertical and lateral complex connections. The major functioning of the visual cortex is to receive the neural signals from the eye and lateral geniculate neuleus thereafter process the information received to derive multidimensional features of the visual information before it is perceived by the brain. Various methods are proposed to model the visual cortex, with an aim to understand the functioning of the various aspects of the cortical layer/cell. The main focus is to understand the detailed structure and the neural mechanisms that underlie the functioning of the visual cortex. But many of these models take approaches which are not biologically plausible. In this thesis, we have used a biologically plausible computational model to work like an eye. The model accept a visual input and immitate a basic function of edge detection. This is done by giving the model a known orientated-synthetic input and thereafter receive the cortical spikes output. These cortical spikes were then analyzed, and various approaches were taken to draw out the information(orientation selectivity) from the output thus received.

# Contents

# List of Figures

# List of Tables

# Chapter 1

# Introduction

## 1.1 Context

Vision is the most important of all the other sensory processes. It provides high resolution and high precision measurements of our surroundings, which is extremely essential for a successful survival in the world. Humans and animals are able to extract a lot of useful information out of visual measurements. It helps them not only to fulfill their biological needs and survice better, but in higher beings like humans it also satisfies the emotional needs. Vision is a multi disciplinary field being investigated/ researched by philosophers, physiologists, neurobiologists, mathematicians, computer scientists and engineers. Theoretical explanation of the brain and thinking process were first suggested by some ancient Greek philosophers, such as Plato and Aristotle. An understanding of the phenomena of seeing and perception remain one of the deepest challenges confronted by scientists.

The recent advancements and emergence of new and complex robotic systems in space, deep sea, manufacturing, and the health sciences have created a demand for better vision systems. The future generation of computers should be able to see and speak so that the present paradigm of writing programs will no more be there. Robots should be able to see and act the way we humans do. The blind people should be able to see with the help of machines. This new thinking has led to a serious exploration of biological vision systems. Such studies have resulted into an increased attempt of understanding of the neuronal morphology of biological vision. Scientists from various disciplines, such as neuro-anatomy and neuro-physiology are discovering exciting facts about the visual pathway which extends from the retina to the visual cortex, through their experiments on various species such as cats, monkeys, rats etc. Substantial progress has also been made in discovering the architectural organization and the functioning of the cells of the visual cortex. Initially it seemed to be a daunting task as there are about $10^5$ neurons per square millimeter of surface, suggesting that the cortex as a whole has about $10^{10}$ (10 billion) neurons. Systematic and painstaking study and gradual improvement in techniques led to better understanding of the visual cortex. Exploration of the visual cortex and other parts of the brain took a quantum jump when regular and modular structures were observed in the visual pathway. Scientists from other disciplines such as system science, computer sciences, electrical engineering, robotics and mathematics are formulating the visual system consisting of the visual pathway and the visual cortex from a computational point of view. These combined studies have led to a better understanding of the neuronal morphology of biological vision, as well as better computational neural substrate for construction of artificial visual system by VLSI designers.

In 1962, Hubel and Weasel [16] provided first adequate description of the visual responses of neurons in the cats primary visual cortex. They mapped the receptive fields of V1 cells by flashing bars. They determined the cells as being seither simple or complex cells. Both simple and complex cells were selective to orientation of the input stimuli and its direction of movement. They classified those cells as **Simple cells** which had regions and responded either to onset or to offset of bright bar not to both. These cells had two distinct excitatory and inhibitory regions like the receptive fields of retina and lateral geniculate nucleus.

Those cells that failed to display any characteristic of a simple cell were termed as **Complex cells**. Simple cells are mainly found in the thalamic layer of visual cortex. The highest proportion of simple cells is found in layer VI. Complex cells are evenly distributed.

An area of the body surface over which a single sensory receptor, or its afferent nerve fiber, is capable of sensing stimuli are called **Receptive fields**. Levine and Shefner(1991) [19] coined the term receptive field as an area in which stimulations leads to response of a particular sensory neuron.

**Orientation selectivity** is defined as capability of cells to respond to a particular orientated input. Orientation selectivity of a simple cell varies from species to species, it also vary from time of birth to time of maturation of the animals. Orientation specific response have been studied in various animals and it is found 75% of cells are orientation selective in adult animal, and only 25% are selective at the time of first visual responses [20]. Orientation selectivity increases with visual experience.

## 1.2 Motivation of the Thesis

There had been various attempts to understand the functioning of the visual system so that either it can be modelled to our benifit or new technologies can be derived out of its study. There have been many attempts to develop the models of receptive fields of simple cells and complex cells. These receptive fields are used to further build an artificial cortex, so that an input (synthetic of real) can be processed through this visual cortex and an output indicating its orientation and spatial information can be calculated. The approach is to use natural methodologies for development of these models so that the model is biologically plausible. In this thesis, we propose the use of biologically plausible model for developing an artificial visual cortex, which can perform a basic function of edge detection from an input for known.

## 1.3 Objectives of the Thesis

The objectives of thesis can be summarized as follows

- To propose and develop biologically plausible model of complex cell receptive field based on biologically realistic assumptions. It is a design goal not to include non biological methods in the model.
- To propose the use of realistic model of Artificial Cortex in developing it for performing the task of simple edge detection for various orientations.

## 1.4 Plan of Work

The work of thesis can be summarized as follows

- To develop the receptive field of complex cells of visual cortex bases on the assumptions of biologically plausible methods.
- To modifiy the model of artificial visual cortex to accept the complex cell receptive field as input parameter where it earlier accepted the receptive field of simple cell only. This new model performed equally satisfactorily.
- To propose a model where the biologically plausible artificial visual cortex performs the edge detection of simple edges (synthetic inputs) of various orientations.

## 1.5 Organization of the Thesis

Chapter 2 provided a brief background about the concepts related to visual pathway, receptive fields of simple cells, complex cells and also orientation selectivity. Chapter 3, gives a brief of the literature survey done on the subjectbasically covering the Modeling approaches of cortex and various models of visual cortex. Chapter 4, presents related works on receptive fields of simple cells and complex cells. This brings out the topological, functional details of Simpla and Complex Cells. In Chapter 5, the proposed model is discussed with implementation details. The results obtained are discussed and analysed. Finally, chapter 6 concludes the thesis with summary and spels out the future work.

# Chapter 2

# Background

In this chapter a brief discussion of the details of Visual Pathway, Simple Cell, Complex Cell, Orientation Selectivity is done. This chapter gives an overview of term of references in context of Visual System.

## 2.1 The Visual Pathway

The visual pathway in humans comprises of nearly 30 visual areas [1], each contributing to different aspects of visual function. The retina is the start point of the visual pathway. It converts light in to electrical signal, which are passed in to the lateral geniculate nucleus (LGN) and the superior colliculus (SC). The SC transmits the signal to the mid brain, which handles the processes of attention and visually guided behavior. The retinal signals reaching the LGN are destined mainly for the cortical areas. The cortical pathways consist of retina, LGN and the visual cortex, which is concerned with vision. The visual pathway is not hierarchical however there is increase in the complexity as we move into higher cortical areas. The changes that occur in the information in the subsequent levels are best represented as the receptive fields (RFs) of individual neuron. The receptive field of a visual neuron is defined as region of space where the visual stimulus can change its ring activity. Receptive fields are the building blocks of the complex visual system. So it's pertinent to study for understanding the functioning of the visual system. Vision is generated by photoreceptors in the

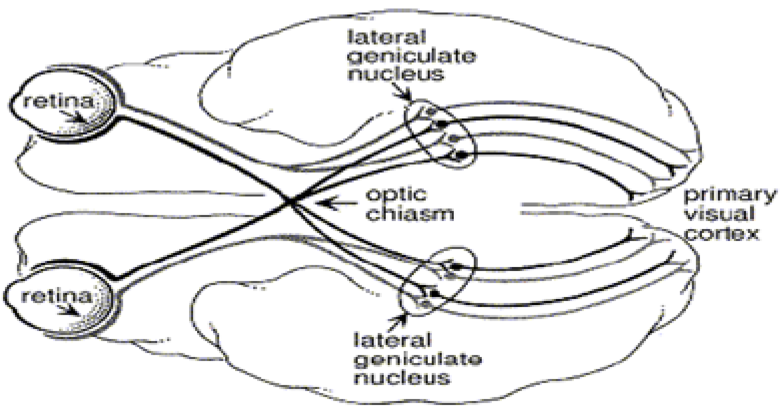


Figure 2.1: Brain Visual Pathway

retina, a layer of cells at the back of the eye. Retina converts light into electrical signals. These electrical Signals are passed on to the Lateral Ganglion Nucleus (LGN) and Superior Colliculus(SC).

The SC transmits signals to the midbrain which handle the process of attention and visually guided behavior. The Retinal Signals reaching the LGN are destined mainly for the cortical areas. The Cortical pathway consisting of, retina, LGN and visual cortex. Complexity of cell responses increases as we move into higher visual areas. Transformation or integration at successive levels is best understood by studying the receptive fields (RFs) of individual neuron. The receptive field of a neuron is a region where a visual stimulus can effect a change in its firing activity. Initial processing of visual signal starts in retina and LGN which involves detection of spatial and temporal changes in illumination patterns, detection of colour, adaptation to illumination level etc. The retinal ganglion cells (RGC) have concentric RFs with ON center and OFF periphery or vice versa. These areas are antagonistic to each other(Barlow et al., 1957) and the sopt in the center is more effective than the area around it.

The optic nerve carries the signal from the retina to LGN. LGN is composed of 75% relay cells and 25% inhibitory interneuron. The relay cells receive excitatory input from around 1-5 retinal cells and relay it to visual cortex. The interneurons make locan connections within LGN and do not project anything to cortex. The receptive fields of LGN are similar to the retinal RFs with surrounding areas being stronger. Both retinal ganglion and geniculate cells are mainly concerned with finding changes in the illumination and are recognize form or orientation of the stimulus.

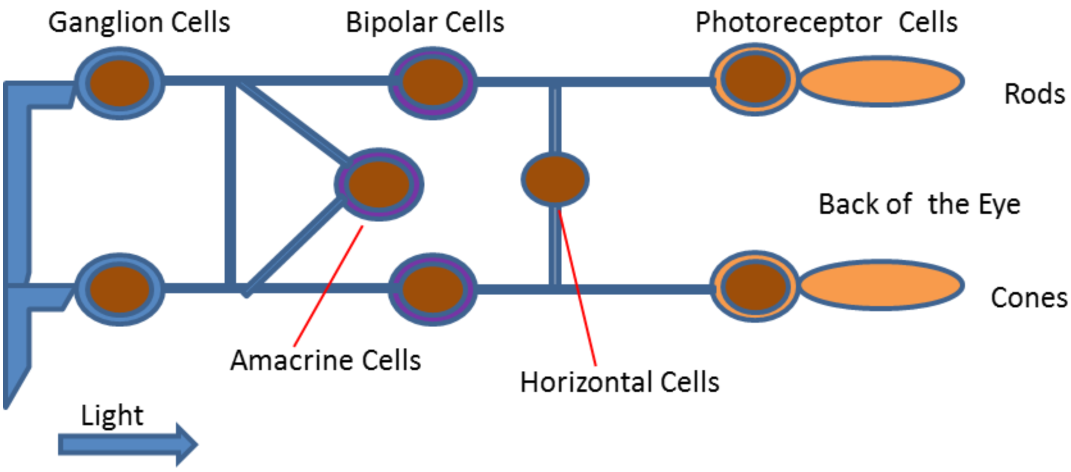


Figure 2.2: Retinal Receptive Field

The RGC and the LGN just capture the change in the illumination or the orientation of the stimulus.

