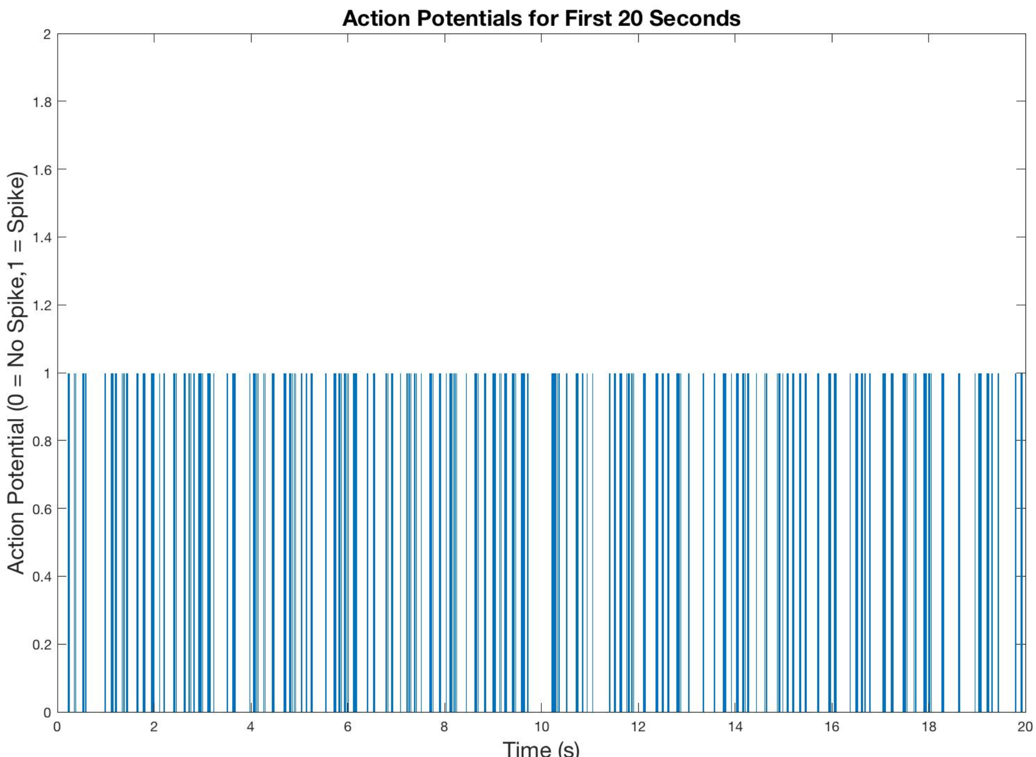
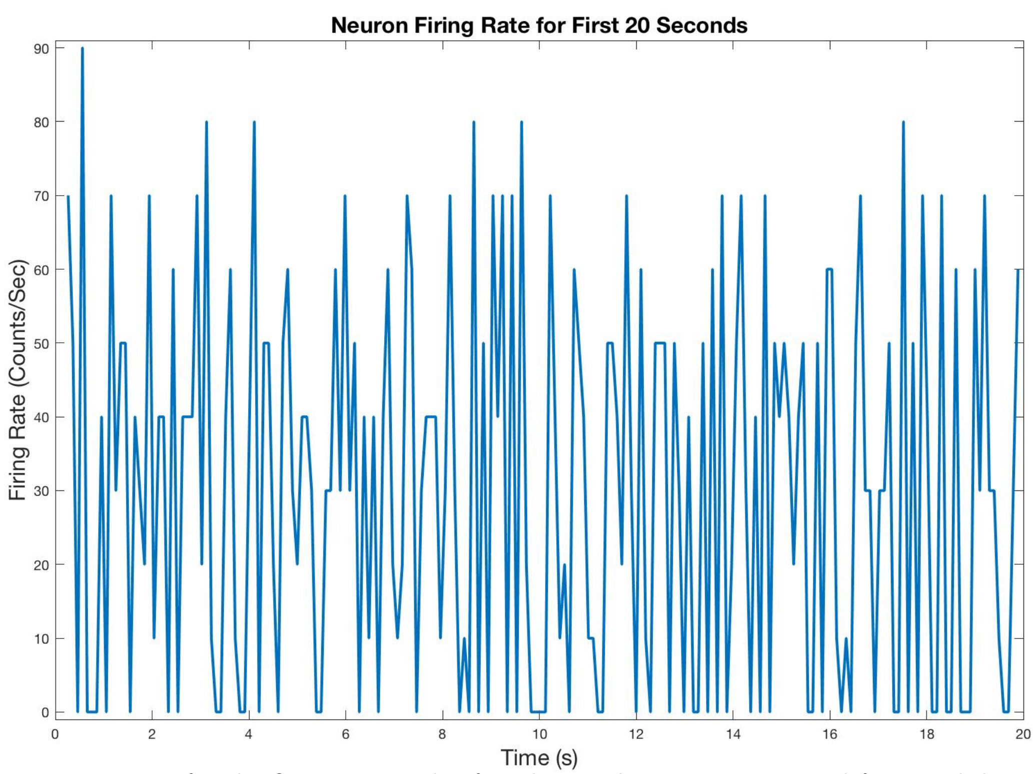
Problem 1: Please see file HW_Code_pt1.m

(a)



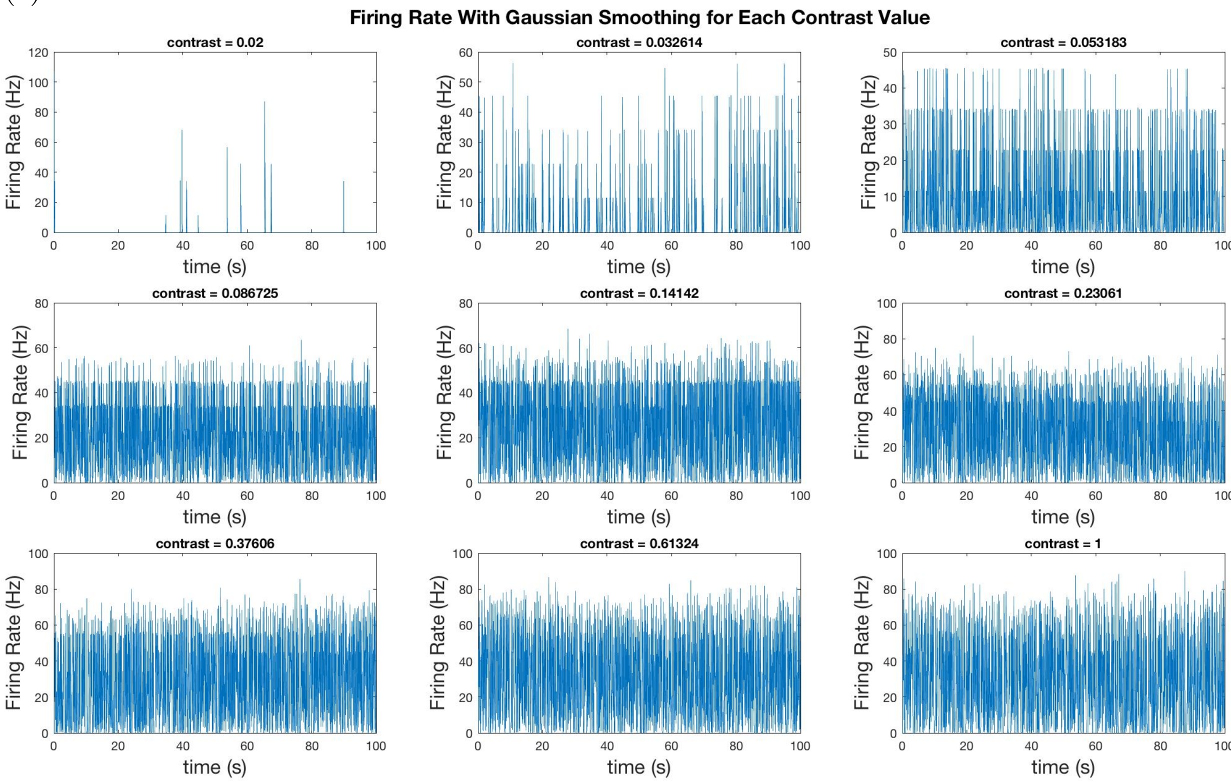
Spike train representation of action potentials for the highest contrast trial (contrast = 1, trial 9). The first 20 seconds of the trial is shown.

