CN530, Spring 2004

# Edge Processing and Featural Noise Suppression in Distance Dependent Shunting Networks.

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9 Feb 2004

**Abstract**

Grossberg has presented a theory of how global visual interactions between depth, length, lightness, and form percepts can occur. This report describes the results of a few simulations of one of the models presented by him - the distance dependent feed-forward network. We evaluate the following properties of the model: edge processing, reflectance processing and featural noise supression. We also simulate and verify some ideas presented in a paper by Grossberg and Levine. They discuss a visual illusion described and explained by Blakemore and present a few plots to illustrate the effect. We try to simulate their illustrative example.

## Introduction

Grossberg has presented a theory of how global visual interactions between depth, length, lightness, and form percepts can occur [1]. This report describes the results of a few simulations of one of the models presented in [1] - the distance dependent feedforward shunting network. We evaluate the following properties of the model: edge processing, reflectance processing and featural noise supression. We also simulate and verify some ideas presented in a paper by Grossberg and Levine [2]. They discuss a visual illusion described and explained by Blakemore and present a few plots to illustrate the effect. We try to simulate their illustrative example.

## Item 4: Edge Processing

### Background

A general feedforward shunting network in which both the excitatory and the inhibitory inputs depend on the distance between cells can be described by the equation (see Eqn. 22 [1]):

$$\frac{dx_i}{dt} = -Ax_i + (B - x_i)\sum_{k=1}^{n} I_k C_{ki} - (x_i + D)\sum_{k=1}^{n} I_k E_{ki},$$

where $x_i$ is the activity of the $i$th cell, $I_i$ is the input to the $i$th cell and $n$ is the total number of cells in the network. $A$, $B$ and $D$ are parameters. The coefficients $C_{ki}$ and $E_{ki}$, which describe the fall-off of the input $I_k$ on cell $v_i$ with the distance between cells $v_k$ and $v_i$, are gaussian functions of distance given by

$$C_{ki} = Ce^{-\mu(k-i)^2},$$
$$E_{ki} = Ee^{-\gamma(k-i)^2}. \tag{1}$$

These coefficients are called kernels or interaction coefficients.

## Simulation

We used the following equation for simulation:

$$\frac{dx_i}{dt} = -Ax_i + (B - x_i) \sum_{k=i-r}^{i+r} I_k C_{ki} - (x_i + D) \sum_{k=i-r}^{i+r} I_k E_{ki}$$

The values for paramaters used are as follows: $A = 0.1$, $B = 0.9$, $D = 1.1$, $r = 4$, $C = 1$, $E = 0.5$, $\mu = 1/4$, $\gamma = 1/16$. The total number of cells in the network was set to 60. The values of $B$ and $D$ were chosen so that the inequality

$$B \sum_{k=1}^{n} C_{ki} \leq D \sum_{k=1}^{n} E_{ki}$$

is enforced.

Figure 1 shows a plot of the interaction coefficients. Figure 2 shows the network response to a series of step functions with same baseline intensity but increasing step-magnitude. $r$ cells in the beginning and the end have not been included in the simulation so that "border effects" are ignored. This holds true for all the simulations discussed in this report. The inputs to the first 30 cells were of magnitude 1 and the inputs to the next 30 cells was varied between 5, 50 and 200 respectively.

## Results

From figure 2, we can observe the following things. As one increases the magnitude of the "step" part of the input step function, the network response changes near the edge:

- The trough amplitude increases successively.
- The peak amplitude doesn't change appreciably.
- Both the peak and the trough get more and more "sharper", the effect is much more pronounced in the trough.

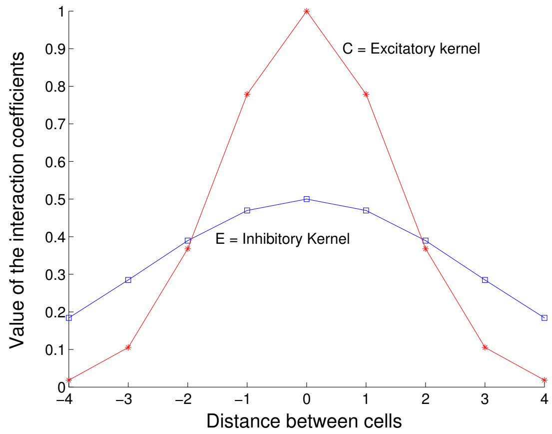


Figure 1: Item 4 - Excitatory and Inhibitory Kernels.

