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Predicting the Response of Complex Cells in the Primary Visual Cortex Using a Neural Network

[redacted]

Abstract

Complex cells are located in the primary visual cortex and show orientation, direction, and movement velocity selectivity. They are differentiated from simple cells by the overlapping ON-OFF subregions of their receptive field. It has been shown that complex cell response can be modulated by varying contour arrangements within the receptive field, but no model has yet been able to completely predict the manner in which this modulation takes place. We propose that a neural network can, with appropriate training, be implemented to detect a pattern in complex cell response and produce accurate predictions based on the properties of stimuli within their receptive fields.

1 Introduction

Contour Orientation Detection in the Visual System

Contour orientation detection in the mammalian visual system relies on a hierarchy consisting of neurons in the Lateral Geniculate Nucleus (LGN) and in the Primary Visual Cortex (V1) [17]. LGN neurons form connections with a type of neuron called simple cells located in layers 4 and 6 of V1 [3]. In turn, simple cells form connections with another type of neuron called complex cells which are located throughout the other layers of V1 [3, 17]. The receptive fields of these neurons are comprised of ON regions where stimuli yields an excitatory response and OFF regions where stimuli inhibits the neuron [16]. Within LGN neurons these ON-OFF subregions do not overlap and are concentric (see Figure 1) [15]. The center portion is known as the classical receptive field, while the surrounding ring is known as the non-classical or center-surround receptive field [16]. Individual LGN neurons

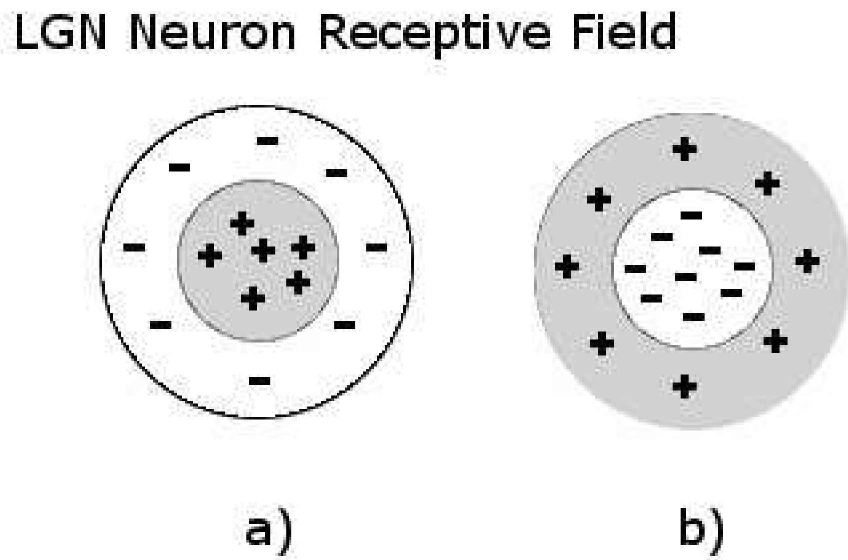

Figure 1: LGN neurons have concentric ON and OFF subregions as shown in the examples above. Example *a* demonstrates the excitatory ON region in the classical center and the inhibitory OFF region in the center-surround portion of the receptive field. Example *b* demonstrates the opposite arrangement with the ON region in the surround and the OFF region in the center.

can either be excited by stimuli in the center and inhibited by center-surround stimuli or they can be inhibited by stimuli in the center and excited by stimuli in the center-surround subregion [17]. The way in which LGN neurons form synapses with simple cells in V1 is responsible for the orientation selectivity exhibited by simple cells [31]. This selectivity is thought to be due to the asymmetry found in the receptive fields of simple cells which are elliptical in shape and are elongated along the vertical axis (see Figure 2) [32]. Within the receptive field, ON-OFF subregions are located roughly in parallel with each other. The pattern of receptive field subregions exhibited by an individual simple cell roughly matches the line orientation for which that neuron is optimally tuned (see Figure 3) [17]. Because of these ON-OFF regions, non-optimally tuned line orientations fall in both regions and the balance of excitation and inhibition leads to a continuous representation of line orientation that follows a gaussian distribution [15].