The LGN then passes the information to the visual cortex through a optical radiation. Visual cortex is formed of similar cells anatomically, but cells are divided as per their functional properties. They show a receptive field profile similar to that of retinal ganglion and geniculate cells. Human Visual System has cells which specialize in their separate functions. Cells here specialize in higher order function of visual system like orientation, motion, depth, form, color etc. Visual cortex has many areas from V1 to V8, V1 is known as Primary visual cortex, as it receives the input from the LGN and does some processing and further distribute it in the higher cortical areas.

The various cells/areas here are specialized in various higher order functions like orientation, motion, depth, colour etc. Primary visual cortex(V1) is the first area that processes the received information from LGN. Some specialized areas are given below:

- V1- Orientation Selectivity.

- V2- Orientation, Form etc.
- V3- Form, Shape.
- V4- Colour, Contrast.
- V5- Movement  Control.

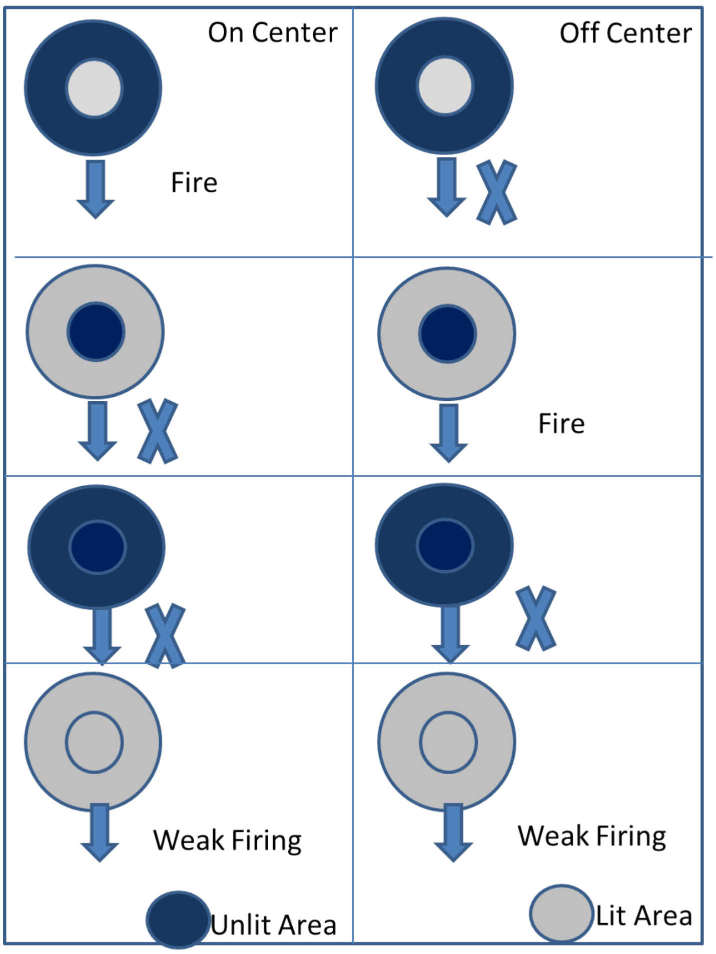


Figure 2.3: Behavior of Receptive Field under various light condidtions

Visual processing begins in the retina - in the receptive surface inside the back of the eye. Light enters the eye, passes through the layers of cells in the retina before reaching the photoreceptors, which are located at the back of the retina. Light activates the photoreceptors, which modulated the activity of bipolar cells located at the front of the retina. The axons of the ganglion cells form the optic nerve, which carries information to the brain. Two other types of neurons-horizontal cells and amacrine cells are primary responsible for lateral interaction in the retina. The bipolar cells and ganglion cells are organized in such a way that each cell responds to a small circular patch of photo receptors, which define the cells receptive fields. The receptive fields of retinal ganglion cells are concentric, consisting of a roughly circular central area and a surrounding ring.

Retinal ganglion cells have two basic types of receptive fields:

- On-center/off-surround.
- Off-center/on-surround.

The center and its surround are always antagonistic and tend to cancel each others activity. An on-center cell is stimulated when the center of its receptive field is exposed to light, and is inhibited when the surround is exposed to light. Off-center cells have just the opposite reaction. On the edge between the two, in mammals, an on-off effect (i.e., discharging at switching on or off but not at duration of either state) is present. Stimulation of the center of an on-center cell's receptive field increase in the firing of the ganglion cell, stimulation of the surround decrease in the firing of the cell, and stimulation of both the center and surround produces only a mild response (due to mutual inhibition of center and surround). An off-center cell is stimulated by activation of the surround and inhibited by stimulation of the center.

The center-surround receptive field organization allows ganglion cells to transmit information not merely about whether photoreceptor cells are exposed to light, but also about the differences in the firing rates of cells in the center and surround. This allows them to transmit information about contrast. The size of the receptive field governs the spatial frequency of the information: small receptive fields are stimulated by high spatial frequencies, fine detail; large receptive fields are stimulated by low spatial frequencies, coarse detail. Retinal ganglion cell receptive fields convey information about discontinuities in the distribution of light falling on the retina; these often specify the edges of objects.

### 2.1.1 Simple Cells

Hubel and Wiesle [16] in 1962 discovered cortical cells in their experiment of visual response of neurons in the cats primary visual cortex(V1). They mapped the receptive fields of V1 by flashing bars. They described these cells as simple and complex. Both simple and complex cells are responsive selectively to the oriented lights static and moving. The cells were classified as simple cells for which they found regions which responded either to onset or for offset of a bright bar not for both. Simple cells have receptive fields which can be divided into excitatory and inhibitory regions, like the RFs of RGC and LGN. A simple cell in the primary visual cortex is a cell that responds primarily to oriented edges and gratings [4] (bars of particular orientations).

They have the following four properties

- They have well segregated ON and OFF regions (distinct excitatory and inhibitory). ON and OFF regions can be identified based on their response to bright and dark stimuli. ON regions increases firing rate and OFF regions suppresses the firing rate and only responds to dark stimuli.

- Each region shows a summation property as it increases the firing rate with the increase in the area of light in a particular region.

- These regions have mutual antagonism - excitatory and inhibitory regions balance themselves out in diffused lighting.

- It is possible to predict responses of moving stimuli given the map of excitatory and inhibitory regions.

Most simple cells display properties of ocular dominance i.e. they are driven only by one eye.

### 2.1.2 Complex Cells

Complex cells can be found in the primary visual cortex (V1), the secondary visual cortex (V2), and Brodmann area 19 (V3). Like a simple cell, a complex cell responds primarily to oriented edges and gratings, however it has a degree of spatial invariance. This means that its receptive field cannot be mapped into fixed excitatory and inhibitory zones. Rather, it will respond to patterns of light in a certain orientation within a large receptive field, regardless of the exact location. Some complex cells respond optimally only to movement in a certain direction.

The difference between the receptive fields and the characteristics of simple and complex cells is of that of hierarchical convergent nature of visual processing. Complex cells receive inputs from a number of simple cells. Their receptive field is therefore a summation and integration of the receptive fields of many input simple cells.

## 2.2 Orientation Selectivity

In the human visual cortex specialized groups of cells extract information about different aspect of a visual scene. One such group of cells are called as orientation selective cells, detects oriented lines in the input visual scene. Models so far developed on orientation selectivity belong to either of the two categories, feed-forward model or recurrent model. In a simple and elegant model Hubel and Wiesel [16][9] hypothesized that the response properties of simple cells in layer 4 of the cortex are dominated by the convergence of highly specific thalamic inputs. The receptive fields (RFs) for simple cells in the visual cortex have adjacent ON and OFF sub-fields having projections from ON-center and OFF-center LGN cells respectively. In Hubel and Wiesels feed-forward model of the visual cortex, orientation selectivity arises from the alignment of receptive fields of LGN neurons pre-synaptic to each cortical simple cell. In the feed-forward model of Hubel and Wiesel, in a cortical simple cell (i) the inputs from LGN cells within its receptive fields are linearly summed and (ii) if this summed input is more than a threshold voltage, spikes are produced by the cortical cell. In the feed-forward model, lateral connections between cortical cells are ignored i.e. only thalamocortical but no intracortical connections are considered.

As thalamocortical connections are excitatory in nature, purely feed-forward models cannot take into account the involvement of inhibition in sharpening the orientation tuning [15]. Intracortical inhibition was found to be strongest in the preferred orientation and weakest at orthogonal. In recurrent circuit models [21], thalamocortical connections provide a very weak orientation selectivity and this weak selectivity is sharpened over time by recurrent excitatory corticocortical connection among cells preferring similar orientations and by inhibitory corticocortical connections among broader range of orientations. Recurrent circuit models account for sharpening of tuning due to inhibition. Cortical inhibition plays a major role in developing orientation tuning in recurrent models. In the intra cortical connections used in recurrent models, however, inhibitory connections form the surround and excitatory connections dominate the center. This pattern is exactly opposite of the actual structure seen in the visual cortex [22]. The cortical connections that extend furthest (>1 mm) are mostly excitatory and link similar orientation preferences [23]. It is also reported that in cat the tuning of excitatory and inhibitory cells in layer 4 and layer 23 are almost same, but in layer 5 the inhibitory cells have broader tuning. The development of sharp tuning in cortical excitatory cells in most recurrent or feedback models [21] depends on the inhibition provided by broadly tuned inhibitory cells.

Short-range corticocortical connections connect cortical cells and long-range corticocortical connections (also referred as long range lateral connections or horizontal connections) connect cortical cells across hypercolumns (A group of neurons in the brain cortex which can be successively penetrated by a probe inserted perpendicularly to the cortical surface, and which have nearly identical receptive fields). Through horizontal connections an individual neuron can integrate information over a retinal area several times larger than its classical receptive fields. The intracortical connections or lateral connections in the cortex are believed to have significant influences on various cortical activities.

# Chapter 3

# Literature Survey

## 3.1 Modeling Approaches for Cortex

Many models have been implemented to study the cortical cell characterestics. The work has been done to understand the function of the various aspects of the cortical cell. The main focus is to understand the detailed structure and the neural mechanisms that underlie the functioning of the cortical cells. Some approaches[34] are described below:

- **Filter Models** These models only a single cells at a high levels of abstraction disregarding all biophysical characterastic. Main advantage of this model is that it gives an analytical treatment. Its scope usually lies beyond modeling of mear orientation behaviour as they often extend into temporal domain by applying spatio-temporal filters. Its a very good modeling approach but cannot model multicell cortex.

- **Development Model** I models large array of cells to gain insight into the processes that forms the map of prefered orientation. these appply a wide range of learning rules, from physiologically realistic rules to abstract rules of self-organising in any maps like structure.

- **Structurally defined Models** these models uses a graphical or one-step computational or mathematical description of the map in an attempt to understand the cortical design principles and the structure of the final map.

