Current Topics in Systems and Behavioral Neuroscience

Lecture 01

Fall Semester 2018

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Instructor:

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Class schedule:

Paper reading for Saturday of each week
Saturdays: Lecture + paper review+ Quiz
Mondays: Discussion + Simulation Workshop

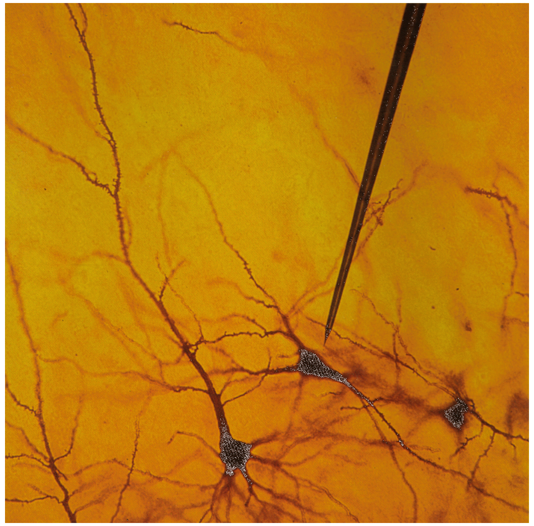
Rubric:

Quizzes 10%
Weekly assignment 50%
Paper presentation 10%
Final Exam 30%

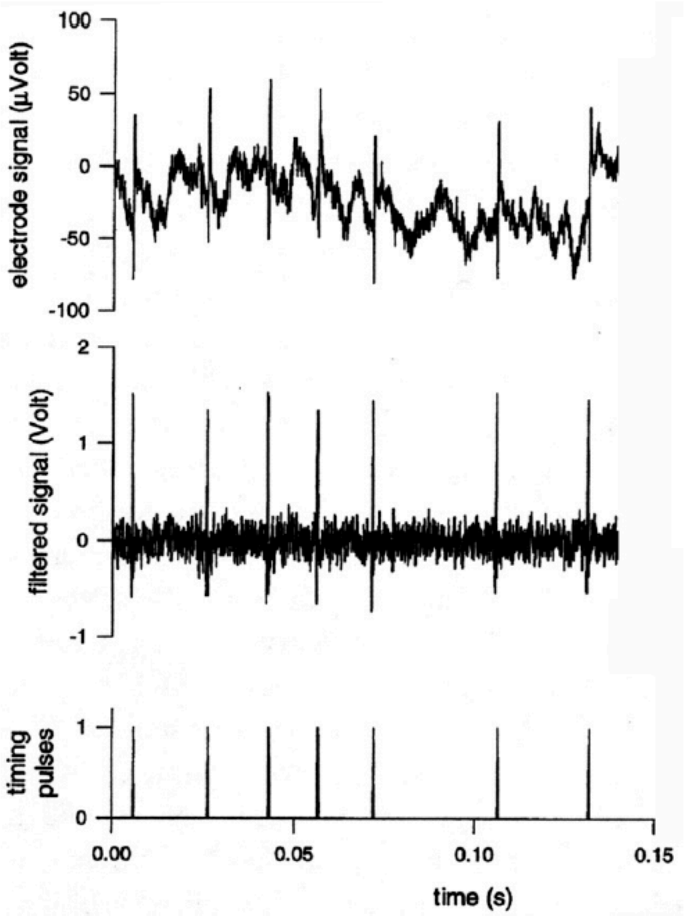
References:

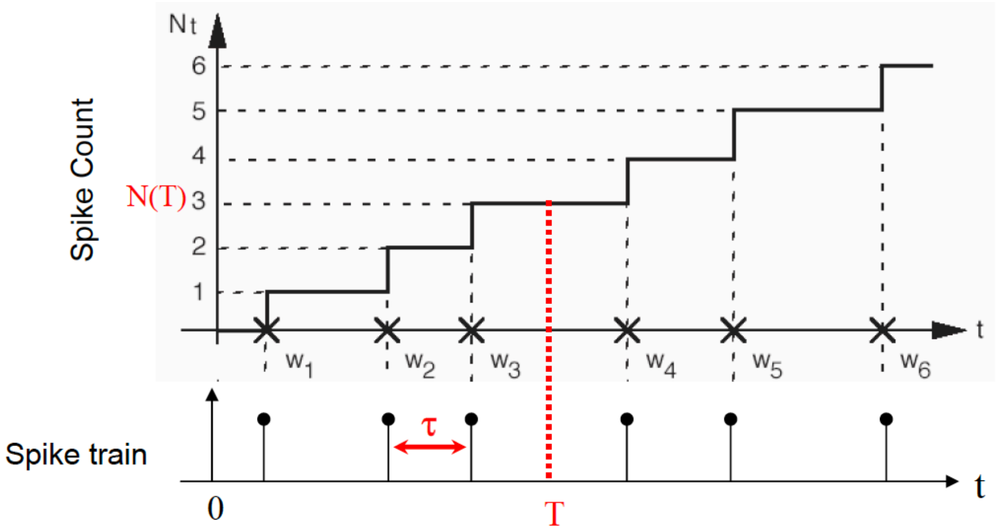
Foundations of neuroscience Lecture notes, Ali Ghazizadeh
Principles of Neural Science, Fifth Edition, Kandel et al
Theoretical Neuroscience: Computational and Mathematical Modeling of Neural Systems, Dayan and Abbott

Review: neural firing as point process



Each action potential can be graphed, with membrane potential on the y-axis and time on the x-axis.





Rieke et al., 1997

Review: Fano Factor

Homogenous and inhomogenous Poisson process

$$\Pr(N(T) = n) = \frac{\lambda T^n}{n!} e^{-\lambda T}$$

$$Fano\ Factor = \frac{Var(N)}{E(N)} = \frac{\lambda T}{\lambda T}=1$$

$$\Pr(N(T) = n) = \frac{(\int_0^T \lambda(t)dt)^n}{n!} e^{-(\int_0^T \lambda(t)dt)}$$

Completely periodic spiking (mean matched to Poisson):

$$Fano\ Factor = \frac{Var(N)}{E(N)} = \frac{0}{\lambda T}=0$$

For a fixed mean firing, Poisson process gives the highest possible fano factor!

Fano factor in cortical neurons in high (Poisson like)