Unlike LGN and simple cells, complex cell ON-OFF regions overlap within their receptive field in a way that has yet to be completely determined [38]. Several models have

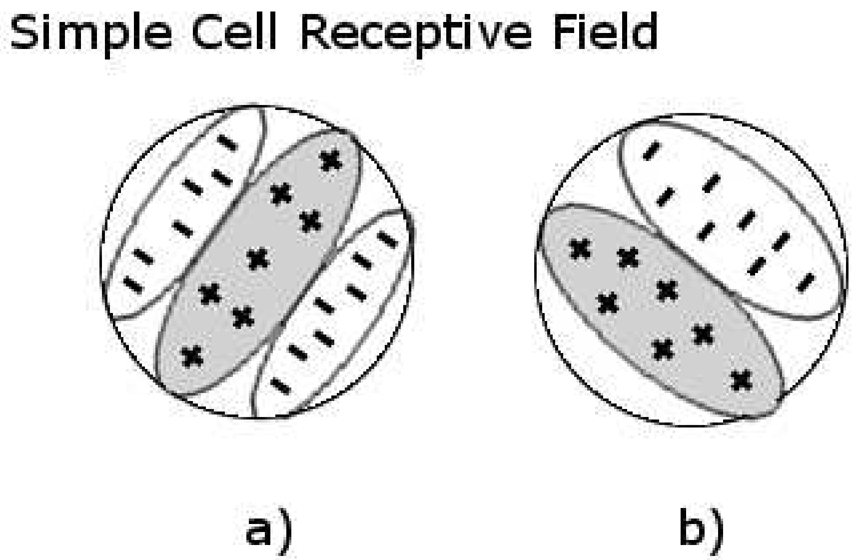

Figure 2: Simple cell receptive fields are composed of elliptical ON and OFF subregions. The arrangement of these subregions is approximately parallel to the optimal line orientation and the division of the receptive field into ON and OFF regions is not symmetrical.

been developed in order to predict the response of complex cells based on the properties of stimuli within their receptive fields, however none have been able to completely describe complex cell behavior [12].

Neural Networks

In the field of computer science, a machine learning technique called neural networks have been applied to a variety of tasks including object recognition for computer systems [28]. Neural networks were designed to mimic the way in which neurons interact in order to solve complex problems such as the recognition of patterns within a set of inputs [8, 22, 36]. Feed-forward neural networks are the most common type of neural network [22]. Visually, we could represent a neural network as a directed graph data structure with weighted edges (see Figure 4). At each vertex in the graph, there is a neural node that encapsulates a continuous threshold function. At each node in the network, the combined weighted inputs are compared against the threshold function. If they exceed threshold, then the node mimics the action potential carried out by biological neurons and activates all of its outgoing edges.

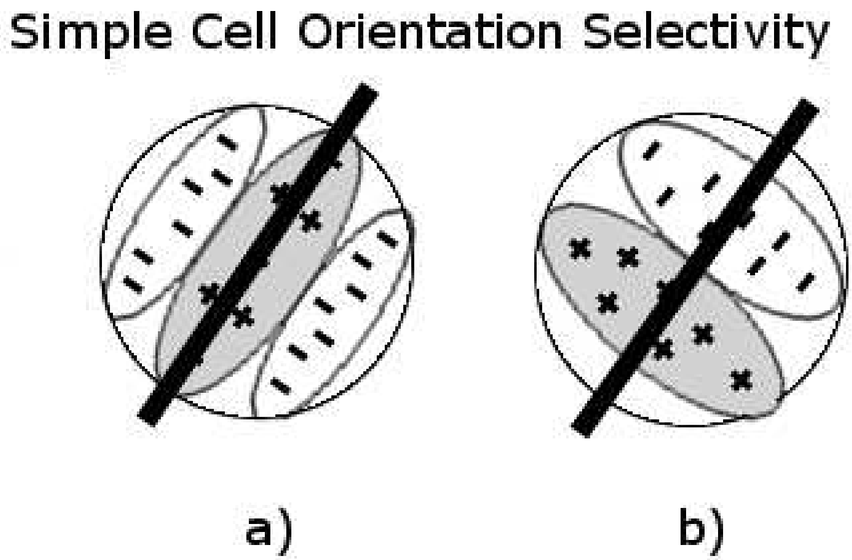

Figure 3: The arrangement of ON and OFF subregions of the Simple Cell receptive field dictates the optimal line orientation. The proportion to which stimuli falls in the ON region versus in the OFF region controls the excitation of the Simple Cell. In example *a* the line falls entirely within the ON region, which would yield the optimum excitatory response meaning that this is the optimal line orientation for this particular simple cell. In contrast, the line in example *b* falls perpendicular to the ON region and the excitatory response caused by the portion of the line within the ON region would be cancelled by the inhibitory response caused by the portion of the line in the OFF region.