- **Biophysically Relistic Models** they are generally used to model complex cells. Differential equation defining membrane characterestic are used to model cortical cells in an effort to reproduce membrane behaviour, control experimentally those parameters otherwise inaccessible. Its a very complex, rather opaque, complete assessment of parameter space is impossible.

## 3.2 Various Models of Visual Cortex

There are a number of models which have attempted to model the visual cortex and account for the behavior of origin of orientation selectivity. There are various computational models for V1 that seek to explain its visual functions in terms of its architecture and connections.These models can be categorized as follows:

- **Feed-forward Models**: This model work on the convergence of oriented thalamocortical input(from LGN). The simple cells receives input from overlapping LGN neurons whose receptive fields centers as per the axis of prefered orientation of the cortical cell. Hers the notion arises from the organisation of the thalamic input to simple cell. This model uses the pattern of inputs to the cortex. This model explains orientation preference but fails to explain orientation selectivity.[Hubel and Wiesel, 1962]

- **Inhibitory Models**:This model employ feed forward bias to establish initial orientation preference of cortical neurons and utilise inhibitory inputs from cortical neurons prefering different orientations to suppress the resoponse at non-preered orientations.[Worgitter and Koch, 1991] Here a weak bias provided by converging thalamic input is sharpened by inhibitory input from neurons prefering diferent orientations.

- **Recurrent Models**: This employs recurrent cortical excitation froom cortical cells prefering similar orientations combined with inhibition from other range of orientation along with the weak bias from thalamic inputs[Somers et al.,1995]. Recurrent excitation models account for selectivity but do not explain how there are both simple and complex cells in V1.

# Chapter 4

# Development of Simple Cell and Complex Cell Receptive Fields

In this chapter the proposed model is discussed with implementation details. The results obtained are discussed and analysed.

## 4.1 Development of Simple Cell Receptive Field

### 4.1.1 Simple Cell Structure

Hubel and Wiesel discovered simple cells in their experiment on cats primary visual cortex in their famous experiment in 1956. They successfully mapped the receptive field of simple cells (V1 cells) by flashing the bars. In their work, they characterized the cells as either simple or complex. they found that both simple and complex cells were responsive to input stimulus and movement.

Simple cells as those cells for which they could find regions that responded either to onset or to offset of a bright bar but not to both. Simple cells have receptive field that can be divided into distinct excitatory and inhibitory regions, like the receptive fields of the neurons in the retina and the lateral geniculate nucleus. They described four characteristics that the receptive field structure of simple cell process. These are:

- Well segregated ON and OFF region.

- Neuron exhibits summation property.
- Antagonism exists between ON and OFF regions.
- Response of the cell to a moving or a static stimulus of any shape can be predicted from arrangement of ON and OFF regions in the cells receptive field.

The responses of simple cells to complicated shapes can be predict from their responses to small-spot stimuli. Like retinal ganglion cells, geniculate cells, and circularly symmetric cortical cells, each simple cell has a small, clearly delineated receptive field within which a small spot of light produces either on or off responses, depending on where in the field the spot falls.

The difference between these cells and cells at earlier levels of visual pathway is in the geometry of the maps of excitation and inhibition. Cells at earlier stages have receptive fields with circular symmetry, consisting of one region, ON or OFF, surrounded by the opponent region, OFF or ON.

### 4.1.2 Formation of Simple Cells Receptive Fields: A Competition and Cooperation based developmental model

A reaction diffusion model which leads to sequential development of orientation and ocular dominance columns in the visual cortex [13]. Reaction diffusion framework is used to achieve the segregation of ON and OFF afferents with in the RF of simple cells [14]. The model is based on competition (reaction) and cooperation (diffusion). Competition for limited amount of neurotrophins presents during development and Cooperation among the near neighboring (i) cortical cells and (ii) same type of i.e. ON-ON and OFF-OFF LGN cells.

Both these assumptions are supported by biological facts. Competition among axons for neurotrophic factors (NTFs) has been reported in neurobiology [12][11]. Cooperation among neighboring cells can occur through release and uptake of diffusible factors.

The development of thalamocortical synaptic strengths is modeled through a differential update rule. The rate of change of a synaptic strength (ON or OFF) is a function of:

- Amount of resources i.e. NTFs available at both the pre (LGN) and the post (cortex) - synaptic sites.
- The amount of diffusible messengers from the near neighboring cortical cells and same type of LGN cells.

We have used fixed resources for both pre and postsynaptic competition. Such competition among synapses for finite resources, such as receptor or factor controlling the number of synapses have been observed.

As the synaptic strengths increase, available resources are used up. Limited supply of resources brings in competition among the afferents and ensures that of the two synapses (ON and OFF) reaching a cortical cell from a given LGN location, while one synapse grows, the other decays. Competition ensures synaptic growth and cooperation among neighboring LGN cells helps in the formation of sub-fields. Large ON (OFF) synapses help neighboring ON (OFF) synapses to grow and force OFF (ON) synapses out of the neighborhood. If the system only had competition between ON and OFF synapses, patchy RFs with scattered ON and OFF connections would result. Synaptic growth stops once most of the available resources have been consumed.

The ability to accurately capture the details of the receptive fields of cortical neurons is of importance in any model for orientation selectivity. As compared to other feed-forward models [1] 'Cooperation and competition' based model obtain more realistic receptive fields. Simulated RFs show a gradual transition from one sub-field (ON/OFF) to other sub-field (OFF/ON) and show a good correspondence with the experimentally mapped receptive fields(naturally occurring receptive fields). Varying the level of cooperation and/or competition in the model, allows us to obtain RFs with varying number of ON and OFF sub-fields. Reduced competition at the post-synapse (increased cortical resource) and reduced cooperation among LGN cells (reduced LGN diffusion) increases the number of sub-fields formed in the receptive fields. A minimum level of pre- and post- synaptic resource must be available to support the formation of synapses of adequate strength.

Cooperation among cortical cells (cortical diffusion) ensures that neighboring cells develop similar RFs, spatial phase and orientation preferences. This helps in obtaining the spatial organization of simple cells into an orientation map. It is seen that a competition and cooperation based system is sufficient for the development of simple cell RFs. But the linear contribution of the feed-forward thalamocortical afferents is not sufficient for providing the cells with sharp orientation selectivity as is reported in experimental findings. This is indicative of other non-linear mechanisms involved in sharpening of orientation selective responses.

In neurobiology, competition is generally associated with sharing of resources; in particular axons compete for neurotropic factors [12],[11]. The models for corticocortical connections are based on resource limited competition and cooperation. Competition among cortical cells is for the limited amount of neurotrophins present during development. During this competition, cells with similar orientation cooperate with each other. Both these assumptions of competition and cooperation are supported by biological facts. Competition among axons for neurotrophic factors (NTFs) has been reported in neurobiology. Both the models are based on the following biologically plausible assumptions:

- Competition for presynaptic resource where a presynaptic cell has a fixed amount of resource to distribute among its branches. This would constrain the number of axonal branches a cortical neuron can maintain. A role for presynaptic resources was first suggested to model the elimination of polyneuronal innervations in neuromuscular system [24].

- Competition between axons for target space where the axons are competing for neurotrophic factors, growth or survival promoting factors, released by the post synaptic cells upon which the axons innervate. Competition for the target space or postsynaptic competition is used for development of ocular dominance [2].

- Hebbian cooperation between cells with similar orientation preference [3].

Orientation selectivity develops in absence of vision [10]. The initial development of both ocular dominance and orientation map in cat is found to be independent of visual activity. It is generally agreed upon that during pre-eye-opening period, some form of spontaneous activity is required for establishment of afferent connections [25]. The development of horizontal connections follows thalamic innervations. The lateral connections are also included, it is assumed that initial orientation bias in the cortical cells is already present and lateral connections develop in presence of activity. Here the cells are competing for resources. Neurotropic factors are released in activity dependent fashion.

### 4.1.3 Model Equation of Simple Cell Receptive Field

For studying the development of thalamo-cortical connections, a two-layer model consisting of a MxM 2D overlapping layers of NxN LGN, one corresponds to ON LGN layer and the other to OFF LGN layer. Each cortical neuron in the model receives thalamic projections from 13x13 LGN region centered at its retinotopic center position. Two types of synapse exist between cortical and LGN cells. ON synapse represents the strength from ON center LGN cells to a cortical cell; similarly OFF synapse represents the synaptic strength from the OFF center LGN cell. Time evolution of the synaptic strengths represents cortical development. Initially, from a given LGN location a model cortical cell receives synapse of nearly equal strength from both ON and OFF cells lying one above the other. The number of axonal branches a LGN cell can support is determined by competition for pre-synaptic resource, where a pre-synaptic cell has a fixed amount of resources to distribute among its branches. Axons from ON and OFF cells compete for target space in the cortex.

In the model $W_{IJ}^{+}$, $W_{IJ}^{-}$ represent the strength of the connection from the ON-center and OFF-center LGN cell at position j in LGN layer to the cortical cell at position i in the cortical layer. A cortical cell receives projections from a 13x13 region of the LGN ON and OFF layers, centered at its retinotopic position in the LGN. The synaptic strength is updated using the following update rule:

$$\frac{\partial W_{IJ}^{+}}{\partial t} = (\gamma_1 - K_1)(\gamma_2 - K_2) A_R(I, J) W_{IJ}^{+} + D_L \frac{\partial^2 W_{IJ}}{\partial J^2} + D_C \frac{\partial^2 W_{IJ}}{\partial I^2}$$

where

- $\mathrm{W_{IJ}} \, \epsilon \{\mathrm{W}_{IJ}^{+}, W_{IJ}^{-}\}$.

- $K_1^2 = \sum_{P=1}^{NxN} (W_{PJ}^+)^2$ is the sum of the square of the synaptic strength of all branches emanating from the LGN cell at location J.

- $\gamma_1$ represents fixed presynaptic resources available in the LGN cell at location J.

- $\gamma_1 - K_1$ enforces competition for resources among axonal branches of a LGN cell.

- Similarly, $\gamma_2 - K_2$ enforces competition among LGN cells for target space in the cortex.

- $K_2^2 = \sum_{P=1}^{MxM} (W_{IP})^2$ is the sum of the square of the synaptic strength of all branches of LGN cells converging on the cortical cell at location I.

- $\gamma_2$ represents fixed postsynaptic resources available in the cortical cell at location I.

- The arbor function $A_R$(I,J) determines the number of synapses being modified.

- $D_L$ and $D_C$ are the diffusion constants in the LGN and the cortex respectively.

- MxM and NxN are the sizes of the LGN and cortex respectively.

A similar equation is used for updating $W_{IJ}^-$ .

Orientation selectivity develops in the absence of vision. The initial development of both ocular dominance and orientation map in cat is found to be independent of visual activity [26]. Its generally agreed upon that during pre-eye opening period, some form of spontaneous Activity is required for establishment of afferent connections [25]. In this model, cells are competing for resources. The cooperation among cells is achieved through diffusion.