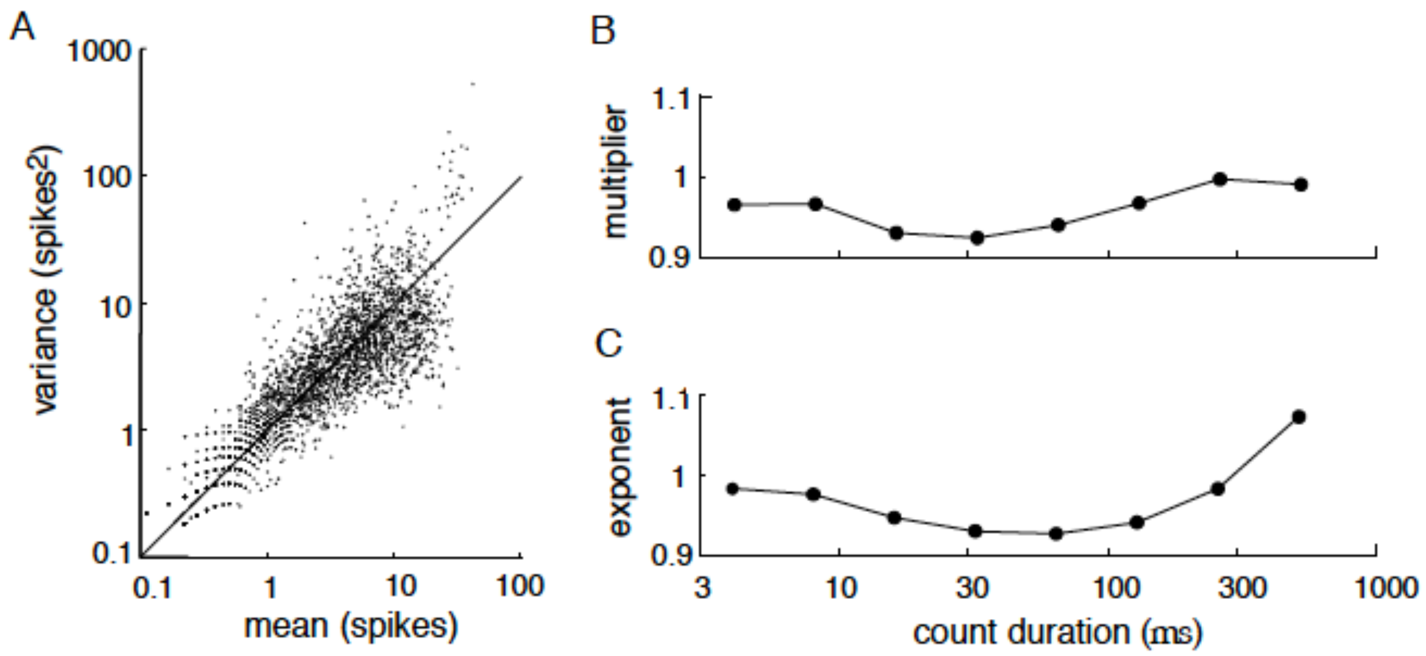


Figure 1.14: Variability of MT neurons in alert macaque monkeys responding to moving visual images. A) Variance of the spike counts for a 256 ms counting period plotted against the mean spike count. The straight line is the prediction of the Poisson model. Data are from 94 cells recorded under a variety of stimulus conditions. B) The multiplier A in the relationship between spike-count variance and mean as a function of the duration of the counting interval. C) The exponent B in this relation as a function of the duration of the counting interval. (Adapted from O'Keefe et al., 1997.)

$$\sigma_n^2 = A\langle n\rangle^B$$

Paper in focus: Softkey and Koch 1993

What make neurons to make such variability in spiking?

Review: C_v

ISI of Poisson process follows exponential distribution

$$Coefficient\ of\ Variation\ (C_V) = \frac{std(\tau)}{E(\tau)} = \frac{\lambda^{-1}}{\lambda^{-1}} = 1$$

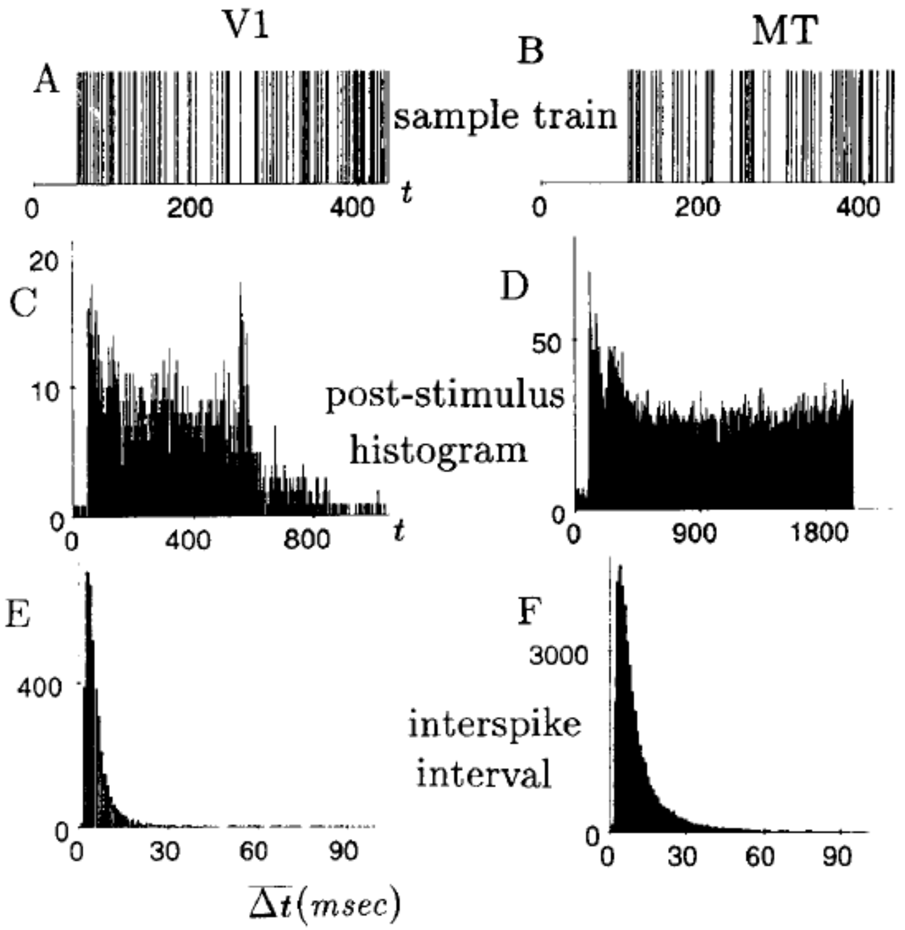
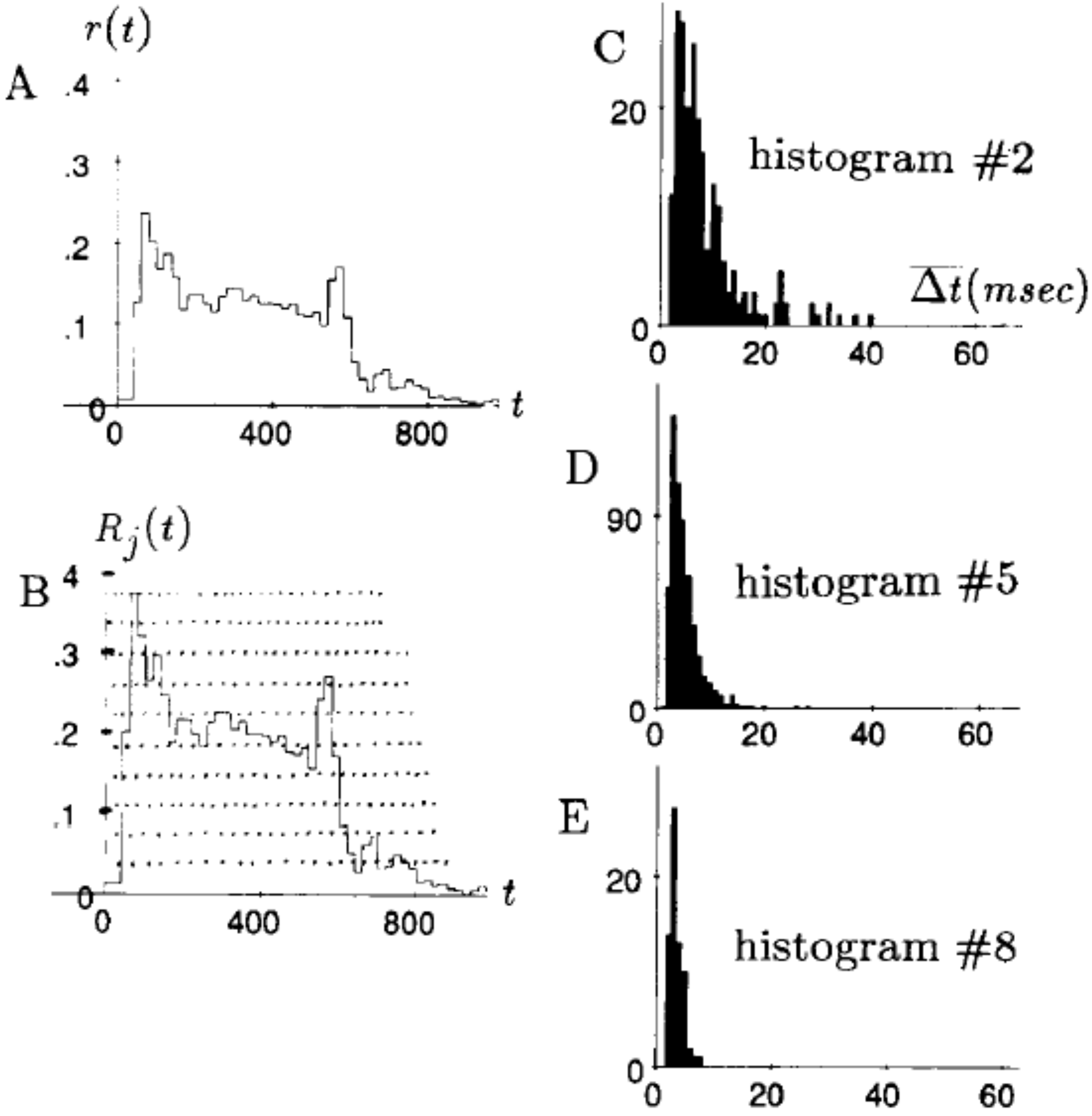


Figure 1. Firing statistics of neurons in areas V1 and MT. *A* and *B*, Sample spike trains from one of the fastest-firing nonbursting neurons recorded in each area. *C* and *D*, PSTHs from the same neuron. *E* and *F*, ISI histograms from the same neuron. These neurons are "typical" in that their firing times seem nearly random at all observed firing rates.



