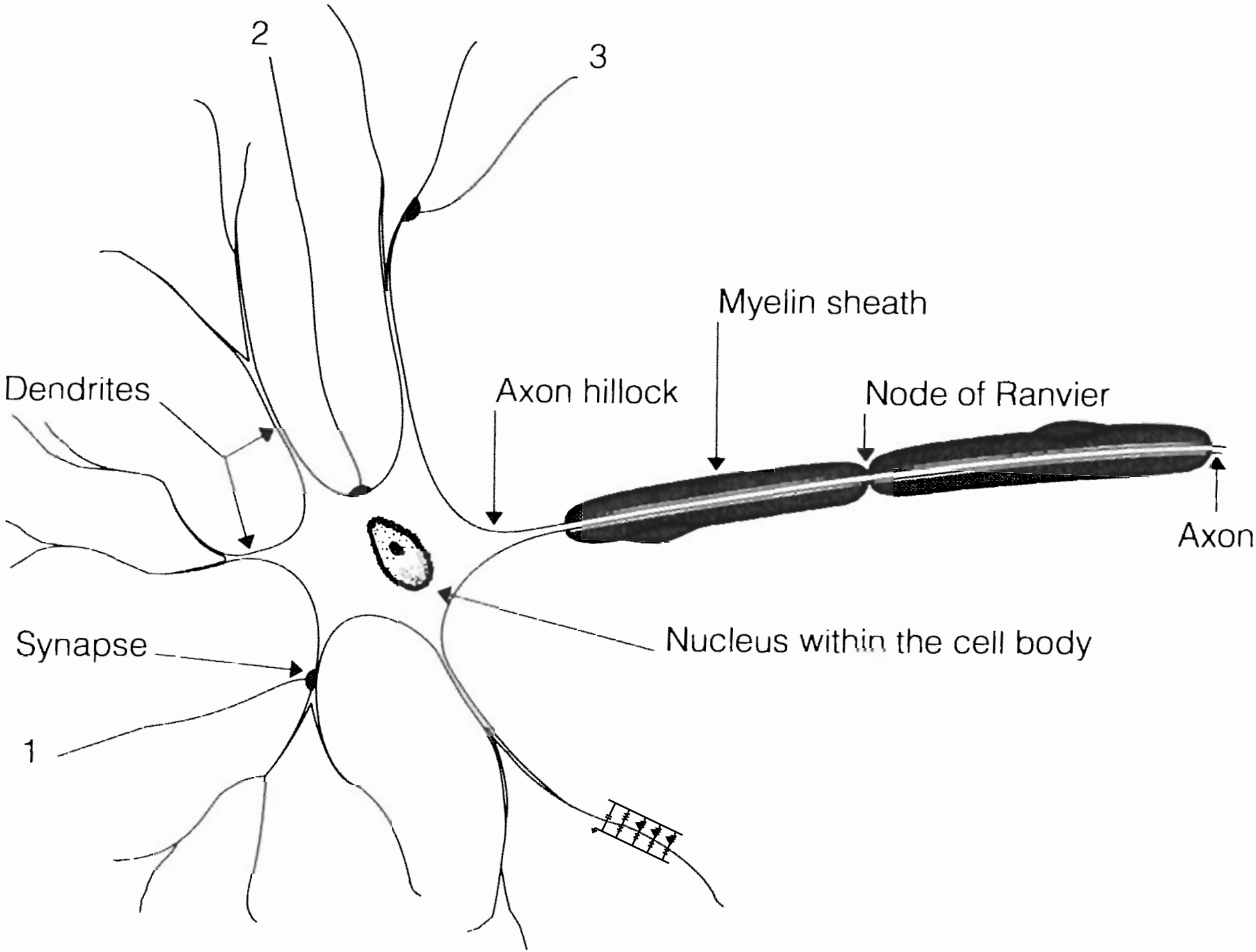
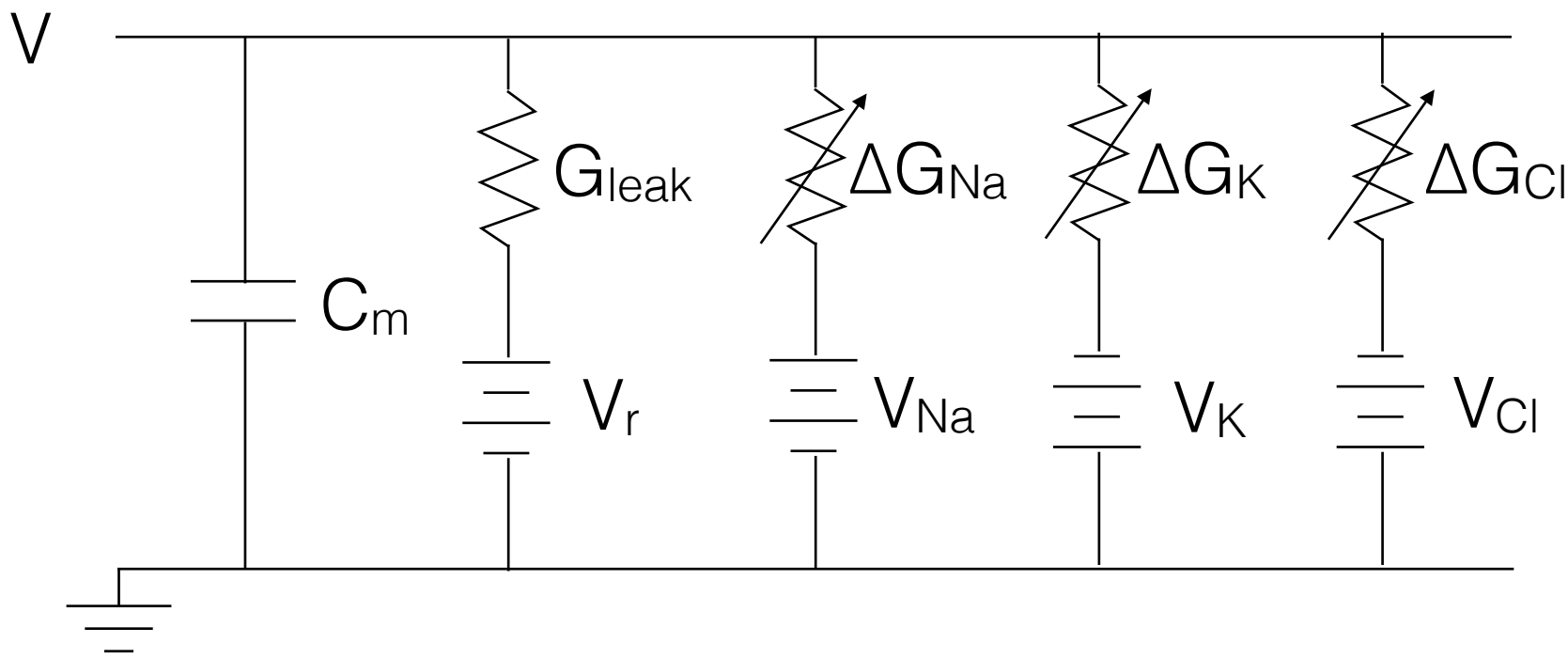
Spikes

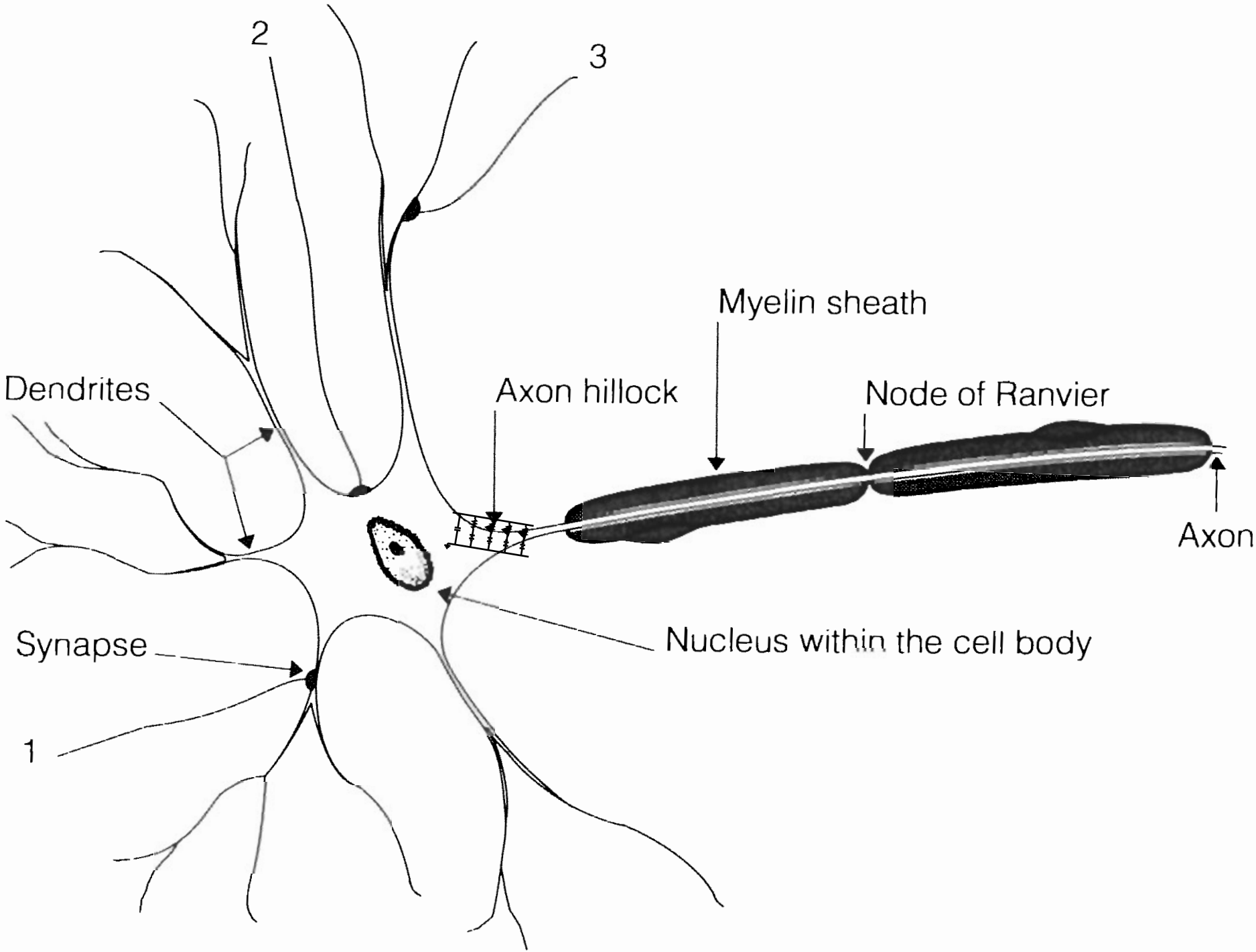

2
3
Myelin sheath
Dendrites
Axon hillock
Node of Ranvier
Axon
Synapse
Nucleus within the cell body
1

Membrane with synaptic inputs

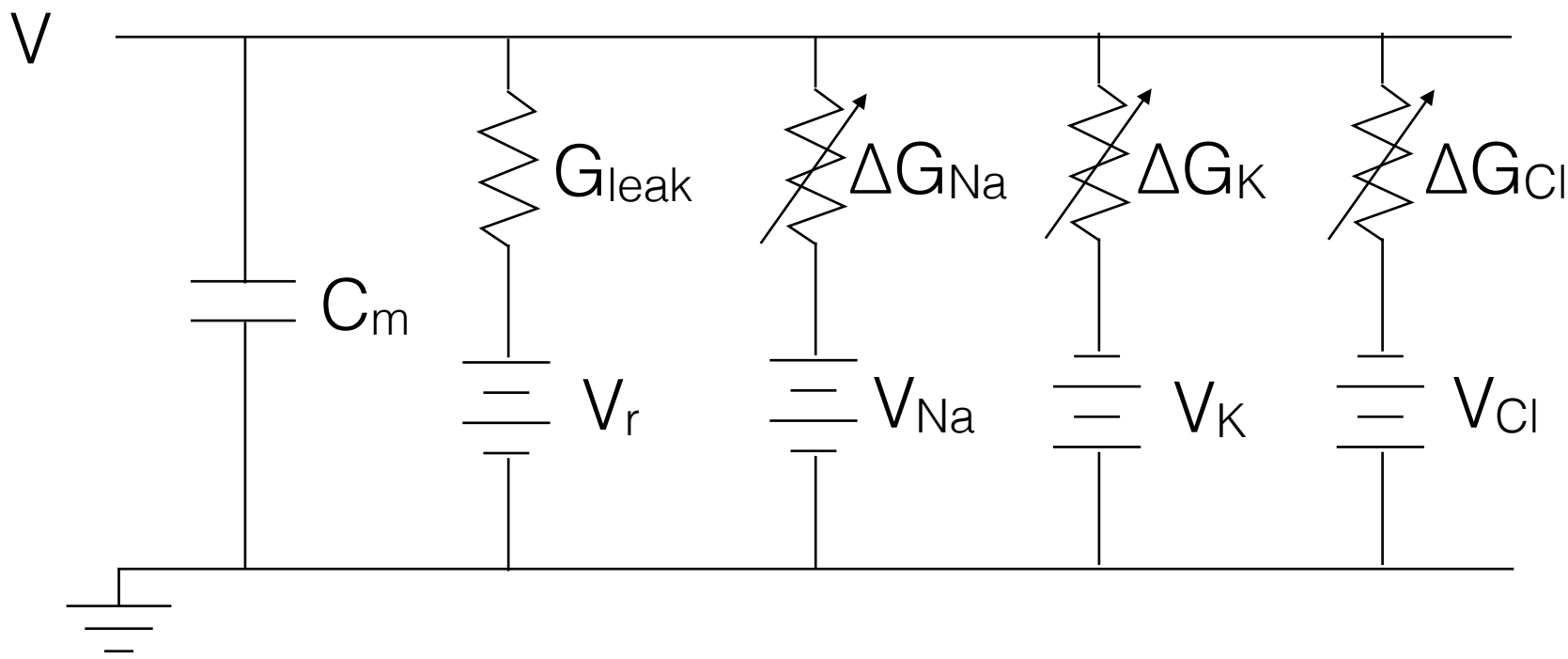


$$\tau \frac{dV}{dt} + V = \frac{V_r\, G_{\text{leak}} + V_{Na}\, \Delta G_{Na} + V_K\, \Delta G_K + V_{Cl}\, \Delta G_{Cl}}{G_{\text{total}}}$$

$$G_{\text{total}} = G_{\text{leak}} + \Delta G_{Na} + \Delta G_K + \Delta G_{Cl} \qquad \tau = \frac{C_m}{G_{\text{total}}}$$


2
3
Myelin sheath
Dendrites
Axon hillock
Node of Ranvier
Axon
Synapse
Nucleus within the cell body
1

