Neural Encoding

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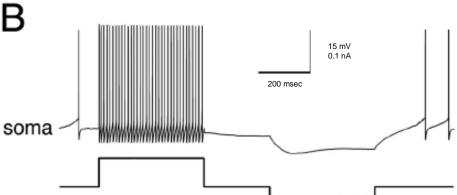
Overview

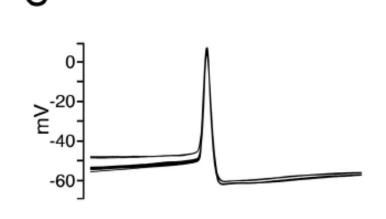
Spike Train Statistics

Measures of Neural Encoding

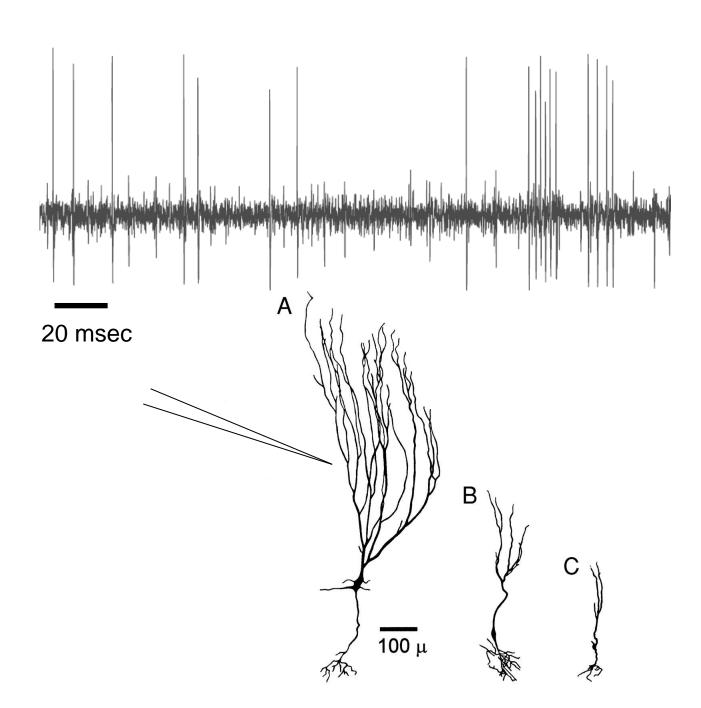
Spike Train Statistics



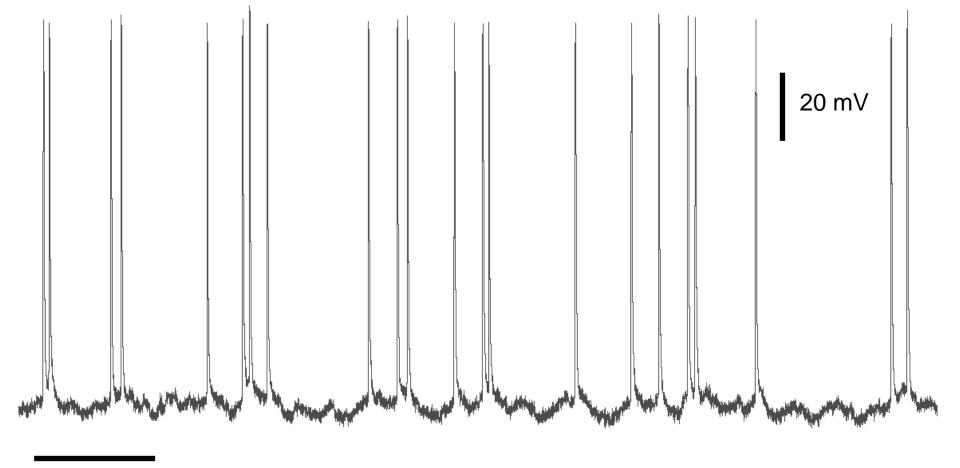




Monsivais et al. 2005

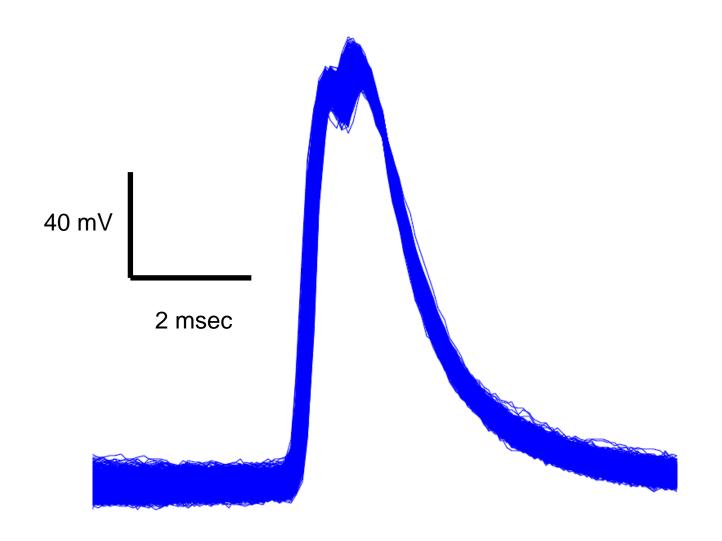


extracellular



200 msec

Intracellular recording

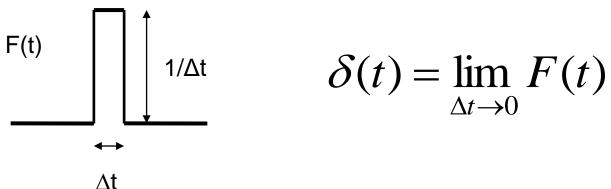


Action potentials are stereotyped

Series of events:

The delta function:

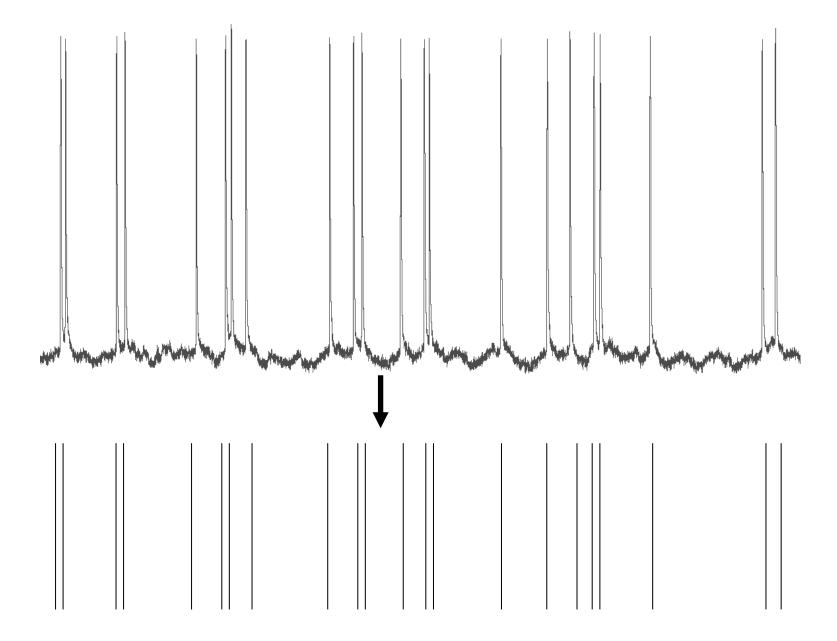
Consider:



Properties:

$$\int dt \, G(\tau - t) \delta(t) = G(\tau)$$

If G(t) is "well-behaved"



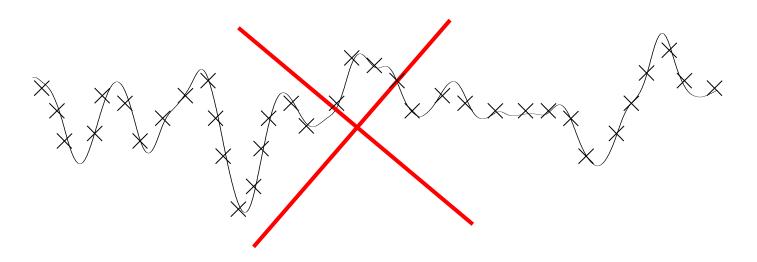
Representing spike trains as series of events

$$X(t) = \sum_{i} \delta(t - t_i)$$

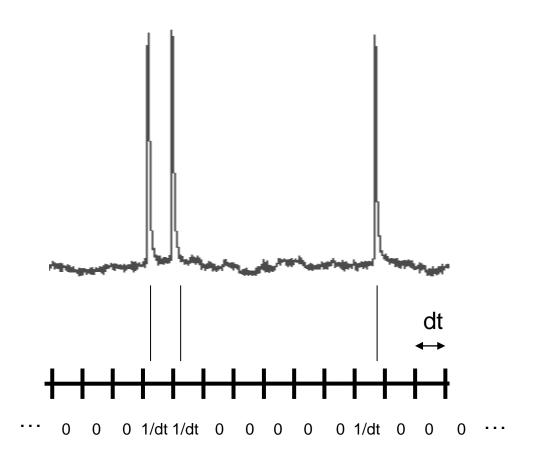
t_i: spike times

In practice

signals are sampled at a finite rate



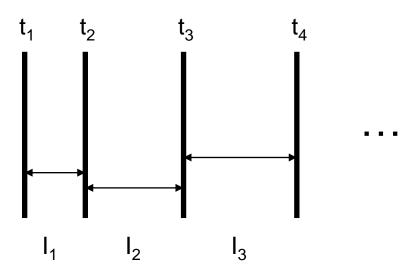
"Binary" Representation of a Spike Train



Interspike Intervals

Interspike interval sequence:

$$I_i = t_{i+1} - t_i$$



Interspike interval probability: P(I)

Probability of observing an ISI with value I

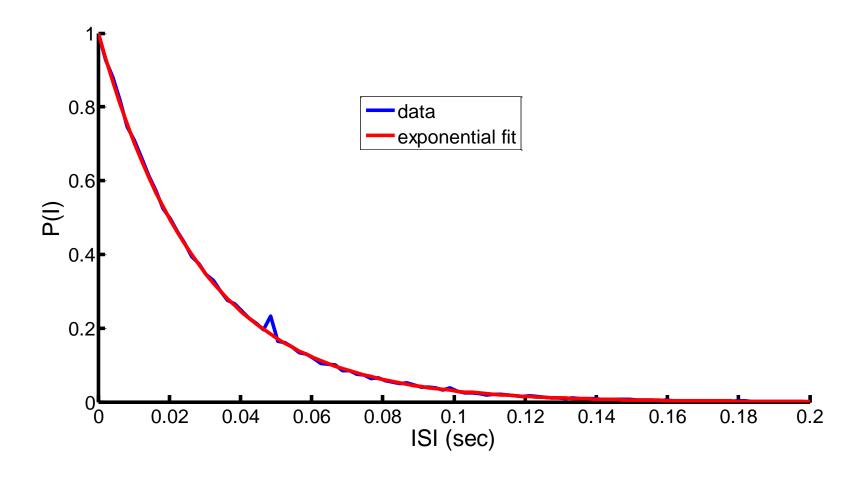
Example: Poisson Process

$$P[(N(t+\tau)-N(t))=k] = \frac{e^{-\lambda\tau} (\lambda\tau)^k}{k!}$$

Probability of obtaining k events in an interval of length τ

$$P[(N(\tau) - N(0)) = 0] = \frac{e^{-\lambda \tau} (\lambda \tau)^{0}}{0!} = e^{-\lambda \tau}$$

Numerical Simulations:



Coefficient of Variation

Neurons are stochastic → Variability

$$CV = \frac{STD(I)}{mean(I)}$$

Example: Poisson process

$$CV = \frac{1/\lambda}{1/\lambda} = 1$$

ISI correlations

Normalized autocorrelation function for the ISIs (assume that Var(I)>0)

$$\Gamma_{j} = \frac{\langle I_{i}I_{i+j} \rangle - \langle I_{i} \rangle^{2}}{\langle I_{i}^{2} \rangle - \langle I_{i} \rangle^{2}}$$

$$\rho_0 \equiv 1$$

For a renewal process:
$$ho_{i
eq 0} = 0$$

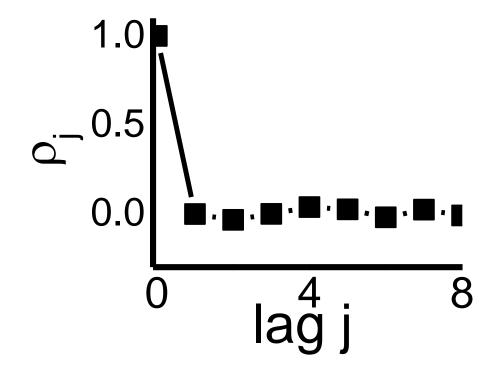
Example: Stochastic IF model driven with white noise

