Running head: RULES OF SEGMENTATION BY MODELED SIMPLE CELLS

Rules by which the brain segments an object from the background:

Evaluation of the Gabor model of simple cell receptive fields

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Abstract

The brain receives and interprets an enormous amount of information from the visual world. The world is rich with objects, colors, shapes, motion, and depth. The brain must somehow find a way to organize and process all of this information to form a coherent picture of the world around us. One of the first steps in visual processing is to organization the massive visual input into meaningful units separated as objects and backgrounds in a process called segmentation (Marr, 1980). Hubel and Weisel (1962) discovered cells in the visual cortex that were sensitive to the orientation or the tilt of the visual stimulus. They called these cells simple cells. Because simple cells respond to specific orientations, they might function to create these outlines that separate an object from the background. This is an exploratory study which will utilize a mathematical model of simple cell receptive fields to examine whether these cells are involved in segmentation. The goal of this study is to attempt to elucidate the rules by which simple cells can do segmentation.

Rules by Which the Brain Segments an Object from the Background:

Evaluation of the Gabor Model of Simple Cell Receptive Fields

The central task of vision is to create a complete and comprehensible view of the world around us. Within each eye, there are more than 100 million photoreceptors, and there are many more cells in the visual cortex that all receive individual bits of information from the visual world. The brain must then find a way to group those discrete elements from individual photoreceptors in the eye and cells in the visual cortex and organize the visual information it receives into meaningful units.

One way the brain may start to organize and simplify visual information is to partition information into two main elements: the figure being inspected and everything else as the background. The concept of figure-ground perception states that an image is divided into the figure and the background, and any features associated with the figure must be grouped together and then separated from the background or any other objects present (Lamme, 1995). An example of the task of figure-ground perception is the Vase-Face Illusion (Figure 1). When this image is examined, there are two ways to interpret and process the information. One can either see a white vase on a black background or two black faces on a white background. Both ways of understanding and interpreting the visual information demonstrate the power of grouping objects into meaningful units that are separate from everything else that surrounds them.

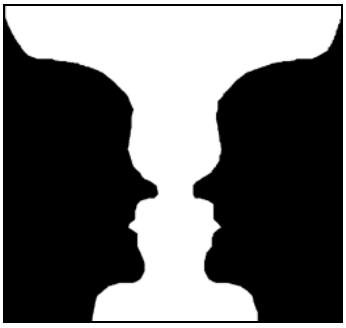


Figure 1. Rubin's vase-face illusion is an example if figure-ground perception.

Figure-ground perception presents a problem for visual processing, however, because it is still very unclear how the visual system divides the world into figures and backgrounds. One way this process is thought to occur is through a process called segmentation. Segmentation is the process of separating an object or figure from its surroundings or background and effectively fulfills the need of the visual system to separate information into different parts (Marr, 1982). Marr suggested that the creation of an outline of the object of interest might be one of the first ways to begin the process of separating a figure from the background. Figure 2, from Marr (1982), displays this concept of outline creation as one of the first steps in visual processing. This outline helps to separate the different parts of the image, such as the basketball player from the wall and basket behind him. The letters of the word "LAKERS" on the player's jersey are a particularly salient example of the separation of each letter from the background of his jersey.

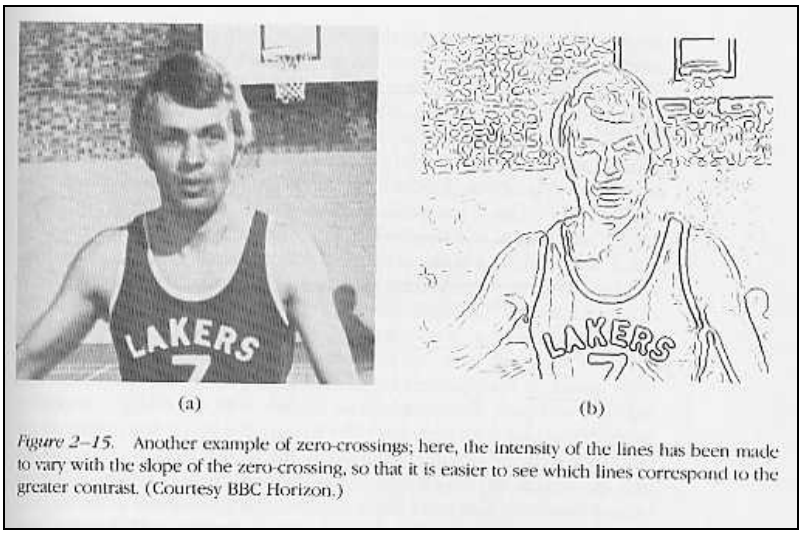


Figure 2–15. Another example of zero-crossings; here, the intensity of the lines has been made to vary with the slope of the zero-crossing, so that it is easier to see which lines correspond to the greater contrast. (Courtesy BBC Horizon.)

Figure 2. Outline creation as one of first steps in visual processing and segmentation of objects.

Various studies have suggested that because of their inherent characteristics, simple cells in the primary visual cortex may be a candidate for the creation of an outline of an object and thereby the segmentation of that object (Marr, 1982). Hubel and Wiesel (1962) were the first to look at the firing rate patterns of responses of cells in the primary visual cortex. They found that

the primary visual cortex is divided into two types of cells depending on their characteristic response patterns to a bar-shaped stimulus: simple cells and complex cells.

Simple cells, when presented with a bar-shaped, stationary stimulus, respond to specific orientations, widths, and positions of that stimulus within its receptive field. A receptive field is defined as an area of the receptor surface that can change the firing rate of the cell being studied. For the visual system, the receptive field of a simple cell in the cortex is the region on the retina where light falling will change the simple cell's firing rate (Krantz, in preparation). Simple cell receptive fields are characterized by a bar-shaped excitatory or inhibitory region surrounded by regions of the opposing activity (Figure 3).

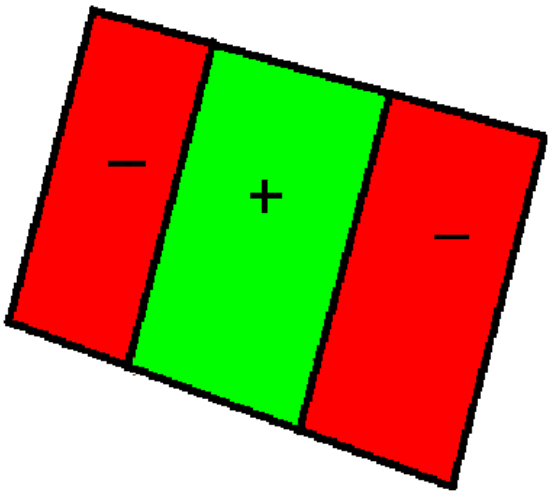


Figure 3. On-center simple cell receptive field and response pattern.

A cell will fire most rapidly when the stimulus is presented at its selected orientation and at its selected position. If the stimulus should be moved into the inhibitory region of the receptive field, the firing rate would decrease to below the baseline level. Changing the orientation of the stimulus has a similar effect in that it would cause a weaker excitatory response or would cause the cell to return to the baseline firing rate.