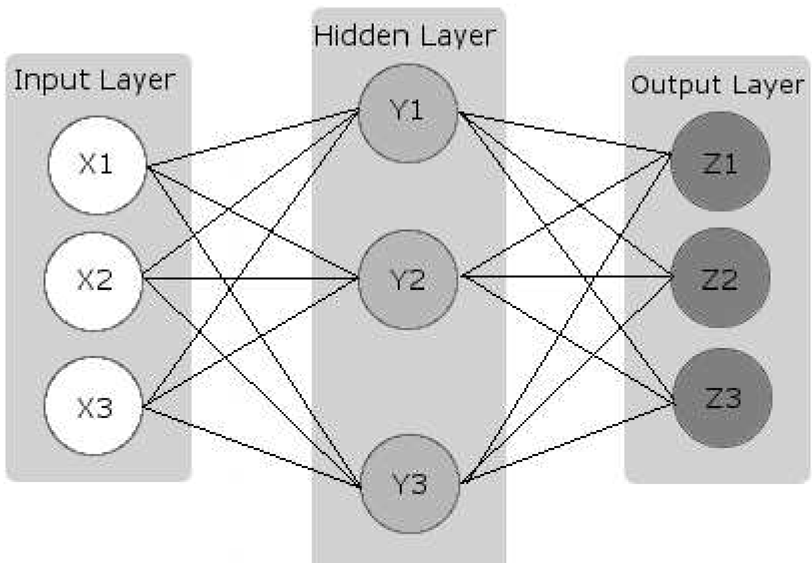

Figure 4: A feedforward neural network can be illustrated as a fully connected, directed graph. Here you will see the nodes of the input layer (X1, X2, X3) the hidden layer (Y1, Y2, Y3) and the output layer (Z1, Z2, Z3). Each of these nodes would encapsulate a sigmoid threshold function that is used to test the weighted input sum of all incoming edges. Each edge is assigned a weight which controls the extent to which activation along that connection affects the downstream nodes. A forward pass for some input starts with the input layers, is passed along the edges to the hidden layer, and is finally passed along to the output layer where the response of the network can be measured using some form of encoding (i.e. binary)

Computationally, this is represented by a series of matrix multiplications [26, 22]. Rather than working like a simple mathematical equation, neural networks must instead be trained in order to determine the appropriate weights and connections for solving a given problem [22]. There are several algorithms that can be employed in order to train a feed-forward neural network; however the most common is called the back-propagation algorithm [22, 26, 36]. The back propagation algorithm works by using a set of inputs for which the desired output is already known called the training set. For each element of the training set, a feed-forward pass through the neural network is performed. The obtained output is compared against the desired output and the weights of the edges in the network are adjusted by a factor of the difference between these values.

2 Prior Work

Much of the research done on complex cell receptive fields has been carried out through electrophysiological single unit recordings [32], however some properties have also been identiied through perceptual analysis [38]. Early work done by Hubel and Weisel described complex cells based on the way that they responded to stimuli within their receptive fields [17]. In comparison to simple cells which have distinct ON and OFF subregions, complex cell receptive fields show no obvious substructure [12]. Stimuli in any portion of the receptive field can evoke either ON or OFF response which relies on factors other than simple spatial placement. It has also been shown that the spike rate response to a single oriented bar in the center of the receptive field can be modulated by the placement of a second oriented bar elsewhere in the receptive field [12]. Furthermore, additional stimuli can suppress or enhance the complex cell's response [38]. The way in which this modulation is controlled seems to involve a variety of factors including the relative contrast between center and surround, the relative phase, the width of the surround region, the relative orientations of the line segments, spatial frequencies, speeds, threshold v. suprathreshold, and individual differences in the neurons [38]. Previous models take some of these factors into account, but fail to account for others. For instance, the MAX-like behavior model [12] and the linear model [16] both base their predictions on the strength of inputs. However, the MAX-like behavior model is limited by not being able to account for various types of inputs. Similarly, the normalization model cannot predict for contrast enhancement and the accellerating transducer function, the collinear lateral excitation, and non-selective lateral inhibition models fail to account for suprathreshold contrasts [38].

A neural network trained on data from single unit recordings of complex cells in the primary visual cortex can be applied in order to accurately predict the firing rate behavior of complex cells in the primary visual cortex based on oriented line stimuli located within a single complex cell's receptive field.