$$\dot{V} = \mu + \xi(t)$$

$$V(t_i) = \theta \Longrightarrow V(t_i^+) = 0$$

ISIs are independent

- Reset rule "erases" the history
- White noise is uncorrelated over time

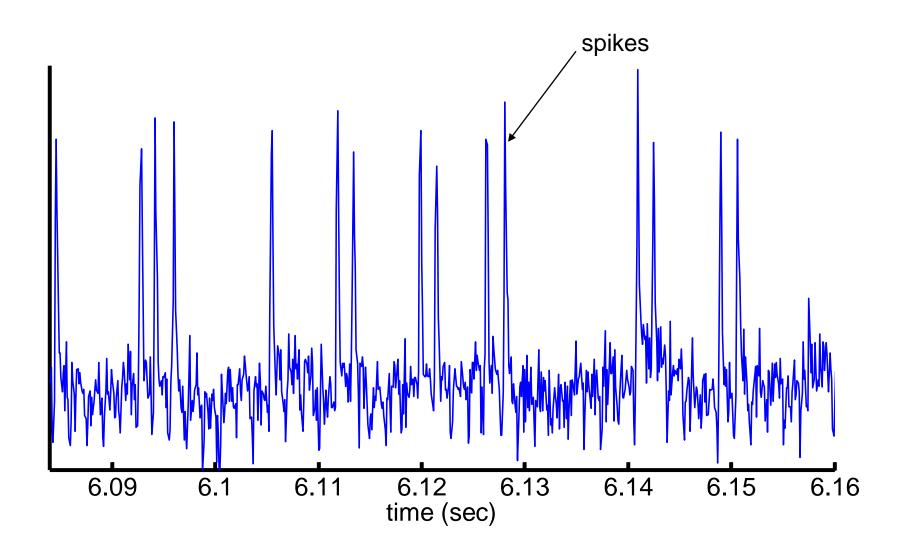


Example: electroreceptor afferent neuron

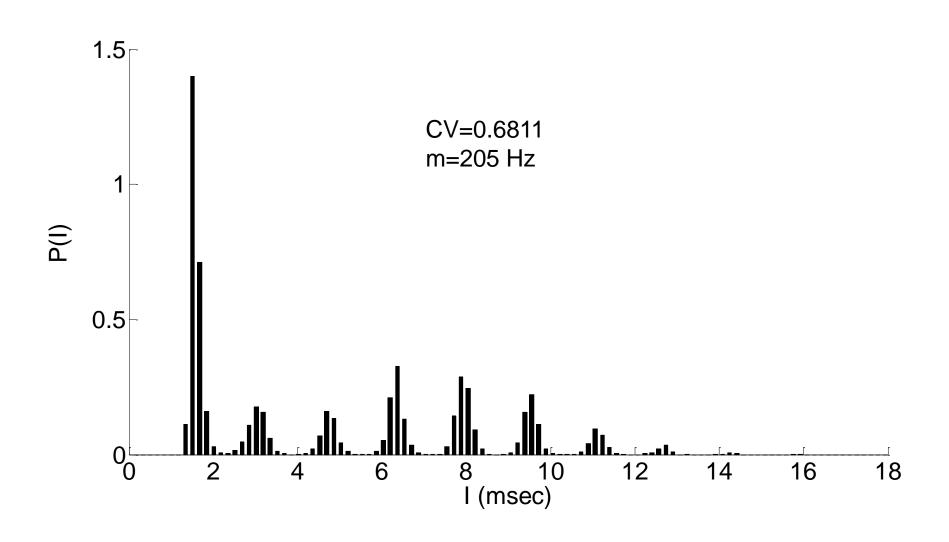
Electric Organ Discharge (EOD) of

Apteronotus leptorhynchus **EOD** waveform 10 ms

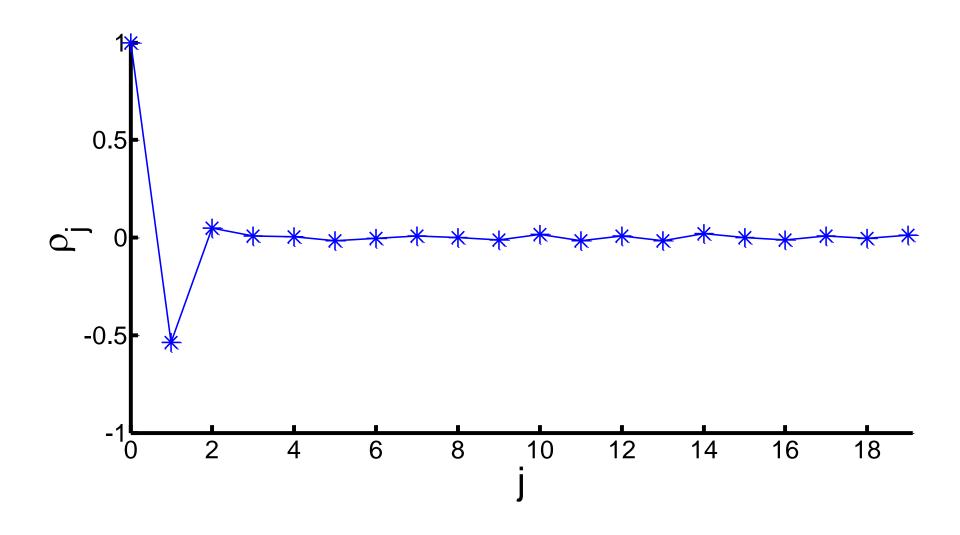
Raw Data



ISI probability density



ISI autocorrelation function



C) Statistics based on event trains

$$X(t) = \sum_{i} \delta(t - t_i)$$

t_i: spike times

Time varying firing rate:

$$r(t) = \langle X(t) \rangle$$

For a stationary process:
$$r(t)=m$$

Autocorrelation Function

$$A(t,\tau) = \langle X(t)X(t+\tau) \rangle - \langle X(t) \rangle \langle X(t+\tau) \rangle$$

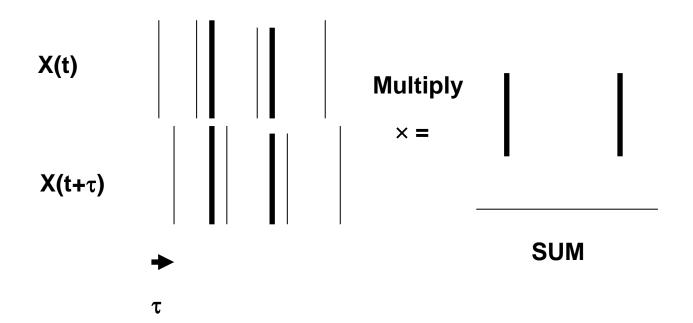
For stationary processes:

$$A(t,\tau) = A(\tau) = \langle X(t)X(t+\tau) \rangle - m^{2}$$

$$m = \langle X(t) \rangle$$

If X(t) and X(t+ τ) are uncorrelated, then A(τ)=0

Autocorrelation Function



Example: Poisson Process with firing rate λ

$$A(\tau) = \lambda \delta(\tau)$$

One often removes this delta function:

$$A^{+}(\tau) = A(\tau) - \lambda \delta(\tau)$$

For most processes:
$$\underset{\tau \to +\infty}{Lim} A(\tau) = 0$$

Power Spectrum

 Fourier Transform of the Autocorrelation function (Wiener-Khintchine Theorem)