An interesting characterization of the visual cortex by Tootell and colleagues (1982) is that neighboring cells in the retina can feed their input to neighboring cells in the visual cortex creating a retinotopic map in which each location on the retina has a corresponding location on the cortex (Figure 4). This image is distorted however, because different areas of the retina have different densities of receptors, and therefore locations near the fovea which have more receptors require more space on the retinotopic map in the cortex, while areas in the periphery require less space.

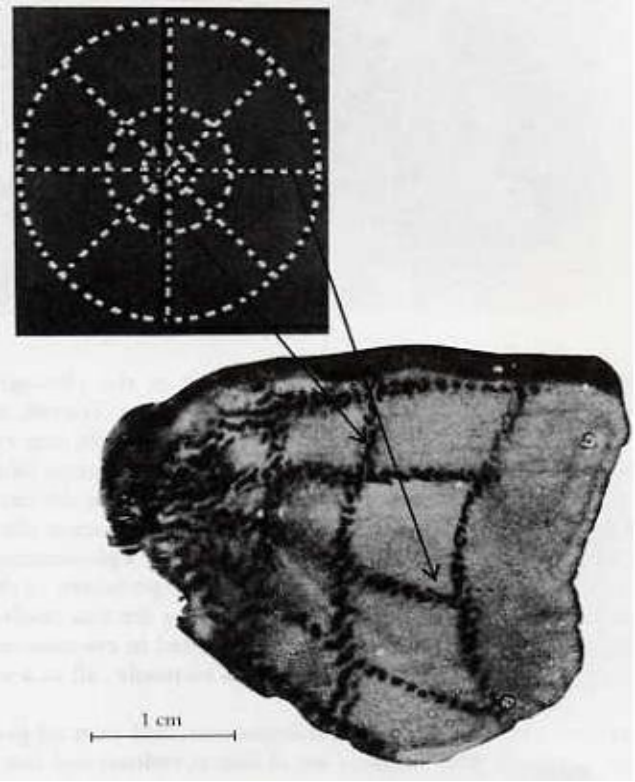


Figure 4. Tootell's characterization of retinotopy in the Macaque visual cortex.

One of the significant limitations of Hubel and Weisel's work, and of many of the physiological studies currently being conducted is that they are limited to single-cell recordings. Single-cell recordings are only able to look at the response patterns of an individual cell, without looking at the cellular response in relation to the responses of neighboring cells or neighboring

groups of cells. The procedures in which single-cell recordings are collected are also quite complex and time-consuming. Researchers have attempted to remedy this dilemma is through mathematical modeling.

Mathematical modeling has frequently been used to characterize receptive fields in the visual system. This method allows the characteristics and behaviors of these cells to be investigated without invasive physiological studies. Enroth-Cugell & Robson (1966, 1984) have applied mathematical modeling to the receptive fields of retinal ganglion cells, and this model has been modified to detect visual elements such as form or shape and color (Blythe & Krantz, 2004). A useful mathematical equation used in receptive field modeling is the Gabor function, first used by Marcelja (1980) as a representation of simple cell receptive fields.

What is lacking in the literature related to this topic is exploration of the idea that simple cells may play a role in segmentation. The use of mathematical models of simple cells may help elucidate how simple cells accomplish the segmentation of figures from their surroundings. An interesting area of this research to pursue would be to use a complex collection of the modeled simple cells that match the organization of the cortex to see how it responds to selected stimuli. In this study, the Gabor function is used to model simple cells in the visual cortex to attempt to elucidate the rules by which segmentation occurs.

Model Description

Step 1: Develop Model

The first step is to develop a working two-dimensional model of the Gabor equation using the computer software *Mathematica* version 4.0 by Wolfram Research. The model was implemented into the program and a trial bar stimulus was sent through the program yielding results that suggest that the Gabor equation displays the same response pattern as physiological

data suggests, with a region of excitatory activity in the center and inhibitory regions along the sides (Figure 5).

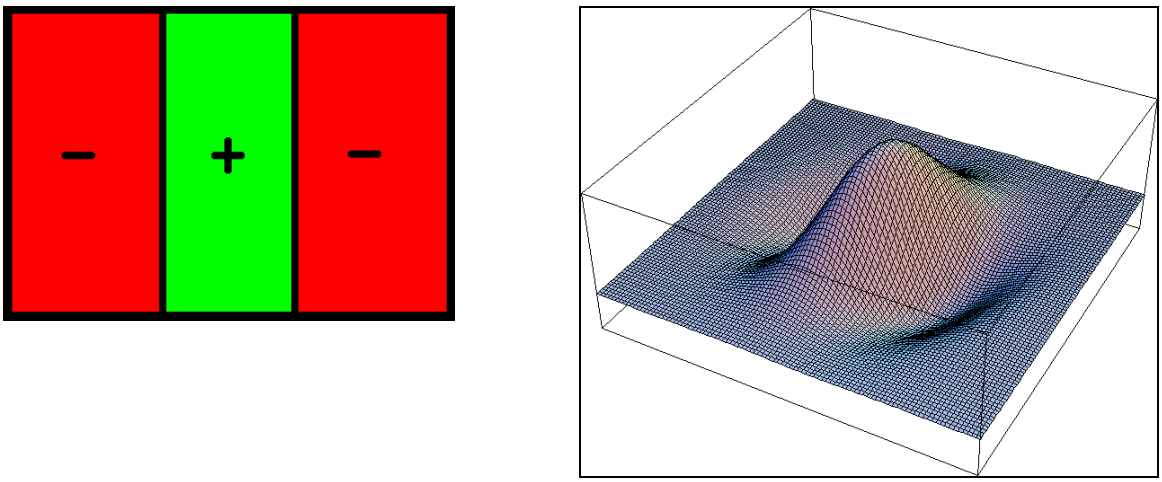
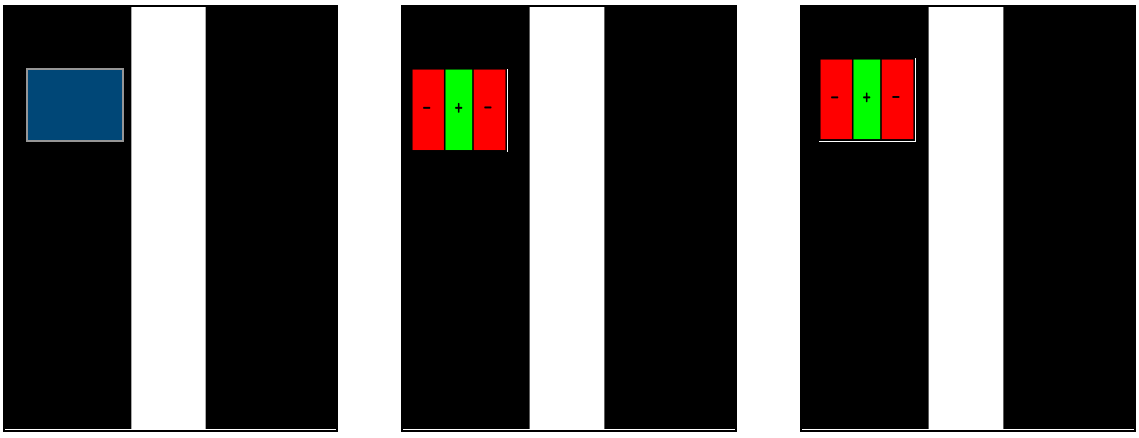


Figure 5. Mathematica generated model of an on-center simple cell receptive field.