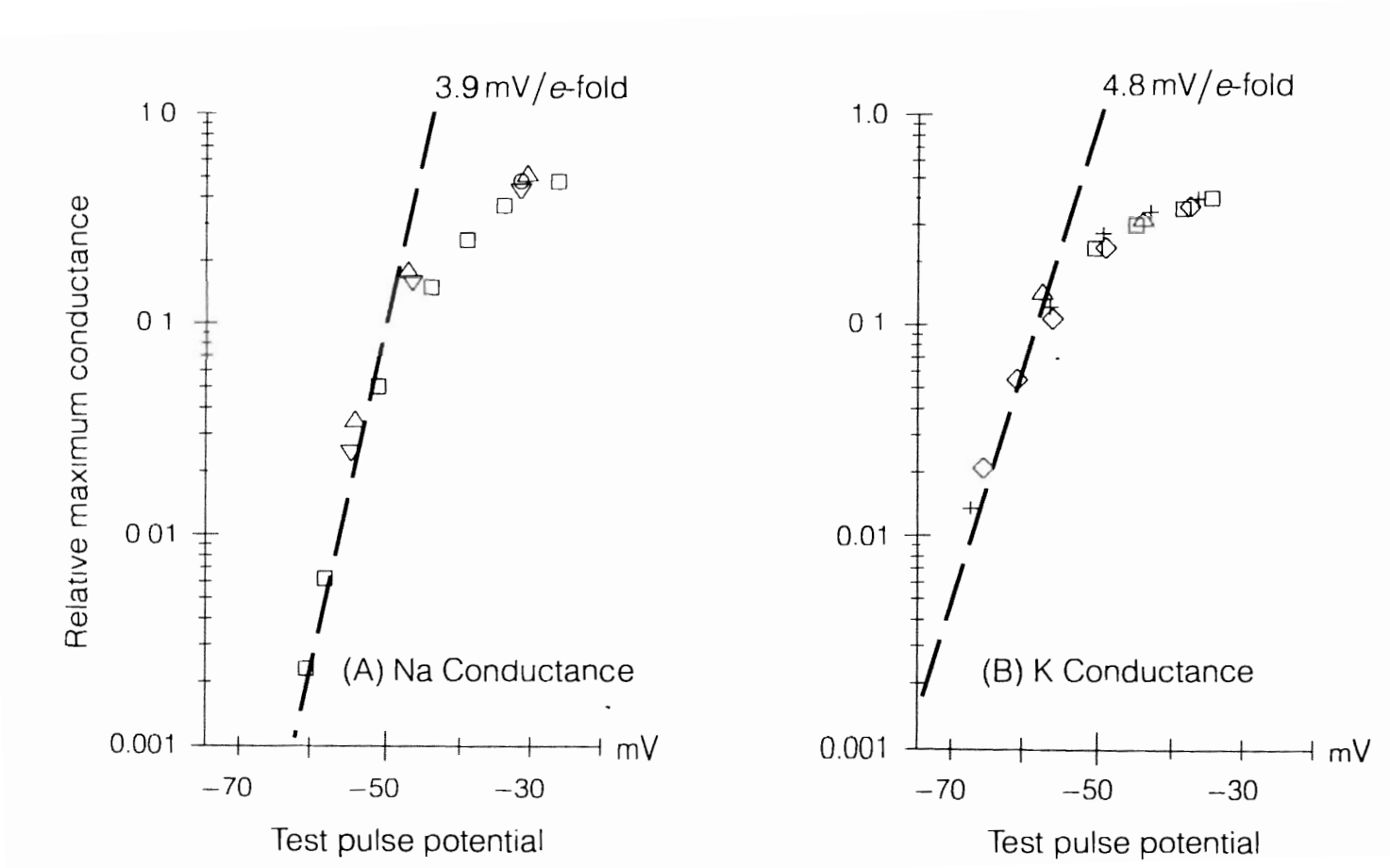
Membrane with synaptic inputs



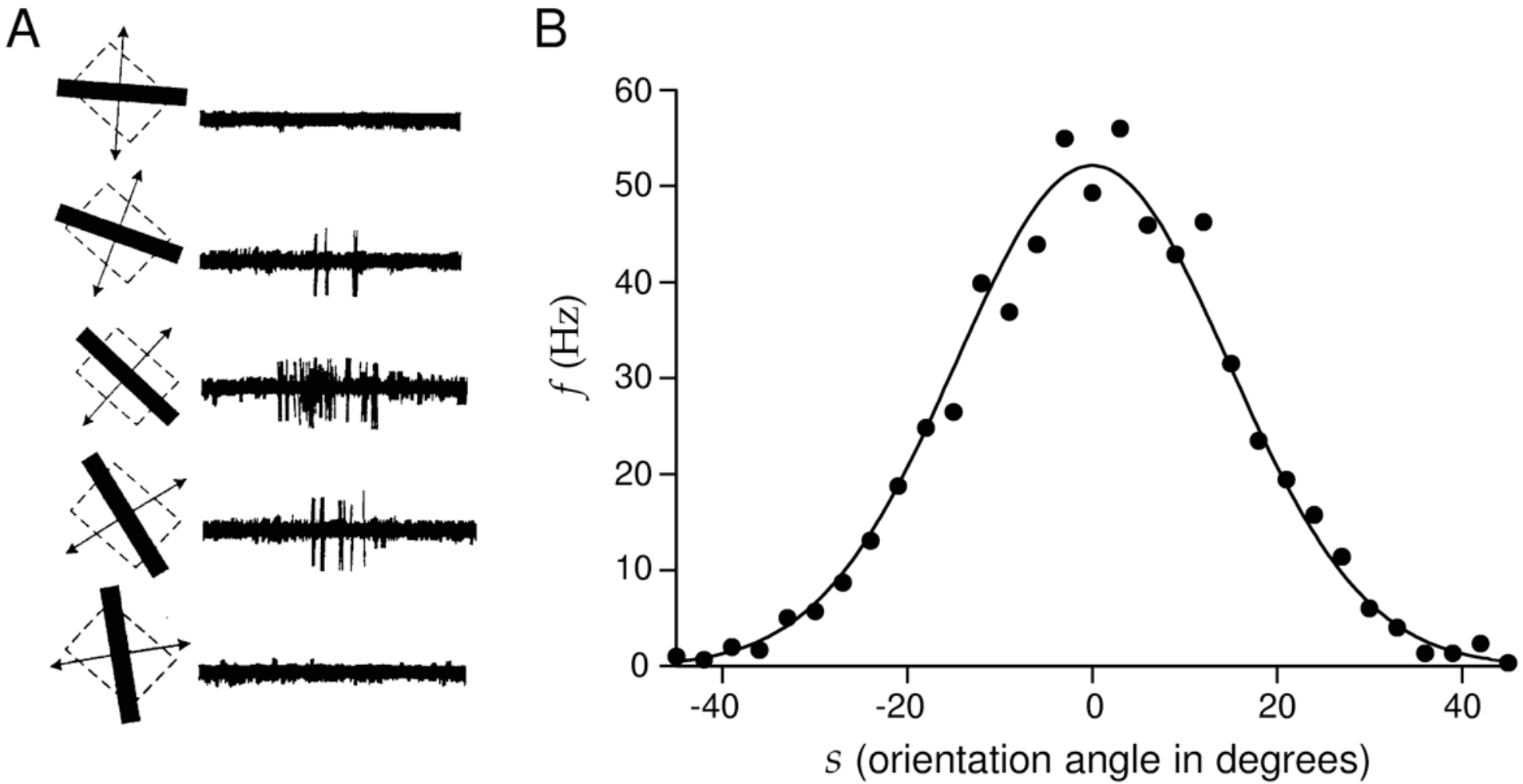
$$\tau \frac{dV}{dt} + V = \frac{V_r\, G_{\text{leak}} + V_{Na}\, \Delta G_{Na} + V_K\, \Delta G_K + V_{Cl}\, \Delta G_{Cl}}{G_{\text{total}}}$$

$$G_{\text{total}} = G_{\text{leak}} + \Delta G_{Na} + \Delta G_K + \Delta G_{Cl} \qquad \tau = \frac{C_m}{G_{\text{total}}}$$

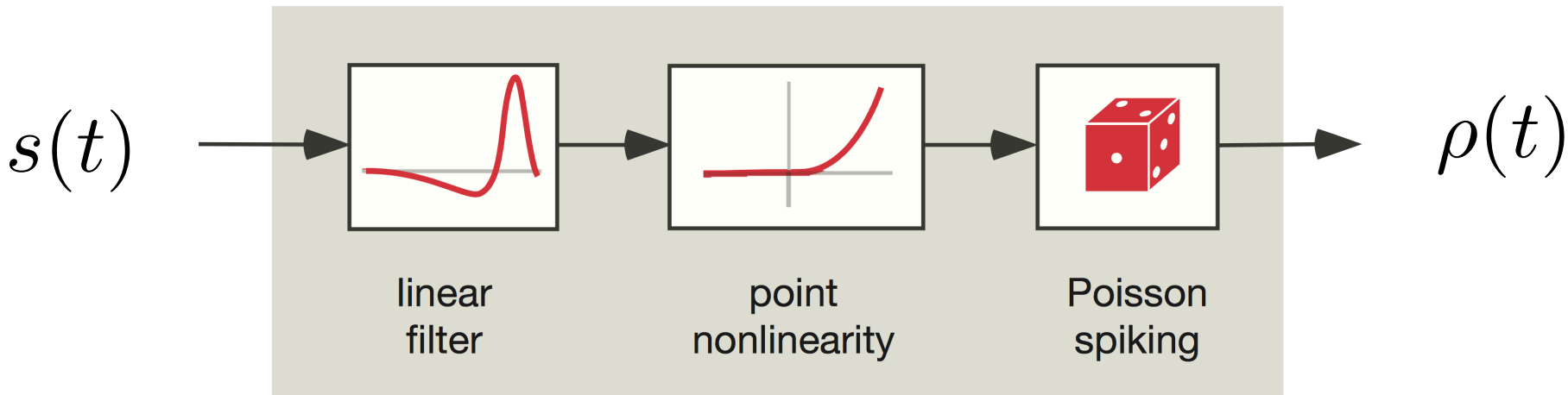
Voltage-gated channels



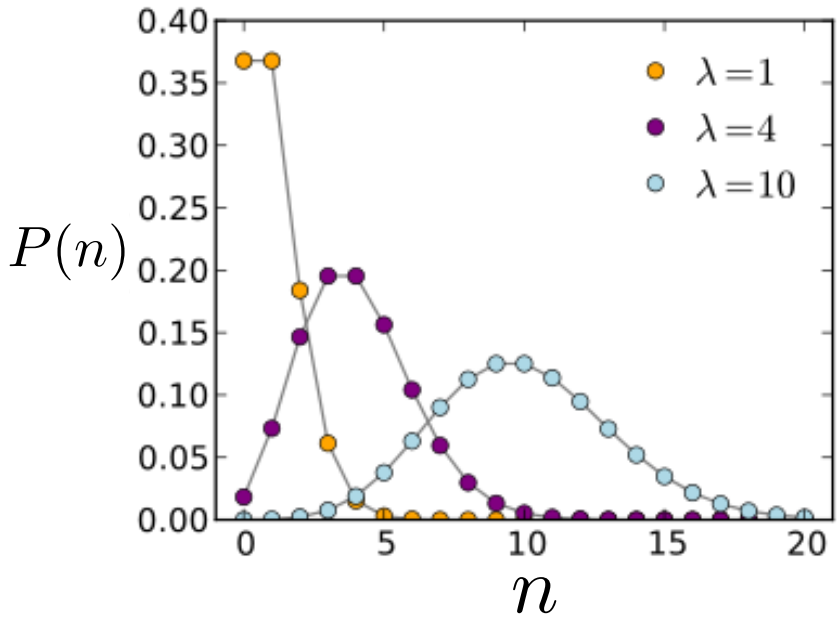
Rate coding hypothesis: the signal conveyed by a neuron is in the *rate* of spiking. Spiking irregularity is largely due to noise and does not convey information.



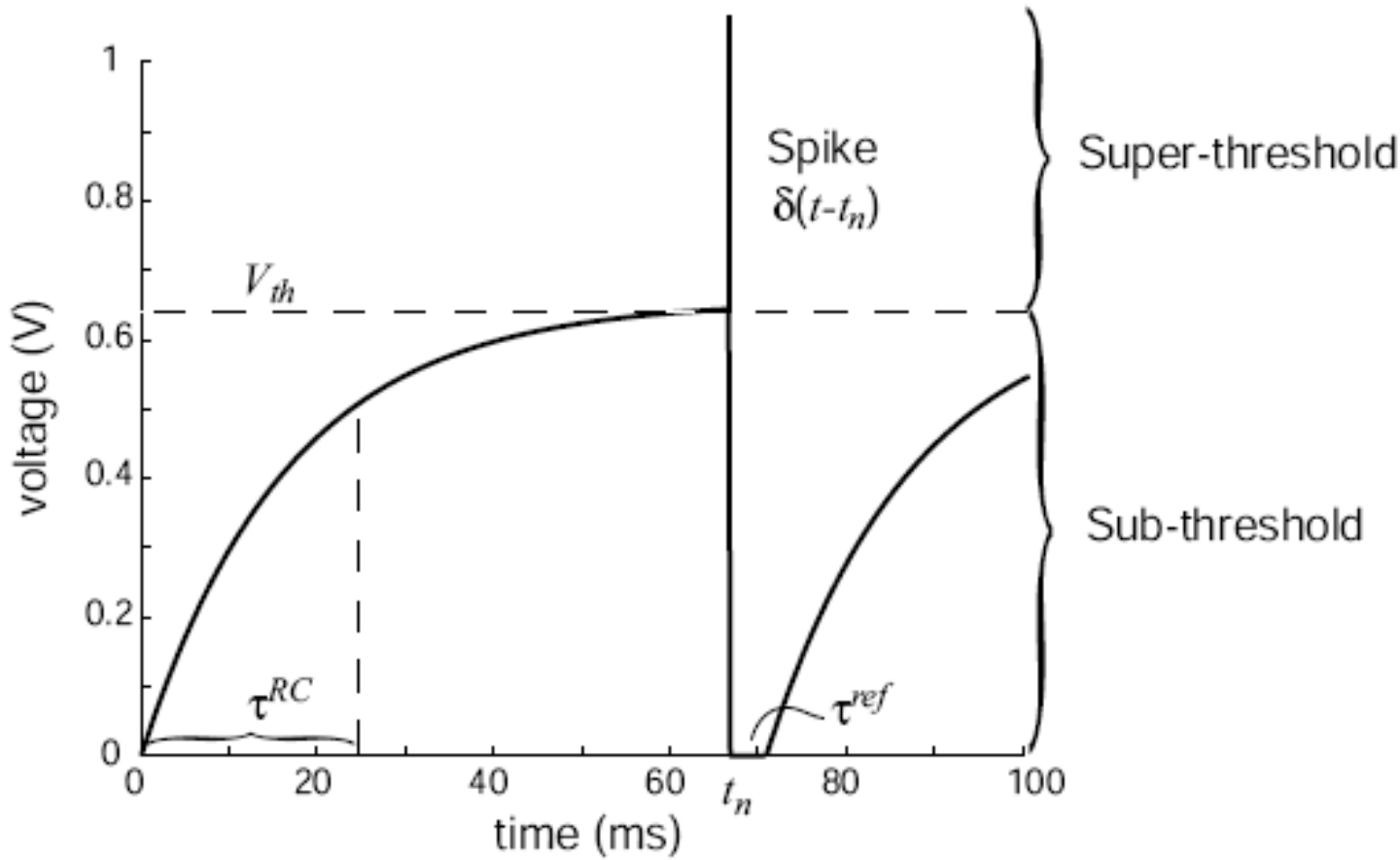
Linear - non-linear - Poisson (LNP) model