- The slope of the curve at the "zero-crossing" increases progressively.

Hence, we can say that trough amplitude and the slope at zero crossing code the magnitude of jump in the step input function.

## Item 5: Reflectance Processing

### Background

Grossberg defines reflectance $\theta_i$ for a given cell $v_i$ as the relative size of the input received by the cell i.e. $\theta_i = I_i / \sum_k I_k$. The background intensity for a given cell $v_i$ is defined as the input to all other cells which is equal to $\sum_{k \neq i} I_k$.

### Simulation

The network used for simulation was as described in the previous item. Here, we observe the network's response to inputs with same reflectances but different total energy. We also evaluate the response for varying values of the decay rate parameter $A$.

The three inputs considered are as follows: (1) Input I – 0.1 for cells 1 through 30, 1 for cells 31 through 60; (2) Input II – 1 for cells 1 through 30, 10 for cells 31 through

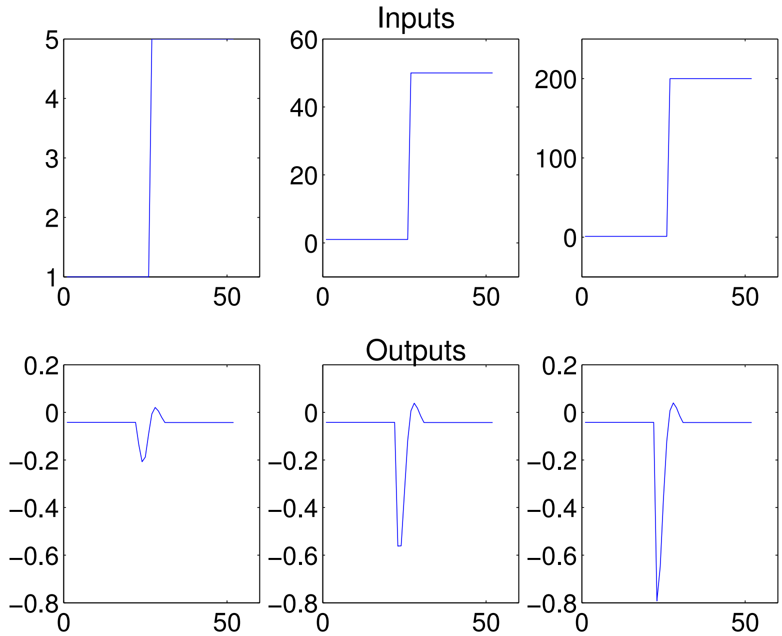


Figure 2: Item 4 - Network response for step functions with same baseline intensity but increasing step-magnitude. Border cells have been ignored. X-axis shows the cell-index and Y-axis shows the value of input/output.

60; (3) Input III – 10000 for cells 1 through 30, 100000 for cells 31 through 60. Figure 3 plots the inputs to the network.

The network is simulated for different values of the decay rate parameter $A$: $A = 0.1$, $A = 1$, $A = 10$ and $A = 100$. Figure 4 summarizes the network response.

## Results

From figure 4, we can draw the following conclusions. Any measure closely tied to the input reflectance should not change if the total input energy is varied because we have kept the input reflectances constant. From the figure, we see that the only feature of the response which remains relatively unchanged is the width of the "perturbation". In other words, it is the number of cells whose outputs form the nonlinear part of the output curve. All other measures change with increasing input energy. For example, the

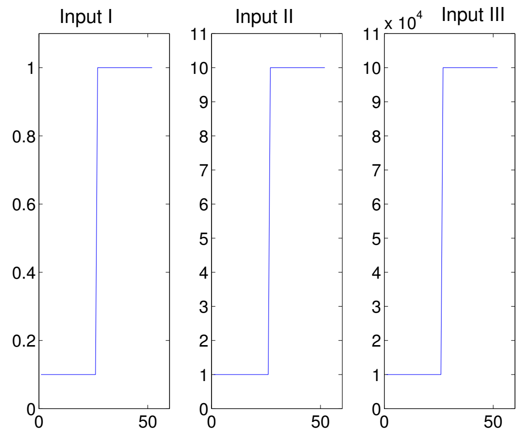


Figure 3: Item 5 - Inputs to the network. The X-axis corresponds to the cell index and the Y-axis corresponds to the magnitude of the input. The proportion of the input on the two sides of the step is a constant.

slope of the middle part of the nonlinear curve increases with increase in energy, though the change is not too perceptible in some cases. We also notice that the amplitude of the peaks also tend to remain the same.