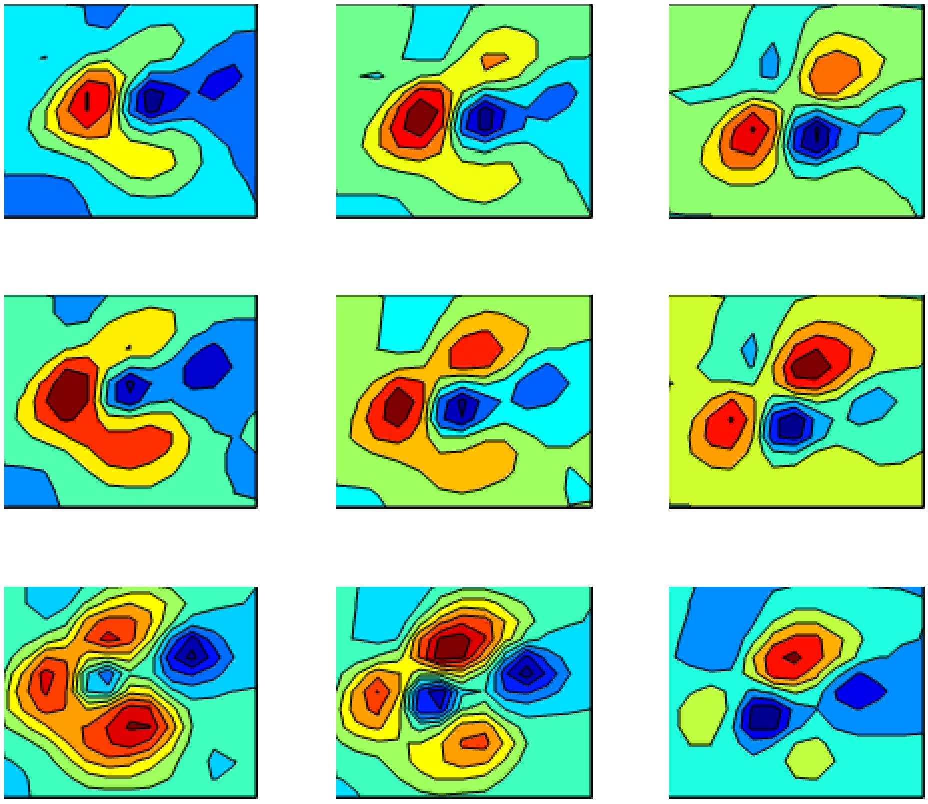

Figure 4.1: Developed Simple Cell Receptive Fields with Various Orientations

### 4.1.4 Simulation Results of Simple Cell Receptive Field

In the figure 4.1 receptive field of cortical simple cells are shown. As is seen, the various sub-regions are clearly visible and the first cell is ON-center OFF-surround cell, whereas the last cell is OFF-center ON-surround. Here red depicts ON cells and blue depicts OFF cells. Various orientations as displayed by these cells are also evident.

## 4.2 Development of Complex Cell Receptive Field

### 4.2.1 Complex Cell Structure

Hubel and Wiesel first proposed that the receptive field of a complex cell can be formed by linearly integrating the receptive fields of simple cells. The development of receptive field of a complex cell is governed by the cells that are forming lateral connections with a cortical cell. Cells that are from a certain range contribute in the formation of the receptive field of a complex cell. The process is shown in the Figure 4.2.

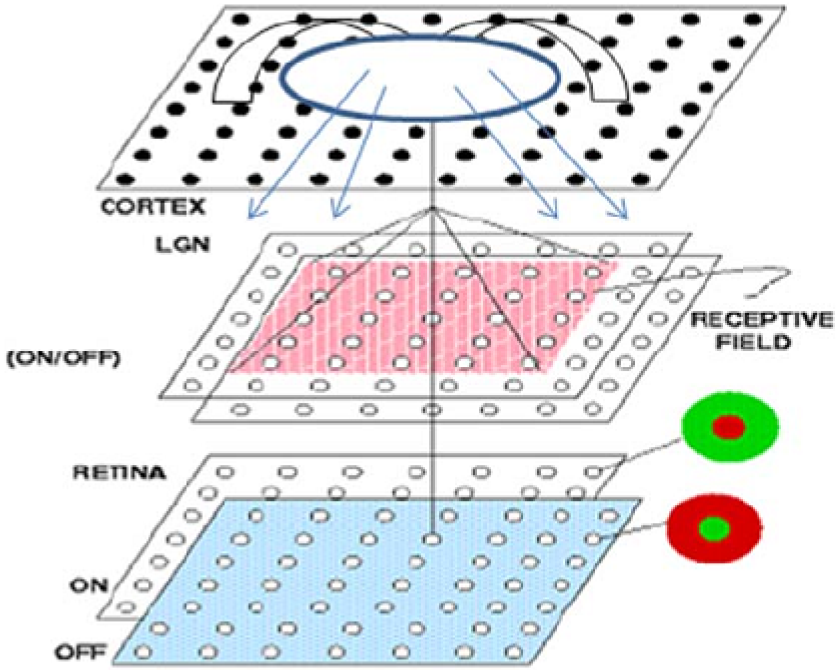


Figure 4.2: Structure of Complex Cell Receptive Field

This proposition is modeled by considering the existence of the simple cells of which the output is fed back to the other simple cells. The important role here is played by an important information of inter-cortical weights or lateral cortical weights. These weights describe the synaptic strength of the connection of the inter cortical neurons. Here the modeling of the complex cell is done in such a way that the simple cell and the complex both develop simultaneously i.e. the growth of both the cells is parallel, as what happens naturally in the pre-eye opening period. The final weights are summed up, as is done in the feed-forward manner.

The weights so developed are having the orientation selectivity and tuning as is observed in the simulated results of the visual cortex.

### 4.2.2 Model Equation of Complex Cell Receptive Field

The following equation is used for modeling the notion of complex cell:

$$\frac{\partial W_I}{\partial t} = \frac{\partial W_{IJ}^{+}}{\partial t} + f_{range} \sum_K \frac{\alpha_K \partial W_{IJ}^{l}}{1 - \partial W_{IK}^{c}}$$

- $f_{range}$, determines the range within which cells that are forming lateral connections with a cortical cell will contribute to the formation of complex cell receptive field.
- $\alpha_k$, determines the amount of contribution that cell K is making.
- $W_{IJ}^{l}$, is the synaptic strength between the LGN and the cortex.
- $W_{IK}^{c}$, is the inter cortical weights at the cortical layer.
- 1-$W_{IK}^{c}$, ensures that cells that are forming strong lateral connections will also contribute more in the complex cell receptive field formation.

### 4.2.3 Simulation Results of Complex Cell Receptive Field

In figure 4.3 developed receptive fields of cortical complex cells are shown. As is seen the various regions are clearly visible but they cannot be clearly demarcated as clear good arrangement of ON and OFF type of cells. They typically display features of a complex cell, like purely ON cells or OFF type of cells. Various orientations as displayed by these cells are also evident.

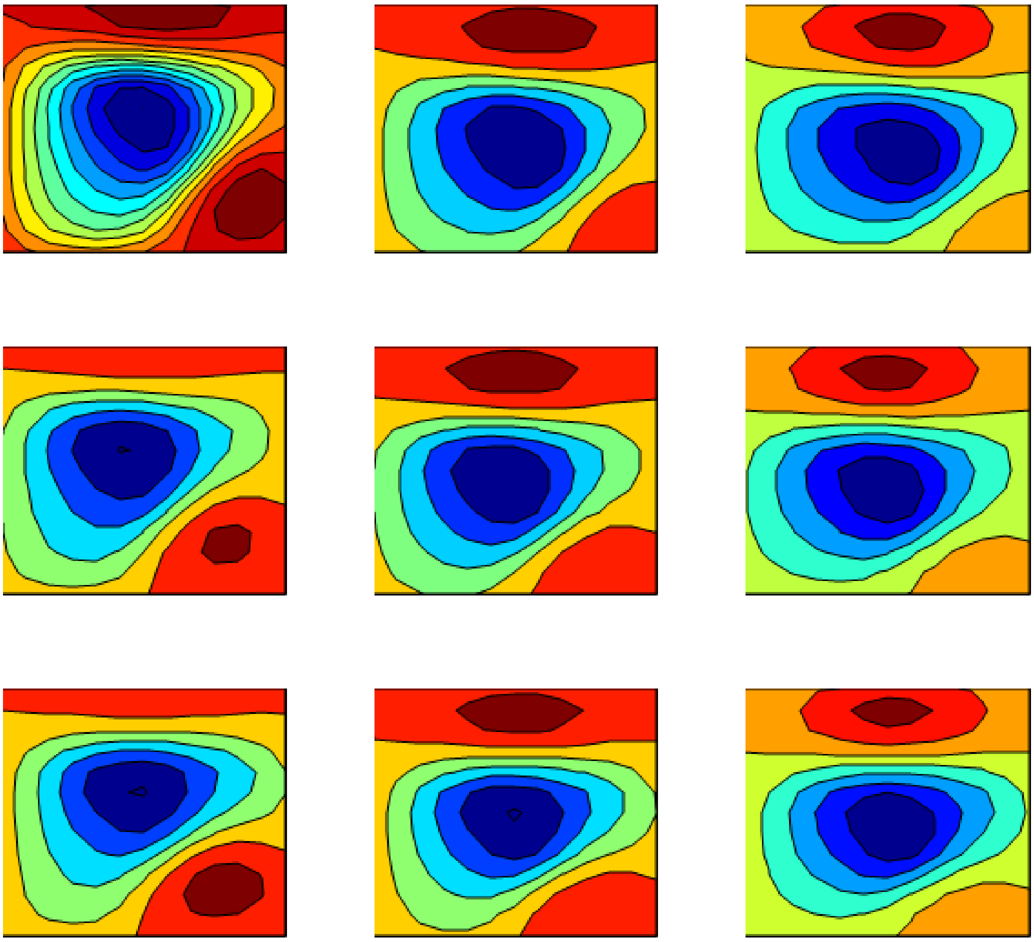

Figure 4.3: Developed Complex Cells with Various Orientations

## 4.3 Role of Model Parameters in Structuring of Simple and Complex Cell Receptive Fields

Now we discuss the parameters important to the weight development equation. These parameters are LGN resource, Cortical resource, LGN Diffusion constant and Cortical Diffusion constant. The parameters are:

- **Cortical resource($\gamma_1$):** Increase in the cortical resource increases the synaptic strength. The number of sub fields however remains the same.

During the development of orientation selectivity axons from LGN cells segregate into ON and OFF sub fields of the cortical cells. For low values of cortical resource in some cells only one type of LGN cells either ON or OFF takes over the whole of the receptive field.

- **LGN resource ($\gamma_2$):** Sub-regions are formed even for lower values of resource, but the synaptic strength are quiet week due to scarcity of resource and as a result, cell will not be fully responsive to the input stimuli. If the resource is increased, the synaptic weight becomes stronger without affecting the number of sub-regions and the structure of the RF.

- **Cortical diffusion constant($D_c$):** The post synaptic event at an active synapse leads to generation of the diffusible signals. This enhances the synapse of the nearby neurons as well. The rate of spread of this diffusiblility depends upon the value of the diffusion constant. Larger the value of diffusion constant, larger is the spread of activity. Cortical diffusion ensures that near neighbors cells have similar receptive fields and orientation preference. So with the increase in the value the sub region size grows throwing out the smaller sub regions from the receptive fields.

- **LGN diffusion constant($D_L$):** The increase in the value of $D_L$ leads to reduction in the number of the sub fields.