$$P(n) = \frac{\lambda^n e^{-\lambda}}{n!}$$

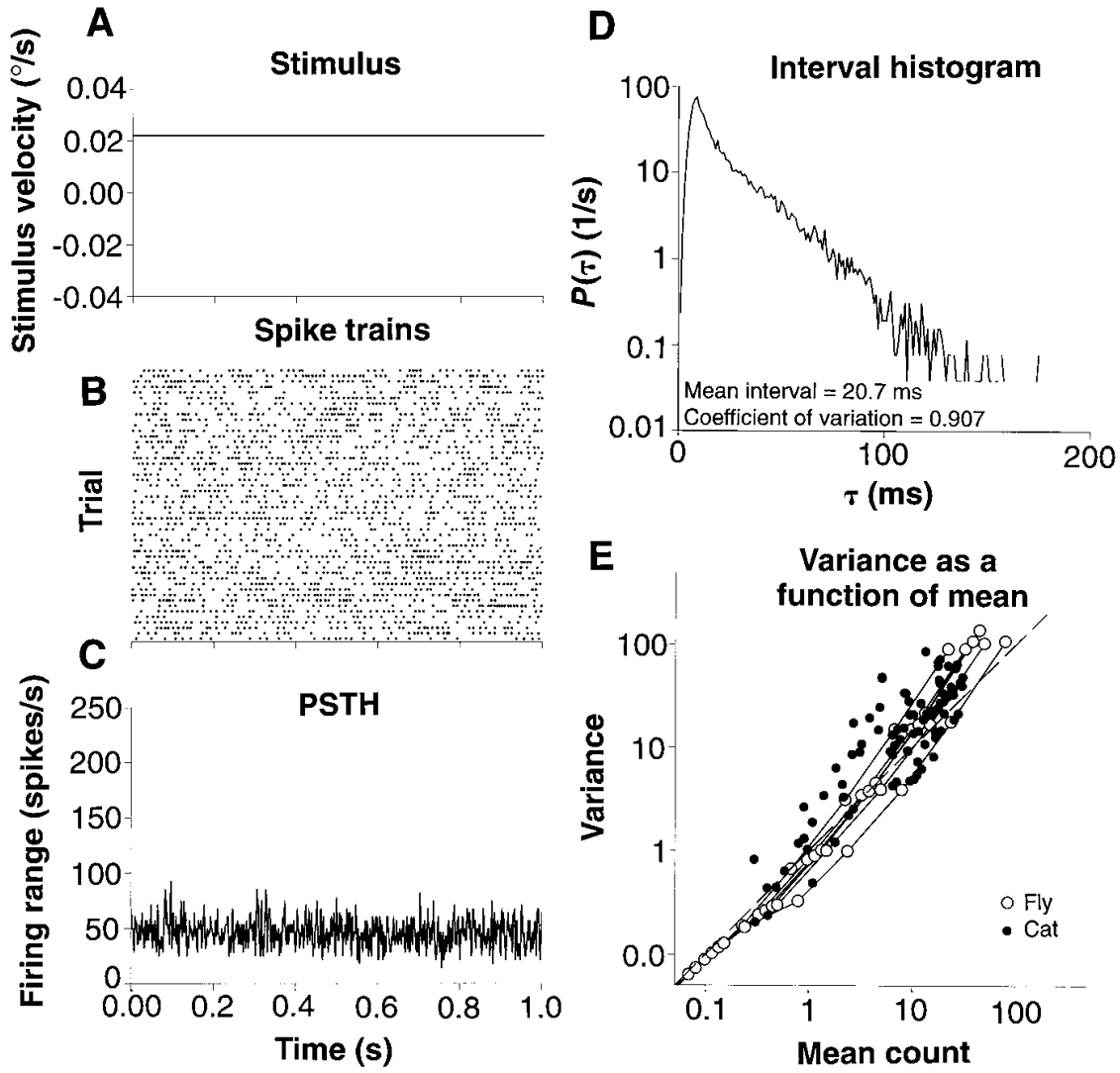


Leaky integrate-and-fire neuron



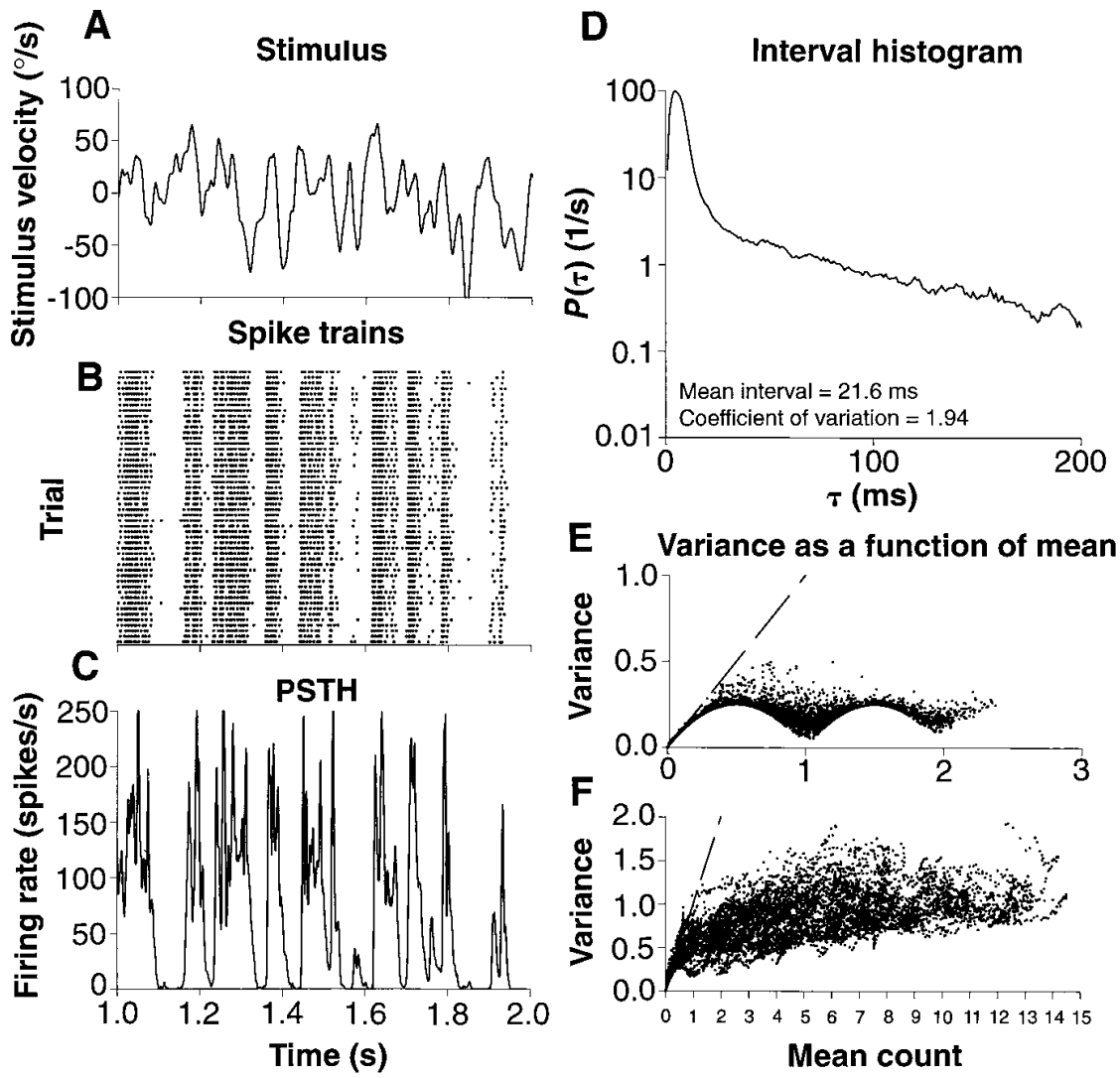
Fly H1 neuron - constant stimulus

(de Ruyter et al., 1997)



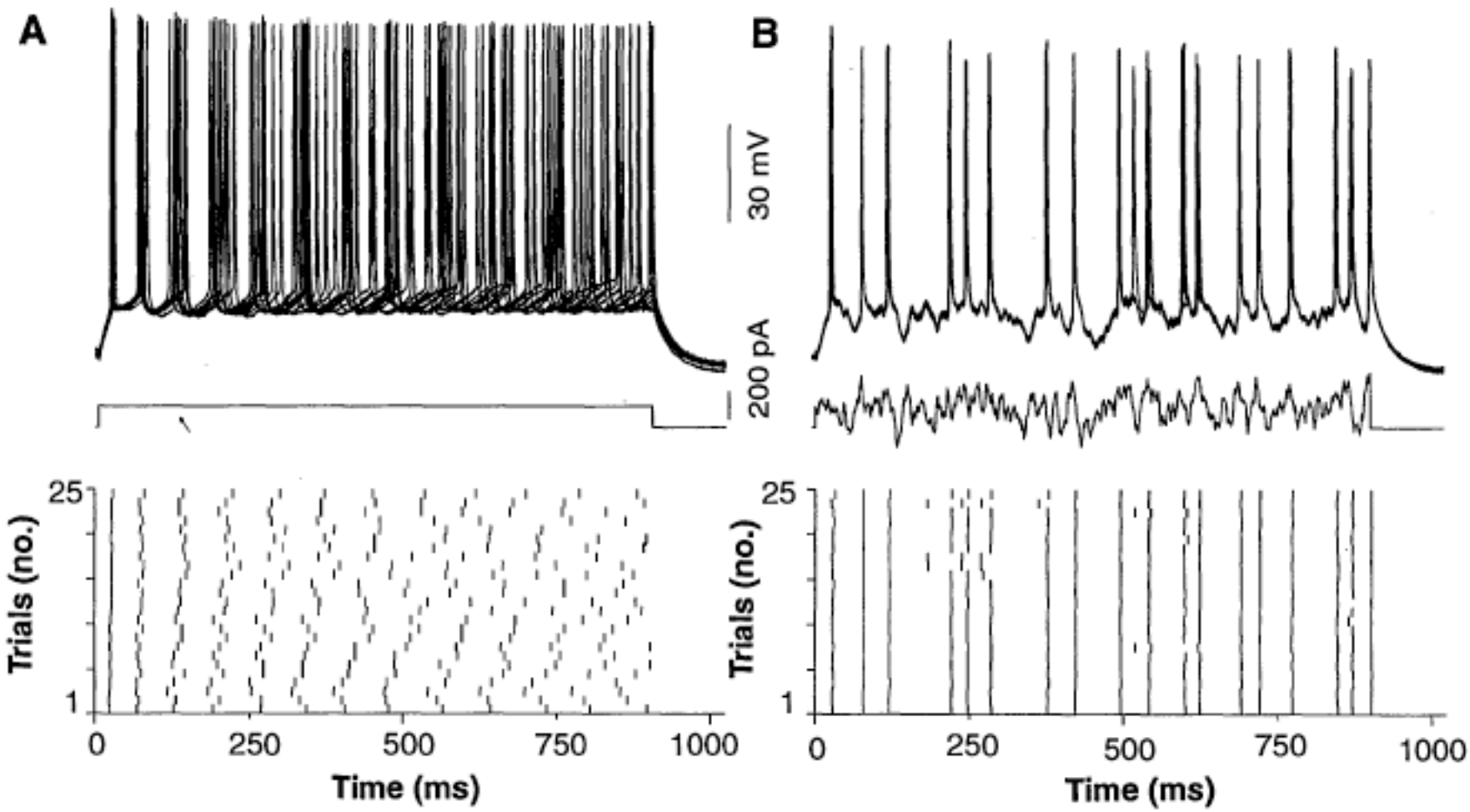
Fly H1 neuron - time-varying stimulus

(de Ruyter et al., 1997)



Spike timing can be very precise in response to *time-varying* signals

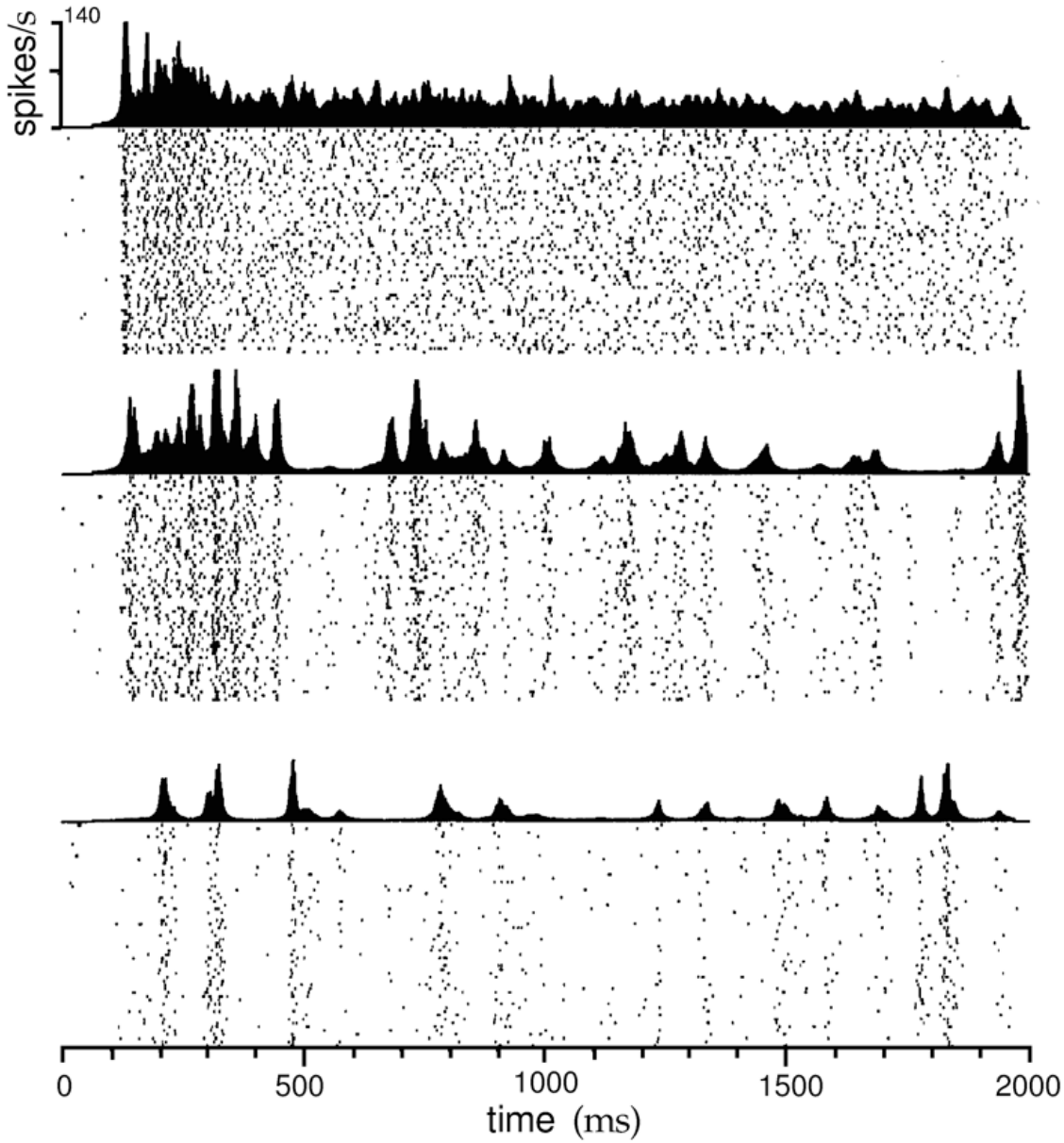
Mainen & Sejnowski (1995)



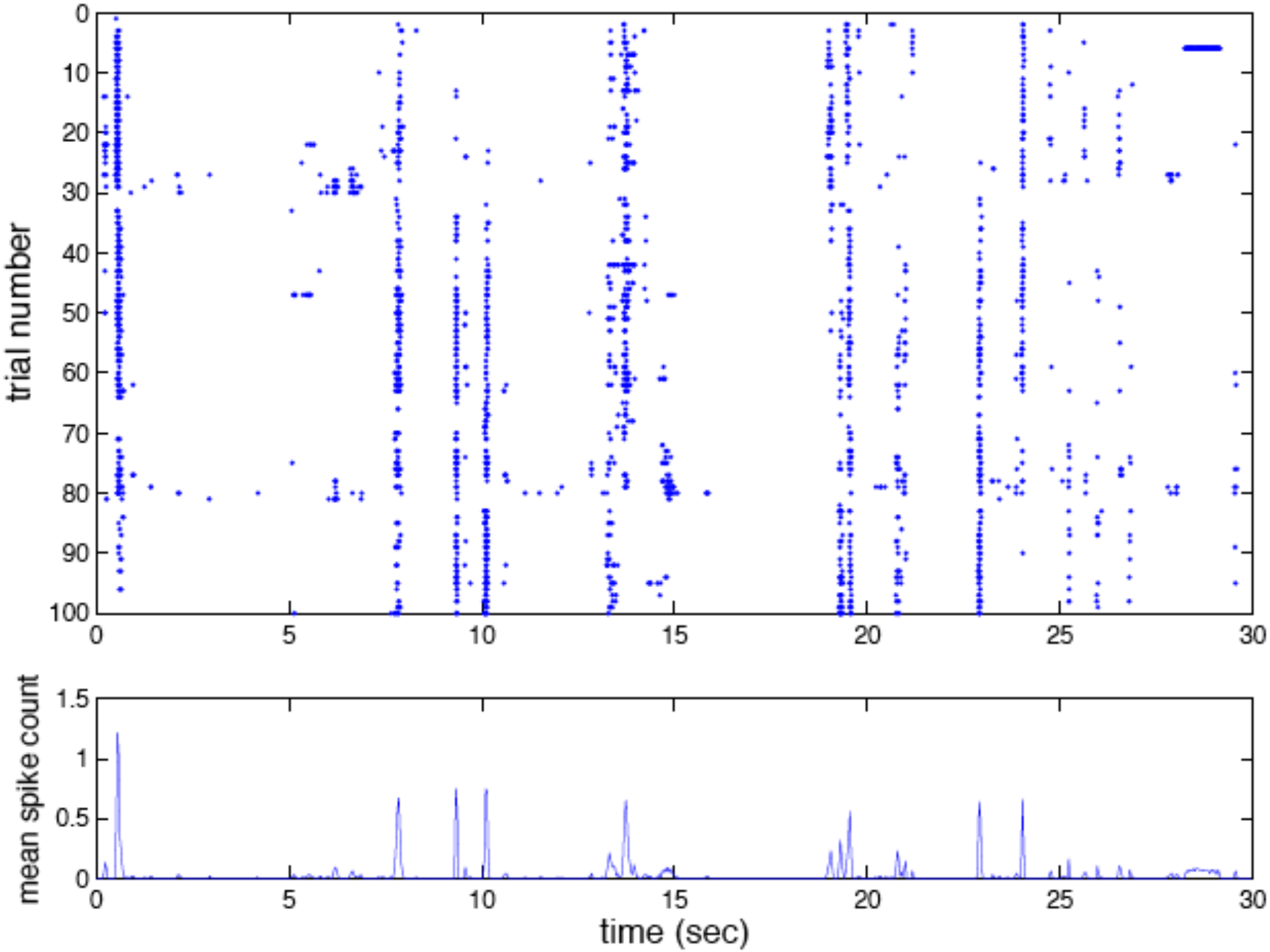
Spike timing can be *very precise* in response to time-varying signals

MT neuron response to stochastic moving dot stimuli at different levels of coherence (Newsom lab)