Now we discuss the qualitative changes observed when the value of the parameter $A$ was changed. We see that the output has the characteristic "trough" and "peak" in the middle when the value of $A$ is lesser or in the range of the input magnitudes ($A = 0.1$ for Input I, $A = 0.1, 1$ for Input II and $A = 0.1, 1, 10, 100$ for Input III). If this condition holds, the peak amplitude remains unchanged even with increase in input magnitude. As we increase the value of $A$ further, these "trough/peak" features become less and less discernible. Finally, with a sufficiently large $A$, the output will almost resemble a straight line.

## Item 6: Reflectance Processing – Clarification

This is what Grossberg has to say about distance dependent shunting networks in the context of testing whether the contrast of the patterned responses changes as a function

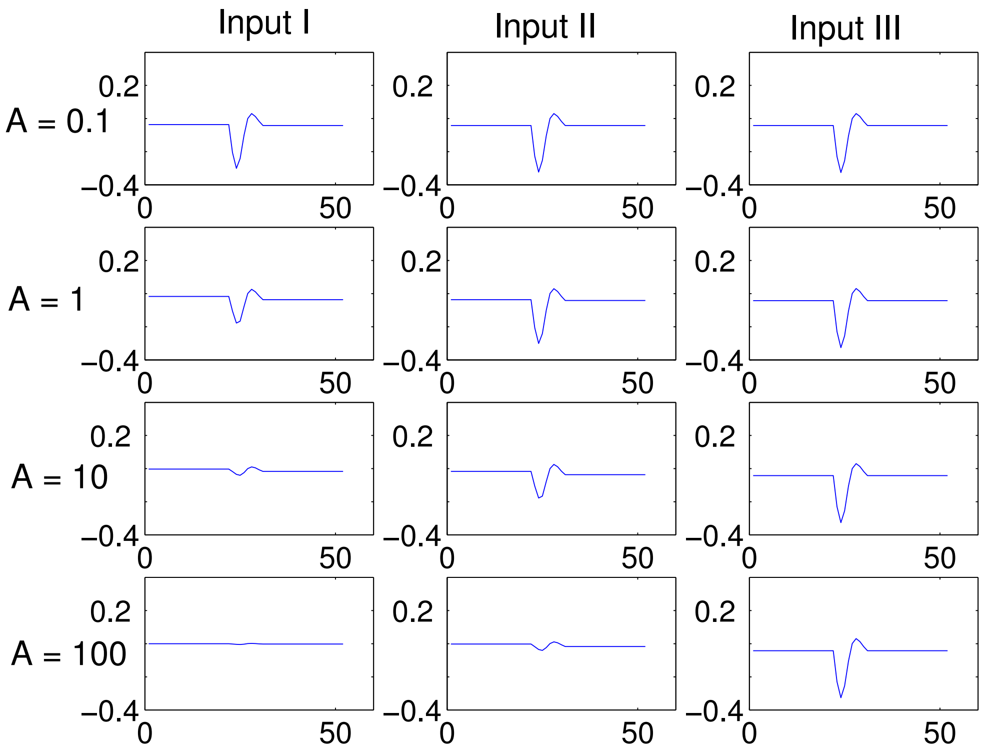


Figure 4: Item 5 - Network response for the inputs of figure 3 and different values of the parameter $A$. X-axis corresponds to the cell-index and the Y-axis corresponds to cell-activity.

of suprathreshold background luminance ([1], page 641) – "In a shunting network with a very narrow excitatory bandwidth and a very broad inhibitory bandwidth, the relative sizes of $x_i$ are independent of $I$. The contrast changes which occur as $I$ increases in the distance dependent case can be viewed as a partial breakdown of reflectance processing at high $I$ levels due to the inability of inhibitory gain control to compensate fully for saturation effects."