The *Mathematica* program first divides the stimulus into smaller squares and each square is sent through a modeled cell. Each "cell," or location on the stimulus, begins at a vertical orientation and subsequently rotates horizontally for 18 orientations in 10-degree increments. This set of orientations was selected because it mirrors the organizational pattern discovered by Hubel and Weisel in 1962. When the location is in an area where there is no visual information given (i.e. the black background), the response of the modeled cell is zero because regardless of the orientation of the, there is nothing the modeled cell can respond to (Figure 6).



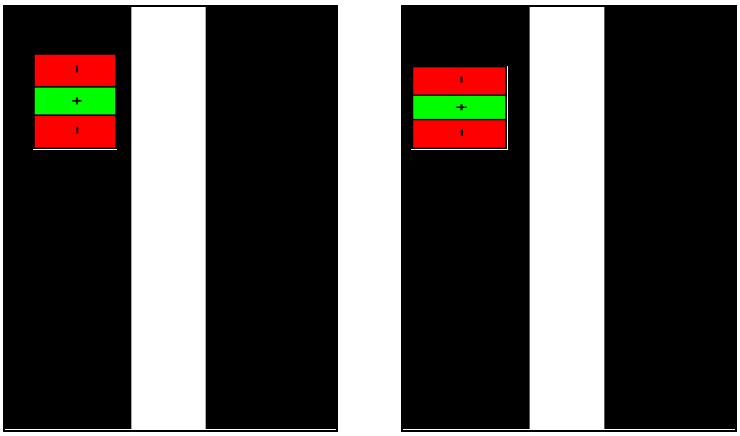


Figure 6. Representation of when the modeled cell is located in an information-neutral area.

However, if the location of the modeled cell falls where there is an edge or where there is visual information to be processed, the firing rate will change from its baseline. The firing rate will be highest where the orientation of the edge and the receptive field correspond (Figure 7).

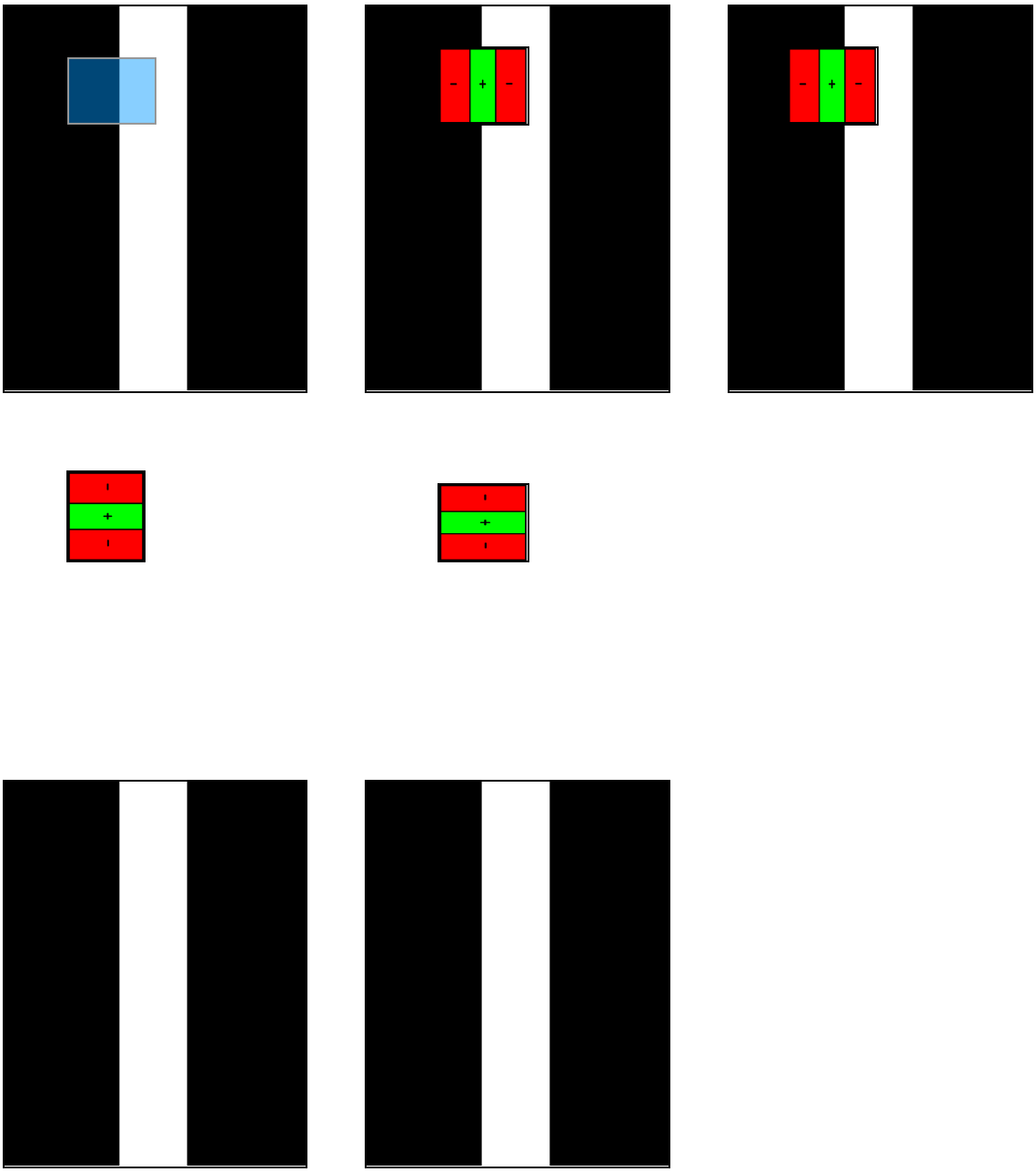


Figure 7. Representation of when the modeled cell is located at an edge.

A basic test was run to detect orientation specificity in the model. The stimulus presented was a vertical white bar on a black background. The putative firing rate was recorded at each orientation of the receptive field and plotted against each orientation (Figure 8). The results show that the orientation of the modeled receptive field that yields the highest response is the one that corresponds with the orientation of the original stimulus.