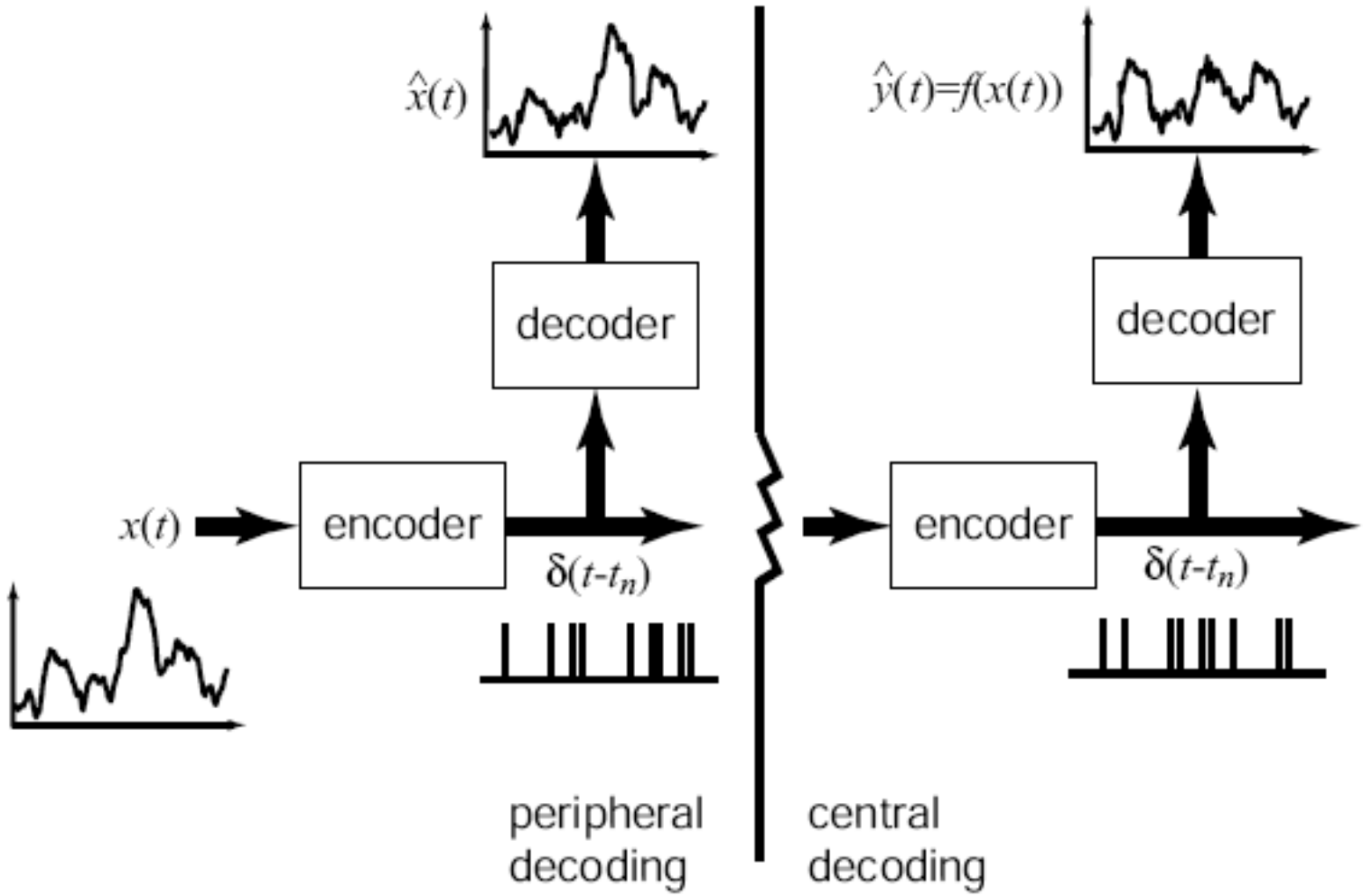
Analysis by Bair & Koch (1996)



Cat V1 - natural movies (J. Baker, S.C. Yen, C.M. Gray, MSU Bozeman)



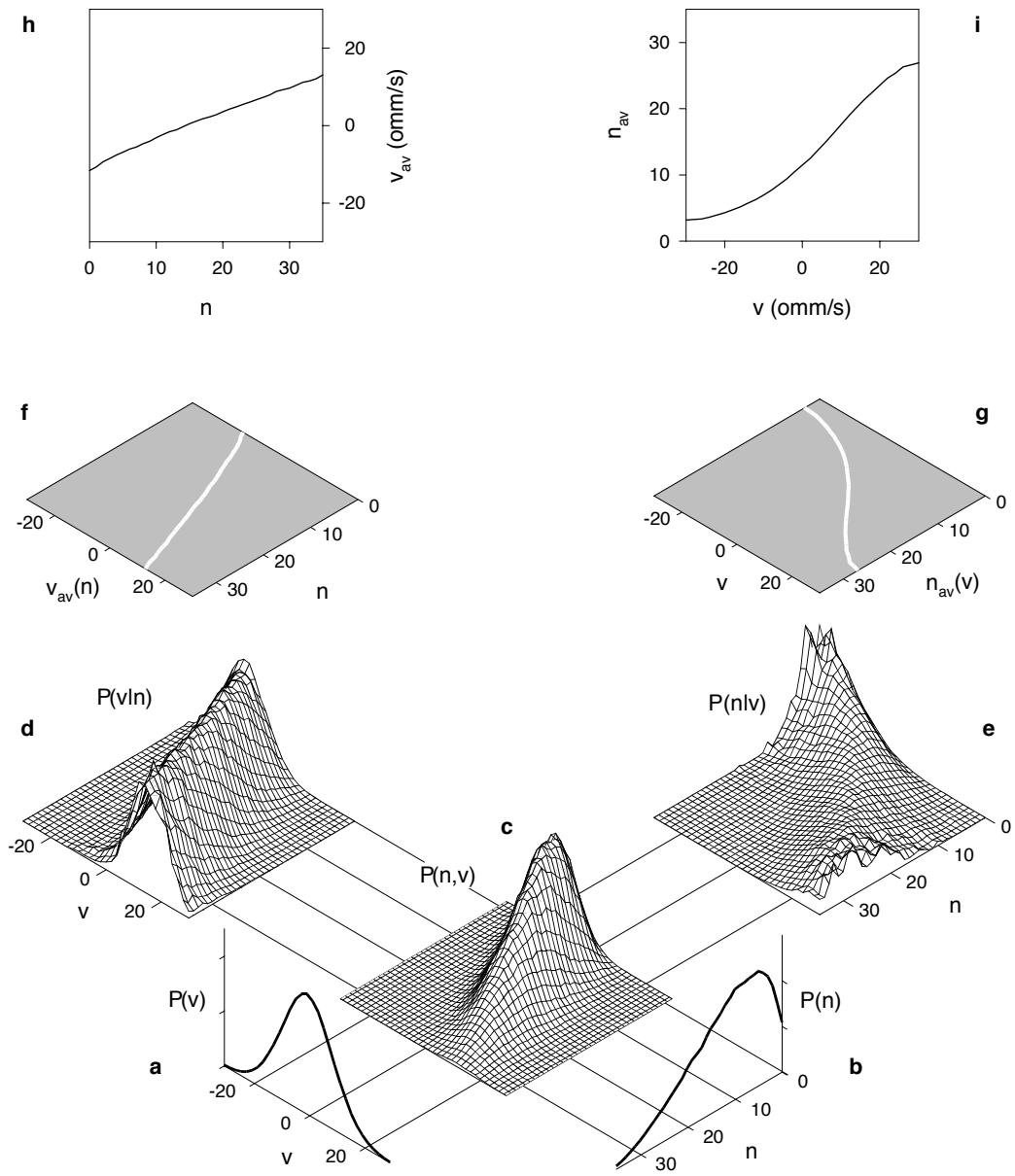
Neural encoding and decoding



Encoding and decoding are related through the joint distribution over *stimulus* and *response*

decoding

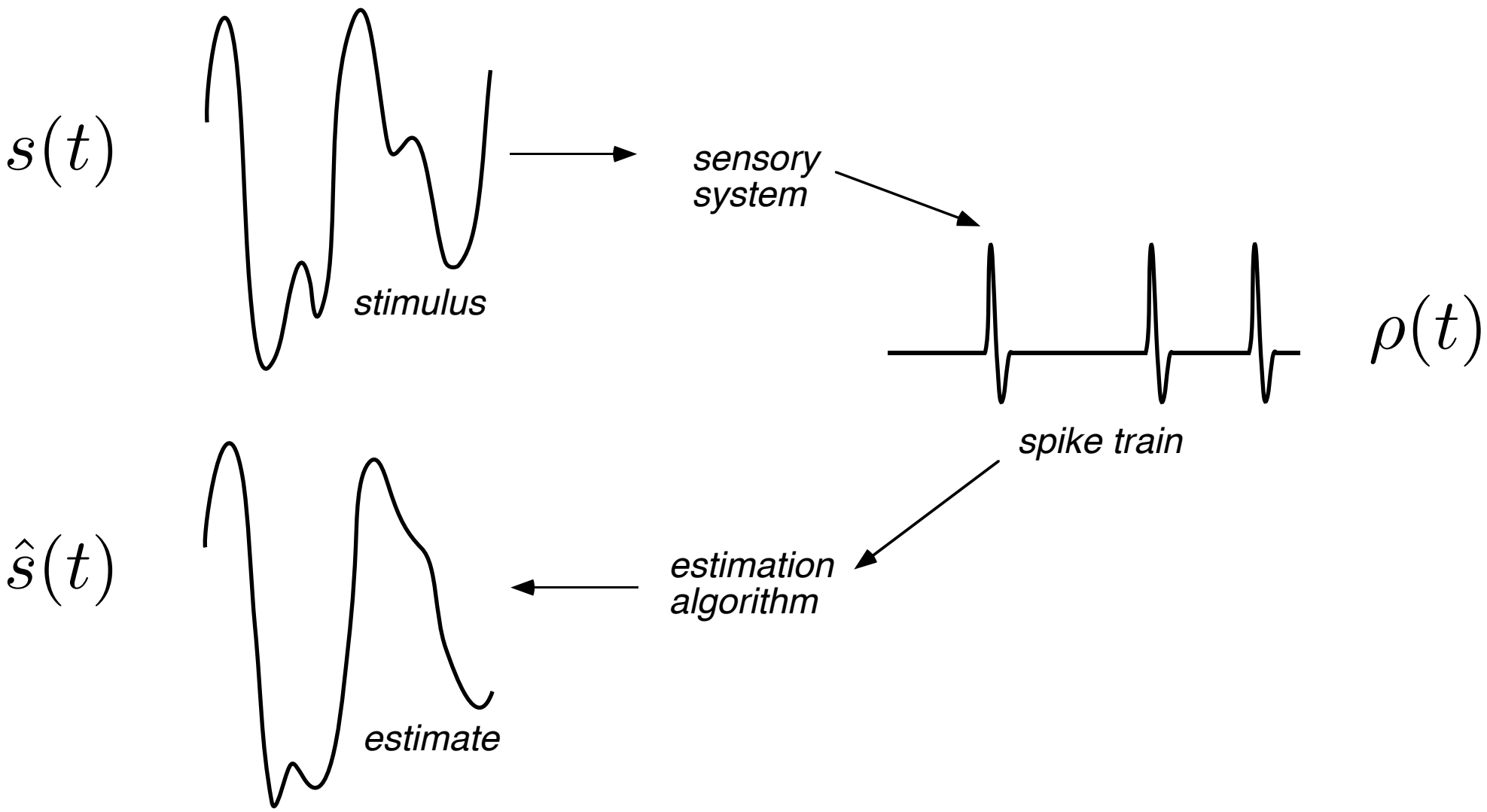
$\hat{v} = g(n)$



encoding

$n = f(v)$

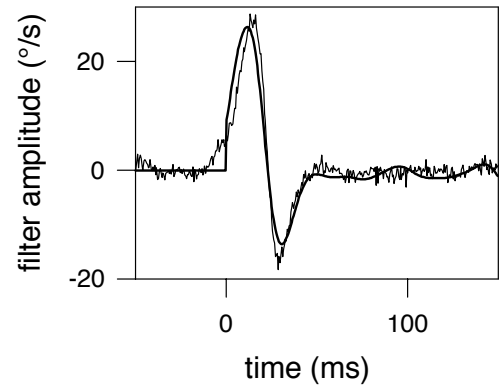
(from *Spikes*)



From *Spikes*, by Rieke, Warland, de Ruyter, & Bialek

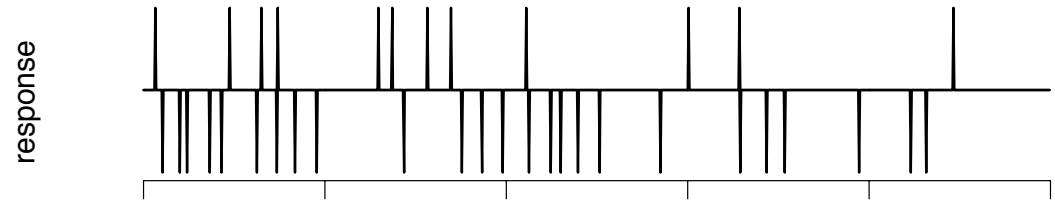
Reconstruction kernel

$k(t)$



Fly H1 neuron response

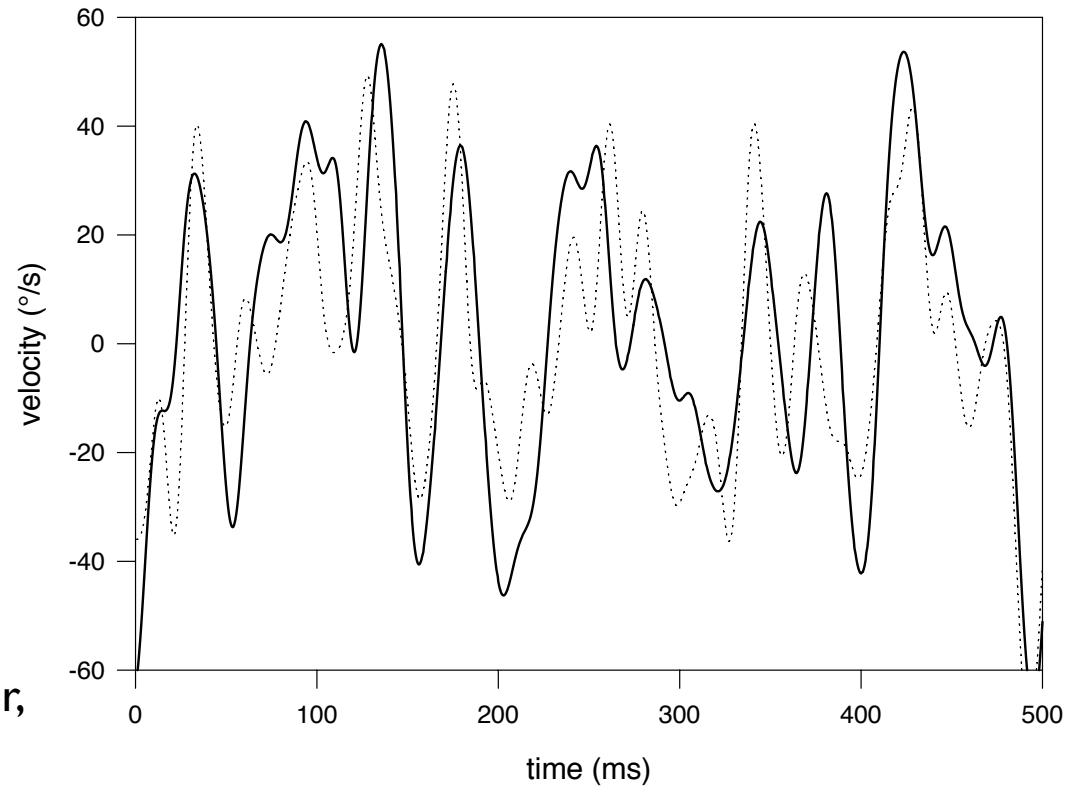
$\rho(t)$



Stimulus reconstruction

$$\hat{s}(t) = \rho(t) * k(t)$$

$$\hat{k}(t) = \arg\min_{k(t)} \left\langle [s(t) - \rho(t) * k(t)]^2 \right\rangle_t$$