(b)



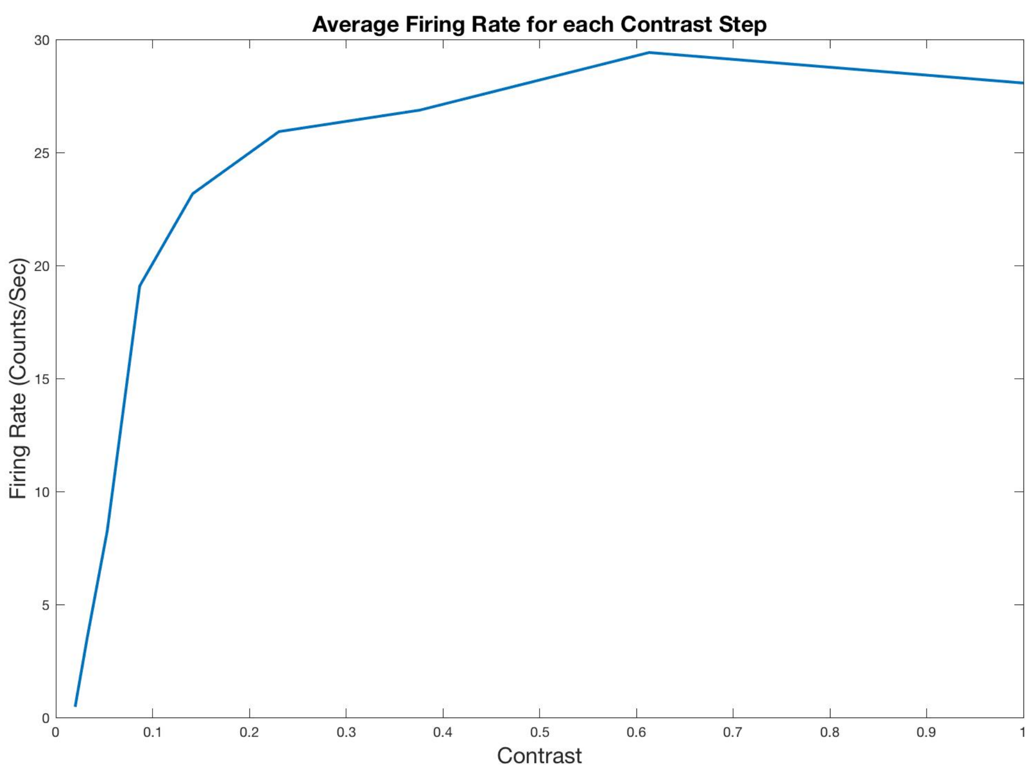
Firing rate for the first 20 seconds of trial 9. High noise, as expected from real data.

(c)



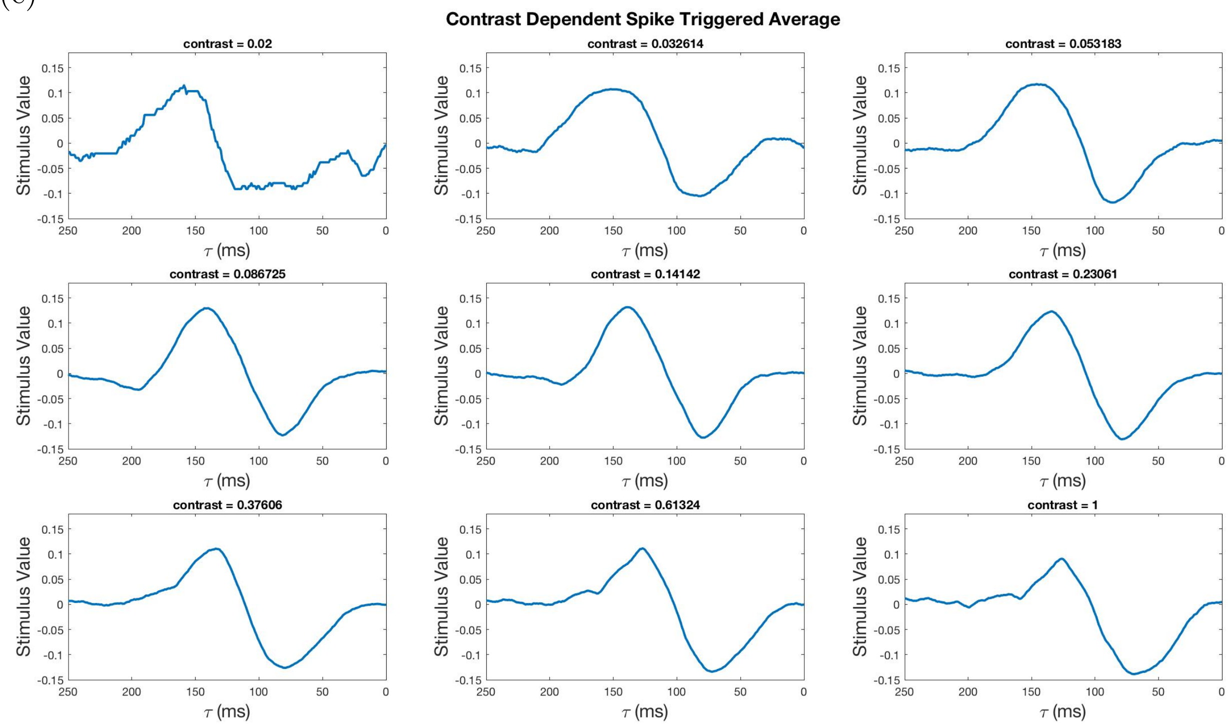
Contrast dependent firing rate with gaussian smoothing. Gaussian window has sigma = 35ms. Gaussian normalized such that *sum(Gaussian Values) = 2000* (experiment sampling rate).

(d)



Overall firing rate plotted as a function of contrast. As stimulus contrast increases, firing rate follows.

(e)



Spike triggered averages (STAs) for each contrast trial (1-9). Note that each stimulus takes on roughly the shame shape for each contrast level. Stimulus values are normalized such that the sum of squared values of the stimulus (for each contrast trial) is 1 (as in vector normalization).

