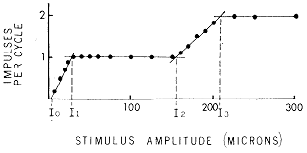
**Problem Set #6**

**Methods in Computational Neuroscience**

Problem #1: Single Neuron Models

In the hairless skin of the primate, mechanoreceptive afferents produce very stereotyped patterns of discharge in response to sinusoidal skin vibrations of varying amplitude: As the amplitude of the sinusoid increases, the neural discharge increases until it reaches a so-called entrainment plateau, over which one spike is produced on each stimulus cycle over a range of amplitudes. With further increases in amplitude, the discharge increases again until another plateau is reached (corresponding to two spikes per cycle, Johnson 1974):



This property of somatosensory afferents can be modeled with a leaky integrate and fire neuron.

The input current should be a 40 Hz sinusoid whose amplitude *A* varies. Because the sinusoid is a current, and there cannot be any negative currents, set any negative values to zero to get a half-wave rectified sinusoid. Vrest is the resting potential, Vthresh is the threshold for a spike, Vspike is the peak voltage during an action potential, and Vreset is the post spike hyperpolarization.

1.1) Simulate the neural response for A=3. Create a figure that compares the time course of the input current and the output membrane voltage over the first 500 ms. What is the firing rate of the simulated neuron? How many spikes does it fire per stimulus cycle?

1.2) Simulate the neural response for 100 amplitude values between A=0 and A=6. Save the spike times that are evoked by the stimuli at each amplitude. Create a spike raster plot of the first 500 ms that illustrates the change in spiking patterns as a function of amplitude. Recreate the Johnson figure above, showing how impulses per cycle varies with increasing stimulus amplitude.

In what way is the model successful in recreating natural behavior? In what ways does it differ? Are any new phenomena predicted by the model? What aspects of the real neuron may not be fully captured by the model?

Problem #2: Classification

The objective of this analysis is determine (1) the extent to which the frequency composition of stimuli can be distinguished on the basis of the responses they evoke in one population of mechanoreceptive afferents (PC afferents) and (2) the extent to which the timing of spikes conveys information. In the data file *spikes.mat*, you will find the responses of 4 PC fibers to noise stimuli with four bandpasses (50-250 Hz, 25-500 Hz, 50-500 Hz, 50-1000 Hz) at five amplitudes each (the first level of the cell array is neuron, the second is different band-passes, the third is amplitude). This is only a small subset of the data so that your code can run relatively fast (you would never use such a small data set). Your objective is to attempt to classify the stimuli based on their frequency composition using spike distance (see below). You will approximately reproduce the right-most panel of Figure 2 in the seminal paper (☺) from my lab: “Millisecond Precision Spike Timing Shapes Tactile Perception,” published in 2012 in the Journal of Neuroscience. The output figure will consist of percentage correct classification (on the ordinate) vs. temporal resolution of the analysis (on the abscissa). The following text is cut and pasted from the Methods of the aforementioned paper and describes in detail the analysis you are to carry out (you can also consult the slides on metric space analysis). We are also providing you with code that computes the spike distance metric (since it is publically available).

*We used a spike distance, Dspike[q], as a parametric measure of the dissimilarity between two spike trains (Victor and Purpura, 1997). This spike distance ascribes the cost of transforming one spike train into the other by using two elementary operations. Spikes can be added or deleted at a cost of one, and spikes can be shifted in time at a cost that is proportional to the amount that they are shifted (a cost of q per second). By changing the parameter q, we can control the temporal asynchrony between two spikes at which it becomes cheaper to delete and reinsert a spike rather than to move it. This parameter thus corresponds to the inverse of a neuron’s temporal resolution in seconds. Thus, q = 500 corresponds to a temporal sensitivity of 2 ms, while q = 0 indicates a rate code, with no penalty to move spikes. Metric space analysis involves first characterizing the dissimilarity of pairs of spike trains using spike distance, Dspike[q] (Victor and Purpura, 1996). Then, for each spike train T, we determine which stimulus category evoked spike trains whose average distance from T was smallest, where stimulus categories are defined on the basis of frequency content. We then measured the proportion of times the stimulus category into which a given spike train was categorized corresponded to the stimulus category that actually evoked it. In other words, what proportion of times is a spike train more similar to other spike trains evoked by stimuli with the same frequency composition (but varying in amplitude) than it is to spike trains evoked by stimuli with a different frequency composition? We measured classification performance for a range of q values.*

*To examine the extent to which information about spectral composition is conveyed independently of stimulus intensity, we included stimuli at a range of amplitudes for each frequency composition. We wished to assess whether stimuli that varied widely in amplitude would still be categorized together if they had the same frequency composition. In other words, does one aspect of the afferent response remain relatively invariant across changes in amplitude to convey information about frequency composition? To ensure that our results were not an artifact of our stimulus selection, we examined the effect of manipulating the amplitude ranges on classification performance and optimal temporal resolution. We found that, as long as multiple amplitudes were included in each category, the optimal temporal resolution, i.e., the location of the peak of each individual classification curve (such as those shown in Fig. 2), remained consistent. We conclude that our results are not an artifact of our choice of stimulus intensities.*