From *Spikes*, by Rieke, Warland, de Ruyter, & Bialek

Strategy for estimating information rate

1. Estimate signal from spikes

$$\rho(t) \rightarrow \hat{s}(t)$$

2. Compute noise in estimate

$$\tilde{n}(\omega) = \tilde{s}(\omega) - \hat{\tilde{s}}(\omega)$$

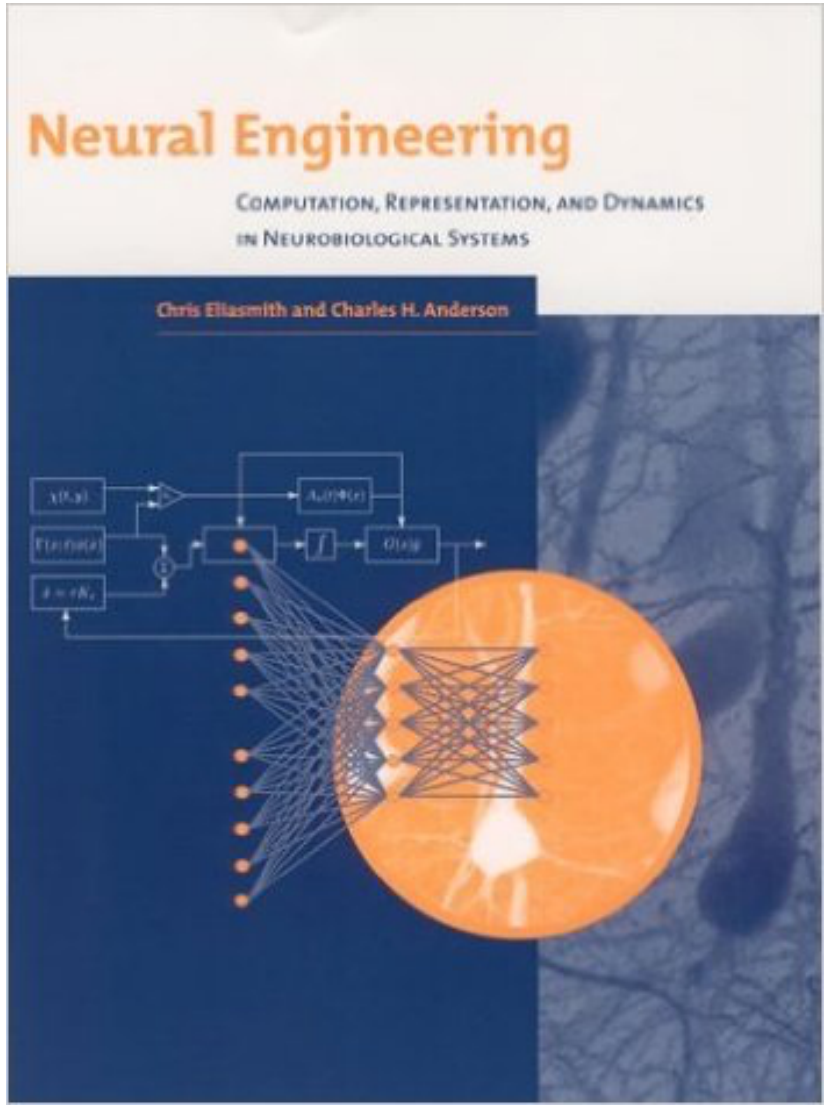
3. Compute SNR

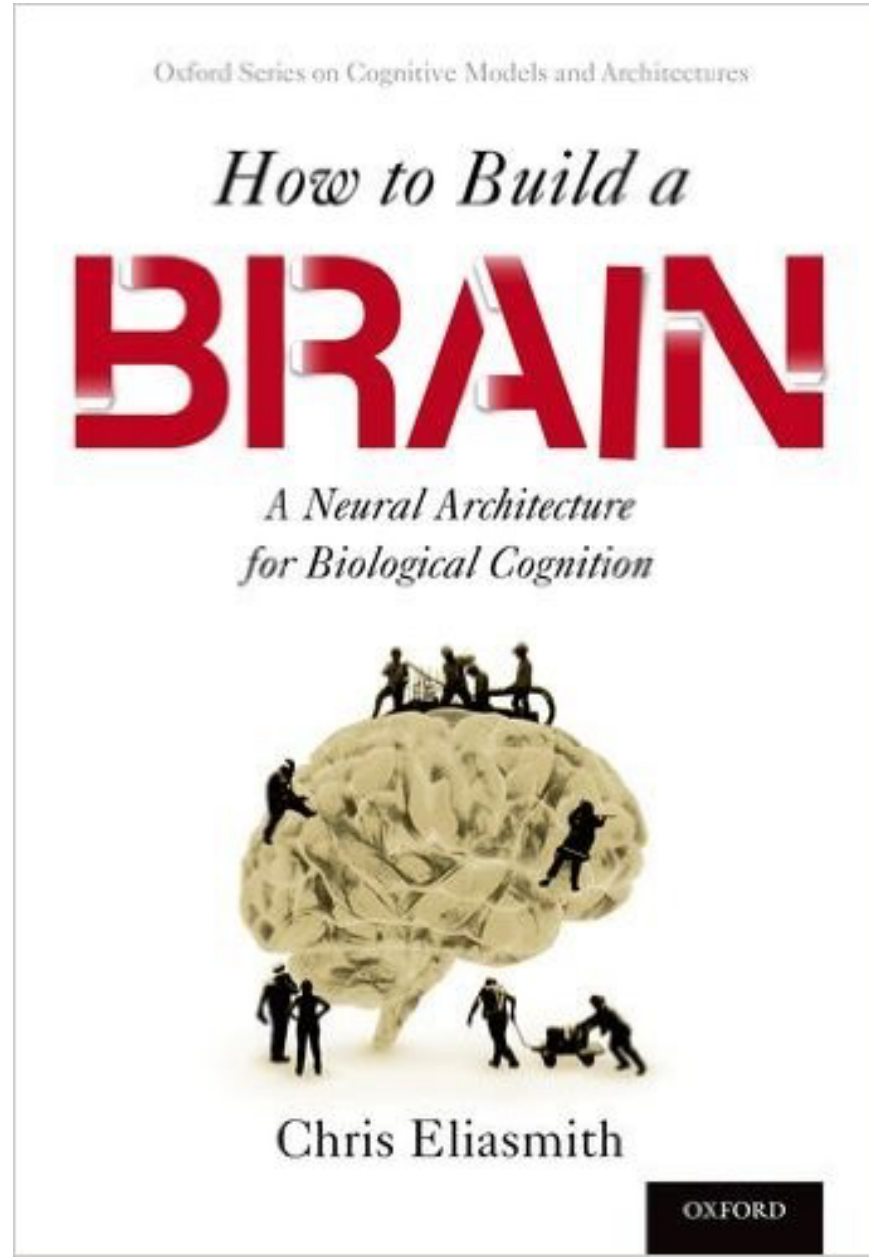
$$\mathrm{SNR}(\omega) = \frac{\langle |\tilde{s}(\omega)|^2 \rangle}{\langle |\tilde{n}(\omega)|^2 \rangle}$$

4. Calculate lower bound to information rate from SNR

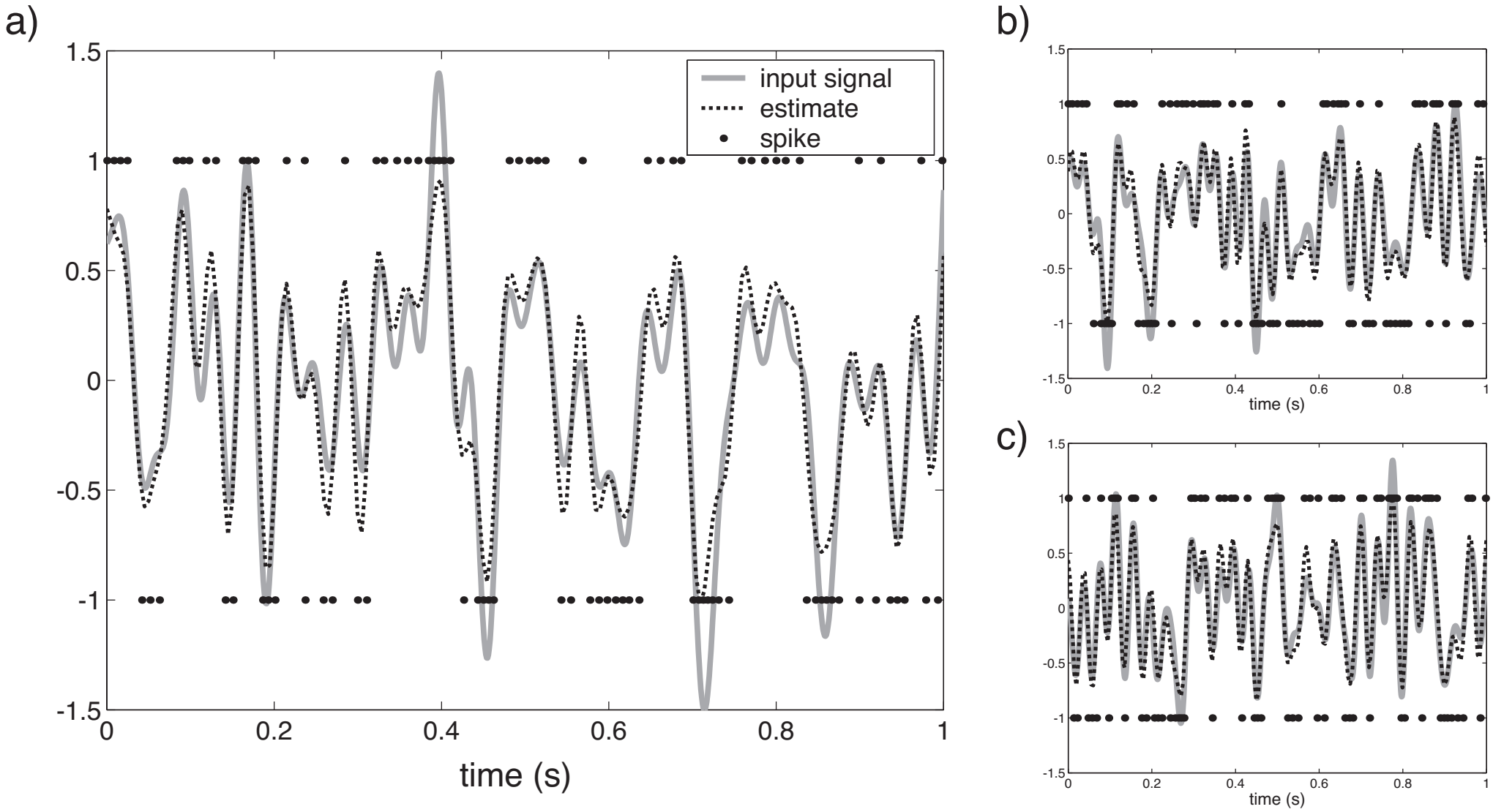
$$R = \frac{1}{2} \int \frac{d\omega}{2\pi} \log_2[1 + \mathrm{SNR}(\omega)]$$

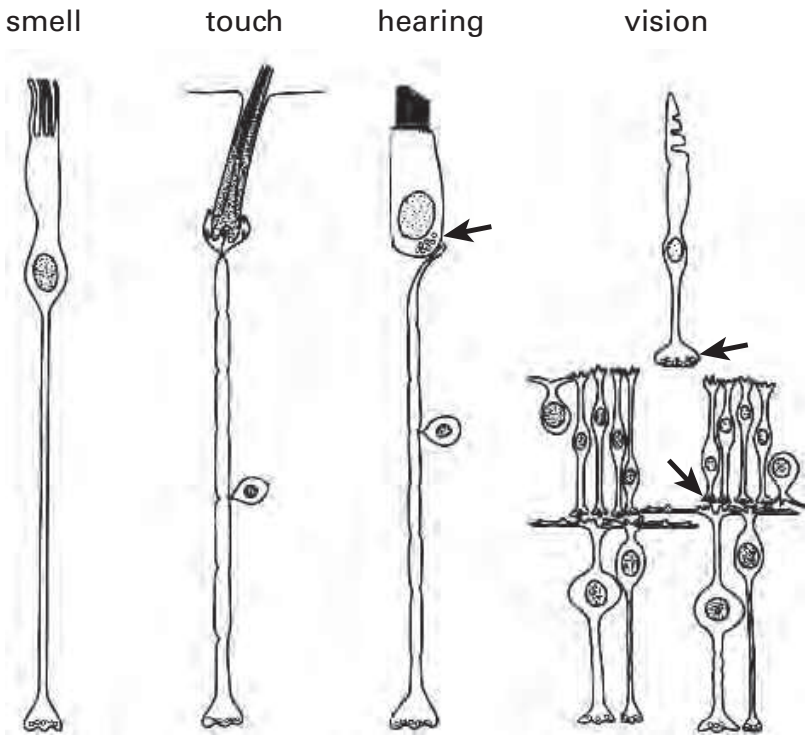
Adapted from *Spikes*, by Rieke, Warland, de Ruyter, & Bialek

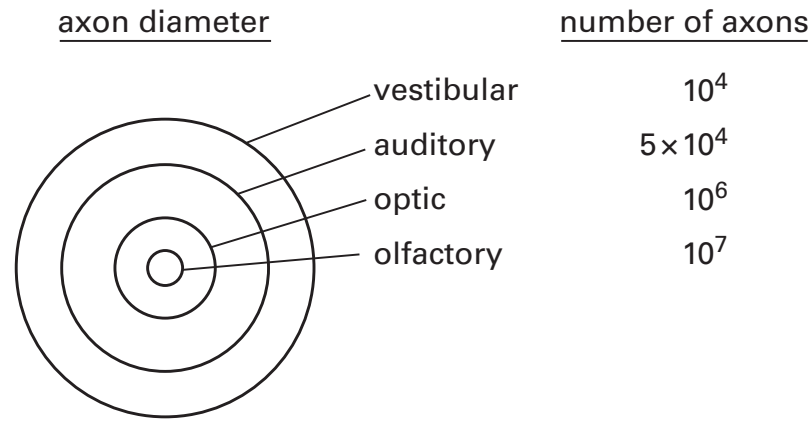

Neural Engineering
Computation, Representation, and Dynamics in Neurobiological Systems
Chris Eliasmith and Charles H. Anderson


Oxford Series on Cognitive Models and Architectures
How to Build a
BRAIN
A Neural Architecture for Biological Cognition
Chris Eliasmith
OXFORD

LIF encoding and decoding
(Eliasmith & Anderson, 2003)




smell
touch
hearing
vision


axon diameter
number of axons
vestibular
auditory
optic
olfactory
10^4
5×10^4
10^6
10^7