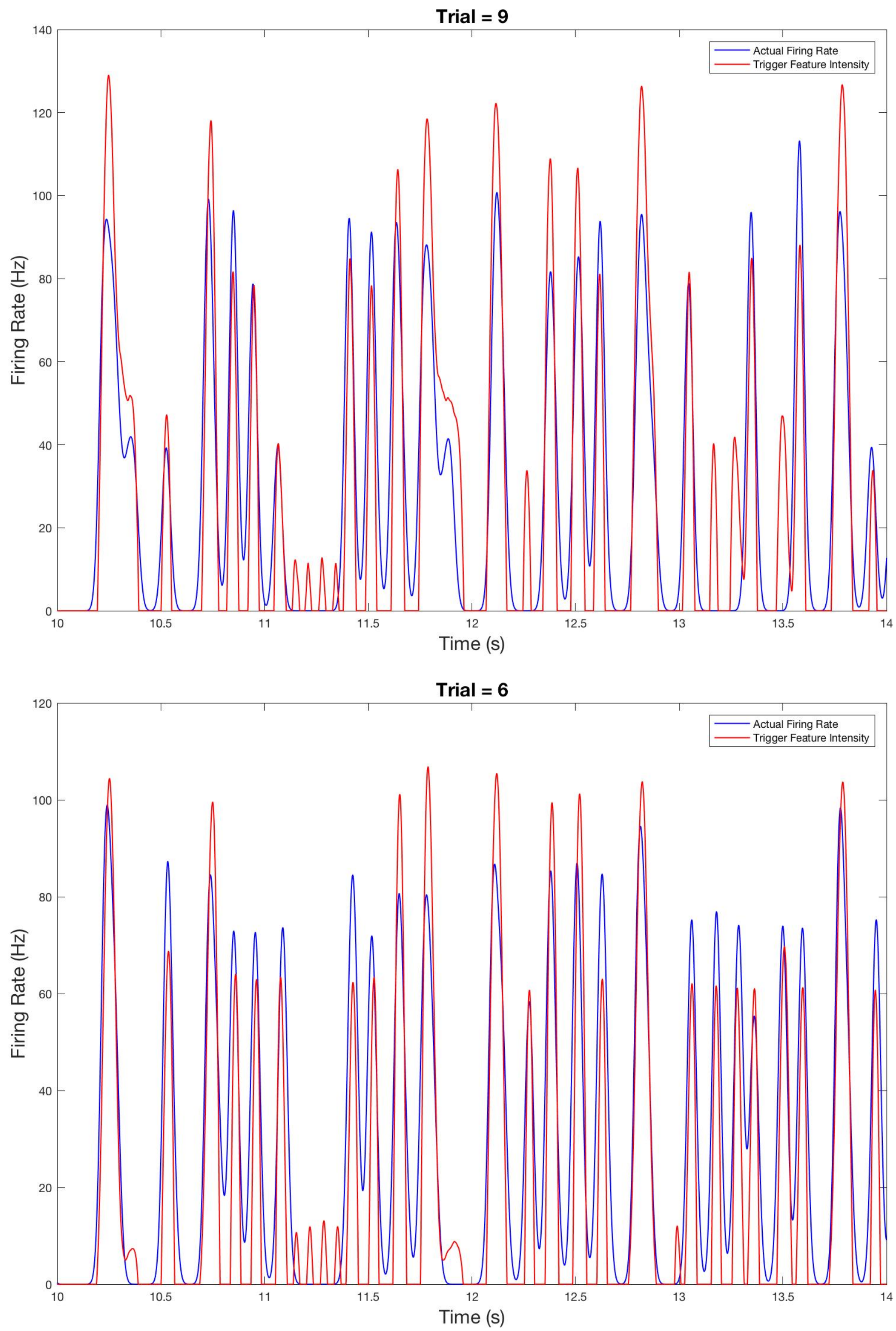
(f)

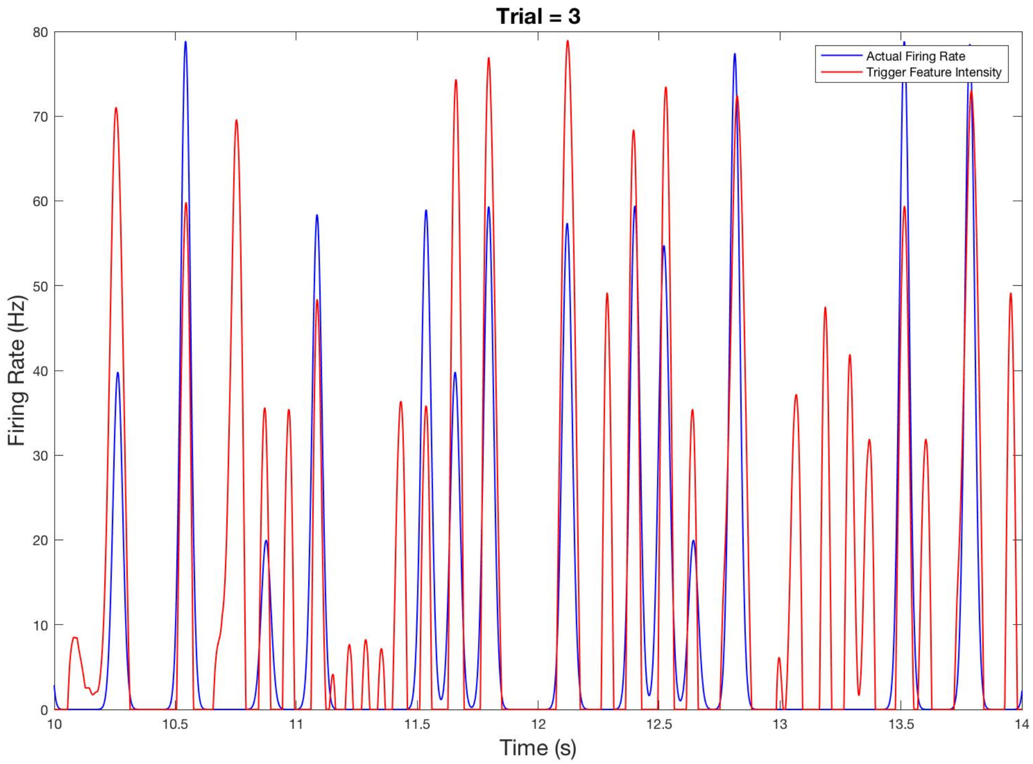
From the above plot (1(e)) we find that the STA becomes more refined as contrast increases. Increase in contrast gives us an increase in temporal precision. Also notice that the response doesn't change much. Hence the cell doesn't care much about contrast.

Problem 2:

(b)