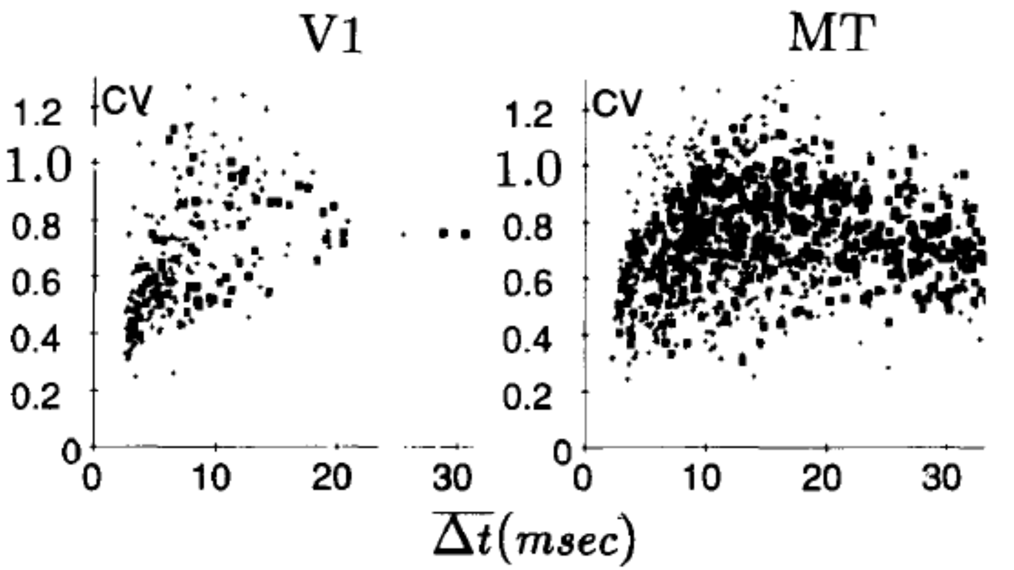


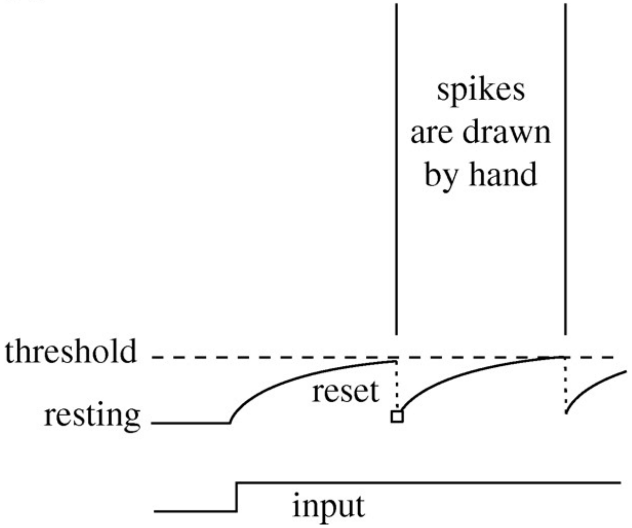
Figure 3. Variability of neurons in areas V1 and MT. C_V characterizes the normalized width of a histogram. The scattered points were obtained from ISI histograms like those in Figure 2 (only points with $\overline{\Delta t} \leq 30$ msec are shown). *Squares* are reliable points ($\sigma_{C_V}/C_V \leq 0.1$); *pluses* are less reliable C_V values. The main systematic bias of the analysis method was to underestimate C_V for large ISIs ($\overline{\Delta t} \geq 20$ msec). The slightly higher firing rates of the V1 neurons resulted from the choice of such faster neurons for analysis; no other differences are apparent between the two areas.

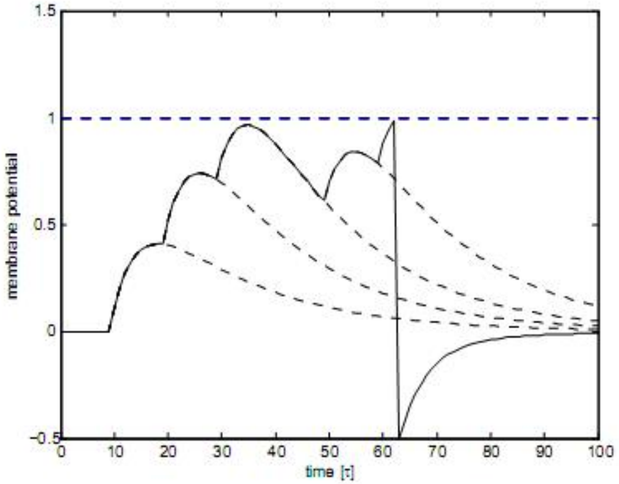
Problem:

Standard integrate and fire (I&F) neuron cannot produce high variability.

Instead they tend to regularize firing output!

(*a*)





$$\tau_m \frac{dV}{dt} = E_L - V + R_m I_e$$

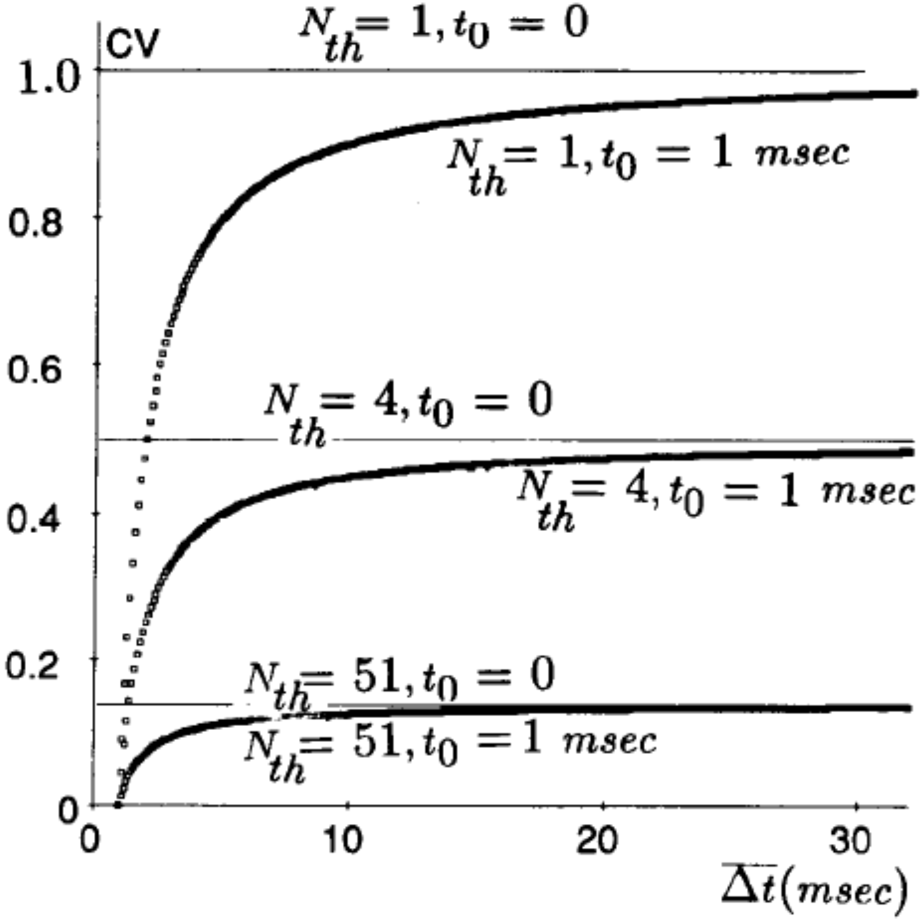


Figure 6. Comparison of C_V from integrator models. *Straight lines* represent predictions of C_V for a neuronal integrator that fires after receiving N_{th} randomly timed input impulses. The *curves* show C_V for such a model, modified to account for an absolute refractory period t_0 = 1.0 msec (curves computed using a different refractory period would have a similar shape, always crossing the $\overline{\Delta t}$ axis at t_0). Note that $C_V \leq 1/\sqrt{N_{th}}$ for all models, such that C_V is quite small (output spikes are regular) for large values of N_{th}.