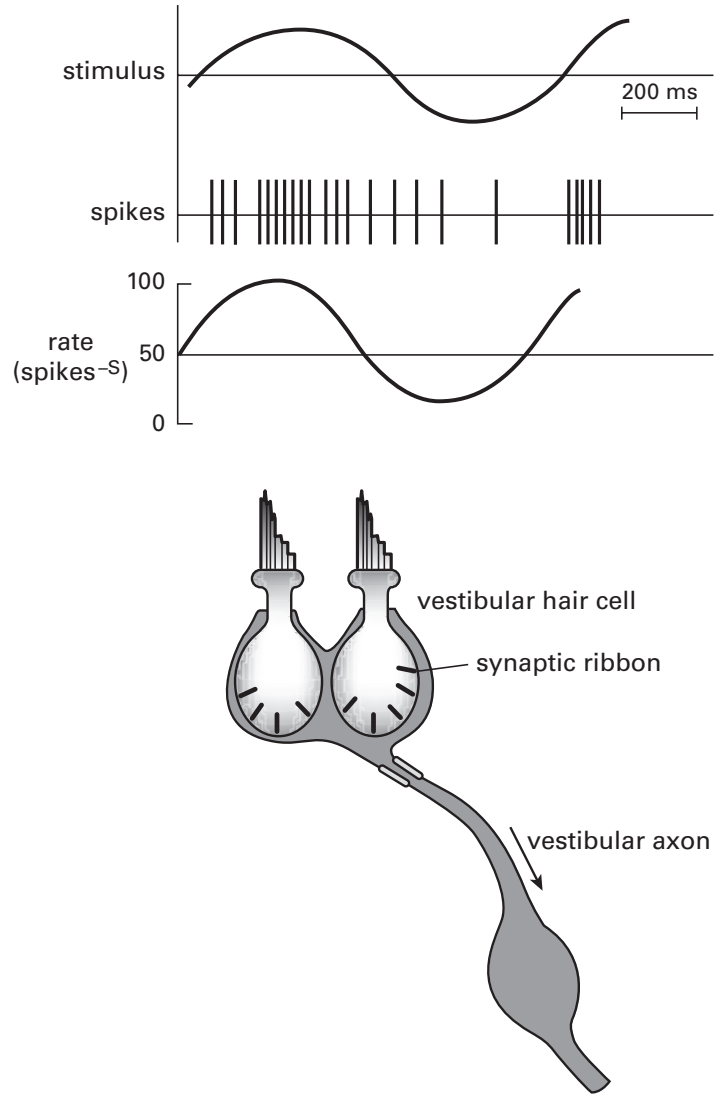
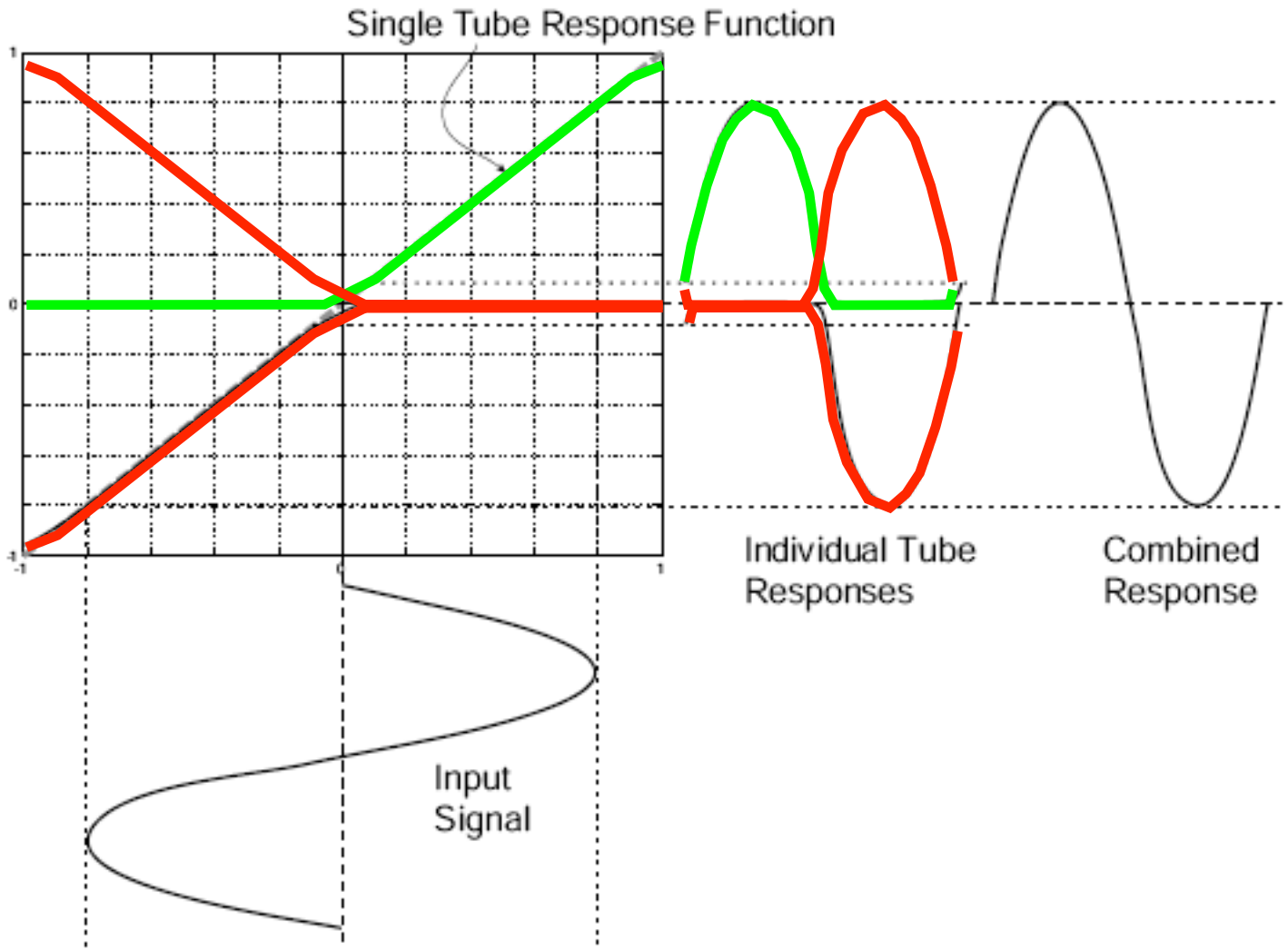


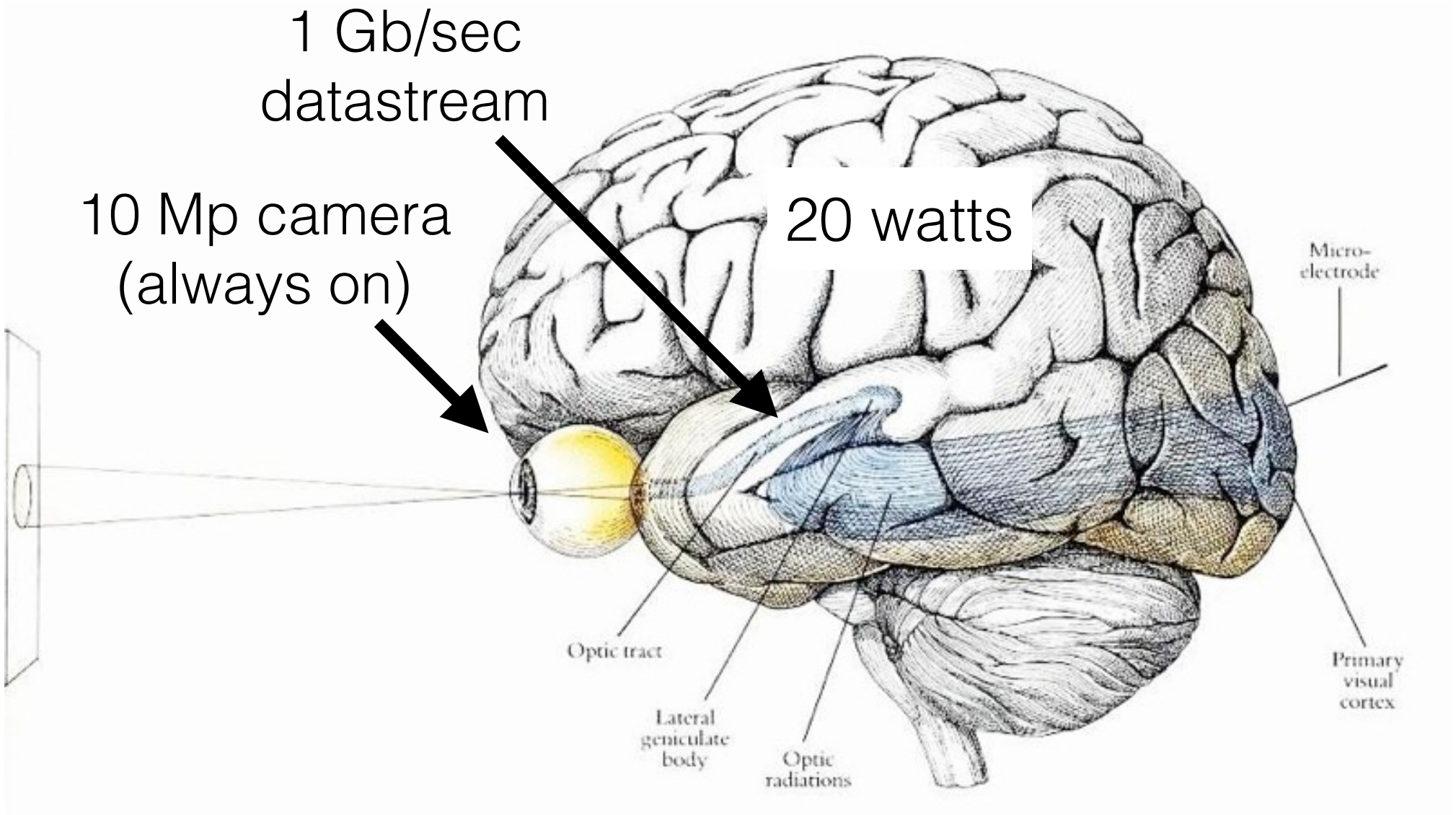
Figure 10.5

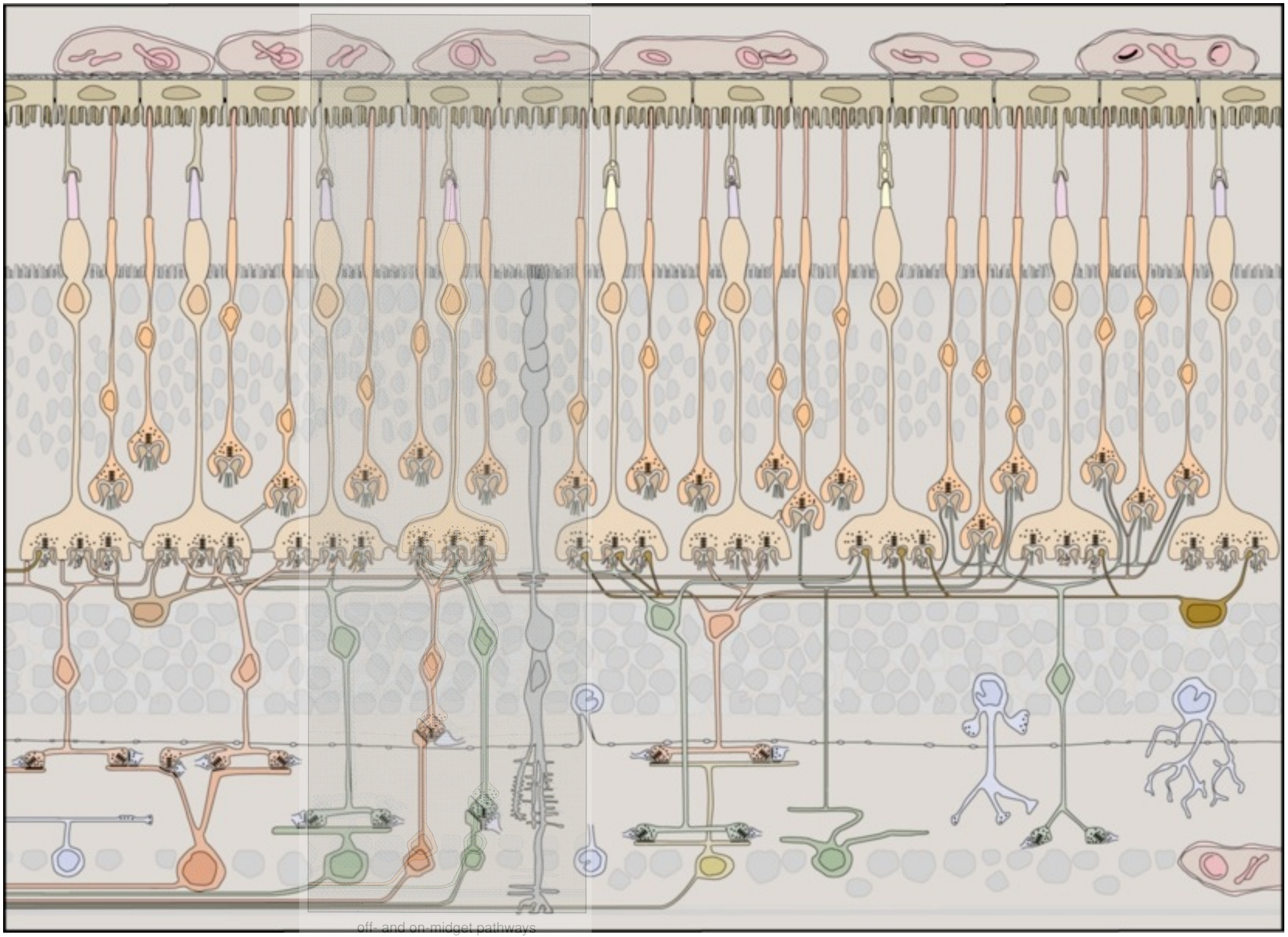
Vestibular hair cells, transducing low frequencies, can sum their analogue signals before recoding to spikes. Upper: Head rotates slowly (1 Hz). Spikes from second-order vestibular axon are modulated linearly through the full cycle around 50 spikes per second. **Lower:** Adjacent hair cells each converge multiple active zones onto single afferent fiber. Modified from Eatock et al. (2008).

Neural responses are half-wave rectified (action potentials are positive-only). Signals are thus combined in a push-pull fashion, similar to push-pull amplifiers.

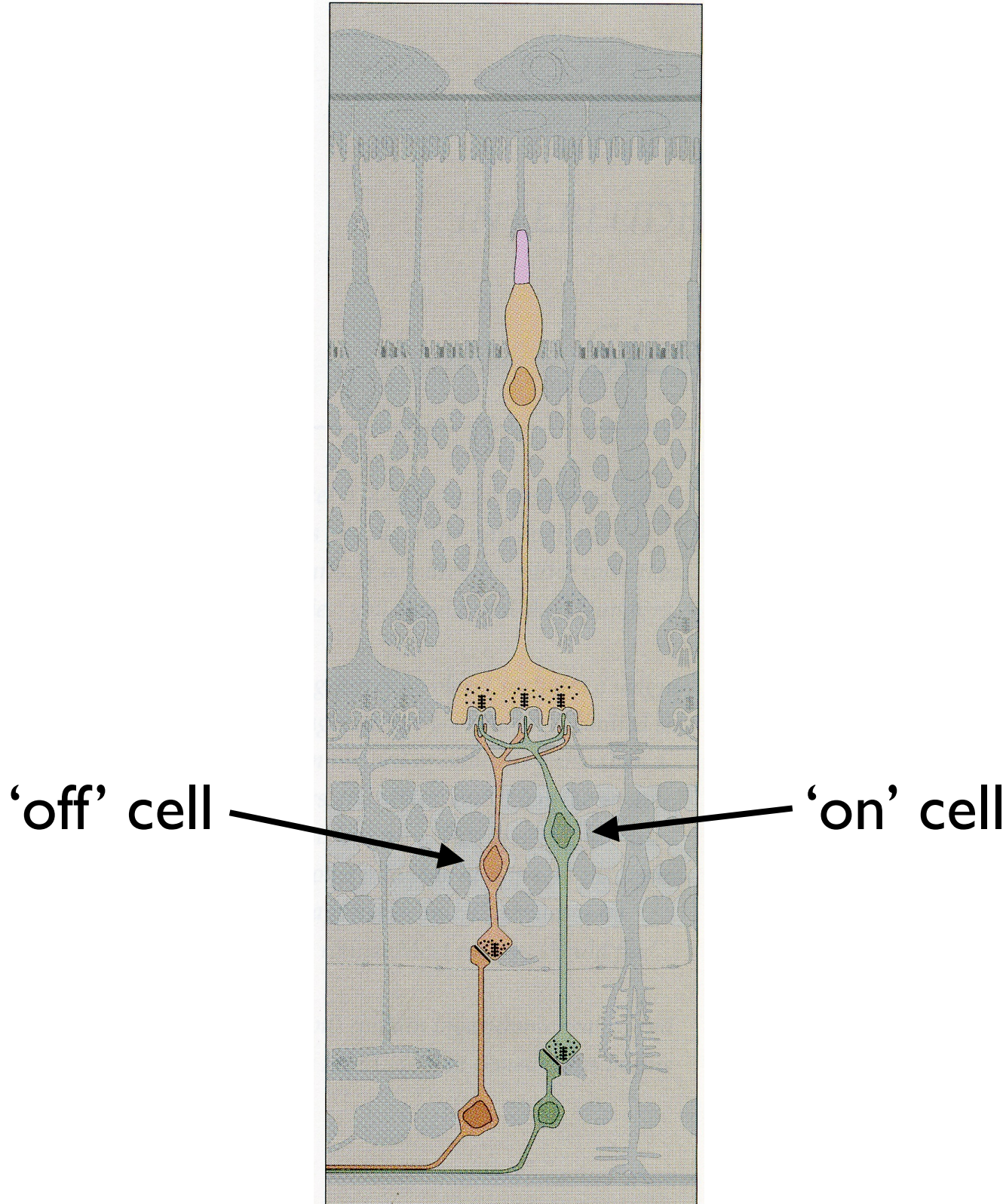


From: *Neural Engineering*, by Eliasmith & Anderson

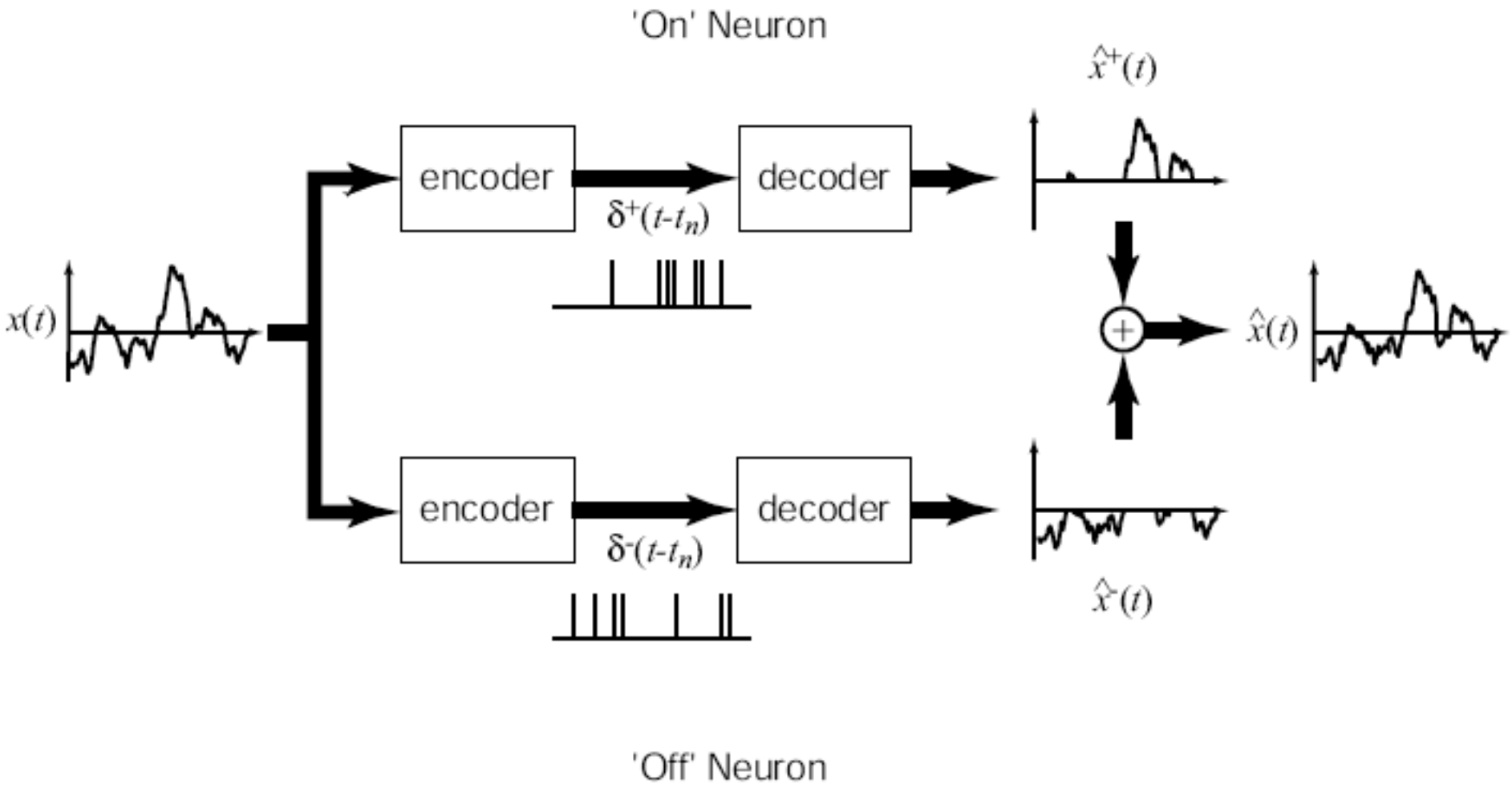

1 Gb/sec
datastream
10 Mp camera
(always on)
20 watts
Micro-
electrode
Optic tract
Lateral
geniculate
body
Optic
radiations
Primary
visual
cortex