Trigger Feature Intensities and Similarity to True Firing Rates

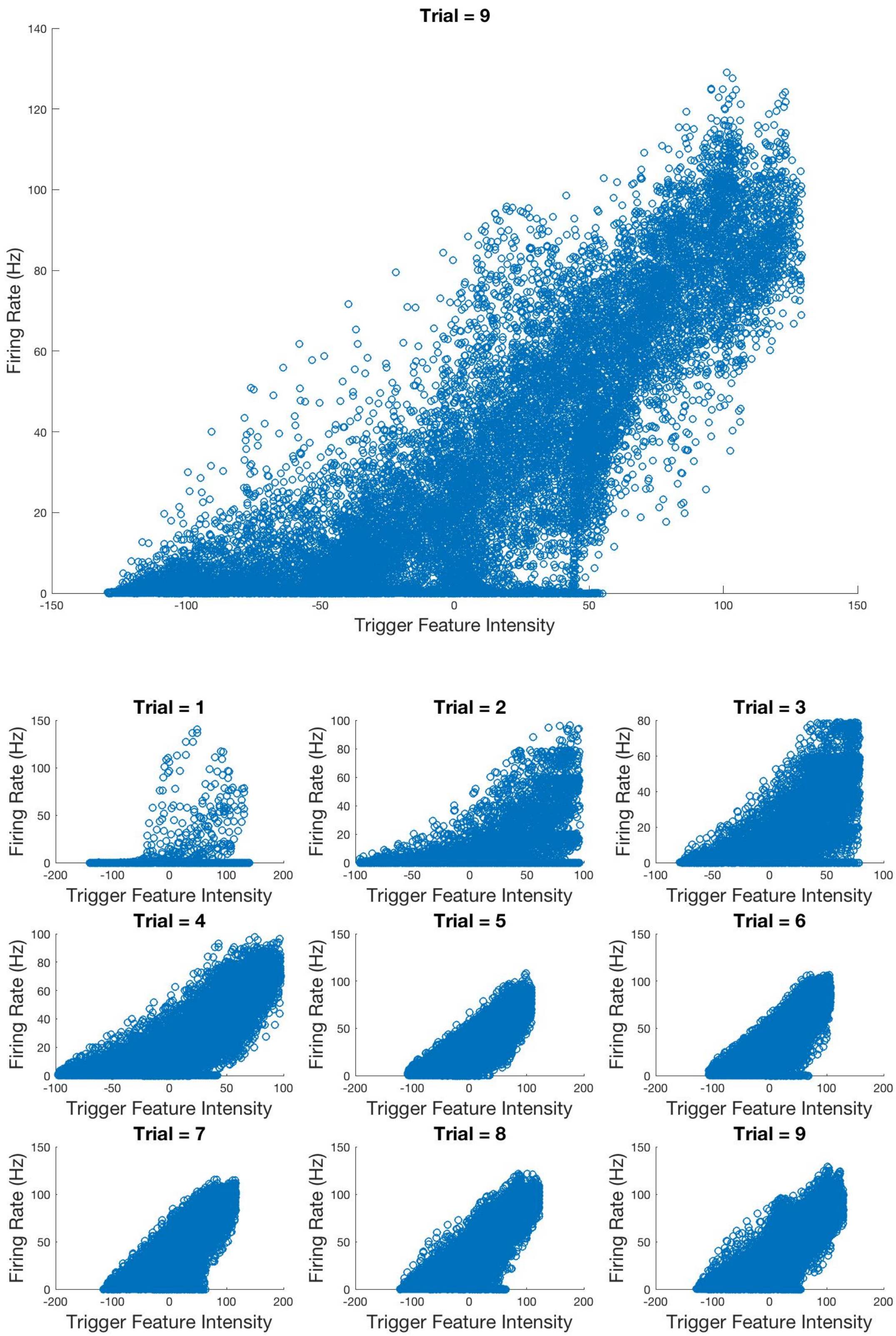




Actual firing rates (blue) and trigger feature intensities (red) shown on same plot for a series of trials. Note, the trigger feature intensities were all scaled by the maximum value of the actual firing rate (for each trial).

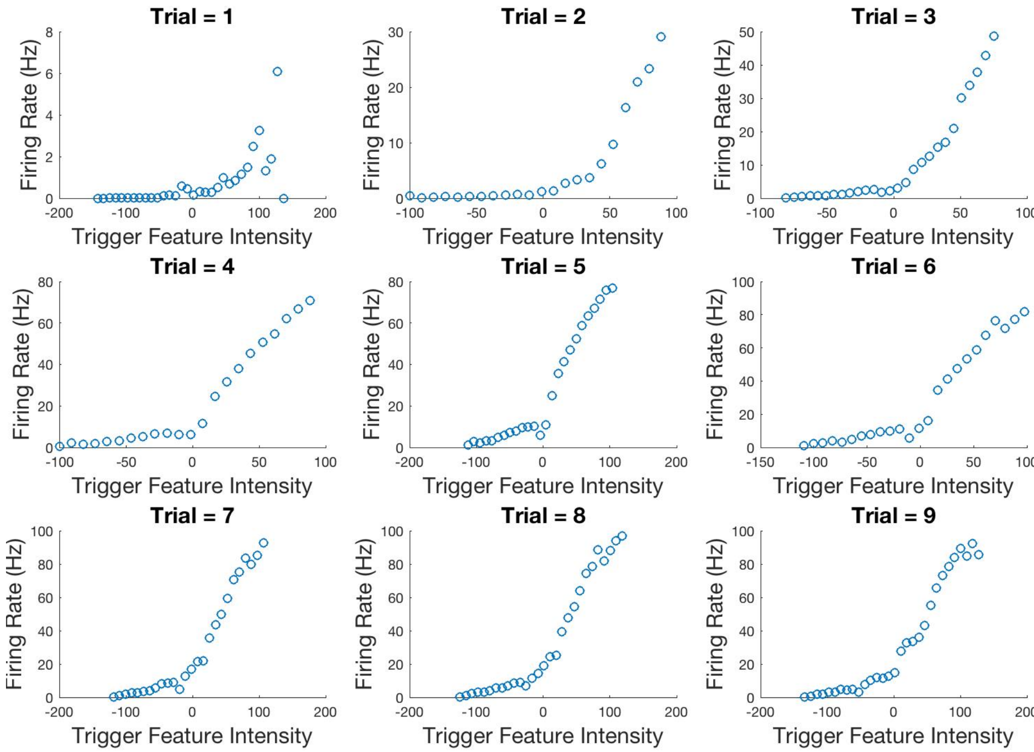
(c)

Relation Between Firing Rate and Filter Output



Scatter plots of firing rates against trigger feature intensity reveals possible sigmoidal relation that becomes stronger with increasing contrast.

(d)