Why does this happen?

Assume we need k- EPSPs to happen to reach threshold and also assume ISI to be much shorter than membrane time constant. If each EPSP arrives from a Piossion process then the resulting ISI will follow Erlang (Gamma) distribution

$$X_i \sim Exp(\lambda) \quad \text{then} \quad \tau = \sum^{k} X_i \sim Erlang(k, \lambda)$$

$$f(x; k, \lambda) = \frac{\lambda^k x^{k-1} e^{-\lambda x}}{(k-1)!} \quad \text{for } x, \lambda \geq 0,$$

$$C_v = \frac{std(\tau)}{E(\tau)} = \frac{\left(\frac{\sqrt[2]{k}}{\lambda}\right)}{\left(\frac{k}{\lambda}\right)} = \frac{1}{\sqrt[2]{k}}$$

The more integration the more regular it becomes

How can we then have I&F mechanism to produce high variability seen in reality?

Solution:

Getting rid of integration

1) Set number needed to threshold =1

2) Set time constant to be really short compared to ISI

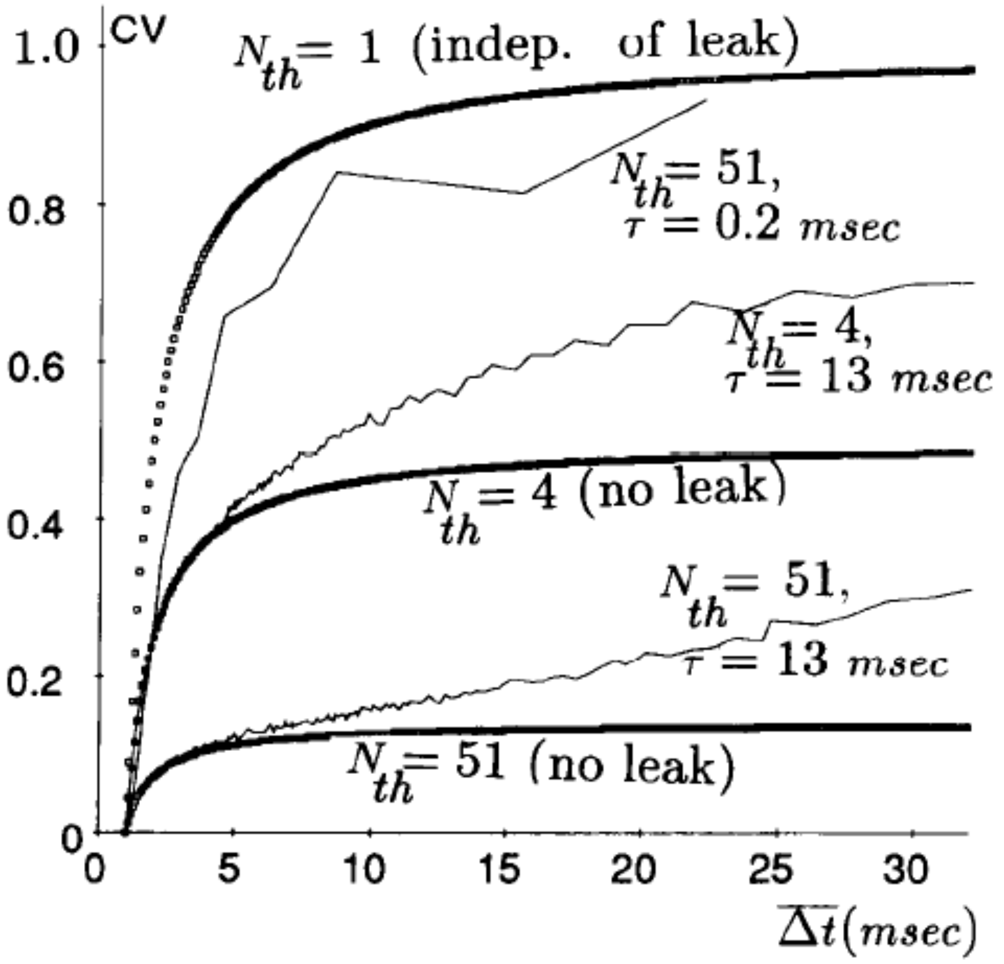


Figure 7. Comparison of leaky and nonleaky integrator models. *Squares* show C_V for the nonleaky integrator model with absolute refractory period $t_0 = 1.0$ msec. *Crooked lines* show simulations of the leaky integrator for three different values of membrane time constant. The leak term has no effect on C_V for the $N_{th} = 1$ integrator, but raises C_V if $N_{th} > 1$. Only for small values of τ ($\ll \overline{\Delta t}$) does C_V approach unity.