off- and on-midget pathways

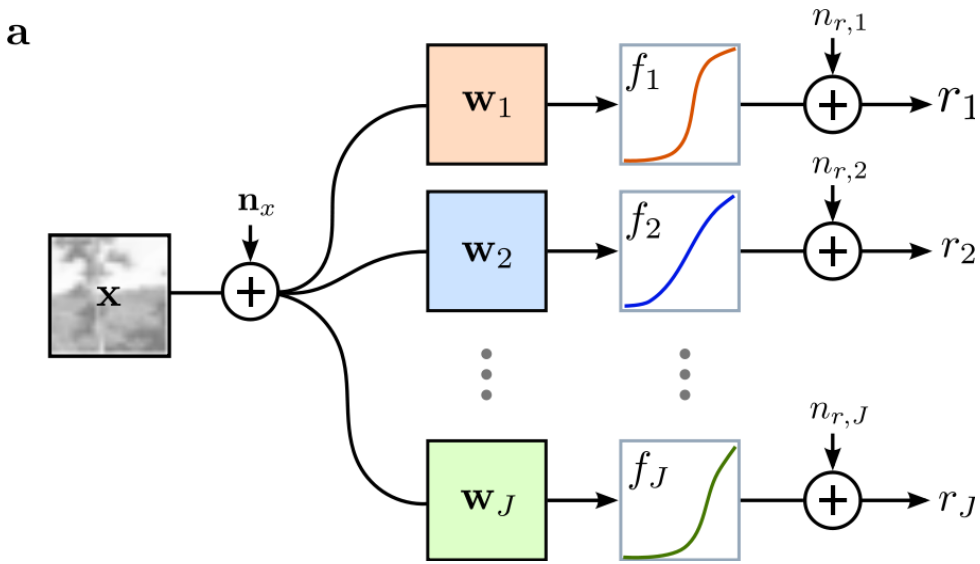

‘off’ cell
‘on’ cell

Push-Pull decoding



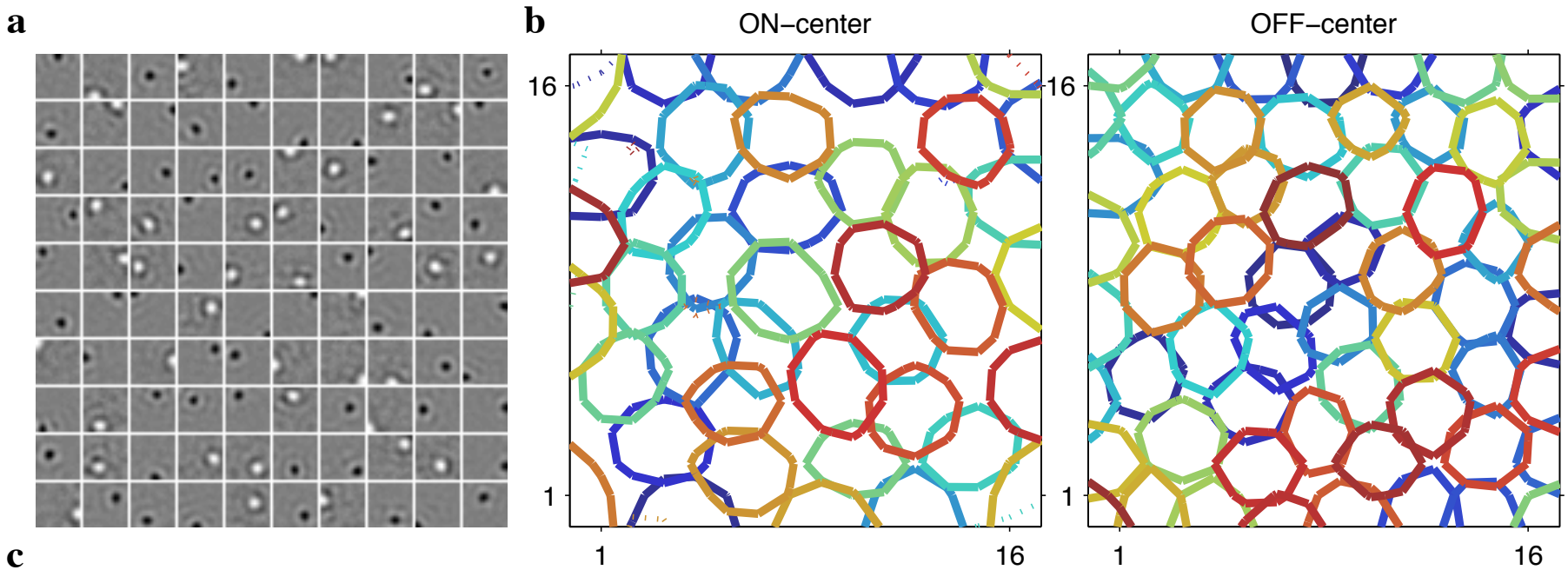
Efficient coding model of retina

(Karklin & Simoncelli 2012)



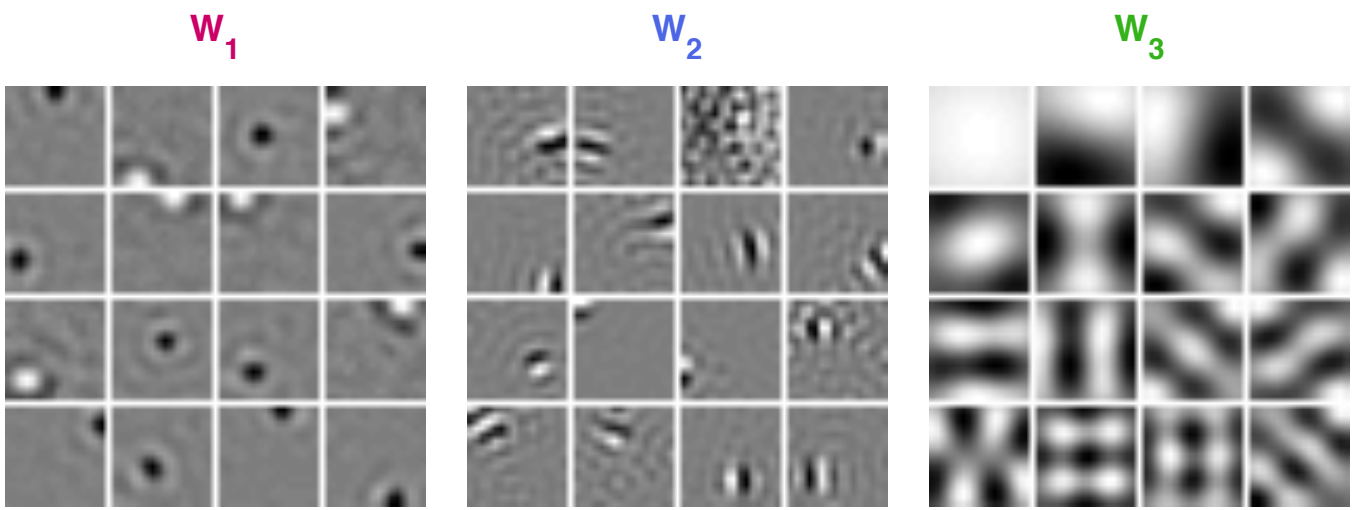
Objective function:

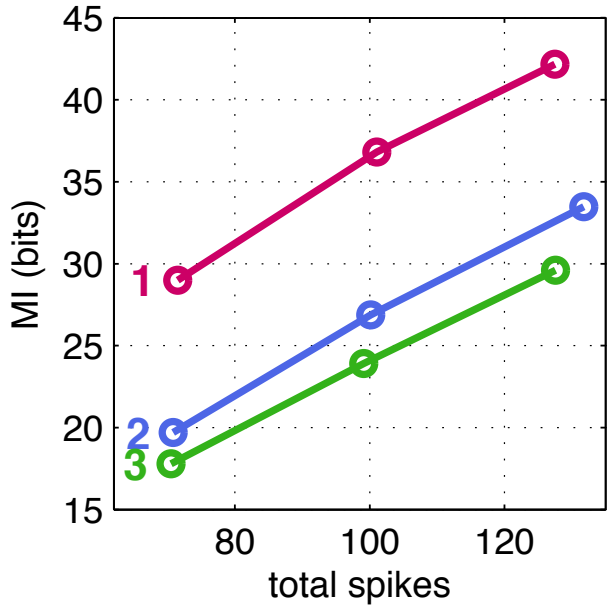
$$I(X;R) - \sum_j \lambda_j \langle r_j \rangle$$



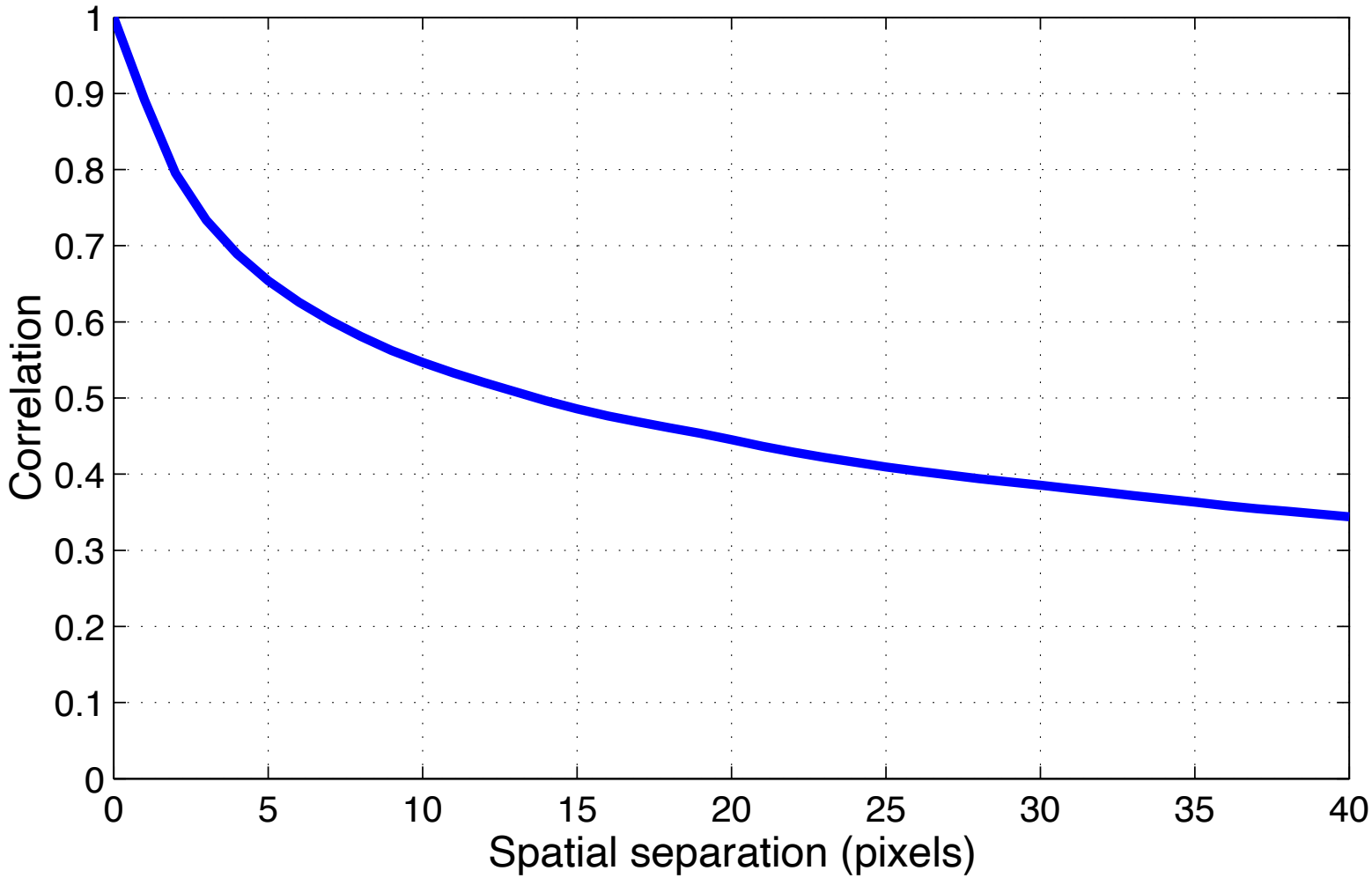
Efficient coding model of retina

(Karklin & Simoncelli 2012)

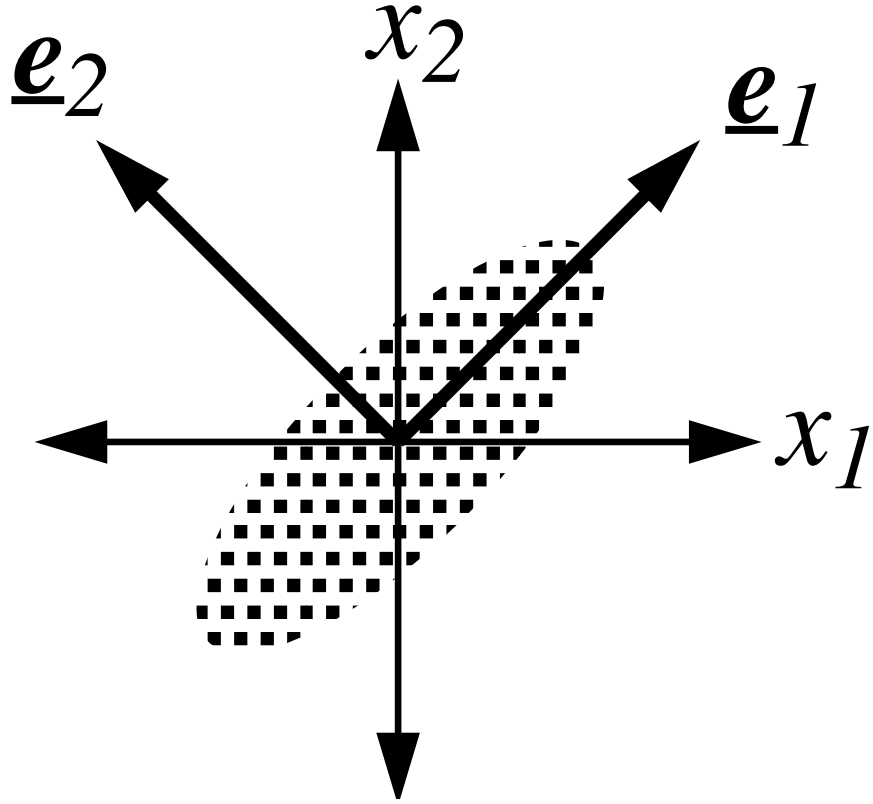




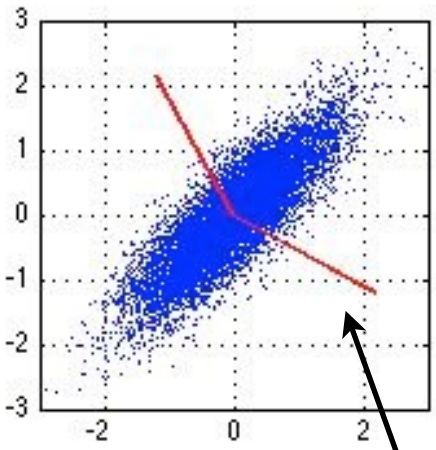
Auto-correlation function of natural images