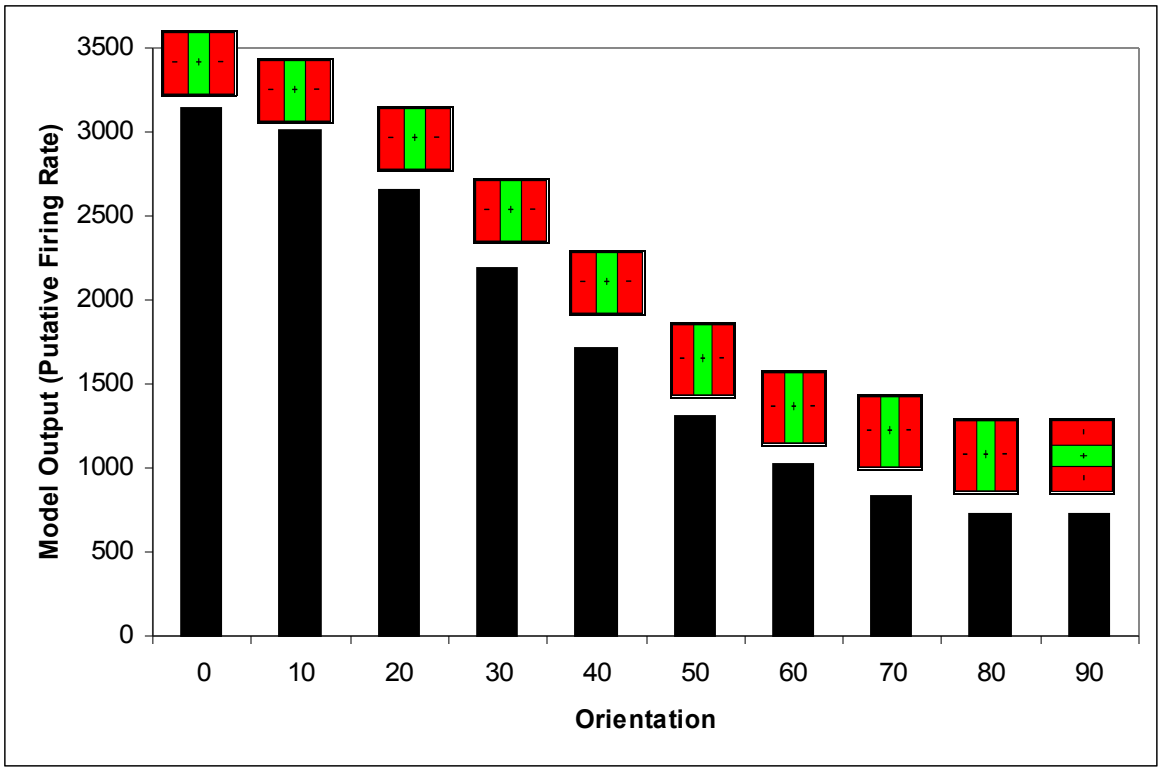


Figure 8. Orientation specificity of modeled simple cells.

The next step is to test a variety of bar-shaped stimuli to attempt to determine the rules by which these modeled cells allow segmentation of an object from its background. The stimulus used was again a white bar on a black background and the width of the bar was varied for each trial.

Step 2: Rule Discovery

Rule 1: Orientation of Model Cell with Most Positive or Negative Output

Most researchers in the field operate under the assumption that the most important information given by simple cells is orientation (Hubel &Weisel, 1962; Marr, 1982). Thus, the first logical rule was to seek the orientation of the modeled cell with the output most different from zero (positive or negative) at each location. The output of a modeled cell was plotted in relation to the orientation of the receptive field (Figure 9). The highest output is at the vertical

orientation, and the output decreases as the orientation of the modeled receptive field becomes further from zero, showing the lowest firing rate at a horizontal orientation.

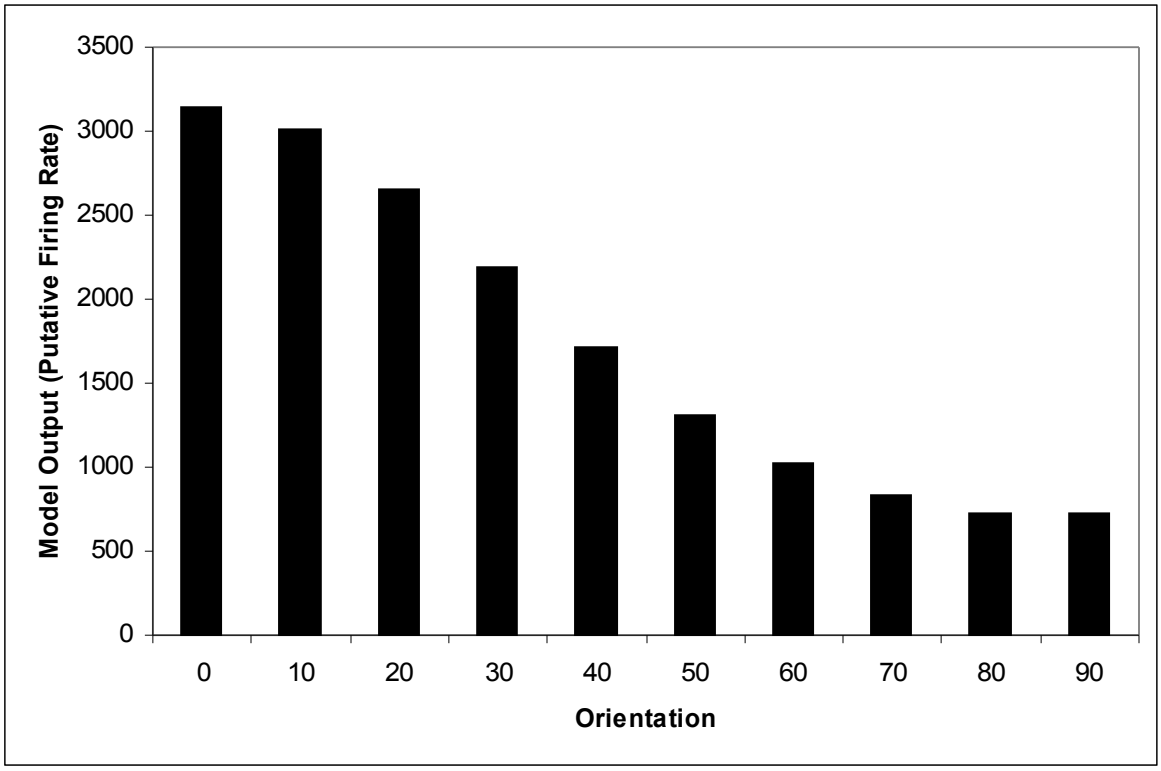


Figure 9. Output of vertical white bar on a black background.

A line is then plotted at that location on the output figure that shows the orientation of modeled cell's sensitivity (Figure 10). Most positive outputs are drawn in white and most negative outputs are drawn in red.

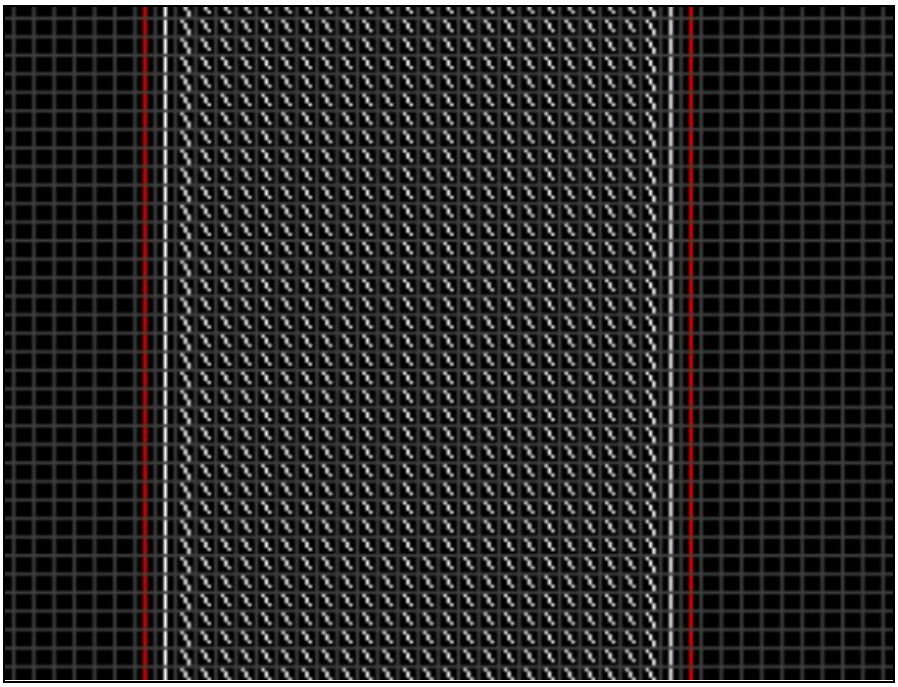


Figure 10. Orientation of modeled cells with most positive or negative output.