  So, primarily the LGN diffusion constant ($D_L$) is the primary parameters ampngst others that determine the profile of the cortical cells receptive field. Increasing value of the LGN diffusion constant ($D_L$) reduces the number of sub regions obtained in a cell. The LGN resource in particular does not affect the receptive fields structure.

# Chapter 5

# Artificial Visual Cortex and Edge Detection

## 5.1 Spike Generation

The action potential or the spike generation of a cortical neuron does not itself carry any information. The numbers, pattern of spikes and timing of spikes of the neuron carries the information. The postsynaptic potentials received by the neurons are integrated and when it exceeds the resting potential of the neuron, the neuron fires an action potential. This model is called Spike Response Model (SRM) [27]. The Spike Response model is, in which the spike rate or spike frequency of the occurrence increases smoothly with the increase in stimulus current starting from zero. Another phenomenon of spike train generation where firing occurs at the resting potential threshold, but with a quantum jump to a non-zero frequency. Models have been developed using the rate (frequency) of the spike train and are called rate-based models.

The important thing is how the message is coded and transported by the action potential in the neuron. There are two approaches to code the signal in to a spike: Pulse code or Rate code.

- Pulse code: Measures the time delay of the first spike from the time of stimulus as seen by postsynaptic neuron which does the coding.
- Rate code: Measures the average rate of the spike occurrence.

These two approaches are though not confirmed through neuro-biological studies, but both approaches are modeled computationally and the parameters are varied to match the experimental output. An important characteristic of Spike Response Model is the time-dependent spike generation. Here the time is important not the spike itself.

## 5.2 Feed Forward and Recurrent Model

Our knowledge of the response of the visual cortex neuron has increased but the mechanism responsible for these properties and the meaning of this information is still illusive and inconclusive. Even the basic properties like orientation tuning and selectivity are not fully understood. There are two major categories of orientation models developed feed forward model and recurrent model. Hubel and Wiesel suggested that orientation selectivity arises from the alignment of receptive field of LGN neurons pre- synaptic to each cortical simple cell.

In the feed forward model in the cortical simple cell:

1. Input from the LGN cells within its subfields are integrated.

2. If this input crosses the threshold, spikes are produced by cortical cell.

Here, the spike threshold prevents the simple cells from responding to the weak stimuli. In the feed forward model only the thalamo-cortical connections are considered, the cortico-cortical connections are ignored which actually contribute in to the orientation sharpening of the cell.

In recurrent model the Thalamocortical connections provide a weak orientation selectivity and this weak selectivity is sharpened over time by recurrent excitatory and inhibitory connections. Recurrence contributes to the tuning in the simple cell. In the intracortical connections used in recurrent models, inhibitory connection from the surround and excitatory connection dominate the center, thus increasing the selectivity. Thalamic feed-forward dominated models of orientation selectivity predict constant selectivity during visual response, whereas intracortical-recurrent models predict dynamic improvement in selectivity. An experimental finding [30] suggests that sustained visual cortical processing does not narrow orientation tuning; rather, intra-cortical contributes to narrow the tuning. Thus combined models which considers both feed forward and the lateral connections, is more realistic in cortex modeling.

The input is received by the eye of the model. Eyes are modeled to accept the visual input by using Retinal Ganglion Cell (RGC) model, which models the retinal ganglion cells of the eye. RGC cells are primarily responsible for accepting the visual input and converting them in to neuronal output. The RGC model is explained in following section.

## 5.3 Retinal Ganglion Cell Model: Implementation

The retinal layer is modeled as two separate 2D 30x30 sheets of ganglion cells lying one over the other. One sheet corresponds to ON-center and the other to OFF-center ganglion cells respectively. Retinal ganglion cells (RGCs) have center-surround receptive field structure with center field being 30' wide [31] and center-to-center spacing between the cells being 12' of the visual angle. The surround field was taken to be 90' wide. The ganglion cell model used here has been used earlier by [32][33][6] to produce realistic temporal responses to visual stimuli.

The retina has two types of receptive fields ON-center and OFF-center. The common feature of the two types of receptive fields is that the center and surround regions are antagonistic. The Difference of Gaussian(DoG) uses simple linear differences to model this center-surround mechanism and the response $R(\boldsymbol{x},t)$, is equal to a measure of contrast of events happening between center and surround regions of the operator. The difference of Gaussian model is composed of the difference of two response functions that model the centre and surround mechanisms of retinal cells.

In the figure 5.1 the upper diagram shows the assumption that signals from elementary areas constituting the centre region and signals from elementary areas constituting the surround region are separately summed and that the resulting signals C and S, have antagonistic effects upon the ganglion cell. For an ON-

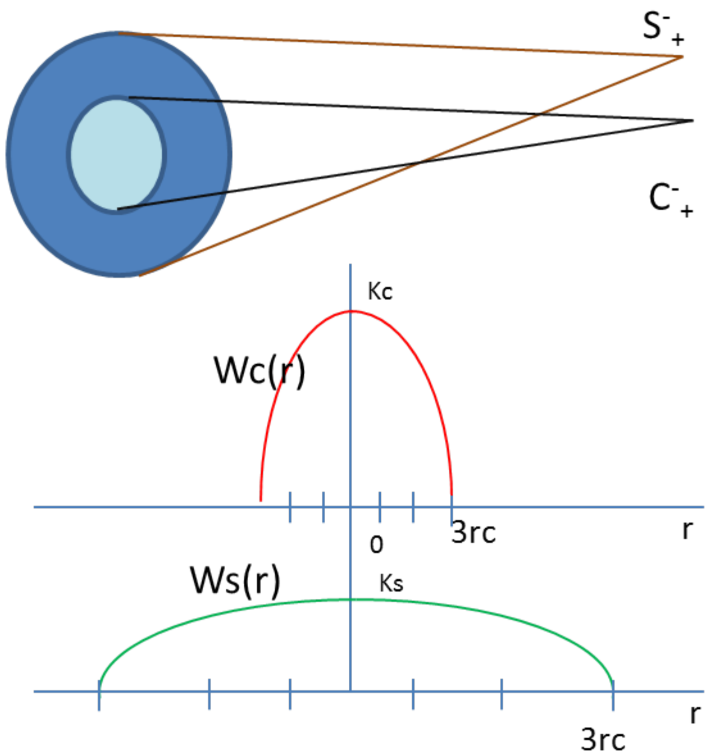


Figure 5.1: Difference of Gaussians method for conversion of Visual Image to Retinal Spike

centre cell the two signals would be described by +C and -S, for an OFF-centre cell by -C and +S. In the lower half of the figure are shown the Gaussian weighting functions assumed to describe the sensitivities of the centre and surround regions respectively. Note that the weighting functions for both centre and surround regions have maxima in the middle of the receptive field.

The special receptive fields of the RGCs were modeled using difference of two Gaussians [7].

$$G\left(x,y\right)=G_{center}\left(x,y\right)-G_{surround}\left(x,y\right)$$

With, $G\left(x,y\right)=\left(K/2\pi\sigma^{2}\right)\exp\left(-\left(x^{2}+y^{2}\right)/2\sigma^{2}\right)$

where $\sigma$ and K values as measured by Linsenmeir et. al., 1982 are used. $\sigma_{\text{center}} = 10.6'$and $\sigma_{\text{surround}} = 31.8'$ and $\text{K}_{\text{center}}/\text{K}_{\text{surround}} = 17/16$. Beyond $3\sigma$ the Gaussian fields were set to zero. The temporal response associated with each

Gaussian is that of a first order low pass filter:

$$H(t) = (1/\tau)\exp(-t/\tau)$$

with $\tau_{center} = 10$ msec and $\tau_{surround} = 20$ msec msec (Richter and Ullman, 1982). The temporal response of retinal X-cells has a band-pass like characteristics. Subtracting the responses of the center and surround results in a band-pass like behaviour. The response of a retinal subfield (center/surround) to any input stimulus I(x,y,t) is obtained by spatio-temporal convolution of the sub-field profile with the input stimulus:

$$R(x,y,t) = \int_{0}^{t}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} G(x',y')H(t')I(x-x',y-y',t-t')\,dx'dy'dt'$$

The response of the ON and OFF retinal ganglion cells are then given by :

$$ON(x,y,t) = [R_{center}(x,y,t) - R_{surround}(x,y,t)]^{+}$$

$$OFF(x,y,t) = [(2 * baseline) - R_{center}(x,y,t) + R_{surround}(x,y,t)]^{+}$$

respectively, where $[.]^{+} = \max(.,0)$. Baseline is defined as the response of an ON cell to uniform background stimulus. Addition of this term to OFF cells insured that ON and OFF cells exhibited the same spontaneous activity levels in response to a uniform field [6]. Binary action potentials are generated from this continuous response function by a Poisson process. The probability that a ganglion cell fires an action potential in the small interval between t and t $+\Delta t$(with $\Delta t << 1$) is given by:

$$p(x,y,t) = p_o \cdot \Delta t \cdot RGC(x,y,t)$$

Where $p_o$ is normalization constant. $RGC(x,y,t)$ represents either the response of an ON center cell "$ON(x,y,t)$" or the response of an OFF center cell, "$OFF(x,y,t)$". Minimum delay between two successive firing instances of a retinal cell is 3 ms.

The LGN layer is also made up of two 2D sheets of cells of size 30x30 each lying one over the other. One sheet comprised of ON-center cells and the other of OFF-center cells. A one-to-one correspondence between the retinal and ganglion cells exists. The firing of the retinal cells is directly relayed to the LGN layer. The normalization constant ($p_o$) was chosen such that the model LGN cells firing rates matched experimental values for the given contrast (Cheng et. al., 1995).

## 5.4 The Three Layer Visual Pathway System

The three layer visual pathway with lateral connections included is shown in Fig 5.2. Retinal cells receive input from visual space and transmit it to LGN. There are ON- center and OFF-center retinal cells sending output to ON- and OFF-center LGN cells respectively. Each cortical cell receives input from both ON- and OFF- types of LGN cells. The retinal layer is modeled as two 2D 30x30 ganglion cells lying one over the other, the first sheet corresponding to ON-center and the other to OFF-center ganglion cells. ON- and OFF- LGN layers are modeled as two 2D 30x30 sheets lying one over the other. Temporal response functions and mechanism for generation of spikes the model in [33] is used for retinal cell's spatial receptive field.

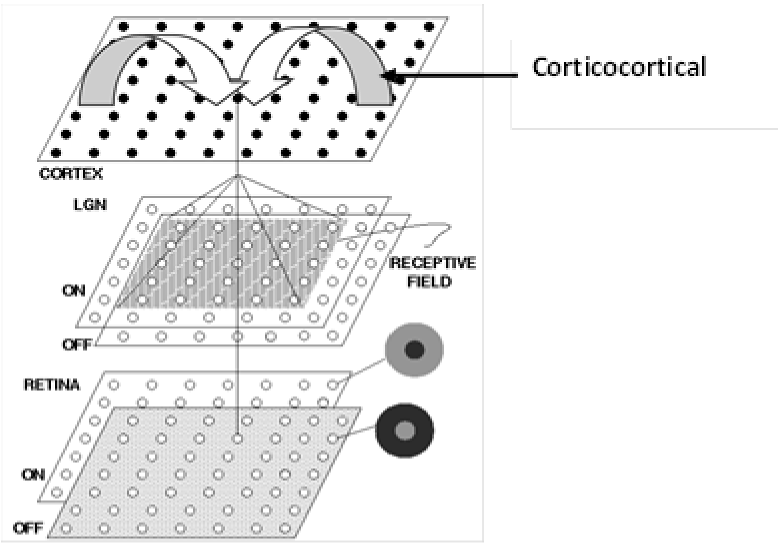


Figure 5.2: Three Layer Artificial Visual Pathway

Figure 5.2 shows a three layer visual pathway with lateral connections. The model consists of retina, LGN and cortex. Retinal cells are divided into ON- and OFF- cells and project to ON-center and OFF-center LGN cells respectively. Each cell receives input from a restricted region of the LGN called its receptive field. The cortical cells receive inputs from other cortical cells via lateral corticocortical connections. Cortical layer models layer 4 simple cells.