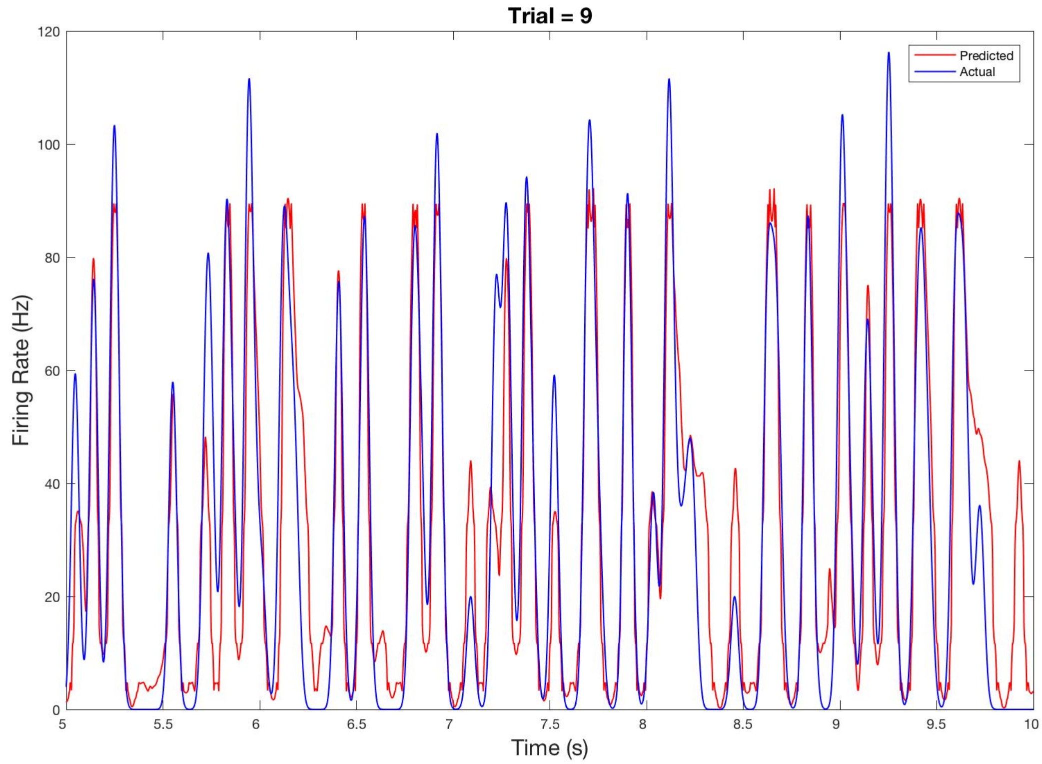


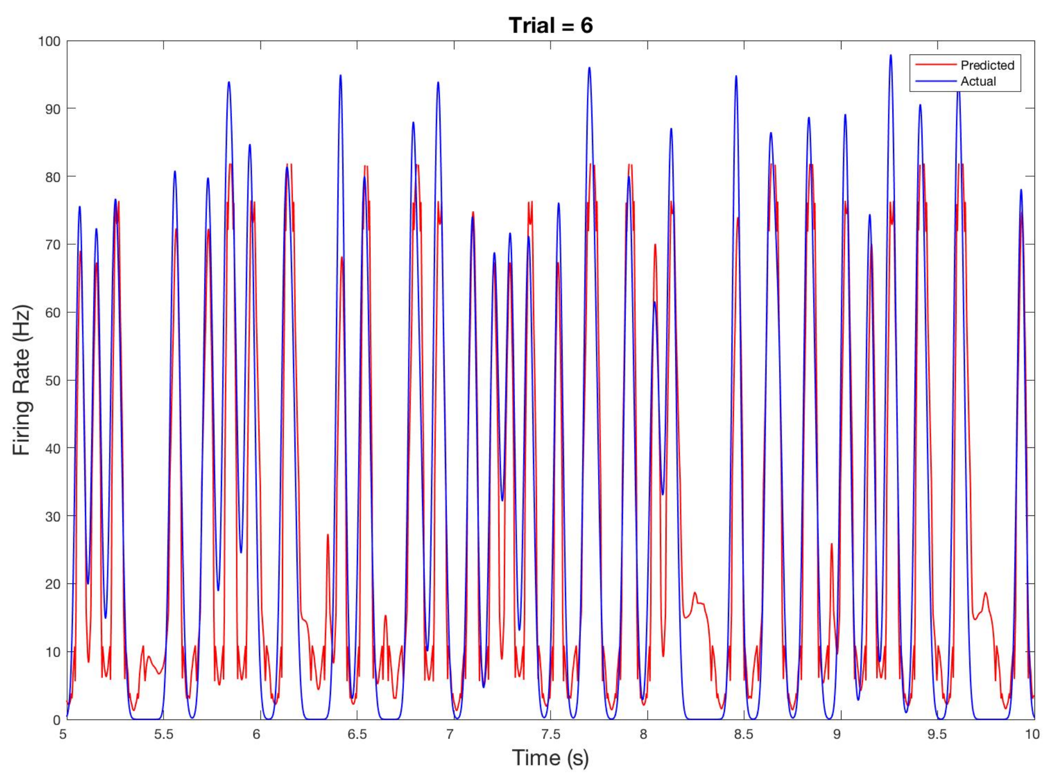
Scatter plot points averaged over the x axis leaving behind a clearer relationship.

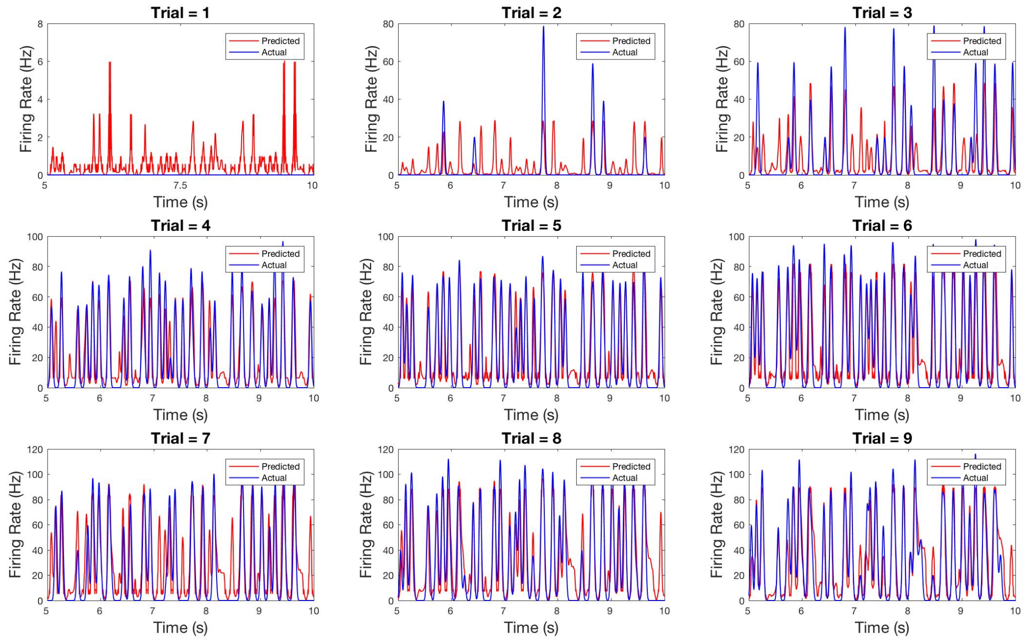
Each trial has approximately the same characteristic nonlinear sigmoidal behavior. With increase in contrast (higher trial number) we find that the curve becomes increasingly more refined and of the expected shape.

(e)