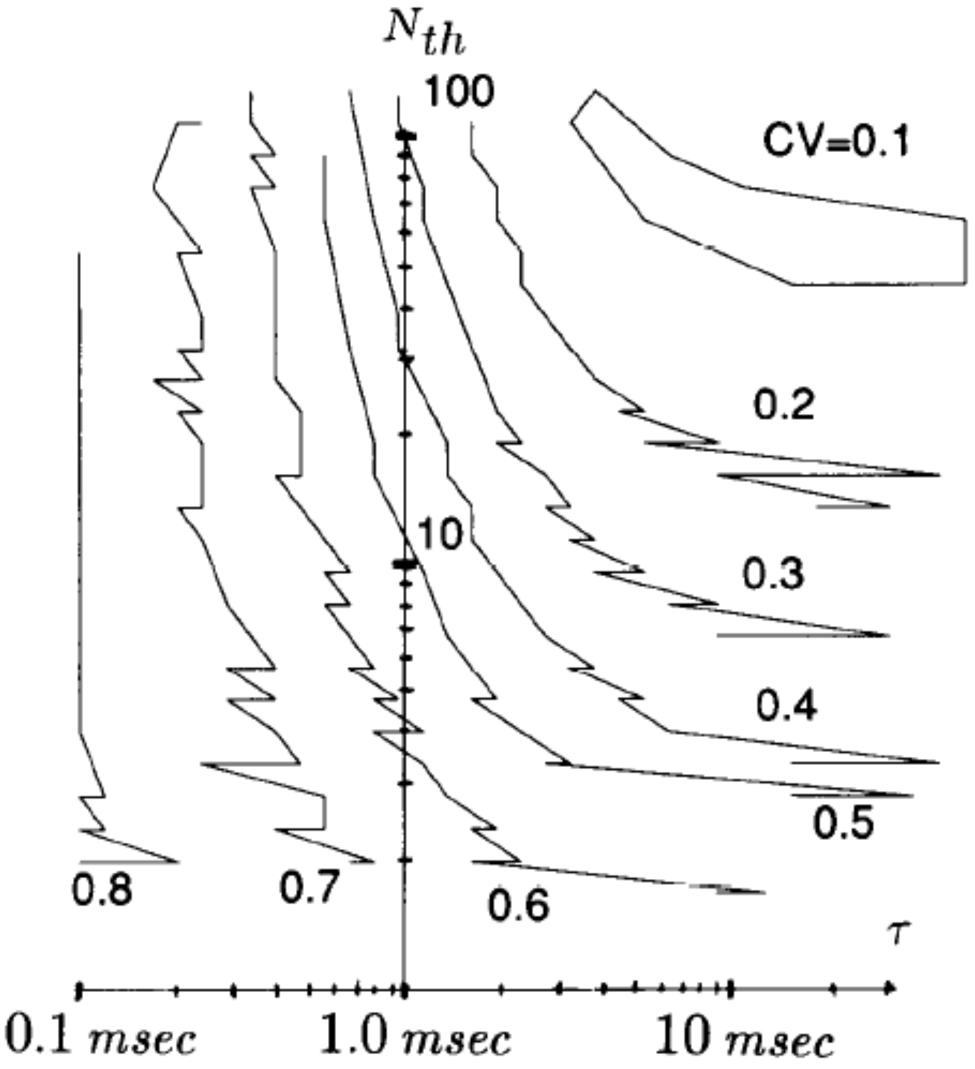


Figure 8. Contour plot of C_V for leaky integrator. Simulations of the leaky integrator model for discrete values of τ and N_{th} (with refractory period t_0 = 1.0 msec) give the C_V values shown when the mean output ISI is $\overline{\Delta t}$ = 5 msec (corresponding to a mean firing rate of 200 Hz). The *jagged contours* result from simulating N_{th} and τ at discrete values. Accepted biological parameters (e.g., $N_{th} > 10$, $\tau > 5$ msec) predict low C_V values (*upper right region*); the C_V values observed in monkey would require either $N_{th} < 3$ or $\tau < 1$ msec (*lower left region*).

Paper in focus: Softkey and Koch 1993

The authors suggest the second mechanism maybe at work for example due to nonlinearities for EPSP summation thus reducing the effective time constant to such low values.

For such a neuron to fire it need **CO-INCIDENT** input from multiple sources.

Thus the timing of spikes must be very important Arguing for temporal code vs rate code.

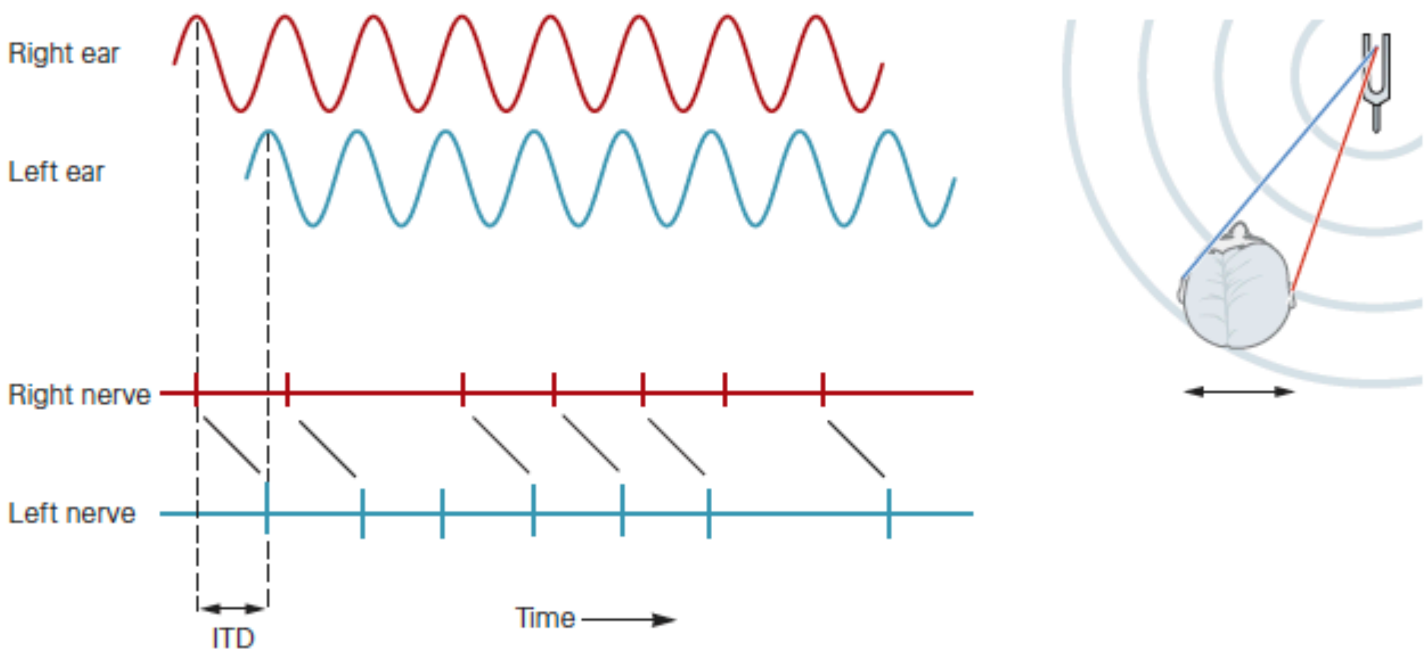
Review:

Rate code: Information is mainly encoded in the average firing rate and exact timing of spikes do not matter

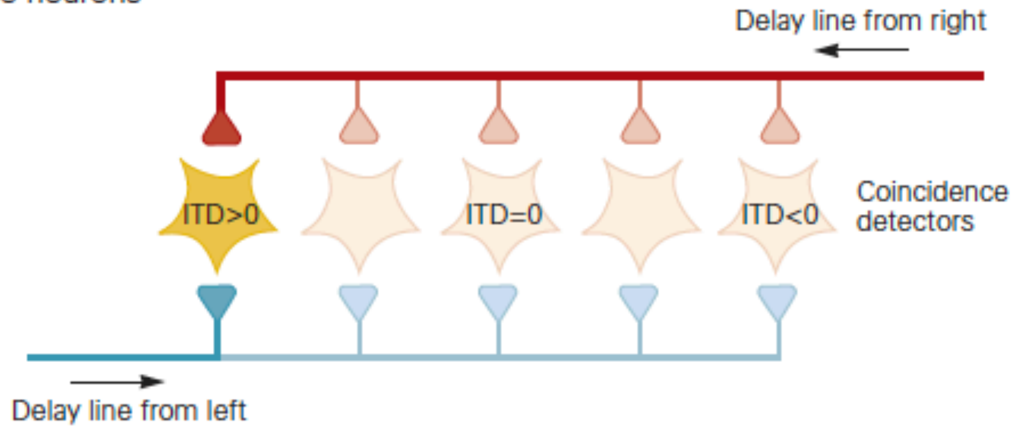
Temporal code: Exact timing of spikes matter. The jitter in timing is not noise but capacity to encode more information by each neuron