When the results of Rule 1 were plotted on the output figure, there is a clear distinction of the figure along the edges, which was expected based on the work done by Marr (1982). However, some unexpected patterns arose, suggesting that something else was happening with respect to the activity of simple cells involved in the segmentation process. In the center of bar, lines specifying orientation appeared where there should not have been any orientation information. The original figure consisted of a plain white bar and there is no sense that the center of the bar tilts to the left, but these lines generated by the model under this rule indicate that this is how the figure is processed. While it was expected that there would be a clear outline of the figure, the appearance of information in the center of the figure was surprising. This led to the development of Rule 2.

Rule 2: Orientation of Model Cell with Most Positive or Negative Output & Model Cells with Limited Range of Activity

At those locations in the center of the bar that showed unexpected orientations, it was observed that there were some common features about the responses of those locations. The responses at all orientations at those locations are both relatively strong, and all approximately the same value (Figure 11). A line was plotted at the orientation that gave the highest output, but that response was not significantly different from the responses for any other orientation.

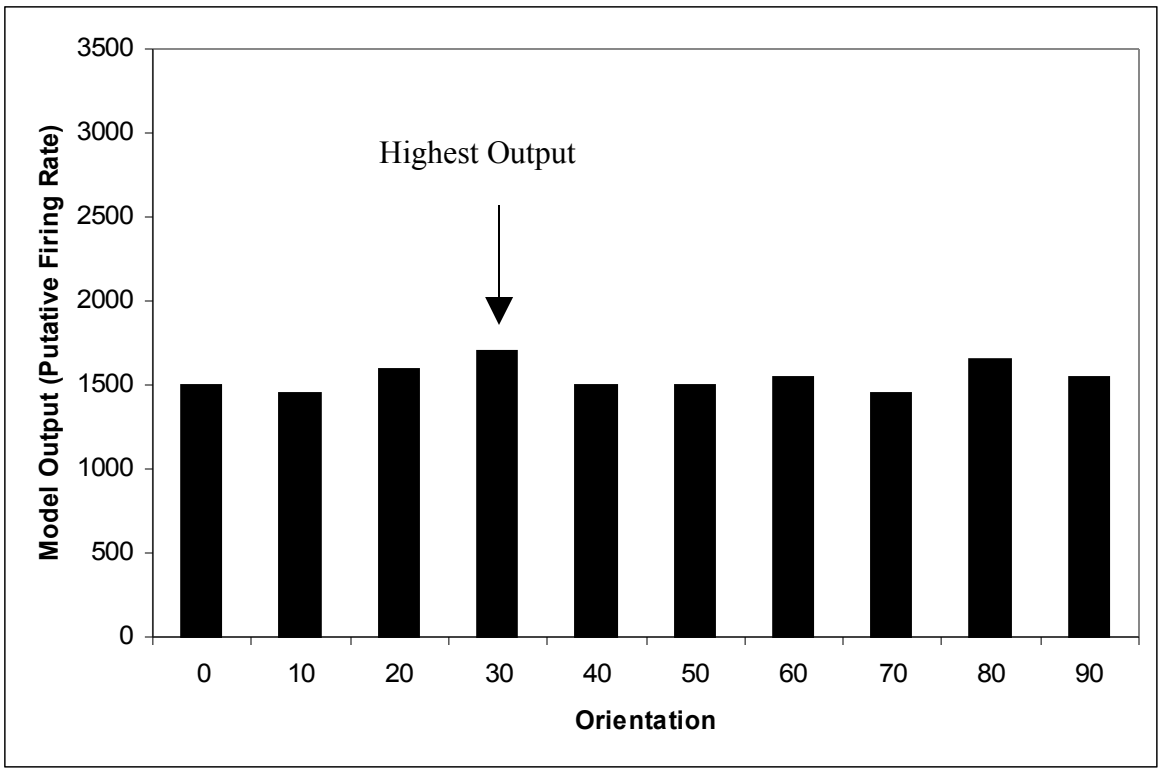


Figure 11. Output of model cell with limited range of activity response pattern.

In this case, modeled cells do not seem to indicate orientation sensitivity. Therefore, it was postulated that these cells are giving information about general activity, which could correspond to information about brightness or luminance, rather than orientation. Locations where there was a limited range of activity are shown as filled-in squares that match the intensity of the output on the output figure (Figure 12). Positive activity is drawn in white and negative activity drawn in red.

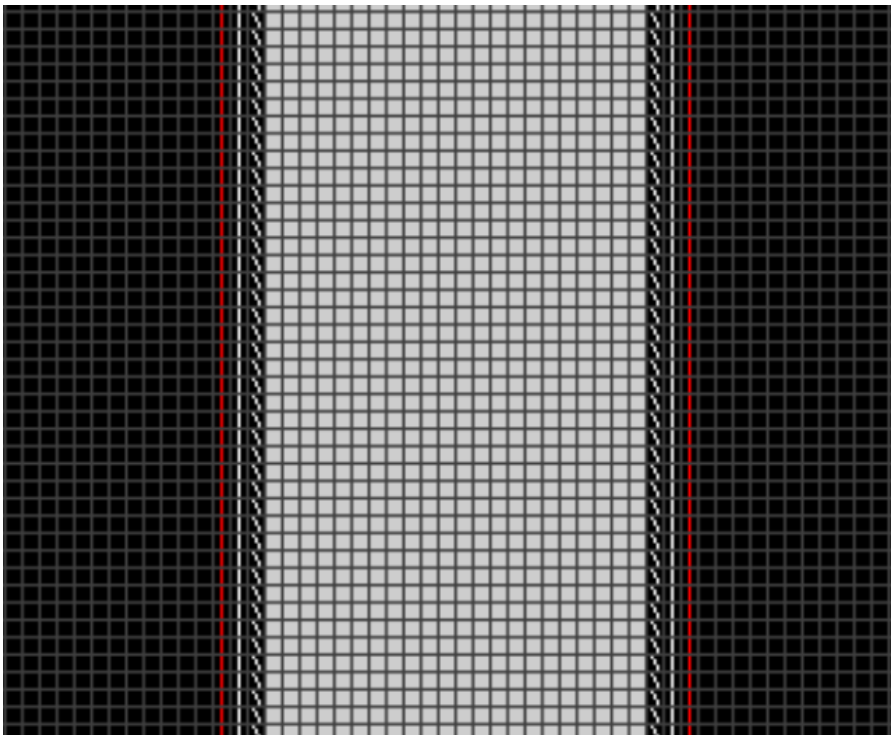


Figure 12. Orientation of model cell with most positive or negative output and model cells with limited range of activity.