Model Predicted Firing Rate





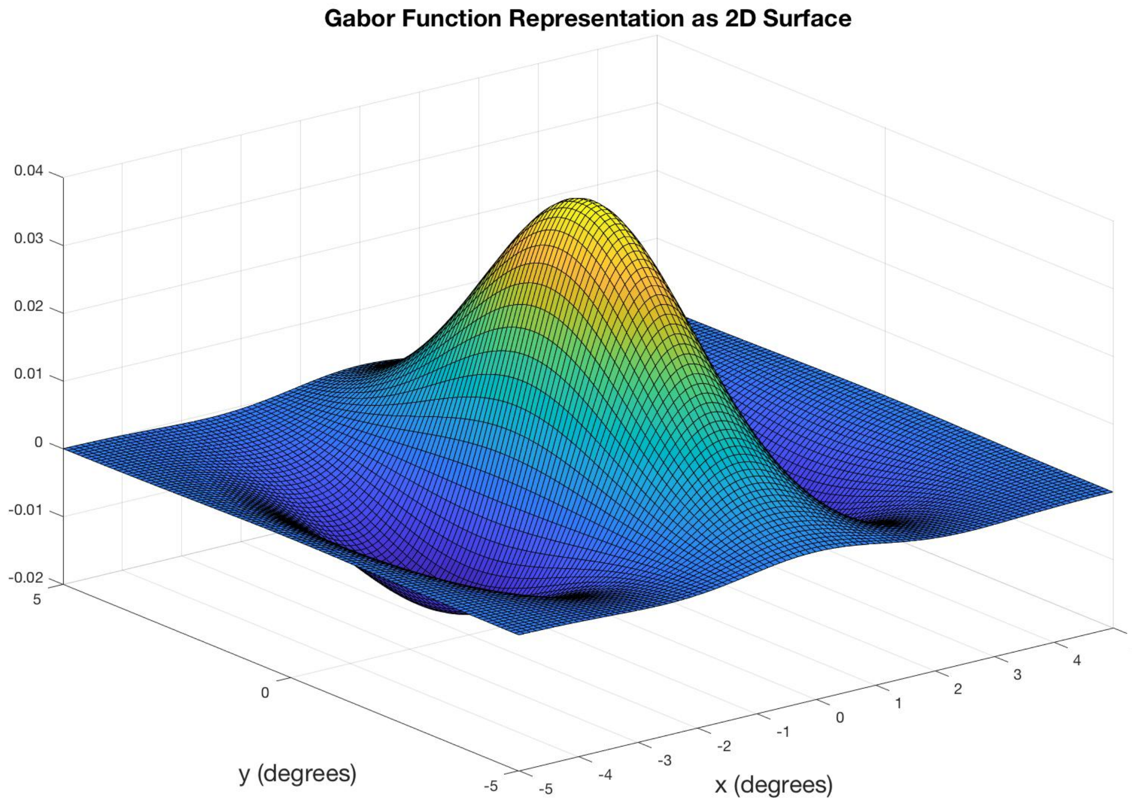


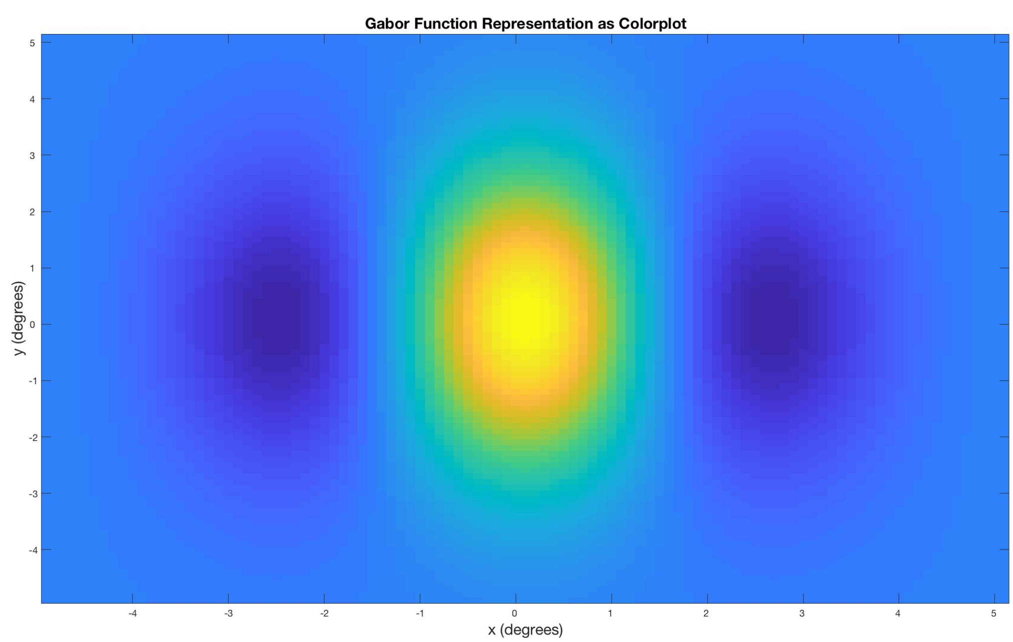
Plots of predicted firing rate (red) with the actual firing rate (blue) over a 5 second duration.

We find that for higher contrast (trial) values, the linear-nonlinear model does an excellent job of predicting the firing rate of the neuron. We find that for lower contrast values, the story is quite different. However, it does not take much in terms of contrast for the model to accurately predict the time evolution of the firing rate.

Problem 3: Please see file HW4_pt2.m

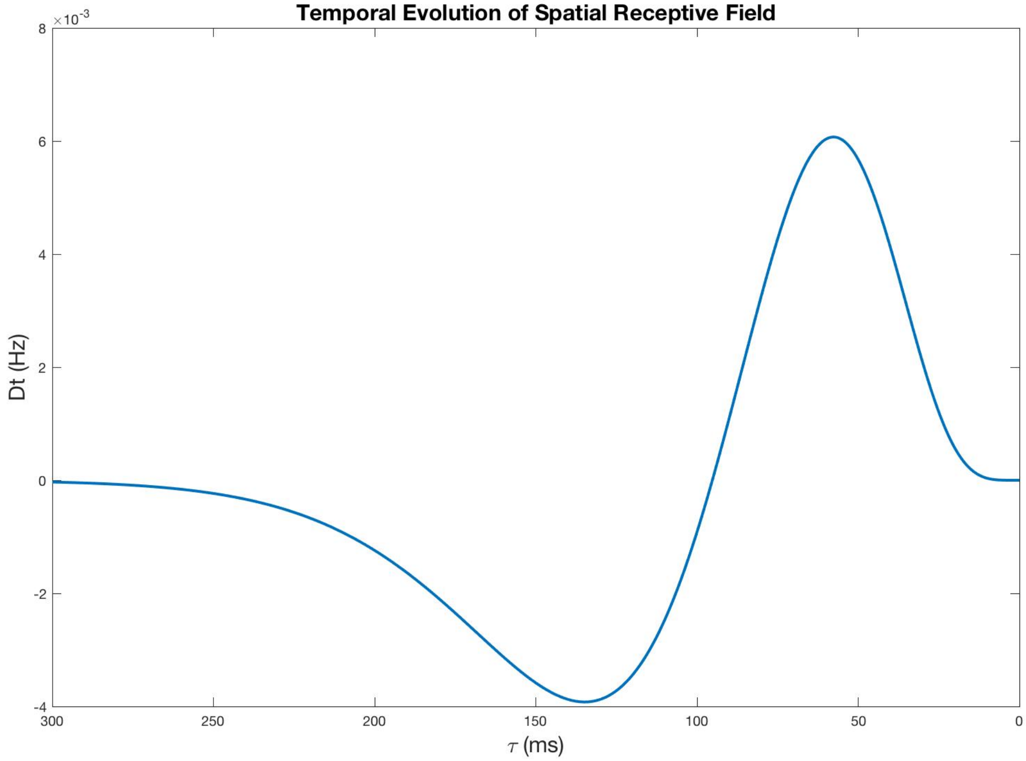
(a)





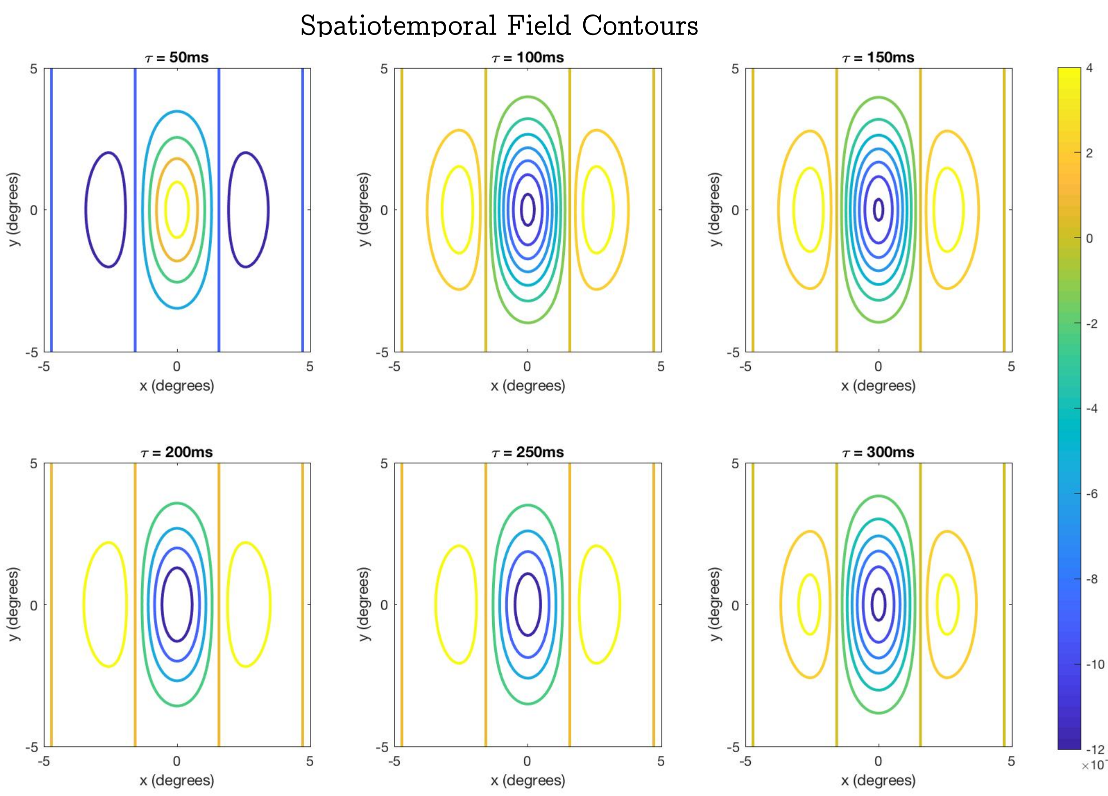
Gabor function plotted as 2d surface in 3 space (plot 1). Color plot representation is shown (plot 2).