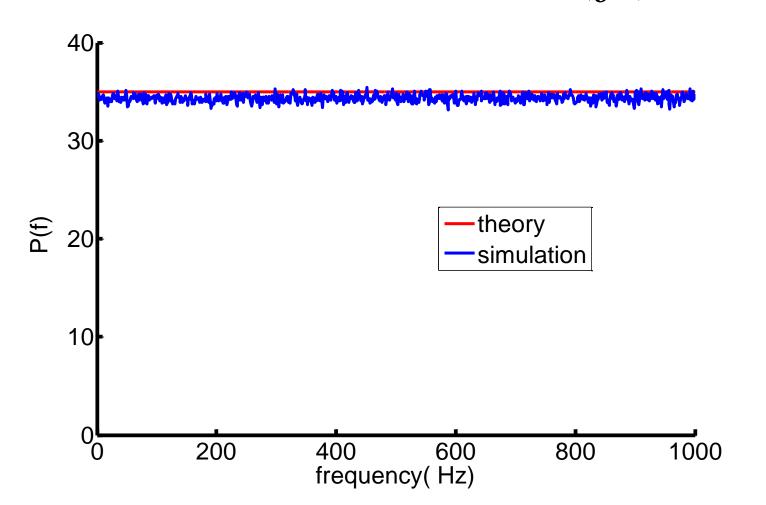
Same information but represented differently

$$P(f) = <\widetilde{X}(f)X(f)>$$

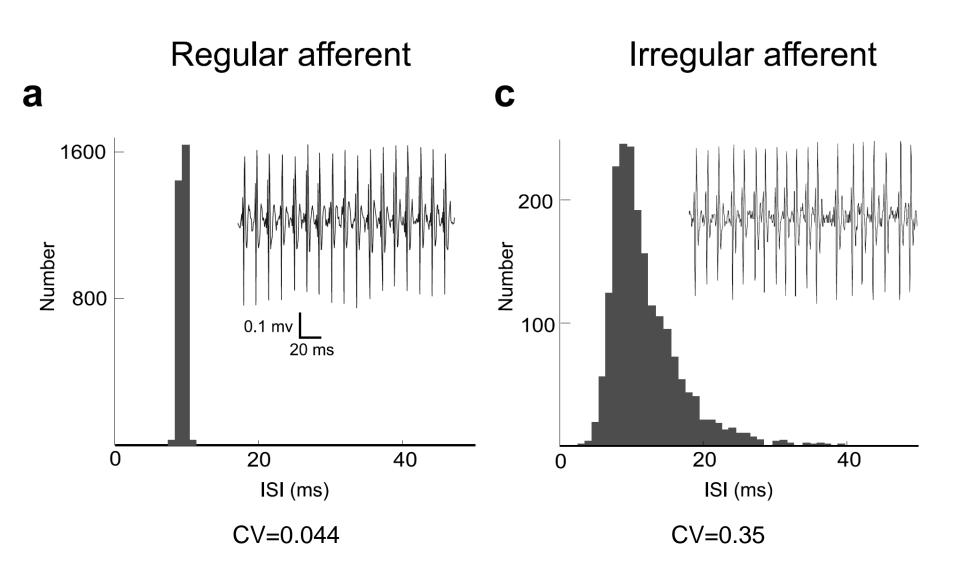
$$\underset{f \to \infty}{Lim} P(f) = \langle X(t) \rangle = m$$
 X(t) stationary

Example: Poisson Process

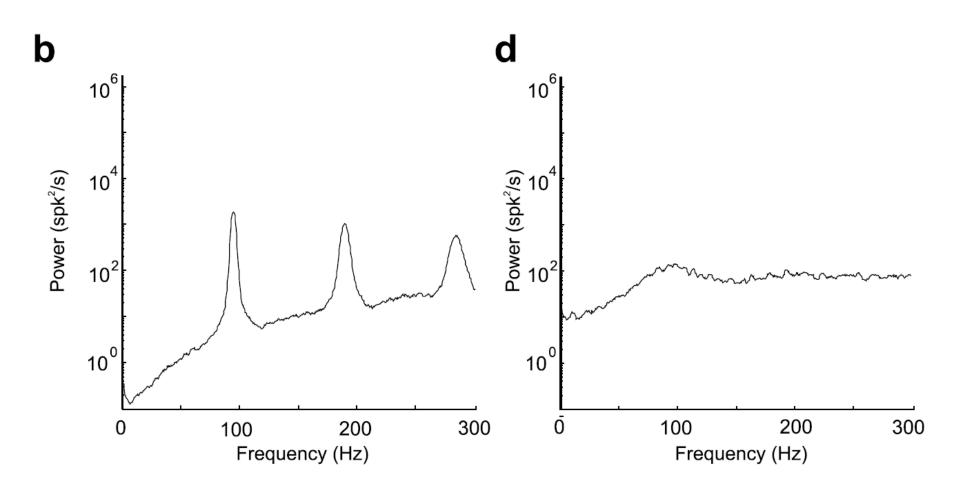
$$A(\tau) = \lambda \delta(\tau) \implies P(f) = \lambda$$