Rule 2 seems to show a clear improvement from Rule 1. It has eliminated the majority of those unexpected orientation lines while simultaneously seeming to give some information that may relate to brightness. It appears that simple cells may be accomplishing more than just outline creation by helping fill in brightness information between the outlines or edges. This idea is novel because most previous research focuses on orientation as the important information given by simple cells in visual processing. These results suggest that orientation information is only one part of the information given by these cells and could imply that simple cells are functioning in much more complex ways than expected. Rule 2 is still slightly problematic in that there is still a column of locations along the edge that are giving unexpected orientation information, yet there is no sense of tilt when looking at the original figure (Figure 13).

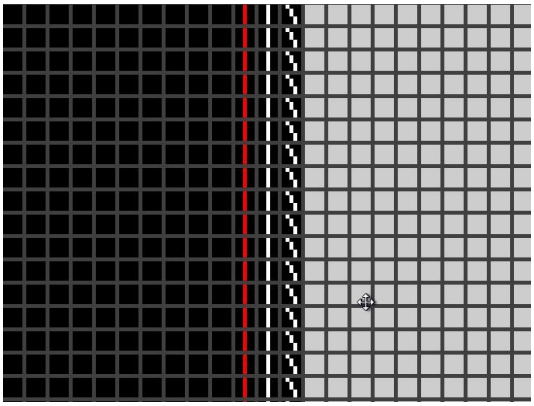


Figure 13. Close-up of orientation of model cell with most positive or negative output and model cells with limited range of activity.

Because Rule 2 is still producing some erroneous orientation information, a new idea was formulated. Up to this point, each location on the output figure has been processed independently of all surrounding locations, but this may not be true to the actual mechanisms of visual processing in the brain. There is evidence elsewhere in visual processing that suggests that individual cell responses depend on both their immediate input and input from neighboring cells. For example, color vision depends on the response of all three types of cones. If the red cone alone is stimulated, red is observed. However, if both red and green cones are stimulated, yellow is observed. It was postulated then that simple cells might behave similarly, in that their activity could depend on neighboring cells.

Rule 3: Orientation of Model Cell with Local Maximum or Minimum Output & Model Cells with Limited Range of Activity

Local maxima are defined as locations compared to their surrounding locations where there is an increase and subsequent decrease in output in a linear fashion. For example, in Figure 14, the bars represent the highest firing rate at any orientation in nine neighboring locations, all surrounding the central location (the location of interest). Looking at positions (1, S2), (2, S2), and (3, S2), the first two locations yield approximately the same output and the third location

shows a lower output than the center. This pattern is not considered a local maximum because the surrounding locations compared to the central location do not display an increase and subsequent decrease in output. However, looking at positions (1, S1), (2, S2), and (3, S3), the firing rate changes characteristically of what is being called a local maximum. Thus, the orientation of the line that produced the highest output (the local maximum) would be plotted at that location. A local maximum can occur in any linear direction, (rows, columns, or diagonals) and the output can be positive or negative. Local maxima are drawn in cyan to distinguish them from the most positive and most negative outputs of Rules 1 and 2.

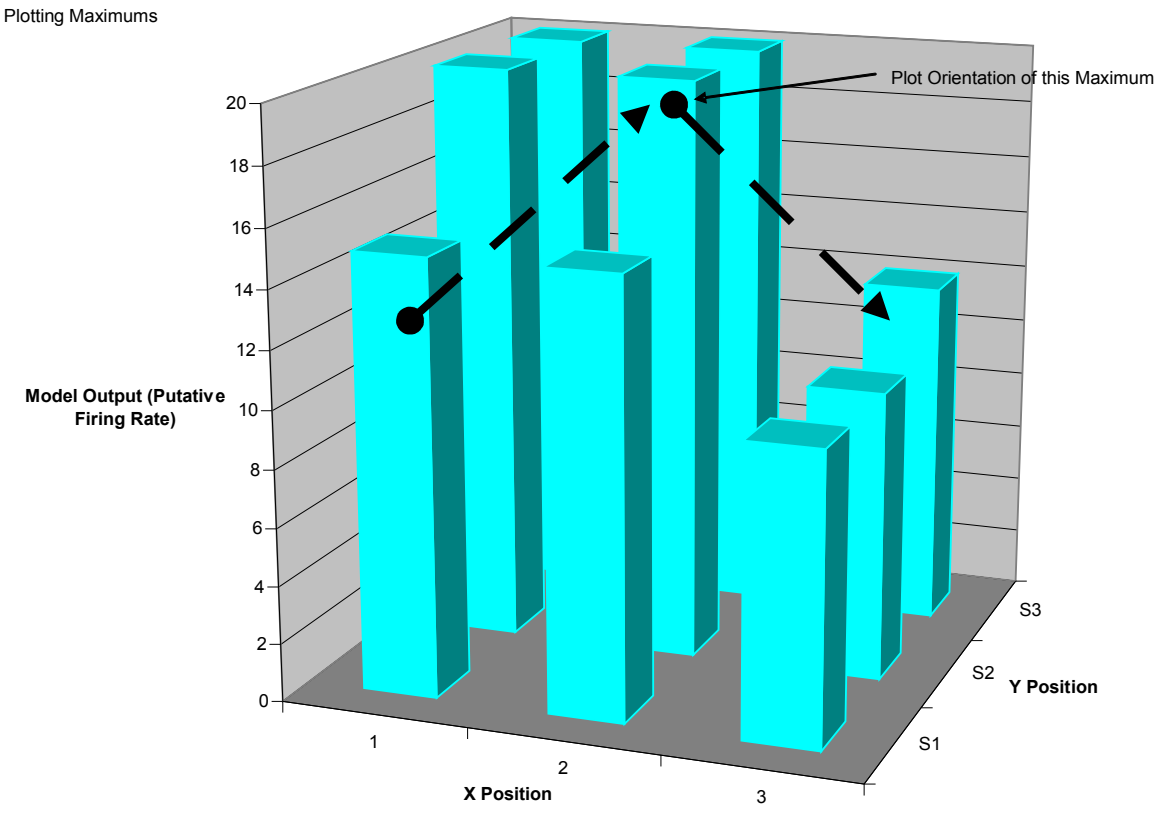


Figure 14. Schematic representation of a model cell that is a local maximum.

Local minima, conversely, are defined as locations compared to their surrounding locations where there is a decrease and subsequent increase in output in a linear fashion. In

Figure 15, looking at positions (1, S1), (2, S2), and (3, S3), the first location produces a higher output than the center and the third location produces a lower output. This pattern is not considered a local minimum because the surrounding locations compared to the central location do not display a decrease and subsequent increase in output. However, looking at positions (2, S1), (2, S2), and (2, S3), the firing rate changes characteristically of a local minimum. Thus the orientation of the line that produced the lowest output would be plotted at that location. Like local maxima, a local minimum can occur in any linear direction, (rows, columns, or diagonals), and the output can be positive or negative. Local minima are drawn in yellow to distinguish them from the most positive and most negative outputs of Rules 1 and 2.