(b)



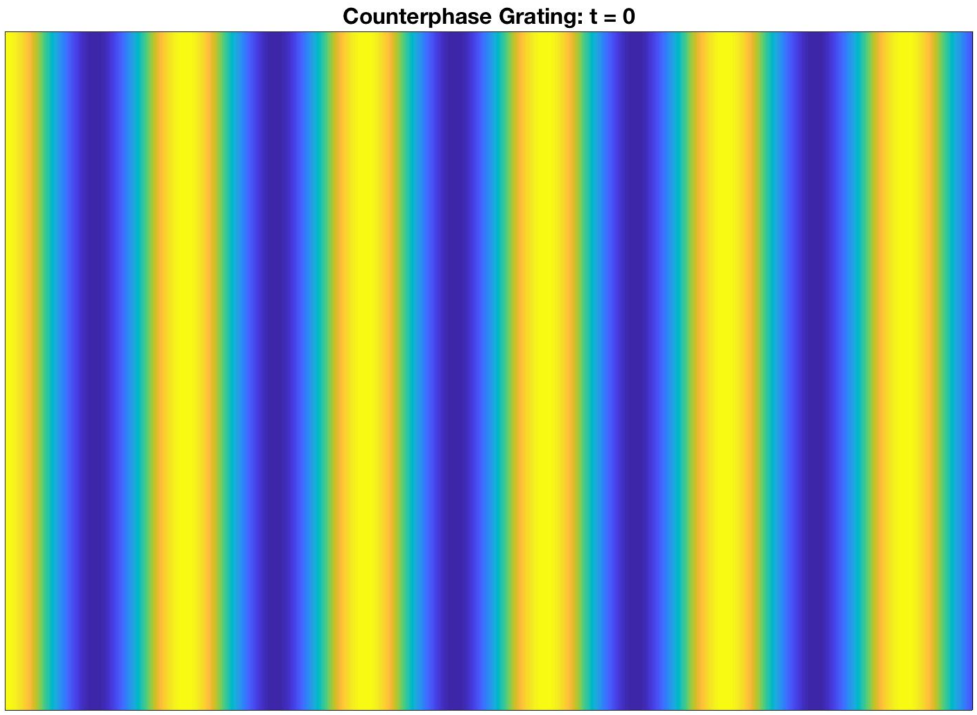
Temporal part of corresponding receptive field with *alpha = 1/(15ms)*. Plot is qualitatively equivalent to figure 2.14 in textbook.

(c)

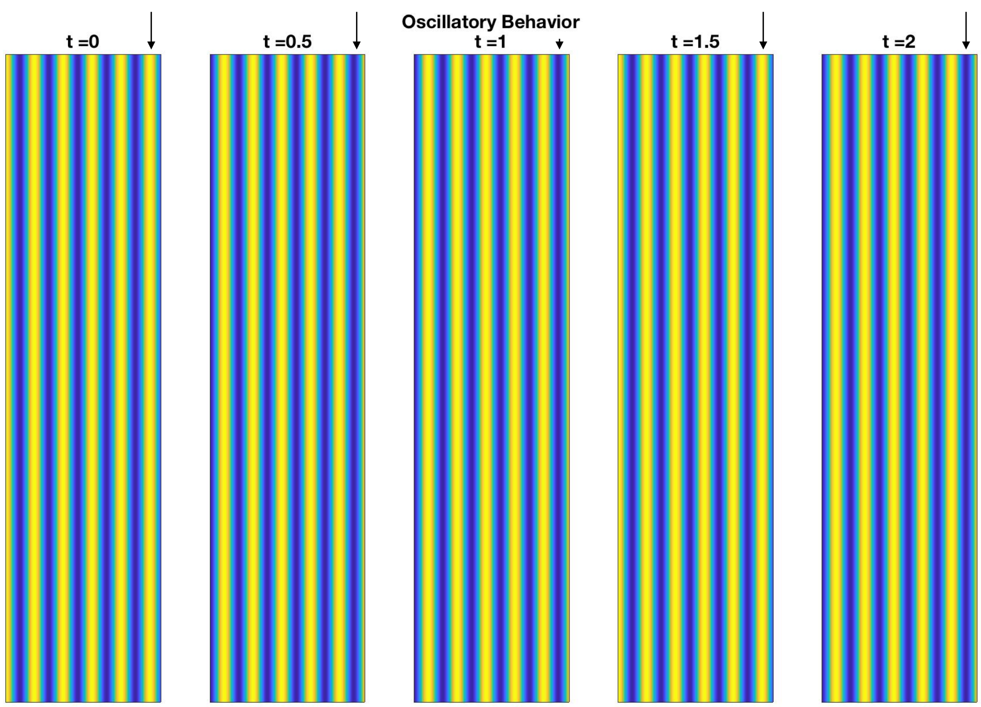


Spatial and temporal fields combined for a spatial temporal field contour plot with time evolution *(tau)* as shown.

(d)

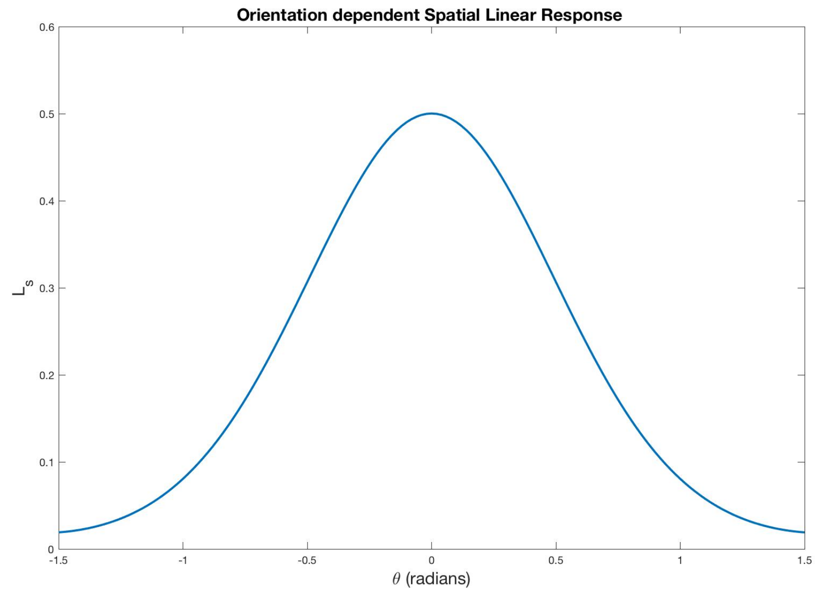


Counterphase grating shown for *time = 0* with nonzero *theta* and *K*.