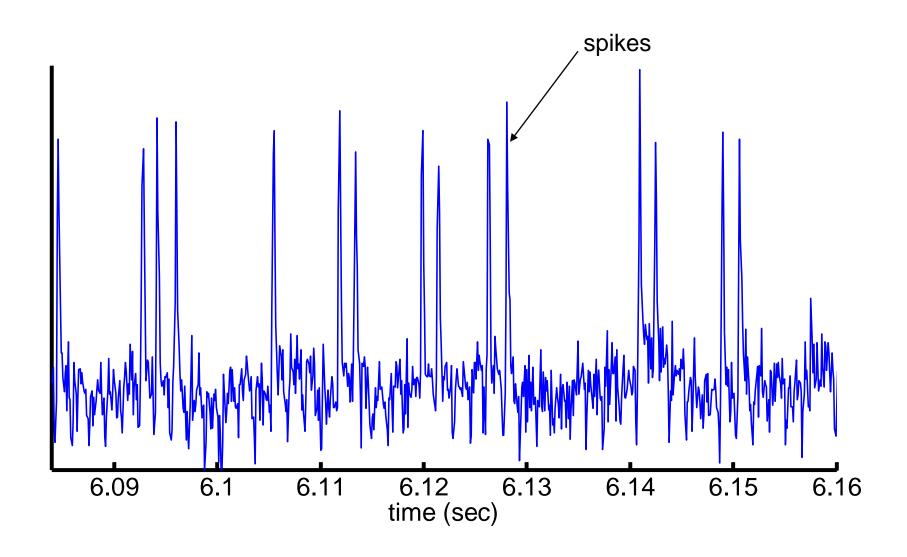
Example: vestibular afferents



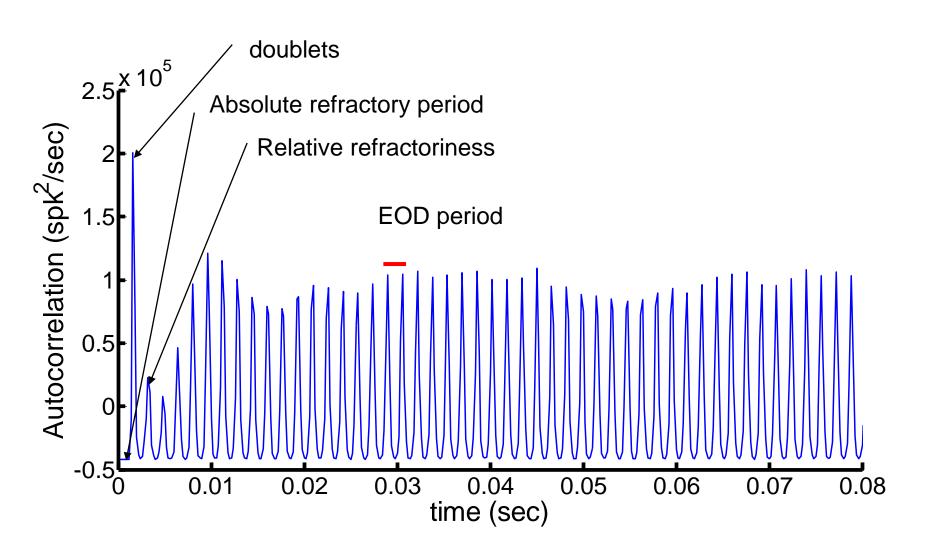
Power Spectra



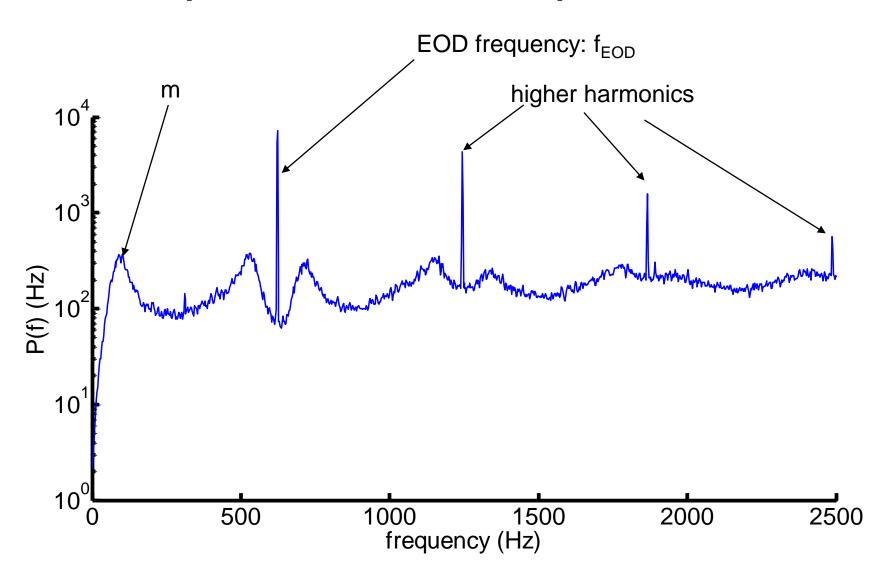
Electroreceptor afferent:



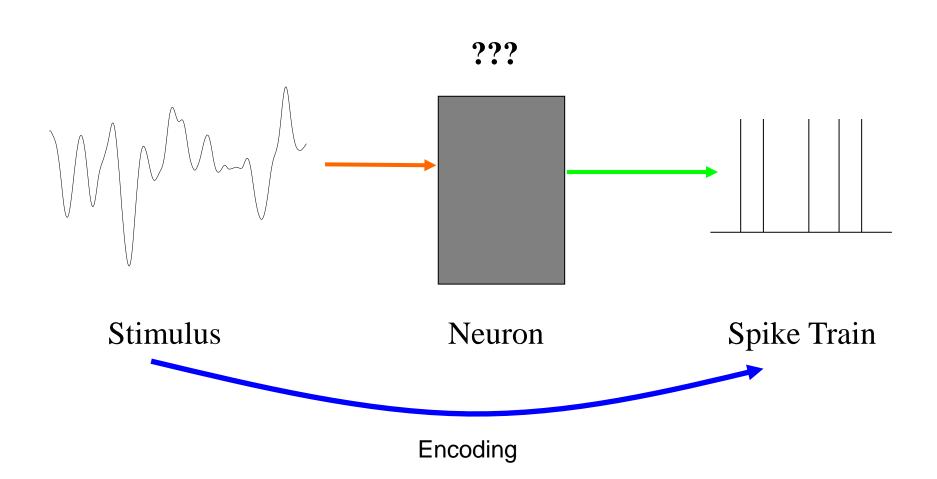
Example: Electroreceptor Afferent



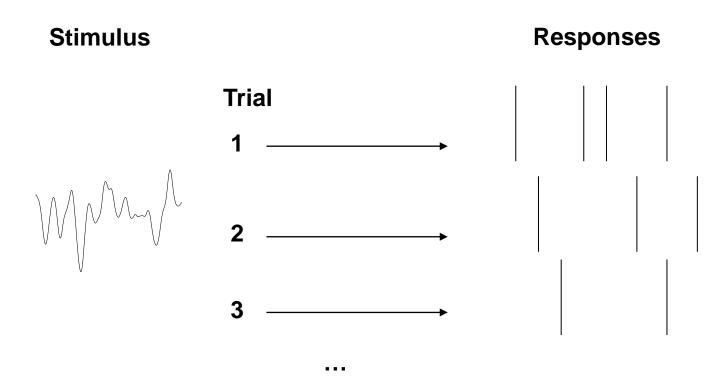
Example: Electroreceptor Afferent



Measures of Neural Encoding

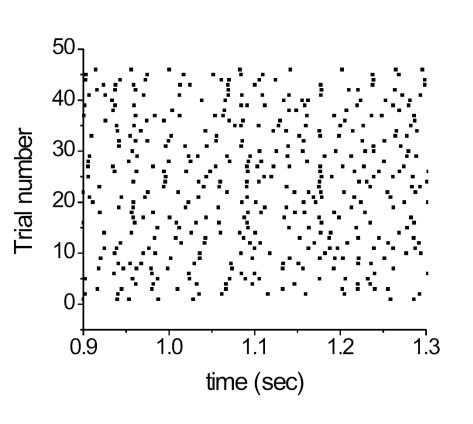


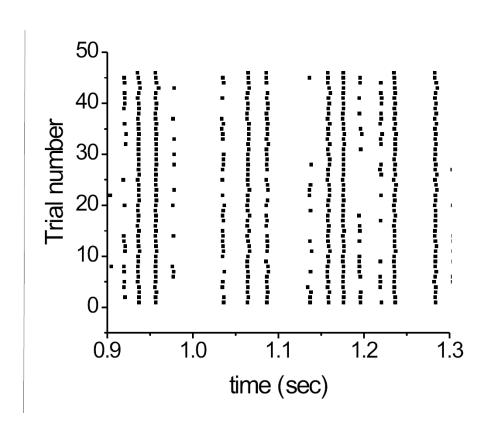
Raster plot





Low variability





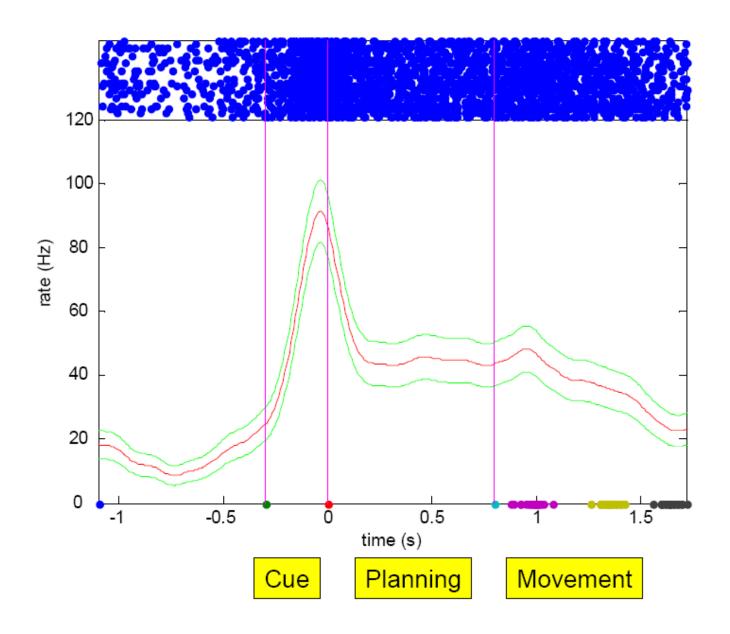
Peri-Stimulus Time Histogram

Responses

Trial **Stimulus**

$$PSTH(t) = \langle X(t) \rangle = \frac{1}{N} \sum_{i=1}^{N} X_i(t)$$

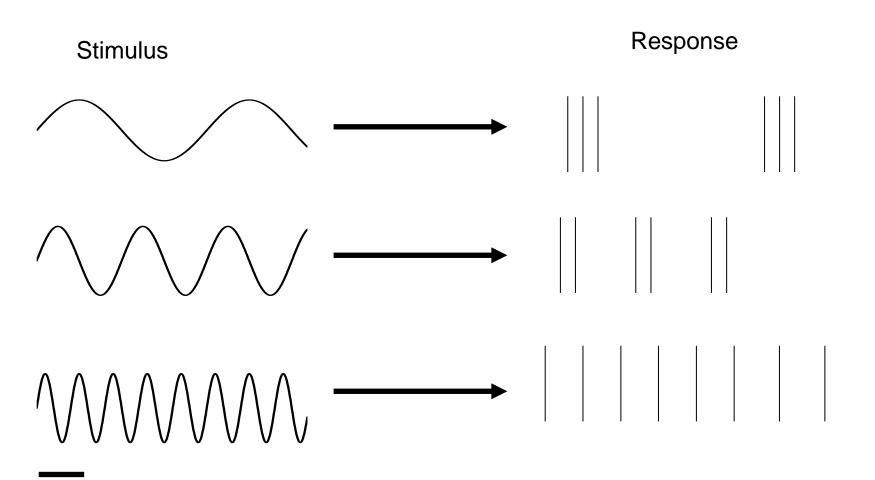
Peri-stimulus time histogram (PSTH)



Tuning Curves

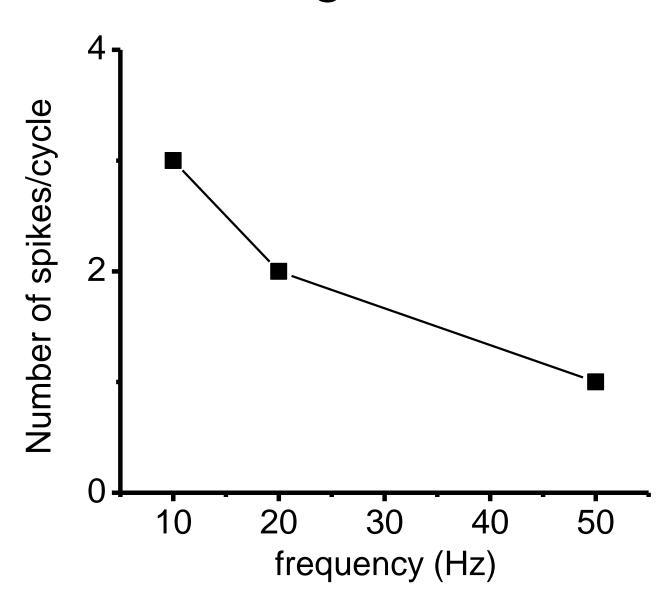
 Plot of response attribute as a function of stimulus attribute