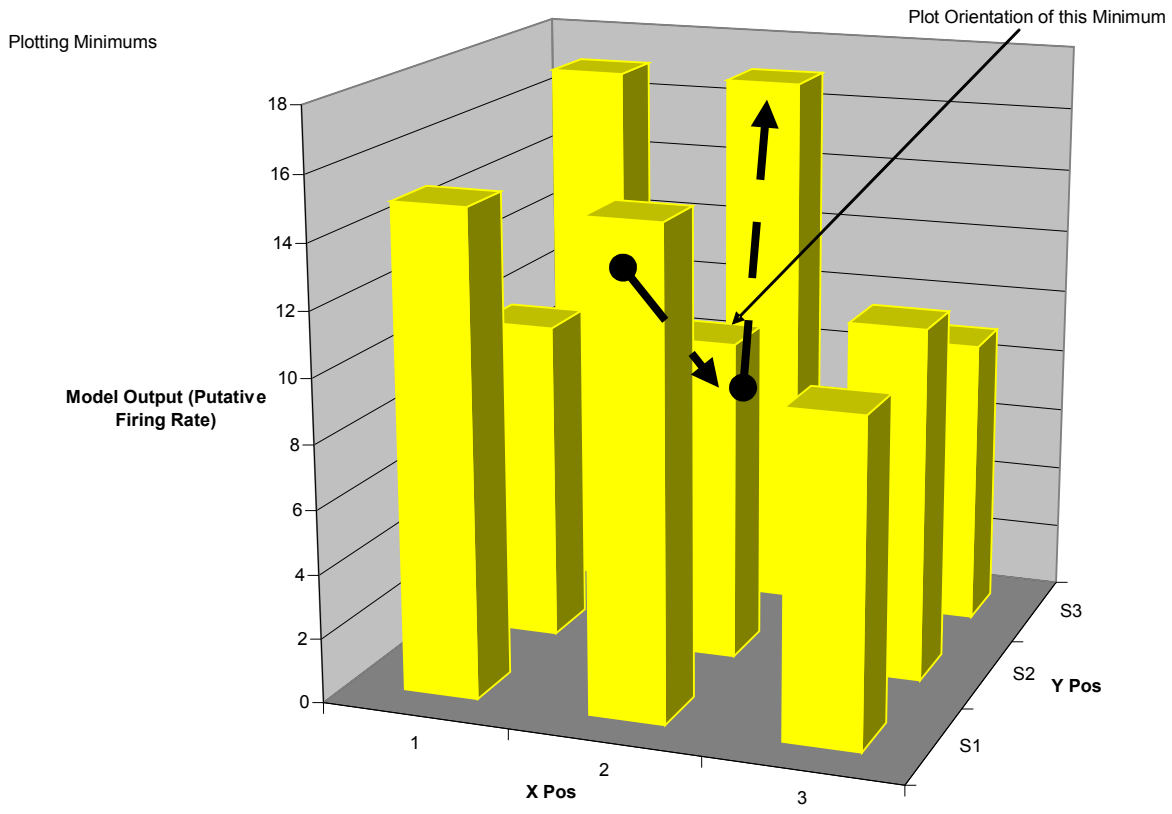
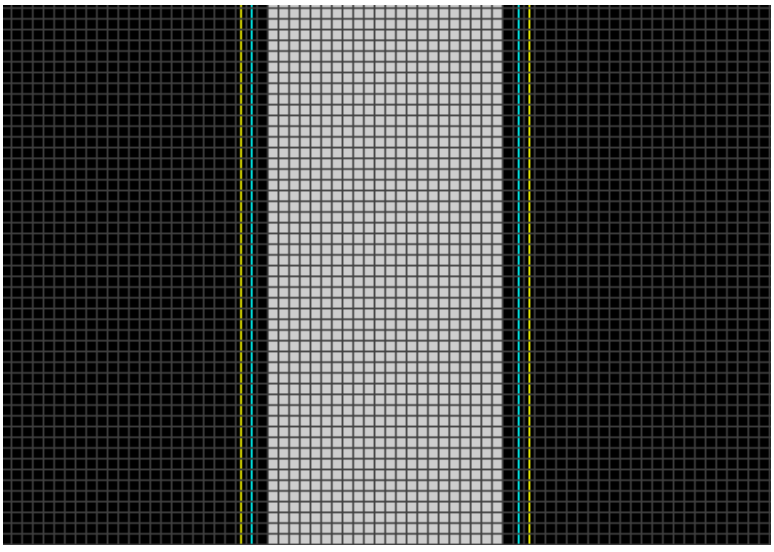


Figure 15. Schematic representation of a model cell that is a local minimum.

The output figure generate from Rule 3 shows a clear distinction of the edges of the figure, similar to what was observed in Rule 1, but this rule has eliminated the column of modeled cells that give orientation information along the edges that should not have appeared. The edges themselves are enhanced such that they appear lighter (more excitatory) on the inside of the figure and darker (more inhibitory) on the outside of the figure, which corresponds to what we know is true of human experience (Figure 16). Physiologically, edge enhancement occurs through a process called lateral inhibition, where there is a reduction of a response to light stimulation of one receptor due to stimulation of nearby receptors (Kuffler, 1953; Hartline & Ratliff, 1957), which causes the cells along the edge to respond more negatively or more positively than their neighboring cells.

In addition, similar to Rule 2 the output figure here also shows a region of general activity in the center of the bar, which seems to indicate brightness information rather than orientation information, a concept which is novel to this study (Figure 16). Rule 3, the orientation of model cells that are local maxima and minima and model cells with limited range of activity, seems to most accurately recreate the important features of the original stimulus, including the edges and the central brightness.



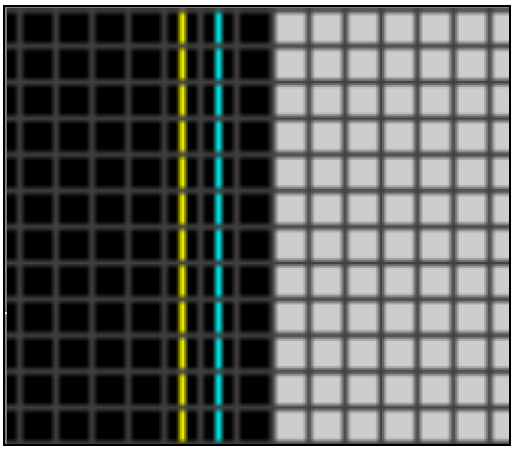


Figure 16. Orientation of model cells that are local maxima and minima and model cells with limited range of activity.

Step 3: Evaluate Rule 3.

The final step is to evaluate Rule 3 compared to what we know to be true in human experience. The Hermann-Hering Grid consists of multiple black squares on a white background, and small, gray circles appear at the intersections of the white lines when looked at indirectly, in the periphery rather than the fovea (Figure 17). Thus, visual processing must be able to segment these circles from their white background in order for them to be seen as separate objects. It was expected that the model working under Rule 3 would allow for the segmentation of the circles seen in the intersections under conditions that mimic the periphery but not the fovea.

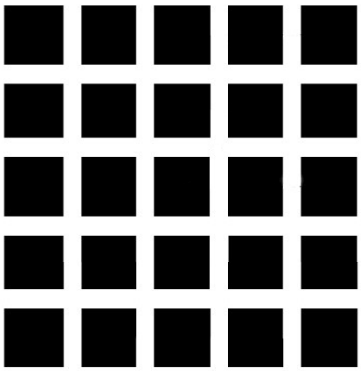


Figure 17. Hermann-Hering Grid.