The output layer models layer 4 cortical cells. The response of cortical cells at a given time is calculated using the SRM model (Spike response model) [28]. The equation for calculating the membrane potential is,

$$\begin{aligned} u_i(t) = \eta\left(t - t_{fC}\right) \, + \beta_L \sum_j W_{ij}^k \sum_{fL} \varepsilon(t - t_{fL}) \, + \beta_{C1} \sum_j w_{ij}^+ \sum_{fC1} \varepsilon_1(t - t_{fC1}) \\ + \beta_{C2} \sum_j w_{ij}^- \sum_{fC2} \varepsilon_2(t - t_{fC2}) \, + R_p \end{aligned} \tag{3.1}$$

where, $u_i(t)$ is the membrane potential of cortical cell at location i at time t and $t_{fC}$ is the time when the cell produced the most recent spike. $W_{ij}^k$ is the strength of the synapse between LGN cell at location j and cortical cell at location i, k is either + or − where $W_{ij}^+(W_{ij}^-)$ represents the synaptic strength between the ON(OFF)-center LGN cell at position j in the LGN layer to the cortical cell at position i in the cortical layer. $\varepsilon(t - t_{fL})$ is the EPSP (Excitatory Post Synaptic Potential) generated in the cortical cell at location i when the LGN cell at location j produces spike at time $\mathrm{t_{fL}}$. Similarly, $\varepsilon_1(t - t_{fC1})$ is the EPSP generated in the cortical cell at location i when the excitatory cortical cell at location j produces spike at time $t_{fC1}$ and $\varepsilon_2(t - t_{fC2})$ is IPSP (Inhibitory Post Synaptic Potential) generated in the cortical cell at location i when the inhibitory cortical cell at location j produces spike at time $t_{fC2}$. The formula used for $\varepsilon_{ij}(t)$ is

$$\varepsilon_{ij}(t) = \left[\exp\left(-\frac{t - t_{ij}^{ax}}{\tau_m}\right) - \exp\left(-\frac{t - t_{ij}^{ax}}{\tau_s}\right)\right] \mathrm{H}\left(t - t_{ij}^{ax}\right)$$

where $\tau_s$, $\tau_m$ are time constants and $t_{ij}^{ax}$ is the axonal transmission delay between node j to node i. $\mathrm{H}\left(t - t_{ij}^{ax}\right)$ is the Heaviside step function which vanishes for $\left(t - t_{ij}^{ax}\right) < 0$ and takes a value of 1 for $\left(t - t_{ij}^{ax}\right) > 0$. The typical form of $\varepsilon_{ij}$ is shown in figure 5.3.

For inhibitory synapses $\varepsilon_{ij}$ is negative. It is taken care of by making $w_{ij} > 0$ for excitatory cells and $w_{ij} < 0$ for inhibitory type cells. The summing up of the

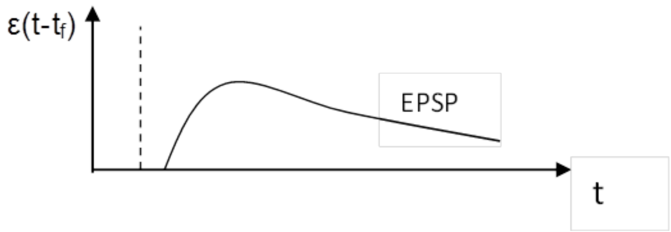


Figure 5.3: Excitatory Post Synaptic Potential

effect of all the spikes of the LGN cell and cortical cells occurring within the past 90 msec from the present time t is done. $\eta(t - t_{fC})$ is the refractory voltage of the cortical cell. The kernel $\eta_i(t)$ is usually non-positive for $t > 0$. A specific mathematical formulation used for $\eta_i(t)$ is

$$\eta_i\left(t\right) = -\vartheta \exp\left(-\frac{t}{\tau}\right) H\left(t\right)$$

Where $\tau$ is a time constant and $H(t)$ is the Heaviside step function. At the moment of firing $u_i(t)$ reaches $-\vartheta$. The effect of the refractory voltage, expressed by the above equation, is to reset the membrane potential $u_i(t)$ to 0. It is depicted in figure 5.4.

$R_p$ is the rest potential of the cortical cell. The output so obtained is 1 if the value of $u_i(t)$ is more than the threshold; otherwise it is zero. In the simulation 70mV is resting potential. The threshold potential for spiking is 35mV for excitatory cells, and 40mV for inhibitory cells to reflect the fact that interneurons spike more than excitatory neurons.

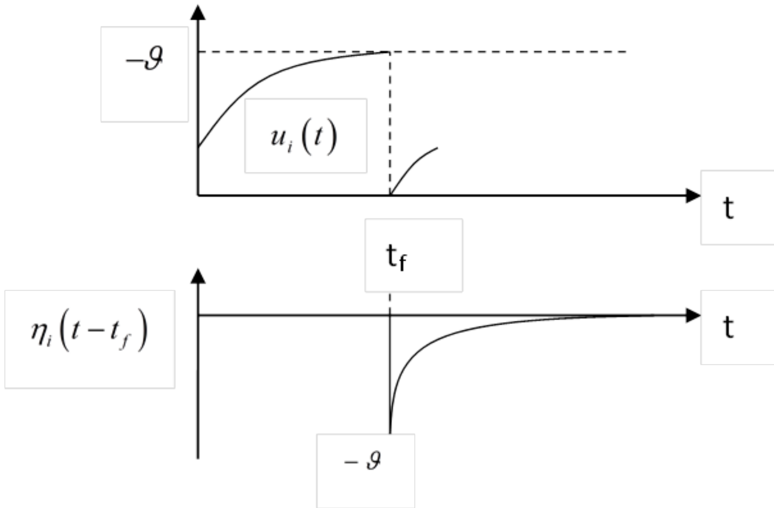


Figure 5.4: Behavior of EPSP with respect to threshold potential

## 5.5 Simulation Arrangement

The setup of the simulation of the artificial visual cortex is given in the figure 5.5.

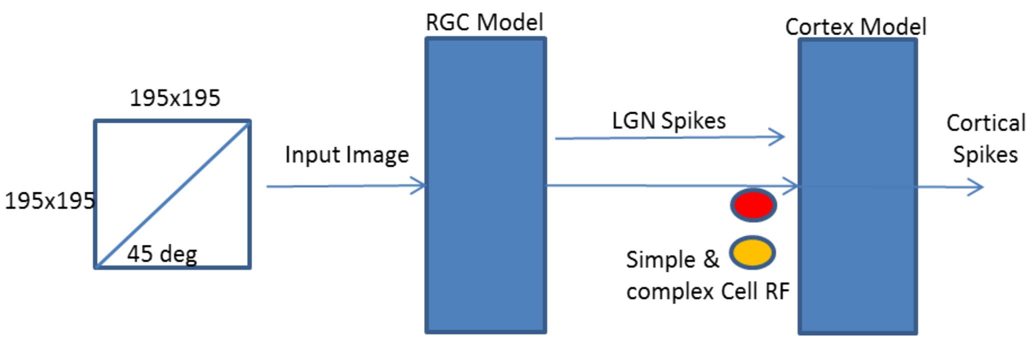


Figure 5.5: Proposed Model

### 5.5.1 Input

The input is the black and white line images of size 195x195. These images are synthetically generated owing to the requirements of the artificial Visual Cortex model. To check the working of the cortex model we first use these synthetic images rather that natural images. These images contain lines of angles between $0°$ to $180°$ with a step of $9°$.

### 5.5.2 RGC Layer

The RGC layer accepts the input from the image of size 195x195. Here the retinal layer is modeled as two sheets of ganglion cells (ON and OFF), lying one over the other. The ganglion cells are modeled here to produce near real temporal response to the visual stimulus. The receptive fields of the retina are modeled by using the difference of Gaussian (DoG) method [29]. The DoG imitates the behavior of the RGC receptive fields and gives it the property of spatial frequency filters. The DoG operator uses simple linear differences to model the centre-surround mechanism and the response (G(x, y)) produced is the measure of contrast of events happening between center and surround regions of the operator. The output of this layer is the temporal response corresponding to ten orientations and for all cells of the LGN layer (42x42). The LGN layer is made up of two 2D sheets of cells of size 42x42. A one-to-one corresponding relationship between retinal and ganglion cells exists. Therefore the firing of the retinal cells output is directly relayed to the LGN layer. The output is produced for both the ON and OFF Retinal layers.

### 5.5.3 Cortex Layer

This layer receives the input from the RGC layer. The response of the cortical layer is calculated by using Spike Response Model (SRM) [28]. The Kernel used here is epsilon($\varepsilon$) which generates the Excitatory Post Synaptic Potential (EPSP) at LGN, EPSP and Inhibitory Post Synaptic Potential (IPSP) at the cortical layer. The value of the cortical potential is calculated by calculating membrane potential. The value of the membrane potential depends up on the occurrence of the input in quick succession. This quick succession of input occurrences, pushes the membrane potential towards the threshold, if crossed, a spike is recorded. The voltage is reset to the reset potential and the process continues. Similarly, the spikes are produced by all the neurons of the cortex corresponding to the input orientations.

### 5.5.4 Simulation Results

There were two types of input use as input stimulus. We used 195x195 sized inputs for the model. The size of our cortex is 50x50. LGN is of size 30x30. After unfolding the LGN it becomes of size 42x42. LGN and retina is of same size. Thus visual space corresponding to retina of size 42x42 is 195x195. This size was chosen as it is the area of the visual space which the cortex of size 50x50 and LGN of size 13x13 can process.

