EXCITATORY AND INHIBITORY INTERACTIONS IN LOCALIZED POPULATIONS OF MODEL NEURONS

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There is one final and crucial assumption upon which this study rests: all nervous processes of any complexity are dependent upon the interaction of excitatory and inhibitory cells. This assertion is supported by the work of Hartline and Ratliff (1958), Hubel and Wiesel (1963, 1965), Freeman (1967, 1968 a, b), Szentágothai (1967), and many others. In fact, this assumption is virtually a truism at this point, yet many neural modelers have dealt with nets composed entirely of excitatory cells (Beurle, 1956; Farley and Clark, 1961; ten Hoopen, 1965; Allanson, 1956). It was just this failure to consider inhibition that led Ashby et al. (1962) to conclude that the dynamical stability of the brain was paradoxical, and it was the introduction of inhibition by Griffith (1963) which dissolved the paradox. Consequently, we take it to be essential that there be both excitatory and inhibitory cells within any local neural population.
Neuronal spiking - a threshold phenomena - is (largely) deterministic

Yet brain activity is noisy on every scale!

From the notes of Brent Dorian
Cortical spiking in particular is irregular

Figure 1. Response variability of a neuron recorded from area MT of an alert monkey. A, Raster and peristimulus time histogram (PSTH) depicting response for 210 presentations of an identical random dot motion stimulus. The motion stimulus was shown for 2 sec. Raster points represent the occurrence of action potentials. The PSTH plots the spike rate, averaged in 2 msec bins, as a function of time from the onset of the visual stimulus. The response modulates between 15 and 220 impulses/sec. Vertical lines delineate a period in which spike rate was fairly constant. The gray region shows 50 trials from this epoch, which were used to construct B and C. B, Magnified view of the shaded region of the raster in A. The spike rate, computed in 5 msec bins, is fairly constant. Notice that the magnified raster reveals substantial variability in the timing of individual spikes. C, Frequency histogram depicting the spike intervals in B. The solid line is the best fitting exponential probability density function. D, Variance of the spike count is plotted against the mean number of spikes obtained from randomly chosen rectangular regions of the raster in A. Each point represents the mean and variance of the spikes counted from 50 to 200 adjacent trials in an epoch from 100 to 500 msec long. The shaded region of A would be one such example. The best fitting power law is shown by the solid curve. The dashed line is the expected relationship for a Poisson point process.

Shadlen & Newsome (J Neurosci 1998)
Balanced excitatory and inhibitory currents can lead to noisy input currents

Denuve & Machens (Nat Neuro 2016)
Balanced currents are observed in vivo under numerous conditions

Spatially Opponent Excitation and Inhibition in Simple Cells of the Cat Visual Cortex

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Figure 1. In vivo stellate recorded responses of a simple cell evoked by a bright bar swept across its receptive field. The arrow indicates the orientation and direction of motion of the stimuli. The bars were 1.75 x 0.5 mm, the vector 45° to the left, and the speed 0.5 mm/s. The responses are shown for various strengths of illumination. The bottom trace in each column (A) represents an average of 10 individual records.

Figure 2. Responses to a moving bright bar recorded simultaneously from a stellate neuron in the cat visual cortex. The receptive field of this cell consisted of a ON region and an OFF region. The bar moved at a rate of 25 deg/sec.

Ferster (J Neurosci 1988)
Balanced currents are observed in vivo under numerous conditions

Atallah & Scanziani (Neuron 2009)
Neocortical Network Activity *In Vivo* Is Generated through a Dynamic Balance of Excitation and Inhibition