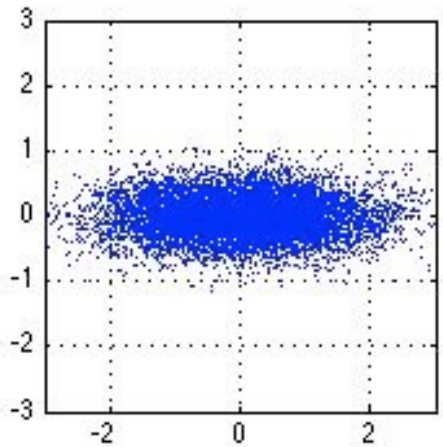
PCA
(Principal Components Analysis)



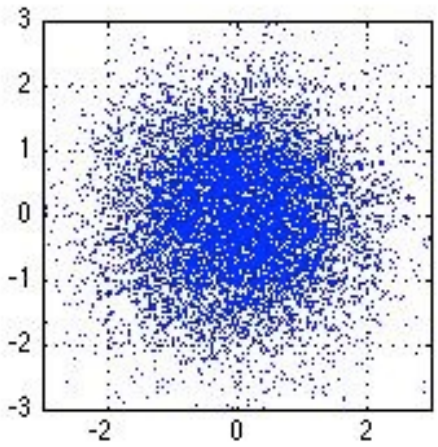
Whitening



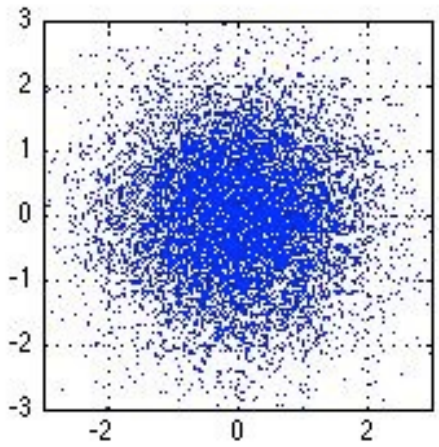
$\mathbf{X}$



$\mathbf{E}^T \mathbf{X}$



$\mathbf{\Lambda}^{-\frac{1}{2}} \mathbf{E}^T \mathbf{X}$

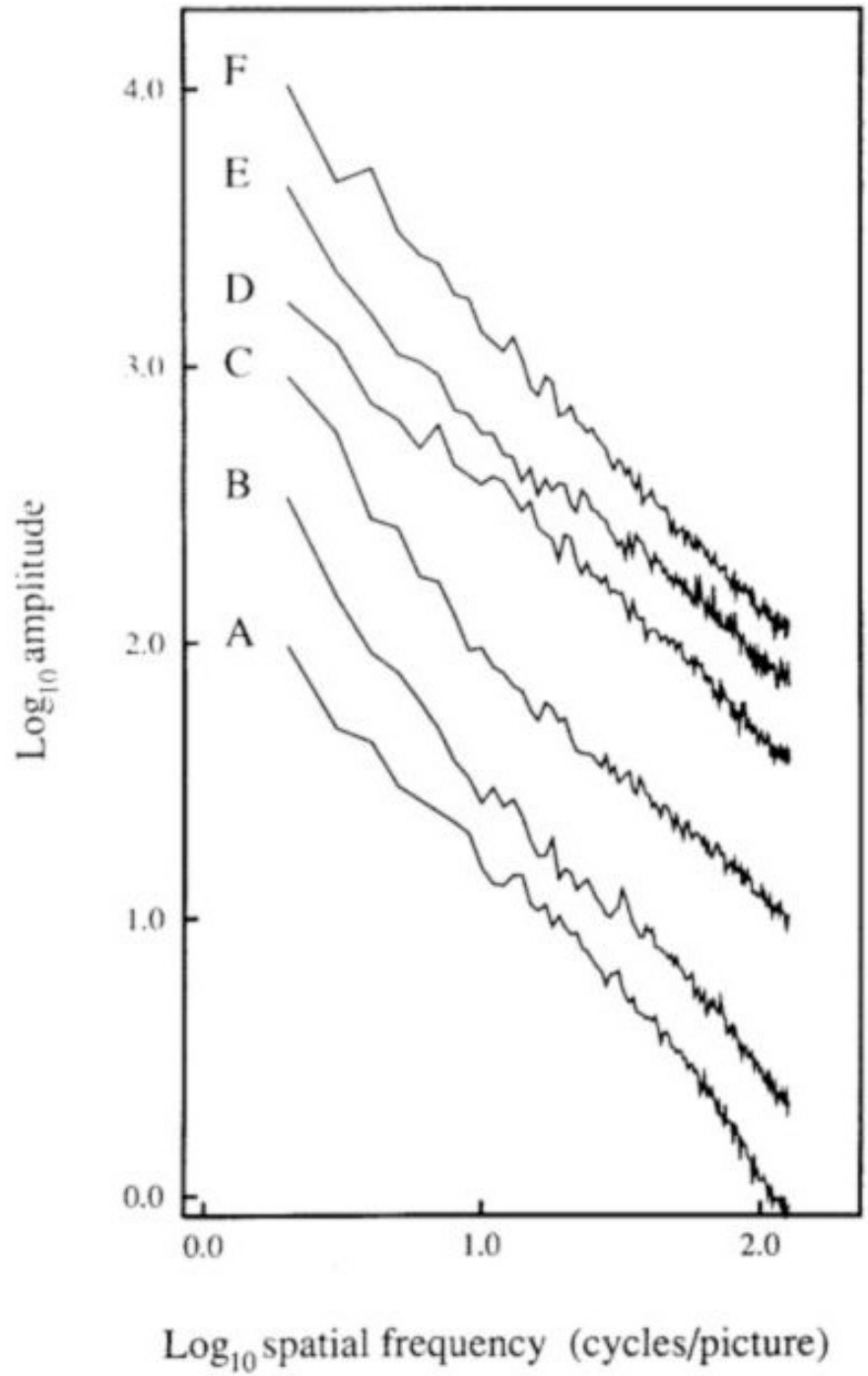


$\mathbf{E} \mathbf{\Lambda}^{-\frac{1}{2}} \mathbf{E}^T \mathbf{X}$

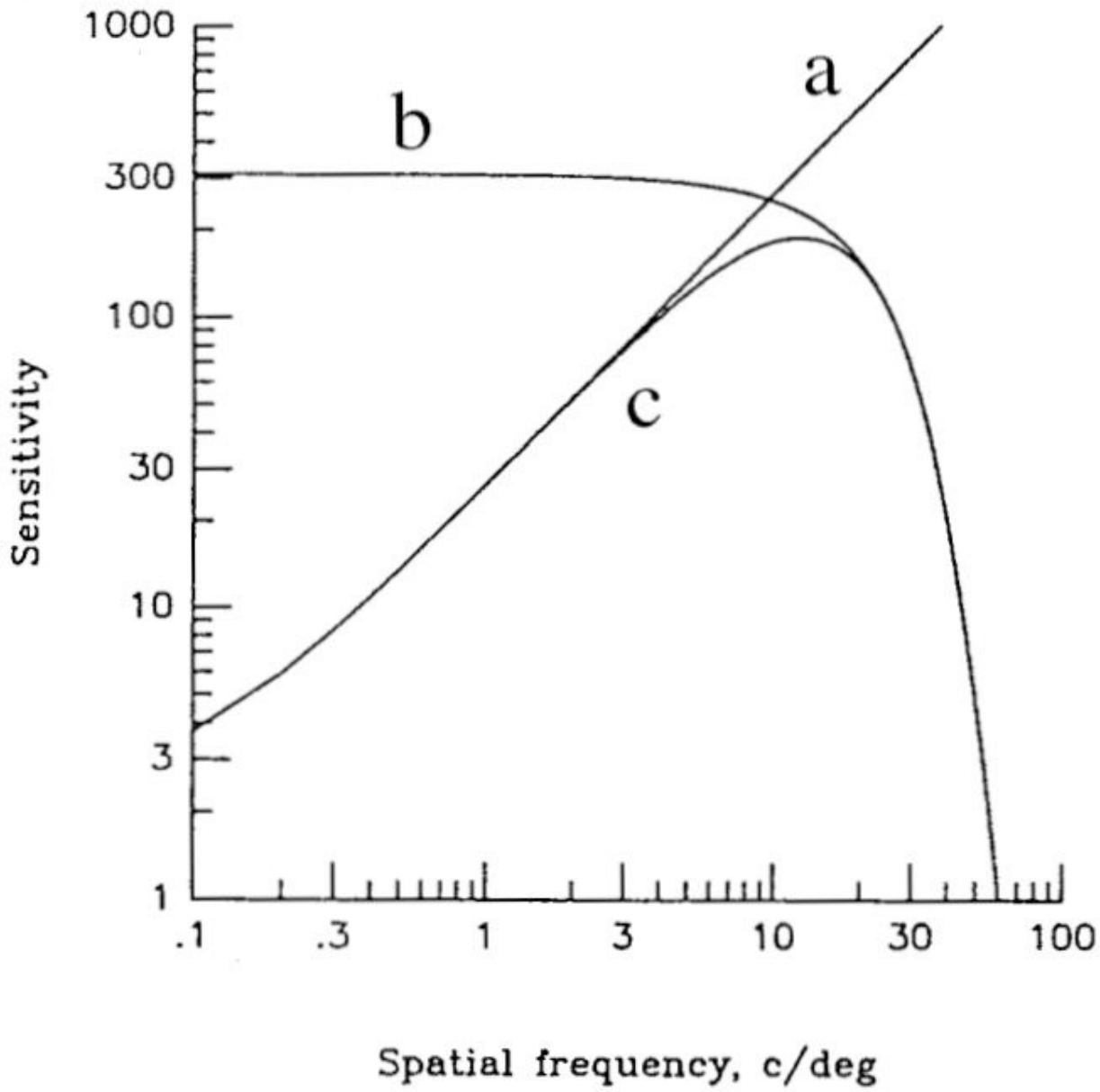
$$\mathbf{Y} = \mathbf{W} \mathbf{X}$$

$$\mathbf{W} = \mathbf{E} \mathbf{\Lambda}^{-\frac{1}{2}} \mathbf{E}^T$$

Power spectrum (Field 1987)

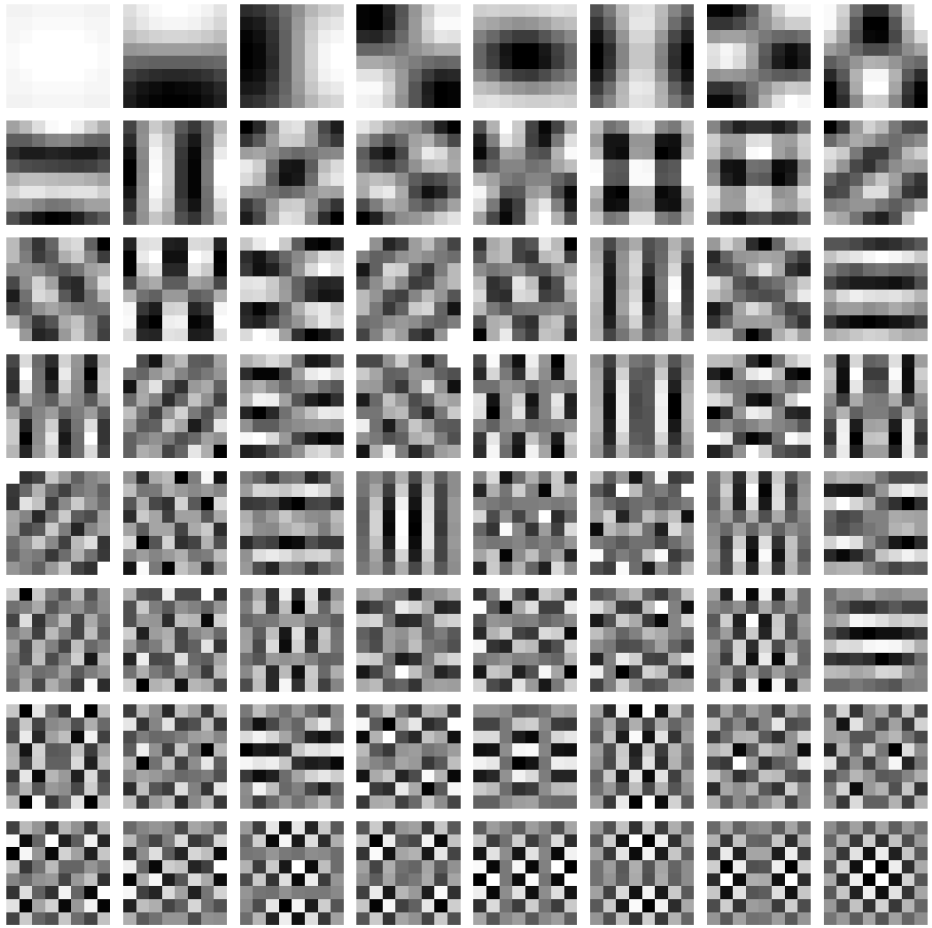


‘Whitening’ (Atick & Redlich, 1990)



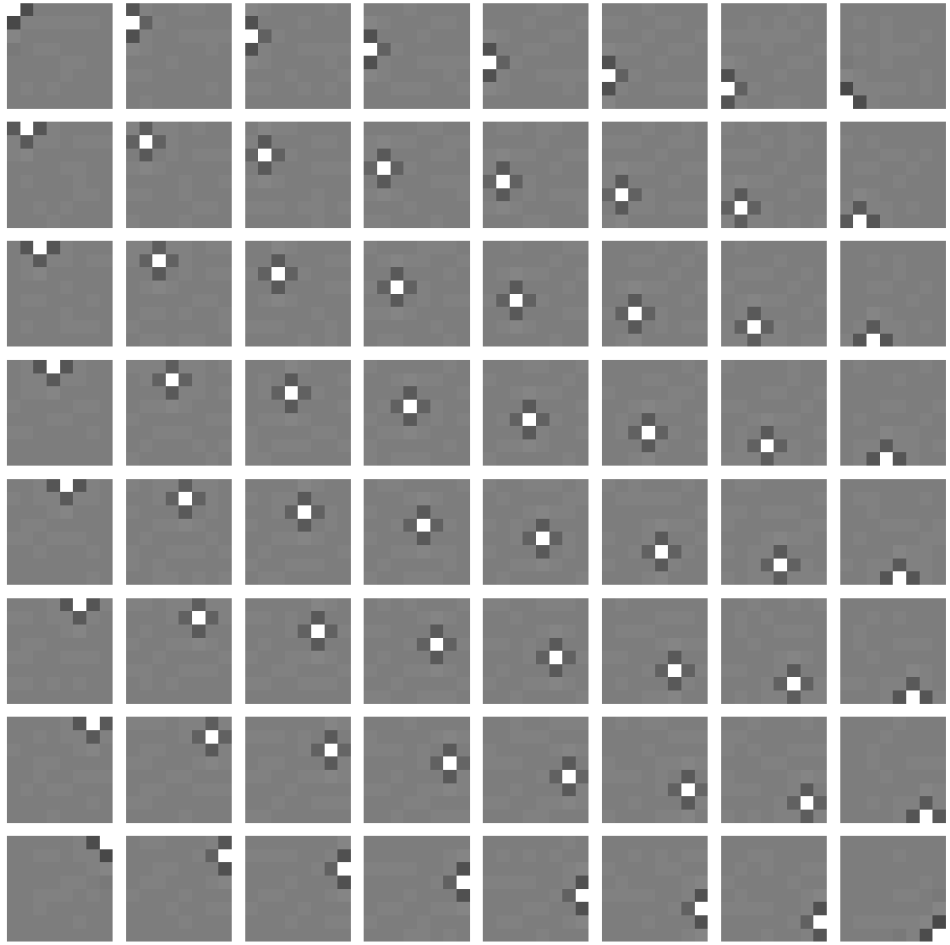
PCA

$$\mathbf{W} = \mathbf{E}^T$$



Whitening

$$\mathbf{W} = \mathbf{E}\mathbf{\Lambda}^{-\frac{1}{2}}\mathbf{E}^T$$



Whitening

before

after