3 Implementation and methodology

Implementation:

This experiment will be carried out on a 2-way dual core 2.2GHz AMD Opteron 272 processor with 4GB of RAM that is running the Fedora 9 operating system. A feed-forward neural network will be implemented in the Java Object-Oriented Neural Engine (JOONE). The neural network will consist of three layers, an input layer, a hidden layer, and an output layer. The input layer will consist of 9 neural nodes to account for the 9 pixels in the input images. The output layer will be a binary representation of the firing rate. The number of hidden nodes will be adjusted as an experimental parameter.

Experimental Data

The network will be trained and tested against experimental data from other published studies. This data will take the form of electrophysiological single unit recordings of complex cell response matched with the image used to evoke that response. This data will be formatted into a set of input-output pairs for use in training and testing the neural network. In order to model the work of simple cells, inputs will be formatted into a 3 x 3 pixel portable grey map image to represent 9 possible positions within the complex cell receptive field. Line orientation will be represented by the color value of the pixel with black representing optimal orientation and white representing perpendicular orientation. Outputs will take the form of a firing rate represented as a positive integer.

Network Training

Network training will be performed by the back-propagation algorithm. Training set size will be adjusted as an experimental parameter. Training sets will be comprised of randomly selected input-output pairs from the overall set of experimental data.

Network Testing

After training, each neural network will be tested on the entire set of input-output pairs. For each pair, the obtained result will be compared against the desired output. Results which fall outside of a .95 confidence interval will be counted as errors.

Metrics

This study aims to test the accuracy of the neural network in predicting the firing rate response of a complex cell based on its input. This will be measured in terms of an error rate derived by dividing the number of errors made during testing by the total number of testing samples for each neural network. The error rates of these networks will be analyzed in conjunction with the size of the training set as well as the number of hidden nodes included in the network. The accuracy of the best neural networks found during this experiment will be compared against the accuracy of other models for complex cell behavior.

4 Research and writing timetable

- September 19 - Proposal Draft 1 Due
- October 3 - Complete suggested revisions of proposal draft
- October 17 - Finalize introduction, prior work, thesis
- October 24 - Finalize methods, conclusion portion
- November 3 - Final Proposal Due
- November 21 - Complete Oral Defense of proposal, make any necessary changes
- December 5 - Complete Chapters 1, 2
- December 12 - Complete implementation of neural network

- January 15 - Complete all introductory chapters
- January 31 - Complete acquisition of training/test cases
- February 13 - Complete training and testing experimentation
- February 28 - Complete Results section, begin conclusion
- March 15 - Complete results, submit draft to readers
- March 31 - Complete written portion, submit
- April 15 - Complete oral defense
- April 30 - Final project complete

5 Conclusion

The intention of this research project is to construct a neural network that can accurately predict the firing rate of a complex cell when presented with a specific visual stimulus. Previous work has focused on directly analyzing data in order to recognize a formula to model complex cell behavior. While the main objective in building models for complex cell center-surround behavior is to derive such a function, a system that can accurately predict the functional behavior can also be valuable. If the neural network can accurately model the behavior of complex cells and make it possible to predict their behavior based on receptive field properties, then it may lead to a new approach for building a computational models of complex cell behavior.

Like previous models, this neural network approach will only account for some of the factors. In this experiment, we aim to train the network on examples which are constructed to show variation in relative orientation and spatial frequency. However, unlike other models, the neural network approach can be easily expanded to include these factors by training the network on examples that exhibit variation in the other factors as well.

In order to create any model, we must assume that complex cells function deterministically based on a certain set of conditions. The difficulty in forming a model directly from experimental data is that each of these conditions must be discovered, isolated, and manipulated. Neural network training, on the other hand, is built to account for and represent unknown and unforseen factors. Because of this, an accurate neural network system that can predict the behavior of a complex cell can itself be analyzed to assist in the creation of a simpler mathematical formula as at any given point, a neural network is a deterministic finite machine.

While this work focuses on firing rate over a period of time as a measure of complex cell behavior, it is possible that they behave in a more complex manner, perhaps using rate-coding, which would use timing and patterns of action potentials in order to relay information about their receptive fields to other neurons. If the firing rate can be predicted by a feed-forward neural network, it would make sense to extend the investigation of complex cell behavior by using neural networks to examine these other possible behaviors of complex cells. A spiking or other pulse-based neural network could be used to model such behavior because of the way they take the time dimension into account.

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