Temporal code example: Coincidence detector

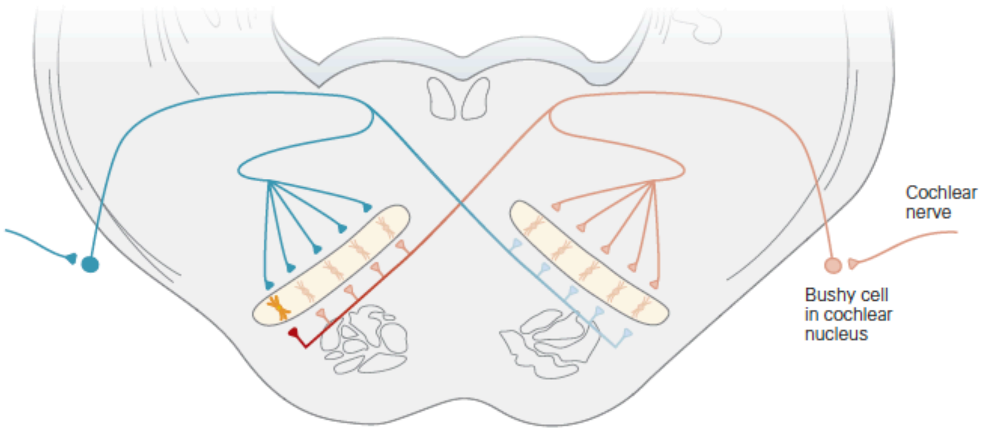
A Phase-locked firing in bushy cells



B Mapping of ITD onto array of neuronal coincidence neurons

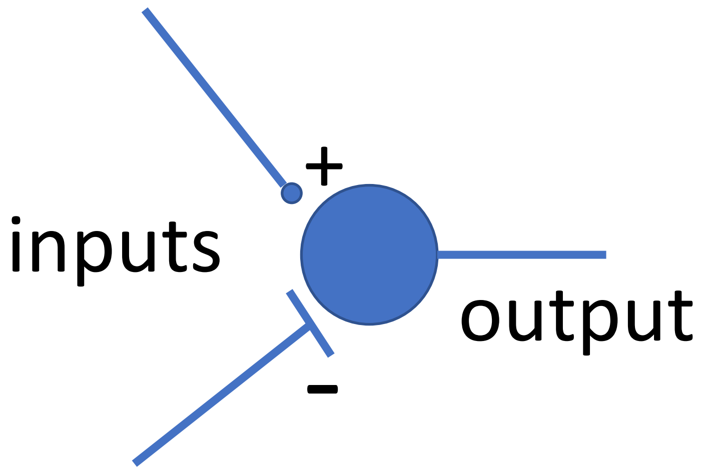


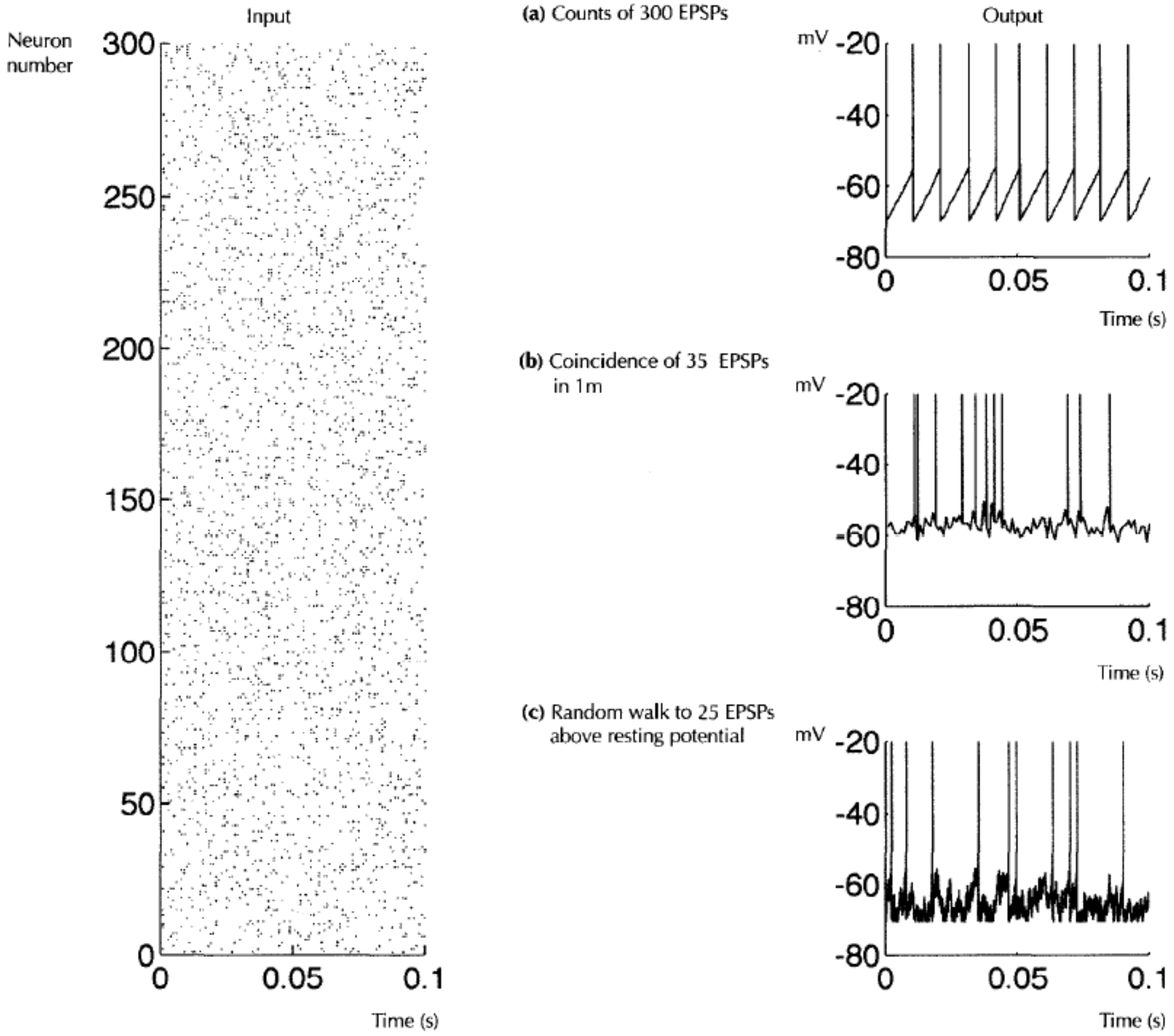
C Bilateral medial superior olivary nuclei



Paper in focus: Shadlen & Newsome 1994

Softky and Koch are wrong. A simple integrator model can create high variability. You just need to add inhibitory input -> IPSP





This resembles a drift diffusion process which can create high variability in ISIs

$$X_0 = 0$$
$$X_t = \nu t + \sigma W_t$$

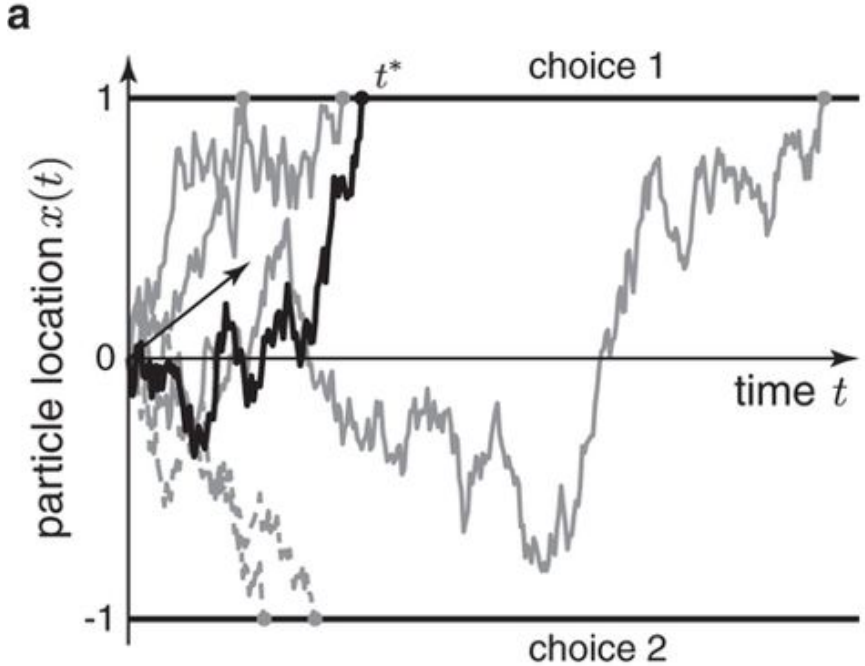
(where W_t is a standard Brownian motion and $\nu > 0$) is a Brownian motion with drift ν.