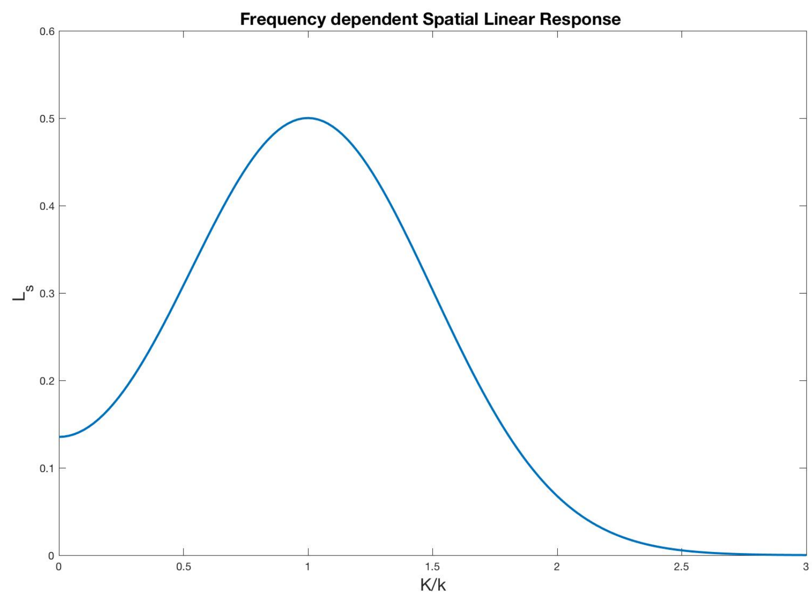


Please see short "movie" in code (part 3(d)) for proof of oscillatory behavior. Alternatively, follow the leading edge of the above plots as time evolves (see arrows). Notice the change in color, suggesting oscillatory behavior.

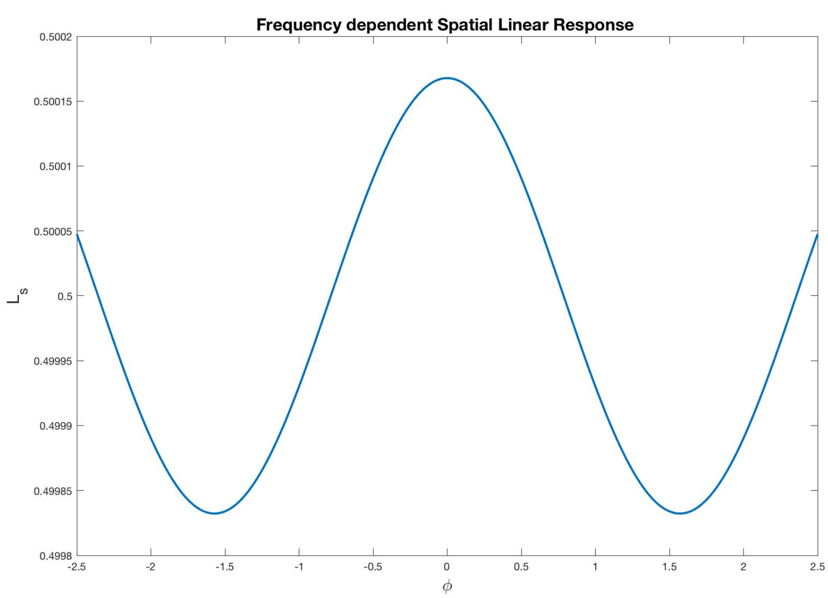
(e)



$k = 1$, $sigma = 2$
$K = k$, $phi = 0$



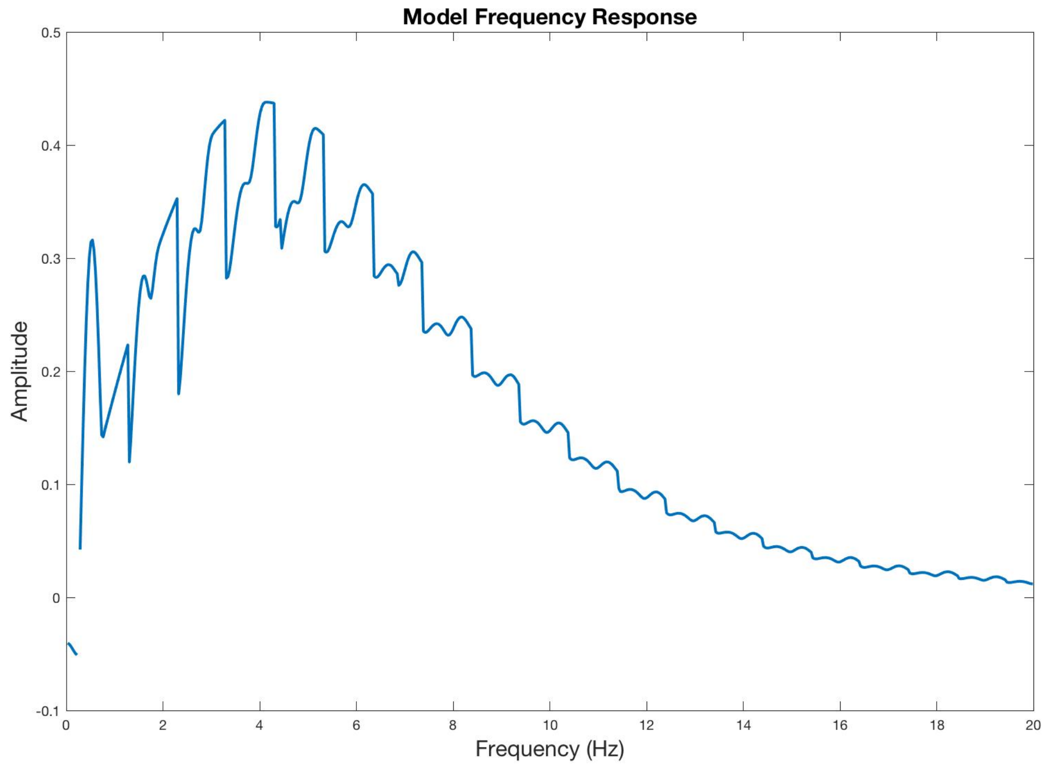
$k = 1$, $sigma = 2$
$Theta = 0$, $phi = 0$



$k = 1$, $sigma = 2$
$Theta = 0$, $k = K$

(f)

Type to enter text



Model frequency response for *omega = 0...2pi * 0.02* . Amplitude of sinusoidal oscillation of Lt(t). Frequency = *omega / 2pi* and *alpha = 1/(15ms)* .

Group Project
Group Members:

- Ilayda Onur
- Isaac Pedisich
- Jacob Nibauer
- Yi Jiang
- Xuan Wang

Topic:

Models of synaptic plasticity and learning

Brief Description:

We are planning on comparing Oja Rule with Spike Timing Dependent Plasticity (STDP). We need to initially decide whether we should generate our own input or use existing data to get meaningful responses from the learning rules that we picked. Since STDP is a time sensitive rule, we ideally want to use an input that reflects this.

We aim to assess the performance of these two model responses and find methods to observe whether neurons' learning could be explained with these models.