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**Figure 7.** Excitatory and inhibitory conductances are proportional and balanced during Up states. A, Plot of calculated excitatory and inhibitory conductances in a single neuron during the course of the Up state (0–500 ms, indicated by progressive movement through color bar) shows that excitation and inhibition remain proportional and nearly equal despite large changes in total conductance (slope of linear fit, $m = 0.98; r^2 = 0.78$). Note that the start of the Up state shows a deviation toward excitation, but rapidly swings toward inhibition and thereafter exhibits a balance between the two. B, Excitation and inhibition are proportional and balanced both within and across neurons during recurrent network activity. Scatterplot of excitatory versus inhibitory conductances for a population of neurons ($n = 8$), calculated for 500 ms from the start of the Up state. Note the linear relationship for each individual neuron, as well as the clustering around a ratio of equal excitatory and inhibitory conductances ($G_e = G_i$); dashed line; 4 of 8 cells biased toward excitation, 3 of 8 cells toward inhibition, 1 of 8 cells approximately equal; population reversal potential, $-37.2 \pm 6.5$ mV).

Haider, Duque, Hasenstaub & McCormick (J Neurosci 2006)
Synaptic scaling rule preserves excitatory–inhibitory balance and salient neuronal network dynamics

Jérémie Barral\textsuperscript{1} & Alex D Reyes\textsuperscript{1}

Barral & Reyes (Nat Neuro 2016)
Network model

van Vreeswijk & Sompolinsky (Science 1996; J Comp Neurosci 1998)
Results for Output-Input network activity

(A) Temporal structure of the inputs and activity of a single excitatory unit. The upper panel shows the total excitatory input (consisting of external input and excitatory feedback) (upper trace) and the total inhibitory input (lower trace), as well as the net input (middle trace). The currents are shown in units of the threshold (dashed line). They were calculated by sampling from the Gaussian statistics of the currents predicted by the theory.

Below, the times when the cell switched to the active state are indicated. The cell is set to the active state when a suprathreshold net input coincides with the update time of the cell. (B) The mean activity of the excitatory neurons (solid line) and the inhibitory ones (dashed line) as functions of the activity of the external units. The activities shown here and in the following figures correspond to firing rates divided by their maximum value. Assuming a neuronal maximum rate of 1000 Hz, a mean activity of 0.1 corresponds to a firing rate of 100 Hz.

van Vresswijk & Sompolinsky (Science 1996; J Comp Neurosci 1998)
The increase in noise is accompanied by an increase in response speed of $m^E$ and $m^I$ to an input.
Neuronal spiking is best driven by noise with the mean input near threshold

Lognormal firing rate distribution reveals prominent fluctuation–driven regime in spinal motor networks

Peter C Petersen, Rune W Berg

eLife 2016;5:e18805. DOI: 10.7554/eLife.18805
Neuronal spiking driven by the envelope of noise

Super-threshold changes in mean

Sub-(but near)-threshold mean plus noise

Lundstrom, Higgs, Spain & Fairhall (Nat Neuro 2008)
Firing Rates of Single Neurons in the *Balanced* Regime

Average current is sub-threshold and spikes are triggered by fluctuations

spiking is temporally irregular

**concavity of the f-l curve makes the rates' distribution right-skewed**
Why is this all not so simple to understand?

- Connections are dense, non-randomly distributed and nonrandomly weighted
- Few strong connections in a sea of weak connections

Song, Sjöström, Reigl, Nelson & Chklovskii (PLoS Biology)
Overrepresentation of bidirectional motifs

Connection strengths are variable and their distribution has a long tail

L5 pyramidal cells, Song et al. (2005)

L5/6 pyramidal cells, Deuchars, West, Thomson (1994)
Mapping receptive fields with two-photon calcium imaging and reverse correlation

Cossell, Iacaruso, Muir, Houlton, Sader, Ko, Hofer & Mrsic-Flogel (Nature 2015)
Relating synaptic connections to receptive fields

Cossell, Iacaruso, Muir, Houlton, Sader, Ko, Hofer & Mrsic-Flogel (Nature 2015)
Similarity of receptive fields predicts probability, strength, and reciprocity of synaptic connections

Spatial correlation is a strong predictor of connectivity
Cell pairs with positive correlations are more likely to connect with strong connections
Reciprocal connections are stronger and exist between cell pairs with similar receptive fields

Cossell, Iacaruso, Muir, Houlton, Sader, Ko, Hofer & Mrsic-Flogel (Nature 2015)