Then the first passage time for a fixed level $\alpha > 0$ by X_t is distributed according to an inverse-Gaussian:

$$T_\alpha = \inf\{t > 0 \mid X_t = \alpha\} \sim \mathrm{IG}\left(\frac{\alpha}{\nu}, \frac{\alpha^2}{\sigma^2}\right).$$

$$C_v = \frac{std(T_\alpha)}{E(T_\alpha)} = \frac{\left(\frac{\sqrt[2]{\alpha}}{\sqrt[2]{\nu^3}}\right)\sigma}{\left(\frac{\alpha}{\nu}\right)} = \frac{1}{\sqrt[2]{\nu\alpha}}\,\sigma$$

Can easily make $C_v > 1$



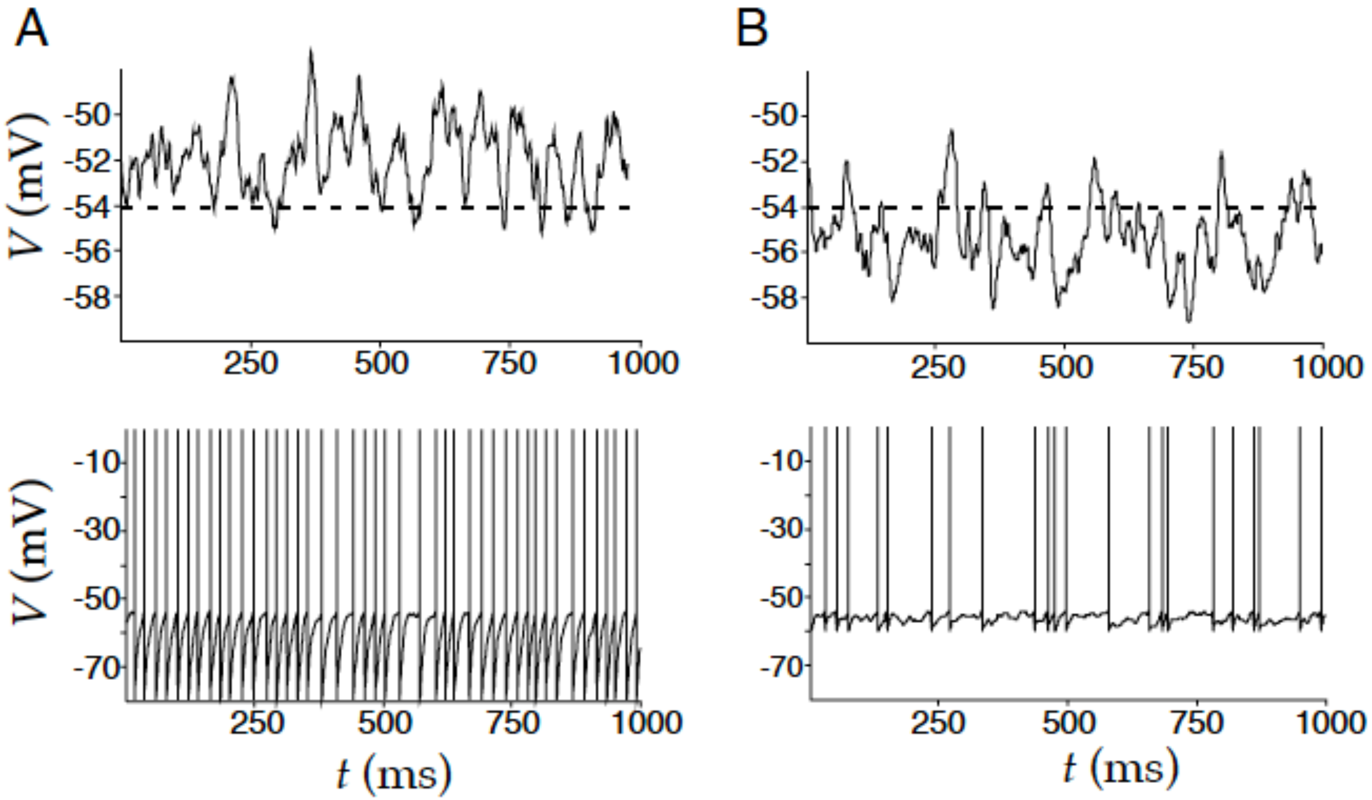


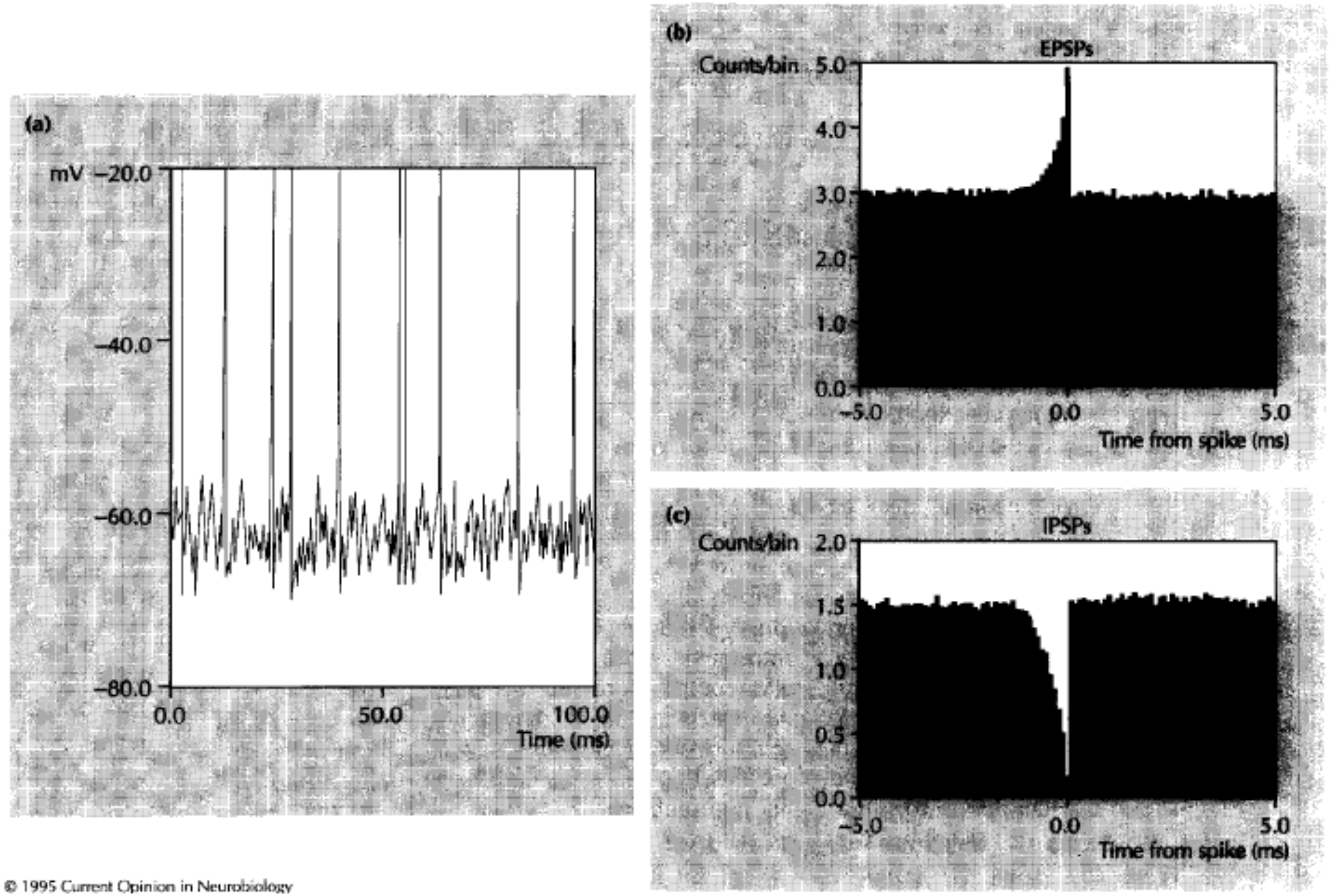
Figure 5.21: The regular and irregular firing modes of an integrate-and-fire model neuron. A) The regular firing mode. Upper panel: The membrane potential of the model neuron when the spike generation mechanism is turned off. The average membrane potential is above the spiking threshold (dashed line). Lower panel: When the spike generation mechanism is turned on, it produces a regular spiking pattern. B) The irregular firing mode. Upper panel: The membrane potential of the model neuron when the spike generation mechanism is turned off. The average membrane potential is below the spiking threshold (dashed line). Lower panel: When the spike generation mechanism is turned on, it produces an irregular spiking pattern. In order to keep the firing rates from differing too greatly between these two examples, the value of the reset voltage is higher in B than in A.