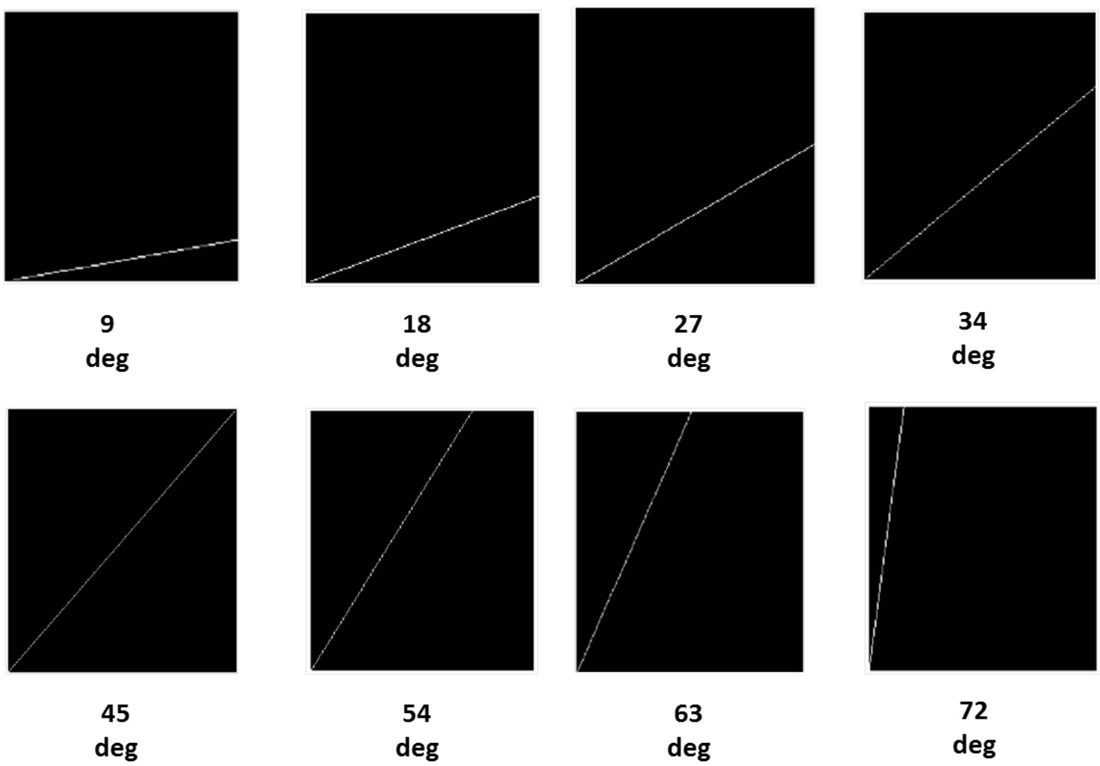


Figure 5.6: Inputs Starting from Vertices of Image

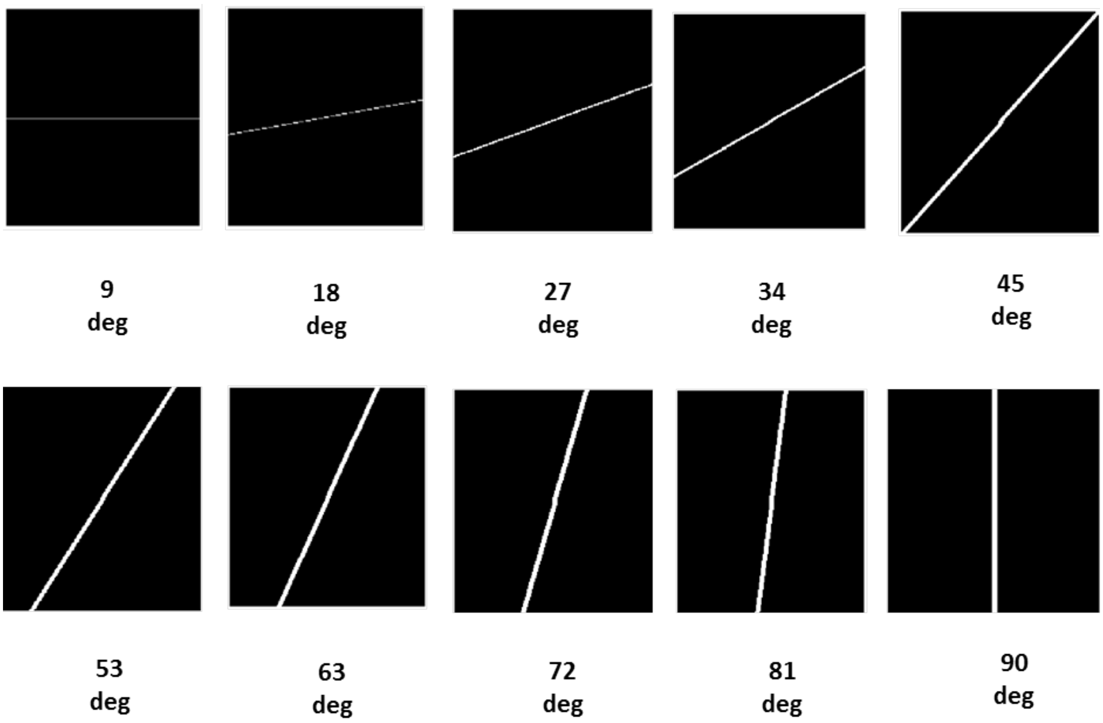


Figure 5.7: Inputs Passing through the Origin

The two types of input are:

- Line image whose origin lies on the vertices as shown in fig 5.6.
- Line image whose origin lies at the center of the image shown in fig 5.7.

The output was in the following form:

- Times at which the spikes were fired from every neuron cell.
- Spike potential values of all the cells for various orientations in the cortex.
- Angles of the receptive fields of the individual cortical cells.

We use the spike potential produced for the ten orientations. This data contains the fired potential of all the neurons for various input orientation. All the cells do not fire all the time, but only those cells fire which are tuned for that orientation.

This means that some neuron cells which fire are the once tuned for some orientation and when that orientation is flashed as input these cells potential cross over the threshold value and fire a potential. The spike response of the cortical cells to various input stimuli was calculated from equation (3.1). Spike rates per second were computed for individual input orientations. Ten responses were thus obtained for ten orientations of input stimulus.

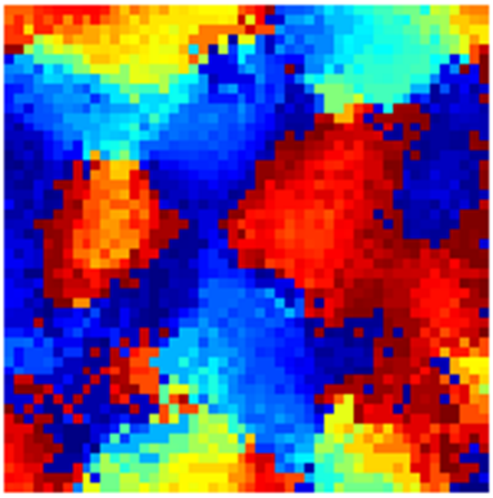

Figure 5.8: Orientation Map

**Approach 1**

First approach was taken of, to use the spike output and compare it with the Orientation map. Orientation map 5.8, is orientation vs Active region map. It maps which region of brain maps to what orientation. Activities from cortical areas are recorded by showing grated stimuli of different orientations. Each pixel represents, vector $(r, \phi)$, $r$ is magnitude of response, $\phi$ is angle of oriented input (Angled Map).

The output obtained in the form of 50x50 containing the magnitude of response of the cortical cell. As the artificial cortex is extremely small of dimension 50x50, in comparison to the actual cortex which is of size $10^{10}$. So we take the largest value among the 50x50 output which we assume is representing the effective output of the small cortex. This $r$ value (magnitude) is then compared with the orientation map values, if the match is found, we find the corresponding angle($\phi$). We now reconstruct this newfound angle.

This approach did not meet the desired results and the calculated angles were not confirming to the known input angles.

| **Input Angle** | **0-18** | **19-36** | **37-54** | **55-72** | **73-90** | **91-108** | **109-126** | **127-144** | **145-162** | **163-180** | **Output Angle** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 110 | 148 | 59 | 68 | 87 | 35 | 35 | 7 | 107 | 35 | **13** |
| **9** | 147 | 57 | 81 | 111 | 33 | 92 | 77 | 68 | 50 | 70 | **4** |
| **18** | 162 | 129 | 8 | 54 | 37 | 38 | 32 | 13 | 151 | 156 | **4** |
| **27** | 115 | 35 | 23 | 88 | 140 | 95 | 16 | 31 | 101 | 68 | **40** |
| **36** | 69 | 48 | 89 | 99 | 84 | 55 | 124 | 47 | 30 | 46 | **58** |
| **45** | **81** | **61** | **66** | **137** | **72** | **56** | **51** | **23** | **23** | **82** | **40** |
| **54** | 109 | 154 | 140 | 38 | 23 | 1 | 123 | 33 | 99 | 8 | **13** |
| **63** | 138 | 16 | 99 | 81 | 69 | 123 | 5 | 67 | 21 | 46 | **4** |
| **72** | 136 | 100 | 42 | 61 | 262 | 13 | 10 | 49 | 1 | 75 | **40** |
| **81** | 55 | 164 | 10 | 27 | 61 | 56 | 55 | 113 | 74 | 4 | **13** |
| **90** | **155** | **47** | **63** | **35** | **66** | **204** | **36** | **1** | **6** | **60** | **80** |
| **99** | 175 | 61 | 94 | 5 | 87 | 33 | 38 | 155 | 12 | 86 | **4** |
| **108** | 198 | 43 | 52 | 175 | 66 | 39 | 31 | 37 | 46 | 8 | **4** |
| **117** | 110 | 18 | 26 | 73 | 152 | 49 | 36 | 31 | 45 | 125 | **40** |
| **126** | 106 | 40 | 129 | 23 | 101 | 94 | 14 | 4 | 43 | 114 | **22** |
| **135** | 167 | 32 | 7 | 102 | 124 | 36 | 2 | 83 | 104 | 41 | **4** |
| **144** | 160 | 31 | 97 | 29 | 25 | 68 | 33 | 69 | 183 | 38 | **76** |
| **153** | 165 | 80 | 118 | 30 | 80 | 77 | 56 | 20 | 21 | 86 | **4** |
| **162** | 142 | 18 | 187 | 41 | 107 | 21 | 40 | 0 | 112 | 21 | **22** |
| **171** | 323 | 87 | 37 | 45 | 9 | 133 | 4 | 68 | 63 | 3 | **4** |
| **180** | 270 | 13 | 45 | 74 | 66 | 4 | 177 | 0 | 12 | 52 | **4** |

Table 5.1: Results for Detected Edges of a Synthetic Oriented Input

**Approach 2**

In this approach, we select the cortical spikes output file which contains the Spike potential of all the cells for various orientations. To derive the meaningful orientation from the output data, we counted the 'number of cells/orientations', which fired the maximum times. We applied a filter to the data to filter out the low firing cells, the output of which was of no relevance and which were spoiling the final output. So, finally the potentials which are beyond a threshold are counted, and the count of number of neurons/orientations is obtained as shown in table 5.1. The orientation for which the number of neuron fired is the highest is the orientation output of the artificial cortex. This orientation is a crude calculation of the orientation of the input image of the orientation. Thus we are able to calculate the indicative orientation, corresponding to the synthetic input angle. This gave us near true angles of 45 °, 90 ° and 0 °. There are some errors in the other orientations. The reason for this behavior could be that this artificial cortex is currently designed for 10 orientations only, i.e. 0°-180°with step of 18 °. So it is only responding for angles which are multiples of 18°. If we have to improve the sensitivity of the artificial cortex model then we have to reduce the step size to a lower value(2°,4°,8°). Lower the value of the step size, higher will be granularity of the model and higher will be the sensitivity of the system.