Let us consider the simulation of Item 4. In that simulation, the inputs were step functions with same baseline intensity but increasing "step" intensity. Figure 5 shows the network response for inputs which have high $I$ values (the same simulation used in Item 4), the baseline intensity is held constant at 1 and the "step" intensity varies

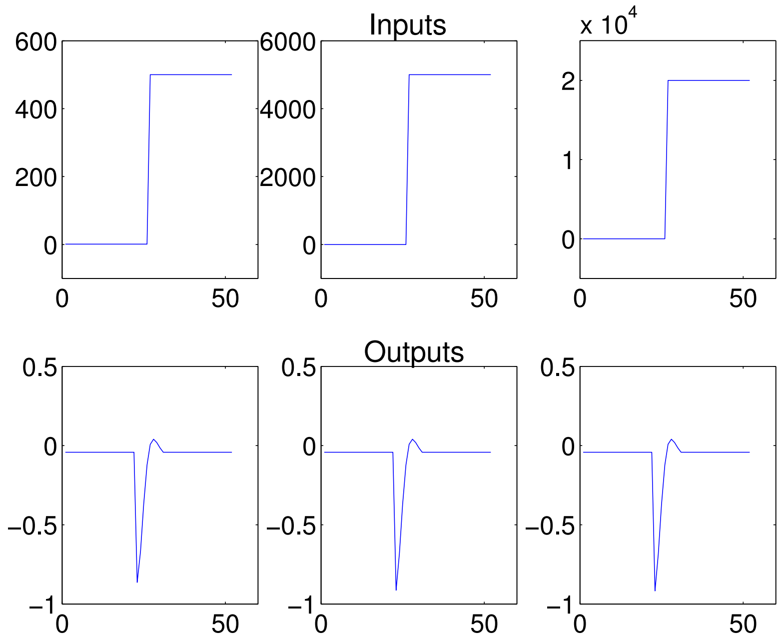


Figure 5: Item 6 - Network response for step functions with same baseline intensity but increasing step-magnitude. Border cells have been ignored. X-axis shows the cell-index and Y-axis shows the value of input/output.

from 500 to 20,000. We first observe that the reflectance of inputs with high $I$ values and same baseline intensities will be very similar. In this case, the baseline reflectance will be approximately zero for all three cases and the "step" reflectance will be 0.0332, 0.03332 and 0.03333 respectively. Hence, practically the reflectances are the same. We notice that the corresponding outputs are not too different from one another. Hence, the network has responded almost identically to input reflectances which are similar. Thus, in this case, there is no breakdown of reflectance processing at high $I$ levels.

## Item 7: Featural Noise Suppression

### Background

If a network of cells suppresses zero spatial frequency patterns, it is said to exhibit the property of featural noise suppression. In other words, only nonuniform reflectances of the input patterns generate output signals (refer section 21 (b), [1]).

### Simulation

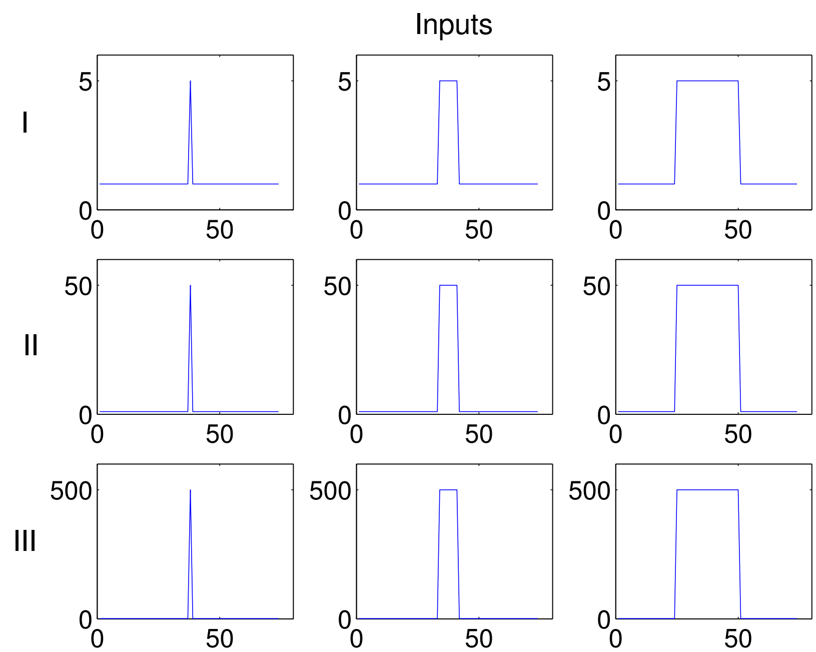


Figure 6: Item 7 - Input sequences used for simulation. X-axis plots the cell-index and Y-axis, the values of the input. Each row represents one sequence, where the "bar thickness" is successively increased. Along a column, the intensity of the bar increases.