The following modified version of the Hermann-Hering Grid was presented to the program (Figure 18). The stimulus was sent through the model in the same fashion as the bar stimuli in the previous experiments. The size of the receptive fields was manipulated in the program to mimic the fovea, which has very small receptive fields, and the periphery, which has much larger receptive fields (i.e. the squares into which the stimulus was divided for processing were very small for the fovea mimic and much larger for the periphery mimic).

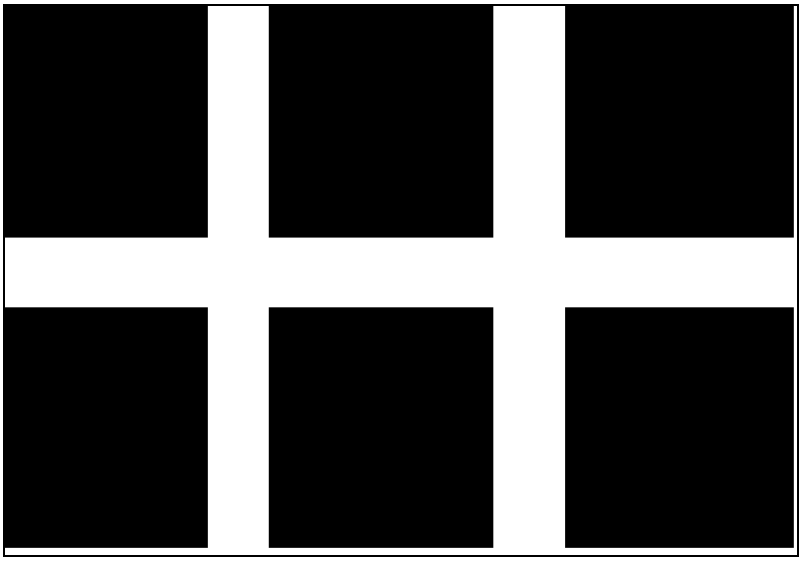


Figure 18. Hermann-Hering Grid stimulus presented to the model.

The conditions mimicking the fovea, or small receptive fields, generated an output figure that looks very similar to the original stimulus (Figure 19). The black squares are separated from each other and from the white background and the edges are enhanced as was observed with the bar stimuli. Brightness information is apparent in the areas of output figure that indicate the white background, also similar to what was observed with the bar stimuli tests. As expected, the model was unable to segment circles in the intersection due to the small size of the receptive fields.

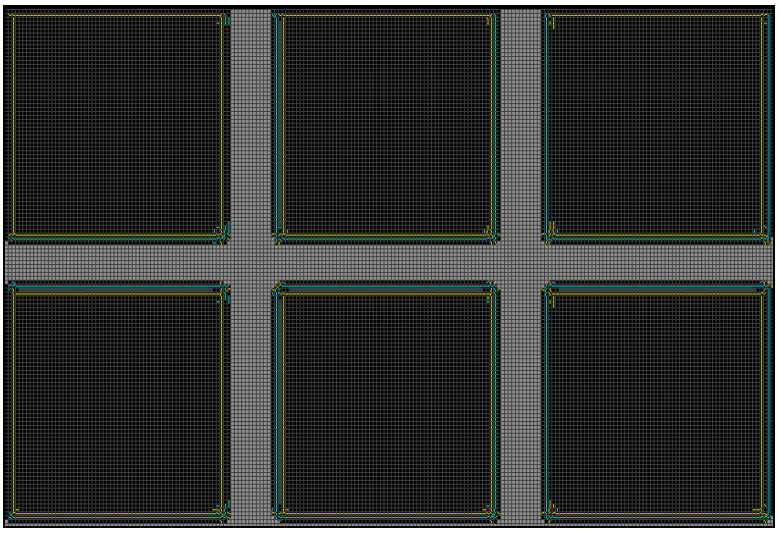


Figure 19. Fovea mimic output figure.

The conditions mimicking the periphery, or large receptive fields, generated an output figure that is a less clear depiction of the original stimulus. This was expected because the periphery contains fewer receptors and the receptors have larger receptive fields, therefore the acuity, or sharpness of an image in the periphery is expected to be much worse than the fovea. The model was able to segment the circles in the intersections under Rule 3. There is also some brightness information inside the circles that seems to distinguish them from their surroundings, which suggest that the circles are processed as separate objects.

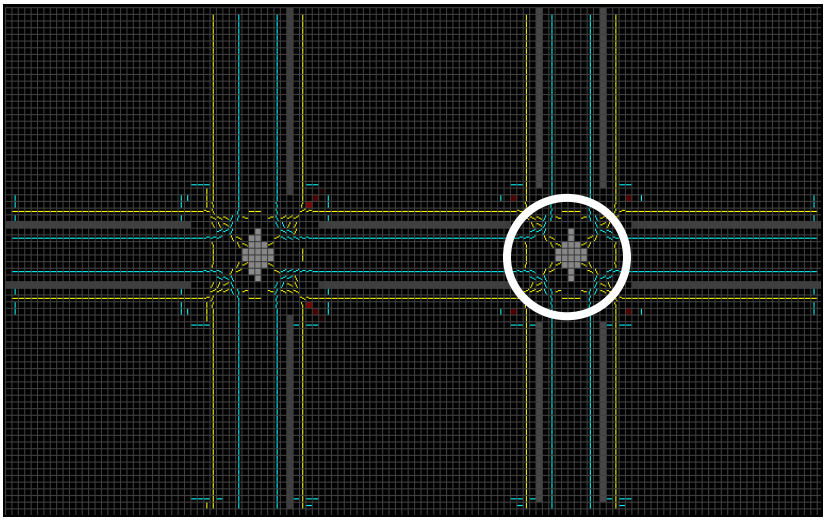


Figure 20. Periphery mimic output figure.

It seems that Rule 3, the orientations of local maxima and minima and limited range of activity, seems to most accurately recreate stimulus as confirmed by human experience. Judging by the results from the Hermann-Hering grid experiments, the small receptive field setting that mimics the fovea does not segment the circles, but the large receptive field setting that mimics the periphery shows segmentation of the circles at the intersections.

Visual processing is a complex task that requires the activity of multiple structures, such as the retina and the visual cortex, all functioning to integrate discrete elements from the visual world into units that can be recognized and understood by the person experiencing the image. The process of segmentation of an object from the background may be the first way in which visual stimuli are organized. Although Marr and others have suggested that outline creation by simple cells may be the first step in segmentation, the results of this study suggest that simple cells have a much more complex role in visual processing. Simple cells seem to function in two distinct ways: by creating the initial outline of the object based on their orientation specificity, and filling in general activity information that may correspond to brightness or luminance information.

In addition, cells firing at the highest rate may not be the best indication of important activity. As was shown with Rule 3, the important information given by simple cells likely depends on input from neighboring cells. Local changes in activity across a group of cells may be much more important than individual high or low firing rates.

Future steps in researching this field ought to attempt to refine the rules by which the model, and thereby simple cells, operates in visual processing. More stimuli ought to be tested to see if the rules generated in this paper continue to hold true.

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