Dayan and Abbot

Paper in focus: Softky 1995

No Shadlen and Newsome are wrong.

Even the I&F neuron with exitation and inhibition is sensitive to the temporal pattern of spikes

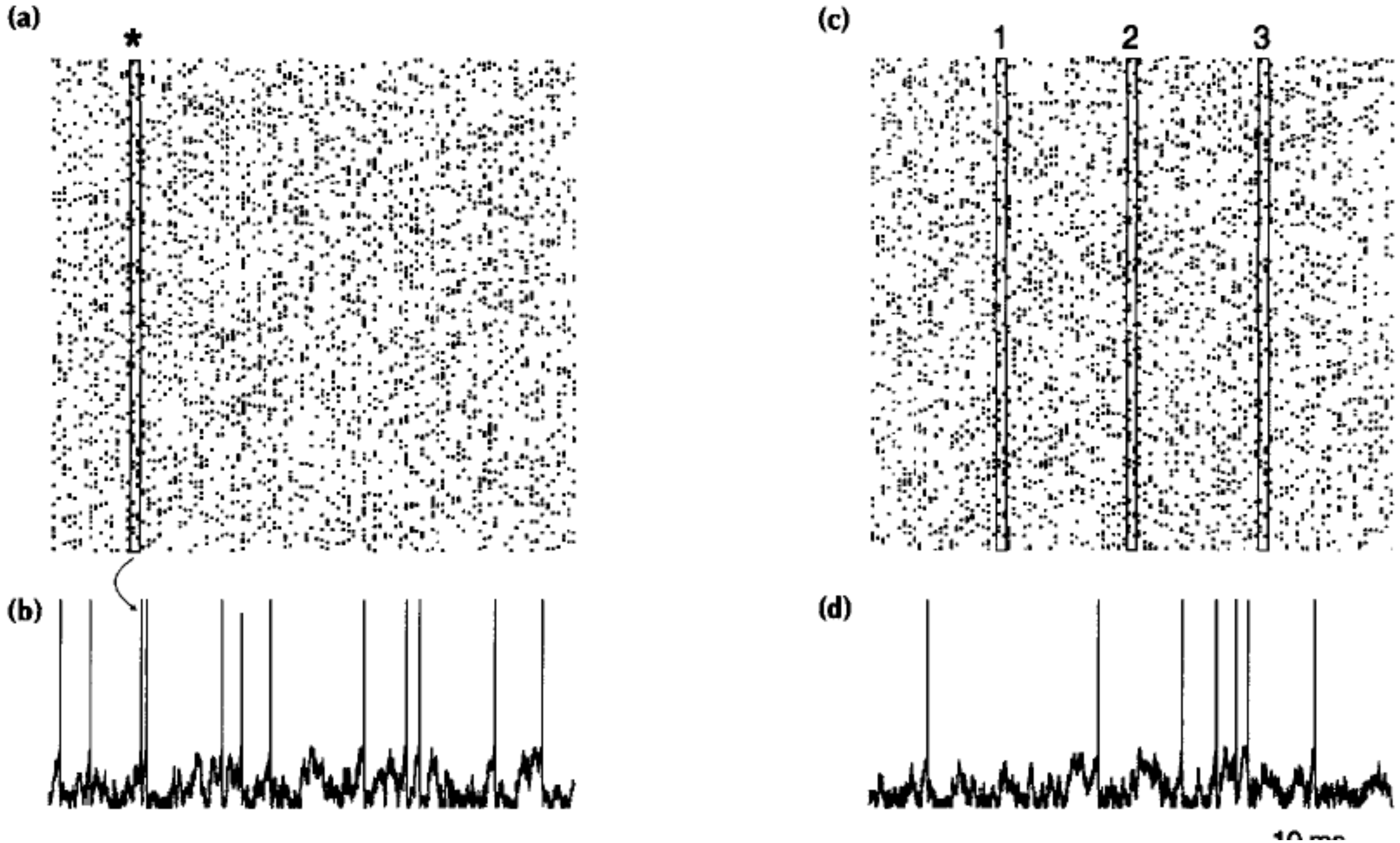


Paper in focus: Shadlen and Newsome 1995

Dear William,

Of course I&F should be sensitive to its inputs how else do you think it should decide to fire?

What you need is to show that neuron is sensitive to temporal pattern of input in short time scale. But for I&F this is not the case.



This is because the efficacy of a pattern depends on the current voltage level (current decision variable in drift diffusion process)

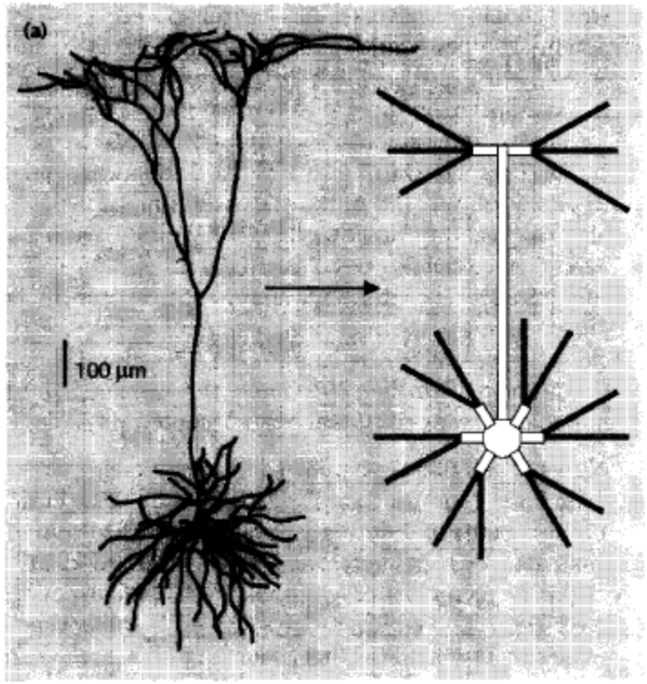
Summary

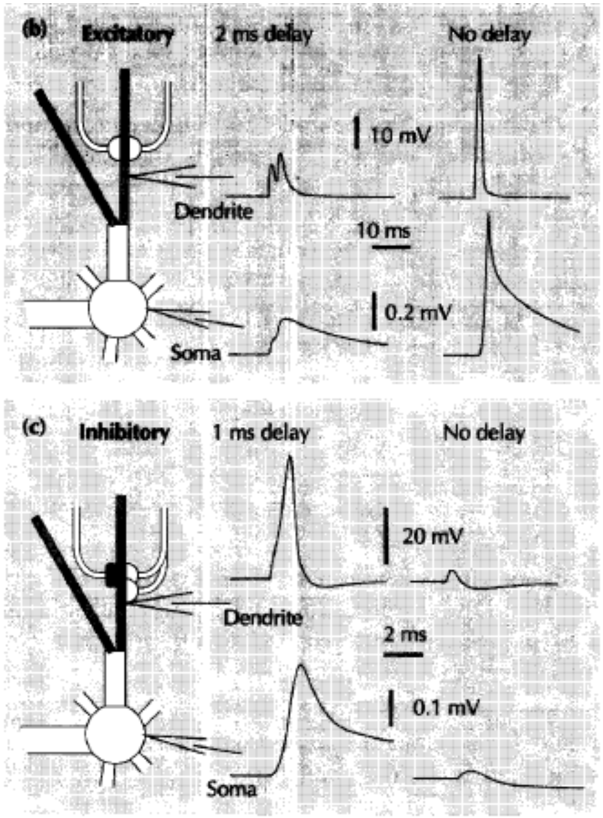
Thus cortical neurons are mostly sensitive to input rate and they themselves do **rate code not temporal code**.

The exact timing of spikes can just be noise.

A combination of excitatory and inhibitory input can account for observed variability in neural firing

But this does not rule out possibility of temporal code





Softky 1995