The network described in Item 4 was used for the simulation. The total number of cells in the network was set to 80 and the value of the parameter $r$ was changed to 3. The values of other parameters were kept the same.

In this simulation, we test the network response for inputs which contain bars of varying “thickness” as shown in figure 6. The baseline intensity for all inputs was set to 1. The intensity of the bars were 5, 50 and 500 for input sequences I, II and III respectively.

Figure 7 shows the network response.

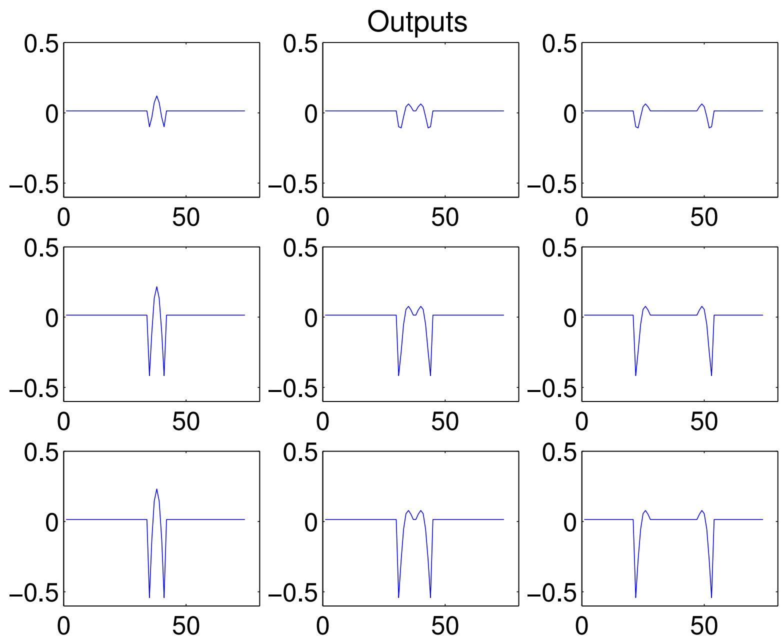


Figure 7: Item 7 - Outputs for the inputs shown in figure 6. X-axis plots the cell-index and Y-axis plots the equilibrium cell activity

## Results

Figure 7 summarizes the network response for the input sequences of figure 6. As we discussed in Item 4, we notice that with increasing energy of the input, the amplitude of the trough increases. As the bar thickness increases (starting with a single cell), the network response starts off having a single peak and then develops two peaks. For bars which have a large thickness, one can observe “featural noise suppression” i.e. the response is noticeable only at the edges of the bar and not anywhere else.

## Item 8: Peak shift with subtractive inhibition

### Background

We now discuss an idea mentioned in [2]. In the discussion of a visual illusion discovered and explained by Blakemore et al. (1970), the authors present a figure to illustrate how the net effect of summing lateral excitatory and inhibitory influences in a certain way can result in the peaks of the sum being shifted outward from the original peaks (refer figure 2, [2]). The aim of this simulation is to verify the claim and reproduce the figure.

### Simulation

The kernels span 500 nodes. Such a large number was chosen so that it approximates a continuous curve. Equations 1 were used for simulation and the parameters used were: $C = 1$, $E = 0.5$, $\mu = 1/16$ and $\gamma = 1/64$. The plots are illustrated in figures 8, 9, 10 and 11. Figures 8 and 9 show the net effect of the excitatory and the inhibitory kernels. Figure 9 shows the same curves as in figure 8 but displaced to the right. When these two curves interact together, the result is the blue curve shown in figure 10. The original curves are shown in red. Figure 11 is a "zoomed in" version of figure 10 and it is easy to see that the peaks of the blue curve are shifted outward when compared to the peaks of the red curves. This is called "peak shift".