Example: sinusoidal stimulation



20 msec

Tuning Curve

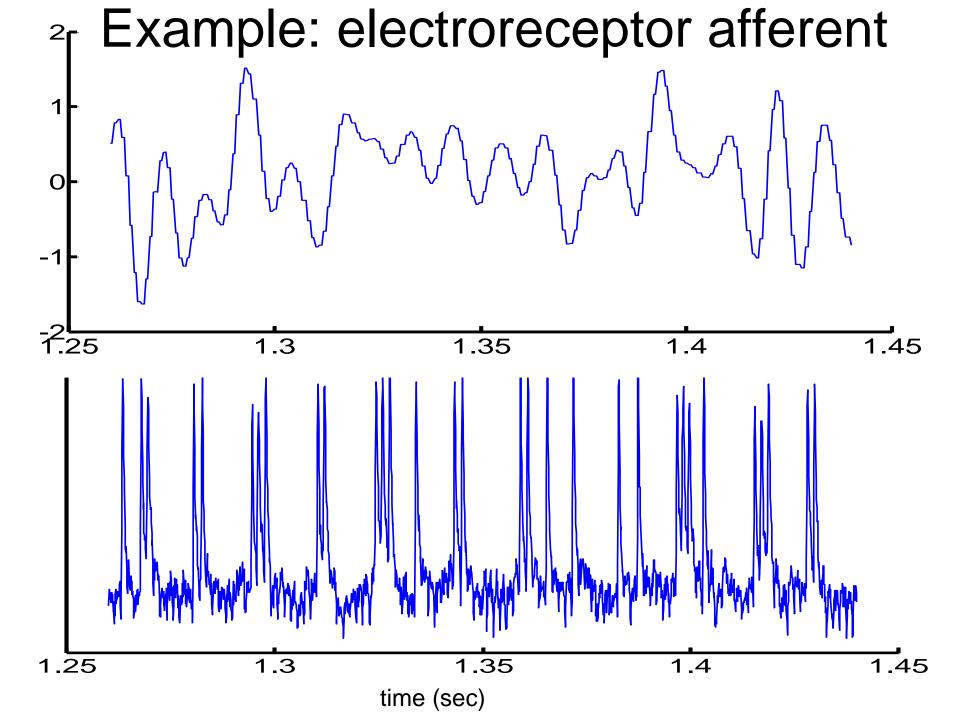


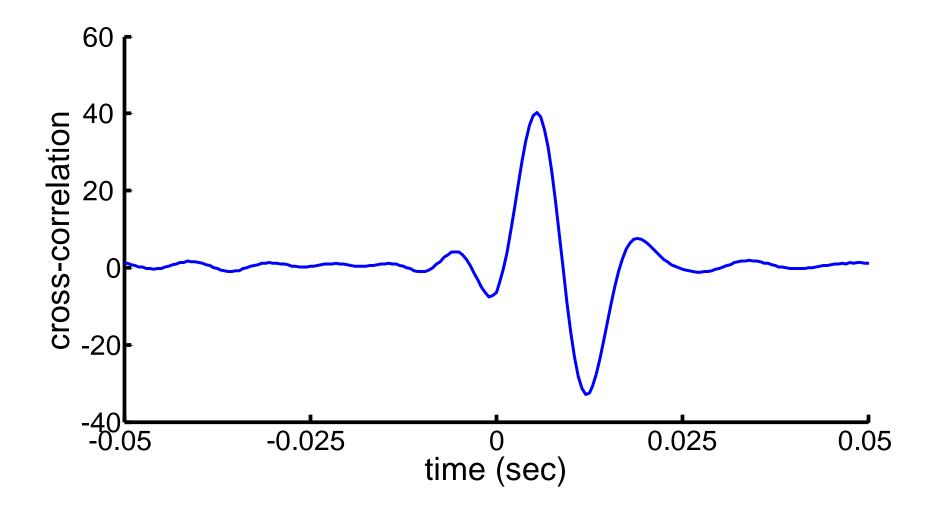
Cross-Correlation Function

$$C(t,\tau) = \langle X(t) S(t+\tau) \rangle - \langle X(t) \rangle \langle S(t+\tau) \rangle$$

For stationary processes: $C(t, \tau) = C(\tau)$

In general, $C(-\tau) \neq C(\tau)$





Cross-Spectrum

 Fourier Transform of the Cross-correlation function

Complex number in general

$$\widetilde{C}(f) = <\widetilde{X}^*(f)\widetilde{S}(f)> -<\widetilde{X}^*(f)><\widetilde{S}(f)>$$

Representing the cross-spectrum:

$$\widetilde{C}(f) = |\widetilde{C}(f)| e^{i\phi}$$

$$|\widetilde{C}(f)|$$
 : amplitude

$$\phi = \arctan\left(\frac{imag[\tilde{C}(f)]}{real[\tilde{C}(f)]}\right)$$
 : phase

Transfer functions:

$$OUT(t) = [T * IN](t) + \xi(t)$$

assume output is a convolution of the input with a kernel T(t) with additive noise. We'll also assume that all terms are zero mean.

$$\widetilde{O}UT(f) = \widetilde{T}(f)\widetilde{I}N(f) + \widetilde{\xi}(f)$$

Transfer function

Calculating the transfer function

$$\widetilde{IN}^*(f)\widetilde{O}UT(f) = \widetilde{IN}^*(f)\widetilde{T}(f)\widetilde{IN}(f) + \widetilde{IN}^*(f)\widetilde{\xi}(f)$$

multiply by: $\widetilde{IN}^*(f)$ and average over noise realizations

$$\widetilde{C}^{*}(f) = \widetilde{T}(f) \langle \widetilde{I}N^{*}(f)\widetilde{I}N(f) \rangle + \langle \widetilde{I}N^{*}(f)\widetilde{\xi}(f) \rangle$$

$$\widetilde{T}(f) = \frac{\widetilde{C}^*(f)}{\widetilde{P}_{IN}(f)}$$

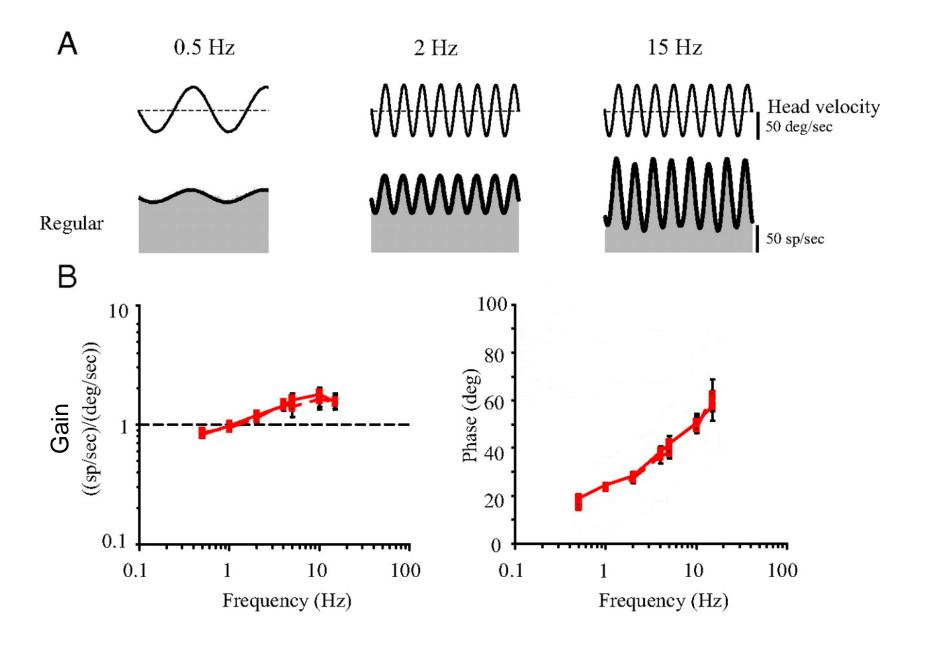
Gain and phase:

$$gain = \left| \widetilde{T}(f) \right|$$

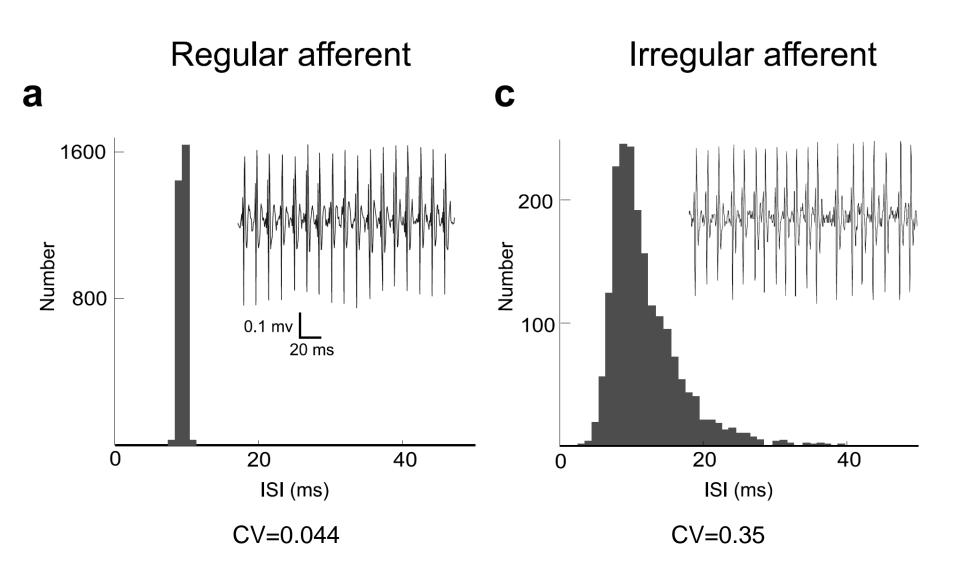
$$\phi = \arctan\left(\frac{imag[\widetilde{T}(f)]}{real[\widetilde{T}(f)]}\right)$$

Sinusoidal stimulation at different frequencies

Response **Stimulus**



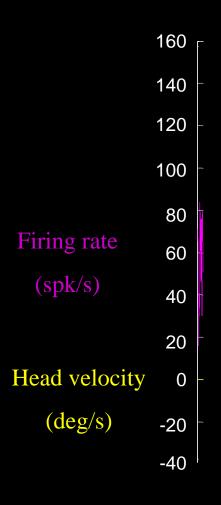
Example: vestibular afferents



Regular afferent

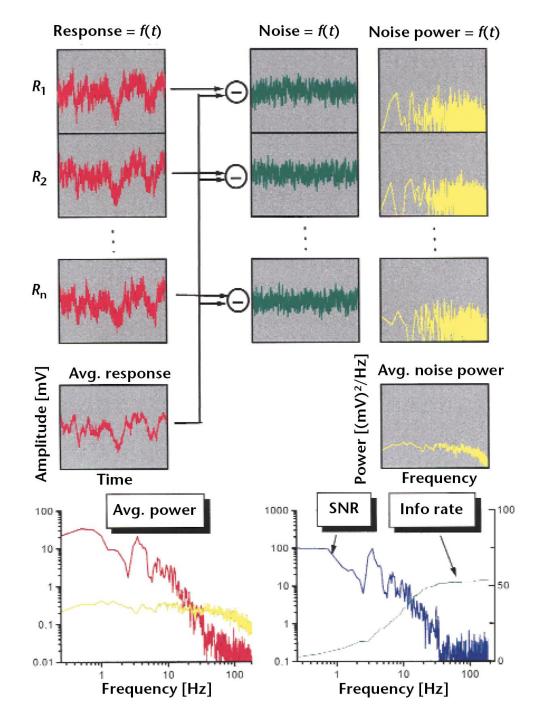


Irregular afferent



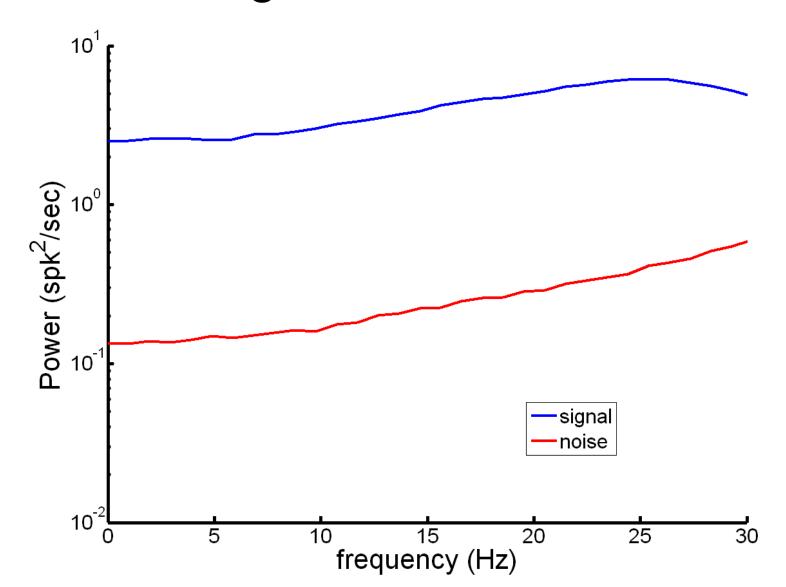
Signal-to-noise Ratio:

$$SNR(f) = \frac{P_{response}(f)}{P_{noise}(f)}$$



Borst and Theunissen, 1999

Signal and noise power for the regular afferent model



Signal and noise power for the irregular afferent model