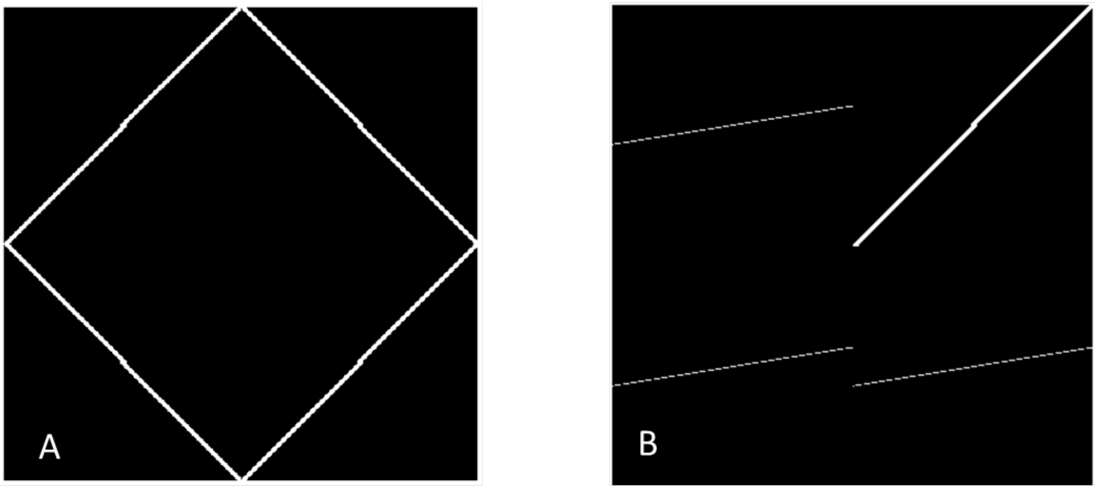


Figure 5.9: Testing of the model with an synthetic Image

### Approach 3

For testing the response behavior of the developed model to an images(both synthetic and natural), we feed the model a big image shown in Figure 5.9. The model was given a 390x390 size image (Figure A) as an input. The model breaks down the image into smaller portions of size 195x195. Then it finds out the corresponding angles of the small images. After having done so it reconstructs the image(Figure B) with the calculated angle. It is observed that the some angles calculated by the model were near correct but some were out of phase by 180 °. There is a need to study this erratic behavior of the model to the various angles. And the correction has to be incorporated in the model in such a way that it is biologically plausible.

# Chapter 6

# Conclusion and Future Work

## 6.1 Conclusion

Hubel and Wiesel pioneered a significant progress in the field of study of the visual cortex. Visual cortex being a complex part of brain has a lots of short and long-range vertical and lateral connections. The major functioning of the visual cortex is to receive the neural signals from the eye and lateral geniculate neuleus and thereafter process the information received to derive multidimensional features of the visual information before it is perceived by the brain. Various methods are proposed to model the visual cortex, with an aim to understand the functioning of the various aspects of the cortical layer/cell. The main focus is to understand the detailed structure and the neural mechanisms that underlie the functioning of the visual cortex. But many of these models take approaches which are not biologically plausible. In this thesis, we have used a biologically plausible computational model for accepting an visual input like an eye and perform like a natural visual system and immitate a basic function of edge detection. This is done by giving the model an known orientation synthetic input and thereafter receive the cortical spikes output. These cortical spikes were then analyzed, and various approaches were taken to draw out the information (orientation selectivity) from the output received.

The various approaches which were taken are as follows:

- **Approach I:** The first approach was to compare the cortical spike output with the Orientation Map values(OMap is a map of spike potential amplitude and the angle associated with it.These are the real brian values which returns the corresponding orientation values if the cortical spike potential is known.), to get the orientation value corresponding to cortical spike. Then we got the orientations of all the spikes ccorresponding to the entire input image and reconstructed the image as per the oriented information received. The results were not much encouraging.

- **Approach II:** In this approach we collected the cortical spikes potential of all the cells for various orientations. To derive the meaningful orientation from the output data, we counted the 'number of cells/orientations', which fired the maximum times for an orientation. Finally, the count of "number of neurons/orientations" is obtained. The orientation for which the number of neuron fired is the highest, is the orientation output of the artificial cortex. Thus we were able to calculate the indicative orientation, corresponding to the synthetic input angle. This approach has given us near true results of degrees of around 45 °, 90 ° and 0 °.

- **Approach III:** To test the response behavior of the developed model, to the input images, both synthetic and natural. We gave an image input the model and evaluated the Neuronal spike output. The output is yet to come to a desired state, but it gives a partial good result. To improve the sensitivity of the artificial cortex model, we have propose to reduce the step size of the orientation to a lower value of 2°, 4° or 8°, which currently is 18° . Lower the value of the step size, higher will be granularity of the model and higher will be the sensitivity of the system, which will enable it to pick angles of input lines with discernable accuracy, enabling increased orientation selectivity and tuning. This is yet to be established.

In view of the observations in the previous section and the summary of the work done, the present thesis have presented a biologically plausible model of visual cortex with simple as well as complex cell receptive fields. The contributions of the present work are as follows:

- Developed a receptive field of a complex cell with biologically plausible preconditions.

- Developed the edge detection capability model of artificial visual cortex.

## 6.2 Future Work

- Characterization of the complex cell receptive field to understand its behaviour, capabilities and effects of various parameters.
- Characterization of the artificial visual cortex. This will open up more dimensions of understanding in to the concepts and further improvements are possible.
- The current model works well for certain orientation, but shows incorrect results for other orientations. There is a need to enhance the granularity of angle selection by the model so that its orientation selectivity increases.

# Bibliography

[1] Miller KD, 1994, A model for development of simple cell receptive fields and ordered arrangement of orientation columns through activity-dependent competition between ON and OFF center inputs. 17

[2] Miller KD, Keller JB, Stryker MP, 1989, Ocular dominance column development: Analysis and simulation. *Science*, 245:605-615.

[3] Hebb DO, 1949, *The Organization of behavior: A Neuropsychological Theory*, Wiley, NY. 18
18

[4] http://hubel.med.harvard.edu/book/b3.htm 10

[5] Gilbert CD, 1977, Laminar Differences in the receptive field properties of cells in the cat primary visual cortex. *Journal of Physiology*, 268:391-421.

[6] Somers DC, Nelson SB, and Sur M, 1995, An Emergent Model of Orientation Selectivity in Cat Visual Cortical Simple Cells. *Journal of NeuroScience*, 15:5448-5465. 28, 30

[7] Enroth-Cuggel C, and Robson JG, 1966, The contrast sensitivity of retinal ganglion cells of the cat. *Journal of Physiology*, 187:517-522. 29

[8] Cheng H. Chino Y, Smith E, Hamamoto J, Yoshida K ,1995 , Transfer characteristics of lateral geniculate nucleus X neurons in the cat: effects of spatial frequency and contrast. *Journal of Neurophysiology*, 74: 2548-2557

[9] Hubel and Wiesel, 1968, Receptive fields and functional architecture of monkey striate cortex. 11

[10] Hubel and Wiesel, 1974, Uniformity of monkey striate cortex: A parallel relationship between field size, scatter, and magnification factor. 18

[11] Purves D, 1994, *Neural activity and growth of the brain.* Cambridge University Press, Cambridge. 16, 18

[12] Purves D, Lichtman JW, 1985, Presynaptic and Postsynaptic competition in models for the development of neuromuscular connections. *Biological Cybernetics*, 68:409-419. 16, 18

[13] Bhaumik B, Markan CM, 2000, Orientation map: A reaction-diffusion based ,model. *Proceedings of International Joint Conference on Neural Networks*, Como, Italy, $24^{th}$-$27^{th}$ July, vol 1., 1228-1233. 16

[14] Bhaumik B, Mathur M, 2002, Diffusive Cooperation and Resource limited Competition based receptive field model. *Proceedings of International Joint Conference on Neural Networks*, Washington DC, $15^{th}$-$19^{th}$ July, vol. 1, 284-289 16

[15] Eysel UT, Crook JM, and Machemer HF, 1990, GABA-Induced Remote Inactivation Reveals Cross-Orientations sInhibition in the Cat Striate Cortex. *Experimental Brain Research*, 80:626-630. 11

[16] Hubel DH, Wiesel TN, 1962, Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. *Journal of Physiology*, 160:106-154. 2, 10, 11

[17] Kisvardy ZF, Crook JM, Buzas P, Eysel UT, 2000, Combined physiological-anamotical approaches to study lateral inhibition. *Journal of Neuroscience Methods* 103:91-106.

[18] Douglas RJ and Martin KAC, 1991, A Functional Microcircuit for Cat Visual Cortex, *Journal of Physiology*, 440:735-769

[19] Levine and Shefner, 1991, Fundamentals of Sensation and Perception (2nd ed.). California: Brooks/Cole Publishing Co. 2

[20] Chapman and Stryker, 1993, Development of orientation selectivity in ferret visual cortex and effects of deprivation. *Journal of Neuroscience* 13: 5251-62. 3

[21] Somers DC, Nelson SB, and Sur M, 1995, An emergent model of orientation selectivity in cat visual cortical simple cells. *Journal of Neuroscience*, 15:5448- 5465. 11, 12

[22] Yousef T, Toth E, Rausch M, Eysel UT, and Kisvarday ZF, 2001, *Topography of Orientation Center Connections in Primary Visual Cortex of the Cat. Neuro Report*, 12(8):1693-1699. 12

[23] Lowel S and Singer W (1992), Selection of Intrinsic Horizontal Connections in the Visual Cortex by Correlated Neural Activity, Science, 255: 209-212. 12

[24] Willshaw DJ, 1981, The establishment and the subsequent elimination of polyneural innervation of developing muscle;the theoretical considerations. *Proceedings of Royal Society of London B.*, 212:233-252. 18

[25] Sur M, Leamy CA, 2001, Development ans plasticity of cortical areas and networks. *Nature Reviews Neuroscience*, 2:251:262. 19, 20

[26] Criar MC, Gillespie DC, Stryker MP, 1998, The role of visual experience in the development of columns in cat visual cortex (area 18): effects on orientation tuning. Journal of NeuroScience, 11:1347-1358. 20

[27] Gerstner W, 1995, Time structure of the activity in neural network models. *Phys. Rev. E*, 51:738-758 26

[28] Gerstner W, 1999, Spiking Neurons, In: *Pulsed Neural Networks*, (eds.) Mass W, Bishop CM, MIT Press, Cambridge, :3-54. 32, 35

[29] Rodieck RW, 1965, Quantitative analysis of cat retinal ganglion cell response to visual stimuli. *Vision Research*, 5:583-601. 35

[30] Sharon D, Grinvald A, 2002, Dynamics and constancy in cortical spatiotemporal patterns of orientation processing. *Science*, 295:512-515. 27

[31] Peichl L, Wassle H, 1979, Size, scatter and coverage of ganglion cell receptive field centers in the cat retina. *Journal of Physiology*, 291:117-141. 28

[32] Wehmeier U, Dong D, Koch C, van Essen D, 1989, Modelling the visual system. In *Methods in Neural Modeling, (eds.)* Koch C and Segev I, pp. 335 359, MIT Press, Cambridge. 28

[33] Worgotter F, Koch C, 1991, A detailed model of the primary visual pathways in the cat: Comparision of afferent excitatory and intracortical inhibitory connection schemes for orientation selectivity. *Journal of Neuro-Science*, 11(7):1959-1979. 28, 31

[34] Worgotter F, 1999, Comparing different modelinf apporaches of visual cortical cell characterestics. In Cerebral Cortex,(Eds. Ulinski et al.),vol 13, Kluwer Academic, Plenum Publishers, New York. 13