### Conclusions

In this simulation assignment we have analyzed the distance dependent feedforward network model of Grossberg. We have analyzed the properties of edge processing, reflectance processing and featural noise suppression. We have gained an understanding of the network behavior when some of the parameters are varied over large ranges. The model successfully explains the above mentioned properties of the visual system. The

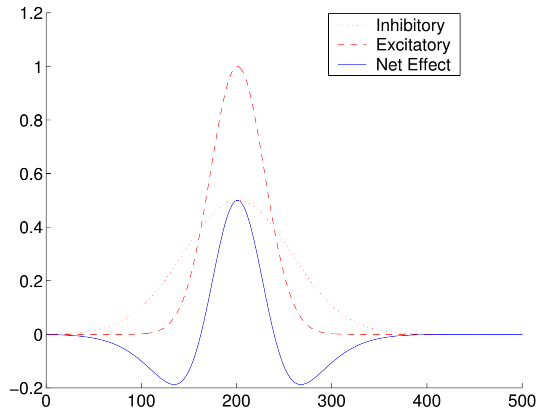


Figure 8: Item 8 - Illustration of peak shift.

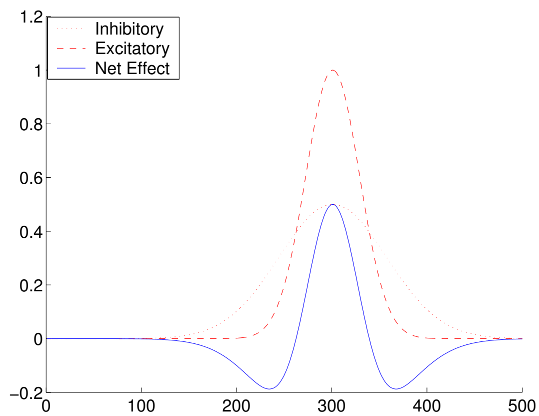


Figure 9: Item 8 - Illustration of peak shift.

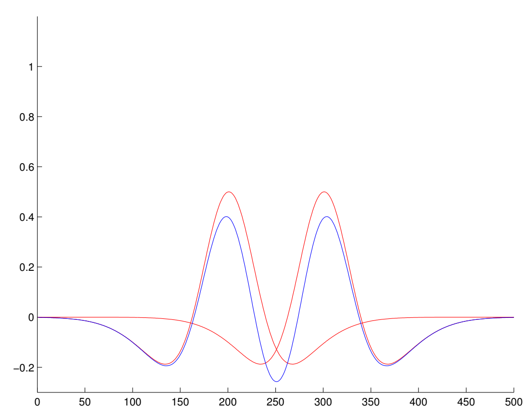

Figure 10: Item 8 - Illustration of peak shift.

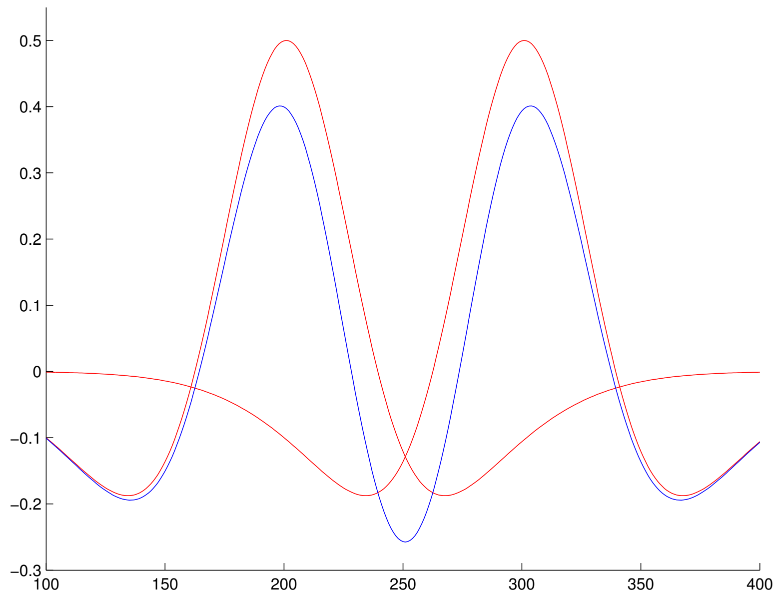


Figure 11: Item 8 - Illustration of peak shift.

model is also robust as shown by the simulations.

# References

[1] Stephen Grossberg. The quantized geometry of visual space: The coherent computation of depth, form, and lightness. *The Behavioral and Brain Sciences*, pages 625–692, 1983.

[2] Daniel S. Levine and Stephen Grossberg. Visual illusions in neural networks: Line neutralization, tilt after effect, and angle expansion. *Journal of Theoretical Biology*, pages 477–504, 1976.